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PREFERENCES FOR FIREARMS AND THEIR IMPLICATIONS FOR REGULATION

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ABSTRACT

This paper estimates consumer demand for firearms with the aim of predicting the likely impacts of firearm regulations on the number and types of guns in circulation. We first conduct a stated-choice-based conjoint analysis and estimate an individual-level demand model for firearms. We validate our estimates using aggregate moments from observational data. Next, we use our estimates to simulate changes in the number and types of guns in circulation under alternative regulations. Importantly, we find that bans or restrictions that specifically target “assault weapons” increase demand for handguns, which are associated with the vast majority of firearm-related violence. We provide distributions of consumer surplus under counterfactuals and discuss how those distributions could be useful for crafting policy.

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1 Introduction

More than 40% of Americans reside in a household that contains at least one firearm (Gallup Poll 2020).¹ Combined, American civilians own roughly 400 million firearms. Both the popularity of firearms and the codification of the right to bear arms in the US Constitution suggest that gun ownership confers substantial utility to consumers in the United States. While the vast majority of purchased firearms are not used in violent crime, the cost of gun-related injuries is high. In 2020, there were more than 45,000 gun-related deaths in the United States (Pew Research).^{2,3} Our goal in this paper is to develop a framework for evaluating gun policy that simultaneously recognizes the individual utility of gun ownership and also takes seriously the externalities associated with guns.

Our framework provides estimates of how alternative firearms regulations affect both overall gun sales and the types of guns in circulation; the latter may matter to the extent that different types of firearms are associated with different crime rates.⁴ In particular, we estimate demand for firearms, allowing for substitution between different gun types as well as rich individual heterogeneity in preferences. We leverage our estimates of consumer price sensitivity and substitution patterns across firearms to speak to both price- and quantity-based regulations in counterfactual simulations. We can evaluate regulations that have never been implemented (e.g., a ban on handguns). This framework can help a policymaker evaluate how well different policies can achieve their intended goals and at what cost to gun owners in terms of consumer surplus. Our consumer surplus estimates can be used to put bounds on the cost of hypothetical buyback programs as well as to predict how different regulations affect different types of consumers.

This paper does not estimate a causal link between gun ownership and crime or deaths. Instead, it estimates the effects of policy on both the number and types of guns sold in the primary market, as well as the consumer surplus that accrues to gun owners from their purchases.⁵ Our framework allows policymakers to combine their prior beliefs about the causal

¹<https://news.gallup.com/poll/264932/percentage-americans-own-guns.aspx>

²54% of those deaths were suicides, 43% homicides and 3% were others, including accidental, law enforcement or undetermined circumstances. <https://www.pewresearch.org/fact-tank/2022/02/03/what-the-data-says-about-gun-deaths-in-the-u-s/>

³Of gun homicides, 61% are domestic violence related. <http://www.shelterhousenwfl.org/resources/domestic-violence-statistics/>.

⁴Handguns are involved in ~91% of gun murders and non-negligent manslaughters where the type of gun is noted. <https://www.pewresearch.org/fact-tank/2019/08/16/what-the-data-says-about-gun-deaths-in-the-u-s/>

⁵While we do not estimate impacts on the secondary market explicitly, primary markets and secondary markets are clearly related. A more restrictive primary market mechanically reduces supply available to secondary markets. It is also worth noting that “secondary” market purchases made through online platforms typically must be finalized through licensed dealers, and our estimates are relevant to these kinds of

link between guns and crime with our estimates in order to evaluate the expected costs and benefits of candidate regulations. While we do not furnish these priors for policymakers, a rich literature has provided a range of estimates (for example, see: Duggan 2001; Helland and Tabarrok 2004; Studdert et al. 2020; Cook and Ludwig 2006; Lott and Mustard 1997), and we hope more work on this important subject will be forthcoming. If a policymaker believes that there is no causal link between the number of guns and gun deaths, our framework can still be helpful, as estimates of consumer surplus shed light on the cost of gun policies to gun owners.

The dearth of data on firearm sales volumes matched with prices is a major challenge in estimating demand in this market. To our knowledge, no centralized database contains information about either individual-level or aggregate gun purchases matched with prices. Aggregate proxies for purchases that have been used in previous research are neither detailed to the gun model nor matched with prices (e.g., background checks as in Kim and Wilbur 2022 and the share of suicides committed with firearms as in Cook 1979; Azrael et al. 2004; Kleck 2004; Evans et al. 2022; Cook and Ludwig 2006). In fact, regulation restricts how certain government agencies collect, process, and share data on firearm ownership.⁶

We address this data availability challenge by conducting a stated-choice-based conjoint analysis. This survey instrument is popular in quantitative marketing, particularly to forecast demand for new products where no sales data is available. It allows us to estimate price sensitivity and substitution patterns between firearms at the individual level (Green and Rao 1971; Green et al. 2001; Allenby et al. 2019; Horsky and Nelson 1992). Conjoint analysis is a survey tool which presents respondents with a sequence of choices between alternative firearms. In the survey, we experimentally manipulate prices and choice sets, facilitating inferences about how respondents trade off different attributes.

There are several advantages to this type of data collection. First, the data comprise detailed individual-level choices matched with prices and respondent demographics. Second, we randomize the prices and choice sets presented to respondents, obviating the need for instruments in demand estimation. Finally, the data include information beyond first choices, such as second choices and consideration sets. The main disadvantage of conjoint is that it may not perfectly simulate a real-life choice setting; without money on the line, consumers may be overconfident in their purchase intent. To address this concern, we validate our

transactions.

⁶The 1996 Dickey Amendment mandates that “none of the funds made available for injury prevention and control at the Centers for Disease Control and Prevention (CDC) may be used to advocate or promote gun control.” PUBLIC LAW 104–208. The Tiahrt Amendment prohibits the Bureau of Alcohol, Tobacco and Firearms (ATF) from maintaining a searchable gun trace database or sharing its data with academic researchers.

estimated parameters using aggregate moments from observational data.

Our demand analysis yields three important findings. First, consumers are relatively price inelastic, but the demand for handguns is most price sensitive. Second, there is considerable cross-substitution from semi-automatic rifles and shotguns (which are often labeled “assault weapons”) to handguns, but little substitution in the reverse direction. Finally, potential first-time gun owners are more price sensitive and tend to prefer handguns more than repeat buyers.⁷

We validate our demand estimates with two sources of aggregate data: data on background checks from the National Instant Criminal Background Check System (NICS) and scraped data on prices and stock-outs from GalleryofGuns.com. Our model predicts just over 37 million gun purchases in 2020, remarkably similar to the 39.7 million background checks processed by the FBI that year.⁸ The model also predicts about 65% of gun purchases are of handguns, while in 2020 handguns accounted for 60% of background checks. Finally, our estimated price elasticities suggest that retailers may be setting prices “too low” from the perspective of single-product profit maximization.⁹ Data from GalleryofGuns.com indicates a high frequency of stock-outs, consistent with this observation.

We next turn to estimating counterfactuals. We consider an assault weapons ban, a handgun ban, and a tax that increases the price of all firearms by 10%.¹⁰ We find that an assault weapons ban would induce many consumers to substitute to handguns and would induce only a minimal reduction in the overall number of firearms sold. A handgun ban, on the other hand, would lead to a substantial shift to the outside option. The reason for this asymmetry is that many consumers who are in the market for handguns do not consider long guns at all, while many consumers that consider purchasing a long gun are also interested in buying a handgun. Finally, we estimate that a 10% price increase leads to a reduction in overall sales similar to that of an assault weapons ban, but at much lower cost in consumer

⁷For the remainder of the text, we will refer to “assault weapons” as the sum of semi-automatic rifles and semi-automatic shotguns. This label obscures some nuance, as “assault weapon” is not really a defined category of firearm, per se. Features such as the length of the barrel and the size of the stock are often invoked in laws concerning “assault weapons,” and some handguns can fall into this category, as well. For the sake of exposition, we will continue to use our less nuanced definition, but recognizing that the categorization is imperfect.

⁸Only a small share of purchasers fail their background check (approximately 0.484%). (Source: <https://www.usatoday.com/story/money/2021/02/10/this-is-how-many-guns-were-sold-in-all-50-states/43371461/>. accessed February 5, 2022.)

⁹A firearm can be viewed as a “razor” with the ammunition being the “blade.” Thus, it may be optimal for firms to mark down the razor and mark up the blade relative to the single product profit maximizing price.

¹⁰These counterfactuals naturally hold preferences fixed. This may not be realistic under more “extreme” counterfactual policies. As a result, these estimates should be viewed as a thought experiment that highlights consumers’ valuation of their guns as well as plausible outcomes under restrictions to the types of guns in question.

surplus. Further, the incidence of the reduction in sales falls disproportionately on first-time would-be gun buyers who would otherwise purchase handguns.

To put our results in context, we highlight a few gun crime and death statistics. In 2020, about 54% of gun deaths were suicides, for which handguns are used in an overwhelming majority of cases. Handguns are involved in approximately 91% of gun murders and non-negligent manslaughters for which the type of gun is noted.¹¹ Mass shootings comprise less than 1% of overall gun deaths. About 81% of mass shootings involve the use of at least one handgun and 60% of mass shootings involve only handguns.¹² Additionally, combining data from background checks, ATF traces, and average time-to-crime, we estimate that the average number of crimes traced by the ATF per background check for a prospective handgun purchase is about 7.5 times larger than for a long gun purchase.¹³ Together, these facts point to the importance of understanding how gun policies influence demand for handguns in particular.

Our estimates also allow us to compute the impacts of counterfactual policies on consumer surplus. These estimates can help us to understand the underlying economic cost of different policies to participants in the firearms markets. Additionally, these estimates may help provide context to the political and fiscal difficulties of enacting policy. As an example, we find that a handgun ban affects more consumers than an assault weapon ban, and consequently that it leads to a bigger reduction in aggregate consumer surplus; however, there is a considerable mass of handgun buyers who have very low consumer surplus losses from a handgun ban. In other words, a marginal gun owner is more likely to be a handgun buyer than a long gun buyer.

These consumer surplus numbers are also helpful in conceptualizing the potential cost of a gun buyback program. A primary challenge in regulating the gun market is that guns are durable goods; an estimated 400 million guns are in circulation in the United States, and these firearms could be transacted in secondary markets. New Zealand spent \$102.2 million on a mandatory buyback for semi-automatic firearms and military-style weapons in 2019, but we know of no estimate for the cost of a similar or expanded program in the US.¹⁴ We estimate the cost of buying back recent gun purchases, focusing on guns that our model predicts would be purchased in the next year. We find that the overall consumer valuation

¹¹<https://www.pewresearch.org/fact-tank/2019/08/16/what-the-data-says-about-gun-deaths-in-the-u-s/>

¹²<https://everytownresearch.org/maps/mass-shootings-in-america/>

¹³To our knowledge, crime statistics for assault weapons in particular are not readily available. We estimate that assault weapons comprise approximately 25% of long gun sales. An upper bound on the relative crimes traced to a prospective assault weapon compared to handgun purchase is therefore approximately 4:7.5.

¹⁴There is an ongoing debate about what share of firearms were bought back in the New Zealand program. <https://www.cnn.com/2019/12/21/asia/new-zealand-gun-buyback-intl/index.html>

of firearm ownership is quite large. Our estimates imply that averting 90% of gun sales over the next year would cost approximately \$6,499 per gun.

This paper contributes to the literature on firearms regulation by using tools from industrial organization and quantitative marketing to predict the effects of price- and quantity-based regulations in the firearms market. The existing literature largely evaluates the effects of existing policies on crime (Anderson et al. 2018; Carr and Doleac 2018; Cheng and Hoekstra 2013; Edwards et al. 2018). Related work focuses on the association between gun ownership and crime, often using variation in existing gun laws to identify effects (Duggan 2001; Helland and Tabarrok 2004; Studdert et al. 2020; Cook and Ludwig 2006; Lott and Mustard 1997). Because these studies are retrospective, they cannot speak to the effects of policies that have yet to be implemented. Additionally, none of these studies can weigh the benefits of regulation (decreased crime) against the cost (welfare of gun owners).

This paper also complements a literature on the determinants of gun demand and regulation. In particular, this strand of the literature studies the impact of crime on gun sales, including Kim (2021), Levine and McKnight (2017), Liu and Wiebe (2019), and Depew and Swensen (2019), while Luca, Malhotra, and Poliquin (2020) study the impact of mass shootings on state regulation. Our paper complements this literature by directly estimating structural demand parameters that are useful for evaluating regulation.

To our knowledge, we are the first to examine the impact of price-based regulations in the market for firearms, perhaps because excise tax variation is so limited and price data itself is scarce. Closest to our work is Bice and Hemley (2002), which estimates the elasticity of demand for the overall handgun category. Our paper goes further by estimating a full demand system, including substitution patterns across gun types, which allows us to directly evaluate price-based regulations, such as taxes. Because we use individual level data and randomly generated prices, our approach affords both flexibility and credibly-identified estimates. We also use data from a more recent time period, which is likely important for policy predictions; twenty years ago, handguns were far less popular than they are today, in both relative and absolute terms.

The paper proceeds as follows. Section 2 presents background information about the market for firearms. Section 3 describes our data. Section 4 explains the research design, including the demand model. We present demand estimates in Section 5 and counterfactual simulations in Section 6. Finally, Section 7 discusses implications.

