# The U.S. Consumer Firearms Industry: Welfare and Policy Implications*

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**Abstract**

This paper studies demand for firearms in the United States and its implications for the design of gun policy. We merge the universe of legal firearm transactions in Massachusetts with national price data for individual gun models to estimate a structural model of firearm demand. Our model demonstrates that preferences for firearm characteristics differ substantially along demographic lines, and that consumers are relatively inelastic to price changes. In order to quantify the impacts of firearm policies on public health, we use data on the universe of gun violence incidents to estimate the elasticity of gun violence with respect to gun purchasing. We then extrapolate out estimates of demand and public health from Massachusetts to the rest of the United States to predict the impact of gun policies on social welfare. We estimate that uniform taxes are more effective than targeted bans, but are dwarfed by the benefits of banning firearms purchases entirely. In particular, we find that doubling average prices with a $1,400 tax on gun purchases would increase welfare by $70 million dollars per year in Massachusetts and $3.3 billion dollars for the entire U.S. Yet, a total ban on firearm sales would increase welfare by $570 million and $33 billion dollars per year, respectively.

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# 1 Introduction

In the United States, firearms are one of the leading causes of death, and recently became the most common way children die.[1] In 2020, over 45,000 deaths involved the use of a gun.[2] Over 20 million guns are sold each year in the United States,[3] and one in three Americans currently own a firearm.[4] The size of this market and its public health implications makes understanding the structure of the U.S. consumer firearms industry a first-order policy question

Despite its potential policy implications, the literature on firearm markets is relatively sparse. Most studies either analyze existing firearm policies or proxies for gun ownership in relation to their downstream effects on crime and mortality (e.g., Lott and Mustard [1997], Duggan [2001]). The few studies that do analyze market structure tend to use highly aggregated data (e.g., Brauer [2013a], McDougal et al. [2020]). Although these studies provide valuable insight into outcomes of the current firearm market, they provide less information about the substitution patterns of gun consumers, making it challenging to predict market outcomes under alternative regulations.

Relatively few national-level regulations operate on the consumer firearm market. One important policy is determined by the judicial history of the Second Amendment to the U.S. Constitution, which protects the individual right to gun ownership. In 1932, the U.S. Congress passed revenue-raising excise taxes of 10 percent on handgun transactions and 11 percent on long guns,[5] which were recently doubled within the state of California.[6] [7] The National Firearms Act of 1934 and the Federal Assault Weapons bans from 19942004 implemented strict controls on the ability of consumers to purchase certain classes of especially dangerous weapons, like machine guns. Although existing research finds that tax policy and weapons bans could dramatically impact the consumer firearms market (Koper and Roth [2001], Moshary et al. [2022]), limited experimentation with national regulation makes it challenging to design efficient firearm policy in the U.S. [Smart, 2018, Smart et al., 2021].[8]

[1]Source: https://www.nytimes.com/interactive/2022/12/14/magazine/gun-violence-children-data-statistics.html

[2]Source: `https://www.pewresearch.org/fact-tank/2022/02/03/what-the-data-says-about-gun-deaths-in-the-u-s/`

[3]Source: `https://www.cnn.com/2021/03/14/us/us-gun-sales-record/index.html`

[4]Source: `https://www.theguardian.com/us-news/2022/dec/15/americans-bought-150m-guns-decade-sandy-hook-shooting.`

[5]Handguns denote firearms such as pistols and revolvers, while long guns consist of rifles and shotguns.

[6]Source: `https://sgp.fas.org/crs/misc/IF12173.pdf`

[7]Source: `https://apnews.com/article/california-guns-ammunition-tax-school-safety-0870a673a3d4e85c78466897cfd7ff6f`

[8]Several other national policies impact the U.S. firearms market. The Federal Firearms Act of 1938 and the Gun Control Act of 1968 jointly impose licensing restrictions on firearm manufactures and retailers, and

This paper studies the structure of the consumer firearms industry in the U.S. and derives implications for the design of gun policy. To understand demand for firearms, we pair administrative microdata on firearm transactions in Massachusetts with 15 years of nationwide data on state-level gun purchase quantities and gun-level prices. We combine these sources of information to estimate a discrete choice model of demand for gun purchase. To study the externalities from firearm ownership, we use an online archive that records incidents of fatalities and injuries from gun violence to estimate the elasticity of gun violence with respect to contemporaneous firearm transactions. Combining our models of firearm demand and gun violence, we evaluate the design of alternative public policies on the U.S. firearms market.

The analysis in this paper is based on a variety of data sources, described in Section 2. We access transaction-level microdata covering every legal handgun and long gun sale in Massachusetts from 20162022. Each record includes the buyer's zip code and gender alongside the firearm's manufacturer, model, and product characteristics. Since these data do not record transaction prices, we scrape historical MSRPs from an industry publication.

In Section 3, we describe features of the data that inform our model of firearm demand. There is considerable variation in the characteristics of firearms available to consumers and meaningful demographic heterogeneity across consumers in different segments of the firearm market. We document that women and individuals in zip codes with larger minority populations are under-represented in the population of potential gun buyers, while individuals in neighborhoods with a conservative voting record are disproportionately likely to buy a high-capacity weapon.

We also develop an instrumental variables method to estimate the price elasticity of firearm demand. Following McDougal et al. [2020], we use prices of firearm inputs on the world commodity market as a cost shock. Our instrument uses intuition from the production process and the proposal of Berto Villas-Boas [2007] to isolate cross-manufacturer heterogeneity in exposure to common cost shocks by interacting manufacturer fixed effects with the time series of commodity prices. This results in a high-dimensional manufacturer-by-commodity instrument set, and we apply the dimension-reduction technique of Belloni et al. [2012] to overcome issues of weak identification. Using these instruments, we estimate a price elasticity of aggregate demand for gun purchase in Massachusetts equal to -2.2. This value reveals elasticity in consumers' extensive margin decisions of whether or not to purchase a gun, highlighting the potential of taxes as a public policy tool in markets for consumer

limit interstate firearm commerce to licensed retailers. In 2005, the Protection of Lawful Commerce in Arms Act extended legal protection to the manufacturers of firearms when their products are used for criminal acts.

firearms.

Section 4 uses these reduced-form facts to develop a model of demand for gun purchase. We specify a preference model in the style of Nevo [2000], allowing utility to depend on the interaction of gun characteristics and consumer demographics, price, fixed effects for gun and weapon-class×year, and gun-year demand shocks. We specify the unobservable, idiosyncratic component of utility as a four level nested logit in which we partition the choice to not purchase a gun from the inside options, the inside options into handguns and long guns, and each weapon class into new and used guns. We estimate the model parameters via maximum likelihood, using a contraction mapping Berry et al. [1995] to pin down the demand shocks. We then recover the price coefficient using the instrument set from Section 3. Our estimated demand model reveals substantial demographic heterogeneity in preferences for firearm characteristics and meaningful differences in preferences for the purchase of any firearm tied to geography, gender, race, and conservative voting patterns. We also find minimal substitutability between handguns and long guns, highlighting distinct motivations for the purchase of each weapon type [Miller et al., 2022].

In order to quantify the public health effects of changes in firearm purchases, Section 5 estimates the causal effect of consumer firearm transactions on downstream incidents of gun violence. To address reverse causality [RAND, 2018], we use the instrumental variable developed by Rosenberg [2023] and isolate variation in firearm transactions due to the net entry of firearm retailers within a zip code over time. We estimate that a 10 percent increase in firearm transactions would lead to a 0.8 percent increase in contemporaneous incidents of gun violence and 0.4 percent increases in fatal and non-fatal injuries. These elasticities agree with the sign of other estimates in the literature but are approximately 30 percent smaller in magnitude. We attribute the difference in magnitudes as arising from our decision to model firearm transactions- rather than firearm ownership- and we discuss how to rescale our estimates to account for gun ownership in our counterfactuals.

To analyze the design of alternative firearm policies, Section 6 uses our estimates of preferences and externalities to simulate the welfare effects of counterfactual changes in gun taxes. In a more conservative set of counterfactuals, we consider policy changes local to Massachusetts. Within Massachusetts, we are able to safely abstract away from industry-wide responses to regulation and to base our predictions on estimates of firearm demand close to our observed transaction microdata. We also pursue a set of counterfactuals based on nationwide changes in gun policy. To extrapolate our estimates of gun demand to the United States, we match our model's predictions to aggregate firearm purchases in each state-year via a vertical shifter in willingness-to-pay that varies freely at the state-year level. In these nationwide counterfactuals, we heavily rely on our model to extrapolate away from our data

and restrict the potential responses of firearm suppliers in equilibrium. Consequently, we interpret our national-level results more cautiously.

We begin our exploration of counterfactual gun policies by computing the consumer surplus produced by the firearm market under the status quo. Massachusetts is an outlier compared to the rest of the U.S., as its consumers value the firearm market at roughly half of the national average. We find that the average adult in the U.S. derives 175 dollars of consumer surplus from the firearm industry each year of our sample period. This implies that the firearms industry provides approximately 43 billion dollars of yearly value to U.S. consumers.[9]

We next consider counterfactually taxing firearm purchase in Massachusetts. We consider a scenario where the regulator has two tax instruments- specific taxes on handguns and long guns. In our baseline analysis, we consider the effects of these levies on the social value of consumer surplus, contemporaneous gun violence, and tax revenue. We find gains to social welfare from increasing taxes on firearms. Low tax rates do little to affect consumers' extensive margin gun purchase decisions, leading to large drops in consumer surplus which are transferred almost one-for-one into gains in tax revenue. At high tax rates, revenue decreases according to the logic of a Laffer curve, but the drop in consumer surplus is more than compensated by a reduction in gun violence. The two tax instruments are complementary in the production of social welfare, and we find that the globally optimal gun policy in Massachusetts is a complete ban on all firearm transactions.

The distinct character of firearm demand in Massachusetts leads to qualitatively distinct implications of firearm policy at the national level. Abstracting from supply-side forces, we find an optimal tax on gun purchase in the U.S. of around 1,400 dollars on all firearms. Taxing only a single weapon class is meaningfully less efficient and can lead to decreases in social welfare. The disparate implications of an identical policy in Massachusetts and the U.S. demonstrates the value of tailoring gun policy to stakeholders within a specific jurisdiction [Rosenberg, 2023], potentially suggesting that firearm regulation could be more efficient when determined below the national level.

Using our model to extrapolate far from the current market, we find that the globally optimal uniform gun tax policy in the U.S. is a complete ban on all consumer firearm transactions. A gun ban would destroy all 43 billion dollars of value that the gun market provides to consumers each year. However, a complete ban, would save society more than 76 billion dollars through the reduction of gun violence, netting a 33 billion dollar increase in social welfare. Although a ban on firearm transactions is unlikely under the current U.S.

[9]Comparable estimates from Grieco et al. [2023] value the new car market in 2016 as producing 150 billion dollars of consumer surplus.

political climate [Gentzkow et al., 2019, Luca et al., 2020] and constitutional law, we view this result as demonstrating the social welfare gained by other industrialized countries that design restrictive policies on their firearm markets. Our health predictions coincide with the observed effects of Australia's 1996 National Firearms Agreement, which implemented broad-scale gun bans across the country [Ramchand and Saunders, 2021]. Moreover, our preference estimates suggest that Australia's sweeping gun policy likely increased social welfare.

Most of the existing literature surrounding firearms has focused on estimating the relationship between guns and crime or violence Duggan [2001], Cook and Ludwig [2006], Koenig et al. [2016], Johnson and Robinson [2021], Studdert et al. [2022]. The evidence is somewhat mixed on how guns relate to public health, but these studies generally point to a positive relationship between gun ownership and violence [RAND, 2018]. We contribute to this literature by utilizing our high resolution data on both legal firearms transactions and gun violence incidents to estimate the effect of firearm transactions on fatal and non-fatal injuries from gun violence. We also combine these estimates with our demand model to study the design of firearm regulations across different weapon classes and at the state and national level.

This paper most closely contributes to a growing body of work that analyzes the design of regulation on consumer firearms markets in the U.S. [Koper and Roth, 2001, Bice and Hemley, 2002, Knight, 2013, McDougal et al.]. We advance the literature on the consumer firearms market by using revealed preferences to estimate a micro-founded model of demand for guns in characteristic space and by using this model to make welfare comparisons against policy alternatives.

Our work is especially close to two recent papers within the literature on gun market regulations. Moshary et al. [2022] use a conjoint experiment and stated preference to estimate a micro-founded model of demand for guns and examine the implications of national firearm policies on consumer surplus. They estimate a low price elasticity for these consumers, consistent with our findings. Rosenberg [2023] assembles 40 years of firearm transaction records from California and estimates a nested logit model of gun retailer choice, jointly estimates preferences for and externalities from firearm ownership, and uses these estimate to evaluate counterfactual regulations on local firearm markets. We view our paper as applying the analysis of high-resolution data on firearm markets and gun violence from Rosenberg [2023] to the questions of national regulation posed by Moshary et al. [2022]. We are also the first paper to our knowledge to use microdata on firearm transactions to estimate the price elasticity of gun demand.

# 2 Data

We now describe the data elements used in the paper.

## 2.1 FRB Firearms Transactions

Our primary dataset is the Massachusetts Firearm Record Bureau's (FRB) repository of firearm transaction records. For each purchase from a Federal Firearms Licensed (FFL) dealer, the state of Massachusetts requires an electronic verification that the consumer has the appropriate license to purchase the firearm. Thus, this dataset captures the universe of legal gun transactions occurring in the state of Massachussetts.[10]

Before completing a transaction, dealers are required to record information about the firearm, which are manually input as text by the dealer. These include the make (manufacturer/brand), model of the gun, type of weapon (handgun, rifle, or shotgun), the caliber of the gun, the barrel length, the surface finish of the weapon, and whether it is a high capacity weapon. Caliber denotes the width of the barrel of the gun, and approximately measures the power of the weapon. Barrel length captures the range and precision of the firearm. High capacity is an official designation by the FRB,[11] as weapons that are high capacity weapons manufactured for the civilian market, or capable of accepting high capacity ammunition devices. Surface finish denotes the material/color on the exterior of the gun. All of this is available in the FRB transactions data. The data includes information on the dealer, such as their FFL number, the zip code of the retail store's location, and the name of the store. It also includes data on the buyer, such as their gender, and the zip code they reside in according to their firearm license. Finally, the transaction date is also recorded. the FRB began recording these transactions in 2006, and began tracking whether weapons are high capacity in 2016. As such, we use data on transactions from 2016-2022. There are 816,000 transactions from retailers recorded in this time period.

To process this data, we convert calibers to a standard unit of inches across all gun models, as caliber is recorded as inches, millimeters, and gauge for shotguns. We do a similar exercise for barrel length. We manually standardize the manufacturer field, among the 100 most popular manufacturers. to avoid counting slightly different listed manufacturers as competitors (e.g. "S & W" is "Smith & Wesson"; both strings are present in the data as makes). We limit most of our analysis to the top 100 makes; these consist of 92% of all transactions in the data.

[10] We use a publicly available version of this data, available here: `https://www.mass.gov/info-details/data-about-firearms-licensing-and-transactions`

[11] For an example roster, see this link: `https://www.mass.gov/doc/large-capacity-firearms-roster-1/download`

## 2.2 Blue Book of Gun Values

Our second dataset is a panel dataset of gun models and their historical prices from the Blue Book of Gun Values (BBGV). Through purchasing a subscription, we were able to collect all available information on guns in the BBGV.[12] For each gun model, BBGV has annual historic prices from 2006-2022, with pricing information varying by the condition of the firearm. For new guns, the BBGV lists the MSRP (manufacturer's suggested retail price), and indicates the gun is currently in production. Used gun prices are distinguished by the grading (condition) of each model, ranging from 10% to 100%. Moshary et al. [2022] notes that there is little geographic variation in gun prices, so MSRP may be a good indicator for the national prices of guns across local markets. We use this as our primary measure of price in this paper. BBGV is organized hierarchically by gun manufacturer, then gun type (e.g. semi-automatic pistols), and then gun model. We manually convert BBGV weapon types to the three types (handgun, rifle, and shotgun) that appear in the FRB. It also includes text metadata on gun models and gun types within each manufacturer. In total, BBGV contains price data on 9,962 unique gun models, across 71 manufacturers. Price data is somewhat incomplete across gun models: MSRP is available for only 27% of gun-year observations, mostly because many guns in the database are no longer manufacturered, and primarily purchased as collectors' items.

Because the gun model names in the FRB dataset are not standardized, we merge this price dataset to the FRB transactions data using a fuzzy string matching algorithm approach. We perform this merge using a multi-step approach, which is described in detail in Appendix A. In total, through this procedure, we are able to match 90% of FRB transactions to a BBGV ID, for a total of 7,616 unique BBGV gun models. About 70% of transactions occur in years where the BBGV models are actively produced, or have a listed MSRP in that year. We assume for the remainder of the paper as if these actively produced guns were purchased new from a retailer and traded at the MSRP price.

## 2.3 Gun Violence Archive

We measure the downstream impacts of consumer firearm ownership using proprietary microdata from the Gun Violence Archive ("GVA").[13] The GVA is an independent, online repository of incident- and individual-level data on gun violence events. It covers fatal and non-fatal incidents of assault, accidental, and officer-involved gun violence but is not designed to record most self-harm incidents.

[12] Downloaded from `https://www.bluebookofgunvalues.com`

[13] `https://www.gunviolencearchive.org/`

Data in the GVA are gathered each day from a combination of automated queries, manual readings of local and state police records, and other sources including media and government information. For inclusion in the GVA, an incident must be verified by an initial researcher and validated through an addition process. Data in the GVA is not crowdsourced or recorded via bots. Although the data collection process has changed over time, discussions with GVA staff suggest that the collection process has been roughly constant since 2014.

in June 2023, we obtained an extract of all records in the GVA.[14] Figure A1 benchmarks counts of gun violence incidents in the GVA against publicly available records of gun fatalities from the CDC. Beginning in 2014, we find an exceptionally close match between counts of gun-related assault fatalities in these two datasets. The CDC does not record non-fatal firearm injuries, but best estimates suggest two non-fatal incidents occur for every fatality (Kaufman et al. 2021), a ratio which we replicate in the GVA. We thus treat the GVA as representing the universe of gun violence incidents, whether fatal or not.

Each recorded incident in the GVA includes its associated counts of fatalities and injuries, the incident date, and the geocoded address at which the incident occurred. We aggregate this microdata to compute counts of gun violence incidents, non-fatal injuries, and fatalities at the zip code-year level.

## 2.4 Auxiliary Datasets

We complement these main datasets with auxiliary data. In order to understand demographic heterogeneity of buyers, we merge demographic data of buyer zip codes from the 2019 5-year American Community Survey (ACS).[15]. This includes the distribution of gender, age, race, education, poverty in the zip code, along with the median zip code income and the density (individuals per square mile).

Given the political nature of gun ownership [Joslyn et al., 2017], we also include a measure of local political ideology. For this, we download the precinct-level vote shares in the 2016 U.S. presidential election, from the Voting and Election Science Team [Voting and Team, 2018].[16] We aggregate precinct-level vote shares s for all conservative candidates in the presidential election[17] in 2016 to construct a "Percent Conservative" measure for each precinct in the United States. We then aggregate this to the zip-code level using the supplied VEST precinct shapefiles along with U.S. Census TIGER ZCTA shapefiles, weighting precincts by

[14]We gratefully thank Mark Bryant and Sharon Williams for access to this data.

[15]Downloaded from the IPUMS NHGIS page: `https://www.nhgis.org/`

[16]Downloaded from `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/NH5S2I`

[17]This includes Donald Trump of the Republican Party, Gary Johnson of the Libertarian Party, Evan McMullin (Independent) and Darrell Castle of the Constitution Party

total number of votes.

Though our data on gun transactions comes only from the state of Massachusetts, we aim to understand national implications of gun policy. to extrapolate our data to other states, we use data on the number of guns sold in each state-year from the FBI's National Instant Criminal Background Check System[18]. For each legal firearm purchase in the United States, a criminal background is required. This is adjusted using the methodology of Brauer [2013b] to produce an estimate of the total number of gun sales in each state-year.

Not all individuals in a geographic area are relevant to the market for firearms. Given that firearms are a polemic public health topic in the United States [Oliver, 2006], some individuals may be ideologically opposed to owning a firearm, and moreover, this likely varies from region to region of the United States, as well as across gender. To account for this, we utilize wave 26 of the American Trends Panel (ATP), conducted by Pew Research, to better identify the set of potential gun purchasers in each market. Specifically, we utilize a question that asked 3,900 respondents whether they owned a gun, or could see themselves owning a gun, as an indicator of being in the market for a gun. We map these to the observed demographic characteristics of the respondents via a LASSO regression [Tibshirani, 1996], to create an estimate of the potential market size in each zipcode-gender cell. This is similar to the approach in Backus et al. [2021] to predict market size for cereal at local grocery stores. Explicitly, we regress the indicator for potential gun buyer on the full set of Pew-provided indicators for gender, age category, education level, race/ethnicity, citizenship, marital status, income category, health insurance, and party affiliation. We perform this regression within each census region of the United States. the Lasso then selects the non-zero variables to include in the linear probability model. We then project these coefficients onto the observed zip code demographics to obtain our estimtes of market size, which are about 1/3 of the adult population in each zipcode. Estimates are shown in Appendix Figure A3. Male, U.S. Citizenship, and Republican party affiliation are the largest predictors of willing to own a gun. Moreover, the importance of demographics vary across different regions of the United States.

