Second-Best Amendment: Market Power and Tax Design in the Firearms Industry*

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Abstract

This paper studies the roles of market power and taxes in determining market surplus and social welfare in the U.S. consumer firearms industry. We construct a dataset combining the prices and characteristics of firearms available to consumers, microdata on firearm transactions from Massachusetts, and aggregate purchase quantities from other states. We account for price endogeneity by constructing an instrument based on heterogeneous exposure to aggregate shocks in the costs of commodity metals, and estimate an own-price elasticity of -2.5 for the average firearm model. Using this data and variation, we estimate a model of national supply and demand for consumer firearms. Although firearm manufacturers charge markups which reduce quantity, a calibrated measure of public health costs implies that the equilibrium quantity of firearm purchases is still inefficiently high. Moreover, we find that the profit-maximizing markups across products do not equate equilibrium prices with the net social costs of firearm sales, creating scope for regulatory intervention. As such, we consider the redesign of a longstanding federal firearms tax, subject to a constraint that firearm consumers are not harmed. We show that a simple tax redesign leads manufacturers to set prices better-targeted towards social welfare, holding constant consumer surplus and industry profits, while improving public health. The distributional implications of this tax redesign suggest that it is politically feasible.

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1 Introduction

In 1918, to raise revenue for World War I, the U.S. government levied an excise tax of 10 percent on sales from firearm manufacturers (Congressional Research Service, 2023). Left untouched since 1954, these taxes have been a constant regulatory presence throughout the twentieth-century expansion of the consumer firearms industry (Brauer, 2013).[1] Manufacturers have developed firearms with new technological features and grown into multi-brand conglomerates, under these constant excise taxes, which help determine how firearms are priced to consumers. These prices guide consumers' choices of which firearms to purchase (Moshary et al., forthcoming), and since firearms are durable, the level and composition of the consumer firearm stock over time (Wertz et al., 2019). In 2015, there were more than 250 million firearms in circulation in the U.S., with implications for both crime and violence at the population level (Azrael et al. 2017, RAND 2018).

In this paper, we study how redesigns of the federal excise tax on firearm manufacturers would affect social welfare and market outcomes in the U.S. consumer firearms industry. To do so, we develop and estimate an equilibrium model of the U.S. consumer firearms industry, from which we simulate the market prices and quantities of firearms under alternate excise taxes. We pair our predictions of firearm quantity flows with a calibrated model of how regional gun stocks relate to firearm homicides, allowing us to quantify non-market implications of taxes on the firearm market. Our model reveals allocative inefficiency in the firearm market—due to heterogeneity across firearms in markups over marginal cost and effects on firearm homicides—which could be addressed through a simple redesign of the excise tax on firearm manufacturers. Tilting the federal rate on handguns to 14.5 percent and on long guns to 0 percent would hold consumer surplus and industry profits constant, while preventing 176 firearm homicides during our sample period.

The key challenge to our analysis is that few datasets match firearm purchase quantities to prices in the U.S. (Moshary et al., forthcoming), which we overcome by linking a variety of data sources, described in Section 2. We access transaction-level microdata with information on the make, model, and product characteristics of every licit handgun and long gun sale in Massachusetts from 2016-2022, as discussed in Armona and Rosenberg (2024). Since these data do not record prices, we scrape historical MSRPs from an industry publication, and merge these suggested prices with the Massachusetts transaction data. We also manually construct the history of mergers and acquisitions made by the 99 largest manufacturers of consumer firearms that sell in the United States. We measure aggregate firearm purchases

[1] In 1954, the rates were changed to 10% for pistols/revolvers, and 11% for all other firearms (e.g. rifles and shotguns)

outside Massachusetts using a standard proxy based on background checks conducted by the FBI as part of the firearm purchase process (Brauer, 2013).

In Section 3, we discuss features of the data that inform our model of the firearms industry. Consumers can choose among hundreds of firearms with heterogeneous physical characteristics, as the space of firearm caliber (a measure of power) and barrel length (a measure of accuracy) is essentially covered by both handgun and long gun models. Prices also vary across these heterogeneous firearms, with a mean of 1,300 dollars and a standard deviation of 1,800.

We then estimate the role of prices in driving firearm demand. To address price endogeneity, we construct an instrument for firearm prices using variation in the world commodity prices of metal inputs to firearm production (McDougal et al., 2020). Our instrument isolates cross-manufacturer heterogeneity in exposure to these common input cost shocks, by interacting manufacturer fixed effects with the time series of primary metal commodity prices (Villas-Boas, 2007). We avoid issues of weak identification with this high dimensional set of potential instruments by applying a dimension-reduction technique to approximate the optimal instruments (Belloni et al., 2012). Isolating these passed-through production costs, consumer responses to price variation imply an own-price elasticity of demand equal to -2.5 for the average firearm model in Massachusetts. This meaningful responsiveness suggests that taxes are a feasible policy instrument to shift firearm purchases.

Based on these facts, Section 4 develops and estimates an equilibrium model of consumers and manufacturers in the firearms industry (Berry et al., 1995). We specify consumers' preferences for heterogeneous firearms as a random coefficients nested logit, allowing preferences to depend on consumer demographics, as well as a number of fixed effects. Our demand estimates reveal substantial observable and unobservable heterogeneity in preferences for price and non-price firearm characteristics. Our estimated nesting parameters indicate limited substitutability between handguns and long guns, highlighting consumers' distinct motivations for purchasing firearms within each class (Azrael et al., 2017). Consumers' preferences for the purchase of any firearm also vary across geography, race, gender, and voting patterns, in-line with survey reports (Parker et al., 2017). We find that

Turning to supply, we assume that multi-product firearm manufacturers compete in Nash-Bertrand fashion under the federal excise tax, maximizing static profits each year by jointly setting prices on their firearms and those of their wholly owned subsidiaries. In setting prices, manufacturers face competition from pre-existing firearms on the second-hand market—which we model by including a composite used handgun and used long gun in the consumer choice set—though we assume that manufacturers do not account for second-hand market dynamics in their pricing decisions (Coase 1972, Goettler and Gordon 2011)[2] Our estimates imply that the average firearm in our estimation sample costs $450 dollars to produce but is priced to consumers at $870 dollars, with producers taking $325 in profit from each new gun sale, and the remainder going to government excise tax revenue. We find similar average price-cost margins for both handguns and long guns, though with considerable heterogeneity in margins across firearms within each class. We also find that the consumer firearms industry delivers substantial value to market participants. In the average year between 2016–2022, the firearm market delivered 71 dollars of consumer surplus to the average U.S. adult, or about $18 billion dollars annually.[3] We estimate that the industry generated 700 million dollars of revenue for the federal government per year, in line with official estimates.[4], and about 2.9 billion dollars of profit for firearm manufacturers.

To quantify the non-market effects of the consumer firearms industry, Section 5 introduces a stylized model of public health that links firearm purchases to firearm homicides. Since the market allocates flows of firearm purchases, but homicides respond to overall gun prevalence (i.e., the firearm stock), we calibrate a law of motion for durable handguns and long guns (Cook and Ludwig, 1996), and infer initial conditions from a survey of firearm owners in 2015 (Azrael et al., 2017). We then calibrate separate elasticities of firearm homicides with respect to the stocks of handguns and long guns, utilizing data on the share of firearm homicides committed with a handgun and existing estimates of the elasticity of firearm homicides with respect to proxy measures of firearms prevalence (Duggan 2001, Cook and Ludwig 2006). We find that on the margin, the average handgun purchase generates 30 times as many firearm homicides as the average long gun purchase. Our calibrations imply that the average firearm purchase in the U.S. generates firearms homicides at a welfare cost of roughly 250 dollars. Accounting for a firearm's full usable lifetime, our model implies that the average handgun purchase produces a flow of future homicides with a present cost of $5,260, while the average long gun purchase produces a present homicide cost of $163. These estimates reflect a key feature of the social costs of firearms: the large and durable existing stock means purchases today have a small impact on homicides. This somewhat limits the scope for interventions occuring solely in the market for new guns to fully address the public health consequences of legal firearms.

Our model estimates imply that neither handguns nor long guns are priced efficiently.

[2]We further assume that, each year, the set of firearms produced by a manufacturer is exogenous to the pricing game and that these firearms can be manufactured at a year-specific constant marginal cost.

[3]Comparable estimates from Grieco et al. (2023) value the new car market as producing 600 dollars of consumer surplus for the average U.S. adult in 2016.

[4]Source: https://www.ttb.gov/system/files?file=images/foia/xls/Quarterly-breakdown-of-FAET-collections.xlsx

The equilibrium price of an average handgun is an order of magnitude smaller than its net social cost, accounting for its marginal cost of production and implications for future firearm homicides. Although handgun manufacturers leverage market power to price above marginal cost, their profit-maximizing markups are too small to fully internalize the net social cost of a handgun sale. Conversely, the equilibrium price of the average long gun is higher than its net social cost, implying that market power is the primary distortion in the long gun market segment. Both distortions, market power and homicide externalities lead to equilibrium prices that create allocative inefficiency in the consumer firearms industry, suggesting a role for regulatory intervention.

In Section 6, we use our fitted models of supply, demand, and public health to study firearm regulation, focusing on a counterfactual redesign of the federal firearms excise tax. Based on a 2024 policy change in California—increasing the tax on firearms sales in the state to double the federal rate—we consider the effects of doubling the federal excise tax on firearm sales nationwide (CA A.B. 28, 2023). This tax change induces large and opposite effects on different welfare components, which net out to a \$320 million dollar increase in overall welfare per year. Notably, the incidence of this tax change falls similarly on firearms consumers (-\$400 million) and manufacturers (-\$570 million). These losses stem from an incomplete pass through of taxes to consumers by manufacturers, and consumer substitution to less preferred used guns (which are not subject to the excise tax). In addition, states with higher Republican vote shares are the most harmed by the tax. Given the politically polarized views on firearm regulation in the U.S., with Republicans generally supporting laxer policy (e.g., Parker et al. 2017, Gentzkow et al. 2019, Luca et al. 2020), this policy is likely to be politically infeasible, despite increasing overall welfare.

Inspired by these political constraints, we next study a Ramsey-style "second-best" problem of setting firearm taxes to maximize social welfare, without decreasing consumer surplus. We estimate gains from setting higher taxes on handgun purchase and lower taxes on long gun purchase, respectively targeting allocative inefficiencies due to the costs of additional firearm homicides and to market power. In particular, tilting the federal excise tax on handguns to 14.4 percent and zeroing out the long gun tax would hold constant consumer surplus and slighlty increase manufacturer profits, while preventing 176 firearm homicide fatalities between 2016 and 2022, leading to welfare gains of \$258 million per year, or 80% of the gain from doubling the excise tax. Moreover, these alternate taxes are consumer-surplus neutral across states with different Republican vote shares, and provide the greatest public health benefits to conservative regions of the U.S. These facts suggest that the economic gains from targeted handgun taxes may be politically feasible as well. We conclude that jointly understanding the nature of supply, demand, public health, and political constraints in the consumer firearms industry can help guide the design of effective firearm policy.

Our work relates to a growing literature on firearm markets (Koper and Roth 2002, Bice and Hemley 2002, Cook et al. 2007, Knight 2013, McDougal et al. 2023, Hüther 2023, Bollman et al. 2025), and is especially close to two recent papers. Moshary et al. (forthcoming) use a survey experiment and stated preference data to develop and estimate a model of firearm demand in product space, accounting for heterogeneous preferences over eighty firearm models and their hypothetical prices. Rosenberg (2024) uses non-overlapping administrative data from California to estimate a model of consumer preferences for an undifferentiated handgun and the relationship between preferences for handgun purchase and public health costs of handgun ownership. In contrast, we estimate consumer preferences over a firearm's price and its physical characteristics, which we pair with supply-side ownership data to recover the cost structure firearm manufacturers. By pairing our model of the firearm market with calibrated models of the firearm stock and its role in firearm homicides, we provide guidance on the effective design of firearm taxes, a topic that has been under-studied due to limited policy variation (Smart, 2021).

We also contribute to the literature concerned with the design of regulation to correct externalities in imperfectly competitive product markets (Pigou 1924, Buchanan 1969). Recent work has studied this question in the domains of beverages (O'Connell and Smith 2024, Conlon and Rao 2023) and personal transportation (Barwick et al. 2023). As in these other settings, we find that product-specific allocative distortions from price-cost margins due to market power are poorly targeted at the distortions due to consumption externalities. In our setting, the mis-targeting of firearm taxes under the status quo can be corrected in a manner that benefits consumers and producers, while also decreasing firearm homicide externalities. We also incorporate political economy considerations into the regulator's problem, an approach well-suited to the United States context.

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.[5] For each purchase from a dealer with a Federal Firearms License

[5] Other papers using these data include Braga and Hureau 2015, Johnson et al. 2023, Balakrishna and Wilbur 2022, and Iwama and McDevitt 2021.

(FFL), 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 at FFLs in the state of Massachusetts.[6]

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 firearm's make (manufacturer/brand), model, weapon class (handgun, rifle, or shotgun), and its physical characteristics (caliber, barrel length, a flag for high capacity, and surface finish). 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 designates weapons capable of accepting high capacity ammunition devices. Surface finish denotes the material/color on the exterior of the gun. The data includes additional information on the dealer/seller of the firearm, 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, including their gender, and the zip code in which they reside according to their state-issued firearm license. Each record also includes the transaction date. 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 can be recorded as inches, millimeters, or gauge (for shotguns). We do a similar exercise for barrel length. We manually standardize the manufacturer field for any manufacturers with at least 30 transactions in the data. We limit most of our analysis to the top 100 makes by transaction volume in Massachusetts, consisting of 92% of all transactions in the data.

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.[7] 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 that 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.

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

[7]Downloaded from https://www.bluebookofgunvalues.com

(forthcoming) documents little geographic variation within a firearm model across FFLs, suggesting that retail prices are set nationally. We take MSRP 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. BBGV 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 an approach based on fuzzy string matching.. We perform this merge in several steps, described in detail in Appendix A. In total, through this procedure, we are able to match 90% of FRB transactions to a unique firearm model in BBGV, for a total of 7,616 firearms with prices and quantities in our analysis. About 70% of these firearms are purchased during years in which they are actively produced. We assume for the remainder of the paper as if these actively produced guns were purchased new from a retailer and sold at the MSRP.

2.3 Auxiliary Datasets

Although the FRB and BBGV datasets list firearm makes, multiple makes may be wholly owned by a single parent company.[8] To account for this common ownership, we manually search for all mergers and acquisitions among the manufacturers appearing in the FRB data.

In order to understand demographic heterogeneity of buyers, we merge demographic data of buyers' zip codes from the 2019 5-year American Community Survey (ACS).[9] This includes the distribution of gender, age, race, education, and poverty in the zip code, along with the zip code's median household income and population density.

For calibrating our model of the effects of firearms stock on homicides, we use data from six sources. We measure the allocation of firearm owners across households in 2015 using the state-level estimates of Schell et al. (2020). We pair these with the count of households by state from the 2015 5-year ACS estimates. Within the household, we use microdata from the 2015 National Firearms Survey (Azrael et al., 2017) to estimate the average number of

[8]For example, the Italian firearm manufacturer Beretta wholly owns the other Italian firearm manufacturers of Benelli and Franchi.

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

firearm owners per household and the average number of firearms per firearm owner.[10] Prior to 2015, we use estimates of the firearm stock in 1994 from Cook and Ludwig (1996) and yearly estimates of the flow of firearms to U.S. consumers from the ATF firearm commerce reports.[11] Turning to public health, we calculate the share of firearm homicides in the U.S. between 2016–2022 that were committed with a handgun, among all firearm homicides in which the weapon class is known to the FBI, using the FBI's crime data explorer.[12]

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 Voting and Election Science Team (2018).[13] We aggregate precinct-level vote shares for all conservative candidates in the presidential election in 2016 to construct a "Percent Conservative" measure for each precinct in the United States.[14] 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 total number of votes.

We complement our transaction microdata in Massachusetts with data on criminal background checks from the FBI's National Instant Criminal Background Check System (NICS) to measure the number of guns sold in each state-year [15]. These 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 background check, so coverage varies from state to state (Lang, 2016). At the same time, because of its national coverage and reporting at a state-level, NICS is some of the highest fidelity data researchers have access to on purchases, so it is a commonly used proxy for the flow of guns from suppliers to consumers. These background checks are then adjusted using the methodology of Brauer (2013) to produce an estimate of the total number of gun sales in each state-year. In Appendix Figure A1, 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.

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. To account for this, we utilize wave 26 of the

[10] We thank Matthew Miller for sharing these data.

[11] Available at https://www.atf.gov/firearms/docs/report/2021-firearms-commerce-report/download.

[12] Available at https://cde.ucr.cjis.gov/LATEST/webapp/#/pages/explorer/crime/crime-trend.

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

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

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

American Trends Panel (ATP), conducted by Pew Research in April 2017, 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 consumer firearms market. We map these to the observed demographic characteristics of the respondents via a LASSO regression (Tibshirani, 1996), to create an estimate of the consumer firearms market size in each zip code-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 (by census region) 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. The LASSO then selects the variables to include in the linear probability model. We project these coefficients onto the observed zip code demographics to obtain our estimates of market size, which are about 2/3 of the adult population in each zipcode. Estimates from this LASSO routine are shown in Appendix Figure A2. 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.

2.4 Summary Statistics

Table 1 displays summary statistics on our set of matched gun models from BBGV to the Massachusetts FRB dataset. Handguns are typically shorter in length, and cheaper on average than long guns (rifles and shotguns). On average, prices for the average new firearm model are around \$1000 (not weighted by sales), though there is significant price variation even within a class of weapons, as indicated by the standard deviation upward of \$600. About 40% of long gun models are shotguns.

In Table 2, we display the demographic characteristics of firearm buyers in this market, based on their gender and zip code characteristics. Column (1) reports the the demographics of the Massachusetts adult population. 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 firearm purchases by weapon type. Relative to even the potential firearms consumer population, active gun buyers are more likely to be male, live in less racially diverse, more rural, and more politically conservative neighborhoods. These demographic patterns are more stark for long gun buyers relative to handgun buyers.

3 Descriptive Evidence

3.1 Trends in Firearm Purchases

We begin by documenting changes over time in the legal firearms market in Massachusetts.

In Panel(a) of Figure 1, we plot the aggregate number of purchases over time in Massachusetts, by month of transaction. About 110,000 firearms are purchased each year in Massachusetts. 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 sustains well into 2022. In Panel (b), we plot the composition of gun purchases in each month, by weapon characteristics. Handgun purchase rates are relatively stable over time, around 2/3 of all transactions. High-capacity weapons, in contrast, are more likely to be purchased in the later years of our sample. Finally, we see a sharp decline in the purchase of new guns in 2021, implying a shift towards used guns in the market. This is consistent with anecdotal evidence that during COVID 19, many gun manufacturers reached binding capacity constraints and were unable to keep up with the surge in demand.[16]

Figure 2 plots the mean and interquartile range of new gun prices (MSRP) of guns models purchased in Massachusetts during our sample. The plot highlights a great deal of cross-sectional variation in gun prices per year. To determine whether price changes over time are driven by changes in the composition of gun models , Figure 3 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 manufacturing industry, which devotes a large share of its expenditures to purchasing of inputs such as steel and copper[17]

In terms of the heterogeneity in firearm purchase patterns across demographic groups, we direct the reader to Armona and Rosenberg (2024), which documents distinct demographic patterns in purchase rates and the types of guns purchased by consumers in Massachusetts. We incorporate this demographic heterogeneity into our demand-side model of preferences in Section 4.

Figure 4 plots the distribution of barrel length and caliber within long guns and handguns.

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

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

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 space, 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.

3.2 Price Elasticity of Demand

We now describe the impact of price on consumer firearm demand. This is a critical object for the design of firearm policy, especially taxes, but challenging due to simultaneity between price changes and unobservable demand shocks. Addressing this simultaneity requires the use of instruments that shift price but are uncorrelated with demand.

We use input cost shocks as instruments for price, a popular approach in the demand estimation literature (Berry and Haile, 2021). This instrument is likely to work well in the firearms industry, where much of the costs are tied up in the purchase of production materials, such as steel and aluminum. According to the 2017 BEA Input-Output Tables, intermediate inputs account for 63% of costs, and among intermediate inputs, 35% of purchases are on primary metals (e.g. steel) and fabricated metal products (e.g. iron molds).[18]

Because we do not observe the exact mix of material used in firearm production, we propose a strategy to construct cost shocks in the spirit of Villas-Boas (2007), by flexibly approximating manufacturer-specific production functions. Explicitly, we assume a unique manufacturer-level response function to the prices of metal commodities. We use these interactions to predict firearm prices, and then use the predicted prices as instruments for the observed prices in the sales data. This mirrors the strategy of McDougal et al. (2020), which uses the prices of hot and cold rolled steel to estimate the price elasticity of aggregate firearm demand.

For our set of potential inputs, we use the prices of primary metal commodities from the Bureau of Labor Statistics' monthly PPI commodity data series.[19] We aggregate these to annual price indices with 2016, the first year of our sample, as the base year. This provides us with 51 time series for the prices of potential firearms inputs, ranging from carbon steel scrap to copper ore. Our rationale for using these commodity prices as instruments is that these raw materials are traded in global commodity markets, and so changes to the price of

[18]Source: author's calculations using intermediate inputs for "Ammunition, arms, ordnance, and accessories manufacturing" commodities (excluding inputs from the same commodity type). Data downloaded from https://www.bea.gov/data/industries/input-output-accounts-data

[19]See https://download.bls.gov/pub/time.series/wp/wp.txt for a description of the dataset. We use all 6-digit commodity series beginning with 101 and 102, denoting iron/steel and nonferrous metals, respectively.

these inputs are unlikely to be related to the demand for firearms in Massachusetts. Our empirical specification is as follows:

$$\log(p_{j,t}) = \gamma_{j,1} + \eta_{c,t,1} + \sum_{k=1}^{51}(\beta_{m(j),k}\log(\tilde{p}_{k,t})) + \epsilon_{j,t} \tag{1}$$

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

where $p_{j,t}$ is price, γ_j denotes gun model fixed effects, $\eta_{c,t}$ denotes year $\times$ weapon class (long gun versus handgun) fixed effects, $\tilde{p}_{k,t}$ denotes the price index in year t of input k, $\beta_{m(j)}$ denotes a coefficient on input prices allowed to vary by manufacturer m of gun model j, and $\xi_{j,t}$ is the unexplained component of sales, stemming from, for example, unobserved demand shocks. To avoid selection bias incurred from some models exiting the sample due to zero sales, 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).[20] Assuming the log approximation is accurate, α represents a price elasticity, and captures both extensive (buying no gun) and intensive (switching to a different gun model) margins of demand.

