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State gun laws and the movement of crime guns between states★

Leo H. Kahane

Department of Economics, Providence College, 1 Cunningham Square, Providence, RI, 02918, United States

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ABSTRACT

Previous research by Kahane (2013) and Knight (2013) studied the relationship between differential state gun laws and the movement of crime guns between states using ATF gun tracing data for 2009. The basic result from these earlier studies is that crime guns tended to flow out of weak-law states and into strict-law states. This paper builds on these earlier studies by employing previously unavailable ATF data on crime gun recoveries for multiple years and with information on the 'time to crime' aspects of gun recovery. Furthermore, a larger scope of state gun laws is considered. Using the gravity model of trade to model crime gun flows, the empirical results find robust results for five state gun laws that are negatively related to interstate crime gun exports: state laws requiring inspections of federally licensed dealers, required permits or licenses for gun purchases, prohibiting individuals with domestic violence-related restraining orders from possessing guns, required reporting of lost or stolen firearms by gun owners, and laws granting local authorities with discretion in deciding whether to grant a concealed carry permit. Furthermore, estimated coefficients for various state gun laws are significantly larger (in absolute terms) when short time to crime gun data are used in comparison to data for all crime gun flows (regardless of time to crime). Given a short time to crime aspect is considered by law enforcement as a key indicator of illegal gun trafficking, previous research by Kahane (2013) and Knight (2013) likely underestimated the relationship between state gun laws and the movement of crime guns between states.

1. Introduction

In 2015 the Bureau of Alcohol, Tobacco, Firearms and Explosives (ATF) reported that 271,018 guns were recovered from crime scenes and were submitted for a trace to determine when and where they were first purchased. Of these, 190,538 (about 70 percent) were successfully traced to the original purchase location.[1] Given the location where these guns were recovered, a total of 53,548 of them (about 28 percent) were purchased in a different state. The ATF analyzes the movement of these 'crime guns' along with a 'time-to-crime' (TTC) measure, equal to the time that elapsed between the original purchase of the gun and when it was recovered at a crime scene. A short TTC (under three years) is a strong indicator of illegal gun trafficking, (Department of the Treasury, 2000). By this definition, 11,556 guns may have been trafficked between states in 2015. This movement of crime guns between states is a concern to state government officials and is the focus of this paper.

Among the factors related to the flow of crime guns between states are the differences in state gun laws that govern who is allowed to purchase a firearm, the process involved in purchases, and laws regarding the oversight of gun dealers. Previous research by Kahane (2013) and Knight (2013) produced empirical evidence that crime gun flows were related to differential state gun laws with crime guns flowing from weak-law states into strong-law states. Both of these previously published papers used ATF crime gun tracing data from 2009, the only year available at the time. Since the publication of these two papers the ATF has released substantially more data and greater details about the TTC for crime gun recoveries.[2]

The goal of this paper is threefold. First, with the availability of multiple years of ATF trace data, a more robust empirical estimation will be implemented. Second, given data regarding the time-to-crime, this information will be used to estimate more precisely the relationship of various state gun laws on the movement of guns that were more likely trafficked.[3] And third, the Kahane (2013) and Knight (2013) papers studied the effects of ten state gun laws on

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E-mail address: lkahane@providence.edu

[1] Bureau of Alcohol, Tobacco, Firearms and Explosives (2017).

[2] The data used by Kahane (2013) and Knight (2013) were obtained from a study produced by Mayors Against Illegal Guns, (2010).

[3] The 2009 tracing data from Mayors Against Illegal Guns, (2010) did not provide a time-to-crime measure.

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the movement of crime guns. These laws were identified in the Mayors Against Illegal Guns (2010) publication as being key factors in curbing illegal gun trafficking. This paper expands upon this list of laws and considers the relationship of sixteen state gun laws on the movement of crime guns between states.

The basic findings strongly support the earlier work by Kahane (2013) and Knight (2013) that differential state gun laws are correlated with the flow of crime guns between states with guns flowing out of states with weak gun laws and into states with strong gun laws. The focus on guns with a short TTC produced estimated effects for several state gun laws that were significantly larger in magnitude than those found for all traced guns regardless of their time to crime. This result suggests that the estimated relationship of various state gun laws on crime gun flow discussed in Kahane (2013) and Knight (2013) were likely underestimates. Lastly, the present research finds a larger number of laws that are related to crime gun flows than what was found in the earlier research. Key laws include those that put greater oversight on gun dealer behavior (e.g. state required inspections of federally licensed dealers) and laws that put greater oversight on buyers (such as requiring purchase permits and mandatory reporting of lost or stolen guns).

2. Model and estimation methodology

In order to study the effects of differential state gun laws on the movement of crime guns between states this paper follows Kahane (2013) by employing a gravity model of trade.[4] While the gravity model has been widely used to study trade between nations, as noted in Kahane (2013), it has been sparingly employed at the state level.[5] Eq. (1) provides the general expression:

$$T_{ijt} = \alpha_0 Y_{it}^{\alpha_1} Y_{jt}^{\alpha_2} \left(Y_{it}/P_{it}\right)^{\alpha_3} \left(Y_{jt}/P_{jt}\right)^{\alpha_4} D_{ij}^{\alpha_5} A_{ijt}^{\alpha_6} \quad (1)$$

The variable T_{ijt} is the number of crime guns exported from state i to state j in year t. The variables Y_{it} and Y_{jt} are real GDP values for states i and j in year t. P_{it} and P_{jt} are state population values for states i and j in year t. Distance between the geographic centers for states i and j is represented by D_{ij} and is measured in kilometers. In addition to simple distance between states, two additional 'proximity' measures are included in the estimated models. One is simply a dummy variable labeled *contiguous*, equal to one if two states share a border, zero otherwise. It is assumed that sharing a border would facilitate the movement of crime guns between states. The other proximity variable included is a measure labeled *remote*. This measure, computed for each state, is equal to the average distance to all other potential trading partners. Anderson (1979) provides an argument for the inclusion of such a measure which essentially says that if two regions (states) are more geographically isolated from other potential trading partners, then they will likely have more trade with each other in comparison to pairs of states that are less isolated, all else equal. Lastly, A_{ijt} is a vector of other factors that may influence the flow of crime guns between states. Included is a measure of police presence, computed as the number of police officers per 1000 people. As noted in Kahane (2013), the effect of greater police presence has an ambiguous effect on the flow of crime guns. On the one hand, greater police presence (in the exporting and/or importing state) may reduce the flow of crime guns between states as it increases the probability of being caught in the act of committing a crime with a gun. On the other hand, greater police presence my lead to greater apprehension rates of criminals using guns during the commission of a crime.[6]

The other main components of A_{ijt} are the presence of various state gun laws in the source state (from which crime guns are 'exported') and recovery states (where crime guns are eventually recovered). As discussed in Kahane (2013), the expected effect of differential state gun laws between the source and recovery states is such that guns would tend to flow out of 'weak law' states and into 'strong law' states. The reasoning behind this expectation can be illustrated with an example. Suppose an individual in the state of California wishes to acquire a handgun for use in criminal pursuits but is prevented by law from legally purchasing one. It may be difficult and costly for this person to acquire an illegal handgun in California as California's gun laws are among the strictest in the country. It may be easier and less costly for this person to acquire a gun from a nearby state, such as Nevada or Arizona, which have very weak gun laws in place. Or, put differently, individuals who are involved in illegal gun trafficking may find it more profitable to acquire guns in states where gun laws are lax and sell them on illegal gun markets in states with strict gun laws. In this scenario, differential state gun laws may create comparative advantage differences between states where a state with a lower relative cost (i.e. weaker gun laws) is able export crime guns to states with higher relative costs (i.e. stricter gun laws).