Our goal is to use the rich transaction-level data in Massachusetts to learn about demand in the United States. To this end, we also use the NICS background check data as our measure of demand for guns in other states in the United States.[19] These background checks occur each time a consumer attempts to buy a firearm from a nationally licensed gun dealer (FFLs), though in some states, gun permit holders can present their permit in place of the

[18]Downloaded from `https://github.com/BuzzFeedNews/nics-firearm-background-checks`

[19]Data downloaded from `https://www.fbi.gov/file-repository/nics_firearm_checks_-_month_year_by_state.pdf/view`

background check, so coverage varies from state to state [Lang, 2016]. At the same time, the FBI reports these data at a state-year level, and in terms of national coverage, is the highest fidelity data researchers have access to, so it is a commonly used proxy for the flow of guns from suppliers to consumers. In Appendix Figure A2, we compare the sales of firearms recorded in FRB to the number of background checks, and show, at least in Massachusetts, that they are very similar.

## 2.5 Summary Statistics

Table 1 displays summary statistics on our set of matched gun models from BBGV. Handguns are typically shorter in length, and cheaper on average than long guns (rifles and shotguns). On average, prices for a new gun are around $1000, though there is significant price variation even within a class of weapons, as indicated by the standard deviation upward of $600. About 40% of longgun models are shotguns. Figure 6 plots the distribution of barrel length and caliber within longguns and handguns. Each point represents a gun model, with size proportional to its (logged) purchase frequency in the FRB data. While historically, analysis of this market has aggregated to the type of gun (handguns, long guns), there are appear to be significant variation in the characteristics, even within a weapon class. The extent to which these characteristics may matter for consumer choice in this market is an empirical question we will visit in our demand model.

Figure 1 plots the median and interquartile range of new gun prices (MSRP) for our set of gun models over time. The plot highlights a great deal of variation in gun prices, suggesting there is a role for product differentiation within these weapon types, since some gun manufacturers are presumably charging different prices to cater to different consumers. Consistent with Table 1, there is greater price variation in the longgun category. Prices for guns have been increasing over time, and this is not simply due to different sorts of guns being offered by manufacturers, or the variety/mix of guns offered in a particular. Figure 2 shows the estimated year fixed effects of a two-way fixed effects regression on log(MSRP), partialling out the time-invariant price levels of each gun model. Estimates are shown relative to 2016, the base year. For both types of weapons, gun prices remained relatively stable until the start of the pandemic, at which point prices increased substantially: within model, in 2022, prices were around average 8% higher than 2 years prior. This is possibly attributable to the well known supply chain issues that plagued many industries in the United States, and in particular, the firearms manufacturering industry, which devotes a large share of its expenditures to purchasing of inputs such as steel and copper[20]

[20]See, for example, this article: `https://shootingindustry.com/discover/supply-chain-woes/`

In Table 2, we display the demographic characteristics of gun buyers in this market, based on their gender and the zip code they reside in. We compare this to the demographics of the Massachusetts adult population in Column (1). In Columns (2), we filter to those predicted to be "in the market" for potentially purchasing a firearm, according to our linear probability model based on the ATP questionnaire. In columns (3)-(5), we weight each demographic based on the number of purchases for buyers with the associated characteristic. Relative to the adult population, potential gun buyers are much more likely to be male, and actual gun-buyers even moreso. Gun buyers in Massachusetts are more likely to live in a less dense and richer zipcode, as well as zipcodes with a lower fraction of racial minorities. Handgun buyers, relative to long gun buyers, are more likely to be female, as well as live in urban areas with more racial minorities.

In Figure 3, we plot the aggregate number of purchases over time in Massachusetts. About 70,000 handguns, the most popular gun category, are purchased each year, and about 40,000 longguns. Gun sales appear to be declining over time during our sample, until the COVID pandemic, at which point there is a spike in purchases that coincides with the observed price increases in guns. If we split this by capacity of the weapon (Figure 5), about 30,000 high-capacity guns are sold each year across handguns and rifles.[21] In Figure 4, we plot new vs used gun purchases (defined as those with an MSRP in the blue book for a particular year). We see that the new guns are more popular, and while both types of guns experience an increase in sales after the COVID-19 pandemic, used guns in particular experience a greater surge.

# 3 Descriptive Evidence

## 3.1 Heterogeneous Demand for Firearms

We begin our analysis by examining the demographic correlates associated with firearm demand, to uncover whether consumers of firearms have heterogeneous purchasing patterns. Note that this section is descriptive in nature, though we do include a rich set of fixed effects to better isolate demand-side responses.

We begin by an analysis of the correlates with gun purchases frequencies across consumers of differing demographics. To do so, we collapse the transaction data to the zip-gender-month $(z, g, t)$ level, our most granular measure of consumer demographics. If some gender-female demographic cells contain no data for a particular month, we infer zero purchases for that period, since the FRB data contains all legal transactions in the state. We then estimate a

[21] High capacity shotguns are extremely rare.

regression of the following form:

$$\frac{\text{Purchases}_{z,g,t}}{\text{Pop}_{z,g} \cdot 1000} = \beta D_{z,g} + \alpha_{t,\cdot,\#\text{Dealers}_{z,t}} + \epsilon_{z,g,t} \tag{1}$$

where $D_{z,g}$ denotes cell-level demographics, and the LHS variable is the number of purchases per 1,000 adults in each month. We include in this regression a set of $year - month$ fixed effects, to partial out temporal patterns in gun purchases, interacted with a fixed effect for the number of licensed gun retailers in the zip code that same month. These latter set of controls serve to better control for the "market structure" that consumers face during any particular purchase decision, in the style of Bresnahan and Reiss [1991]. Thus, the thought experiment is as follows: given two consumers with differing demographics, but purchasing at the same time with the same number of local retailers in their neighborhood, how do they differ in their likelihood of purchasing a weapon? This serves to capture heterogeneity in the "extensive margin" of gun purchases.

We include in $D_{z,g}$ a dummy variable for being female, the fraction conservative voters as of 2016, and the fraction white and with a bachelor's degree or higher education, as well as the (logged) median income and population density. The gender variable comes from the FRB, the political affiliation measure comes from the VEST dataset, while the rest of the demographics come from the 2019 5-year ACS.

We also analyze the demographic heterogeneity in the characteristics of weapons that consumers choose to purchase. To do so, we utilize the tranasaction-level micro data, and estimate an analogous regression:

$$X_{i,j,t} = \beta D_i + \alpha_{t,\#\text{Dealers}_{z,t}} + \epsilon_{i,t} \tag{2}$$

Where $X_{i,j,t}$ denotes a characteristic of the gun consumer $i$ chose to purchase, and $\alpha$ denotes the same fixed effects as Equation 1. Note that because this directly utilizes the transaction-level data, this regression is done conditional on purchasing a weapon, so differs qualitatively from the previous exercise. The corresponding thought experiment to Equation 2 is: Conditional on purchasing a gun at the same time with a similar assortment of gun retailers in my neighborhood, how do the attributes of the gun I choose to purchase differ in attributes in relation to $D_i$? Correspondingly, we label this the "intensive" margin of consumer heterogeneity in gun purchasing.[22]

Figure 7 displays the estimates from these regressions. Standard errors are clustered at

[22]Typically, intensive vs extensive margin refers to choosing to buy, versus how many products to purchase. Because we lack individual identifiers in our data, we cannot perform this exercise; so Equation 1 will capture both extensive and intensive margins under that usage of the terms.

the zip-code level. In Panel (a), we plot estimates of $\beta$ in Equation 1. Note that we scale the effects of logarithmic variables so they are of similar magnitude to effect of binary/fraction demographics. The panel shows that areas with more white adults and conservative voters are correlated with more gun purchases, controlling for market structure, suggesting that these consumers enjoy purchasing firearms more frequently. The coefficient on female is precise and negative, consistent with the findings from the ATP Survey that women are less likely to be willing to own a gun.

Panel (b) of the Figure presents demographic correlates with gun characteristics. On the left side, we display correlates with the discrete type of weapon (handgun, rifle, shotugn, or high capacity), while the right side shows correlates with caliber and barrel length of the weapon (in terms of the sample standard deviations of these attributes). Conditional on purchasing a firearm, women are more likely to purchase handguns, while those in white neighborhoods are more likely to purchase traditional low-capacity long guns. We also find that those in conservative neighborhoods are more likely to purchase high capacity weapons. Consumers living in more urban and affluent areas are more likely to buy smaller weapons.

It bears repeating that this analysis is descriptive in nature. Nontheless, the results show meaningful demographic heterogeneity in the types of weapons firearms consumers choose to purchase, and are highly suggestive that demographic heterogeneity may play a significant role in firearms preferences, beyond propensities to purchase guns. We will incorporate this into our demand-side model in Section 4.

## 3.2 Demand Price Response

A critical component of firearms policy, in particular taxes placed on these products, is the price response of firearms consumers. Because these may be correlated with demand responses. Because individual gun models may have particular characteristics driving changes in demand, that we as econometricians cannot observe, this requires the usage of instruments that shift price but are uncorrelated with demand. Given the large role that purchase of materials play in the firearm production process,[23], cost shocks, a popular approach in the demand estimation literature [Berry and Haile, 2021], seem like a fruitful approach. However, because we do not have direct access to inputs data of these individual firms, we propose an instrumental variable strategy in the spirit of Berto Villas-Boas [2007], which flexibly estimate proxies to the production functions of manufacturers. Explicitly, we use manufacturer IDs interacted with the price of inputs as instruments for the price of firearms. We then use

[23]The IBISWorld report on the industry (subscription required) `https://www.ibisworld.com/united-states/market-research-reports/guns-ammunition-manufacturing-industry/` reports that 40% of costs come from purchases, while wages are only 18% of costs.

the predicted prices as instruments for the observed prices in the sales data.

For our set of potential inputs, we use the price indices of hot and cold rolled steel, which are used for estimating aggregate demand for firearms in McDougal et al.. We also use the price of aluminum, which is also a common input in the production of firearms.[24] We obtain our data on these prices at the monthly level from FRED, originating from the Bureau of Labor Statistics, and aggregate them to annual price indices with 2016, the first year of our sample, as the base year.[25]

Our empirical specification is as follows:

$$\log(p_{j,t}) = \gamma_{j,1} + \eta_{c,t,1} + \sum_{k=1}^{3}(\beta_{m(j)} \log(\tilde{p}_{k,t})) + \epsilon_{j,t} \tag{3}$$

$$IHS(q_{j,t}) = \gamma_{j,2} + \eta_{c,t,2} + \alpha \log(p_{j,t}) + \xi_{j,t} \tag{4}$$

where $p_{j,t}$ is price, $\gamma_j$ denotes gun model fixed effects, $\eta_{c,t}$ denotes year $\times$ class (longgun vs handgun) fixed effects, $\tilde{p}_{k,t}$ denotes the price index in year $t$ of input $k$, $\beta_{m(j)}$ dennotes a coefficient on input prices allowed to vary by manufacturer $m$ of gun model $j$, and $\xi_{j,t}$ is the unexplained component of this mean utility, stemming from, for example, unobserved demand shocks. To take advantage of the full sample of guns with purchase data in Massachusetts, we use the inverse hyperbolic sine in place of the log transformation, to retain those guns we know are available (listed MSRP that year), but report zero sales in MA (about 1/3 of our gun-year observations).[26] Assuming the log approximation is accurate, $\alpha$ represents a price elasticity.

The specification in Equations 3 and 4 may be estimated using a two-stage least squares approach, instrumenting for the price of each gun with the manufacturer-specific production function. Besides ensuring relevance, for the price coefficient to be correctly identified, we must also assume that the excluded instruments only affect the demand through their impact on guns.

Figure 8 shows the annual variation in input prices used for identification, in comparison to the CPI over the same period. As we can see, the largest shock of these input prices coincides with the COVID-19 pandemic, which spurred a series of supply chain issues across

[24]See for example `https://bloximages.newyork1.vip.townnews.com/galvnews.com/content/tncms/assets/v3/editorial/a/8f/a8f655e4-75cb-11e3-a8d0-001a4bcf6878/52c8f03bf155c.pdf.pdf`

[25]Explicitly, we use data on "Producer Price Index by Industry: Rolled Steel Shape Manufacturing: Cold Rolled Steel Sheet and Strip, Made from Purchased Steel ","Producer Price Index by Industry: Aluminum Sheet, Plate, and Foil Manufacturing", and "Producer Price Index by Industry: Iron and Steel Mills and Ferroalloy Manufacturing: Hot Rolled Steel Sheet and Strip, Including Tin Mill Products". The index for cold-rolled steel is made from purchased steel, and while a general price index for cold-rolled steel exists, its coverage since COVID is incomplete, though the indices look very similar.

[26]Results are very similar if we use the $\log(x+1)$ transformation.

the globe. COVID also coincides with a large increase in gun sales [Sokol et al., 2021]. In our estimation, we do not want to ascribe potential demand shocks due to COVID to changes input prices. For this reason, our year fixed effects $\eta$ are critical to identification.

With year fixed effects in place, the residual variation captured by our instruments is the *heterogeneous exposure* of manufacturers to input price shocks. For example, if a manufacturer primarily uses hot rolled steel to produce firearms, they will be more exposed to the jump in hot rolled steel price in 2021, relative to a manufacturer that uses primarily aluminum. The primary threat to identification would be if demand shocks, such as COVID-19, were correlated with the reliance of certain manufacturers on certain inputs. For example, if the surge in gun demand during COVID-19 was driven by a surge in demand for guns made out of aluminum specifically, then our estimation procedure would violate the exclusion restriction. Note however, that these would need to be national demand shocks: We estimate demand in Massachussetts, which only accounts for about .8% of national firearms sales,[27] so it is likely manufacturers do not set national prices with the Massachusetts market in mind.

Because the set of instruments are large (nearly 300), we worry about weak instruments impacting identification. For some firms, production processes may be standardized and mimic those of their competitors. For this reason, we follow the routine described in Belloni et al. [2012] and estimate the first stage via a Post-OLS lasso IV. The lasso is a widely used machine learning algorithm that implements a L1 penalty on regression coefficients, both downweighting the magnitude of coefficients, and allowing for some coefficients to be set to zero. Under certain conditions, this algorithm has an "oracle" property, meaning that it can recover the true set of relevant covariates among a large set of candidate covariates. The procedure in Belloni et al. [2012] uses a data-driven penalty based on econometric theory that, when used as the first stage to select the instruments, can be used in a standard 2SLS IV approach and the conventional standard errors are valid. Explicitly, the procedure is as follows:

1. using the data-driven penalty to recover the set of non-zero instruments, allowing for independent but heteroskedastic errors.

2. run a post-lasso OLS of price on the selected instruments.

3. Construct $\hat{p}_{j,t}$ as the fitted values from the post-lasso OLS regression.

4. Estimate the second stage using $\hat{p}$ as the instrument for the observed prices.

Throughout, both the LASSO and IV are run with year and gun fixed effects always partialed out.

[27] Calculated from NICS Background check data.

Table 3 shows the results for the Post-lasso IV in the reduced form. We restrict the sample to those 850 models that have at least 10 purchases during our sample period; this is about 85% of all transactions on new guns. This is the same restriction we make when estimating our demand model in Section 4.

In Column (1), we report the OLS estimates from regressing purchases on price using two-way fixed effects. Perhaps unsurprisingly given the low importance of Massachusetts in the national market for firearms, we observe a negative, but statistically insignificant and low in value (-.59), price elasticity. In Column (2), we report 2SLS the results using the full set of 287 instruments, with two-way fixed effects. The point estimate is once again low in magnitude (-1.1), and statistically imprecise, basically due to the noise from weak instruments. In Column (3), we report the Post-Lasso IV estimate. From the potential set of 287 instruments, only nine are selected, suggesting that the pruning done in the first stage is important and many of the manufacturer-specific coefficients are uninformative and add noise to the regular first stage regression. Here, the point estimate is larger in magnitude. Are estimated price elasticity changes qualitatively, to -2.2, and is now conventionally significant. Because the standard F-test is invalid for testing relevance, due to the fact that we are estimating the IV using those instruments that were found *ex-post* to be important, we instead use the recommended sup-score test statistic from Belloni et al. [2012], which tests for joint significance of the excluded instruments, accounting for lasso selection. The test confirms relevance as the estimated test statistic of 14 is well above the critical value of 4.56 for 1% significance. Column (4) adds class $\times$ year in place of year fixed effects, allowing for differential trends of long guns and hand guns. The point estimate is similar to Column (3).

After our selection procedure, the 10 instruments selected in column (4) apply to 154 of the 824 gun models in our sample, meaning our price estimates are not being driven by the price changes of only a few models. The Lasso-selected IV specifications suggest a price elasticity for firearms of around -2. This estimate is more elastic than, but similar to, the estimates of Moshary et al. [2022]. We estimate that gun while firerarms consumers are responsive to price changes, in a meaningful way, the relatively price inelastic demand suggests gun taxes may be a less effective policy tool in this market.

# 4 A Model of Firearm Demand in Massachusetts

In this section, we introduce a model of demand for guns for consumers in the U.S. population. We estimate a discrete choice model in the style of Berry et al. [1995] based on transaction data in Massachusetts. The model accounts for heterogeneous preferences based on gender and characteristics of the neighborhood consumers of guns live in, which is the full

set of demographic data available from the FRB. We also allow for unobserved differences in individual-preferences in sub-groups of products, as well as idiosyncratic errors, via a nested logit specification We then extrapolate these parameters to the rest of the United States using moment matching conditions, assuming consumers differ across state years only in a vertical taste-shifter for guns.

## 4.1 Consumer Choice

We define a market $t$ as a U.S. state $\times$ year. Within each state, the market size $M_t$ is defined to be the total number of predicted potential gun owners based on the Pew survey on gun ownership described in Section 2, combined with the 2015-2019 ACS estimates of adult population in each state. Note market size is assumed to be constant across years.

We model preferences of consumer $i$ with demographics $d$ in year $y$. Preferences are over guns $j$ in weapons classes $c(j) \in \{\text{handgun,longgun}\}$. We refer to the set of guns in class $c$ as $\mathcal{J}_{c,y}$, and the entire set of guns on the market as $\mathcal{J}_y = \cup_c \mathcal{J}_{c,y}$. We define these $\mathcal{J}$ to be all actively produced (those with MSRP data) guns with at least 10 purchases in the year in Massachusetts, totalling 850 unique models, which varies across years. We use the FRB transaction data from 2016-2022.

Indirect utility from purchasing gun $j$ is defined as follows:

$$u_{i,j,t} = \beta_{i,c} X_j + \delta_{j,t} + \epsilon_{i,j,t}. \tag{5}$$

$$\delta_{j,t} = \alpha p_{j,y} + \delta_j + \tau_t + \phi_{y,c(j)} + \xi_{y,j} \tag{6}$$

$$\beta_{i,c} = \beta_c + D_i \Pi_c \tag{7}$$

where $X_j$ denotes gun $j$'s characteristics, $\delta_{j,t}$ denotes the mean utility of a gun in market $t$, $\tau_t$ denotes market-level shifters in taste, $\phi$ denotes class-by-year demand shocks, and $\delta_j$ denotes the time invariant taste for gun $j$. Note that we normalize $\tau_t = 0$ each year during our demand estimation, so that values are understood relative to Massachusetts, since we only observe transaction-level data in one state. So mean utilities for estimation can be equivalently expressed as $\delta_{j,y}$. $\beta_c$ denotes the baseline taste for gun characteristics. $D_i$ is a matrix of consumer demographics, and $\Pi_c$ is a class-specific matrix controlling heterogeneous preferences for characteristics. The price of gun $j$ in year $y$ is denoted $p_{j,y}$, and is the (CPI-adjusted) MSRP. The price sensitivity of consumers is determined by $\alpha$.