The specification in Equations 1 and 2 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 demand through their impact on price.

Figure 5 shows the annual variation in the 51 input price indices used for identification, grouped by the 2-digit code of each commodity. As we can see, there is large variation in the evolution of these commodity prices, with many commodities doubling in price since 2016. The largest shock to these input prices coincides with the COVID-19 pandemic, which spurred a series of supply chain issues across 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 in input prices. For this reason, our year fixed effects η 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 carbon steel scrap to produce firearms, they will be more exposed to the jump in the carbon steel scrap price in 2021, relative to a manufacturer that uses other metals during production, and so would have a positive coefficient $\beta_{m,\text{carbon steel scrap}}$.

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

The primary threat to identification would be if demand shocks, such as COVID-19, were correlated with the reliance of certain manufacturers on particular inputs. For example, if the surge in gun demand during COVID-19 was driven by a surge in demand for guns made out of carbon steel scrap specifically, then our estimation procedure would violate the exclusion restriction. As additional protection against this type of simultaneity, we note that firearm pricing is likely to respond to national demand shocks, while we estimate demand from consumers in Massachusetts, which accounts for only 0.8% of national firearms sales.[21] Thus, even if our exclusion restriction were to be invalid at the national level, it may still hold within Massachusetts, where local demand shocks are unlikely to affect pricing strategy.

We restrict the estimation sample to those 422 models that have at least 100 purchases during our sample period; this accounts for 93% of all transactions on new guns, and represents 66 manufacturers in the data. As a result, we have $66 \times 51 > 3,000$ potential instruments, more than the number of gun-year observations in our sample, leaving our OLS first-stage regression un-identified. Even if we pruned the set of commodities to have a manageable set of instruments, weak instruments impacting our identification would be a major concern. Since, for some manufacturers, production processes may be standardized and mimic those of their competitors, yielding little useful variation in production.

For this reason, we apply the routine described in Belloni et al. (2012) and estimate the first stage via a Post-OLS LASSO IV. 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 time and gun model fixed effects always partialed out.

Figure 6 displays the selected (non-zero) coefficients from our baseline specification with gun model and weapon-class times year fixed effects (Panel A), along with the fit of the annual change in LASSO predicted prices versus the annual change in observed MSRP (Panel B),

[21] Calculated from NICS Background check data.

indicating a good fit and a strong first stage. From the potential set of 3,366 instruments, 6 are selected, suggesting that the pruning done in the first stage is important and many of the manufacturer-specific coefficients are uninformative. Unsurprisingly, the 6 instruments selected in the first stage are associated with the largest manufacturers in the data. The selected instruments shift the prices of 40% of the gun models in our sample, ensuring our elasticity estimates are not driven by the price changes of only a few models.

Table 3 shows the results for the Post-LASSO IV in the reduced form. In Column (1), we report the OLS estimates from regressing purchases on price using two-way fixed effects. We estimate a negative price elasticity that implies inelastic demand (-0.73). Because consumers in Massachusetts may be subject to national product-level shocks that are considered when manufacturers set MSRP, this estimate may be biased. In Column (2), we report the Post-LASSO IV estimate. Here, the point estimate is larger in magnitude. The estimated price elasticity changes qualitatively, to -2.6, implying consumers are fairly elastic to changes in gun prices. Because the standard F-test for relevance is invalid, 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 12.4 is well above the critical value of 4.56 for 1% significance. Column (3), our preferred estimate, adds class $\times$ year in place of year fixed effects, allowing for differential time trends in demand for long guns and hand guns. The point estimate is similar to Column (2) and estimated to be -2.49.

In Appendix Table A1, we vary the granularity of the commodity indices used from 1-digt (ferrous versus non-ferrous metals) to 6-digit (our original 51 commodity price indices). Our results are not sensitive to this choice and consistently estimate an own-price elasticity of around -2.

This estimate is more elastic than the estimates of Moshary et al. (forthcoming), which relied on survey data to elicit willingness-to-pay. Our contrasting results suggest that price-based policy instruments, such as changes to federal excise taxes, may be an effective policy tool to shift consumer choice in this market. However, these estimates are specific to the average firearm model, and they do not speak to the differential models of substitution (e.g., exiting the market or buying a different weapon) in which consumers may engage. With this limitation in mind, the following section introduces a model of supply and demand in the firearm market. By imposing additional assumptions on the behavior of firearm consumers and manufacturers, our model allows us to better isolate the forces described in this section and to evaluate the efficacy of certain firearm regulations.

4 An Equilibrium Model of the Legal Firearms Market

We estimate a model of firearm demand and imperfectly competitive firearm supply in the style of Berry et al. (1995), based on firearm transaction data from Massachusetts. The model accounts for heterogeneous preferences based on a consumer's gender and the characteristics of the neighborhood in which they reside. We also allow for unobserved differences in individual-preferences via random coefficients and a nested logit structure. We extrapolate our estimated parameters from Massachusetts to the rest of the United States using moment matching conditions, assuming the distributions of unobservable preferences 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 fraction of predicted potential gun owners based on the Pew survey on gun ownership described in Section 2, multiplied by the 2015-2019 ACS estimates of adult population in each state. Market size is constant within state s over years y.

We define the choice set $\mathcal{J}_y$ to be constant across consumers and to include all actively produced guns (those with MSRP data) that have at least 50 purchases in a particular year y in the FRB transaction data, and prices below \$2,500. This totals 341 unique firearm models across 58 manufacturers, providing 1,330 model-by-year observations.

Indirect utility from consumer i purchasing a new gun $j \in \mathcal{J}_y$ in market t is defined as follows:

$$u_{i,j,t} = -\alpha_i p_{j,y} + \beta_i X_j + \delta_{j,t} + \epsilon_{i,j,t}. \tag{3}$$

$$\delta_{j,t} = \delta_j + \tau_t + \phi_{c,y} + \xi_{j,y} \tag{4}$$

$$\beta_i = \beta + D_i \Pi + \Sigma \vec{\nu}_i \tag{5}$$

$$\alpha_i = \exp(\alpha + D_i' \Pi_\alpha + \sigma_\alpha \nu_{i,\alpha}) \tag{6}$$

$\delta_{j,t}$ denotes the mean utility of a gun in market t. It is composed of fixed effects by product δ_j, market τ_t, class-year $\phi_{c,y}$, as well as an unobservable product-year demand shock $\xi_{j,y}$. As we only observe transaction data from one state, we normalize $\tau_t = 0$ for Massachusetts each year during estimation, so that $\tau_t \neq 0$ measures the vertical taste for firearm purchase relative to consumers in Massachusetts. Under this normalization, mean utilities in Massachusetts can be equivalently expressed as $\delta_{j,y}$, which we exploit during estimation.

β_i denotes the consumer taste for the physical, non-price characteristics of a firearm. D_i is a matrix of consumer demographics, and Π is a matrix mapping demographics to preferences for gun characteristics. $\vec{\nu}_i \sim N(0, I)$ is an i.i.d. random taste for gun characteristics, and Σ is a diagonal matrix controlling the importance of random unobserved heterogeneity for each characteristic. α_i is defined analogously to be the consumer's price sensitivity to the (CPI-adjusted) MSRP $p_{j,y}$, which is assumed to be constant across states each year. We exponentiate to ensure that consumers dislike higher prices $\alpha_i > 0$.

We assume that the idiosyncratic error term ϵ follows the distribution of a three-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 parameter ρ_0 controls the degree of correlation between the idiosyncratic errors of all guns. We then partition the inside goods into two nests based on weapon class c (long gun, which includes rifles and shotguns, and handgun). The parameter $\rho_1 \leq \rho_0$ controls the degree of correlation for guns within a class. In particular, the error term ϵ has the following structure:

$$\epsilon_{i,j,t} = \zeta_{i,0,t} + \rho_0 \zeta_{i,c,t} + \rho_1 \tilde{\epsilon}_{i,j,t}$$

Values of $\rho \approx 0$ imply a high degree of correlation within a nest, while $\rho \approx 1$ implies no correlation. ζ denote idiosyncratic shocks that are common within each nest, 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.

Though we take a characteristic-based modeling approach for the actively produced guns, a substantial fraction of guns purchased in Massachusetts are not under active production, since guns are a durable good. These guns may differ from the guns purchased "brand new," that we explicitly model in $\mathcal{J}_y$, due to variation in condition and price. For this reason, we also include in the choice set $\mathcal{J}_y$ a class-specific composite good $\omega_{c,y}$, representing guns that are no longer in production (82% of transactions in the composite good), guns that are purchased at a low frequency (< 50 purchases, 16% of transactions), guns with very high prices ($\geq$ \$2500, 1.1% of transactions), or guns which we are unable to match to a BBGV gun model (0.2% of transactions). Given its makeup, this composite good $\omega_{c,y}$ effectively represents used guns, and some niche products with a small market share. The utility the consumer derives from this used good composite is:

$$u_{i,\omega,c,t} = \delta_{\omega,c,y} + D_i \Pi_\omega + \sigma_\omega \nu_{i,\omega} + \epsilon_{i,\omega,c,t} \tag{7}$$

Where $\delta_{\omega,c,y}$ includes all utility components found for new guns in Equation 4.

Finally, we specify the value of the outside option, choosing to not legally purchase a firearm from a licensed dealer, as having mean utility normalized to zero with an i.i.d.

extreme value type I shock:

$$u_{i,0,t} = \epsilon_{i,0,t}. \tag{8}$$

Demographics D_i are composed of a binary gender variable, and characteristics of the zip code in which the consumer resides. These zip code characteristics are: % White, % Conservative (as measured by the % voting for a conservative candidate in 2016), the logged median household income of the zip code, and the logged population density per square mile. We center each coefficient around the national mean, so that the coefficients α, β can be understood as the taste for characteristics for a consumer with average U.S. demographics. For gun 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 indicators for long guns and shotguns.

For notational convenience, we write the utility of a consumer i from choosing product j in market t as a component $V_{i,j,t}$ plus the idiosyncratic shock:

$$\begin{aligned} u_{i,j,t} &\equiv V_{i,j,t} + \epsilon_{i,j,t} \\ V_{i,j,t} &= -\alpha_i p_{j,y} + \beta_i X_j + \delta_{j,t} \end{aligned}$$

Given the nesting structure specified for $\epsilon_{i,j,t}$, we can express the probability of a consumer i with characteristics $D_i, \vec{\nu}_i$ purchasing gun j as the product of three nest-level probabilities. As is typical in nested logit models, we express these as functions of the inclusive value of each nest, representing the expected utility derived from the best gun in each nest. Integrating out the idiosyncratic error term $\epsilon_{i,j,t}$, and moving from the lower to upper nests, these probabilities are:

$$Pr(j|i,t,j \in c) = \frac{\exp(V_{i,j,t}/\rho_c)}{\sum_{k \in c} \exp(V_{i,k,t}/\rho_c)} \tag{Product Shares | on Class}$$

$$IV_{i,c,t} = \log(\sum_{k \in c} \exp(V_{i,k,t}/\rho_c)) \tag{Inclusive Value of Class}$$

$$Pr(j \in c|i,t,j \neq 0) = \frac{\exp(\frac{\rho_1}{\rho_0} IV_{i,c,t})}{\sum_{c'} \exp(\frac{\rho_1}{\rho_0} IV_{i,c',t})} \tag{Class Shares | Inside Good}$$

$$IV_{i,1,t} = \log(\sum_{c} \exp(\frac{\rho_1}{\rho_0} IV_{i,c,t})) \tag{Inclusive Value of Inside Good}$$

$$Pr(j \neq 0|i,t) = \exp(\rho_0 IV_{i,1,t})/(1 + \exp(\rho_0 IV_{i,1,t})) \tag{Inside Good Share}$$

$$E[\max_j u_{i,j,t}] = \log(1 + \exp(\rho_0 IV_{i,1,t})) \tag{Expected Utility}$$

$$Pr(j|i,t) = Pr(j|i,t,j \in c) \cdot Pr(j \in c|i,t,j \neq 0) \cdot Pr(j \neq 0|i,t) \tag{Unconditional Market Shares}$$

We define the expected utility value $E[\max u_{i,j,t}]$ as consumer surplus, and convert from utils to dollars by rescaling using the inverse of the price coefficient $1/\alpha_i$ for each consumer.

4.2 Estimation Routine

We estimate the demand model in three steps. First, we estimate the mean utilities and parameters governing preference heterogeneity $\theta = (\delta_{j,t}, \rho, \alpha, \Pi, \Sigma, \Pi_\alpha, \sigma_\alpha, \Pi_\omega, \sigma_\omega)$ via constrained MLE ((Goolsbee and Petrin, 2004), (Train, 2009)) using the FRB transaction data in Massachusetts. Next, we estimate the baseline parameters governing tastes for characteristics β via a projection of δ_j on the time-invariant characteristics X_j. That is, we run the linear regression specified in Equation 4, then use the estimated fixed effects $\hat{\delta}_j$ to estimate β via a GLS regression, weighted by the variance matrix of fixed effects $\hat{V}$ (Nevo, 2000). Finally, we estimate the market-specific tastes for firearms τ_t across state-years using the NICS background check data.

4.2.1 Gun Choice

We collapse the Massachusetts FRB data by gender-zip code-demographic cell, denoted d, each year y. Let $\mathcal{T}_{MA}$ denote the markets (state-years) in Massachusetts, $N_{j,d,t}$ the number of individuals purchasing product j in demographic cell d, and $\mathcal{D}_{MA}$ the set of these demographic cells. Conditional on d, consumers in each cell differ only due to the normally distributed unobserved heterogeneity, so demographic cell market shares are as follows:

$$Pr(j|d,c) = \int_{\vec{\nu}} Pr(j|D_i = d, t, \nu_i = \nu)\phi(\vec{\nu})d\vec{\nu} \tag{9}$$

where ϕ represents the standard multivariate normal pdf. As this high-dimensional integral has no closed form, we approximate its value using sparse grid quadrature (Conlon and Gortmaker, 2020). We solve the following constrained maximum likelihood problem:

$$\max_{\theta} \sum_{y} \sum_{d \in \mathcal{D}_{MA}} \sum_{j \in \mathcal{J}_{y(t)}} N_{j,d,t} \log(Pr(j|d,c)) \tag{10}$$

$$\text{Subject to: } Pr(j|t) = \hat{s}_{j,t} \quad \forall j \in \mathcal{J}_{y(t)}, t \in \mathcal{T}_{MA} \tag{11}$$

$$E[\xi_{j,y} \cdot \vec{Z}_{j,y}] = 0 \tag{12}$$

$$E[\phi_{c,y} \cdot \tilde{J}_{cy}] = 0 \quad \forall c. \tag{13}$$

This is a standard MLE problem, with three sets of additional constraints which we explain below. Equation 11 constrains the predicted state-level choice probabilities $Pr(j|t)$

to match the empirically observed choice probabilities/market shares $\hat{s}_{j,t}$ in the FRB data (Goolsbee and Petrin, 2004). Given θ, $Pr(j|t)$ can be calculated by integrating over the distribution of demographic cells d in Massachusetts.

$$s_{j,t} = Pr(j|t) = \frac{\sum_{d\in\mathcal{D}_{MA}} M_{d,t} Pr(j|d,t)}{\sum_{d\in\mathcal{D}_{MA}} M_{d,t}} \tag{14}$$

where $M_{d,t}$ is the market size (potential gun consumers) belonging to demographic cells d. The empirical analogue to this model-derived probability is the quantity $\hat{s}_{j,t}$, the empirically observed probability of gun j being chosen in market t:

$$\hat{s}_{j,t} = \frac{\sum_{d\in\mathcal{D}_{MA}} N_{j,d,t}}{\sum_{d\in\mathcal{D}_{MA}} M_{d,t}}$$

This constraint exactly identifies the mean utilities $\delta_{j,t}$ across products. We implement this constraint via the contraction mapping suggested in Conlon and Gortmaker (2020).

A threat to identification of θ, and in particular α, is that the national MSRP $p_{j,y}$ may be correlated with the unobserved product-year demand shock $\xi_{c,y}$, due to market power among firearm manufacturers. For this reason, we also impose during optimization the moment in Equation 12, that the demand shock is orthogonal to a matrix of instruments. For identifying α, we use the same (residualized) manufacturer specific commodity response functions $Z_{1,j,t}$ described in Section 3.2[22]. This ensures that α is identified off of price shifts unrelated to demand shifts. It is analogous to the moments used in Berry et al. (1995) to identify price sensitivity in a method of moments demand estimation framework.

Identification of the nesting parameters ρ_1, ρ_0 requires instruments that shift the market shares of products conditional on class $Pr(j|i,t,j\in c)$, and weapon class shares conditional on purchase $Pr(j \in c|i,t,j \neq 0)$, respectively (Verboven, 1996). To identify ρ_1, we include in $\vec{Z}_{j,t}$, a variant of the differentiation instruments proposed in Gandhi and Houde (2019), denoted $Z_{2,j,t}$, that measures the relative impact of cost shocks with respect to rival goods in the same nest:

$$Z_{2,j,t} = \sum_{k\in c(j), f(j)\neq f(k)} (Z_{1,j,t} - Z_{1,k,t})^2 \tag{15}$$

This instrument captures the relative impact of cost shocks on demand for product j, relative to its competitors owned by different firms f that are in the same class, and should be negatively correlated with conditional product shares.

[22]Residuals are taken by regressing the instrument on product and class-year fixed effects. To increase the power of these instruments, we perform the LASSOIV procedure on all products seen in the BBGV data that share a manufacturer with a product in the demand model. Note also that the composite goods $\omega_{c,y}$ are excluded from this expectation.

Our final constraint (Equation (13)) uses variation in the choice set size to identify the outside option nesting parameter ρ_0. We implement this identification econometrically by satisfying that the time series of preference shocks ϕ_{cy} is orthogonal to time series variation in the (de-meaned) count of firearm models $\tilde{J}_{c,y} = |\mathcal{J}_{cy}| - \frac{1}{N_{c,y}} \sum_{c,y} |\mathcal{J}_{cy}|$ in each class. This moment condition extends the approach of identifying the nesting parameter based on the entry and exit of goods from the choice set to our setting with multiple levels of nesting (e.g., Miller and Weinberg 2017, Gandhi and Nevo 2021). Choice set size, ceterus paribus, should be positively correlated with conditional class shares.

To interpret the choice set variation that identifies the nesting parameter ρ_0, Panel (a) of Appendix Figure A3 shows the variation from year-to-year in the size of the choice set $|\mathcal{J}_{c,y}|$ over our sample. Much of the variation in the choice set size comes from eight mergers and acquisition activities occurring across the 58 manufacturers in our sample. For example, in Panel (b), we plot a case study of the change in the number of models produced (according to the Blue Book of Gun Values) by Remington and Marlin Firearms, two manufacturers owned by Remington Outdoor Company. In 2020, Remington Outdoor Company filed for bankruptcy, and the two manufacturers were sold to different companies (Sturm Ruger and Roundhill Group).[23] Collectively, these manufacturers accounted for approximately 5% market share of new guns sold in Massachusetts prior to the bankruptcy in 2019, dropping to less than 1% percent by 2021, in part because Roundhill group delayed production and eventually closed a major firearms plant.[24]

To identify the parameters governing heterogeneous tastes for gun characteristics $\Pi, \Pi_\alpha, \Pi_\omega$, we use the differential buying patterns within a product across consumers in different gender-zip code cells. We identify the scale of the unobserved heterogeneity $\Sigma, \sigma_\alpha, \sigma_\omega$ via the entry and exit of products with differing characteristics.

4.2.2 Baseline Tastes

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

[23]Source: https://www.nytimes.com/2020/07/28/business/remington-bankruptcy-guns.html

[24]Source: https://www.wktv.com/news/top-stories/remarms-ilion-operation-to-close-march-2024/article_55edb272-8fbd-11ee-9b84-1b80825a8ee7.html

4.2.3 Market-level Tastes

Finally, we use the NICS background check data to identify the vertical taste-shifter for firearm purchase τ_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 τ_t affects all goods equally in any market, it can be separated from the inclusive value of the inside good. We solve for the value of τ_t in each market that sets the model-predicted choice probabilities to their observed inside good share:

$$Pr(j \neq 0|t) = \frac{\sum_{d \in \mathcal{D}_t} M_{d,t} Pr(j \neq 0|d,t)}{\sum_{d \in \mathcal{D}_t} M_{d,t}} = \frac{1}{\sum_{d \in \mathcal{D}_t} M_{d,t}} \sum_{d \in \mathcal{D}_t} M_{d,t} \int_v \frac{\exp(\tau_t + \rho_0 I_{i,1,t}(d,v))}{1 + \exp(\tau_t + \rho_0 I_{i,1,t}(d,v))} \phi(v) dv.$$

Where $I_{i,1,t}(d,v)$ denotes the implied inclusive value of the inside good for a consumer with observed demographics d, unobserved random preferences v, and a taste shifter of $\tau = 0$.

Our approach of identifying preference heterogeneity from a single market, then extrapolating to others (up to a vertical taste shifter) is similar in spirit to the approach taken by Elliott et al. (2023) to infer demand for mobile phones in France. Their work uses microdata from a single firm and aggregate data from the market to infer demand for different products. Whereas, we use microdata from a single state (Massachusetts) to estimate the heterogeneous structure of preferences across products, and then aggregate NICS data on the inside good to infer market-level demand shifters τ.

4.3 Assumption and Limitations

The above demand model is able to flexibly estimate heterogeneous preferences among consumers with different observable characteristics, accounting for various unobservable sources of utility and correlated patterns of substitution across firearm products. Moreover, casting the demand model as a discrete choice problem allows for tractable estimation. However, the model has several key assumptions we wish to highlight here.