A total of sixteen state gun laws are included in A_{ijt}, each of which falls into one of five different categories. Table 1 provides a description of each gun law considered. The categories include: laws regarding gun dealer oversight, restrictions on the types of guns allowed for sale, laws regarding buyer oversight, laws that ban certain individuals from possessing guns, and a law that specifically makes gun trafficking illegal. In some cases the state gun laws considered herein run parallel to federal laws. For example, the Federal Gun Control Act of 1968 includes language that tasks the ATF with the responsibility of inspecting federal firearms licensees (FFLs) for the purpose of "...ensuring compliance with the record keeping requirements."[7] Included in the sixteen laws considered in this paper is one that requires *state* inspections of licensed gun dealers. This parallel law may be important given that the ATF has had difficulty keeping up with their required inspections of licensed gun dealers. Indeed, according to a 2013 Department of Justice report, the "ATF did not meet its goal of inspecting all FFLs on a cyclical basis, resulting in over 58 percent of FFLs not being inspected within 5 years," (U.S. Department of Justice Office of the Inspector General Evaluation and Inspections Division, 2013, p. ii).

We will begin by following Knight (2013), where differential state gun laws between source and recovery states are represented as the difference between two dummy variables, one for the source state and one for the recovery state, for each of the sixteen laws. In addition, these differences are lagged one period to account for the fact that some gun laws may have been implemented late in a calendar year and as such may have not been in place long enough to have a measurable impact on crime gun movement. As an example of the constructed difference in law dummies, we can consider the variable $inspection_{t-1}$, which captures whether either state has a law in place in the previous year that requires state FFL inspections. This variable takes on one of three values. It will be 0 if both states have or don't have this law in place in the previous year. It will have

[4] See the work by Rose (2000, 2004) for examples of expanding the factors entering gravity models of trade. Regarding the theoretical justification for gravity model of trade, see: Anderson (1979); Bergstrand (1985), 1989) and Anderson and van Wincoop (2003). Anderson (2011) provides a literature review discussing the development the gravity model of trade.

[5] Wolf (2000) and Michalski and Ors (2012) employ gravity models to study trade flows of goods between states. Knight (2013) employs a model which has elements similar to a gravity model.

[6] Reverse causality is possible with regard to police presence. That is, states with higher crime rates committed with guns in one period may devote more police resources to combat such crimes in subsequent periods. Regressions using lagged police presence data produced nearly identical results to those that employ contemporaneous police presence data.

[7] The Gun Control Act of 1968, Public Law 90-618. Title 18 U.S.C. Chapter 44.

Table 1
State gun law descriptions.

Category	Law	Description
	sales records	All private sellers and licensed dealers are required to keep and retain records of handgun sales.
Dealer Oversight	*sales reports*	All private sellers and licensed dealers are required to report handgun sales records to the state.
	inspection	State law requiring mandatory police inspections of dealers.
	junk gun	Ban on the sale of 'junk guns' (sometimes called 'Saturday night specials').
Gun Type Resrictions	*assault weapons ban*	Bans the sale of assault pistols and other assault weapons.
	magazine cap	Bans the sale of assault pistol ammunition and other large capacity magazines.
	permit	Buyers must have a license or permit to purchase a handgun.
	may issue	Law provides authorities with discretion in deciding whether to grant a concealed carry permit.
	gun show	Background checks must be performed for sales of handguns at gun shows.
Buyer Oversight	*lost or stolen*	Firearm owners are required to report any and all loss or theft of their firearms.
	one gun per month	Buyers can purchase no more than one handgun per month with no or limited exceptions.
	waiting period	Waiting period is required on all handgun purchases from dealers.
	mental health check	Background checks for private sales require a search of state mental health records (may or may not include licensed dealers).
Possession Bans	*restraining order*	State law prohibits domestic violence-related restraining order subjects from possessing firearms.
	violent misdemeanor	State law that prohibits individuals from possessing a handgun when they have committed a violent midemeanor pubishable by less than one year in prison.
Trafficking	*trafficking prohibited*	No person may purchase a handgun with the intent to re-sell to a person who is prohibited from buying or possessing a firearm.

a value of 1 if the source state has the law and the recovery state does not in the previous year. Lastly, it will have a value of -1 if the source state does not have the law in place in the previous year, but the recovery state does. When the source state has the law in place and the recovery state does not, it is expected that crime gun exports would be reduced. In the opposite case, crime gun exports are expected to be greater. Both of these scenarios are examples of crime guns tending to flow out of 'weak law' states and into 'strong law' states.

While using the difference of the source and recovery states' dummy variables for the sixteen laws is convenient as it reduces the number of estimated coefficients in the regression model, it does come at a price. Specifically, it assumes that the impact of a gun law in the source state has the same magnitude of impact as it does in the recovery state, but in the opposite direction. Further, the difference in the dummy variables, when equal to zero, does not distinguish between the case where both states have the law in place versus neither state having the law in place. In order to consider these possibilities the model in Eq. (1) will also be estimated with separate dummy variables for the laws in place in the source and recovery states.[8] An interaction term for each of the laws will also be included to capture the case where both states have a given law in place.

3. Volume and direction of crime gun exports

The number of crime gun exports has grown steadily over the period of 2010–2015.[9] Fig. 1a shows that a total of 41,612 guns were recovered in 2010 and this figure to grew to 53,548 in 2015, with a growth rate of about 4.8 percent per year. Crime gun exports with a short time to crime (under three years) grew at a faster pace. Fig. 1b shows that in 2010 there were a total of 6781 short time to crime exports. This figure grew to 11,556 in 2015, with a growth rate of about 11.2 percent per year. As shown in Table 2, which provides state-pair summary statistics for gun export for 2010–2015, there were on average 18.2 crime guns that flowed between one state to another. There were about 3.4 crime guns exports between states with a short time to crime. Fig. 2 displays a heatmap of short time to crime gun exports per 100 thousand people (averaged over the

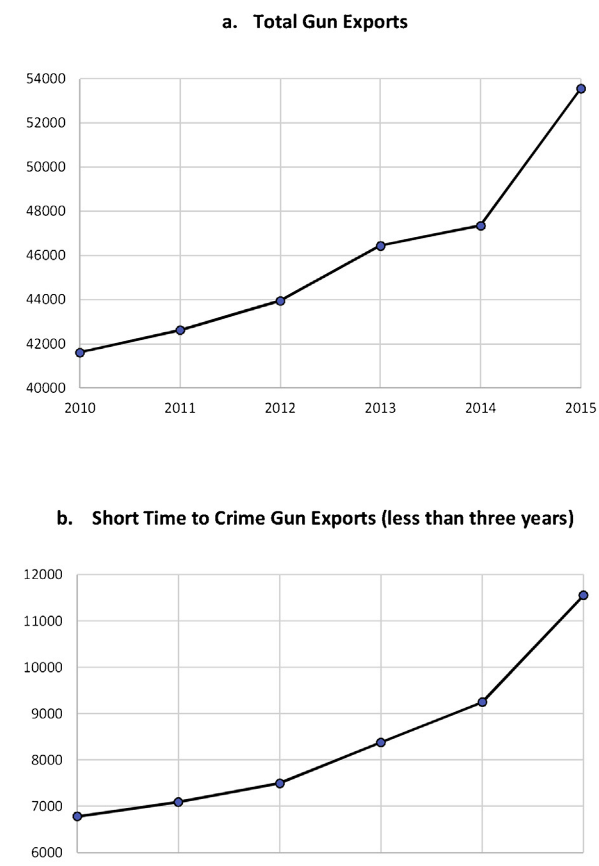

Fig. 1. Crime Gun Exports. (a) Total Gun Exports. (b) Short Time to Crime Gun Exports (less than three years).

Table 2
Crime gun exports, 2010-15, by time to crime. (n = 14,700).

Time to Crime	Mean	Std. Dev.	Min	Max
<3 months	0.367	2.050	0	75
3 months to <7 months	0.403	1.887	0	66
7 months to <1 year	0.485	2.097	0	76
1 year to <2 years	1.129	4.368	0	160
2 years to <3 years	1.055	3.893	0	139
>3 years	14.779	41.573	0	940
All traced guns	18.218	54.200	0	1450
Short TTC (<3 years)	3.439	13.569	0	510

[8] This is the approach used in Kahane (2013).

