Review of Economics & Finance
Submitted on 12/09/2013
Article ID: 1923-7529-2014-01-33-11

The Impact of Right-to-Carry Laws on Crime: An Exercise in Replication[1]

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Abstract: In an article published in 2011, Aneja, Donohue and Zhang found that shall-issue or right-to-carry (RTC) concealed weapons laws have no effect on any crime except for a positive effect on assault. This paper reports a replication of their basic findings and some corresponding robustness checks, which reveal a serious omitted variable problem. Once corrected for omitted variables, the most robust result, confirmed using both county and state data, is that RTC laws significantly reduce murder. There is no robust, consistent evidence that RTC laws have any significant effect on other violent crimes, including assault. There is some weak evidence that RTC laws increase robbery and assault while decreasing rape. Given that the victim costs of murder and rape are much higher than the costs of robbery and assault, the evidence shows that RTC laws are socially beneficial.

JEL Classification: K42

Keywords: Shall issue law, Right to carry, Gun control, Crime

[1] The views expressed in this paper are those of the authors and not necessarily those of the U.S. Federal Trade Commission. The authors thank The Crime Prevention Research Center for its support.

1. Introduction

Shall-issue laws, also known as right-to-carry (RTC) concealed weapons laws require that officials issue concealed carry permits to all persons who meet certain legislated requirements. Aside from Illinois, the only state that still bans concealed carry, states that have not passed right-to-carry laws leave it up to the issuing authorities, typically local police or sheriff's departments, to determine whether or not to grant the applicant a concealed weapon permit. Such states, especially in urban areas, tend to issue very few concealed carry permits. An interesting policy question is whether RTC laws, which can be expected to increase the number of concealed carry permits, increase or decrease crime.

The theory is based on the cost benefit calculations that a criminal makes in deciding whether to commit a given crime. The criminal must weigh the expected gain against the expected costs. The expected gain is given by the probability of success times the monetary value of the result of a successful outcome. The expected cost is the probability of apprehension, prosecution, and a finding of guilty times the expected length of sentence. Violent crime requires personal contact between criminal and victim, entailing the additional risk of personal injury or death if the victim is armed. RTC laws would increase the probability of personal injury and death to the criminal while decreasing the probability of success of a violent crime. This by itself could be expected to reduce violent crime. In addition, criminals, knowing that ordinary citizens might be carrying firearms, but being unable to discern who is armed and who is not, are likely to increase their subjective probability of confronting an armed victim and are thereby deterred from initiating a violent crime. In this way, people who carry firearms create a positive externality by protecting those who do not carry weapons. We would therefore expect that states that pass RTC laws to find their violent crime rates reduced. The implications of the RTC law with respect to property crime are less straightforward. The implied rise in the ratio of cost to benefit of violent crime could encourage the substitution of nonviolent crime such as burglary or auto theft or it could discourage potential criminals from committing any crime at all.

The alternative argument is as follows. Because the RTC law encourages more people to carry firearms, encounters between people, more of whom are armed, could result in more violent crime. The act of carrying a firearm could cause people who would otherwise be wary of conflict to be more aggressive, the "instrumentality" effect, and the use of firearms could make the resulting altercations more deadly, the "lethality" effect, or cause more serious injuries turning common assaults into aggravated assaults.

Thus, theoretically the carrying of concealed handguns both increases and decreases violent crime. The net effect depends on the relative strengths of the deterrent, instrumentality, and lethality effects which is an empirical question.

2. The Research by Aneja, Donohue and Zhang

Recently, Aneja, Donohue, and Zhang (2011), hereafter ADZ, attempted to replicate some of the results published in the National Research Council, hereafter NRC, review of the effect of RTC laws on crime (NRC 2005, pp. 120-151). The majority of the NRC blue ribbon panel found that the evidence was too weak to determine whether or not RTC laws had any effect on crime, although some of their own regressions indicated a negative effect on murder, a result that led to a more optimistic conclusion by James Q. Wilson (NRC 2005, pp. 269-271). ADZ attempted to replicate the NRC tables, but failed. They concluded that the NRC data set provided by John R. Lott, was flawed:

> *Thus an important lesson for both producers and consumers of econometric evaluations of law and policy is to understand how easy it is to get things wrong. In this case, it appears that Lott's data set had errors in it, which then were transmitted to the NRC committee for use in evaluating Lott and Mustard's hypothesis. The committee then published tables that could not be replicated…. (Aneja, et al. 2011, p. 614)*

However, it turns out that the data were not flawed. ADZ had in fact estimated the wrong model, an error that they eventually acknowledged.