Our assumption of discrete choice demand allows us to treat observed purchases as effectively the "share" of consumers in a market who purchase a firearm. Yet, it is a well known fact that around two-thirds of firearm purchases are made by repeat buyers who already own at least one firearm (Miller et al., 2022). As we lack data on individual identifiers in the FRB data, we cannot disentangle first-time and repeat buyers, who may differ unobservably in their preferences. Therefore, we interpret our estimated demand parameters as a purchase-weighted blend of extensive and intensive margin preferences for firearms. This affects our interpretation of consumer surplus in counterfactuals, but does not affect our interpretation of firearm supply, where the relevant object is firearm purchases, regardless of the buyer's characteristics.

Our strongest assumption is that the distribution of preferences for firearms differ only due to individual demographics and the market-specific vertical shifter τ_t representing market-level heterogeneity in tastes for firearms. As we have access to transaction-level data for only the state of Massachusetts, our parameters (besides τ_t) are entirely identified by variation within that state. Moreover, Massachusetts has atypically stringent firearm regulations for the U.S.,[25] including the provision that all handguns models on offer to consumers must be registered on the state's approved firearms roster.[26] Our estimation strategy requires that the set of firearms available in Massachusetts $\mathcal{J}_y$ are the same as elsewhere in the U.S. Insofar as choice sets differ across states, this may load onto τ_t and bias our estimates of consumer welfare across markets. In practice, many large-scale manufacturers produce firearm models that are compliant with Massachusetts' regulations and available on the roster, but offer a slightly modified version to consumers in other states.[27] In Section 4.5, we evaluate the predictive power of our model outside of Massachusetts, and find it broadly aligns with out-of-sample moments of national demand.

4.4 Supply

With our estimates of national gun demand, we estimate the supply side of the market, allowing us to recover the structure of marginal costs and markups. We assume that firms set national prices $p_{j,y}$ each year accounting for the demand in the entire U.S.. Firms f are defined as owners-by-years, and set prices in a static fashion. These firms f are the holding corporations of each gun manufacturer, and so a single firm may be responsible for setting gun prices across multiple manufacturers (e.g. brands). We assume that firms are endowed with a constant marginal cost of production $c_{j,y}$ for each gun model j produced by the firm in year y.

We also incorporate the excise taxes—stable since 1954 (Congressional Research Service, 2023)—into the the firm's optimization problem. In particular, there is an ad valorem excise tax of v_j imposed at the production stage on each product j. In the current equilibrium, $v_j = 0.11$ for long guns, and $v_j = 0.10$ for hand guns.

Firms engage in Nash-Bertrand competition to maximize static profits in each year under

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

[26] See https://www.mass.gov/lists/approved-firearms-rosters. Long guns are under no such restrictions in Massachusetts.

[27] Frequently this modification is at a finer level than we can measure with our choice of product characteristics X_j, limiting the practical impact of this potential misspecification.

the excise taxes:

$$\max_{\vec{p}_f} \sum_{j \in \mathcal{J}_f} (1 - v_j) p_{j,y} \cdot q_{j,y}(\vec{p}_y) - c_{j,y} \cdot q_{j,y}(\vec{p}_y) \tag{16}$$

where $\mathcal{J}_f$ are the set of new guns sold in each year by firm f, $\vec{p}_f$ is the vector of MSRPs for these products, and $\vec{p}_y$ is the MSRP of all new guns on the market in year y. The function $q_{j,y}(\vec{p}_y)$ is the aggregate demand across states for product j in year y at prices $\vec{p}_y$.

$$q_{j,y}(\vec{p}_y) = \sum_{t \in \mathcal{T}_y} \sum_{d \in \mathcal{D}_t} M_{d,t} Pr(j|d,t)$$

where $\mathcal{T}_y$ is the set of markets in year y. The first order condition for firm f's profit maximization is as follows:

$$\frac{\partial \Pi_f}{\partial p_j} = (1 - v_j) q_{j,y} + \sum_{k \in \mathcal{J}_f} (1 - v_k) p_{k,y} \frac{\partial q_{k,y}}{\partial p_j} - c_{k,y} \frac{\partial q_k}{\partial p_j} = 0 \tag{17}$$

Re-arranging this first order condition, we obtain an expression for the marginal cost of firearms production:

$$\vec{c}_f = (1 - \vec{v}_f) \otimes (\vec{p}_f - \Delta_f^{-1} \cdot \vec{q}_f) \tag{18}$$

where Δ_f is the $|\mathcal{J}_f| \times |\mathcal{J}_f|$ matrix of cross-price derivatives (e.g. $\Delta_{j,k} = \partial q_j / \partial p_k$). Given estimates of demand using the approach outlined in Section 4.2, we can recover the marginal cost directly from the firm's first-order condition.

In choosing prices $\vec{p}_f$, each firm f faces competition from its competitors f' operating in the same year and from used firearms $\omega_{c,y}$. We assume that used firearms are competitively supplied, such that firm pricing of new guns cannot affect the price of used firearms. We also assume that firms do not account for the impact of their sales today on the availability of used firearms in the future (Coase, 1972).

4.5 Model Estimates

We now describe our demand estimates. In Table 4, we report the full set of preference parameters (besides the mean utilities) recovered from the Massachusetts data, along with standard errors.[28] The outside option has a nesting parameter of $\rho_0 = .89$, suggesting reasonable flexibility between buying a gun and choosing to purchase nothing. Our estimate of intra-class substitution is more substantial, as indicated by the estimate of $\rho_1 = .24$. Our estimates of σ suggest that there are substantial unobserved preferences for used guns,

[28] Standard errors are calculated using the corrected formula for constrained maximum likelihood described in Moore et al. (2008).

and shotguns, while there is more flexible substitution between guns with different calibers, lengths, and capacities.

In order to more easily interpret our demand estimates, we present in Table 5 preferences for characteristics β_i in money-metric terms, scaling our estimates by the price coefficient α_i, so estimates can be interpreted in terms of a consumer's willingness to pay (in dollars) for each characteristic. In the first column, we report the average willingness-to-pay for each characteristic, while the remaining columns report the difference from this average along each demographic dimension. We find that consumers across the demographic distribution have similar average tastes for firearms with longer barrel lengths, but differ in taste for higher caliber weapons. Consumers living in denser, richer, and more racially diverse zip codes have higher tastes for handguns (relative to long guns) and high capacity weapons. In contrast, those living in white and conservative areas have higher tastes for long guns. These patterns are consistent with the distinct market segments served by these firearms. For example, more than 70 percent of handgun owners cite protection from people as a reason for ownership, while more than 50 percent of long gun owners cite hunting as a reason (Azrael et al., 2017).

Panel (a) of Figure 7 displays the estimated own price elasticities at the product level in the United States.[29] We estimate an average (median) own-price elasticity of -2.4 (-2.2), consistent with our reduced form results. Average Elasticities are very similar across firearm classes (-2.44 for handguns and -2.33 for long guns), though elasticities are more dispersed within long guns (Standard deviations of 0.5 and 0.9 by class, respectively).

Panel (b) shows how consumers substitute across product types. We display the average diversion ratios (Conlon and Mortimer, 2021) by gun type to other firearms and the outside option. These diversion ratios capture the probability that a consumer who chooses not to purchase a product due to a marginal price increase (switchers) will choose to another alternative k instead. About 20% of new gun buyers and 40% of used gun buyers exit the market when switchingfrom their product. As our estimate of ρ_1 implies strong intra-class preference, across all products, substitution to another class of weapon is very small. The estimates also imply a moderate degree of substitution between new and used guns within class. These substitution patterns imply distinct price elasticities for gun classes compared to those for specific gun models. We simulate a uniform 1% price increase for new handguns (long guns), and find that the aggregate class-specific price elasticity is -.34 for all handguns (-.22 for long guns). This is driven in part by substitution to used guns when new guns increase in price.

Figure 8 uses our estimated demand parameters to plot the annual average consumer

[29] In both panels, estimates are very similar if we focus on only Massachusetts. Price elasticities are slightly lower in Massachusetts, as its consumers tend to have higher incomes.

surplus (per adult) from the legal firearms market. We estimate that the annual consumer surplus from the firearms market is 17.95 billion dollars, or 71 dollars per adult. There is substantial variation across U.S. states, in a manner consistent with gun ownership rates across these geographies Schell et al. (2020). In Massachusetts, where we estimate the demand system, consumer surplus is relatively low, only $23 per person per year.

The differences in consumer surplus across states stem from a combination of the differences in demographic preferences for firearms, along with the market-specific taste shifter τ_t. In Appendix Figure A4, we display the average estimate of the cross-market taste for firearms τ_t/α_i for each state during our sample period. This quantity captures additional preference for firearm purchase relative to Massachusetts, after accounting for differing demographics across the U.S. The figure shows considerable variation in taste for firearms, ranging up to a thousand dollars. Some interesting patterns emerge from the figure. For example, North Carolina has a firearm purchase rate of 3.5%, similar to Massachusetts. Yet North Carolina's consumers are willing to pay $325 less on average for the same firearm, conditional on demographics. This stems from the preference estimates in Table 5: North Carolina is a more right-leaning, rural, and whiter state, so our demographic preferences predict that demand should be higher. The fact that we see individuals buy firearms in North Carolina at a rate similar to Massachusetts implies that consumers in North Carolina must have an unobservably lower preferences for firearms.

We now turn to our estimates of the supply side of the market. In Panel (a) of Figure 9, we display estimates of the markups charged by firearms manufacturers, defined as the difference in revenue received by the manufacturer $p_j(1-v_j)$ and marginal cost c_j from each new gun sale. The average markup in our sample is $325, implying 43% of the price of the average gun model is attributable to supply-side market power. While this average is similar across class, markups vary substantially within class, from $200 to $600. These markups collectively imply that about 2.9$ billion is generated each year in industry profits, which is comparably to industry estimates of 2$ billion during our sample period (Khaustovich, 2025) About 1% of our marginal cost estimates are below zero, due to firms setting prices on the inelastic portion of their residual firearm demand curve.

Across weapon classes, we find that long guns are more expensive to produce than handguns, with average costs of $494 and $420, respectively. We decompose the differences in marginal cost across firearm models by projecting their yearly cost of production onto their time-invariant physical characteristics and year fixed effects, using an approach parallel to Section 4.2.2. Panel (b) displays the estimates. Notably, all of the characteristics that make a gun more lethal (caliber, barrel length, and high-capacity) are associated with higher marginal costs. Appendix Figure A5 displays the distribution of margins (as a fraction of price, i.e., the Lerner index) in our sample, by weapon class.

In Figure 10, we assess the fit of our demand model, using out-of-sample moments from three distinct data sources. In Panel (a), we use additional information from NICS on the share of hand vs long gun background checks in each state, allowing us to compare the fraction of handgun purchases observed in each state against the fraction predicted by our model, conditional on any purchase.[30] This is an out of sample test, since the vertical taste-shifter τ_t is estimated from only transaction data in Massachusetts and total NICS checks in other states. Therefore, variation in the predicted share of handgun purchases is driven solely by the demographic differences across state. This captures the extent to which our estimates of demographic preferences from Massachusetts can explain handgun purchase rates in other states. Our model is unable to exactly fit the data, over-predicting the share of handgun purchases in most states. This may be due to differences in laws concerning handgun purchases across states, which are not accounted for in our model, but may also be due to non-trivial differences in reporting standards that make interstate comparison of NICS data challenging (Smucker et al., 2022). At the same time, the model predicts patterns in the right direction: the correlation between our predicted handgun purchase rate and the observed handgun background check rate is 0.28.

In Panel (b), we compare the predicted total quantity of new gun purchases attributable to each firm in our model, to the total number of new guns manufactured by each firm in 2016, according the ATF. Like the background check data, we would not expect a one-to-one relationship between guns sold and guns produced, since it may take time for guns to travel from the manufacturer to the end user. Nonetheless, we estimate a strong correlation between our model's predictions and the data: the correlation in the log quantities of the model predictions for each firm and the ATF data is 0.69. Importantly, there does not appear to be a systemic under or over prediction of the number of guns produced by each firm. In Panel (c), we plot the the implied excise tax revenue over time for newly produced guns $\sum_{j \in \mathcal{J}_\dagger} p_j q_j v_j$ from our structural model, along with the actual excise tax revenue collected by the U.S. government by quarter.[31] We observe similar trends, though the peak in revenue due to COVID purchasing occurs slightly later in the reported government data than our model. However, the level is accurate, suggesting our price measure is well-calibrated: The average revenue is \$697 million per year according to our model, compared to \$636 million per year in the data. This suggests our model is able to accurately capture national patterns in firearm demand, despite using only data on aggregate quantities in states other than

[30] We exclude Nebraska, District of Columbia, Iowa, North Carolina, Michigan, and Hawaii from the figure, as these states are partial permit states that do not require background checks for every gun purchase.

[31] Data collected from https://www.ttb.gov/system/files?file=images/foia/xls/Quarterly-breakdown-of-FAET-collections.xlsx

Massachusetts.

5 A Model of Legal Firearm Purchases and Homicides

This section specifies a model connecting the flow of firearms in a market to public health consequences, via firearm homicides downstream. Estimation of the causal effect of firearms on public health is a challenging exercise, and outside the scope of this paper, but important for quantifying the social costs and benefits of alternative firearms policies. To this end, we instead calibrate a stylized model of public health using estimates from the prior literature, allowing us to predict public health outcomes under alternative flows of firearms in the market. Our model accounts for three key forces relevant for the impact of firearms policy on public health: (i) firearm homicides are a function of the prevalence of guns in a market, (ii) firearms are durable goods that persist in a geographic market over time, and (iii) firearms affect downstream public health outcomes differentially, depending on their characteristics.

5.1 Model structure

We specify a two-equation model linking the demand $q_{c,s,y}$ for new firearms by class c in a market (state s during year y), to the firearm stock $Q_{c,s,y}$ and corresponding homicides $d_{c,s,y}$:

$$\begin{aligned}
&\text{(Gun stock law of motion)} \qquad && Q_{c,s,y} = (1-\varphi)Q_{c,s,y-1} + q_{c,s,y} \\
&\text{(Distribution of gun homicides)} \qquad && d_{c,s,y} \sim \text{Poisson}(Q_{c,s,y}^{\kappa_c}\zeta_{s,y})
\end{aligned}$$

The first equation of our model specifies the law of motion for the firearm stock by class, $Q_{c,s,y}$, accounting for the durable nature of firearms. Each year y, a uniformly random fraction $\varphi \in (0,1)$ of firearms degrade and exit circulation, while a fraction $1-\varphi$ persist. An additional flow of new firearms $q_{c,s,y}$ is added, depending on the outcomes in the legal firearms market. We treat the firearm stock in 2015 $Q_{c,s,2015}$ as an initial condition to be calibrated from data, and determine the flow in 2016-2022 based on our model predictions of new gun purchases.[32] This captures the notion that, even if the U.S. were to ban the sales of new firearms altogether, firearm homicides would persist, due to the large stock of existing firearms.

In the second equation, we model firearm homicides $d_{c,s,y}$ as a Poisson random variable with expectation $Q_{c,s,t}^{\kappa_c}\zeta_{s,y}$. The Poisson assumption matches the prior literature, with many studies using proxy measures of firearms prevalence to estimate a constant elasticity model of

[32] We implicitly assume that used guns captured by the composite good are already counted in the firearms stock.

homicides from firearms (Duggan (2001); Azrael et al. (2004); Cook and Ludwig (2006); Kim and Wilbur (2022)). We use the predicted stock of firearms as our measure of gun prevalence in the population, enabling us to connect gun prevalence to our equilibrium model of the legal firearms market.

We also allow for the impact of the firearm stock on homicides to depend on the particular class of weapon (long gun versus handgun). This is motivated by a prior literature suggesting that a firearm's characteristics are an important determinant in the likelihood that a violent incident results in death (Zimring, 1972; Libby and Corzine, 2007; Braga and Cook, 2018; Braga et al., 2021). To capture this channel, we allow the parameter κ_c governing the homicide elasticity to vary across weapon class. We also allow for an unobserved state-year homicide shock $\zeta_{s,y}$ that captures other determinants of expected firearm homicides across markets (e.g., changes in criminal justice policy).

Our equilibrium model of the legal firearms market described in Section 4 will allow us to predict the flow of firearms under alternative policies during our sample. In order to translate these changes in flows to changes in homicides, we further require estimates of the class-specific elasticities, κ_c, the initial firearms stock by state and weapon class in 2015 $Q_{c,s,2015}$, and the degradation rate of firearms φ. We now describe how we calibrate these parameters.

5.2 Calibration

We calibrate the parameters of our homicide model using measurements from the existing literature, summarised in Table 6.

Our calibration of the initial firearm stock utilizes the following decomposition:

$$Q_{c,s,2015} = \text{HH}_{s,2015} \times \frac{\text{Adults with gun in HH}_{s,2015}}{\text{Adults}_{s,2015}} \times \frac{\text{Gun owners}_{2015}}{\text{HH with gun}_{2015}} \times \frac{\text{Guns}_{c,s,2015}}{\text{Gun Owner}_{s,2015}}.$$

We are able to measure the first two terms—the number of households per state and the share of adults living in a household with a firearm—using publications from the ACS and Schell et al. (2020), respectively.

We measure the final two terms of this decomposition using microdata from the 2015 National Firearm Survey (Azrael et al., 2017). To calculate the number of firearm owners per household with at least one firearm, we compute the average number of firearm owners per household, as reported by survey respondents who personally owned a firearm. To estimate the count of class c firearms per owner, we take the average class-specific guns per gun owner at the Census region level to avoid survey noise in small states.[33]

To calibrate the degradation of firearms from the stock φ, we utilize existing estimates of the national stock from two distinct points in time, and calculate the implied degradation rate. In particular, we utilize Cook and Ludwig (1996)'s estimate by class the 1994 national firearm stock Q_{1994} (192M), and Azrael et al. (2017)'s estimate of the 2015 firearm stock by class Q_{2015} (265M). For firearms flows q_y in the intervening years 1995–2014, we use the ATF's yearly measure of new firearms manufactured (plus net imports). We calibrate the value of φ that satisfies the assumed law of motion between these years, similar to the exercise in Azrael et al. (2017):

$$Q_{2015} = (1-\varphi)^{2015-1994} Q_{1994} + \sum_{y=1995}^{2015} (1-\varphi)^{2015-t} q_y,$$

This procedure leads to a calibrated value of $\varphi = 0.015$. This estimate are quite low but consistent with the prior literature on firearm ownership. For example, Moody (2010) and McDougal et al. (2020) assume 0% degradation, while Azrael et al. (2017) suggest 1%. In the context of our public health model, these estimates suggest that an increase in the flow of new firearm purchases will have long lasting effects on homicides.

Turning to the elasticity of firearm homicides with respect to the firearm stock κ_c, we choose these two parameters to match two moments from existing studies. First, we use the FBI Uniform Crime Reports data to compute that, among all firearm homicides in which the weapon class is known, 92 percent are committed with a handgun.[34] Assuming this ratio holds among the full population of firearm homicides,[35] Our calibration requires that a handgun be responsible for 92 percent of firearm homicides predicted by our model between 2016–2022:

$$0.92 = \sum_{y=2016}^{2022} \sum_s \frac{d_{s,y}}{\sum_y d_y} E\Big[\frac{d_{h,s,y}}{d_{s,y}} \big| s, y\Big] = \sum_s \sum_y \frac{d_{s,y}}{\sum_y d_y} \frac{Q_{h,s,y}^{\kappa_h}}{Q_{h,s,y}^{\kappa_c} + Q_{l,s,y}^{\kappa_l}}.$$

The expectation can be calculated using the law of iterated expectations, which allows the firearm homicide shock $\zeta_{s,y}$ to cancel out of the ratio. Intuitively, this moment controls the difference in elasticities κ_h and κ_l.

To ensure the average elasticity of homicides with respect to firearms stock is accurate, we calibrate our model to match the estimated state-year elasticities with respect to a gun

[33]In practice, the average guns of each class per owner do not vary much by region, so this assumption is relatively unimportant.

[34]Data collected from https://cde.ucr.cjis.gov/LATEST/webapp/#/pages/explorer/crime/shr

[35]In other words, we assume that the class of weapon is missing at random in the population of homicides.

prevalence proxy, $\kappa = 0.294$, from Cook and Ludwig (2006) and Duggan (2001).[36] Notably, since these aggregate elasticity estimates rely on a proxy for overall firearm ownership, they cannot distinguish firearms by class c, and so differ from the structure of our model. To accommodate these existing estimates, we assume that these aggregate elasticities represent the change in homicides $d_{s,y}$ with respect to a change in gun prevalence, holding fixed the fraction of handguns in the overall stock $f_{h,s,y} = Q_{h,s,y}/Q_{s,y}$. Holding this share fixed, we have the *ceterus paribus* implied elasticity as follows:

$$0.294 = \left.\frac{\partial \log(E[d_{s,y}])}{\partial \log(Q_{s,y})}\right|_{f_{h,s,y}} = \kappa_h E[d_{h,s,y}/d_{s,y}] + \kappa_l E[d_{l,s,y}/d_{s,y}].$$

The right-hand expression is a convex combination of the class-specific elasticities, with weights equal to the share of firearm homicides committed with each class c.[37]

Matching these two moments, we estimate that the elasticities of firearm homicides with respect to weapon class stocks are $\kappa_h = 0.307$ and $\kappa_l = 0.144$. This is consistent with the estimates suggesting that handguns are more likely than long guns to translate to deaths (Braga and Cook, 2018). For example Libby and Corzine (2007) estimates that, conditional on a shooting and controlling for incident characteristics, handguns are 5 times more likely (in terms of odds ratio) to result in a fatality than rifles.

5.3 Implementation and Interpretation

Our assumed structure is conducive to analyzing the effects of changes in the firearm stock on firearm homicides. In particular, the Poisson model implies the log-linear relationship

$$\log(d_{c,s,y}) = \kappa_c \log(Q_{c,s,y}) + \zeta_{s,y}.$$

Rearranging then allows us to express the change in firearm homicides when shifting the level of the firearm stock from the status quo $Q_{c,s,y}$ to an alternative level $Q'_{c,s,y}$ due to alternative policies in the legal firearms market, as

$$d'_{c,s,y} - d_{c,s,y} = d_{c,s,y}\left((Q'_{c,s,y}/Q_{c,s,y})^{\kappa_c} - 1\right), \tag{19}$$

[36] Cook and Ludwig (2006) estimates an elasticity of 0.272, using the fraction of suicides committed by guns as a proxy measure. Duggan (2001) estimates a very similar elasticity of 0.316 using subscriptions to *Guns and Ammo* as a proxy measure for gun prevalence. We take the average of these two estimates.