2 Background

Firearms are typically partitioned into two categories: handguns (including semi-automatic pistols and revolvers) and long guns (including rifles and shotguns).¹⁵ The two categories differ in size. Handguns are smaller than long guns and are designed to be shot using only one’s hands, while long guns are designed to be fired from the shoulder. Within the long gun category, shotguns and rifles differ in the design of the bore; shotguns have a smooth rather than rifled bore, which reduces friction at the cost of accuracy. Within the handgun category, revolvers differ from pistols because they contain a multi-chamber cylinder that spins with each cock of the hammer. In contrast, pistols typically contain a removable magazine into which ammunition is loaded.¹⁶ We study semi-automatic firearms, where each squeeze of the trigger fires a single bullet. The sale of fully automatic firearms, which continuously fire bullets until the trigger is released (e.g., machine guns), is banned in the United States.¹⁷

Firearm sales and ownership are regulated both at the state and federal levels. Most federal regulations are focused on the individual purchasing the gun rather than the gun itself. These include the Gun Control Act of 1968, which prohibits most felons, drug users, and people found mentally incompetent from purchasing guns.¹⁸ The Gun Control Act also restricts purchases of rifles and shotguns to adults aged 18 years and older. The age requirement is 21 years for pistols and revolvers. Following the 1993 Brady Act, federally-licensed firearm dealers must contact the National Instant Criminal Background Check System (NICS) to secure background checks on prospective buyers to verify that an individual is eligible for firearm ownership. Not all gun sales are mediated by federal firearm licensees; federal law does not require licensure by casual sellers (those who sell from time-to-time out of their private collections).¹⁹ In principle, our framework can speak to these kinds of regulations targeted at individuals insofar as demand heterogeneity is predictive of the propensity to commit crimes. However, in this paper, we will primarily focus on regulations on the gun market itself.

Existing regulations on the firearms market itself are primarily enacted through state-level legislation. These include bans on specific types of firearms, licensure requirements, and mandatory waiting periods during the firearm purchase process. While now confined to

¹⁵<https://www.atf.gov/firearms/docs/guide/atf-guidebook-importation-verification-firearms-ammunition-and-implements-war/download>

¹⁶<https://www.pbs.org/wgbh/pages/frontline/shows/guns/more/faq.html>. Accessed November 22, 2021.

¹⁷There is an exception for automatic weapons manufactured before 1986. <https://www.vox.com/policy-and-politics/2017/10/4/16412910/automatic-guns-las-vegas-shooting>

¹⁸<https://www.fbi.gov/services/cjis/nics> Accessed 11/22/2021.

¹⁹<https://www.atf.gov/file/100871/download>. Accessed 11/22/2021.

seven states and the District of Columbia, assault weapons bans are a commonly proposed gun regulation, and in fact were part of federal law from 1994-2004, though previously purchased weapons were grandfathered in as legal.^{20,21} Ten states mandate a delay between the time when a buyer purchases and possesses a firearm.²² Other requirements include licensure and training. As an example, California requires gun owners to obtain a Firearm Safety Certificate. In contrast, the Idaho constitution forbids the creation of a firearm licensure system. State taxes are few: Washington state imposes a \$25 fee per firearm sale; Pennsylvania a \$3 fee; Cook County, Illinois a \$25 fee.²³

Of these types of regulations, our framework can speak directly to the effects of a hypothetical assault weapons ban or an increase in fees. Indirectly, our framework can conceptualize many of the other regulations that impose additional requirements to obtain a firearm as qualitatively similar to increasing the cost of buying a gun. Importantly, our framework permits evaluation of regulations on the market that have never been implemented.

3 Data and the Market for Firearms

We collect primary survey data in three waves, all administered by Harris Poll. First, we ran a general survey of firearm ownership and attitudes, connected with demographic information. We use this information to understand the size of the market for firearms, the motivation(s) for firearm ownership, and the prevalence of gun ownership. We call this survey our “Preliminary Survey.”

The main source of data that we use to estimate our empirical model comes from a stated-choice based conjoint (Green and Rao 1971; Green et al. 2001; Allenby et al. 2019; Horsky and Nelson 1992). The basic idea of the survey instrument is to ask respondents to select their most preferred gun among a small set of alternatives in a hypothetical purchase scenario. After each choice, the respondent is asked whether they would “buy” their preferred firearm at the given price or “leave the store.” Each respondent is given seven of these choice

²⁰While the exact definition of an “assault weapon” varies by state, it usually includes semi-automatic firearms with detachable magazines and some subset of features that facilitate rapid fire or extraordinary damage. The definition used in the now lapsed 1994 Federal Assault Weapons ban is provided here: <https://giffords.org/lawcenter/1994-aw-ban-definition/>

²¹The states that ban assault weapons are California, Connecticut, Hawaii, Maryland, Massachusetts, New Jersey, New York, and the District of Columbia. Erica Goode. The New York Times. "Even Defining ‘Assault Rifles’ Is Complicated.", Giffords Law Center.

²²States include: California (10 days), Hawaii (14 days), Illinois (3 days), Maryland (7 days for handguns), Minnesota (7 days for handguns and assault weapons), New Jersey (7 days for handguns), Rhode Island (7 days), and Washington (10 days for semiautomatic rifles). Source: Giffords Law Center, accessed November 22, 2021.

²³<https://www.rand.org/research/gun-policy/analysis/essays/firearm-and-ammunition-taxes.html>

tasks. For each task, we randomize prices and choice sets, facilitating inferences about how respondents trade off different attributes. Conjoint data is particularly helpful for the study of firearms because observational data on consumer choices in the field are extremely limited and too sparse to identify the substitution patterns that are important for policy counterfactuals.

We conducted the conjoint survey in two stages. First, we conducted a pilot conjoint on a sample of 11,089 adults residing in the US. The purpose of this pilot was to make sure that the implementation was successful and to identify any potential problems before eventually running a final survey. We call this conjoint the “Pilot.”

Finally, after making adjustments based on comments and issues in the pilot, we ran our final conjoint survey on 22,522 adults residing in the US. The survey participants are drawn from the general population of survey takers available to Harris Poll.²⁴ Of these adults, 4,018 report owning a gun, interest in buying a gun in the next twelve months, or interest in purchasing a gun more generally. Of these respondents, 2,460 are interested in purchasing in the next twelve months. Our survey comprises four sets of questions:

1. Firearm Ownership and Interest Questions: these questions probe current firearm ownership and interest in buying a firearm in the next year, such as the motivation(s) for owning a firearm, including hunting, recreation, personal or home protection, collecting, and other. Respondents who either own or are interested in buying a firearm (4,018 out of 22,522 respondents) proceed to the next set of questions. All remaining respondents move directly to step 4.
2. Firearm Consideration Questions: these questions ask whether respondents would consider purchasing pistols, revolvers, shotguns and/or rifles. Respondents can select multiple firearm types of interest.
3. Choice Questions: the survey asks each respondent to complete seven hypothetical firearm purchase tasks, each of which comprises two parts. In each task, the respondent is presented with three firearms. The respondent is first asked to choose his or her preferred firearm among the three alternatives, and then in a second step, they are asked whether they would indeed like to purchase that firearm or if they would prefer not to make a firearm purchase at this time. The three alternatives sample predominantly from the category(ies) of gun that the respondent reported that they would consider purchasing, but for each non-considered category we include a firearm

²⁴These survey takers are not necessarily fully nationally representative, but they are drawn from all regions of the United States, with considerable coverage across demographics. We currently present estimates based on an unweighted sample, but alternative weightings may be revisited.

from that category in one of the choice tasks.²⁵ We quote prices in the conjoint based on the prices advertised on `GalleryofGuns.com`, where we generate exogenous price variation by randomly adding/subtracting 0%, 20%, 50% from the average quoted price for the gun type. We describe the data from `GalleryofGuns.com` in more depth below. We model the design of the choices to mirror the user interface at `GalleryofGuns.com`. Demographic Questions: these include questions on gender, race, and region and are standard at Harris Poll. All survey takers, including those that do not take the conjoint, answer the demographic questions.

A natural concern with simulated choice data is that respondents may not state their true preferences. They might not take the survey as seriously as they would a real-life gun purchasing decision. Additionally, some respondents might bias their answers to survey questions depending on their assessment of the survey’s purpose. For the former issue, we will use aggregate moments from observational data to validate our estimates. For the latter issue, at the beginning of the survey, respondents are told that the survey is for market research, but the affiliation with the University of Chicago is not revealed until the conclusion of the survey.²⁶ Attrition might also be a threat to survey validity. However, everyone that advanced to the conjoint survey completed the conjoint. This is perhaps not surprising, as respondents do not get compensated by the survey platform unless they complete the survey.

3.1 Price Data

We scrape gun prices from `GalleryofGuns.com`, an aggregator that provides information on gun availability (both prices and retail locations) to consumers. We collect prices and model information for 520 ZIP codes in the US. Handgun data was collected between October 2020 and November 2020, and long gun data was collected between March 2021 and May 2021. A first finding is that there is relatively little price variation within model across the country; the mean within-model coefficient of variation is 0.044. Figure 1 shows the geographic distribution of prices for the Glock 43, a popular semi-automatic pistol. Roughly 87% of stores have the identical price. In contrast, there is substantial variation in the prevalence of firearm dealerships across states, as shown by Figure 2.

²⁵Naturally, respondents that indicate that they would consider all four types of firearms are only shown models that they would consider.

²⁶We were concerned that some respondents might worry that the survey is meant to inform gun legislation or to help gun manufacturers set higher prices. We therefore include a freeform question at the end of the pilot that elicits their impression of the survey’s purpose: only 2.5% of respondents give answers that reference policy or gun control. Our results using the pilot data are robust to eliminating these respondents. As a result, we ultimately think this concern is not first order.

Table 1: Distribution of Firearm MSRPs (\$) in the Conjoint Sample

	Obs.	Mean	St. Dev	Min.	1st Qu.	Median	3rd Qu.	Max.
Pistols	20	596.1	158.7	316.6	533.8	599.0	700.8	849.0
Revolvers	20	819.4	390.6	245.7	517.0	801.0	991.5	1,799.0
Rifles	20	821.3	317.5	417.0	558.2	797.2	1,002.2	1,499.0
Shotguns	20	778.1	513.9	110.0	449.7	611.0	990.8	1,999.0

Notes: For each firearm in the conjoint sample, the MSRP used was the MSRP listed on GalleryofGuns.com. If GalleryofGuns.com did not provide an MSRP for a firearm, the MSRP used was the one provided by the manufacturer on their website.

Fortunately, our demand estimation is not stymied by the limited geographic price variation, but instead relies on randomly generated price variation that is implemented in our conjoint analysis. Table 1 shows the MSRP for each type of firearm.

3.2 Auxiliary Data on Background Checks & Traces

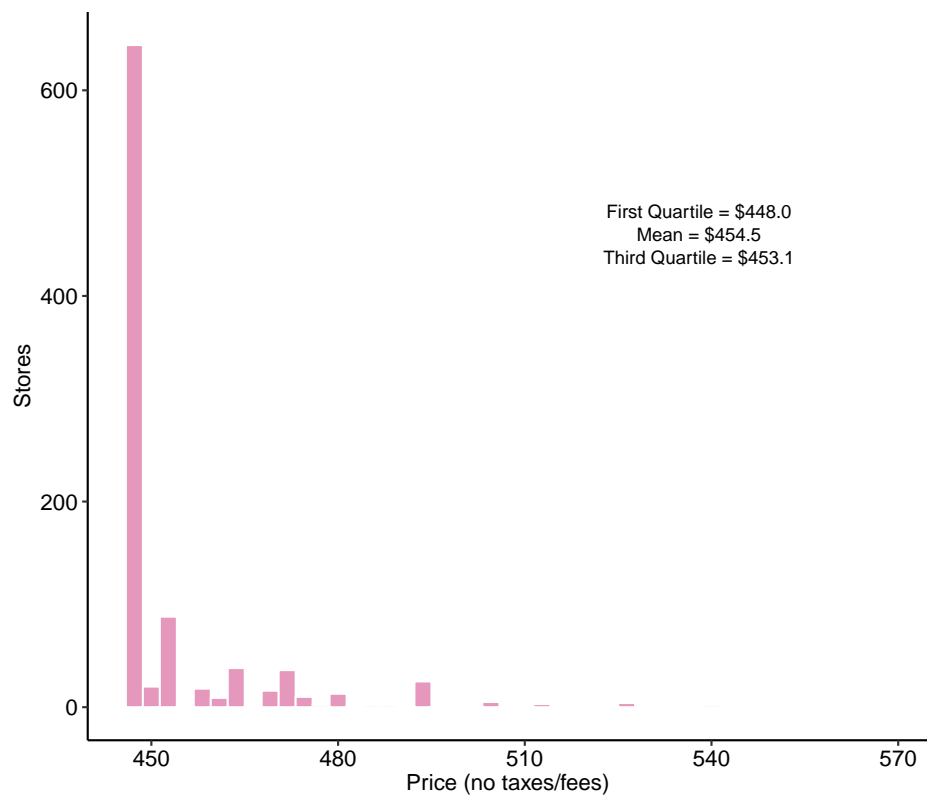
Data from our conjoint survey form the backbone of our demand estimation because observational data on quantities is limited. This limitation is due, in part, to restrictions on how government agencies collect, store, and share data on firearms. For example, Alabama requires that dealers and state agencies destroy records of firearm sales. Minnesota requires that state records be destroyed at the request of the purchaser.²⁷ There are two national datasets that speak to firearm prevalence on an aggregate level: FBI National Instant Criminal Background Check System (NICS) data on background checks and ATF data on Firearm Traces. The NICS data comprise information on background check volume by state, aggregated to the handgun or long gun category level. It does not include firearm sales by private sellers, who need not conduct a background check (those who sell from time-to-time out of their private collection and are therefore part of the secondary market for firearms).²⁸ Nineteen states use intermediate background checks, acting as a partial or full “point-of-contact,” creating a friction in the reporting and collection of NICS data; it is not clear when agencies in these states choose to use the NICS system. We are careful to account for differences in reporting when using the NICS data to validate our analysis. The ATF data provides information on the volume of firearm traces by state each year. Traces provide law enforcement agents information on a firearm’s initial point of sale based on serial number.²⁹ Thus,

²⁷Other states with restrictions include New Hampshire and Utah. Accessed November 22, 2021.<https://giffords.org/lawcenter/state-laws/maintaining-records-of-gun-sales-in-minnesota/>

²⁸<https://www.atf.gov/file/100871/download>. Accessed 11/22/2021.