Though we take a characteristic based modeling approach for the actively produced guns in each market, a substantial fraction of guns purchased in Massachusetts are previously owned, due to guns being a durable good. These guns may vary from the guns purchased

"brand new" that we explicitly model in $\mathcal{J}$, due to variation in condition and price. For this reason, we also include in choice sets a composite good $\omega_{c,y}$, varying at the class and year level, that represents a choice of any used guns purchased that year, guns that are purchased at a very low frequency ($< 10$), or guns which we are unable to match to a BBGV gun model. The utility the consumer derives from this product is:

$$u_{i,\omega,c,t} = \delta_{\omega,c,y} + \epsilon_{i,\omega,t} \tag{8}$$

Where $\delta_{\omega,c,y}$ includes all utility components found for new guns in Equation 6, except for price. Equivalently, we assume the price of used guns is $p_{\omega,c,y} = 0$ and all price-specific tastes for the composite good are loaded in the unobserved demand shock, $\xi_{\omega,c,y}$. We assume that the idiosyncratic error term $\epsilon$ follows the distribution of a four-level nested logit [Train, 2009], to allow for unobserved correlation between guns. We place the outside option into a separate nest from the inside goods. The inside good nesting parameter is $\rho_0$. We then partition the inside goods into 2 nests based on weapon class $c$. The parameters that govern substitutability across the class nests are $\rho_c \leq \rho_0$. Finally, because we do not explicitly model the individual used gun models found in the composite good, we also place the composite good $\omega_{c,y}$ in a separate nest from new products $\mathcal{J}_{c,y}$ within each class, to capture non-independent substitution from used guns to individual guns that are sold as new. The parameter controlling this substitution is denoted $\rho_c^u \leq \rho_c$. $\epsilon$ is assumed to have the following structure:

$$\epsilon_{i,j,t} = \zeta_{i,1,t} + \rho_0\zeta_{i,c,t} + \rho_c\zeta_{i,c,u,t} + \rho_c^u\tilde{\epsilon}_{i,j,t}$$

Values of $\rho \approx 0$ imply a high degree of correlation within a nest, while $\rho \approx 1$ implies no correlation. $\zeta$ denote idiosyncratic shocks that are common within each nest, that are conjugate to the extreme value type I distribution [Cardell, 1997], and $\tilde{\epsilon}_{i,j,t}$ is a standard i.i.d extreme-value type 1 shock.

Finally, we specify the value of our outside option as

$$u_{i,0,t} = \tilde{\epsilon}_{i,0,t}. \tag{9}$$

Demographics $D_i$ are composed of a binary gender variable, and characteristics of the zip code the consumer resides in. These zip code characteristics are the % White, % Conservative (as measured by the zip-code % voting for Donald Trump in 2016), the % with a Bachelor's degree or higher, the logged median income of the zip code, and the logged population density per square mile. For each zip code demographic, we center these at the national mean, so that the coefficient $\beta_c$ can be understood as the average taste for a characteristic. For

characteristics $X_j$, we include caliber, barrel length, a dummy for high-capacity, a constant term (to capture heterogeneous tastes for the outside good), and a dummy for the gun being new, or in $\mathcal{J}_y$ (to capture heterogeneous tastes for used guns).

For notational convenience, it will be useful to write the utility of a consumer $i$ with demographics $d = D_i$ from choosing product $j$ in market $t$ as

$$\begin{aligned} u_{i,j,t} &= v_{d,j,t} + \epsilon_{i,j,t} \\ v_{d,j,t} &= \delta_j + \phi_{y(t),c} + \tau_t + \xi_{\omega,c,y(t)} + \mathbf{1}(j \in \mathcal{J}_y(t))(\beta_{d,c(j)} X_j + \alpha p_{j,y(t)}). \end{aligned}$$

Given the nesting structure specified for $\epsilon_{i,j,t}$, we can express the probability of a consumer $i$ with demographics $d = D_i$ purchasing an individual product $j$ as the product of four nest-level probabilities.

$$Pr(j|d,t) = Pr(j \neq 0|d,t) \cdot Pr(c|d,t,j \neq 0) \cdot Pr(j \in \mathcal{J}_{c,y}|d,t,c) \cdot Pr(j|d,t,j \in \mathcal{J}_{c,y}) \tag{10}$$

$$Pr(\omega_{c,y}|d,t) = Pr(j \neq 0|d,t) \cdot Pr(c|d,t,j \neq 0) \cdot Pr(\omega|d,t,c) \tag{11}$$

$$\tag{12}$$

Within a class $c$, excluding the composite good, and integrating out the idiosyncratic shock $\tilde{\epsilon}_{i,j,t}$ the probability of consumer $i$ choosing a particular gun model $j$ conditional on buying a new gun $j \in \mathcal{J}_c$ in market $t$ takes the following form:

$$Pr(j|d,t,j \in \mathcal{J}_{c,y}) = \frac{\exp\left(\frac{v_{d,j,t}}{\rho_c^u}\right)}{\sum_{k \in \mathcal{J}_c} \exp\left(\frac{v_{d,k,t}}{\rho_c^u}\right)}. \tag{13}$$

As is typical in nested logit models, we proceed by calculating the inclusive value of each nest, then using it to express the choice probability in the next highest nest. The inclusive value, $I_{d,c,n,t}$ for new guns of class $c$ in market $t$ is:

$$I_{d,c,n,t} = \log\left(\sum_{j \in \mathcal{J}_c} \exp\left(\frac{v_{d,j,t}}{\rho_c^u}\right)\right). \tag{14}$$

Moving up the nesting structure, to the used vs new gun choice within class, we can

express these conditional choices as as:

$$Pr(\omega_{c,y}|d,t,c) = \frac{\exp\left(v_{\omega,c,t}\right)}{\exp\left(v_{\omega,c,t}\right) + \exp(\rho_c^u I_{d,c,n,t})} \tag{15}$$

$$Pr(j \in \mathcal{J}_{c,y}|d,t,c) = \frac{\exp(\rho_c^u I_{d,c,n,t})}{\exp\left(v_{\omega,c,t}\right) + \exp(\rho_c^u I_{d,c,n,t})} 1 \tag{16}$$

From which we may derive the class-nest level inclusive values $I_{d,c,t}$:

$$I_{d,c,t} = \log(\exp\left(\frac{\rho_c^u}{\rho_c} v_{\omega,c,t}\right) + \exp(\frac{\rho_c^u}{\rho_c} I_{d,c,n,t})) \tag{17}$$

And corresponding class-level choice probabilities, conditional on not choosing the outside option:

$$Pr(c|d,t,j \neq 0) = \frac{\exp(\rho_c I_{d,c,t})}{\sum_{c' \in \{\text{handgun,longgun}\}} \exp(\rho_{c'} I_{d,c',t})} \tag{18}$$

Finally, this yields an inclusive value for all guns, or the inside good:

$$I_{d,1,t} = \log(\sum_c \exp(\frac{\rho_c}{\rho_0} I_{d,c,t})) \tag{19}$$

Which generates the choice probabilities for the inside versus outside option:

$$Pr(j \neq 0|d,t) = \frac{\exp(\rho_0 I_{d,1,t})}{1 + \exp(\rho_0 I_{d,1,t})} \tag{20}$$

$$Pr(j = 0|d,t) = \frac{1}{1 + \exp(\rho_0 I_{d,1,t})} \tag{21}$$

completing our characterization of the choice probabilities.

The log of the denominator in these top-level choice probabilities plays a role analogous to a standard logit choice model. The quantity $\log(1 + \rho_0 I_{d,1,t})$ represents the expected value of the best item in the choice set for a consumer in demographic group $d$ and market $t$ (Train [2009]). We define this value as consumer surplus and convert from utils to dollars by rescaling using the inverse of the price coefficient $1/\alpha$. In this sense, our model of demand allows for flexible cross-good substitution patterns while maintaining a well-defined interpretation of consumer surplus.

## 4.2 Estimation Routine

We estimate the demand model in five steps. First,using, we estimate the gun model choice multinomial logits within class, to recover $\delta_{j,t}$, $\Pi_c$, and $\rho_c^u$. We then jointly estimate the

outside-option and class-choice models, taking the within class nest estimates as given, to recover $\rho_c, \rho_0$, and $\psi_{y,c}$. We then estimate $\alpha$, the price parameter, using the instrumental variable for price from Section 3.2. Next, we estimate the baseline parameters governing tastes for characteristics via a projection of $\delta_j$ on the time-invariant characteristics $X_j$. Finally, we estimate the market-specific tastes $\tau_t$ across state-years using the NICS background check data.

### 4.2.1 Gun Choice

For each $c$, we solve the gun choice problem, conditional on choosing class $c$, to estimate the parameters governing within-class choice, denoted $\theta_c$, via a constrained maximum likelihood formulation that requires state-level market shares to be equal to their observed value, as in [Train, 2009]. We do so using the Massachusetts FRB transaction data. Note that the parameters of the model governing individual-specific preferences are a function only of gender and zip code demographics. Therefore, we collapse the FRB data to the gender-zip demographic cell level, denoted $d$, by year $y$. Let $N_{y,d,j}$ denote the number of individuals purchasing product $j$ in demographic cell $d$, and $\mathcal{D}_{MA}$ the set of these demographic cells. We solve the following constrained maximum likelihood problem for each class $c$:

$$\max_{\theta_c} \sum_{y} \sum_{d \in \mathcal{D}_{MA}} \Big( N_{d,\omega} Pr(\omega|d,c) + \sum_{j \in \mathcal{J}_c} N_{d,j} \log(Pr(j|d,c)) \Big) \tag{22}$$

$$\text{Subject to: } Pr(j|y,c) = \hat{s}_{j,y,c} \quad \forall y, j \in \mathcal{J}_c \tag{23}$$

$$\frac{\rho_c^u}{\rho_c} \leq 1 \tag{24}$$

Where the product chocie conditional on class is $Pr(j|d,c) = Pr(j \in \mathcal{J}_{c,y}|d, t(d), c) \cdot Pr(j|d, t(d), j \in \mathcal{J}_{c,y})$ as defined in Equations 13 and 16. The class-level parameters $\theta_c$ are the used vs new good nesting parameter $\rho_c^u$, the product-level taste shifters $\delta_{j,t}$, and the heterogeneous tastes for all characteristics $X_j$ besides the constant term, since this is identical across the choices $\mathcal{J}_{c,y} \cup \{\omega_{c,y}\}$. $Pr(j|y,c)$ is the conditional probability of choosing the gun across, integrating out demographics; given $\theta_c$, this can be calculated by integrating over the distribution of demographic cells $d$ in Massachusetts.

$$Pr(j|y,c) = \int_{d \in d} Pr(j|d,c)) \partial F(d)$$

where $F(d)$ is the empirical distribution of demographic cells. The empirical analogue to this model-derived probability is the quantity $\hat{s}_{j,y,c}$, the empirically observed probability of

gun $j$ being chosen in year $y$ conditional on a firearm from class $c$ purchased:

$$\hat{s}_{j,y,c} = \frac{\sum_{d \in \mathcal{D}_{MA}} N_{y,d,j}}{\sum_{j \in \mathcal{J}_{c,y}} \sum_{d \in \mathcal{D}_{MA}} N_{y,d,j}}$$

During our likelihood optimization, at each iteration, we exactly identify the $\delta_{j,t}$ mean utilities (relative to the mean utility for the composite good, which is normalized to zero each year) via the constraints that set state-level market shares each year to be identical to those we observe in the data. We do so via the contraction mapping suggested in Conlon and Gortmaker [2020]. We also impose the constraint that $\rho_c^u/\rho_c \leq 1$ to guarantee the recovered used vs new nesting parameter is . In practice, the level of $\rho_c$ is not identified in this subproblem, since both the new and composite used good are within the class nest. Instead, we estimate the ratio of the two terms directly; this still preserves the choice probabilities described in the prior section.[28] Among products within a class, we use the differential buying patterns of consumers of different gender and zip codes to identify the heterogeneous taste for characteristics, $\Pi_c$. Finally, variation in the choice set of $\mathcal{J}_{c,y}$, and it's correlation with the change in the composite good's class-conditional share, identifies $\rho_c^u$

### 4.2.2 Class Choice

Given estimates $\theta_c$, we calculate the class-level inclusive values $I_{d,y,c}$, and use these to estimate the parameters $\theta_0$ governing choices across gun classes, and the outside option. These parameters are the class-year demand shocks $\phi_{y,c}$, the heterogeneous preferences for classes of guns (i.e. the portion of the matrix $\Pi_c$ corresponding to the constant term), and the nesting parameters $\rho_c, \rho_u$. We set up a similar constrained maximum likelihood problem to the gun choice model to estimate these parameters:

$$\max_{\theta_0} \sum_{y} \sum_{d \in \mathcal{D}_{MA}} \left( N_{d,0,y} Pr(j \neq 0|d) + \sum_{c \in \{\text{handgun,longgun}\}} N_{d,c,y} \log(Pr(c|d)) \right) \tag{25}$$

$$\text{Subject to: } Pr(c|y) = \hat{s}_{y,c} \quad \forall y, c \in \{\text{handgun,longgun}\} \tag{26}$$

$$\rho_c \leq \rho_0 \leq 1 \quad \forall c \in \{\text{handgun,longgun}\} \tag{27}$$

Where the class-level choice probabilities $Pr(c|d) = Pr(j \neq 0|d) \cdot Pr(c|j \neq 0, d)$ are given by Equations 18 and 20, and $Pr(j \neq 0|d)$ is given by Equation 21. $N_{d,c,y}$ is defined analogously to the gun choice section as the number of individuals observed buying a particular class, and $N_{0,d,y} \equiv M_d - N_{d,y}$, the market size of potential gun consumers in a demographic cell, versus

[28] After estimating $\rho_c$ in the class-choice section, we multiply all parameters by $\rho_c$ to ensure both the class and gun choice parameters are on the same scale and consistent with each other.

the total number of observed gun purchases in a year. The first set of constraints enforce that the model-predicted class-choice probabilities in the state of Massachusetts, $Pr(c|y)$, match the empirically observed probabilities $\hat{s}_{y,c}$. These exactly identify the class-year shocks $\phi_{y,c}$.[29] The second set of constraints ensure we estimate nesting parameters that are consistent with the hierarchical structure of the nests. Heterogeneous tastes for classes are identified by the differential propensities of individuals of with differing gender and zip code characteristics to purchase handguns, longguns, or the outside option. The correlation between $\mathcal{J}_{c,y}$, which shifts the class-level inclusive values and likelihood of choosing a particular firearm class, conditional on purchasing a firearm, identifies $\rho_c$. Finally, the correlation between changes to $\mathcal{J}_y$ and the outside good identify $\rho_0$.

### 4.2.3 Additional Estimation Steps

Having recovered the mean utilities $\delta_{j,t}$ from the gun and class choice models, we use these quantities to identify the utility components that do not vary across individuals. First, we estimate $\delta_j$ and $\alpha$ using the following 2SLS regression with two-way fixed effects:

$$p_{j,t} = \delta_{j,1} + \psi_{c,y,1} + \sum_{k=1}^{3}(\beta_{m(j)}\tilde{p}_{k,t}) + \epsilon_{j,t} \tag{28}$$

$$\delta_{j,y} = \delta_j + \psi_{c,y} + \alpha\hat{p}_{j,t} + \xi_{j,t} \tag{29}$$

Where we use the same instrumental variables as in Section 3.2, and the same LASSOIV procedure, to identify the price coefficient $\alpha$. Note this regression excludes those guns with zero sales, as they imply a value of $\delta_{j,t} = -\infty$, as well as the composite goods $\omega$.

Next we take our estimates of unobserved, time-invariant differences in gun models, $\hat{\delta}_j$, and project these onto the the time-invariant characteristics $X_j$ to construct estimates of $\beta_c$. We do so using the approach outlined in Nevo [2000], which weights the mean tastes $\delta_j$ by the estimated variance of the fixed effects.

Finally, we use the NICS background check data to identify $\tau_t$. Explicitly, We assume that the number of state-year background checks are equal to the inside good share $\hat{s}_{1,t}$ in each market $t$. Since $\tau_t$ affects all goods equally in any market, it can be pulled out to the inside good choice probability. We solve for the value of $\tau_t$ in each market that sets the model-predicted choice probabilities to their observed inside good share:

$$\tau_t: \quad Pr(j \neq 0|t) = \int_d \frac{\exp(\tau_t + \rho_0 I_{d,1,t})}{1 + \exp(\tau_t + \rho_0 I_{d,1,t})} F_t(d) = \hat{s}_{1,t}$$

[29] These class year shocks $\phi_{y,c}$ are then added to the gun choice estimates of product-level mean utilities, $\hat{\delta}_{j,t}$, to get our final estimates of the mean utilities, e.g. $\delta_{j,t} = \phi_{y(t),c(j)} + \rho_{c(j)\cdot\hat{\delta}_{j,t}}$

where $F_t(d)$ is the distribution of zip code characteristics $\times$ gender in market $t$.

## 4.3 Assumption and Limitations

The above demand model is able to flexibly estimate heterogeneous demand by consumer types, various sources of unobservable utility, as well as account for non-independent substitution patterns across weapon products. Moreover, casting the problem as a discrete choice problem allows for tractable estimation. However, there are some key assumptions we make in the model we wish to highlight here. First, we model the gun purchasing decision as a discrete choice problem, treating observed purchases as effectively the "share" of consumers in a market who purchase a firearm. However, it is a well known fact that most gun purchases are from those who are repeat buyers and already own a weapon [Miller et al., 2022]. Because we lack data on individual identifiers in the FRB data, we cannot disentangle these two types of consumers, who may differ in their preferences. Second, we constrain that $\alpha$, the price sensitivity of the consumer, is homogeneous across the population. This is due to our lack of demographic-level variation in exogeneous price shocks. In their conjoint analysis, Moshary et al. [2022] allow for the price coefficient to vary along demographics, and show, at least for income and age, statistically significant differences in price heterogeneity, although they claim that this price heterogeneity is not particularly important for their analysis. Finally, and certainly our strongest assumption, is that the differences in demand for firearms differ only demographics and the vertical market taste shifter $\tau_t$. We only have access to transaction-level data for the state of Massachusetts, so our parameters (besides $\tau$) are entirely identified by demand variation within that state. Massachusetts is not a typical state with respect to its attitudes towards firearms: it one of the most restrictive states in terms of gun control[30]. For a handguns to be legally sold to consumers, they must be registered on the state's approved firearms roster,[31] which impacts the choice sets $\mathcal{J}_{c,y}$ we infer are available to consumer's in other state in a particular year. Because of this, we focus much of our counterfactual exercises on policy changes occurring solely in the state of Massachusetts. At the same time, we also provide demand-side estimates of the impacts of these policies in the entire United States, for those readers willing to extrapolate our estimated demand parameters to the rest of the country, but these estimates should be viewed more cautiously.

[30]Source: `https://www.rand.org/research/gun-policy/firearm-mortality.html`

[31]See `https://www.mass.gov/lists/approved-firearms-rosters`

## 4.4 Demand Estimates

We now describe our demand estimates. In Table 4, we report the nesting parameters, along with p-values for the hypothesis test that there is greater intra-nest substitution (e.g. for $\rho_c$, the test that $\rho_c < \rho_0$). The outside option displays a nesting parameter of $\rho_0 = .9$, suggesting reasonably flexiblity between buying a gun and choosing to purchase nothing. However, this is eclipsed by the class-level nesting parameters, $\rho_c$ which are around 0.3. These imply that consumers have strong preferences to substitute only to other products that are the same type of weapon; this tendency is slightly less so for longgun consumers, meaning they are more likely to view handguns as acceptable substitutes to their preferred firearm class. Regarding the the used vs new good substitution, we estimate that there is reasonably flexible substitution between the used composite good and new firearms: we cannot reject the hypothesis that $\rho_c^u = \rho_c$ at conventional statistical levels. This is consistent with the anecdotal evidence that during COVID 19, when many gun manufacturers reached binding capacity constraints and were unable to keep up with demand.[32], as well as the relative increase in used gun purchases in Figure 4.

In Appendix Table A1, we report the estimate of the price coefficient from estimating the 2SLS system in Equations 28 and 29. The coefficient is relatively stable across specifications. Our preferred estimate is located in Column (2), with class $\times$ year fixed effects. We use this coefficient to estimate both the price response of firearms consumers, as well as express the remaining other parameters of the model in $ terms.

Panel (a) of Figure 9 displays the estimated own price elasticities at the gun-product level in the state of Massachusetts.[33] We estimate an average (median) own-price elasticity of -1.5 (-1.2), consistent with the inelastic demand estimates of Moshary et al. [2022]. Elasticities differ somewhat across gun types: handgun consumers are slightly more price elastic than longgun consumers (-1.6 vs -1.4), but for both types of firearms, there is a long left tail of models with elastic demand. Panel (b) shows how consumers substitute across products classes. In particular, it calculates the average diversion ratios Conlon and Mortimer [2021] from handgun and longguns to weapon classes and the outside option. Diversion ratios are a statistic that represent the following thought experiment: given a price increase in product $j$, what will the consumers who choose to no longer purchase the product choose instead? Our low estimates of $\rho_c$ imply that the consumers have strong intra-class preferences: for example, the vast majority of handgun consumers will switch to another handgun when the price of their own product increases. The remaining consumers who do not buy another handgun will

[32]See for example `https://cbsaustin.com/unprecedented-demand-on-guns-and-ammo-putting-pressure-on-supply-chain`

[33]In both panels, estimates are very similar for the entire United States.

instead, more often than not, switch to the outside option, and choose to purchase no guns, instead of, say, purchasing a longgun when handgun prices increase. This,combined with the relatively inelastic demand estimates, suggests that class-level bans may be an effective tool to push consumers away from purchasing firearms.