[37] This relationship continues to hold if we match the elasticity of realized firearm homicides, instead of expected firearm homicides. This is because the purely idiosyncratic Poisson error cancels out when taking the ratio.

where the firearm homicide shocks $\zeta_{s,y}$ are absorbed into the status quo outcome $d_{c,s,y}$. For our welfare evaluation of policies $\mathcal{P}$, we compute the public health consequences $\mathcal{H}$ by applying Equation 19 to the predicted demand for new guns (and consequently, the firearms stock) implied by our equilibrium model under $\mathcal{P}$, relative to the baseline:

$$\mathcal{H}(\mathcal{P}) - \mathcal{H}_0 = \iota \cdot \sum_{y=2016}^{2022} \sum_{t \in \mathcal{T}_y} \sum_{c \in \{h,l\}} d'_{c,s(t),y} - d_{c,s(t),y}, \tag{20}$$

which we convert into dollars using the statistical value of a life ι. In particular, we apply an estimate of ι =-9.5 million dollars as the statistical value of a firearm homicide (Peterson et al., 2021).

Using this model, we are able to measure the average contemporaneous marginal social cost of the purchase of a new firearm during our sample.[38] From 2016–2022, the contemporaneous marginal social cost of a new handgun purchase was 3.58×10^{-5} homicides, or \$340, and the cost of a new long gun purchase was 1.11×10^{-6} homicides, or \$11. Since our model predicts that 80 percent of new firearm purchases during our sample were handguns, the average marginal social cost of a firearm purchase was 2.6×10^{-5} homicides, or 247 dollars in social harm, due to expected firearm homicides during its first year.

Classic pigouvian taxation theory suggests that firearms should be priced according to their net social cost (marginal cost of production + public health cost). This marginal homicide cost is comparable in magnitude to the \$380 dollar difference between the average firearm's price and marginal cost of production, so that market power in part "corrects" this contemporaneous externality to some extent. However, this comparison masks both heterogeneity in public health costs across weapons, along with the durability of these costs. A back of the envelope calculation, discounting the costs of future homicide at a 5% rate annually, suggests that the net present homicide cost of the marginal new handgun purchase is about \$5,262, and \$163 for long guns.[39] Therefore, average margins are substantially higher than the social cost of long guns, while the social cost of handguns dwarfs their average markup. Alternative regulation that better aligns market prices with net social costs have the capacity improve social welfare. We explore such alternatives in the next section.

[38]This is the calculated as the expected number of homicides created during the first year a firearm of class c enters the stock in each market, averaged over state years with weights proportional to observed firearm purchases by class-state-year.

[39]This is calculated by assuming the marginal social cost depreciates at a rate proportional to φ over time, and then this future socially cost is discounted at a rate of $\beta = 0.95$, leading to a net present cost of $\sum_{t=0}^{\infty} \beta^t (1 - \varphi^t) \cdot SC_c = SC_c/(1 - \beta(1 - \varphi))$, where SC_c is the contemporaneous marginal social cost described in the text.

Our model of public health has several features that suggest our public health estimates provide a *lower bound* on the social costs of firearms. First, Equation 20 only accounts for the impact of the firearm stock on firearm homicides over our sample period. Since firearms are durable, this means that we do not account for the potential costs created by a firearm years or decades into the future. As such, we are only able to capture the impact of alternative policies at a medium-run horizon of 7 years. Second, we value firearm homicides using an estimate of the statistical value of a fatality derived from all homicides, but in practice, victims of firearms homicides are more likely to be younger, increasing the statistical value of their life Miller et al. (2024). Third, we only model the effect of firearms purchases on homicide, yet firearms are also associated with other public health costs, such as suicides (Miller et al., 2015) and non-fatal injuries (Fowler et al., 2015). For some other outcomes, existing work suggests minimal effects of the firearm stock on non-gun homicide and non-violent crimes (Duggan (2001), Cook and Ludwig (2006)).

6 Counterfactuals

In this section, we synthesize our empirical results to study the impacts of counterfactual regulations on the consumer firearms industry.

6.1 Policy Framework and Implementation

Before presenting counterfactual predictions, we first describe the framework we use to compute welfare estimates across our proposed policies.

We consider policy alternatives $\mathcal{P}$ based on counterfactual excise taxes v'_c (e.g. suppliers' revenue from the sales of firearms in class c is taxed at a rate v'_c). We also separate tax rates on newly produced handguns and long guns in $\mathcal{J}_{c,y}$, such that each policy $\mathcal{P}$ is defined by a pair of tax rates (v'_h, v'_l). Since 1954, the status quo firearm regulation in the U.S. has set $v_h = 0.1$ and $v_l = 0.11$. Matching the structure of current regulation, we do not consider counterfactuals that tax the composite good representing used firearms, $\omega_{c,y}$. We additionally assume that our considered policies do not affect the value of the composite good, $\omega_{c,y}$, or equivalently, that the prices of used guns do not respond to changes in the tax on new firearms.

The pricing conduct of firearm manufacturers is essential in determining the effect of excise taxes on the firearm market. Since these taxes are statutorily levied on firms, the extent to which firms pass-through these taxes to consumers ultimately determines changes in the market allocation. To this end, we take the market and cost structure from Section 4.4

as given and assume that firms choose prices to maximize profits, with taxes (imperfectly) passed through to consumers in the form of higher prices. If we were to instead assume that the supply side is competitive, then firms act as price takers, and prevailing prices would be set such that $p_{j,t}(1 - v_{c(j)}) = c_{j,t}$, such that net profits would zero for each product. We explore the implications of both of these conduct assumptions later in this section, but use the Nash-Bertrand assumption as our baseline.

We now describe the welfare components we consider in our counterfactual analysis. Given a counterfactual set of firearm excise taxes implied by $\mathcal{P}$, we solve for the counterfactual prices of firearms in each year y so that firms maximize profits as in Equation 16:

$$\vec{p}_f(\mathcal{P}) = \vec{p}_f(v'_h, v'_l, \vec{p}_{-f}) = \arg\max_{\vec{p}_f} \sum_{j \in \mathcal{J}_f} (1 - v'_{c(j)}) p_{j,y} \cdot q_{j,y}(\vec{p}_y) - c_{j,y} \cdot q_{j,y}(\vec{p}_y) \tag{21}$$

which can be found by jointly setting the first order conditions for the price $p_{j,y}$ of each new gun to zero. These new prices $\vec{p}_f(\mathcal{P})$ will imply new prevailing quantities $\vec{q}_y(\mathcal{P})$. Aggregate profits Π across the industry are then given by:

$$\Pi(\mathcal{P}) = \sum_f \Pi_f(\mathcal{P}) = \sum_{j \in \mathcal{J}_y} (1 - v'_{c(j)}) p_{j,y}(\mathcal{P}) \cdot q_{j,y}(\mathcal{P}) - c_{j,y} \cdot q_{j,y}(\mathcal{P}) \tag{22}$$

Given new prices, consumer surplus CS is calculated, in its typical form, as expected utility divided by the price coefficient:

$$CS(\mathcal{P}) = \sum_t \sum_{i \in t} E[\max u_{i,j,t}/\alpha_i] = \sum_t M_t \int_i \frac{1}{\alpha_i} \log\big(1 + \exp(\rho_0 I_{i,1,t}(\mathcal{P}))\big) \partial F_t(i) \tag{23}$$

where $I_{i,1,t}(\mathcal{P})$ is the inclusive value of the inside good from the Expected Utility Equation for each consumer i, recalculated to account for the new prices. The integral is taken over the distribution $F_t(i)$ of both the demographics and random unobserved heterogeneity ν in the population.

While consumer surplus and industry profits will tend to decrease with the tax, there are two potentially offsetting benefits. Increasing the tax rate can drive changes in government revenue $\mathcal{G}$, given by:

$$\mathcal{G}(\mathcal{P}) = MVPF \cdot \sum_{j \in \mathcal{J}_y} v'_{c(j)} \cdot p_{j,y}(\mathcal{P}) \cdot q_{j,y}(\vec{p}_y(\mathcal{P})) \tag{24}$$

Where $MVPF$ is the marginal value of public funds (Hendren and Sprung-Keyser, 2020). We assume that the regulator has access to lump sum transfers, such that one dollar of tax revenue is equivalent to one dollar of social welfare, and $MVPF = 1$, as in O'Connell and

Smith (2024). Raising the tax can also affect public health $\mathcal{H}$, as calculated in Equation 20 of Section 5. As mentioned in Section 5, we follow prior work and value each gun homicide at -9.5 million dollars (Peterson et al., 2021).

We calculate aggregate welfare changes $\Delta W(\mathcal{P})$ implied by moving from the existing policy[40] to proposed policy $\mathcal{P}$ as follows:

$$\Delta \mathcal{W}(\mathcal{P}) = \Delta CS(\mathcal{P}) + \Delta \Pi(\mathcal{P}) + \Delta \mathcal{G}(\mathcal{P}) + \Delta \mathcal{H}(\mathcal{P}) \tag{25}$$

We consider two broad types of counterfactuals. The first set of counterfactuals mirror existing policy proposals. In particular, we consider the welfare implications of the recently passed California bill AB 28, which would raise the excise tax on firearm sales in California by 11 percentage points.[41] We consider the effects of setting this at the national level, effectively doubling federal taxes on firearms, when accounting for the equilibrium adjustments of firearm manufacturers with national distribution. We also consider the impact of the opposite policy: setting excise taxes v_j to zero on all firearms sold, which has been proposed by gun rights advocates.[42] Both are uniform tax changes that treat each type of firearm equally.

Inspecting Equation 25, it is clear that doubling or removing firearms taxes will have implications on who the relative winners and losers are, with higher taxes hurting consumers and firms, while benefiting public health and (potentially) government revenue. These differential gains may impact the political feasibility of firearm policies, regardless of the change in aggregate welfare. In particular, views on firearm regulation are politically polarized in the U.S., with conservatives tending to support laxer regulations ((Gentzkow et al., 2019), (Luca et al., 2020)). Firearm advocacy groups, like the National Rifle Association (NRA), have millions of members[43] and play a significant role in shaping political representation and firearms policy at the national level, especially in the Republican party (Leff and Leff, 1981; Lipford, 2000; Kenny et al., 2004; Reich and Barth, 2017; Lacombe, 2019).

In our second set of counterfactuals, we consider a set of alternative tax policies that incorporate the political economy of gun regulation. In particular, we suppose that the social planner seeks to maximize aggregate welfare, subject to the constraint that "gun

[40] As discussed in Section 4.5, 4% of marginal cost estimates are negative. In all counterfactuals, we assume these negative marginal costs are zero and resolve the current equilibrium so that counterfactual changes are benchmarked relative to that simulation (this changes aggregate outcomes in a negligible manner).

[41] See this link for the legislation: `https://legiscan.com/CA/text/AB28/id/2842856`

[42] Example: `https://clyde.house.gov/news/documentsingle.aspx?DocumentID=265`

[43] Source: `https://www.washingtontimes.com/news/2023/apr/25/national-rifle-association-alive-and-thriving-5-`

consumers are not harmed:"

$$\max_{v_h, v_l} \Delta \mathcal{W}(v_h, v_l) \tag{26}$$

$$\text{subject to: } CS(v_h, v_l) \geq CS_0 \tag{27}$$

where CS_0 denotes a benchmark consumer surplus, which we set to the status quo consumer surplus in our sample (18.2B$ per year). This constraint mirrors the consumer welfare standard used in U.S. merger review (Heyer, 2014).[44] This problem resembles the classic Ramsey tax problem (Ramsey, 1927), only in this case, the regulator must ensure consumers, instead of the firm, receive a threshold surplus level.

To connect our proposed consumer surplus constraint to the political economy of gun regulation, Figure 13 plots the relationship between consumer surplus and proxy measures of the NRA's influence. For this, we collect data from the FEC on large ($200+) individual contributions to the NRA's Political Action Committee from 2016-2022, and match these to the zip code level consumer surplus estimates from our model.[45]. We complement this with a dataset of grades issued to House representatives in 2018 by the NRA,[46] reflecting their political stances on gun rights legislation. We then aggregate to the congressional district level.[47] Panel (a) shows that individuals in districts with higher consumer surplus from legal firearms tend to donate to the NRA more. Panel (b) shows that this also translates to the elected political representation of these constituents: U.S. House members representing congressional districts with higher consumer surplus tend to receive higher grades from the NRA.[48] While these grades are highly correlated with the political party of the representative, this relationship is not driven entirely by political preferences of constituents: Appendix Figure A6 shows that, even within Republicans representatives, higher consumer surplus is associated with higher NRA grades.

Under the framework implied by Equation 26, uniformly increasing firearm taxes is infeasible. Consequently, the social planner must raise taxes on one class of firearms while

[44] Alternatively, we could formulate the problem as the regulator maximizing welfare with a distortionary weight of $1 + \lambda > 1$ on $CS(\mathcal{P})$, representing the relative importance of gun consumers on the regulator's welfare, as has been done in prior work (Tang, 2022; Castillo, 2023).

[45] Source: https://www.fec.gov/data/browse-data/?tab=bulk-data. We filter for donations to both the regular NRA PAC and the Political Victory fund, the NRA's Super PAC.

[46] Source: https://www.thetrace.org/2018/10/nra-grades-republican-candidates/. These are derived primarily based on voting history and a questionnaire the NRA issues to candidates; an example questionnaire can be found here: https://afj.org/wp-content/uploads/2020/01/Wilson-Attachments-p450-453.pdf

[47] Zip codes are aggregated to the congressional district level using the HUD crosswalk from December 2018: https://www.huduser.gov/portal/datasets/usps_crosswalk.html.

[48] Panel (b) is constructed at the congressional district level, for districts whose incumbent candidates running for re-election received grades (85%).

lowering taxes on the other. Given the large estimated differences in the social costs of handguns and long guns in Section 5, along with the similar in magnitude markups across class, one natural candidate policy is to set the excise tax on long guns to zero, while raising the handgun tax as high as possible, such that consumers are not harmed on aggregate. We perform this counterfactual to gauge both the efficacy of targeting firearm tax policy, and the stringency of political constraints facing the social planner. For comparison, we also consider an inverse policy, where the handgun tax is set to zero and the long gun tax is raised as high as possible. For all of these policies, we assume that there is a one-time change in 2016 to the tax regime, and that the policy is held constant through 2022.

This welfare framework involves some significant assumptions on the behavior of firms, consumers, and spillovers to other markets. We model both consumers and firms as static decision-makers when choosing products and setting prices, despite the fact that guns are durable goods (Coase, 1972). Because we lack data on individual identifiers, estimating the dynamics of gun purchasing is infeasible in our context. We also implicitly assume that the illicit market for guns and the behavior of used guns suppliers are constant over these policy shifts, violations of which could have meaningful public health implications (Cook (2018), Lee and Persson (2022), Schnell (2024)). For these reasons, we feel that our model is unfit to predict the effects of large policy changes (e.g., a firearms ban), and we instead focus on counterfactuals more local to the current equilibrium.

6.2 Counterfactual Gun Policies

Panel (a) Figure 11 plots the average annual changes to welfare in equilibrium from each of the policies we consider. In terms of aggregate welfare, doubling or removing excise taxes on firearms create meaningful shifts in aggregate welfare, yielding changes of 321 and -276 million dollars per year during our sample, respectively. However, these policies have markedly different implications for the distribution of surplus. Doubling taxes would involve a transfer of \$397M per year from gun consumers (via reduced CS), generating \$607M per year for the overall population (via public health benefits). A similar transfer occurs from firm profits to government revenue. Notably, the incidence of this counterfactual tax increase is shared by both consumers and firms, highlighting the elasticity of both supply and demand in the consumer firearms industry.

In contrast, setting a targeted tax on handguns of 14.5% would generate gains of 258\$M per year, without harming consumers. Interestingly, even though neither manufacturer profits nor tax revenues are explicit constraints on Equation 26, we also find neither quantity meaningfully decreases under this tax system. Targeted handgun taxes thus maintain market surplus while considerably boosting public health. In contrast, taxing only long guns (at a rate of 33.4% to keep consumer surplus the same) leads to large losses in welfare, as it shifts consumers away from firearms that cause little social harm.

Since public health effects are dependent on the overall stock of guns, which evolves dynamically over time, these aggregates may mask the longer-run benefits of firearm regulation. In Panel (b), we plot the estimated overall welfare benefits of each policy by year. The returns to both the handgun tax and uniform 11% increase in excise taxes improve over time, as the policies further reduce the stock of socially harmful guns. By the end of 2022, 7 years after the policy has been implemented in our counterfactuals, doubling taxes would increase annual welfare by over 800 million dollars, surpassing annual welfare gains from the handgun-only tax scheme by 2019. This suggests that on a long-run horizon, the benefits uniformly higher firearm taxes may be substantial.

In Figure 12, we plot the equilibrium changes to market-level variables (quantity and price) from each policy by firearm class. Panel A displays the changes to annual quantities from different policies. We estimate that doubling taxes would reduce all firearm purchases by 328,000 units per year, or about 2.0%. This policy induces a partial substitution from new to used guns, which are not subject to excise taxes: new gun purchases are reduced by 8%, while used gun purchases increase by about 6.4%. The handgun tax, in contrast, leads to a small net change in new gun purchases per year of .6%, but induces a compositional change in the firearms purchased by consumers. In particular, the handgun market share, conditional on new gun purchases, falls from 72.8% to 70.1%.

Panel (b) displays the distribution of price changes as a result of tax polices. The dot in each violin plot represents the average price change, in percentage terms, while the horizontal line represents the implied change in prices if firms perfectly passed the increased taxes entirely into prices (e.g. price = marginal cost, so firms set new prices to $p'_j = p_j(1-v_j)/(1-v'_j)$). Price changes lower in magnitude than this reference line indicate incomplete pass-through of taxes to consumers. Given the substantial markups we estimate on the supply side, it is unsurprising that we find incomplete pass-through in prices. Across policies, we find an approximately 65% pass-through rate of the tax into the price of the average handgun, and 61% passthrough for long guns, though there is significant dispersion within policy and gun type. Market power,, dampens the impacts of taxes on public health targets, by reducing the shift away from taxed firearms by consumers, suggesting equilibrium responses on both sides of the market must be accounted for when evaluating policies.

In Appendix Figure A7, we test this conduct hypothesis more directly, by estimating the welfare effects under the assumption that taxes are perfectly passed-through to prices. Since this pricing behavior is consistent with assuming price equals marginal cost, we show the overall welfare effects with and without the implied change in profits to firearms manufacturers.[49] We find that, excluding profits, this pricing behavior leads to estimates that imply doubling taxes is a much more effective policy in overall welfare, increasing welfare by $1 billion per year. This occurs primarily because government revenue can increase without harming firm profits. When we include profits in our welfare calculations, the net welfare effects of all policies increase in magnitude from our equilibrium estimates in Figure 11. This occurs primarily through intensified public health effects. This suggests that failure to properly account for market power and supply-side conduct among firearm manufacturers could overstate the efficacy of redesigned firearm regulation.

We motivated our discussion of political constraints on federal regulators through a discussion of the role that gun owners (and their advocacy organizations) play in federal policy. As documented in Table 2, gun purchasing is more likely in conservative neighborhoods in Massachusetts, and national surveys find that gun ownership is twice as common among Republicans as Democrats (Parker et al., 2017). Insofar as our tax counterfactuals are politically feasible, they would require support from Republican legislators at the national level, which in turn may depend on how the tax would affect their constituents.

With this in mind, Figure 14 plots the welfare effects of the counterfactual taxes at the state-level, as a function of political preferences (measured by the 2016 state-level vote share of Donald Trump in 2016).[50] In this plot, we only include consumer surplus and public health, as the geographic distribution of benefits from government revenue and profits is unclear. The sum of consumer surplus and public health is labeled "Population Surplus," to represent that these are benefits accruing directly to the state population. In Panel (a), we plot the effects of the 11% increase in taxes by state. Population Surplus is inversely correlated with Republican vote share, such that the states most harmed by the firearm tax increase are those with the highest Republican vote share. California, where this tax increase was actually introduced in 2024, unsurprisingly experiences a net benefit. However, 19 states experience a net loss in population surplus, underscoring the political challenges of passing this tax increase at the national level.

In Panel (b), we plot the welfare effects of the targeted handgun tax. While on net aggregate consumer surplus is unchanged, the gradient of consumer with respect to voting behavior is also relatively flat. In Appendix Figure A8, we document that this pattern is replicated among congressional districts with higher NRA donations per capita, and the doubling of taxes hurts districts with high NRA presence the most. With respect to population

[49]For these policy exercises, we re-solve for the targeted hand or long gun only taxes that set consumer surplus equal. These are 14.0% and 37.6%.

[50]We exclude Hawaii because it does not report background checks to NICS, and so we cannot estimate consumer surplus.

surplus, Republican states that benefit the most. This occurs through a substitution channel. Because those in conservative neighborhoods prefer long guns, according to our demand estimates, the elimination of taxes on long guns coupled with increased taxes on handguns induce substitution to these less deadly weapons, without harming many politically conservative consumers. This in turns lead to large gains in public health at no systematic cost to consumer surplus across the political spectrum of states. To our surprise, we find that all states experience a net gain in population surplus. Effectively, at the state level, the targeted handgun tax is a politically palatable Pareto improvement over existing taxes in the consumer firearms industry.

7 Conclusion

In this paper, we provide the first estimates of supply and demand for consumer firearms in the U.S., that are based on observed firearm transactions and the prices facing consumers. Through descriptive analysis and a structural model, we show that firearms consumers are moderately price elastic, that demographics are a substantial input into preferences over the characteristic space of firearms, and that substitution across firearm classes is relatively low. We estimate that market power plays a significant role in the supply side of the firearms market, leading to large markups and incomplete pass-through of taxes to consumers, which meaningfully impacts the welfare implications of alternative policies. In order to benchmark the effect of changes to market outcomes on firearms externalities, we calibrate a stylized model of public health. In our counterfactual policy exercises, we show that targeted taxes on handguns are more welfare enhancing than uniform taxes, primarily because of the distinct social costs across firearms. Moreover, these targeted policies have properties that may make them politically feasible: gun consumers on net do not lose surplus, and the largest beneficiaries are those living in conservative states, which historically have been the largest barriers to new firearms legislation.

