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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 evaluating the likely impacts of firearm regulations. 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.

*Calculated (or derived) based on data from The Harris Poll. The conclusions drawn from the data are those of the researchers and do not reflect the views of The Harris Poll. The Harris Poll is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. This work is supported by the Becker Friedman Institute at the University of Chicago, the True North Endowment Fund and the Robert King Steel Fund at the University of Chicago Booth School of Business.

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 some 400 million firearms in total. 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 respects the individual utility of gun ownership and also takes seriously the externalities caused by 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 or a significant industry-wide tax). 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 also be used to put bounds on the cost of hypothetical buyback programs.

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 link between guns and crime with our estimates in order to evaluate the expected

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

[2] 54% 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/

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

[4] Handguns 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/

[5] While we do not estimate impacts on the secondary market, primary markets and secondary markets are clearly related. A more restrictive primary market mechanically reduces supply available to secondary markets.

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 estimated parameters using aggregate moments from observational data.

[6]The 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.

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, because consumers are relatively price insensitive, we estimate that a 10% price increase leads to a small reduction in sales.

To put our results in context, we highlight a few gun crime and death statistics.

[7]For 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.

[8]Only 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.)

[9]A 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.

[10]These 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.

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 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

[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/

[13] To 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.

[14] There 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

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,

[15] https://www.atf.gov/firearms/docs/guide/atf-guidebook-importation-verification-firearms-ammunition download

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

[17] There 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.

and mandatory waiting periods during the firearm purchase process. While now confined to 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 prevelance 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 pur-

[20]While 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/

[21]The 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.

[22]States 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`

chase 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 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

[24] These 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.

sample predominantely 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 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 quoted price. 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`.

4. 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

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

[26] We 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 Prices ($) from GalleryofGuns.com

	Obs.	Mean	St. Dev	Min.	1st Qu.	Median	3rd Qu.	Max.
Pistols	8,724	1,307	306	697	1,174	1,424	1,549	1,894
Revolvers	4,778	663	279	115	655	700	771	1,278
Rifles	80,863	1,661	584	360	1,230	1,718	1,995	5,561
Shotguns	23,742	943	598	200	588	667	1,323	4,873

Notes: An individual observation is a UPC-store pair. Handgun data was scraped between October and November of 2020, and long gun data was scraped between March 2021 and May 2021.

and May 2021. Table 1 shows the mean prices for each type of firearm. 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. However, we do see substantial variation in access, as shown by Figure 1.

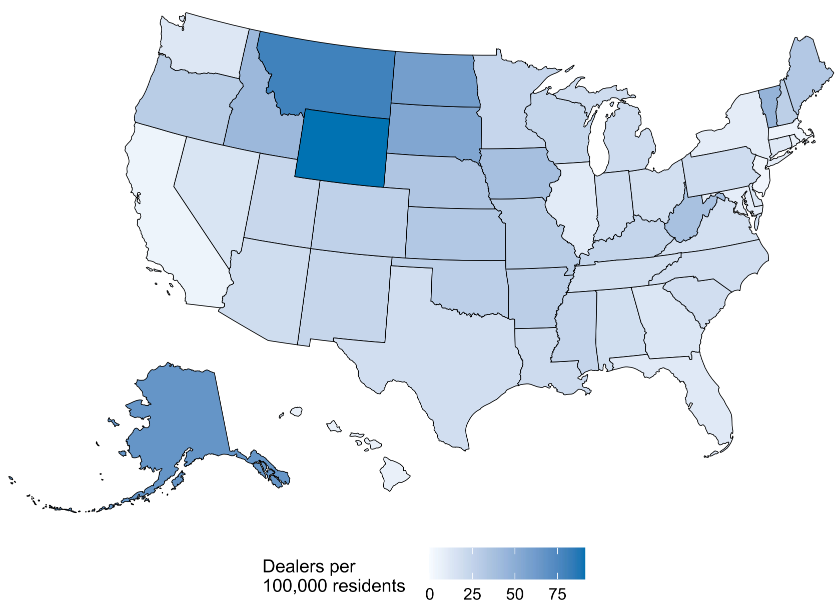
3.2 Auxiliary Data on Background Checks & Traces

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

[27] Other 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.

Figure 1: Map of Federally-Licensed Gun Retailer Locations



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

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, 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 6 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%).

