Regulatory Spillovers in Interstate Crime Gun Sourcing

October 15, 2026

Abstract

How do regulations in one jurisdiction reshape economic activity across jurisdictional boundaries? We study this question in the context of interstate firearm sourcing in the United States, where regulatory authority is decentralized but firearms move across state borders. First, we develop a theoretical model based on a Ricardian framework in which the geographic origins of recovered crime guns—firearms recovered during criminal investigations and traced to their original retail sale—are determined by state-level acquisition accessibility and bilateral geographic frictions. The model delivers a gravity structure and predicts that sourcing shares decline with distance, stricter source-state regulations reduce sourcing from those states, and stricter recovery-state regulations induce substitution toward out-of-state sources. Second, using bilateral firearm tracing data from 2009–2023, we find empirical patterns consistent with these predictions. Moreover, we uncover substantial spatial heterogeneity: regulatory spillovers diminish with distance, but their magnitude and geographic reach increase with source-state population. Third, we structurally estimate the model and conduct counterfactual experiments showing how unilateral regulatory changes propagate through the national sourcing network, while regulatory harmonization redistributes sourcing shares across states. Our findings show how geographic frictions and market size shape the transmission of regulatory spillovers in a decentralized policy environment, highlighting the importance of accounting for cross-jurisdictional substitution when evaluating place-based regulations.

Keywords: Firearms; Gun Laws; Crime Guns; Regulatory Spillovers; Gravity Model
JEL Codes: D04, I18, K42

Declaration of competing interest. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

1 Introduction

Gun markets in the United States operate across state borders, while the laws governing firearm acquisition vary substantially across states. This heterogeneity creates the potential for regulatory spillovers: regulations adopted in one state may influence the geographic origins of firearms recovered both within that state and elsewhere. Firearm-tracing data reveal patterns consistent with such spillovers. Traced crime guns—firearms recovered during criminal investigations and successfully traced to their original retail sale—frequently originate outside the state in which they are recovered. In particular, states with stricter firearm regulations tend to recover a larger share of guns originally sold in more permissive states. These patterns suggest that regulatory conditions and geographic proximity may systematically shape the origins of recovered crime guns. Consequently, systematic economic forces, rather than purely idiosyncratic or local factors, shape the interstate origins of recovered crime guns.

It is important, however, not to interpret every interstate recovery as evidence of trafficking through a criminal network. An interstate source–recovery link identifies where a firearm was first sold and subsequently recovered, but does not establish how or why it crossed state lines. A firearm may move with its lawful owner, change hands through secondary-market transactions, or cross state borders following theft or an illicit transfer. We therefore study the geographic composition of recovered firearms without attributing all interstate recoveries to a particular transfer mechanism.

We develop a theoretical and empirical framework to analyze interstate firearm recoveries, drawing on insights from trade theory and the economics of crime. Adapting the sourcing structure of Eaton and Kortum (2002), we model the distribution of origins among recovered firearms as an equilibrium allocation shaped by source-state acquisition accessibility and bilateral geographic frictions. We use "flows" to describe bilateral source–recovery counts and "shares" to describe each source state's contribution to recoveries in a destination state. The model characterizes these sourcing shares, taking the total number of recoveries in each destination as given. It therefore provides a framework for studying how regulatory differences shape the composition of recovered firearms, rather than their aggregate availability.

The model delivers four main theoretical predictions. First, a source state's share of recoveries in a destination declines as bilateral geographic frictions increase. As a result, bilateral crime-gun shares exhibit a gravity-like structure, in which proximity plays a central role. Second, greater regulatory stringency in a source state, which lowers acquisition accessibility, reduces its share of recoveries elsewhere. Third, greater regulatory stringency in the recovery state raises the share of recovered firearms originating outside that state by making local sourcing relatively less attractive. This substitution mechanism concerns the composition of recoveries and does not imply an increase in their total number. This result suggests that state-level policies may reallocate, rather than eliminate, the availability of crime guns. Fourth, the effects of regulatory differences scale with population and decay with distance, indicating that policy spillovers are strongest among populous geographically proximate states.

We test these predictions using a comprehensive panel of state-level bilateral crime-gun recoveries from 2009 to 2023, combining Bureau of Alcohol, Tobacco, Firearms and Explosives (ATF) tracing records with measures of state gun laws. Our empirical strategy estimates gravity specifications motivated by the model, relating bilateral recoveries to regulatory conditions and geographic frictions while accounting for destination recovery totals, to observed patterns of bilateral crime-gun shares. We examine alternative lags of regulatory measures because firearms may be recovered many years after their original retail sale. Our identifying assumption is that lagged regulatory measures are uncorrelated with unobserved determinants of bilateral recovery shares, conditional on source-state, destination-state, and year fixed effects and the included controls. This assumption is arguably more plausible for source-state regulations, which are primarily shaped by conditions in the source state, than for destination-state regulations, which may respond to local conditions that also affect firearm recoveries.

The results support the model's central sourcing predictions. Bilateral recovery shares decline with geographic distance. Stricter source-state regulations are associated with smaller shares of firearms originating from those states, whereas stricter destination-state regulations are associated with greater reliance on out-of-state sources. Finally, the effects of regulatory differences are concentrated among geographically proximate states, consistent with distance decay in interstate spillovers. We further show that this decay is not uniform across states: the geographic reach of regulatory spillovers expands with the population of the affected state, so that policy changes in large states propagate substantially farther than comparable changes in small states – a margin not addressed in prior gravity-based studies of firearm recoveries.

The estimated effects of firearm regulations are generally larger in magnitude when laws are measured several years before recovery. This pattern is consistent with delayed policy effects and the long intervals between original retail sales and subsequent recoveries. However, estimates from separate lag specifications do not identify the full dynamic response to policy adoption. Finally, we examine which types of laws drive the results and find evidence that prohibitions against high-risk owners, possession regulations, buyer regulations, and background checks contribute to the main findings.

We next use the model to quantify how counterfactual regulatory changes alter the distribution of sources among recovered firearms. After structurally estimating bilateral frictions and state-level accessibility parameters, we use the estimated model to simulate how changes in regulatory conditions affect the sourcing shares across all destinations. These exercises capture substitution across the national sourcing network while holding geographic frictions and other fundamentals fixed. They quantify changes in sourcing composition, not changes in total recoveries or crime.

To quantify these mechanisms, we conduct two counterfactual policy experiments. The first counterfactual examines a policy change in a single large state. Motivated by ongoing debates over firearm regulation in New York, we simulate a scenario in which New York reduces its measured number of gun laws to the level observed in Texas in 2023, while keeping other states' regulations at their baseline levels. Because New York is geographically connected to several densely popu-

lated states, this experiment illustrates how policy changes in a single jurisdiction reshape sourcing patterns across the national network. The largest adjustments occur within New York itself. The model predicts a substantial increase in the share of firearms recovered in New York that were originally sold within the state. New York also becomes a more prominent source of firearms recovered elsewhere, with the strongest spillovers occurring in nearby states. In Massachusetts, New Jersey, and Vermont, the share of recovered firearms originating in New York increases, while the shares originating from local markets and alternative sources, such as Florida, decline. Spillovers to distant states are much smaller. States such as California and Texas exhibit only modest changes in sourcing patterns, including small increases in New York's contribution to their recoveries.

We then turn to a system-wide counterfactual to examine the role of cross-state regulatory differences. The second counterfactual considers a hypothetical reform in which all states adopt the median number of gun laws observed in 2023. This exercise eliminates cross-state differences in the measured law count, while holding geographic frictions and other fundamentals fixed. Equalizing law counts does not impose an identical set of regulations across states; instead, the exercise isolates the contribution of differences in the regulatory index to predicted sourcing patterns. This counterfactual illustrates how regulatory harmonization reallocates sourcing shares across the national network.

These findings have implications for the design and evaluation of state firearm policies. State-level gun laws do not operate in isolation: regulatory asymmetries generate incentives for interstate acquisition, weakening the effectiveness of strict regulations in high-control states. This substitution mechanism highlights the importance of considering interstate spillovers when evaluating state-level policies and the potential role of regional or federal coordination. The geographic concentration of these spillovers also suggests that nearby states' regulatory conditions are particularly relevant.

Our paper contributes to the literature on interstate firearm sourcing in three ways. First, we develop a theoretical model based on a Ricardian framework that characterizes the distribution of recovered firearms across source states as a function of acquisition accessibility and geographic frictions. This framework provides a structural foundation for the gravity relationships observed in interstate firearm sourcing. Second, using a bilateral panel covering 20092023, we provide empirical evidence consistent with the model's predictions regarding regulatory spillovers. We further show that these spillovers are geographically concentrated and that their magnitude increase with source-state population. Third, we structurally estimate the model and conduct counterfactual experiments to quantify how changes in state-level firearm regulations reallocate the predicted origins of recovered firearms across the national sourcing network.

The rest of the paper proceeds as follows. Section 2 discusses the related literature. Section 3 provides background on firearm tracing and interstate crime-gun recovery patterns. Section 4 develops the theoretical framework and derives testable propositions. Section 5 describes the data and estimation strategy. Section 6 presents the reduced-form results. Section 7 estimates the structural parameters and evaluates counterfactual policy experiments. Section 8 discusses the

policy implications. Section 9 concludes.

2 Related Literature

The topic of gun trafficking has been of significant interest in the economics and public health space. Webster et al. (2009) explores the effects of state-level firearm laws on gun trafficking using a cross-sectional approach and city-level (54) data from 2000 to 2002. The main outcome variable in the study was the number of "likely 'trafficked' crime guns" sold by an in-state dealer divided by the number of older (three or more years old) crime guns – also sold by an in-state dealer.[1] Webster et al. (2009) finds that the share of likely trafficked crime guns is decreasing in dealer regulations and the regulation of private sales. Surprisingly, however, Webster et al. (2009) finds no evidence that distance significantly affects the share of likely trafficked crime guns. Similarly, Collins et al. (2018) examine the share of crime guns recovered in a state that were originally sold in the same state. Using an index similar to the one we use here, they find that states with more gun laws had fewer guns traced to an in-state dealer.

A separate literature examines interstate crime gun flows using a gravity-model framework (Kahane, 2013; Knight, 2013; Andrade et al., 2020; Roberts et al., 2024). Kahane (2013) applies this approach and finds that crime guns follow patterns reminiscent of international trade: flows respond strongly to market size and especially to distance; the latter result stands in apparent tension with the null distance finding for intrastate trafficking in Webster et al. (2009). The same study also shows that interstate flows are influenced by gang activity and differences in state gun laws. Using the same 2009 recovery data, Knight (2013) derives the gravity specification from micro-foundations. A limitation of both studies is their cross-sectional design, which prevents causal claims about how changes in state gun laws affect interstate gun trafficking. Kahane (2020) builds further on Kahane (2013) by demonstrating the main results hold in a panel context – though with limited fixed effects due to the short nature of the panel (2010-2015). Roberts et al. (2024) also explores crime gun sources using a gravity model framework and reports results similar to those discussed above, while also finding that flows are higher if the source and destination states are connected via a major interstate highway. Finally, and similar to our own work, Roberts et al. (2024) shows that gun laws in the origin state decrease recoveries in the destination state, while a similar increase in destination state gun laws increases gun recoveries originating from out of state. None of these studies explore how the effects of regulations scale with population and distance.

A third area of related research involves the economic analysis of crime, illegal goods, and underground markets. Seminal work by Becker (1968) conceptualizes criminal behavior as an economic choice shaped by incentives, risks, and enforcement. Subsequent research has applied this framework to illegal drug markets, human trafficking, poaching, and tax evasion, emphasizing how enforcement, regulation, and market structure shape illicit transactions. Our paper

[1] A crime gun is defined as a gun that is recovered during the course of a criminal investigation. Likely trafficked guns are defined as guns that were recovered less than one year after their retail sale.

extends this line of inquiry by modeling firearm trafficking as an equilibrium outcome influenced by regulatory frictions and geographic distance. Firearm-specific research has primarily examined the relationship between gun regulations/gun laws (c.f., Edwards et al., 2018) and crime and/or firearm prevalence (c.f., Duggan, 2001; Wiebe et al., 2009; Siegel et al., 2013; Steidley et al., 2017; Johnson et al., 2024; Chalak et al., 2022; Johnson and Robinson, 2024). Much of this literature relies on state-level or county-level variation in firearm laws to study how legal access affects crime rates, homicides, or gun purchasing behavior. In contrast, our paper focuses on the cross-state flow of recovered crime guns - an explicitly spatial phenomenon – and shows that trafficking responds systematically to regulatory asymmetries across states.

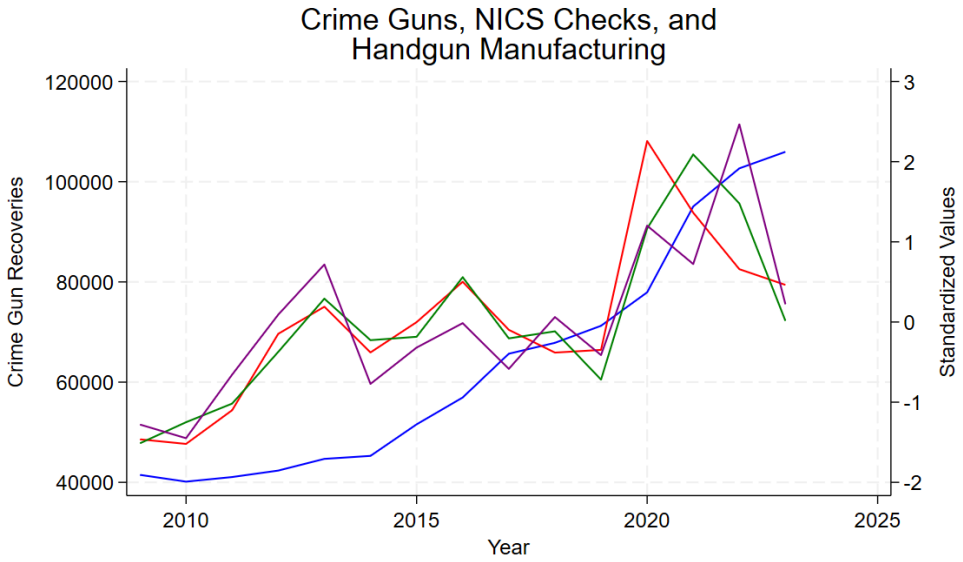
Our empirical framework is based on the gravity model, which has become a central tool for analyzing bilateral flows across a wide range of economic settings. Originally developed to explain international trade in goods, gravity models consistently document that flows decline with distance and rise with economic size and source-destination characteristics. Beyond goods markets, the gravity structure has been used to study trade in financial assets (Portes and Rey, 2005), foreign direct investment (Ramondo, 2014), cross-border digital content consumption (Broocks and Studnicka, 2025), and even the global migration of professional athletes (Hamilton, 2024). These diverse applications highlight the robustness of gravity models in capturing frictions, spatial decay, and cross-location substitutability.

We bring this framework to the study of firearm trafficking or, more technically, crime gun recoveries. Although firearms are not typically traded legally across state lines (especially handguns), the underlying economic forces – searching for lower-cost sources, regulatory arbitrage, and geographic frictions – closely mirror those governing international trade. Our structural model adapts the Eaton and Kortum (2002) Ricardian framework to an illicit market, showing that trafficking networks select source states in the same cost-minimizing manner as firms selecting suppliers in global trade. This "trade" approach has also been applied to other contexts, such as abortion. For example, Molina and Siegal (2025) finds that individuals are significantly less likely to move to states that adopt stricter abortion laws. Our work expands on this idea that there are often regulatory spillovers while also highlighting the limits of unilateral state regulation.

3 Background on Crime Guns and Gun Laws

In this section, we provide an overview of the firearm ecosystem. This includes gun manufacturing, background checks, Google searches, crime-gun tracing data, trafficking patterns, and other key empirical facts that motivate our theoretical and empirical analysis. While we use the term trafficking for narrative clarity, it is important to note that tracing events are not limited to trafficking in a strict legal sense. Many traced firearms come from possession-related offenses which, although not formally classified as trafficking, often involve informal or questionable transfers that share similar economic dynamics and blur the line between trafficking and sloppy gun stewardship. That said, as we will discuss, the mechanisms that affect trafficking are likely similar to those

Figure 1: Gun Interest/Transactions and Recoveries (2009-2023)



Notes: Number of guns successfully traced (blue) and standardized NICS checks (red), handguns manufactured (green), and Google searches with the word "gun."

that determine the share of gun owners who are likely to engage in sloppy practices.

3.1 Gun Interest/Transactions and Recoveries

In Figure 1, we present trends of standardized measures of gun transactions/interest along with the total number of guns successfully traced from 2009 to 2023. The measures of gun transactions/interest are National Instant Criminal Background Check System (NICS) Checks explicitly for a gun, handgun manufacturing, and Google Searches with the word "Gun." As expected, each of these variables moves together and shares the same ebbs and flows.

Additionally, trends in interest/transactions follow recoveries; however, recoveries are much smoother. This likely reflects that while crime gun recoveries are positively related to demand shocks, the total number of recoveries in a particular year is also more driven by the existing gun stock, which is significantly larger than the new guns produced each year. Finally, the interest/transaction data paired with the recovery data foreshadow a lagged relationship between gun recovery and original sale, with recoveries noticeably increasing in 2014, or roughly five years after the noticeable increase in interest that occurred from 2010 to 2013.

3.2 Average Time to Crime

The ATF also keeps track of the average time-to-crime by state pair. These data span 2010 to 2023.[2] Over this period, the average time to crime (which is an average of the averages) is 13.88 years. The average time to crime for guns that were recovered in the state where they were originally

[2]Similar data for 2009 was not available at the time of writing.

sold is 13.54 years, and the average time to crime for guns that were recovered in a different state from where they were originally sold is 13.90 years. This difference is not statistically significant (heteroskedastic t-test: $p = .0625$). While the means are not significantly different, the medians are. The median average time to crime for guns recovered in the same state where they were sold is 10.87 years, compared with 12.94 years for guns recovered in a different state from where they were originally sold.[3] This difference is statistically significant ($p < .001$).

Average time to crime by year and source is found in Figure 13 (Appendix) along with the overall distributions. Since 2010, the average time to crime has decreased from about 14 and a half years from 2010 to 2018 and closer to 12 years from 2020 onward. This decline is likely not due to COVID/Floyd-related unrest as the decline started in 2014 and continued until 2021, with a slight uptick occurring in 2022. The time to crime for domestic crime guns (guns recovered in the same state they were originally sold) is remarkably consistent over time, with the only obvious drop corresponding to the 2020-related unrest. This is not the case for exported crime guns.

We focus on the average time to crime because the ATF files that we use do not provide this information. Instead, the files break the time-to-crime into different bins of unequal sizes (e.g., less than 3 months, 3 to 7 months, 7 months to under 1 year, etc., with the final bin being 3 years and over). That said, we can infer some information about the median time to crime over the course of the panel based on the total number of guns recovered and the total number of guns recovered that had a time to crime under 3 years. The logic here is that if more than half of the recovered guns have a time to crime under 3 years, then the median has to be under three years.

Of the 33,840 observations (pair-years), we can find the percent of recovered guns with a time to crime less than 3 years 27,595 times; the remaining pair-years had no recoveries and are excluded. Of these cases, 2,894 have a share above 50 percent and therefore mechanically must have a median time to crime less than 3 years. On average, 21 percent of all recovered crime guns have a time to crime less than 3 years, but this share has been increasing over the panel and started at around 15 percent in 2010 and was double that in 2021 (30 percent).

The big takeaway here is that we have a range of plausible lags in which there is expected to be a relationship between gun law changes and crime gun recoveries. Large significant effects should not be seen until about the fourth or fifth lag and should decline after about the tenth to thirteenth lag.

3.3 Crime Gun Flows

To understand firearm flows, we begin by examining firearm tracing data from the ATF. Figure 14 (Appendix) presents the most common reasons for firearm tracing requests between 2012 and 2019, as published by the ATF alongside source-recovery data. Notably, explicit trafficking accounts for less than 3% of all firearm traces, indicating that most traced guns are linked to other types of offenses, including illegal possession, firearms that were found, and violent crimes. Unfortunately,

[3]Note this is the median across state-pairs of the pair-level average time-to-crime, not the median of the individual gun level time-to-crime distribution.

source-recovery data by crime is not available.

A significant share of crime guns originate from informal sources rather than traditional retail channels (Braga et al., 2002). According to the Bureau of Justice Statistics (Alper et al., 2019), 43.2% of firearms used in crimes originate from off-the-street or underground markets, while 25.3% are obtained from individuals through informal exchanges. In 2016, only 10.1 % of the guns used in crimes originated from a retail source, and much lower than what was reported in the early 90's (Harlow, 2002). These figures highlight the importance of secondary markets and informal transactions in the supply of crime guns. The persistence of underground markets suggests that firearm trafficking operates through decentralized, illicit networks rather than centralized, large-scale smuggling operations. Some of this likely reflects differences in the average "quality" of gun owners and/or predisposition to carry across states. For instance, a state like Mississippi, with relatively few gun laws and high crime, will likely have a larger share of gun owners who are legally prohibited from owning/carrying firearms in a more progressive state or who are more likely to carry a gun. If these individuals move, it will naturally lead to an increase in gun recoveries from Mississippi, but these recoveries would not be due to activity reasonably related to or classified as trafficking so long as the gun was legally acquired in the first place (e.g., a gun dealer in Mississippi).

Most crime guns are recovered in the same state where they were first sold. The majority of guns traced by the ATF are pistols (58%), though revolvers and rifles each make up about 15 %. On average, roughly 69% of guns traced by the ATF were originally sold in the domestic state, and 31% were first sold in a different state. The largest importer (California) accounted for around 14 percent of all the imported crime guns and makes up about 28 % of all the guns traced by the ATF to a state different from where they were recovered.[4] The sources of out-of-state crime guns are stable. This is shown in Figure 2, which presents the sources of crime guns for each state by census division in 2010 and 2023. In each subplot, line width and opacity indicate the number of crime guns, while the arrows indicate the direction of the flow. For example, the large arrow going from Indiana to Illinois in the top-left panel of Figure 2 indicates that a large number of guns recovered in Illinois in 2010 were originally sold in Indiana.

Figure 2 shows that several consistent patterns emerge. First, some states are persistent "non-players." These states are generally found in the New England and West North Central divisions. States in these regions neither export nor import many crime guns. Demographically, these states tend to be sparsely populated and predominantly White. Second, states with large amounts of crime (though not necessarily high crime rates) and relatively strict gun laws tend to import many crime guns, with the bulk often originating in neighboring states with fewer firearm restrictions. A slight exception is found in the Mid-Atlantic states, which frequently receive crime guns from South Atlantic states along the I-95 corridor. Third, crime gun sources tend to be geographically clustered; all else equal, border states are the most common sources of out-of-state crime guns. Finally, these networks and relationships are remarkably stable. Arizona, for example, is the largest

[4]To put some of these shares in context, the import-to-GDP ratio is roughly 14% with China–the US's largest trading partner–accounting for roughly 20 % of these imports.

source of out-of-state crime guns recovered in California in both 2010 and 2023.

There is also evidence that these patterns are shared at a more micro-level and was also recently discussed in Johnson and Robinson (2024), which introduces a measure of gun presence/dealers that implicitly adjusts for the possibility of seepage by allowing the measure of gun presence to increase (or decrease) as a function of the gun dealers in the counties adjacent to the central/queen county. This idea is later expanded on in Johnson et al. (2024), who do so with a crime-gun database much like the ATF data used here, from the state of Pennsylvania, and show that while the bulk of crime guns come from within the same county they were sold, there is seepage from outside sources. Figure 15 (Appendix) builds on this further by presenting the source of traced crime guns for the state of Pennsylvania in 2019. Here we note patterns reminiscent of those in Figure 2. Crime guns that are from out-of-country sources are often from neighboring counties and/or counties with large populations (e.g., Allegheny County is a common source of crime guns recovered in Philadelphia County). The "non-player" counties also resemble the "non-player" states and have small populations and are predominantly White.

3.4 Gun Laws, Gun Prices, and Interstate Crime Gun Flows

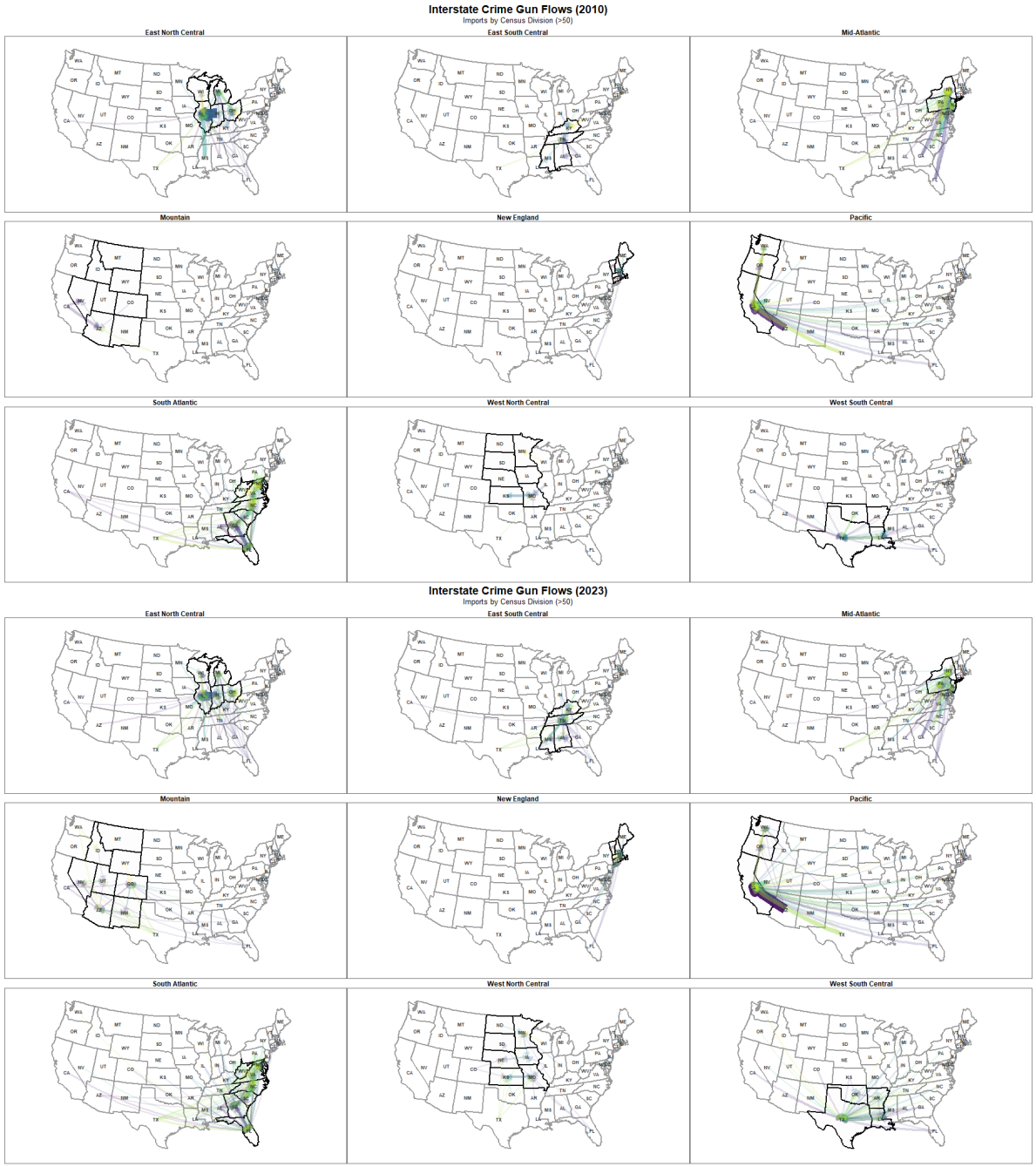
State-level gun laws share an important feature with gun sales, concealed carry permits, and gun markets: their variation is highly structured. For instance, Johnson and Topaz (2025) and Topaz and Johnson (2025) show that gun sales and gun markets are "low-dimensional," with one or two principal components explaining 85–95% of their total variance. Additionally, in panel specifications, geographic fixed effects (county or state, as appropriate) and year fixed effects jointly explain over 90% of the variance in gun sales, concealed carry permits, and NICS checks. These results suggest that much of the variation can be characterized by persistent geographic differences and common temporal patterns.

Gun laws exhibit similarly structured variation, but their temporal patterns differ. Using the updated gun law database (see Siegel et al., 2017), we regress the total number of gun laws in state i and year t on alternative combinations of fixed effects and linear trends. We estimate these specifications for both the full sample (1976–2024) and the period most relevant to our analysis (1996–2024). Table 1 reports the fit of each specification. Unlike the patterns documented for gun sales, adding year fixed effects or a common linear time trend contributes little explanatory power beyond state fixed effects. This indicates that changes in gun laws are not well characterized by a shared national temporal pattern. By contrast, adding state-specific linear trends explains nearly all remaining variation. Furthermore, these trends are strongly aligned with political leaning: the correlation between a states time trend and the vote share for Mitt Romney in the 2012 presidential election is -0.70 across both the full sample and sub-sample.

We also conduct principal components analysis with states as observations and annual gun-law totals as variables to further illustrate the structure.[5] As expected, gun laws are also highly

[5]Each years totals are standardized across states, subtracting the annual cross-state mean and dividing by the annual cross-state standard deviation. The analysis therefore captures differences in states relative positions rather than changes

Figure 2: Out of State Crime Gun Sources



Notes: Maps display the primary sources of out-of-state crime guns recovered in each destination state, organized by census division. Line width and opacity are proportional to the number of traced crime guns flowing from origin to destination. Arrows indicate the direction of flows. The top panels show 2010 patterns and the bottom panels show 2023 patterns.

Table 1: Variance Decomposition of Gun Laws

	Full Sample				1996-2024			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	No	No	No	Yes	No	No
Linear trends	No	No	Yes	No	No	No	Yes	No
State-specific linear trends	No	No	No	Yes	No	No	No	Yes
Observations	2450	2450	2450	2450	1450	1450	1450	1450
R-squared	0.7105	0.7843	0.7808	0.9540	0.9056	0.9212	0.9189	0.9770
Adjusted R-squared	0.7046	0.7754	0.7762	0.9521	0.9023	0.9168	0.9160	0.9753

Notes: This table reports R^2 and adjusted R^2 from regressions of gun law totals on alternative sets of fixed effects and trends. Columns (1)(4) use the full sample; columns (5)(8) restrict the sample to 1996 onward. All specifications include state fixed effects. Column (2)/(6) additionally include year fixed effects; column (3)/(7) include a common linear time trend; and column (4)/(8) include state-specific linear trends.

low-dimensional. In the full sample (with year indicators), two principal components explain 95% of the total variance in annual state-level gun-law totals, and the first component is also highly correlated with the Republican vote share in the 2012 presidential election ($\rho = -0.639$).[6]

We document a positive correlation between the number of state-level gun laws and the proportion of imported crime guns. To highlight this case, in Figure 3, we present a scatterplot of the standardized number of gun laws in every state from 2009 to 2023 (left panel) and the standardized share of imported crime guns (right panel) also from 2009 to 2023. We also highlight two states with different gun policy: California, which has become a more restrictive state, and Texas, which has become more permissive. In both of these cases, there is a positive relationship between the share of imported crime guns and the number of gun laws in the state. Moreover, in the other states, there is suggestive evidence that this relationship is not unique.

Perhaps surprisingly, in some states, up to 80% of crime guns were first sold in another state, whereas in others, less than 20% were imported. A similarly wide range exists for state firearm regulations – some states have over 50 firearm-related laws, while others have zero state laws.

Year-to-year gun law changes are relatively rare. From 1977 to 2024, the average absolute annual change in the number of gun laws is about 0.33. The years with the largest average changes were 1994 (1.36) and 2013 (1.02). Law totals are also highly serially correlated. In fixed-effects linear regressions, the relationship between the number of gun laws in state i in year t and its value in $t-1$ is 1.00, with deeper lags showing smaller relationships (for example, the fifth-lag coefficient is 0.78).

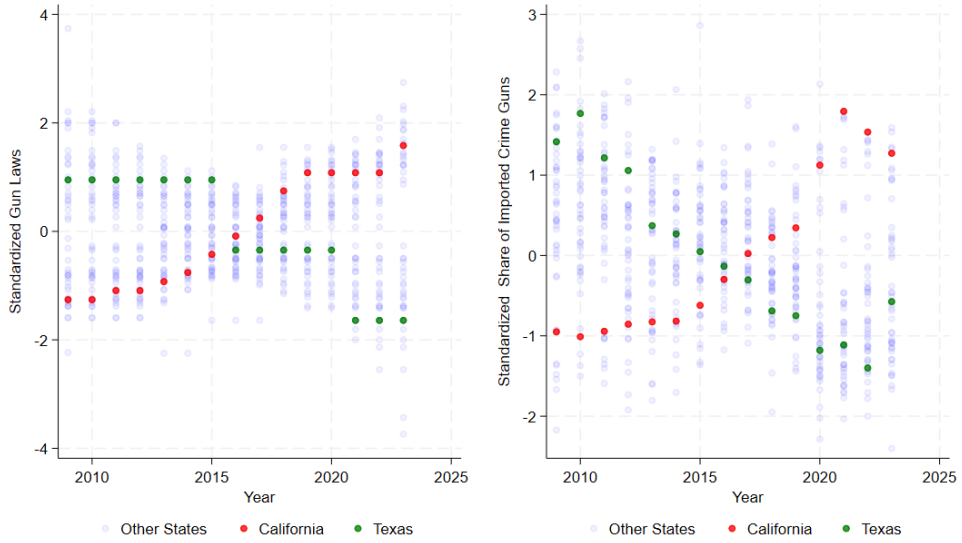
At the risk of getting ahead of ourselves, one of the key assumptions underlying both our empirical and structural analyses is that pretax gun retail prices are relatively constant across states.[7] We believe this assumption is mostly supported by the data. Figure 17 (Appendix) presents the

in the common annual mean.