While our paper is an important step towards understanding this market, many questions are left unanswered. This paper does not speak to potential regulation on the illicit market for firearms, and how this may respond to changes in government policy. The dynamics of the gun market are not explicitly modeled, though we show that these dynamics are important for understanding the public health benefits, because guns are highly durable goods. Finally, this paper cannot speak to larger-scale reforms of firearms regulation, such as universal buyback programs or bans on certain types of firearms. Much of this is due to the limitations facing researchers on assembling data about the firearms industry. Our hope is that further work on this topic can aid both researchers and policymakers in understanding the consequences of firearms regulation when accounting for the market structure of this industry.

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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

Figure shows the average characteristics of firearms in the Blue Book of Gun Values that are matched to models in the FRB Massachusetts transaction data (e.g. those purchases in Massachusetts from 2016-2022). MSRP is calculated only for those guns in active production during this period. The 100% used gun price is calculated for all 7,616 gun models.

	(1) Adult Pop.	(2) Potential Gun Buyers	(3) Gun Buyers	(4) Handgun Buyers	(5) Longgun Buyers
Female	0.521	0.430	0.085	0.107	0.048
Fraction White in Zipcode	0.718	0.738	0.813	0.804	0.828
Poverty Rate in Zipcode	0.106	0.100	0.081	0.083	0.078
Conservative Vote Share (2016)	0.365	0.380	0.440	0.437	0.444
Density of Zipcode	1,940	1,677	666	712	587
Median Zipcode Income	87,263	87,715	88,528	88,031	89,381
Fraction BA+ in Zipcode	0.438	0.433	0.402	0.399	0.407

Table 2: Demographics of Gun Buyers in Massachusetts

Figure reports the average demographic characteristics of sub-populations in Massachusetts. Each row reports a particular gender-by-zipcode demographic cell, with the columns varying the weights used. Column (1) weights by the adult population in each cell, estimated from the 2015-2019 ACS. Column(2) weights by the predicted # of potential gun buyers (those who own or are willing to own a gun). Column (3) weights by the number of gun purchases in each cell from 2016-2022. Column (4) weights by the number of handgun purchases in each cell from 2016-2022. Column (5) weights by the number of long gun purchases in each cell from 2016-2022.

	(1)	(2)	(3)
	IHS(Purchases)	IHS(Purchases)	IHS(Purchases)
Log(MSRP)	-0.726**	-2.156**	-2.491***
	(0.331)	(0.858)	(0.828)
Observations	2457	2457	2457
Gun Model FE	Yes	Yes	Yes
Year FE	Year	Year	Class x Year
# Potential Instruments		3366	3366
# Selected Instruments		8	6
Sup-Score Test Statistic		12.43	12.55
First Stage Sig. (p-value)		0.0000	0.0000
Method	OLS	IVLASSO	IVLASSO

Table 3: Estimated Price Elasticity of Demand for Firearms

Table displays the estimated own-price elasticity of demand from the IVLASSO routine described in Section 3.2. The sample in this table is restricted to guns with at least 100 purchases in Massachusetts from 2016-2022. Column (1) reports the estimates from an OLS regression of IHS(# Purchases) on Log(MSRP), with gun model and year fixed effects. Columns (2) and (3) reports the estimates using the metals commodity cost shock variable as an instrument for MSRP, with year and weapon class by year fixed effects, respectively. Standard errors in parentheses are robust to heterogeneity. * denotes $p < .1$, ** denotes $p < .05$, *** denotes $p < .01$.

Consumer Characteristic:	Baseline	Female	Frac White	Frac Conservative	Log(Median Inc)	Log(Density)	Nesting Parameter (ρ)	Random Coef. (σ)
Handgun (vs No Gun)	-0.726***	-1.108***	0.857***	0.993***	-0.700***	-0.089***	0.890*	
	(0.004)	(0.067)	(0.057)	(0.049)	(0.018)	(0.002)	(0.073)	
Long gun (vs Handgun)	-0.179***	-0.723***	0.626***	0.218***	-0.107***	0.001	0.240***	
	(0.005)	(0.076)	(0.072)	(0.032)	(0.015)	(0.001)	(0.019)	
Shotgun (vs Rifle)	-0.230***	-0.231***	0.065*	-0.243***	0.670***	0.060***		0.032
	(0.006)	(0.023)	(0.034)	(0.045)	(0.053)	(0.005)		(0.671)
Used Gun (vs New for $0)	1.154***	-0.743***	0.527***	0.396***	0.261***	0.011***		0.082
	(0.023)	(0.058)	(0.047)	(0.044)	(0.023)	(0.002)		(0.099)
Caliber (In.)	0.198***	-0.195***	0.193***	0.433***	-0.173***	-0.068***		0.012
	(0.012)	(0.030)	(0.063)	(0.086)	(0.029)	(0.007)		(4.427)
Barrel Length (Ft.)	0.106***	-0.063***	0.193***	0.041***	-0.347***	-0.008***		0.000
	(0.004)	(0.008)	(0.019)	(0.014)	(0.029)	(0.001)		(19.286)
High Capacity Weapon	0.079***	-0.119***	-0.138***	0.018*	0.147***	0.010***		0.004
	(0.002)	(0.010)	(0.013)	(0.010)	(0.012)	(0.001)		(1.314)
Price Coef. (Multiplier)	-0.085	0.771***	-0.413***	-0.386***	-0.636***	-0.056***		0.436***
	(0.090)	(0.013)	(0.017)	(0.024)	(0.012)	(0.002)		(0.008)

Table displays estimates of the non-linear parameters of our demand model. Standard errors are in parantheses and calculated using corrected formula for constrained maximum likelihood described in Moore et al. (2008). Stars indicate statistical significance of p-values. For all parameters θ except the nesting parameters (ρ_0, ρ_c), this is the $Pr(\theta) = 0$; for ρ_0, this is $Pr(\rho_0 < 1)$; for ρ_c, this is $Pr(\rho_c < \rho_0)$. In brackets, we display p-values for the following tests: for ρ_0, the test that $\rho_0 \leq 1$, for ρ_c, the test that $\rho_c \leq \rho_0$, and for ρ_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.
* denotes $p < .1$, ** denotes $p < .05$, *** denotes $p < .01$,

Table 4: Demand Parameters

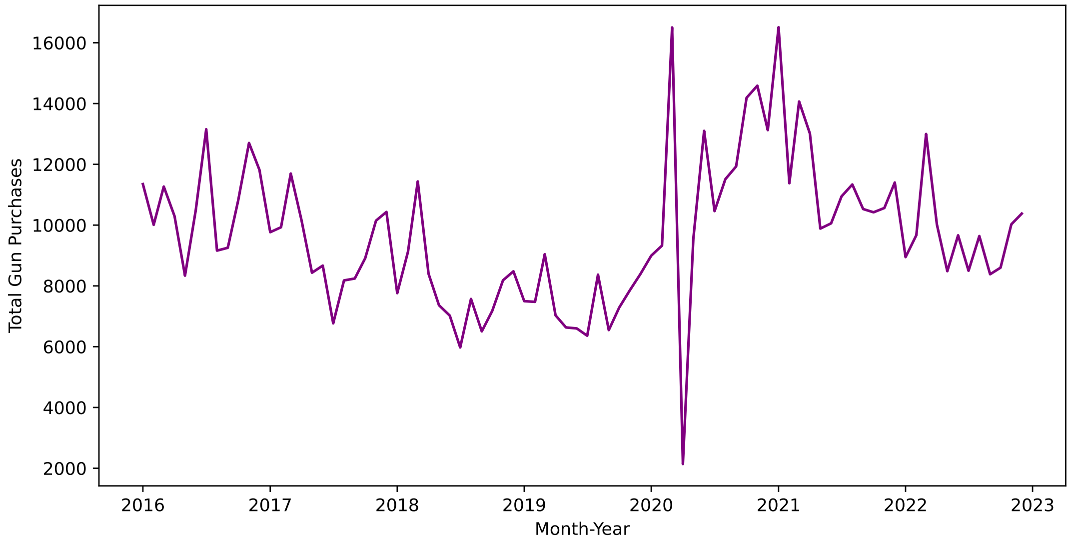
	Average WTP	ΔWTP by Demographic				
		Female	Above Avg. % White	Above Avg. % Conservative	Above Avg. Median Inc.	Above Avg. Density
Handgun (vs No Gun)	-1,356.76	0.33	214.54	202.59	-400.22	-252.25
Long gun (vs Handgun)	-448.67	-174.01	114.98	64.59	-84.95	-62.17
Shotgun (vs Rifle)	-108.91	-72.56	-56.07	-75.91	159.28	91.72
Used Gun (vs New for $0)	1,138.99	-809.09	292.90	134.85	266.51	18.72
Caliber (In.)	59.80	-116.41	154.43	117.38	-44.84	-94.81
Barrel Length (Ft.)	-3.33	-27.88	45.16	33.36	-80.32	-37.22
High Capacity Weapon	111.80	-102.54	-21.78	-15.09	52.04	25.77

Table displays estimates of consumer preferences over firearm characteristics, in terms of 2022 dollars. For the Average WTP column, we display the average $E[\beta_{i,c}/\alpha_i]$ for each characteristic c, with weights according to market size. For columns denoted ΔWTP by demographic split d, we display $E[\beta_{i,c}/\alpha_i|d] - E[\beta_{i,c}/\alpha_i]$, the difference in WTP between the demographic group and the average WTP.

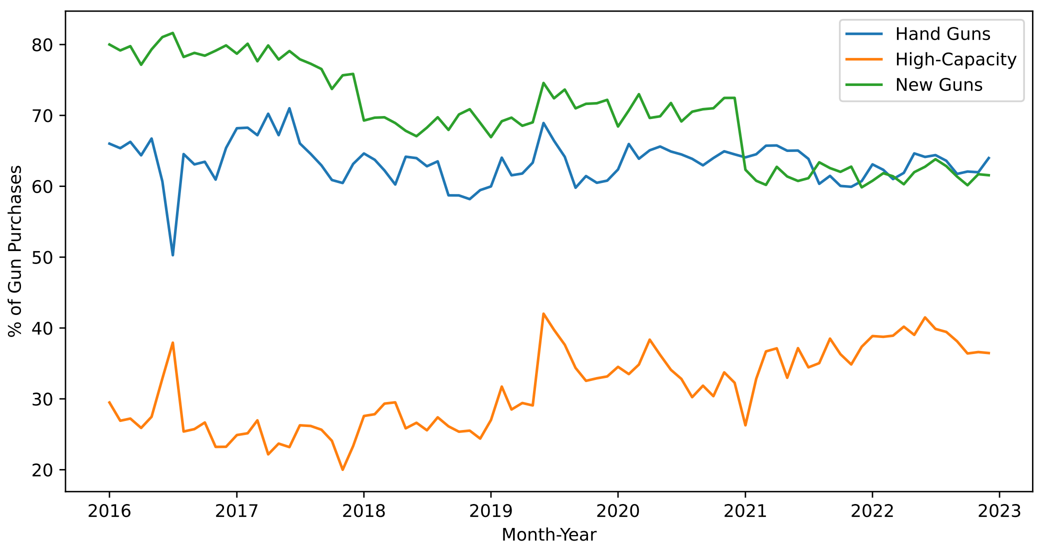
Table 5: Preferences for Gun Characteristic (in $)

Table 6: Calibration sources for public health model

Object	Value	Source
Panel A: Firearm law of Motion		
$\text{Households}_{s,2015}$	———	2015 ACS, 5-year estimate
$Pr(\text{Adult has gun in HH})_{s,2015}$	———	Schell et al. (2020)
$\text{Gun owners per HH with gun}_{2015}$	1.705	Azrael et al. (2017)
$\text{Guns per Gun Owner}_{c,s,2015}$	———	Azrael et al. (2017)
Degradation rate φ	0.015	Cook and Ludwig (1996), Azrael et al. (2017), ATF firearms commerce report
Panel B: Public Health Target Outcomes		
$Pr(\text{Shot handgun} \mid \text{Gun homicide})$	0.92	FBI Crime Data Explorer
Elasticity of gun homicide wrt HH gun ownership	0.294	Duggan (2001), Cook and Ludwig (2006)
Panel C: Public Health Calibrated Parameters		
κ_h: Elasticity of gun homicide wrt handgun stock	0.307	
κ_l: Elasticity of gun homicide wrt long gun stock	0.145	
Welfare cost, 1 gun homicide	\$9.5m	Peterson et al. (2021)
Panel D: Average marginal homicides from firearm purchase		
Handgun	3.58×10^{-5}	
Long gun	1.11×10^{-6}	
Share handguns among purchases	0.8	
Average marginal homicides	2.65×10^{-5}	



(a) Aggregate Gun Purchases Over Time



(b) Composition of Purchases Over Time

Figure 1: Firearm Purchase Trends in Massachusetts

Figure displays the time series of gun purchases in Massachusetts from 2016-2022. Panel (a) displays the total number of gun purchases each month, while Panel (b) displays the composition of these purchases by weapon class. Hand guns refers to those transactions classified as a handgun in the FRB data. For new gun and high-capacity weapon, these characteristics are only defined for guns we match to the blue book data, so we divide by the total number of purchases matched to a blue book gun in each month.

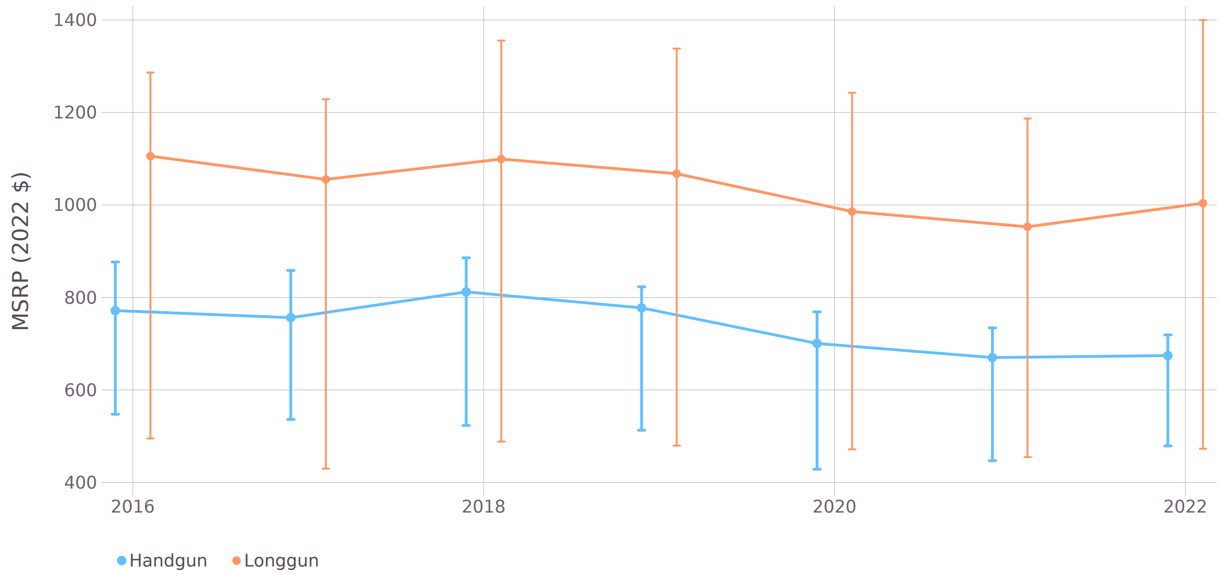


Figure 2: New Gun Prices over Time

Figure displays the Manufacturer's Suggested Retail Price (MSRP) of guns in active production that we match to the Massachusetts microdata, by weapon class. dots indicate the mean price of a new purchased gun in each year, while error bars indicate the interquartile range.

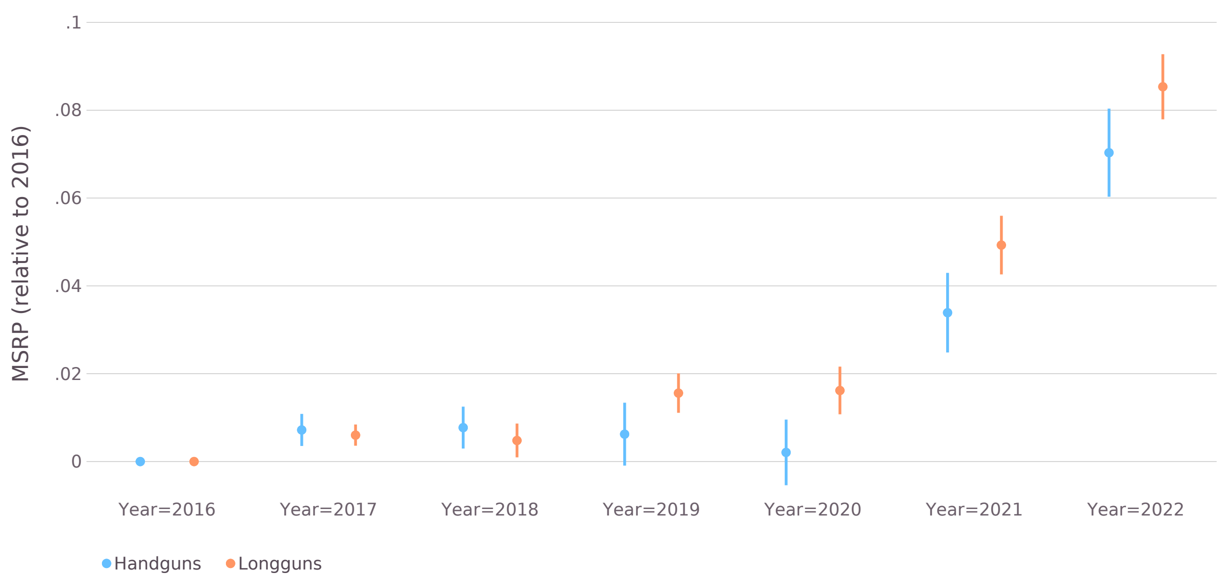


Figure 3: New Gun Prices over Time (Controlling for Variety)

Figure displays estimates from a regression of log(MSRP) of new gun models we match to the Massachusetts FRB microdata by year (relative to 2016), controlling for class-year and firearm model fixed effects.

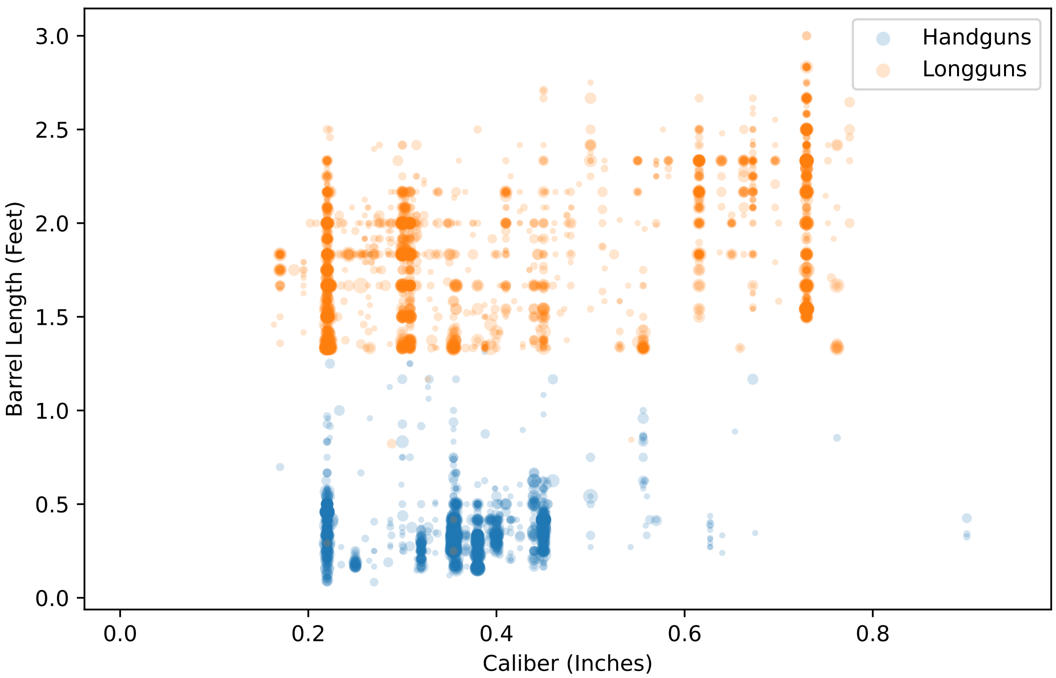


Figure 4: Caliber and Barrel Length Distribution Across Gun models

Figure displays the distribution of gun models by caliber (in inches) and barrel length (in feet), split by weapon class. Each model's dot size is proportional to the the number of units sold in Massachusetts from 2016-2022.