[9] Note that crime gun export figures only include guns that were recovered at a crime scene in a state other than where the gun was originally purchased. The total number guns recovered at crimes scenes, which includes guns purchased and recovered in the same state, is much larger.

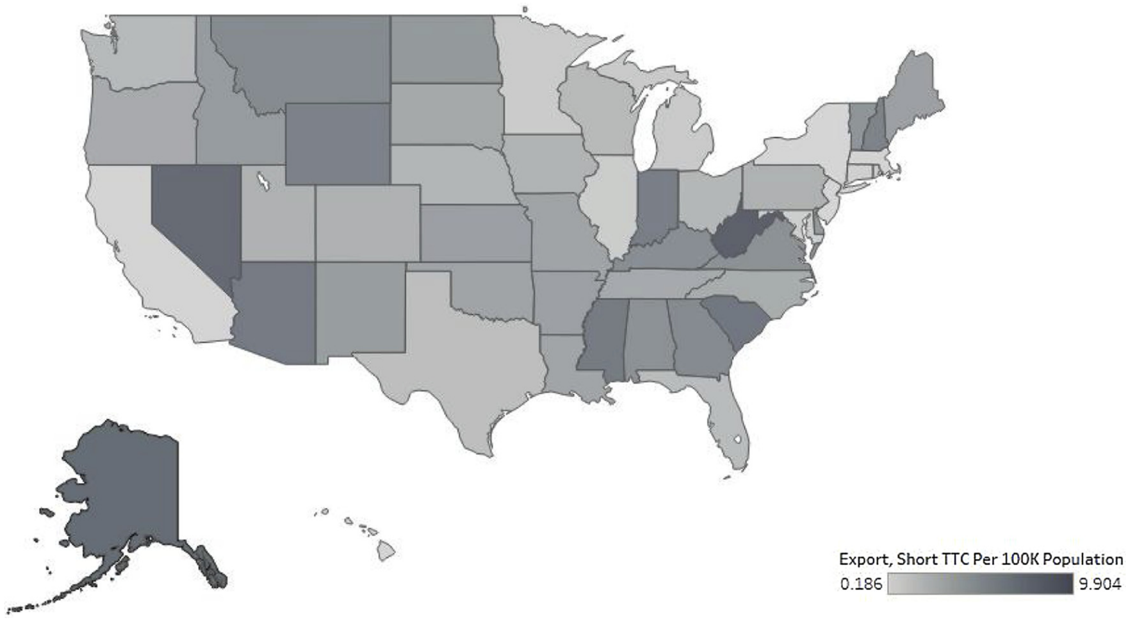

Fig. 2. Crime Gun Exports with Short TTC, per 100k Population (Averaged over 2010–2015).

Table 3
Top and bottom ten net exporters of crime guns, 2010-15.

Top Ten Net Exports Per 100 k Population			Top Ten Net Exports Short TTC Per 100k Population		
State	Year	Net Exports	State	Year	Net Exports
West Virginia	2010	41.77	Nevada	2015	12.42
West Virginia	2013	40.80	West Virginia	2015	9.81
West Virginia	2014	40.51	West Virginia	2014	8.11
West Virginia	2015	39.42	Vermont	2015	7.99
Mississippi	2015	39.07	Arizona	2015	7.91
Mississippi	2013	37.31	Wyoming	2015	7.68
Mississippi	2010	36.19	Montana	2015	7.65
Mississippi	2012	34.97	Mississippi	2015	7.62
Mississippi	2014	33.84	West Virginia	2010	7.56
West Virginia	2011	33.53	West Virginia	2013	7.45
Bottom Ten Net Exports Per 100k Population			**Bottom Ten Net Exports Short TTC Per 100k Population**		
State	Year	Net Exports	State	Year	Net Exports
Illinois	2012	−21.73	New Jersey	2015	−4.25
Illinois	2014	−21.78	Illinois	2011	−4.45
Maryland	2010	−22.26	Illinois	2012	−4.69
Illinois	2015	−23.71	Maryland	2011	−4.84
Maryland	2011	−26.01	Illinois	2014	−4.96
Maryland	2012	−26.36	Maryland	2012	−5.18
North Dakota	2014	−27.30	Maryland	2014	−6.38
Maryland	2014	−28.28	Illinois	2015	−6.42
Maryland	2013	−30.09	Maryland	2013	−6.96
Maryland	2015	−35.33	Maryland	2015	−10.16

period of 2010–2015) and shows a clustering of major exporters in the south-eastern region of the U.S. as well as in the west with significant exports coming from Nevada and Arizona.

In terms of net exporters, Table 3 presents data on net exports of crime guns (overall and short time to crime) per 100 thousand people, averaged over the period 2010–2015. The top half of the table shows the top ten exporters. Dominating this group are West Virginia and Mississippi for all exports, and Nevada and West Virginia for all short time to crime exports. The bottom half of this table shows the bottom ten net exporters. Illinois and Maryland dominate this group with both being the largest net *importers* of crime guns (overall and with short time to crime).

There are some major channels of crime gun flows. Table 4 shows the top ten export-import state pairs over the 2010-15 period for all gun flows and short time to crime flows. Also included in the table is the percent of the sixteen state gun laws considered in this paper in place in the exporting and importing states. Two common elements appear in this table. First, the state pairs are generally two states that are close to each other, and in many cases share a border (e.g., Nevada and California, Arizona and California, Pennsylvania and New York, Pennsylvania and New Jersey). Second, in every case the source state has a smaller (often much smaller) percentage of the sixteen laws in place compared to the recovery state. This result is in agreement with the earlier discussion noting that crime guns are generally expected to flow from 'weak law' states into 'strong law' states. Several of the major channels shown in Table 4 fall along the notorious 'Iron Pipeline' – a reference to the Interstate 95 highway on the east coast that connects several weak

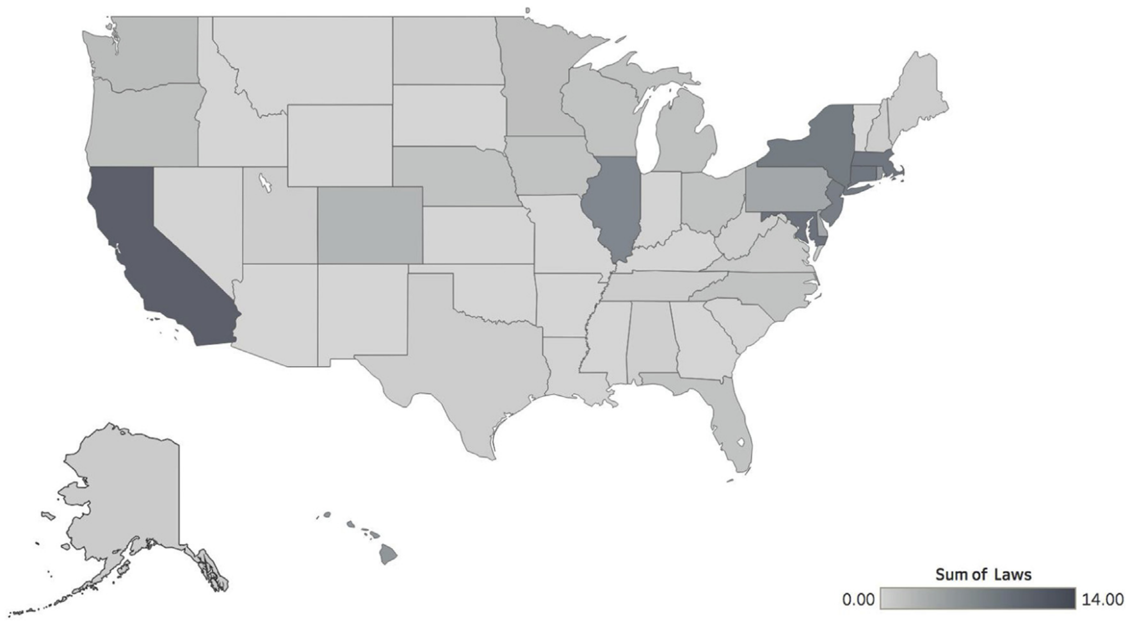

Fig. 3. The Number of State Gun Laws in Place (Averaged over 2010–2015).