In Table 5, we present estimates of $\beta_c$ and $\Pi_c$ in money-metric terms, by dividing these estimates by the price coefficient $\alpha$. This allows us to interpret parameter estimates in terms of a consumer's willingness to pay (in \$) for products that are identical besides their characterics. The full table of estimated utility parameters, with standard errors, can be found in Appendix Table A2. The large estimated coefficients on the constant term suggest most consumer heterogeneity in loads onto whether the firearm is a handgun or longgun, which practically serve very different purposes. For example, in the Pew ATP survey, 72% of handgun owners say protection is major reason they own a gun, while for longgun owners, it is only 35% (and instead, hunting is the most popular reason). Among the most significant drivers are gender, and political leaning, racial composition, and education levels of neighborhoods (zip codes). Regarding individual gun characteristics, we find that females display strong preferences for smaller guns, while those living in Republican or white areas. Those from more affluent neighborhoods have relatively higher taste for high capacity weapons, as well as shotguns.

In Figure A4, we display the average estimate of the $\tau_t/\alpha$ for each U.S. state during our sample period. Note that $\tau_t$ represents a vertical firearms taste shifter by market, conditional on demographics, so this parameter captures any additional preference for firearms beyond what could be explained by differing demographics across U.S. states. The Figure shows there is considerable variation in taste for firearms, ranging in the thousands of dollars. These estimates of $\tau$ are relative to Massachusetts, the setting we estimate our firearms demand model. Considering Massachusetts has one of the lowest inside good shares in the country (3.7%), it is unsurprising that it's value is low relative to other states. Some interesting patterns emerge from the Figure. For example, California, which has a similar inside share to Massachusetts of 4.2%, is estimated to be willing to pay \$1,700 more for the same firearms, conditional on demographics. This stems from the preference estimates in Table 5: California is a racially diverse and politically left-leaning state, so the demographic preferences predict that demand should be quite low for firearms in a state with that demographic composition. The fact that we see even more individuals buy firearms in California than in Massachusetts implies that Californians must have unobservably higher preferences for firearms.

# 5 A Model of Public Health

Although firearms connect to a wide array of outcomes across society,[34] many of these are determined through potential incidents of firearm violence [Lott and Mustard, 1997, Duggan, 2001]. Recent critical reviews have noted the potential for bias in existing estimates of this parameter due to errors in the measurement of firearms Kleck [2015] and the potential for reverse causality [RAND, 2018]. In this section, we use the high-resolution fatal and non-fatal incident data from Gun Violence Archive, along with the instrumental variable proposed and implemented in Rosenberg [2023]- entry of gun retailers- to estimate the causal effect of gun purchases on public health incidents. We will use these estimates to quantify the net welfare effects of gun policy counterfactuals, accounting for the downstream effects of purchases on public health.

## 5.1 Model Specification

We propose to model the log of gun violence incidence in five-digit zip code $z$ during year $t$ as a logarithmic function of contemporaneous transactions on the consumer firearm market:

$$\log\left(1 + \#\text{GunViolence}_{zt}\right) = \theta \log\left(1 + \#\text{GunTransactions}_{zt}\right) + \psi_{z4} + \phi_t + \omega_{zt}. \tag{30}$$

Where $\#\text{GunTransactions}_{zt}$ denotes the number of gun transactions recorded in FRB in particular year in that zip. In our analysis, we will use different types of transactions (e.g. new guns only, handguns vs longguns), in additional to overall transactions. As we observe many zip code-years with no incidents of gun violence—and a handful with no firearm transactions—we utilize the $\log(1 + \cdot)$ transformation to accommodate zero-valued variables in our analysis. This regression specification further includes fixed effects for four-digit zip code $\psi_{z4}$ and year $\phi_t$.[35] We treat the regression errors $\omega_{zt}$ as idiosyncratic violence shocks that capture other causes of gun violence aside from contemporaneous gun purchases (e.g., pre-existing firearm owners, transactions on the illicit market, transactions in other geographies).

For a particular level of gun transactions, the model predicts gun violence as follows:

$$\#\text{GunViolence}_{zt}\Big(\#\text{GunTransactions}_{zt}\Big) = \left(\#\text{GunTransactions}_{zt}\right)^{\theta} \exp\left(\psi_{z4} + \phi_t + \omega_{zt}\right) - 1, \tag{31}$$

[34] `https://everytownresearch.org/report/the-economic-cost-of-gun-violence/`

[35] Gun violence is, thankfully, rare enough that most observations of the dependent variable are zero, leading fixed effects at the zip code level to absorb nearly all variation in the data. Inclusion of the typical panel 5-digit zip code and year fixed effects produces noisier, though qualitatively similar estimates.

Evaluating the model at zero gun transactions defines a baseline level of gun violence

$$\#\text{GunViolence}_{zt}\Big|_{\#\text{GunTransactions}_{zt}=0} = \exp\left(\psi_{z4} + \phi_t + \omega_{zt}\right) - 1,$$

From this baseline, the model a implies constant elasticity effect of $\theta$ from additional gun transactions.

## 5.2 Estimation and Instruments

Two factors complicate estimation of the regression in Equation (30), making the direct applications of ordinary least squares inappropriate. A primary issue is the potential for endogeneity. In particular, the unobservable shocks to gun violence $\omega_{zt}$ may be correlated with the gun transactions we observe in the data. This is a natural possibility as personal protection is the most commonly stated reason for gun ownership [Parker et al., 2017] and individuals change their gun registration behavior in response to episodes of local violence [Depew and Swensen, 2019].

To overcome the issue of endogeneity, we leverage the entry and exit of firearm retailers into local markets as shifters of gun demand. These instruments are developed by Rosenberg [2023], who discusses the local retail market for firearms at length and conducts a number of tests for instrument relevance and validity. The key exclusion restriction is that firearm retailers do not vary the timing of their entry and exit decisions in response to local variation in gun violence. In addition to the extensive checks conducted by Rosenberg [2023], this is an *a priori* reasonable assumption as (i) economics suggests that entry and exit should be driven by profit and (ii) the highly regulated nature of the retail firearm market makes it challenging for potential entrants to anticipate violence shocks.

We specify our instrument for firearm transactions as the natural log of one plus the number of firearm retailers in a local market.

$$w_{zt} = \log\left(1 + \text{FirearmRetailers}_{zt}\right).$$

We use two alternatives for measuring firearm retailers. Our preferred method utilizes the transaction data from Massachusetts to recreate the set of firearm retailers that were open within each zip code-period.[36] Although this method is accurate, it is data intensive—requiring detailed firearm transaction data—and cannot be used across most of the U.S., where this data is absent. Thus, we also utilize the count of Federal Firearms Licensees

[36]Specifically, we use the last and first year retailers had at least one transaction to determine whether they are in the market.

("FFLs"), representing all entities who are licensed to sell firearms [Wiebe et al., 2009] There is a gap between these two measures of firearm retailers because many FFLs are kitchen-table dealers and personal collectors who are in fact unavailable to most individuals who may wish to purchase a firearm. Thus, FFLs represent an observable but relatively inaccurate source of information about firearm supply.[37]

## 5.3 Results

Figure 10 presents first-stage estimates. Both instrumental variables—verifiable firearm retailers in Massachusetts and FFLs—positively covary with firearm transactions. However, the relationship is stronger and more precise for verifiable retailers than FFLs. This result matches our intuition of the measurement and interpretation of these two variables. It also further clarifies verifiable firearm retailers as our preferred instrument, when it can be constructed. When we utilize retailer entry for a subset of firearm transactions (e.g., new firearms) we ignore the potential endogeneity caused from omitting other transactions (e.g., used firearms) from the model. The effect of retail entry on transactions is similar for new guns, and slightly larger for handguns than longguns.

Table 6 presents two-stage least squares estimates of the regression in Equation (30) for all gun transactions on gun violence incidents. In Appendix Table A3, we show estimated elasticities for each incident and transaction type pair. As would be expected based on our first-stage results, estimates that utilize entry and exit in verifiable firearm retailers over time produce estimates that are similar in magnitude and uncertainty than those using simple counts of FFLs. Across the board, higher volumes of firearm transactions induced by the entry of firearm retailers cause contemporaneous increases in firearm-related incidents, injuries, and fatalities.

We estimate that increasing the number of firearm transactions in a zip code-year by 10 percent would increase incidents of firearm violence by 0.8 percent. These additional incidents of gun violence would generate 0.4 percent increases in each of non-fatal and fatal firearm injuries. We repeat this exercise using as dependent variables only new firearm transactions, handgun transactions, or long gun transactions. Regressions based on each of these endogenous dependent variables deliver similar estimates.

[37] A regression of Massachusetts retailers on FFLs has a coefficient of approximately 0.3,imply that only 1-in-3 FFLs are truly in the market.

### 5.4 Using the model

The estimates from our constant elasticity model are easy to use for counterfactuals. For example, suppose we contemplate a counterfactual that *ceterus paribus* shifts gun transactions in one zip code-year from $g_{zt}$ to $g'_{zt}$. Using Equation 31, the expected change in gun-related incidents is

$$\#\text{GunViolence}_{zt}\Big(g'_{zt}\Big) - \#\text{GunViolence}_{zt}\Big(g_{zt}\Big) = \#\text{GunViolence}_{zt}\Big(g_{zt}\Big) \times \left\{ \left( \frac{1+g'_{zt}}{1+g_{zt}} \right)^{\theta} - 1 \right\}. \tag{32}$$

This quantity depends on observed levels of violence and both observed and and counterfactual firearm transactions, while the unobservable components of the model differences out. By evaluating the right-hand side, we can recover the implied effects on gun violence of any specified change in gun transactions. Summing these differences across time and space provides a natural method of aggregating public health effects under the model.

Less clear is how to convert our results across different outcome variables into money-metric welfare measures. To do so, we utilize calibrations from the criminology literature that value each life lost due to gun violence at 8.5 million dollars [Heaton, 2010] and each non-fatal firearm injury at 105 thousand dollars [Peterson et al., 2021]. Although these are challenging quantities to estimate, we view them as a useful tool for summarizing the disparate consequences of firearm regulation on a single, interpretable scale.

The estimated magnitudes in these transaction-based regressions are about one-third the size of estimated causal effects of gun ownership on gun violence [Duggan, 2001, Cook and Ludwig, 2006, Rosenberg, 2023]. We view this difference as representing distinct epidemiological features of the existing literature and our model. It is ultimately gun ownership that generates downstream risks, and only a subset of transactions go to new owners, making it is appropriate that our estimates are smaller in magnitude. We thus interpret our estimated model as providing a lower bound on the impact of licit-market consumer firearm purchasing on downstream incidents of gun violence.

## 6 Counterfactuals

In this section, we synthesize our empirical results to study the impacts of counterfactual regulations on the market for consumer firearms. Given a regulatory proposal, we use our estimates of preferences for gun purchase to predict its effect on consumer surplus, government revenues, and the allocation of firearm transactions. We then use our estimated public

health model to translate these changes in firearm transactions into the changes in firearm violence they imply. We carry out this exercise twice, once focusing only on Massachusetts as the source of our data and a second time extrapolating from Massachusetts to the entire U.S.

In our counterfactuals, we do not allow firearm manufacturers to adjust their decisions on the supply-side of the market in response to policy. This is a good approximation of the likely supply-side effects from regulation specific to Massachusetts, which makes up only a small fraction of the national firearms market. However, it likely provides a poor guide to the effects of national-level policy. In addition, it requires extrapolation of the demand model estimated with only Massachusetts data to reflect tastes for firearms across the United States (up to a vertical preference shifter $\tau$ across markets). Therefore, we interpret our counterfactual exercises as reasonable approximations for the effects of policy changes in Massachusetts, and a demand-side only analysis of the effect of these policies throughout the United States.

## 6.1 Mechanics and Implementation

Before presenting counterfactual predictions, we first describe the machinery and auxiliary assumptions we use to compute welfare estimates across our proposed policies.

We first consider policy alternatives based on counterfactual specific additive taxes (e.g. \$100 increase in price) on handguns and long guns. We focuses on additive taxes, as opposed tax rates, because this price increase is well defined for both new gun in $\mathcal{J}_{]\dagger}$ and the used gun composite $\omega_{cy}$, which in our demand model does not have a set price. The taxes we consider range from a moderate subsidyin which we decrease the price of each gun buy 100 dollarsto a 5,000 dollar price increase, representing a quadrupling in the price of the average gun.

We now describe implementation of the additive taxes, and our framework for welfare evaluation. Let $T_j$ denote a specific tax amount for product $j$. Since taxes affect consumer utility homogeneously, we implement these taxes in our model by shifting the mean utilities for each product $\delta_{t,j}$:

$$\delta_{j,t}(T_j) = \delta_{j,t} + \alpha T_j$$

and recalculating choice probabilities $s_{j,t}$ from Equation 10 according to the new $\delta_{j,t}(T_j)$. Consumer surplus is calculated in the typical form for discrete choice models

$$CS(\vec{T}) = \sum_t CS_t(T_j) = \sum_t M_t \int_d -\frac{1}{\alpha} \log\left(1 + \exp(\rho_0 I_{d,1,t}(\vec{T}))\right) \partial F_t(d) \tag{33}$$

where $t$ indexes markets, $\vec{T}$ is the vector of taxes across all products, $M_t$ is market size, and

$I_{d,1,t}(\vec{T})$ is the inclusive value of the inside option from Equation 19, recalculated to account for the new mean utilities $\delta_{j,t}(T_j)$.

While consumer surplus will decrease from the policies, there are two potentially offsetting benefits: increases in tax revenue, and increases in public health. For taxes these are simply calculated as:

$$\mathcal{T}(\vec{T}) = MVPF \cdot \sum_t M_t \sum_j T_j \cdot s_{j,t}(\vec{T}) \tag{34}$$

Where $MVPF$ is the marginal value of public funds Hendren and Sprung-Keyser [2020]. We follow O'Connell and Smith [2021] and value each dollar of tax revenue raised by the government as producing one dollar of social welfare, i.e. $MVPF = 1$. Public health benefits are calculated as in Equation 32

$$\mathcal{PH}(\vec{T}) = \sum_i \alpha^i \sum_t \sum_{z \in t} \bar{h}_{i,z,t} \Big( \frac{1 + \sum_j q_{j,z,t}(\vec{T})}{1 + \sum_j q_{j,z,t}(\vec{0})} \Big)^{\theta^i - 1} \tag{35}$$

where $i$ denotes incident types (injury, fatality), $\alpha_i$ denotes the conversions of incident $i$ to dollars, $\bar{h}_{i,z,t}$ denotes the baseline incidents observed with no taxes, $q_{z,j}$ is predicted purchases of each product in a zip code from the demand model, and $\theta^i$ is the incident elasticity estimated in Section 5. As mentioned in Section 5, we follow prior work and value each gun assault fatality at -8.5 million dollars [Heaton, 2010] and each non-fatal firearm injury at -0.105 million dollars [Peterson et al., 2021]. As our health model only estimates the effect of gun transactions on contemporaneous firearm violence, we take this short-term view as our baseline measure of externalities and discuss how our estimates would change under alternative persistence assumptions.

Putting these together, we calculate aggregate welfare changes from gun taxes as follows:

$$\mathcal{W}(\vec{T}) = \Delta CS(\vec{T}) + \mathcal{T}(\vec{T}) + \mathcal{PH}(\vec{T}) \tag{36}$$

Where $\Delta CS$ is the change in consumer surplus.

In a second set of counterfactuals, we consider bans on certain classes of firearms. These are equivalent to taxes $T_j = \infty$ on certain products in the market, or equivalently, setting the inclusive value corresponding to these classes as $I_{d,c,t} = -\infty$, while also setting $\mathcal{T} = 0$, and so compatible with the framework laid out above.[38]

We consider (jointly) two types of taxes in this paper: taxes on all handguns, and taxes on all longguns. We evaluate counterfactuals under the complete two-dimensional grid spanned

[38] We implement these numerically by instituting a one million dollar tax on all covered products of the ban; We verify that empirically no consumer purchases any affected products.

by our counterfactual tax rates. We show that this generates insights distinct from uni-dimensional policies.

For estimating counterfactuals in the entire United States, we require an additional first-step to align the resolution of the data with the resolution of our model. In particular, certain model componentsincluding the health modelare non-linear aggregates of zip code-year level transaction quantities. However, outside Massachusetts, we only observe quantities of firearm transactions at the state-year or market level. To bridge this gap, we use our fitted demand model to impute firearm transaction quantities under the status quo for each zip code-gender-year outside of Massachusetts, which is feasible since we do have zip-code level data on demographics for the entire United States. The mechanics of this imputation are identical to our predictions within Massachusetts under counterfactual prices.

## 6.2 Counterfactual Gun Policies

We begin our analysis in Panel A of Figure 11 by examining the value of the firearm market to consumers. In Massachusetts, where we estimate our demand system, we find that the licit firearm market produces approximately 300 million dollars of consumer surplus each year, about 55 dollars per adult per year. This value varies meaningfully over time, reflecting peaks and troughs in demand for gun purchase within the population.

Figure 12 considers how intermediate outcomes , as well as total welfare, change as a function of specific taxes on the purchase of handguns and long guns, on average across years of our sample. In the Figure, we vary the tax from \$0 to \$1,400, which would roughly double the prices of firearms. In Panel (a), we see that demand slopes downward in our estimated preference model, as sales of each weapon type are decreasing in their respective tax. We estimate that there is non-negligible cross-substitution, in terms of sales, to the type of weapon that is not taxed for the class-specific taxes. However, as our estimated class-level nesting parameters imply, the amount of substitution is quantitatively small. For example, at a \$200 increase in taxes for handguns, approximately 6,100 less handguns are sold per year, but 420 more longguns are purchases.

In Panel (b), we plot the various welfare components from Equation 36 as a function of the tax amount. To be of the same sign as other components, consumer surplus is shown in terms of how much it decreases as we raise taxes. The Figure shows that there is a direct tradeoff between consumer surplus and public health, as higher gun taxes worsen market outcomes but prevent gun violence. Tax revenue follows a Laffer curve, but the price inelasticity of demand leads to a peak at specific tax values of greater than 1,000 dollars per handgun. Overall welfare benefits are increasing, but concave, in higher taxes.

In Figure 13, we plot the frontiers of positive outcomes (government revenue and public health) against consumer surplus from each type of firearm tax. Implementing the tax rate that maximizes this Laffer curve would require more than doubling the price of the average new handgun in our sample. For public health, We find that the drop in gun violence from high tax rates pays for itself in terms of social welfare at high tax rates. The relative length of each frontier in Figure 13 demonstrates a complementarity between taxes on hand guns and long guns. Taxes on individual classes, of up to $5,000, fail to reach a net positive welfare outcome due to substitution to other firearms. But by taxing all firearms at high amounts, we adequately push sufficient consumers out of firearms purchases that public health benefits outweigh decreases in consumer surplus.

Figure 14 expands the policy space to consider jointly varying taxes on both handguns and long guns, by plotting the average welfare benefit per year of a particular tax scheme. We find that raising taxes on handguns or long guns would increase welfare. The two tax instruments work complementarily. The best outcomes from a social welfare perspective are achieved when both taxes are simultaneously high. Setting high taxes on a single weapon class without addressing the other leads to the least socially desirable outcomes. These patterns follow from the challenge of designing policies strong enough to deter gun purchases and decrease gun violence, rather than to merely decrease consumer surplus.

In Figure 15, considers bans on weapon classes, which are the strongest policies available to regulators. We benchmark these bans against a $100 gun tax, which would represent a $\approx 10\%$ increase in guns, and a $1,400 tax, which would roughly double prices. Similar to our tax results, we find that unilateral bans on one weapon class would decrease consumer surplus by more than they would decrease gun violence, due to substitution effects, leading to a net negative welfare impact. However, banning both weapon classes- closing the Massachusetts gun market- would drastically reduce gun violence and improve social welfare by 570 million dollars each year. Most importantly, the figure shows that the effect of banning all guns dwarfs the effects of even doubling gun prices ($70 million increase in welfare), despite the potential government revenue benefits of taxes.