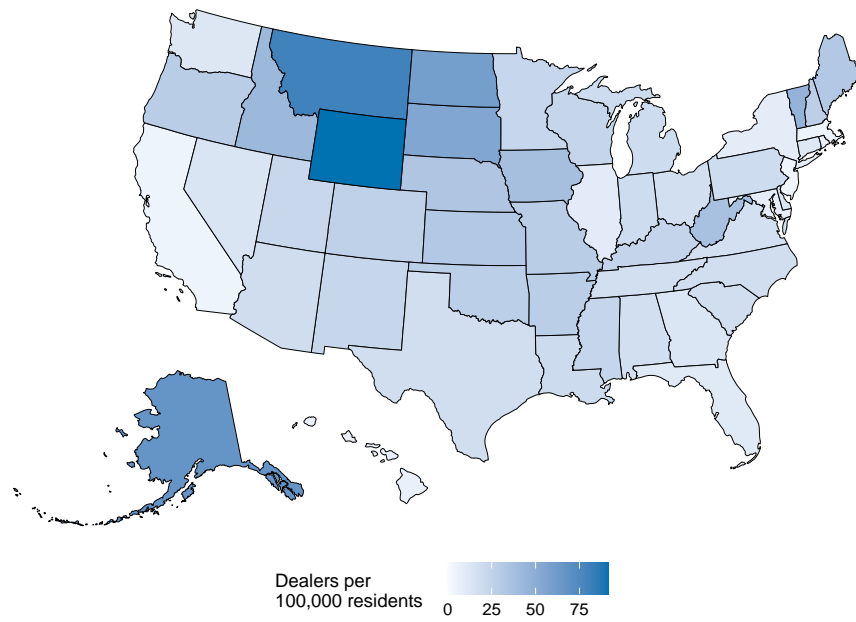
²⁹See the ATF website for more information on the National Tracing Center.

Figure 1: Distribution of Prices for Glock 43 Across Federally Licensed Dealers



Notes: The price shown excludes state-specific taxes and fees.

Figure 2: Map of Federally-Licensed Gun Retailer Locations



Notes: Based on the locations of federally-licensed dealers operating as of January 2022.

traces speak to the types of weapons involved in crime rather than to the broader market for firearms.

3.3 Survey Results on Gun Ownership and Attitudes

Our preliminary survey reveals that firearms ownership and interest is pervasive: 29% of respondents own a gun, 43% live in a household with a gun, and a further 41% of respondents who do not currently own a firearm report that they would consider buying one in the future.³⁰ Appendix Figure 8 shows the distribution of firearm ownership among households that own at least one firearm; the majority of these households contain multiple firearms. Table 2 gives a sense for the demographics of survey respondents and gun owners in the final conjoint survey. We find that women are less likely to own a gun than men. Baby boomers are the most likely generation to own a gun, though younger generations are more likely to be newly interested gun buyers. The latter point is natural; relative to an older individual interested in gun ownership, a younger individual has had fewer opportunities to purchase a first gun. Gun ownership is lowest in the Northeast compared to other regions. We note, however, that this heterogeneity is modest. The motivation for firearm ownership is also similar across respondents: more than 80% report personal or home protection as a reason to purchase a gun. Other motivations include recreation (45%), hunting (27%), and collecting (22%).

³⁰Note this matches very closely with numbers from Gallup 2020.

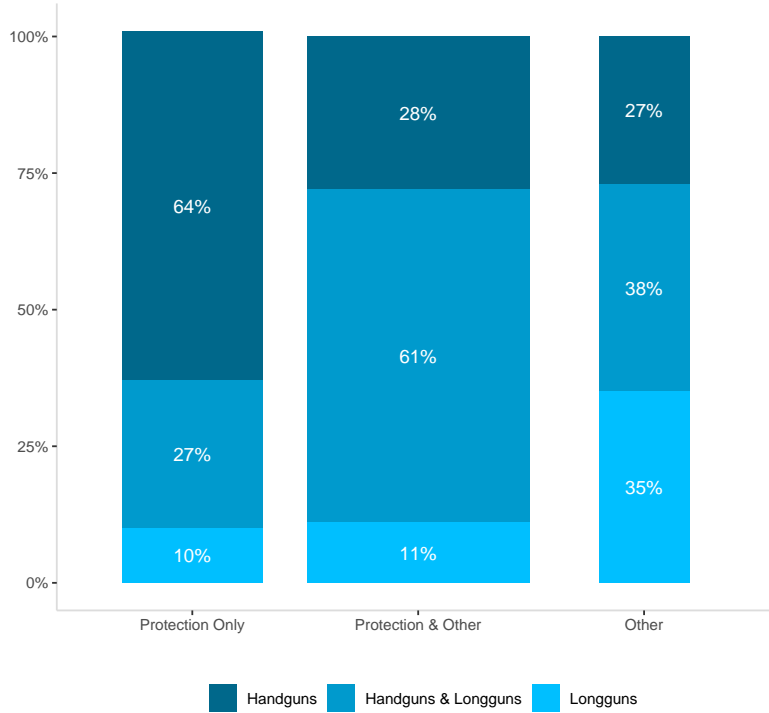
Table 2: Descriptive Statistics: Survey Respondents and Current and Prospective Firearm Owners

Demographic	Share of Respondents (%)			
	Full Sample	Conjoint Takers	Owners	New Buyers
Age				
Boomer	35.01	33.05	36.49	25.28
Silent	6.17	4.18	5.20	2.19
Gen X	22.67	25.54	25.62	25.58
Millennial	26.38	28.72	27.49	32.30
Gen Z	9.77	8.51	5.20	14.64
Gender				
Male	36.92	48.13	57.37	32.75
Female	63.08	51.87	42.63	67.25
Income				
Above 100K	21.31	21.18	24.13	16.23
50K to 100K	33.19	37.28	40.09	31.32
Below 50K	45.50	41.54	35.78	52.45
Education				
Less than HS	4.69	3.33	2.58	4.68
HS degree	58.48	65.28	61.91	71.32
4-year college	36.83	31.38	35.51	24.00
Region				
South	38.95	45.12	47.48	41.21
West	18.52	17.15	16.39	18.94
Northeast	20.14	14.04	13.34	14.94
Midwest	22.39	23.69	22.80	24.91
Obs.	22,522	4,018	2,557	1,325

Notes: Data from the final survey. Conjoint-takers (N=4,018) comprise individuals who indicated that they own or are interested in owning a firearm. Of this group, 66 later indicated that they neither owned nor were interested in owning, and nine non-owners provided no information on future purchases.

Handguns are more popular than long guns, with 85% of respondents indicating that they would consider purchasing a handgun, but only 61% indicating interest in a long gun. Of respondents considering the purchase of a long gun, 69% are interested in sport and hunting, although 62% also report interest in purchasing a handgun and list protection as an additional motivation. Figure 3 shows the overlap in interest across different firearm types; few consumers are interested in long guns alone, and most would at least consider purchasing a pistol. These patterns suggest meaningful variation in substitution across different types

Figure 3: Interest in Firearm Types (Final Survey)



of firearms and motivate our use of a limited consideration model of demand.

4 A Model of Firearm Purchasing

We model consumer preferences for firearms with a random utility model with limited consideration. We model the utility that consumer i receives from purchasing product j on purchase occasion $t \in \{1, \dots, 7\}$, where a purchase occasion corresponds to a task in our conjoint survey:

$$\begin{aligned}
 u_{ijt} &= X_j' \beta_i - \alpha_i \cdot p_{ijt} + \epsilon_{ijt} \\
 u_{i0t} &= 0
 \end{aligned}
 \tag{1}$$

where p_{ijt} is the price of firearm j for consumer i on occasion t , X_j is a vector of product characteristics, including gun type fixed effects and brand fixed effects, α_i (which we constrain

to be positive) captures consumer i 's price disutility, β_i captures consumer i 's taste for characteristics, and ϵ_{ijt} is an individual-firearm-occasion specific taste shock that we assume is distributed extreme value type I. We normalize the utility of the outside option to zero, which in this case refers to declining to buy a firearm on this purchase occasion. The probability that a consumer with taste parameters (α_i, β_i) selects product j on purchase occasion t where the set of alternatives is C_t (including the outside option) is:

$$s_{ijt} = Pr\{u_{ijt} \geq u_{ikt}, k \in C_t\} = \frac{\exp(X_j' \beta_i - \alpha_i \cdot p_{ijt})}{\sum_{k \in C_t} \exp(X_k' \beta_i - \alpha_i \cdot p_{ikt})}.$$

As described in section 3.3, consumers often do not consider all types of firearms. Many only consider purchasing pistols and revolvers, for example. We incorporate this consumer tendency into our model in two different specifications. First, and as a base case, we assume that consideration sets are exogenous. Consumers have immutable “types,” and some types simply have no use for certain kinds of firearms. For example, a consumer type could be related to use cases, so that a possible type could be someone who enjoys hunting large game, such as deer. Such a consumer type would not consider purchasing a revolver because revolvers are insufficiently powerful and accurate at longer distances for hunting deer. In this case, we assume that non-consideration of a category is not the outcome of a search process. Rather, consumers know that non-considered firearm categories will not satisfy their needs. In this base model, consideration sets do not change in counterfactual simulations.

Second, we augment the model by assuming that consideration sets are the outcome of a consumer search process. We adopt an approach similar to Honka (2014) and incorporate a search friction γ_i that consumer i must pay to evaluate the alternatives in each firearm class; that is, we assume that consumers know their tastes for each class of firearms β'_i , but that they must incur cost γ_i to explore a category (i.e., they incur γ_i to learn their idiosyncratic match ϵ_{ijt} for all models in the category). In estimation, we impose a sign restriction on γ_i so that it is weakly positive for all consumers. A real-world analog to this data-generating process is one where consumers select a retailer based on their tastes and expectations of the retailer’s assortment. For example, a hunting enthusiast looking to buy a shotgun might shop at a BassPro store. That is, this model takes seriously the intuition that retail assortments are endogenous to consumer tastes for firearms.³¹

The consumer chooses a consideration set based on the incremental expected utility from each category, or the inclusive value (IV). Given the logit error structure, the IV for category l for individual i can be expressed as:

³¹We incorporate this DGP into our conjoint design by drawing the firearm options from the categories for which the respondent indicates interest.

$$IV_{il} = \ln \left[\sum_{k \in l} \exp(X'_k \beta_i - \alpha_i \cdot \bar{p}_k) \right].$$

It follows that each consumer that participates in the in the market will choose one of the four consideration sets: their most preferred category, their most and second-most preferred categories, all-but-least-preferred category, and all categories. This model of consideration also implies that the minimum IV of the categories searched is higher than the maximum of the IV of the categories that are not considered. Let l_i be consumer i 's consideration set. The model implies the following constraints on the consideration set selected by a consumer with preferences (α_i, β_i) and search cost γ_i :

$$\ln \left[\sum_{k \in l} \exp(X'_k \beta_i - \alpha_i \cdot \bar{p}_k) \right] \geq \ln \left[\sum_{k \in l+1} \exp(X'_k \beta_i - \alpha_i \cdot \bar{p}_k) \right] - \exp(\gamma_i) \quad (2)$$

$$\ln \left[\sum_{k \in l} \exp(X'_k \beta_i - \alpha_i \cdot \bar{p}_k) \right] - \exp(\gamma_i) \geq \ln \left[\sum_{k \in l-1} \exp(X'_k \beta_i - \alpha_i \cdot \bar{p}_k) \right] \quad (3)$$

$$\min_{c \in l} \ln \left[\sum_{k \in c} \exp(X'_k \beta_i - \alpha_i \cdot \bar{p}_k) \right] \geq \max_{\tilde{c} \notin l} \ln \left[\sum_{k \in \tilde{c}} \exp(X'_k \beta_i - \alpha_i \cdot \bar{p}_k) \right] \quad (4)$$

Inequalities (2) and (3) stem from revealed preference: the respondent who elects to consider n categories must do weakly worse if they consider one more/fewer categories. Inequality (4) concerns the identity of the categories considered: the worst category considered must be weakly preferred to the best category of firearms that is not considered, otherwise switching the two categories would increase expected utility.

Turning back to the base model, we specify the likelihood that respondent i was shown the set of alternatives C_t on choice occasion t . Because the conjoint task randomly selects models from the categories selected by each respondent, the likelihood of any particular draw of models on occasion t is simply:³²

$$Pr\{C_{it}|l_i\} = \binom{|l_i|}{3}.$$

We then have all components necessary to construct likelihood that consumer i selects prod-

³²For the base model, we exclude tasks where the respondent was shown a firearm model outside of their selected consideration set. Appendix Section D describes how this term is adjusted when we estimate the search cost model to account for tasks where the respondent is shown a firearm model that was not in their reported consideration set.

uct j on purchase occasion t given taste parameters θ_i :

$$Pr\{y_{it}|\theta_i\} = s_{ijt} \cdot Pr\{C_t|l_i\} \cdot 1\{l_i|\theta_i\} \quad (5)$$

where $1\{l_i|\theta_i\}$ is an indicator that inequalities (2) - (4) hold (this indicator is only included for estimating the extended model).