Table 4
Major channels of crime gun movement, 2010-15.

Total Gun Exports over 2010-15 and Percent of 16 Laws in Place				
Exporter	% 16 Laws	Importer	% 16 Laws	Total Guns
Arizona	0.0	California	87.5	6605
Indiana	2.1	Illinois	56.3	6391
Nevada	1.0	California	87.5	4033
Virginia	8.3	Maryland	71.9	3013
Georgia	0.0	Florida	12.5	2789
Texas	6.3	California	87.5	2724
Virginia	8.3	New York	65.6	2539
South Carolina	2.1	North Carolina	12.5	2491
Pennsylvania	31.3	New York	65.6	2194
Georgia	0.0	New York	65.6	2128
Total Short TTC Gun Exports over 2010-15 and Percent of 16 Laws in Place				
Exporter	% 16 Laws	Importer	% 16 Laws	Total Guns
Arizona	0.0	California	87.5	1909
Indiana	2.1	Illinois	56.3	1781
Nevada	1.0	California	87.5	1215
Virginia	8.3	Maryland	71.9	722
South Carolina	2.1	North Carolina	12.5	632
Georgia	0.0	Florida	12.5	564
Pennsylvania	31.3	New Jersey	62.5	516
Texas	6.3	California	87.5	510
Pennsylvania	31.3	New York	65.6	486
Georgia	0.0	New York	65.6	484

law states, like Virginia and Georgia, to strong law states further north, such as Maryland and New York.[10]

4. Weak and strong law states

The strictness of state gun laws varies greatly across states. Fig. 3 displays a heatmap of the U.S. for the sum of the sixteen laws, (averaged over the period 2010–2015), that are in place. California is shaded the darkest indicating it had the greatest number of these laws (14) in place over the period. Maryland (11.5), Connecticut (11), Massachusetts (11), New York (10.5), New Jersey (10), and Illinois (9) have the next six highest totals. In contrast, there are fifteen states that had none of these laws in place.[11] These states are clustered in the South and Midwest regions of the U.S.

Over the six years covered in this study there were several changes in the number of the sixteen laws in place (see Table A1).[12] The average number of laws in place was 2.62 in 2010. This figure dropped slightly, then rose to 2.98 in 2015. Several states did noticeably increase their totals. In 2013 Connecticut increased their total by two laws, and Delaware increased their total by four. In 2014 Washington dramatically increased their total, going from one to six laws in place. Oregon increased their total by two laws in 2015. Other states, in fact, reduced their totals. Michigan, South Carolina and Virginia each reduced their totals by one law in 2012. Alabama reduced their total by one in 2013. Wisconsin reduced their total by one 2011, and did so again in 2015. Of all the states with an increase in their total number of laws between 2010 and 2015, the average number of laws in place over the entire period was 5.23. The average number of laws in place for states with a decrease in their total was one. These results suggest a pattern of law changes where strong-law states became stronger and weak-law states became weaker.

As discussed earlier, crime guns are expected to flow from weak-law states into strong-law states. Fig. 4 contains a plot with the number of short TTC gun exports per 100 thousand people averaged over the period 2010–2015 on the vertical axis, and the average number of the sixteen laws in place during that period. The downward-sloping solid line is the simple least-squares regression line for these two measures. The negative slope is consistent with the theory that crime guns tend to flow from weak-law states into strong-law states. Of course, this graph is only suggestive as there are many factors affecting the movement of crime guns between

[10] For a discussion of the 'Iron Pipeline' see, "Target on Trafficking: New York Crime Gun Analysis," published by the State of New York's Office of the Attorney General, (available at: https://targettrafficking.ag.ny.gov/trafficking-report.pdf).

[11] Alaska, Arkansas, Arizona, Georgia, Idaho, Kansas, Kentucky, Missouri, Mississippi, Montana, New Mexico, Oklahoma, South Dakota, Vermont and Wyoming.

[12] The source for state guns laws is the database created and maintained by Michael Siegel. The database and codebook can be downloaded at: http://www.statefirearmlaws.org/. The database contains information on over 130 laws implemented (or removed) by all 50 states dating from 1991 onward.

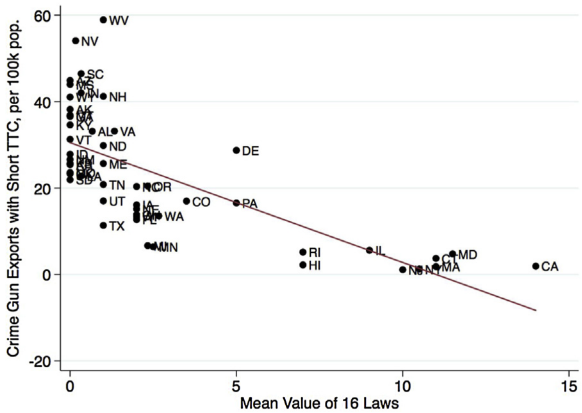

Fig. 4. Mean Crime Gun Exports and State Gun Laws.2010–2015.

Table 5
Summary statistics for state gun laws, 2010–2015 (n = 14,700).

Laws	Mean	Std. Dev.	Min	Max
sales records	0.200	0.400	0	1
sales reports	0.170	0.376	0	1
inspection	0.040	0.196	0	1
junk gun	0.127	0.333	0	1
assault weapons ban	0.110	0.313	0	1
magazine cap	0.120	0.325	0	1
permit	0.254	0.435	0	1
may issue	0.203	0.402	0	1
gun show	0.194	0.396	0	1
lost or stolen	0.140	0.347	0	1
one gun per month	0.067	0.249	0	1
waiting period	0.177	0.381	0	1
mental health check	0.157	0.363	0	1
restraining order	0.410	0.492	0	1
violent midemeanor	0.090	0.286	0	1
trafficking prohibited	0.270	0.444	0	1

Table 6
Summary statistics of covariates (n = 14,700).

Variable	Mean	Std. Dev.	Min	Max
real GDP (millions of 2015 $)	333820.50	406862.60	28782.54	2458535.00
real GDP per capita	0.052	0.010	0.034	0.087
police (per 1000 people)	2.029	0.477	0.169	3.529
remote (km)	1973.037	848.590	1285.671	6596.538
distance (km)	1979.390	1468.497	62.259	8229.413
contiguous	0.086	0.280	0	1

states. A more careful modeling of the movement of crime guns is warranted and can be implemented by estimating the model provided earlier in Eq. (1). The next section discusses the methodology used to estimate Eq. (1) and the specific explanatory variables employed.

5. Estimation methodology and data description

The expression in Eq. (1) is non-linear in parameters and thus the direct application of ordinary least-squares estimation is not possible. The typical approach in a case like this is to linearize the equation by taking natural logs of both sides of the expression. Indeed, this was the approach of Tinbergen (1962), and it has been the approach of many other researchers who have worked with the gravity model of trade.[13] This approach, however, has several drawbacks. First, given the log of zero is not defined, a log transformation approach will eliminate all cases where trade is equal to zero.[14] If it is the case that these zero values are not randomly distributed across state-pairs, then excluding them may introduce a sample selection bias. Another approach that has been used is to add an arbitrarily small amount to zero values so that their log can be computed.[15] However, work by Flowerdew and Aitkin[note: this should not be the end of the paragraph. It should continue as one paragraph down to footnote 16.]