> *Subsequent to the publication of this article [Aneja, et al. 2011], members of the NRC panel demonstrated to the authors that the results in question were replicable if the authors used the data and statistical models described in Chapter 6 of the NRC (2004) report. The results presented in … the article [Aneja, et al. 2011] do not replicate the NRC results because different data and models were used in the attempted replication effort. (Aneja, et al. 2012).*

See Moody, *et al.* (2012, 2013) for further details.

In addition to failing to replicate the NRC tables, ADZ claim to have demonstrated, using a different data set and different econometric methods than those used by the NRC, that RTC laws have no significant effect on crime, except for a small positive effect on aggravated assault.

> *Overall, the most consistent, albeit not uniform, finding to emerge from both the state and the county panel data models conducted over the entire 1977-2006 period with and without state trends and using three different models is that aggravated assault rises when RTC laws are adopted. For every other crime category, there is little or no indication of any consistent RTC impact on crime. (Aneja, et al., 2011, p. 566.)*

In this paper we replicate the major ADZ results and then show that their assertion that RTC laws have no effect on crimes other than assault is incorrect because their models suffer from omitted variable bias.

3. Replicating ADZ

ADZ make an important point concerning econometric methodology. Ever since Mullainathan, *et al*. (2004), researchers doing differences-in-differences studies with panel data have tended to cluster their standard errors in an attempt to avoid biasing their t-ratios because of serial correlation. We agree, although there is a recent study that has shown that clustering in the presence of a small number of policy changes will overestimate the t-ratios (Conley and Tabor 2011). However, since 33 states have passed RTC laws in our sample period we are confident that we have a sufficiently large number of policy changes to justify clustering standard errors. ADZ also devote an entire section to a discussion of the advantages and disadvantages of controlling for individual state trends. The decision is actually quite simple. If there are good theoretical reasons for modeling the data with individual state trends (there are) and if the trends are significant as a group using a standard F-test (they are, as shown below), then they should be included in the model. In fact, under these conditions, any model that does not include state trends is misspecified due to omitted variables. On the basis of this argument, ADZ tables 2a, 2b, 3a, 3b, 4, 6a, 7a, 8a, 9a, 10a, 11a, and 13 are all invalid because of omitted variable bias.

Also, ADZ have admitted that they estimated the wrong model when they attempted to replicate the "Lott-Mustard controls" model (Aneja, *et al*. 2012). They used the arrest rate for all violent crimes for the murder, rape, robbery, and assault equations and the overall arrest rate for property crime when estimating the burglary, larceny, and auto theft equations. The correct

specification was the arrest rate for the crime in question, i.e. the arrest rate for murder in the murder equation, etc. This mistake invalidates their tables 5, 6b, and 8b. Finally, they used the wrong data set when attempting to replicate the NRC results, in that they used the data set they collected instead of the data set provided by the NRC, thus invalidating Table 1b. As a result, of the 13 tables published by ADZ, the only tables not invalidated by omitted variables or other mistakes are tables 7b, 9b, 10b, 11b, and 12. All but Table 12 report results from ADZ's "preferred controls" model. However, as we demonstrate below, their "preferred controls" model suffers from omitted variable bias, thus invalidating tables 7b, 9b, 10b, and 11b, leaving only one valid table (Table 12 which does not report regression results) out of thirteen published tables (although parts of Table 1 appear to be mistake-free).

3.1 Replication and Robustness Checks Using County Data, Violent Crime

In Table 1 below, we report our replications of ADZ Table 7b, containing the results of the estimation of their "preferred controls" model using their updated county data set for 1977-2006 (without 1993 data which is currently unavailable from the ICPSR), weighted by county population, with clustered standard errors and individual state trends. ADZ publish the results of three models: a dummy model, a post law trend (spline) mode, and a "hybrid" model which includes both a dummy and a post law trend. Since both the dummy and spline models are nested in the hybrid model, we report the results of the hybrid model only. Table 1 shows that we can replicate the ADZ results exactly. None of the coefficients on either the RTC dummy or post law trend are significant at the .05 level, including those in the assault equation. Thus, ADZ in their "preferred controls" model using county data do not find that RTC laws significantly increase assault. Note that the F-tests for the individual state trends are all highly significant, indicating that the results from their "preferred controls" model without the state trends are rejected by the data.