[6] In the 1996–2024 sample, *a single principal component explains 95% of the variance.* The correlation of this component with the Republican vote share in the 2012 presidential election is -.68.

[7] For reference, California imposes an 11% state excise tax on firearm sales, which we exclude when comparing base prices.

Figure 3: Gun Laws and Imported Crime Guns



Notes: The left panel is the (within-state) standardized number of gun laws in each state (i.e., Z-scores). The right panel is the (within-state) standardized share of recovered crime guns in each state that originated out-of-state, Red highlights California and Texas is highlighted green. The remaining states are blue.

average price of handguns based on common calibers traced by the ATF (9mm, .38 Special, .45 ACP, .22 LR, and .40 S&W) and excluding those costing over $ 30,000. The figure reports 95% confidence intervals, together with the first, second, and third quartiles for each state's distribution of prices as well as for the pooled national sample. These data come from archived listings on Guns International, a major firearm sales platform, covering the period 2016–2020. To assign prices to states, we match each listing to the state corresponding to the three-digit area code of the seller's contact number. We successfully match roughly 90% of listings; the primary source of unmatched observations is the use of toll-free area codes (e.g., 866) that do not map to specific geographic locations or Parts Unknown (PU in Figure 17).

Overall, retail firearm prices are remarkably similar across states, with the median price of almost all states being within the interquartile range of the overall distribution. This empirical regularity supports the assumption that price differences do not drive interstate firearm flows and allows us to focus on regulatory frictions and geographic factors as the primary determinants of trafficking patterns.

3.5 Formal Trafficking or "High-Risk" Owners?

As we are using the universe of guns that were successfully traced by the ATF, a natural question is whether we are documenting formal trafficking networks or the migration of higher-risk gun owners? The answer is probably largely both because the two are intrinsically related.

For instance, Figure 4 presents the number of likely trafficked (or probably better called something along the lines of "More Likely Trafficked" guns) – guns less than 7 months old – and all the

guns exported from a handful of states in 2023 and 2010. If there were a clear difference between the Likely Trafficked Gun totals and all exported crime guns, it would suggest that formal trafficking and broader crime-gun recoveries are driven by different underlying mechanisms. Instead, states that export many (few) crime guns also tend to export many (few) Likely Trafficked Guns.

More formal analysis supports this interpretation. A simple Pearson correlation between Likely Trafficked Guns (recovered in a different state) and gun recoveries more broadly (also recovered in a different state) is .87 at the state-pair level, and the correlation of the first differences of the two is .56. Standard panel approaches also confirm the significant relationship between the two with one additional likely trafficked gun being associated with 3.8 additional gun recoveries (state-pair clustered standard errors; $p < .0001$ & $n = 31,584$). A log-log approach also generates a similar relationship, with a 1 percent increase in Likely Trafficked Guns being associated with a .33 percent increase in gun recoveries (state-pair clustered standard errors; $p < .0001$ & $n = 10,170$).

4 A Theoretical Model of Interstate Firearm Sourcing

This section develops a model of interstate firearm sourcing based on a Ricardian structure in the spirit of Eaton and Kortum (2002). Acquisition opportunities vary across potential source states, and agents choose the source that minimizes total acquisition costs, accounting for state-level accessibility and bilateral geographic frictions. We use this sourcing structure to model the distribution of source states among recovered firearms, taking total recoveries in each recovery state as given. The model delivers closed-form expressions for bilateral sourcing shares, which imply a gravity equation linking these shares to distance and state-level regulatory characteristics. These relationships motivate the reduced-form and structural estimation strategies.

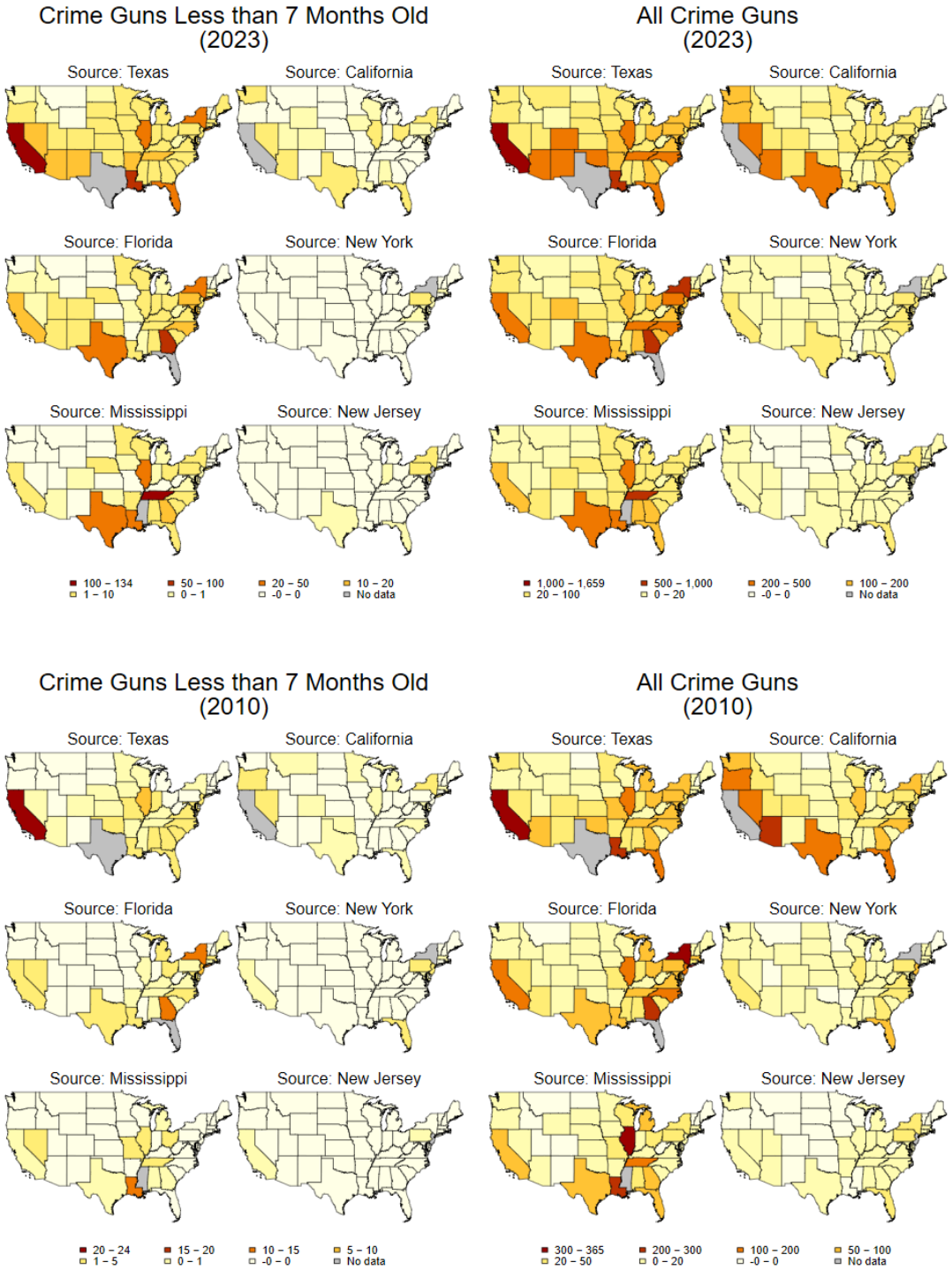
4.1 Model Description

Consider a country with N states indexed by i for source states and j for recovery states. Each state enforces its own gun laws, which affect how easily firearms can be acquired within its borders. Let $c_i > 0$ denote the baseline monetary cost of legally purchasing a gun in state i.[8] We use this cost as a benchmark for the broader acquisition environment. Firearms may subsequently change hands through private sales, gifts, inheritance, theft, or other transfers, and may cross state borders when their owners relocate. These transfers and movements may involve non-monetary frictions, including search costs, regulatory requirements, and transaction-specific uncertainty, that vary across transactions and states. Accordingly, a firearm's source state identifies the location of its first retail sale, without specifying its subsequent ownership history or the mechanism through which it reaches the recovery state.

To capture heterogeneity in acquisition opportunities, consider the set of firearms recovered by law enforcement in recovery state j and successfully traced to their first retail sale. For each

[8] In practice, pretax gun prices exhibit little cross-state variation; see Figure 17. This empirical regularity allows us to focus on differences arising from regulatory frictions rather than price dispersion.

Figure 4: Geographic Distribution of Recent and Total Interstate Crime Guns, 2023



Notes: Maps report the number of traced crime guns recovered in each destination state that were originally sold in the indicated source state. The left panel shows crime guns recovered less than seven months after retail sale, while the right panel shows all traced crime guns. Darker shading indicates a larger number of recoveries. Top panel corresponds to 2023 recoveries; bottom is 2010. Source: ATF Firearms Trace Reports.

potential source state i, the acquisition environment is summarized by an idiosyncratic draw $z_i > 0$. A higher z_i reflects more favorable conditions for obtaining a gun associated with that source state, such as greater market depth or easier access to sellers, which effectively lowers the cost of acquisition. We assume that these draws are independent across potential source states and that z_i follows a Fréchet distribution:

$$F_i(z) = \Pr(Z_i \leq z) = \exp\left(-T_i z^{-\theta}\right), \tag{1}$$

where $T_i > 0$ is a state-specific parameter capturing the *accessibility* of guns in state i, and $\theta > 0$ is a common parameter across all states that governs the dispersion of acquisition costs. The parameter T_i summarizes the combined effect of regulatory stringency, enforcement intensity, private-party participation, and other institutional features that affect how easily guns can be obtained within a state. A higher T_i shifts the distribution of acquisition costs downward, increasing the probability of low-cost acquisition opportunities. A larger θ implies less dispersion in acquisition costs.

Given a draw z_i, the acquisition cost of sourcing a gun from state i is given by c_i/z_i. Thus, variation in z_i generates a continuum of opportunity-specific acquisition costs, while variation in T_i governs how frequently low-cost opportunities arise.

Geographic separation introduces additional frictions between source state i and recovery state j. We summarize these frictions by a multiplicative cost factor $d_{ij} > 1$ for $i \neq j$, capturing transportation expenses and other geographic barriers to access. We normalize within-state frictions to $d_{ii} = 1$ and assume symmetric bilateral frictions, $d_{ij} = d_{ji}$. This formulation summarizes the geographic relationship between first retail sale and subsequent recovery; it does not require a direct shipment between the two states.

Combining acquisition and geographic frictions, the effective sourcing cost associated with source state i and recovery state j is

$$p_{ij} = \frac{c_i}{z_i} d_{ij}, \qquad i = 1, \ldots, N.$$

Among all potential source states, the agent selects the one with the lowest effective sourcing cost:

$$p_j = \min\left\{p_{1j}, p_{2j}, \ldots, p_{Nj}\right\}.$$

This framework represents the source states of firearms recovered by law enforcement in recovery state j as draws from a sourcing distribution. Differences in state-level accessibility T_i, bilateral frictions d_{ij}, and idiosyncratic acquisition opportunities z_i jointly determine bilateral sourcing patterns and give rise to a gravity structure in source–recovery shares. The model characterizes the source composition of recovered firearms, taking total recoveries in each state as given.

4.2 Equilibrium

Given the independent acquisition-opportunity draws across source states and the effective sourcing cost $p_{ij} = (c_i/z_i)d_{ij}$, the distribution of minimum sourcing costs in recovery state j follows from standard properties of the Fréchet distribution. The cumulative distribution function (CDF) of the lowest sourcing cost in state j is

$$G_j(p) = 1 - \exp\Big(-\Phi_j p^{\theta}\Big), \qquad p \geq 0,$$

where

$$\Phi_j = \sum_{i=1}^{N} T_i (c_i d_{ij})^{-\theta}$$

is a composite sourcing parameter that summarizes the accessibility of low-cost acquisition opportunities across all source states, including recovery state j itself.

The probability that state i is the lowest-cost source for recovery state j is the probability that p_{ij} is the minimum among all potential sources. Under the model's interpretation of sourcing conditional on recovery, this probability gives the bilateral sourcing share:

$$\pi_{ij} = \frac{T_i (c_i d_{ij})^{-\theta}}{\sum_{k=1}^{N} T_k (c_k d_{kj})^{-\theta}}. \tag{2}$$

Equation (2) characterizes the equilibrium distribution of source states among firearms recovered in state j, where π_{ij} denotes the share first sold at retail in state i. These shares sum to one across source states, with π_{jj} representing within-state sourcing. Holding other fundamentals fixed, greater source-state accessibility T_i, a lower baseline acquisition cost c_i, or lower bilateral frictions d_{ij} increases the share sourced from state i. The expression is formally identical to sourcing probabilities in Ricardian trade models and exhibits the same gravity structure, with bilateral shares depending on source-state acquisition conditions, bilateral frictions, and the dispersion parameter θ, relative to acquisition opportunities across all potential sources.

4.3 Comparative Statics

This subsection derives theoretical predictions for how bilateral sourcing shares respond to geographic frictions and state-level acquisition accessibility. We interpret changes in accessibility as regulatory changes when stricter regulations reduce accessibility. We formalize these relationships as testable propositions.

Proposition 1 (Geographic Frictions)**.** *For any pair of distinct states (i, j), an increase in bilateral geographic frictions d_{ij} reduces source state i's share of firearms recovered in state j, holding other fundamentals fixed.*

Proof. Differentiating equation (2) yields

$$\frac{\partial \pi_{ij}}{\partial d_{ij}} = -\frac{\theta \pi_{ij}(1-\pi_{ij})}{d_{ij}} < 0.$$

□

An increase in d_{ij}, which raises the effective sourcing cost associated with source state i and recovery state j, reduces the probability that i is the lowest-cost source. According to equation (2), the sourcing weight $T_i(c_i d_{ij})^{-\theta}$ declines relative to those of other source states. If bilateral frictions increase with geographic distance, the model predicts that more distant sources account for smaller recovery shares, holding source-state acquisition conditions and other bilateral frictions fixed. This relationship favors geographically proximate sources, although differences in accessibility and baseline acquisition costs also shape sourcing patterns. Every source retains a positive share at finite costs, while its share approaches zero as its bilateral friction d_{ij} becomes arbitrarily large.

Proposition 2 (Source-State Accessibility)**.** *An increase in source-state accessibility T_i raises its sourcing share π_{ij} in every recovery state j, including itself, holding other fundamentals fixed.*

Proof. Differentiating equation (2) yields

$$\frac{\partial \pi_{ij}}{\partial T_i} = \frac{\pi_{ij}(1-\pi_{ij})}{T_i} > 0.$$

□

The parameter T_i summarizes how easily guns can be acquired in state i, reflecting regulatory stringency, enforcement, and market conditions. A higher T_i increases the likelihood of low-cost acquisition opportunities. From equation (2), an increase in T_i raises the relative weight on state i in the distribution of sources among firearms recovered in state j. Intuitively, when low-cost acquisition opportunities are more common in state i, a larger share of firearms recovered in each state, including state i itself, is sourced from state i.

Because the shares π_{ij} are defined relative to all potential source states, changes in T_i reallocate the composition of recovered firearms across sources. An increase in accessibility in state i increases its share while reducing the shares of all other sources, including recovery state j when $j \neq i$. Consequently, cross-state differences in regulatory environments can shape the source composition of recovered firearms through their effects on acquisition accessibility.

Proposition 3 (Recovery-State Accessibility)**.** *An increase in recovery-state accessibility T_j raises the within-state sourcing share π_{jj} and lowers every external sourcing share π_{ij}, $i \neq j$, holding other fundamentals fixed.*

Proof. Differentiating equation (2) yields

$$\frac{\partial \pi_{ij}}{\partial T_j} = -\frac{\pi_{ij}\pi_{jj}}{T_j} < 0 \quad \text{for } i \neq j, \qquad \frac{\partial \pi_{jj}}{\partial T_j} = \frac{\pi_{jj}(1-\pi_{jj})}{T_j} > 0.$$

□

An increase in T_j, which may result from relaxing gun laws in state j, makes low-cost local acquisition opportunities more likely and reduces the relative cost of acquiring a gun from local sources. As local sourcing becomes more attractive, the within-state sourcing share π_{jj} increases, while each external sourcing share π_{ij}, $i \neq j$, decreases.

Conversely, stricter regulations that reduce T_j make local acquisition opportunities less favorable. Licensing requirements, background checks, waiting periods, or restrictions on legally available firearms may increase acquisition frictions, making external sources relatively more attractive.[9] Although one might expect stricter laws to reduce the availability of crime guns, the model highlights a separate compositional response: firearms first sold in other states account for a larger share of recoveries. This substitution does not require an increase in aggregate demand, nor does it rule out a decline in total firearm availability.

Regulatory asymmetries help explain this substitution. If state j tightens its regulations while a neighboring state i maintains a more permissive environment, and the reform lowers T_j, the effective cost gap between sourcing locally and sourcing from i widens. As a result, state i captures a larger share of sourcing in j. When nearby states already account for substantial recovery shares, this reallocation can reinforce geographically concentrated source–recovery links resembling interstate corridors.

For a given recovery state, all external sourcing shares have the same elasticity with respect to T_j. Consequently, changes in local accessibility leave the relative shares among external sources unchanged. Sources with larger initial shares experience larger absolute changes in their recovery shares; geographic proximity and greater source-state accessibility can contribute to those larger initial shares. Established connections to sellers or intermediaries in nearby states could also facilitate adjustment in practice. However, the static model does not explicitly incorporate these connections or determine the speed or persistence of adjustment.

This comparative static illustrates a broader feature of the equilibrium. Tighter local regulations do not eliminate the role of external acquisition opportunities in shaping the source composition of recoveries. When nearby states retain high accessibility, stricter regulations in a recovery state can increase its reliance on firearms first sold in those states, even if total recoveries decline. This possibility motivates consideration of regional coordination, although the model does not establish that coordination is necessary or sufficient to reduce firearm-related harm.

Proposition 4 (Distance Decay of Regulatory Spillovers)**.** *Consider any source–recovery pair* (i, j) *with*

[9] For example, California's handgun roster restricts the set of legally available models.

$i \neq j$. If $\pi_{ij} < 1/2$, then

$$\frac{\partial}{\partial d_{ij}} \left| \frac{\partial \pi_{ij}}{\partial T_i} \right| < 0 \quad \textit{and} \quad \frac{\partial}{\partial d_{ij}} \left| \frac{\partial \pi_{ij}}{\partial T_j} \right| < 0.$$

That is, greater bilateral geographic frictions reduce the magnitudes of the marginal effects of source- and recovery-state accessibility on the bilateral sourcing share, holding other fundamentals fixed.

Proof. Differentiating the marginal effects yields

$$\frac{\partial}{\partial d_{ij}} \left| \frac{\partial \pi_{ij}}{\partial T_i} \right| = -\frac{\theta \pi_{ij}(1-\pi_{ij})(1-2\pi_{ij})}{T_i d_{ij}}, \qquad \frac{\partial}{\partial d_{ij}} \left| \frac{\partial \pi_{ij}}{\partial T_j} \right| = -\frac{\theta \pi_{ij}\pi_{jj}(1-2\pi_{ij})}{T_j d_{ij}}.$$

Both expressions are negative if $\pi_{ij} < 1/2$. □

The restriction $\pi_{ij} < 1/2$ requires that source i account for less than half of recoveries in state j, as observed in our data. Equivalently, its contribution to sourcing opportunities must be smaller than that of all alternative sources combined. This restriction allows for heterogeneous acquisition conditions across states; it rules out an external source that dominates the recovery state's sourcing.[10]

Regulatory spillovers decay with distance under this condition because greater bilateral frictions make a source less competitive. As geographic frictions increase, effective sourcing costs rise and the probability that the source provides the lowest-cost acquisition opportunity falls. The resulting decline in its sourcing share reduces the absolute marginal effects of changes in T_i and T_j. Both marginal effects approach zero as d_{ij} approaches infinity.

This attenuation provides a mechanism for geographically concentrated regulatory spillovers. A tightening of regulations in a source state that lowers its accessibility reduces its share of firearms recovered in other states, with larger absolute marginal effects at lower bilateral frictions. Likewise, a tightening of regulations in a recovery state that lowers local accessibility increases its reliance on external sources. Under the proposition's condition, the absolute marginal response of an external source's share is smaller at higher bilateral frictions. Geographic proximity can therefore contribute to stronger responses, although differences in accessibility and baseline acquisition costs also matter.

The mechanism reflects competition among acquisition opportunities across source states. Distance serves as a bilateral cost shifter, while accessibility parameters determine the distribution of acquisition costs. Geographically proximate sources tend to be more competitive when other acquisition conditions are comparable. However, sufficiently favorable acquisition draws can make even distant sources the lowest-cost option. Distance therefore attenuates their contribution to sourcing without eliminating them from the set of potential sources.

[10] With two states and symmetric acquisition fundamentals, frictionless sourcing implies $\pi_{ij} = 1/2$, and positive bilateral frictions imply $\pi_{ij} < 1/2$. Adding sources further lowers π_{ij}, holding existing fundamentals fixed. The condition can fail if an external source's acquisition advantage is sufficiently large to overcome bilateral geographic frictions and outweigh the combined acquisition opportunities offered by the recovery state and all other sources. Such dominance, however, is unlikely in empirically relevant settings.

This result predicts distance attenuation in the marginal effects of accessibility on sourcing-share levels. It does not predict declining elasticities of those shares with respect to accessibility. Empirical specifications that interact regulatory measures with distance in a log conditional mean therefore examine a different form of heterogeneity and are not direct tests of this proposition.

The geographic concentration of these responses motivates consideration of regional coordination. When nearby states maintain different regulatory environments, tightening regulations in one recovery state can increase the share of its recovered firearms sourced from more accessible neighbors. However, the model does not establish that spillovers are exclusively regional or that coordination produces the greatest reduction in firearm-related harm. Such conclusions require evidence on total firearm acquisition, recoveries, and harm beyond the sourcing composition examined here.

5 Data and Estimation Strategy

5.1 Data

This section describes the construction of the state-level and bilateral datasets used in the empirical and structural analyses. The sample covers the contiguous 48 states from 2009 to 2023. We exclude Alaska and Hawaii because they are geographically separated from the contiguous states. The District of Columbia (DC) is also omitted because the gun law database we use does not include DC.

Firearm Tracing Data The firearm tracing data come from the Bureau of Alcohol, Tobacco, Firearms and Explosives (ATF) *Firearm Trace Reports* for 2010–2023, combined with data for 2009 from Knight (2013). We study firearms recovered during criminal investigations and successfully traced to their first retail sale, which we refer to as "recovered crime guns." For each traced firearm, the ATF records the state in which the firearm was originally sold. Using these source–recovery pairs, we construct a panel dataset where x_{ijt} denotes the number of firearms recovered in state j in year t that were originally sold in state i.

The ATF provides complete state-pair information beginning in 2010. Although historical trace summaries exist prior to this date, the reports from 2007–2008 are incomplete, with several states missing source-state identifiers. To maintain consistent coverage, we restrict attention to the 2009–2023 period. Guns that cannot be traced to a source state are excluded from the bilateral dataset. Because Hawaii and Alaska are not connected to the US mainland, they are omitted. The resulting panel contains $48 \times 48 = 2,304$ directed state pairs per year, yielding 34,560 observations over the full 15-year sample. The constructed panel has no missing state-pair-year observations, although some pairs have zero recorded recoveries. The baseline interstate regressions exclude within-state observations, leaving $48 \times 47 = 2,256$ directed pairs per year and 33,840 observations before any reductions associated with lead specifications or other data requirements. Within-state recoveries remain relevant to the structural analysis.

A reasonable concern with ATF trace data is that recovered and successfully traced firearms are not a random sample of all firearms used in crime. Tracing will depend on a number of factors, such as local crime, law enforcement practices, and cooperation with federal agencies. These factors can affect both the number and the composition of traced firearms. Variation in tracing intensity would leave sourcing shares unchanged if, within a recovery state and year, it affected firearms from all source states proportionally. Our interpretation of the observed shares therefore relies on tracing selection being sufficiently source-neutral, conditional on the included controls and fixed effects. If recovery or tracing probabilities differ systematically by source state, observed shares may not represent the source composition of the broader population of crime guns.

A related concern is that tracing activity may be correlated with state firearm regulations. For example, a state experiencing a significant ghost-gun problem (i.e., an increase in privately manufactured firearms or weapons with obliterated serial numbers) may both submit more firearms for tracing and enact stricter regulations on 3D-printed firearm components or unfinished frames. Changes in firearm-related crime or enforcement priorities may influence both tracing practices and policy adoption, creating an association between regulations and observed recoveries that does not reflect changes in acquisition accessibility alone. To account for variation in tracing activity, we construct a pair-specific measure equal to the total number of traced firearms recovered in state j in year t, less x_{ijt}. This measure captures recoveries attributed to sources other than state i. It may proxy for broader tracing activity in the recovery state, but it also reflects changes in crime, migration, and sourcing patterns. Moreover, because it is constructed from recovery counts and equals total recoveries minus the dependent variable, it is not an independent measure of tracing effort. Including it may introduce mechanical dependence or condition on outcomes affected by regulations, particularly when total recoveries also enter as an exposure variable (e.g., a potential bad control problem when the total number of crime guns is used as an exposure variable). We therefore conduct extensive robustness checks using alternative measures of tracing intensity, as discussed in Section B.

State-Level Firearm Regulation Measures of firearm regulatory stringency (the raw number of gun laws) are taken from the database developed by Siegel et al. (2017), which was updated in 2024. For each state-year, we observe the total number of firearm-related statutory provisions, denoted by $\text{GunLaws}_{i,t}$. This index varies substantially across states and over time: some states have fewer than ten firearm regulations throughout the sample period, while others have more than 50. The measure aggregates across multiple regulatory domains, including background checks, licensing rules, dealer requirements, and restrictions on high-risk purchasers. We use it as a proxy for the overall stringency of a state's regulatory environment.

It has both advantages and limitations. The main advantage of this measure is that it uses a common set of provisions across states and years. It leaves little room for researcher discretion; in other words, we are not cherry-picking laws to obtain a particular result. Its main limitation

is that it weights all provisions equally.[11] That said, it is difficult to argue that these laws are exceptionally weak ex-ante. There are many possession, registration, background checks, permits, etc related regulations. The weakest or least relevant are likely the age restrictions for ammo purchases, assault weapon restrictions, and limits on magazine capacity.

We think this is a reasonable approach because the Siegel et al. (2017) database classifies 72 different laws into 12 broad categories (though 2 are contain only a single law). The total number of states with each of these laws, by category, is shown in Figures 22 through 30 in the Appendix. These figures illustrate the main challenge in identifying the effects of specific gun laws on outcomes: law changes are rare, and they often occur in bundles, with multiple laws changing at the same time.

We face more challenges than standard difference-in-differences studies. This is because while a "burn-in" period is expected with any law (e.g., take time to train and inform law enforcement), for crime guns this "burn-in" period will be much longer. Because the median time to crime is roughly 6 years, recovery years cannot be interpreted as cleanly corresponding to the year a law was passed. Some post-enactment recovery years may still reflect guns acquired before the law took effect, while some pre-trend periods may already include guns exposed to the law. This problem is likely even more severe than stated here because the average time to crime is a little over 12 years. Put another way, a very plausible pre-trend window could be composed entirely of years in which the law was already in effect, so the estimated "pre-trends" may not be true pre-treatment periods at all.

This problem is also presented graphically in Figures 22 through 30 in the Appendix. In each of these figures, we highlight the rough middle of our panel 2016 (red vertical line) and highlight 2 other vertical lines. The first indicates 4 years in the past and corresponds to the lower end of the median time to crime of reported crime guns and illustrates the earliest we would expect to see the laws have some bite. The next vertical line corresponds to 10 years and corresponds to the lower end of the average time to crime. In other words, to get some responsible pre-tends, we would need a law that changed sometime between 2004 and 2012. These complications are then effectively doubled because we have to also consider the laws in the other state in the pair, and even the effect(s) should be concentrated in adjacent states. Finally, in all of these figures we provide the description of each of the law copied verbatim from the Siegel et al. (2017) codebook.

Our primary analysis therefore treats the index as a summary measure of the regulatory environment rather than attributing the results to any single provision. States with more provisions are classified as more regulated under this measure, although equal counts need not imply equivalent policy environments. Within the theoretical framework, these provisions may collectively affect acquisition accessibility through requirements and restrictions governing firearm purchases, possession, and transfers. The empirical analysis examines how this measured regulatory environment is associated with the source composition of recovered firearms. States are not preventing trafficking or dubious transfers through specific gun laws but are rather nagging the overall gun

[11] So the marginal effect of a hypothetical law that banned all guns is treated the same as the effect of a different hypothetical law that paused gun sales every February 29th.

market into submission through death by a thousand cuts, or, conversely, are giving the gun rights community too much candy by repealing laws that imposed frictions on potentially harmful transfers.[12]

Geographic Distance, Border Adjacency, and Interstate Highway Connections The geographic distance between source state (i) and recovery state (j) is computed as the distance between their population-weighted centroids. Centroid coordinates are taken from the U.S. Census Bureau's geographic reference files, and distances are calculated in miles using the spherical law of cosines.[13]

We construct a binary adjacency indicator, Border_{ij}, which equals one if states i and j share a land or river boundary and zero otherwise. We construct this indicator from the Census Bureau's County Adjacency File, excluding state pairs that share only a lake or other offshore boundary. Under this definition, Nebraska and Iowa are adjacent, whereas Michigan and Illinois are not.[14] Finally, $\text{Shared_Interstate}_{ij}$ equals one if the same Interstate Highway route passes through both states and zero otherwise. For example, Florida and North Carolina both lie along I-95.

State Characteristics State population and racial composition data are obtained from the Centers for Disease Control and Prevention's WONDER database, which draws on U.S. Census Bureau population estimates. State unemployment rates are obtained from the U.S. Bureau of Labor Statistics.

For each state-year, we include both source-state and recovery-state populations in the regression specifications. These variables flexibly control for population-related differences in firearm market size at both ends of each source–recovery pair. We also include source-state and recovery-state fixed effects to account for time-invariant state characteristics.

Interstate source–recovery patterns may partly reflect migration, as firearms can move across state borders when their owners relocate. State population may capture some of this migration-related variation. In our data, the correlation between the natural logarithm of migration from state j to state i and the population of state j is approximately 0.55; the corresponding correlation with the population of state i is similar. These correlations support including population as a partial control for migration-related variation, although population alone does not fully account for bilateral migration patterns.

Summary statistics presented here are based on observations from 2009 to 2023. However, we want to emphasize that our panel uses lagged versions of these variables that go back to the late 90s and early 80s. This is illustrated in Figure 16 (Appendix) which compares the early averages of contemporaneous explanatory variables of interest with their 20-year lag. The point here is that

[12] Having clarified our focus and our reasons why, we also note that we do some exploratory analysis of what classes of laws might matter. These estimates are found in Figure 31. Note: these estimates are exploratory in nature and do not take into account the full data-generating process (e.g., the interaction between laws and distance).

[13] Population centroid data are available from the U.S. Census Bureau at: https://www.census.gov/geographies/reference-files/time-series/geo/centers-population.html.

[14] The County Adjacency File is available from the U.S. Census Bureau at: https://www.census.gov/geographies/reference-files/time-series/geo/county-adjacency.html.

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Panel A. State-level variables				
State Population	6,651,695	7,209,933	559,851	39,557,044
Traced Guns (Total)	4804.133	6119.325	75	48,299
Total Gun Laws	12.8	13.5	0	62
% Black	.11	.10	.003	.385
U. Rate	.05	.02	.02	.14
Panel B. Bilateral variables				
Traced Guns ($i = j$)	3,484.8	4,730.5	49	41,772
Traced Guns ($i \neq j$)	28.07	99.19	0	4,701
Distance$_{ij}$ (miles)	1,034.49	602.00	36.16	2,656.11
Shared_Interstate$_{ij}$	.40	.49	0	1
Border$_{ij}$	0.09	0.29	0	1

we can preserve our sample even with very deep lags of the explanatory variables.

Regulatory Measures and Transformations Following Roberts et al. (2024), our main regulatory measure is the number of firearm provisions in each state. We interpret the aggregate count as a proxy for regulatory frictions affecting acquisition accessibility. This measure captures the overall regulatory environment rather than the effect of an individual law. That distinction is useful because changes in specific provisions are relatively infrequent and often occur in bundles, making their separate effects difficult to identify.

