Regulating Firearm Markets: Evidence from California

Adam M. Rosenberg*

Job market paper

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Abstract

This paper studies the relationships between consumer demand and public health in firearm markets, and their roles in determining the impacts of firearm regulation. My analysis uses 20 years of administrative data from California, recording all licit handgun purchases in the state, the consumer and retailer in each transaction, and the universe of gun and non-gun fatalities. Isolating variation from the entry timing of firearm retailers in local markets, the presence of a first firearm retailer increases handgun purchases by 30 percent. The purchases on the margin of retailer entry are made by both repeat and first-time handgun purchasers, and these marginal handgun owners increase both homicide and suicide fatalities. To study the trade-off between consumer surplus and public health, I develop and estimate a model of consumer handgun purchase and its impact on fatalities. My estimates imply that handgun owners are adversely selected—those with a higher willingness to pay for a handgun also generate more expected fatalities—such that the expected public health costs of handgun ownership outweigh the private benefits of handgun purchase. Using the model to simulate counterfactual policies, California's 2024 statewide sales tax on firearm purchase approximately maximizes tax revenues, but is too low when jointly accounting for consumer surplus and public health. More efficient policies target high tax rates to areas where marginal handgun purchasers have lower willingness to pay and higher expected fatalities. In particular, county-specific taxes could achieve a larger reduction in homicides and a smaller drop in consumer surplus by setting high tax rates around San Francisco and Los Angeles, while leaving the rest of the state at the status quo.

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1 Introduction

How should policymakers regulate firearm markets? Firearms in the U.S. are popular consumer goods with public health consequences. Consumers purchase billions of dollars of firearms each year, and one in three U.S. households has a firearm (Berrigan et al. 2022). Each year, firearms are also involved in 40,000 fatalities and 80,000 non-fatal injuries (Kaufman et al. 2021). The design of effective firearm regulation depends on the relationship between consumers' preferences for firearm purchase and their public health externalities from firearm ownership, analogous to other externality-producing products (Pigou 1924).

The limited availability of data on firearm markets has led empirical work to study either consumer preferences or externalities in isolation, potentially hampering the design of effective regulation (Wellford et al. 2004). With minimal empirical foundation, experts on firearm policy express divergent and variable views about the potential effects of regulations on firearm markets: tax changes, entry restrictions on retailers, minimum age requirements, and gun buybacks (Smart et al. 2021). This provides little guidance to the numerous state and local policymakers now exploring these instruments (Brownlee 2024).[1]

The connection between consumer preferences and public health in firearm markets creates a fundamental asymmetry in the impact of regulation. Regulation affects the surplus of all potential firearm purchasers, but only affects externalities through the decisions of consumers changing their firearm purchase on the margin. These marginal purchasers may differ in number and composition from one regulation to the next—and relative to potential purchasers as a whole—due to consumer heterogeneity in preferences, heterogeneity in public health externalities, and the persistence of firearm ownership over time. Without evidence on these forces, the unknown structure of heterogeneity in firearm markets limits the ability of policymakers to design effective firearm regulation (Fleischer 2015).

In this paper, I explore the design of regulation on firearm markets by developing and estimating a model of consumer preferences for firearm purchase in which firearm ownership can affect fatalities. I estimate the model for California's licit handgun market, leveraging a 20-year consumer panel of individual handgun transactions at firearm retailers, paired with a set of individual-level morgue records, both constructed from administrative data with near-universal coverage across the state. I use the estimated model to characterize the relationship between consumers' preferences for handgun purchase and their externalities from handgun ownership. Based on these estimates, I study the design of counterfactual regulations on firearm markets relevant to the current policy discussion: adjusting taxes on

[1] For instance, when California implemented a new statewide sales tax on firearm purchase in July 2024, its chosen rate simply doubled the federal firearms tax from the omnibus 1918 Revenue Act (CA A.B. 28, 2023).

handgun purchase, restricting the entry of firearm retailers, increasing the minimum age for handgun purchase, and re-pricing offers at gun buybacks.

The key empirical challenge to my analysis of handgun purchase and public health is endogeneity: guns may cause crime, and crime may cause guns (Duggan 2001, Depew and Swensen 2019). I address this challenge by using variation from the timing of 823 market entries and exits of firearm retailers, and the timing of regulations these retailers must meet prior to entry. Using event study methods (Borusyak et al. 2024), I document that the average entry of a first firearm retailer in California's average zip code would increase within-zip code handgun purchases by 30 percent. This increase in purchasing occurs on-entry and displays no evidence of pre-entry trends. Analyzing heterogeneity, I find that entries create less purchasing in more-distant zip codes, more purchasing in zip codes without an incumbent retailer, opposite effects to retailer exit, and similarly elastic responses from repeat and first-time handgun purchasers. A limitation of my data is that they do not record transaction prices, though firearm pricing is approximately uniform across retailers in the U.S. (Moshary et al. forthcoming). Together, these facts demonstrate that consumers are elastic across the margins of handgun purchase and ownership.

When a retailer enters, the increase in handgun ownership from marginal purchasers harms public health. Applying an identical event study design, the average entry of a first firearm retailer increases both handgun ownership and homicide fatalities in the entered zip code. Relative to this event study, my preferred estimator achieves greater precision by leveraging variation from the full set of firearm retailer entries and exits in California via an instrumental variables strategy. These estimates imply that—local to an average retailer entry—increasing handgun ownership in a zip code-quarter by 10 percent would increase homicide fatalities by 11 percent and suicide fatalities by 2 percent. Relative to the prior literature, my estimates imply somewhat larger effects of handgun ownership on homicide fatalities, and similar effects for suicide fatalities, perhaps reflecting the particular public health characteristics of handgun owners on the margin of net entry (RAND 2018b, RAND 2018c). Leveraging the heterogeneous effects of net entry on the composition of handgun ownership via a control function approach (Wooldridge 2015), I document that handguns induce more homicide fatalities if owned by men, Whites, and those under age 30, as well as if owned by consumers living in areas with lower income, lower population density, and higher rates of violent crime.

To study the design of firearm regulation, I develop a model of consumer handgun purchase from firearm retailers in which ownership affects fatalities. Each consumer makes a sequence of repeated static choices over whether or not to purchase a handgun and from which firearm retailer to purchase, with all handguns assumed undifferentiated. I specify preferences as a random coefficients nested logit, with consumers considering their present value from the purchase of an additional handgun, the price, a local demand shock, and the set of available firearm retailers, characterized by heterogeneous travel distances and vertical qualities. As handguns are durable goods, a consumer's purchase in one period affects their ownership into the future. Handgun ownership affects fatalities—potentially positively or negatively—based on a consumer's observable demographics, the geographic characteristics of their residential zip code, and the (partially unobservable) determinants of their present value of handgun purchase. The model allows for selection into handgun ownership on externality-relevant characteristics, as a common set of variables affects both preferences and fatalities. This leads me to apply tools from other settings with selection on unobservables in specifying my model and its estimator (e.g., Heckman 1979, Cohen and Einav 2007, Bundorf et al. 2012, Einav et al. 2022).

I estimate the model via minimum distance, combining likelihood- and moment-based information from the data on handgun purchasing and fatalities. In addition to satisfying several first-order conditions of the log-likelihood, my estimator also matches the event-study estimates of retailer entry on handgun purchasing, and the observed levels of handgun purchasing across California. I calibrate the price coefficient using my estimates of consumer disutility from distance to a firearm retailer and the monetary cost of travel implied by one mile of distance in California's firearm market. To estimate the effect of individual handgun ownership on fatalities, my estimator leverages the correlations of fatality outcomes with variation in the level and composition of handgun ownership, created by the net-entry timing of firearm retailers.

The estimated model reveals marked heterogeneity in consumer preferences for handgun purchase. Across California's adults, a 1 standard deviation higher value for handgun purchase represents approximately 230 dollars, or about 40 percent of the median pre-tax handgun price in the U.S. (Moshary et al. forthcoming). In choosing a firearm retailer from which to purchase, California's average handgun purchaser is willing to travel 50 percent further, about 9 additional miles, to purchase from a retailer 1 standard deviation higher in the quality distribution.

My estimates also demonstrate that consumers are adversely selected into handgun purchase and ownership, with respect to their expected externalities. Conditional on observables, a consumer with a 1 standard deviation higher preference for handgun purchase would create 0.006 additional homicide fatalities from handgun ownership each year. This is similar to the difference in homicide fatalities between male and female handgun owners, and about twice as large as being over age 30, when individuals "age out of crime" (Farrington 1986). Handgun ownership also increases the prevalence of suicide fatalities, although I find no evidence of heterogeneity across consumers.

The structure of externalities from handgun ownership, in particular adverse selection, generates allocative inefficiency in the handgun market. At each point in the distribution of willingness-to-pay for handgun purchase, the average consumer generates a negative public health externality larger than the value of tax revenue and consumer surplus their purchase would create. That is, the average consumer's handgun purchase is net welfare decreasing, no matter how high is their willingness to pay.

Leveraging the estimated model, I explore the effects of counterfactual regulations on California's licit handgun market. Analyzing the firearm sales tax implemented by California in 2024, I find that such a tax in the average year would destroy 7.5 million dollars of consumer surplus while averting 400 homicide fatalities. Surprisingly for such a new policy, this tax would also approximately maximize public revenues achievable from the licit handgun market, raising 1.5 million dollars of revenue each year. Weighing the drop in consumer surplus against the fiscal values of averted homicides and additional tax revenues, California's 2024 firearm sales tax improves social welfare.[2]

When directly valuing the cost of fatalities produced by California's licit handgun market, the welfare maximizing policy is to ban all handgun purchases. Due to adverse selection, an increase in the tax rate also increases the average externality cost among residual purchasers, driving up optimal rates and leading the regulator to (optimally) shut down the market. Of course, predicting the potential impacts from such a large policy change requires a great degree of extrapolation—especially to the dynamics of the the illicit firearms market—making the optimality of a ban highly ambiguous (e.g., Cook 2018, Lee and Persson 2022, Schnell 2024).

I also consider a statewide increase in the minimum legal age for handgun purchase, placing targeted bans on purchases by consumers who have yet to age out of crime. Under my estimated model, raising the minimum legal age for handgun purchase in California to 30 would effectively screen out an observably high-risk group of handgun purchasers, while maintaining status-quo consumer surplus for the majority of the market. The welfare gains from targeting firearm regulation to observably risky consumers suggests that other targeted restrictions on firearm ownership—such as universal background checks or extreme risk protection orders—may improve welfare as well (Smart et al. 2023).

Inspired by the system of local firearm taxes implemented by the city of San Jose in 2022, I find that targeting taxes across California's geographic heterogeneity can consider-

[2]My analysis values each homicide fatality using either the value of a statistical life (8.5 million dollars, Heaton 2010) or a more conservative estimated fiscal cost of a fatal shooting from the city of San Jose (0.17 million dollars, Liccardo 2022). My analysis values one dollar of tax revenue as one dollar of social welfare.

ably improve upon statewide policy.[3] In particular, setting tax rates optimally in each of California's 58 counties, it would be possible to achieve welfare gains in public health and tax revenue equivalent to California's 2024 statewide tax, with a 40 percent smaller drop in consumer surplus. Alternatively, maintaining the same drop in consumer surplus, the county-specific optimal taxes would achieve a 50 percent larger welfare gain, by preventing 200 additional homicide fatalities each year.

The county-specific optimal taxes on handgun purchase are highly differentiated, in ways that may facilitate the design and implementation of firearm regulation. The largest gains in welfare come from targeting higher taxes to California's coastal population centers, while leaving most of the state at the regulatory status quo. This targeting addresses heterogeneity in adverse selection, as consumers along the coast tend to derive less value from handgun purchase and generate more costly externalities from handgun ownership. Moreover, since these coastal consumers are also more supportive of firearm regulation, much of the efficiency gains from local taxes could be achieved politically by allowing local jurisdictions to set their own firearm policy.

In higher geographic resolution, I use the model to simulate the effects of city-wide bans on the operation of firearm retailers, as implemented by Chicago from 2010–2014.[4] Across California's 20 highest-population cities, bans on firearm retailers create markedly different effects, according to the city's local characteristics. Perversely, because of geographic heterogeneity in the severity of adverse selection, the cities with smaller changes in handgun purchasing following a retailer ban are also the cities with the greatest welfare benefits from stricter firearm regulation. Relative to citywide bans on firearm retailers, it is more efficient to "target" firearm policy via a uniform statewide tax, which could achieve the same public health gains with a smaller drop in consumer surplus.

I also use the estimated model to study the design of gun buybacks in California. These are popular programs in which regulators offer a uniform price to consumers for the repurchase of their firearms (Ferrazares et al. 2021). I compute the optimal tax when the regulator disregards the direct effect of handguns on fatalities and instead values each handgun not sold at the typical price of 100 dollars from California's gun buybacks. The optimal tax under this buyback objective is with 30 dollars of California's 2024 rate, suggesting that prices at gun buybacks undervalue the fiscal costs of handgun ownership.

This paper contributes to a literature studying firearm markets (e.g., Koper and Roth 2002, Bice and Hemley 2002, Cook et al. 2007, Knight 2013, McDougal et al. 2023, Hüther 2023), and is especially close to two recent papers. Moshary et al. (forthcoming) conduct a

[3]See `https://records.sanjoseca.gov/Ordinances/ORD30716.pdf`.

[4]See `https://blogs.chicagotribune.com/files/chicago-gun-shop-ordinance.pdf`.

stated-preference experiment in a survey of U.S. consumers who may be interested in acquiring a firearm, use these stated choices to estimate heterogeneous preferences over different firearms, and discuss the importance of preferences and externalities in studying firearm policy. Whereas, this paper leverages administrative data and revealed preference to estimate heterogeneous preferences for handgun purchase among California's adult population, to recover the heterogeneous public health implications of consumer handgun ownership, and to analyze the design of regulation in handgun markets. In subsequent work, Armona and Rosenberg (2024) analyze product differentiation and market power in the U.S. firearms industry, utilizing a more-restrictive model of public health and a non-overlapping collection of datasets.

This paper also contributes to long literatures on the impacts of existing firearm policy and of firearm ownership on public health and crime (e.g., Krug 1968, Zimring 1968, Lott and Mustard 1997, Cook and Ludwig 2006). I extend this literature by using the net entry of firearm retailers to develop an instrument for firearm ownership, which addresses concerns of endogeneity and measurement error discussed in critical reviews (e.g., Wellford et al. 2004, Kleck 2015).[5] In developing this instrument, my analysis builds on a set of papers studying the direct effect of firearm retailers on crime (e.g., Wiebe et al. 2009, Duggan et al. 2011, Pear et al. 2023).

More generally, this paper relates to the design of policy for product markets that generate externalities (e.g., Pigou 1924, Buchanan 1969) when preferences and externalities may vary across the population (Diamond 1973, Jacobsen et al. 2020). Recent applications study heterogeneous externalities in the domains of personal transportation (Edlin and Karaca-Mandic 2006, Jacobsen 2013, Anderson and Auffhammer 2014, Knittel and Sandler 2018, Barahona et al. 2020, Jacobsen et al. 2023, Barwick et al. 2023), energy-intensive consumer durables (Allcott et al. 2015, Borenstein and Bushnell 2022, Armitage 2022, Allcott and Greenstone 2024), and beverages (Griffith et al. 2019, O'Connell and Smith 2024, Griffith et al. 2022, Conlon and Rao 2023). My analysis of firearm regulation leverages tools from the study of selection markets (Einav et al. 2021) to account for an unobservable and uninternalized consequence of each decision maker's choice that may be correlated with their preferences (e.g., Einav et al. 2010, Einav et al. 2012, Fowlie et al. 2016, Wagner 2022, Tebaldi forthcoming, Aspelund and Russo 2024, Chen et al. 2024).

The remainder of the paper is as follows. Section 2 describes the regulatory environment and data. Section 3 uses the entry and exit of firearm retailers to study handgun pur-

[5] The other instruments for firearm ownership used by this literature between 2003–2018 were subscriptions to outdoor- and firearm-related magazines, Google searches for hunting-related terms, the 1988 Presidential Election Republican vote share, and military veterans per capita (RAND 2018b, RAND 2018c).

chasing, handgun ownership, and public health. Section 4 builds and estimates a model of handgun purchase in which handgun ownership affects public health, and Section 5 presents model estimates. Section 6 uses the estimated model to study counterfactual regulations on California's licit handgun market. Section 7 concludes.

2 Setting and data

2.1 Regulatory environment

I study California's licit market for consumer handguns between 2005–2015. California law mandates that almost every handgun transfer to an individual be implemented by a state-licensed firearm retailer.[6] Additionally, each retailer must record all the licit handgun transfers they implement using a standardized form, reproduced in Figure OA.1, and transmit this information to California's Department of Justice.

Participants in the market face considerable regulation beyond handgun transfer recording. Prior to selling their first firearm potential retailers must, in-serial, find a physical location from which to conduct business, undergo local business permitting, receive a Federal Firearms License with a two-month waiting period, and receive an analogous license from California. After opening, state law prohibits retailers from most forms of advertising, and federal law requires that transactions occur on the retailer's premises or at a gun show. Federal law also restricts inter-state commerce in arms to licensed retailers, preventing inter-state transactions that involve at least one private individual.

On the consumer side, California and Federal law jointly limit handgun purchase to legal residents of the state, over the age of 21, who have successfully completed a state-run firearm safety course. Before each licitly attempted firearm acquisition in California the acquirer must pass an instant background check conducted by the FBI. Following a licit firearm purchase, California law mandates a 10-day waiting period prior to acquisition, with the firearm held at the retailer's physical location until the purchaser picks it up.

In addition, California's handgun market is affected by several sources of price regulation. The federal government taxes handgun sales from manufacturers to retailers at a 10 percent rate, established by and held approximately constant since the 1918 Revenue Act (Congressional Research Service 2023). Handgun sales from retailers to consumers are subject to California state and district sales tax, between 6.25–8.75 percent in 2006 and 7.5–10

[6]This includes transfers from retailers, between most private individuals, at gun shows, through online platforms, and from any manufacturer. The only licit handgun transfer between private individuals not recorded are bequests to immediate family. Long gun transfers were not systematically tracked until 2014.

percent in 2015.[7] The California Department of Justice also charges a fee to administer its record-keeping system, which increased from 19 dollars in 2005–2010 to 20 dollars in 2011–2015.[8] Firearm retailers may charge up to 10 dollars per firearm to perform transfers between private parties within California, and an unlimited amount to administer transfers from out-of-state.

California's firearm retailers do not transmit price data to the Department of Justice. Across the U.S., consumers on the licit market in 2015 faced a modal handgun price of around 400 dollars (Azrael et al. 2017). Moreover, prices are remarkably uniform within a make and model, such that the average within-model coefficient of variation in pre-tax prices across retailers was 0.044 in the fall of 2020 (Moshary et al. forthcoming).

Some firearm transactions in California occur illicitly, which cannot be systematically tracked by California's regulators. These illicit transactions are punishable as either a misdemeanor or felony under California and Federal Law, and can exacerbate the severity of other criminal charges.[9] The potential for legal sanction generates transaction costs which thin out the illicit firearms market (Cook et al. 2007). As a consequence, available data suggest the illicit firearm market operates at three times higher prices and considerably lower transaction volume than the licit market (Braga et al. 2012, Cook 2018).

2.2 Data construction and description

To implement my analysis, I construct a dataset with information on consumer handgun purchasing and ownership, the operation of firearm retailers, the occurrence of fatal and non-fatal criminal incidents, and summary geographic characteristics.

2.2.1 Handgun purchases and ownership

I access the complete set of California's handgun transfer records from 1996–2015 through a data sharing agreement between Stanford Health Policy and the state's Department of Justice. These records match consumers with retailers at the transfer level, contain panel identifiers for consumers and retailers, and include consumer characteristics, such as age, race, and sex. From 2005–2015, these records also contain the zip code of the consumer and the retailer.[10]

[7] Source 2006: `https://www.zillionforms.com/2005/P115129.PDF`
Source 2015: `https://www.cdtfa.ca.gov/taxes-and-fees/ArchiveRates-04-01-15-06-30-15.pdf`

[8] See `https://oag.ca.gov/system/files/media/dros-fee-2nd-cert-sria-revised.pdf`, California SB 1080 (2010), and California SB 843 (2016).

[9] See `https://oag.ca.gov/ogvp/overview-firearm-law`

[10] I transform zip codes to five-digit zip code tabulation areas (ZCTA5s) using the cross-walk provided by the U.S. Census. When a zip code crosses multiple ZCTA5s, I assign it to the modal ZCTA5 by square-mile

I use these transfer records to construct time-varying and consumer-specific measures of handgun purchasing and ownership. From 2005–2015, I measure handgun purchasing by consumer-quarter as a binary indicator, equal to one if a consumer purchased at least one handgun during the quarter. My measure of the distance between a consumer and a retailer is the number of straight-line miles between their zip code centroids, equal to zero for consumer-retailer pairs within the same zip code. Handgun purchasers must travel this one-way distance four times in order to licitly purchase a handgun: one round trip for the transaction, and another to pick up the handgun after the waiting period. I record a consumer's handgun ownership in a quarter t as a binary indicator, equal to one if a consumer purchased at least one handgun between January 1, 1996 and the end of the quarter t.[11]

To measure purchasing and ownership within a consumer segment (e.g., the count of handgun owners in a zip code-quarter), I sum across all individuals within the segment. As my data contain all licit handgun purchases in California, I measure market size as the number of adults residing in the state, per the 2010 Census and unadjusted for variation between 2005–2015.

Table 1 provides summary statistics. Panel A shows that 4.4 percent of Californian adults purchased a handgun between 2005–2015, with higher rates for men, Whites, and consumers who owned a handgun prior to 2005. Among handgun purchasers, the average consumer resided 17 miles from their retailer and acquired a handgun in 1.8 quarters, though a heavy tail of consumers purchase more frequently. By the end of 2015, 6.3 percent of Californian adults owned a handgun.

Panel B considers the set of zip code-quarters in my analysis. In the average zip code-quarter, 5.1 percent of consumers own a handgun, and 0.4 percent of consumers purchase a handgun. Zip code-quarters with lower income, lower population density, lower rates of violent crime, and later in the study period all tend to have higher rates of handgun purchasing.

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area. Although my analysis is based on ZCTA5s, I refer to them as zip codes for ease of presentation. I exclude from my analysis zip codes with fewer than 1,000 adult residents, zip code with fewer than 50 licit handgun owners at the start of 2005, and zip codes that correspond primarily to U.S. military base installations.

[11]In California, less than three percent of first-time handgun purchasers subsequently cease handgun ownership (Swanson et al. 2022). A survey of the California adult population finds that 10 percent of adults owned a handgun in 2018, somewhat higher than my measure of ownership in 2015 (Kravitz-Wirtz et al. 2020). Nationwide, among consumers who lived in a household with a firearm during the past five years, two percent of their households subsequently ceased all firearm ownership, with two-thirds of such consumers over the age of 65 (Wertz et al. 2019).

2.2.2 Firearm retailer operations

California's handgun transfer records also provide information about the operation of firearm retailers, ranging from small independents to national chains like Bass Pro Shops. Using the matched consumer-retailer nature of the data, I identify and prune the smallest-scale "kitchen table dealers" from my sample, as their licenses are only for personal use, and not for the operation of an establishment that sells firearms to other consumers (Sugarmann and Rand 1992).[12]

I treat a retailer as available to consumers between the quarters of its first and last recorded handgun transfer in my data. I measure a retailer's quarter of entry as the quarter of its first recorded handgun transfer. Symmetrically, I measure a retailer's quarter of exit as the quarter of its last recorded handgun transfer. I do not measure entries occurring in the first quarter of my sample, nor exits in the last. Figure OA.2 shows that my measure of entry based on a retailer's first recorded transfer closely aligns with an administrative measure based on a firearm retailer's completion of the permitting process.

Table 2 provides summary statistics of firearm retailers in my sample. The average retailer operates for 26 quarters between 2005–2015, sells 153 handguns per quarter, and sells to an average consumer residing 19 miles away. A right tail of higher-volume retailers dominate the market: relative to the median, the 75th percentile operates for 120 percent more quarters, sells 130 percent more handguns per quarter, and sells to an average consumer who resides 23 percent further away. The five retailers with the most firearm transaction during my sample are Martin Retting (Culver City), ProForce Law Enforcement (Brea), Turner's Outdoorsman (Pasadena), Turner's Outdoorsman (San Bernardino), River City Gun Exchange (Sacramento).[13] I find that entrants during my sample sell more handguns per quarter than the average firearm retailer, and that exitors sell fewer than average per quarter.

Panel B of Table 1 shows that, in zip code-quarters with at least one operational firearm retailer, consumers purchase 25 percent more handguns and travel 23 percent less distance to purchase, relative to consumers in zip code-quarters without a firearm retailer. This pattern could arise from demand (consumers purchase more handguns when retailers are more available) or supply (more retailers locate where consumers purchase more handguns), which I explore in Section 3.

[12] I prune retailers that are neither (i) in the top quartile of total sales nor (ii) operating for at least one year and in the top quartile of sales per quarter. These restrictions remove retailers with fewer than 246 total sales, and if open for more than a year, with fewer than 78 yearly sales. Kitchen table retailers account for 74 percent of the retailers in California's records, but they account for less than 11 percent of total purchases.

[13] Turner's Outdoorsman is a large chain of outdoor stores in California and Arizona, accounting for 11 of the state's 20 highest-volume firearm retailers.

2.2.3 Fatalities and non-fatal crime

I measure the occurrence and characteristics of fatalities in California between 2005-2015 using the universe of individual-level morgue records from the California Department of Public Health. I measure the location and quarter of a fatality based on the deceased's residential zip code and time of death. To measure cause of death, I use the underlying cause of death code, included in the morgue record according to the International Classification of Diseases, Tenth Revision (ICD10) scheme.[14]

I measure the occurrence and characteristics of non-fatal criminal activity using the FBI's Uniform Crime Reports. These data provide rates of violent crime (aggravated assault, rape, and robbery) and property crime (larceny and burglary) by county-year. Notably, the county-year resolution of data on non-fatal crime is less granular than the zip code-quarter resolution I use for the fatality data.

Panel B of Table 1 shows that California's average zip code-quarter has 0.4 homicide fatalities and 0.9 suicide fatalities, both with considerable heterogeneity, and negative correlation. Zip code-quarters with higher income, higher population density, higher rates of violent crime, and later in the study period all have higher homicide rates and lower suicide rates.

2.2.4 Geographic characteristics

I use the 2010 Census to measure zip code population, density, and median family income. California's Employment Development Department reports the county-year average hourly wage, using microdata from the Bureau of Labor Statistics. I use the Internal Revenue Service's Statistics of Income to construct measures of average household income, population, and population density by zip code-year. Following Martin and Yurukoglu (2017), I map precinct-level election returns to zip codes and construct measures of turnout and Republican vote share in a zip code-quarter's most recently completed presidential and congressional elections.

3 Impacts of firearm retailer entry

This section measures how variation in the firearm market—due to the entry and exit of firearm retailers—creates marginal changes in handgun purchasing, handgun ownership, and public health outcomes.

[14] I measure firearm homicide fatalities using codes X93–X95, non-firearm homicide fatalities using codes X85–X91, firearm suicide fatalities using codes X72–X74, and non-firearm suicide fatalities using codes X60–X71 and X75–X84 (e.g., Studdert et al. 2020, Studdert et al. 2022, Miller et al. 2022).

3.1 Firearm retailer entry and handgun purchasing

I use a panel of zip codes in California to measure changes in handgun purchasing around the entry of a first firearm retailer into a zip code. A first entrant is a retailer that begins to operate in a zip code-period in which no other firearm retailers are operational. I index these first entrants by n, and denote the identity of the entering retailer by $j(n)$, the entered zip code by $z(n)$, and the six-month period of entry by $t(n)$.[15] To avoid contaminating the effect of first entrants, I restrict my sample to include zip code-periods around first entries n that are more than three years removed from any other retailer entry or exit in $z(n)$. I further remove compositional bias by restricting the sample of first-entries n to those occurring between January 1, 2008–June 30, 2013, for which a full three years of zip code-periods are available pre- and post-entry. I pair this panel data around first entrants with control zip codes, in which no firearm retailers were ever operational between January 1, 2005–December 31, 2015.

To measure changes around the average first entry in this sample, I estimate the event study regression

$$\frac{q_{z(n)t}}{M_{z(n)}} = \sum_{t'=-6}^{5} \beta_{t'} \mathbf{1}\left(t' = t - t(n)\right) + \psi_{z(n)} + \phi_t + \xi_{z(n)t}, \tag{1}$$

where q_{zt} is an outcome representing the quantity of handguns purchased. As zip codes have different market sizes, I normalize quantity outcomes by the number of adults in the 2010 Census M_z, and weight regressions by adult population M_z.

The coefficients of interest are the vector $\beta_{t'}$, which measures the change in handgun purchasing per adult q_{zt}/M_z exactly t' periods relative to a first entry. Formally, the control zip codes with no operational firearm retailers in any period have $t' = -\infty$ in all zip code-periods. The model also includes fixed effects for zip code ψ_z and period ϕ_t. Thus, $\beta_{t'}$ is identified by over-time variation in q_{zt} around a first entry n, accounting for time-series patterns common to the zip code-periods with no operational firearm retailers in this sample. The model residual ξ_{zt} represents other determinants of handgun purchasing within a zip code-period. Section OA.1 provides additional details on implementation, including my procedures for estimation and inference (Borusyak et al. 2024).[16]

[15] This section uses six-month periods to improve estimator precision. The estimators in subsequent sections are more precise, allowing me to specify periods as quarters.

[16] Roughly, my estimator compares handgun purchases per capita in zip code-periods that are three or fewer years after their first entry $t' \in \{0, \ldots, 5\}$ to handgun purchases per capita in zip code-periods with no firearm retailers. Only data from zip code-periods pre-entry $t' < 0$ are used to estimate the fixed effects for zip code ψ_z and period ϕ_t. Figure OA.3 shows similar estimates when fitting the model via OLS with two-way fixed-effects.

Panel A of Figure 1 visualizes estimates of $\beta_{t'}$ and their 95-percent confidence intervals. As an outcome variable, dark lines represent handgun purchases per adult population of the entered zip code $z(n)$, regardless of the retailer from which they purchased. Light lines represent handgun purchases per adult population among these same consumers, but restricted to only purchases made at the entering firearm retailer $j(n)$. To ease interpretation, I scale my estimates of $\beta_{t'}$ by the average zip code population in California $E[M_z] \approx 22,000$, allowing the figure to be read as level-changes that would be created if the average first entry in this sample occurred in California's average zip code.

The magnitudes in Figure 1 demonstrate that, on the margin, changes in the firearm market affect the quantity of handguns consumers purchase. One year after a first entry, on average, consumers would purchase 30 percent more handguns than if the entry had not occurred.[17] A 30 percent increase in handgun purchases would close the entire gap in handgun purchasing per capita between zip code-quarters with and without a firearm retailer, reported in Table 1. Accounting for uncertainty, my confidence intervals are compatible with a 15–45 percent increase in handgun purchases following a first entry.

These post-entry changes in handgun purchasing represent both the market expansion and business stealing effects of entry. The darker series in panel A of Figure 1 provides a direct estimate of market expansion: on the margin, consumers purchase 30 percent more handguns post entry. Combining this with information from the lighter series provides an estimate of business stealing. In particular, purchases from the entrant comprise both the 30 percent market expansion on the margin and the reallocation of one-fifth as many infra-marginal purchases from already-existing firearm retailers elsewhere in the state, representing business stealing from incumbents.[18] My estimates cannot reject that the average first entrant into a zip code steals no business from incumbent firearm retailers elsewhere in the state.

3.2 Heterogeneous effects of entry and identifying assumptions

The effects of firearm retailer entry follow intuitive patterns of treatment effect heterogeneity. The entry of a retailer into a zip code with at least one incumbent creates more business stealing and less market expansion than a first-entry (Figure OA.4). Entrants also expand the market less among consumer's in more-distant zip codes (Figure OA.5). A retailer's exit

[17] One year after entry, summing periods 1 and 1.5, consumers in the average zip code would purchase 98 additional handguns. As the average zip-code year has $169 \times 2{=}338$ handgun purchases, this represents a $98/338{\approx}30$ percent increase.

[18] One year post-entry in the average zip code, purchasing by consumers in the entered zip code would expand by 98 handguns, with the entrant selling 118 handguns to these consumers. Thus, among these consumers, the entrant steals $(118 - 98)/98 \approx 1/5$ as many handgun purchases from incumbent retailers elsewhere in California.

produces a time path of market expansion opposite to and smaller in magnitude than a first entrant (Figure OA.6). The difference in magnitudes between entrants and exitors could reflect differences in the quality of retailers across these two groups, as documented by the sales quantities in Table 2.

Following a first entry, the expansion of handgun purchasing also expands handgun ownership. Although there are more repeat handgun purchasers than first-time buyers in the average zip code-period, Panel B of Figure 1 shows a proportional 30-percent expansion in the quantity of handgun purchases among both consumer segments post-entry.[19] Through these first-time purchasers, the first entry of a firearm retailer in the average zip code-period would generate a 3 percent increase in contemporaneous handgun ownership.[20]

The key assumption of my research design is that a first entrant's choice of when $t(n)$ and where $z(n)$ to enter are uncorrelated with residual handgun purchasing $\xi_{z(n),t(n)+t'}$ for periods $t' \in \{0, \ldots, 5\}$ post entry. Under this assumption, and conditional on the fixed effects $\psi_z + \phi_t$, a first-entry n could just as well have occurred in any zip code-period with no operational firearm retailers. This makes over-time variation from other zip codes with no operational firearm retailers a valid counterfactual for post-entry variation in $z(n)$ during post-entry periods $t(n) + t'$. Such locally quasi-random entry timing and positioning is a plausible assumption in the California retail firearms market, where, in addition to the typical challenges of opening a retail business, state and federal regulations create delay between a retailer's decision to enter and their right to legally sell firearms. As discussed by Gentzkow et al. (2011), these assumptions are compatible with firearm retailers making dynamic decisions over entry and positioning to maximize expected profits, with the caveat that residual variation in the time-path of expected profits does not systematically correlate with residual variation in post-entry shocks to handgun purchasing $\xi_{z(n),t(n)+t'}$.

The assumption of quasi-random timing and positioning behind my research design is consistent with the time path of $\beta_{t'}$. In particular, Figure 1 shows that there there is no deviation from trends in total handgun purchasing prior to entry n, relative to other not-yet entered zip codes and control zip codes that never have an operational firearm retailer. This lack of pre-trends implies that retailers are not selecting zip code-periods for their operations based on pre-exising trends in handgun purchasing. In the period of entry, purchases increase sharply at the entrant and in the market overall, and remain stable for several year thereafter. Figure OA.7 documents a quantitatively similar time path of $\beta_{t'}$ without the assumption of

[19]First purchasers increase by 30/120=23 percent one year post entry. Repeat purchasers increase by 69/218≈32 percent one year post entry.

[20]In the average zip code, a first entry generates 30 more first-time handgun purchasers one year post entry. As the average zip code-period has 890 handgun owners, one year post entry would expand handgun ownership by 30/890≈3 percent.

quasi-random positioning $z(n)$, by re-estimating on a sample that excludes control zip codes and includes only zip code-periods three years or fewer from a first retailer entry. The patterns of treatment effect heterogeneity across entry events and zip codes also align with the plausible effects of heterogeneous entries.

3.3 Public health implications of handgun ownership

I also use variation from the entry and exit timing of firearm retailers to estimate the effect of handgun ownership on fatalities. Figure 2 visualizes the identifying variation, implementing the event-study around first-entries of firearm retailers from the prior sections. Panel A shows that the stock of handgun owners grows at a constant rate each period post-entry, reflecting the level shift in the flow of first-time handgun purchases from Figure 1. Panel B shows that the growing stock of handgun owners increases the occurrence of homicide fatalities. Together, these estimates imply that, among consumers for whom handgun ownership is marginal to the first entry of a firearm retailer within their zip code, adding 100 such owners for 1 year would generate 0.45 additional homicide fatalities.[21] Notably, this estimate relies only on a narrow set of retailer entries, which limits power when studying less-frequent fatality outcomes.

My preferred approach to recovering the effect of handgun ownership on fatalities achieves higher power by implementing a two-stage least-squares estimator, leveraging the full set of entries, exits, and zip code-quarters in California. Letting g_{zt} represent the count of licit handgun owners observed in a zip code-quarter, and y_{zt} a count of fatalities, I estimate the linear regression

$$\frac{y_{zt}}{M_z} = \mu \frac{g_{zt}}{M_z} + \kappa_z + \eta_t + \omega_{zt}, \tag{2}$$

where μ represents the level change in fatalities within a zip code-quarter created by licitly allocating a first handgun to one of z's adult residents.[22]

Equation (2) also includes fixed effects by zip code κ_z and quarter η_t. These fixed effects parameterize sources of fatalities unrelated to licit handgun ownership that are either time-constant and heterogeneous across zip codes (e.g., κ_z absorbs baseline crime rates)

[21] Aggregating across the full post-entry period, yearly handgun ownership in the average zip code would increase by 111 consumers, and homicides would increase by 0.5 fatalities. The Wald estimator thus implies that adding 100 handgun owners would generate $100 \times 0.5/111 \approx 0.45$ homicide fatalities.