Table 1. Replication of ADZ Table 7b (county data)

	Murder	Rape	.Robbery	Assault
Dummy	-.0297	-.1296	.0148	-.0022
Post-law trend	-.0035	-.0646	-.0085	.0061
Pr(state trends)	**.0000**	**.0000**	**.0000**	**.0000**
	Burglary	Auto Theft	Larceny	
Dummy	-.0325	.0229	-.0235	
Post-law trend	-.0186	-.0101	-.0221	
Pr(state trends)	**.0000**	**.0000**	**.0000**	

Notes: values taken from application of ADZ do-files to ADZ data downloaded from Donohue's website. Bold numbers indicate significance at .05 level. Pr(state trends) are the p-values from the F-test for the joint significance of the individual state trends. All data, programs and results can be downloaded from the senior author's website, http://cemood.people.wm.edu/REF.zip.

As a robustness check we engage in a simple modeling exercise. According to Ayres and Donohue (2003) "It is well known, however, that aggregation can at times lead to misleading conclusions in statistical studies. For example, the model would be misspecified if one tried to estimate a uniform effect from the RTC law while the law had systematically different effects across states." (p. 138) They cite Simpson's Paradox and aggregation bias revealed in a famous study of gender discrimination in graduate school admissions. (Bickel, Hammel and O'Connel 1975). After estimating disaggregated hybrid models they assert "We take these disaggregated (state-specific) hybrid regressions to be our most definitive results for the county based data" (Ayres and Donohue 2003, p. 143).

We took their advice and re-estimated the ADZ "preferred controls" model reported above with the dummy and post-law trend variables disaggregated to the state level. We also note that ADZ have omitted some variables which are likely to be significant in the crime equation. The fixed-effect model is a pure time series model, yet ADZ estimate a static model. We generalize their model by including a lagged dependent variable to capture dynamic effects. Also, ADZ include only six demographic variables, the proportion of black and white males age 10-19, 20-29, and 30-39. While these groups may represent the majority of criminals, other age/race/gender variables may represent potential victims. For example the proportion of young women could have an effect on the number of rapes while the number of old people could have an effect on robbery. We include a complete set of demographic variables (all age groups, by three racial categories, black, white, and other, and both genders). Finally, we include the assault rate and robbery rate in the murder equation because many murders begin as assaults or robberies, and these variables also control for the overall level of violent crime. (Cook and Ludwig 2006) These crimes are not simultaneous with the murder rate because if more than one crime is committed in a single incident only the most serious crime is counted in the FBI crime statistics. Thus, if a murder occurs in the course of a robbery, only the murder is counted.[2]

We estimate this more general crime equation and then engage in a number of diagnostic tests. The first is whether the demographic variables are significant as a group. We also test the individual state trends for significance as a group. We find that the state trends are always highly significant and should not be omitted, thus rejecting all the ADZ models where these trends are omitted. We test whether the control variables omitted by ADZ but included in our general model are significant as a group. This test is called a "parsimonious encompassing test" (PET) by Hendry (1993, pp. 511-532). If the omitted variables are significant as group, then the ADZ "preferred controls" model is mis-specified. Also, we test the null hypotheses that the individual state coefficients on the dummy and the post-law trend are equal across states. If these tests are significant, then the coefficients are not equal and the ADZ aggregate model is rejected by the data. As a final exercise, we use a theorem by Wallace (1964) and Rao (1971) which states that dropping variables with t-ratios less than one will reduce the mean square error (variance plus bias squared) of the remaining variables, thus improving the regression estimates.

We treat the demographic variables and individual state trends as groups, but drop those controls with very low t-ratios from the ADZ set of "preferred" controls (lagged prison population (prison_1), lagged police (lpolicerate), real per capita personal income (rpcpi), real per capita unemployment insurance payments (rpcui), real per capita income maintenance payments (rpcim), real per capita pension payments (rpcrpo), the unemployment rate (unemp), and the poverty rate (povrate). We test the dropped variables as a group using a standard F-test. This is the same parsimonious encompassing test (PET) we used to test the ADZ controls omitted from the generalized ADZ model. If this test is not significant, we are justified in dropping the control variables in question. This allows us to estimate different models for different crimes. There is no theoretical reason to suppose that all crime equations have identical specifications, an implication of the ADZ one-size-fits-all approach to modeling crime.