Several states report one or more years with zero gun laws. To retain these observations, GunLaws$_{it}$ in the estimating equations denotes the natural logarithm of one plus the raw provision count. This transformation preserves 1,833 observations that would otherwise be excluded when taking the logarithm of the raw count. The policy coefficients therefore describe responses to changes in the transformed index, rather than exact elasticities with respect to the number of laws.

Finally, to facilitate interpretation of specifications with interactions, all explanatory variables are mean-centered after transformation and before constructing interaction terms. The variable names in the estimating equations refer to these centered measures; the recovery-total offset is retained in its original logged form. Centering allows the main regulatory coefficients in the distance-interaction specification to be interpreted at mean log distance.

Summary Statistics Table 2 reports summary statistics for the main variables used in the analysis. State-level variables include population, total traced firearm recoveries, the number of gun laws, the unemployment rate, and the percentage of residents who identify as Black or African American. State-pair variables include bilateral traced firearm recoveries, covering both within-state and interstate pairs, geographic distance, and the border indicator. Interstate firearm traces

are substantially smaller than within-state traces on average, a pattern consistent with geographic frictions, although it also reflects the division of external sourcing across multiple states. The average distance between state population centroids exceeds 1,000 miles, and approximately 9 percent of state pairs share a common border.

5.2 Estimation Strategy

The empirical strategy is designed to examine the relationships between bilateral firearm recovery shares, geographic frictions, and regulatory conditions in source and recovery states. The theoretical model characterizes sourcing shares as a function of acquisition accessibility and bilateral geographic frictions. These relationships motivate a gravity specification that relates bilateral recovery counts to geographic characteristics and state firearm regulations while accounting for total recoveries in each recovery state.

A naive specification Linking Propositions to Empirical Specifications. Propositions 1–3 predict that bilateral sourcing shares decline with geographic frictions, fall when source-state regulations reduce acquisition accessibility, and rise when recovery-state regulations reduce local acquisition accessibility.

An illustrative linear specification is

$$\log s_{ijt} = \beta_G \text{GeoFrictions}_{ij} + \beta_{Law}^{Source} \text{GunLaws}_{it} + \beta_{Law}^{Recovery} \text{GunLaws}_{jt} + \varepsilon_{ijt}, \tag{3}$$

where s_{ijt} denotes the share of firearms recovered in recovery state j in year t that were first sold at retail in source state i, GeoFrictions_{ij} captures bilateral geographic frictions, and GunLaws_{it} and GunLaws_{jt} measure firearm regulations in source state i and recovery state j, respectively, in year t. Propositions 1–3 predict that $\beta_G < 0$, $\beta_{Law}^{Source} < 0$, and $\beta_{Law}^{Recovery} > 0$.

This specification provides a starting point but has several limitations. First, contemporaneous regulations may not adequately capture the acquisition environments relevant to current recoveries. The median time between the first retail sale and subsequent recovery, commonly termed "time-to-crime," is approximately three to six years (Johnson et al., 2024; ATF, 2023). Average time-to-crime is also longer for firearms recovered from out-of-state sources. These intervals suggest that policy changes propagate with delay and regulations in earlier years may be relevant to current sourcing patterns, motivating the use of lagged policy measures.

Second, nearly half of interstate sourcing shares are zero. Taking logs would instead exclude zero observations and discard a substantial and potentially systematic portion of the sample. These features motivate an estimator that accommodates zeros.

Finally, the specification omits persistent differences across states and common changes over time that may affect sourcing patterns and correlate with firearm regulations. Source-state and recovery-state fixed effects account for time-invariant characteristics of each state, while year fixed effects absorb common annual shocks.

Baseline PPML Specification with Lagged Regulations. To address these limitations, we use bilateral recovery counts as the dependent variable and estimate a Poisson pseudo-maximum-likelihood (PPML) model with source-state, recovery-state, and year fixed effects. This approach accommodates zero recoveries and preserves the multiplicative form of the model's sourcing relationship. To allow current recoveries to reflect earlier regulatory environments, we replace contemporaneous firearm regulations with their k-year lags and estimate separate specifications for each lag length k. Finally, we include the natural log of total recoveries in the recovery state as an exposure term, with its coefficient fixed at one, so that expected bilateral counts scale with total recoveries:

$$Y_{ijt} = \text{Recovery}_{jt} \cdot \exp\Big\{\boldsymbol{\beta}_G' \mathbf{GeoFrictions}_{ij} + \beta_{Law}^{Source} \text{GunLaws}_{i,t-k} + \beta_{Law}^{Recovery} \text{GunLaws}_{j,t-k} + \boldsymbol{\gamma}' \mathbf{Z}_{ijt} + \vartheta_i + \psi_j + \phi_t \Big\} + \varepsilon_{ijt}, \tag{4}$$

where Y_{ijt} is the number of firearms recovered in recovery state j in year t that were first sold at retail in source state i, Recovery_{jt} is the total number of firearms recovered in state j in year t.

We now specify GeoFrictions_{ij} as a vector, $\mathbf{GeoFrictions}_{ij}$, containing Distance_{ij}, the natural log of geographic distance in miles between the states' population-weighted centroids; Border_{ij}, an indicator for a shared border; and $\text{Shared_Interstate}_{ij}$, an indicator for an Interstate Highway connection. Distance is expected to increase bilateral frictions, while shared borders and Interstate Highway connections are expected to reduce them. The variables $\text{GunLaws}_{i,t-k}$ and $\text{GunLaws}_{j,t-k}$ are the natural logs of the number of firearm regulations in the source and recovery states, respectively, k years before recovery. Estimates across separate lag specifications describe how the effect varies with the timing of measured regulations; they do not identify cumulative policy effects or the full dynamic response to policy changes.

The vector $\mathbf{Z}_{ijt}$ includes the natural log of population, the unemployment rate, and the percentage of residents who identify as Black or African American in both the source and recovery states. The fixed effects ϑ_i and ψ_j absorb time-invariant characteristics of the source and recovery states, respectively, while ϕ_t absorbs shocks common to all states in a given year. These common shocks may include changes in federal legislation and nationwide changes in firearm demand following elections or mass shootings (Johnson et al., Forthcoming; Johnson and Roach, 2025).

We do not include source–recovery pair fixed effects because they would absorb the time-invariant geographic characteristics whose coefficients we seek to estimate. We also do not include state-specific time trends. This is because our main variable of interest (Gun Laws) are effectively are nearly collinear with state-specific time trends. Standard errors are clustered at the bilateral state-pair level.

PPML Specification with interactions with Distance Motivated by Proposition 4, we extend the baseline specification in equation (4) by interacting firearm regulations with geographic distance.

The proposition predicts that the absolute marginal effects of acquisition accessibility on bilateral sourcing shares decline with distance. Thus, we examine whether the proportional effects of firearm regulations also vary systematically with distance.

We estimate the following specification:

$$
\begin{aligned}
Y_{ijt} = \text{Recovery}_{jt} \cdot \exp\Big\{ & \boldsymbol{\beta}_G' \mathbf{GeoFrictions}_{ij} + \beta_{Law}^{Source} \text{GunLaws}_{i,t-k} + \beta_{Law}^{Recovery} \text{GunLaws}_{j,t-k} \\
& + \beta_{Law \times Distance}^{Source} \left(\text{GunLaws}_{i,t-k} \times \text{Distance}_{ij}\right) \\
& + \beta_{Law \times Distance}^{Recovery} \left(\text{GunLaws}_{j,t-k} \times \text{Distance}_{ij}\right) \\
& + \boldsymbol{\gamma}' \mathbf{Z}_{ijt} + \vartheta_i + \psi_j + \phi_t \Big\} + \varepsilon_{ijt},
\end{aligned}
\tag{5}
$$

The interaction terms allow the effects of firearm regulations to vary with distance. The source-state and recovery-state regulatory elasticities are $\beta_{Law}^{Source} + \beta_{Law \times Distance}^{Source} \text{Distance}_{ij}$ and $\beta_{Law}^{Recovery} + \beta_{Law \times Distance}^{Recovery} \text{Distance}_{ij}$, respectively.

A positive source-state interaction coefficient, $\beta_{Law \times Distance}^{Source} > 0$, would indicate that a negative source-state regulatory elasticity becomes less negative with distance. Tighter source-state regulations would therefore reduce sourcing shares proportionally more for nearby recovery states. Similarly, a negative recovery-state interaction coefficient, $\beta_{Law \times Distance}^{Recovery} < 0$, would indicate that a positive recovery-state regulatory elasticity becomes less positive with distance. Tighter recovery-state regulations would therefore increase sourcing shares proportionally more from nearby source states.

As a robustness check, we extend the specification to allow regulatory effects to vary jointly with distance and source-state population. These specifications include the relevant lower-order terms alongside the three-way interactions. The motivation is that proximity and relatively permissive regulations need not translate into a large contribution to recoveries if the source state has a small population. For example, only 83 firearms first sold at retail in Vermont were recovered in New York in 2023, despite the states sharing a border and Vermont having relatively permissive firearm regulations. Vermont's small population may help explain its limited contribution to New York's recoveries.

6 Empirical Results

This section presents empirical evidence on the determinants of interstate sourcing flows of crime guns. We begin with the baseline PPML specification in equation (4) and the distance interactions in equation (5). We then extend the analysis to examine how regulatory effects vary with source-state population, geographic distance, and Interstate Highway connections.

We assess the sensitivity of the results to alternative regulatory lags, tracing-intensity controls, and treatments of total recoveries, including specifications without the exposure term. We also examine leads of firearm regulations and conduct permutation tests that randomly reorder regula-

tions over time within states and state pairs. Additional analyses consider within-state recoveries and the characteristics of paired external states, as well as separate categories of firearm regulations. Appendix D reports these robustness checks and supplementary analyses in detail.

6.1 Main Estimation Results

We begin with the specification in equation (4). Table 3 reports estimates for $k = -2, -1, 0, 1, \ldots, 10$, where negative values denote leads and positive values denote lags. Across specifications, the coefficients on geographic characteristics and source-state population remain relatively stable, while the estimated impact of gun laws evolves systematically with the lag length.[15]

Geographic frictions play a central role. The elasticity of sourcing shares with respect to distance is approximately -0.99 across specifications: a one-percent increase in distance is associated with approximately a one-percent decrease in a source state's share of recoveries, holding other regressors fixed. The shared-border coefficient is approximately 0.63, implying that adjacent states have bilateral sourcing shares about 87 percent higher than otherwise comparable non-adjacent pairs. Interstate Highway connections are also positively associated with sourcing shares. Their coefficient of approximately 0.25 corresponds to shares about 28 percent higher for connected pairs. Together, these estimates highlight the importance of geographic proximity and transportation connections in interstate sourcing patterns.

The source-state regulatory coefficient is negative in every specification.[16] At $k = 6$, a one-percent increase in the number of source-state firearm regulations is associated with a 0.19 percent decrease in its share of recoveries in another state. The coefficient generally becomes more negative at longer lags, reaching approximately -0.22 at $k = 10$, although the pattern is not strictly monotonic. The contemporaneous coefficient is smaller, at approximately -0.07, but remains statistically significant. The two-year lead and the one-year lead are not statistically significant significant at the five-percent level.

Recovery-state regulations exhibit a different pattern. The contemporaneous coefficient is close to zero and statistically insignificant. The coefficient becomes positive at longer lags, reaching approximately 0.04 at $k = 4$ and ranging from 0.054 to 0.092 between $k = 6$ and $k = 10$. Thus, regulations measured six to ten years before recovery are positively associated with the share sourced from a given external state. This pattern is consistent with substitution toward external sources when local acquisition becomes more restrictive. Both lead coefficients are statistically insignificant.

Overall, the regulatory coefficients are consistent with the model's directional predictions: stricter source-state regulations are associated with smaller external sourcing shares, while stricter recovery-state regulations are associated with greater reliance on external sources. The generally

[15] One possible concern is that recoveries from non-i states enter into the models multiple times. To address this concern, we also consider specifications in which we do not include the exposure variable. These estimates are found in Table 7 in the Appendix.

[16] Because the law index aggregates distinct regulations, these coefficients summarize the relationship with the overall number of regulations rather than identify the causal effect of any particular law.

Table 3: Lagged Effects of Source- and Recovery-State Gun Laws on Bilateral Firearm Recoveries: Baseline Specification

	k=-2	k=-1	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
GunLaws $_{i,t-k}$	-0.0420	-0.0609*	-0.0722**	-0.0897***	-0.112***	-0.133***	-0.156***	-0.176***	-0.192***	-0.192***	-0.178***	-0.185***	-0.219***
	(-1.27)	(-1.92)	(-2.49)	(-2.88)	(-3.14)	(-3.64)	(-4.43)	(-5.25)	(-5.88)	(-5.48)	(-4.91)	(-4.20)	(-4.01)
GunLaws $_{j,t-k}$	0.000585	-0.00742	-0.00630	-0.0177	0.00385	0.0335*	0.0420**	0.0525**	0.0541**	0.0650**	0.0739**	0.0918**	0.0875**
	(0.03)	(-0.39)	(-0.37)	(-1.04)	(0.21)	(1.73)	(2.10)	(2.39)	(1.98)	(1.99)	(2.16)	(2.52)	(2.01)
Shared Interstate	0.248***	0.248***	0.248***	0.248***	0.248***	0.248***	0.248***	0.248***	0.248***	0.247***	0.248***	0.247***	0.247***
	(5.13)	(5.11)	(5.09)	(5.10)	(5.10)	(5.10)	(5.10)	(5.10)	(5.10)	(5.10)	(5.10)	(5.09)	(5.09)
Distance	-0.981***	-0.986***	-0.990***	-0.989***	-0.989***	-0.989***	-0.989***	-0.989***	-0.989***	-0.989***	-0.989***	-0.990***	-0.990***
	(-24.40)	(-24.35)	(-24.34)	(-24.35)	(-24.35)	(-24.35)	(-24.35)	(-24.34)	(-24.35)	(-24.35)	(-24.36)	(-24.35)	(-24.33)
Border	0.620***	0.625***	0.628***	0.628***	0.628***	0.628***	0.627***	0.627***	0.627***	0.627***	0.627***	0.628***	0.628***
	(10.57)	(10.54)	(10.52)	(10.51)	(10.51)	(10.51)	(10.51)	(10.51)	(10.51)	(10.51)	(10.51)	(10.51)	(10.51)
Population $_{i,t-k}$	1.384***	1.284***	1.320***	1.404***	1.483***	1.464***	1.423***	1.418***	1.414***	1.396***	1.451***	1.479***	1.503***
	(2.84)	(2.79)	(3.16)	(3.21)	(3.41)	(3.67)	(3.73)	(3.94)	(4.04)	(4.04)	(4.14)	(4.25)	(4.30)
Population $_{j,t-k}$	-0.214	0.0285	0.315	0.455	0.480	0.581*	0.725**	0.765***	0.766***	0.699**	0.590**	0.406	0.228
	(-0.68)	(0.09)	(1.09)	(1.53)	(1.58)	(1.96)	(2.45)	(2.60)	(2.63)	(2.46)	(2.16)	(1.60)	(0.98)
Guns $\neq_{i_t}$	-0.640***	-0.680***	-0.685***	-0.696***	-0.697***	-0.702***	-0.706***	-0.711***	-0.714***	-0.708***	-0.707***	-0.686***	-0.668***
	(-12.17)	(-12.13)	(-12.19)	(-12.00)	(-11.73)	(-11.84)	(-11.80)	(-11.78)	(-11.83)	(-11.98)	(-11.98)	(-12.15)	(-12.29)
U. Rate $_{i,t-k}$	-0.0590	-0.0842**	-0.119***	-0.104**	-0.0665	-0.0454	-0.0648	-0.0633	-0.0694	-0.0636	-0.0670	-0.0551	-0.0176
	(-1.46)	(-2.03)	(-2.80)	(-2.25)	(-1.17)	(-0.72)	(-1.07)	(-1.03)	(-1.01)	(-0.84)	(-0.93)	(-0.96)	(-0.41)
U. Rate $_{j,t-k}$	0.0361	0.0798*	0.176***	0.159***	0.0412	-0.0263	-0.0320	-0.0706	-0.101**	-0.111***	-0.151***	-0.0989**	-0.0792*
	(0.87)	(1.80)	(3.79)	(3.77)	(0.96)	(-0.52)	(-0.63)	(-1.48)	(-2.52)	(-2.80)	(-3.48)	(-2.28)	(-1.89)
% Black $_{i,t-k}$	0.630***	0.631***	0.639***	0.618***	0.531***	0.471***	0.478***	0.451***	0.436***	0.390**	0.341**	0.313**	0.308**
	(3.35)	(3.36)	(3.67)	(3.55)	(3.24)	(2.98)	(3.15)	(3.01)	(2.82)	(2.54)	(2.22)	(2.13)	(2.27)
% Black $_{j,t-k}$	-0.351*	-0.420*	-0.424**	-0.429**	-0.411***	-0.397**	-0.414***	-0.411***	-0.433***	-0.429***	-0.426***	-0.380***	-0.324***
	(-1.70)	(-1.94)	(-2.03)	(-2.47)	(-2.58)	(-2.43)	(-2.58)	(-2.65)	(-2.92)	(-3.05)	(-3.18)	(-3.11)	(-3.00)
Constant	-5.252***	-5.300***	-5.544***	-5.677***	-5.700***	-5.754***	-5.845***	-5.844***	-5.791***	-5.689***	-5.571***	-5.461***	-5.357***
	(-16.55)	(-16.58)	(-17.65)	(-16.93)	(-16.61)	(-17.63)	(-18.29)	(-18.69)	(-19.04)	(-19.51)	(-20.23)	(-21.43)	(-22.81)
OBS	29328	31584	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840
Pairs	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256
R2	0.874	0.878	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881

Notes: Estimated effects using a fixed-effects Poisson estimator. Column k includes GunLaws$_{i,t-k}$ and GunLaws$_{j,t-k}$ as regressors. All models include origin state fixed effects, destination state fixed effects, and year fixed effects. The lag is indicated by the column label. Standard errors clustered at the pair level are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All of the models, except for those using leads, have 33,840 observations.

larger magnitudes at longer lags are also consistent with the intervals between first retail sale and subsequent recovery; interstate gun flow shares adjust gradually but systematically to regulatory environments in both origin and destination states.

Source-state population is positively associated with sourcing shares. Its coefficient ranges from approximately 1.28 to 1.50, indicating that a one-percent increase in source-state population is associated with a 1.28–1.50 percent increase in its share of recoveries elsewhere. The recovery-state population coefficient is less stable and is statistically significant only at selected lags. These estimates therefore provide stronger evidence that interstate gun flows scale with market size, while sourcing shares become more dispersed as destination markets grow.

Unemployment exhibits a different temporal pattern. Contemporaneous source-state unemployment is negatively associated with bilateral sourcing shares, whereas contemporaneous recovery-state unemployment is positively associated with them. The source-state relationship generally becomes statistically insignificant at longer lags, while the recovery-state coefficient turns negative and is statistically significant from $k = 6$ onward.

Finally, recoveries attributed to sources other than i are negatively associated with source i's share when total recoveries enter as an exposure term. The corresponding coefficient becomes positive when the exposure term is omitted. Because this regressor is mechanically related to bilateral and total recoveries, we interpret the sign change cautiously. It does not independently identify tracing intensity, firearm demand, or migration.

6.2 Geographic Heterogeneity in Regulatory Effects

We now examine how the effects of firearm regulations vary with distance. Table 4 reports distance interactions for regulations in both source and recovery states. Because the explanatory variables are demeaned, the main regulatory coefficients represent the estimated effects at mean log distance.

The interaction between source-state regulations and distance is positive across all reported lags. Combined with the negative, although statistically insignificant, main source-state coefficient, this indicates that the negative regulatory effect becomes less negative as distance increases, approaching zero for more distant state pairs. Recovery-state regulations exhibit a corresponding pattern: their positive effect on bilateral recoveries becomes smaller at greater distances, approaching zero for sufficiently distant state pairs. These interpretations apply over the distance range in which the estimated effects retain their respective signs. The regulatory estimates generally become larger in magnitude and more statistically significant at longer lags, broadly consistent with the patterns in Table 3.

Figure 5 illustrates these relationships by plotting the implied regulatory effects at the 5th, 25th, 50th, 75th, and 95th percentiles of distance across selected lags.[17] The figure includes longer lags and additional leads beyond those reported in Table 4. The estimated regulatory effects are

[17] We also estimate the specification without the exposure term. These estimates are reported in Table 8 in the Appendix.

Table 4: Lagged Effects of Source- and Recovery-State Gun Laws on Bilateral Firearm Recoveries: Interactions with Distance

	k=-2	k=-1	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
GunLaws $_{i,t-k}$	0.0707	0.0494	0.0367	0.0264	0.0101	-0.00811	-0.0337	-0.0485	-0.0605	-0.0629	-0.0399	-0.0389	-0.0565
	(1.60)	(1.17)	(0.95)	(0.65)	(0.22)	(-0.18)	(-0.77)	(-1.17)	(-1.55)	(-1.57)	(-0.99)	(-0.83)	(-0.98)
GunLaws $_{j,t-k}$	-0.00174	-0.0106	-0.0101	-0.0230	-0.000509	0.0294	0.0394*	0.0509**	0.0555**	0.0639**	0.0701**	0.0880***	0.0758*
	(-0.07)	(-0.43)	(-0.44)	(-1.01)	(-0.02)	(1.29)	(1.73)	(2.10)	(2.00)	(2.07)	(2.15)	(2.58)	(1.93)
Shared Interstate	0.213***	0.215***	0.214***	0.212***	0.210***	0.210***	0.210***	0.210***	0.211***	0.212***	0.213***	0.212***	0.211***
	(4.58)	(4.58)	(4.58)	(4.55)	(4.52)	(4.52)	(4.53)	(4.54)	(4.57)	(4.61)	(4.64)	(4.65)	(4.64)
Distance	-1.016***	-1.016***	-1.016***	-1.018***	-1.020***	-1.018***	-1.016***	-1.014***	-1.013***	-1.013***	-1.014***	-1.017***	-1.021***
	(-24.81)	(-24.58)	(-24.49)	(-24.52)	(-24.50)	(-24.58)	(-24.75)	(-24.87)	(-24.94)	(-25.07)	(-25.21)	(-25.27)	(-25.28)
GunLaws $_{i,t-k}$ × Distance	0.158***	0.157***	0.158***	0.170***	0.185***	0.192***	0.203***	0.213***	0.221***	0.227***	0.237***	0.249***	0.264***
	(5.87)	(5.85)	(5.98)	(6.40)	(6.84)	(7.02)	(7.29)	(7.51)	(7.67)	(7.80)	(8.00)	(8.20)	(8.39)
GunLaws $_{j,t-k}$ × Distance	-0.0146	-0.0167	-0.0183	-0.0185	-0.0181	-0.0181	-0.0196	-0.0210	-0.0222	-0.0229	-0.0234	-0.0245	-0.0245
	(-0.56)	(-0.64)	(-0.69)	(-0.68)	(-0.65)	(-0.64)	(-0.68)	(-0.73)	(-0.75)	(-0.77)	(-0.78)	(-0.81)	(-0.79)
Border	0.573***	0.580***	0.585***	0.584***	0.583***	0.584***	0.585***	0.587***	0.588***	0.591***	0.593***	0.594***	0.594***
	(9.90)	(9.89)	(9.88)	(9.87)	(9.86)	(9.87)	(9.90)	(9.94)	(9.96)	(9.99)	(10.00)	(10.01)	(10.00)
Population $_{i,t-k}$	1.502***	1.386***	1.413***	1.477***	1.523***	1.473***	1.422***	1.413***	1.408***	1.368***	1.408***	1.431***	1.446***
	(2.83)	(2.79)	(3.15)	(3.19)	(3.34)	(3.51)	(3.53)	(3.71)	(3.86)	(3.91)	(4.02)	(4.17)	(4.20)
Population $_{j,t-k}$	-0.217	0.0505	0.351	0.512*	0.531*	0.611**	0.774***	0.799***	0.782***	0.670**	0.530*	0.319	0.145
	(-0.67)	(0.16)	(1.20)	(1.72)	(1.76)	(2.06)	(2.60)	(2.69)	(2.69)	(2.34)	(1.93)	(1.25)	(0.63)
Guns $\neq_{i_t}$	-0.661***	-0.704***	-0.712***	-0.722***	-0.716***	-0.718***	-0.720***	-0.722***	-0.721***	-0.708***	-0.696***	-0.666***	-0.644***
	(-12.32)	(-12.21)	(-12.26)	(-12.17)	(-11.99)	(-12.03)	(-11.94)	(-11.94)	(-12.01)	(-12.04)	(-11.90)	(-11.98)	(-12.18)
U. Rate $_{i,t-k}$	-0.0457	-0.0698	-0.106**	-0.0893*	-0.0563	-0.0352	-0.0650	-0.0575	-0.0615	-0.0578	-0.0650	-0.0586	-0.0199
	(-1.08)	(-1.59)	(-2.34)	(-1.81)	(-0.96)	(-0.55)	(-1.10)	(-1.02)	(-0.96)	(-0.80)	(-0.94)	(-1.07)	(-0.47)
U. Rate $_{j,t-k}$	0.0288	0.0759	0.176***	0.166***	0.0471	-0.0390	-0.0448	-0.0905*	-0.125***	-0.133***	-0.160***	-0.0970**	-0.0814**
	(0.60)	(1.50)	(3.48)	(3.70)	(1.05)	(-0.74)	(-0.84)	(-1.81)	(-3.04)	(-3.32)	(-3.72)	(-2.25)	(-1.96)
% Black $_{i,t-k}$	0.652***	0.658***	0.667***	0.645***	0.560***	0.494***	0.513***	0.475***	0.452***	0.414***	0.376**	0.352**	0.357***
	(3.12)	(3.15)	(3.45)	(3.33)	(3.08)	(2.85)	(3.19)	(3.09)	(2.92)	(2.69)	(2.41)	(2.36)	(2.59)
% Black $_{j,t-k}$	-0.343	-0.413*	-0.401*	-0.418**	-0.408**	-0.378**	-0.388**	-0.377**	-0.389**	-0.376***	-0.380***	-0.343***	-0.310***
	(-1.55)	(-1.80)	(-1.81)	(-2.21)	(-2.31)	(-2.10)	(-2.19)	(-2.25)	(-2.49)	(-2.61)	(-2.78)	(-2.76)	(-2.82)
Constant	-5.277***	-5.334***	-5.588***	-5.725***	-5.734***	-5.761***	-5.876***	-5.860***	-5.800***	-5.665***	-5.529***	-5.405***	-5.296***
	(-16.21)	(-16.35)	(-17.60)	(-17.20)	(-16.91)	(-17.76)	(-18.42)	(-18.76)	(-19.15)	(-19.44)	(-20.04)	(-21.25)	(-22.59)
OBS	29328	31584	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840
Pairs	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256
R2	0.878	0.881	0.884	0.884	0.884	0.885	0.885	0.885	0.885	0.885	0.886	0.886	0.886

Notes: Estimated effects using a fixed-effects Poisson estimator. All models include origin state fixed effects, destination state fixed effects, and year fixed effects. The lag is indicated by the column label. Z-statistics from pair-clustered standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

generally smaller in absolute magnitude for more distant state pairs, while the lead estimates are close to zero across the distances considered. These patterns indicate geographic heterogeneity in proportional regulatory effects, complementing the model's prediction of distance attenuation in marginal effects on sourcing-share levels.

6.3 Heterogeneity in Regulatory Effects by Distance and Population

We extend the distance-interaction specification by introducing three-way interactions between gun laws, geographic distance, and source-state population, together with all lower-order terms. This specification allows the effects of both source- and recovery-state regulations to vary with source-market size and geographic frictions. Because individual coefficients do not summarize regulatory effects in this specification, we report the implied effects at selected combinations of distance and source-state population. Point estimates are reported in Table 9 in the Appendix.[18]

As in Figure 5, Figure 6 presents results across different distances. In these plots, we also consider different population sizes: 10th percentile [blue], first quartile [red], median [green], third quartile [yellow], and 90th percentile [purple]. As in Figure 5, we also include the joint effects of deeper lags and leads than those shown in Table 9.

The estimates suggest two patterns. First, regulatory effects are generally smaller in absolute magnitude at greater distances. Stricter source-state regulations are associated with fewer bilateral recoveries, with the negative relationship weakening as distance increases. Stricter recovery-state regulations are associated with greater reliance on external sources, but this positive relationship also weakens with distance. Second, both relationships are generally larger in absolute magnitude for pairs with larger source-state populations. Thus, source-market size helps explain heterogeneity in the estimated effects of regulations in either state.

As a result, policy changes in larger states generate substantially larger spillovers. For example, a decrease in gun laws in a small state such as Wyoming has little effect on recoveries in Colorado, whereas a comparable change in a larger state such as Colorado can have a substantial impact on recoveries in Wyoming.

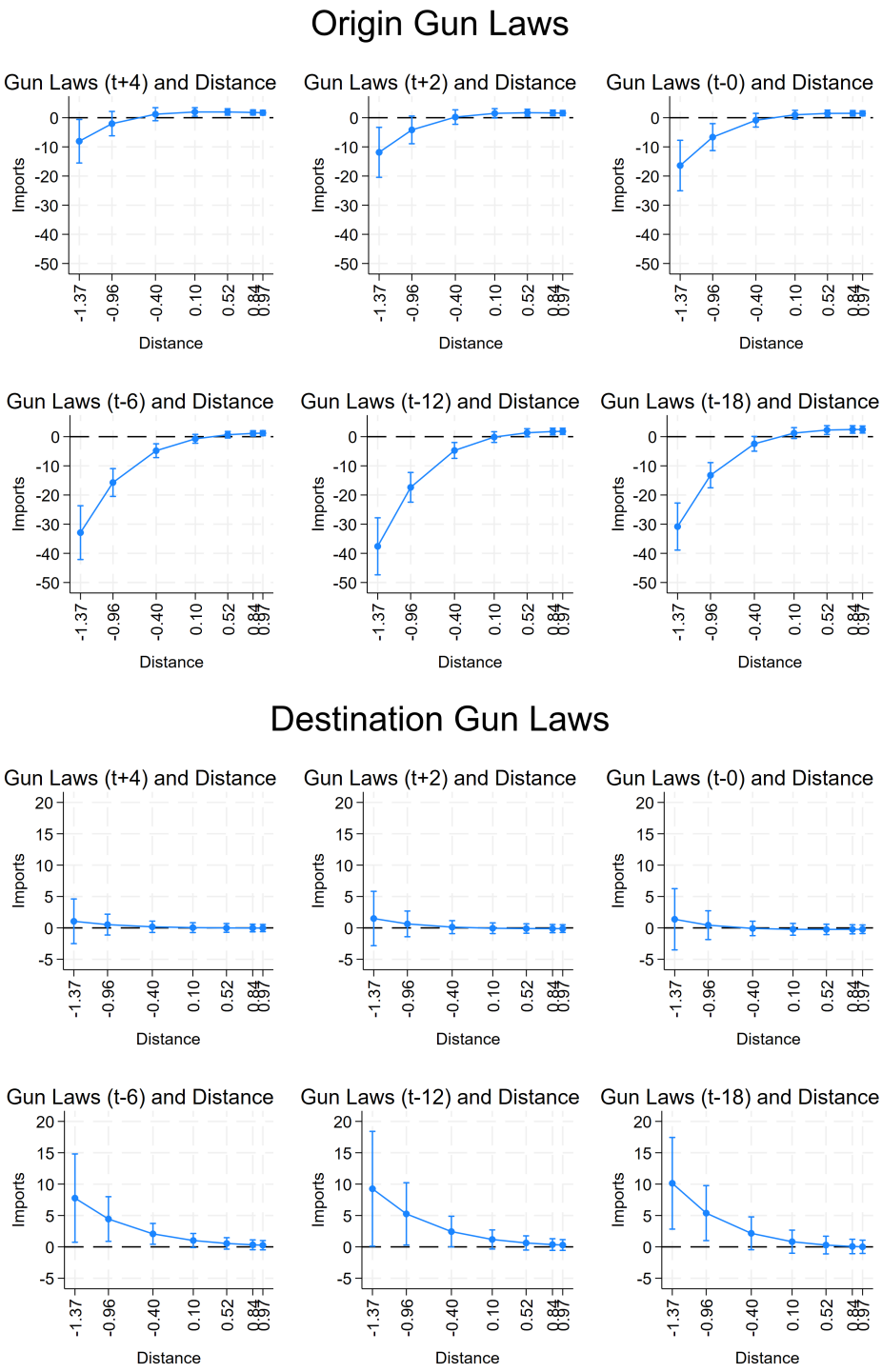
The estimated relationships are generally stronger at longer regulatory lags, while lead estimates remain close to zero across the distances and population values considered. This pattern is consistent with the known time to crime of recovered crime guns, the long intervals between first retail sale and subsequent recovery.