(1982) and Santos Silva and Tenreyro (2006) show that such an approach can lead to misleading results as the estimated coefficients in a regression using this approach can be sensitive to the size of the amount added to zero trade values. Both Flowerdew and Aitkin (1982) and Santos Silva and Tenreyro (2006) suggest an alternative estimator, specifically the Poisson pseudo-maximum-likelihood (PPML) estimator. The PPML estimator has several qualities that make it a desirable choice. First, it can naturally handle zero values for the dependent variable thus avoiding the loss of information that these cases may contain. Second, it produces consistent estimates that are robust to various forms of heteroskedasticity which, as Santos Silva and Tenreyro (2006) emphasize, can be a serious empirical problem when estimating gravity equations. Third, the dependent variable is, in fact, a count variable. In this case, PPML is well-suited for such a dependent variable.[16]

Given the panel data nature of the data set employed two other sets of control variables are included. First, in order to take into account year-specific factors that may potentially affect the flow of crime guns across all states, year dummies are included in all estimations. Second, each observation in the data set has a source state and a recovery state. Given six years of crime gun export data, this means that each state-pair (source state and recovery state) is observed six times. This gives rise to the possibility of employing state-pair fixed effects in regressions. However, the within-pair variances of the state gun laws considered in this paper are quite small. For this reason, fixed effects at a more aggregated level (specifically, census division pairs) are employed.[17]

As noted earlier, the data set employed covers the 50 states over the period 2010–2015. The resulting state-pair sample contains 14,700 observations. Descriptive statistics for the 16 laws considered in this paper are presented in Table 5. The most common state gun law in place is *restraining order*, which is present in about 41 percent of the observations. The least common law is *inspection*, only appearing in approximately 4 percent of the observations. Table 6 contains summary statistics for the other covariates employed in the regression models.

6. Empirical results

The main regression results for estimating Eq. (1) appear in Table 7. The pseudo-R^2 value is 0.742 indicating a good overall performance of the regression. The results reported have standard errors clustered at the state-pair level. A regression using a clus-

[13] For example: Anderson and van Wincoop (2003); Rose (2000, 2004). Knight (2013) also uses a log transformation.
[14] In the present study, of the total 14,700 state-pair values over the years 2010-15, approximately 21 percent of the crime gun export values are zero. Approximately 52 percent of short time-to-crime export values are zero.
[15] See, for example: McCallum (1995); Raballand (2003).
[16] An alternative to the PPML when it comes to count data is the negative binomial estimator. Regressions using the negative binomial estimator produced very similar results.
[17] Briggs and Tabarrok (2014) employ census division-pair fixed effects in a state panel data regression analysis for similar reasons. There are 9 census divisions. Thus, there are a total of 9x9 = 81 possible division pairs for each pair of states.

Table 7
Short time to crime gun exports regressions.

Variables		Variables	
ln(real GDP$_s$)	0.856***	*assault weapons ban$_{t-1}$*	−0.217***
	(0.0403)		(0.0827)
ln(real GDP$_r$)	0.892***	*magazine cap$_{t-1}$*	−0.108
	(0.0366)		(0.133)
ln(real GDP per capita$_s$)	−1.878***	*permit$_{t-1}$*	−0.248***
	(0.233)		(0.0583)
ln(real GDP per capita$_r$)	−0.802***	*may issue$_{t-1}$*	−0.165**
	(0.214)		(0.0771)
ln(police per capita$_s$)	−0.252***	*gunshow$_{t-1}$*	−0.0845
	(0.0805)		(0.0966)
ln(police per capita$_r$)	0.108	*lost or stolen$_{t-1}$*	−0.335***
	(0.0824)		(0.0880)
ln(distance)	−0.975***	*one gun per month$_{t-1}$*	0.0473
	(0.0923)		(0.0720)
ln(remote$_s$)	0.359	*waiting period$_{t-1}$*	−0.162*
	(0.327)		(0.0962)
ln(remote$_r$)	1.632***	*mental health check$_{t-1}$*	−0.173
	(0.275)		(0.115)
contiguous	0.872***	*restraining order$_{t-1}$*	−0.117**
	(0.0851)		(0.0472)
sales record$_{t-1}$	−0.183**	*violent misdemeanor$_{t-1}$*	0.0783
	(0.0914)		(0.142)
sales report$_{t-1}$	−0.0479	*trafficking prohibited$_{t-1}$*	−0.0664
	(0.0834)		(0.0479)
inspection$_{t-1}$	−0.577**	*year dummies*	yes
	(0.225)	*division pair fixed effects*	yes
junk gun$_{t-1}$	0.0341	Observations	14,700
	(0.0896)	Pseudo-R^2	0.742

Robust standard errors, clustered at the state-pair level, in parentheses. Census division pair fixed effects inluded.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

tering at the census division-pair level produced virtually the same results regarding statistical significance.[18]

Regarding the estimated coefficients, the positive and significant coefficients for the log of real GDP suggest that crime gun exports are increasing with this measure in both the source and recovery states, (subscript *s* denotes the source state, subscript *r* the recover state). The estimated elasticities are 0.86 for the source state, and 0.89 percent for the recovery. These results are similar, albeit somewhat smaller to those found in Kahane (2013). The positive coefficients suggest that larger economies may be associated with larger markets for crime guns as transactions are facilitated in 'thicker' markets.[19]

The estimated coefficients to the log of real GDP per capita are negative and significant with the coefficients for the source state being notably larger than those for the recovery state. These results are consistent with Kahane (2013) and suggest that states with wealthier populations may be less involved with the crime gun market.

Regarding the effects of police personnel, a one percent increase in the number of police per 1000 people in the source state reduces crime gun exports by about 0.25 percent. Increases in police presence in the recovery state, however, do not show a significant effect on crime gun flows.

The three measures of proximity between source and recover states, *distance, remote* and *contiguous* have the predicted signs. A one percent increase in the distance between states reduces crime gun exports by about one percent as well. The estimated 'remoteness' coefficients have a positive sign, but only the value for the recovery state is statistically significant. Lastly, sharing a border greatly increases crime gun flow. The estimated coefficient to the *contiguous* dummy variable suggests that sharing a border increases crime gun exports by about 139 percent.[20] [21]

Turning to the state gun laws, we can see in Table 7 that, of the 16 laws considered, eight are statistically significant and these eight have negative coefficients. These are: *sales record*, *inspection*, *assault weapons ban, permit, may issue, lost or stolen*, *waiting period* and *restraining order.* Recall that law variables are constructed by subtracting the law dummy in the source state from that of the recovery state. Thus, negative coefficients to these law variables show predicted reductions to crime gun flow as laws become relatively stricter in the source state.[22] The estimated coefficients to *sales record, assault weapons ban, may issue* and *waiting period* are similar in size and suggest that, when in place in the source state, they tend to be associated with an estimated 15–19.5 percent decrease in crime gun flows.[23] Regarding the law *restraining order*, the effect of this law is more modest, with an estimated reduction in crime guns on the order of 11 percent. Of the eight laws that achieve statistical significance, three stand out as having a pronounced, highly significant relationship to the flow of crime guns. The law *permit*, when put in place in the source state, is associated with about 22 percent fewer crime gun exports. The law *lost or stolen* is associated with a decrease of about 28.5 percent. The strongest estimated relationship, however, comes from the law *inspection*. The estimated coefficient suggests that when a source state has this law in place it is associated with a 43.8 percent reduction in crime gun exports. These results are consistent with previous research documenting the key role that corrupt, federally licensed gun dealers play in the diversion of guns to the illegal market.[24]

6.1. Short time-to-crime vs. all traced guns

The earlier work by Kahane (2013) and Knight (2013) utilized a single year of crime gun tracing data (from 2009) and these data included all guns successfully traced by the ATF, without distinction of the time-to-crime element. The ATF later made crime gun trace data available for 2010 and subsequent years with a breakdown by time to crime as shown in Table 2. Given the earlier discussion of how a short TTC is a strong indicator of illegal gun trafficking, the earlier work by Kahane (2013) and Knight (2013) using all traced guns may produce an underestimate of the relationship between state gun laws and crime gun exports.[25] In order to consider this possibility, the PPML regression shown in Table 7 is re-estimated using all traced guns regardless of TTC. Table 8 contains this newly estimated regression alongside the regression results from Table 7 for comparison purposes. The table also shows an empirical test for the equivalence of estimated coefficients across the two regressions.[26] The last row of Table 8 considers the simple difference between the source state's number of the 16 laws in

[18] Unclustered results produced substantially smaller standard errors resulting in all but one gun law (*junk gun*) being statistically significant.
[19] This point is made in Cook et al. (2007 p. F569).