A key limitation of our counterfactual analysis so far is its relatively stark timing assumption on the downstream effect of gun transactions. In particular, we only estimate the effect of gun transactions on contemporaneous incidents of gun violence. Since gun transactions change violence in part by changing gun ownership, and gun ownership persists for many years, a focus on only the contemporaneous effects overlooks the potential long-term benefits of gun regulation. To understand the potential role of such long-term effects, we consider a range of extrapolations from current gun transactions to future gun violence. To capture potentially strong persistence we consider a market discount rate 0.98, which we contrast

against lower discount rates of 0.98/2 and 0.98/4. The lower discount rates capture the idea that current changes in gun violence may be easily offset by other factors in future periods. For all discount rates, we use a horizon of 6.68 years (i.e., the un-discounted contemporaneous effect and 5.68 future years). This choice of horizon reflects a mean "time-to-crime" of 6.68 years from legal purchase for firearms recovered at crime scenes and traced by the FBI.[39] Figure A5 shows that our baseline analysis provides a conservative benchmark on the potential for gun taxes to decrease gun violence, if we believe that restricting purchases contemporaneously has decreasing effects on future gun violence.

We also conduct our partial equilibrium counterfactuals for the U.S. as a whole. These are shown in Panel (b) of Figures 11,14,15.

In Panel B of Figure 11, we consider the spatial distribution of consumer surplus from the firearm market across the U.S. The average adult in the continental U.S. enjoyed 174 dollars of consumer surplus in the average year from 20162022. Using a U.S. adult population of approximately 330 million, we value the U.S. firearm market as producing approximately 57 billion dollars of value for consumers each year. However, these gains are unevenly distributed across space. Consumers in urban centers and along the oceanic coasts value the consumer firearms market at roughly one-half of the U.S. population mean. Consumers on the Gulf Coast and in the northern plains value the firearms market at 50 and 100 percent higher than the average, respectively.

Panel B of Figure 14 extends our analysis of joint class taxes to the full U.S. We find a qualitatively similar pattern as in Massachusetts. However, because consumer surplus is higher on average in other U.S. states, their are more areas of the policy space that result in decreases in overall welfare. Unlike in Massachusetts, we find an interior optimum on our grid of counterfactual taxes at a 1,400 tax on the purchase of both handguns and long guns, roughly a 100% increase in the average gun price.

Contrasting the US and Massachusetts panels in Figure 14 reveals the importance of flexibility and locally tailoring firearm policy. In particular, since demand for guns in the U.S. is much higher than in Massachusetts, optimal taxes differ significantly for these markets. A qualitative implication of this result is that, if each statue or locality is able to set their own firearm policy, they may better capture this tradeoff. Rosenberg [2023] pursues this research question for cities in California. In our context, we would conclude that optimal tax rates in Massachusetts and other states with low demand for guns may be quite different from optimal policy in other parts of the U.S.

In Panel B of Figure 15, we display the effects of shutting down the entire market for consumer firearms in the U.S. This counterfactual is far from the observed data in the U.S.

[39]Source: `https://www.atf.gov/resource-center/firearms-trace-data-massachusetts-2021`

but is closer to the minimally active firearm markets in other industrialized countries. We find that a complete ban on all firearm transactions would increase welfare in the U.S. by 32.6 billion dollars per year. The reduction in gun violence is far larger than what is achieved through more intermediate tax policy, leading complete bans to dominate taxes from a social welfare perspective.

# 7 Conclusion

In this paper, we provide the first characterization of demand for licit firearms in the United States based on observed transactions. Through descriptive analysis and a structural model, we show that firearms consumers are relatively price inelastic, and differ demographically in their preferences over the characteristic space of firearms in meaningful ways. We then estimate a public health model to quantify the externalities in terms of gun violence that result from increased gun purchases. In our counterfactual policy exercises, we show that even though substitution between types of firearms is relatively low, uniform taxes are more welfare enhancing than targeted taxes. However, due to the limited price responsiveness of these consumers, the largest gains are obtained when we shut down the firearms market entirely. While our paper is an important step towards understanding this market, many questions are left unanswered. In particular, our demand-side analysis fails to account for the supply-side response to taxes, and how this may impact estimates of overall welfare, both through the price response of gun manufacturers, as well as the reduced profits this industry may enjoy. Additionally, this paper does not speak to potential regulatory on the illicit market for firearms, and how this may respond to changes in government policy. Further work is necessarily in the market to better understand the implications of the large scale policies proposed in this paper.

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| | (1) Handguns | (2) Longguns |
|---|---|---|
| Caliber (Inches) | 0.363 | 0.453 |
| | ( 0.093) | ( 0.217) |
| Barrel Length (inches) | 4.452 | 22.585 |
| | ( 2.169) | ( 4.530) |
| High Capacity Weapon | 0.188 | 0.154 |
| | ( 0.391) | ( 0.361) |
| Shotgun | 0.000 | 0.396 |
| | ( 0.000) | ( 0.489) |
| 100% Grading Used Price ($) | 905.741 | 1354.701 |
| | ( 1099.337) | ( 2487.826) |
| MSRP ($) | 958.340 | 1635.588 |
| | ( 663.283) | ( 3033.530) |
| Number of Gun Models | 2835 | 4781 |

Table 1: Gun Characteristics summary statistics

| | (1) Adult Pop. | (2) Potential Gun Buyers | (3) Gun Buyers | (4) Handgun Buyers | (5) Longgun Buyers |
|---|---|---|---|---|---|
| Female | 0.513 | 0.225 | 0.085 | 0.107 | 0.047 |
| Fraction White in Zipcode | 0.681 | 0.687 | 0.813 | 0.804 | 0.828 |
| Poverty Rate in Zipcode | 0.105 | 0.103 | 0.081 | 0.083 | 0.078 |
| Fraction BA+ in Zipcode | 0.410 | 0.402 | 0.402 | 0.399 | 0.406 |
| Density of Zipcode | 1,437 | 1,236 | 665 | 710 | 587 |
| Median Zipcode Income | 79,878 | 78,950 | 88,456 | 87,961 | 89,304 |

Table 2: Demographics of Gun Owners in Massachusetts

| | (1) IHS(Purchases) | (2) IHS(Purchases) | (3) IHS(Purchases) | (4) IHS(Purchases) |
|---|---|---|---|---|
| Log(Price) | -0.579 | -1.099 | -2.242** | -2.315** |
| | (0.446) | (0.770) | (1.028) | (1.027) |
| Observations | 4465 | 4465 | 4465 | 4465 |
| R-Squared | 0.73 | 0.00 | -0.00 | -0.00 |
| Gun Model FE | Yes | Yes | Yes | Yes |
| Year FE | Year | Year | Year | Class x Year |
| # Selected Instruments | | 287 | 9 | 10 |
| Sup-Score Test Statistic | | | 14.36 | 14.46 |
| First Stage Sig. (p-value) | | | 0.0000 | 0.0000 |
| Method | OLS | 2SLS | IVLASSO | IVLASSO |

Table 3: Estimated Price Elasticity of Demand for Firearms

| | Used vs New Good Nesting | Class-level Nesting |
|---|---|---|
| Handgun | 0.238 | 0.291 |
| | (0.044) | (0.090) |
| | [0.1130] | [0.0000] |
| Longgun | 0.325 | 0.365 |
| | (0.080) | (0.255) |
| | [0.3096] | [0.0185] |
| Inside Good | | 0.896 |
| | | (0.098) |
| | | [0.1445] |

Table displays estimates of $\rho_{c,u}$ under Used vs New Good Nesting, and Estimates of $\rho_c$ for Handguns and Longguns under Class-level Nesting, while $\rho_0$ estimates are displayed in the row corresponding to inside good. Estimates are displayed, followed by standard errors in parentheses underneath. In brackets we display p-values for the following tests: for $\rho_0$, the test that $\rho_0 \leq 1$, for $\rho_c$, the test that $\rho_c \leq \rho_0$, and for $\rho_c^u$, the test that $\rho_c^u \leq \rho_c$. These significance tests are performed using a one-sided z-score test, treating the upper bound of the test as a known number.

Table 4: Nesting Parameters

| Characteristic | Weapon Class | All | Frac Conservative | Female | Frac BA+ Edu | Frac White | Log(Median Inc) | Log(Density) |
|---|---|---|---|---|---|---|---|---|
| Constant | Handgun | 3,892.57 | 2,563.14 | -4,766.25 | -3,870.97 | 3,725.35 | 524.93 | -111.40 |
| | Longgun | 6,028.71 | 1,197.41 | -6,639.10 | -3,585.86 | 6,621.11 | 130.64 | -152.14 |
| Barrel Length (Inches) | Handgun | -268.73 | -121.60 | -286.34 | 64.73 | 70.91 | -14.49 | -5.89 |
| | Longgun | -119.54 | -19.66 | -23.31 | 62.20 | 132.09 | -12.97 | -2.78 |
| Caliber (Inches) | Handgun | -1,983.90 | 693.61 | -1,886.02 | -1,091.18 | -977.42 | 113.05 | 21.92 |
| | Longgun | -954.46 | 96.79 | -378.55 | -563.95 | -868.80 | -194.26 | 15.01 |
| High Capacity Weapon | Handgun | 302.70 | 53.20 | -216.88 | 211.87 | -392.66 | 184.20 | 12.57 |
| | Longgun | 171.42 | 91.98 | -272.58 | 356.70 | -558.24 | 428.14 | 24.89 |
| New Gun | Handgun | -2,689.34 | 358.53 | 1,837.69 | -67.28 | 1.90 | -12.20 | 16.92 |
| | Longgun | -3,518.04 | 396.26 | 607.02 | -1,464.07 | -2,251.79 | 233.56 | 40.52 |
| Shotgun | Longgun | 610.35 | -245.91 | 287.53 | 385.09 | -17.98 | 182.72 | 10.59 |

Table displays estimates of consumer preferences over firearm characteristics, in terms of 2022 dollars. For the All column, the baseline taste for a preference, we display $\beta_c/\alpha$, and for columns referring to a particular demographic, we display $\Pi_c/\alpha$.

Table 5: Preferences for Gun Characteristic (in $)

| | log(1+Occurences) | | |
|---|---|---|---|
| | Incidents | Injuries | Fatalities |
| | (1) | (2) | (3) |
| log(1+GunTransactions) | 0.079** | 0.044 | 0.036* |
| | (0.040) | (0.031) | (0.020) |
| Zip-4 FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| Clusters | 127 | 127 | 127 |
| F | 10.41 | 10.41 | 10.41 |
| Observations | 3,591 | 3,591 | 3,591 |
| $R^2$ | 0.594 | 0.567 | 0.402 |

Table 6: Gun Transactions and Gun Violence Incidents: Linear IV Estimates

Note: Table presents two-stage least squares estimates of the effect of firearm transactions on gun violence using the number of gun retailers as an instrumental variable. Column 1 is the count of incidents of gun violence. Column 2 is non-fatal gun violence injuries. Column 3 is gun assault fatalities. All variables are transformed by $\log(1 + \cdot)$. Estimates are computed in a balanced panel of zip code-year observations. All regressions include fixed effects for 4-digit zip code and year. Standard errors clustered by four-digit zip code.

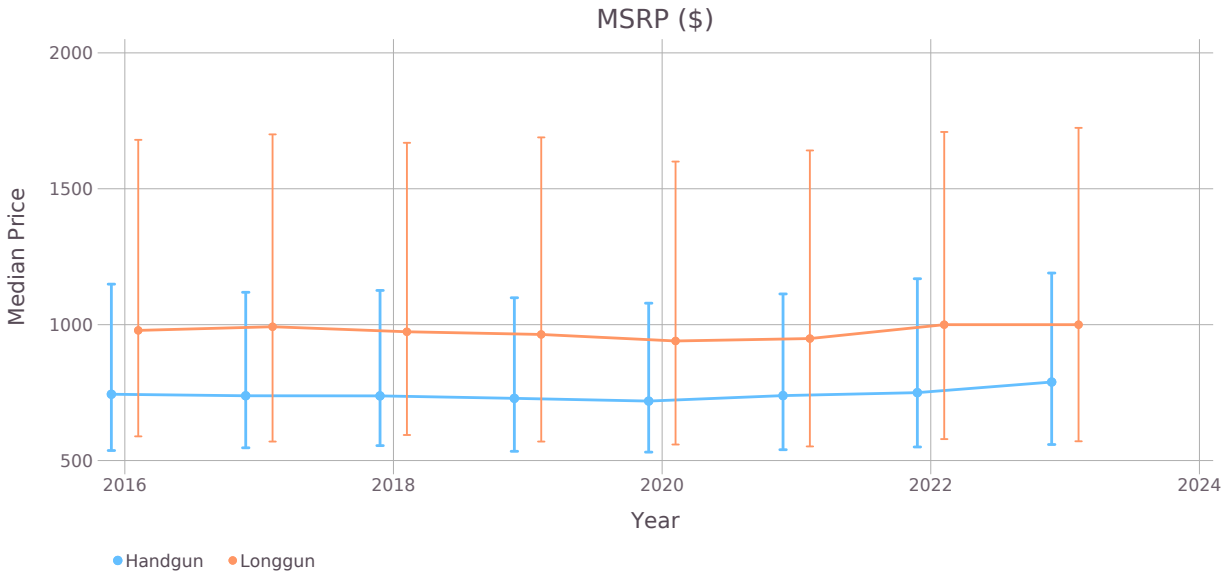



Figure 1: New Gun Prices over Time

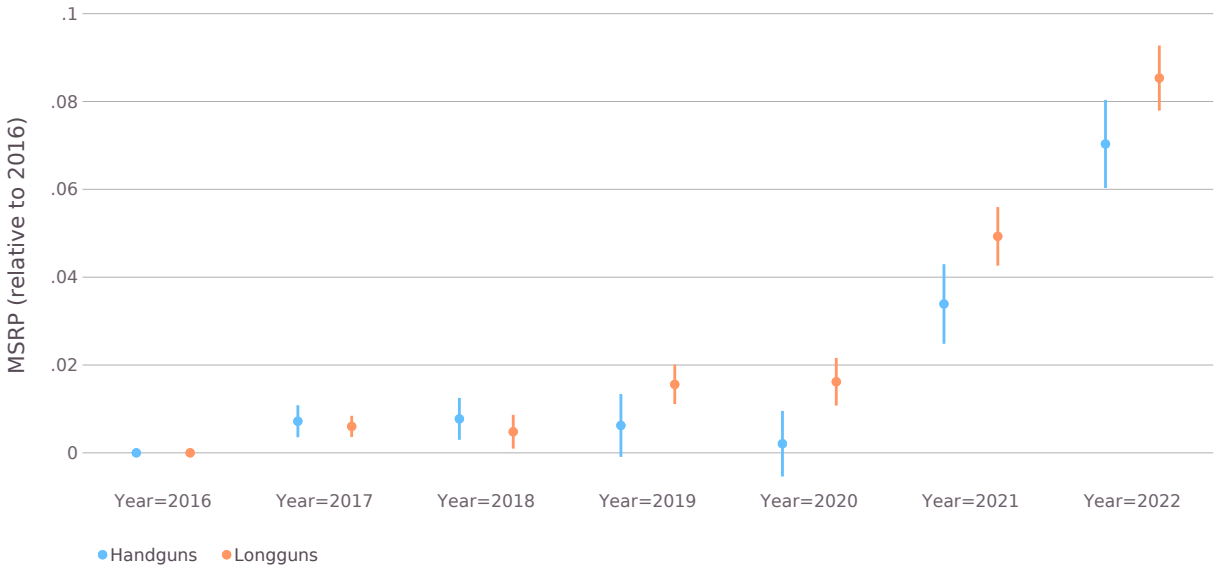



Figure 2: New Gun Prices over Time (Controlling for Variety)

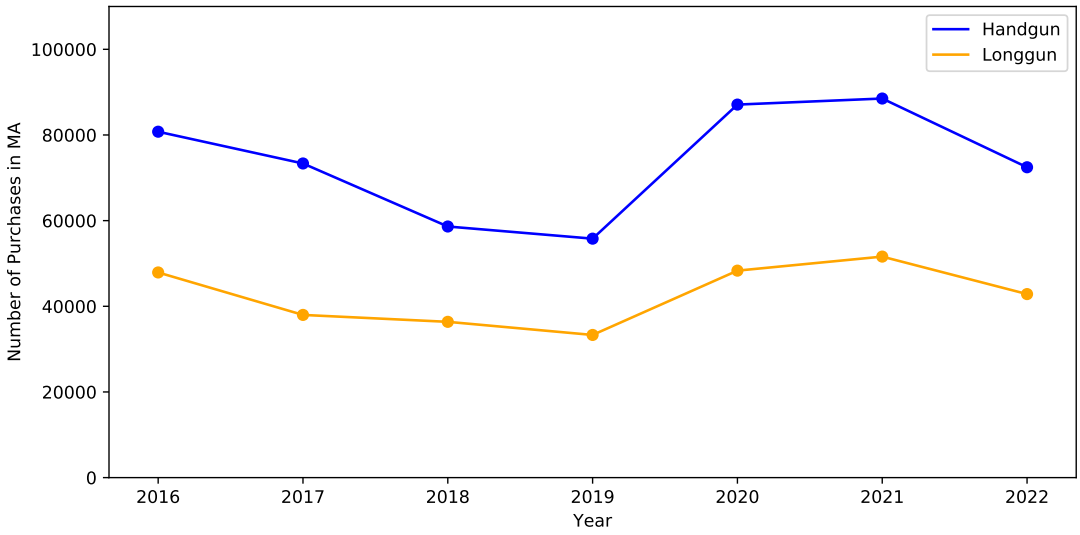



Figure 3: Aggregate Purchases by Weapon Class in Massachusetts

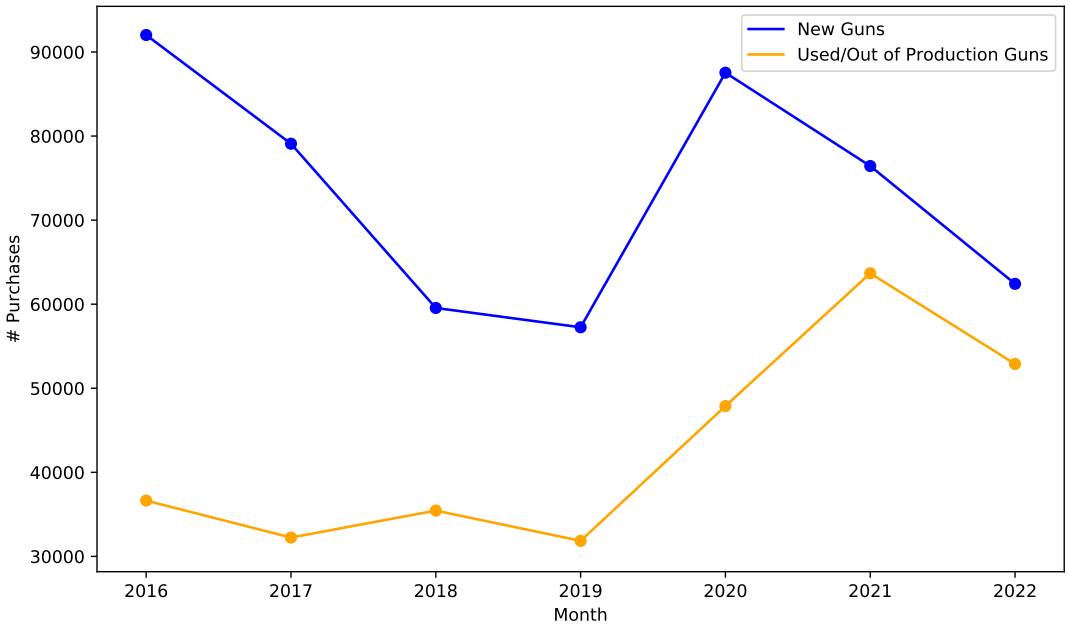



Figure 4: Aggregate Gun Purchases by Used vs New in Massachusetts

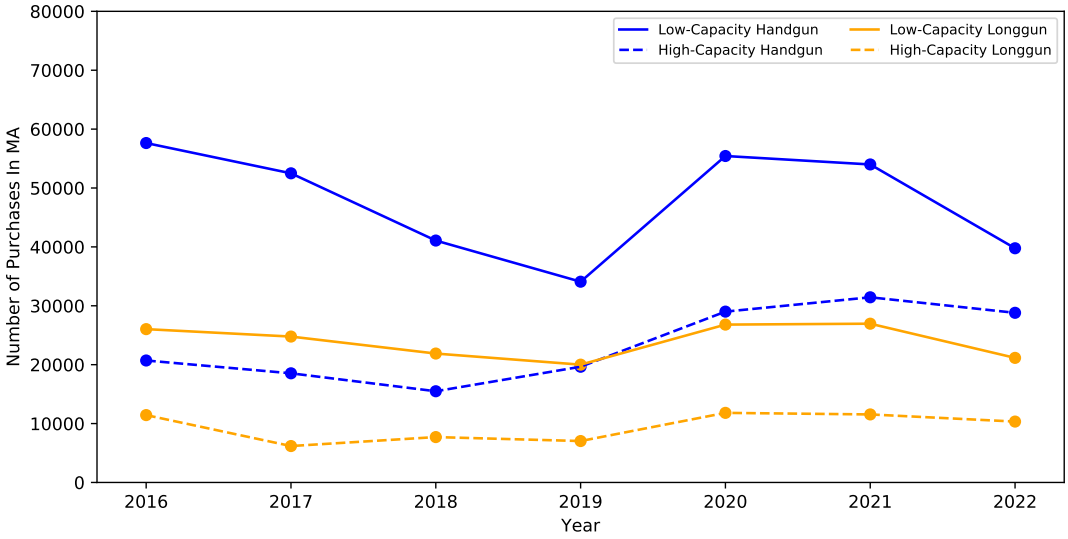



Figure 5: Aggregate Purchases by Weapon Class and High-Capacity Status in Massachusetts