[22] A practical reason I prefer the linear specification to one in logs is because of the large number of zeros in fatality outcomes y_{zt} by zip code-quarter (Chen and Roth 2024). More substantively, the multiplicative structure of a specification in logs or a Poisson regression model would imply that removing all licit handgun owners would prevent all fatalities $y_{zt} \to 0$ as $g_{zt} \to 0$. This is not a reasonable assumption, as illicit handgun ownership can also affect fatality outcomes.

or changing in aggregate for the whole of California over time (e.g., η_t absorbs statewide criminal justice policy). Other sources of fatalities unrelated to licit handgun ownership (e.g., a local crime wave) are included in the residual fatality shock ω_{zt}.

Handgun ownership g_{zt} in Equation (2) is likely endogenous to fatalities y_{zt} (Duggan 2001), which I address by constructing an instrument from the entry and exit of firearm retailers.[23] My instrument is the count of firearm retailers in operation within a zip code-quarter. By conditioning on fixed effects for zip code κ_z and quarter η_t, this instrument's first-stage isolates variation in handgun ownership created by the timing of net entry within a zip code, similar to the event studies in Figures 1 and 2. Unlike the event study analysis, this first-stage simultaneously combines information from all entries and exits in the data, as well as from zip codes that experience neither entry nor exit. Figure OA.8 shows that, within a zip code, neither the lagged occurrence of homicide fatalities nor the lagged rates of handgun purchasing can predict the entry or exit of firearm retailers in California. Appendix OA.2 describes this instrumental variables estimator in detail.

Table 3 shows the first-stage regression of handgun ownership per capita on the count of firearm retailers. The net entry of firearm retailers produces a relevant instrument, with a first-stage F-statistic of 52, as visualized in Figure OA.9. Table 3 also shows the expansion of handgun purchasing from the average net entry, which falls in between the event study estimates of market expansion due to retailer entries in zip codes with and without an incumbent retailer, reported in Section 3.1.

Panel A of Table 3 presents estimates of the effect of licit handgun ownership on fatality outcomes μ, both firearm-related and overall. The estimates in Column 1, Panel A indicate that handgun ownership causes firearm-related homicide fatalities, among consumers whose first handgun purchase is marginal to the net entry timing of firearm retailers within their zip code. I interpret the magnitude of μ by quantifying its implications for the average zip code-year, where increasing ownership by 10 percent, through the allocation of handguns to marginal owners, would cause a 13 percent increase in firearm-related homicide fatalities.[24]

In addition to firearm homicides, Panel B shows that handgun ownership also causes firearm-related suicides. In particular, a 10 percent increase in handgun ownership would cause a 3 percent increase in firearm-related suicide fatalities. Among licit handgun owners on the margin of net entry, and relative to firearm homicides, firearm suicides create 75 percent smaller level changes in fatalities and drive 66 percent less variation in their respective fatality

[23]The use of instrumental variables for estimation also addresses the potential for mis-measurement of handgun ownership discussed in Section 2.

[24]Table 3 shows that the average zip code-year has 890 handgun owners and 1.12 firearm-related homicide fatalities. Thus, my estimate of $\mu = 0.159/100/4$ implies that a 10 percent increase in ownership would cause a $4 \times \mu \times 890/10/1.12 \approx 13$ percent increase in firearm-related homicide fatalities.

rate.

Column 2 of Table 3 presents OLS estimates of the effect of handgun ownership on homicide and suicide fatalities. These estimates are qualitatively similar to their IV counterparts, and the two cannot be statistically distinguished from one another. This pattern suggests that the potential for endogeneity between handgun ownership and fatalities can be predominantly addressed with high-resolution data, allowing me to control for detailed fixed effects by zip code and quarter.

The estimates in Table 3 also suggest that changes in firearm-related fatalities do not generate spillovers or substitution with non-gun fatalities. In fact, my estimates cannot statistically reject that the entire effect of handgun ownership on fatalities is driven by firearm-related injuries, with estimates for non-firearm fatalities in Table OA.1. Moreover, Figure OA.10 shows that handgun ownership has no effect on placebo fatality outcomes (e.g., pneumonia), that should logically not respond to handgun ownership. Beyond fatalities, Table OA.2 shows a small increase in non-fatal violent crime in response to handgun ownership, though my subsequent analysis focuses only on fatalities.[25] Altogether, these results suggest that increases in licit handgun ownership, among owners marginal to the entry and exit of firearm retailers, cause firearm homicides and fail to deter violent crime (e.g., Lott and Mustard 1997, Duggan 2001).

Table OA.3 explores alternate specifications of Equation (2) and the net entry instrument, isolating different components of variation to estimate the effect of handgun ownership on fatalities. My results are robust to the specification of richer fixed effects by county-quarter; the inclusion of zip code-year controls for income, population, and political views; and the inclusion of zip code-specific linear time trends. I also find quantitatively similar estimates from a re-specified instrument, in which the effects of net entry accumulate based on the number of quarters in which retailers remain in operation, as in Figure 2.

3.4 Heterogeneous effects of handgun ownership on fatalities

This section demonstrates that the effect of handgun ownership on fatalities—μ from Equation (2)—is not constant across the population. To do so, I document systematic heterogeneity in the effects of handgun ownership across consumers with observably heterogeneous

[25] Non-fatal and geographically diffuse firearm violence are important considerations in the design of firearm regulation (e.g., Cabral et al. 2021, Pienkny et al. 2024, Currie et al. 2024). My analysis abstracts from these outcomes due to the empirical challenges of measuring their occurrence and developing valid instrumental variables.

characteristics, studying regressions of the form

$$\frac{y_{zt}}{M_z} = \mu_{zt}\frac{g_{zt}}{M_z} + \kappa_z + \eta_t + \omega_{zt}.$$

This regression is analogous to Equation (2), but with heterogeneous effects μ_{zt} of handgun ownership g_{zt}/M_z on fatalities per capita y_{zt}/M_z. Allowing for heterogeneity creates two challenges: both the level of handgun ownership g_{zt}/M_z and its heterogeneous effects μ_{zt} vary at the same zip code-quarter frequency, and both may be correlated with the unobservable zip code-quarter fatality shock ω_{zt}. I address these challenges by placing additional structure on my regression specification, laying groundwork for the richer model in Section 4.

To structure the variability of heterogeneous effects μ_{zt} across zip code-quarters, I assume that aggregate heterogeneity arises from individual consumers i, each with systematic heterogeneity in both their causal effect of handgun ownership on fatalities and in their binary handgun ownership status $g_{it} \in \{0, 1\}$. In particular, letting W_{xz} denote a vector of observable characteristics of consumer i in demographic group $x(i)$ and zip code $z(i)$, heterogeneous effects of handgun ownership are given by the average[26]

$$\mu_{zt} \equiv \sum_{i:z(i)=z} \frac{g_{it}}{g_{zt}} \overbrace{\left(\mu + \zeta^W W_{x(i)z(i)}\right)}^{\text{average effect for } i}.$$

The parameters on the right-hand side of this equation govern systematic heterogeneity in the causal effect of handgun ownership across observably heterogeneous consumers. The parameter μ is an intercept, capturing the component of causal effects that is common across consumers. The vector of slopes ζ^W captures heterogeneous effects of handgun ownership across the dimensions of observable characteristics in W_{xz}. The summation thus expresses the effect of handgun ownership in a zip code-quarter μ_{zt} as the average causal effect among its handgun owners $g_{it} = 1$, $z(i) = z$. Under this structure, both the level of handgun ownership g_{zt}/M_z and the observable composition of handgun owners $\sum_{i:z(i)=z} g_{it}W_{x(i)z}/g_{zt}$ could be correlated with the residual fatality shock ω_{zt}. For example, an unobservable in ω_{zt} (e.g., a local crime wave) might jointly increase fatalities, drive more consumers to purchase handguns, and shift the observable characteristics of handgun purchasers.

I account for the possibility that the level of handgun ownership g_{zt}/M_z and its heterogeneous effects μ_{zt} may correlate with the fatality shock ω_{zt} by employing a control function

[26] Demographic observables in W_{xz} are an indicator for male gender, an indicator for age under 30, and an indicator for race non-Hispanic White. Geographic observables are a zip code's log median family income, log population density, and the log of its county's violent crime rate from 2000–2004. I transform all geographic observables to have mean zero and unit variance within my sample of zip codes. Formal definitions are given in OA.2.

approach (Wooldridge 2015), continuing to rely on variation created by the entry and exit of firearm retailers. In particular, I assume that the fatality shock ω_{zt} can be written as

$$\omega_{zt} = \chi R_{zt} + \tilde{\omega}_{zt},$$

where $\tilde{\omega}_{zt}$ is a purely random error and R_{zt} is a vector of residuals from separate regressions of the potentially endogenous level and composition of handgun ownership (g_{zt}/M_z and $\sum_{i:z(i)=z} g_{it} W_{x(i)z(i)}/g_{zt}$) onto the count of firearm retailers within a zip code-quarter and fixed effects for zip code and quarter. Specifically, these regressions apply the first-stage of the two-stage least squares estimator for Equation (2) over the full set of potentially endogenous regressors.[27] As such, the residuals in R_{zt} are a control function, representing all sources of time-varying variation in the level and composition of handgun ownership within a zip code-quarter, *not* due to the contemporaneous operation of firearm retailers. The parameters χ thus measure the magnitude of bias that would be created by failing to account for these potentially omitted variables. If $\chi \equiv \vec{0}$, then there is no omitted variable bias, and the regression in Equation (2) could be consistently estimated via OLS.

Combining these assumptions—the model of treatment effect heterogeneity and the specification of the control function—produces the linear regression

$$\frac{y_{zt}}{M_z} = \frac{g_{zt}}{M_z} \overbrace{\left(\mu + \zeta^W \sum_{i:z(i)=z} \frac{g_{it}}{g_{zt}} W_{x(i)z} \right)}^{\text{average causal effect} \equiv \mu_{zt}} + \kappa_z + \eta_t + \chi R_{zt} + \tilde{\omega}_{zt}, \tag{3}$$

which is estimable via OLS in zip code-quarter panel data. If there were no systematic heterogeneity in the causal effect of handgun ownership $\zeta^W = 0$, the above regression would collapse to the specification in Equation (2).

More specifically, my procedure for estimating Equation (3) follows a two-step approach. In the first step, I construct an estimate of the control function R_{zt} by separately regressing each endogenous variable on the count of firearm retailers in a zip code-quarter and fixed effects for zip code and quarter. In the second-step, I substitute these first-step residuals $\hat{R}_{zt}$ into the regression in Equation (3) and estimate the parameters governing heterogeneity in the causal effects of handgun ownership (μ, ζ^W) and the parameters on the control function χ.[28] By construction, the variation identifying these second-step estimates arises within a

[27] I exclude the dimensions of geographic heterogeneity from the vector of residuals R_{zt}, as these are perfectly multi-collinear with the residuals in the level of handgun ownership (i.e., there is no variation in geographic characteristics across consumers in the same zip code).

[28] Under the assumption that there is no systematic heterogeneity in the causal effect of handgun ownership $\zeta^W = 0$, such that the control function R_{zt} is uni-dimensional, this procedure produces an estimate of the

zip code and is due to the contemporaneous entry or exit of a firearm retailer, as well as changes in the level and composition of handgun ownership from prior periods.[29] I conduct inference valid for this two-step procedure via a Bayesian Bootstrap.

Figure 3 presents estimates of observable heterogeneity in the effect of handgun ownership on fatalities. The horizontal dotted line represents homicide fatalities created by a handgun owner with observable characteristics W_{xz} equal to the average handgun owner in California, analogous to the homogeneous effects reported in Table 3. Each pair of bars shows the magnitude of heterogeneous effects ζ^W, relative to the average handgun owner, by applying a one standard deviation shift in a single dimension of observable heterogeneity W_{xz} around the average, and computing the implied change in homicide fatalities.

My estimates imply that consumers living in places with lower median household income, lower population density, and/or higher rates of violent crime would generate more homicide fatalities through their private handgun ownership. I also find larger homicide effects among consumers who are White, male, and/or under 30 years of age. Among all the dimensions of observable heterogeneity W_{xz}, I find especially large effects of being male and/or being under age 30. These match well-known demographic patterns in criminal behavior, particularly the fact that consumers "age out of crime" around 30 (Farrington 1986). Although most handgun owners are male, my estimates imply that a large share of female consumers would prevent homicide fatalities if they were to become handgun owners.

Table OA.4 provides estimates of all parameters in Equation (3), using outcomes for homicide or suicide fatalities, with or without firearm involvement. These complete estimates show that essentially all heterogeneity in the effect of handgun ownership on homicide fatalities is driven by heterogeneity in firearm-related homicides. Moreover, I find parameters on the control function χ significantly different from zero, indicating the presence of omitted variables that jointly affect homicide fatalities as well as the level and composition of handgun ownership. Unlike homicides, the effect of handgun ownership on suicide fatalities does not appear to be heterogeneous across the population. In addition, the suicide control function parameters χ are also small in magnitude, suggesting that there is no unobservable variable jointly driving both suicide fatalities and handgun ownership.

The analysis of heterogeneity in this section relies on several assumptions. I follow the public health literature and model heterogeneity in the causal effect of a consumer's first handgun acquisition $g_{it} \in \{0, 1\}$, abstracting from the effect of their subsequent handgun

average causal effect μ that is numerically identical to the two-stage least-squares estimator for Equation (2) (Wooldridge 2015).

[29] A maintained assumption of this design is that consumers do not select into handgun ownership in period t on the basis of other fatality shocks in other periods $\omega_{z,t+t'}$. Appendix OA.3 provides a thorough discussion of this assumption.

purchases and the ownership of other consumers $g_{i't}$ (Studdert et al. 2022). I also assume that the causal effect of handgun ownership is constant within a consumer throughout the period during which they reside in a zip code. This requires that demographic heterogeneity in the effects of handgun ownership W_x is constant within a consumer, while the geographic heterogeneity W_z would vary if consumers were re-allocated across zip codes. I also implicitly assume that any unobservable heterogeneity in the causal effects of handgun ownership across consumers is purely random distributed.

An additional technical assumption in this section is the linear model of the fatality shock $\omega_{zt} = \chi R_{zt} + \tilde{\omega}_{zt}$. This linearity is required by the control function approach to estimating Equation (3), but would not be required by a two-stage least-squares estimator (Wooldridge 2015).[30] However, the two-stage least-squares estimator would have poor finite-sample performance in this setting, due to the large number of interactions between potentially endogenous regressors, each one requiring a separate instrument. Imposing linearity on the fatality shock allows me to address endogeneity using a smaller number of variables, providing a useful increase in finite-sample efficiency when studying less-frequent fatality outcomes. In the following section, I develop a richer model that allows me to relax and further interpret many of these assumptions.

4 Model

This section microfounds the effects of retailer entry in Section 3 by developing a model of consumer handgun purchasing from firearm retailers, in which handgun ownership affects fatalities. I fit the model using data from licit handgun purchases in California and discuss identification. Section 5 presents estimates. Section 6 uses the estimated model to measure changes in social welfare from counterfactual regulations on California's licit handgun market.

4.1 Preferences, purchases, and ownership

All adults in California, consumers $i = 1, \ldots, M$, make a sequence of repeated static choices over quarters $t = 1, \ldots, T$, deciding whether to purchase a handgun $q_{it} \in \{0, 1\}$ and from which firearm retailer to purchase $j_{it}|q_{it}{=}1 \in \mathcal{J}_{zt}$. Consumers face heterogeneous choice sets $\mathcal{J}_{zt}$, containing all firearm retailers in operation during period t within 200 miles of their residential zip code $z(i)$, accommodating spatial heterogeneity and retailer entry and exit.[31]

[30] Appendix OA.3 presents a statistical model of the fatality process, allowing me to state sufficient conditions under which the decomposition will hold.

[31] The 200 mile limit on $\mathcal{J}_{zt}$ eases computation, with fewer than 2 percent of purchases occurring beyond this distance.

I assume that all handguns have undifferentiated characteristics and a uniform tax-inclusive price p_t, reflecting the structure of my data.[32] A consumer's handgun purchase q_{it} in period t affects their handgun ownership $g_{it} \in \{0,1\}$ in subsequent periods $t+t'$, accounting for the durable nature of handguns. The model accounts for sources of unobservable heterogeneity across consumers, and observables including demographics $x(i)$, pre-period handgun ownership g_{i0}, and residential zip code $z(i)$.[33]

Indirect utility of consumer i from choosing to purchase a handgun at firearm retailer j during period t is

$$\begin{aligned} u_{ijt} &= \overbrace{\nu_i - \alpha^p_{xz} p_t + \xi_{xzt}}^{\text{extensive margin}} + \overbrace{\delta_j - \alpha^d_{xz} d_{ij} + \varepsilon_{ijt}}^{\text{retailer choice}} \\ u_{i0t} &= \varepsilon_{i0t}, \end{aligned} \tag{4}$$

with u_{i0t} indirect utility from the no-purchase outside option. Utility from the inside options u_{ijt} depends on an extensive margin component, common within a consumer-quarter, and a retailer choice component that varies by consumer-retailer-quarter.

The extensive margin component shifts the indirect utility that i receives from the purchase of a handgun $q_{it} = 1$, relative to not purchasing $q_{it} = 0$. It depends on an individual-specific, time-invariant present value from handgun purchase ν_i, given by

$$\nu_i = \psi_{xz} + \gamma_x g_{i0} + \sigma_x \tilde{\nu}_i.$$

The first term ψ_{xz} is a fixed effect, representing determinants of the present value of handgun purchase common across consumers in the same demographic-zip code (e.g., the baseline crime rate, community tradition). This is shifted for pre-period handgun owners $g_{i0} = 1$ by γ_x, which allows consumers in demographic x who purchased prior to 2005 to behave differently from those who did not, as in Table 1. The residual $\tilde{\nu}_i \sim N(0,1)$, scaled by the demographic-specific standard deviation σ_x, captures remaining unobservable determinants of present value for handgun purchase (e.g., i's differential risk of criminal victimization or

[32] Moshary et al. (forthcoming) document uniform pricing across firearm retailers. Past analyses of consumer behavior in firearm markets highlight the role of differentiation across firearm classes (i.e., handguns and long guns), but also abstract from within-class product differentiation (e.g., Bice and Hemley 2002, Azrael et al. 2017, Moshary et al. forthcoming).

[33] Demographics $x(i)$ include gender, race, and age quintile. If a consumer would cross age quintiles over time, I assign them to their sample mode. I allow consumers to exogenously move across zip codes over time, with their residential zip code tracked by $z(it)$. I assume that moves occur in such a way that M_z does not vary over time. To keep notation manageable, I drop the time subscripts from consumer locations. I measure pre-period handgun ownership g_{i0} as a binary indicator for an observed handgun purchase in California between 1996–2004.

differential familial tradition, relative to others in their demographic zip-code community).[34]

Consumers trade off their time-invariant present value ν_i against time-varying determinants of extensive margin utility. One source of over-time variation is the tax-inclusive price of a handgun p_t, converted into utils by the price coefficient α^p_{xz} with heterogeneity by consumer observables. The final term ξ_{xzt} is a demand shock that varies by demographic-zip code-quarter (e.g., a local crime wave). I assume that the time-varying components of utility are centered such that $E[\xi_{xzt} - \alpha^p_{xz}(p_t - \overline{p})|xz] = 0$, where $\overline{p} = \sum_t p_t/T$ (i.e., the composite of demand shocks and price variation is mean-zero across quarters t within demographic-zip code xz). This specification rules out individual-specific drift in extensive margin preferences for handgun purchase over time.[35]

The remaining retailer-choice portion of indirect utility affects both consumer i's extensive margin choice q_{it} and their choice of firearm retailer j_{it}. Retailers j are vertically differentiated by quality δ_j (e.g., staff training, non-handgun inventory) and spatially differentiated by zip code $z(j)$.[36] Spatial differentiation leads to a travel distance d_{ij} from consumer i to retailer j, which consumers dislike based on the distance coefficient $\alpha^d_{xz} = \exp(\alpha_x + \alpha_z)$.[37] The final term ε_{ijt} is an idiosyncratic shock to preferences for handgun purchase by consumer-retailer-quarter. As all these sources of preference heterogeneity are either common, observable, or idiosyncratic across consumers, my specification rules out the existence of unobservable, consumer-retailer taste shocks that may correlate with travel distance d_{ij}.

For tractability, I assume that the idiosyncratic components of indirect utility $(\varepsilon_{i0t}, \varepsilon_{ijt})$ follow a generalized extreme value distribution meeting the distributional requirements of a

[34] I do not attempt to separate the role of place-specific factors in ψ_{xz} from the average of consumer-specific factors (i.e., the individual average familial tradition). These could be separated with data on consumer migration and the evolution of their handgun purchasing behaviors (e.g., Bronnenberg et al. 2012, Finkelstein et al. 2016). My data on handgun purchases does not systematically track consumer migration, which complicates this style of analysis.

[35] Without drift, my specification rules out single-agent dynamics (e.g., consumer i managing a stock of durable handguns over time t) or peer effects (e.g., consumer i's preferences depend on handgun purchasing by i'). These assumptions are consistent with the patterns of post-entry handgun purchase from Section 3.1, where I document that purchases increase on-entry and remain high, with similarly elastic responses among both first-time and repeat handgun purchasers.

[36] For identification of quality δ_j in the presence of the composite $\psi_{xz} - \alpha^p_{xz} + \xi_{xzt}$, I set the location normalization that $\delta_j = 0$ for the firearm retailer with the largest number of handgun sales in my data. A richer specification could control for cross-retailer unobservable heterogeneity in prices and firearm inventory, by allowing quality δ_j to vary with demographics x, geography z, and period t (i.e., allowing δ_{jxzt}). The more-restrictive specification of quality δ_j in Equation (4) affords an increase in power during estimation by imposing that all consumers derive identical utility from unobservable cross-retailer heterogeneity in prices and product inventory.

[37] In particular, α_z is a vector of fixed effects for a zip code's county and for quintiles of a zip code's median family income, square-mile area, and population density. I exclude the third quintiles from α_z for identification, but include the full set of county fixed effects. α_x is a vector of fixed effects for a consumer's gender, race, and age quintile. I exclude indicators for male, White, and third-age quintile from α_x for identification.

nested logit, with all retailers $j > 0$ in one nest and the outside option $j = 0$ in a separate nest. I denote the nesting parameter by $\rho \in [0, 1]$, with $\rho = 0$ representing perfectly inelastic substitution between the nests. At $\rho = 1$, the nesting structure vanishes, and it is as if all $|\mathcal{J}_{zt}| + 1$ shocks were standard type-1 extreme value. I also assume that $(\varepsilon_{i0t}, \varepsilon_{ijt})$ are *iid* within each consumer over time and *iid* within each demographic-zip code-quarter.[38]

By utility maximization, the realization of indirect utility u_{ijt} each period generates each consumer's choice of handgun retailer j_{it}:

$$j_{it} = \arg \max_{j \in \mathcal{J}_{z(i)t} \cup \{0\}} u_{ijt},$$

with binary handgun purchase determined by

$$q_{it} = \mathbf{1}(j_{it} > 0) = \mathbf{1}\big(\overbrace{\max_{j \in \mathcal{J}_{z(i)t}} u_{ijt} - u_{i0t}}^{\equiv u_{it}} > 0\big),$$

where u_{it} is i's utility from purchasing a handgun at the best firearm retailer in their choice set $\mathcal{J}_{z(i)t}$, less the opportunity cost of the no-purchase outside option ε_{i0t}.

Due to the durable nature of firearms, consumer i owns a handgun in all periods after their first purchase. Thus, binary handgun ownership is determined by the law of motion:

$$g_{it} = g_{i,t-1} + (1 - g_{i,t-1})q_{it},$$

with initial condition g_{i0} observable.[39]

4.2 Externalities and fatalities

I model externalities from handgun ownership by extending the model of heterogeneous causal effects of handgun ownership from Section 3.4 to account for unobservable heterogeneity across consumers and the structure of the preference specification in Equation (4).

Consumer i's licit handgun ownership $g_{it} \in \{0, 1\}$ generates an externality $e_i \in \mathbb{R}$, measured as an expected shift in the count of fatalities $y_{zt} \in \mathbb{Z}_{\geq 0}$ within consumer i's residential zip code during quarter t. Alongside other contributors, externalities e_i affect fatalities

[38] The location normalizations and distributional assumptions above imply that the expected value of indirect utility u_{ijt} is a known shift of only the extensive margin utility component, if the highest-volume firearm retailer in California j^{big} were located in consumer i's zip code $E[u_{ij^{\text{big}}t}] = \nu_i - \alpha^p_{xz} p_t + \xi_{xzt} + E[\varepsilon_{ijt}]$, where $E[\varepsilon_{ijt}]$ is the Euler-Mascheroni constant.

[39] Since the market size M_z is fixed, this law of motions implies that the first handgun purchase by consumer i changes the distribution of preferences among both handgun owners and non-owners in the demographic-zip code $x(i)z(i)$.

per-capita y_{zt}/M_z according to

$$\frac{y_{zt}}{M_z} = \overbrace{\frac{1}{M_z}\sum_{i:z(i)=z} e_i g_{it}}^{\text{externalities}} + \overbrace{\kappa_z + \eta_t + \chi\frac{1}{M_z}\sum_{i:z(i)=z} \xi_{x(i)zt} + \tilde{\omega}_{zt}}^{\text{base rate}}\,. \tag{5}$$

The first component captures the externalities from handgun-owning residents of a zip code-quarter. The second component represents a baseline fatality rate that would obtain in the absence of licit handgun ownership $g_{it} = 0$, all i: $z(i) = z$ (e.g., due to a zip code's long-run crime rate or a local crime wave). I allow separate processes to govern homicide and suicide fatalities, both with and without firearm involvement, allowing the terms in Equation (5) to differ across cause of death, and imposing no restrictions across these different specifications.[40]

Parameterizing further, externalities e_i are a time-invariant linear function of a consumer's observable demographic and geographic characteristics W_{xz} and the determinants of their present value of handgun purchase $V_i = (\psi_{xz}$, g_{i0}, and $\tilde{\nu}_i)$: Collecting these terms in the vector (W_{xz}, V_i), externalities created by consumer i are given by the linear regression

$$e_i = \mu + \zeta^W W_{x(i)z(i)} + \zeta^V V_i + \tilde{e}_i, \tag{6}$$

with common intercept μ, vector of slopes $\zeta = (\zeta^W, \zeta^V)$, and idiosyncratic error $\tilde{e}_i$ distributed *iid* and mean zero conditional on the other regression components.[41] As in Section 3.4, parameter ζ^W captures observable dimensions of heterogeneity in externalities from handgun ownership (e.g., living in a high-crime area, having aged out of crime), which may be correlated with present value of handgun purchase ν_i, but imperfectly so. More closely related to handgun purchase, the parameter ζ^ψ allows heterogeneity based on the average present value of handgun purchase ψ_{xz} among consumers in i's demographic-zip code (e.g., whether high-crime areas in which consumers like handgun purchase more have different externalities from those in which consumers like it less). At the individual level, ζ^{g_0} allows consumers who owned a handgun prior to 2005 to generate different externalities from consumers who

[40]Appendix OA.3 provides a statistical model of fatality counts y_{zt}, compatible with the specification in Equation (5), accounting for the zero lower bound on fatalities y_{zt}.

[41]This specification restricts the patterns of externalities that can be generated by the model. Time invariance implies that externalities are invariant to the number of firearms purchased by i, the duration since i's most recent purchase, and the handgun purchasing of other consumers i', all of which are topics of ongoing research (e.g., Braga and Cook 2018, Studdert et al. 2020, Studdert et al. 2022, Miller et al. 2022). Moreover, *iid* errors $\tilde{e}_i$ imply that consumers with identical extensive margin preferences for handgun purchase generate identical externalities in expectation (e.g., consumers who live in a zip code z with many firing ranges generate the same average externalities as consumers who live in a zip code z' with a high need for self defense, so long as $\psi_{xz} = \psi_{xz'}$), up to conditioning on observables (w_{xz}, g_{i0}).

acquired their first handgun during the study period. The final term ζ^ν generates correlation between the unobservable component of consumer i's present value of handgun purchase $\tilde{\nu}_i$ and their externalities from handgun ownership e_i. Without systematic heterogeneity in externalities $\zeta = 0$, the common intercept μ corresponds to the parameter in Equation (2).

The specification of externalities in Equations (5) and (6) embodies selection into handgun ownership in the spirit of Heckman (1979). Selection arises because a consumer only generates externalities when they own a handgun $e_i g_{it}$, and the partially unobservable present value of handgun purchase ν_i affects both e_i and g_{it}. Thus, the average externality under consumers' chosen allocation of handgun ownership may differ from the average under an alternative allocation. Similar to Heckman (1979), Equation (6) imposes linear relationships between externalities e_i and the determinant of choice, allowing separate slopes for its different components: ψ_{xz}, g_{i0}, and $\tilde{\nu}_i$.[42]

Beyond externalities, the base fatality in Equation (5) has a fixed effects structure, similar to Equation (3). Unlike in the descriptive analysis, I use the structure of preferences in Equation (4) to construct a uni-dimensional control function using shocks to the indirect utility from handgun purchase ξ_{xzt} (e.g., the extent to which a local crime wave that drives fatalities also drives handgun purchase), with an independent and mean-zero residual $\tilde{\omega}_{zt}$.[43] In particular, the preference specification implies that an omitted variable correlated with fatalities y_{zt} could only directly affect contemporaneous variation in the level and/or composition of handgun ownership within a zip code through the omitted variable's correlation with the systematic preference shock ξ_{xzt}. The control function in Section 3.4 is an estimable, high-dimension approximation to this lower-dimension structural relationship.

4.3 Estimation

The model has four sets of parameters Θ to recover: those governing extensive margin preferences $\Theta^\nu = (\psi_{xz}, \gamma_x, \sigma_x, \alpha^p_{xz}, \xi_{xzt})$, those governing retailer choice $\Theta^\delta = (\delta_j, \alpha_x, \alpha_z)$, the nesting parameter ρ, and the parameters of the fatality process $\Theta^e = (\mu, \zeta, \kappa_z, \eta_t, \chi)$. My estimator of Θ, uses both likelihood- and moment-based information from the data, as detailed in Appendix OA.3, and briefly summarized below.

In Appendix OA.3, I derive the log-likelihood $\mathcal{L}(\Theta)$ of the binary (logit) sequences of

[42] I assume that $E[e_i|\varepsilon_{ijt}] = E[e_i] = 0$, which rules out selection on unobservable and idiosyncratic shocks to indirect utility from purchasing from specific firearm retailers (e.g., Dubin and McFadden 1984, Abdulkadiroğlu et al. 2020, Barahona et al. 2023, Einav et al. 2022). Appendix OA.3 discusses this assumption in greater detail.

[43] This assumption rules out non-linearity between fatalities per capita y_{zt}/M_z and demand shocks ξ_{xzt}, which could be modeled with additional parameters. I follow the literature by imposing linearity to reduce the burden of additional parameters during estimation (Agarwal 2015). Appendix OA.3 further discusses the role of linearity and presents results that relax this assumption.

handgun purchases $(q_{i1}, \ldots, q_{iT})$, observed among all adults in California between 2005–2015, and the multinomial (logit) choice of firearm retailer $j_{it}|q_{it} = 1$, made by consumers each quarter in which they choose to purchase a handgun. As the unobservable component of present value from handgun purchase $\tilde{\nu}_i$ enters consumer i's extensive margin choice q_{it} in all periods $t = 1, \ldots, T$, I use quadrature to numerically integrate the likelihood of the sequence $(q_{i1}, \ldots, q_{iT})$ over the distribution of $\tilde{\nu}_i \sim N(0, 1)$. Since the unobservable $\tilde{\nu}_i$ is constant across retailers, it does not enter the probability of retailer choice $j_{it}|q_{it} = 1$.

My estimator $\hat{\Theta}$ simultaneously satisfies seven sets of roots through an exactly-identified minimum distance procedure, combining information from the log-likelihood $\mathcal{L}(\Theta)$ with other moments of the data. I assume the technical conditions such that these roots have a unique asymptotic solution under the model (Newey and McFadden 1994). Appendix OA.3 provides the formulas for these roots, details on computation, and a discussion of uniqueness.

A number of my estimator's roots are first-order conditions of the log-likelihood $\mathcal{L}(\Theta)$ with respect to many of the parameters governing extensive margin preferences Θ^ν and the full set of parameters governing retailer choice Θ^δ. My estimator does not use the first-order conditions of the log-likelihood with respect to the nesting parameter ρ or externalities Θ^e.

Also absent from these first-order conditions are the composite sources of extensive margin preferences $\psi_{xz} - \alpha^p p_t + \xi_{xzt}$. Instead, I estimate these composites by matching moment conditions: that observed handgun purchases q_{it} align with the model's prediction $P_{it}(q = 1; \Theta)$ on average across consumers within each demographic-zip code-quarter. Imposing these moments allows me to solve for the composite terms through the contraction mapping of Berry et al. (1995), drastically reducing the dimension of the non-linear search during optimization and providing a computationally feasible alternative to maximization of the full likelihood (Goolsbee and Petrin 2004, Grieco et al. 2023, Li 2023).[44]

I separate the terms within these composites $\psi_{xz} - \alpha^p_{xz} p_t + \xi_{xzt}$ by imposing further conditions on their location and scale. As a location normalization, I center the time-varying determinants of extensive margin preferences around the fixed effects ψ_{xz}. For the price coefficient α^p_{xz}, I impose a scaling between the average disutility from one mile of travel distance α^d_{xz} and one dollar of price paid α^p_{xz}:

$$\alpha^p_{xz} = \frac{\alpha^d_{x(i)z(i)}}{\$\text{Cost 1 mile}_z},$$

calibrating the monetary cost of one mile of travel distance in California's licit handgun

[44]In simulations from a model with similar structure, my estimator attains a slightly higher finite-sample likelihood than the estimator of Goolsbee and Petrin (2004), though both estimators come close to full likelihood maximization.

market:

$$\text{\$Cost 1 mile}_z = \underbrace{2}_{\text{Trips}} \times \underbrace{2}_{\text{There/back}} \times \left(\underbrace{\frac{10.9 \text{ minutes}}{5.3 \text{ miles}}}_{\text{Drive time}} \times \underbrace{\text{County wage}_z}_{\text{\$/hour}} + \underbrace{\frac{7.9 \text{ driven miles}}{5.3 \text{ miles}}}_{\text{Drive distance}} \times \underbrace{\frac{0.529 \text{ dollars}}{1 \text{ driven mile}}}_{\text{CA travel reimbursement}} \right),$$

analogous to Dolfen et al. (2023). The terms outside of parentheses provide the total number of one-way trips required for a handgun transaction in California: a first round-trip to purchase the handgun, and a second round-trip after the 10-day waiting period to pick up the handgun from the retailer. Inside of parentheses is the dollar-cost of 1 mile of straight-line travel $d_{ij} = 1$, accounting for the time-cost of lost wages and vehicle depreciation, both using prices specific to California in 2010 (Einav et al. 2016).

For another root of my estimator, I impose that market expansion predicted by the model 5–8 quarters post-entry exactly matches the data.[45] I recover this quantity in data using my event-study estimates $\hat{\beta}_{t'}$ from Equation (1). These estimates are local to the set of entries in which there is neither contaminating variation from other entries or exits within the same zip code, nor censoring from entries too near to the ends of the sample, as described in Section OA.1. I construct an analogous measure of market expansion for these entries under the model—at candidate Θ, computing the expected decrease in handgun purchases per capita in zip code $z(n)$ that would occur if the entrant $j(n)$ were counterfactually unavailable to consumers—which I then average across the same set of entries n used in the event study. The counterfactual experiment of removing an entrant $j(n)$ from a consumer's choice set $\mathcal{J}_{zt}$ is closely related to the nesting parameter ρ, a point I develop further when discussing identification.