[20] Computed as: $(e^{\alpha} - 1) \times 100$, where α is the estimated coefficient to *contiguous*.
[21] This large effect is likely being driven by the large trade flows between source states Arizona and Nevada into the recovery state of California, as well as the flow from source state Indiana into recovery state Illinois, (see Table 4).
[22] Alternatively, we can consider the cases where the recovery state *eliminates* a law, thus increasing the difference by one. The elimination of gun laws, however, is much less common than the implementation of laws.
[23] Computed as: $(e^{\alpha} - 1) \times 100$, where α is the estimated coefficient to the respective law.
[24] See: Bureau of Alcohol, Tobacco, Firearms and Explosives (2000); Cook and Braga (2001).
[25] Guns recovered at a crime scene with a longer TTC may have moved across state lines for reasons other than illegal gun trafficking. For example, gun owners who purchased a gun in one state, then later relocated to another state and subsequently lost, had stolen or sold their guns.
[26] The test of equivalent coefficient estimates was carried out with Stata's 'suest' command.

Table 8
Poisson regressions comparing short time to crime to all gun exports. (n = 14,700).

VARIABLES	Guns with Short TTC	All Traced Guns	H_0: $\beta_{short} = \beta_{all}$
sales record$_{t-1}$	−0.183**	−0.149**	0.85
	(0.0914)	(0.0701)	
sales report$_{t-1}$	−0.0479	0.0252	3.40*
	(0.0834)	(0.0613)	
inspection$_{t-1}$	−0.577**	−0.362**	5.05**
	(0.225)	(0.162)	
junk gun$_{t-1}$	0.0341	−0.0582	5.67**
	(0.0896)	(0.0711)	
assault weapons ban$_{t-1}$	−0.217***	−0.0423	15.57***
	(0.0827)	(0.0669)	
magazine cap$_{t-1}$	−0.108	−0.0957	0.04
	(0.133)	(0.102)	
permit$_{t-1}$	−0.248***	−0.169***	8.63***
	(0.0583)	(0.0477)	
may issue$_{t-1}$	−0.165**	−0.142**	0.41
	(0.0771)	(0.0587)	
gunshow$_{t-1}$	−0.0845	−0.175**	3.82**
	(0.0966)	(0.0766)	
lost or stolen$_{t-1}$	−0.335***	−0.243***	5.95**
	(0.0880)	(0.0718)	
one gun per month$_{t-1}$	0.0473	−0.00908	2.6
	(0.0720)	(0.0527)	
waiting period$_{t-1}$	−0.162*	0.00301	17.55***
	(0.0962)	(0.0760)	
mental health check$_{t-1}$	−0.173	−0.0592	4.87**
	(0.115)	(0.0822)	
restraining order$_{t-1}$	−0.117**	−0.144***	1.68
	(0.0472)	(0.0383)	
violent misdemeanor$_{t-1}$	0.0783	0.146	1.24
	(0.142)	(0.110)	
trafficking prohibited$_{t-1}$	−0.0664	0.0427	25.68***
	(0.0479)	(0.0382)	
(laws$_s$ - laws$_r$)$_{t-1}$	−0.111***	−0.0736***	65.21***
	(0.0102)	(0.00790)	

Robust standard errors, clustered at the state-pair level, in parentheses. Both regressions contain a full set of covariates, year dummies and Census division pair fixed effects. Chi-squared statistic shown for hypothesis test of equal coefficients.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 9
Poisson regression with disaggregated laws and interactions.

Gun Law	Source State	Recovery State	Interaction	Combined
sales record$_{t-1}$	0.0339	0.139	−0.213	−0.0400
	(0.135)	(0.0917)	(0.146)	(0.168)
sales report$_{t-1}$	−0.549***	−0.318***	−0.0421	−0.909***
	(0.148)	(0.112)	(0.214)	(0.182)
inspection$_{t-1}$	−0.427	−0.0215	−1.105**	−1.553***
	(0.288)	(0.203)	(0.442)	(0.459)
junk gun$_{t-1}$	0.104	0.106	−0.172	0.0380
	(0.124)	(0.124)	(0.193)	(0.226)
assault weapons ban$_{t-1}$	0.00609	0.182**	−0.809**	−0.621
	(0.206)	(0.0924)	(0.351)	(0.387)
magazine cap$_{t-1}$	0.0469	0.474***	−0.298	0.223
	(0.149)	(0.135)	(0.273)	(0.311)
permit$_{t-1}$	−0.431***	0.156*	0.225	−0.0494
	(0.106)	(0.0898)	(0.142)	(0.162)
may issue$_{t-1}$	−0.169	−0.00922	−0.379*	−0.557**
	(0.138)	(0.0870)	(0.222)	(0.231)
gunshow$_{t-1}$	0.270*	0.393***	−0.298**	0.364*
	(0.139)	(0.106)	(0.151)	(0.193)
lost or stolen$_{t-1}$	−0.394**	0.139	−0.115	−0.370
	(0.172)	(0.0962)	(0.250)	(0.291)
one gun per month$_{t-1}$	0.0413	0.170*	−0.0549	0.157
	(0.102)	(0.0877)	(0.144)	(0.152)
waiting period$_{t-1}$	−0.484***	−0.0231	0.277	−0.230
	(0.127)	(0.119)	(0.177)	(0.206)
mental health check$_{t-1}$	0.0348	0.235*	−0.199	0.0708
	(0.143)	(0.137)	(0.183)	(0.207)
restraining order$_{t-1}$	−0.153*	−0.0133	−0.0337	−0.200**
	(0.0839)	(0.0788)	(0.0876)	(0.101)
violent misdemeanor$_{t-1}$	−0.509***	−0.561***	0.612	−0.459
	(0.185)	(0.142)	(0.470)	(0.487)
trafficking prohibited$_{t-1}$	−0.252***	−0.161**	0.124	−0.288***
	(0.0726)	(0.0747)	(0.0882)	(0.102)
Observations	14,700			
Pseudo-R^2	0.757			

Robust standard errors clustered at the state-pair level in parentheses. A full set of covariates, time dummies and census division pair fixed effects included.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

place compared to the recovery state. The result in this case show that as the difference increases by one law, the short TTC regression shows an associated decrease in crime gun exports by about 10.5 percent compared to a predicted 7.1 percent decrease for all traced guns. The test of equivalent coefficients is strongly rejected.

Regarding the individual laws, the results in Table 8 show that the test of equivalent coefficients from the two regressions is rejected for ten of the sixteen laws. In eight of these ten cases the size of the estimated coefficient for the regression using guns with a short TTC is larger, in absolute terms. Of these eight laws, five have estimated coefficients in the short TTC regression that are statistically significant (*inspection*, *assault weapons ban*, *permit*, *lost or stolen* and *waiting period*). Regarding *inspection*, the short TTC regression shows an associated decrease in crime gun exports by 43.8 percent when the source state implements this law, whereas the regression for all traced guns shows a decrease of about 30.4 percent. The results for *assault weapons ban* show that the short TTC coefficient suggests an associated decrease of 19.5 percent where the results for all traced guns shows no statistical relationship. For *permit*, the estimates are a decrease of 22 percent compared to 15.5 percent. And for *lost or stolen*, the estimated decrease for short TTC exports is 28.5 percent compared to 21.6 percent for all traced guns. For *waiting period*, the short TTC results suggest a reduction of 15 percent, while the results for all traced guns are not statistically different from zero. Taken together, these results provide strong evidence that the estimated relationship of these five laws to illegal gun trafficking is larger than one would find when using the somewhat blunt measurement of all traced crime guns. Lastly, the one contrary result is for *gunshow*. Here the short TTC coefficient is not statistically significant, but the one for all traced guns suggests that this law is associated with a 16.1 percent reduction in crime gun flows. It is interesting that this particular law, which was also found to be important in Kahane (2013) when all traced guns are considered, is not statistically important in regressions using the short time to crime dependent variable. This is likely due to the fact that many secondhand guns are sold at gun shows (Bureau of Alcohol, Tobacco, Firearms and Explosives, 2017), and those later recovered at crime scenes may tend to have a time to crime that is greater than three years.