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

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

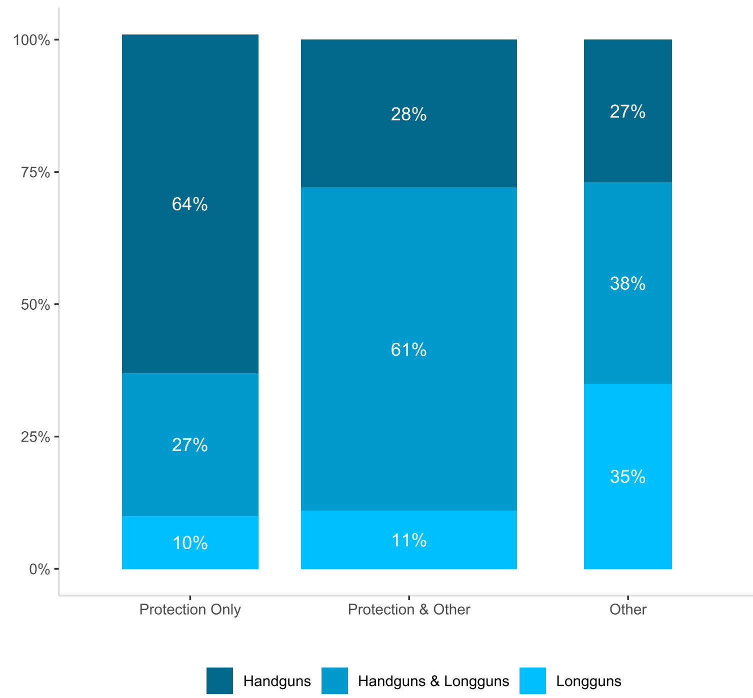
Table 2: Descriptive Statistics: Survey Respondents and Current and Prospective Firearm Owners

	Share of Respondents (%)			
Demographic	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
Millenial	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 2 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

Figure 2: Interest in Firearm Types (Final Survey)



across different types 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 $t \in \{1, .., 7\}$, 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:

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

As described in section 3.3, consumers often do not to 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). 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

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

category l for individual i can be expressed as:

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

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:

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

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

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

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]

$$Pr\{C_t | l_i\} = \binom{|l_i|}{3}.$$

[32]For the base model, we exclude tasks where the respondent was shown a firearm model outside of their selected consideration set. Note that this term will require adjustment in estimating the search cost model to account for tasks where the respondent is shown a firearm model that was not in their elected consideration set.

We then have all components necessary to construct likelihood that consumer i selects product j on purchase occasion t given taste parameters θ_i:

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

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

$$\theta_i = \Delta' z_i + u_i$$
$$u_i \sim MVN(0, V_\theta)$$

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). We specify priors $V_\theta \sim IW(\nu, V)$ and $vec(\Delta)|V_\theta \sim N\left(vec(\bar{\Delta}), V_\theta \otimes 100 \cdot I\right)$. The exact procedure is 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:

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

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

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. 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.

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

Table 3: Estimates of Demand Parameters & Elasticities

	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 individual heterogeneity in the price cofficient and pistol intercpets that is predicted by demographic factors. While there is considerable unobserved heterogeneity as indicated by the standard deviations in Table 3, we find only small differences in the distributions of preference parameters across geography, employment, education, gender, or income.

Table 4: 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 esimates under the Price header are multiplied by $1,000$.

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 (New 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 3, 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.