My estimator's final set of roots characterizes the OLS estimate of the linear regression

[45] I match only on quarters 5–8 to avoid short-run dynamics in the first year of entry, seen in Figure OA.7. I match the average across quarters 5–8, rather than matching quarter-by-quarter, which simplifies identification at the cost of some efficiency. I target the value in Figure OA.7—rather than Figure 1 in the main text—due to path dependence in my estimation procedure, but intend to shift to this alternate value in future drafts)

model for fatalities per capita y_{zt}/M_z, as implied by Equations (5) and (6):

$$\frac{y_{zt}}{M_z} = \overbrace{\frac{g_{zt}}{M_z}\left(\mu + \zeta E_{zt}\big[\big(W_{x(i)z(i)}, V_i(\Theta^\nu)\big) \,\big|\, g_{it} = 1\big]\right)}^{\text{Expected externality}} + \overbrace{\kappa_z + \eta_t + \chi \sum_{i:z(i)=z} \frac{\xi_{x(i)zt} - \alpha^p_{x(i)z} p_t}{M_z}}^{\text{Expected base rate}}$$
$$+ \underbrace{\tilde{\omega}_{zt} + \sum_{i:z(i)=z} \frac{g_{it}\tilde{e}_i}{M_z}}_{\text{Residual}}, \tag{7}$$

separately by cause of death. The residual in this regression comprises the final two terms, accounting for both the unobservable fatality shocks $\tilde{\omega}_{zt}$ and for the unobservable consumer-specific deviations from the expected externality $\tilde{e}_i$ among handgun owners.[46] Appendix OA.3 shows that—because these roots can be satisfied at any value of the demand parameters $(\Theta^\nu, \Theta^\delta, \rho)$—the point estimates from my joint minimum distance estimator behave as if demand $(\Theta^\nu, \Theta^\delta, \rho)$ were estimated in a first-step, with externalities Θ^e estimated in a subsequent step conditional on $(\hat{\Theta}^\nu, \hat{\Theta}^\delta, \hat{\rho})$.

With estimates of the population parameters $\hat{\Theta}$ in hand, I estimate consumer-specific distributions of the present value of handgun purchase ν_i and externalities from handgun ownership e_i, using information from the consumer-level data (Revelt and Train 2000, Fowlie 2010, Von Gaudecker et al. 2011, Marone and Sabety 2022). In particular, I treat the population distribution of ν_i at $\hat{\Theta}$ as a prior, and form a posterior for consumer i based on their observed characteristics $(x(i), z(i), g_{i0})$ and the likelihood of their full sequence of extensive margin choices $(q_{i1}, \ldots, q_{iT})$, implied by the model at $\hat{\Theta}$. The posterior distribution of present value ν_i induces a posterior distribution of the externality e_i under Equation (6). As the consumer panel grows long $T \to \infty$, these posteriors concentrate, providing more precise information about each consumer's value of (ν_i, e_i).

4.4 Identification

Certain features of the data play a key role in each component of my estimator, which I discuss heuristically as identifying different parameters of the model.

Beginning with extensive margin preferences Θ^ν, the aggregate components $\psi_{xz} - \alpha^p p_t +$

[46] In implementing this regression, the composition of observable characteristics among handgun owners—$E_{zt}[w_{zt} \,|\, g_{it} = 1]$ and $E_{zt}[g_{i0} \,|\, g_{it} = 1]$—can be directly read off the data. I utilize first-step estimates of $\hat{\Theta}^\nu$ to incorporate the composition of mean unobservable preferences $E_{zt}[\psi_{xz} \,|\, g_{it} = 1]$, individual-specific preferences $E_{zt}[\tilde{\nu}_i \,|\, g_{it} = 1]$, and the time-varying demand component $\xi_{xzt} - \alpha^p_{xz} p_t$. Although prices $\alpha^p_{xz} p_t$ do not appear directly in Equation (5), the inclusion of two-way fixed effects $\kappa_z + \eta_t$ ensures that price variation generates only additive, random measurement error on the structural demand shocks ξ_{xzt}, which is formally a component of the model residual $\tilde{\omega}_{zt}$.

ξ_{xzt} are identified from panel data on handgun purchasing per capita q_{xzt}/M_{xz} by demographic-zip code-quarter. The level of handgun purchasing per capita pins down the composite, with several of its components separately identified by normalizations of the model—that the shocks are mean zero—and the calibrated scaling between disutility from travel distance α^d_{xz} and price α^p_{xz}. Since I do not observe prices in my data, I do not attempt to decompose the composite into the separate effects of price variation $-\alpha^p_{xz}p_t$ and demand shocks ξ_{xzt}.

The remaining parameters in Θ^ν—σ_x and γ_x—interact with consumer-specific characteristics, and they are identified by panel data on each consumer's sequence of handgun purchases $(q_{i1}, \ldots, q_{iT})$, conditional on the aggregate components of Θ^ν. The pre-ownership shifter γ_x is identified by the conditional difference in purchase frequency $\sum_t q_{it}/T$ between pre-existing handgun owners $g_{i0} = 1$ and other consumers $g_{i0} = 0$, within a demographic x. The standard deviation of the unobservable preference σ_x is identified by the conditional variance in purchase frequency across consumers with the same demographics x and prior ownership g_{i0}. Greater variance implies more differentiation across observably identical consumers, corresponding to a larger scaling σ_x on the unobservable component of present value $\tilde{\nu}_i$. These features of the data interact with σ_x and γ_x through the likelihood, which my estimator leverages by satisfying the log-likelihood's first-order conditions $0 = \partial\mathcal{L}(\Theta)/\partial\gamma_x = \partial\mathcal{L}(\Theta)/\partial\sigma_x$, all x.

Turning to retailer-choice Θ^δ, these parameters are identified by demographic-zip code-quarter data on travel distances to retailers and their market shares, leveraging variation across demographic-zip code-quarters. In particular, a retailer has higher quality δ_j if it consistently captures a larger market share than its similarly-distant competitors. Conversely, consumers have higher distaste for travel α^d_{xz} if closer-by retailers consistently capture a larger market share than their more-distant competitors of similar quality. These comparisons leverage three sources of choice set variation: each quarter, consumers who live in different zip codes face different travel distances to a common set of retailers, consumers in different demographics within the same zip code face different distance disutilities from a common set of travel distances, and consumers within a demographic-zip code face different sets of retailers due to entry and exit. My estimator synthesizes these sources of choice set variation using the first-order conditions of the log-likelihood $0 = \partial\mathcal{L}(\Theta)/\partial\Theta^\delta_l$, all $l = 1, \ldots, |\Theta^\delta|$.

Linking handgun purchase and retailer choice, the nesting parameter ρ is identified by the average expansion of handgun purchasing per-capita in the 5–8 quarters following the average entry of a firearm retailer. Heuristically, the nesting parameter ρ governs the elasticity of substitution on the extensive margin of handgun purchase q_{it}, and it is identified by data on consumer substitution across the extensive margin in response to the recent entry of a firearm retailer within their zip code. For consistency with utility-maximization $\hat{\rho} \in [0, 1]$, which I do not impose during estimation, providing a testable restriction of the model (Train 2009).

The last set of parameters Θ^e governs the fatality process, according to the regression in Equation (7). My estimator of these parameters uses panel data variation in fatalities per capita y_{zt}/M_z: leveraging its conditional correlation with variation in the level of handgun ownership g_{zt}/M_z and the composition of handgun owners $E_{zt}[(W_{x(i)z(i)}, V_i)|g_{it} = 1]$, as created by the entry and exit of firearm retailers. In particular, conditioning on the time-varying components of consumer preferences $\xi_{xzt} - \alpha^p_{xz} p_t$ operates as a control function. Alongside the fixed effects for zip code κ_z and quarter η_t, these terms absorb all variation in fatalities y_{zt} that would otherwise correlate with indirect utility u_{it}, affecting contemporaneous handgun purchase q_{it} and creating endogeneity with ownership g_{it}. Under the preference specification in Equation (4), the only remaining source of systematic variation by zip code-quarter is in travel distance d_{ij}, which varies within a zip code over time due to retailer entry and exit from the choice set $\mathcal{J}_{zt}$. Thus, the externality intercept μ is identified by variation in the level of handgun ownership g_{zt}/M_z, induced by contemporaneous retailer entry and exit, holding fixed the composition of handgun owners $E_{zt}[(W_{x(i),z(i)}, V_i) \mid g_{it} = 1]$. Conversely, the slopes ζ are identified by entry- and exit-induced variation in the contemporaneous composition of handgun owners, conditioning out variation in the level of handgun ownership. Beyond contemporaneous entry and exit, I leverage further identifying variation created by the persistence over time of past changes in the level and composition of handgun ownership, conditionally uncorrelated with the contemporaneous fatality shock $\tilde{\omega}$. Appendix OA.3 provides sufficient conditions for this identification argument.

5 Model estimates

This section presents estimates of the model parameters Θ from Section 4. It also uses the fitted model to study allocative efficiency in the licit handgun market, constructing the joint distribution of preferences for handgun purchase and externalities from handgun ownership across California's adult population.

5.1 Parameters

Table 4 presents estimates of the parameters $(\Theta^\nu, \Theta^\delta, \rho)$ that govern indirect utility u_{ijt}. Panel A documents variation in the extensive margin preference for handgun purchase $\hat{\Theta}^\nu$. There is considerable time-invariant preference heterogeneity across consumers. For instance, a consumer with an unobservable preference for handgun purchase $\tilde{\nu}_i$ that is 1 standard deviation above average would be willing to pay $E[\sigma_x]/[\alpha^p_{xz}]$≈120 dollars more to purchase a handgun each quarter, relative to the average consumer. Since the typical handgun price is around 600 dollars (Moshary et al. forthcoming), this higher-preference consumer purchases handguns similar to an average consumer facing a $120/600 \times 100 = 20$ percent discount on the handgun price. I find similarly-sized differences for the role of handgun ownership prior to 2005 γ_x and the preference fixed effects ψ_{xz}. By contrast, the time varying preference components ξ_{xzt} play a more-muted role, as a 1 standard deviation shock would lead the average consumer to purchase as if there were a 0.54/0.02≈30 dollar discount on the handgun price. Figure OA.11 shows how time-varying preferences ξ_{xzt} changed around the 2015 terrorist attack in San Bernardino, California.

Panel B presents the retailer choice parameters $\hat{\Theta}^\delta$. I find meaningful heterogeneity in retailer quality δ_j—with a mean of -1.1 only somewhat larger in magnitude than the standard deviation of 0.9—consistent with the heterogeneity across retailers documented in Table 2. The average distance coefficient in the population is $\sum_i \alpha^d_{x(i)z(i)}/M \approx 0.11$. These values imply that the average consumer would be willing to forgo a 50 dollar discount on their handgun purchase in order to purchase at full-price from a retailer that is either 1 standard deviation higher in the quality δ_j distribution or located 9 fewer miles outside of the consumer's zip code (a 50 percent decrease in average travel distance from Table 1). Table OA.5 presents the 79 parameters (α_x, α_z) that govern distance disutility α^d_{xz}, reporting that older and younger consumers, Whites, and women find travel more costly, as do consumers in zip codes with lower income, larger square-mile area, and higher population density.

Panel C reports a nesting parameter of $\hat{\rho} = 0.64$. This point estimate suggests that the idiosyncratic determinants of preferences for firearm retailers ε_{ijt} are sufficiently uncorrelated to allow substitution across the extensive margin of handgun purchase q_{it} in response to variation in the other, systematic components of utility u_{it}. In particular, Figure OA.12 shows that a stylized counterfactual—moving all firearm retailers 10 miles further from all consumers—would decrease handgun purchasing by 50 percent and ownership by 20 percent, relative to the 2015 status quo reported in Panel A of Table 1. The standard error of 0.06 on $\hat{\rho}$ produces confidence intervals well within $[0, 1]$, demonstrating that the estimated preference parameters $(\hat{\Theta}^\nu, \hat{\Theta}^\delta)$ and the estimates of post-entry market expansion from the event study in Equation (4) are both jointly consistent with the assumption that consumer choice maximizes indirect utility in Equation (1).

Beyond preferences, Table 5 presents my estimates of the parameters Θ^e governing externalities from handgun ownership, with estimates for homicide fatalities in Columns 1–3. My preferred control function estimates in Column 1 imply that the licit handgun owners generating more costly homicide externalities are White, male, and/or under age 30, as well as those who live in lower-income, less-dense, and/or higher-crime areas. These patterns of observable heterogeneity match my estimates from Table OA.2, which construct a control function from the net entry of firearm retailers. In addition, I find more costly homicide externalities among consumers who did not own a handgun $g_{i0} = 0$ prior to 2005, but have a high demand (unobservable preference $\tilde{\nu}_i$) for handgun purchase between 2005–2015.

Focusing on the unobservable determinant of demand for handgun purchase $\tilde{\nu}_i$, Column 1 of Table 5 reports an estimate of $\zeta^{\nu} = 0.00144$. This value implies that each standard deviation increase in a handgun owner's value of $\tilde{\nu}_i$ would increase the expected count of homicides within their zip code by 0.00144 each quarter. The effect of a 1 standard deviation difference in $\tilde{\nu}_i$ is slightly larger than the gender gap ζ^{male} in homicide fatalities from licit handgun ownership, and about twice as large as begin over 30 and having "aged out of crime" $\zeta^{>30}$. The positive correlation $\zeta^{\nu} > 0$ between unobservable preferences $\tilde{\nu}_i$ and homicide fatalities e_i is robust to the exclusion of other sources of heterogeneity (Column 2) and to estimation under an alternative two-stage least-squares estimator (Column 3, described in Appendix OA.3). This positive correlation demonstrates that, all else equal, consumers with a higher preference for handgun purchase $\tilde{\nu}_i$ generate more costly homicide externalities through their handgun ownership e_i.

Columns 4–6 show minimal heterogeneity in the effect of licit handgun ownership on suicide fatalities, matching the patterns from Section 3. For instance, the effect of a 1 standard deviation increase in the unobservable preference ζ^{ν} is 20 times smaller for suicide than homicide fatalities. Without clear evidence of heterogeneity, my preferred estimates for suicide externalities assume a homogeneous effect of handgun ownership $\zeta = 0$ and use the inclusive value instrument $I_{xzt}(\hat{\Theta})$ from Column 2 of Table OA.1.

Across all specifications, I find small-in-magnitude coefficients on the control function χ.[47] This includes 5, as well as the specifications in Tables OA.7 and OA.8: estimated separately for firearm and non-gun homicides, and allowing a richer control function with demographic-specific heterogeneity $\chi_x \hat{\xi}_{xzt}$.

[47] Column 1 implies that a 1 standard deviation increase in all the demand shocks in a zip code quarter ξ_{xzt} would coincide with $0.000001 \times 0.54 \times 21,635 = .012$ additional homicide fatalities in the average zip code-quarter. By contrast, increasing the unobservable preference $\tilde{\nu}_i$ among all handgun owners in the average zip code quarter would generate $0.00144 \times 2.46 \times 1,100 = 3.9$ additional homicide fatalities. Table 1 provides counts of population and handgun owners. Table 4 provides standard deviations of demand shocks ξ_{xzt} and unobservable preferences σ_x.

5.2 Consumer heterogeneity and allocative inefficiency

Panel A of Figure 4 uses the estimated model $\hat{\Theta}$ to construct the joint distribution of private surplus from handgun purchase and externalities from handgun ownership across consumers in California's average quarter.

The horizontal axis is dollars of private surplus from handgun purchase u_{it}/α^p_{xz}. Consumers to the right of the vertical axis derive positive surplus, and so choose to purchase a handgun $q_{it} = 1$ in expectation. I limit the figure to consumers with private surplus in the interval $(-600, 200)$, with the full distribution presented in Figure OA.13.

The vertical axis is the dollar cost of fatality externalities a consumer would be expected to create from their licit handgun ownership. I convert counts of fatalities e_i into a fiscal cost by applying a social cost of a homicide fatality of 8.5 million dollars, a social cost of a suicide fatality of 1.5m dollars, and discounting social to fiscal costs using a multiplier of 8/442 from a study by San Jose, California (Heaton 2010, Shepard et al. 2016, Liccardo 2022).[48] Consumers above the horizontal axis generate a beneficial fatality externality (i.e., decrease homicides) through their handgun ownership.

To populate Figure 4, I compute each consumer's expected private surplus $\hat{E}[u_{it}/\alpha^p_{xz}]$ and fatality externalities $\hat{E}[e_i]$ implied by the model at parameter $\hat{\Theta}$, integrating over the realizations of $(\alpha^p_{xz}p_t + \xi_{xzt}, \mathcal{J}_{z(i)t})$ and the theoretical distributions of $(\tilde{\nu}_i, \varepsilon_{ijt}, \varepsilon_{i0t}, \tilde{e}_i)$. I also include the conditional expectation function $\hat{E}[e \,|\, \hat{E}[u_{it}/\alpha^p_{xz}]]$, which is downwards sloping, due to adverse selection into handgun purchase.[49] Despite this downward slope, there is considerable heterogeneity in externalities across consumers, with both beneficial and harmful effects of handgun ownership at each point along the distribution of willingness to pay for handgun purchase.

Without pre-existing handgun ownership $g_{i,t-1} = 0$, Figure 4 also visualizes the allocative efficiency of consumer choice in California's licit handgun market. Allocative efficiency is characterized by four regions, demarcated by the vertical axis and a negative 45-degree line. This line separates efficient from inefficient handgun purchases by intercepting the vertical axis at the marginal value of tax revenue generated by a consumer's handgun purchase. I

[48] The value of 8/442 is the ratio of "direct" fiscal costs to firearm violence in San Jose, relative to the total costs of firearm violence from (Liccardo 2022). The San Jose multiplier is meant to down-weight the statistical value of a lost life to capture only the direct fiscal costs of a fatality (e.g., deploying law enforcement and health care resources). I use the fiscal, rather than social, costs of a firearm fatality to more closely align with the stated objectives of regulators. Accounting for non-fiscal costs related to homicide fatalities (e.g., the well-being of the deceased and their community and lost future wages) would increase the magnitude of externalities e_i and elongate the scale of the vertical axis.

[49] This conditional expectation function can be interpreted as the profile of marginal treatment effects from assigning licit handgun ownership to consumers, who have heterogeneous willingness to pay for their own handgun acquisition (Heckman and Vytlacil 2005). The figure also includes the 10th, 25th, 75th, and 90th percentiles of the externality e_i, as a function of private surplus $\hat{E}[u_{it}/\alpha^p_{xz}]$.

assume that the regulator has access to lump-sum transfers, so that 1 dollar of tax revenue generates 1 dollar of social welfare. I also assume a status quo tax revenue per handgun purchase of 600×0.08725 dollars, using the median handgun price from Moshary et al. (forthcoming) and the average of the mid-point sales taxes in California from 2006 and 2015.

Figure 4 displays two regions of allocative inefficiency. In the lower-right are consumers who choose to purchase a handgun, but create a costly enough externality that their purchase is allocatively inefficient. Conversely, the upper-left region contains consumers who choose not to purchase a handgun, but generate externalities beneficial enough that their purchase would increase social welfare. I note that the distribution of consumers in the upper-left region relies heavily on extrapolating the functional form of the model, as few consumers with such low willingness to pay for handgun purchase are ever observed as handgun owners.

My estimates imply that, at essentially any value of private surplus u_{it}/α^p_{xz}, it would be inefficient to allocate the typical consumer to the purchase of a first handgun. Visually, in Figure 4, the conditional expectation function $E[e_i|E[u_{it}/\alpha^p_{xz}]]$ lies only in regions of allocative inefficiency. This extent of allocative inefficiency is possible due to adverse selection. Consumers with an indirect utility high enough to choose to purchase a handgun $u_{it} > 0$ generate a public health externality e_i sufficiently harmful to outweigh the private surplus and tax revenue generated by handgun purchase, on average. Conversely, consumers with lower utility $u_{it} < 0$ do not generate a sufficiently beneficial externality to offset their distaste for handgun purchase, on average, making their decision to not purchase socially efficient.

Figure 4 addresses the following hypothetical: If no consumers owned a handgun, would consumers' privately optimal handgun purchases be allocatively efficient in the average quarter? On average, the answer is no. However, this analysis falls short of a full welfare calculation, as it does not account for the durability of handguns, leading ownership to persist from one period to the next. In the following section I use information from Figure 4 to study the design of alternate regulations on the handgun market when accounting for the persistence of handgun ownership.

6 Counterfactual regulations for consumer firearms

This section analyzes welfare under counterfactual regulations on California's licit handgun market between 2005–2015.

6.1 Implementation

My approach simulates the effects of counterfactual regulations by adjusting the choice sets facing consumers each quarter, altering either the tax-inclusive price of a handgun p_t or the set of firearm retailers in operation $\mathcal{J}_{zt}$. Under each alternate configuration of the market, I compute each consumer's sequences of expected handgun purchase $(E[q_{i1}], \ldots, E[q_{iT}])$ and ownership $(E[g_{i1}], \ldots, E[g_{iT}])$, integrating over both the idiosyncratic shocks $(\varepsilon_{i0t}, \varepsilon_{ijt})$ and the present value of handgun purchase ν_i. Similarly, I compute the sequence of expected private surplus as $E[\max\{u_{it}, 0\}]$, integrating over these same terms. I transform expected purchases into expected changes in tax revenue using the counterfactual change in the tax-inclusive price. To transform expected ownership into expected changes in fatalities, I integrate Equation (6) over the present value ν_i. When aggregating over multiple periods, I take sums of each variable over time (e.g., the expected count of consumer i's handgun purchases is $\sum_{t=1}^{T} E[q_{it}]$). As my focus is on the impact of stricter regulations, I condition on the set of consumers observed to purchase a handgun under the status quo, and study the implications from varying the size and composition of this group under counterfactual regulations.

My analysis utilizes several methods for measuring the impacts of counterfactual regulations on California's handgun market. Most directly, I compare changes in social welfare at counterfactual handgun tax increase τ:

$$W(\tau) = \sum_i \sum_t \lambda^u \overbrace{E[u_{it}(\tau)/\alpha^p_{x(i)z(i)}]}^{\text{consumer surplus}} + \lambda^e \overbrace{E[e_i]E[g_{it}(\tau)]}^{\text{externality}} + \lambda^r \overbrace{(\tau + 600 \times 0.11)E[q_{it}(\tau)]}^{\text{government revenue}},$$

by taking a weighted sum of private surplus and external impacts, both on fatalities and tax revenue. My calibration from Section 5.2 set weights of $\lambda^u = 1$, $\lambda^e = 8.5m \times 8/442$, and $\lambda^r = 1$.

Beyond measuring social welfare, I contemplate other objective functions that could be used to evaluate counterfactual firearm regulations. At one extreme, I consider only the total amount of tax revenue generated from California's handgun market (i.e., $\lambda^u = 0$, $\lambda^e = 0$, and $\lambda^r > 0$). At the other extreme, I consider an objective that trades off consumer surplus and the social value of tax revenue against the total quantity of handguns purchased by consumers. This objective provides a stylized representation of a gun buyback program, in which each handgun sold produces a social cost equal to regulators' observed willingness to pay to repurchase a handgun from a consumer, approximately 100 dollars in California (i.e., $\lambda^u = 1$, $\lambda^e = 0$, and $\lambda^r = 1 - 100/(\tau + 600 \times 0.11)$).[50]

[50] See `https://www.longbeach.gov/police/press-releases/lbpd-to-host-gun-buy-back-event-`

Panel B of Figure 4 illustrates how these counterfactual regulations are implemented under the model, using a hypothetical tax of 66 dollars on handgun purchase. Such a tax creates a mass of marginal consumers—who purchase under the status quo but not under the tax increase—and a mass of inframarginals who purchase under both regulatory environments. These consumer segments are separated by the vertical black line, shifted right from the vertical axis by 66 dollars. The line of allocative inefficiency also shifts down by 66 dollars, as the tax increase means that each purchase generates 66 dollars of additional tax revenue.

Integrating over the distribution of marginal consumers, with willingness to pay between 0–66 dollars, the tax increase generates three welfare-relevant effects. Since these consumers switch out of handgun purchase, they no longer generate tax revenue, leading to a drop in welfare equal to the value of tax revenue from a handgun purchase under the status quo. Lost tax revenue is uniform across purchases, by assumption, so this effect is represented by the top shaded rectangle on the figure.

As the tax distorts consumers' choices over handgun purchase, it also leads to a drop in consumer surplus in excess of forgone tax revenue. The cost of this distortion is proportional to a consumer's willingness to pay for handgun purchase, which is represented as the middle shaded triangle on the figure.[51]

A tax that distorts handgun purchasing also affects handgun ownership and the externalities it generates. Although these externalities vary across consumers, the average welfare change among consumers at a specific willingness to pay is given by the difference between their average externality (the conditional expectation function $E[e \mid \hat{E}[u_{it}/\alpha^p_{xz}] = u])$ and the gross welfare cost of forgone tax revenue and consumer surplus. This is represented as the bottom shaded region on the figure.

Turning to inframarginals, the tax generates no net welfare cost among these consumers. Their choices remain the same, so the tax only transfers surplus from consumers to the government, represented as the right shaded trapezoid.

My evaluation of counterfactual regulations numerically constructs these regions and integrates over the distribution of consumer willingness to pay, accounting for the realizations of preferences u_{it} and handgun ownership g_{it} each quarter. I then aggregate these sequences of welfare changes across quarters, generating the average yearly effects of a regulation on different components of welfare and overall.

`on-june-10/`, `https://www.smcgov.org/ceo/news/sheriffs-office-and-partners-host-anonymous-gun-buyback-event-may-4.`, and `http://shq.lasdnews.net/pages/newsrelease.aspx?id=1001`.

[51] There is no loss of consumer surplus in the limiting case of a marginal tax change (Chetty 2009).

6.2 State-wide taxes

Figure 5 presents the outcomes—consumer surplus, homicide fatalities, and tax revenues—that could be achieved through increasing the statewide tax on handgun purchase in California between 2005–2015. Consumer surplus decreases monotonically in the tax rate, as higher taxes degrade the private value of handgun purchase to consumers. Homicide fatalities also decrease monotonically in the tax, as would be suggested by the negative relationship between private surplus and externalities in Figure 4. Tax revenue is non-monotone, and instead follows a U-shaped Laffer curve.

The tax rate that would have maximized tax revenue from California's licit handgun market is 63 dollars per handgun. This is similar to the rate implemented by California in 2024 of approximately 66 dollars per handgun. It is surprising that California's 2024 rate optimizes a well-defined policy objective, as it was set by doubling a federal excise tax from a 1918 omnibus bill

In the average year between 2005–2015, implementing California's revenue-maximizing tax would generate approximately 1.5m dollars of revenue, destroy approximately 7m dollars of consumer surplus, and avert approximately 400 homicide fatalities. Applying the fiscal cost of a homicide fatality, and not counting suicide fatalities, these taxes would have improved social welfare by approximately $1.5 - 7 + 400 \times 8.5 \times 8/442 = 56$ million dollars each year. As such, California's 2024 tax appears to be sound policy.

Directly valuing fatalities created by handgun ownership at their fiscal cost leads to higher optimal taxes on handgun purchase and larger gains in social welfare. In fact, the welfare-optimizing tax on handgun purchase is high enough to shut down California's licit handgun market. The fiscal benefits of averted homicide fatalities outweigh the total value of consumer surplus and tax revenues generated by the opportunity to licitly purchase a handgun. This is driven by the extent of adverse selection into handgun purchase on public health externalities, documented in Figure 4. Any increase in the tax leaves behind a residual pool of handgun purchasers with above-average externality costs, driving up the optimal rate, and leading the regulator to optimally shut down the market. The extent of adverse selection also rules out the optimally of a uniform handgun subsidy, despite the considerable mass of consumers with positive externalities, as the average marginal purchaser always generates a welfare decrease through their handgun ownership.

To further interpret the difference between the optimal tax and California's 2024 chosen rate, I use a policy inversion. In particular, I assume that California's 2024 tax on handgun purchase were set optimally based on an assumed homogeneous handgun price of 600 dollars (Moshary et al. forthcoming), the social costs of fatalities measured by Heaton (2010) and Shepard et al. (2016), and in accordance with my model at parameter $\hat{\Theta}$. Under these assumptions, I search for the weight on the social cost of fatalities $\tilde{\lambda}^e$ that rationalizes the chosen tax of 600×0.11 dollars as optimal.[52] This exercise implies a discount of approximately $\tilde{\lambda}^e = 17/10,000$, suggesting that, California's 2024 tax could be rationalized as optimal if regulators were willing to trade off one homicide fatality with 8.5m$\times$17/10,000$\approx$15,000 dollars of consumer surplus or tax revenue.[53]

Instead of maximizing social welfare, the policy objective based on the quantity of handguns sold, valued at their gun buyback price, leads to a lower optimal tax rate of 98 dollars per handgun. Although higher than the rate that maximizes tax revenue, this rate falls short directly valuing the fiscal costs of fatalities. Thus, the regulator's willingness to pay to buy back handguns is compatible with neither the objectives implied by California's 2024 firearm tax nor the public health costs of private firearm ownership.

6.3 Gains from geographic regulation

The heterogeneity across California implies that geographically targeted policies, as pursued by the city of San Jose, could improve on policies set uniformly at the state level. Such a system of geographically heterogeneous tax rates would the design of aggregate sales taxes across California's cities and the regulation of other externality producing goods, including alcohol, tobacco, and gambling.

Panel A of Figure 6 shows that optimally setting taxes on handgun purchase across California's 58 counties shifts out the frontier of gains in public health and tax revenue that can be achieved for any decrease in consumer surplus, relative to the outcomes feasible under uniform statewide taxation. In particular, it would be possible to achieve the same gains in public health and tax revenue as California's 2024 statewide tax, with a 40 percent smaller drop in consumer surplus. Conversely, while maintaining the same drop in consumer surplus, it would be feasible to achieve a 50 percent larger gain from public health and tax revenue.

Panel B of Figure 6 maps the county-specific tax rates that maximize gains from public health and tax revenue, while leaving consumer surplus equivalent to California's 2024 statewide tax. Setting rates optimally by county leads to a highly differentiated system of taxes across space. In particular, most of California's counties remain at the regulatory status quo, while the state's coastal population centers around the San Francisco Bay and

[52] I search over the welfare weight $\tilde{\lambda}^e$ rather than the social costs directly, since both homicides and suicides are counted in the social cost of externalities e_i. It would not be possible to identify separate costs for each fatality type from observing a single choice of a one-dimensional tax rate τ. I achieve identification by imposing a proportional scaling on both types of fatalities. With one-dimensional fatality costs (e.g., only homicide fatalities affect social welfare), it is isomorphic to search over the welfare weight $\tilde{\lambda}^e$ or the fatality cost.

[53] California's chosen tax could also be rationalized as arising from political constraints, different information about the effects of firearm taxation, or to balance objectives outside my model.

LA County have high optimal rates. The high rates in population centers reflect their high population density and baseline fatality rate, allowing changes in handgun ownership to create large shifts in the level of fatality outcomes. However, the high rates in these areas also reflect the composition of their consumer populations, who derive less value from handgun purchase than consumers elsewhere in the state, allowing gains in public health to be achieved with relatively smaller drops in consumer surplus. The combined implications of preferences and externalities among consumers along California's coast exacerbate adverse selection into handgun ownership (i.e., consumers value handgun purchase less and produce a greater level of harm), which can be addressed via high tax rates.

The geographic heterogeneity of optimal taxes in Panel B carries lessons for the design and implementation of firearm policy. Figure OA.14 shows that the regions of California where high tax rates on handgun purchase are economically efficient are also the regions where the Democratic party—and by extension firearm regulation—is more politically popular (Parker et al. 2017, Gentzkow et al. 2019, Luca et al. 2020). Moreover, the welfare gains from high taxes in these regions are nearly large-enough to match the gains from California's 2024 statewide tax, without adjusting regulation in areas with less political support for firearm regulation. At least in California, it appears most economically efficient to prioritize the design of policy for the licit firearm market in areas already amenable to tighter regulation.

Conversely, geographic heterogeneity reduces the efficiency of city-wide bans on the operation of firearm retailers, as implemented by the city of Chicago from 2010–2014, and predicted for California's 20 largest cities in Figure OA.15. The effects of bans are variable because of the heterogeneity in consumer populations and market structures across California. Closing retailers in Bakersfield, a sprawling city with many firearm retailers in an otherwise unpopulated area, has large effects on handgun purchasing. Whereas a retailer ban in San Francisco, a dense city with few pre-existing firearm retailers, would have a minimal impact. Perversely, Figure OA.16 shows that the cities where retailer bans have the largest effects are also those cities where optimal taxes are lowest. Thus, my results suggest that geographic bans on where firearms can be bought and sold have negative targeting properties, and are less efficient than uniform statewide regulation.

6.4 Gains from consumer targeting: Minimum age requirements

Rather than targeting taxes by geography, I consider alternate regulations that target consumers with observably different characteristics. In particular, I simulate minimum age requirements for handgun purchase, similar to other industries with consumption externalities (e.g., alcoholic beverages and rental cars). Minimum age requirements may be especially beneficial in consumer firearm markets, as most criminal actors offend before age 30 and then "age out of crime" (Farrington 1986, RAND 2018a).[54]

Figure 6 also traces out the effect of increasing the minimum required age for handgun purchase, from the status quo of 21 to a complete ban at a minimum required age of 100. There are considerable targeting gains from screening younger consumers out of handgun purchase. In fact, it would be more efficient—in the sense of delivering larger welfare gains at lower consumer surplus cost—to screen out handgun purchasers under age 30, than to implement the equivalently costly system of optimal handgun taxes across zip codes.

The targeting gains from raising the minimum age for handgun purchase quickly deteriorate after age 30, becoming less efficient than county-specific taxation around age 35. This pattern highlights that there are other meaningful determinants of externalities from handgun ownership that vary across space, even conditional on the purchaser's age. If regulators were willing to implement a policy that induced the same drop in consumer surplus as California's 2024 firearm tax, it would be less efficient to raise the minimum age than to set county-specific optimal taxes.

These results help clarify the strengths and limitations of many firearm policies that attempt to target on consumer observables.[55] Targeting offers an efficiency gain, increasing welfare by leveraging additional observable information about the externalities of potential firearm owners. However, my results also suggest that too little information on externalities may be available for these targeted regulations, preventing them from addressing the full scope of external harms created by handgun ownership (Degli Esposti et al. 2023). As such, it may be beneficial to pair highly efficient targeted regulations with a broad market-based policy—like higher taxes on handgun purchase—that can have a larger impact on handgun ownership and externalities.

7 Conclusion

The paper studies demand, public health, and regulatory design in licit firearm markets. To do so, I utilize 20 years of administrative data from California, recording all licit handgun purchases in the state, the consumer and retailer in each transaction, and the universe of

[54] My estimates of externalities $\hat{\Theta}^e$ imply that there could be gains from targeting subsidies to certain observable consumer segments, such as non-White women over 30 years of age. I am aware of no regulator proposing such demographically-intensive targeted policy, and I do not systematically pursue its implications in this paper. It is also doubtful that such a policy would be Constitutional.

[55] Smart et al. (2023) discuss several such policies. For instance universal background checks aim to screen out individuals whose past criminal history may make them an especially costly firearm owner in the future. Similarly, extreme risk protection orders seek to temporarily remove access to firearms for individuals at a particularly risky life stage.

fatality incidents by cause-of-death and geographic location.

Using these data, and variation created by the entry and exit of firearm retailers, I document that the flow of handgun purchase has welfare implications. Following the entry of a firearm retailer, handgun purchasing, handgun ownership, and homicide fatalities all increase.

To extrapolate beyond handgun purchases on the margin of retailer entry, I develop and estimate a model of consumer handgun purchase in which ownership affects fatality outcomes. The estimated model demonstrates adverse selection into handgun purchase on the basis of externality-relevant characteristics. Adverse selection is so severe in California's legal handgun market that, no matter a consumer's willingness to pay to purchase a handgun, their handgun acquisition would decrease net welfare.

I use the estimated model to evaluate several alternate regulations on California's licit handgun market. The firearm sales tax implemented by California in 2024 approximately maximizes tax revenues, and improves social welfare, but is set too low when accounting for its effects on consumer surplus and public health. Regulators' observed willingness to pay to repurchase firearms from consumers also appears to undervalue the public health consequences of private handgun ownership. Due to adverse selection, directly maximizing social welfare would lead regulators to set taxes high enough to shut down the state's licit handgun market.

Rather than setting uniform regulation statewide, I find that there is scope to design more efficient policy by targeting stricter regulations to consumer segments in which adverse selection is most severe. The most efficient single policy I consider is a minimum age restriction on handgun purchase, which effectively targets a group known to be at higher-risk of criminal activity. Further gains are achievable by targeting taxes on handgun purchase across California's different regions. This geographic targeting produces the highest optimal rates in the state's coastal population centers—around the San Francisco Bay and LA County—where firearm regulation has broad political support. Optimal rates are low in the rest of the state, where firearm regulation is less politically popular.

The results of these counterfactual policy evaluations have a number of caveats related to the model and data. This paper only models licit handgun demand and its public health implications, abstracting away from the effect of regulation on the actions of firearm retailers (Moshary et al. forthcoming), the behavior of the long gun market (Azrael et al. 2017, Armona and Rosenberg 2024), and the market for illicit firearms (Cook 2018, Lee and Persson 2022, Schnell 2024). Accounting for these additional margins of adjustment could potentially affect my analysis of policy counterfactuals, especially in response to policies further from the current equilibrium. It would be valuable for future work to provide greater evidence on these effects.