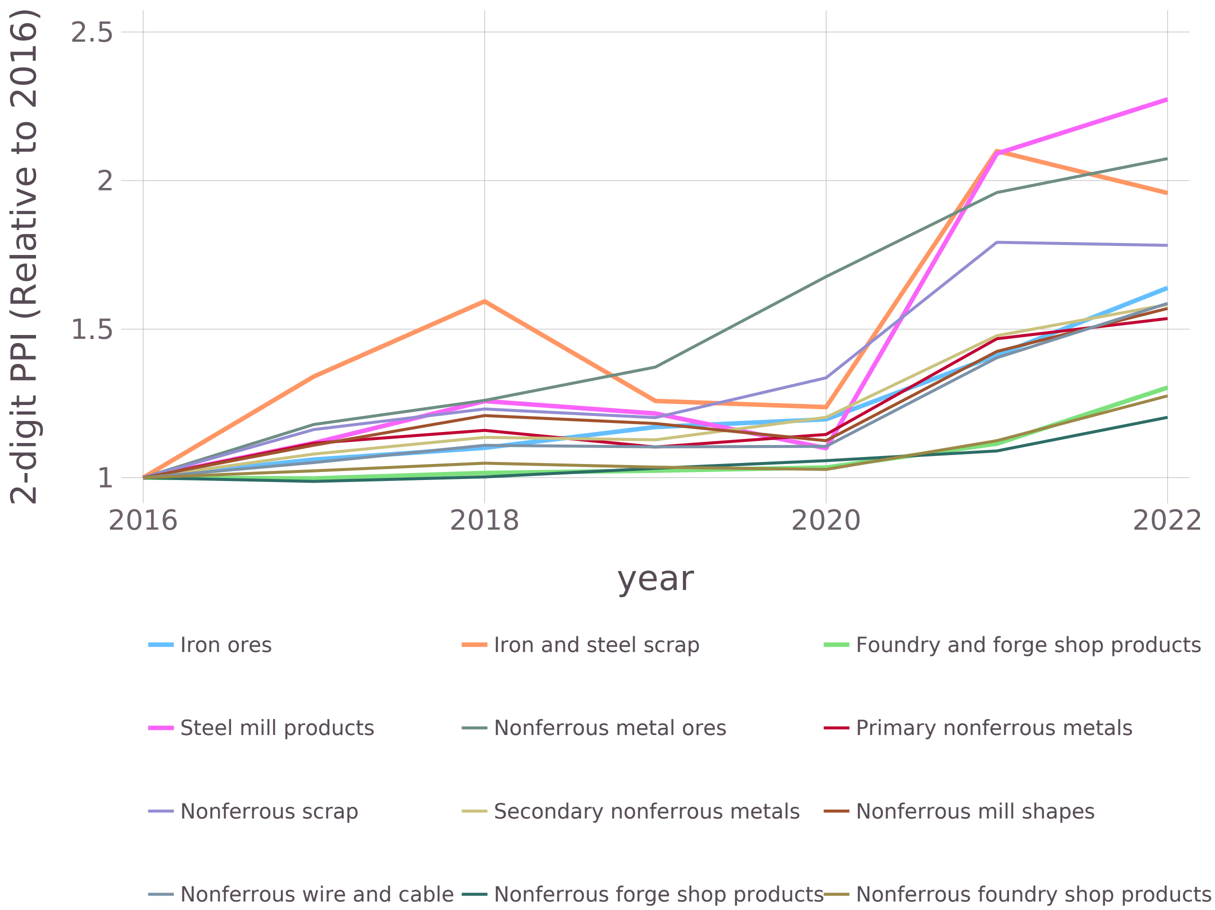
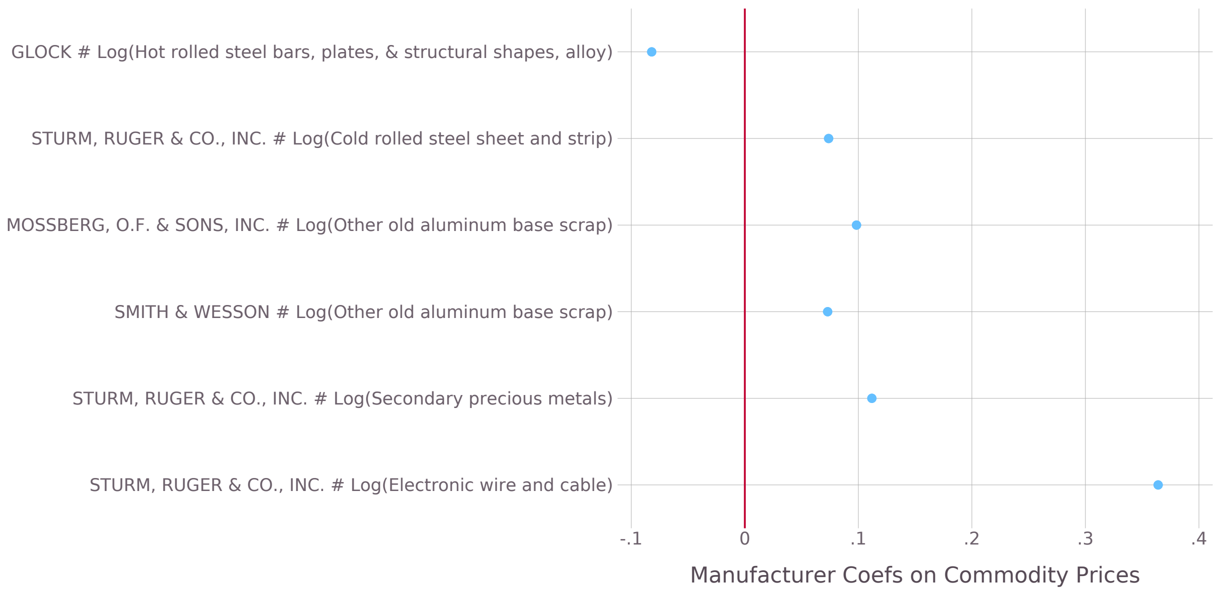
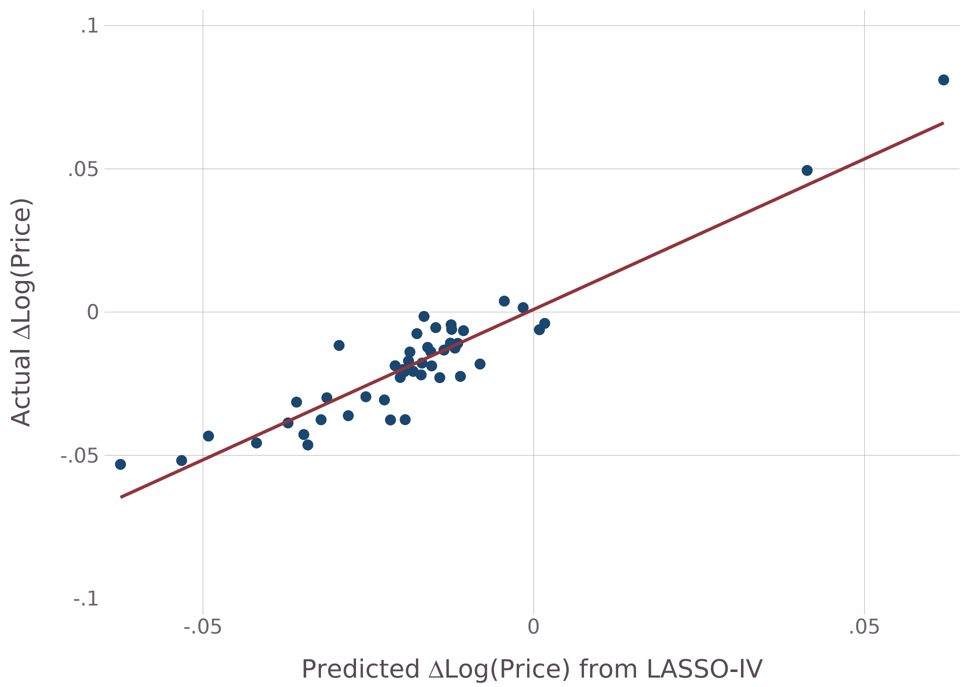


Figure 5: Time Series of Annual Price Indices for Firearms Production Inputs

Figure shows the annual time series of all 2-digit parimary metal commodity PPIs, from the Bureau of Labor Statistics. The PPIs are normalized to be 1 in 2016.



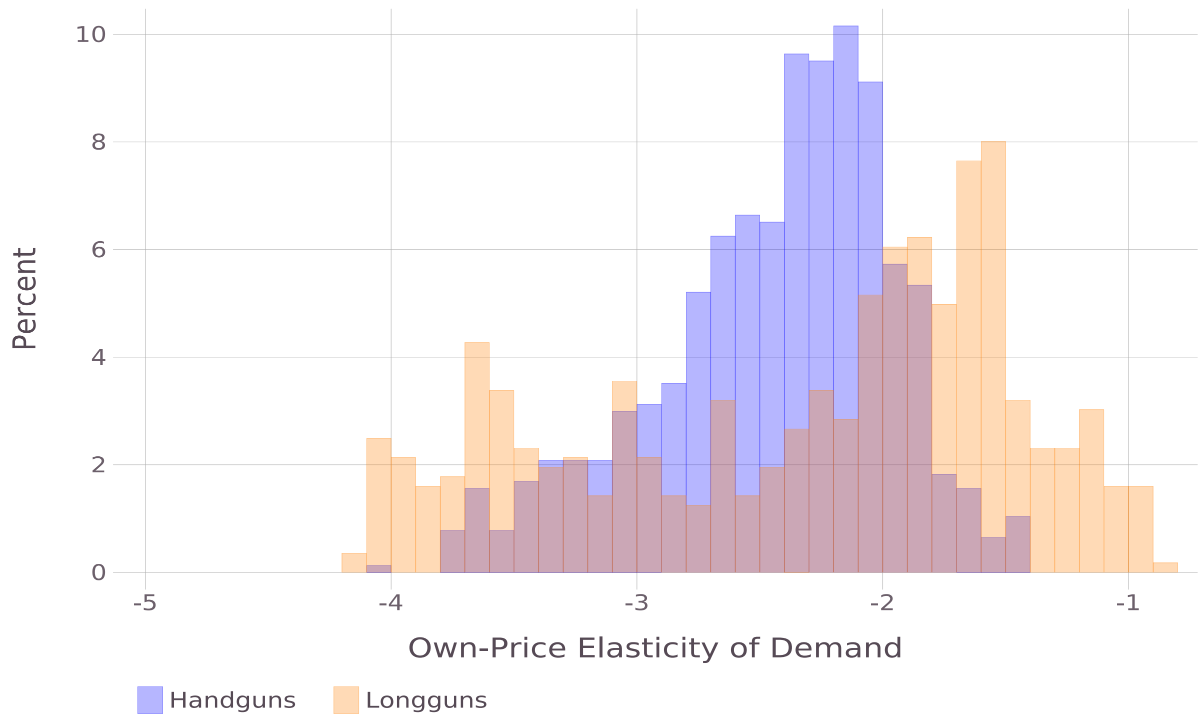
(a) Estimated Non-Zero coefficients for IVLASSO of Prices



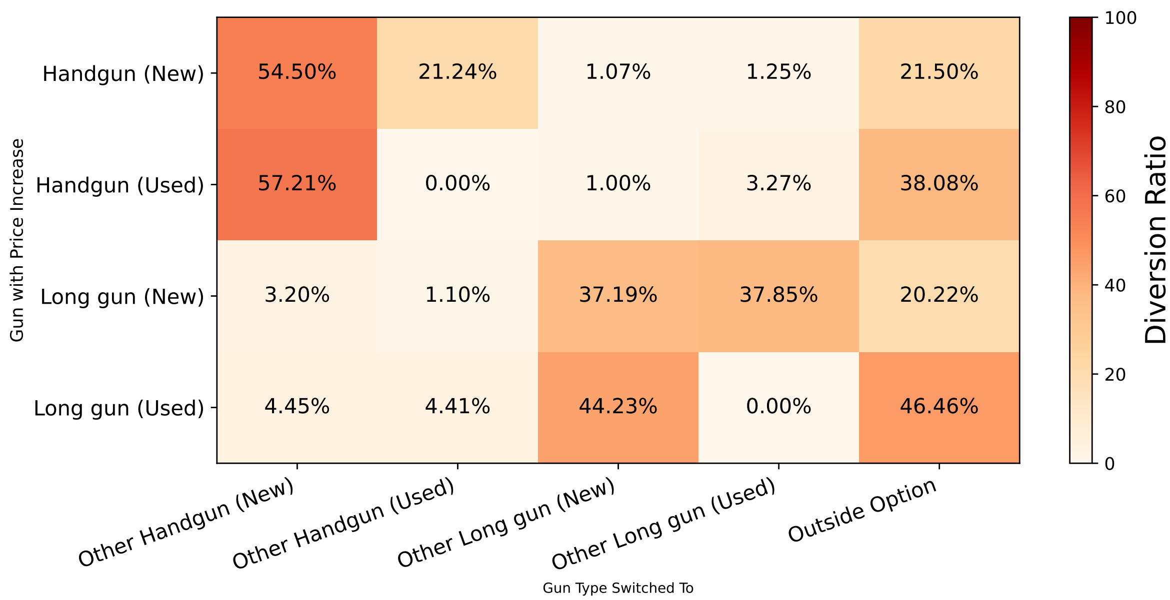
(b) Binscatter of Predicted IVLASSO and Actual Prices

Note: Panel (a) plots the magnitude of the selected coefficients from a lasso of log(MSRP) on logged commodity prices interacted with an ID for manufacturer, with gun model and weapon class times year fixed effects. Panel (b) plots the binscatter of year-to-year changes in residualized predicted and actual MSRP, for gun models produced by manufacturers with non-zero coefficients.

Figure 6: First Stage Estimates for IVLASSO of Prices



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



(b) National Substitution Patterns (Diversion Ratios) across Gun Types

Figure 7: Own and Cross Firearm Substitution Patterns

Panel (a) displays the distribution of own-price elasticities across new guns, split by weapon class. Panel (b) displays the average diversion ratio across gun types, defined as $-(\sum_{k\in G,k\neq j}\partial dq_{k,y}/dp_{j,y})/(\partial q_{j,y}/\partial p_{j,y})$ for each group G. Diversion ratios are weighted by the quantity associated with each gun model sold within group.

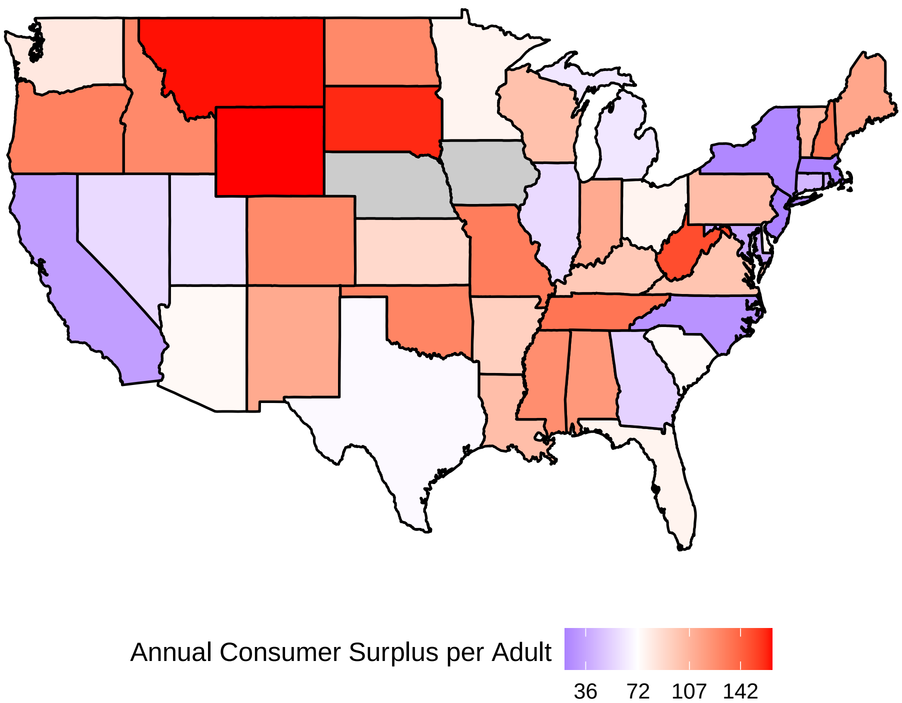
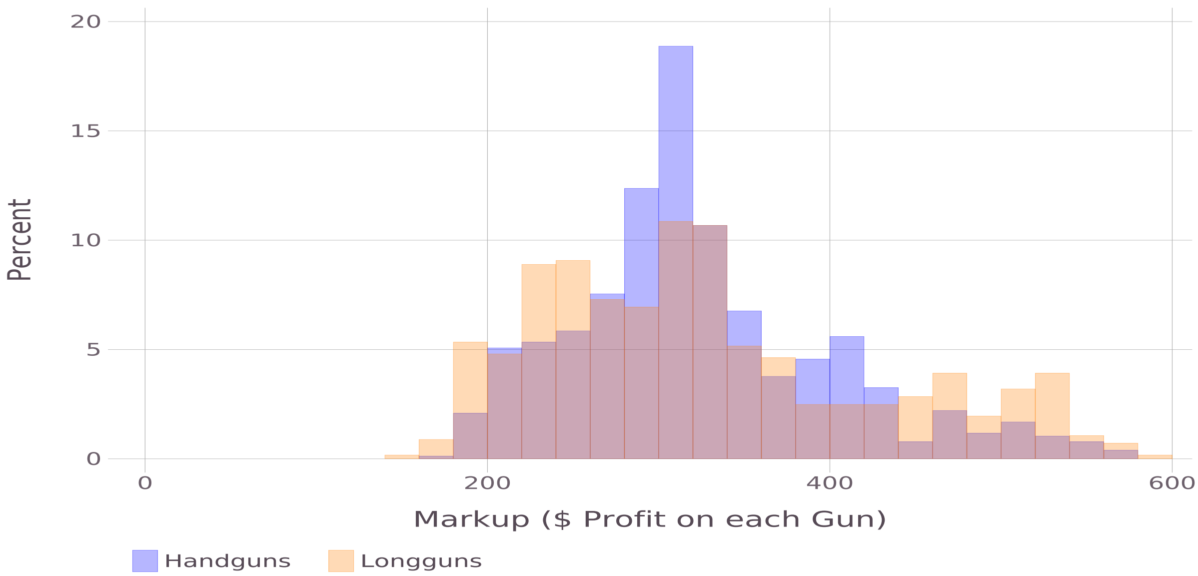
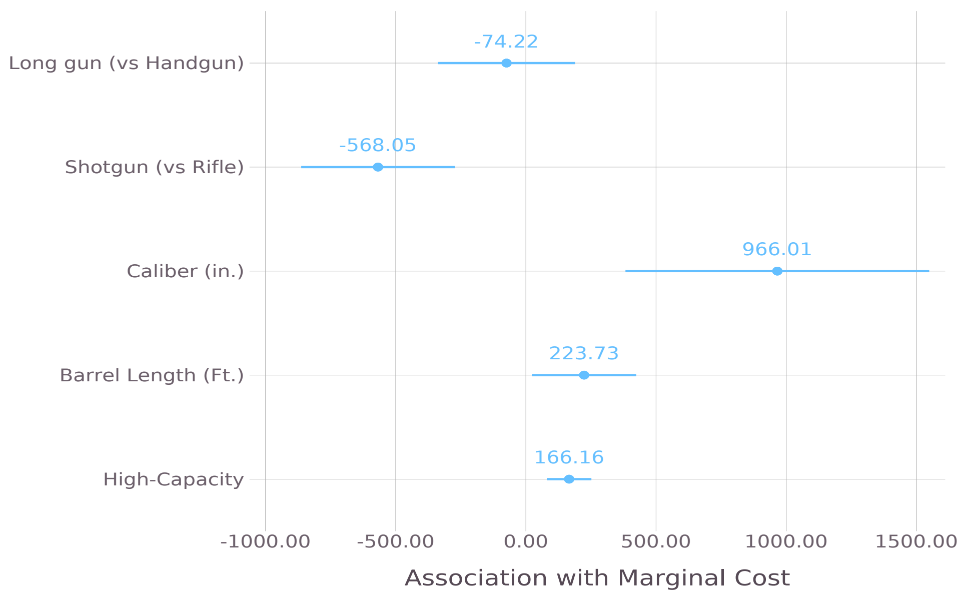


Figure 8: Consumer Surplus from the Firearms market in the U.S.

Figure displays the annual dollar value of consumer surplus per adult in each state, averaged over 2016-2022. 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) Distribution of Markups, by Gun Class



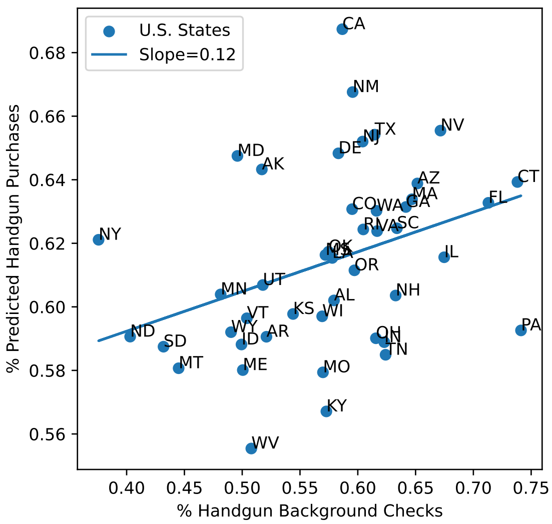
(b) Correlates of Marginal Costs with Gun Characteristics

Figure 9: Marginal cost estimates

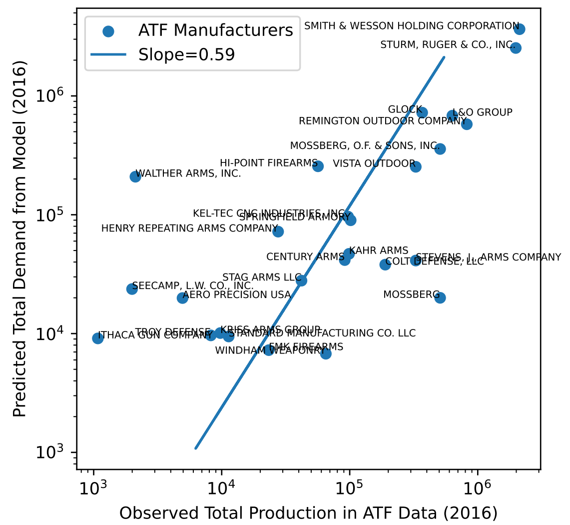
Panel (a) displays the distribution of estimated markups, defined as $p_{j,t}(1 - v_j) - c_{j,t}$, the dollar amount taken as profit by manufacturers, split by weapon class. Panel (b) displays the estimated correlates of marginal cost from the following two-step regression:

$$\begin{aligned} c_{j,y} &= c_j + \delta_y + \omega_{j,y} \\ c_j &= \beta X_j + \omega_j \end{aligned}$$

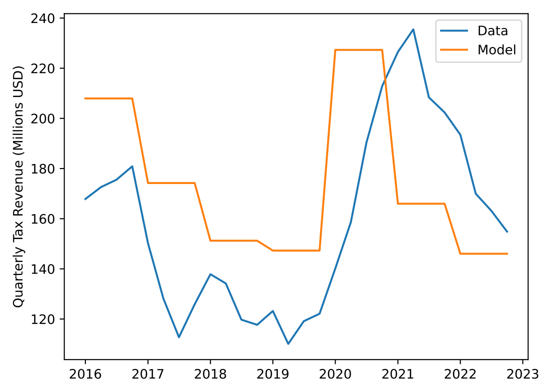
Where the second regression is estimated via GLS with weights proportional to the variance of the estimated fixed effects.