6.4 The Role of Interstate Highway Connections

We next examine whether the heterogeneity documented in Section 6.3 differs between state pairs with and without an Interstate Highway connection. We augment the specification by interacting the shared-highway indicator with firearm regulations, geographic distance, and source-state population, including all lower-order terms. This specification allows the relationship between

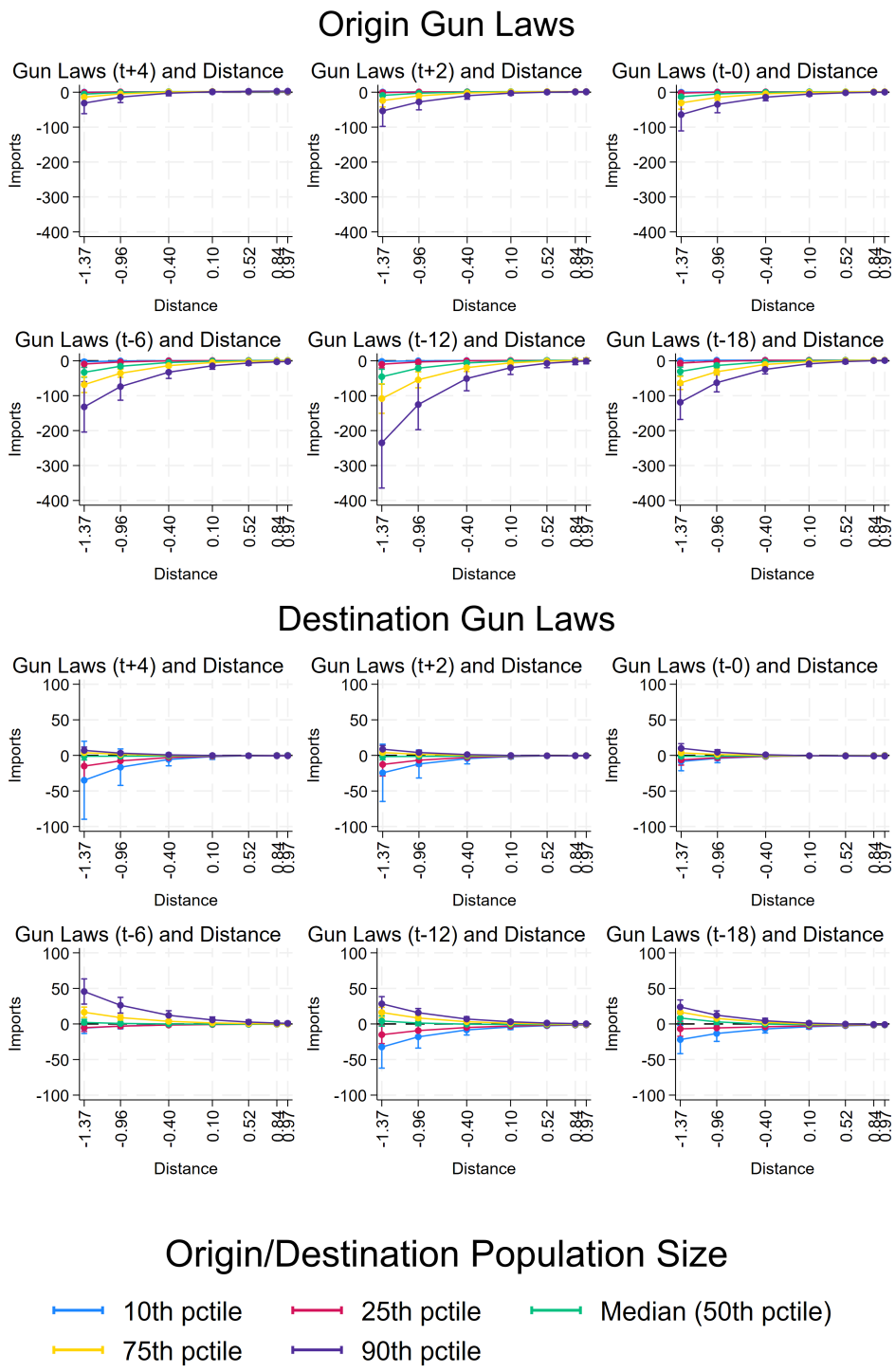
[18] Estimates without the exposure term are reported in Table 10.

Figure 5: Joint Effect of Distance and Gun Laws



Notes: Estimated effect of gun laws on gun recoveries. The figure heading label indicates gun laws. Control variables include the population in the origin and destination state, border adjacency status, destination state fixed effects, origin state fixed effects, and year fixed effects. Error bars indicate the 95% confidence interval using pair-clustered standard errors. All models use the Poisson estimator.

Figure 6: Joint Effect of Distance, Population, and Gun Laws



Notes: Estimated effect of gun laws on gun recoveries. The figure heading label indicates gun laws. Control variables include the population in the origin and destination state, border adjacency status, destination state fixed effects, origin state fixed effects, and year fixed effects. Marginal effects are calculated for the 10th percentile [blue], first quartile [red], median [green], third quartile [yellow], and 90th percentile [purple] of state population. Error bars indicate the 90% confidence interval using pair-clustered standard errors. All models use the Poisson estimator. Joint effects from models without the exposure variable are found in Figure 21.

regulations and bilateral recoveries to vary jointly with geographic distance, source-state population, and highway connectivity.

We disaggregate these interaction effects by interacting population, gun laws, and distance with a shared interstate connection dummy (e.g., I-95). The motivation for this interaction comes from prior research showing that crime-gun recoveries are also shaped by interstate linkages, with recoveries from other states rising in interstate connectedness. To examine this possibility, we estimate models similar to those above but now interact the shared interstate connection indicator with population, gun laws, distance, and all of their possible interactions (i.e., four main effects, six two-way interactions, four three-way interactions, and the single four-way interaction).

We estimate two models. The first, intended as a placebo, interacts distance and interstate status with the lead of population and gun laws. The second interacts distance and state population with the 12th lag of gun laws and state population. We expect the leads of origin-state gun laws and population to show little or no relationship with the share of guns recovered in the destination state that originated in the origin state. In contrast, the lagsconsistent with earlier resultsshould be significant. We also expect interstate connectedness to strengthen the joint effect of distance and population.

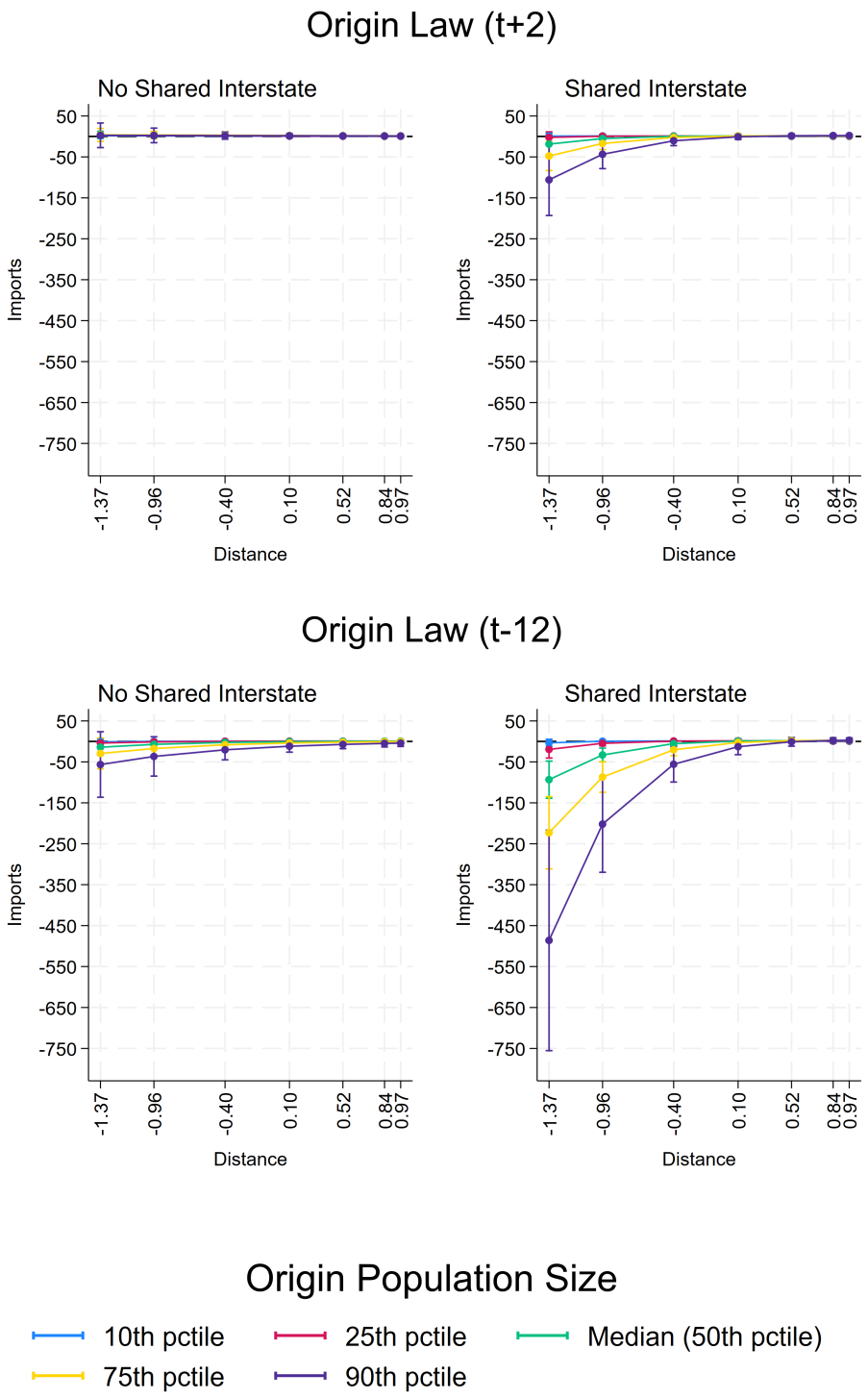
Figure 7 presents the implied regulatory effects. Point estimates are reported in Table 11 in the Appendix. The estimated effects of the leads of source-state regulations are generally close to zero, although some are slightly negative. In contrast, regulations measured twelve years before recovery exhibit a negative relationship with bilateral recoveries. This relationship becomes weaker with distance and stronger with source-state population, consistent with the preceding results.

6.5 Robustness Checks

We assess the sensitivity of the results to alternative treatments of total recoveries, controls for tracing intensity, and the timing of firearm regulations. We also conduct permutation tests and examine within-state recoveries. These exercises generally support the negative relationship between source-state regulations and bilateral recoveries, while highlighting the importance of accounting for tracing intensity when estimating the relationship with recovery-state regulations.

First, we reestimate the baseline and interaction specifications without the exposure term. The baseline specification constrains expected bilateral recoveries to scale proportionally with total recoveries in the recovery state. Removing this restriction allows us to examine whether the results depend on this normalization. Table 7 shows that the estimated regulatory relationships remain close to the baseline estimates. The source-state coefficient is approximately -0.20 at the sixth lag and -0.23 at the tenth lag, while the recovery-state coefficient becomes positive at longer lags. The coefficients on distance, shared borders, and Interstate Highway connections also remain similar. Tables 8–10 extend this exercise to the interaction specifications, with the implied effects from the population interactions presented in Figure 21. The positive interaction between source-state regulations and distance remains statistically significant, consistent with a weaker negative regulatory relationship at greater distances.

Figure 7: Joint Effect of Distance, Population, Gun Laws and Interstate Connections



Notes: Estimated effect of gun laws on gun recoveries. The figure heading label indicates gun laws. Control variables include the population in the origin and destination state, border adjacency status, destination state fixed effects, origin state fixed effects, and year fixed effects. Marginal effects are calculated for the 10th percentile [blue], first quartile [red], median [green], third quartile [yellow], and 90th percentile [purple] of state population. Error bars indicate the 90% confidence interval using pair-clustered standard errors. All models use the Poisson estimator.

Second, we consider alternative controls for tracing intensity. Differences in tracing practices may affect observed recoveries and correlate with firearm regulations. Moreover, controls constructed from recovery counts may themselves respond to regulations. Appendix B therefore compares specifications using alternative recovery-based controls, treating total recoveries as an ordinary regressor rather than an exposure term, and omitting the tracing controls or exposure term. We also consider an alternative control incorporating homicide data and the 2012 Republican presidential vote share. As shown in Figure 18, the negative relationship with lagged source-state regulations persists across these specifications. The recovery-state estimates are more sensitive: omitting both the exposure term and tracing controls produces estimates close to zero, while retaining the exposure term without a separate tracing control produces positive and statistically significant lead coefficients. These differences indicate that the estimated relationship with recovery-state regulations depends more strongly on how tracing intensity is accounted for.

Third, we extend the range of regulatory leads and lags. Figure 18 shows that the source-state estimates are generally small for future regulations and become increasingly negative when regulations are measured several years before recovery. The lagged relationships strengthen over approximately the first six years and generally stabilize at longer horizons. This pattern is consistent with the long intervals between first retail sale and subsequent recovery. However, estimates from separate lag specifications do not identify the full dynamic response to policy changes, and small lead coefficients do not by themselves establish causality.

Fourth, we conduct permutation tests that randomly reorder regulations over time within states and state pairs while preserving their underlying distributions. We repeat the exercise 100 times for contemporaneous regulations, a four-year lead, and six- and ten-year lags. Figure 20 compares the resulting coefficient distributions with the estimates using the observed timing of regulations. For source-state regulations, the permutation distributions are centered near zero, while the six- and ten-year lag estimates lie well away from these distributions. The contemporaneous and lead estimates are closer to the permutation distributions. The separation is less pronounced for recovery-state regulations. This exercise provides additional support for the importance of the observed timing of source-state regulations.

Finally, Appendix D examines whether the characteristics of a paired external state predict recoveries of firearms first sold within the recovery state itself. Tables 12 and 13 show little relationship between these within-state recoveries and the paired external state's regulations or other characteristics. The estimated relationship with the recovery state's own regulations is negative. We interpret this exercise as a supplementary diagnostic rather than a strict test of the model, since regulations in other states can affect within-state sourcing shares through substitution across sources.

7 Counterfactual Policy

This section presents a counterfactual policy experiment in which firearm regulations are harmonized nationwide. To be precise, we consider two hypothetical reforms. The first considers a scenario in which all states adopt the median level of gun laws observed in 2023. The second considers a scenario in which New York, in 2023, adopts the same gun policy as Texas. While the structural parameters are estimated using the full sample period (2009–2023), the counterfactuals are implemented as a one-time policy change in 2023, holding fixed all geographic frictions and baseline economic fundamentals.

The exercise proceeds in three steps. First, we recover bilateral interstate frictions using the model's equilibrium restrictions and verify that these frictions are well explained by geographic distance and adjacency. Second, conditional on these frictions, we invert the model to recover state-year firearm accessibility parameters. Third, we use the estimated relationship between accessibility and gun laws to simulate the equilibrium allocation of firearm shares under a uniform national regulatory environment.

7.1 Structural Estimation

Our structural procedure follows directly from the equilibrium condition in equation (2). The key objects are: (i) the bilateral friction terms B_{ij} and (ii) the state-year parameters T_{it} and c_{it}. Identification exploits the multiplicative separability of bilateral frictions and state-specific fundamentals.

However, because T_{it} and c_{it} enter the model multiplicatively and cannot be separately identified, we estimate only the composite state-specific accessibility term $\widetilde{T_{it}} = T_{it} \left(c_{it}\right)^{-\theta}$ as a sufficient statistic.

Step 1: Recovering Bilateral Frictions Equation (2) implies the model-imposed double-ratio restriction:

$$\frac{\pi_{ij,t}}{\pi_{jj,t}} \cdot \frac{\pi_{ji,t}}{\pi_{ii,t}} = \left(d_{ij} d_{ji}\right)^{-\theta}. \tag{6}$$

This restriction implies that the double ratio of bilateral sourcing shares identifies a symmetric bilateral friction term. Rather than immediately impose a parametric functional form for distance, we first construct a nonparametric bilateral friction measure B_{ij} directly from the data.

$$B_{ij} \equiv \left(d_{ij} d_{ji}\right)^{-\theta}.$$

By construction, bilateral friction is symmetric: $B_{ij} = B_{ji}$ From Equation (6), it follows that the bilateral friction measure B_{ij} is linked to observed sourcing shares via

$$B_{ij} = \mathbb{E}\left[\left(\frac{\pi_{ij,t}}{\pi_{jj,t}} \cdot \frac{\pi_{ji,t}}{\pi_{ii,t}}\right)\right],$$

Table 5: Geographic Determinants of Bilateral Frictions

	Linear	Quadratic		Cubic	
	(1) coef	(2) coef	(3) marginal	(4) coef	(5) marginal
$\log(\text{Distance}_{ij})$	1.4091***	4.3654***	1.3301***	-50.1179***	1.5572***
	(0.0899)	(1.4581)	(0.0985)	(13.7134)	(0.1172)
$\log(\text{Distance}_{ij})^2$		-0.2196**		8.2534***	
		(0.1089)		(2.1420)	
$\log(\text{Distance}_{ij})^3$				-0.4353***	
				(0.1107)	
Border_{ij}	-2.7174***	2.1559	-3.4214***	-45.0326***	-3.8423***
	(0.1722)	(2.1986)	(0.3648)	(16.4924)	(0.5909)
$\text{Border}_{ij} \times \log(\text{Distance}_{ij})$		-0.8282**		15.1223***	
		(0.3725)		(5.7884)	
$\text{Border}_{ij} \times \log(\text{Distance}_{ij})^2$				-1.3373***	
				(0.5070)	
Observations	1,128	1,128		1,128	
R-squared	0.449	0.451		0.457	
Adjusted R-squared	0.448	0.449		0.454	

Notes: The dependent variable is the symmetric bilateral friction $\log B_{ij}$, where B_{ij} is the symmetric bilateral friction measure constructed from the double ratio of interstate firearm shares. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

where $\pi_{ij,t}$ denotes the share of firearms recovered in state j that were originally sold in state i.

In practice, we estimate B_{ij} non-parametrically by averaging the empirical double ratio across years:

$$\widehat{B}_{ij} = \frac{1}{T} \sum_t \left(\frac{\pi_{ij,t}}{\pi_{jj,t}} \cdot \frac{\pi_{ji,t}}{\pi_{ii,t}} \right).$$

Under the assumption of symmetric distance costs ($d_{ij} = d_{ji}$), $\widehat{B}_{ij}$ provides a consistent proxy for $(d_{ij})^{-2\theta}$ up to sampling variation.

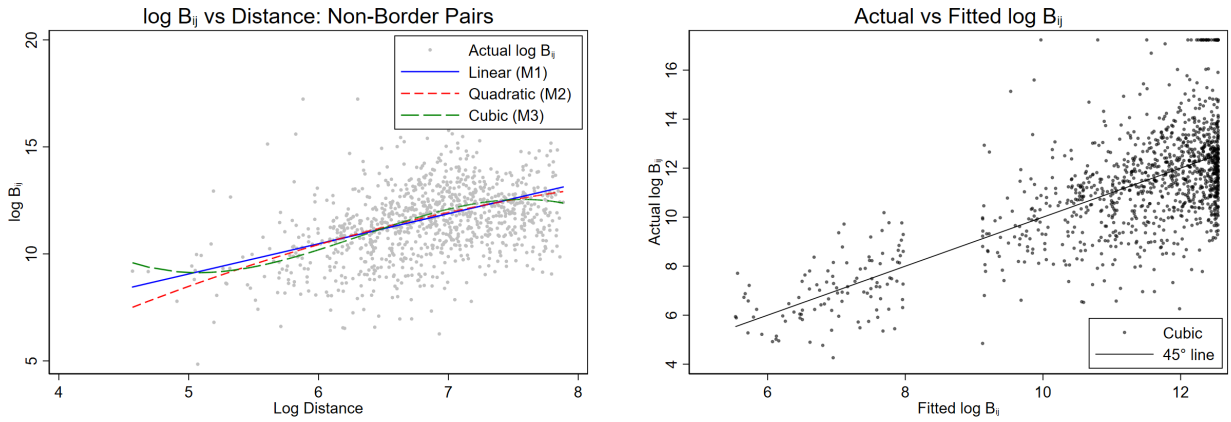
To validate this procedure, we relate the estimated bilateral friction measure $\widehat{B}_{ij}$ to geographic distance and border adjacency:

$$\log B_{ij} = f(\text{Distance}_{ij}, \text{Border}_{ij}) + \varepsilon_{ij}.$$

We estimate this relationship using linear, quadratic, and cubic specifications in distance. The results, reported in Table 5, show that the fitted curves closely track the empirical bilateral friction measure, with only modest differences in marginal effects across functional forms. These findings provide support for the gravity structure implied by the model and validate the use of $\widehat{B}_{ij}$ as a measure of bilateral geographic frictions.

The fitted values from this regression define the smoothed bilateral friction term used in the structural inversion. Consistent with the gravity structure of the model, geographic distance is a strong predictor of bilateral frictions, thereby validating the theoretical restriction imposed by

Figure 8: **Estimated Bilateral Frictions and Geographic Distance**



(a) log B_{ij} and fitted distance relationship.

(b) Actual vs. fitted log B_{ij}.

Notes: This figure corresponds to Step 2 of the structural estimation, in which we recover bilateral friction terms B_{ij} implied by the model. Panel (a) plots the estimated log B_{ij} against geographic distance between state pairs, along with the fitted curves. Panel (b) compares the actual estimated log B_{ij} to the fitted values from the distance-based specification.

Equation (6).

As expected, bilateral frictions increase with geographic distance and decline for adjacent state pairs. Across specifications, the estimated marginal effects of distance range from approximately 1.33 to 1.56, while the adjacency indicator reduces bilateral frictions by between 2.7 and 3.8 log points.

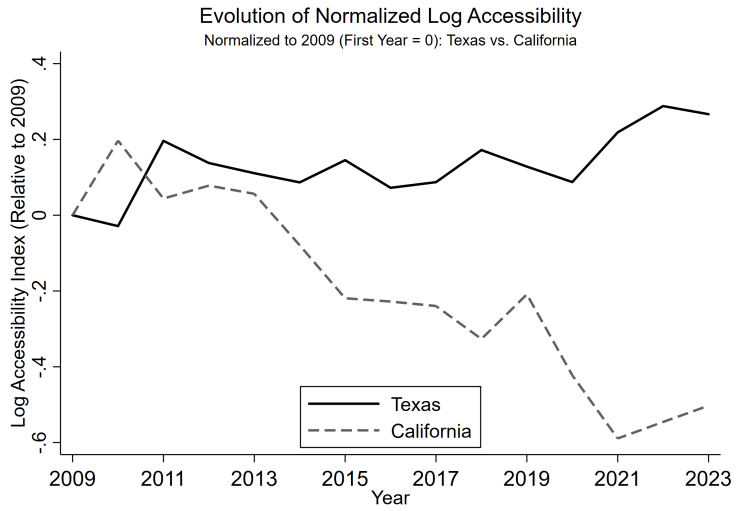
Figure 8 illustrates these findings. Panel (a) shows that the linear, quadratic, and cubic specifications produce very similar fitted relationships between log B_{ij} and distance. Panel (b) compares the empirical bilateral friction measure to the fitted values from the preferred specification and demonstrates that the model closely matches the estimated frictions. The adjusted R^2 values are approximately 0.45 across all three specifications, indicating that distance and adjacency explain a substantial share of the cross-sectional variation in bilateral firearm frictions.

Step 2: Recovering State-Year Accessibility Parameters The goal of this step is to recover the composite state-specific accessibility term $\widetilde{T}_{it} = T_{it} (c_{it})^{-\theta}$.

From Equation (2), and under the assumption of symmetric distance ($d_{ij} = d_{ji}$), the ratio of inflows from state i to state j relative to domestic sourcing in j can be written as

$$\frac{\pi_{ij}}{\pi_{jj}} = \frac{\widetilde{T}_{it}\sqrt{B_{ij}}}{\widetilde{T}_{jt}}.$$

Figure 9: **Evolution of Firearm Accessibility Index, Normalized to 2009.**



Notes: This figure plots the log normalized firearm accessibility index (T_{it}) for Texas and California from 2009 to 2023. The index is normalized to the base year 2009, so that both states equal zero in 2009. Positive values indicate higher accessibility relative to 2009, while negative values indicate lower accessibility relative to the base year.

Dividing both sides by $\sqrt{B_{ij}}$ yields

$$\frac{\pi_{ij}}{\pi_{jj}\sqrt{B_{ij}}} = \exp\left(\log \widetilde{T}_{it} - \log \widetilde{T}_{jt}\right). \tag{7}$$

Equation (7) shows that, within a destination-year, relative friction-adjusted sourcing shares identify relative accessibility across origin states. Intuitively, after netting out bilateral frictions, variation in observed sourcing probabilities reflects differences in state-specific firearm accessibility.

We estimate Equation (7) using Poisson pseudo-maximum likelihood (PPML) to recover $\log(\widetilde{T}_{it})$. The specification includes state fixed effects, which identify accessibility parameters up to a normalization, and year fixed effects, which absorb aggregate nationwide shifts in firearm markets that are common across states.

This procedure yields a panel of state-year accessibility parameters $\log(\widetilde{T}_{it})$ for the period 2009–2023.

Figure 9 illustrates the time path of the estimated firearm accessibility index. Texas, which became more permissive by reducing firearm laws from 10 in 2009 to 6 in 2023, experienced a sustained increase in accessibility. By contrast, California expanded its firearm regulations from 45 to 62 laws over the same period and exhibits a corresponding decline in the estimated accessibility parameter.[19]

[19] In the replication file, note that the laws are shifted up by one to preserve zeros.

Step 3: Linking Accessibility to Gun Laws We next relate the state-year accessibility parameters to regulatory stringency. Specifically, we estimate the following specification:

$$\log \widetilde{T}_{it} = \beta_1 \log(\text{Population}_{i,t-k}) + \beta_2 \text{GunLaws}_{i,t-k} + \delta_i + \gamma_t + \varepsilon_{it},$$

where δ_i and γ_t denote state and year fixed effects, respectively, and k indexes the lag structure. The lag allows firearm accessibility to adjust gradually to changes in population and regulatory environments.

The coefficient $\widehat{\beta}_2$ maps changes in gun laws into proportional shifts in the accessibility parameter. Because the dependent variable is in logs, β_2 can be interpreted as the semi-elasticity of firearm accessibility with respect to regulatory stringency.

Results are found in Table 6. Consistent with the reduced-form evidence, stricter gun laws significantly reduce firearm accessibility. The estimated effects are economically meaningful and become strongest at lags of six to eight years, suggesting gradual adjustment in sourcing networks and cross-state flows. Population enters positively, reflecting scale effects in sourcing capacity. Its impact is most pronounced at shorter horizons, typically within one to three years.

7.1.1 Step 4: Constructing counterfactual

We begin by computing the benchmark equilibrium shares of firearm flows, $\pi^0_{ij,t}$, using the estimated time-invariant bilateral frictions B_{ij} and the estimated accessibility parameters $\widetilde{T}_{it}$:

$$\pi^0_{ij,t} = \frac{\widetilde{T}_{it}\sqrt{B_{ij}}}{\sum_{k=1}^{N} \widetilde{T}_{kt}\sqrt{B_{kj}}}.$$

Let GunLaws^{cf}_{it} denote the counterfactual level of firearm regulations in state i in year t. For each state-year, we compute the counterfactual accessibility parameter as

$$\log \widetilde{T}^{cf}_{it} = \log \widetilde{T}_{it} + \widehat{\beta}_2 \left(\text{GunLaws}^{cf}_{it} - \text{GunLaws}_{it} \right).$$

For the counterfactual analysis, we adopt the estimates from the five-year lag ($k = 5$) specification because it provides the best fit to the data according to Table 6 and captures the long-run adjustment of firearm accessibility to regulatory changes. While a single parameter vector must be chosen for simulations, the specific choice of lag length, within a reasonable window, is not driving our counterfactual patterns and not all that important; estimates from adjacent lags yield substantively similar network reallocations and structural accessibility shifts. This is unexpected given the results discussed in Section 6.

Using the structural share equation, we then recompute equilibrium sourcing shares based on the time-invariant bilateral frictions B_{ij} and the counterfactual accessibility parameters $\widetilde{T}^{cf}_{it}$:

$$\pi^{cf}_{ij,t} = \frac{\widetilde{T}^{cf}_{it}\sqrt{B_{ij}}}{\sum_{k=1}^{N} \widetilde{T}^{cf}_{kt}\sqrt{B_{kj}}}.$$

Table 6: Lagged Effects of Law Measure on the Outcome

	$k = 0$	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$	$k = 7$	$k = 8$	$k = 9$	$k = 10$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\text{GunLaws}_{i,t-k}$	-0.013**	-0.013**	-0.019***	-0.019***	-0.022***	-0.030***	-0.032***	-0.034***	-0.035***	-0.031***	-0.033***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
$\log(\text{Population}_{i,t-k})$	1.330**	1.441**	1.408**	1.380**	1.267**	1.098**	1.027**	0.922*	0.838*	0.858*	0.795*
	(0.580)	(0.590)	(0.599)	(0.569)	(0.537)	(0.503)	(0.468)	(0.469)	(0.479)	(0.476)	(0.465)
Observations	720	720	720	720	720	720	720	720	720	720	720
R^2	0.919	0.919	0.921	0.920	0.920	0.923	0.922	0.922	0.921	0.919	0.919
Adj. R^2	0.911	0.911	0.913	0.912	0.913	0.915	0.915	0.914	0.914	0.911	0.911
RMSE	0.223	0.223	0.221	0.221	0.221	0.218	0.219	0.219	0.220	0.223	0.223
AIC	-2220	-2219	-2237	-2232	-2233	-2256	-2251	-2249	-2242	-2224	-2221
BIC	-2206	-2206	-2224	-2219	-2220	-2242	-2237	-2235	-2228	-2211	-2207

Notes: All regressions include state fixed effects and year fixed effects. Column k uses regressors lagged by k periods. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

This procedure yields a full counterfactual matrix of bilateral firearm flows for each year. Because bilateral frictions are held fixed, all changes arise from adjustments in relative accessibility across states induced by the policy intervention. The counterfactual therefore captures the general-equilibrium reallocation of sourcing shares across origin states.

Finally, we compute the change in sourcing shares as

$$\Delta\pi_{ij} = \pi_{ij}^{cf} - \pi_{ij}^{0}.$$

7.2 Counterfactual Analysis

We conduct two counterfactual policy experiments to quantify how changes in gun laws reshape interstate gun flows in general equilibrium. The first examines a policy change in a single large state. Motivated by ongoing debates over gun regulation in New York, we simulate a scenario in which New York modifies its gun laws while all other states remain at their baseline levels. The second counterfactual considers a hypothetical reform in which all states adopt the median number of gun laws. This exercise isolates the role of regulatory asymmetries by eliminating cross-state differences in regulatory stringency.

7.2.1 Counterfactual I: New York Policy Change

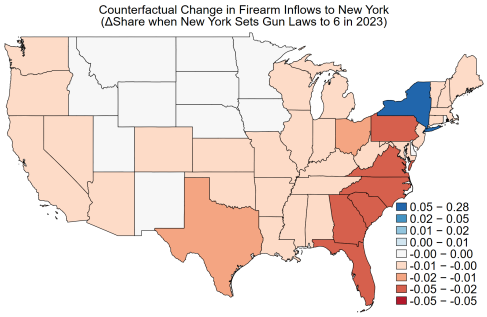
We first consider a scenario in which New York adopts the gun policy of Texas, reducing the number of gun laws from 48 to 6. Figure 10 illustrates the predicted changes in interstate gun flows under this policy shift. The counterfactual generates two main effects. First, New York sharply reduces its inflows from other states, as lower regulatory stringency makes local sourcing more competitive. Second, New York simultaneously becomes a larger origin state, increasing its share of interstate gun flows to other destinations.

The largest adjustments occur within New York itself. The model predicts a substantial increase in the share of crime guns originating within the state. Spillovers are strongest among geographically proximate states. Nearby states such as Massachusetts, New Jersey, and Vermont experience increased inflows from New York while reducing reliance on alternative sources, including their own markets and distant states such as Florida. These patterns reflect a gravity-type mechanism in which regulatory changes shift sourcing toward nearby low-cost origin states.

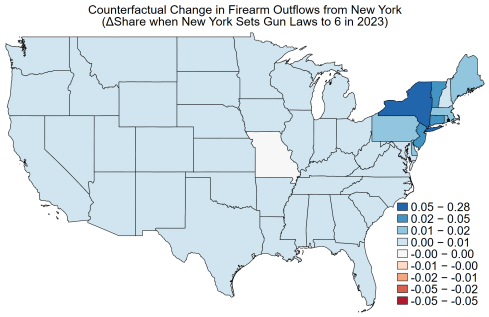
By contrast, spillovers to distant states are limited. States such as California and Texas are sufficiently distant from New York that the counterfactual generates only modest changes in their sourcing patterns. Nevertheless, inflows from New York increase slightly, reflecting an expansion of New York's role as an origin state even at longer distances.

Overall, this counterfactual highlights the joint role of geographic frictions and regulatory differences in shaping interstate gun flows. Policy changes in a large state generate substantial local adjustments and geographically concentrated spillovers, with effects that decay rapidly with distance.