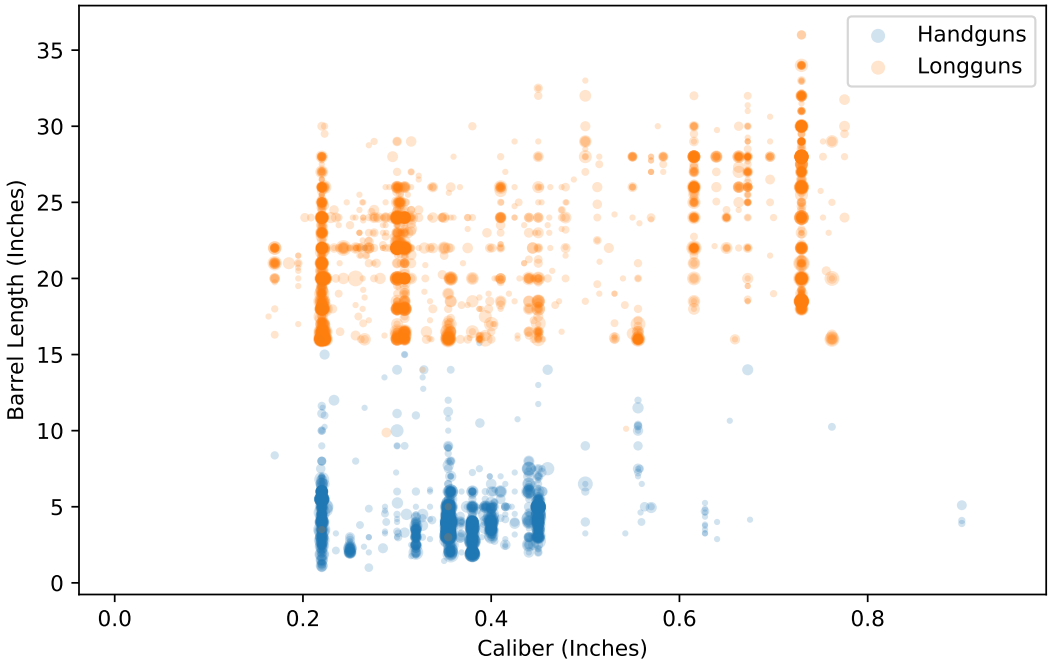
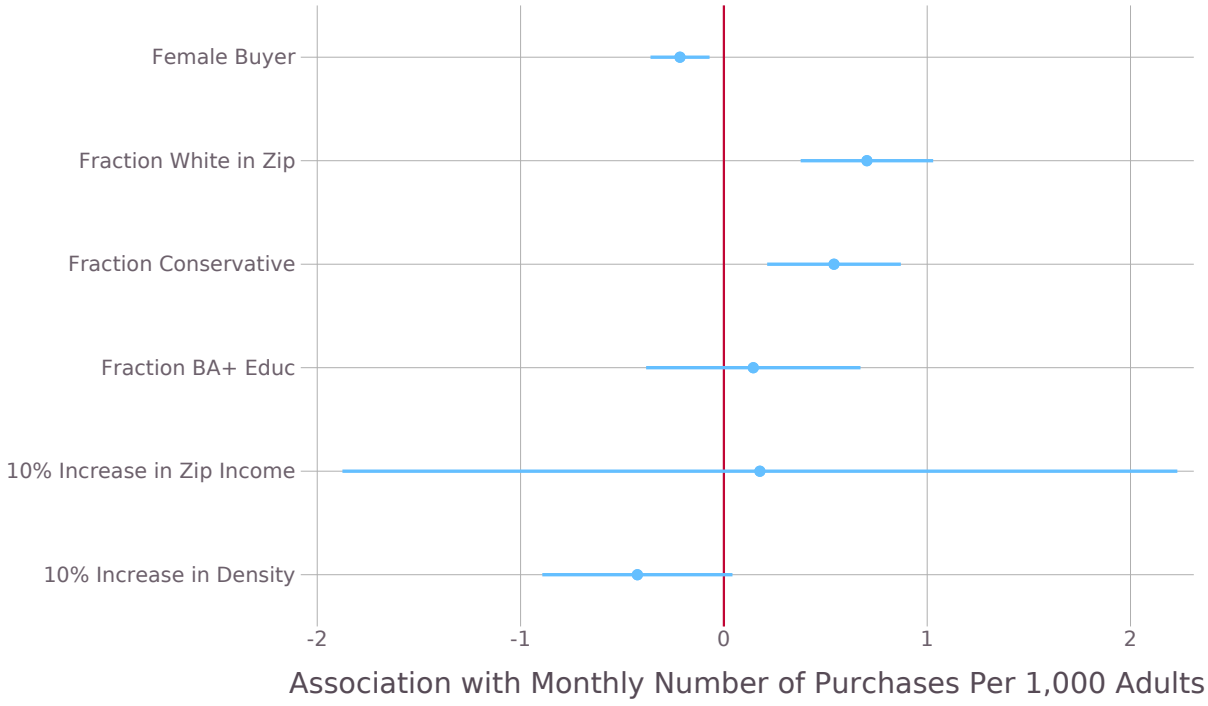
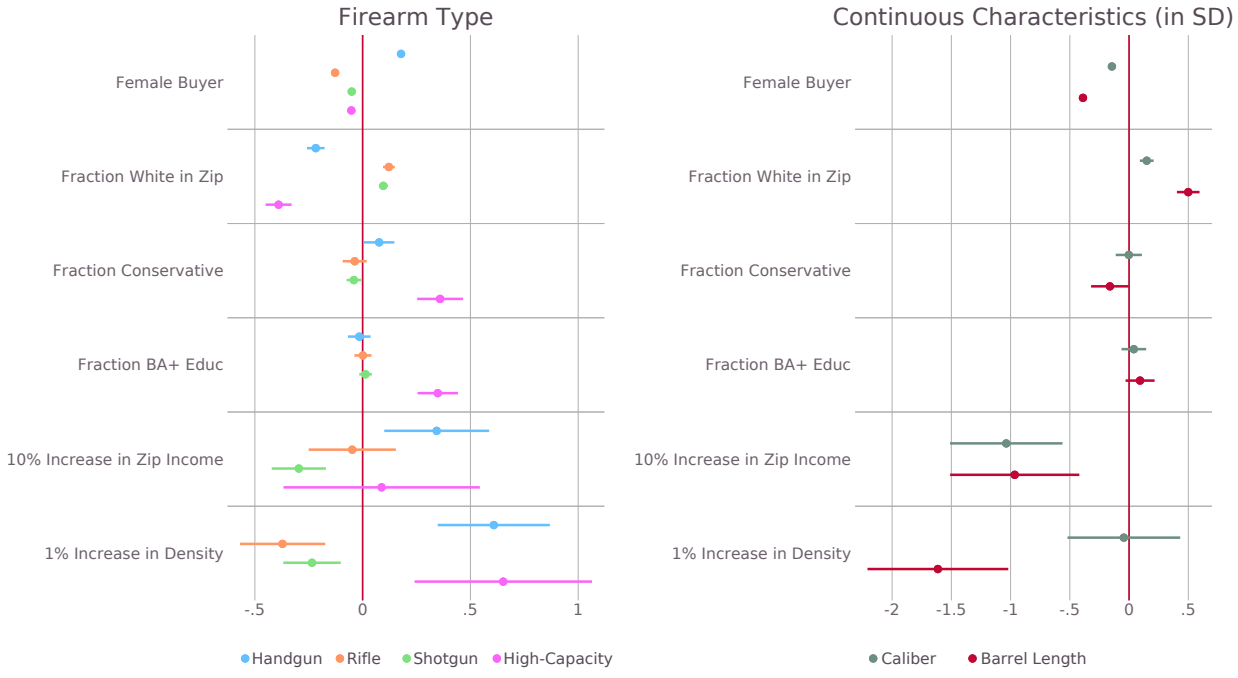



Figure 6: Caliber and Barrel Length Distribution Across Gun models




(a) Gun Purchase Frequencies (Extensive Margin)




(b) Gun Characteristics (Intensive Margin)

Figure 7: Correlates of Demographics with Gun Purchases, Controlling for Market Structure

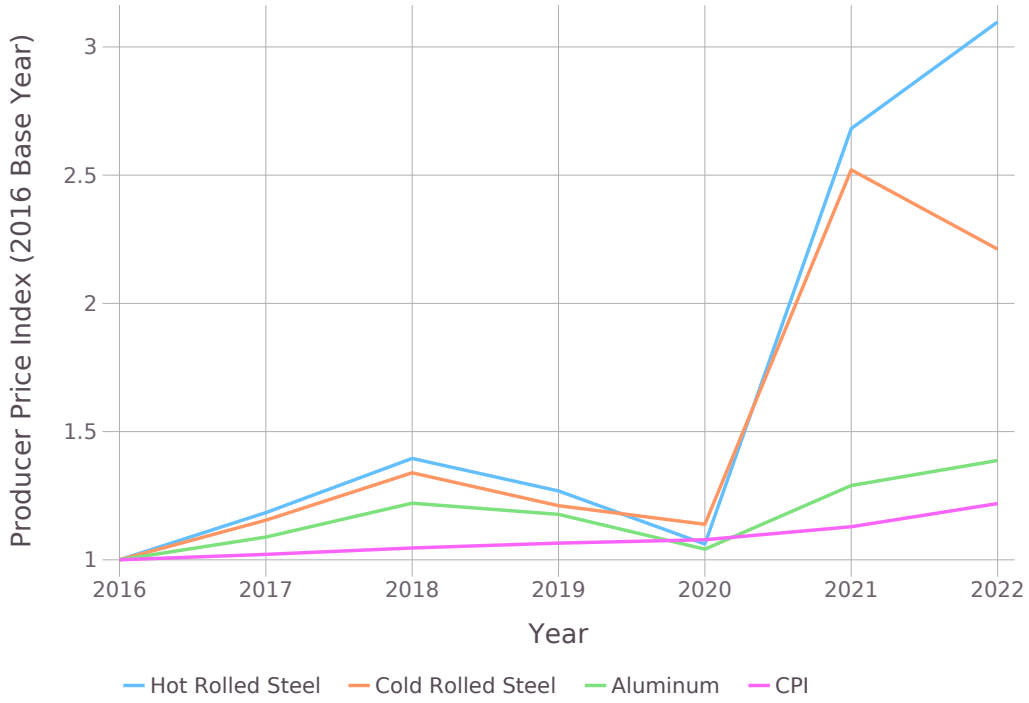
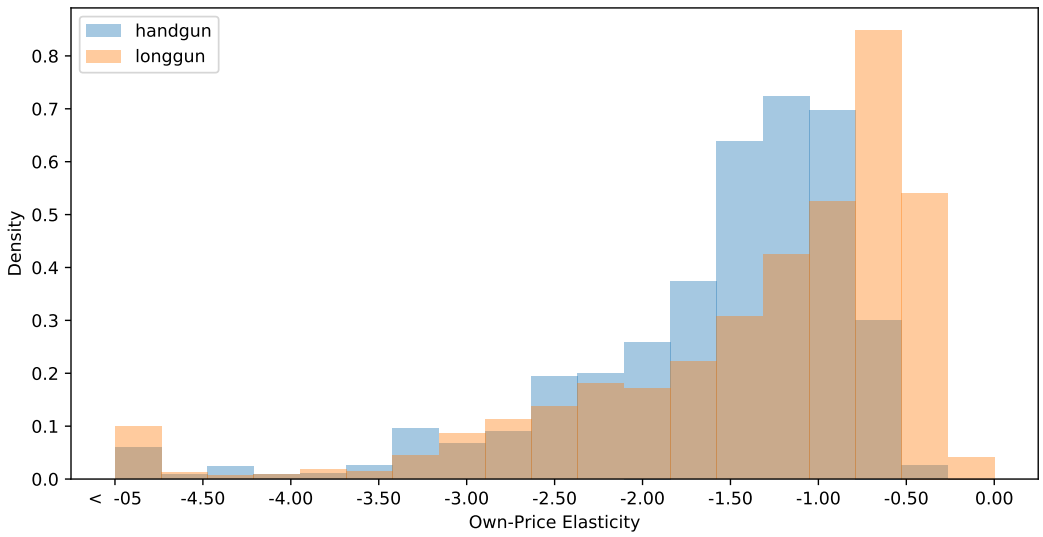
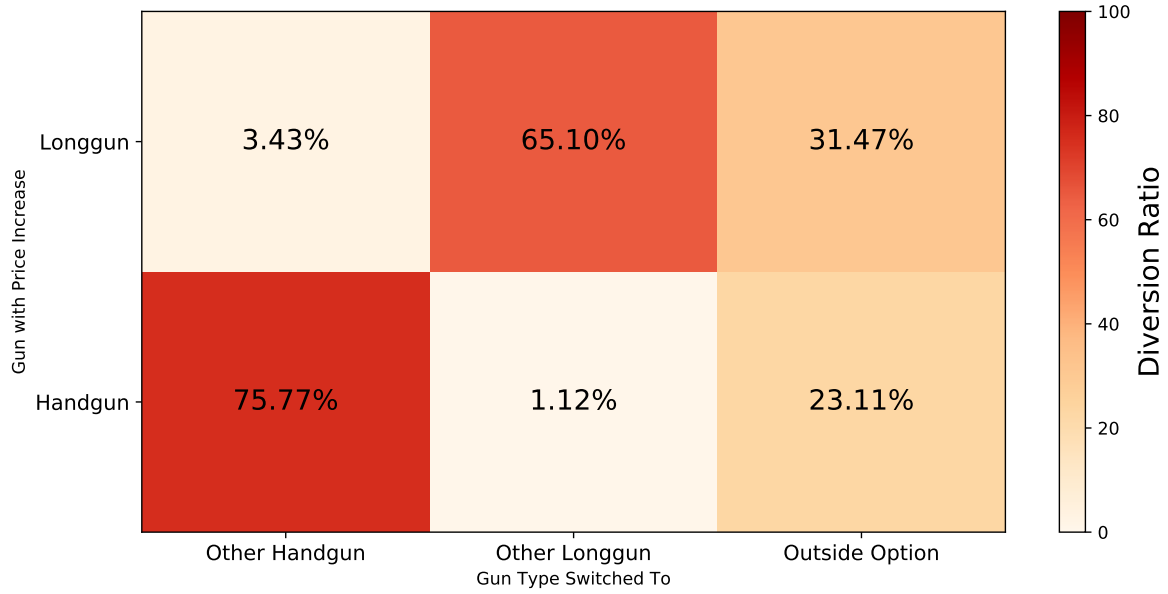



Figure 8: Time Series of Annual Price Indices for Firearms Production Inputs




(a) Distribution of Own-Price Elasticities in Massachusetts, by Gun Class




(b) Substitution Patterns (Diversion Ratios) across Gun Classes in Massachusetts

Figure 9: Own and Cross Firearm Substitution Patterns

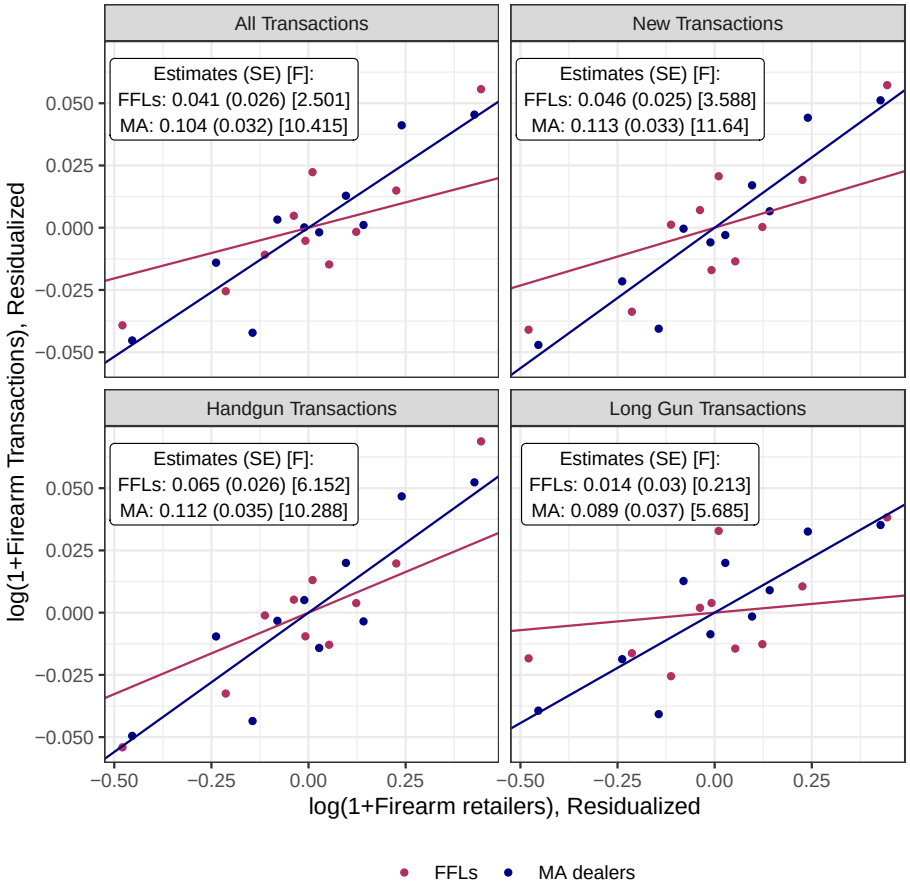



Figure 10: Gun Retailer Entry and Consumer Firearm Transactions

Note: Figure plots residualized binscatter between firearm retailers and firearm transactions within a zip code-year in pre pandemic data. Residualization is by zip code and year, with binning by deciles. Estimates, standard errors, F-statistics, and best-fit lines are from a regression on the underlying balanced panel of zip code-year observations and include fixed effects for 5-digit zip code and period. Panel A is all licit-market firearm transactions, Panel B is transactions of weapons we code as in production, Panel C is transactions of handguns, and Panel D is transactions of long guns. Blue corresponds to measures of firearm retailers using the active firearm retailers from the transaction data. Red corresponds to measures of firearm retailers using the count of federal firearms licensees.