Finally, we allow for both observed and unobserved heterogeneity in the taste for firearms. We allow demographic groups to differ in their taste for different types of firearms: revolver, pistol, rifle, and shotgun.³³ The demographics include gender, three income brackets ($< \$50k$, $[\$50k, \$100k)$, $\geq \$100k$), four regions, an indicator for completing college, and current employment status. We also allow price sensitivity and search costs to vary across these demographics, Z . We model

$$\begin{aligned} \theta_i &= \Delta' z_i + u_i \\ u_i &\sim MVN(\mu, V_\theta) \end{aligned}$$

so that the matrix Δ governs differences in taste across observable characteristics and V_θ the degree of unobserved heterogeneity. We constrain the coefficient on price to be negative by modeling θ_i^{price} as normally distributed and letting the the price coefficient from equation (1) $\alpha_i = -exp(\theta_i^{price})$.

4.1 Estimation

Estimation proceeds via Bayesian MCMC using Metropolis-in-Gibbs sampling following Rossi, Allenby, and McCulloch (2005). The exact procedures for both the base and search cost models are provided in Appendix C.

4.2 Identification

There are four sources of variation in our data that jointly inform the model parameters. The main sources of variation are:

1. Variation across consumers in product choice varying choice sets but holding prices fixed.

³³Within gun types, we further specify subtypes that categorize the firearms into similar vertical quality buckets and give those subtypes their own intercepts.

2. Variation across consumers in product choice varying prices but holding choice sets fixed.
3. Variation within consumer in product choices across choice occasions (conjoint tasks) as both prices and choice sets change.
4. Variation across consumers in consideration set choices.

Variation in (1)-(3) is exogenous because prices and choice sets are randomized both across consumers and within consumer across choice occasions. Variation in consideration sets (4) alone does not non-parametrically pin down the search cost parameter, so we show respondents a firearm from each “non-considered” groups in at least one choice occasion. This provides independent variation to separately identify α , β , and γ .

5 Demand Estimates

5.1 Base Model Estimates

Our primary estimates are based on the simpler base version of the demand model in Section (4) that treats consideration sets as exogenous (hence we do not estimate a distribution of search costs).³⁴ We map the model to data by assuming that each task comprises a decision to purchase either one among the three firearms presented in the task or the outside option of not purchase, in which case the consumer earns zero utility.

Table 3 presents estimates of the posterior means and standard deviations of the demand parameters. Turning first to the posterior mean of the coefficient for each gun type, we see that pistols are most desirable, followed by semi-automatic rifles and shotguns (assault weapons), and then non-semi-automatic rifles. For tractability, in lieu of presenting eighty model-level elasticity estimates, we report the median model-level elasticity by group in column 5. Across all models, own price elasticities are small in magnitude, but are largest for pistols and revolvers. Consumers appear to be quite price insensitive. This pattern suggests that firms are underpricing relative to the monopoly benchmark, although it could reflect a two-part tariff (e.g., razors-and-blades) approach to pricing guns and ammunition (Schmalensee 1981). The pattern also suggests that price-based regulations may have minimal effect on overall gun sales or relative gun shares, although that also depends on cross-price elasticities.

³⁴We are in the process of estimating the richer model including search and will update this draft accordingly.

Table 3: Estimates of Demand Parameters, Elasticities, & Market Shares

	Estimated Parameters				Estimated Model Implied	
	Posterior Mean	SD	2.5%	97.5%	Own-Price Elasticity	Market Share
Price	-0.013	0.022	-0.077	-0.000	–	–
Revolver	0.824	1.211	-1.610	3.109	-1.134	15.134
Pistol	1.888	1.205	-0.663	4.047	-1.046	37.336
Rifle	0.887	1.038	-1.267	2.727	-0.871	7.482
Shotgun	0.342	0.982	-1.718	2.157	-0.979	9.168
Assault Weapon	1.151	1.222	-0.956	3.478	-0.747	11.396
Outside Option	–	–	–	–	–	19.484

Notes: Reported own-price elasticities are the median within each category. A separate intercept is estimated for each individual and sub-type of rifle, shotgun, and revolver. The posterior means shown in this table are the average of these estimates. For example, the ‘Rifle’ estimate is the mean of the individual estimates for bolt, lever, pump, and single-shot rifles.

Table 4 describes heterogeneity in the demand for firearms by demographic group. Recall that our specification allows for the price coefficient, brand intercepts, and gun type intercepts to differ at the individual level. Appendix Table 9 presents estimates of the price coefficient and pistol intercept by demographic group. Table 4 illustrates how this flexibility translates to differences in estimated market shares across groups. One salient difference is the interest in assault weapons between men and women; at current market prices, the share of men who would purchase an assault rifle is more than twice as high as the share of women who would purchase an assault weapon. Conversely a higher share of women would purchase a handgun. Note that these estimates do not imply that more women purchase handguns than men because these shares comprise shares conditional on the market definition (i.e., gun owners or those interested in buying a gun). Thus, Table 4 shows that conditional on being in the market, demand is relatively similar across region, education, and income. Where we do see a meaningful difference across income groups is in the predicted share of the outside option: higher incomes are associated with a higher inside share. This pattern is unsurprising as consumers with higher incomes ought to be less price sensitive.

Table 4: Estimated Market Shares by Demographic

Demographic	Revolver	Pistol	Rifle	Shotgun	Assault Weapon	Outside Option
Gender						
Female	17.88	38.47	6.26	7.38	7.41	22.59
Male	12.17	36.11	8.80	11.09	15.69	16.13
Income						
Below 50K	15.64	36.78	6.93	9.43	10.07	21.16
50K to 100K	15.27	37.57	7.13	8.90	11.54	19.60
Above 100K	13.91	38.02	9.20	9.14	13.75	15.99
Region						
South	15.01	38.46	6.87	9.10	11.86	18.71
Midwest	15.28	36.69	8.45	8.08	10.11	21.39
West	15.56	36.70	7.96	9.34	12.22	18.23
Northeast	14.76	35.60	7.24	11.01	11.08	20.31
Education						
HS and below	15.37	37.93	7.32	8.76	11.18	19.44
College	14.61	36.04	7.84	10.05	11.86	19.59

Notes: This table reports estimated market shares separately by demographic group. The shares across each row sum to 100

We focus next on prospective first-time gun owners, defined as respondents who do not already own a firearm. This sample is more price sensitive and has a higher relative preference for handguns compared to the overall sample. Regulators may be particularly interested in understanding the preferences of these buyers if the incremental risk of gun-related violence is greatest when a household purchases its first firearm compared to when it buys a second, third, fourth, etc, firearm.

Table 5: Estimates of Demand Parameters, Elasticities & Market Shares for First-Time Buyers

	Estimated Parameters				Estimated Model Implied	
	Posterior Mean	SD	2.5%	97.5%	Own-Price Elasticity	Market Share
Price	-0.014	0.023	-0.080	-0.000	–	–
Revolver	0.852	1.209	-1.510	3.143	-1.186	17.318
Pistol	1.978	1.172	-0.538	4.080	-1.070	40.094
Rifle	0.899	1.034	-1.387	2.711	-0.791	8.363
Shotgun	0.278	0.989	-1.848	2.120	-0.927	5.830
Assault Weapons	1.120	1.180	-0.915	3.474	-1.076	7.534
Outside Option	–	–	–	–	–	20.861

Notes: Reported own-price elasticities are the median within each category. A separate intercept is estimated for each individual and sub-type of rifle, shotgun, and revolver. The posterior means shown in this table are the average of these estimates. For example, the ‘Rifle’ estimate is the mean of the individual estimates for bolt, lever, pump, and single-shot rifles.

We turn next to substitution. Diversion ratios and cross-price elasticities are presented in Figure 4, which present heat maps describing category-level substitution patterns. Panel (a) displays diversion ratios. Entries across the top are darker in color and are larger. This shading indicates that as consumers substitute away from other models, they are very likely to substitute towards pistols and revolvers. Notably, substitution away from assault weapons is much more likely to go towards pistols or other assault weapons rather than to the outside option. Panel (b) displays cross-price elasticities. Entries on the diagonal are larger, which indicates that cross-price elasticities are higher among models of the same category. Cross-price elasticities from other models to pistols tend to be small because the share of pistols is large, making it difficult for a smaller share category to move the pistol share much. The substitution patterns suggest that regulation targeting assault weapons may induce considerable substitution to pistols while inducing little substitution to the outside option. We explore this counterfactual in Section 6.

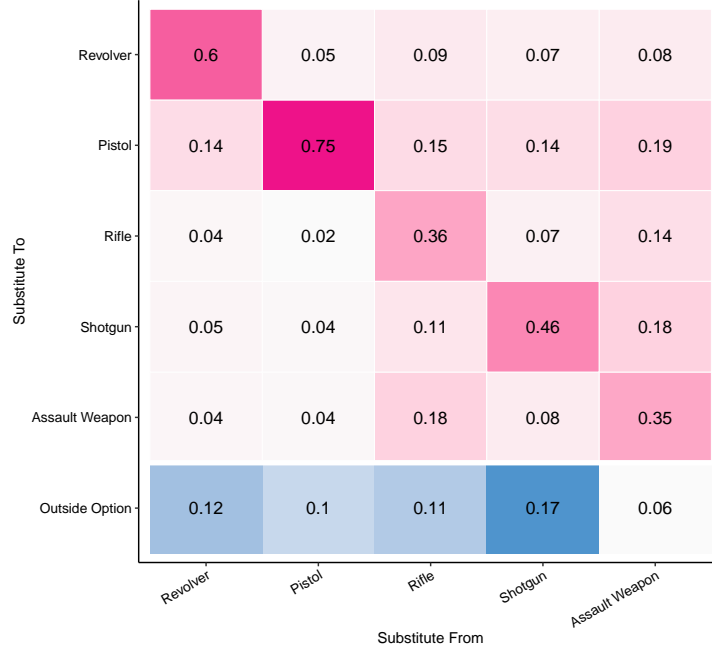
5.2 Validation

As a joint test of the conjoint experiment and demand model, we compare predictions from our estimated demand model to external observational data from several sources.

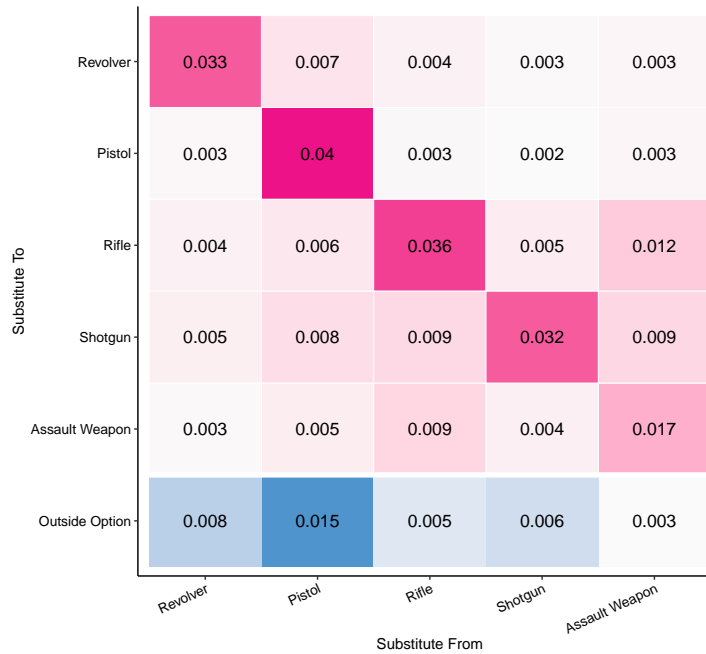
First, we show that our predicted aggregate quantity demanded is similar to observed sales as proxied by background checks. We estimate, \hat{p} , the average firearm purchase probability at MSRPs in 2021 (from `GalleryofGuns`) among respondents who indicate interest in firearms. Implied national gun sales based on data from the pilot are $4,018/22,522 \times 0.805 \times 258.3$

Figure 4: Diversion Ratios & Cross Price Elasticities for Firearms

(a) Diversion Ratios



(b) Cross Price Elasticities

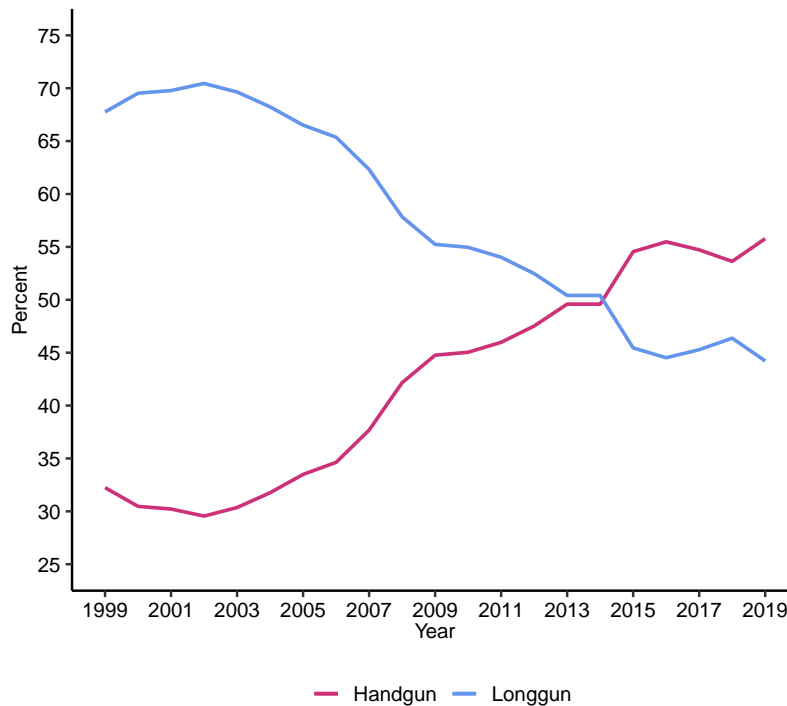


Notes: These figures provide heat maps describing diversion ratios and cross-price-elasticities. Each square is the mean diversion ratio or cross-price elasticity within that category. For example, the top right square in the left panel describes the average of the diversion ratios of each side-by-side shotgun to each pistol.

million \approx 37.1 million, which is similar to the number of background checks conducted in the 2020, approximately 39.7 million.³⁵

Second, we compare our predicted market shares of handguns (pistols and revolvers) versus long guns to the observed share of background checks. The estimated model-implied market share for handguns is approximately 65%, which is close to the observed share of background checks that are for handguns, which is shown in Figure 5.