Table 2 reports the results for rape and robbery. We concentrate on violent crime to conserve space and because violent crime has much higher victim costs than property crime. The RTC dummy and post-law trend entries report the population weighted sum of the individual state coefficient estimates. In these instances Stat refers to the corresponding F-test that the weighted sum is zero. Otherwise, the control variable coefficients have the usual t-ratios.

[2] Using lagged robbery and assault rates in the murder equation did not affect the results.

Table 2. Alternative models for rape and robbery, county data

	Rape				Robbery			
	General Model		Specific Model		General Model		Specific Model	
	Coeff	Stat	Coeff	Stat	Coeff	Stat	Coeff	Stat
RTC dummy	-0.0168	0.16	-0.0124	0.09	0.0068	0.06	0.0061	0.05
post-law trend	**-0.0811**	**8.18**	**-0.0797**	**9.14**	0.0033	0.13	0.0023	0.06
Yt-1	**0.3288**	**6.10**	**0.3291**	**6.04**	**0.3358**	**3.92**	**0.3357**	**3.92**
prison_1	0.0003	0.83			-0.0035	-1.71	-0.0003	-1.18
lpolicerate2	-0.0003	-0.20			-0.0011	-1.06	-0.0010	-1.02
Rpcpi	**-0.0115**	**-3.66**	**-0.0111**	**-3.46**	-0.0035	-1.71	-0.0037	-1.86
Rpcui	0.0000	0.11	0.0001	1.33	0.0000	0.22		
Rpcim	0.0001	1.23	-0.0089	-1.24	0.0000	1.01	0.0000	1.08
Rpcrpo	-0.0087	-1.21			-0.0029	-0.50		
Unemp	-0.0056	-0.44			0.0085	0.93		
Povrate	-0.0078	-0.91			0.0098	1.31	0.0115	1.39
Density	**-0.0321**	**-6.65**	**-0.0314**	**-6.60**	**-0.0290**	**-4.37**	**-0.0295**	**-4.45**
Test	P-value		P-value		P-value		P-value	
demographics	**0.0000**		**0.0000**		**0.0000**		**0.0000**	
state trends	**0.0000**		**0.0000**		**0.0000**		**0.0000**	
equal(dum)	**0.0000**		**0.0000**		**0.0000**		**0.0000**	
equal(trend)	**0.0000**		**0.0000**		**0.0000**		**0.0000**	
ADZ spec	**0.0000**		**0.0000**		**0.0000**		**0.0000**	
PET			0.6921				0.6644	

Notes: bold numbers indicate significance at the .05 level, two-tailed. The RTC dummy and post-law trend coefficients are the population weighted sum of the individual state coefficients. Stat refers to F-tests of the null hypothesis that the weighted sum coefficients is zero for the dummy and post-law trend, and standard t-ratios for the control variables. Demographics is the p-value for the F-test for the significance of the demographic variables as a group, state trends is p-value for the F-test for the significance of the individual state trends as a group, equal (dummies) is the p-value of the F-test on the equality of the coefficients of the RTC dummy across states, equal (trends) refers to the test of equality of the post-law trend coefficients across states, and ADZ spec refers to the joint significance of the variables included in the general murder model that are omitted from ADZ's "preferred controls" model; PET is the p-value for the parsimonious encompassing test for the specification of the specific model. The ADZ county data set is used for all calculations. All results data and programs can be downloaded from the lead author's website, http://cemood.people.wm.edu/REF.zip.

We also report the p-values for the five specification tests for each model: joint significance of the demographic variables, joint significance of the individual state trends, equality of the RTC dummy coefficients across states, equality of the post-law trend coefficients across states, and a test for omitted variables from the ADZ "preferred controls" model. All five specification tests are highly significant, indicating that the aggregate ADZ "preferred controls" model is rejected by the data for all five tests. That is, ADZ omit relevant demographic variables, omit individual state trends, omit a lagged dependent variable, and estimate an aggregate model which incorrectly assumes that the coefficients are equal across states. In addition to the five specification tests listed

above, we report the P-value for the PET for the specific model which tests for the joint significance of the variables dropped from the general model. If this test is not significant, then the specific model is a valid reduction of the general model. This modeling exercise allows us to create a parsimonious model for each crime that does not necessarily include exactly the same controls as all the other crimes. We note that the coefficient on the post-law trend is negative and significant at the .05 level in the rape equation, indicating that, in contrast to the ADZ results reported in Table 1, RTC laws will tend to reduce rape over time. In the ADZ hybrid model the coefficient on the post-law trend is much more important than the coefficient on the dummy variable. If the signs of the coefficients on the dummy and the trend are the same, then they reinforce each other. However, if the signs differ, the trend dominates because, holding everything else constant, as t goes to infinity the effect of the post-law trend will eventually swamp any effect of the dummy variable (see Moody and Marvell 2008).[3]

Table 3 reports the results of the same simple modeling exercise for murder and assault. The general assault equation has the same control variables as the models reported in Table 2.