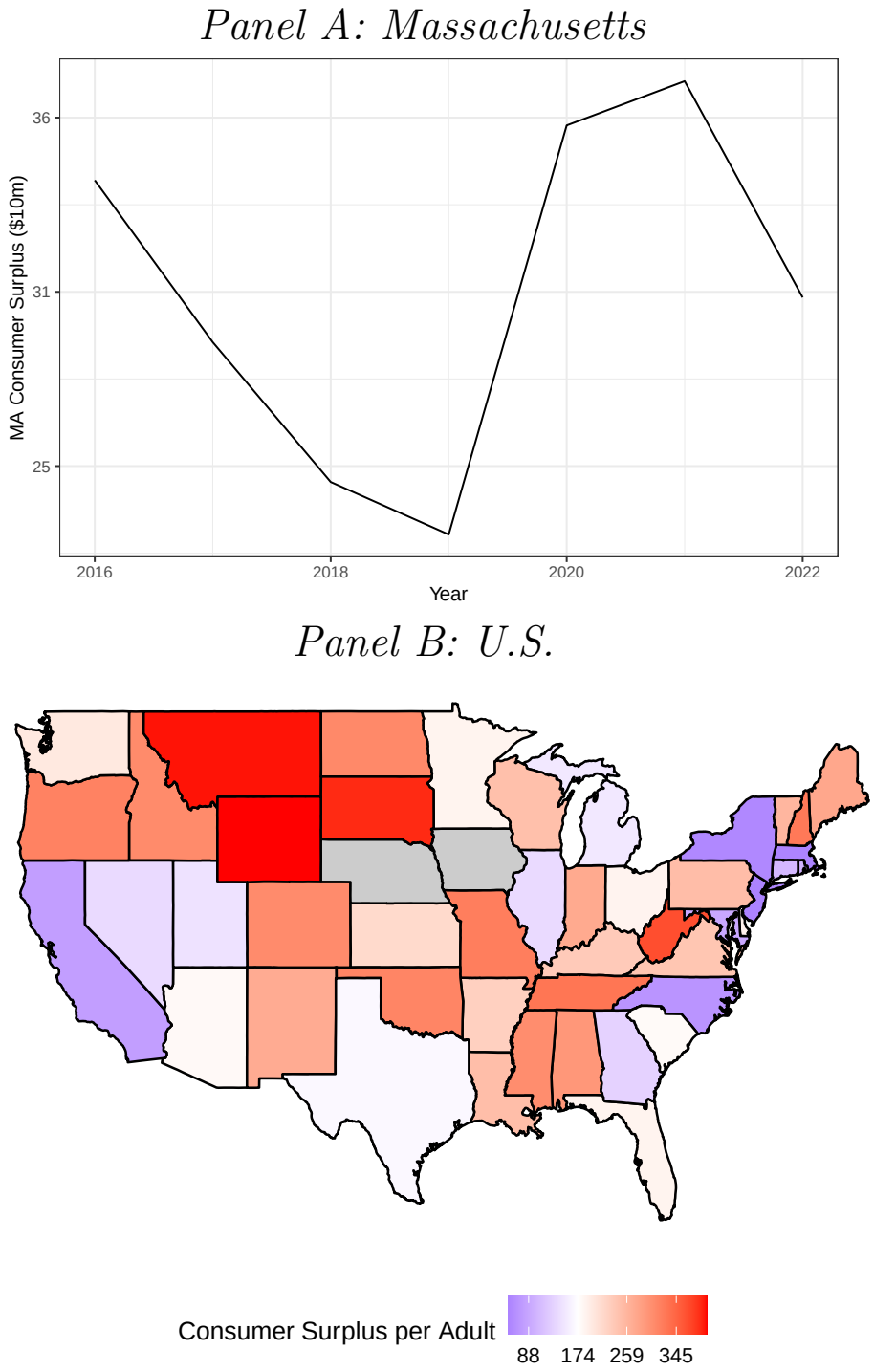
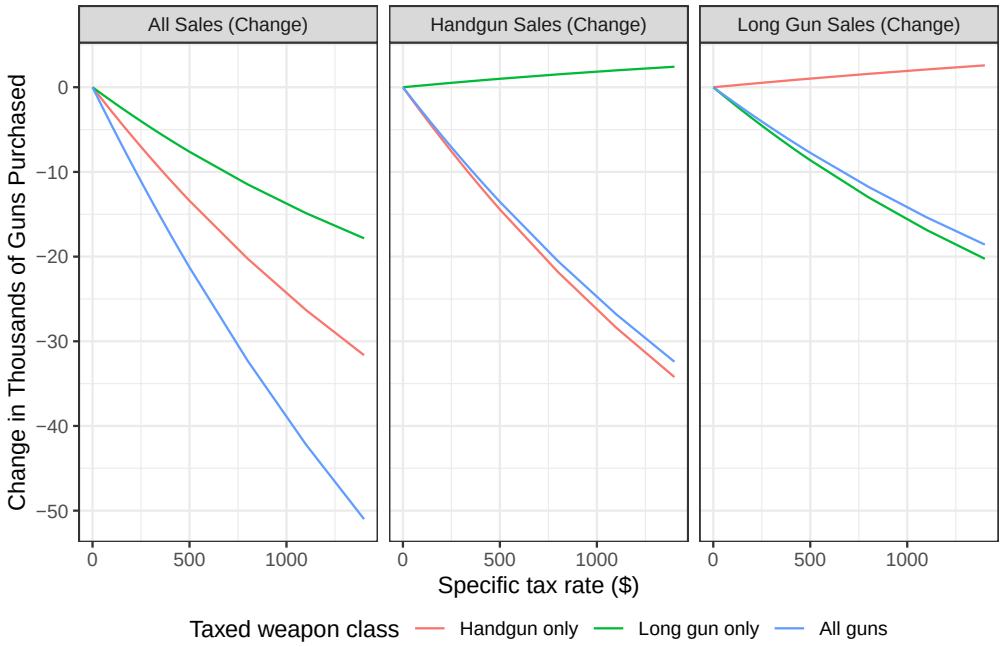
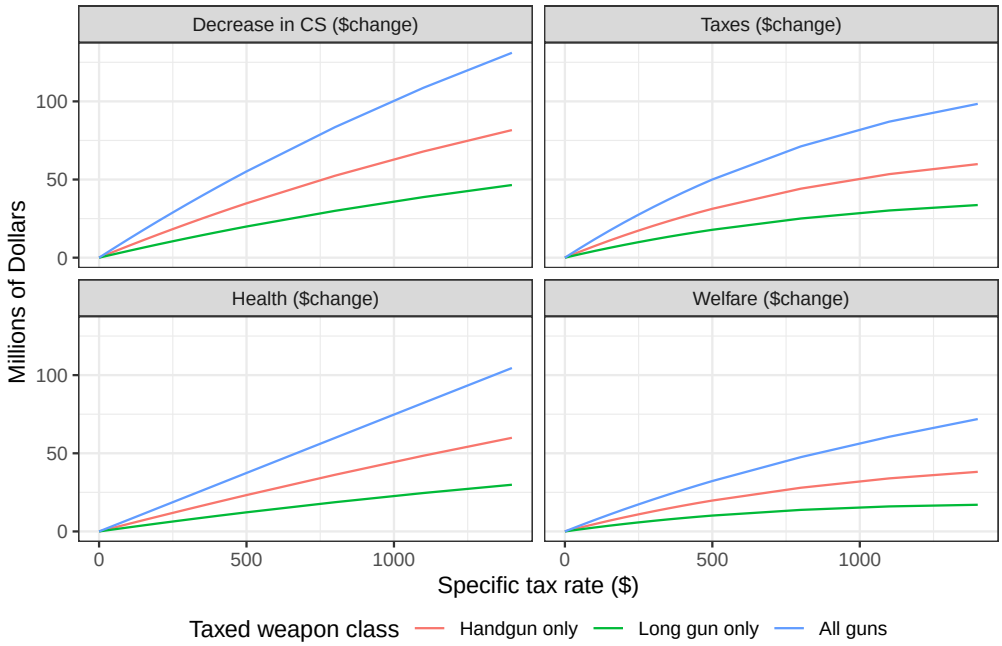



Figure 11: Consumer Surplus from the Firearm market in Massachusetts and the U.S.

Figure shows dollar value of consumer surplus from the firearms market. Panel A shows overall consumer surplus in Massachusetts each year. Panel B shows the dollar value of consumer surplus per adult in each state, averaged over the periods in Panel A. White represents the population-weighted mean consumer surplus per adult in the U.S. Scale ticks represent population-weighted standard deviations of consumer surplus per adult.




(a) Firearm Sales




(b) Welfare Components

Figure 12: Intermediate Outcomes as a Function of Taxes on Handguns and Long guns in Massachusetts

Figure shows changes in intermediate outcomes as a function of the specific tax rate on handguns and long guns in Massachusetts. Horizontal axis is the tax amount. Color represents the weapon class being taxed. Vertical axis is the value of the intermediate outcome. Intermediate outcomes in the top sub-figure are the change in total firearm sales, handgun sales, and long gun sales. In the bottom subfigure are dollar changes in tax revenue, consumer surplus, the value of gun violence avoided, and overall welfare.

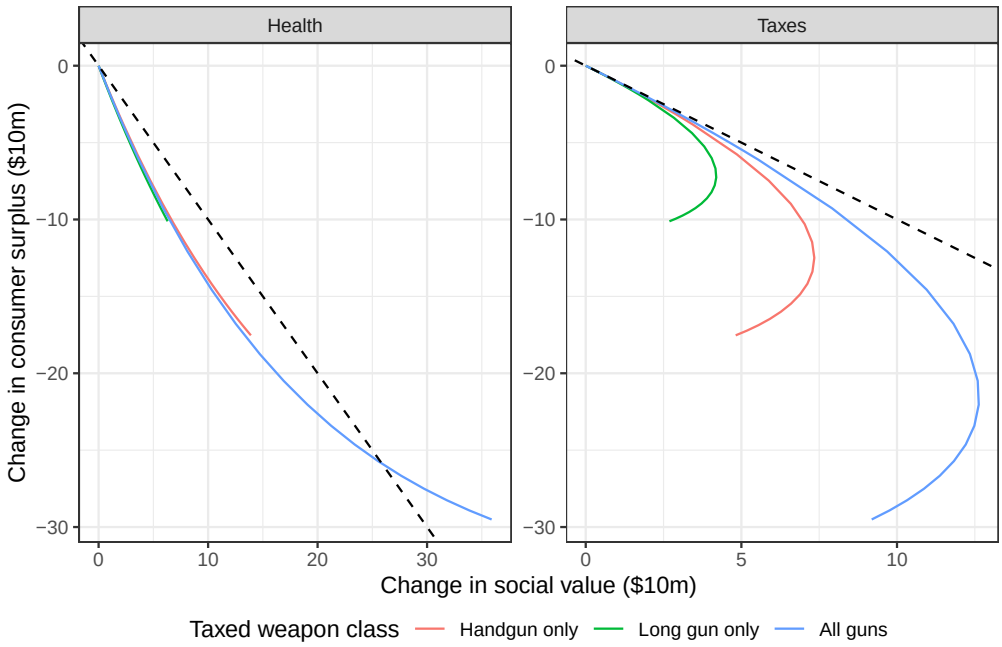



Figure 13: Policy Frontiers Generate by Taxes on Handguns and Long guns

Figure shows frontier between private-market consumer surplus and social value generated by alternative taxes on the Massachusetts firearm market. Vertical axis is the change in consumer surplus from the no-tax status quo. Horizontal axis is the change in social value from gun violence (left panel) and tax revue multiplied by a Marginal Value of Public Funds of 0.15 (right panel). Color is the tax rate on long guns. Dotted line is negative 45-degree line.

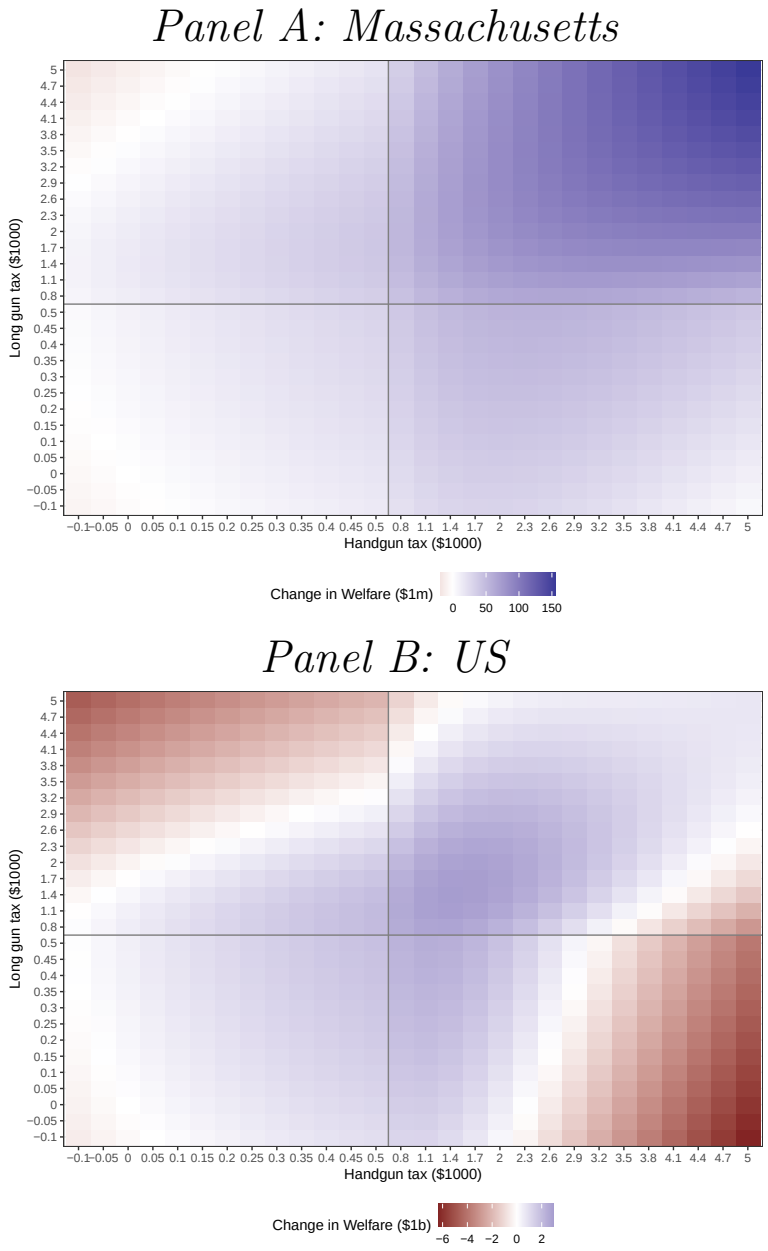



Figure 14: Changes in Welfare as a Function of Taxes on Handguns and Long Guns

Figure shows heat map of change in social welfare from counterfactual taxes on handguns and long guns. Panel A is outcomes in Massachusetts, Panel B is outcomes in the U.S. Horizontal axis is handgun tax. Vertical axis is long gun tax. Color represents the change in social welfare from the no-tax status quo. Gray lines denote a change in the scaling of their respective axes.

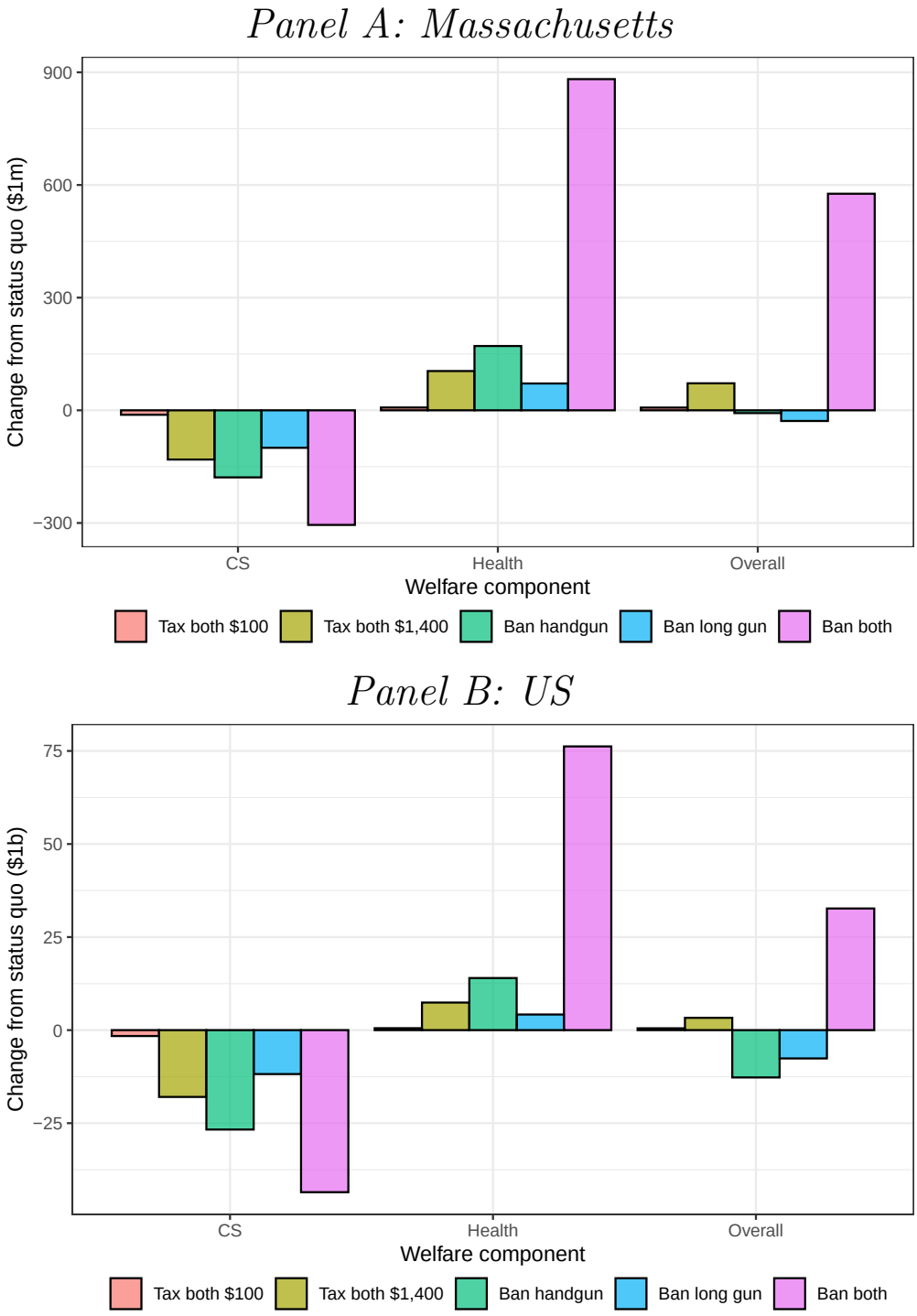



Figure 15: Changes in Welfare from Gun Bans

Figure shows change social welfare from counterfactual bans on handguns and long guns. Panel A is Massachusetts and Panel B is U.S. Color indexes counterfactual taxes or bans on handguns and long guns. Horizontal axis is welfare component. Vertical axis is its change from status quo in dollars of social value.

# A Matching of Blue Book and FRB Gun Models

In this section, we describe our matching procedure to merge models in the FRB to BBGV gun IDs. First, we manually match all makes, by unique (lowercase) string, with at least 30 transactions in our time period in Massachusetts to their corresponding manufacturer ID in BBGV. 95% of all transactions in FRB are matched to a BBGV manufacturer ID.

We then preprocess gun model names in both datasets. We remove non-alphanumeric characters, remove the standalone word "model", which we view as uninformative, and appears in many FRB and BBGV model names, convert roman numerals to numbers (e.g. $II \to 2$), and then tokenize the string so that words appear in alphabetical order, followed by any tokens that are numbers. This latter point is done to ensure that the model numbers, which are often the key identifiers of guns, occupy the same part of the string and therefore the matching algorithm weights these corresponding more closely. We then match processed gun names, in the FRB, to the most similarly named gun in BBGV. The candidate BBGV models are constrained to be within manufacturer and weapon class, as well as have price data (new or used) in the years we observe transactions in the FRB.[40] We use the weighted ratio score of the `fuzzywuzzy` Python package to match strings, and retain matches with at least a 60% similarity score. We choose this relatively low threshold to ensure as many matches as possible, and we do not ignore some transactions in our demand estimation simply due to a low quality string match; though this will introduce additional estimation error to our demand system. We proceed assuming the matched BBGV gun model is the true gun model represented in the FRB data. If there are ties, we break them by an indicator of whether the gun is in active production (has an MSRP for the year), followed by the number of years for which MSRP data is available. In total, through this procedure, we are able to match 90% of FRB transactions to a BBGV ID, for a total of 7,616 unique BBGV gun models. About 70% of transactions occur in years where the BBGV models are actively produced.

Finally, we complete the merge by assigning each transaction a common set of gun characteristics by BBGV model ID, taken as the median FRB value in the FRB, across transactions. As a validation of the merge, the imputed values agree with the recorded gun model characteristics: the imputation for high-capacity agrees 80% of the time, and the standard deviation of the imputation error for barrel length is 85% lower than the standard deviation of barrel length.

[40] This latter condition is used to avoid matching FRB guns to BBGV models that were released after we observe transactions.