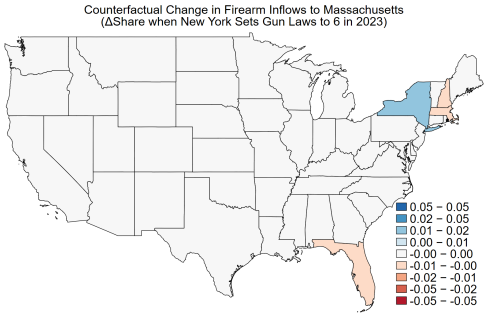
Figure 10: **Predicted Flows of Crime Guns**



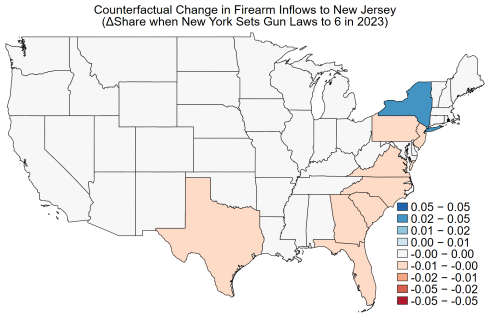
(a) New York – Inflow



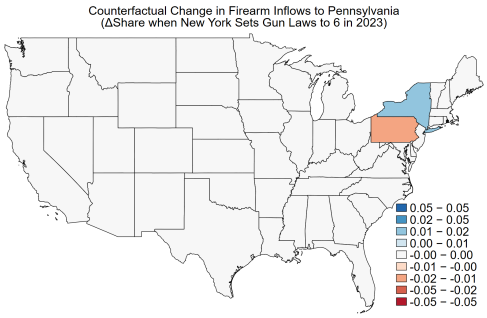
(b) New York – Outflow



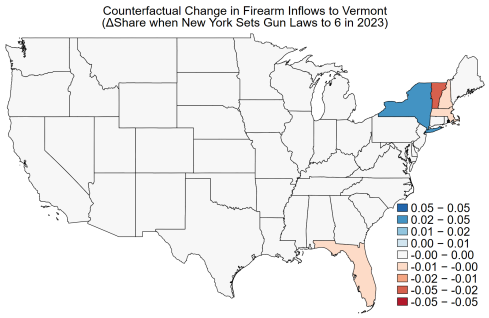
(c) Massachusetts – Inflow



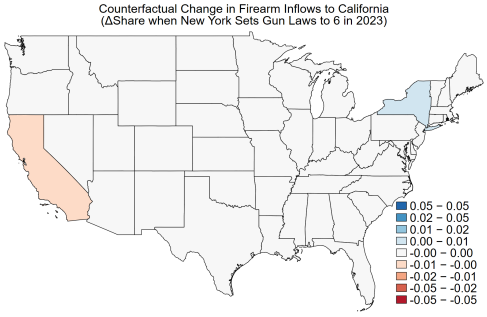
(d) New Jersey – Inflow



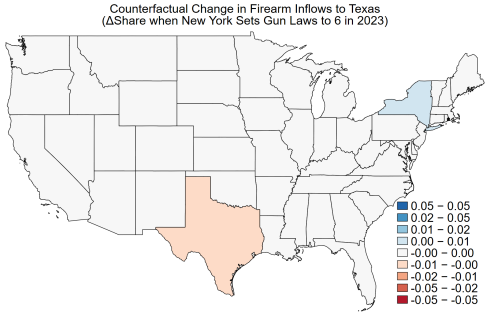
(e) Pennsylvania – Inflow



(f) Vermont – Inflow



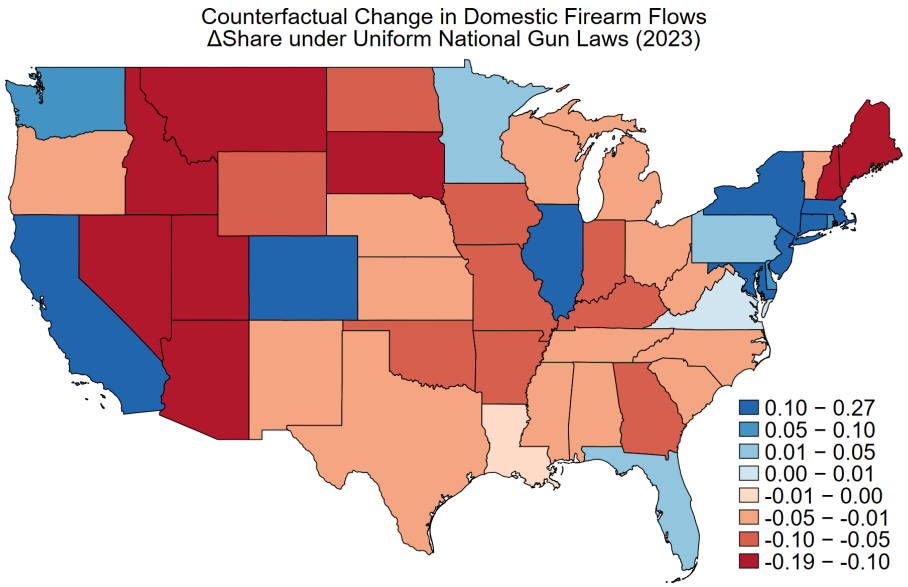
(g) California – Inflow



(h) Texas – Inflow

Notes: The figure reports predicted changes in interstate gun shares under a counterfactual policy in which New York adopts six gun laws in 2023, while all other states remain unchanged. Colors indicate the change in the share of crime guns linking each origin–destination pair. Blue denotes an increase in the share, while red denotes a decrease. Values close to zero (< 0.0005) are treated as having no effect.

Figure 11: **Counterfactual Change in Domestic Firearm Flows**



Notes: The figure shows the predicted change in interstate firearm import shares under a counterfactual policy in which all states adopt the national median number of gun laws observed in 2023. Colors represent the change in the share of crime guns recovered in each destination state that originate from other states. Blue indicates an increase in imported crime-gun shares, while red indicates a decrease. Values close to zero (<0.0005) are treated as having no effect.

7.2.2 Counterfactual II: Uniform National Gun Laws

Figure 11 visualizes the predicted change in domestic gun shares when all states adopt the national median number of gun laws observed in 2023. The map reports the resulting change in the share of crime guns recovered in each destination state that originate from within the state. Blue regions indicate increases in domestic shares, while red regions indicate declines.

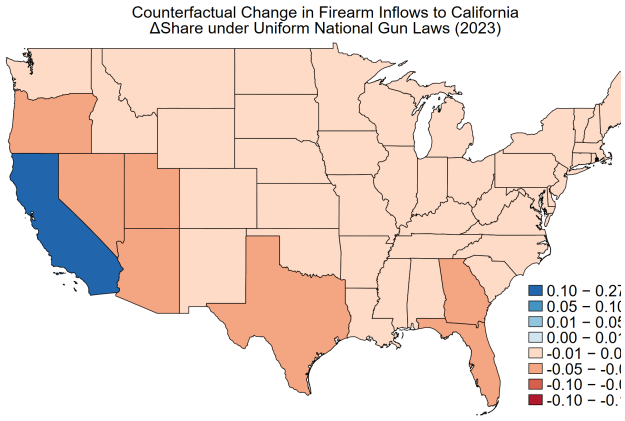
The spatial pattern reflects how harmonization compresses cross-state regulatory differences. States that initially maintained relatively strict regulatory environments experience declines in inflows of crime guns. As more permissive states raise their regulatory standards toward the national median, incentives for cross-state sourcing weaken, particularly among nearby states. As a result, these states become more reliant on domestically sourced guns.

Conversely, states that initially had relatively permissive regulations experience increases in inflow shares. For these states, harmonization represents a tightening of local regulations, which raises the relative attractiveness of sourcing from other states. The model therefore predicts an increase in interstate inflows as agents substitute toward external sources.

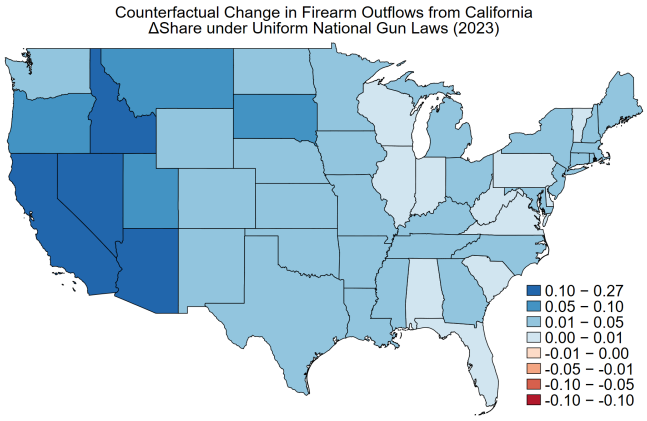
Figure 12 presents selected counterfactual outcomes for three states spanning the distribution of regulatory stringency: California (strict), Pennsylvania (moderate), and Texas (permissive). The left column reports predicted percentage changes in inflows, and the right column reports predicted percentage changes in outflows under the harmonization scenario.

For California (top), harmonization increases the domestic share of crime guns and reduces

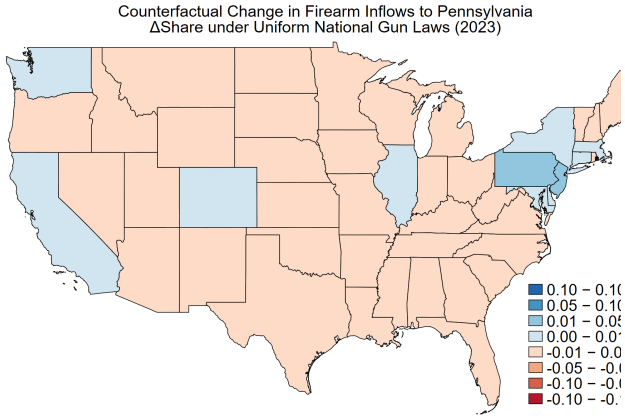
Figure 12: **Inflow and Outflow of Crime Guns: California, Pennsylvania, and Texas**



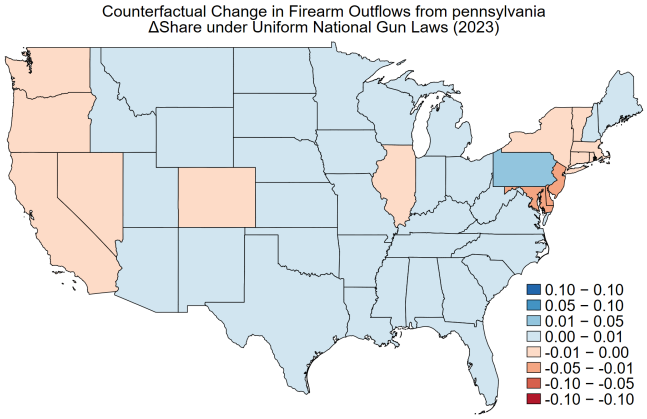
(a) California – Inflow



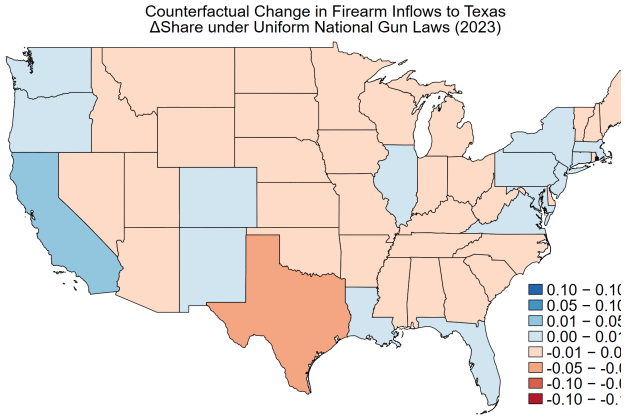
(b) California – Outflow



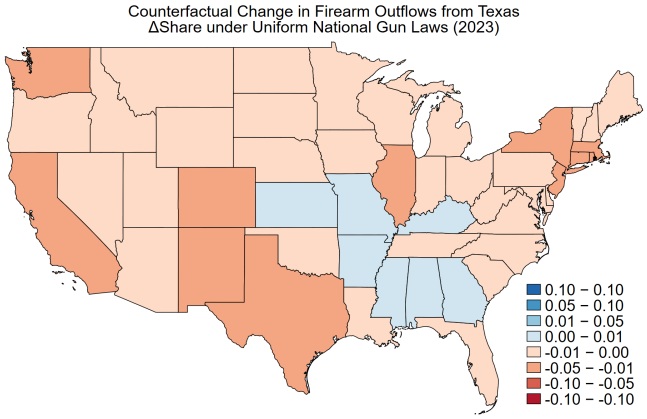
(c) Pennsylvania – Inflow



(d) Pennsylvania – Outflow



(e) Texas – Inflow



(f) Texas – Outflow

Notes: The figure reports predicted changes in interstate gun shares under a counterfactual policy in which all states adopt the national median number of gun laws observed in 2023. Each row corresponds to a focal state (California, Pennsylvania, and Texas). The left column shows firearm inflows (guns recovered in the state but originally sold elsewhere), while the right column shows firearm outflows (guns sold in the state but recovered elsewhere). Colors indicate the change in the share of crime guns linking each origin–destination pair. Blue denotes an increase in the share, while red denotes a decrease. Values close to zero (< 0.0005) are treated as having no effect.

inflows from most other states. The largest declines occur among nearby states with more permissive regulations, such as Arizona. At the same time, outflows from California increase, particularly toward nearby destinations such as Nevada.

Texas (bottom), which has one of the most permissive regulatory environments, exhibits the opposite pattern. Harmonization reduces the domestic share of crime guns recovered in Texas and increases inflows from several neighboring states, including Colorado, New Mexico, and Kansas. Because the policy represents a substantial increase in regulatory stringency for Texas, outflows decline across most destinations, with the largest reductions concentrated among nearby states.

Pennsylvania (middle) represents an intermediate case. As with California, adopting the median number of gun laws increases the domestic share of recovered crime guns. Inflows from neighboring states with stricter initial regulations – particularly New York and New Jersey – also rise. Outflows from Pennsylvania generally increase, though the effects are more muted.

These patterns generalize across states. Harmonization reduces cross-state regulatory differences, compressing incentives for interstate sourcing. States with initially strict laws experience declines in inflows, while initially permissive states experience reductions in outflows. Overall, the counterfactual highlights the central mechanism of the model: interstate gun flows respond to relative regulatory environments rather than absolute levels. By reducing regulatory differences, harmonization attenuates cross-state sourcing patterns, particularly among geographically proximate states.

8 Policy Implications

A growing body of work studies how state-level regulations generate spillovers across jurisdictional borders. Examples include alcohol and tobacco sales, abortion policy, environmental regulation, and labor market reforms (Lovenheim, 2008; Dube et al., 2010; Molina and Siegal, 2025). In these settings, policy differences across states create incentives for cross-border substitution or arbitrage, weakening the effectiveness of state-level interventions. Our findings add a new dimension to this literature by documenting substantial regulatory spillovers in firearm acquisition. Our results have several implications for the design of firearm regulations in a federal system where states retain primary authority over gun policy, but firearms move across state lines. Three insights emerge.

First, state-level regulations generate systematic spillovers. Changes in firearm laws in one state affect firearm availability in other states in a predictable manner. Stricter source-state regulations are associated with smaller shares of recoveries originating from those states, whereas stricter recovery-state regulations are associated with greater reliance on out-of-state sources. These relationships concern the composition of recovered firearms rather than changes in the total number of recoveries. Because these effects decay with distance but remain substantial among neighboring states, the effectiveness of unilateral state regulation depends critically on the policies of nearby states. This suggests that gun policy operates on a regional margin, not a purely state-specific

margin.

Second, regulatory differences across states are associated with systematic variation in the geographic origins of recovered crime guns. These patterns are consistent with cross-state substitution in firearm acquisition, although the tracing data do not distinguish illicit trafficking from other mechanisms through which firearms move between states. When two adjacent states differ sharply in regulatory stringency, the model predicts – and the data confirm – that traffickers reallocate flows toward the more heavily regulated state. These incentives arise even though legal acquisition costs are nearly uniform across states. The primary drivers of these flows are differences in accessibility parameters, which reflect how regulations shape the ease of obtaining firearms in informal or semi-legal markets. Policies that increase this regulatory gap, without coordination, may unintentionally heighten trafficking pressures.

Third, policies that reduce firearm accessibility in high-supply states generate benefits that extend beyond their borders. Because states with relatively permissive regulations disproportionately serve as source states, efforts to raise enforcement intensity or tighten acquisition rules in these states can reduce the volume of trafficked guns recovered elsewhere. This implies that regulatory tightening in large, high-population source states generates positive externalities for the national system. Our structural estimates allow us to quantify these gains and show that the magnitude of the external effect is strongly increasing in the size of the source state.

A broader implication follows from these results. Since interstate firearm flows respond to relative rather than absolute regulations, effective reductions in trafficking require some degree of policy coordination. This coordination can take several forms: harmonizing specific regulatory components across regions, aligning enforcement priorities along high-volume trafficking corridors, or establishing federal minimum standards that compress the cross-state dispersion in acquisition frictions. In each case, the model implies that narrowing regulatory differentials reduces the profitability of cross-state arbitrage and weakens the economic mechanisms that sustain trafficking networks.

In short, in a setting where firearms are mobile and trafficking responds systematically to policy differentials, the consequences of state-level decisions extend well beyond state boundaries. If reducing cross-state movement of crime guns is a policy objective, designing policies that take cross-state feedback into account is central.

9 Conclusion

This paper develops a theoretical and empirical framework to study interstate crime gun recoveries in the United States. Building on a Ricardian structure, we model these flows as an equilibrium outcome shaped by differences in regulatory environments and geographic frictions. The model delivers four main predictions: interstate crime gun flows decline with distance; stricter regulations in an origin state reduce its outflows; stricter regulations in a destination state increase its reliance on inflows; and all regulatory effects weaken with distance. Using data on crime-gun

recoveries and state-level gun laws from 2009–2023, we provide systematic evidence supporting these predictions using crime gun recoveries while also noting potential selection in tracing/gun recoveries.

We then use the estimated structural model to quantify how interstate crime gun flows adjust under two counterfactual policy scenarios. The first considers a change in gun laws in a single large state, highlighting how local policy shifts propagate through the network of origin–destination linkages. The second examines a harmonization of gun laws across states, isolating the role of cross-state regulatory differences. These counterfactuals illustrate how policy changes generate general-equilibrium reallocation of interstate crime gun flows. These results underscore the limitations of unilateral state regulation in a federal system where agents reallocate sourcing in response to policy differences. More broadly, the findings highlight the general-equilibrium nature of gun markets: policy changes in one state affect availability in others, and the magnitude of these spillovers depends on distance, population, and baseline regulatory stringency.

The main limitation of our work is that it does not explore which particular laws have the largest effects. Since our measure of gun control is the total number of gun laws, two states each adding a different law would, for example, have the same marginal effect. This is not necessarily a realistic assumption. While Siegel et al. (2017) already categorizes laws into distinct groups (such as dealer regulations), using that granularity introduces severe empirical trade-offs. To identify their independent effects over time would require running a battery of many different continuous event studies, defending the parallel trends assumption multiple times over, taking into account distance/border adjacency, all while states are introducing and removing other gun laws, while also defending why certain results are or are not reasonable (e.g., explaining why are ammo restrictions significant but assault weapon bans not?).[20] Our paper also does not weigh in on the debate concerning the relative importance of formal trafficking and migration patterns in generating crime gun recoveries – e.g., Cook et al. (2014) and Kleck (2020).

Policies that treat gun markets as isolated systems risk overstating the impact of state-level interventions and understating the importance of regional or national coordination. Future work may extend this framework to incorporate heterogeneity in sourcing networks, specific laws, enforcement responses, or substitution between legal and informal markets. Future work could also distinguish regulatory spillovers from compositional spillovers. States differ not only in firearm regulations but also in the characteristics of their gun-owning populations. Interstate migration may therefore change firearm markets by relocating individuals with systematically different propensities to own, transfer, carry, or misuse firearms. Such extensions may further clarify the channels through which gun laws propagate across states and shape the broader distribution of crime guns in the United States.

[20] This is fundamentally a different paper and, in our view, a dumpster fire waiting to happen.

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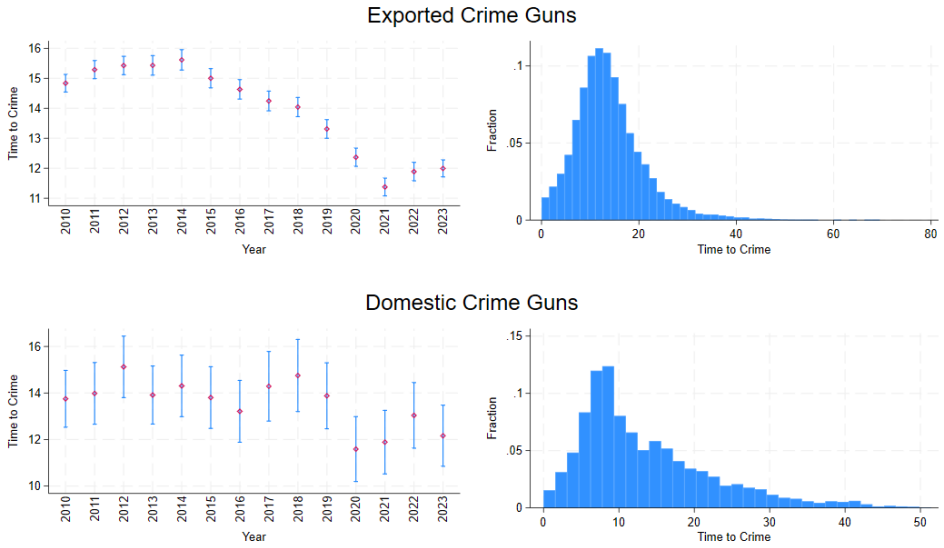
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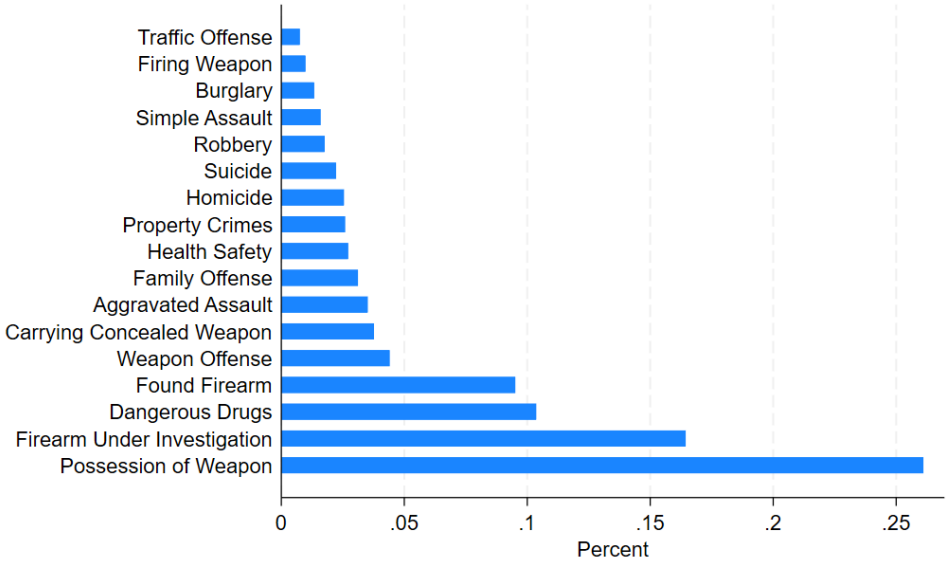
A Background Figures

Figure 13: Average Time to Crime



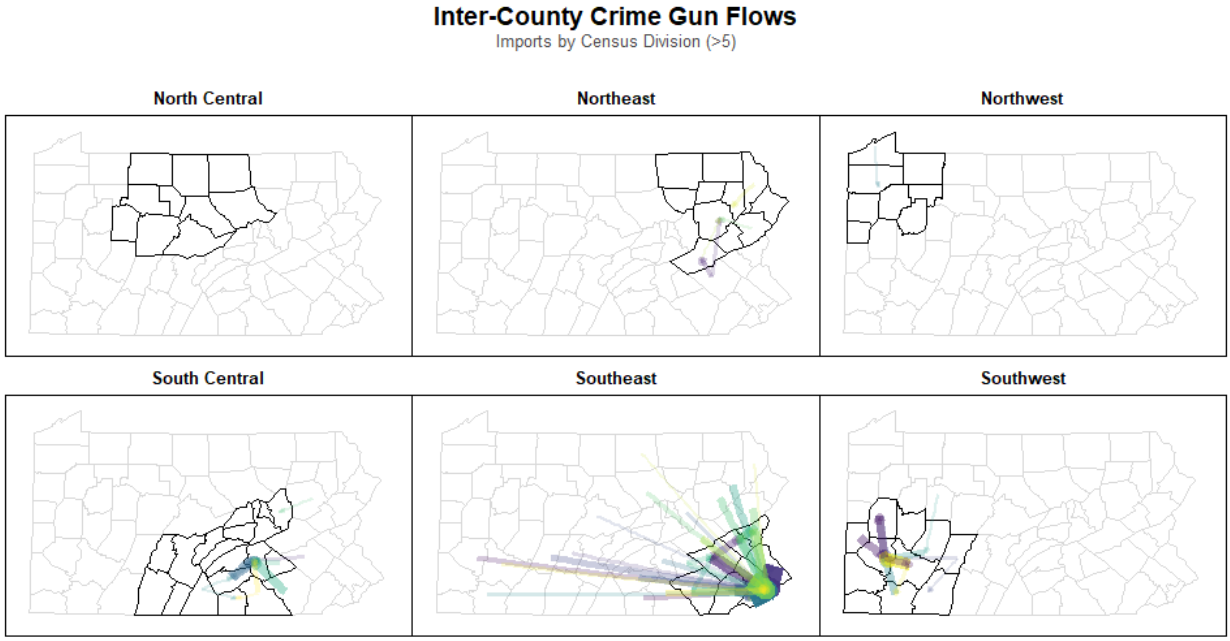
Notes: Left: time between gun recovery and original sale by year and source. Error bars correspond to 95% confidence intervals. Right: Distribution of average time to crime by crime gun source.

Figure 14: Common Events Leading to a Firearm Tracing



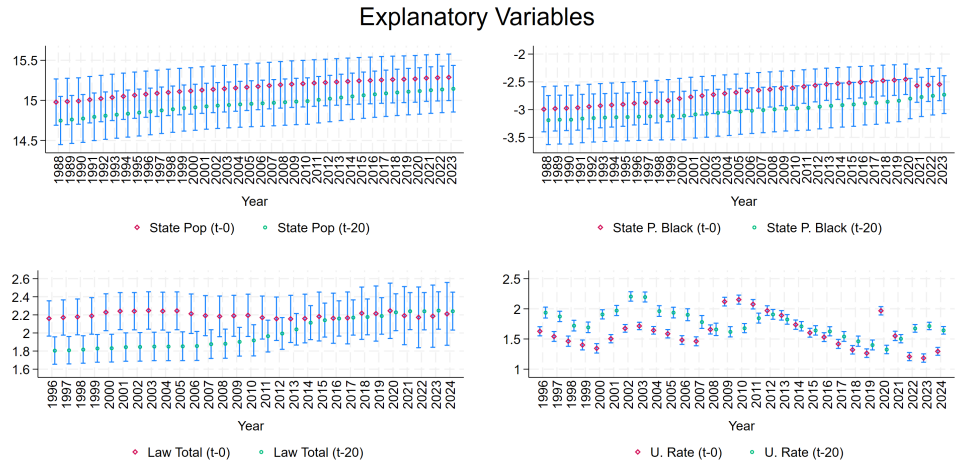
Notes: Bars report the share of ATF firearm trace requests, 2012 - 2019, associated with each underlying offense or circumstance prompting the trace

Figure 15: Out of County Crime Gun Sources



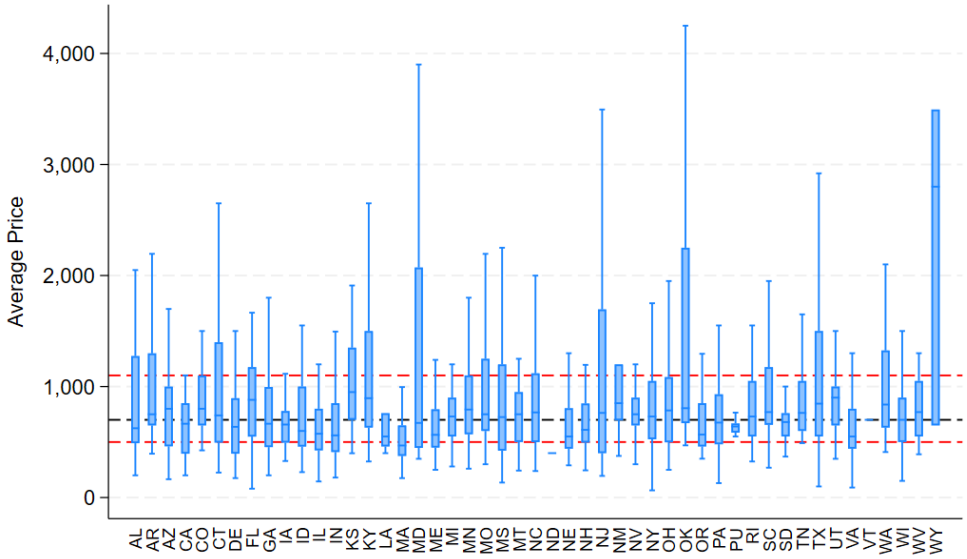
Notes: Maps display the primary sources of out-of-county crime guns recovered in each destination county. Line width and opacity are proportional to the number of traced crime guns flowing from origin to destination. Arrows indicate the direction of flows. Data is from Johnson et al. (2024).

Figure 16: Contemporaneous and Lagged Explanatory Variables



Notes: Each panel plots the mean (points) and variation (vertical bars) by year for explanatory variables used in the main regressions and compares the contemporaneous value to its 20-year lag. Panels show: (top left) log state population; (top right) log state percent Black; (bottom left) total number of state firearm laws (log); (bottom right) unemployment rate (log).

Figure 17: Gun Prices Across States



Notes: Boxplots show the distribution of average handgun prices by state for the five most commonly traced calibers (9mm, .38 Special, .45 ACP, .22 LR, and .40 S&W), excluding listings priced above $30,000. Boxes denote the first, second (median), and third quartiles of each state's price distribution, with whiskers indicating 95% confidence intervals; dashed lines mark the corresponding quartiles for the pooled national sample. Prices are constructed from archived 20162020 listings on Guns International and assigned to states based on the area code of the seller's contact number. "PU" denotes Parts Unknown, i.e. listings with toll-free or otherwise unidentifiable area codes that could not be matched to a state.

B Addressing the Destination-State Endogeneity Concern

Figure 18 plots coefficients estimated from different leads (8) and lags (25) of import- and export-state gun laws under alternative specifications that differ in how they account for tracing intensity or lack thereof; other than this distinction, models are identical to what is presented in Equation 4. The top-left panel reports our preferred specification, which uses recoveries from all states other than j as a control for tracing intensity. Each dot (and error bar) corresponds to a different model – so each panel has 31 different models that vary only in the choice of k within the panel. The top middle and right panels also use some variation of this approach and control for intensity with the number of recoveries from j (domestic recoveries) and the total number of recoveries (i.e., treating the exposure variable as a typical control variable). Bottom middle drops the total imports variable altogether, and the bottom-right panel includes the contemporaneous exposure variable but does not include a separate measure of tracing intensity. We will defer discussion of the bottom left panel for later.

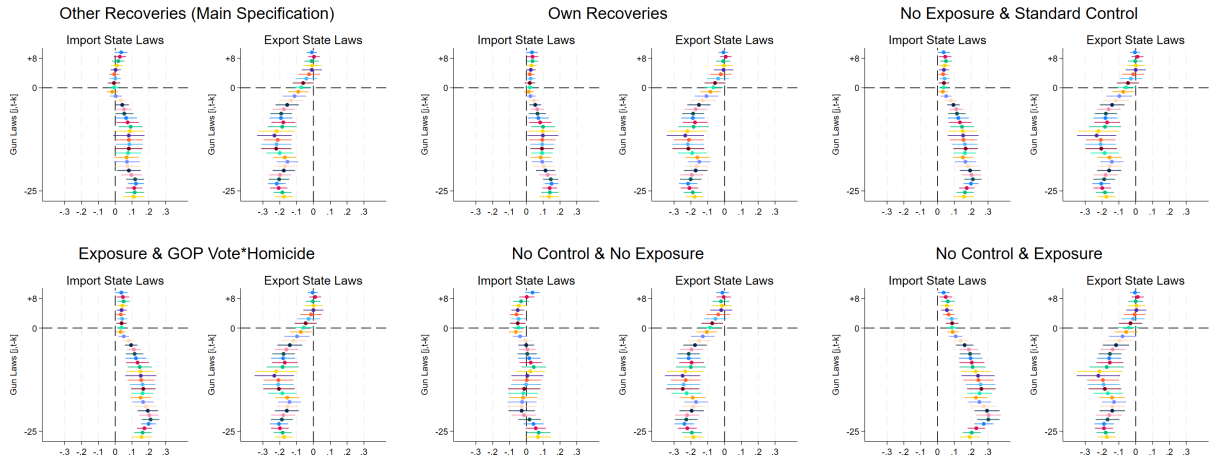
Here we first note that the relationship between gun laws and gun recoveries is remarkably consistent with the observed time to crime. First, there is a general nonlinear relationship between the lag of gun laws and their effect on crime gun recoveries. In all cases, the effect begins small and then increases to around the sixth lag, where it begins to stabilize. The effect then peaks at around the twelfth lag and remains steady after. Importantly, the elbow around zero (the transition from small lead estimates to increasingly pronounced lagged estimates) is hard to reconcile with a simple explanation based solely on smooth state-level trends. Given this timing, the pattern is highly suggestive of a causal relationship between gun laws and crime gun recoveries. Furthermore, in the top three panels, the pattern of the different lags is very similar both directionally and in magnitude. Leads are generally not statistically significant or are very small in absolute terms.