Table 3. Alternative models for murder and assault, county data

	Murder				**Assault**			
	General Model		Specific Model		General Model		Specific Model	
	Coeff	Stat	Coeff	Stat	Coeff	Stat	Coeff	Stat
RTC dummy	-0.0213	1.40	-0.0218	1.46	0.0164	0.47	0.0224	0.87
post-law trend	**-0.0220**	**7.36**	**-0.0216**	**8.37**	0.0153	2.80	0.0128	2.25
yt-1	**0.0691**	**3.14**	**0.0692**	**3.14**	**0.5990**	**7.16**	**0.5991**	**7.17**
Ratrob	**0.0009**	**2.81**	**0.0009**	**2.82**				
Rataga	**0.0011**	**5.53**	**0.0011**	**5.57**				
prison_1	-0.0004	-1.94	**-0.0004**	**-2.05**	0.0000	0.20		
lpolicerate2	-0.0003	-0.43			0.0008	0.77		
Rpcpi	**-0.0056**	**-2.66**	**-0.0056**	**-2.65**	-0.0022	-1.14	-0.0023	-1.19
Rpcui	0.0001	0.85			0.0000	-0.03		
Rpcim	0.0000	-0.30			0.0000	0.59		
Rpcrpo	-0.0013	-0.25			0.0001	0.02		
Unemp	-0.0147	-1.53	-0.0149	-1.63	0.0006	0.08		
Povrate	-0.0052	-1.10	-0.0053	-1.16	0.0091	1.17	0.0096	1.15
Density	0.0183	1.48	0.0183	1.48	**-0.0165**	**-4.26**	**-0.0164**	**-4.39**
Test		P-value		P-value		P-value		P-value
demographics		**0.0000**		**0.0000**		**0.0000**		**0.0000**
state trends		**0.0000**		**0.0000**		**0.0000**		**0.0000**
equal(dummies)		**0.0000**		**0.0000**		**0.0000**		**0.0000**
equal(trends)		**0.0000**		**0.0000**		**0.0000**		**0.0000**
ADZ spec		**0.0000**		**0.0000**		**0.0000**		**0.0000**
PET				0.8415				0.9370

Notes: (1) See notes to Table 2 above; (2) Ratrob and rataga are robbery and assault rates.

[3] As *t* goes to infinity the crime rate goes to positive infinity if the coefficient on the trend is positive or zero if the coefficient is negative.

We note that the ADZ "preferred controls" model is again rejected by the data for both the assault and murder equations. We find, using our more general disaggregated model, that neither the dummy nor the post-law trend for assault is significant at the .05 level, confirming the ADZ results that RTC laws have no significant effect on assault in models with state trends estimated on county data. The results with respect to the murder equation are, on the other hand, much different from those reported by ADZ. The robbery rate, assault rate, lagged dependent variable and demographics are all highly significant, indicating that the ADZ murder equation is misspecified.

In addition, the F-test for the variables included in our model but excluded by ADZ is highly significant, indicating that the ADZ model suffers from significant omitted variable bias and is decisively rejected by the data. We find that the post-law trend is negative and significant at the .05 level. This is consistent with the hypothesis that RTC laws cause a long run reduction in murder. We also note that the effect of prison on murder was not significant at the .05 level in the general equation, but is negative and significant in the specific model after the highly insignificant variables were removed. The parsimonious encompassing test, PET, is not significant. Thus the specific model is a valid reduction from the general model, whereas the ADZ "preferred controls" model is not a valid reduction from the more general model.