Figure 5: Share of NICS Background Checks for Long guns and Handguns over Time



Notes: We exclude nineteen states that serve as partial or full "point-of-contact" states for NICS-reporting purposes from the data presented in this graph. The following states are excluded: California, Colorado, Connecticut, Florida, Hawaii, Illinois, Maryland, Nebraska, Nevada, New Hampshire, New Jersey, North Carolina, Oregon, Pennsylvania, Tennessee, Utah, Virginia, Washington, and Wisconsin.

Third, our model estimates imply firms under-price relative to a monopoly benchmark. If our model estimates are correct, we would predict stock-outs in observational data if inventory is fixed in the short term. Alternatively, it could be that our conjoint elicitation of preferences fails to generate honest trade-offs with price. We find evidence of the former, as stock-outs are frequent in our **GalleryofGuns** data: on average, 62% (50%) of the handgun

³⁵<https://www.businessinsider.com/gun-sales-boom-2020-background-checks-hit-record-highs-2021-1>

(long gun) models available within a county in October (March) were out of stock by the end of November (May).

6 Counterfactuals

We study three counterfactual firearm regulations to illustrate the scope for structural demand analysis to contribute to the policy debate. First, we consider a current policy proposal in Congress: a federal ban on assault weapons. Such a ban was in effect between 1994-2004, and a renewal of the ban was most recently introduced by Rep David Cicilline as H.R. 1808 in 2021.³⁶ We simulate an assault weapons ban by removing all semi-automatic rifles and semi-automatic shotguns from consumers' choice sets (eight of the eighty firearms included in the conjoint survey). We also consider two policies that have received less attention in policy circles: a tax that raises the price of all guns by 10%³⁷ and an outright ban on handguns.³⁸ While banning handguns has not been seriously discussed at the federal level in the United States, other countries such as Canada have recently banned handgun sales.³⁹ Further, this exercise remains informative as to the likely directional impacts of a more modest restriction on handguns or a tax directed specifically at handguns, for example. For each counterfactual, we first calculate both the implied change in the number of firearms sold, which is a function of how consumers substitute across different firearm types and the outside option of not buying a firearm. These estimates are of first-order importance for regulators hoping to reduce firearm-related injuries and deaths by reducing the number of guns sold. Second, we calculate the expected compensating variation under alternative firearm regulations. Again, these estimates are informed by respondents' price sensitivity and substitution patterns in our conjoint survey. These estimates may be considered important in their own right, but can also be helpful in two other respects. First, estimated compensating variation can be informative about the potential cost of a gun buyback program focused on recent purchasers. Second, the estimates may shed light on the political feasibility of candidate regulations, allowing policymakers to pinpoint regulations that accomplish policy aims at a low cost in

³⁶The text of the proposed ban can be found here: <https://www.congress.gov/bill/117th-congress/house-bill/1808/text>.

³⁷Since 1919, Congress has levied an excise tax on firearms that ranges from 10-11% depending on the firearm type (The Bureau of Alcohol, Tobacco, Firearms, and Explosives <https://www.atf.gov/firearms/firearms-guides-importation-verification-firearms-ammunition-and-implements-war-firearms>).

³⁸For each of these counterfactuals, we hold preferences fixed. To the extent that policies may change preferences (e.g., if a handgun ban increased the intercepts associated with assault weapons), our counterfactuals will be biased. That being said, they remain a useful starting point.

³⁹Giulia Heyward, "Trudeau orders an immediate freeze on the sale of handguns in Canada," NPR, October 21, 2022. <https://www.npr.org/2022/10/21/1130608885/justin-trudeau-canada-handgun-sales-freeze>

consumer surplus. More broadly, this framework can be adapted to objective functions that put differential weight on consumer surplus and the externalities associated with firearm sales.

Our main estimates of consumer surplus do not incorporate logit draws. Our choice is motivated by the well-known concern that in markets with many products, incorporating these draws mechanically yields large estimates of consumer surplus. Following Petrin (2002), we proceed under the assumption that the consumer chooses a product to purchase based only on the deterministic part of their utility function. We implement this method by integrating over the posterior distribution of preference parameters for each type of consumer. A limitation of this approach is that ignoring the logit draws may understate the importance of horizontal differentiation in the market for firearms. Therefore, we also report estimates of consumer surplus that incorporate logit draws in Appendix 10.

There are important limitations to our counterfactual analysis. While our estimates are not definitive, we believe they are nonetheless informative. Our analysis provides a ballpark estimate of the impacts of regulation on the number and types of guns in circulation and a prediction of the types of buyers most affected by different regulations.

The principal limitation of our analysis is that it does not incorporate general equilibrium effects of policy changes on consumer preferences or supply side reactions. For example, the value of gun ownership for some consumers may depend on the ownership rates of others in their community. Ehrlich and Saito (2010) model this relationship as one where gun ownership affects crime rates and thus the demand for protection via guns.⁴⁰ If consumers value guns less in an environment where gun ownership rates are lower (either through the crime channel or social influence channel), then our analysis would over-estimate consumer surplus losses under tighter gun purchasing regulations.⁴¹ Conversely, tighter regulations on gun purchasing could increase the value of existing firearms. An increase could occur if consumers directly value being one among only a few people who own a firearm or if regulations increase secondary and/or black market prices, worsening the outside option and leading us to understate true consumer surplus losses. Equilibrium effects can also operate through supply-side responses. As an example, under a counterfactual handgun ban that diverts demand to long guns, firms may raise prices for long guns, further reducing gun sales and consumer surplus. As these examples illustrate, our estimates are not unequivocal and therefore should not be taken as the last word on gun policy. Rather, they provide a baseline

⁴⁰One market where this type of demand function has been studied is the market for light trucks (Li, 2012).

⁴¹One way to test this hypothesis would be to study the gun purchases of households following a move from a low- to high- gun ownership community or vice versa. Unfortunately, our dataset does not contain information on migration patterns.

set of predictions that can inform our collective priors. We hope these kinds of estimates will be refined in future work.

Table 6: Market Shares under Alternative Policy Proposals

		Market Share (%)		
		Handgun	Long Gun	None
All	Assault Weapons Ban	57.25	22.47	20.27
	Handgun Ban	0	49.45	50.54
	10% Price Increase for All Guns	51.60	27.67	20.73
New Buyers	Assault Weapons Ban	61.27	17.28	21.45
	Handgun Ban	0	40.46	59.54
	10% Price Increase for All Guns	56.39	21.4	22.21

Notes: Market shares computed with estimated demand parameters while implementing the counterfactual policy. Prices are assumed to be held fixed in the gun ban counterfactuals.

Table 6 presents results of our counterfactual simulations. We find that the first order effect of an assault weapons ban is to shift purchases to handguns; in a counterfactual simulation without assault weapons, only 0.79% of consumers switch to the outside option. This finding highlights the potential pitfall of considering quantity regulations in a vacuum. Because handguns are involved in more crimes and deaths than assault weapons, banning assault weapons could potentially increase gun deaths, acting counter to the intention of the regulation.

A tax that increases the price of all guns by 10% also has modest effects, reducing the overall probability of firearm purchase by only 1.25 percentage points. While this estimate suggests that taxation may not substantially reduce demand for firearms, it also suggests that such a tax may be useful for revenue generation. Because first-time gun buyers are more price sensitive than those consumers who already own a firearm, a tax would have a relatively larger impact on their purchases.

Finally, we consider a hypothetical handgun ban.⁴² Such a ban induces a massive shift of consumers to the outside option of not buying a gun. This result comes directly from the fact that a large fraction of consumers exclusively consider handguns, so that removing them from

⁴²While a handgun ban is not under active consideration in any notable localities, evaluating the effect of a hypothetical handgun ban provides insight into how much consumers value these products as well as how relatively efficient removing handguns from the market could be versus the more popularly proposed assault weapons ban.

the market leaves those consumers no alternative but the outside option. We note that while our base model does not allow consideration sets to adjust in counterfactual simulations, in reality some consumers might choose to consider other gun types in the event of a regulation such as a handgun ban. As a result, these results can be thought of as an upper bound on substitution to the outside option and consumer surplus loss. In Appendix D, we extend our model to allow for changes in consideration sets under counterfactual regulations and find that they are relatively modest. This finding is in line with simple descriptives from the conjoint responses. In 27.5% of choice tasks ($N = 7,746$), we include a model from a “non-considered” class of firearms. On these choice occasions the model from the “non-considered” group is quoted at the average quoted price for a gun of its type, while the two models from the “considered” group are quoted at 50% above the average quoted price for their respective gun types. Respondents seldom select the “non-considered” alternative as their most preferred option (13.3% choice probability).⁴³

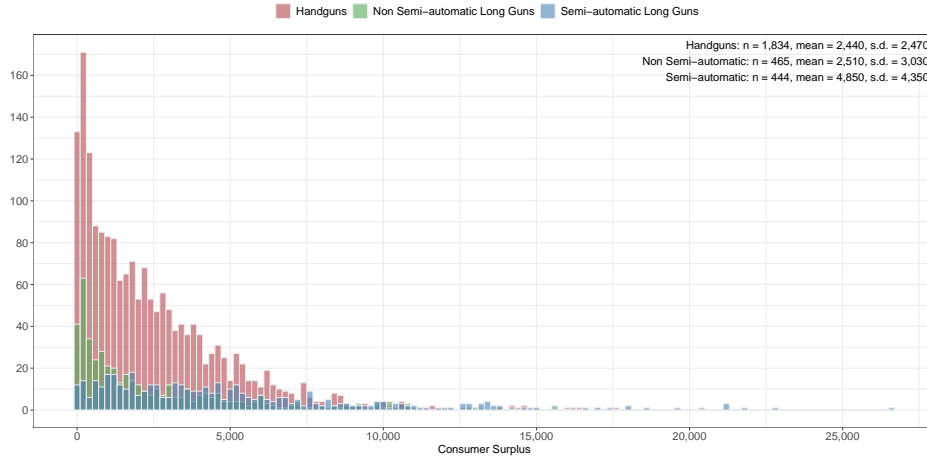
Our demand estimates can also be used to estimate consumer surplus, which we do by disregarding the logit draws, but integrating over draws from the full posterior distribution of the preference parameters. Figure 6a presents a histogram of consumer surplus under the status quo for respondents in our sample. A first observation is that the consumer surplus associated with firearms is high. The Figure also gives a sense for the types of guns that consumers value. Consistent with the market shares Table 3, the number of respondents who enjoy positive consumer surplus from handgun purchases is higher than for long guns. However, most handgun purchases confer relatively modest levels of consumer surplus. In contrast, semi-automatic long gun purchases are associated with a more diffuse distribution consumer surplus. In other words, the total consumer surplus associated with semi-automatic long gun purchases is smaller than for handguns, but the per-purchase surplus is higher. This point is further illustrated in the companion Figure 6b, which plots the density of consumer surplus separately by gun type.

Table 7 presents our estimates of consumer surplus for each counterfactual policy proposal. Removing access to handguns leads to a \$4,184 loss in surplus for the average consumer in the firearms market, while removing access to assault weapons leads to a reduction in surplus of \$1,507. The handgun estimates are so large in part because handguns are the most popular guns (so the hypothetical ban forces more changes), and also because the next best

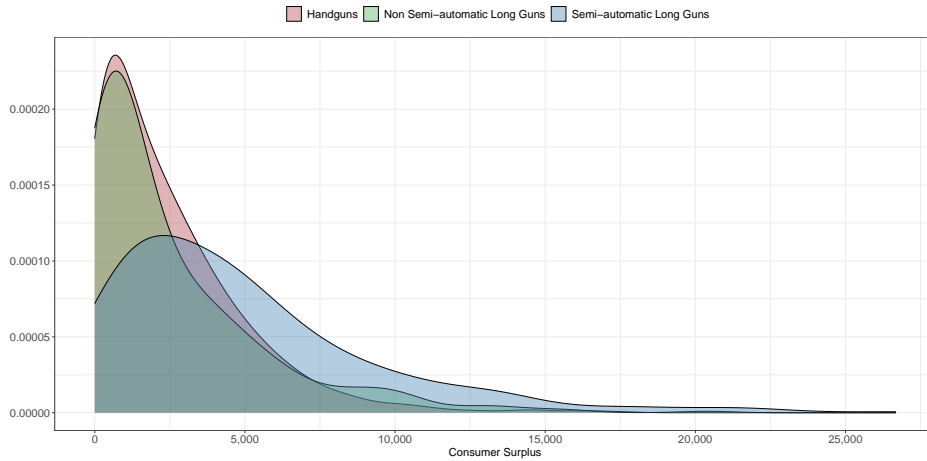
⁴³The total number of choice tasks was 28,126. For each non-considered category, a respondent is shown one task that includes a firearm from that category. As a result, a respondent who only considers a single firearm type is shown more choice tasks with non-considered firearms than a person who considers more than one.