Consistent with our prior that export state gun laws (j) are mostly exogenous to recoveries in state i, we find that gun recoveries from state j in i are mostly not significantly related to the lead of j's gun laws. Put differently, if j introduces some gun law in 2018, it is unlikely to affect gun recoveries in state i in 2016. This changes as the leads turn to lags. In all cases here, increases in state j's gun laws reduce the share of crime guns recovered in i from state j. On the other hand, domestic (or i's) gun laws are a bit different, but the results are still consistent with the identifying assumption that future gun laws are plausibly exogenous to contemporaneous crime gun recoveries – though this is only true once tracing intensity is properly controlled for.

This is illustrated in the bottom right panel, where leads of destination-state gun laws become positive and statistically significant. Because future laws cannot plausibly affect current recoveries, these estimates are most naturally interpreted as evidence of omitted variable bias. The exposure variable is partly proxying for persistent determinants of gun recoveries (e.g., underlying tracing practices) that both generate higher contemporaneous recoveries and are correlated with subsequent policy adoption. Once tracing intensity is separately controlled for, these lead effects disappear.

We are reasonably confident that this is tracing intensity based on analysis using homicide data

Figure 18: Lags/Leads of Gun Laws and Crime Gun Recoveries

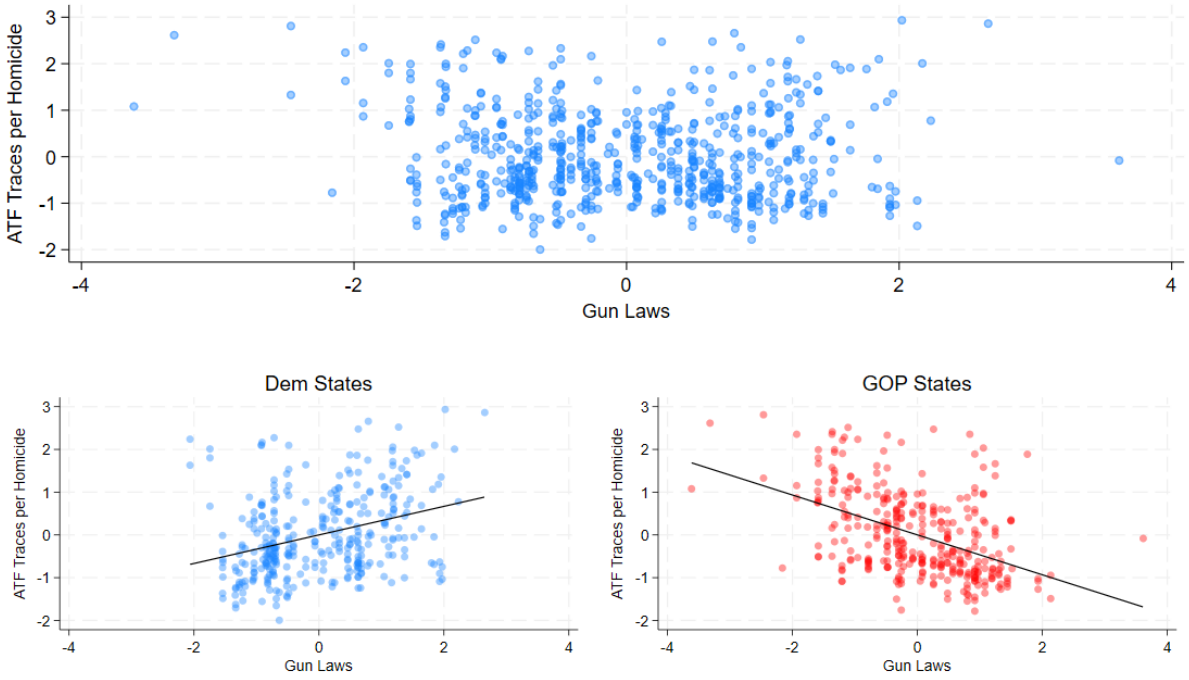


Notes: Estimated relationship between leads/lags of gun laws (both destination and origin) and the share/number of imported crime guns. Top left panel corresponds to the estimates presented in Table 3, which uses the natural log of the total number of recoveries from non-j states as a control for tracing intensity. Top middle uses the number of crime guns from i (the originating state) as the control for tracing intensity. Top right has no exposure variable but controls for tracing intensity using the total number of reported crime guns. Bottom left uses the interaction between the GOP vote share in the 2012 election and the number of successful traces per homicide, and includes the exposure variable. Bottom middle includes no exposure variable or control for trace intensity, and bottom right has no specific control for tracing intensity but does include the exposure variable. All models using a lag of gun laws have 33,840 observations.

and 2012 presidential vote shares. To start, for each state we find the total number of crime guns successfully traced by the ATF per homicide. We then standardize the number of traces per homicide (within state) and plot it against standardized gun laws. The resulting scatter plot ($n = 720$) is presented in the top panel of Figure 19. Here we first note there is no obvious correlation between standardized gun law counts and standardized successful traces per homicide ($\rho = -.07$). However, when we separate states based on 2012 presidential election results (Democratic states defined as states with below-median support for Mitt Romney in the 2012 election; Republican states at or above the median), we see a clear bifurcation. Gun laws in relatively more Democrat-voting states have a positive relationship with the number of traces per homicide ($\rho = .33$), while in relatively more Republican-voting states, the relationship is the opposite ($\rho = -.46$). This relationship is robust. When we run intercept-less regression using the two standardized variables and use state-clustered standard errors, we find that the relationship between traced crime guns per homicide and gun laws is not significant ($p = 0.479$) but is significant when we separate by 2012 presidential election votes (Democratic-voting states: $p = 0.013$; Republican-voting states: $p < 0.001$).

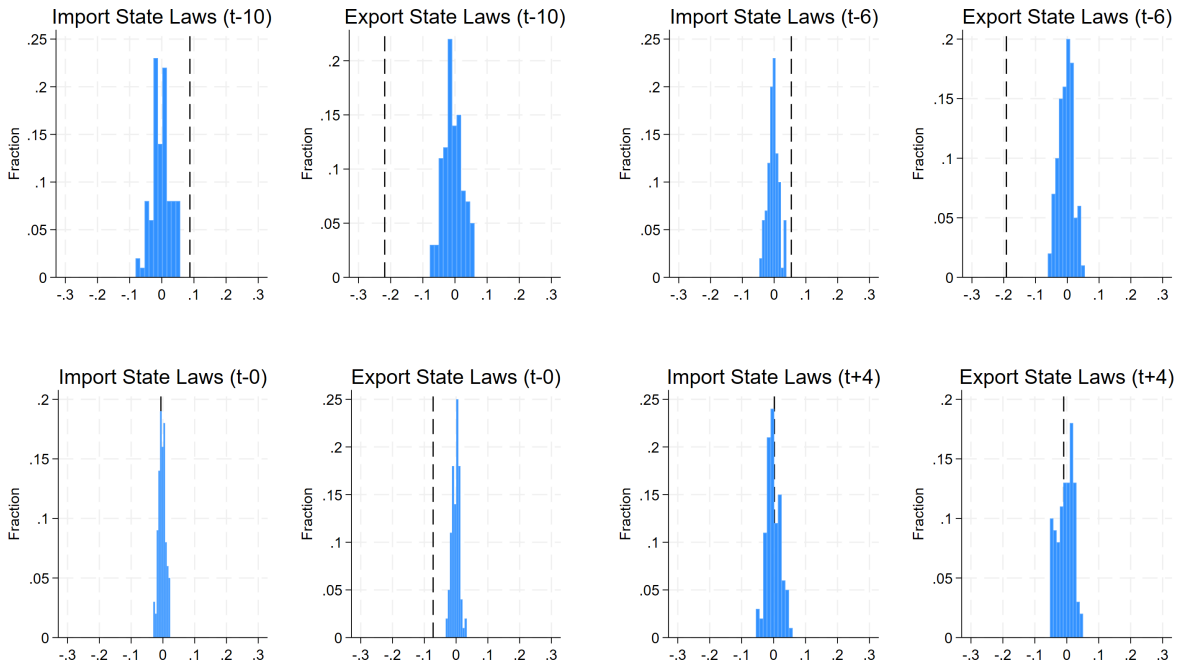
This finding brings us back to the bottom left plot of Figure 18. There, instead of controlling for trace intensity with some measure based on gun recoveries, we instead use the interaction of (log) homicides with the log percent of the electorate in state i that voted for Mitt Romney in the 2012 presidential election. This is a completely different approach and does not have a potential "bad control" problem. Overall, we find that this alternative measure of trace intensity produces results

Figure 19: Heterogeneous Relationship between Trace Intensity and Gun Laws



Notes: Top panel: Overall scatterplot of successful ATF traces per homicide versus gun law count (both standardized within states). Bottom panels: The same relationship split by state political leaning (Dem vs. GOP, based on median voting in the 2012 election). Black line is the fitted relationship (correlation).

Figure 20: Permutation Test



Notes: Permutation placebo distributions for import- and export-state gun laws. Histograms display coefficient estimates from 100 permutation placebo tests in which the timing of contemporaneous and lagged gun laws is randomly shuffled within state and state pair while preserving the underlying distribution of laws. Dashed vertical lines denote the corresponding point estimates from the main specifications reported in Table 3. Panels compare results for contemporaneous laws (t=0), lead (t+4), lags (t-6), and deep lags (t-10) for both import- and export-state laws.

that are visually close to the other trace intensity measures. This also helps illustrate the role of differential tracing effects: in the bottom middle panel, where we don't control for any measure of tracing, we find the relationship between domestic gun laws and recoveries is effectively zero for all lags and leads of gun laws. Given the relationship in Figure 19, this result is fairly reasonable.

We argue that gun laws in, for example, Maine are plausibly exogenous to gun recoveries in North Carolina, particularly when lagged several years. To test this further, we implement a permutation placebo test in which we shuffle contemporaneous and lagged gun laws within the state and state pair (e.g., the ordering of laws for the Maine – North Carolina pair can differ from the MaineFlorida pair, while preserving the mean and variance of Maine laws across state pairs) and estimate the $k = 0, k = 6, k = 10$ models from Table 3 and a k=-4 model. We repeat this exercise 100 times for each (k), producing eight different distributions of coefficients and benchmark these distributions against the relevant point estimates from Table 3 and the deep lead ($k = -4$). The hypothesis being evaluated is that the permutation distributions for both import- and export-state laws should be centered around zero for all k but the point estimates in the lag cases ($k = 10$ and $k = 6$) should be relatively further from the distribution relative to the point estimates in the $k = 0$ and $k = -4$ cases.

Results are presented graphically in Figure 20. In the case of export-state gun laws, we find evidence consistent with a causal interpretation; both distributions are centered around zero, the point estimate from the $k = 6$ and $k = 10$ model lies far from the permutation distributions, and, in the $k = 0$ and $k = -4$ cases, the point estimate lies relatively close to a permutation distribution centered near zero. This is also true with the permutation distributions of the import laws. Both distributions are centered around zero and are relatively close to the point estimates.

Finally, all of these robustness checks are consistent with the structure of the variance in state-level gun laws documented in Section 3. As noted there, gun laws are low-dimensional and well-characterized by state fixed effects and state-specific time trends. In practical terms, this implies that short-run local conditions leave very little room to drive changes in state gun laws relative to the slow-moving trends driven by broader political dynamics. Consequently, a reverse causality mechanism is highly implausible: it is unlikely that states modify their firearm regulations in response to shifts in the origin shares of recovered guns, or because the outflow of guns traced back to their state has changed.

C Robustness Checks

Table 7: Lagged Effects of Origin and Destination Gun Laws on Bilateral Firearm Flows (No Exposure Variable)

	k=-2	k=-1	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
GunLaws $_{i,t-k}$	-0.0406	-0.0603*	-0.0728**	-0.0915***	-0.116***	-0.137***	-0.161***	-0.182***	-0.199***	-0.200***	-0.187***	-0.195***	-0.231***
	(-1.17)	(-1.82)	(-2.42)	(-2.83)	(-3.09)	(-3.59)	(-4.38)	(-5.18)	(-5.79)	(-5.41)	(-4.83)	(-4.10)	(-3.87)
GunLaws $_{j,t-k}$	-0.00189	-0.0103	-0.00925	-0.0214	0.00129	0.0320	0.0407**	0.0512**	0.0526*	0.0643*	0.0732**	0.0923**	0.0872*
	(-0.11)	(-0.53)	(-0.52)	(-1.21)	(0.07)	(1.60)	(1.97)	(2.24)	(1.85)	(1.90)	(2.07)	(2.45)	(1.94)
Shared Interstate	0.245***	0.246***	0.245***	0.245***	0.245***	0.245***	0.245***	0.245***	0.245***	0.245***	0.245***	0.245***	0.245***
	(4.85)	(4.83)	(4.81)	(4.81)	(4.81)	(4.81)	(4.81)	(4.81)	(4.81)	(4.81)	(4.81)	(4.81)	(4.80)
Distance	-1.000***	-1.006***	-1.009***	-1.009***	-1.009***	-1.009***	-1.009***	-1.008***	-1.008***	-1.009***	-1.009***	-1.009***	-1.010***
	(-23.92)	(-23.86)	(-23.85)	(-23.85)	(-23.85)	(-23.85)	(-23.85)	(-23.85)	(-23.86)	(-23.86)	(-23.86)	(-23.85)	(-23.84)
Border	0.636***	0.641***	0.645***	0.644***	0.644***	0.644***	0.644***	0.644***	0.644***	0.644***	0.644***	0.644***	0.645***
	(10.57)	(10.54)	(10.53)	(10.53)	(10.52)	(10.52)	(10.52)	(10.52)	(10.52)	(10.52)	(10.52)	(10.52)	(10.52)
Population $_{i,t-k}$	1.442***	1.340***	1.379***	1.475***	1.561***	1.542***	1.496***	1.488***	1.484***	1.465***	1.523***	1.552***	1.580***
	(2.83)	(2.79)	(3.14)	(3.15)	(3.32)	(3.57)	(3.66)	(3.88)	(3.99)	(4.01)	(4.11)	(4.20)	(4.24)
Population $_{j,t-k}$	-0.222	0.0369	0.342	0.490	0.517	0.624**	0.774**	0.816***	0.816***	0.744**	0.631**	0.436	0.249
	(-0.68)	(0.12)	(1.14)	(1.58)	(1.64)	(2.02)	(2.49)	(2.63)	(2.66)	(2.49)	(2.20)	(1.64)	(1.02)
Guns $\neq_{i_t}$	0.328***	0.286***	0.279***	0.268***	0.267***	0.262***	0.257***	0.252***	0.248***	0.254***	0.255***	0.278***	0.298***
	(5.67)	(4.62)	(4.48)	(4.16)	(4.06)	(3.99)	(3.88)	(3.77)	(3.72)	(3.89)	(3.93)	(4.48)	(4.99)
U. Rate $_{i,t-k}$	-0.0615	-0.0878**	-0.124***	-0.107**	-0.0645	-0.0409	-0.0593	-0.0578	-0.0638	-0.0576	-0.0615	-0.0507	-0.0136
	(-1.47)	(-2.05)	(-2.79)	(-2.23)	(-1.07)	(-0.60)	(-0.91)	(-0.88)	(-0.88)	(-0.73)	(-0.82)	(-0.85)	(-0.30)
U. Rate $_{j,t-k}$	0.0359	0.0825*	0.183***	0.165***	0.0400	-0.0309	-0.0383	-0.0810	-0.114***	-0.123***	-0.166***	-0.109**	-0.0844*
	(0.83)	(1.79)	(3.71)	(3.74)	(0.89)	(-0.57)	(-0.69)	(-1.55)	(-2.59)	(-2.91)	(-3.61)	(-2.39)	(-1.93)
% Black $_{i,t-k}$	0.655***	0.659***	0.670***	0.647***	0.555***	0.492***	0.498***	0.472***	0.458***	0.412**	0.363**	0.333**	0.328**
	(3.26)	(3.27)	(3.55)	(3.40)	(3.10)	(2.85)	(3.00)	(2.86)	(2.69)	(2.43)	(2.13)	(2.05)	(2.18)
% Black $_{j,t-k}$	-0.371*	-0.443*	-0.449**	-0.453**	-0.435**	-0.422**	-0.439**	-0.435***	-0.459***	-0.455***	-0.452***	-0.403***	-0.344***
	(-1.67)	(-1.89)	(-1.98)	(-2.42)	(-2.55)	(-2.42)	(-2.56)	(-2.62)	(-2.88)	(-3.01)	(-3.14)	(-3.08)	(-2.98)
Constant	2.502***	2.445***	2.186***	2.041***	2.014***	1.957***	1.865***	1.868***	1.924***	2.031***	2.154***	2.269***	2.377***
	(7.64)	(7.40)	(6.71)	(5.79)	(5.53)	(5.63)	(5.48)	(5.60)	(5.93)	(6.54)	(7.36)	(8.38)	(9.54)
OBS	29328	31584	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840
Pairs	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256
R2	0.870	0.873	0.876	0.876	0.876	0.876	0.876	0.877	0.877	0.877	0.876	0.876	0.876

Notes: Estimated effects using a fixed effects Poisson estimator. Column k includes GunLaws$_{i,t-k}$ and GunLaws$_{j,t-k}$ as regressors. All models include origin state fixed effects, destination state fixed effects, and year fixed effects. The lag is indicated by the column label. Standard errors clustered at the pair level are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Lagged Effects of Origin and Destination Gun Laws on Bilateral Firearm Flows II (No Exposure Variable)

	k=-2	k=-1	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
GunLaws $_{i,t-k}$	0.0753	0.0533	0.0396	0.0283	0.0108	-0.00834	-0.0343	-0.0501	-0.0631	-0.0661	-0.0429	-0.0432	-0.0638
	(1.63)	(1.22)	(0.99)	(0.68)	(0.23)	(-0.17)	(-0.75)	(-1.16)	(-1.55)	(-1.57)	(-1.00)	(-0.86)	(-1.01)
GunLaws $_{j,t-k}$	-0.00872	-0.0183	-0.0179	-0.0314	-0.00765	0.0233	0.0334	0.0447*	0.0487*	0.0575*	0.0634*	0.0822**	0.0689*
	(-0.35)	(-0.70)	(-0.73)	(-1.30)	(-0.33)	(0.97)	(1.40)	(1.75)	(1.67)	(1.78)	(1.85)	(2.31)	(1.68)
Shared Interstate	0.211***	0.212***	0.212***	0.210***	0.208***	0.208***	0.207***	0.208***	0.208***	0.210***	0.210***	0.210***	0.209***
	(4.36)	(4.36)	(4.35)	(4.33)	(4.30)	(4.30)	(4.30)	(4.32)	(4.34)	(4.38)	(4.41)	(4.42)	(4.42)
Distance	-1.028***	-1.029***	-1.029***	-1.030***	-1.032***	-1.031***	-1.028***	-1.027***	-1.026***	-1.026***	-1.027***	-1.030***	-1.034***
	(-24.43)	(-24.19)	(-24.09)	(-24.11)	(-24.08)	(-24.15)	(-24.30)	(-24.42)	(-24.47)	(-24.62)	(-24.78)	(-24.84)	(-24.84)
GunLaws $_{i,t-k}$ × Distance	0.162***	0.162***	0.163***	0.176***	0.191***	0.199***	0.210***	0.220***	0.229***	0.235***	0.245***	0.257***	0.274***
	(5.84)	(5.83)	(5.99)	(6.42)	(6.87)	(7.07)	(7.33)	(7.56)	(7.72)	(7.85)	(8.05)	(8.23)	(8.40)
GunLaws $_{j,t-k}$ × Distance	-0.0224	-0.0250	-0.0269	-0.0273	-0.0271	-0.0273	-0.0289	-0.0305	-0.0318	-0.0327	-0.0332	-0.0346	-0.0349
	(-0.80)	(-0.90)	(-0.96)	(-0.95)	(-0.91)	(-0.91)	(-0.95)	(-0.99)	(-1.01)	(-1.03)	(-1.04)	(-1.07)	(-1.06)
Border	0.592***	0.599***	0.604***	0.603***	0.603***	0.604***	0.605***	0.606***	0.608***	0.610***	0.612***	0.613***	0.613***
	(9.91)	(9.92)	(9.92)	(9.91)	(9.89)	(9.91)	(9.93)	(9.97)	(10.00)	(10.03)	(10.04)	(10.05)	(10.04)
Population $_{i,t-k}$	1.565***	1.446***	1.476***	1.552***	1.605***	1.553***	1.495***	1.483***	1.478***	1.437***	1.479***	1.504***	1.523***
	(2.83)	(2.79)	(3.14)	(3.15)	(3.27)	(3.43)	(3.47)	(3.67)	(3.84)	(3.88)	(3.99)	(4.13)	(4.15)
Population $_{j,t-k}$	-0.225	0.0591	0.378	0.548*	0.571*	0.659**	0.829***	0.855***	0.837***	0.718**	0.572**	0.350	0.165
	(-0.67)	(0.18)	(1.24)	(1.77)	(1.83)	(2.13)	(2.66)	(2.74)	(2.73)	(2.39)	(1.98)	(1.31)	(0.68)
Guns $\neq_{i_t}$	0.308***	0.262***	0.253***	0.242***	0.248***	0.246***	0.243***	0.240***	0.241***	0.255***	0.267***	0.299***	0.322***
	(5.27)	(4.15)	(3.96)	(3.71)	(3.79)	(3.76)	(3.69)	(3.63)	(3.66)	(3.98)	(4.20)	(4.97)	(5.66)
U. Rate $_{i,t-k}$	-0.0485	-0.0739	-0.111**	-0.0920*	-0.0540	-0.0301	-0.0592	-0.0513	-0.0550	-0.0509	-0.0587	-0.0541	-0.0158
	(-1.10)	(-1.63)	(-2.35)	(-1.81)	(-0.86)	(-0.43)	(-0.93)	(-0.85)	(-0.81)	(-0.67)	(-0.81)	(-0.96)	(-0.36)
U. Rate $_{j,t-k}$	0.0287	0.0785	0.184***	0.172***	0.0456	-0.0448	-0.0524	-0.102*	-0.139***	-0.146***	-0.175***	-0.106**	-0.0864**
	(0.57)	(1.49)	(3.43)	(3.67)	(0.98)	(-0.79)	(-0.91)	(-1.89)	(-3.09)	(-3.41)	(-3.84)	(-2.36)	(-1.99)
% Black $_{i,t-k}$	0.679***	0.688***	0.698***	0.675***	0.585***	0.515***	0.532***	0.494***	0.472***	0.434**	0.397**	0.373**	0.379**
	(3.06)	(3.09)	(3.37)	(3.23)	(2.97)	(2.74)	(3.05)	(2.94)	(2.77)	(2.56)	(2.31)	(2.26)	(2.47)
% Black $_{j,t-k}$	-0.364	-0.437*	-0.428*	-0.444**	-0.433**	-0.403**	-0.413**	-0.401**	-0.414**	-0.400***	-0.405***	-0.366***	-0.329***
	(-1.54)	(-1.77)	(-1.78)	(-2.19)	(-2.31)	(-2.11)	(-2.20)	(-2.25)	(-2.48)	(-2.59)	(-2.75)	(-2.75)	(-2.81)
Constant	2.477***	2.412***	2.143***	1.993***	1.980***	1.950***	1.833***	1.851***	1.915***	2.055***	2.197***	2.326***	2.440***
	(7.38)	(7.16)	(6.52)	(5.70)	(5.51)	(5.65)	(5.40)	(5.56)	(5.93)	(6.63)	(7.49)	(8.60)	(9.80)
OBS	29328	31584	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840
Pairs	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256
R2	0.874	0.877	0.880	0.880	0.880	0.881	0.881	0.881	0.882	0.882	0.882	0.882	0.882

Notes: Estimated effects using a fixed effects Poisson estimator. All models include origin state fixed effects, destination state fixed effects, and year fixed effects. The lag is indicated by the column label. Z-statistics from pair clustered standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Lagged Effects of Origin and Destination Gun Laws on Bilateral Firearm Flows III

	k=-2	k=-1	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
GunLaws $_{i,t-k}$	0.0842*	0.0660	0.0527	0.0389	0.0153	-0.00214	-0.0262	-0.0368	-0.0509	-0.0594	-0.0487	-0.0557	-0.0630
	(1.90)	(1.55)	(1.32)	(0.96)	(0.37)	(-0.05)	(-0.67)	(-0.93)	(-1.25)	(-1.35)	(-1.12)	(-1.16)	(-1.19)
GunLaws $_{j,t-k}$	-0.0441	-0.0501*	-0.0465*	-0.0637**	-0.0397	-0.0235	-0.0141	-0.0149	-0.0395	-0.0463	-0.0553	-0.0480	-0.0387
	(-1.53)	(-1.71)	(-1.66)	(-2.29)	(-1.52)	(-0.90)	(-0.54)	(-0.55)	(-1.27)	(-1.33)	(-1.51)	(-1.22)	(-0.96)
Population $_{i,t-k}$ × GunLaws $_{i,t-k}$	-0.116***	-0.123***	-0.121***	-0.127***	-0.159***	-0.183***	-0.189***	-0.176***	-0.154***	-0.120**	-0.0787	-0.0423	-0.146**
	(-2.99)	(-3.26)	(-3.35)	(-3.56)	(-4.46)	(-5.13)	(-5.13)	(-4.33)	(-3.15)	(-2.24)	(-1.44)	(-0.71)	(-1.97)
GunLaws $_{i,t-k}$ × Distance	0.126***	0.127***	0.127***	0.138***	0.151***	0.161***	0.173***	0.183***	0.189***	0.192***	0.199***	0.209***	0.222***
	(4.33)	(4.33)	(4.38)	(4.62)	(4.86)	(5.08)	(5.26)	(5.33)	(5.32)	(5.28)	(5.38)	(5.47)	(5.59)
GunLaws $_{i,t-k}$ × Distance × Population $_{i,t-k}$	-0.0271	-0.0301	-0.0287	-0.0268	-0.0219	-0.0249	-0.0253	-0.0261	-0.0256	-0.0215	-0.0170	-0.0118	-0.00640
	(-1.01)	(-1.10)	(-1.05)	(-0.97)	(-0.77)	(-0.86)	(-0.85)	(-0.85)	(-0.81)	(-0.67)	(-0.53)	(-0.37)	(-0.20)
Population $_{j,t-k}$ × Distance	0.144***	0.141***	0.140***	0.143***	0.148***	0.150***	0.151***	0.152***	0.154***	0.156***	0.157***	0.160***	0.163***
	(4.40)	(4.20)	(4.17)	(4.22)	(4.34)	(4.41)	(4.44)	(4.48)	(4.56)	(4.59)	(4.60)	(4.63)	(4.68)
Guns $\neq_{i_t}$	-0.646***	-0.686***	-0.691***	-0.694***	-0.678***	-0.674***	-0.678***	-0.682***	-0.680***	-0.676***	-0.669***	-0.646***	-0.619***
	(-12.53)	(-12.29)	(-12.24)	(-12.23)	(-12.31)	(-12.60)	(-12.65)	(-12.68)	(-12.60)	(-12.60)	(-12.37)	(-12.46)	(-12.62)
Shared Interstate	0.205***	0.206***	0.207***	0.205***	0.204***	0.203***	0.203***	0.204***	0.205***	0.206***	0.207***	0.207***	0.207***
	(4.54)	(4.56)	(4.56)	(4.54)	(4.51)	(4.51)	(4.51)	(4.53)	(4.56)	(4.60)	(4.62)	(4.64)	(4.64)
Distance	-1.108***	-1.106***	-1.103***	-1.099***	-1.097***	-1.091***	-1.086***	-1.081***	-1.077***	-1.075***	-1.074***	-1.074***	-1.074***
	(-25.73)	(-25.46)	(-25.28)	(-25.18)	(-25.09)	(-25.04)	(-25.03)	(-24.94)	(-24.84)	(-24.86)	(-24.95)	(-24.98)	(-24.95)
Population $_{i,t-k}$ × Distance	0.146***	0.149***	0.146***	0.139***	0.129***	0.126***	0.121***	0.117***	0.113***	0.110***	0.104***	0.0974***	0.0896***
	(4.78)	(4.81)	(4.73)	(4.53)	(4.25)	(4.15)	(4.02)	(3.88)	(3.75)	(3.62)	(3.45)	(3.22)	(2.96)
Population $_{j,t-k}$ × GunLaws $_{j,t-k}$	0.0444	0.0378	0.0331	0.0521	0.0697*	0.106***	0.102**	0.119***	0.185***	0.196***	0.237***	0.249***	0.237***
	(1.53)	(1.29)	(1.15)	(1.62)	(1.94)	(2.70)	(2.48)	(2.77)	(3.90)	(4.22)	(4.73)	(4.58)	(4.36)
GunLaws $_{j,t-k}$ × Distance	-0.00517	-0.00648	-0.00740	-0.0111	-0.0135	-0.0163	-0.0219	-0.0282	-0.0339	-0.0398	-0.0445	-0.0513	-0.0547
	(-0.17)	(-0.21)	(-0.24)	(-0.34)	(-0.40)	(-0.47)	(-0.62)	(-0.78)	(-0.91)	(-1.05)	(-1.16)	(-1.31)	(-1.37)
GunLaws $_{j,t-k}$ × Distance × Population $_{j,t-k}$	-0.0723***	-0.0730***	-0.0744***	-0.0761***	-0.0801***	-0.0808***	-0.0792***	-0.0779***	-0.0777***	-0.0754**	-0.0744**	-0.0734**	-0.0760**
	(-3.06)	(-3.02)	(-3.06)	(-3.06)	(-3.12)	(-3.08)	(-2.93)	(-2.78)	(-2.67)	(-2.53)	(-2.47)	(-2.43)	(-2.51)
Border	0.613***	0.620***	0.625***	0.625***	0.624***	0.625***	0.625***	0.626***	0.628***	0.630***	0.630***	0.631***	0.630***
	(10.58)	(10.58)	(10.56)	(10.55)	(10.53)	(10.54)	(10.55)	(10.59)	(10.62)	(10.63)	(10.62)	(10.61)	(10.59)
Population $_{i,t-k}$	1.315***	1.199***	1.242***	1.301***	1.359***	1.321***	1.216***	1.174***	1.163***	1.232***	1.363***	1.431***	1.420***
	(2.92)	(2.79)	(3.15)	(3.17)	(3.42)	(3.73)	(3.55)	(3.57)	(3.51)	(3.69)	(4.07)	(4.43)	(4.50)
Population $_{j,t-k}$	-0.0246	0.218	0.486*	0.646**	0.660**	0.748**	0.949***	1.020***	1.104***	0.932***	0.739***	0.479*	0.262
	(-0.08)	(0.70)	(1.65)	(2.14)	(2.18)	(2.49)	(3.14)	(3.40)	(3.78)	(3.28)	(2.73)	(1.93)	(1.20)
U. Rate $_{i,t-k}$	-0.0771*	-0.103**	-0.138***	-0.120***	-0.0771	-0.0455	-0.0850	-0.0819	-0.0848	-0.0754	-0.0780	-0.0622	-0.0273
	(-1.92)	(-2.52)	(-3.29)	(-2.61)	(-1.39)	(-0.75)	(-1.46)	(-1.37)	(-1.24)	(-0.99)	(-1.11)	(-1.19)	(-0.68)
U. Rate $_{j,t-k}$	0.0349	0.0804	0.176***	0.167***	0.0497	-0.0253	-0.0175	-0.0541	-0.0771**	-0.0843**	-0.113***	-0.0616	-0.0469
	(0.71)	(1.58)	(3.45)	(3.73)	(1.15)	(-0.53)	(-0.38)	(-1.25)	(-2.18)	(-2.37)	(-2.88)	(-1.52)	(-1.15)
% Black $_{i,t-k}$	0.576***	0.536***	0.511***	0.500***	0.413***	0.348**	0.396***	0.370***	0.348**	0.323**	0.296**	0.291**	0.268**
	(3.22)	(3.05)	(3.09)	(3.10)	(2.83)	(2.50)	(2.88)	(2.66)	(2.42)	(2.21)	(2.01)	(2.10)	(2.23)
% Black $_{j,t-k}$	-0.296	-0.354*	-0.337*	-0.333**	-0.298**	-0.244*	-0.287**	-0.289**	-0.291**	-0.292**	-0.285**	-0.263**	-0.194**
	(-1.52)	(-1.73)	(-1.73)	(-2.12)	(-2.18)	(-1.74)	(-2.00)	(-2.06)	(-2.17)	(-2.25)	(-2.30)	(-2.34)	(-2.03)
Constant	-5.353***	-5.372***	-5.596***	-5.766***	-5.809***	-5.891***	-6.005***	-6.021***	-6.105***	-5.967***	-5.867***	-5.724***	-5.548***
	(-17.48)	(-17.54)	(-18.27)	(-17.24)	(-16.95)	(-17.98)	(-18.32)	(-18.47)	(-18.77)	(-19.61)	(-20.80)	(-22.39)	(-24.09)
OBS	29328	31584	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840
Pairs	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256
R2	0.881	0.884	0.887	0.887	0.887	0.887	0.888	0.888	0.888	0.888	0.888	0.888	0.888