Moreover, the model assumes a specific structure of preferences and externalities that eases computation, but which may not hold exactly in the data. Following the public health literate, I assume that fatalities depend on the level and composition of binary handgun ownership across consumers, and not on a consumer's count of handgun purchases (e.g., Duggan 2001, Cook and Ludwig 2006, RAND 2018b, RAND 2018c, Studdert et al. 2020, Studdert et al. 2022, Miller et al. 2022). Instead, if externalities were monotone in each individual's count of handgun purchases, my model would understate the efficacy of a uniform statewide handgun tax.[56] Moreover, many of the model's parameters are identified by variation from the entry and exit of firearm retailers, requiring the model to extrapolate these local effects when studying broader policy counterfactuals. Even more extrapolation would be required to predict the effects of firearm regulations outside of California's legal handgun market between 2005–2015, as the features of my sample may differ from other geographic areas or time periods.

Nevertheless, my results show that it is possible to achieve welfare gains through tighter regulations on the licit handgun market, and even greater gains by further tightening regulation in common-sense ways and where politically popular.

References

Abdulkadiroğlu, Atila, Parag A Pathak, Jonathan Schellenberg, and Christopher R Walters, "Do parents value school effectiveness?," *American Economic Review*, 2020, *110* (5), 1502–39.

Acquisti, Alessandro and Catherine Tucker, "Guns, privacy, and crime," Technical Report, National Bureau of Economic Research 2022.

Agarwal, Nikhil, "An empirical model of the medical match," *American Economic Review*, 2015, *105* (7), 1939–1978.

Allcott, Hunt and Michael Greenstone, "Measuring the welfare effects of residential energy efficiency programs," *National Bureau of Economic Research*, 2024.

[56] With binary ownership, taxes can prevent fatalities by distorting a consumer's status quo choice of handgun ownership on the extensive margin, but have no effect on externalities from inframarginal owners. With purchases as a count, taxes can prevent fatalities by distorting a consumer's status quo choices of both whether to purchase a handgun and how many handguns to purchase. The structure of optimally targeted policies may differ under an alternate specification of externalities.

___ , **Christopher Knittel, and Dmitry Taubinsky**, "Tagging and targeting of energy efficiency subsidies," *American Economic Review*, 2015, *105* (5), 187–191.

Anderson, Michael L and Maximilian Auffhammer, "Pounds that kill: The external costs of vehicle weight," *Review of Economic Studies*, 2014, *81* (2), 535–571.

Armitage, Sarah, "Technology Adoption and the Timing of Environmental Policy: Evidence from Efficient Lighting," *Available at SSRN 4108312*, 2022.

Armona, Luis and Adam M. Rosenberg, "The U.S. Consumer Firearms Industry: Welfare and Policy Implications," *Mimeo*, 2024.

Aspelund, Karl M. and Anna Russo, "Additionality and Asymmetric Information in Environmental Markets: Evidence from Conservation Auctions," *Mimeo*, 2024.

Azrael, Deborah, Lisa Hepburn, David Hemenway, and Matthew Miller, "The Stock and Flow of U.S. Firearms: Results from the 2015 National Firearms Survey," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 2017, *3* (5), 38–57.

Barahona, Nano, Cauê Dobbin, and Sebastián Otero, "Affirmative action in centralized college admission systems," *Mimeo*, 2023.

___ , **Francisco A Gallego, and Juan-Pablo Montero**, "Vintage-specific driving restrictions," *The Review of Economic Studies*, 2020, *87* (4), 1646–1682.

Barwick, Panle Jia, Hyuk soo Kwon, and Shanjun Li, "Attribute-based subsidies and market power: an application to electric vehicles," 2023.

Berrigan, John, Deborah Azrael, and Matthew Miller, "The number and type of private firearms in the United States," *The ANNALS of the American Academy of Political and Social Science*, 2022, *704* (1), 70–90.

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, *63* (4), 841–890.

Bice, Douglas C and David D Hemley, "The market for new handguns: an empirical investigation," *The Journal of Law and Economics*, 2002, *45* (1), 251–265.

Borenstein, Severin and James B Bushnell, "Headwinds and tailwinds: Implications of inefficient retail energy pricing for energy substitution," *Environmental and energy policy and the economy*, 2022, *3* (1), 37–70.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess, "Revisiting event-study designs: robust and efficient estimation," *Review of Economic Studies*, 2024, p. rdae007.

Braga, Anthony A and Philip J Cook, "The association of firearm caliber with likelihood of death from gunshot injury in criminal assaults," *JAMA network open*, 2018, *1* (3), e180833–e180833.

_ , Garen J Wintemute, Glenn L Pierce, Philip J Cook, and Greg Ridgeway, "Interpreting the empirical evidence on illegal gun market dynamics," *Journal of Urban Health*, 2012, *89*, 779–793.

Braghieri, Luca, Ro'ee Levy, and Alexey Makarin, "Social media and mental health," *American Economic Review*, 2022, *112* (11), 3660–3693.

Bronnenberg, Bart J, Jean-Pierre H Dubé, and Matthew Gentzkow, "The evolution of brand preferences: Evidence from consumer migration," *American Economic Review*, 2012, *102* (6), 2472–2508.

Brownlee, Chip, "Seven States Move to Tax Guns and Ammo," 2024.

Buchanan, James M, "External diseconomies, corrective taxes, and market structure," *The American Economic Review*, 1969, *59* (1), 174–177.

Bundorf, M Kate, Jonathan Levin, and Neale Mahoney, "Pricing and welfare in health plan choice," *American Economic Review*, 2012, *102* (7), 3214–3248.

Cabral, Marika, Bokyung Kim, Maya Rossin-Slater, Molly Schnell, and Hannes Schwandt, "Trauma at school: The impacts of shootings on students' human capital and economic outcomes," Technical Report, National Bureau of Economic Research 2021.

Callaway, Brantly and Pedro HC Sant'Anna, "Difference-in-differences with multiple time periods," *Journal of econometrics*, 2021, *225* (2), 200–230.

Chen, Jiafeng and Jonathan Roth, "Logs with zeros? Some problems and solutions," *The Quarterly Journal of Economics*, 2024, *139* (2), 891–936.

Chen, Qiaoyi, Nicholas Ryan, and Daniel Yi Xu, "Adverse Selection in Carbon Offset Markets: Evidence from the Clean Development Mechanism in China," *Mimeo*, 2024.

Chetty, Raj, "Sufficient statistics for welfare analysis: A bridge between structural and reduced-form methods," *Annu. Rev. Econ.*, 2009, *1* (1), 451–488.

Cohen, Alma and Liran Einav, "Estimating risk preferences from deductible choice," *American economic review*, 2007, *97* (3), 745–788.

Congressional Research Service, "Firearms and ammunition excise tax (FAET)," 2023.

Conlon, Christopher and Nirupama L Rao, "The Cost of Curbing Externalities with Market Power: Alcohol Regulations and Tax Alternatives," Technical Report, National Bureau of Economic Research 2023.

Cook, Philip J and Jens Ludwig, "The social costs of gun ownership," *Journal of Public Economics*, 2006, *90* (1-2), 379–391.

_ , _ , Sudhir Venkatesh, and Anthony A Braga, "Underground gun markets," *The Economic Journal*, 2007, *117* (524), F588–F618.

Cook, Phillip J., "Gun Markets," *Annual Review of Criminology*, 2018, *1*, 359–377.

Currie, Janet, Bahadir Dursun, Michael Hatch, and Erdal Tekin, *The Hidden Cost of Firearm Violence on Infants in Utero* 2024.

Depew, Briggs and Isaac D Swensen, "The decision to carry: The effect of crime on concealed-carry applications," *Journal of Human Resources*, 2019, *54* (4), 1121–1153.

Diamond, Peter A, "Consumption externalities and imperfect corrective pricing," *The Bell Journal of Economics and Management Science*, 1973, pp. 526–538.

Dolfen, Paul, Liran Einav, Peter J Klenow, Benjamin Klopack, Jonathan D Levin, Larry Levin, and Wayne Best, "Assessing the gains from e-commerce," *American Economic Journal: Macroeconomics*, 2023, *15* (1), 342–370.

Dubin, Jeffrey A and Daniel L McFadden, "An econometric analysis of residential electric appliance holdings and consumption," *Econometrica: Journal of the Econometric Society*, 1984, pp. 345–362.

Duggan, Mark, "More guns, more crime," *Journal of political Economy*, 2001, *109* (5), 1086–1114.

_ , Randi Hjalmarsson, and Brian A Jacob, "The short-term and localized effect of gun shows: Evidence from California and Texas," *Review of Economics and Statistics*, 2011, *93* (3), 786–799.

Edlin, Aaron S and Pinar Karaca-Mandic, "The accident externality from driving," *Journal of Political Economy*, 2006, *114* (5), 931–955.

Einav, Liran, Amy Finkelstein, and Heidi Williams, "Paying on the margin for medical care: Evidence from breast cancer treatments," *American Economic Journal: Economic Policy*, 2016, *8* (1), 52–79.

_ , _ , **and Mark R Cullen**, "Estimating welfare in insurance markets using variation in prices," *The quarterly journal of economics*, 2010, *125* (3), 877–921.

_ , _ , **and Neale Mahoney**, "The IO of selection markets," in "Handbook of Industrial Organization," Vol. 5, Elsevier, 2021, pp. 389–426.

_ , _ , **and** _ , "Producing health: measuring value added of nursing homes," Technical Report, National Bureau of Economic Research 2022.

_ , **Mark Jenkins, and Jonathan Levin**, "Contract pricing in consumer credit markets," *Econometrica*, 2012, *80* (4), 1387–1432.

Esposti, Michelle Degli, Jason Goldstick, Jason Gravel, Elinore J Kaufman, M Kit Delgado, Therese S Richmond, and Douglas J Wiebe, "How have firearm laws changed in states with unexpected decreases or increases in firearm homicide, 1990–2019?," *SSM-Population Health*, 2023, *22*, 101364.

Farrington, David P, "Age and crime," *Crime and justice*, 1986, *7*, 189–250.

Ferrazares, Toshio, Joseph J Sabia, and D Mark Anderson, "Have US Gun Buyback Programs Misfired?," Technical Report, National Bureau of Economic Research 2021.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams, "Sources of geographic variation in health care: Evidence from patient migration," *The quarterly journal of economics*, 2016, *131* (4), 1681–1726.

Fleischer, Victor, "Curb your enthusiasm for Pigovian taxes," *Vand. L. Rev.*, 2015, *68*, 1673.

Fowlie, Meredith, "Emissions trading, electricity restructuring, and investment in pollution abatement," *American Economic Review*, 2010, *100* (3), 837–869.

_ , **Mar Reguant, and Stephen P Ryan**, "Market-based emissions regulation and industry dynamics," *Journal of Political Economy*, 2016, *124* (1), 249–302.

Gaudecker, Hans-Martin Von, Arthur Van Soest, and Erik Wengström, "Heterogeneity in risky choice behavior in a broad population," *American Economic Review*, 2011, *101* (2), 664–694.

Gentzkow, Matthew, Jesse M Shapiro, and Matt Taddy, "Measuring group differences in high-dimensional choices: method and application to congressional speech," *Econometrica*, 2019, *87* (4), 1307–1340.

_ , _ , **and Michael Sinkinson**, "The effect of newspaper entry and exit on electoral politics," *American Economic Review*, 2011, *101* (7), 2980–3018.

Goolsbee, Austan and Amil Petrin, "The consumer gains from direct broadcast satellites and the competition with cable TV," *Econometrica*, 2004, *72* (2), 351–381.

Grieco, Paul LE, Charles Murry, Joris Pinkse, and Sagl Stephen, "Conformant and Efficient Estimation of Discrete Choice Demand Models," *Mimeo*, 2023.

Griffith, Rachel, Martin O'Connell, and Kate Smith, "Tax design in the alcohol market," *Journal of Public Economics*, 2019, *172*, 20–35.

_ , _ , **and** _ , "Price floors and externality correction," *The Economic Journal*, 2022, *132* (646), 2273–2289.

Heaton, Paul, *Hidden in Plain Sight: What Cost-of-Crime Research Can Tell Us About Investing in Police*, Santa Monica, CA: RAND Corporation, 2010.

Heckman, James J, "Sample selection bias as a specification error," *Econometrica: Journal of the econometric society*, 1979, pp. 153–161.

_ **and Edward Vytlacil**, "Structural equations, treatment effects, and econometric policy evaluation 1," *Econometrica*, 2005, *73* (3), 669–738.

Hüther, Niklas, "More Guns Lead to More Crime: Evidence from Private Equity Deals," *Mimeo*, 2023.

Jacobsen, Mark R, "Fuel economy and safety: The influences of vehicle class and driver behavior," *American Economic Journal: Applied Economics*, 2013, *5* (3), 1–26.

_ **, Christopher R Knittel, James M Sallee, and Arthur A Van Benthem**, "The use of regression statistics to analyze imperfect pricing policies," *Journal of Political Economy*, 2020, *128* (5), 1826–1876.

_ **, James M Sallee, Joseph S Shapiro, and Arthur A Van Benthem**, "Regulating untaxable externalities: Are vehicle air pollution standards effective and efficient?," *The Quarterly Journal of Economics*, 2023, *138* (3), 1907–1976.

Jr, John R Lott and David B Mustard, "Crime, deterrence, and right-to-carry concealed handguns," *The Journal of Legal Studies*, 1997, *26* (1), 1–68.

Kaufman, Elinore J, Douglas J Wiebe, Ruiying Aria Xiong, Christopher N Morrison, Mark J Seamon, and M Kit Delgado, "Epidemiologic trends in fatal and nonfatal firearm injuries in the US, 2009-2017," *JAMA internal medicine*, 2021, *181* (2), 237–244.

Kleck, Gary, "The impact of gun ownership rates on crime rates: A methodological review of the evidence," *Journal of criminal justice*, 2015, *43* (1), 40–48.

Knight, Brian, "State gun policy and cross-state externalities: Evidence from crime gun tracing," *American Economic Journal: Economic Policy*, 2013, *5* (4), 200–229.

Knittel, Christopher R and Ryan Sandler, "The welfare impact of second-best uniform-Pigouvian taxation: evidence from transportation," *American Economic Journal: Economic Policy*, 2018, *10* (4), 211–242.

Koper, Christopher S and Jeffrey A Roth, "The impact of the 1994 federal assault weapons ban on gun markets: An assessment of short-term primary and secondary market effects," *Journal of quantitative criminology*, 2002, *18* (3), 239–266.

Kravitz-Wirtz, Nicole, Rocco Pallin, Matthew Miller, Deborah Azrael, and Garen J Wintemute, "Firearm ownership and acquisition in California: findings from the 2018 California Safety and Well-being Survey," *Injury prevention*, 2020, *26* (6), 516–523.

Krug, Alan S, "The relationship between firearms ownership and crime rates: A statistical analysis," *Congressional Record*, 1968, pp. H570–572.

Lee, Samuel and Petra Persson, "Human trafficking and regulating prostitution," *American Economic Journal: Economic Policy*, 2022, *14* (3), 87–127.

Li, Anran, "Commitment, Competition, and Preventive Care Provision," *Mimeo*, 2023.

Liccardo, Sam, "Gun harm reduction ordinance," Technical Report 2022.

Luca, Michael, Deepak Malhotra, and Christopher Poliquin, "The impact of mass shootings on gun policy," *Journal of public economics*, 2020, *181*, 104083.

Marone, Victoria R and Adrienne Sabety, "When should there be vertical choice in health insurance markets?," *American Economic Review*, 2022, *112* (1), 304–342.

Martin, Gregory J and Ali Yurukoglu, "Bias in cable news: Persuasion and polarization," *American Economic Review*, 2017, *107* (9), 2565–2599.

McDougal, Topher L, Daniel Montolio, and Jurgen Brauer, "Modeling the US firearms market: the effects of civilian stocks, legislation, and crime," *International social science journal*, 2023.

Miller, Matthew, Yifan Zhang, Lea Prince, Sonja A Swanson, Garen J Wintemute, Erin E Holsinger, and David M Studdert, "Suicide deaths among women in California living with handgun owners vs those living with other adults in handgun-free homes, 2004-2016," *JAMA psychiatry*, 2022, *79* (6), 582–588.

Moshary, Sarah, Bradley Shapiro, and Sara Drango, "Preferences for Firearms and Their Implications for Regulation," *American Economic Review: Insights*, forthcoming.

Newey, Whitney K and Daniel McFadden, "Large sample estimation and hypothesis testing," *Handbook of econometrics*, 1994, *4*, 2111–2245.

O'Connell, Martin and Kate Smith, "Optimal sin taxation and market power," *American Economic Journal: Applied Economics*, 2024, *16* (4), 34–70.

Parker, Kim, Juliana Menasce Horowitz, Ruth Igielnik, J Baxter Oliphant, and Anna Brown, "The demographics of gun ownership," *Pew Research Center*, 2017, *22.*

Pear, Veronica A., Garen J. Wintemute, Nicholas P. Jewell, Magdalenad Cerdá, and Jennifer Ahern, "Community-Level Risk Factors for Firearm Assault and Homicide: The Role of Local Firearm Dealers and Alcohol Outlets," *Epidemiology*, 2023, *34* (6), 798–806.

Petrin, Amil and Kenneth Train, "A control function approach to endogeneity in consumer choice models," *Journal of marketing research*, 2010, *47* (1), 3–13.

Pienkny, Max, Maya Rossin-Slater, Molly Schnell, and Hannes Schwandt, "The Lasting Impacts of School Shootings on Youth Psychotropic Drug Use," *AEA Papers and Proceedings*, May 2024, *114*, 387–93.

Pigou, Arthur Cecil, *The Economics of Welfare*, Macmillan, 1924.

RAND, "The Effects of Minimum Age Requirements," Technical Report 2018.

_ , "The Relationship Between Firearm Prevalence and Suicide," Technical Report 2018.

— , "The Relationship Between Firearm Prevalence and Violent Crime," Technical Report 2018.

Revelt, David and Kenneth Train, "Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier," 2000, (Working Paper No. E00-274).

Roth, Jonathan, "Interpreting event-studies from recent difference-in-differences methods," *arXiv preprint arXiv:2401.12309*, 2024.

— and Pedro HC Sant'Anna, "When is parallel trends sensitive to functional form?," *Econometrica*, 2023, *91* (2), 737–747.

Schnell, Molly, "Physician behavior in the presence of a secondary market: The case of prescription opioids," *Mimeo*, 2024.

Shepard, Donald S, Deborah Gurewich, Aung K Lwin, Gerald A Reed Jr, and Morton M Silverman, "Suicide and suicidal attempts in the United States: costs and policy implications," *Suicide and Life-Threatening Behavior*, 2016, *46* (3), 352–362.

Smart, Rosanna, Andrew R. Morral, and Terry L. Schell, *The Magnitude and Sources of Disagreement Among Gun Policy Experts: Second Edition*, Santa Monica, CA: RAND Corporation, 2021.

— , — , Rajeev Ramchand, Amanda Charbonneau, Jhacova Williams, Sierra Smucker, Samantha Cherney, and Lea Xenakis, *The Science of Gun Policy: A Critical Synthesis of Research Evidence on the Effects of Gun Policies in the United States, Third Edition*, Santa Monica, CA: RAND Corporation, 2023.

Studdert, David M, Yifan Zhang, Erin E Holsinger, Lea Prince, Alexander F Holsinger, Jonathan A Rodden, Garen J Wintemute, and Matthew Miller, "Homicide deaths among adult cohabitants of handgun owners in California, 2004 to 2016: a cohort study," *Annals of Internal Medicine*, 2022.

— , — , Sonja A Swanson, Lea Prince, Jonathan A Rodden, Erin E Holsinger, Matthew J Spittal, Garen J Wintemute, and Matthew Miller, "Handgun ownership and suicide in California," *New England journal of medicine*, 2020, *382* (23), 2220–2229.

Sugarmann, Josh and Kristen Rand, *More gun dealers than gas stations: A study of federally licensed firearms dealers in America*, Violence Policy Center Washington, DC, 1992.

Swanson, Sonja A, Matthew Miller, Yifan Zhang, Lea Prince, Erin E Holsinger, Zachary Templeton, and David M Studdert, "Patterns of handgun divestment among handgun owners in California," *Injury epidemiology*, 2022, *9*, 1–6.

Tebaldi, Pietro, "Estimating equilibrium in health insurance exchanges: Price competition and subsidy design under the aca," *Review of Economic Studies*, forthcoming.

Train, Kenneth E, *Discrete choice methods with simulation*, Cambridge university press, 2009.

Verboven, Frank and Biliana Yontcheva, "Private Monopoly and Restricted Entry-Evidence from the Notary Profession," *Journal of Political Economy*, forthcoming.

Wagner, Katherine RH, "Adaptation and adverse selection in markets for natural disaster insurance," *American Economic Journal: Economic Policy*, 2022, *14* (3), 380–421.

Wellford, Charles F, John V Pepper, and Carol V Petrie, "Firearms and violence: A critical review," 2004.

Wertz, Joseph, Deborah Azrael, and Matthew Miller, "Americans who become a new versus a former gun owner: implications for youth suicide and unintentional firearm injury," *American Journal of Public Health*, 2019, *109* (2), 212–214.

Wiebe, Douglas J, Robert T Krafty, Christopher S Koper, Michael L Nance, Michael R Elliott, and Charles C Branas, "Homicide and geographic access to gun dealers in the United States," *BMC Public Health*, 2009, *9*, 1–10.

Wooldridge, Jeffery M., "Control Function Methods in Applied Econometrics," *Journal of Human Resources*, 2015.

Zimring, Franklin E, "Games with guns and statistics," *Wisconsin Law Review*, 1968, p. 1113.

Table 1: Summary Statistics on Consumers and Zip Code-Quarters

	1(Purchase) per 100 (1)	Purchases | purchase (2)	**1**(Own) per 100 (3)	Distance | purchase (4)	Homicide per 100k (5)	Suicide per 100k (6)	Consumers (7)	Zip-quarters (8)
Panel A: Consumers by 2015								
All	4.43	1.86	6.31	17.34			28,683,439	1,304
	(4.43)	(1.97)	(6.31)	(30.43)				
Own pre-2005	4.43	2.81	6.31	18.12			749,331	1,304
Not pre-own	4.43	1.67	6.31	17.01			27,934,108	1,304
Men	4.43	1.94	6.31	17.42			14,151,156	1,304
Women	4.43	1.32	6.31	16.52			14,532,283	1,304
White	4.43	1.90	6.31	17.52			12,917,359	1,304
Minority	4.43	1.76	6.31	16.95			15,766,080	1,304
Panel B: Zip code-quarters								
All	0.39		5.12	19.83	1.68	3.93	21,635	57,376
	(0.33)		(3.51)	(14.95)	(5.50)	(8.88)		
Has retailer	0.45		5.62	16.62	1.53	4.07	27,662	16,604
No retailer	0.36		4.91	21.14	1.75	3.88	19,181	40,772
High income	0.32		4.02	16.41	1.78	3.26	33,705	28,688
Low income	0.45		6.22	23.27	1.59	4.61	9,566	28,688
Dense	0.27		3.40	14.87	1.86	3.05	28,947	28,688
Sparse	0.50		6.84	24.81	1.51	4.81	14,324	28,688
High crime	0.35		4.62	18.49	2.24	3.46	23,284	28,556
Low crime	0.43		5.61	21.15	1.13	4.40	20,002	28,820
2005	0.22		3.47	19.91	1.93	3.51	21,635	5,216
2015	0.58		7.44	19.18	1.58	4.36	21,635	5,216

Mean, (SD)

Panel A provides summary statistics on California's adult population in the last quarter of 2015. Columns represent (1) the percent of consumers purchasing one or more handguns between 2005–2015, (2) the number of handguns purchased conditional on at least one purchase occurring, (3) the percent of consumers who purchased one or more handguns 1996–2015, (4) the distance between a purchasing consumer's and implementing retailer's zip code centroids, (7) adult population, and (8) the count of zip codes in the sample. Minority is all non-White consumers

Panel B provides summary statistics on zip code-quarters in California between 2005–2015. Columns represent (1) the percent of residents purchasing one or more handguns, (3) the percent of residents who have purchased at least one handgun from 1996–the current quarter, (4) the distance between a purchasing resident's and implementing retailer's zip code centroids, (5) the count of homicide fatalities per 100,000 adults, (6) the count of suicides per 100,000 adults, (7) average population of adult residents among zip code-quarters, and (8) the count of zip code quarters. Zip codes quarters are (i) high-income if they are above the median of median family income in my sample, (ii) dense if they are above the median population density within my sample, and (iii) high-crime if their county has above median violent crime rate from 2000–2004.

Table 2: Summary Statistics on Firearm Retailers

	Mean (1)	SD (2)	P10 (3)	P25 (4)	P50 (5)	P75 (6)	P90 (7)	Retailers (8)
Panel A: All retailers								
Sales	3829	6737	340	608	1407	3897	8615	992
Quarters	26	14	7	13	24	44	44	992
Sales/Quarter	153.4	194.8	12.49	31.56	79.67	181.12	408.97	992
Sale distance	19.02	13.86	11.45	13.89	17.12	21.09	26.67	992
Share private	0.59	0.17	0.37	0.48	0.61	0.71	0.8	992
$\mathbf{1}$(Corporate)	0.03	0.16	0	0	0	0	0	992
Panel B: Entrants								
Sales	3163	4340	494	751	1551	3842	7690	476
Quarters	18	9	7	11	16	24	32	476
Sales/Quarter	180.37	189.95	32.14	57.47	108.53	232.46	418.51	476
Sale distance	18.44	8.74	11.59	13.98	17.1	20.81	26.09	476
Share private	0.6	0.17	0.38	0.49	0.61	0.71	0.8	476
$\mathbf{1}$(Corporate)	0.02	0.15	0	0	0	0	0	476
Panel C: Exitors								
Sales	1829	2293	206	442	973	2320	4798	347
Quarters	19	11	6	10	17	28	37	347
Sales/Quarter	113.39	122.08	12.06	29.97	71.54	151.66	278.84	347
Sale distance	19.3	12.88	11.26	13.64	17.1	20.61	28.24	347
Share private	0.59	0.16	0.37	0.49	0.6	0.7	0.79	347
$\mathbf{1}$(Corporate)	0.01	0.08	0	0	0	0	0	347

Table presents summary statistics of firearm retailers used in my analysis. Panel A is all retailers. Panel B is the subset of retailers who enter during the sample. Panel C is the subset of retailers who exit during the sample. Retailers that enter and subsequently exit appear in all panels. Within a panel, rows 1–3 are total sales, total quarters of operation, and average sales per quarter. Rows 4 and 5 are the average distance consumers travel for a purchase and the share of sales that are between private parties. Rows 6 is an indicator for whether a retailer is registered as a corporate retailer with California's Department of Justice.

Table 3: Effect of 100 Licit Handgun Owners on Yearly Fatalities

	IV (1)	OLS (2)	Sample Mean (3)
Panel A: Homicides			
Firearm	0.159 (0.056)	0.101 (0.012)	1.120
All	0.188 (0.059)	0.107 (0.013)	1.551
Panel B: Suicides			
Firearm	0.042 (0.045)	0.044 (0.009)	1.090
All	0.065 (0.072)	0.069 (0.015)	2.782
Panel C: Handguns (Average year with +1 retailer)			
Owners (first-stage)		277.2 (38.6)	890
Purchases		60.6 (6.3)	283.8
Zip code FE	Y	Y	
Quarter FE	Y	Y	
First-stage F	51.67		
Zip code clusters	$1,304$	$1,304$	
Zip code-quarters	$57,376$	$57,376$	$57,376$

Estimate, (SE)

Panels A and B present the effect of 100 handgun owners on yearly fatalities in their residential zip code, computed as $4 \times 100 \times \mu$ using the specification of Equation (2). Values in Panels A and B are estimated by regressing fatalities per capita on handgun owners per capita, using a panel of zip code-quarter observations. Column 1 presents estimates using an instrument based on firearm retailer net entry from Section 3.3. Column 2 presents estimates from OLS. Column 3 is the zip code-year sample mean. Panel C presents the effect of firearm retailers' net entry on handgun ownership and handgun purchasing. Values are estimated by regressing handgun owners per capita or handgun purchases per capita on the count of firearm retailers in a zip code-quarter, using a panel of zip code-quarter observations. Panel C scales these regression estimates by 4 times the average zip code population $E[M_z]$, to report estimates for the average zip code in the average year following a net entry. Row 1 of Panel C is the first-stage regression used for the IV column of Panels A and B, and all panels present comparable scalings of the regression coefficients. Standard errors are clustered by zip code. Estimates in Columns 1–2 weighted by zip code population M_z. Sample mean in Column 3 unweighted.

Table 4: Estimated preference parameters $(\Theta^{\nu}, \Theta^{\delta}, \rho)$

	Mean (1)	SD (2)	P10 (3)	P90 (4)	#Values (5)
Panel A: Handgun purchase Θ^{ν}					
σ_x	2.46	0.71	1.71	3.26	50
	(0.06)		(0.01)	(0.22)	
γ_x	1.82	2.02	-1.61	4.00	50
	(0.17)		(0.06)	(0.04)	
$\psi_{xz} - \alpha^p \overline{p}$	-8.48	2.07	-10.89	-5.89	$51,813$
$\xi_{xzt} - \alpha^p (p_t - \overline{p})$		0.54	-0.64	0.71	$692,467$
α^p_{xz}	0.02	0.004	0.01	0.02	$32,711$
Consumer observations					$28,683,439$
Panel B: Retailer choice Θ^{δ}					
δ_j	-1.14	0.91	-2.34	-0.03	992
α^d_{xz}	0.11	0.02	0.08	0.14	$32,711$
Purchase observations					$2,765,428$
Panel C: Nesting parameter ρ					
ρ	0.64				1
	(0.06)				
Entry observations					183

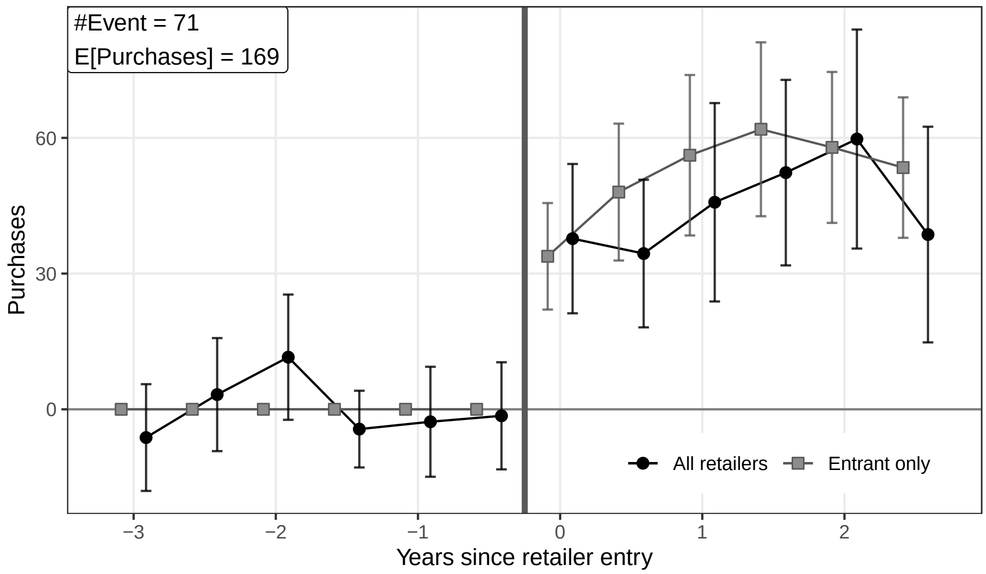
Value, (SE)

Table presents estimates of preference parameters from Section 4. Panel A: Preferences for handgun purchase Θ^{ν}, excluding demographic-zip code-quarters with zero purchase. Panel B: Preferences for retailer choice Θ^{δ}, with determinants of distance disutility α^d_{xz} in Table OA.5. Panel C: Nesting parameter is signed so $\rho = 0$ implies no substitution between handgun retailers and outside option. Delta method standard errors in parentheses. Panel A standard errors reported for the point estimate closest to the mean, 10th, or 90th percentile.

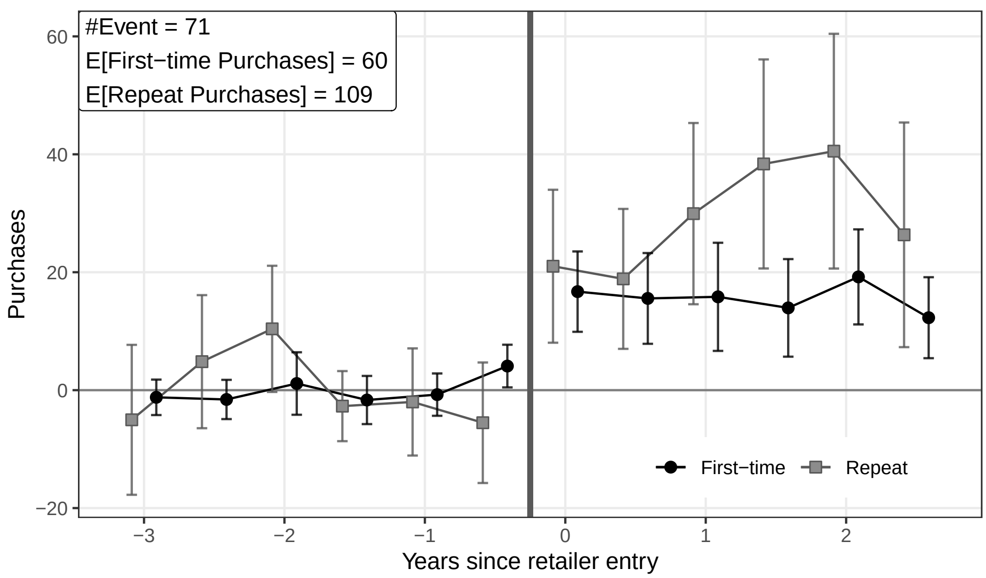
Table 5: Estimated externality parameters $100 \times \Theta^e$

	Homicide			Suicide		
	Control function		2SLS	Control function		2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
μ	−0.3415	−0.1347	−0.3677	−0.0386	0.0301	−0.2195
	(0.0542)	(0.0251)	(0.1564)	(0.0611)	(0.0329)	(0.1212)
ζ^{inc}	−0.0024			0.0027		
	(0.0021)			(0.0033)		
ζ^{den}	−0.0040			−0.0039		
	(0.0025)			(0.0033)		
ζ^{crime}	0.0016			0.0005		
	(0.0012)			(0.0018)		
ζ^{male}	0.1417			0.0516		
	(0.0391)			(0.0493)		
$\zeta^{<30}$	0.0662			0.0416		
	(0.0216)			(0.0310)		
ζ^{white}	0.0673			0.0116		
	(0.0123)			(0.0121)		
ζ^{g_0}	−0.1186			0.2870		
	(0.0612)			(0.0895)		
ζ^{ψ}	−0.00003			0.0005		
	(0.0020)			(0.0034)		
ζ^{ν}	0.1436	0.1314	0.3198	−0.0074	−0.0104	0.1928
	(0.0232)	(0.0218)	(0.1281)	(0.0276)	(0.0260)	(0.0986)
χ	0.0001	0.0001		0.00001	0.00003	
	(0.0001)	(0.0001)		(0.0001)	(0.0001)	
Zip code FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Instrument	$\vec{d}_{it}$	$\vec{d}_{it}$	$(1, \psi_z)^\top I_{zt}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$(1, \psi_z)^\top I_{zt}$
Zip code clusters	1,304	1,304	1,304	1,304	1,304	1,304
Zip code-quarters	57,079	57,079	57,079	57,079	57,079	57,079

Estimated externality parameters from Equations (5) and (6). Columns 1–3 use all homicides as cause of death. Columns 4–6 use all suicides as cause of death. Columns 1, 2, 4, and 5 use the control function estimator developed in Section 4, in which travel distances from consumers to retailers $\vec{d}_{z(i)t} = (d_{i1t}, \ldots, d_{iJt})$ operates as an excluded instrument. Columns 3 and 6 use an alternative two-stage least-squares estimator with instruments $I_{zt} = \sum_{i:z(i)=z} I_{x(i)z}/M_z$ and $I_{zt} \times \sum_{i:z(i)=z} \psi_{x(i)z}/M_z$, as discussed in Appendix OA.3. Standard errors clustered by zip code. All estimates weighted by zip code population. Estimates disaggregated by firearm and non-gun fatalities in Tables OA.7 and OA.8. Observations differ from Table 3 as some zip code-quarters do not have certain control variables available.