3.2 Replication and Robustness Checks Using State Data, Violent Crime

In Table 4 we report our replications of the ADZ "preferred controls" model estimated on state data. We report the hybrid model only for the same reasons as above

Table 4. Replication of ADZ Table 9b

	Murder	Rape	Robbery	Assault
Dummy	.0011	-.0370	.0217	.0368
Post-law trend	.0083	.0019	.0044	**.0321**
Pr(state trends)	**.0000**	**.0000**	**.0000**	**.0000**
	Burglary	Auto Theft	Larceny	
Dummy	.0165	**.0926**	.0199	
Post-law trend	-.0027	**-.0211**	.0020	
Pr(state trends)	**.0000**	**.0000**	**.0000**	

Notes: values taken from application of ADZ do-files to ADZ data downloaded from Donohue's website. Bold numbers indicate significance at .05 level. Pr(state trends) are the p-values from the F-test for the joint significance of the individual state trends. All data, programs and results are available for download from the senior author's website, http://cemood.people.wm.edu/REF.zip

We are able to replicate the ADZ Table 9b results exactly. We note that the F-test for the significance of the individual state trends is highly significant, indicating that the ADZ models that omit these trends are rejected by the state level data.

Again, following the advice of Ayres and Donohue, we disaggregate the ADZ "preferred controls" model and repeat the simple modeling exercise using the ADZ state data set for the four violent crimes. The results are presented in Table 5. The ADZ "preferred controls" models are again decisively rejected by the data. The beneficial effects on rape found in the county data are not confirmed using the state data set. We find, however, a positive coefficient on the dummy variable for robbery using state data, indicating a one-time shift in the mean of robberies after the passage of an RTC law.

Table 5. Alternative models for rape and robbery, state data

	Rape				Robbery			
	General Model		Specific Model		General Model		Specific Model	
	Coeff	Stat	Coeff	Stat	Coeff	Stat	Coeff	Stat
Dummy	-0.0134	2.24	-0.0100	1.67	**0.0258**	**9.11**	**0.0279**	**8.66**
Trend	0.0033	0.93	0.0007	0.06	0.0012	0.09	-0.0006	0.03
Yt-1	**0.5059**	**11.70**	**.5260**	**13.28**	**0.6046**	**21.91**	**0.6026**	**21.77**
prison_1	0.0000	-0.57			**-0.0005**	**-2.89**	**-0.0005**	**-2.86**
lpolicerate	0.0002	0.98			**-0.0005**	**-2.31**	**-0.0005**	**-2.30**
Rpcpi	0.0000	-0.51			0.0000	1.66		
Rpcui	-0.0001	-0.98			0.0000	-0.12		
Rpcim	0.0003	1.90	**0.0003**	**2.26**	0.0001	0.57	0.0001	0.51
Rpcrpo	**-0.0001**	**-4.11**	**-0.0001**	**-3.56**	**-0.0001**	**-2.61**	**-0.0001**	**-2.55**
Unemp	-0.0068	-1.58	**-0.0067**	**-2.07**	0.0076	1.07	0.0076	1.42
Povrate	0.0022	1.49	0.0018	1.21	0.0022	1.28		
Density	-0.0002	-1.29	-0.0002	-1.83	0.0002	1.22	0.0002	1.30
Test		P-value		P-value		P-value		P-value
Demographics		**0.0000**		**0.0000**		**0.0000**		**0.0000**
state trends		**0.0000**		**0.0000**		**0.0000**		**0.0000**
equal(dum)		**0.0000**		**0.0000**		**0.0000**		**0.0000**
equal(trend)		**0.0000**		**0.0000**		**0.0000**		**0.0000**
ADZ spec		**0.0000**		**0.0000**		**0.0000**		**0.0000**
PET				0.5216				0.2654

Notes: (1) See notes to Table 2; (2)Bold numbers indicate significance at the .05 level.

We also repeated our modeling exercise with respect to murder and assault using the state data set. The results are presented in Table 6.

Table 6. Alternative models for murder and assault, state data

	Murder				Assault			
	General Model		Specific Model		General Model		Specific Model	
	Coeff	Stat	Coeff	Stat	Coeff	Stat	Coeff	Stat
dummy	0.0036	0.09	0.0028	0.07	-0.0022	0.06	-0.0024	0.07
Trend	**-0.0146**	**5.81**	**-0.0142**	**6.30**	**0.0117**	**9.94**	**0.0118**	**13.46**
yt-1	**0.1514**	**3.36**	**0.1525**	**3.43**	**0.6446**	**28.39**	**0.6437**	**28.79**
Ratrob	**0.0014**	**5.38**	**0.0014**	**5.47**				
Rataga	**0.0002**	**2.26**	**0.0002**	**2.14**				
prison_1	**-0.0005**	**-3.31**	**-0.0005**	**-3.35**	-0.0001	-1.26	-0.0001	-1.26
lpolicerate	-0.0002	-0.78			0.0000	-0.20		
Rpcpi	0.0000	0.31			0.0000	-0.04		
Rpcui	0.0001	0.64			-0.0002	-1.58	-0.0002	-1.66
Rpcim	0.0001	0.58			-0.0002	-1.78	**-0.0002**	**-2.23**