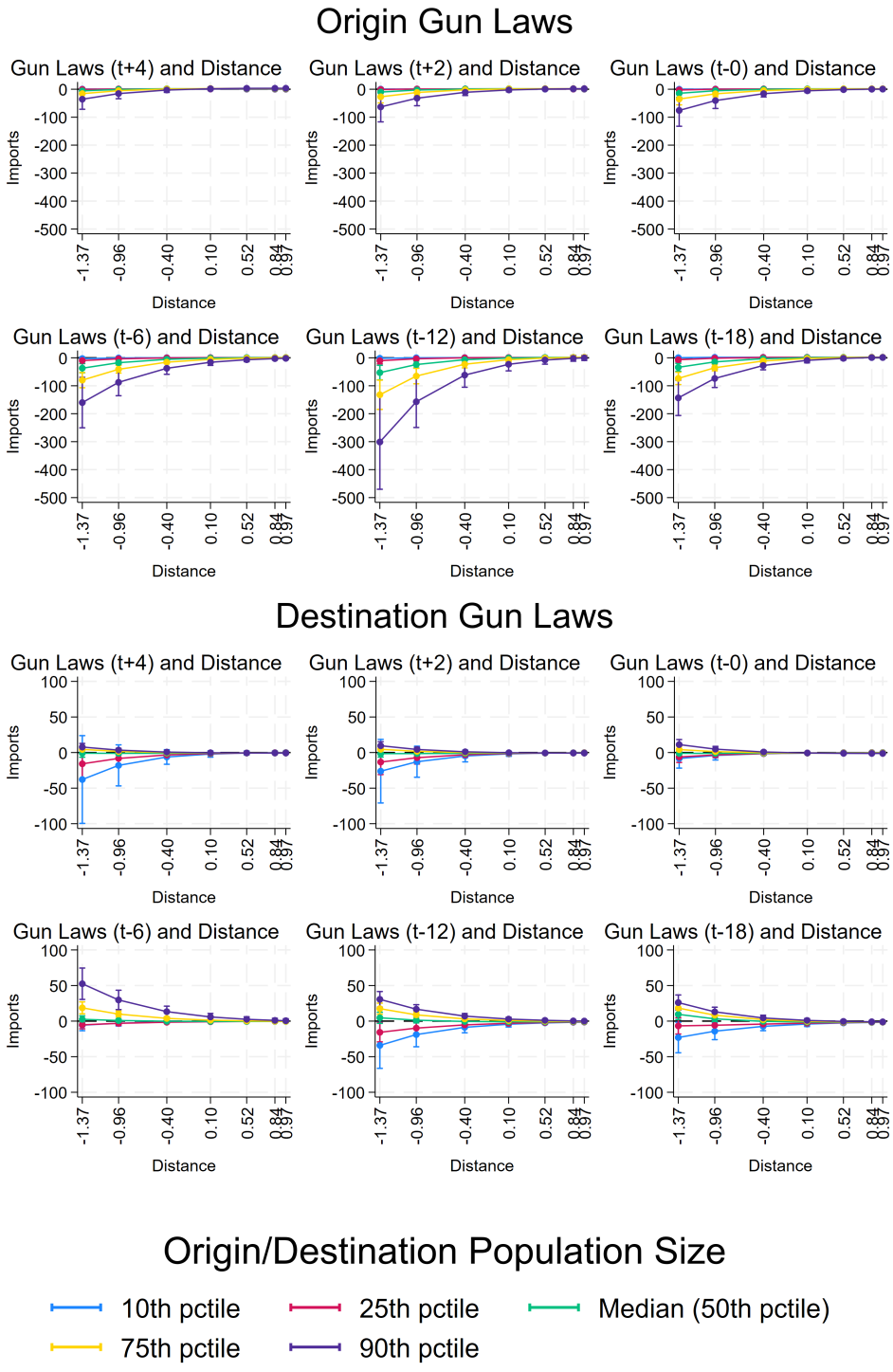
Notes: Estimated effects using a fixed effects Poisson estimator. All models include origin state fixed effects, destination state fixed effects, and year fixed effects. The lag is indicated by the column label. Z-statistics from pair clustered standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Marginal effects found in Figure 6.

Table 10: Lagged Effects of Origin and Destination Gun Laws on Bilateral Firearm Flows III (No Exposure Variable)

	k=-2	k=-1	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
GunLaws $_{i,t-k}$	0.0910**	0.0721	0.0578	0.0431	0.0182	-0.000119	-0.0247	-0.0361	-0.0513	-0.0603	-0.0492	-0.0565	-0.0655
	(1.97)	(1.63)	(1.40)	(1.03)	(0.42)	(-0.00)	(-0.61)	(-0.87)	(-1.21)	(-1.31)	(-1.08)	(-1.11)	(-1.14)
GunLaws $_{j,t-k}$	-0.0529*	-0.0590*	-0.0552*	-0.0733**	-0.0482*	-0.0316	-0.0219	-0.0235	-0.0497	-0.0569	-0.0665*	-0.0588	-0.0509
	(-1.75)	(-1.91)	(-1.87)	(-2.50)	(-1.76)	(-1.16)	(-0.81)	(-0.82)	(-1.53)	(-1.56)	(-1.74)	(-1.43)	(-1.21)
Population $_{i,t-k}$ × GunLaws $_{i,t-k}$	-0.118***	-0.125***	-0.123***	-0.130***	-0.163***	-0.188***	-0.193***	-0.179***	-0.156***	-0.121**	-0.0789	-0.0445	-0.158**
	(-2.91)	(-3.17)	(-3.27)	(-3.49)	(-4.40)	(-5.09)	(-5.07)	(-4.25)	(-3.06)	(-2.17)	(-1.39)	(-0.72)	(-2.00)
GunLaws $_{i,t-k}$ × Distance	0.133***	0.134***	0.134***	0.146***	0.160***	0.171***	0.183***	0.194***	0.201***	0.204***	0.211***	0.222***	0.236***
	(4.41)	(4.42)	(4.49)	(4.74)	(5.00)	(5.24)	(5.43)	(5.51)	(5.51)	(5.48)	(5.58)	(5.68)	(5.80)
GunLaws $_{i,t-k}$ × Distance × Population $_{i,t-k}$	-0.0266	-0.0296	-0.0279	-0.0257	-0.0202	-0.0231	-0.0235	-0.0243	-0.0236	-0.0192	-0.0145	-0.00898	-0.00314
	(-0.96)	(-1.05)	(-0.99)	(-0.89)	(-0.69)	(-0.77)	(-0.76)	(-0.77)	(-0.72)	(-0.58)	(-0.44)	(-0.27)	(-0.10)
Population $_{j,t-k}$ × Distance	0.153***	0.149***	0.149***	0.152***	0.158***	0.160***	0.161***	0.162***	0.165***	0.166***	0.168***	0.171***	0.174***
	(4.52)	(4.32)	(4.29)	(4.35)	(4.47)	(4.55)	(4.59)	(4.63)	(4.71)	(4.74)	(4.76)	(4.79)	(4.85)
Guns $\neq_{i_t}$	0.323***	0.279***	0.274***	0.270***	0.287***	0.291***	0.286***	0.281***	0.283***	0.288***	0.295***	0.321***	0.349***
	(5.71)	(4.54)	(4.41)	(4.31)	(4.73)	(4.95)	(4.87)	(4.75)	(4.79)	(4.90)	(5.01)	(5.70)	(6.59)
Shared Interstate	0.203***	0.204***	0.205***	0.203***	0.202***	0.201***	0.201***	0.202***	0.203***	0.204***	0.205***	0.205***	0.205***
	(4.31)	(4.33)	(4.32)	(4.31)	(4.28)	(4.28)	(4.28)	(4.30)	(4.33)	(4.37)	(4.39)	(4.41)	(4.42)
Distance	-1.122***	-1.120***	-1.117***	-1.113***	-1.110***	-1.105***	-1.100***	-1.094***	-1.090***	-1.088***	-1.087***	-1.087***	-1.087***
	(-25.31)	(-25.03)	(-24.83)	(-24.73)	(-24.64)	(-24.57)	(-24.56)	(-24.48)	(-24.39)	(-24.42)	(-24.53)	(-24.56)	(-24.54)
Population $_{i,t-k}$ × Distance	0.140***	0.142***	0.139***	0.131***	0.121***	0.117***	0.112***	0.107***	0.103***	0.0995***	0.0940***	0.0866***	0.0782**
	(4.44)	(4.47)	(4.38)	(4.17)	(3.87)	(3.76)	(3.61)	(3.47)	(3.34)	(3.21)	(3.03)	(2.79)	(2.52)
Population $_{j,t-k}$ × GunLaws $_{j,t-k}$	0.0458	0.0382	0.0330	0.0526	0.0710*	0.109***	0.104**	0.123***	0.191***	0.202***	0.243***	0.256***	0.244***
	(1.49)	(1.23)	(1.08)	(1.54)	(1.85)	(2.58)	(2.37)	(2.66)	(3.76)	(4.10)	(4.61)	(4.45)	(4.29)
GunLaws $_{j,t-k}$ × Distance	-0.0135	-0.0151	-0.0161	-0.0202	-0.0231	-0.0262	-0.0322	-0.0391	-0.0452	-0.0517	-0.0568	-0.0642	-0.0682
	(-0.41)	(-0.46)	(-0.48)	(-0.59)	(-0.65)	(-0.72)	(-0.86)	(-1.02)	(-1.14)	(-1.28)	(-1.40)	(-1.56)	(-1.62)
GunLaws $_{j,t-k}$ × Distance × Population $_{j,t-k}$	-0.0756***	-0.0766***	-0.0783***	-0.0803***	-0.0845***	-0.0853***	-0.0836***	-0.0822***	-0.0821***	-0.0796**	-0.0786**	-0.0776**	-0.0804**
	(-3.10)	(-3.06)	(-3.11)	(-3.11)	(-3.17)	(-3.13)	(-2.98)	(-2.82)	(-2.71)	(-2.57)	(-2.52)	(-2.48)	(-2.56)
Border	0.631***	0.640***	0.645***	0.644***	0.643***	0.644***	0.644***	0.645***	0.647***	0.649***	0.650***	0.650***	0.650***
	(10.57)	(10.58)	(10.57)	(10.56)	(10.54)	(10.55)	(10.56)	(10.60)	(10.63)	(10.64)	(10.64)	(10.63)	(10.61)
Population $_{i,t-k}$	1.370***	1.250***	1.297***	1.367***	1.431***	1.392***	1.280***	1.234***	1.223***	1.293***	1.427***	1.495***	1.486***
	(2.91)	(2.78)	(3.12)	(3.10)	(3.32)	(3.62)	(3.48)	(3.52)	(3.49)	(3.67)	(4.04)	(4.38)	(4.44)
Population $_{j,t-k}$	-0.0246	0.234	0.520*	0.689**	0.708**	0.803**	1.012***	1.085***	1.171***	0.989***	0.787***	0.513**	0.284
	(-0.08)	(0.73)	(1.70)	(2.20)	(2.24)	(2.56)	(3.19)	(3.44)	(3.79)	(3.30)	(2.76)	(1.97)	(1.25)
U. Rate $_{i,t-k}$	-0.0800*	-0.107**	-0.144***	-0.123**	-0.0746	-0.0400	-0.0796	-0.0765	-0.0795	-0.0699	-0.0733	-0.0594	-0.0252
	(-1.91)	(-2.51)	(-3.25)	(-2.57)	(-1.27)	(-0.61)	(-1.27)	(-1.21)	(-1.11)	(-0.88)	(-1.01)	(-1.11)	(-0.61)
U. Rate $_{j,t-k}$	0.0347	0.0829	0.183***	0.172***	0.0482	-0.0311	-0.0248	-0.0654	-0.0903**	-0.0965**	-0.126***	-0.0692	-0.0507
	(0.67)	(1.55)	(3.38)	(3.68)	(1.08)	(-0.61)	(-0.50)	(-1.41)	(-2.37)	(-2.56)	(-3.06)	(-1.64)	(-1.19)
% Black $_{i,t-k}$	0.600***	0.562***	0.537***	0.523***	0.431***	0.362**	0.411***	0.386**	0.365**	0.342**	0.315*	0.310**	0.285**
	(3.14)	(2.97)	(2.99)	(2.97)	(2.71)	(2.39)	(2.75)	(2.53)	(2.31)	(2.11)	(1.94)	(2.02)	(2.15)
% Black $_{j,t-k}$	-0.315	-0.377*	-0.363*	-0.357**	-0.320**	-0.263*	-0.307**	-0.309**	-0.311**	-0.312**	-0.306**	-0.282**	-0.209**
	(-1.50)	(-1.70)	(-1.70)	(-2.11)	(-2.19)	(-1.76)	(-2.02)	(-2.06)	(-2.17)	(-2.24)	(-2.30)	(-2.35)	(-2.07)
Constant	2.398***	2.373***	2.136***	1.953***	1.903***	1.815***	1.700***	1.684***	1.598***	1.744***	1.851***	2.002***	2.188***
	(7.61)	(7.52)	(6.71)	(5.52)	(5.21)	(5.18)	(4.84)	(4.81)	(4.57)	(5.35)	(6.14)	(7.34)	(8.96)
OBS	29328	31584	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840
Pairs	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256
R2	0.877	0.880	0.883	0.883	0.883	0.884	0.884	0.884	0.884	0.884	0.884	0.884	0.884

Notes: Estimated effects using a fixed effects Poisson estimator. All models include origin state fixed effects, destination state fixed effects, and year fixed effects. The lag is indicated by the column label. Z-statistics from pair clustered standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 21: Joint Effect of Distance, Population, and Gun Laws



Notes: Estimated effect of gun laws on gun recoveries. The figure heading label indicates gun laws. Control variables include the population in the origin and destination state, border adjacency status, destination state fixed effects, origin state fixed effects, and year fixed effects. Marginal effects calculated for the 10th percentile [blue], first quartile [red], median [green], third quartile [yellow], and 90th percentile [purple] of state population. Error bars indicate the 90% confidence interval using pair-clustered standard errors. All models use the Poisson estimator. Interactions

Table 11: Joint Effect of Distance, Population, Gun Laws and Interstate Connections

	k=2	k=6
	Model 1	Model 2
Distance	-1.062***	-1.015***
	(-21.25)	(-16.40)
Gun Laws $_{i,t-k}$	0.121**	-0.0226
	(2.47)	(-0.38)
Distance × Gun Laws $_{i,t-k}$	0.0551	0.115
	(1.46)	(1.62)
Shared Interstate=1	0.128**	0.157***
	(2.24)	(2.84)
Shared Interstate=1 × Distance	-0.502***	-0.535***
	(-6.81)	(-6.63)
Shared Interstate=1 × Gun Laws $_{i,t-k}$	-0.0636	0.0569
	(-1.25)	(0.74)
Shared Interstate=1 × Distance × Gun Laws $_{i,t-k}$	0.0756	0.194**
	(1.31)	(1.98)
Population $_{i,t-k}$	1.078**	1.204***
	(2.54)	(3.95)
Distance × Population $_{i,t-k}$	0.203***	0.159**
	(3.80)	(2.33)
Gun Laws $_{i,t-k}$ × Population $_{i,t-k}$	-0.0991**	-0.141**
	(-2.49)	(-2.18)
Distance × Gun Laws $_{i,t-k}$ × Population $_{i,t-k}$	-0.0447	-0.0445
	(-1.23)	(-0.89)
Shared Interstate=1 × Population $_{i,t-k}$	0.0978**	0.0590
	(2.14)	(1.19)
Shared Interstate=1 × Distance × Population $_{i,t-k}$	-0.0407	-0.0771
	(-0.59)	(-0.93)
Shared Interstate=1 × Gun Laws $_{i,t-k}$ × Population $_{i,t-k}$	0.000834	-0.0518
	(0.02)	(-1.03)
Shared Interstate=1 × Distance × Gun Laws $_{i,t-k}$ × Population $_{i,t-k}$	0.0421	0.0487
	(0.91)	(0.94)
Guns $\neq_{i_t}$	-0.709***	-0.632***
	(-12.12)	(-12.94)
U. Rate $_{j,t-k}$	0.0909*	-0.00672
	(1.70)	(-0.15)
U. Rate $_{i,t-k}$	-0.0870**	0.00188
	(-2.12)	(0.04)
% Black $_{j,t-k}$	-0.309	-0.115
	(-1.52)	(-1.28)
% Black $_{i,t-k}$	0.559***	0.235**
	(3.18)	(2.04)
Distance	0	0
	(.)	(.)
Gun Laws $_{j,t-k}$	-0.0654*	-0.130**
	(-1.65)	(-2.56)
Distance × Gun Laws $_{j,t-k}$	-0.122***	-0.200***
	(-3.34)	(-3.33)
Shared Interstate=1 × Gun Laws $_{j,t-k}$	0.146***	0.263***
	(3.28)	(3.94)
Shared Interstate=1 × Distance × Gun Laws $_{j,t-k}$	0.239***	0.313***
	(3.92)	(3.71)
Population $_{j,t-k}$	0.358	0.194
	(1.13)	(1.02)
Distance × Population $_{j,t-k}$	0.135**	0.164***
	(2.53)	(2.70)
Gun Laws $_{j,t-k}$ × Population $_{j,t-k}$	-0.0162	0.121*
	(-0.42)	(1.94)
Distance × Gun Laws $_{j,t-k}$ × Population $_{j,t-k}$	0.0227	0.0532
	(0.55)	(0.97)
Shared Interstate=1 × Population $_{j,t-k}$	-0.103**	-0.140***
	(-2.56)	(-3.03)
Shared Interstate=1 × Distance × Population $_{j,t-k}$	-0.0550	-0.0754
	(-0.76)	(-0.95)
Shared Interstate=1 × Gun Laws $_{j,t-k}$ × Population $_{j,t-k}$	0.0578	0.0716
	(1.59)	(1.43)
Shared Interstate=1 × Distance × Gun Laws $_{j,t-k}$ × Population $_{j,t-k}$	-0.0854*	-0.115*
	(-1.67)	(-1.81)
Constant	-5.426***	-5.298***
	(-17.50)	(-24.80)
OBS	31584	33840
Pairs	2256	2256
R2	0.880	0.884

Notes: Estimated effects using a fixed effects Poisson estimator. All models include origin state fixed effects and year fixed effects. The lag is indicated by the column label. Z-statistics from pair clustered standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Placebo Test

As a placebo test, we examine whether characteristics of the paired origin state (population, gun laws, border status, and distance) predict the share of crime guns recovered in a destination state that originate from that same state. We refer to these as domestic recoveries. The hypothesis is that origin-state characteristics (as in the pair) should not affect guns that were both sold in state j and recovered in state j.

Results are presented in Table 12. The model specification follows Equation 4, with the same lags used in Table 3. The only difference is that the outcome variable is the share of domestic recoveries. We find a negative relationship between domestic recoveries and domestic gun laws. As expected, the characteristics of the paired origin state have either no significant relationship with the share of domestic recoveries or the relationship is a precise zero (e.g., border and distance). This includes population, border status, distance, and gun laws. So, for example, the population and the number of gun laws in California do not affect the number of guns sold in and later recovered in Utah.

Finally, we note the high R^2 in the estimates presented in Table 12. This, coupled with the precise zeros, may cause some to question our results. First, the high R^2 is driven by the inclusion of variables that are highly correlated with the number of crime guns recovered in state j and from state j. These variables are state fixed effects, state population, and the total number of guns recovered in the state (the exposure variable). When we remove these variables, we find the R^2 falls but the null relationship between gun laws in state i and domestic recoveries remains. These results are found in the Table 13.

Table 12: Lagged Effects of Gun Laws on Domestic Recoveries

	k=-2	k=-1	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
GunLaws $_{i,t-k}$	0.00000453	-0.0000146	-0.0000276	-0.0000410	-0.0000489	-0.0000602	-0.0000727	-0.0000991	-0.000128	-0.000132	-0.000124	-0.000139	-0.000166
	(0.00)	(-0.00)	(-0.01)	(-0.01)	(-0.01)	(-0.02)	(-0.02)	(-0.02)	(-0.03)	(-0.03)	(-0.02)	(-0.02)	(-0.02)
GunLaws $_{j,t-k}$	-0.00914***	-0.00667***	-0.00615***	-0.00554***	-0.0159***	-0.0330***	-0.0428***	-0.0503***	-0.0553***	-0.0620***	-0.0656***	-0.0721***	-0.0879***
	(-4.74)	(-3.38)	(-3.40)	(-3.02)	(-7.28)	(-12.87)	(-15.86)	(-18.08)	(-18.33)	(-18.54)	(-18.75)	(-18.88)	(-17.79)
Shared Interstate	-0.0000850	-0.0000954	-0.000102	-0.000104	-0.000104	-0.000106	-0.000108	-0.000109	-0.000112	-0.000116	-0.000117	-0.000115	-0.000114
	(-1.09)	(-1.14)	(-1.18)	(-1.19)	(-1.22)	(-1.21)	(-1.20)	(-1.19)	(-1.19)	(-1.20)	(-1.19)	(-1.18)	(-1.17)
Distance	-0.000981***	-0.00103***	-0.00106***	-0.00108***	-0.00108***	-0.00111***	-0.00112***	-0.00113***	-0.00116***	-0.00120***	-0.00122***	-0.00120***	-0.00119***
	(-7.91)	(-7.63)	(-7.47)	(-7.40)	(-7.29)	(-7.19)	(-7.19)	(-7.14)	(-7.12)	(-7.16)	(-7.23)	(-7.26)	(-7.30)
Border	0.00263***	0.00274***	0.00282***	0.00287***	0.00287***	0.00295***	0.00298***	0.00301***	0.00310***	0.00321***	0.00325***	0.00320***	0.00317***
	(8.14)	(7.93)	(7.78)	(7.69)	(7.59)	(7.57)	(7.61)	(7.62)	(7.69)	(7.76)	(7.80)	(7.81)	(7.81)
Population $_{i,t-k}$	0.00150	0.00144	0.00149	0.00146	0.00132	0.00117	0.00113	0.00115	0.00120	0.00122	0.00130	0.00138	0.00144
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Population $_{j,t-k}$	0.402***	0.301***	0.172***	0.115***	0.0479	-0.0259	-0.107***	-0.151***	-0.185***	-0.177***	-0.121***	-0.0503*	0.0287
	(10.56)	(8.88)	(5.86)	(3.80)	(1.45)	(-0.72)	(-2.94)	(-4.22)	(-5.41)	(-5.45)	(-3.98)	(-1.76)	(1.09)
Guns $\neq_{i_t}$	0.170***	0.177***	0.183***	0.187***	0.187***	0.191***	0.194***	0.195***	0.201***	0.208***	0.211***	0.208***	0.206***
	(24.78)	(23.34)	(22.35)	(21.04)	(19.66)	(19.21)	(19.62)	(19.60)	(20.28)	(21.08)	(21.60)	(21.56)	(21.53)
U. Rate $_{i,t-k}$	-0.0000428	-0.0000504	-0.0000691	-0.0000545	-0.0000344	-0.0000489	-0.0000534	-0.0000218	-0.00000229	0.0000230	0.0000634	0.0000905	0.0000961
	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.00)	(-0.01)	(-0.01)	(-0.00)	(-0.00)	(0.00)	(0.01)	(0.01)	(0.01)
U. Rate $_{j,t-k}$	-0.0570***	-0.0762***	-0.108***	-0.0938***	-0.0611***	-0.0311***	-0.0295***	-0.0158***	0.00290	0.0180***	0.0281***	0.0206***	0.0328***
	(-11.42)	(-13.21)	(-16.39)	(-16.85)	(-12.15)	(-5.54)	(-5.34)	(-2.77)	(0.57)	(4.20)	(7.88)	(5.39)	(8.40)
% Black $_{i,t-k}$	0.000252	0.000263	0.000272	0.000278	0.000278	0.000309	0.000317	0.000329	0.000359	0.000384	0.000397	0.000398	0.000389
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
% Black $_{j,t-k}$	0.267***	0.283***	0.284***	0.315***	0.355***	0.388***	0.407***	0.398***	0.404***	0.394***	0.377***	0.347***	0.316***
	(7.73)	(7.51)	(7.54)	(9.22)	(10.94)	(11.38)	(12.09)	(12.15)	(12.61)	(12.76)	(12.79)	(12.57)	(12.43)
Constant	-1.006***	-0.941***	-0.842***	-0.806***	-0.764***	-0.724***	-0.664***	-0.622***	-0.604***	-0.615***	-0.657***	-0.693***	-0.737***
	(-19.18)	(-19.16)	(-20.07)	(-20.47)	(-20.28)	(-20.24)	(-21.29)	(-22.19)	(-23.06)	(-23.64)	(-24.95)	(-25.91)	(-27.67)
OBS	29328	31584	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840
Pairs	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256
R2	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996	0.996

Notes: Estimated effects using a fixed effects Poisson estimator. All models include origin state fixed effects, destination state fixed effects, and year fixed effects. The lag is indicated by the column label. Z-statistics from pair clustered standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

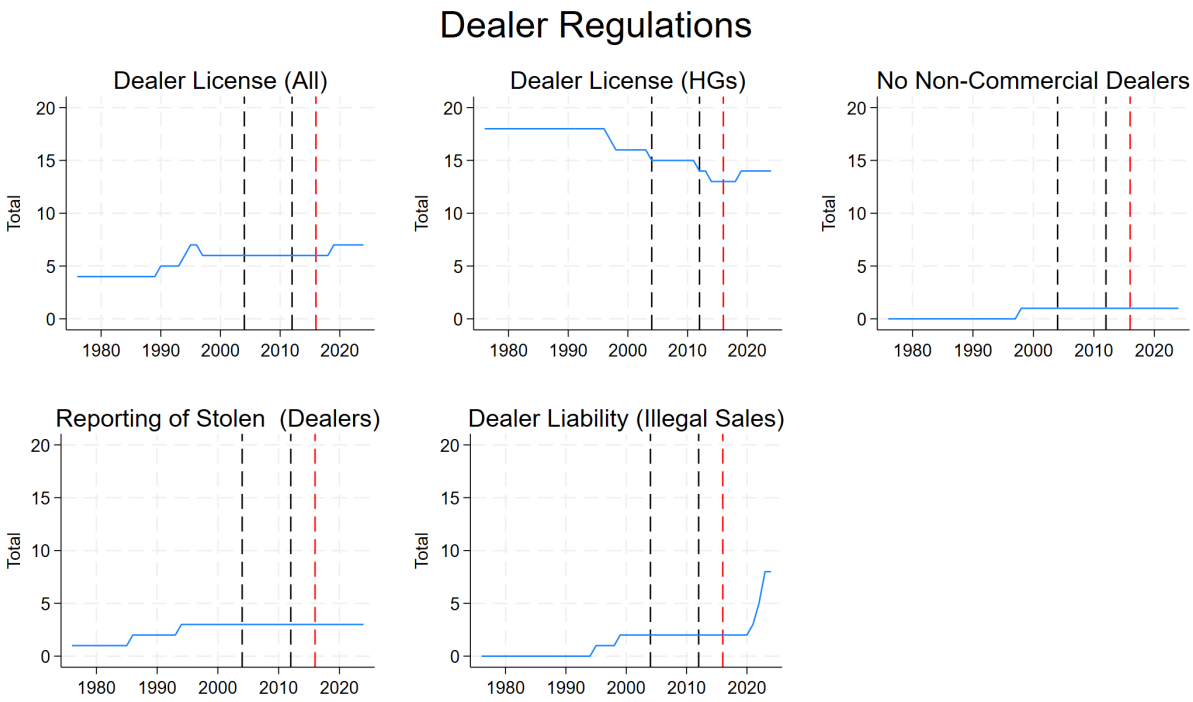
Table 13: Lagged Effects of Gun Laws on Domestic Recoveries II

	k=-2	k=-1	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10
GunLaws $_{i,t-k}$	-0.00158***	-0.00163***	-0.00224	-0.00234	-0.00221	-0.00219	-0.00225	-0.00247	-0.00272	-0.00252	-0.00248	-0.00267	-0.00271
	(-3.71)	(-3.50)	(-0.58)	(-0.59)	(-0.53)	(-0.50)	(-0.50)	(-0.51)	(-0.49)	(-0.42)	(-0.41)	(-0.38)	(-0.34)
GunLaws $_{j,t-k}$	-0.00947***	-0.00708***	-0.0951***	-0.101***	-0.113***	-0.123***	-0.132***	-0.141***	-0.148***	-0.157***	-0.166***	-0.173***	-0.181***
	(-4.96)	(-3.64)	(-27.11)	(-27.85)	(-29.63)	(-31.52)	(-33.68)	(-35.62)	(-36.79)	(-38.27)	(-38.86)	(-39.36)	(-38.46)
Population $_{i,t-k}$	0.00344***	0.00341***	0.00529	0.00538	0.00578	0.00617	0.00723	0.00799	0.00846	0.00730	0.00550	0.00424	0.00290
	(9.32)	(8.64)	(0.09)	(0.09)	(0.09)	(0.10)	(0.11)	(0.13)	(0.15)	(0.13)	(0.10)	(0.08)	(0.06)
Population $_{j,t-k}$	0.404***	0.305***	-0.226***	-0.220***	-0.208***	-0.200***	-0.192***	-0.179***	-0.169***	-0.158***	-0.147***	-0.137***	-0.131***
	(10.73)	(9.14)	(-14.85)	(-14.39)	(-13.70)	(-13.21)	(-12.70)	(-11.87)	(-11.22)	(-10.52)	(-9.70)	(-8.99)	(-8.40)
Shared Interstate	0.000277	0.000247	-0.00726	-0.00616	-0.00489	-0.00432	-0.00388	-0.00374	-0.00363	-0.00345	-0.00331	-0.00295	-0.00277
	(0.64)	(0.56)	(-0.99)	(-0.84)	(-0.68)	(-0.61)	(-0.55)	(-0.54)	(-0.53)	(-0.51)	(-0.50)	(-0.45)	(-0.42)
Distance	-0.00469***	-0.00470***	-0.00459	-0.00497	-0.00542	-0.00726	-0.00858	-0.0101	-0.0117	-0.0127*	-0.0132*	-0.0135*	-0.0135*
	(-7.17)	(-6.96)	(-0.61)	(-0.66)	(-0.73)	(-0.99)	(-1.18)	(-1.40)	(-1.63)	(-1.78)	(-1.85)	(-1.88)	(-1.86)
Border	0.0194***	0.0194***	0.0132	0.0123	0.0112	0.00914	0.00791	0.00668	0.00552	0.00477	0.00438	0.00391	0.00386
	(8.50)	(8.29)	(1.04)	(0.98)	(0.91)	(0.75)	(0.67)	(0.57)	(0.48)	(0.42)	(0.39)	(0.35)	(0.34)
Guns $\neq_{i_t}$	1.163***	1.171***	1.309***	1.304***	1.293***	1.287***	1.282***	1.274***	1.267***	1.260***	1.253***	1.246***	1.241***
	(172.04)	(156.40)	(83.72)	(83.42)	(83.91)	(84.33)	(84.32)	(84.21)	(84.26)	(84.30)	(83.63)	(82.87)	(81.57)
U. Rate $_{i,t-k}$	0.00189	0.00190	-0.00326	-0.00280	-0.00261	-0.00283	-0.00285	-0.00259	-0.00249	-0.00237	-0.00224	-0.00149	-0.00107
	(0.85)	(0.78)	(-0.41)	(-0.34)	(-0.33)	(-0.34)	(-0.32)	(-0.30)	(-0.32)	(-0.31)	(-0.28)	(-0.18)	(-0.13)
U. Rate $_{j,t-k}$	-0.0560***	-0.0748***	-0.227***	-0.198***	-0.156***	-0.127***	-0.121***	-0.114***	-0.104***	-0.0981***	-0.0893***	-0.0835***	-0.0653***
	(-11.40)	(-13.19)	(-17.42)	(-16.35)	(-14.76)	(-12.71)	(-12.65)	(-12.35)	(-11.69)	(-10.85)	(-9.65)	(-8.85)	(-7.02)
% Black $_{i,t-k}$	-0.000654	-0.000614	0.00195	0.00170	0.00121	0.00110	0.00102	0.00111	0.00113	0.00113	0.000993	0.00101	0.00103
	(-1.60)	(-1.44)	(0.12)	(0.10)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
% Black $_{j,t-k}$	0.263***	0.280***	-0.105***	-0.101***	-0.0989***	-0.0993***	-0.0978***	-0.0950***	-0.0928***	-0.0906***	-0.0877***	-0.0843***	-0.0801***
	(7.71)	(7.50)	(-17.60)	(-17.17)	(-16.88)	(-16.94)	(-16.85)	(-16.47)	(-16.18)	(-15.89)	(-15.46)	(-15.05)	(-14.40)
Constant	6.738***	6.801***	7.266***	7.278***	7.286***	7.285***	7.277***	7.281***	7.285***	7.288***	7.289***	7.288***	7.284***
	(129.75)	(139.92)	(862.26)	(900.61)	(922.02)	(907.46)	(875.96)	(872.38)	(851.57)	(822.61)	(791.86)	(769.86)	(750.81)
OBS	29328	31584	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840	33840
Pairs	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256	2256
R2	0.996	0.996	0.982	0.982	0.983	0.983	0.983	0.983	0.983	0.984	0.984	0.984	0.984

Notes: Estimated effects using a fixed effects Poisson estimator. All models include origin state fixed effects and year fixed effects. The lag is indicated by the column label. Z-statistics from pair clustered standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

E Gun Law Totals by Law Type

Figure 22: Total Number of Dealer Regulations (1976-2024)



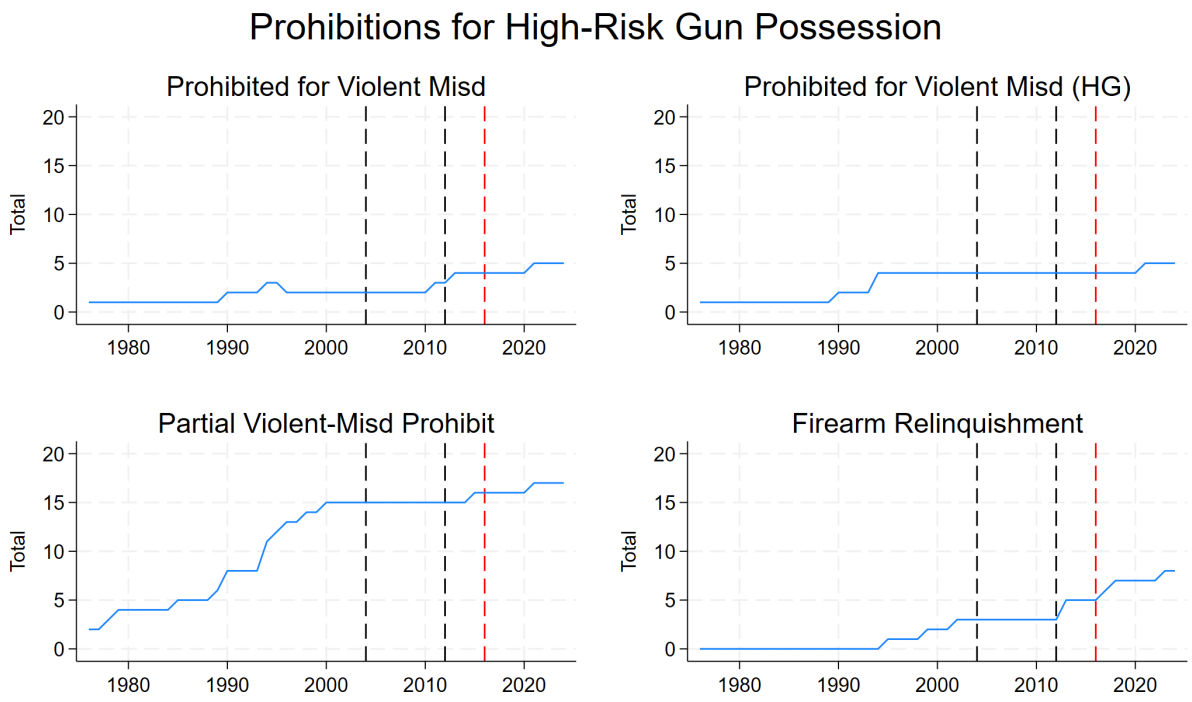
Notes: From top left to bottom right: State dealer license required for sale of all firearms, State dealer license required for sale of handguns, Ban on non-commercial dealers, Mandatory reporting of stolen guns by all firearm dealers, and Dealers are liable for damages resulting from illegal gun sales. Descriptions are taken verbatim from the Siegel code book.