6.2. Disaggregated state gun laws

As noted earlier, using the difference in the source and recovery states' law dummies is convenient as it reduces the number of estimated coefficients to the gun laws considered. But it also restricts the effect of these laws in the source and recovery states to be equal in size, but with opposite directions. In order to relax this restriction, Eq. (1) is re-estimated using a separate dummy variable for the source and recovery states for each of the sixteen laws. In addition, it may be the case that states with matching gun laws experience even less crime gun flows compared to states with non-matching laws. In order to consider this possibility interaction terms between the source-state law dummies with the recovery-state law dummies are included. Table 9 contains the 32 estimated coefficients for the gun laws and their interaction terms. To conserve on space, the table excludes the estimated coefficients on the other covariates.[27] As can be seen in table, seven gun laws for the source state are significant (*sales report, permit, lost or stolen, waiting period, restraining order, violent misdemeanor* and *trafficking prohibited*) and all seven have the expected negative sign. The one exception is for *gunshow* that has an unexpected positive coefficient. Six of the laws for the recovery state have the expected positive sign and are significant (*assault weapons ban, magazine cap, permit, gunshow, one gun per month* and *mental health check*). Three other laws are significant, but with an unexpected positive sign (*sales report, violent misdemeanor* and *trafficking prohibited*). The four interaction terms that are significant (*inspection, assault weapons ban, may issue* and *gunshow*) all have negative coefficients indicating that when the source and recovery states have these matching laws there is an additional decrease in crime gun flows. The creation of the interaction terms, however, expectedly introduces a higher degree of multicollinearity which may lead to some of the estimated coefficients for the source and recovery states' laws losing individual significance or having the wrong signs. Thus, in order to consider the effects of matching laws the last column in Table 9 reports the combined effect of both states having the given law in place compared to the base case of neither state having the law in place. This last column shows that five laws (*sales report, inspection, may issue, restraining order* and *trafficking prohibited*) have a significantly negative relationship with crime gun flows when both states have them in place. The largest relationship appears to come from *inspection* which suggests that when both states have this law in place crime gun flows tend to be about 78 percent less compared to the case where neither state has such a law. Again, the one anomaly is the law *gunshow* which has a positive coefficient and is significant at the ten percent level.[28]

7. Conclusion

There are a lot of guns in the United States. Estimates of the gun stock range from 250 million (Cook and Ludwig, 2010) to about 310 million (Krouse, 2012). There are also many additions to the gun stock each year. In 2015 there were more than 23 million background checks carried out by federal firearms licensees, and presumably most of these were related to purchases of new guns.[29] The great majority of these gun purchases, as well as those that take place between private individuals or at gun shows, result in the acquisition of firearms by law-abiding individuals who use their weapons responsibly. However, many new and existing guns are diverted to the illegal market each year. Indeed, the Chicago Police Department confiscated 6521 illegal guns in 2015, or about one every 74 min. Baltimore police estimated they confiscated approximately 3500 in the same year.[30]

Diversions to the illegal market may occur in a variety of ways. Cook and Leitzel (2001), for example, estimate that more than half a million guns are stolen each year. The ATF reported in 2015 that over 8600 firearms were determined to be 'lost' by FFLs.[31] Unregulated sales by private individuals or at gun shows, Illegal 'straw' purchases, and corrupt FFLs are also primary sources of guns diverted to illegal markets. Many of these diverted guns are eventually trafficked out of state and end up being recovered at crime scenes. The purpose of this study was to build on the previous research by Kahane (2013) and Knight (2013) and try to understand how differential state gun laws between states are related to the pattern of interstate crime gun flows. These earlier papers employed the same data set (2450 state-pair observations from 2009), used somewhat different empirical models, and produced several shared results.[32] Namely, both papers found three state laws that were negatively related to crime gun exports: laws requiring the reporting of lost or stolen guns, laws granting local law authorities discretion as to whether to grant concealed carry permits, and state laws (that parallel federal law) against straw purchases.[33]

The present analysis employs a *significantly* larger data set and wider menu of state gun laws. ATF crime gun trace data from 2010–2015 for all state-pairs (14,700 observations in total) are employed. Further, information on the 'time to crime' element of traced guns is used to focus on crime guns recovered within three years of first being sold – a key indicator of illegal gun trafficking. A total of sixteen state gun laws and their relationship to crime gun flows are included in the empirical model.

The empirical results point to several laws that were found to be consistent across most regressions. State laws requiring inspections of FFLs (*inspect*) were found to be strongly negatively related to crime gun flows in most cases. Laws that regulate buyers in the form of required permits or licenses to purchase a handgun (*permit*) were also negatively related to crime gun exports whereas requiring a waiting period for gun purchases (*wait*) had mixed results. Two regulations for gun owners, one requiring the reporting of lost or stolen firearms (*lost or stolen*) and another that allows local authorities to use discretion with regard to issuing concealed carry permits (*may issue*) were also associated with decreased crime gun exports.[34] Lastly, laws banning the sale of assault weapons had a moderate negative relationship with crime gun exports. The estimated negative correlation of these laws with crime gun flows is shown to be generally larger when the short TTC data are used, a result that is consistent with the views of law enforcement that a short TTC is a key indicator of illegal gun trafficking.

As for policy recommendations, the current patchwork of state gun laws compromises the goal of reducing the presence of illegal guns. States looking to tighten their gun laws to make it more difficult for criminals to acquire guns face a potential negative externality when other nearby states do not have strict gun laws. This is because the adoption of stricter gun laws may incentivize criminals in these nearby states to export their 'lower cost' guns and ultimately reducing the impact of stricter gun laws for the adopting state. This negative externality is generally supported by the results presented in Table 9 showing that when both states have a given law in place there is an overall decrease in crime gun flow between them. The one exception was the result for the requirement of back-

[27] The sign, size and significance of the coefficients excluded from the table are very similar to those shown in Table 7.

[28] As noted earlier, this may be due to guns purchased at gunshows being generally older than otherwise acquired crime guns. In fact, running the separated law regression shown in Table 9 for all recovered guns (not just those with a short TTC) produced results for the *gunshow* variable that are more in line with the theory of crime gun movement discussed in this paper.

[29] Federal Bureau of Investigation, "NICS Firearm Background Checks," accessed on May 23, 2018 at: https://www.fbi.gov/file-repository/nics_firearm_checks_-_month_year.pdf/view.

[30] The Trace, "15 Statistics That Tell the Story of Gun Violence in 2015," accessed on May 23, 2018 at: https://www.thetrace.org/2015/12/gun-violence-stats-2015/.

[31] Noted in "ATF Releases 2015 Federal Firearms Licensee Theft and Loss Report," accessed on May 23, 2018 at: https://www.atf.gov/news/pr/atf-releases-2015-federal-firearms-licensee-theft-and-loss-report.

[32] Knight (2013) works with a smaller sample as Alaska and Hawaii are excluded due to their remoteness. States with zero trade flow are also excluded from the main regression analysis.

[33] Kahane (2013) also found that laws requiring permits to purchase guns, local laws (paralleling federal law) that punish FFLs for not conducting background checks, and laws requiring background checks for purchases at gun shows were negatively related to crime gun flows.

[34] Research by Khalil (2017) employs police jurisdiction-level data to show that the number of stolen firearms has a positive impact on future firearm aggravated assaults, homicides and robberies.