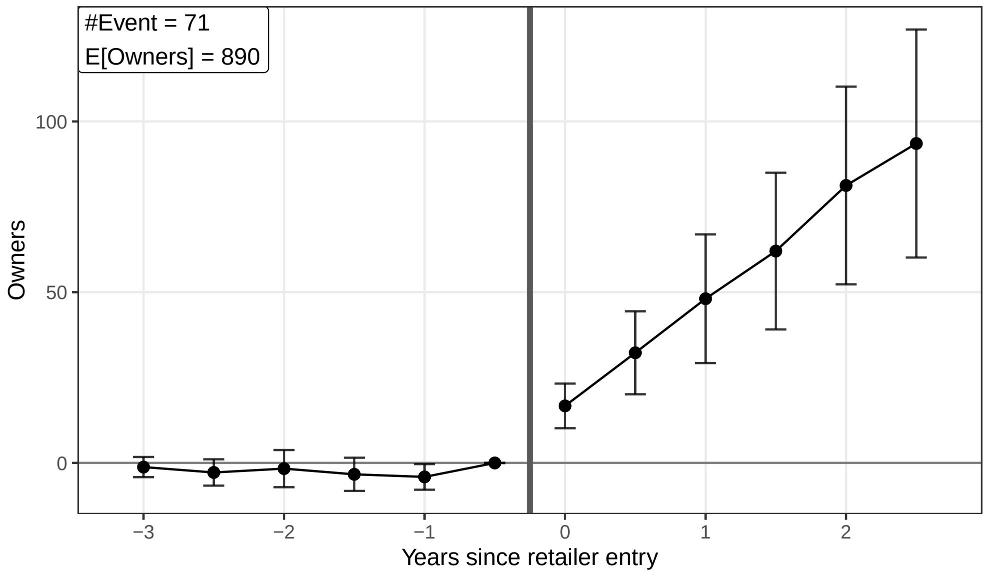
Panel A: Market expansion and business stealing



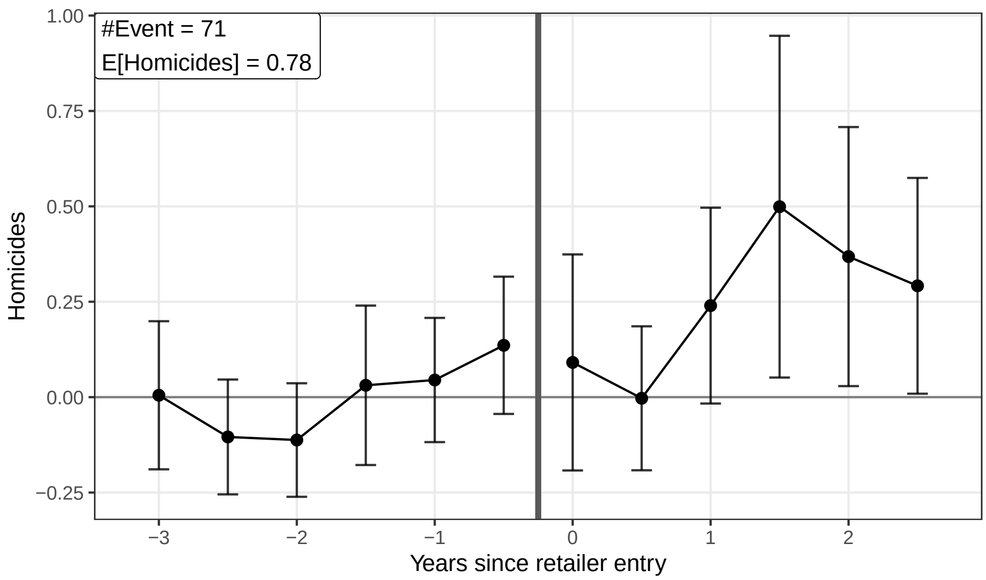
Panel B: Market expansion of first-time and repeat purchasers

Figure 1: Effects of firearm retailer first entries on handgun purchases

Figure presents the effect of a firearm retailer's entry on handgun transactions in the entered zip code. Panel A presents effects on market expansion (darker circle, handgun purchases from any retailer in California) and only at the entering firearm retailer (lighter square). Panel B presents effects on market expansion for first-time purchasers (darker circle) and repeat purchasers (lighter square). Horizontal axis is periods from the retailer entry, with pre- and post-entry separated by the thick vertical line. Vertical axis is the effect on handgun purchases per capita $\beta_{t'}$, scaled by the average zip code's population in California. Data for model fitting is restricted to zip code-periods that are either within three years of the entry of their first firearm retailer or that never have an operational firearm retailer during my sample. To remove composition bias, effects are calculated for first entry events with three years of data fully observed before and after the period of entry. Points are point estimates and intervals are 95-percent pointwise confidence intervals computed from a Bayesian bootstrap of zip codes.



Panel A: Handgun ownership



Panel B: Homicides fatalities

Figure 2: Effects of firearm retailer first entries on handgun ownership and homicide fatalities

Figure presents the effect of a firearm retailer's entry on handgun ownership (Panel A) and homicide fatalities (Panel B) in the entered zip code. Horizontal axis is periods from the retailer entry, with pre- and post-entry separated by the thick vertical line. Vertical axis is the effect on handgun ownership or homicide fatalities, both per capita $\beta_{t'}$, scaled by the average zip code's population in California. Data for model fitting is restricted to zip code-periods that are either within three years of the entry of their first firearm retailer or that never have an operational firearm retailer during my sample. To remove composition bias, effects are calculated for first entry events with three years of data fully observed before and after the period of entry. Points are point estimates and intervals are 95-percent pointwise confidence intervals computed from a Bayesian bootstrap of zip codes.

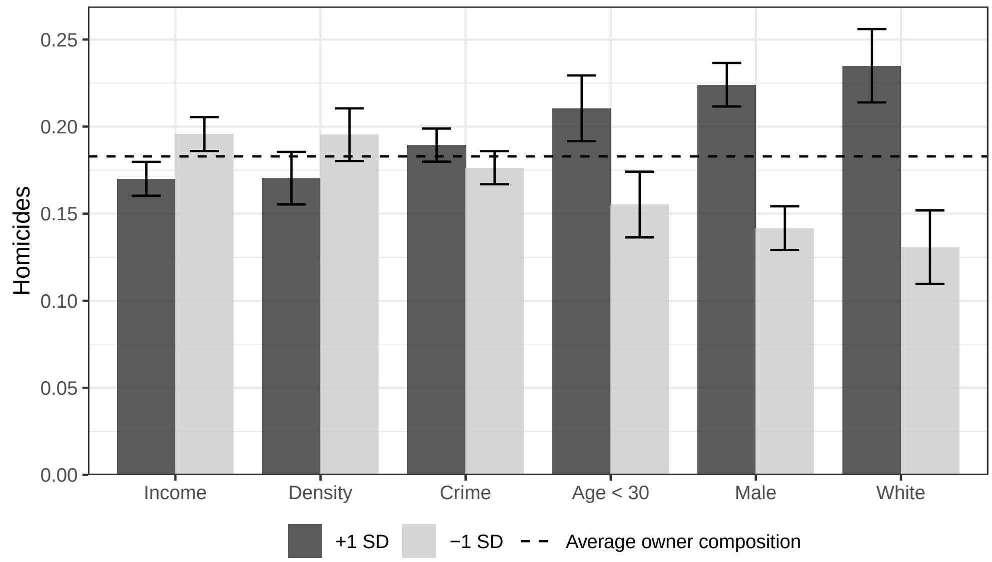
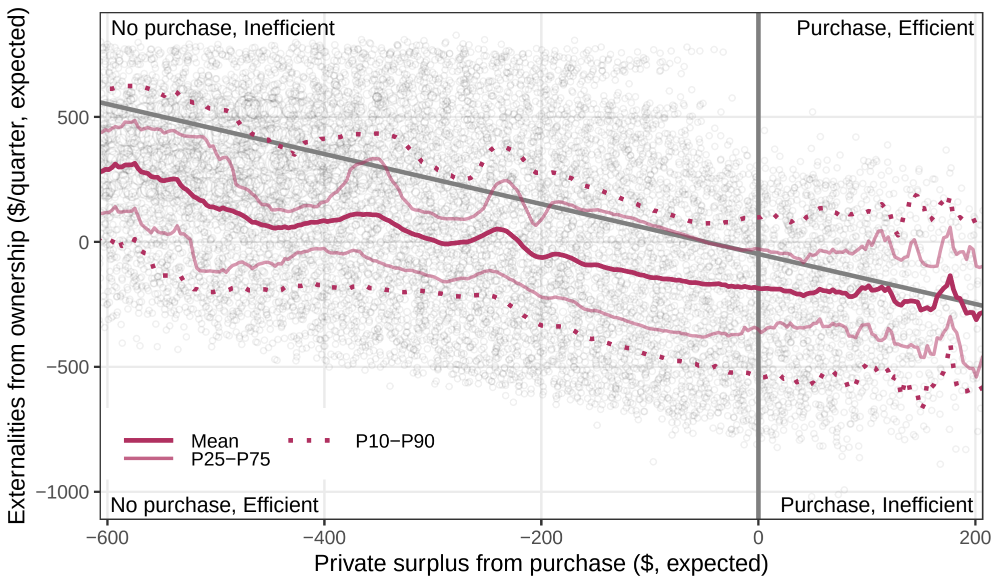
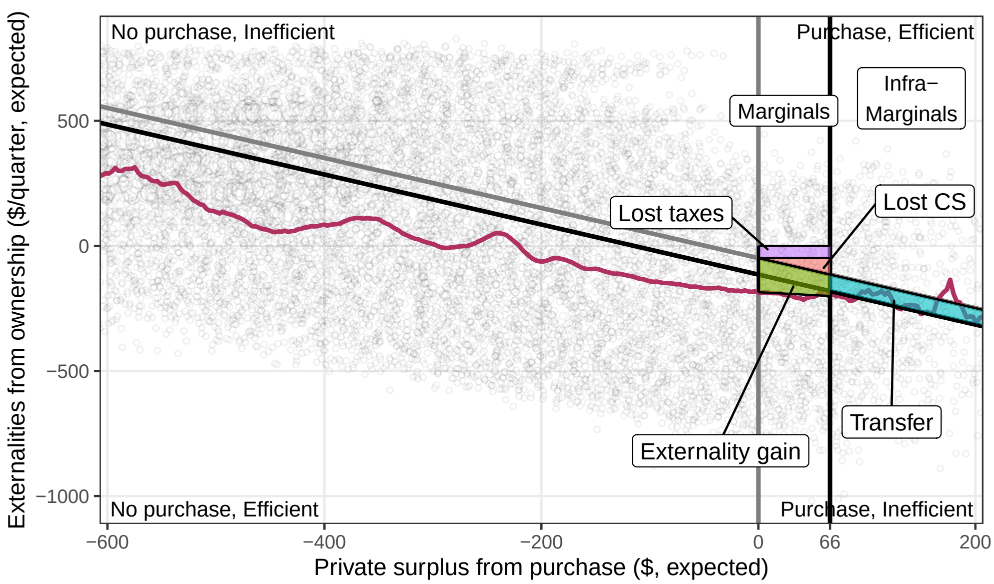


Figure 3: Observable heterogeneity in the effect of 100 handgun owners on yearly fatalities

Figure presents observable heterogeneity in the effect of handgun ownership on fatalities, as estimated in Section 3.4. Horizontal axis is dimensions of observable heterogeneity: the log of a consumer's county's violent crime rate 2000–2004, the log of a consumer's zip code's population density, the log of a consumer's median household income, an indicator for consumer age under 30 years, consumer's race White, and consumer's gender male. Horizontal dotted line is the effect of adding 100 handgun owners with the average in-sample handgun owner's observable characteristics. Bars show homicide fatalities when changing, all else equal, each observable characteristic of the 100 added owners by 1 standard deviation of the full sample composition of handgun owners (e.g., the 100 owners are 1 standard deviation more male than average). Full sample composition standard deviations are, respectively 0.67 (income), 0.78 (density), 0.98 (crime), 0.07 (age < 30), 0.03 (male), and 0.21 (White). Each pair of bars averages to the dotted line. Bands are 95 percent confidence intervals from changing a single characteristic of the 100 added owners, uses a Bayesian bootstrap and treating the average owner's homicide fatalities as known.



Panel A: Allocative efficiency from handgun purchase, without prior ownership



Panel B: The effect of a 66 dollar tax on handgun purchase

Figure 4: Joint distribution of preferences and externalities in California's handgun market

Figure presents allocative efficiency from consumer choice in handgun markets when $g_{i,t-1} = 0$. Horizontal axis is private surplus from purchase. Vertical axis is expected quarterly external costs of handgun ownership. Downward sloping line has slope of -1 and intersects the vertical axis at the value of tax revenue generated by handgun purchase. Points are consumers in California's average quarter. Solid series is the conditional expectation function in this space, estimated via kernel regression with a bandwidth of 5 and a Logistic kernel. Light lines are quantiles 25 and 75, while dotted lines are quantiles 10 and 90, all computed under the same kernel and bandwidth. Marginal value of public funds is 1, marginal value of a homicide fatality is $8,500,000 \times (8/442)$, marginal value of a suicide fatality is $1,500,000 \times (8/442)$, and the tax is 600×0.0875, described in Section 4. Panel A shows California's status quo regulation. Panel B shows the effect of a counterfactual 66 dollar tax on handgun purchase, described in detail in Section 5.2.

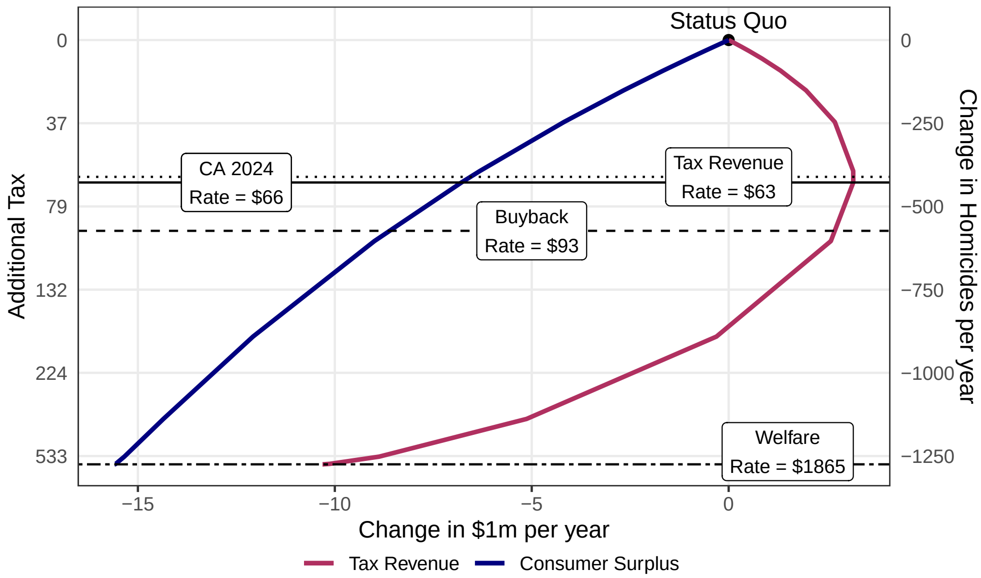
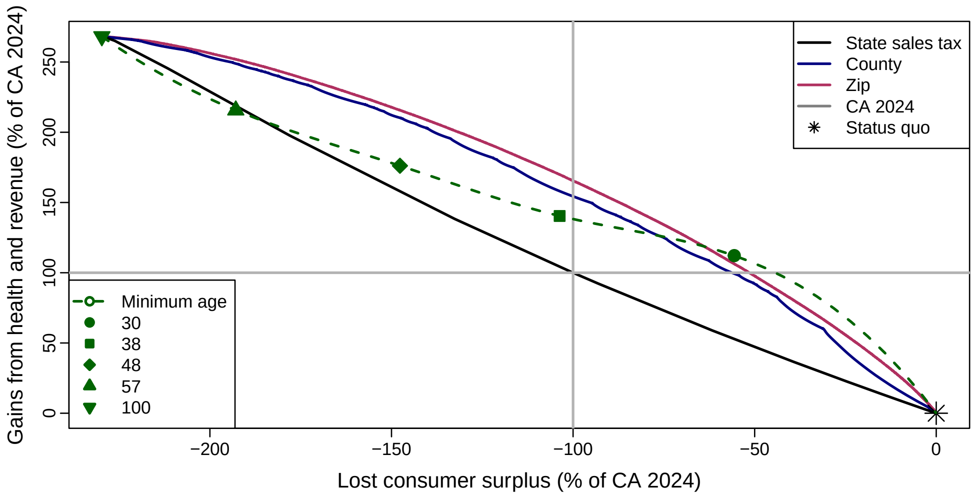
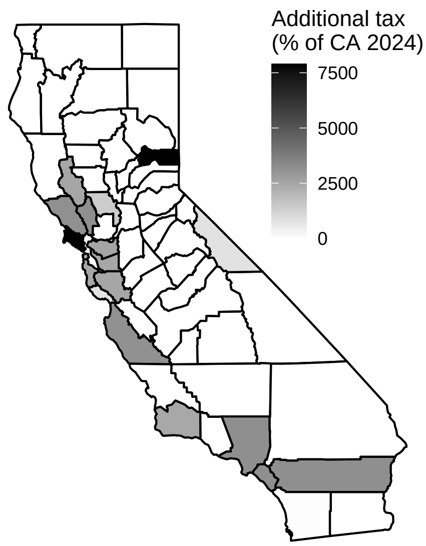


Figure 5: Feasible outcomes from statewide taxes on California's handgun market

Figure presents the effect of increases in handgun purchase taxes on changes in consumer surplus, homicide fatalities, and tax revenue. Horizontal axis is changes in dollars. Left axis is change in homicide fatalities. Right axis is the tax increase that implements the change in homicides (a non-linear transformation). Center point is the regulatory status quo. Right series is tax revenue. Left series is consumer surplus. Horizontal lines show additional taxes that optimize various objectives: tax revenue, consumer surplus and the social value of tax revenue less buyback cost, welfare (weighting fatalities by San Jose's estimated fiscal cost), and welfare (using the weighting on fatalities revealed by California's 2024 tax on handgun purchase). See Sections 5.2 and 6.1 for details.



Panel A: Frontiers of feasible outcomes



Panel B: Optimal county-specific taxes with same consumer surplus loss as CA 2024 statewide tax

Figure 6: Feasible outcomes from targeted regulations on California's handgun market

Figure presents feasible outcomes from alternate taxes on California's handgun market. Panel A is the frontier of welfare-maximizing outcomes achievable under targeted regulations. Solid lines are from taxes with varying geographic resolution. Filled points represent the effect of raising the minimum age for handgun purchase to quintiles of the age distribution among California's handgun purchasers, relative to the status quo minimum age in California of 21, and are connected via a cubic spline. Horizontal axis is the change in consumer surplus, relative to lost consumer surplus under California's 2024 tax. Vertical axis is the joint value of changes in fatalities and tax revenue, relative to joint value under California's 2024 tax. Inner series is statewide taxes, as in Figure 5. Middle series is county-specific taxes, set optimally. Outer series is zip code-specific taxes. Point is observed-tax status quo. Straight, light lines shows the changes implied by California's 2024 tax on handgun purchase. See Sections 5.2 and 6.1 for details. Panel B presents the welfare-maximizing county-specific taxes that generate the same drop in consumer surplus as California's 2024 tax on handgun purchase.

Online appendix to

Regulating Firearm Markets: Evidence from California

Adam M. Rosenberg

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OA.1 Details on firearm retailer event study

This section provides additional details for the results in Section 3.1.

OA.1.1 Defining clean entries and exits

I study a set of clean entries $\mathcal{N}$. Each clean entry $n \in \mathcal{N}$ is associated with exactly one entered zip code $z(n)$ and period of entry $t(n)$. I also study an analogously defined set of clean exits $x \in \mathcal{X}$

I define an entry n as clean if its period of entry $t(n)$ is not too close to either end of my sample $t \in \{1, T\}$, and if there are neither entries nor exits in the entered zip code $z(n)$ too close to the period of entry $t(n)$. Let $\overline{\mathcal{N}}$ be the full set of entries in the sample and $\overline{\mathcal{X}}$ be the full set of exits, such that $\mathcal{N} \subseteq \overline{\mathcal{N}}$ and $\mathcal{X} \subseteq \overline{\mathcal{X}}$.

Suppose the target parameters in Equation (1) are $\beta_{\underline{t}'}, \ldots, \beta_0, \ldots, \beta_{\overline{t}'}$ (e.g., in Section 3.1, $\underline{t}' = -8$ and $\overline{t}' = 8$). Then, an entry $n \in \overline{\mathcal{N}}$ is also a clean entry $n \in \mathcal{N}$ if the following two conditions hold:

1. **Full observation**: The target parameters $\beta_{t'}$ have effects only during the sample period for each entry n. That $t(n) + \underline{t}' \geq 1$ and $t(n) + \overline{t}' \leq T$.

2. **Asynchronous timing**: The target parameters $\beta_{t'}$ have effects that do not overlap with the parameterized effects of any other retailer entry or exit in the same zip code $z(n)$. That $\{t(n) + \underline{t}', \ldots, t(n) + \overline{t}'\} \cap \{t(v) + \underline{t}', \ldots, t(v) + \overline{t}'\} = \emptyset$, for all $v \in (\overline{\mathcal{N}} \cup \overline{\mathcal{X}}) \setminus \{n\}$ in which $z(v) = z(n)$.

Analogous conditions define clean exits $x \in \mathcal{X}$.

OA.1.2 Estimation sample, target parameter, and estimator

I estimate the target parameters $\beta_{t'}$ representing the effect of entry in Equation 1 using the estimator proposed by Borusyak et al. (2024). Their estimator proceeds in two steps. First I estimate the fixed effects for each zip code ψ_z and period ϕ_t. Then, I estimate a weighted average of differences between observed handgun purchases q_{zt} and those predicted from the first-step fixed effects.

I construct a first-step estimation sample using zip code-periods that are either "pure controls" or have not yet experienced an entry event. Pure controls $\mathcal{C}$ are zip codes that experience the net entry of firearm retailers in no quarter of the data (i.e., in which there is the same number of operational firearm retailers every quarter). Not-yet entered zip code-periods are those entries $n \in \mathcal{N}^{s1}$ that satisfy 2. **Asynchronous timing**. This includes

(i) all clean entries $\mathcal{N}$, (ii) the subset of all entries $\overline{\mathcal{N}}$ that satisfy asynchronous timing but do not satisfy 1. **Full observation**. Among these entries $n \in \mathcal{N}^{s1}$, let $n(zt)$ denote the (unique) identity of the retailer entering into zip code z during quarter t. Then, the first-step estimation sample uses all pre-entry observations within $\underline{t}'$ periods of these entries $\mathcal{C} \cup \{z, t : n(zt) \in \mathcal{N}^{s1} \text{ and } t(n) + \underline{t}' \leq t < t(n)\}$. Utilizing data from pure controls and entries that satisfy asynchronous timing but not full observations allows me to increase estimation power from a larger sample in which no confounding retailer entry nor exit events are observed.

I construct first step estimates of ψ_z and ϕ_t by estimating Equation (1) using zip code quarters that are pure controls $\mathcal{C}$ or before entry events $n \in \mathcal{N}^{s1}$, imposing $\beta_{\underline{t}'}, \ldots, \beta_{-1} = 0$.

The weighted averages I target with the second-step estimator recover the effect of the average clean entry in California during my sample on handgun purchases exactly t' periods from the entry event. I target this parameter as a weighted sum—of differences between observed handgun purchases q_{zt} and those predicted from the estimates of fixed effects ψ_z and ϕ_t—across all zip code-periods t' periods from an entry in the first-step estimation sample $n \in \mathcal{N}^{s1}$.

Weights are equal to $1/|\mathcal{N}|$ for clean entries $n \in \mathcal{N}$, and equal to 0 for entries in the first-step estimation sample that are not clean $n \in (\mathcal{N}^{s1} \setminus \mathcal{N})$. This weighting scheme removes compositional bias in the estimates of the effect of retailer entry on handgun purchasing $\beta_{t'}$. In particular, it allows zip code-periods before all entries that satisfy asynchronous timing to contribute to first-step estimates of the fixed effects $\hat{\psi}_n + \hat{\phi}_t$, while the effect of entry on handgun purchasing $\beta_{t'}$ is estimated only for the set of clean entries in which handgun purchasing q_{zt} can be observed in all periods $t(n) + \underline{t}', \ldots, t(n) + \overline{t}'$ necessary for construction of the estimator. I do not weight this average by adult population $M_{z(n)}$, such that my target estimate is the effect of the average retailer entry event.

I use an analogous estimator for the effect of clean retailer exits $\mathcal{X}$.

I also consider an alternate estimator of $\beta_{t'}$ by fitting Equation (1) via OLS using the zip code-periods around all entries used to construct the first-step estimation sample $\{z, t : n(zt) \in \mathcal{N}^{s1} \text{ and } t(n) + \underline{t}' \leq t \leq t(n) + \overline{t}'\}$.

The results in the main text consider the effect of first entrants into a zip code (i.e., going from zero retailers to one retailer). These first entries are a subset of the sample of entries in $\mathcal{N}$ and $\mathcal{N}^{s1}$. For comparability, these estimates also restrict to the subset of clean zip code-quarter controls in $\mathcal{C}$ that never have an operational firearm retailer during the sample. When considering the effects of subsequent entrants, I use data forming the complement of the data for effect of first-entrants.

OA.1.3 Inference

I conduct inference on the estimates of $\beta_{t'}$ from the procedure of Borusyak et al. (2024) via a Bayesian bootstrap of zip codes z around the entry events $n \in \mathcal{N}^{s1}$ or clean controls $\mathcal{C}$ with 500 replicate. I use these replicates to estimate the standard error of the estimator, and construct asymptotically valid 95 percent pointwise confidence intervals via a Normal approximation at each period from entry t'.

I conduct inference on the estimates of $\beta_{t'}$ from the OLS procedure via a Normal approximation accounting for clustering by entry event n. I construct asymptotically valid 95 percent pointwise confidence at each period t'.

OA.1.4 Pre-trends

The pre-trends I report in Figure 1 are estimates of $\hat{\beta}_{t'}$ for $t' < 0$. This corresponds to the proposal of Callaway and Sant'Anna (2021).

The pre-trend test proposed by Borusyak et al. (2024) involves testing the slope of this series (Roth 2024). This corresponds to testing whether for some researcher-chosen t^*, with $\underline{t}' \leq t^* < -1$, it is the case that $\beta_{t'} = E[\beta_{t''}|\underline{t}' \leq t'' \leq t^*]$ for all t' such that $t^* < t' < 0$. The software provided by Borusyak et al. (2024) uses a default choice of $t^* = \underline{t}'$ (i.e., testing whether any pre-period after the earliest differs from the earliest). For power, Braghieri et al. (2022) propose a choice of t^* that equates the number of pre-entry periods before and after t^*, corresponding to $t^* = -1.5$ years in my setting. As visually demonstrated by Figure 1, there is if anything a downward slope in $\beta_{t'}$ prior to entry, demonstrating a potential decline in handgun purchasing in entered zip codes relative to never-entered zip codes.

I also consider re-estimating Equation (1) via OLS under transformations of the dependent variable from purchases per capita q_{zt}/M_z to either (i) the level of purchases q_{zt} or (ii) the log of purchases $\log(q_{zt})$. My estimates of $\beta_{t'}$ for pre-entry periods $t' < 0$ cannot be statistically distinguished from one another under the test of Roth and Sant'Anna (2023). Their results thus imply that the population of zip code-quarters around uncontaminated retailer entries can be partitioned into a subgroup for which entry timing is effectively randomly assigned and another subgroup in which the distribution of potential handgun purchasing outcomes (i.e., with and without retailer entry) are stable over time. This results provides further support for the assumption of quasi-random local entry timing used for the research design in Section 3.1.

OA.2 Details on instrument for handgun ownership

This section provides additional details for the results in Section 3.3. All analyses in this section and in Section 3.3 are weighted by population.

OA.2.1 Instrument construction

I use the count of firearm retailers in a zip code quarter N_{zt} as an instrument for handgun ownership. The first-stage used to estimate Equation (2) is

$$\frac{g_{zt}}{M_z} = \tilde{\beta} N_{zt} + \tilde{\psi}_z + \tilde{\phi}_t + \tilde{\xi}_{zt}, \tag{8}$$

where $\tilde{\psi}_z$ and $\tilde{\phi}_t$ are fixed effects by zip code and quarter, and $\tilde{\xi}_{zt}$ is residual handgun ownership by zip code-quarter. The instrument N_{zt} is relevant if $\tilde{\beta} \neq 0$, shown to be rejected in Table 3 with F=51.7. The instrument N_{zt} is excludable if $\tilde{\xi}_{zt} \perp \omega_{zt}$, as discussed in Section 3.3.

Table OA.3 uses alternate specifications of the first-stage regression in Equation (8). Panel A continues to use the count of firearm retailers in a zip code-quarter N_{zt} as an instrument, but adds additional covariates that vary by zip code-quarter to the regressions in Equations (2) and (8). Row 2 replaces the quarter fixed effects ψ_t with richer fixed effects $\psi_{c(z)t}$ that vary by county-quarter. Row 3 allows both county-quarter fixed effects $\psi_{c(z)t}$ and time-varying observables that capture over-time changes in a zip code's economic well-being and political characteristics. I control for economic well-being by including covariates for the log of the population and the log of the average household income each zip code-year. I control for political characteristics by including covariates for the republican vote share the log of voter turnout in the last congressional and presidential elections. Row 4 returns to the fixed effects specification of Equations (2) and (8), and includes as its only covariate zip-code specific linear time trends.

Panel B of Table OA.3 uses an alternate transformation of retailer net entry to construct an instrument in the first-stage regression:

$$\frac{g_{zt}}{M_z} = \tilde{\beta} \sum_{t'=1}^{t} (N_{zt'} - N_{z1}) + \tilde{\psi}_z + \tilde{\phi}_t + \tilde{\xi}_{zt},$$

where the summation represents the change in the number of firearm retailers within a zip code accumulated over quarters t', from the first $t' = 1$ to the present $t' = t$. This instrument captures the idea from Figure 2 that a change in the number of firearm retailers creates a change in the flow of firearm owners, which accumulates over time. The different rows of Panel B use identical covariate specifications to Panel A.

OA.2.2 Non-fatal crime

I also use the timing of net entry by firearm retailers to study the effects of licit handgun ownership on non-fatal crime. Studying non-fatal crime poses a challenge with the resolution of the data, as entry and exit creates variation traceable over zip codes z and quarters t, but crime is systematically tracked by county $c(z)$ and year $a(t)$. As such, this analysis uses data on non-fatal crimes by county-year, data on licit handgun ownership aggregated to the county-year level, and a method to transform variation in firearm retailers at the zip code-quarter level to the county year.

In particular, I estimate the following regressions via two-stage least-squares using data by county c and year a:

$$\begin{aligned}
\frac{y_{ca}}{M_c} &= \mu \frac{g_{ca}}{M_c} + \kappa_c + \eta_a + \omega_{ca} \\
\frac{g_{ca}}{M_c} &= \tilde{\beta} \underbrace{\sum_{z:c(z)=c} \frac{M_z}{M_c} \sum_{t:a(t)=a} \frac{\tilde{N}_{zt}}{4}}_{\text{instrument}} + \tilde{\psi}_c + \tilde{\phi}_a + \tilde{\xi}_{ca},
\end{aligned}$$

where the underlying variation in the instrument is created by averaging over-time changes in the number of firearm retailers in a zip code after conditioning on zip code and quarter fixed effects:

$$N_{zt} = \upsilon_z + \upsilon_t + \tilde{N}_{zt}.$$

In particular, the instrument is constructed as a weighted average of averages. The inner average is across the four quarters within a zip code-year and captures changes in the residual number of firearm retailers $\tilde{N}_{zt}$. The outer average is across zip code-years within a county and weights these changes in residual firearm retailers $\tilde{N}_{zt}$ by the zip code's share of the county population. Intuitively, if the effect of an additional firearm retailer is proportional to zip code population, as maintained in Section 3, then entries into zip codes that account for a larger share of the county population will also be entries that drive larger changes in county-level handgun ownership. This produces a moderately powerful instrument, with a first-stage F-static of 23.

I also estimate the two-stage least-squares specification above replace the residual count of firearm retailers $\tilde{N}_{zt}$ with the residualized version of the inclusive value of the average consumer's conditional choice of firearm retailer $E_z t[I_{xzt}(\hat{\Theta})]$, as in Section 4.4 and Column 2 of Table 3. As with the analysis of zip-code quarter data, using the additional information from the inclusive value $I_{xzt}(\hat{\Theta})$ produces a stronger instrument, with a first-stage F-statistic of 36.

Table OA.2 present estimates of the effect of handgun ownership on non-fatal crime. Columns 1 and 2 consider the count of property crimes—burglary, larceny-theft, and motor vehicle theft—*per capita*. The point estimates indicate that handgun owners on the margin of retailer net entry may have a deterrent effect on property crime (e.g., Acquisti and Tucker 2022). However, these estimates are not significant at conventional levels. Using the fact that there are approximately 21,000 handgun owners in the average county-year, a 10-percent increase in handgun ownership would decrease the county of property crimes by $12.48/100 \times 21,000/10 = 262$ incidents per year. This would correspond to a $262/18741 \times 100 = 1.4$ percent decrease in property crime.

Columns 3 and 4 present estimates of the effect of handgun ownership on the count of non-fatal violent crimes—rape, robbery, and aggregated assault—*per capita*. The point estimates suggest that licit handgun ownership exacerbates violent non-fatal crime, but are not statistically significant at conventional levels. My estimates imply that increasing licit handgun ownership by 10 percent in the average county-year would increase non-fatal violent crime by $3.07/100 \times 21,000/10 = 65$ incidents per year. This would correspond to a $65/3023 \times 100 = 2.2$ percent increase in non-fatal violent crime.

The results in this section suggest that non-fatal criminal incidents are less elastic to variation in licit handgun ownership than firearm-related homicides. This could represent real criminological features of the environment, but could also arise from attenuation of my retailer entry instrument in the lower-resolution data on non-fatal crime.

OA.2.3 Observable heterogeneity in handgun owners

I collect a consumer's time-invariant observable characteristics into the vector $W_{x(i)z(i)} = (W_{x(i)}, W_{z(i)})$. The vector $W_{x(i)}$ specifies a consumer's observable demographics in the average quarter:

$$W_{x(i)} = \left(\mathbf{1}(\text{male})_i,\ \mathbf{1}(\text{age} < 30)_i,\ \mathbf{1}(\text{white})_i\right).$$

Similarly, the vector $W_{z(i)}$ specifies the observable geographic characteristics of a consumer's residential zip code in the average quarter:

$$W_{z(i)} = \left(\log(\text{MedianHHIncome})_{z(i)},\ \log(M_{z(i)}/\text{mi}^2_{z(i)}),\ \log(\text{ViolentCrimes}_{c(z(i)),t=0}/M_{c(z(i))}\right).$$

These terms are respectively, the log of zip code median household income, the log of zip code population density, and the log of the zip code's county's violent crime rate from 2000–2004. I separately standardize all three of the dimensions of W_z, such that they have mean zero and standard deviation one across the population of California's zip codes in my analysis (unweighted by zip code population).

OA.3 Details on model estimation

This section discusses estimation of the model parameters Θ from Section 4.

OA.3.1 Choice probabilities and parameterization

Much of my estimation procedure is based on the log-likelihood $\mathcal{L}(\Theta)$ of observed handgun purchases q_{it} and retailer choices j_{it} across all consumer-quarters. Under the parametric model of Section 4, this log-likelihood is

$$\mathcal{L}(\Theta) = \sum_{i=1}^{M} \log \int_v \prod_{t=1}^{T} P_{it}\left(q_{it}; \tilde{\nu}_i = v, \Theta\right) P_{it}\left(j_{it} | q = 1; \Theta^{\delta}\right)^{q_{it}} \varphi(v) dv,$$

with $\varphi(\cdot)$ the standard normal density, and choice probabilities $P_{it}(\cdot)$ derived below.

Building up the likelihood requires the probability that each consumer i chooses retailer or no-purchase option $j \in \mathcal{J}_{z(i)t} \cup \{0\}$ during period t, implied by the model at parameter Θ and unobservable preference $\tilde{\nu}_i$:

$$P_{it}(j;\, \Theta) = \underbrace{\frac{\exp\left(\delta_j - \exp(\alpha_x + \alpha_z) d_{ijt}\right)^{1/\rho}}{\exp(I_{xzt}(\Theta^{\delta}, \rho))}}_{P_{it}(j|q=1;\, \Theta^{\delta}, \rho)} \times \underbrace{\frac{\exp(\psi_{xz} + \gamma_x g_{i0} + \sigma_x \tilde{\nu}_i - \alpha^p_{xz} p_t + \xi_{xzt} + \rho I_{xzt}(\Theta^{\delta}, \rho))}{1 + \exp(\psi_{xz} + \gamma_x g_{i0} + \sigma_x \tilde{\nu}_i - \alpha^p_{xz} p_t + \xi_{xzt} + \rho I_{xzt}(\Theta^{\delta}, \rho))}}_{P_{it}(q=1;\, \Theta^{\nu}, \Theta^{\delta}, \rho)}, \tag{9}$$

where $I_{xzt}(\Theta^{\delta}, \rho)$ is the inclusive value from consumer i's marginal firearm retailer choice problem $j | q_{it} = 1$:

$$I_{xzt}(\Theta^{\delta}, \rho) = \log \sum_{j>0} \exp\left(\delta_j - \exp(\alpha_x + \alpha_z) d_{ijt}\right)^{1/\rho}.$$

The first term in the choice probability represents the probability of choosing retailer j conditional on handgun purchase $P_{it}(j | j > 0)$. While the second provides the unconditional probability of purchasing a handgun $P_{it}(j > 0)$. Under the natural parameterization, both choice probabilities depend on the nesting parameter ρ, and the handgun purchase probability depends on the retailer choice parameters Θ^δ through the inclusive value $I_{xzt}(\Theta^\delta, \rho)$.