Figure 6: Consumer Surplus by Gun Type

(a) Histogram across All Gun Types



(b) Density Separately by Gun Type



Notes: Consumer surplus is calculated by disregarding the logit draws, but integrating over draws from the full posterior distribution of the preference parameters.

alternative for a large fraction of those who choose handguns is the outside option (many consider handguns exclusively). The assault weapons ban directly affects the choices of fewer people (if a consumer does not consider assault weapons, removing them from the market does not affect his or her consumer surplus), and most consumers who consider assault weapons also consider other types of firearms, so their consumer surplus loss is somewhat mitigated.

Compared to an assault weapons ban, a tax that increases the price of all guns by 10% averts more gun purchases overall at a drastically smaller cost to consumer surplus. The lower cost in terms of surplus is by design. A price increase averts purchases from marginal consumers, precisely those who have the lowest consumer surplus. Meanwhile, the assault weapons ban would avert purchases from some individuals who have a very high willingness to pay for assault weapons, inducing large consumer surplus losses. Further, under an assault weapons ban, many of those who would otherwise purchase assault weapons instead purchase handguns. This substitution does not decrease the total number of guns, but still substantially reduces consumer surplus because these consumers are no longer able to purchase their most-preferred gun. Finally, because we estimate that new-to-category buyers have higher price sensitivity and a stronger preference for handguns, we find that a tax would avert more purchases specifically from first-time buyers.

Table 7: Consumer Surplus under Alternative Policy Proposals

	Distribution of Consumer Surplus (\$)						Mean MSRP
	Median	Mean	Min.	1st Qu.	3rd Qu.	Max.	
Assault Weapons Ban							
All	-20	-1,507	0	0	-680	-85,647	
If Considered	-367	-2,468	0	-44	-2,117	-85,647	1,066
If Chose	-6,342	-9,489	-122	-3,215	-12,040	-85,647	
Handgun Ban							
All	-976	-4,184	0	-39	-4,669	-74,901	
If Considered	-1,683	-4,942	0	-243	-5,783	-74,901	708
If Chose	-4,897	-8,336	-70	-2,044	-10,801	-70,049	

Notes: Consumer surplus is calculated by disregarding the logit draws, but integrating over draws from the full posterior distribution of the preference parameters. "If Considered" provides the distribution of consumer surplus loss for those consumers who considered the gun category in question. "If Chose" provides the distribution of consumer surplus loss for those consumers who, at their mean posterior preference parameters, choose the gun category in question absent the hypothetical restriction.

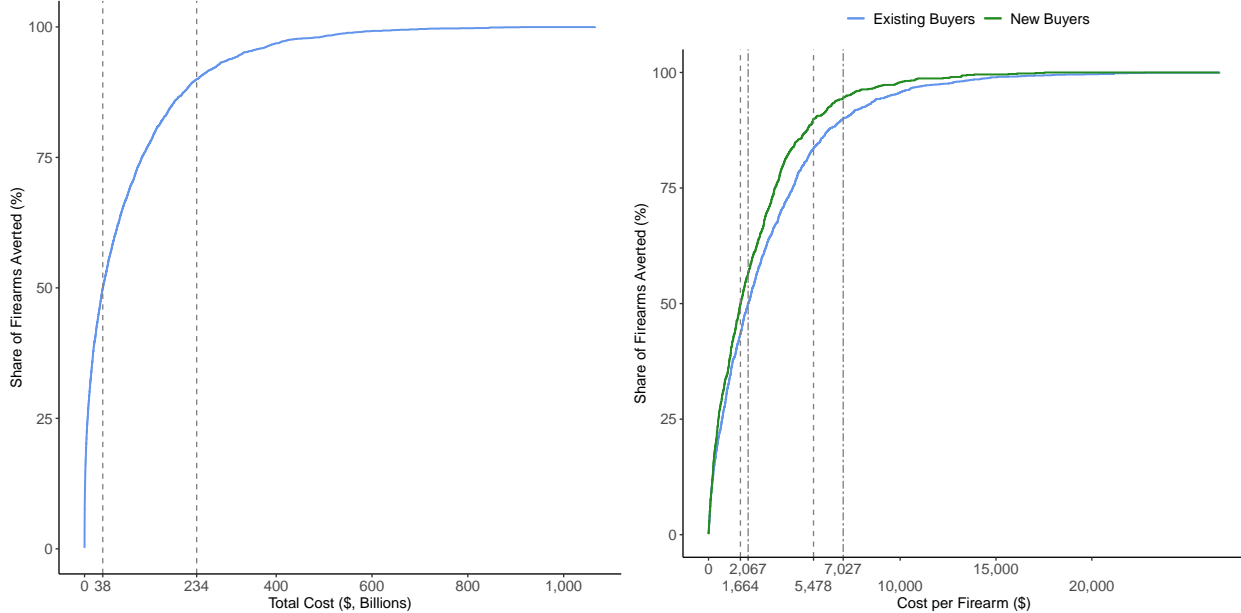
We illustrate how these results can be used to estimate the cost of reducing gun sales by paying consumers to opt out of the market. The intuition for this exercise is akin to a buyback program, albeit one aimed at recent and prospective gun-purchasers. For a fixed

policy budget B , we calculate the maximum number of averted gun purchases using the following procedure. Our demand model and parameter estimates predict which respondents would choose to purchase a gun in the next year and what consumer surplus they would realize from that purchase. We can then calculate the share of purchasers who would forgo their purchase for a cash payment b (i.e., the share whose consumer surplus is weakly less b). This is the CDF of consumer surplus for consumers who opt into the market, $F(b)$. To maximize the number of averted purchases with budget B , the per-person payment b must satisfy $B = b \cdot F(b) \cdot 40$ million (recall that approximately 40 million guns were sold in the US in 2020). Figure 7 below plots the share of firearm purchases averted as a function of the budget B . The left panel shows the aggregate expenditure required to avert a certain percentage of gun sales, while the right panel shows the price per averted firearm separately by gun ownership status. A 50% reduction in gun sales over a one-year horizon would cost an estimated \$1,902 per gun, at a total cost of approximately \$38.0 billion. A 90% reduction in one-year purchases requires a much higher payment of \$6,499 per gun (\$234.0 billion in total). One consideration in designing a voluntary buyback is selection into participation, and indeed, a buyback could be explicitly targeted to reduce sales of specific guns, such as those with higher mortality risk. In this simple case, we note that a uniform voluntary buyback disproportionately reduces purchases by new buyers because on average they earn lower consumer surplus relative to consumers who already own a firearm. The green line plots the share of averted firearm sales for new buyers, indicating that a smaller payment of \$1,664 per gun reduces sales to new buyers by 50% versus \$2,067 per gun to reduce sales to existing buyers by 50%. These estimates should be interpreted as a thought exercise, as a buyback policy would require many other considerations, such as a means of compliance to ensure that individuals who take up the payment do not find other avenues to purchase a gun.

7 Discussion

This paper leverages tools from quantitative marketing and industrial organization to better our understanding of regulation in the market for firearms. We estimate a random utility model of firearm demand using data from a state-choice-based conjoint survey. A virtue of this approach is that we randomize prices in the conjoint questions, eliminating typical price endogeneity concerns in demand estimation. Our findings indicate that demand for firearms is relatively inelastic. Accordingly, we find little change in purchasing in a counterfactual simulation where a tax raises the price of all firearms by 10%. This suggests that taxing

Figure 7: Estimated Cost of Averting Firearm Purchases in the Next 12 Months



Notes: Based on consumer surplus estimates that do not incorporate the logit error draws and use mean parameter values for each respondent. The blue line indicates the share of sales averted for all market participants. The green line indicates the share of sales averted for new buyers.

firearms could generate substantial public revenues with minimal excess burden. A simulated assault weapons ban does induce a change in firearm purchases, shifting consumers from long guns to handguns. Our estimates imply that few would-be assault weapons purchasers opt out of the market. In contrast, we find that a simulated handgun ban dramatically reduces the rate of firearm purchasing. We find that a simulated handgun ban also dramatically reduces consumer surplus enjoyed by market participants.

Our framework can evaluate policies beyond those considered here, and we hope it can be a tool for policymakers in assessing the costs and benefits of candidate firearm regulation. The current approach also has limitations that could be addressed in future work. In particular, we abstract from the general equilibrium effects of gun policy. For example, if crime rates fall, then some consumers may see less need for self-protection and their willingness-to-pay for a firearm may fall, as in Ehrlich and Saito (2010). Our counterfactual analysis also abstracts from supply responses. For example, by reducing competition, an assault weapons ban could put upward pressure on the prices of other firearms, which could ultimately reduce transaction volumes. However, manufacturers might adjust their product lines to exploit loopholes in the law, which would tend to counteract the ban. We hope to see more work in this arena to understand the likely magnitude of such general equilibrium effects.

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Appendix

A Additional Tables & Figures

Figure 8 shows a histogram of the number of firearms per household from our pilot survey. About 35% of firearm owning households have only one firearm. Meanwhile, about 7% of firearm owning households have ten or more.

Figure 8: Distribution of Firearms per Household

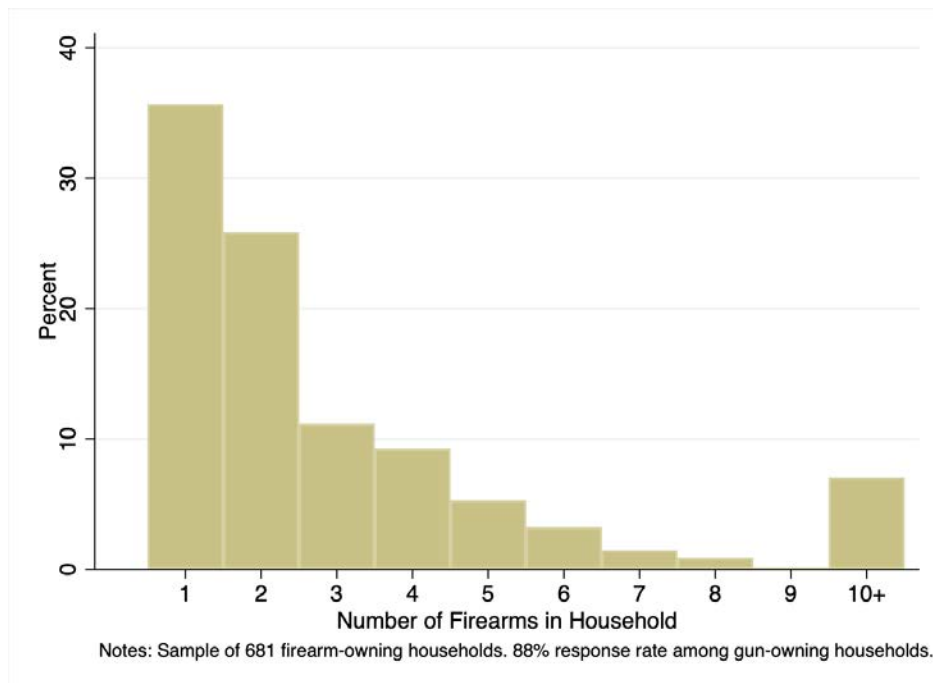


Table 8 presents our counterfactual predictions using the provided weights by Harris Poll to make our sample of gun purchasers representative of the national population. As selection into gun ownership is likely non-random on unobservables, these weights do not necessarily make our sample representative of the gun buying population. We as researchers also do not know exactly the formula used by Harris Poll to create the weights. However, the weighted and unweighted estimates are both qualitatively and quantitatively similar.

Table 8: Population-Weighted Market Shares & Consumer Surplus under Alternative Policy Proposals

		Market Share (%)			Consumer Surplus Loss (\$)	
		Handgun	Long Gun	None	Unweighted	Weighted
Assault Weapons Ban	Unweighted	57.25	22.47	20.27	-1,649	-2,367
	Weighted	58.04	24.14	17.81		
+10% Prices Increase	Unweighted	51.60	27.67	20.73	-51	-54
	Weighted	51.65	30.27	18.07		
Handgun Ban	Unweighted	0	49.45	50.54	-7,405	-8,967
	Weighted	0	54.91	45.10		

Notes: The *Weighted* rows reflect the market share of each category once the conjoint sample is re-weighted to be nationally representative. Each individual is given equal weight in the *Unweighted* columns. Individual weights used are provided by The Harris Poll.

Table 9 provides more information on how heterogeneity in estimated parameters is correlated with observables. None of these estimates is critical to our underlying analysis and interpretation, but are provided in the interest of transparency.

Table 9: Heterogeneity Across Demographics

	Price			Pistol		
	Post. Mean	SD	CI	Post. Mean	SD	CI
Age	-0.054	0.007	(-0.067, -0.042)	-0.024	0.323	(-0.659, 0.607)
Employed	-0.011	0.011	(-0.032, 0.011)	0.649	0.341	(-0.028, 1.302)
Female	-0.009	0.014	(-0.035, 0.020)	0.017	0.361	(-0.731, 0.671)
High School or Below	0.001	0.016	(-0.028, 0.033)	0.870	0.313	(0.270, 1.501)
Region						
Northeast	0.005	0.011	(-0.015, 0.028)	0.031	0.177	(-0.291, 0.412)
South	0.048	0.013	(0.023, 0.075)	-0.072	0.155	(-0.382, 0.233)
West	0.018	0.013	(-0.007, 0.047)	-0.197	0.209	(-0.613, 0.191)
Income						
50K-100K	-0.021	0.014	(-0.049, 0.006)	0.093	0.140	(-0.170, 0.372)
100K+	-0.096	0.024	(-0.148, -0.050)	0.015	0.185	(-0.339, 0.374)

Notes: The differences in the price parameter are small across demographics, so the estimates under the Price header are multiplied by 1,000.