(a) % Handgun Sales by State (Model vs NICS Data)



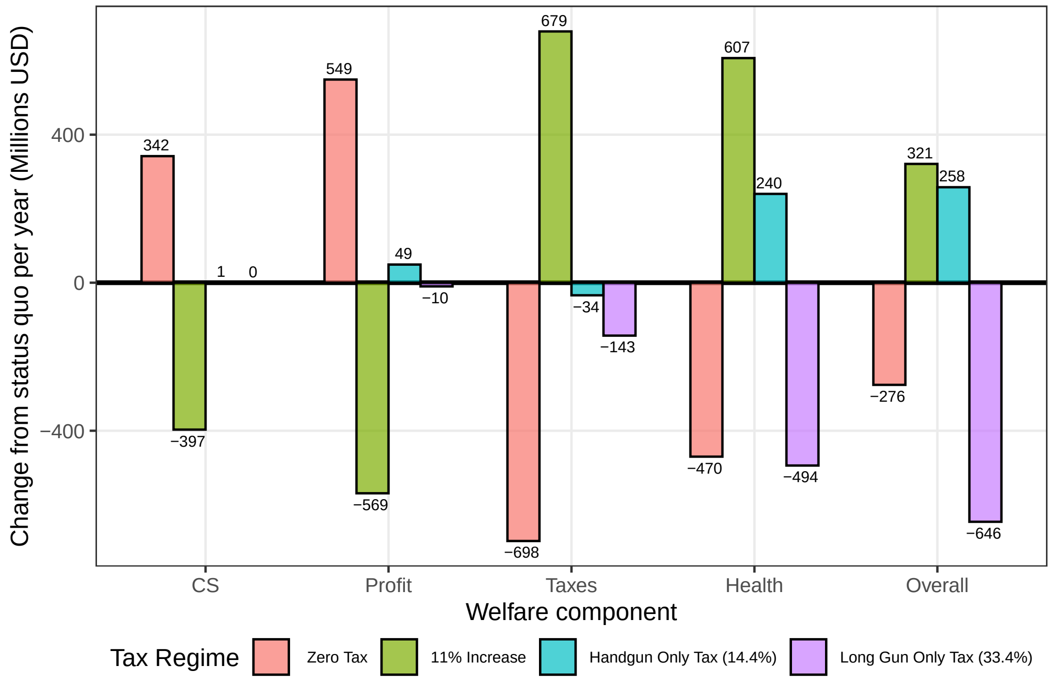
(b) 2016 Sales by Domestic Firms (Model vs ATF Production Data)



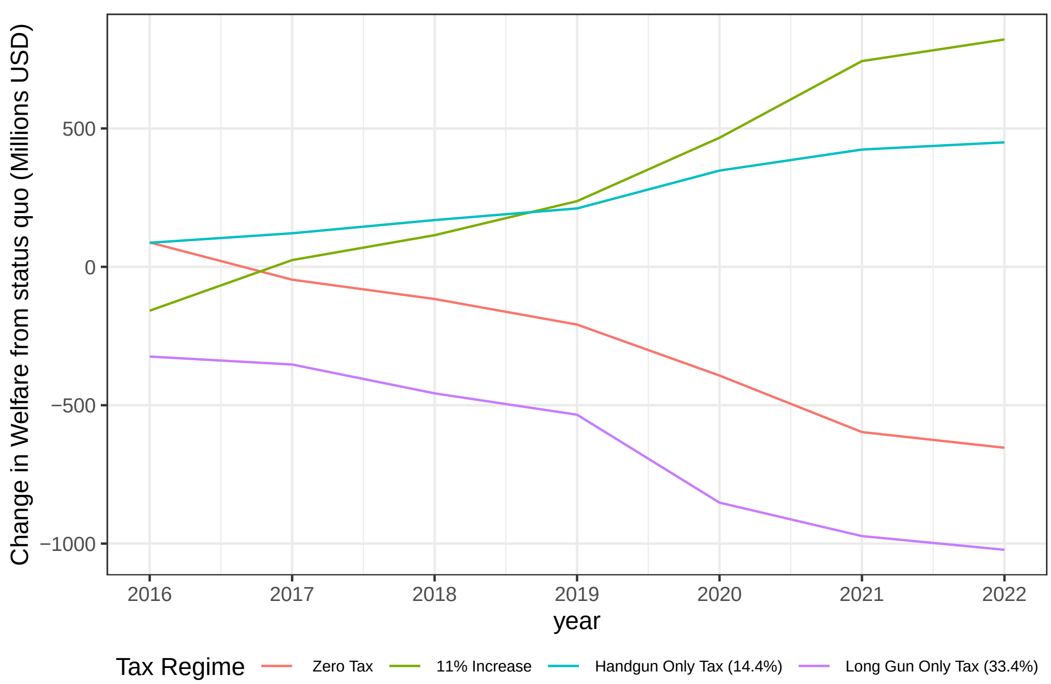
(c) Excise Tax Revenue by Quarter (Model vs FAET Filings)

Figure 10: Out-of-Sample Moments of National Demand vs Structural Model

Panel (a) displays the proportion of NICS background checks attributable to handgun purchases on average, compared to the predicted % of all gun purchases that are handguns, according to our demand model. Panel (b) displays the predicted quantity of guns from our demand model in 2016 purchased from each manufacturer, compared to the observed number of guns produced by these manufacturers in 2016. Both panels have an OLS prediction line with the estimated slope. Panel (c) displays the predicted quarterly tax revenue from the model (we divide the implied annual revenue by 4), compared to the actual revenue collected by the FAET.



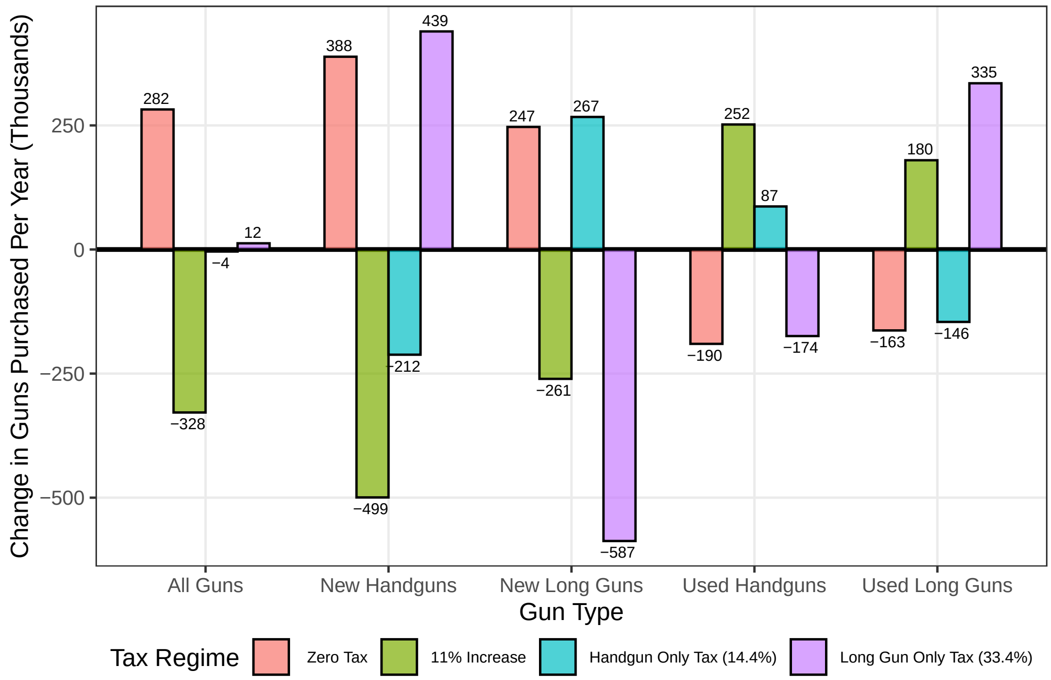
(a) Average Welfare Effects



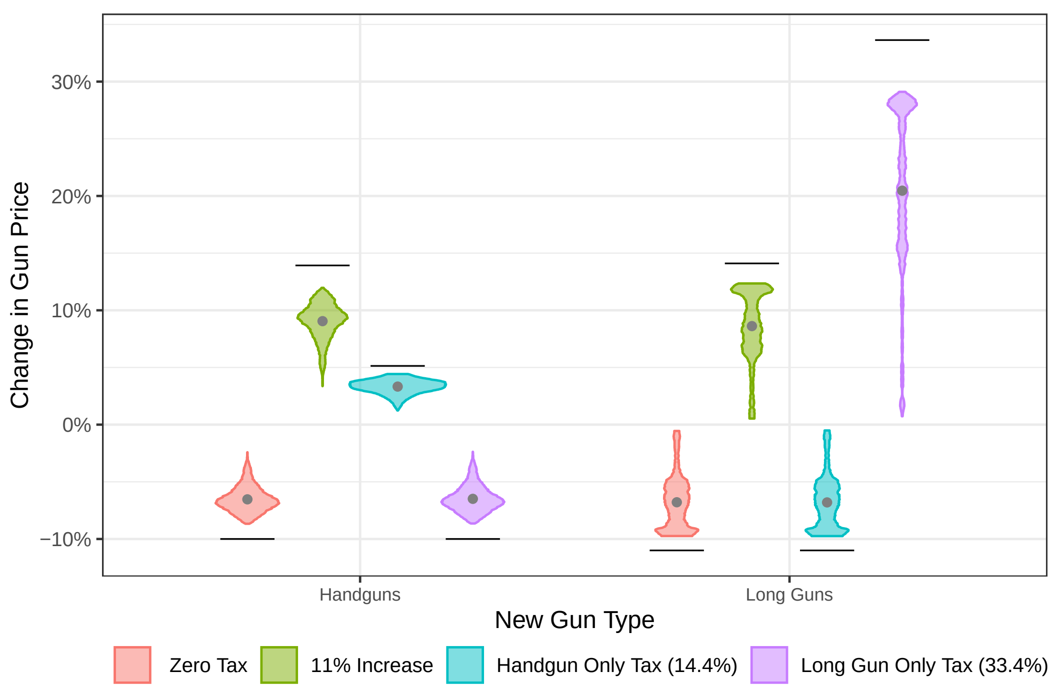
(b) Overall Welfare Effects By Year

Figure 11: Equilibrium Welfare Effects of Firearms Tax Policies

Figure shows changes in welfare from the different tax policies we consider. In Panel (a), we show the average annual welfare effects of different tax policies in the U.S. during our sample, broken down by welfare components. In Panel (b), we show the overall welfare effects of different tax policies by year.



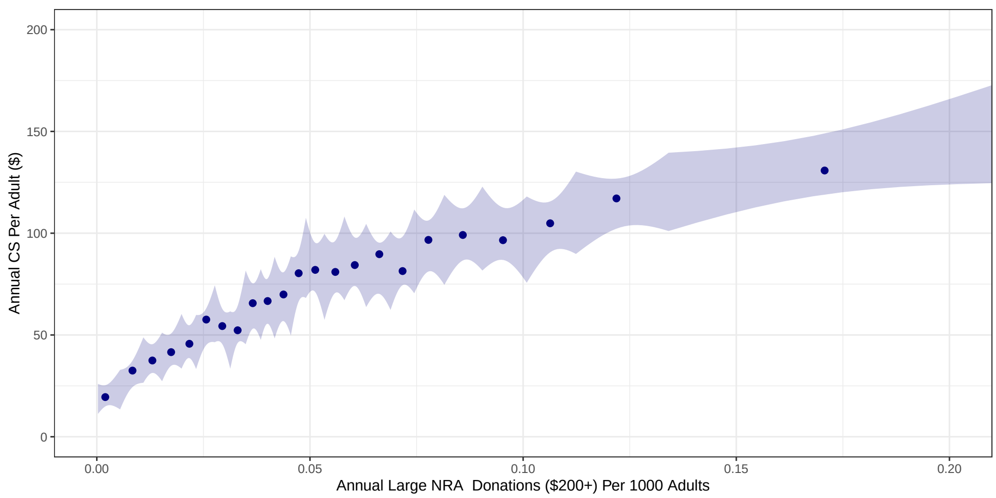
(a) Change in Purchases by Gun Type



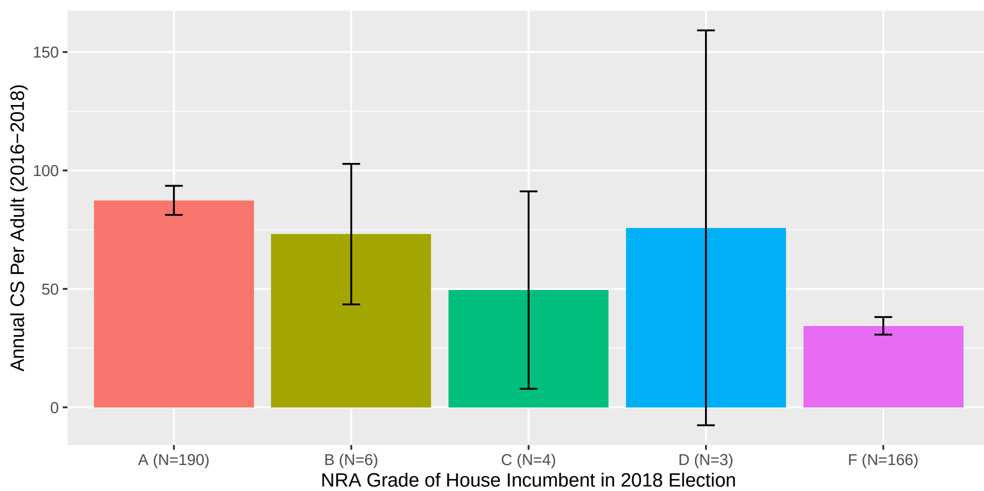
(b) Change in Prices

Figure 12: Effects of Firearms Tax Policies on Prices and Quantities

Figure shows changes in prices and quantities from the different tax policies we consider. In Panel (a), we show the aggregate change in gun sales by year, by type of firearm. In Panel (b), we display a violin plot of the distribution of the change in gun prices by product, among new guns. The dot in each density plot represents the average percentage change in prices, by weapon class. The horizontal lines shows the implied change if price were equal to marginal cost, as a benchmark.



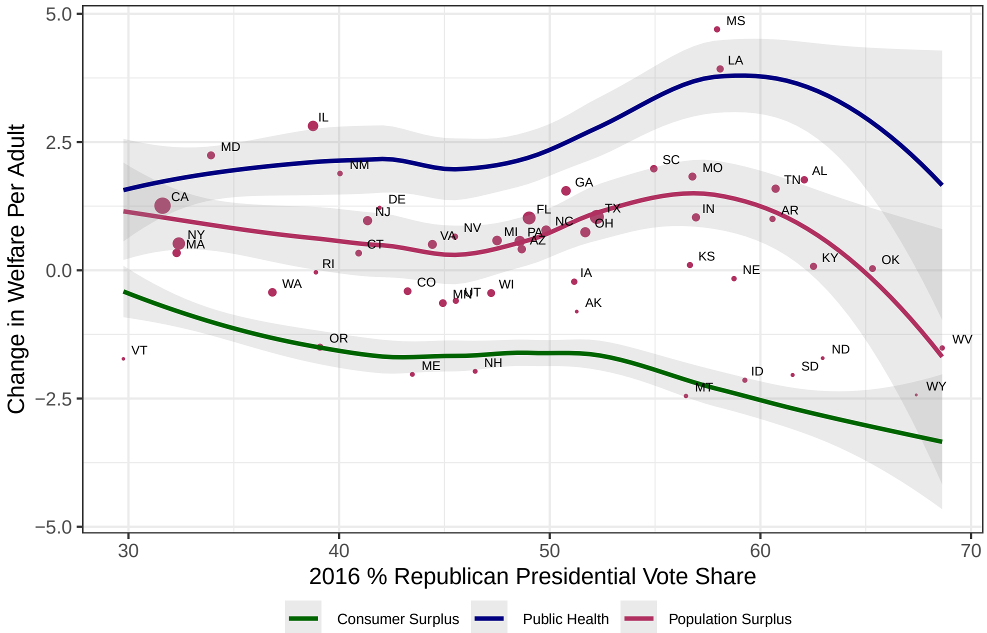
(a) NRA Donations



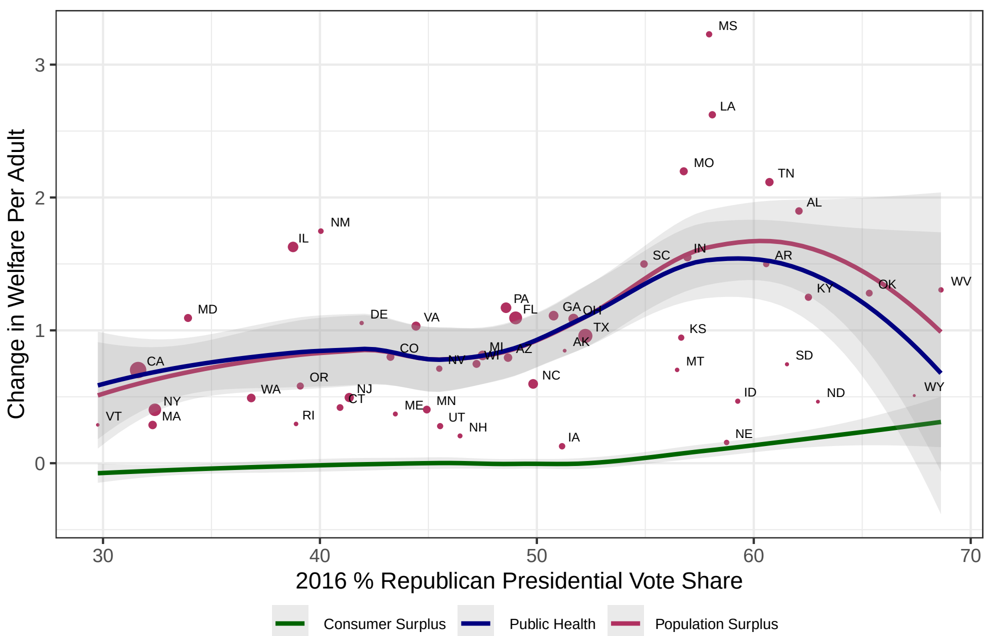
(b) NRA Grades for Incumbent Congress Members

Figure 13: Consumer Surplus and NRA Importance in Neighborhoods

Figure shows consumer surplus estimates at the congressional district level plotted against measures of the National Rifle Association's prominence in the zip code. Panel (a) displays a binscatter 95% confidence bands against the number of donations per 1,000 adults. Bins are chosen via the data-driven procedure of Cattaneo et al. (2019). Panel (b) displays the average consumer surplus per adult by congressional district from 2016-2018, partitioned by the NRA grade given to their House representatives from 2017-2018, running for re-election in 2018. Panel only includes districts for which grades are given to the incumbents (85%).



(a) 11% increase in Excise Tax



(b) Handgun only Tax (13.6%)

Figure 14: Average Welfare Effects by Political Preferences

Figure shows changes in welfare components by U.S. State in equilibrium. Population Surplus is defined as the sum of consumer surplus, and the change in public health effects. The x-axis is the state-level % of votes for Donald Trump in the 2016 U.S. presidential election. The y-axis is the change in the welfare component from the tax policy, in 2022 dollars per adult. For each component, we plot a LOESS fit of the data, weighted by state population. The markers correspond to population surplus estimates and their size is proportional to the population of the state. In Panel (a), we plot the effects of a 11% increase in the excise tax on firearms. In Panel (b), we plot the effects of a 13.6% handgun excise tax coupled with no tax on long guns.

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. $II \rightarrow 2$), 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.[51] 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.

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

	(1) 1-digit	(2) 2-digit	(3) 4-digit	(4) 6-digit
Log(MSRP)	-1.797**	-2.142**	-2.565***	-2.491***
	(0.875)	(0.888)	(0.858)	(0.828)
Observations	2457	2457	2457	2457
Gun Model FE	Yes	Yes	Yes	Yes
Year FE	Class x Year	Class x Year	Class x Year	Class x Year
# Potential Instruments	132	792	2376	3366
# Selected Instruments	5	4	5	6
Sup-Score Test Statistic	12.41	12.47	12.55	12.55
First Stage Sig. (p-value)	0.0000	0.0000	0.0000	0.0000
Method	IVLASSO	IVLASSO	IVLASSO	IVLASSO

Table A1: Estimated Price Elasticity using Different Aggregations of commodities

Table displays the estimated own-price elasticity of demand from the IVLASSO routine described in Section 3.2. The sample in this table is restricted to guns with at least 100 purchases in Massachusetts from 2016-2022. Columns vary in the fidelity of the price indices used. Column (1) reports the estimates using 1-digit commodity indices (2 price indices), Column (2) 2-digit (12 indices), Column (3) four-digit (36 indices), and Column (4) 6-digit (51 indices). Each estimate includes gun model and class-year fixed effects. Standard errors in parentheses are robust to heterogeneity. * denotes $p < .1$, ** denotes $p < .05$, *** denotes $p < .01$.