To make the above choice probabilities easier to work with, I reparameterize the following elements of Θ^δ and Θ^ν:

$$\begin{aligned}
\tilde{\delta}_j &\equiv \delta_j/\rho \\
\tilde{\alpha}_{g(z)} &\equiv \alpha_{g(z)} \\
\tilde{\alpha}_{c(z)} &\equiv \alpha_{c(z)} - \log(\rho) \\
\tilde{\xi}_{xzt} &\equiv \psi_{xz} - \alpha^p_{xz} p_t + \xi_{xzt} + \rho I_{xzt}(\Theta^\delta, \rho),
\end{aligned}$$

where $\alpha_{g(z)}$ are the components of distance disutility that depend on geographic characteristics (income, area, density), $\alpha_{c(z)}$ are county fixed effects, and $\tilde{\alpha}_z = (\alpha_{g(z)}, \alpha_{c(z)})$. I denote $\tilde{\Theta}^\delta = (\tilde{\delta}_j, \tilde{\alpha}_x, \tilde{\alpha}_z)$ and $\tilde{\Theta}^\nu = (\sigma_x, \gamma_x, \tilde{\xi}_{xzt})$.

Under this reparameterization, the choice probabilities become

$$P_{it}(j;\, \Theta) = \underbrace{\frac{\exp(\tilde{\delta}_j - \exp(\alpha_x + \tilde{\alpha}_z) d_{ijt})}{\sum_{j'>0} \exp(\tilde{\delta}_{j'} - \exp(\alpha_x + \tilde{\alpha}_z) d_{ij't})}}_{P_{it}(j|q=1;\, \tilde{\Theta}^\delta)} \times \underbrace{\frac{\exp(\gamma_x g_{i0} + \sigma_x \tilde{\nu}_i + \tilde{\xi}_{xzt})}{1 + \exp(\gamma_x g_{i0} + \sigma_x \tilde{\nu}_i + \tilde{\xi}_{xzt})}}_{P_{it}(q=1;\, \tilde{\Theta}^\nu)}. \tag{10}$$

Unlike the natural parameterization, the choice probabilities under the reparameterized model are governed by disjoint sets of parameters, with an implicit dependence on the nesting parameter ρ. I exploit this separation in the reparameterized parameter space to separately estimate the parameters governing retailer choice $\tilde{\Theta}^\delta$ and handgun purchase $\tilde{\Theta}^\nu$ under the reparameterization. I recover the nesting parameter ρ in a subsequent step, which allows me to transform these reparameterized estimates back to the natural parameterization using the Continuous Mapping Theorem.

OA.3.2 Estimator roots

My estimator $\hat{\Theta}$ uses an exactly-identified minimum distance procedure, simultaneously satisfying the roots

$$(R1) \qquad 0 = \frac{\partial \mathcal{L}(\Theta)}{\partial \gamma_x} = \frac{\partial \mathcal{L}(\Theta)}{\partial \sigma_x}, \text{ all } x$$

$$(R2) \qquad 0 = \frac{\partial \mathcal{L}(\Theta)}{\partial \Theta^\delta_l} \text{ for } l = 1, \ldots, |\Theta^\delta|$$

$$(R3) \qquad 0 = \sum_{i:x(i)=x,\, z(i)=z} q_{it} - P_{it}\left(q = 1; \Theta\right), \text{ all } x, z, t$$

$$(R4) \qquad 0 = \sum_t \xi_{xzt} - \alpha^p_{xz}(p_t - \overline{p}), \text{ all } x, z$$

$$(R5) \qquad \alpha^p_{xz} = \frac{\alpha^d_{x(i)z(i)}}{\$\text{Cost 1 mile}_z}$$

$$(R6) \qquad \sum_{t'=5}^{8} \hat{\beta}_{t'} = \frac{1}{|\mathcal{N}|} \sum_{n \in \mathcal{N}} \sum_{t:5 \le t - t(n) \le 8} \frac{1}{M_{z(n)}} \left(q_{z(n)t} - \sum_{i:z(i)=z(n)} P_{it}\big(q = 1 | \mathcal{J}_{z(i)t} \setminus \{j(n)\}; \Theta\big) \right)$$

$$(R7) \qquad 0 = \frac{\partial \sum_z \sum_t \left(\tilde{\omega}_{zt} + \sum_{i:z(i)=z} g_{it} \tilde{e}_i / M_z \right)^2}{\partial \Theta^e_l} \text{ for } l = 1, \ldots, |\Theta^e|.$$

As discussed intuitively in Section 4:

- $(R1)$ is the set of first-order conditions of the log-likelihood $\mathcal{L}(\Theta)$ with respect to the pre-ownership preference shifter γ_x and the dispersion of the unobservable preference for handgun purchase σ_x. It has dimension $|\gamma_x| + |\sigma_x| = 2 \times |x|$.

- $(R2)$ is the set of first-order conditions of the log-likelihood $\mathcal{L}(\Theta)$ with respect to the retailer choice parameter Θ^δ. It has dimension $|\Theta^\delta|$.

- $(R3)$ is the moment condition governing composite sources of extensive margin preferences $\psi_{xz} - \alpha^p p_t + \xi_{xzt}$. It imposes that observed handgun purchases q_{xzt} match the model's prediction $\sum_{i:x(i)=x,\, z(i)=z} P_{it}\left(q = 1; \Theta\right)$ within each demographic-zip code-quarter. It has dimension $|x| \times |z| \times |t|$.

- $(R4)$ imposes the location of the composite source of extensive margin preferences $\psi_{xz} - \alpha^p p_t + \xi_{xzt}$. It centers this value around the preference fixed effect ψ_{xz} over quarters t. It has dimension $|x| \times |z|$.

($R5$) imposes the calibrated scaling between the disutility of travel distance and the disutility of price. It has dimension $|\alpha^d_{xz}| = |x| \times |z|$.

($R6$) imposes that post-entry market expansion observed in data (left-hand side) exactly matches the model's prediction (right-hand side), for quarters 5–8 post-entry, among the set of clean entries $\mathcal{N}$. Clean entries $\mathcal{N}$ are those in which there is neither contaminating variation from other entries or exits within the same zip code, nor censoring from entries too near to the ends of the sample, as described in Section OA.1. It has dimension $|\rho| = 1$.

($R7$) characterizes the OLS solution to the model-implied fatality regression in Equation (7). It has dimension $|\Theta^e| = |\mu|+|\zeta|+|\chi|+|\kappa_z|+|\eta_t| = 1+\big(|W_{xz}|+|V_i|\big)+1+|z|+|t|$.

I check that these roots have a unique solution by initializing my search from multiple starting values, conducting a grid search, and estimating on data simulated from the model. All of these approaches suggest a unique solution. Below, I show that in finite samples, a unique solution to ($R1$)–($R7$) requires only that ($R1$) has a unique solution separately by demographic x and conditional on ($R2$)–($R7$).

OA.3.3 Likelihood maximization

I estimate the retailer choice parameters $\tilde{\Theta}^\delta$ by maximizing the log likelihood of cross-retailer choices observed among handgun buyers $j_{it}|q_{it} = 1$. Since preferences over retailers do not vary systematically at the individual level, the log-likelihood aggregates to a function of only retailer market shares by demographic-zip code-quarter, either observed in data $s_{xzt}(\cdot)$ or implied by the model $P_{xzt}(\cdot)$:

$$\log \mathcal{L}(\tilde{\Theta}^\delta) = \sum_z \sum_x \sum_t \sum_{j=1}^{J} M_{xz} s_{xzt}(j \mid q > 0) \log P_{xzt}(j \mid q > 0;\, \tilde{\Theta}^\delta),$$

with M_{xz} the number of consumers in a demographic-zip code cell. Note that $\sum_{j>0} s_{xzt}(j \mid q > 0) = \sum_{j>0} P_{xzt}(j \mid q > 0;\, \tilde{\Theta}^\delta) = 1$.

Similarly, I estimate parameters governing handgun purchase preferences $\tilde{\Theta}^\nu$ by maximizing the likelihood of consumers' observed sequences of handgun purchase decisions $\vec{q}_i = (q_{i1}, \ldots, q_{iT})$. A challenge to likelihood maximization is that a component of preferences $\tilde{\nu}_i$ is unobserved and affects handgun purchase q_{it} each period t. This leads me to write the likelihood of the choice sequence $\vec{q}_i$ integrating over this source of one-dimensional unobserved heterogeneity. Since all the parameters $\tilde{\Theta}^\nu$ that govern the likelihood of these choice sequences $\vec{q}_i$ are indexed by consumer demographics x, this maximization is further separable across demographic cells x, each with log-likelihood

$$\log \mathcal{L}(\tilde{\Theta}_x^\nu) = \sum_{i:x(i)=x} \log \int_v \prod_t P(q_{it};\, \gamma_x g_{i0}, \sigma_x v, \tilde{\xi}_{xz(i)t})\varphi(v)dv,$$

where φ is the standard normal density. As this integral has no closed form, I calculate the likelihood by numerically integrating over the marginal distribution of $\tilde{\nu}_i$.[57] While the parameters interacting with individual-specific heterogeneity—γ_x and σ_x—are only two-dimensional, the remainder of the likelihood is controlled by a high-dimensional vector of fixed effects $\dim(\vec{\tilde{\xi}}_x) = 1,304 \times 44$, making it computationally infeasible to directly optimize the log-likelihood.

To make estimation of $\tilde{\Theta}_x^\nu$ feasible, I solve a constrained problem asymptotically equivalent to maximizing $\mathcal{L}(\tilde{\Theta}_x^\nu)$.[58] Following Goolsbee and Petrin (2004), I constrain the model-predicted inside share to match the inside-share observed in data within each demographic-zip code-quarter $q_{xzt}/M_{xz} = \hat{P}_{xzt}(q=1;\, \tilde{\Theta}_x^\nu)$. Unlike Goolsbee and Petrin (2004), I incorporate finite-sample information into my predictions, by conditioning on consumer-specific choice sequences $\vec{q}_i$, using the procedure of Revelt and Train (2000) to estimate a consumer-specific distribution of the unobservable preferences $\hat{f}_{\tilde{\nu},i}(\cdot|\vec{q}_i;\tilde{\Theta}_x^\nu)$, and forming predicted inside shares by integrating the choice probabilities over these consumer-specific distributions.[59] These constraints implicitly define the fixed effects as a function of the other model parameters $\tilde{\xi}_{xzt}(\gamma_x, \sigma_x)$, limiting the non-linear search to two dimensions, with $\tilde{\xi}_{xzt}$ pinned

[57] In practice, I use quadrature to integrate $\sigma_x \tilde{\nu}_i \sim N(0, \sigma_x)$ over the grid $\{-20, -19.75, \ldots, 20\}$. I verify that my estimates $\hat{\sigma}_x$ place little mass at the endpoints of this grid. Using a constant grid across candidate values of σ_x helps simplify the likelihood and some of the subsequent numeric integrals required for estimation and counterfactuals, in which I aggregate across the unobserved preferences $\tilde{\nu}_i$ of consumers with different demographics x.

[58] A simulation study of a similar model shows that my estimator attains slightly higher likelihood than the procedure of Goolsbee and Petrin (2004), but is more time-intensive. Neither constrained procedure attains the unconstrained maximum, but both perform quite well. I conjecture that my procedure attains a higher likelihood than Goolsbee and Petrin (2004) by perturbing their constraints in the direction of the data, which relaxes the problem in finite samples.

[59] This procedure ensures that predictions from my model are consistent—under Bayes rule—with the observed data on handgun purchasing $\vec{q}_i$ at any value of $\tilde{\Theta}_x^\nu$. The model predictions are:

$$\hat{P}_{xzt}(q=1;\, \tilde{\Theta}_x^\nu) = \frac{1}{M_{xz}} \sum_{i:x(i)=x, z(i)=z} \int_v P(q=1;\, v, g_{i0}, \tilde{\Theta}_x^\nu)\hat{f}_{\tilde{\nu},i}(v \,|\, \vec{q}_i; \tilde{\Theta}_x^\nu)dv,$$

with $\hat{f}_{\tilde{\nu},i}(v \,|\, \vec{q}_i; \tilde{\Theta}_x^\nu)$ produced from the procedure of Revelt and Train (2000). Notably, since the reparameterization is continuous and monotone, the probabilities $P_{it}(q_{it})$ of observed handgun purchase must coincide under the natural parameterization Θ_x^ν and the reparameterization $\tilde{\Theta}_x^\nu$ (else the likelihood would not be maximized). This guarantees that the consumer-specific distributions of $\tilde{\nu}$ coincide under either parameterization: $\hat{f}_{\tilde{\nu},i}(v \,|\, \vec{q}_i; \tilde{\Theta}_x^\nu) = \hat{f}_{\tilde{\nu},i}(v \,|\, \vec{q}_i; \tilde{\Theta}_x^\nu)$.

down via a contraction mapping (Berry et al. 1995).[60] Because of the contraction mapping, my estimate of $\tilde{\xi}_{xzt}$ is undefined in demographic-zip code-quarters with no handgun purchase, which I drop from my analysis.

Estimation of $\tilde{\Theta}^{\delta}$ and $\tilde{\Theta}^{\nu}$ fully characterizes the choice probabilities in Equation (10), leading me to estimate the remaining model parameters (ρ, Θ^{e}) using other moments of the data. I present succinct versions of these moment conditions in Section 4, and here focus on the details of their construction.

OA.3.4 Nesting parameter, market expansion, and the price coefficient

To estimate the nesting parameter ρ, I align market expansion from the entries $n \in \mathcal{N}$ studied in Section 3.1 as estimated in data $\hat{\beta}_{t'}$ and predicted from my model. In particular, I find the value $\hat{\rho}$ such that

$$\sum_{t'=5}^{8} \hat{\beta}_{t'} = \frac{1}{|\mathcal{N}|} \sum_{n \in \mathcal{N}} \sum_{t:5 \leq t-t(n) \leq 8} \frac{1}{M_{z(n)}} \sum_{i:z(i)=z(n)} \overbrace{\hat{P}_{it}\left(q = 1 \,|\, \mathcal{J}_{z(i)t};\ \widehat{\tilde{\Theta}^{\nu}_{x}}\right)}^{\text{choice prob, observed mkt}} - \overbrace{\hat{P}_{it}\left(q = 1 \,|\, \mathcal{J}_{z(i)t} \setminus \{j(n)\};\ \widehat{\tilde{\Theta}^{\nu}}, \widehat{\tilde{\Theta}^{\delta}}, \hat{\rho}\right)}^{\text{choice prob, without retailer } j(n)}$$

where the final term is the probability that consumer i purchases a handgun in period t with entrant $j(n)$ counterfactually removed from the choice set. Since this counterfactual choice probability is strictly increasing in $\hat{\rho}$ for each consumer-period, there is a unique value $\hat{\rho}(\widehat{\tilde{\Theta}^{\nu}}, \widehat{\tilde{\Theta}^{\delta}})$ satisfying this moment condition, conditional on the values of $\widehat{\tilde{\Theta}^{\delta}}$ and $\widehat{\tilde{\Theta}^{\nu}}$ that maximize the log-likelihood of consumers' observed choices.

Conditional on the estimated nesting parameter $\hat{\rho}$, I use the Continuous Mapping Theorem to invert the transformations that define the reparameterized values $\widehat{\tilde{\Theta}^{\delta}}$ and $\widehat{\tilde{\Theta}^{\nu}}$, recovering estimates of the natural parameters $\widehat{\Theta^{\delta}}$ and $\widehat{\Theta^{\nu}}$, respectively. I also use the Continuous Mapping Theorem to estimate the inclusive value of the marginal retailer choice problem $\hat{I}_{xzt} = I_{xzt}(\widehat{\Theta^{\delta}}, \hat{\rho})$. As described in the main text, separating $\tilde{\xi}_{xzt} - \hat{\rho}\hat{I}_{xzt}$ into its components $(\hat{\psi}_{xz}, \widehat{-\alpha^{p}_{xz}p_t + \xi_{xzt}})$ requires the location normalization $E[-\alpha^{p}_{xz}(p_t - \sum_t p_t/T) + \xi_{zt} \,|\, xz] = 0$.

Since prices p_t are not observable in my data, I recover the price coefficient $\hat{\alpha}^{p}_{xz}$ by

[60] For a correctly specified model, my constrained estimator of $\tilde{\Theta}^{\nu}_{x}$ is asymptotically equivalent to the maximum likelihood estimator. As the sample size grows, the Bernstein-von Mises Theorem ensures that the distribution of any growing mixture of draws from the conditional distribution $\tilde{\nu}_i \sim f_{\tilde{\nu},i}(\cdot \,|\, \vec{q}_i; \tilde{\Theta}^{\nu}_{x})$ converges to the unconditional distribution $f_{\tilde{\nu}}(\cdot; \tilde{\Theta}^{\nu}_{x})$, as described by Revelt and Train (2000). The procedure of Goolsbee and Petrin (2004) imposes constraints identical to mine, but forms predictions by integrating over the unconditional distribution $f_{\tilde{\nu}}(\cdot; \tilde{\Theta}^{\nu}_{x})$. Thus, my constraints are asymptotically equivalent to those used by Goolsbee and Petrin (2004), which are also asymptotically satisfied at the unconstrained MLE (Train 2009).

imposing ($R5$), as described in Section 4. Without observable prices p_t, it is not possible to further decompose $(\widehat{-\alpha^p_{xz}p_t + \xi_{xzt}})$, even with estimates of the price coefficient $\hat{\alpha}^p_{xz}$.

OA.3.5 Fatality process and control function

I estimate the parameters of the fatality process Θ^e conditional on my estimates of the other model parameters $(\widehat{\Theta^\delta}, \widehat{\Theta^\nu}, \hat{\rho})$ by using OLS to fit the regression in Equation (7), separately by cause of death. For ease of reference, I write $H_i \equiv (W_{x(i)z(i)}, V_i(\Theta^\nu))$ in reproducing this regression below:

$$\frac{y_{zt}}{M_z} = \overbrace{\frac{g_{zt}}{M_z}\big(\mu + \zeta E_{zt}\big[H_i(\Theta^\nu)\,|\,g_{it} = 1\big]\big)}^{\text{Expected externality}} + \overbrace{\kappa_z + \eta_t + \chi \sum_{i:z(i)=z} \frac{\xi_{x(i)zt} - \alpha^p_{x(i)z}p_t}{M_z}}^{\text{Expected base rate}} + \overbrace{\tilde{\omega}_{zt} + \sum_{i:z(i)=z} \frac{g_{it}\tilde{e}_i}{g_{zt}}}^{\text{Residual}}$$

As the coefficients in this regression are exactly identified, the first-order conditions in ($R7$) can always be satisfied exactly, conditional on any value of the other model parameters $(\Theta^\delta, \Theta^\nu, \rho)$. This implies that the estimation of $\hat{\Theta}^e$ provides no information about the values of other model parameters. I leverage this fact to estimate $\hat{\Theta}^e$ in a subsequent step, conditional on my estimates of $(\hat{\Theta}^\nu, \hat{\Theta}^\delta, \hat{\rho})$.

To construct the composition of handgun ownership $E_{zt}[H_i(\Theta^\nu)\,|\,g_{it} = 1]$ in the above regression, I use my estimates of the the demographic-zip code preference fixed effect $\hat{\psi}_{xz}$ and the distribution of the unobservable preference $\hat{f}_{\tilde{\nu},i}(\cdot; \hat{\Theta}^\nu)$, numerically mixing the latter across consumers to compute the average of $\tilde{\nu}_i$ among handgun owners.

I form the control function for Equation (7) by conditioning on the average value of the estimated time-varying preference $\widehat{\xi_{xzt} - \alpha^p_{xz}p_t}$ among all consumers in a zip code-quarter. I omit from the average all demographic-zip code-quarters with zero handgun purchases $q_{xzt} = 0$, for which this estimate is undefined. This regressor controls for all potential endogeneity between the level of handgun ownership g_{zt}/M_z and its composition $E_{zt}[H_i(\Theta^\nu)|g_{it} = 1]$, after assuming independence from other sources of heterogeneity through the following technical conditions:

1. **Local shocks**: Conditional on the time-varying preference $\xi_{xzt} - \alpha^p_{xz}p_t$ in zip code z during quarter t, the fatality residual $\tilde{\omega}_{zt}$ does not correlate with the time-varying preference in other zip codes z' or quarters t':

$$E[\tilde{\omega}_{zt} \mid \xi_{xzt} - \alpha^p_{xz}p_t,\ \xi_{xz't'} - \alpha^p_{xz'}p_{t'}] = E[\tilde{\omega}_{zt} \mid \xi_{xzt} - \alpha^p_{xz}p_t].$$

This condition implies that other time-varying determinants of demand do not correlate with the fatality shock in other zip code-quarters. It ensures, for example, that changes in the level and composition of handgun ownership due to *past* demand shocks do not affect *present* fatality shocks, and analogously for neighboring zip codes. It would be violated if consumers were accurately forward looking, such that the correct perception of anomalously high crime in zip code z during period $t' > t$ drove demand in zip code z during period t. It would be possible to relax this assumption by including other time-varying preferences $\xi_{xz't'} - \alpha^p_{xz'} p_{t'}$ in Equation (5). The lack of pre-entry trends in handgun ownership and homicide fatalities in Figure 2 supports this assumption.

2. **Ignorable retailers**: Preference shocks over firearm retailers $(\varepsilon_{ijt}, \varepsilon_{i0t})$ are independent of fatality shocks $\tilde{\omega}_{zt}$ and externality regression errors $\tilde{e}_i$:

$$E[\omega_{zt} \mid \varepsilon_{ijt}] = E[\tilde{\omega}_{zt}] = 0, \text{ all } t = 1, \ldots, T;\ i = 1, \ldots, M;\ j = 0, \ldots, |\mathcal{J}_{z(i)t}|$$
$$E[\tilde{e}_i \mid \varepsilon_{ijt}] = E[\tilde{e}_i] = 0, \text{ all } t = 1, \ldots, T;\ i = 1, \ldots, M;\ j = 0, \ldots, |\mathcal{J}_{z(i)t}|.$$

This condition implies that consumers generating larger externalities or purchasing in zip code-quarters with anomalously high fatalities do not have systematically higher unobservable preferences to purchase from one retailer j over another j' in any zip code-quarter. It ensures, for example, that changes in the level and composition of handgun ownership due to handgun purchases from certain firearm retailers do not generate more fatalities than purchases from another. It would be violated if consumers with higher unobservable externalities $\tilde{e}_i$ (e.g., convicted felons determined to re-offend) had a particular preference for purchasing from a specific retailer j (e.g., a retailer willing to violate the law and sell them a handgun). It would be possible to relax this assumption by including estimates of retailer shocks ε_{ijt} in Equation (5) (e.g., Dubin and McFadden 1984, Abdulkadiroğlu et al. 2020, Barahona et al. 2023, Einav et al. 2022).

3. **Linear control function**: The fatality residual from Equation (7) must be centered around a linear function over the average time-varying preference component $\xi_{xzt} - \alpha^p_{xz} p_t$ at all values:

$$E\left[\chi \sum_{i:z(i)=z} \frac{\xi_{x(i)zt} - \alpha^p_{x(i)z} p_t}{M_z} + \tilde{\omega}_{zt} + \sum_{i:z(i)=z} \frac{g_{it}\tilde{e}_i}{g_{zt}}\right] = \chi \sum_{i:z(i)=z} \frac{\xi_{x(i)zt} - \alpha^p_{x(i)z} p_t}{M_z}, \text{ almost everywhere.}$$

A sufficient condition for linearity is tri-variate Normality of $(\xi_{xzt} - \alpha^p_{xz} p_t,\ \tilde{\omega}_{zt},\ \tilde{e}_i)$ (e.g., Heckman 1979, Petrin and Train 2010, Agarwal 2015). In the Normal case, the variance-covariance matrix provides an interpretation for the coefficient on the control function:

$$\chi = \frac{\text{SD}(B)}{\text{SD}(A)} \text{Corr}\left(\overbrace{\sum_{i:z(i)=z} (\xi_{x(i)zt} - \alpha^p_{x(i)z} p_t)/M_z}^{A},\ \overbrace{A + \tilde{\omega}_{zt} + \sum_{i:z(i)=z} g_{it}\tilde{e}_i/g_{zt}}^{B} \right).$$

The assumption of linearity ensures that the fatality specification in Equation (5) is correct. It would be possible to relax this assumption by conditioning on non-linear functions of the time-varying preference $\xi_{xzt} - \alpha^p_{xz} p_t$. For instance, Tables OA.7 and OA.8 include specifications in which this term enters with a different coefficient χ_x for every demographic group x. It would also be possible to include other non-linear functions, for instance a quadratic.

The assumption of a linear control function implies a distribution of the dependent variable y_{zt}/M_z with full support over the real line.[61] Without bounds on the time-varying components of demand $\xi_{xzt} - \alpha^p_{xz} p_t$, this assumption cannot hold for all potential realizations of the data. Since y_{zt} is a count variable, it is bounded below at 0. To investigate the implications of this assumption under the observed data, I place further distributional assumptions on the fatality process from Equation (5).

Before specifying this more-restrictive model, I discuss an alternative two-stage least-squares estimator that relaxes the assumption of full support. In particular, I construct instruments for the level and composition of handgun ownership using the average inclusive value $\sum_{i:z(i)=z} I_{x(i)zt}(\hat{\Theta})$ and its interaction with the preference fixed effect $\sum_{i:z(i)=z} I_{x(i)zt}(\hat{\Theta}) \times \hat{\psi}_{x(i)z}$. As I only specify two instruments, I seek only to estimate the externality intercept $\hat{\mu}$ and the slope of externalities with respect to the unobservable preference ζ^ν. Intuitively, the inclusive value instrument shifts the level of handgun ownership (i.e., entry drives up handgun ownership). The interaction changes the composition of handgun owners (i.e., entries into areas where consumers generally like handgun purchase ψ_{xz} pulls in consumers lower down the distribution of unobservable preferences $\tilde{\nu}_i$). These two dimensions of variation allow me to estimate the two target parameters $\hat{\mu}$ and $\hat{\zeta}^\nu$, under only the standard conditions of instrument relevance and excludability, without imposing the additional three assumptions discussed above (Wooldridge 2015). Table 5 shows that the two-stage least-squares estimates match the signs of the control function estimates, though imply a steeper relationship between unobservable preferences $\tilde{\nu}_i$ and externalities e_i.

Building intuition for the variation that identifies the externality parameters—μ and ζ—

[61] Conditional on the other regression coefficients allowing one $\xi_{xzt} \to \infty$ implies $y_{zt} \to \infty$. The reverse is true for $\xi_{xzt} \to -\infty$.

retailer entry and exit alters the probability of consumer i's handgun purchase according to

$$\log \frac{P_{it}(q=1;\, \nu_i, \Theta)}{1-P_{it}(q=1;\, \nu_i, \Theta)} = \nu_i - \alpha^p p_t + \xi_{xzt} + \rho \overbrace{\log \sum_{j \in \mathcal{J}_{zt}} \exp\left(\delta_j - \alpha^d_{xz} d_{ij}\right)^{1/\rho}}^{\equiv I_{xz}(\Theta)}.$$

Where $I_{xz}(\Theta)$ is the inclusive value of consumer i's conditional choice $j|q_{it}=1$ of firearm retailer, summarizing the full vector of travel distances $(d_{i1t}, \ldots, d_{i|\mathcal{J}_{z(i)t}|})$, adjusted for retailer quality δ_j. The information in $I_{xz}(\Theta)$ creates variation that helps to identify the externality parameters Θ^e, relative to the more parsimoniously constructed net-entry instrument from Section 3. In particular, Figure OA.9 shows that panel data variation in $I_{xz}(\hat{\Theta})$ is more predictive of variation in handgun ownership g_{zt}/M_z than the net-entry instrument for Equation (2) (Verboven and Yontcheva forthcoming). Comparing columns 1 and 2 of Table 3 shows that both instruments—the inclusive value $I_{xz}(\hat{\Theta})$ and retailer net entry—imply similar effects of handgun ownership on fatalities, but estimates utilizing $I_{xz}(\hat{\Theta})$ are 50 percent more precise. Table OA.6 shows similarly strong relationships between variation in the inclusive value $I_{xz}(\hat{\Theta})$ and variation in the composition of handgun ownership $E_{zt}[H_i|g_{it}=1]$. Of course, these linear relationships only approximate the identifying variation produced by the inclusive value $I_{xz}(\hat{\Theta})$, due to its non-linear effect on the probability of handgun purchase.

OA.3.6 A statistical model of fatalities

I specify an additively separable Poisson model of fatality counts y_{zt}, separately for each cause of death. The count of fatalities in a zip code-quarter absent licit handgun ownership is a Poisson random variable with parameter $M_z(\kappa_z + \eta_t + \chi \sum_{i:z(i)=z}(\xi_{x(i)zt} - \alpha^p_{xz} p_t)/M_z + \tilde{\omega}_{zt})$. Separately, fatalities created and prevented by licit handgun owner i are Poisson random variables—independent of each other and across consumers—with means $g_{it}e^+_i$ and $g_{it}e^-_i$, respectively. When sufficiently many fatalities are expected to be prevented, through $g_{it}e^-_i$, total fatalities are censored below at 0, leading to the conditional distribution of fatality counts

$$y_{zt}\big|(g_{1t}, \ldots, g_{M_{zt}}) \sim \text{Pois}\left(\max\left\{M_z(\kappa_z + \eta_t + \chi \sum_{i:z(i)=z} \frac{\xi_{x(i)zt} - \alpha^p_{x(i)z} p_t}{M_z} + \tilde{\omega}_{zt}) + \sum_{i:z(i)=z} g_{it} \overbrace{(e^+_i - e^-_i)}^{\equiv e_i},\ 0\right\}\right).$$

This Poisson model shares the same conditional expectation function as the model in Equation (5) in all zip code-quarters without censoring. Thus, sufficient conditions for the validity of a linear control function on the support of my observed data are that (i) The above

Poisson model is correctly specified and (ii) the process generating the observed data under the above Poisson model is never censored. Recognizing that the no-owner Poisson mean can never be negative, a sufficient condition to prevent censoring for the data generating process is that the expected beneficial externalities from handgun ownership e_{it}^{-} are always weakly lower than harmful externalities e_{it}^{+} in aggregate among all handgun owners each zip code-quarter.

OA.3.7 Inference

I perform inference on estimates of model parameters separately for each step of the estimation routine using asymptotic approximations. I currently do not adjust my estimates of $(\hat{\rho}, \hat{\Theta}^{e})$ for first-step estimation error in $(\widehat{\tilde{\Theta}^{\delta}}, \widehat{\tilde{\Theta}^{\nu}})$, making my variance estimates of these parameters anti-conservative. I expect that adjusting for first-step estimation variance will be negligible in practice given that the number of observations in my data far exceeds the number of model parameters. I do adjust my variance estimates of $\hat{\rho}$ and $\hat{\Theta}^{e}$ for clustering by zip code, analogous to the descriptive analysis of Section 3.

Currently, I am working on implementing a Bayesian Bootstrap procedure to permit jointly valid inference on all parameters Θ.

Table OA.1: Effect of 100 Licit Handgun Owners on Yearly Fatalities

	IV Net entry (1)	IV Model-based (2)	OLS (3)	Sample Mean (4)
Panel A: Homicides				
Firearm	0.159 (0.056)	0.137 (0.031)	0.101 (0.012)	1.120
Non-gun	0.029 (0.025)	0.026 (0.012)	0.007 (0.004)	0.431
All	0.188 (0.059)	0.164 (0.036)	0.107 (0.013)	1.551
Panel B: Suicides				
Firearm	0.042 (0.045)	0.050 (0.016)	0.044 (0.009)	1.090
Non-gun	0.023 (0.054)	0.041 (0.024)	0.025 (0.010)	1.692
All	0.065 (0.072)	0.091 (0.029)	0.069 (0.015)	2.782
Panel C: Handguns (Average year with +1 retailer)				
Owners (first-stage)			277.2 (38.6)	890
Purchases			60.6 (6.3)	283.8
Zip code FE	Y	Y	Y	
Quarter FE	Y	Y	Y	
First-stage F	51.67	331.85		
Zip code clusters	$1,304$	$1,304$	$1,304$	
Zip code-quarters	$57,376$	$57,376$	$57,376$	$57,376$

Estimate, (SE)

Panels A and B present the effect of 100 handgun owners on yearly fatalities, computed as $4 \times 100 \times \mu$ using the specification of Equation (2). Values in Panels A and B are estimated by regressing fatalities per capita on handgun owners per capita, using a panel of zip code-quarter observations. Columns 1–2 are estimators of this effect using instruments based on (1) retailer net entry from Section 3.3 and (2) the Inclusive Value $\sum_{i:z(i)=z} I_{x(i)zt}/M_z$ discussed in Section 4.4. Column 3 is OLS. Column 4 is the sample mean. Panel C presents the effect of firearm retailers' net entry on handgun ownership and handgun purchasing. Values are estimated by regressing handgun owners per capita or handgun purchases per capita on the count of firearm retailers in a zip code-quarter, using a panel of zip code-quarter observations. Panel C scales these regression estimates by 4 times the average zip code population $E[M_z]$, to report estimates for the average zip code in the average year following a net entry. Row 1 of Panel C is the first-stage regression used for the IV in Column (1) of Panels A and B, and all panels present comparable scalings of the regression coefficients. Standard errors are clustered by zip code. Estimates in Columns 1–3 weighted by zip code population M_z. Sample mean in Column 4 unweighted.

Table OA.2: Effect of Handgun Ownership on Non-Fatal Criminal Incidents

	Criminal Incidents			
	Property		Violent, non-fatal	
	(1)	(2)	(3)	(4)
100 Handgun owners	−12.48	−19.89	5.62	3.07
	(14.48)	(16.01)	(3.17)	(3.31)
Depvar Mean	18741	18741	3023	3023
Gun owners Mean	20724	20724	20724	20724
Instrument	#GunRetailers	Inclusive Value	#GunRetailers	Inclusive Value
First-stage F	23	36	23	36
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Clusters	56	56	56	56
Observations	616	616	616	616

Table shows effect of handgun ownership on non-fatal criminal incidents. Regression specification is analogous to Equation (2). Instrument is predicted change in handgun ownership by county-year predicted from retailer net entry within the county, as described in Section OA.2. Standard errors clustered by county. All estimates weighted by county population.

Table OA.3: Effect of 1 Licit Handgun Owner on Quarterly Fatalities, Alternate Specifications

	Owners	Homicide	Suicide
Panel A: IV = #GunRetailers$_{z,t}$			
IV	0.003	0.0005	0.0002
	(0.0004)	(0.0001)	(0.0002)
IV + county-quarter FE	0.001	0.0005	0.00003
	(0.0003)	(0.0003)	(0.0004)
IV + county-quarter FE + zip-year controls	0.001	0.0005	-0.00003
	(0.0003)	(0.0003)	(0.0004)
IV + zip-trend	0.0003	0.004	-0.002
	(0.0002)	(0.003)	(0.003)
Panel B: IV = $\sum_{t'=1}^{t}$ **#GunRetailers**$_{z,t'}$ − **#GunRetailers**$_{z,1}$			
IV	0.0002	0.0004	0.0002
	(0.00004)	(0.0002)	(0.0002)
IV + county-quarter FE	0.0001	0.0005	0.0003
	(0.00003)	(0.0004)	(0.0004)
IV + county-quarter FE + zip-year controls	0.0001	0.0005	0.0002
	(0.00003)	(0.0004)	(0.0004)
IV + zip-trend	0.0002	0.0001	-0.001
	(0.00002)	(0.0004)	(0.0005)
Zip code FE	Y	Y	Y
Quarter FE	Y	Y	Y
Zip code clusters	1,304	1,304	1,304
Zip code-quarters	57,376	57,376	57,376

Estimate, (SE)

Table shows effect of handgun ownership on quarterly fatalities from alternate specifications. Column 1 is the first stage effect of the IV on handgun owners *per capita*. Column 2 is the IV estimate on homicide fatalities. Column 3 is the IV estimate on suicide fatalities. Panel A uses the IV developed in Section 3. Panel B uses an alternate instrument developed in Appendix OA.2, defined as the rolling sum of the change in the number of handgun retailers in operation during a zip code-quarter, relative to the zip code' first quarter of data.