Table 10 provides our estimates of consumer surplus under counterfactuals that include utility gained from logit shocks. Naturally, these estimates are higher than the estimates which disregard the logit shocks, but the relative ordering of the consumer surplus loss under different counterfactuals is preserved. Ultimately we prefer the estimates without the logit shocks included for the sake of our exercise because (1) they are more conservative and (2) we find it unlikely that each gun purchaser is actively considering over 80 models of firearms. As a result, we believe including the logit shocks overestimates the benefit of variety to consumers. The “true” consumer surplus is likely in between these two numbers.

Table 10: Consumer Surplus (Logit Draws Included)

	Distribution of Consumer Surplus (\$)						Mean MSRP
	Median	Mean	Min.	1st Qu.	3rd Qu.	Max.	
Assault Weapons Ban							
All	-110	-1,649	0	0	-1,254	-69,900	
If Considered	-776	-2,700	0	-193	-2,833	-69,900	1,066
If Chose	-6,089	-8,825	-124	-3,176	-11,873	-69,900	
Handgun Ban							
All	-2,821	-7,405	0	-368	-8,801	-103,017	
If Considered	-4,089	-8,746	-26	-1,109	-10,367	-103,017	708
If Chose	-7,939	-13,352	-150	-3,638	-17,350	-103,017	

Notes: Consumer surplus is calculated incorporating the logit draws (the logsum scaled by the inverse price coefficient). "If Considered" provides the distribution of consumer surplus loss for those consumers who considered the gun category in question. "If Chose" provides the distribution of consumer surplus loss for those consumers who, at their mean posterior preference parameters, choose the gun category in question absent the hypothetical restriction.

B Conjoint Details

This section provides more details about our conjoint survey.

B.1 Survey Pool

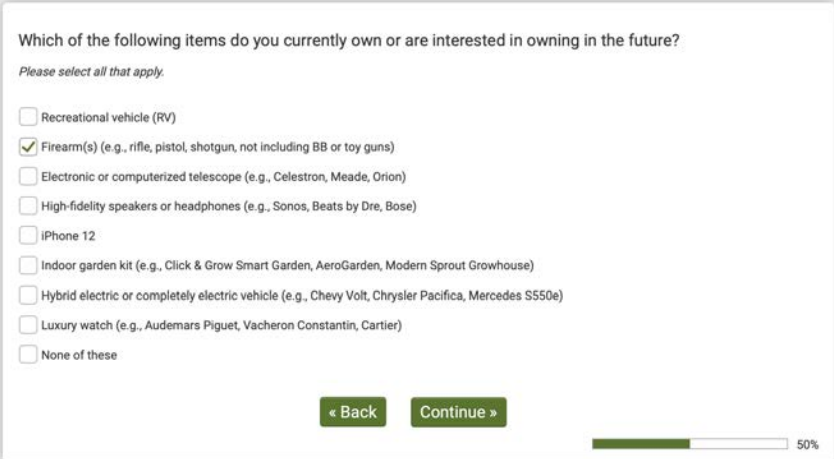
We ran three surveys in collaboration with Harris Poll that we refer to as the Preliminary Survey, Pilot 1, and Full Roll-Out. None of the surveys is constructed to be nationally representative. All three surveys begin by drawing from the pool of survey respondents maintained by Harris Poll and its partners. A disadvantage of working with their sample is that we do not know their exact procedure for recruiting participants to the pool. However, we see two advantages of working with their respondents: first, they are familiar with conjoint-like tasks; and second, by partnering with a commercial firm, we do not prime respondents to

answer the survey based on our status as academic researchers. The Preliminary Survey and Pilot 1 pull from the survey pool in a way that is meant to avoid heavy skews in the demographics, but it is not nationally representative by design. The final conjoint is designed to be more representative in that Harris Poll dynamically adjusts its sampling procedure if it notices that certain demographic groups are being over- or under-sampled. Harris Poll also attempted to target firearm owners for the third survey in order to deliver the number of conjoint-takers more economically. For all three surveys, Harris Poll uses a battery of standard checks to ensure sample quality. As an example, it includes check questions that ask respondents unrelated but simple questions that gauge attention and engagement (e.g., asking a respondent to select answer “C” for a given question). Harris Poll also eliminates respondents who spent too little time answering questions to have plausibly read the question prompt. Respondents who fail these checks are eliminated from the survey, and consequently, we do not receive any data on these respondents.

B.2 Survey Questions

The survey begins with Harris Poll’s standard demographic questions. Respondents are then asked questions specific to our study, which begin with a question intended to select those who are in the market for firearms:

Figure 9: Initial Screen Question



Which of the following items do you currently own or are interested in owning in the future?

Please select all that apply.

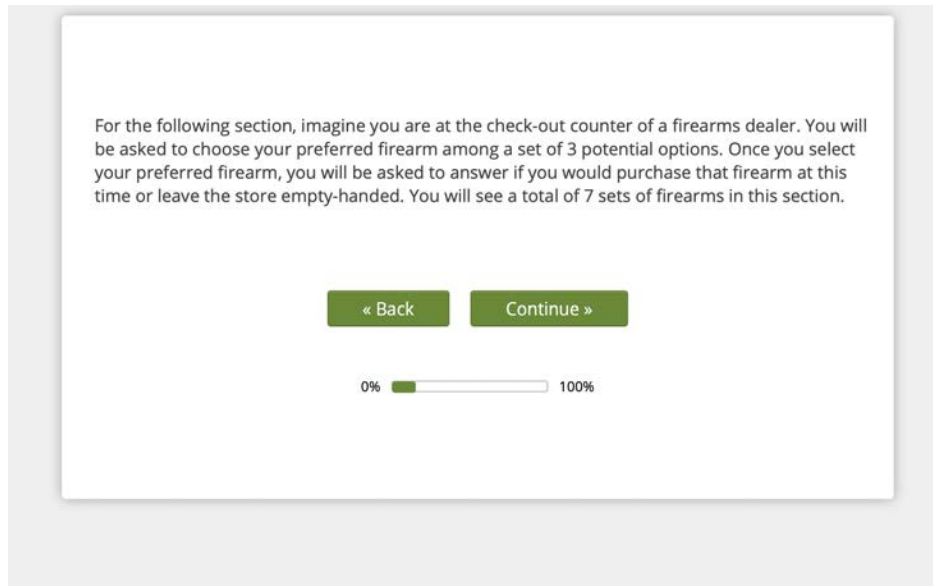
- Recreational vehicle (RV)
- Firearm(s) (e.g., rifle, pistol, shotgun, not including BB or toy guns)
- Electronic or computerized telescope (e.g., Celestron, Meade, Orion)
- High-fidelity speakers or headphones (e.g., Sonos, Beats by Dre, Bose)
- iPhone 12
- Indoor garden kit (e.g., Click & Grow Smart Garden, AeroGarden, Modern Sprout Growhouse)
- Hybrid electric or completely electric vehicle (e.g., Chevy Volt, Chrysler Pacifica, Mercedes S550e)
- Luxury watch (e.g., Audemars Piguet, Vacheron Constantin, Cartier)
- None of these

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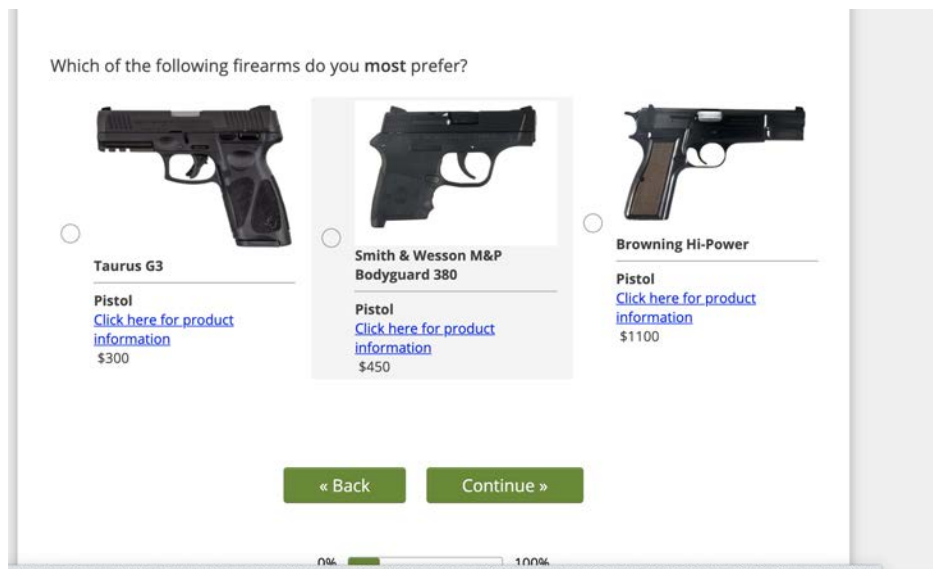
All respondents who indicate an interest in firearms are then asked to complete a series of hypothetical purchase decisions. The figure below displays the task description shown to respondents:

Figure 10: Conjoint Instructions



And an example task is shown below:

Figure 11: Example Conjoint Question



Respondents that click to learn more product information are shown details in the following form:

Figure 12: Example Conjoint Question

Semi-Automatic
Capacity: 13+1
Caliber: 9mm Å
Barrel Length: 4.6 in.
Single Action
Weight: 32 oz.

B.3 Firearm Models

The conjoint survey includes eighty different firearm models, including twenty from each of the four broad categories of firearm (pistol, revolver, shotgun, and rifle). The models were chosen based on their popularity on GunBroker.com: we use their 2020 list of highest selling firearms on the platform as a benchmark. For each sub-category, we try to include the firearms in order of popularity with some exceptions. For example, we replace *Mossberg 590A1* with *Remington 870 Express* to increase brand variety among pump-action shotguns. Table 11 enumerates the models included in the survey.

Table 11: Firearm Models Included in the Conjoint Survey

Pistol	Revolver	Rifle	Shotgun
Glock G19	Colt Python	Smith & Wesson M&P Sport II	Israel Weapon Industries TS12
Glock G43	Ruger Wrangler	Ruger AR-556	Benelli M4 Tactical
Springfield Armory Hellcat	Heritage Arms Rough Rider	Ruger Mini 14 Ranch	Mossberg 940 Pro
Smith & Wesson M&P9 Shield	Smith & Wesson 642	Sig Sauer SIGM400	Browning A5 Stalker
Ruger 57	Ruger SP101	Ruger 10/22 Sporter	Benelli M2 Field
Sig Sauer P365	Ruger LCRx	KelTec Sub2000	Beretta 1301
Glock G44	Ruger GP100	Springfield Armory Saint AR-15	Mossberg 590 Shockwave
Sig Sauer P320	Ruger LCR	Ruger PC Carbine	CZ-USA 612
Taurus G2	Smith & Wesson 648	Smith & Wesson M&P15-22	Benelli Nova Pump
Smith & Wesson M&P Bodyguard 380	Standard Manufacturing S333	Colt M4 Carbine	Winchester SXP
Taurus G3	Taurus 856	Ruger American Rifle	Mossberg 500
Kimber Micro 9	Kimber K6S	Ruger American Rimfire	Mossberg 590M Mag-Fed
Glock G17	Smith & Wesson 360PD	Thompson Center Compass II	KelTec KS7
Colt 1911	Colt King Cobra	Ruger Precision Rimfire	Remington 870 Express
Glock G26	Taurus 513 Raging Judge Magnum	Marlin 1895 SBL	Savage Arms 301
Beretta 92FS	Smith & Wesson 442	Marlin 1894	American Tactical Nomad
Springfield Armory XD(M)	Colt Single Action Army	Henry Repeating Arms X Model	Mossberg Silver Reserve II
Springfield Armory 1911 Mil-Spec	Ruger Vaquero	Rossi R92	Stoeger Condor
Armscor/Rock Island Armory M1911	Ruger Single-Six	Henry Repeating Arms Octagon	Stoeger Coach Gun
Glock G23	Ruger Blackhawk	Ruger No. 1 Standard	CZ-USA Bobwhite

B.4 Prices

The prices quoted in the conjoint survey are based on the average `GalleryofGuns.com` price for the corresponding type of gun. The eleven types of guns are: (i) semi-automatic rifles, (ii) lever rifles, (iii) single shot rifles, (iv) bolt and pump rifles, (v) semi-automatic shotguns, (vi) single shot shotguns, (vii) pump, over-under, and side-by-side shotguns, (viii) pistols, (ix) expensive revolvers, (x) mid-priced revolvers, and (xi) inexpensive revolvers. These groups were selected so that the MSRP of each gun lies within $\pm 50\%$ of its group mean. Note that our demand specification includes indicators for each type of gun, eliminating concerns about price endogeneity. We randomly draw an offered price based on the following distribution: -50% group average quoted price, -20% group average quoted price, group average quoted price, +20% group average quoted price, and +50% group average quoted price. Prices are rounded to the nearest dollar to be more realistic. This procedure is modified when we ask respondents to evaluate a firearm model that was not in their stated consideration set. In these instances, the non-considered alternative is always presented at the average quoted price for its corresponding type, and the other alternatives are quoted at +50% of the average quoted price for their corresponding type. This design was chosen to shed light on whether an economically meaningful change in relative prices can induce substitution to firearms outside of current consideration sets.