Figure 23: Buyer Regulations (1976-2024)



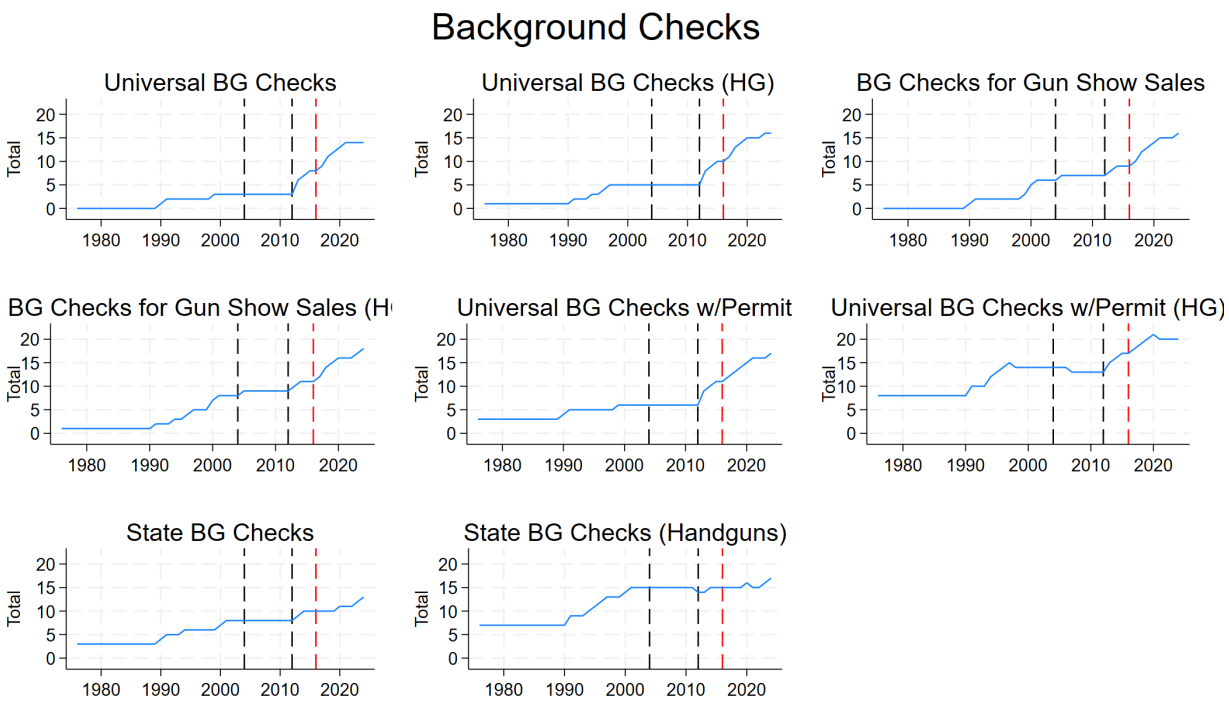
Notes: From top left to bottom right: Waiting period is required on all firearm purchases from dealers, Waiting period is required on all handgun purchases from dealers, A license or permit is required to purchase all firearms A license or permit is required to purchase handguns, Gun owners must register their firearms with the state, Gun owners must register their handguns with the state, De facto registration of firearms is in place because of a record-keeping requirement for all gun sales, De facto registration of handguns is in place because of a record - keeping requirement for all handgun sales, Purchase of handguns from licensed dealers and private sellers restricted to age 21 and older, Purchase of long guns from licensed dealers and private sellers restricted to age 18 and older, Purchase of long guns from licensed dealers and private sellers restricted to age 21 and older, Mandatory reporting of lost and stolen guns by firearm owners, and Buyers can purchase no more than one handgun per month with no or limited exceptions. Descriptions are taken verbatim from the Siegel code book.

Figure 24: Prohibitions for High Risk Gun Possession (1976-2024)



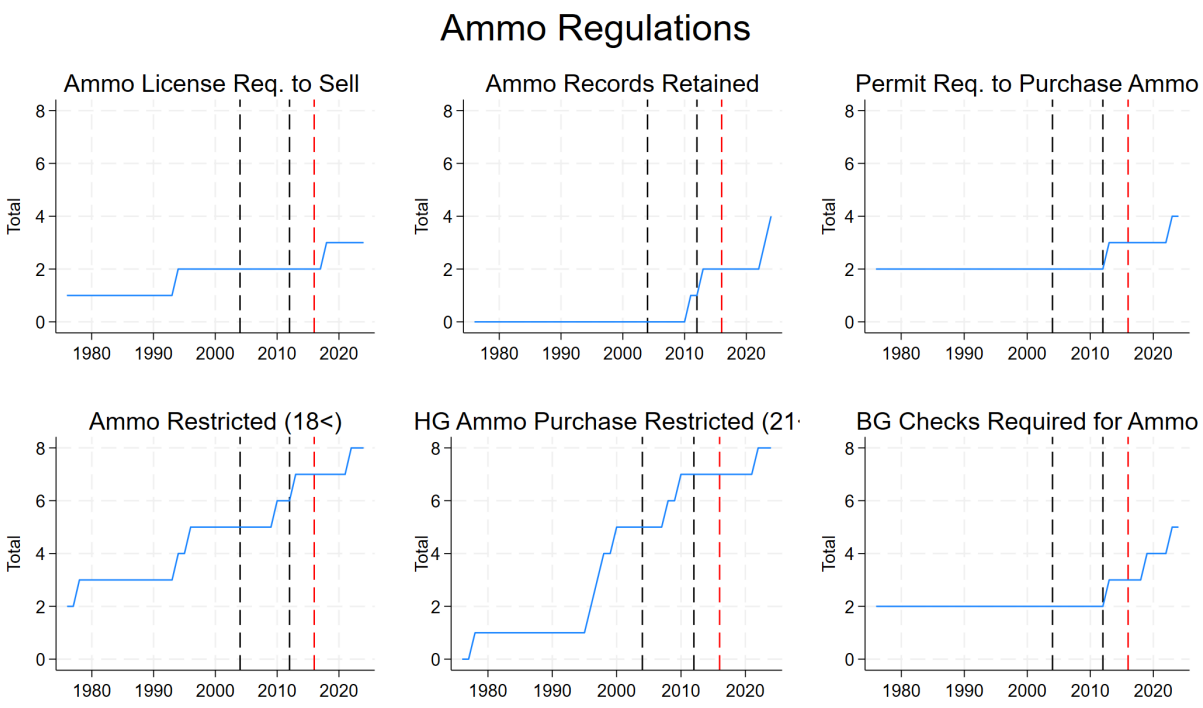
Notes: From top left to bottom right: Waiting period is required on all firearm purchases from dealers, Firearm possession is prohibited for people who have committed a violent misdemeanor punishable by less than one year of imprisonment, Handgun possession is prohibited for people who have committed a violent misdemeanor punishable by less than one year of imprisonment, Firearm possession is prohibited for people who have committed a violent misdemeanor punishable by more than one year of imprisonment, and People are required to relinquish their firearms after they become prohibited from possessing them. Descriptions are taken verbatim from the Siegel code book.

Figure 25: Background Checks (1976-2024)



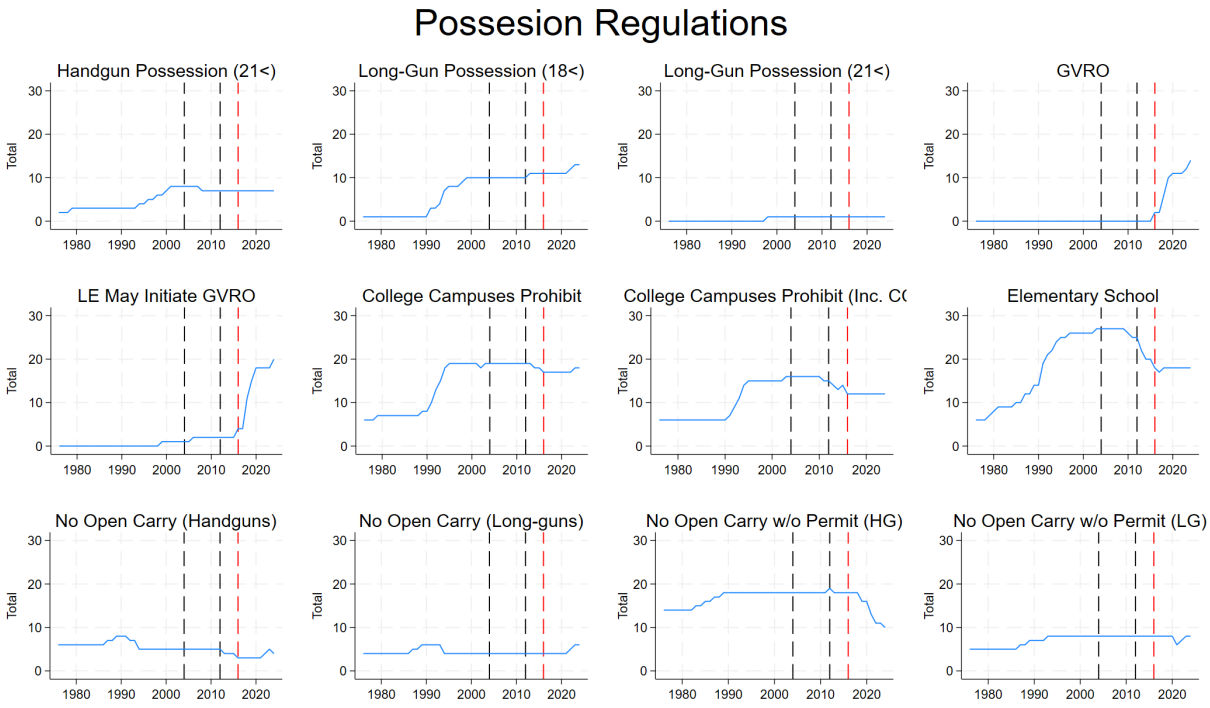
Notes: From top left to bottom right: Universal background checks required at point of purchase for all firearms, Universal background check required at point of purchase for handguns, Background checks required for all gun show firearm sales at point of purchase, Background checks required for gun show handgun sales at point of purchase, Background checks conducted through permit requirement for all firearm sales (or universal background checks) Background checks conducted through permit requirement for all handgun sales (or universal background checks), State conducts separate background checks beyond the federal NICS check for all firearms, State conducts separate background checks beyond the federal NICS check for handguns. Descriptions are taken verbatim from the Siegel code book.

Figure 26: Ammo Regulations



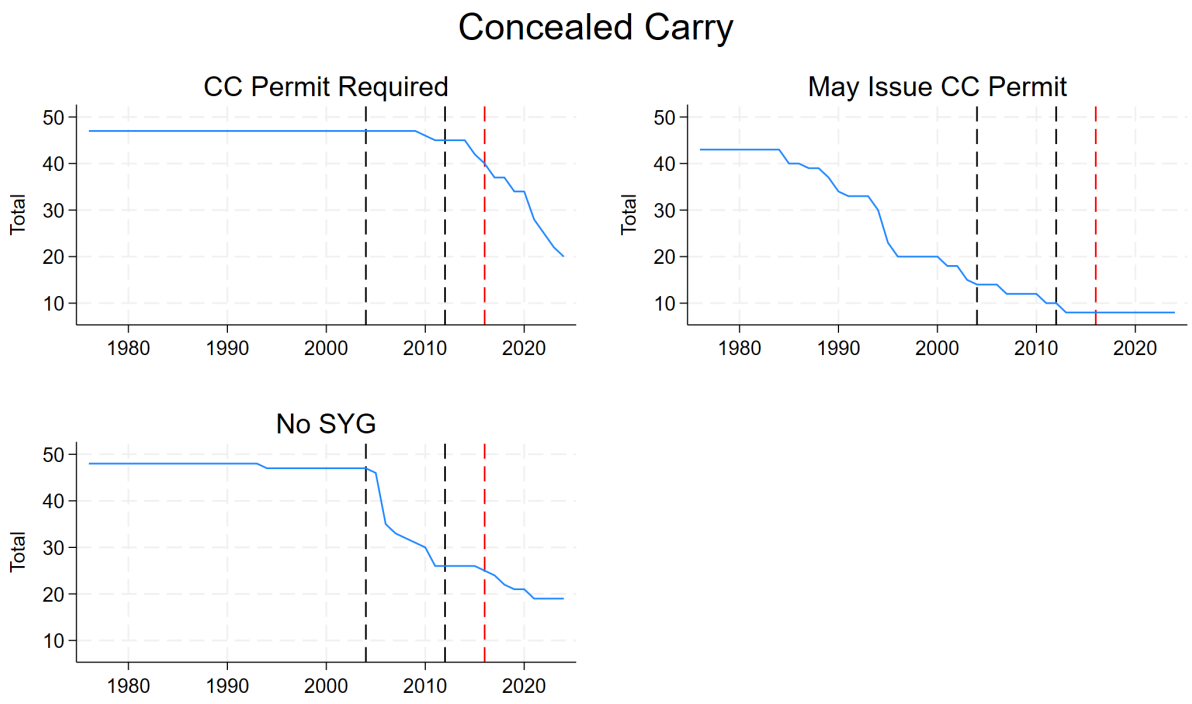
Notes: From top left to bottom right: Vendor license required to sell ammunition, Records of ammunition sales must be retained, Permit required to purchase ammunition, Purchase of any type of ammunition restricted to age 18 and older, Purchase of handgun ammunition restricted to age 21 and older, and Background checks required for ammunition purchase. Descriptions are taken verbatim from the Siegel code book.

Figure 27: Possession Regulations



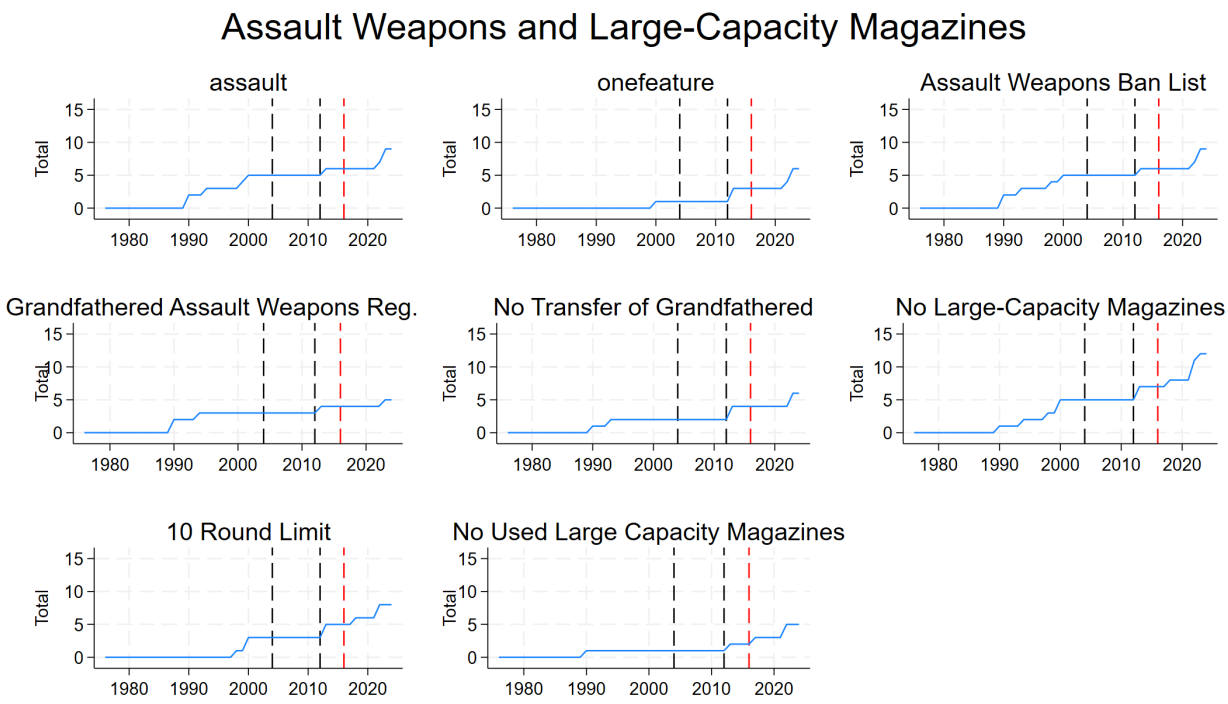
Notes: From top left to bottom right: No possession of handguns until age 21, No possession of long guns until age 18, No possession of long guns until age 21, Family members or law enforcement officers can confiscate firearms from any person who is deemed by a judge to represent a threat to themselves or others, Law enforcement officers can confiscate firearms from any person who is deemed by a judge to represent a threat to themselves or others, No gun carrying allowed on college campuses except for concealed weapon permittees, No gun carrying on college campuses including concealed weapons permittees, No gun carrying on elementary school property, including concealed weapons permittees, No open carry of handguns is allowed in public places, No open carry of long guns is allowed in public places, No open carry of handguns is allowed in public places unless the person has a concealed carry or handgun carry permit, and No open carry of long guns is allowed in public places unless the person has a permit. Descriptions are taken verbatim from the Siegel code book.

Figure 28: Concealed Carry and Stand Your Ground



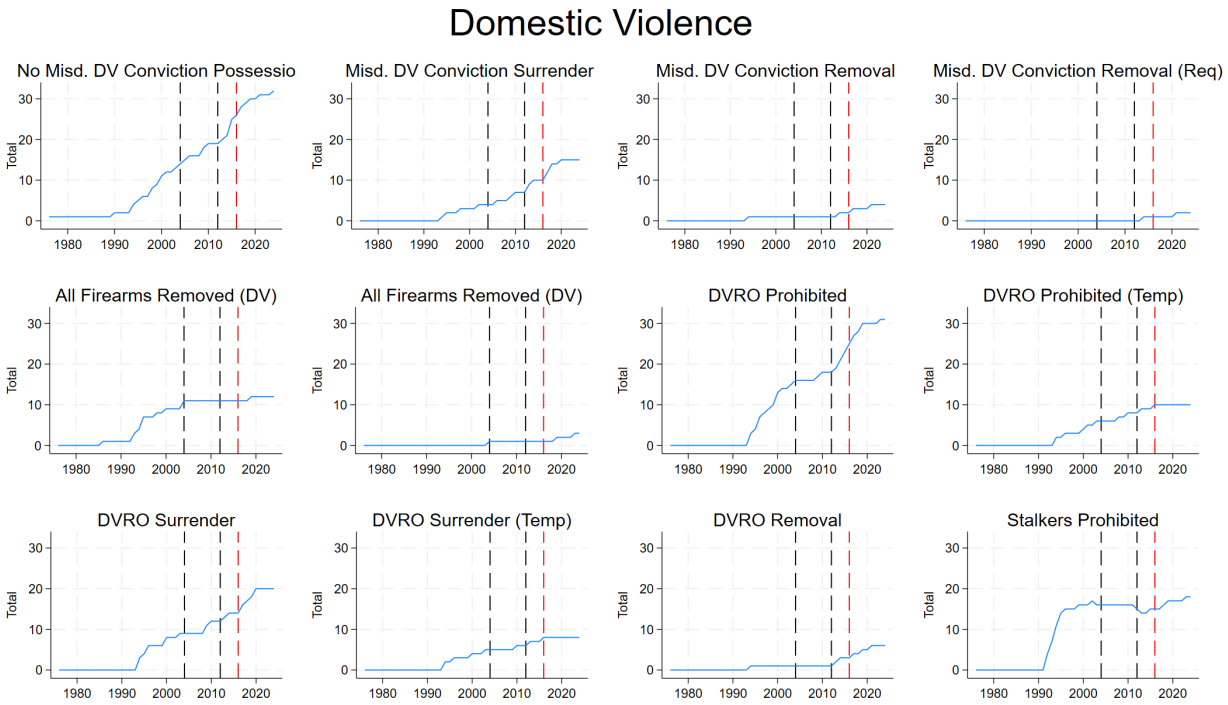
Notes: From top left to bottom right: Permit required to carry concealed weapons, "May issue" state, and No stand your ground law. Descriptions are taken verbatim from the Siegel code book.

Figure 29: Assault Weapon and Magazine Capacity Limits



Notes: From top left to bottom right: Ban on sale of assault weapons beyond just assault pistols, Ban on sale of assault weapons using a one-feature definition, Ban on sale of assault weapons which includes a list of banned weapons, Grandfathered weapons must be registered, Transfer of grandfathered weapons is prohibited, Ban on sale large capacity magazines beyond just ammunition for pistols, No magazines with a capacity of more than 10 rounds of ammunition may be sold, and Possession of pre-owned large capacity magazines is prohibited. Descriptions are taken verbatim from the Siegel code book.

Figure 30: Domestic Violence



Notes: From top left to bottom right: People convicted of a misdemeanor crime of domestic violence against a spouse, ex-spouse, or cohabitating partner are prohibited from possessing firearms, People convicted of a misdemeanor crime of domestic violence against a spouse, ex-spouse, or cohabitating partner are required to surrender their firearms, State law allows law enforcement to remove firearms from MCDV offenders State law requires law enforcement officers to remove firearms from MCDV offenders, State law requires law enforcement to remove firearms from the scene of a domestic violence incident, All firearms must be removed from the scene of a domestic violence incident, State law automatically prohibits domestic violence-related restraining order (DVRO) subjects from possessing firearms, Ex parte (temporary) DVRO subjects are automatically prohibited from possessing firearms State law requires DVRO subjects to surrender their firearms, State law requires ex parte DVRO subjects to surrender their firearms, Law enforcement officials are required to remove firearms from people subject to a domestic violence-related restraining order, and A stalking conviction is prohibitive for firearm possession. Descriptions are taken verbatim from the Siegel code book.

F What Laws Probably Matter?

We now consider which laws may be driving the observed effects. Recall that there are 11 broad classifications of laws. Two of these classifications (Stand Your Ground and Child Access Prevention) contain only a single law. We do not estimate the effect of Child Access Prevention laws due to limited variation, but we do estimate the effect of Stand Your Ground laws because there is sufficient variation (see Figure 28). To do so, we use a specification similar to that described in Equation 4 and estimate the same underlying model with different lags and leads (closely following 3). There are three key differences, however: 1) rather than using the natural log of law counts, the main variables of interest are the raw counts of laws (e.g., the number of Concealed Carry laws in a given state-year), implying that estimates should be interpreted as semi-elasticities; 2) we control for the total number of "other" laws in place as well as the number of relevant laws 25 years prior; and 3) we restrict the sample to pairs in which both states exhibit variation (e.g., we drop a pair if one state always has two dealer laws when estimating the dealer law effect).[21]

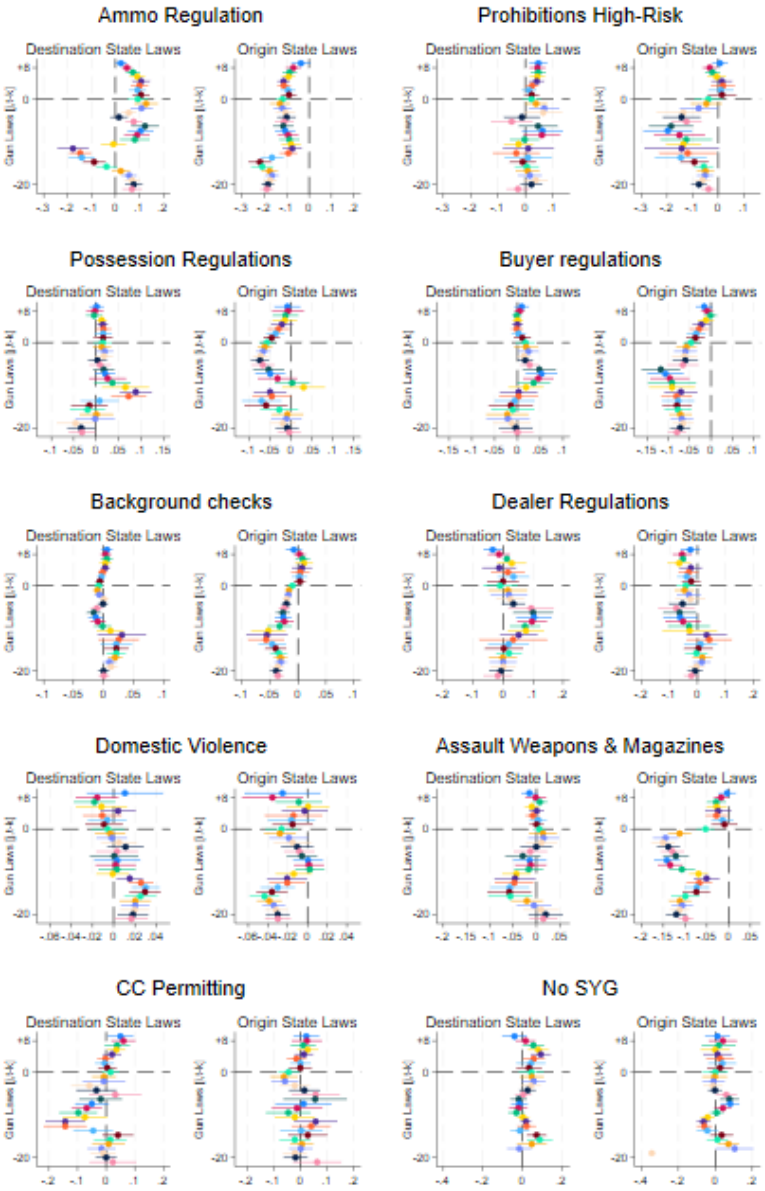
Estimation results are presented in Figure 31. Each panel shows the estimated relationship between different lags and leads of specific gun law types and the share of crime guns originating from a given state. The panel title indicates the law type. In most cases, each panel includes 29 estimated effects: 8 leads (serving as a rough pre-trend test), 20 lags, and the contemporaneous measure. When fewer than 29 estimates are shown, this reflects collinearity issues.

With respect to potential violations of pre-trends, ammo laws (both import and export) and possession restrictions (particularly for export states) appear the least reliable. In these cases, the leads are statistically significant, suggesting that the estimated effects are unlikely to be causal and are instead driven by serial correlation. Stand Your Ground laws (or more precisely, their absence) also do not appear to have meaningful effects, as estimates generally remain close to zero for both import and export states. The most plausible effects, based on the overall patterns, are for laws restricting purchases by high-risk individuals, buyer regulations, background checks, and domestic violence laws. In these cases, pre-trends are generally small or not statistically different from zero. Moreover, the presence of these laws in import states tends to increase imports, while their presence in export states reduces the share of guns recovered in import states.

Dealer laws, assault weapon laws, and concealed carry permit laws exhibit patterns that are suggestive of real effects, though each includes some estimates that warrant caution. Increases in dealer regulations in destination state increase the share of crime guns coming from out of state. However, these same laws in the origin state also have a positive relationship with the share of recoveries in the destination state. In the case of Assault Weapons and Magazine restrictions laws, the origin state laws behave almost ideally; the effect plummets to zero at $t = 0$ and the leads are mostly not different from zero. At first glance, the destination state laws also behave almost perfectly but note here the sign is in the opposite direction that is predicted by theory. The presence

[21] Importantly, this variation requirement is applied separately for each lag and lead. When estimating the effect of a given lag (tk) of a particular law, we restrict the sample to state pairs that exhibit variation in that law at the relevant lag. In other words, pairs that do not change at horizon (tk) are excluded from that specific regression but may still be included when estimating other lags or leads.

Figure 31: Gun Regulations and Recoveries



Notes: Effect of gun laws (by type) on interstate imports. Estimates from Poisson regressions including origin and destination measures of gun laws, population, unemployment rate, percent Black (for both source and destination state), log distance, and a border dummy. Models include source fixed effects, destination fixed effects, and year fixed effects. Models also exclude pairs in which one state always has the same number of gun laws of one particular type (consistently always treated). Standard errors clustered by state pair. Each panel has (at most) 29 separate estimates (8 leads of gun laws of a given type, 20 lags, and the contemporaneous law count).

of these laws decreasing gun recoveries from origin states. Moreover, the timing of the export state laws is questionable. The time to crime suggests gun laws will have a long burn in period so an instantaneous effect here is suggestive of something else. Concealed carry permit laws also have effects that are contrary to theory but these are more sensible ex-post. Here we find, in the case laws in the import state, the presence of these laws decrease the share of crime guns coming from outside the state while concealed carry permit laws in the exporting state have no effect on the recoveries in the importing state. This "null" result for export state and negative effect for import state laws could be explained by individuals carrying less (or more responsibly) after moving to a state with relatively stricter concealed carry requirements.