Table OA.4: Heterogeneity in the Effect of 100 Handgun Owners on Quarterly Fatalities

	Homicide			Suicide		
	All	Firearm	Non-gun	All	Firearm	Non-gun
	(1)	(2)	(3)	(4)	(5)	(6)
μ	−0.2713	−0.2618	−0.0095	−0.0517	−0.0421	−0.0096
	(0.0443)	(0.0400)	(0.0170)	(0.0504)	(0.0358)	(0.0345)
ζ^{inc}	−0.0048	−0.0036	−0.0012	0.0034	0.0021	0.0013
	(0.0020)	(0.0016)	(0.0010)	(0.0030)	(0.0020)	(0.0023)
ζ^{den}	−0.0040	−0.0044	0.0004	−0.0052	−0.0023	−0.0029
	(0.0025)	(0.0021)	(0.0011)	(0.0032)	(0.0021)	(0.0025)
ζ^{crime}	0.0017	0.0012	0.0004	0.0003	0.0005	−0.0002
	(0.0012)	(0.0010)	(0.0006)	(0.0017)	(0.0013)	(0.0013)
ζ^{male}	0.3022	0.2844	0.0178	0.0459	0.0533	−0.0074
	(0.0487)	(0.0451)	(0.0162)	(0.0511)	(0.0364)	(0.0366)
$\zeta^{<30}$	0.1047	0.1083	−0.0036	0.0630	0.0100	0.0530
	(0.0351)	(0.0325)	(0.0142)	(0.0444)	(0.0297)	(0.0346)
ζ^{white}	0.0624	0.0562	0.0063	0.0096	0.0051	0.0045
	(0.0132)	(0.0112)	(0.0052)	(0.0107)	(0.0080)	(0.0094)
χ	−0.0421	−0.0338	−0.0083	0.0045	0.0036	0.0009
	(0.0163)	(0.0157)	(0.0066)	(0.0188)	(0.0119)	(0.0139)
χ^{male}	−0.0246	−0.0220	−0.0027	0.0054	0.0017	0.0037
	(0.0047)	(0.0046)	(0.0016)	(0.0042)	(0.0025)	(0.0030)
$\chi^{<30}$	−0.0052	−0.0055	0.0003	−0.0030	0.0002	−0.0032
	(0.0024)	(0.0023)	(0.0007)	(0.0018)	(0.0011)	(0.0016)
χ^{white}	−0.0059	−0.0058	−0.0002	−0.0018	0.0003	−0.0021
	(0.0019)	(0.0019)	(0.0008)	(0.0017)	(0.0010)	(0.0015)
Zip code FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
Zip code clusters	1,304	1,304	1,304	1,304	1,304	1,304
Zip code-quarters	57,079	57,079	57,079	57,079	57,079	57,079

Table shows effect of handgun ownership on fatalities per capita by cause of death accounting for observable heterogeneity across consumers, as described in Section 3.4. Standard errors from a Bayesian Bootstrap of zip codes. All estimates weighted by zip code population. Observations differ from Table 3 as some zip code-quarters do not have certain control variables available.

Table OA.5: Parameters governing disutility from travel distance

	Mean (1)	SD (2)	P10 (3)	P90 (4)	#Values (5)
α_1^{age}	0.01				1
α_2^{age}	0.005				1
α_4^{age}	0.02				1
α_5^{age}	0.07				1
$\alpha_{\text{asian}}^{\text{race}}$	-0.11				1
$\alpha_{\text{black}}^{\text{race}}$	-0.07				1
$\alpha_{\text{hispanic}}^{\text{race}}$	0.01				1
$\alpha_{\text{other}}^{\text{race}}$	-0.05				1
$\alpha_{\text{female}}^{\text{gender}}$	0.03				1
α_1^{inc}	0.08				1
α_2^{inc}	0.01				1
α_4^{inc}	0.02				1
α_5^{inc}	-0.004				1
$\alpha_1^{\text{sq.mi}}$	-0.04				1
$\alpha_2^{\text{sq.mi}}$	-0.05				1
$\alpha_4^{\text{sq.mi}}$	0.14				1
$\alpha_5^{\text{sq.mi}}$	0.12				1
α_1^{den}	-0.16				1
α_2^{den}	-0.12				1
α_4^{den}	0.06				1
α_5^{den}	0.12				1
α^{cty}	-2.96	0.28	-3.40	-2.66	58
Purchase observations					$2,765,428$

Value, (SE)

Table shows parameters that govern consumer disutility from travel distance α_{xz}^{d} in Equation (4).

Table OA.6: Isolating variation in the level and composition of handgun ownership using variation in firearm retail

	Owners/Pop (1)	×Inc (2)	×Den (3)	×Crime (4)	×Male (5)	×Young (6)	×White (7)	$\times g_{i0}$ (8)	$\times \psi_{xz}$ (9)	$\times E[\tilde{\nu}_i \mid g_{it}=1]$ (10)
$E_{zt}[I_{xzt}]$	0.0185	0.0104	−0.0119	−0.0176	0.0146	0.0055	0.0162	0.0382	−0.1557	0.0236
	(0.0009)	(0.0013)	(0.0015)	(0.0027)	(0.0007)	(0.0003)	(0.0009)	(0.0018)	(0.0076)	(0.0011)
$E_{zt}[\xi_{xzt}]$	0.0055	0.0079	−0.0015	−0.0036	0.0045	0.0015	0.0049	0.0118	−0.0522	0.0072
	(0.0004)	(0.0005)	(0.0006)	(0.0007)	(0.0003)	(0.0001)	(0.0004)	(0.0008)	(0.0035)	(0.0005)
Zip code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Zip code clusters	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304
Zip code-quarters	57,079	57,079	57,079	57,079	57,079	57,079	57,079	57,079	57,079	57,079

Estimate (SE)

Table shows regression of the right-hand side variables in root $(R7)$ on the average estimated inclusive value of consumer's marginal retailer choice I_{xzt} from Section 4.4 and on the average estimated demand shock ξ_{xzt}. All regressions include fixed effects by zip code and quarter. Standard errors adjusted for clustering by zip code.

Table OA.7: Estimated homicide externality parameters $100 \times \Theta^e$

	Firearm					Non-gun				
	Control function				2SLS	Control function				2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
μ	−0.3166	−0.2962	−0.2666	−0.1191	−0.3033	−0.0249	−0.0245	−0.0169	−0.0156	−0.0643
	(0.0487)	(0.0485)	(0.0555)	(0.0229)	(0.1357)	(0.0191)	(0.0194)	(0.0240)	(0.0097)	(0.0482)
ζ^{inc}	−0.0017	−0.0009	0.0005			−0.0007	−0.0007	−0.0011		
	(0.0018)	(0.0018)	(0.0020)			(0.0010)	(0.0010)	(0.0013)		
ζ^{den}	−0.0049	−0.0053	0.0016			0.0009	0.0008	0.0023		
	(0.0022)	(0.0022)	(0.0023)			(0.0011)	(0.0011)	(0.0012)		
ζ^{crime}	0.0012	0.0011	0.0117			0.0004	0.0005	0.0012		
	(0.0010)	(0.0010)	(0.0040)			(0.0006)	(0.0006)	(0.0019)		
ζ^{male}	0.1466	0.1219	0.1497			−0.0048	−0.0041	−0.0181		
	(0.0357)	(0.0348)	(0.0432)			(0.0150)	(0.0153)	(0.0192)		
$\zeta^{<30}$	0.0562	0.0675	−0.0149			0.0100	0.0097	0.0022		
	(0.0192)	(0.0194)	(0.0199)			(0.0100)	(0.0103)	(0.0119)		
ζ^{white}	0.0589	0.0607	0.0724			0.0084	0.0090	0.0144		
	(0.0106)	(0.0115)	(0.0152)			(0.0045)	(0.0050)	(0.0064)		
ζ^{g_0}	−0.1749	−0.1702	−0.1338			0.0562	0.0512	0.0470		
	(0.0553)	(0.0545)	(0.0513)			(0.0281)	(0.0282)	(0.0291)		
ζ^{ψ}	−0.0004	−0.0003	0.0032			0.0003	0.0005	0.0004		
	(0.0017)	(0.0017)	(0.0025)			(0.0010)	(0.0010)	(0.0016)		
ζ^{ν}	0.1250	0.1210	0.1064	0.1171	0.2641	0.0186	0.0184	0.0198	0.0143	0.0556
	(0.0211)	(0.0208)	(0.0204)	(0.0200)	(0.1113)	(0.0087)	(0.0089)	(0.0096)	(0.0081)	(0.0395)
χ	0.0002			0.0002		−0.00002			−0.00003	
	(0.0001)			(0.0001)		(0.00003)			(0.00003)	
Zip code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County-Quarter FE			Y					Y		
Zip-Quarter Controls			Y					Y		
χ_x		Y	Y				Y	Y		
Instrument	$\vec{d}_{it}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$(1, \psi_z)^\top I_{zt}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$(1, \psi_z)^\top I_{zt}$
Zip code clusters	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304
Zip code-quarters	57,079	57,079	56,420	57,079	57,079	57,079	57,079	56,420	57,079	57,079

Estimated externality parameters from Equations (5) and (6). Columns 1–5 use firearm homicide as cause of death. Columns 6–10 use non-gun homicide as cause of death. Columns 1, 4, 6, and 9 use the control function estimator developed in Section 4, in which travel distances from consumers to retailers $\vec{d}_{z(i)t} = (d_{i1t}, \ldots, d_{iJt})$ operates as an excluded instrument. Columns 2, 3, 6, and 7 use the same control function, adding controls for demographic-zip code-quarter shocks $\phi_{xt} + \xi_{zt} + \varphi_{xzt}$. Columns 3 and 7 add further controls for fixed effects by county-quarter and controls for time-varying observable characteristics of a zip code (which are missing in 659 zip code-quarters). Columns 5 and 10 use an alternative two-stage least-squares estimator with instruments $I_{zt} = \sum_{i:z(i)=z} I_{x(i)z}/M_z$ and $I_{zt} \times \sum_{i:z(i)=z} \psi_{x(i)z}/M_z$, as discussed in Appendix OA.3. Standard errors clustered by zip code. All estimates weighted by zip code population.

Table OA.8: Estimated suicide externality parameters $100 \times \Theta^e$

	Firearm					Non-gun				
	Control function				2SLS	Control function				2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
μ	−0.0028	−0.0024	−0.0049	0.0342	0.0111	−0.0357	−0.0208	−0.0187	−0.0039	−0.2300
	(0.0455)	(0.0466)	(0.0518)	(0.0224)	(0.0723)	(0.0428)	(0.0435)	(0.0520)	(0.0233)	(0.0951)
ζ^{inc}	0.0025	0.0032	0.0036			0.0003	0.0010	−0.0002		
	(0.0021)	(0.0022)	(0.0023)			(0.0024)	(0.0025)	(0.0025)		
ζ^{den}	−0.0013	−0.0013	−0.0012			−0.0026	−0.0030	−0.0021		
	(0.0023)	(0.0023)	(0.0027)			(0.0024)	(0.0024)	(0.0027)		
ζ^{crime}	0.0003	0.0004	0.0006			0.0001	0.0001	0.0016		
	(0.0012)	(0.0012)	(0.0035)			(0.0013)	(0.0013)	(0.0042)		
ζ^{male}	0.0609	0.0574	0.0902			−0.0093	−0.0201	−0.0531		
	(0.0338)	(0.0349)	(0.0422)			(0.0351)	(0.0362)	(0.0433)		
$\zeta^{<30}$	0.0124	0.0163	0.0081			0.0291	0.0319	0.0229		
	(0.0209)	(0.0217)	(0.0248)			(0.0235)	(0.0246)	(0.0269)		
ζ^{white}	0.0038	0.0050	0.0016			0.0078	0.0045	0.0150		
	(0.0085)	(0.0090)	(0.0107)			(0.0096)	(0.0103)	(0.0125)		
ζ^{g_0}	0.1124	0.1125	0.1064			0.1742	0.1710	0.1759		
	(0.0596)	(0.0597)	(0.0606)			(0.0660)	(0.0662)	(0.0661)		
ζ^{ψ}	0.0012	0.0012	0.0037			−0.0006	−0.0004	−0.0033		
	(0.0022)	(0.0023)	(0.0030)			(0.0022)	(0.0022)	(0.0031)		
ζ^{ν}	−0.0273	−0.0258	−0.0252	−0.0188	0.0017	0.0198	0.0184	0.0093	0.0084	0.1906
	(0.0191)	(0.0195)	(0.0201)	(0.0176)	(0.0583)	(0.0203)	(0.0206)	(0.0214)	(0.0189)	(0.0779)
χ	−0.00001			0.00001		0.00002			0.00002	
	(0.0001)			(0.00005)		(0.0001)			(0.0001)	
Zip code FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
County-Quarter FE			Y					Y		
Zip-Quarter Controls			Y					Y		
χ_x		Y	Y				Y	Y		
Instrument	$\vec{d}_{it}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$(1, \psi_z)^\top I_{zt}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$\vec{d}_{it}$	$(1, \psi_z)^\top I_{zt}$
Zip code clusters	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304	1,304
Zip code-quarters	57,079	57,079	56,420	57,079	57,079	57,079	57,079	56,420	57,079	57,079

Estimated externality parameters from Equations (5) and (6). Columns 1–4 use firearm suicide as cause of death. Columns 5–8 use non-gun suicide as cause of death. Columns 1, 4, 6, and 9 use the control function estimator developed in Section 4, in which travel distances from consumers to retailers $\vec{d}_{z(i)t} = (d_{i1t}, \ldots, d_{iJt})$ operates as an excluded instrument. Columns 2, 3, 6, and 7 use the same control function, adding controls for demographic-zip code-quarter shocks $\phi_{xt} + \xi_{zt} + \varphi_{xzt}$. Columns 3 and 7 add further controls for fixed effects by county-quarter and controls for time-varying observable characteristics of a zip code (which are missing in 659 zip code-quarters). Columns 5 and 10 use an alternative two-stage least-squares estimator with instruments $I_{zt} = \sum_{i:z(i)=z} I_{x(i)z}/M_z$ and $I_{zt} \times \sum_{i:z(i)=z} \psi_{x(i)z}/M_z$, as discussed in Appendix OA.3. Standard errors clustered by zip code. All estimates weighted by zip code population.

STATE OF CALIFORNIA
BOF 929 (Rev. 01/2014)

DEPARTMENT OF JUSTICE
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CALIFORNIA DEPARTMENT OF JUSTICE
BUREAU OF FIREARMS
Dealer's Record of Sale (DROS) Worksheet

CFD No.: DROS No.:

Transaction Information

Transmission Date:	Transmission Time:	Delivery Date:	Delivery Time:	Gun Show Transaction ☐ Yes ☐ No

Firearm Type: ☐ Long Gun ☐ Handgun

Transaction Type: (All but "Dealer Sale" cert-list exempt) ☐ Dealer Sale ☐ Private Party Transfer ☐ Curio/Relic/Olympic/Other Exempt ☐ Loan ☐ Pawn/Consignment Return ☐ Peace Officer

Transaction exempt from 1 handgun per 30 day limit. ☐

Waiting Period Exemptions

Purchaser claims the following waiting period exemption pursuant to Penal Code sections 26950 through 26970 and 27650 through 27670.

☐ PEACE OFFICER STATUS (must have agency letter)
☐ CA FIREARMS DEALER Enter CFD Number:
☐ SPECIAL WEAPONS PERMIT Enter Type and Permit Number. (does not include CCW permit) Permit Type Permit Number
☐ COLLECTOR STATUS (curio/relic only) Enter COE Number:

Firearm Information

Make: (Colt, Remington, etc.)	Model: (Commander, 870, etc.)	Caliber(s):	Barrel Length:	Serial Number:	Other Number: (if different)

Firearm Type: ☐ Long Gun ☐ Handgun

If Long Gun: ☐ Rifle ☐ Shotgun

If Handgun: ☐ Revolver ☐ Semi-Auto ☐ Other: ☐ Single Shot ☐ Derringer:

Frame Only: ☐ Yes ☐ No

New Firearm: ☐ Yes ☐ No

Firearm Origin: (USA, Italy, etc.)	Firearm Color: (Black, Green, Silver, etc.)	Comments:

Purchaser Information

First Name:	Middle Name:	Last Name:	Suffix:
Alias First Name:	Alias Middle Name:	Alias Last Name:	Alias Suffix:

Street Address:	City:	Zip Code:

One of the following forms of identification is required to legally purchase firearms in California: California driver license (CDL), California ID (CID) card issued by the DMV, or Military ID (MID) for active duty military accompanied by permanent duty station orders indicating that the purchaser is stationed in California.

ID Type: (check one) ☐ CDL ☐ CID ☐ MIL

ID Number:

US Citizen: ☐ Yes ☐ No

If NO, enter Alien Registration or I-94 Number and Country of Citizenship

Alien Registration or I-94 Number Country of Citizenship

Telephone Number: ( )	Date of Birth: (mm/dd/yyyy)	Place of Birth:	Race:

Sex:	Height:	Weight:	Hair Color:	Eye Color:	HSC Number or Exemption Code: (handguns only)

☐ Yes ☐ No Has purchaser ever been convicted of a felony or of any offense specified in Penal Code sections 23515 and 29905, or convicted of assault, battery, or other misdemeanor offense specified in Penal Code section 29805 in the last 10 years?

☐ Yes ☐ No Is purchaser a danger/threat to self or others pursuant to Welfare and Institutions Code section 8100, or a person who has been admitted to a mental health facility as a danger to self or others pursuant to Welfare and Institutions Code sections 5150 through 5152 within the past 5 years?

☐ Yes ☐ No Has purchaser ever been adjudicated by a court to be a danger to others, found not guilty by reason of insanity, found incompetent to stand trial, or placed under a conservatorship, pursuant to Welfare and Institutions Code section 8103?

☐ Yes ☐ No Is purchaser currently the subject of any restraining order pursuant to Family Code section 6380?

I declare under penalty of perjury under the laws of the State of California that the foregoing is true and correct.

Signature of Purchaser Date

Private Party Transfer (Seller Information)

First Name:	Middle Name:	Last Name:	Suffix:

Street Address:	City:	Zip Code:

ID Type: (check one) ☐ CDL ☐ CID ☐ MIL

ID Number:

US Citizen: ☐ Yes ☐ No

If NO, enter Alien Registration or I-94 Number and Country of Citizenship:

Alien Registration or I-94 Number Country of Citizenship

Date of Birth: (mm/dd/yyyy)	Place of Birth:	Race:	Sex:	Height:	Weight:	Hair Color:	Eye Color:

I declare under penalty of perjury under the laws of the State of California that the foregoing is true and correct.

Signature of Seller Date

Dealer Information

Firearm Safety Device Description and/or Comments:	Telephone Number: ( )

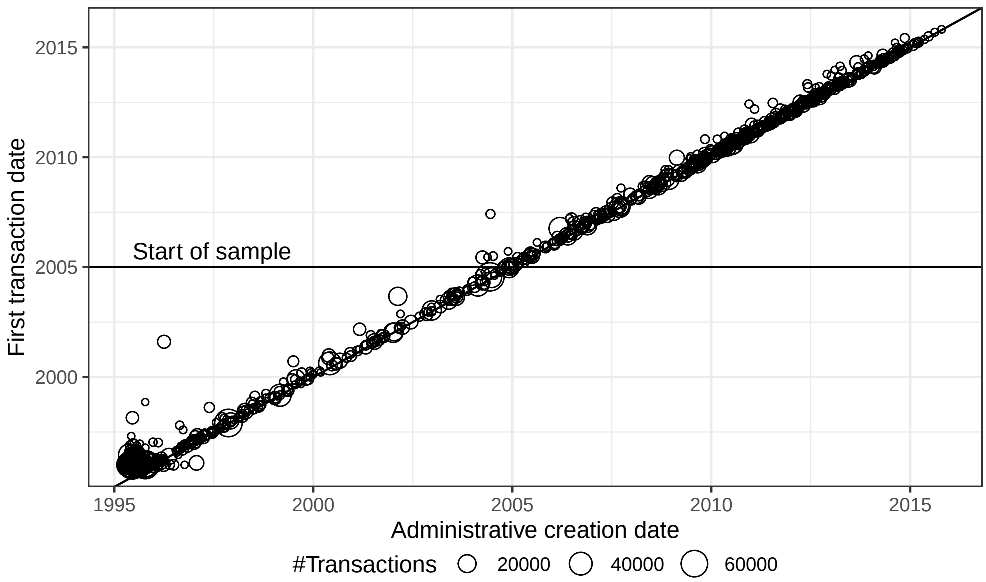
Sales Person Printed Name and COE Number if Issued:

I declare under penalty of perjury under the laws of the State of California that the foregoing is true and correct.

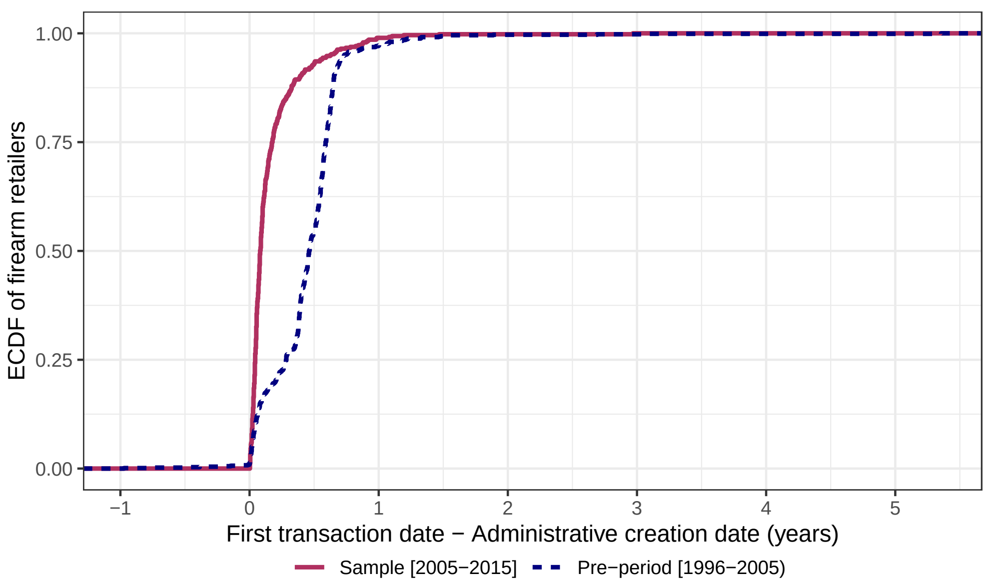
Signature of Salesperson Date

Falsification of information on this form is a crime, punishable by up to 18 months in state prison. (Pen. Code, § 28250.)

Figure OA.1: Handgun Transfer Form Completed by Firearm Retailers



Panel A: Entry dates across firearm retailers



Panel B: Distribution of differences in entry dates across firearm retailers

Figure OA.2: Dates of Firearm Retailer Entry, Administratively and in Data

Figure shows entry dates across firearm retailers in my sample. Administrative creation dates are based on permits from the CA DOJ. Data-based entry dates are the date of a firearm retailer's first recorded transaction in the DROS data, and the dates used in my analysis.

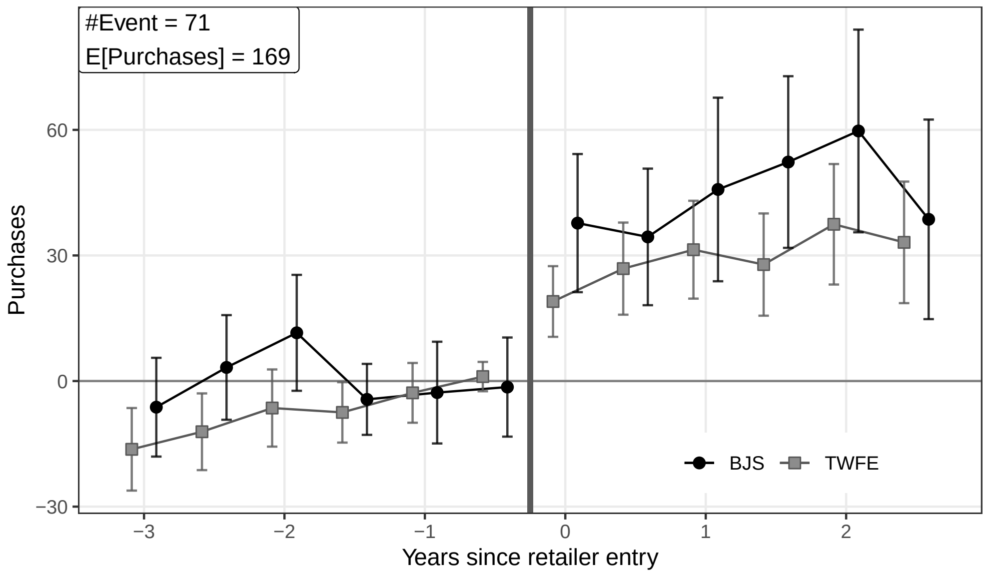
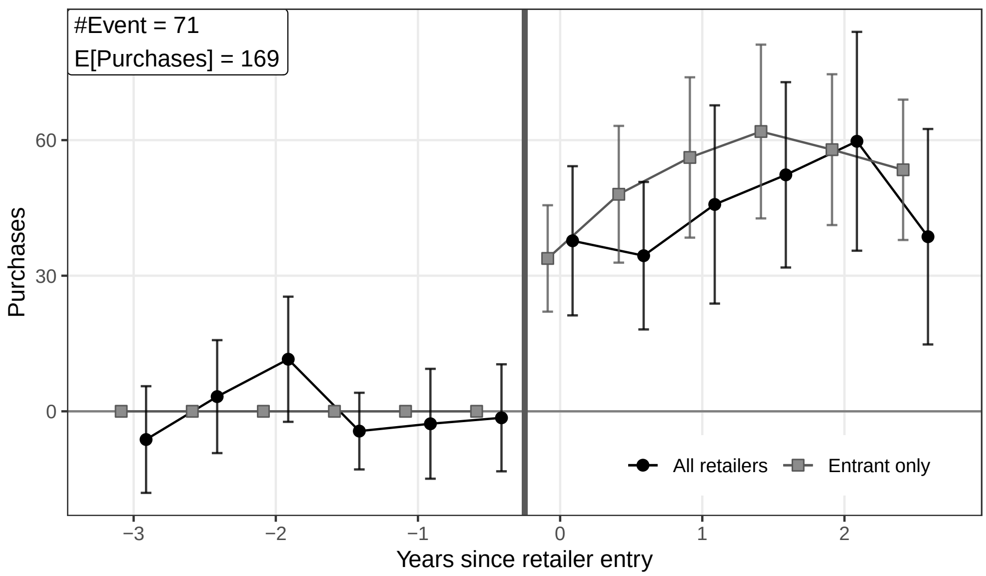
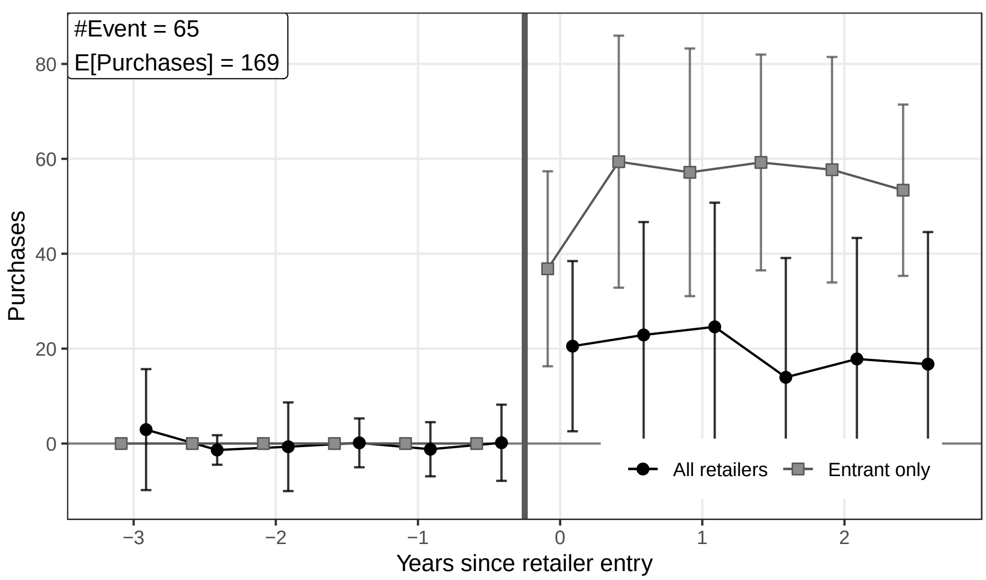


Figure OA.3: Market expansion from firearm retailer first entries. Estimation via two-way fixed effects

Figure presents the effect of a firearm retailer's entry on handgun transactions in the entered zip code. Darker circles use my preferred estimator (Borusyak et al. 2024) of Equation (1). Lighter squares estimate the same model via two-way fixed effects. Horizontal axis is periods from the retailer entry, with pre- and post-entry separated by the thick vertical line. Vertical axis is the effect on handgun purchases per capita $\beta_{t'}$ scaled by the average zip code's population in California. Data for model fitting is restricted to zip code-periods that are either within three years of the entry of their first firearm retailer or that never have an operational firearm retailer during my sample. To remove composition bias, effects are calculated for first entry events with three years of data fully observed before and after the quarter of entry. Points are point estimates and intervals are 95-percent pointwise confidence intervals computed from a Bayesian bootstrap of zip codes.



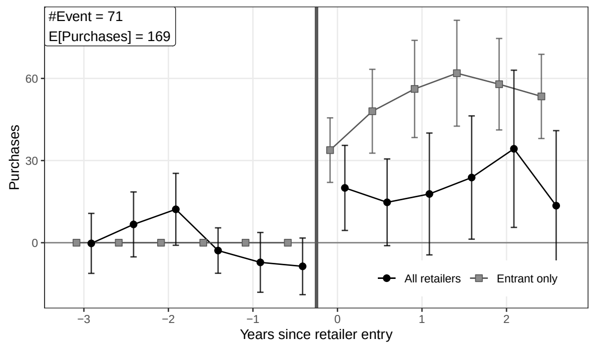
Panel A: First entrants



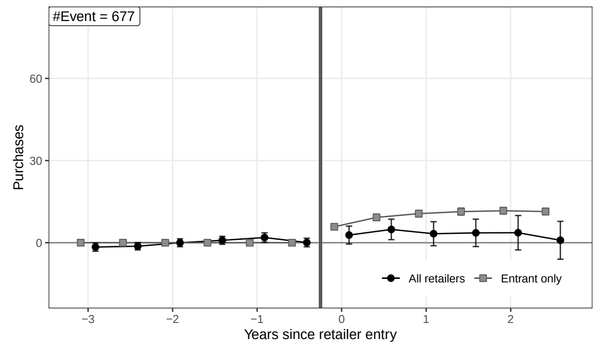
Panel B: Subsequent entrant

Figure OA.4: Effects of firearm retailer entries on handgun purchases. Heterogeneity by pre-entry market structure

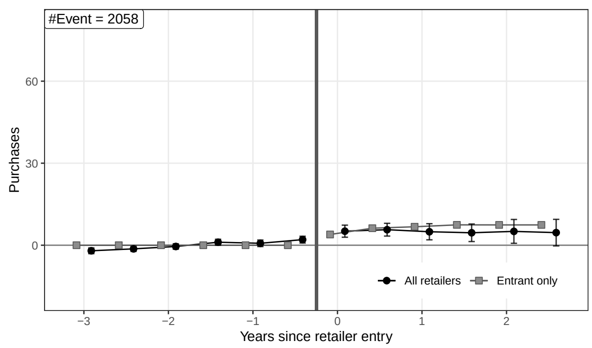
Figure presents the effect of a firearm retailer's entry on handgun purchases in the entered zip code. Panel A reproduces the effect of a first-entrant from Panel A of Figure 1. Panel B presents effects for subsequent entrants, using zip code-periods with at one least firearm retailer in operation. Both panels present estimates of market expansion (darker circle, handgun purchases from any retailer in California) and only at the entering firearm retailer (lighter square). Horizontal axis is periods from the retailer entry, with pre- and post-entry separated by the thick vertical line. Vertical axis is the effect on handgun purchases per capita $\beta_{t'}$, scaled by the average zip code's population in California. To remove composition bias, effects are calculated for entry events with data fully observed before and after the period of entry. Points are point estimates and intervals are 95-percent pointwise confidence intervals computed from a Bayesian bootstrap of zip codes.



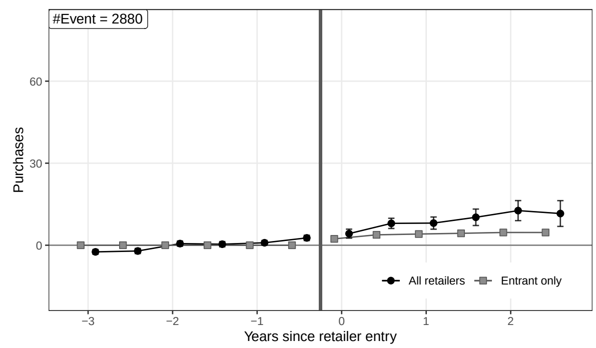
Panel A: Within-zip



Panel B: (0–5] miles



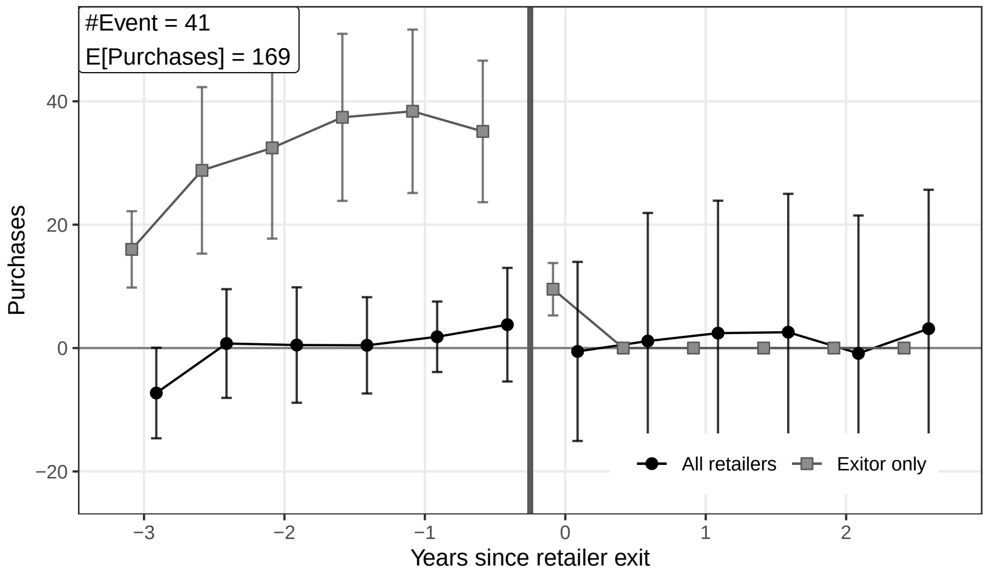
Panel C: (5–10] miles



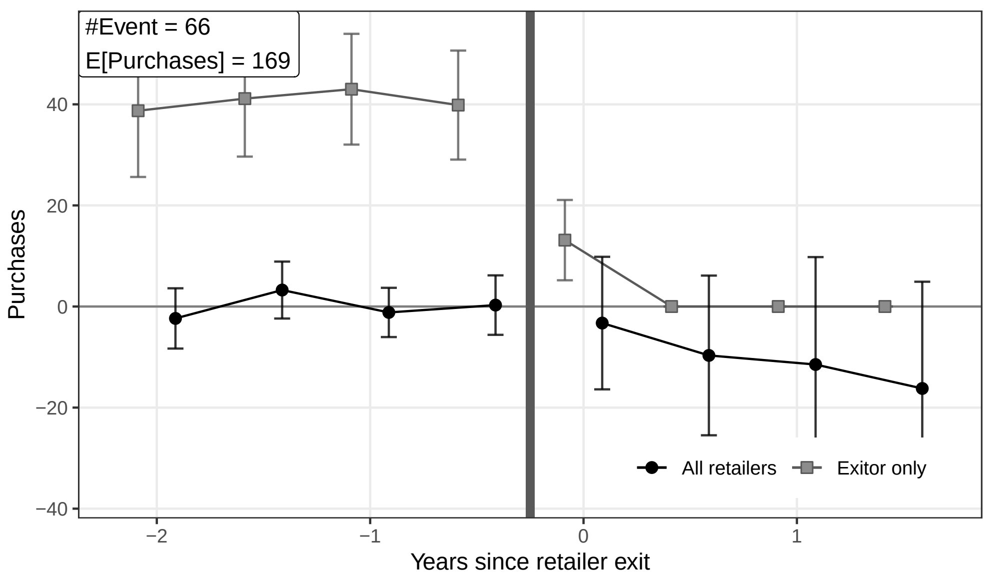
Panel D: (10–15] miles

Figure OA.5: Effect of first retailer entry on handgun purchases at different distances from the entered zip code

Figure presents the effect of a first firearm retailer's entry on handgun purchases in zip codes different distances away. Panel A reproduces the within zip code effects from Panel A of Figure OA.7, excluding never-entered zip code $t' = -\infty$ from the sample. Panels B–D show effects using the same design for zip codes whose centroid is (0,5], (5,10], (10,15] miles from the zip code centroid of the entering firearm retailer, respectively. All panels present estimates of market expansion (darker circle, handgun purchases from any retailer in California) and only at the entering firearm retailer (lighter square). Horizontal axis is periods from the retailer entry, with pre- and post-entry separated by the thick vertical line. Vertical axis is the effect on handgun purchases per capita $\beta_{t'}$, scaled by the average zip code's population in California. To remove composition bias, effects are calculated for entry events with data fully observed before and after the period of entry. Points are point estimates and intervals are 95-percent pointwise confidence intervals computed from a Bayesian bootstrap of zip codes.