C Estimation Details

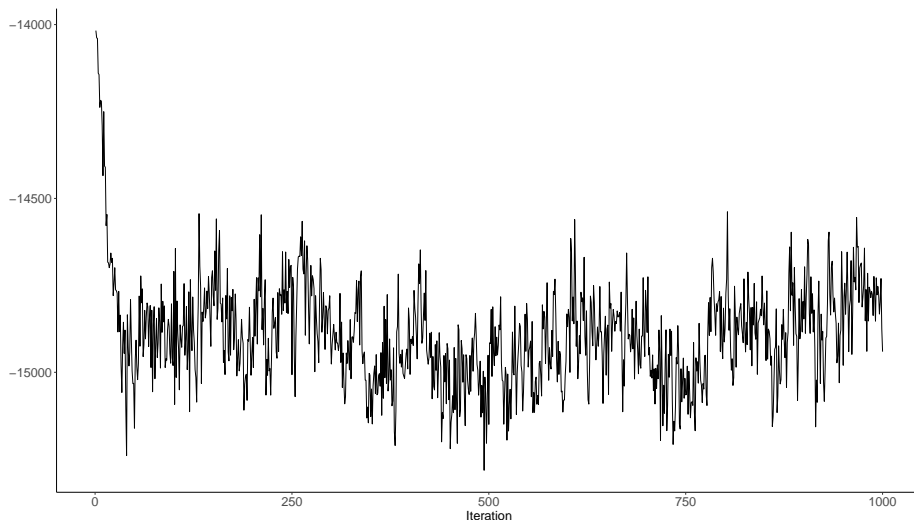
Base Model

Following Rossi, Allenby, and McCulloch (2005), we use the Metropolis-in-Gibbs sampler `rhierMnlRwMixture` from the `bayesm` package in R. We specify the following priors to estimate the base model:

$$\begin{aligned}\mu &\sim MVN(\bar{\mu}, V_\theta \otimes a_\mu^{-1}) \\ \text{vec}(\Delta) &\sim MVN(\text{vec}(\bar{\Delta}), 100 \cdot I) \\ V_\theta &\sim IW(\nu, V)\end{aligned}$$

where $u_i \sim MVN(\mu, V_\theta)$. We use the package defaults for $\bar{\mu}$, a_μ^{-1} , $\bar{\Delta}$, ν , and V . By default, the `bayesm` sampler does not include an intercept in the demographics vector z_i ; this is why we impose a prior on μ . We retain every 300th draw from a Markov Chain with 300,000 after a burn in of 30,000 draws.

Figure 13: Log-Likelihood across Draws



Search Cost Model

To estimate the search cost model, we write our own Metropolis-in-Gibbs sampler since we cannot adjust for the likelihood in the *bayesm* sampler. We impose the following priors:

$$V_\theta \sim IW(\nu, V)$$

$$vec(\Delta)|V_\theta \sim N(vec(\bar{\Delta}), V_\theta \otimes 100 \cdot I)$$

where $u_i \sim MVN(0, V_\theta)$. The estimation of the search cost model proceeds as follows:

0. *Initialize.* Pick a guess for $\theta_i = \{\alpha_i, \beta_i, \gamma_i\}$. Run a logit group-by-group based on the respondent's elected consideration set. This gives a partial vector β_i of for each respondent. Use this to construct $\hat{\mu}_\beta$. For sets that the respondent did not elect to consider, we take a draw from the distribution $\hat{\mu}_\beta$ that is truncated above by the inequality constraints.
1. *Metropolis Step* for θ . Generate draws of $\tilde{\theta}_i = \{\alpha_i, \beta_i, \gamma_i\} \sim MVN(\theta_{i(s)}, b^2 V_{\theta(s)})$ one respondent at a time. The parameter b is a scaling parameter, which we set to be $\frac{2.93}{\sqrt{|\theta|}}$ following Rossi, Allenby, and McCulloch (2005). Repeat for all respondents. That is, for each respondent:

(a) Let $a = \min \left\{ 1, \frac{Pr\{Y|\tilde{\theta}_i\}P\{\tilde{\theta}_i|\Delta_{(s)},V_{\theta_{(s)}}\}}{Pr\{Y|\theta_{i(s)}\}P\{\theta_{i(s)}|\Delta_{(s)},V_{\theta_{(s)}}\}} \right\}$ where

$$Pr\{Y|\theta\} = \frac{\exp(X_j^l\beta_i - \alpha_i \cdot p_{ijt})}{\sum_{k \in C_t} \exp(X_k^l\beta_i - \alpha_i \cdot p_{ikt})} \cdot \frac{|l_i|!}{3! \cdot (|l_i| - 3)!} \cdot 1\{l_i|\theta\}$$

$$Pr\{\theta|\Delta_{(s)},V_{\theta_{(s)}}\} = \frac{1}{(2\pi)^{|l_i|/2}} |V_\theta|^{-1/2} \exp\left(-\frac{1}{2}(\theta - \Delta'_{(s)}z_i) V_{\theta_{(s)}}^{-1}(\theta - \Delta'_{(s)}z_i)'\right)$$

(b) Draw $u \sim U[0, 1]$. Let $\theta_{i(s+1)} = \begin{cases} \tilde{\theta}_i & \text{if } u \leq a \\ \theta_{i(s)} & \text{otherwise} \end{cases}$.

2. *Gibbs Sampler for Δ, V .* Draw from $\Delta_{(s+1)}, V_{(s+1)}$ given $\vec{\theta}_{(s+1)}$ from step (1) using the following distributions:

$$\begin{aligned} vec(\Delta_{(s+1)})|V_{(s)}, \vec{\theta}_{(s+1)} &\propto Pr\{\theta_{(s+1)}|\Delta_{(s+1)}, V_{(s)}\}Pr\{\Delta_{(s+1)}|V_{(s)}\} \\ &\propto N((\theta_{(s+1)} - \Delta'_{(s+1)}Z), V_{(s)}) \cdot N(vec(\bar{\Delta}), V_{(s)} \otimes 100 \cdot I) \\ &\propto N((Z'Z + 0.01 \cdot I)^{-1}(Z'\theta_{(s+1)} + 0.01 \cdot vec(\bar{\Delta})), V_{(s)} \otimes (Z'Z + 0.01 \cdot I)^{-1}) \\ V_{(s+1)}|\Delta_{(s)}, \vec{\theta}_{(s+1)} &\sim IW(\nu + n, V + S) \\ \text{where } S &= (\theta - Z\tilde{\Delta})'(\theta - Z\tilde{\Delta}) + 0.01 \cdot (\tilde{\Delta} - \bar{\Delta})'(\tilde{\Delta} - \bar{\Delta}) \\ \text{and } \tilde{\Delta} &= (Z'Z + 0.01 \cdot I)^{-1}(Z'\theta + 0.01 \cdot \bar{\Delta}) \end{aligned}$$

Return to step (1).

We retain every 500th draw from a Markov Chain with 500,000 after a burn in of 50,000 draws.

D Demand Model with Endogenous Consideration Sets

Adjusting the Likelihood for the Inclusion of Non-Considered Alternatives

To estimate the distribution of search costs, we include choice tasks that ask respondents to evaluate firearms that are outside of their stated consideration set. In particular, for each non-considered category (of which there may be up to three), one of the seven choice tasks is randomly selected to feature an alternative from that non-considered category. (To be clear, the total number of alternatives in each choice task remains fixed at three.) For respondents who indicate that they would not consider multiple categories, the alternatives from different non-considered categories are introduced into different questions. The conditional probability that task t for respondent i comprises choice set C_{it} given stated consideration set l_i is then:

$$Pr\{C_{it}|l_i\} = Pr\{C_{it}|l_i, C_{it} \subset l_i\} \cdot Pr\{C_{it} \subset l_i|l_i\} + Pr\{C_{it}|l_i, C_{it} \not\subset l_i\} \cdot Pr\{C_{it} \not\subset l_i|l_i\}$$

$$Pr\{C_{it} \not\subset l_i|l_i\} = \frac{4 - \frac{|l_i|}{20} - \sum_{\tau=1}^{t-1} 1\{C_{i\tau} \not\subset l_i\}}{7 - (t - 1)}$$

where $C_{it} \subset l_i$ indicates that all models in the task t choice set are in the respondent's consideration set (i.e., the choice set is a subset of the consideration set), and we make use of the following probabilities:

$$Pr\{C_{it}|l_i, C_{it} \subset l_i\} = \binom{|l_i|}{3}$$

$$Pr\{C_{it}|l_i, C_{it} \not\subset l_i\} = \binom{|l_i|}{2} \cdot \frac{1}{20}$$

$$Pr\{C_{it} \not\subset l_i|l_i\} = \frac{4 - \frac{|l_i|}{20} - \sum_{\tau=1}^{t-1} 1\{C_{i\tau} \not\subset l_i\}}{7 - (t - 1)}.$$

Model Estimates

We begin by presenting estimates of search costs in dollars below in Figure 14. The median search cost is \$100, which is approximately 22% of the cost of the median gun purchase predicted by the model.

Figure 14: Distribution of Search Costs

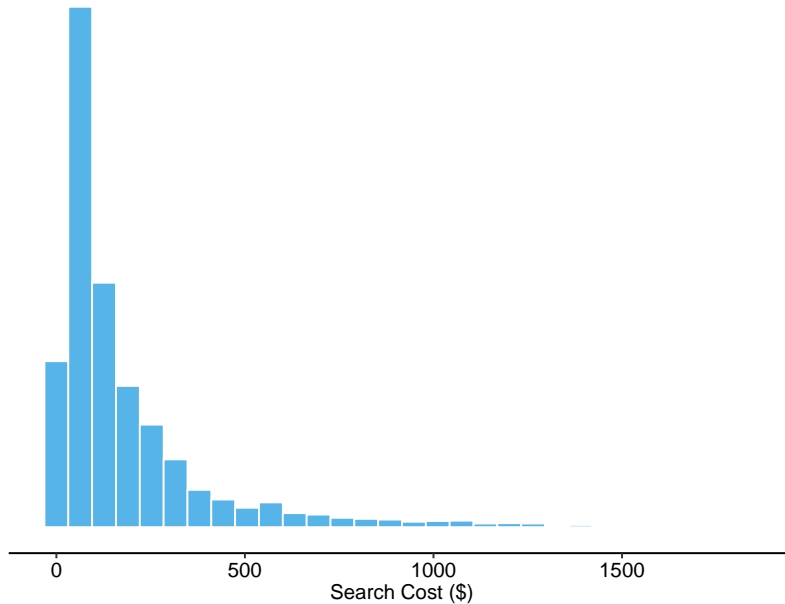


Table 12 presents estimates from both the search cost and baseline demand models. The two models produce similar own-price elasticities (shown in columns 1 and 3), which hover around -1. Estimates from both models indicate that demand is more price elastic for handguns relative to long guns, with the exception of assault weapons, which are relatively more price sensitive in the search cost model. Turning to market shares, the relative share of handguns to long guns is similar across the two models: 64.80% in the search cost model compared to 65.09% in the baseline model. Where the two models diverge is in the share of the market predict to elect the outside option as the search cost model implies a much smaller share of respondents electing the outside option (8.8%) under the status quo. One reason for this difference is that the search cost model incorporates tasks where a respondent is presented with a non-considered alternative at relatively low prices. In 13.3% of these tasks, respondents do indeed choose the non-considered alternative. Intuitively, the model can fit such choices by increasing price sensitivity and model intercepts.

Counterfactual predictions under the search cost model are presented in Table 13. Estimates of market shares and mean consumer surplus are calculated as percentage point changes relative to the status quo estimates from Table 12. As for our baseline results, we see that the assault weapons ban leads to little substitution to the outside option (+0.5 percentage points). Substitution to the outside option is more than twice as large under 10% price increase. Substitution to the outside option is greatest for the handgun ban, more than doubling relative to the status quo outside option share (+10.1 percentage points). As expected, the share of consumers electing the outside option under a handgun ban is smaller than the estimates from the baseline model. In the baseline model, consumers who report that they would not consider purchasing a long gun must (mechanically) elect the outside option under a handgun ban. In contrast, in the search cost model, some of these consumers find it optimal to consider and purchase a long gun under a hypothetical handgun ban. This flexibility is a feature of the search cost model. We note, however, that these substitution patterns are estimated based on somewhat atypical conjoint questions as we ask respondents to evaluate guns that they had already indicated they would not consider purchasing. We might worry that respondents are less able to evaluate these “non-considered” alternatives if they are less familiar with them. These pros and cons motivate us to present estimates from both models. It is reassuring that both models yield qualitatively similar predictions about the substitution induced by the three policy alternatives that we study.

Table 12: A Comparison of Price Elasticities & Market Shares for the Search Cost & Baseline Demand Models

	Search Cost Model Implied		Baseline Model Implied	
	Own-Price Elasticity	Market Share	Own-Price Elasticity	Market Share
Revolver	-1.17	19.5	-1.13	15.1
Pistol	-1.16	39.6	-1.05	37.3
Rifle	-1.11	10.0	-0.87	7.5
Shotgun	-0.83	10.8	-0.98	9.2
Assault Weapon	-1.11	11.3	-0.75	11.4
Outside Option	–	8.8	–	19.5

Table 13: Search Cost Model Market Shares under Alternative Policy Proposals

	Market Share (Change in p. p.)		
	Handgun	Long Gun	None
Status Quo	59.1	32.1	8.8
Assault Weapons Ban	+9.4	-9.9	+0.5
Handgun Ban	-59.1	+49.0	+10.1
+10% All Gun Prices	-0.8	-0.4	+1.2