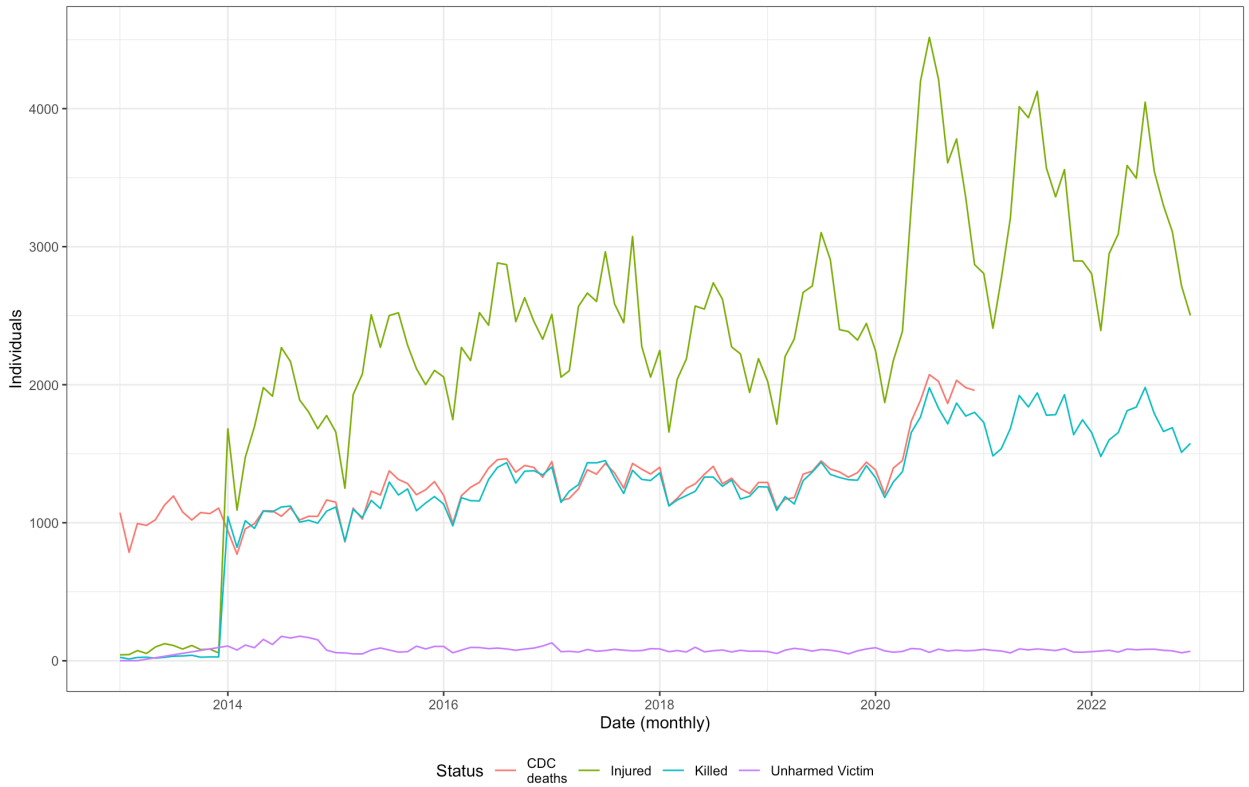



Figure A1: Incidents of Gun Violence in GVA and CDC Records

Figure shows time series of different measures of gun violence. Horizontal axis is the date in months. Vertical axis is the number of individuals affected by gun violence during a month. Color indexes measure of gun violence. Orange is deaths from gun-related assault fatalities in the U.S as recorded by the CDC under ICD10 codes X93, X94, and X95. Blue is the same quantity recorded by the GVA. Green is non-fatal injuries from gun violence in the U.S as recorded by the GVA. Purple is non-injurious incidents of gun violence in the U.S as recorded by the GVA.

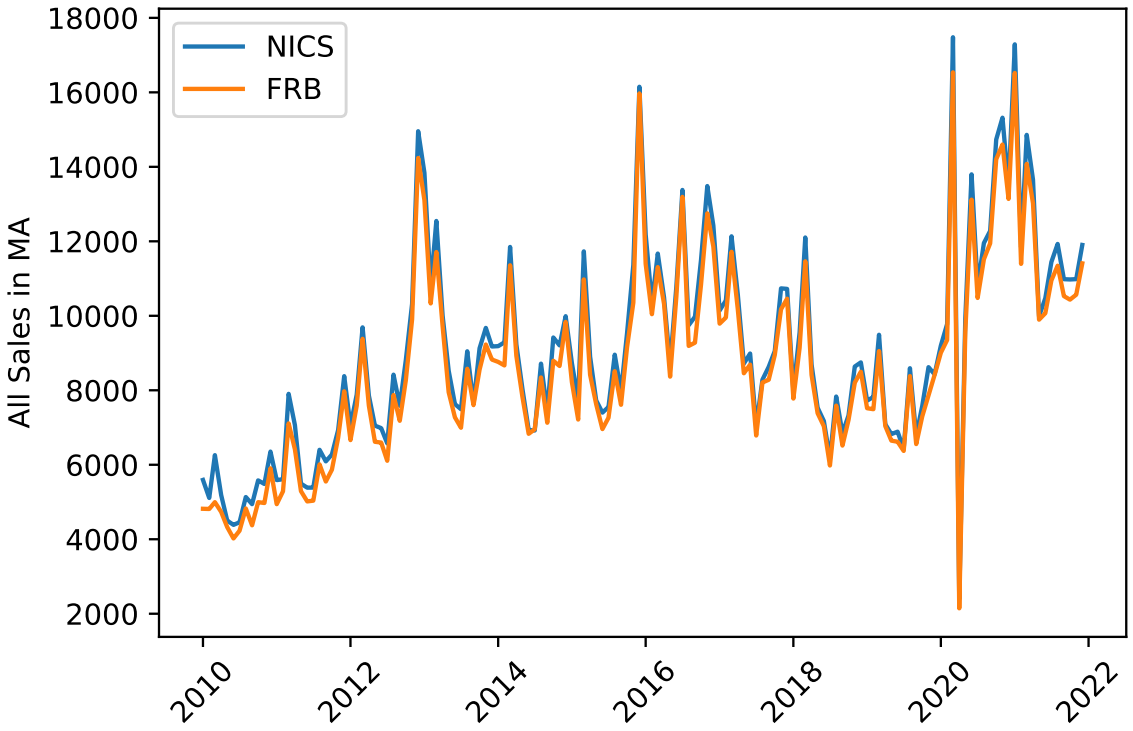



Figure A2: FRB Recorded Gun Transactions vs NICS Background Checks in Massachusetts, by Month

| | (1) Mean Util $\delta_{j,t}$ | (2) Mean Util $\delta_{j,t}$ | (3) Mean Util $\delta_{j,t}$ |
|---|---|---|---|
| Price Coef. $\alpha$ | -0.00037** | -0.00041*** | -0.00053*** |
| | (0.00015) | (0.00014) | (0.00018) |
| Observations | 2884 | 2884 | 2884 |
| R-Squared | -0.03 | -0.04 | -0.07 |
| Gun Model FE | Yes | Yes | Yes |
| Year FE | Year | Class x Year | Type x Year |
| # Selected Instruments | 7 | 12 | 3 |
| Sup-Score Test Statistic | 10.83 | 11.01 | 10.66 |
| First Stage Sig. (p-value) | 0.0000 | 0.0000 | 0.0000 |

Table A1: Estimated Price Coefficient From Structural Model

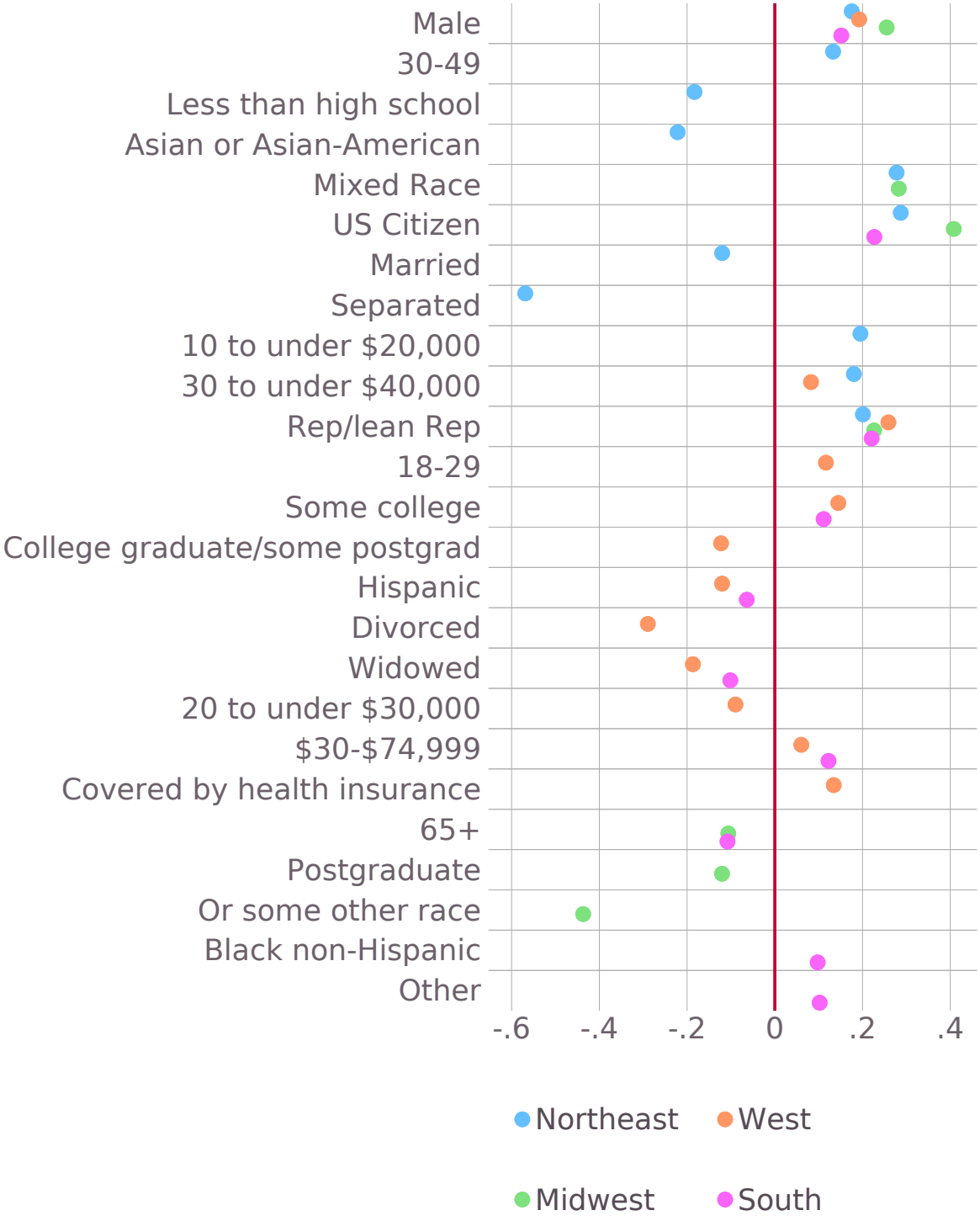



Figure A3: Estimated Lasso Coefficients for Predicting Market Size, From Pew's American Trends Panel

| Characteristic | Weapon Class | All | Frac Conservative | Female | Frac BA+ Edu | Frac White | Log(Median Inc) | Log(Density) |
|---|---|---|---|---|---|---|---|---|
| Constant | Handgun | 1.606*** | 1.057*** | -1.966*** | -1.597*** | 1.537*** | 0.217*** | -0.046*** |
| | | (0.023) | (0.040) | (0.026) | (0.026) | (0.050) | (0.011) | (0.001) |
| | Longgun | 2.487*** | 0.494*** | -2.739*** | -1.479*** | 2.731*** | 0.054*** | -0.063*** |
| | | (0.024) | (0.050) | (0.062) | (0.045) | (0.091) | (0.018) | (0.002) |
| Barrel Length (Inches) | Handgun | -0.111*** | -0.050*** | -0.118*** | 0.027*** | 0.029*** | -0.006* | -0.002*** |
| | | (0.001) | (0.012) | (0.022) | (0.009) | (0.007) | (0.003) | (0.001) |
| | Longgun | -0.049*** | -0.008 | -0.010*** | 0.026*** | 0.054*** | -0.005** | -0.001*** |
| | | (0.000) | (0.006) | (0.003) | (0.008) | (0.014) | (0.002) | (0.000) |
| Caliber (Inches) | Handgun | -0.818*** | 0.286** | -0.778*** | -0.450*** | -0.403*** | 0.047 | 0.009* |
| | | (0.019) | (0.138) | (0.145) | (0.144) | (0.104) | (0.050) | (0.005) |
| | Longgun | -0.394*** | 0.040 | -0.156* | -0.233 | -0.358** | -0.080 | 0.006 |
| | | (0.023) | (0.250) | (0.086) | (0.246) | (0.171) | (0.102) | (0.010) |
| High Capacity Weapon | Handgun | 0.125*** | 0.022 | -0.089*** | 0.087*** | -0.162*** | 0.076*** | 0.005*** |
| | | (0.003) | (0.016) | (0.017) | (0.021) | (0.031) | (0.015) | (0.001) |
| | Longgun | 0.071*** | 0.038 | -0.112*** | 0.147*** | -0.230*** | 0.177*** | 0.010*** |
| | | (0.004) | (0.046) | (0.031) | (0.055) | (0.062) | (0.047) | (0.003) |
| New Gun | Handgun | -1.109*** | 0.148** | 0.758*** | -0.028 | 0.001 | -0.005 | 0.007*** |
| | | (0.024) | (0.058) | (0.132) | (0.052) | (0.037) | (0.022) | (0.002) |
| | Longgun | -1.451*** | 0.163 | 0.250*** | -0.604*** | -0.929*** | 0.096* | 0.017*** |
| | | (0.026) | (0.137) | (0.070) | (0.169) | (0.224) | (0.053) | (0.006) |
| Shotgun | Longgun | 0.252*** | -0.101 | 0.119** | 0.159 | -0.007 | 0.075 | 0.004 |
| | | (0.010) | (0.119) | (0.047) | (0.119) | (0.069) | (0.050) | (0.005) |

Table displays estimates of consumer preferences over firearm characteristics, in terms of utils. For the All column, the baseline taste for a preference, we display $\beta_c$, and for columns referring to a particular demographic, we display $\Pi_c$. Below each parameter, standard errors are shown. * denotes $p < .1$, ** denotes $p < .05$, *** denotes $p < .01$, from a z-score test that the parameter is zero.

Table A2: Characteristic Preferences (in utils)

| Outcome | Transactions | log(1+MA Dealers) | log(1+FFLs) |
|---|---|---|---|
| Incidents | Total | 0.079 | 0.097 |
| | | (0.040) | (0.030) |
| Injuries | Total | 0.044 | 0.056 |
| | | (0.031) | (0.026) |
| Fatalities | Total | 0.036 | 0.043 |
| | | (0.020) | (0.016) |
| Incidents | New-Gun | 0.079 | 0.097 |
| | | (0.040) | (0.030) |
| Injuries | New-Gun | 0.045 | 0.057 |
| | | (0.031) | (0.026) |
| Fatalities | New-Gun | 0.036 | 0.043 |
| | | (0.020) | (0.016) |
| Incidents | Handgun | 0.078 | 0.095 |
| | | (0.039) | (0.029) |
| Injuries | Handgun | 0.044 | 0.055 |
| | | (0.031) | (0.025) |
| Fatalities | Handgun | 0.035 | 0.042 |
| | | (0.020) | (0.016) |
| Incidents | Long gun | 0.082 | 0.102 |
| | | (0.042) | (0.032) |
| Injuries | Long gun | 0.046 | 0.060 |
| | | (0.033) | (0.028) |
| Fatalities | Long gun | 0.037 | 0.046 |
| | | (0.021) | (0.017) |
| | Observations | 3591 | 3591 |
| | Clusters | 127 | 127 |
| | Year FE | Y | Y |
| | Zip-4 FE | Y | Y |

Table A3: Gun Transactions and Gun Violence Incidents: Linear IV Estimates

Note: Table presents estimates of the effect of firearm transactions on gun-related incidents using the number of gun retailers as an instrumental variable. Column 1 is the outcome, Column 2 is the endogenous explanatory variables, Columns 3 and 4 present the elasticity estimates that correspond to two alternative measurements of the instrument . All variables are transformed by $\log(1+\cdot)$. Estimates are computed in a balanced panel of zip code-year observations. All regressions include fixed effects for 4-digit zip code and year. Standard errors clustered by four-digit zip code.

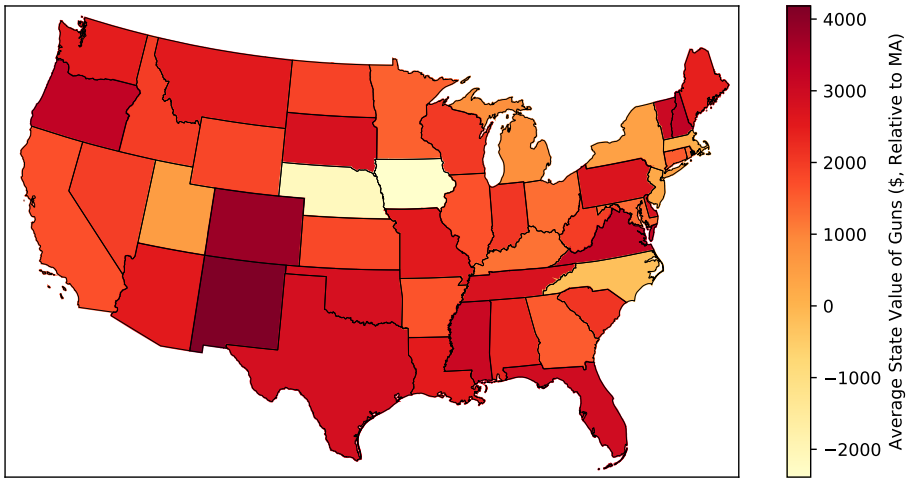



Figure shows the average value of $\tau_t$, $\bar{\tau}_s = \sum_{t:state(t)=s} \tau_t$ for each U.S. state from 2016-2022, divided by the price coefficient $\alpha$, to express the heterogeneity in willingness-to-pay for firearms across markets in dollar terms.

Figure A4: Average State-year Taste Shifters for Firearms, $\tau_t$, by State, in 2022 $

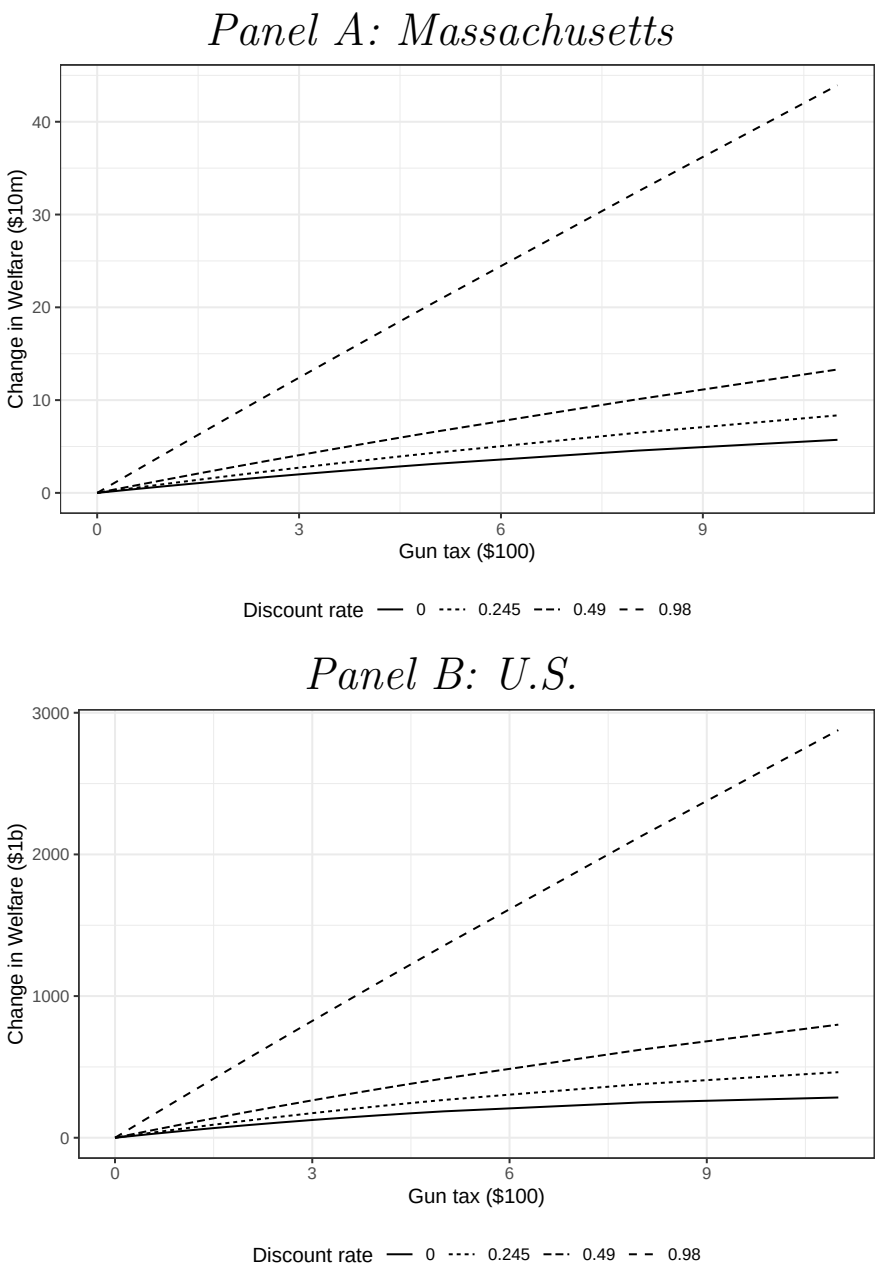



Figure A5: Changes in Welfare from Future Decreases in Firearm Violence

Figure shows change social welfare from counterfactual taxes on handguns and long guns under alternative assumptions about their future effects. Panel A is outcomes in Massachusetts, Panel B is outcomes in the U.S. Horizontal axis is tax set on both handguns and long guns tax. Color represents discounting horizon in years and line type represents the discount rate. Solid line corresponds to the diagonal of the matrix in Figure 14.