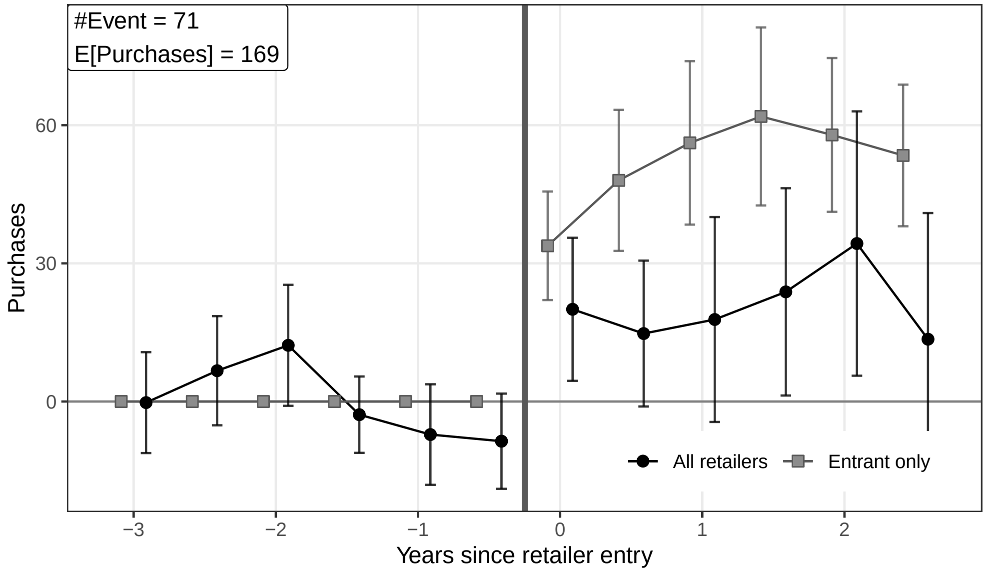
Panel A: With pure controls



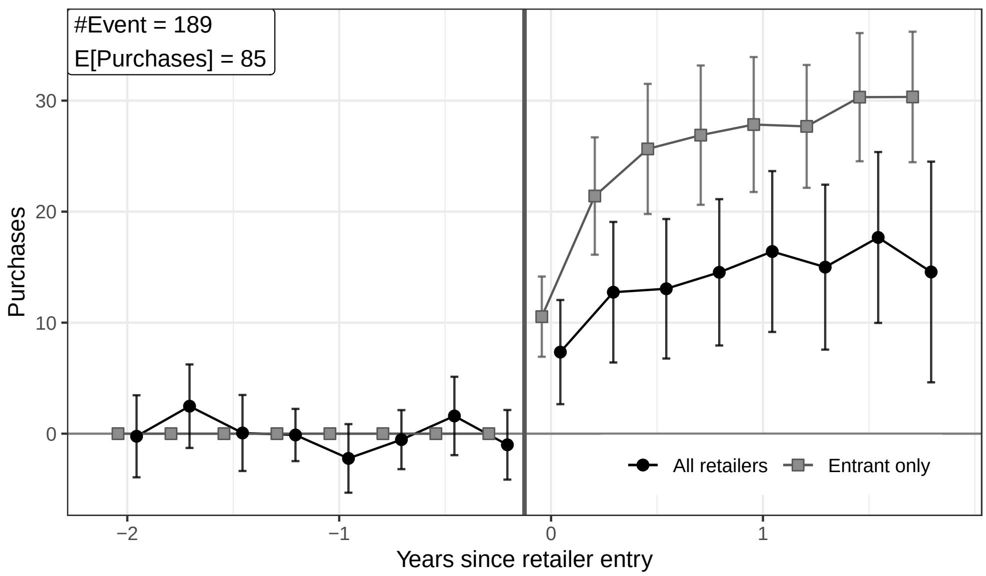
Panel B: Only zip codes with exit

Figure OA.6: Effects of firearm retailer exits on handgun purchases

Figure presents the effect of a firearm retailer's exit on handgun transactions in the exited zip code. Panel A uses the specification from Figure 1, where pure controls are zip codes with at least one firearm retailer and no net entry during the sample. Panel B uses the specification from Figure OA.7, in which only zip code that experience an exit are used in estimation. Panel B uses a shorter 2-year bandwidth around exits to increase the sample of zip code-quarters available for estimation. Both panels present estimates of market contraction (darker circle, handgun purchases from any retailer in California) and only at the exiting firearm retailer (lighter square). Horizontal axis is periods from the retailer entry, with pre- and post-entry separated by the thick vertical line. Vertical axis is the effect on handgun purchases per capita $\beta_{t'}$, scaled by the average zip code's population in California. To remove composition bias, effects are calculated for exit events with data fully observed before and after the period of exit. Points are point estimates and intervals are 95-percent pointwise confidence intervals computed from a Bayesian bootstrap of zip codes.



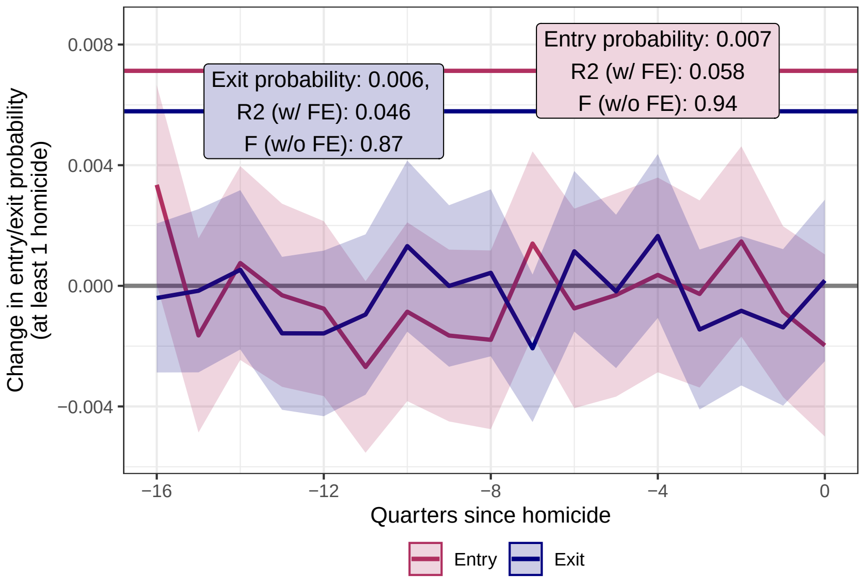
Panel A: First entrants, two-quarter periods, three-year bandwidth



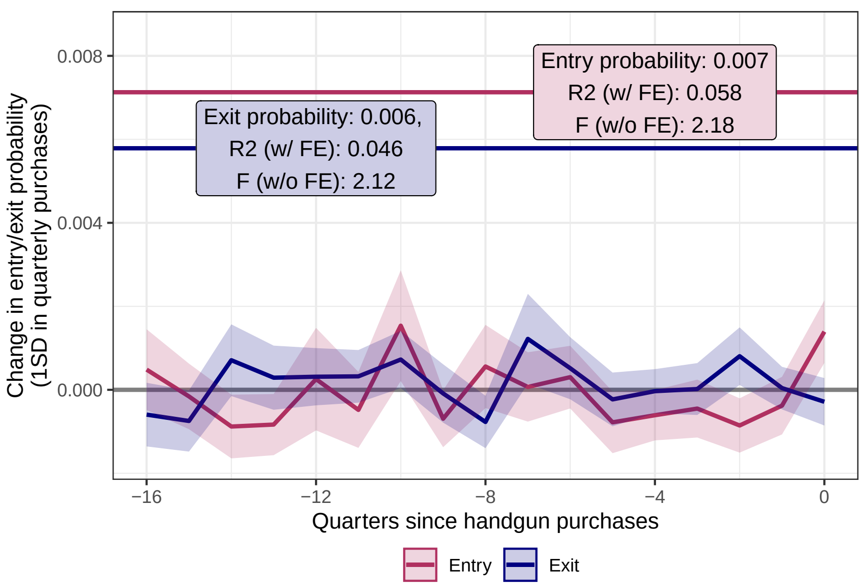
Panel B: All entrants, one-quarter periods, two-year bandwidth

Figure OA.7: Effects of firearm retailer entries on handgun purchases. Removing never-entered zip codes

Figure presents the effect of a firearm retailer's entry on handgun purchases in the entered zip code. Estimation samples further restrict those of Section 3.1 by including only zip code-quarters with at least one retailer entry (i.e., excluding never-entered zip codes). Panels A and B present effects using different specifications of an event (first entrants v. first or subsequent entrants), period length (one v. two quarters), and the number of years before and after entry (three years v. two years). Both panels present estimates of market expansion (darker circle, handgun purchases from any retailer in California) and only at the entering firearm retailer (lighter square). Horizontal axis is periods from the retailer entry, with pre- and post-entry separated by the thick vertical line. Vertical axis is the effect on handgun purchases per capita $\beta_{t'}$, scaled by the average zip code's population in California. To remove composition bias, effects are calculated for entry events with data fully observed before and after the period of entry. Points are point estimates and intervals are 95-percent pointwise confidence intervals computed from a Bayesian bootstrap of zip codes.



Panel A: Lagged homicide fatalities



Panel B: Lagged handgun purchases

Figure OA.8: Lagged variables do not predict firearm retailer entry or exit

Figure shows coefficients from regressions of indicators for retailer entry or exit in a zip code-quarter on lagged variables over the previous 16 quarters and fixed effects for zip code and quarter. Panel A uses lags of a binary indicator for the occurrence of a homicide fatality. Panel B uses lags for the count of handgun purchases per capita. Series are point estimates. Bands are 95-percent confidence intervals, adjusted for clustering by zip code. R^2 from the regression includes fixed effects. F-statistic excludes fixed effects and is adjusted for clustering. Horizontal lines are probabilities of retailer entry and exit in the average zip code quarter.

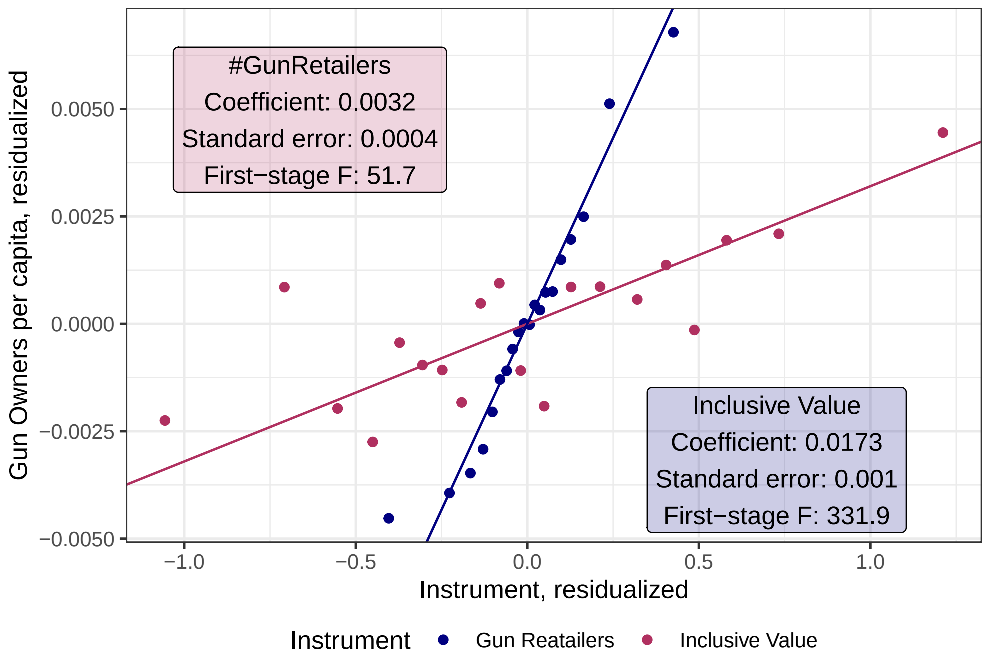


Figure OA.9: Instrumenting for Handgun ownership with the Entry and Exit of Firearm Retailers

Figure shows residualized binned scatterplots between handgun ownership per capita within a zip code-quarter and changes in firearm retail. Red measures changes in firearm retail using the the count of firearm retailers within a zip code, as in Section 3. Blue measures changes in firearm retail using the inclusive value from consumer i's marginal retailer choice problem $I_{xt}(\vec{d}_{z(i)t}; \Theta)$, averaged over all consumers in a zip code, as in Section 4. All statistics are calculated on the full set of zip codes, condition on two-way fixed effects by zip code and quarter, weight by zip code adult population, and adjust for clustering at the zip code level.

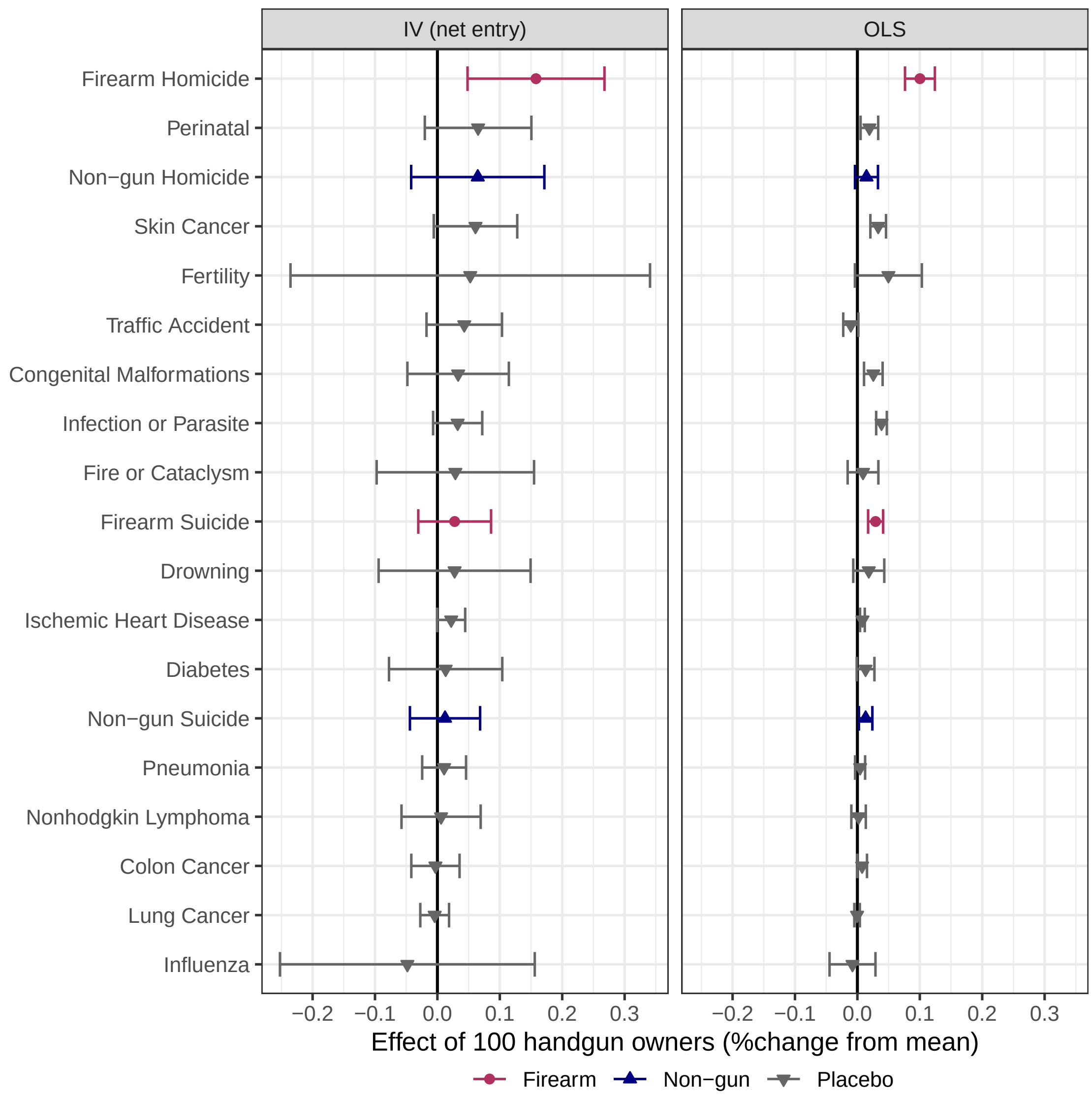


Figure OA.10: Effects of handgun ownership on fatality outcomes

Figure shows the effect of handgun ownership on several fatality outcomes. Panels are estimators for the effect of handgun ownership on fatalities. Left panel (IV) corresponds to the estimator for Column 1 of Table 3. Right panel (OLS) corresponds to the estimator for Column 3 of Table 3. Horizontal axis is the estimated effect of adding 100 handgun owners on fatality counts, relative to the number of fatalities in the average zip code-quarter. Vertical axis is cause fatality. Firearm fatalities (red, circle) and non-gun fatalities (blue, upward triangle) are defined in Section 2. Placebo outcomes (gray, downward triangle) are defined by ICD10 codes: Perinatal (P00–P96), Skin cancer (C43–C44), Fertility-related (O00-O94, O9A), Traffic accidents (V00–V89), Congenital malformations (Q00–Q99), Infectious or parasitic diseases (A00–B99), Fire or natural cataclysm (X00–X08, X30–X39), Drowning (W16, W65–W74), Ischemic heat disease (I20–I25), Diabetes (E08–E13), Pneumonia (J12–J18), Non-hodgkin lymphoma (C85), Colon cancer (C18), Lung cancer (C34), Influenza (J08–J11).

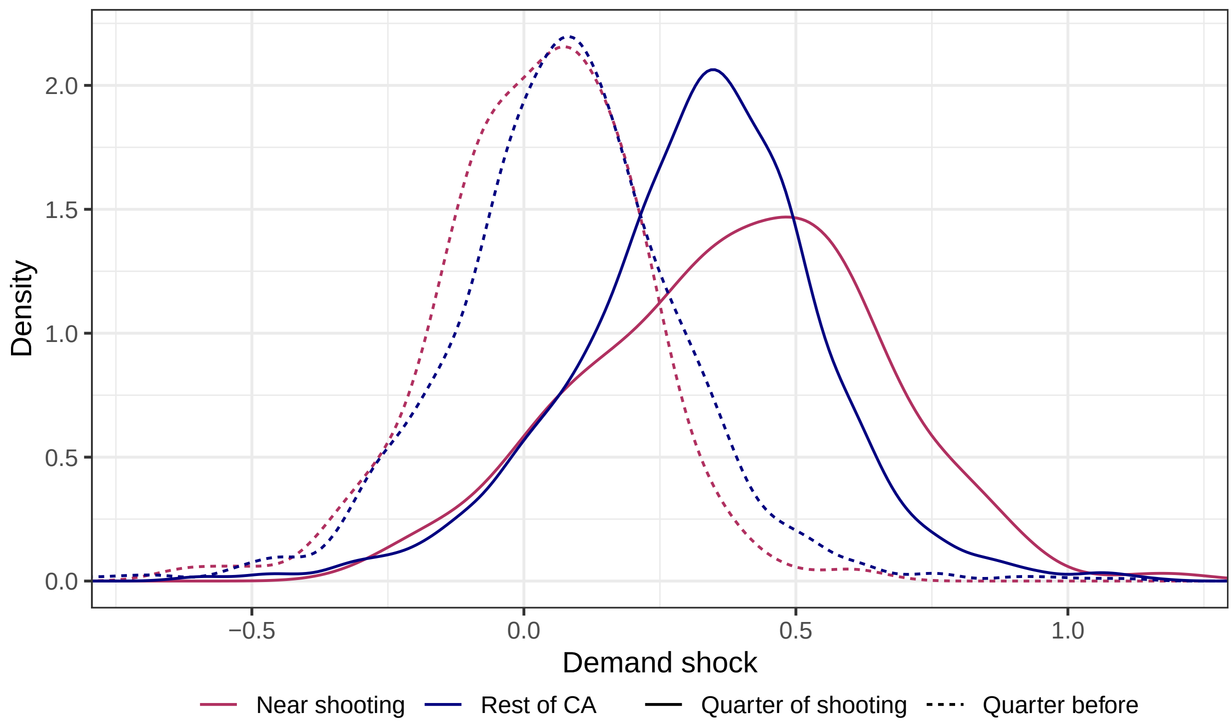


Figure OA.11: Handgun demand around the Sen Bernardino mass shooting event

Figure shows the distribution of the estimated demand shock ξ_{xzt} around the San Bernardino mass shooting event. Areas near the shooting are in the Inland Empire counties of San Bernardino and Riverside. Quarter of shooting is 2015Q4. Quarter before shooting is 2015Q3.

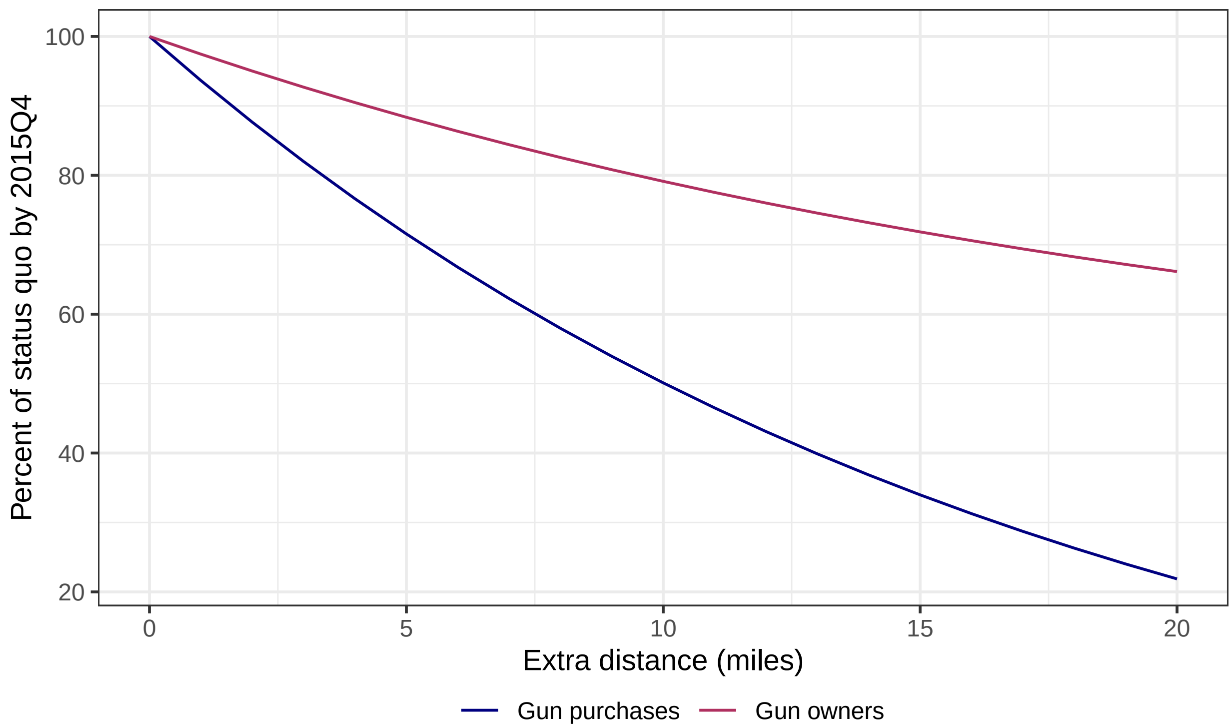


Figure OA.12: Effect of travel distance on handgun purchasing and ownership

Figure shows percent changes in handgun purchasing and ownership from increasing travel distance d_{ijt} between all consumers and retailers, as implied by my estimated preference parameters $(\hat{\Theta}^{\nu}, \hat{\Theta}^{\delta}, \hat{\lambda})$. Purchase probability at alternative travel distances is calculated according to the choice probabilities in Appendix OA.3 and averaged across the estimated distribution of indirect utility u_{it} within each zip code-quarter.

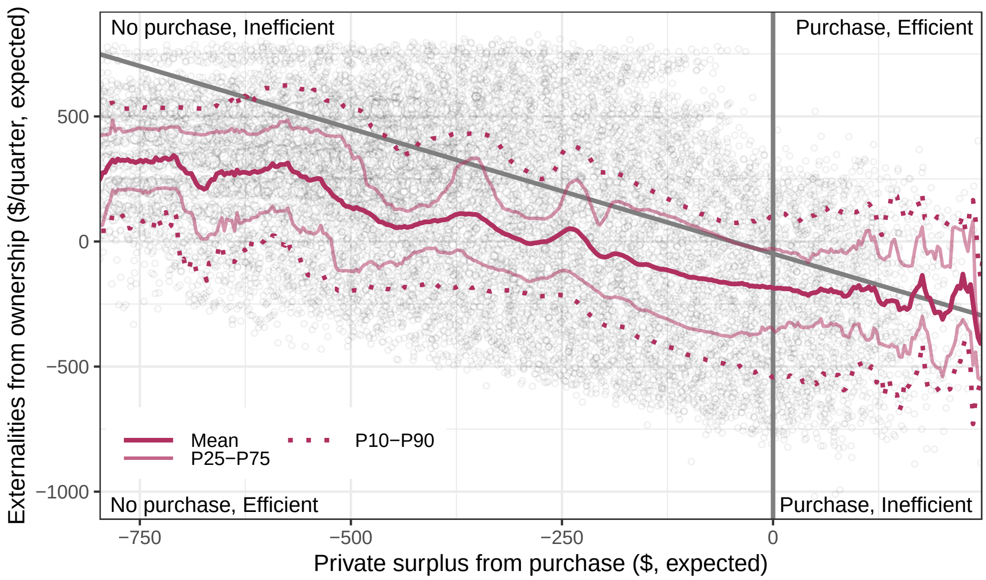
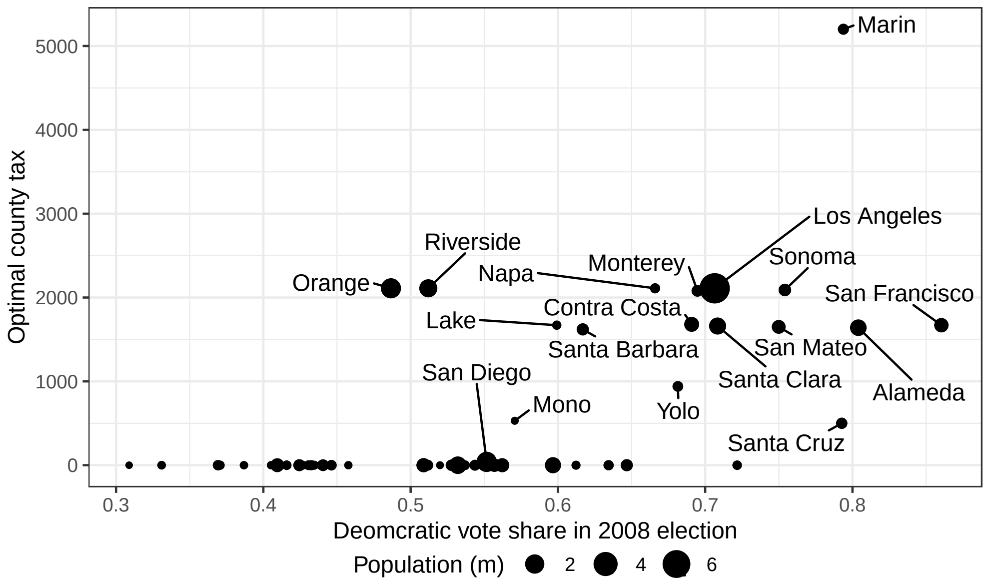
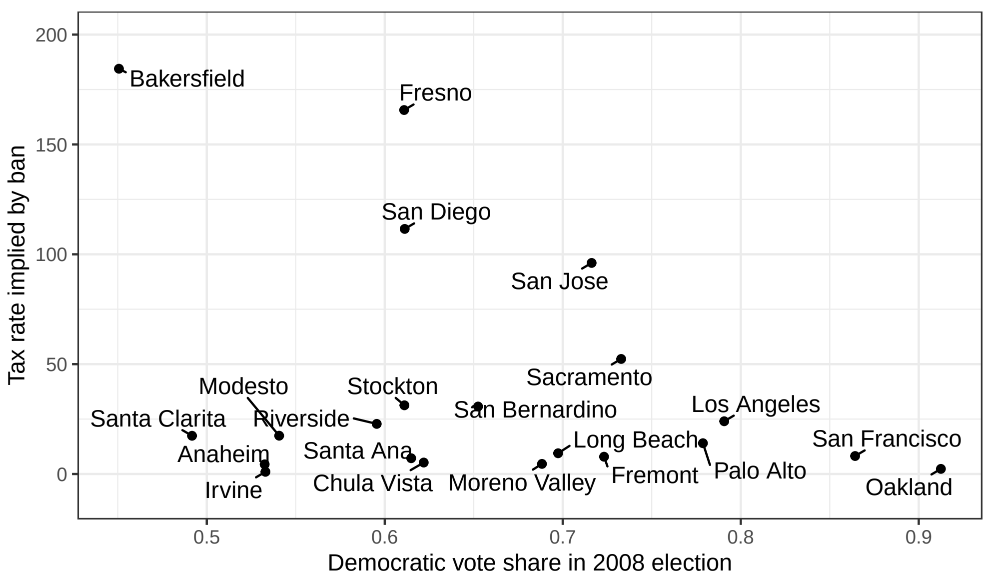


Figure OA.13: Full distribution of preferences and externalities in California's legal handgun market

Figure presents allocative efficiency from consumer choice in handgun markets when $g_{i,t-1} = 0$. Horizontal axis is private surplus from purchase. Vertical axis is expected quarterly external costs of handgun ownership. Downward sloping line has slope of -1 and intersects the vertical axis at the value of tax revenue generated by handugn purchase. Points are consumers in California's average quarter. Solid line is the conditional expectation function in this space, estimated via kernel regression with a bandwidth of 5 and a Logistic. Light lines are quantiles 25 and 75, while dotted lines are quantiles 10 and 90, all computed under the same kernel and bandwidth. Marginal value of public funds is 1, marginal value of a homicide fatality is $8,500,000 \times (8/442)$, marginal value of a suicide fatality is $1,500,000 \times (8/442)$, and the tax is 600×0.0875, described in Section 4.



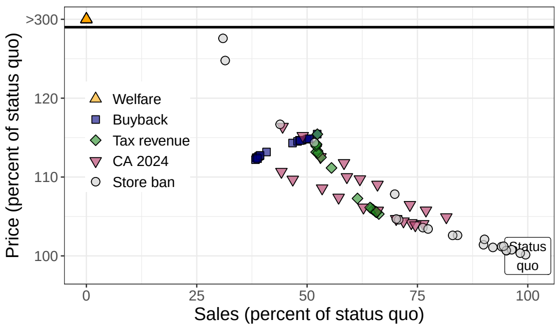
Panel A: Democratic vote share and county optimal taxes



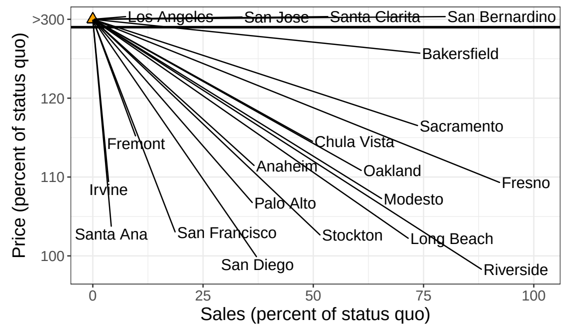
Panel B: Democratic vote share and the effect of city-wide bans

Figure OA.14: Correlation of handgun regulations and Democratic vote share

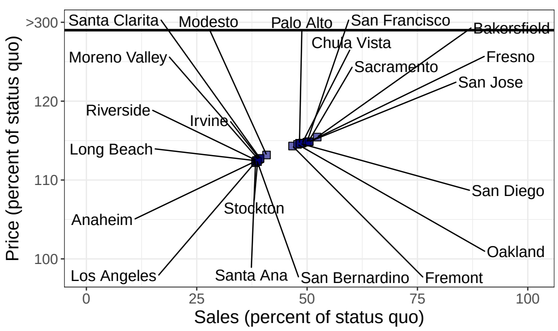
Figure shows the relationship between a zip code's Democratic vote share in 2008 and heterogeneous regulations on the handgun market. Panel A shows the county-specific optimal rate on handgun purchase that maintains the same drop in consumer surplus from California's 2024 tax, as in Panel A of Figure 6. Panel B shows the price implied by a city-wide ban from Figure OA.15, using the vote share from all zip codes that cross the city's borders.



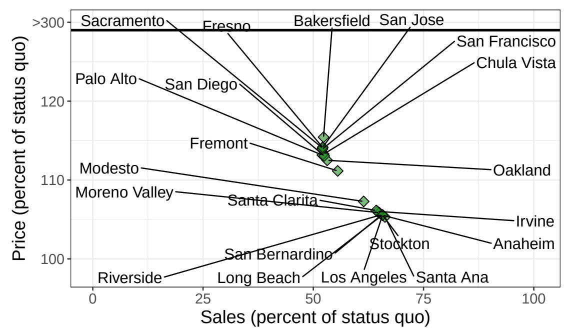
Panel A: All objectives



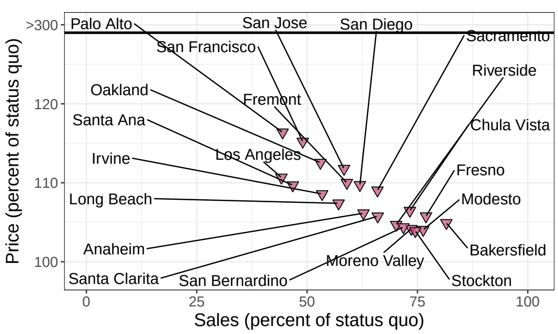
Panel B: Welfare maximizing



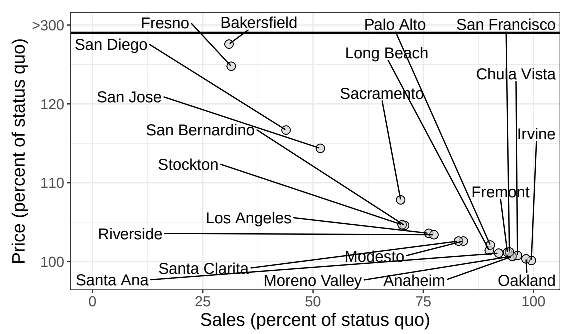
Panel C: Buyback



Panel D: Tax revenue



Panel E: CA 2024



Panel F: Store ban

Figure OA.15: Retailer bans and optimal taxes on handgun purchase across California's cities

Figure presents the taxes on handgun purchase that optimize various policy objectives in California's 20 largest cities and Palo Alto. Points are cities. Horizontal axis is purchase quantity from 2005–2015, as a percent of the regulatory status quo. Vertical axis is the dollar increase in the handgun purchase price. Panels are different policies, with all policies in Panel A. Triangle (upward) maximizes welfare (weighting fatalities by San Jose's estimated fiscal cost), Square maximizes consumer surplus and the social value of tax revenue, less buyback cost. Diamond maximizes tax revenue. Triangle (downward) maximizes welfare (using the weighting on fatalities revealed by California's 2024 tax on handgun purchase). Circle is the tax-purchase quantity pair that implements the same changes in purchases as a city-wide ban on the operation of firearm retailers. See Sections 5.2 and 6.1 for details.

Figure OA.16: The effects of firearm retailer bans and optimal tax rates by city

Figure shows the relationship between the effect of a city-wide firearm retailer ban and the optimal optimal citywide tax on firearm purchase. Horizontal axis is the effect of a retailer ban, measured as the price increase required to induce the same drop in handgun purchases as a retailer ban, following Figure OA.15. Vertical axis is the population-weighted average tax rate on handgun purchase that arises from maximizing statewide welfare subject to not harming statewide consumer surplus more than California's 2024 tax, as in Figure 6.