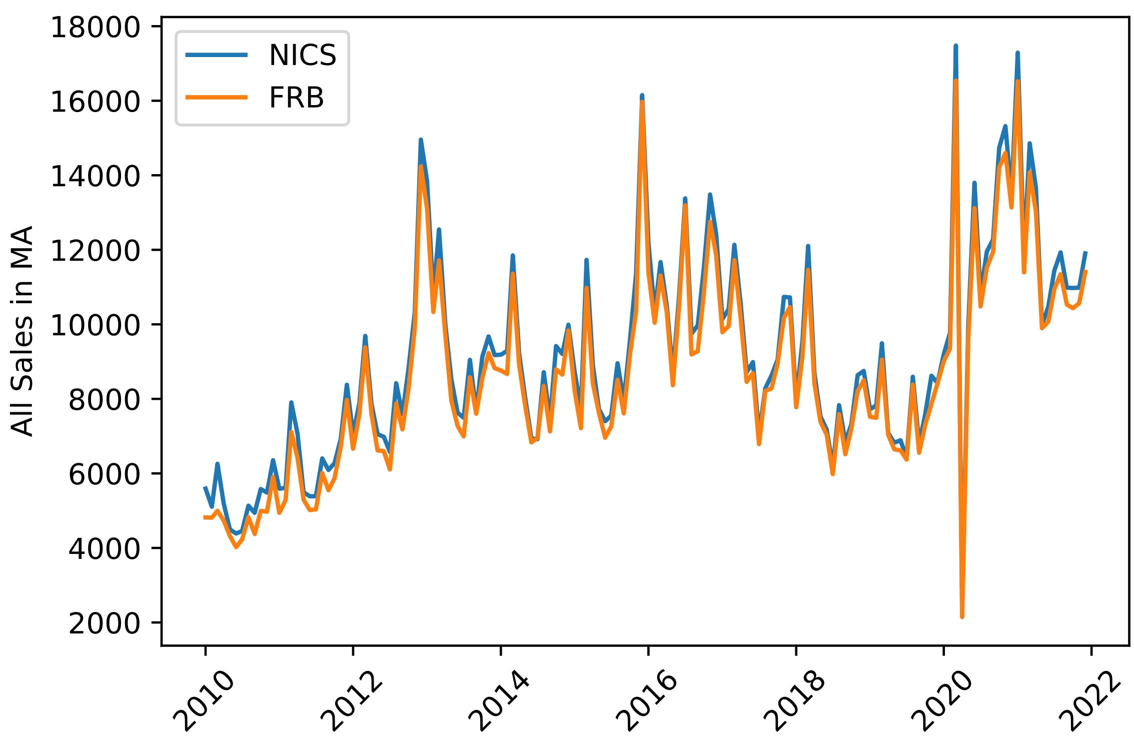


Figure A1: FRB Recorded Gun Transactions vs NICS Background Checks in Massachusetts, by Month

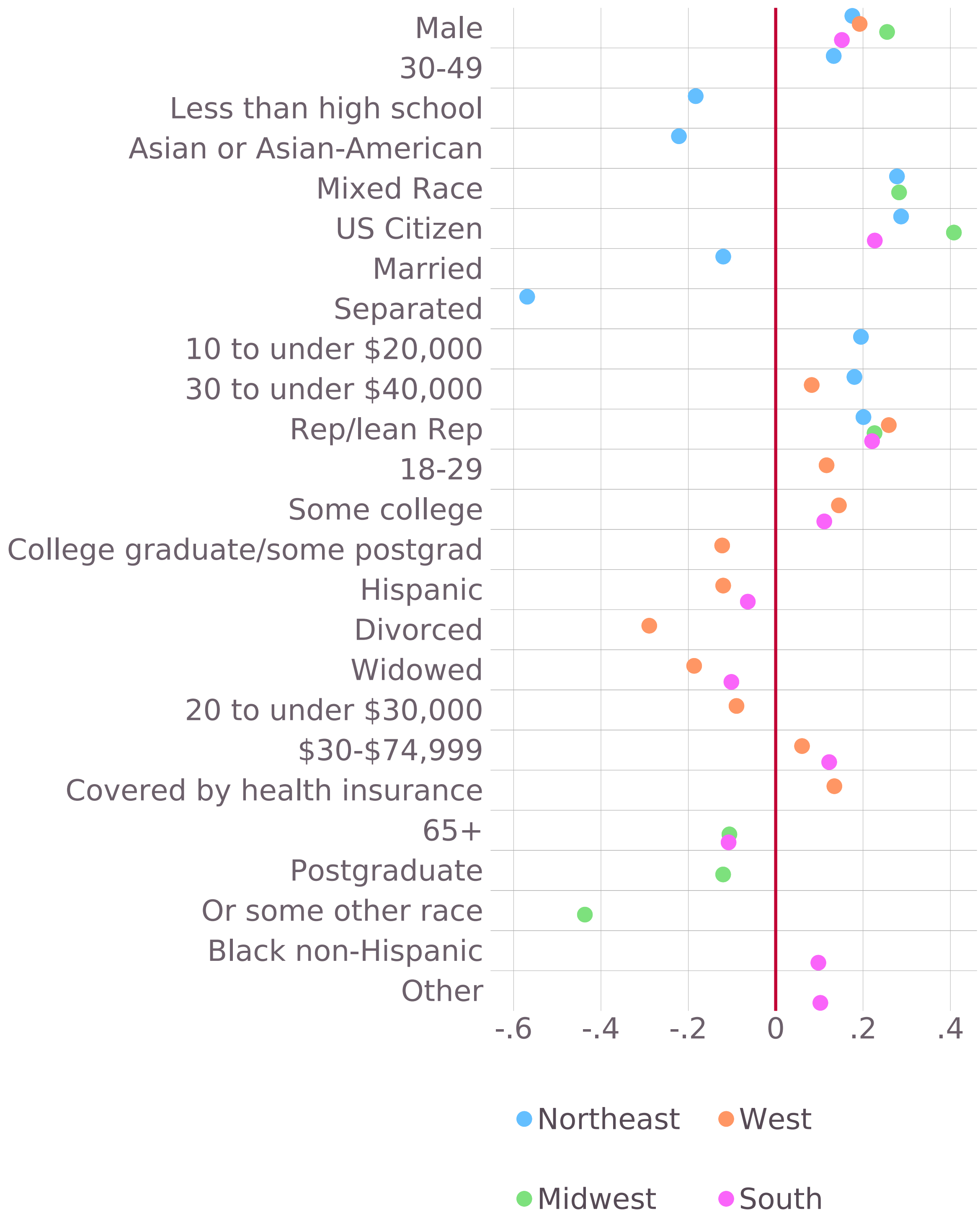
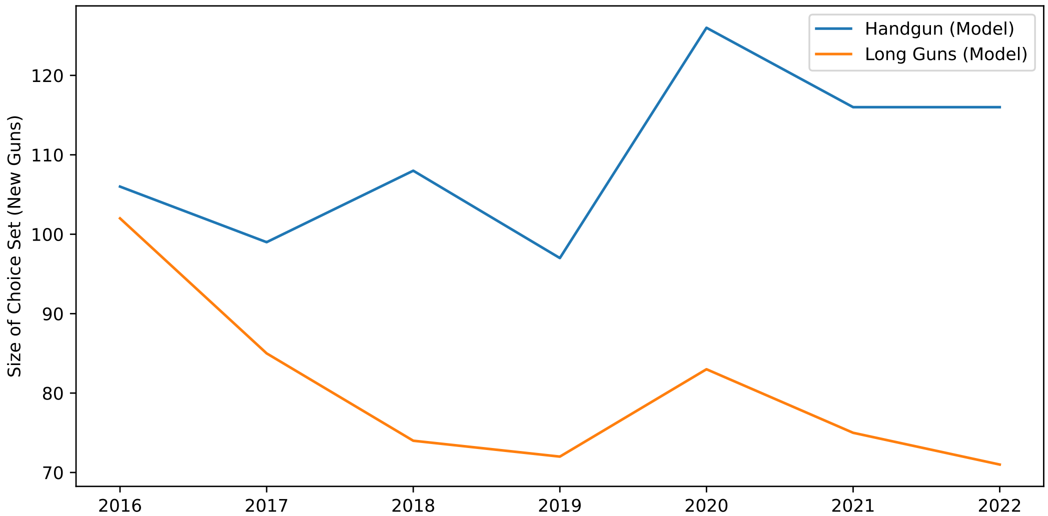
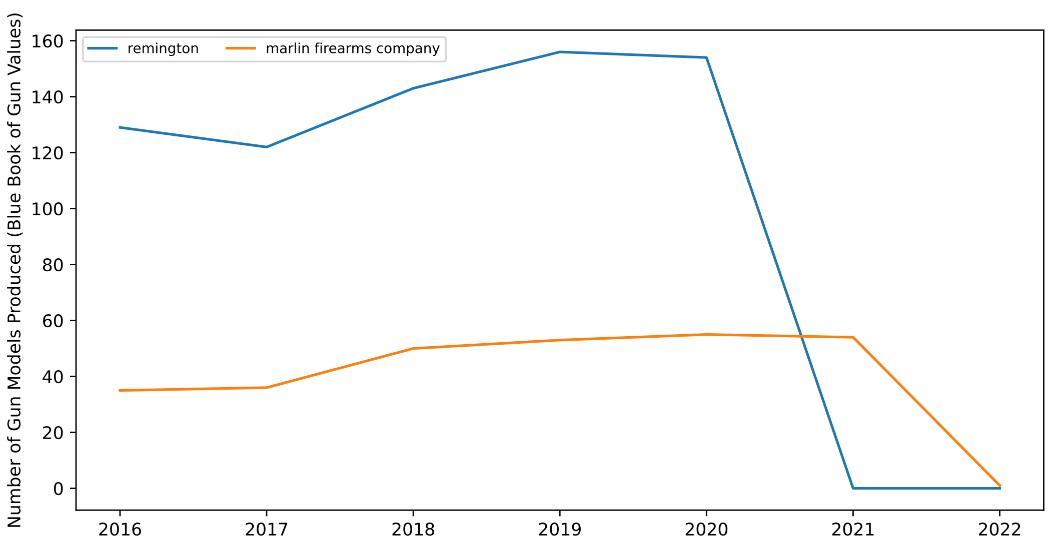


Figure A2: Estimated Lasso Coefficients for Predicting Market Size, From Pew's American Trends Panel



(a) Choice sets $\mathcal{J}_{c,y}$ by Weapon Class and Year



(b) Case Example: Remington's Exit from Firearm Production

Figure A3: Choice Sets in Demand Model over Time

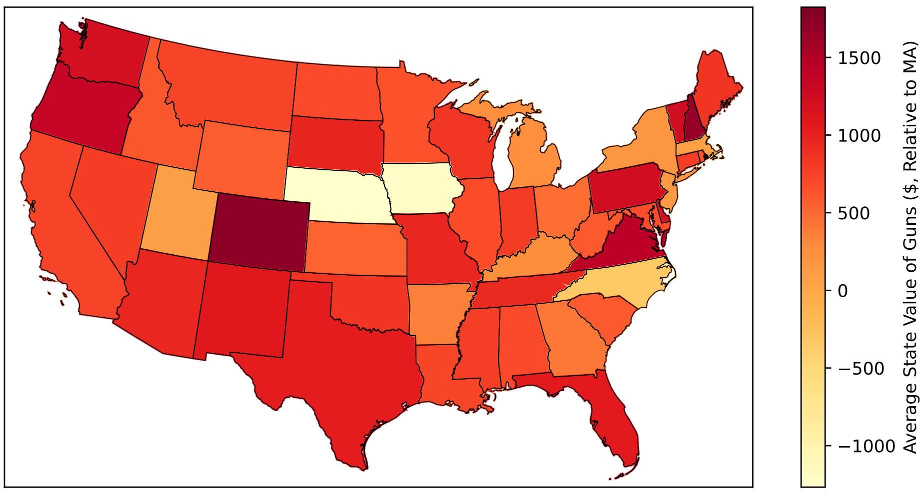


Figure A4: Average State-year Taste Shifters for Firearms by State , in $

Figure shows the average value of τ_t/α_i, $\bar{\tau}_s = E[\tau_t/\alpha_i|i \in s]$ for each U.S. state s from 2016-2022, to express the differences in willingness-to-pay for firearms across markets in dollar terms.

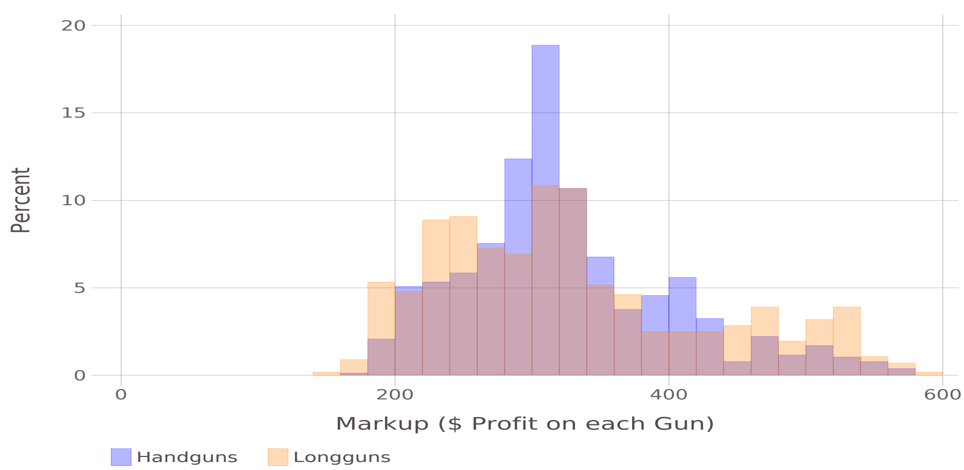


Figure A5: Distribution of Markups, by Gun Class

Figure displays the distribution of estimated markups as a fraction of price $(p_{j,y}(1-\tau) - c_{j,y}/p_{j,y})$ for new guns in our structural model, split by weapon class.

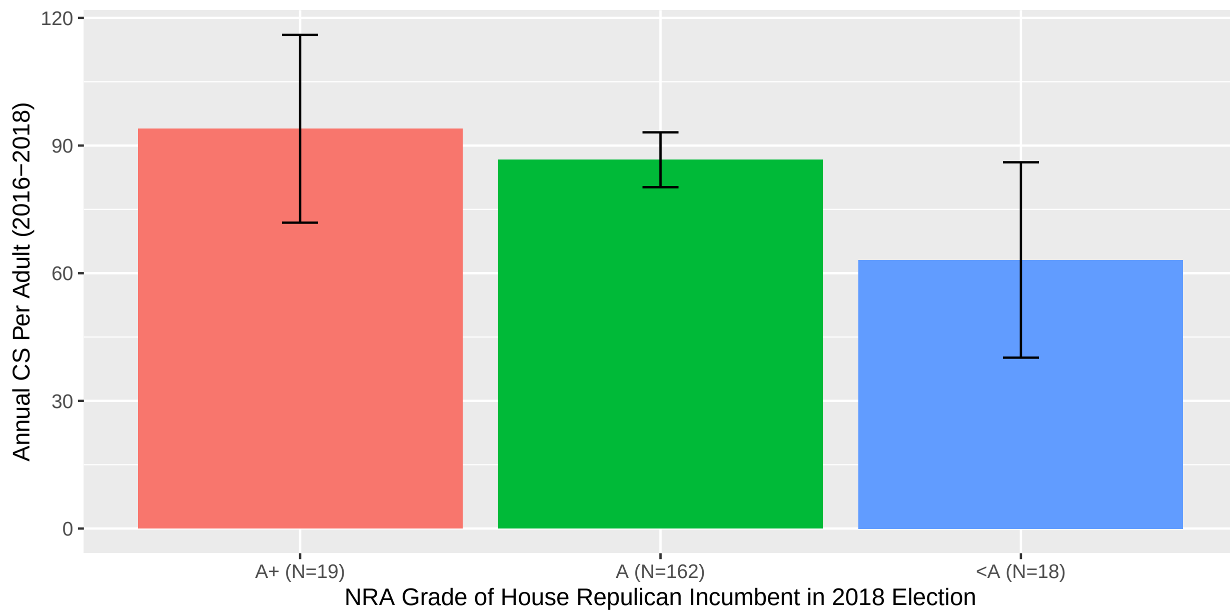


Figure A6: Consumer Surplus and NRA Congressional Grades, Among Republican Seats

Figure displays the average consumer surplus per adult by congressional district from 2016-2018, among Republican-controlled seats, partitioned by the NRA grade given to their House representatives from 2017-2018, running for re-election in 2018. Panel only includes districts for which grades are given to the Republican incumbents.

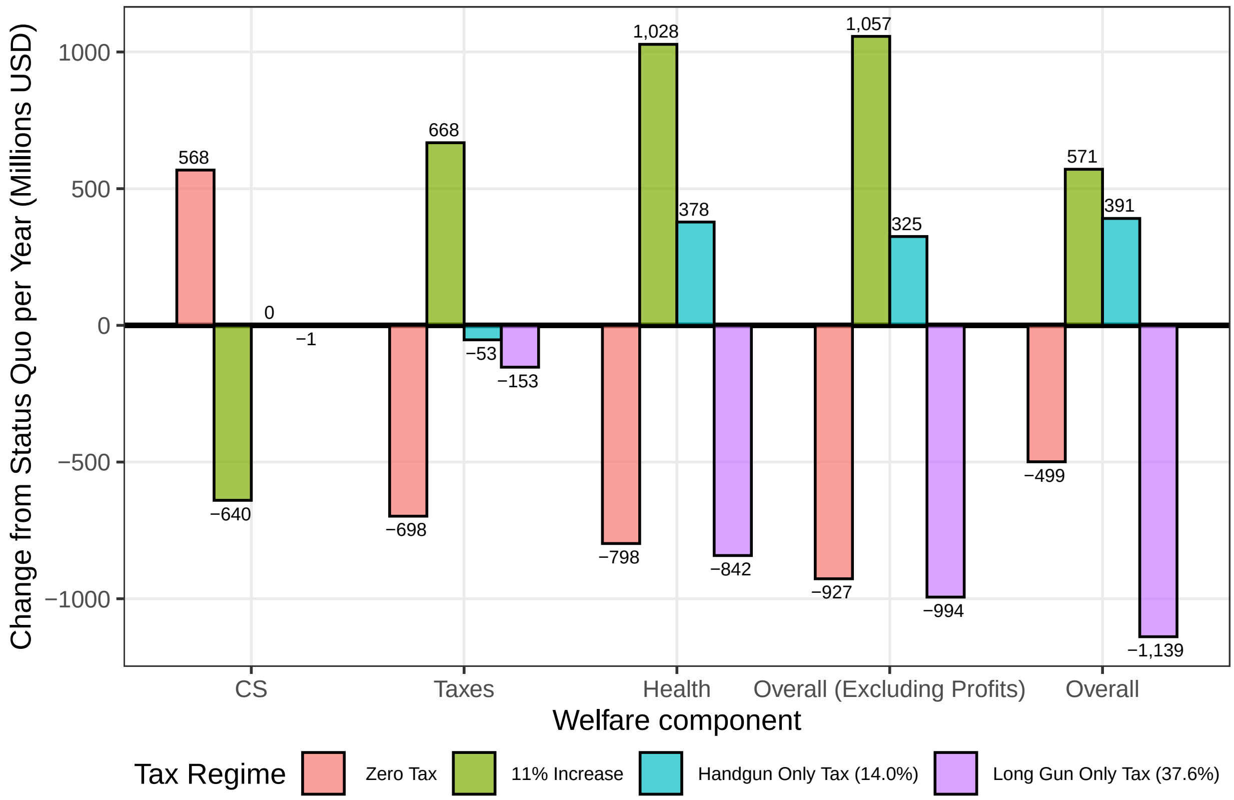


Figure A7: Welfare Effects of Firearms Tax Policies, with No Supply Response

Figure shows the average annual welfare effects of different tax policies in the U.S. during our sample, broken down by welfare components, assuming that manufacturers of new guns set prices at marginal cost.

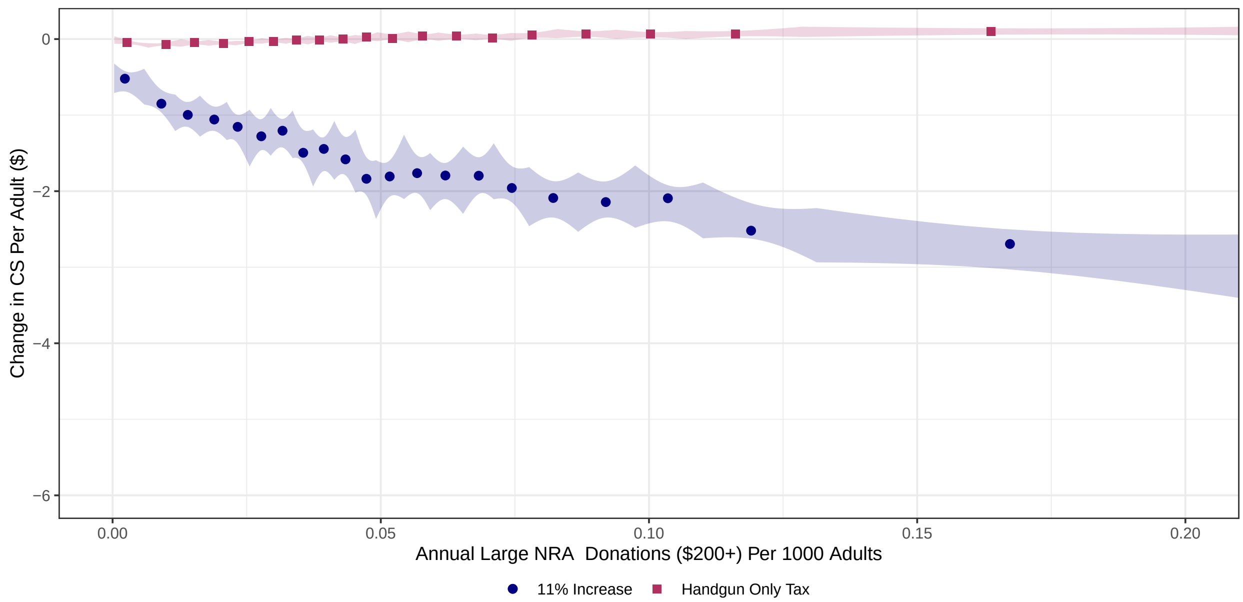


Figure A8: Effect of Tax Reforms on Consumer Surplus, by NRA Prominence (Donations Per Capita)

Figure shows a binscatter of the change in consumer surplus estimates at the congressional district level plotted against donations per capita. Bins are chosen via the data-driven procedure of Cattaneo et al. (2019).