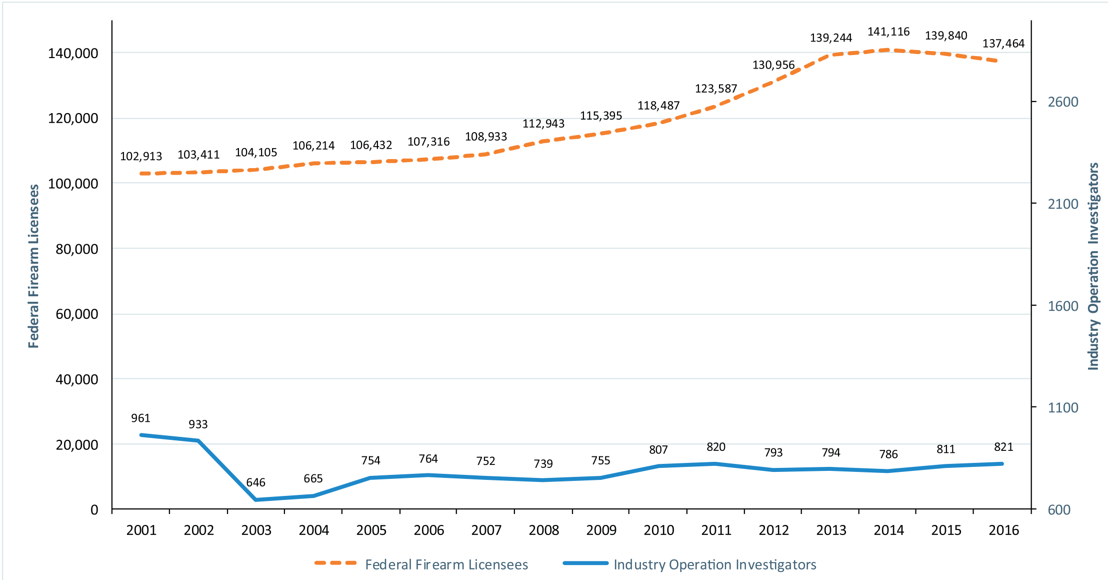

Fig. 5. Federal Firearm Licensees (FFLs) and Industry Operation Investigators (IOIs).10–2016.
Sources: FFLs — *Firearms Commerce in the United States, Annual Statistical Update, 2017*. Accessed on May 30, 2018 at: https://www.atf.gov/resource-center/docs/undefined/firearms-commerce-united-states-annual-statistical-update-2017/download. IOIs — *Fact Sheet - Staffing and Budget*, United States Department of Justice, Bureau of Alcohol Tobacco, Firearms and Explosives, Accessed on May 30, 2018 at: https://www.atf.gov/resource-center/fact-sheet/fact-sheet-staffing-and-budget.

ground checks for handguns sold at gunshows which had a positive combined relationship to crime gun flow. This unexpected result remains as an avenue for future research particularly given that the 'gunshow loophole' is a frequent topic among advocates for tighter gun control laws.

Given the compromising effect that weak law states have on reducing crime gun flows an argument can be made for the adoption of national laws that govern the purchasing process of firearms (requiring purchase permits) and the legal requirement of owners to report lost or stolen guns. In addition, the results in the present study strongly support the need for regular inspections of licensed gun dealers. While this law already exists at the federal level, the ATF is currently unable to meet its obligation to inspect FFLs. According to the ATF, of the 134,738 FFLs in fiscal year 2017 only 11,009, or about 8 percent, were inspected.[35] At that rate, it would take about 12 years before the ATF could inspect all licensed dealers, far longer than the ATF's goal of inspecting FFLs every three to five years. The primary reason for the ATF not being able to inspect FFLs in a timely way is clearly displayed in Fig. 5 which plots the number of FFLs and the number of ATF Industry Operation Investigators, (IOIs), whose job is to inspect FFLs, from 2001 to 2016. As can be seen in the graph, the number of FFLs has increased dramatically over the 16-year period by about 34 percent whereas the number of IOIs *fell* by about 15 percent. In 2001, there were about 107 FFLs per IOI, while in 2016 there were about 167 FFLs per IOI. Clearly there is a need to increase funding for the hiring of more inspectors.

Lastly, it is important to point out two ways in which the present analysis could be improved. First, given little within-state variation in state gun laws during the time period studied (see Table A1 in this regard), the finding that certain state laws are negatively related to crime gun flows stems from between state variation of gun laws. As more data on crime gun flows becomes available, a longer panel data set may allow for the effective use of state-pair fixed effects which, if employed, may lessen the possible effects of unmeasured confounding factors. Second, an issue not addressed in this paper is the possible endogeneity of state gun laws with crime gun flows. Future research may focus on efforts to deal with this possibility, perhaps employing an instrumental variables approach if suitable instruments can be found.[36]

Appendix A

Table A1
Totals and changes in the 16 state gun laws, 2010-15.

State	2010	2011	2012	Year 2013	2014	2015	Net Change
Alabama	1	1	1	0	0	1	0
Alaska	0	0	0	0	0	0	0
Arizona	0	0	0	0	0	0	0
Arkansas	0	0	0	0	0	0	0
California	14	14	14	14	14	14	0
Colorado	2	2	2	5	5	5	3
Connecticut	10	10	10	12	12	12	2
Delaware	3	3	3	7	7	7	4
Florida	2	2	2	2	2	2	0
Georgia	0	0	0	0	0	0	0
Hawaii	7	7	7	7	7	7	0
Idaho	0	0	0	0	0	0	0
Illinois	9	9	9	9	9	9	0
Indiana	0	0	0	0	1	1	1
Iowa	2	2	2	2	2	2	0
Kansas	0	0	0	0	0	0	0
Kentucky	0	0	0	0	0	0	0
Louisiana	0	0	0	0	1	1	1
Maine	1	1	1	1	1	1	0
Maryland	11	11	11	12	12	12	1
Massachusetts	11	11	11	11	11	11	0

[35] *Fact Sheet - Federal Firearms Compliance Inspections and Revocation Process*, (ATF, May 2018). Accessed on May 29, 2018 at: https://www.atf.gov/resource-center/fact-sheet/fact-sheet-federal-firearms-compliance-inspections-and-revocation-process.

[36] Given that this paper focuses on differential state gun laws between pairs of states, the likelihood that such differences are endogenous would seem to be somewhat reduced as law makers in a given state cannot determine the laws adopted in another state.

Table A1 (*Continued*)

State	2010	2011	2012	Year 2013	2014	2015	Net Change
Michigan	3	3	2	2	2	2	−1
Minnesota	2	2	2	2	3	4	2
Mississippi	0	0	0	0	0	0	0
Missouri	0	0	0	0	0	0	0
Montana	0	0	0	0	0	0	0
Nebraska	2	2	2	2	2	2	0
Nevada	0	0	0	0	0	1	1
New Hampshire	1	1	1	1	1	1	0
New Jersey	10	10	10	10	10	10	0
New Mexico	0	0	0	0	0	0	0
New York	10	10	10	11	11	11	1
North Carolina	2	2	2	2	2	2	0
North Dakota	1	1	1	1	1	1	0
Ohio	2	2	2	2	2	2	0
Oklahoma	0	0	0	0	0	0	0
Oregon	2	2	2	2	2	4	2
Pennsylvania	5	5	5	5	5	5	0
Rhode Island	7	7	7	7	7	7	0
South Carolina	1	1	0	0	0	0	−1
South Dakota	0	0	0	0	0	0	0
Tennessee	1	1	1	1	1	1	0
Texas	1	1	1	1	1	1	0
Utah	1	1	1	1	1	1	0
Vermont	0	0	0	0	0	0	0
Virginia	2	2	1	1	1	1	−1
Washington	1	1	1	1	6	6	5
West Virginia	1	1	1	1	1	1	0
Wisconsin	3	2	2	2	2	1	−2
Wyoming	0	0	0	0	0	0	0

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