Rpcrpo	0.0000	0.17			0.0000	-0.73		
Unemp	**-0.0156**	**-2.81**	**-0.0138**	**-2.57**	0.0012	0.28	0.0013	0.28
Povrate	-0.0049	-1.90	-0.0050	-1.96	**-0.0037**	**-2.55**	**-0.0037**	**-2.54**
Density	**0.0007**	**2.88**	**0.0007**	**3.27**	0.0002	1.27	0.0002	1.30
Test		P-value		P-value		P-value		P-value
Demographics		**0.0000**		**0.0000**		**0.0000**		**0.0000**
state trends		**0.0000**		**0.0000**		**0.0000**		**0.0000**
equal(dummies)		**0.0000**		**0.0000**		**0.0000**		**0.0000**
equal(trends)		**0.0000**		**0.0000**		**0.0000**		**0.0000**
ADZ spec		**0.0000**		**0.0000**		**0.0000**		**0.0000**
PET				0.6398				0.8896

Notes: (1) See notes to Table 2; (2) Bold numbers indicate significance at the .05 level.

With respect to assault, the results estimated on county data are not confirmed. The post-law trend for assault is now significantly positive. On the other hand the results estimated on county data are confirmed in the state data set for murder. The post-law trend for murder is again significantly negative in both the general and specific model. RTC laws are again found to have a negative and significant effect on murder.

Unlike the results from county data, the RTC dummy variable for robbery is positive and significant, as is the post-law trend for assault. RTC laws therefore have a positive indirect effect on murder through robbery and assault. However, the results not affected if we adjust for the indirect effect of robbery and assault. There is a small 0.6% increase in the mean and virtually no change in the trend. The small increase in the mean is eliminated in the first year of the post-law trend.

Overall, the only robust, consistent effect using a general disaggregated model on both county and state data is that RTC laws reduce murder. Even if we accept the relatively weak findings that RTC laws increase assault and robbery and decrease rape, we would have to conclude that RTC laws reduce crime in terms of victim costs. We take victim costs from the standard source (Miller, Cohen, and Wiersema 1996). The costs are adjusted to 2012 dollars using the consumer price index for urban consumers, all items.[4] In 2012 dollars the costs of a murder is $4.3 million, the other crime costs are: rape $127,312, robbery $11,707, assault $13,756, burglary $2,409, auto theft $5,414, and larceny $541. Thus, the victim cost of a murder is over 300 times that of an assault and a rape is almost ten times the cost of an assault or a robbery. For this reason, we argue that, even if we accept the weak evidence that RTC laws increase assault and robbery, they also reduce murder and rape. Thus we are led to conclude that RTC laws reduce the victim costs of crime. Any policy, such as repealing RTC laws, that increases murder and rape while decreasing assault and robbery fails a cost-benefit test and is clearly disadvantageous for women.

4. Summary and Conclusions

ADZ tried to replicate the NRC tables and failed. They also tried to model the effect of RTC laws on crime. Their models suffer from significant aggregation bias and significant omitted variable bias. The most robust result, confirmed on both the ADZ county and state data sets is that the net effect of RTC laws is to decrease murder. This is consistent with the theory that the deterrent effect of concealed firearms is greater than the instrumentality and lethality effects.

[4] ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt

There is no robust, consistent evidence that RTC laws have any significant effect on other violent crimes. However, there is some evidence from state data only that RTC laws may also increase robbery and assault. This could reflect a higher instrumentality effect of firearms for those crimes. There is also some evidence from county data only that RTC laws decrease rape. RTC laws could increase the proportion of women who carry concealed weapons. If so, the increased probability of encountering an armed victim could be a powerful deterrent to potential rapists. In any case, given that the victim costs of murder and rape are orders of magnitude greater than those of robbery and assault, we conclude that RTC laws are socially beneficial.

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