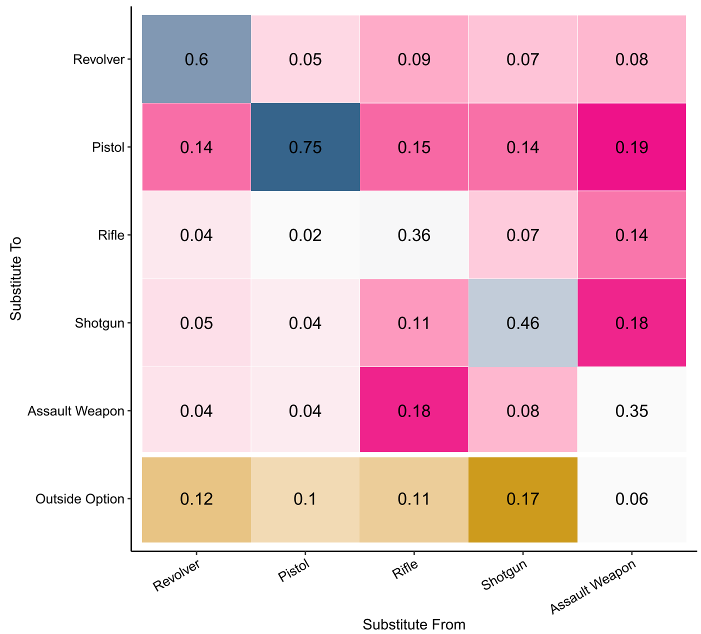
5.2 Validation

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

Figure 3: Diversion Ratios & Cross Price Elasticities for Firearms

(a) Diversion Ratios



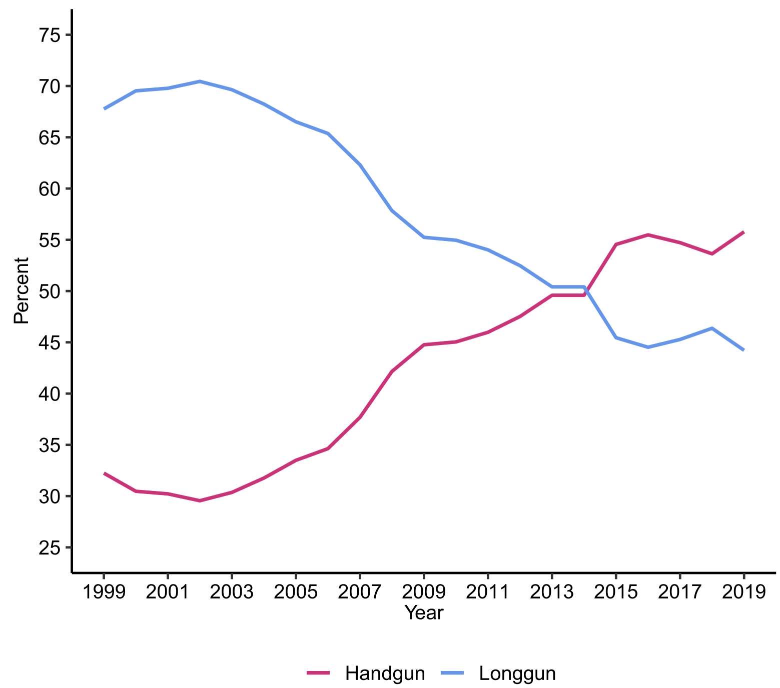
(b) Cross Price Elaticities

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.

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 ${}^{4{,}018}/_{22{,}522} \times 0.805 \times 258.3$ million ≈ 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 4.

Figure 4: 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 stockouts in observational data if inventory is fixed in the short term. Alternatively, it could be that our conjoint elicitation

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

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 (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. We also consider two policies that have received less attention in policy circles: a tax that raises the price of all gun by 10% and an outright ban on handguns.[37]

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 sales. Second, we calculate the compensating variation under alternative firearm regulations. Again, these estimates are informed by respondents' 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 interpreted as an estimate of the potential cost of a gun buyback program focused on recent purchasers. Second, the estimates shed light on the political feasibility of alternative regulations, allowing policymakers to pinpoint regulations that accomplish policy aims at a low cost in consumer surplus. More broadly, this framework can be adapted to different objective functions that put differential weight on consumer surplus and firearm sales (and their associated externalities, which we return to below).

We calculate the implied consumer surplus using two methods. First, we present estimates using standard techniques that incorporate logit draws (estimate 1). One concern is that in markets with many products, incorporating the logit draws mechanically yields

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

[37] For 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.

large estimates of consumer surplus. Following Petrin (2002), we therefore also report consumer surplus ignoring those draws, 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 (estimate 2).

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 have higher price sensitivity, a tax would have a relatively larger impact on their purchases.

Finally, we consider a hypothetical handgun ban.[38] 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 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.

Overall, the consumer surplus associated with firearms is high. Including (ignoring) logit shocks, removing access to handguns leads to a $7,405 ($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 $1,649 ($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 alternative for a large fraction of those who

[38]While a handgun ban is not under active consideration in any notable localities, evaluating the effect of a hypotethetical 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.

choose handguns is the outside option (many consider handguns exclusively). The assault weapons ban directly affects the choices of fewer people, and most consumers who consider assault weapons also consider other types of firearms, so their consumer surplus loss is somewhat mitigated. Taxes have little effect on behavior, and because price coefficients are relatively small, the tax also has relatively little impact on surplus.

Table 7 breaks down the consumer surplus numbers by quantiles and by which consumers are affected.[39] The median consumer who chooses a handgun at their mean parameters loses \$4,897 in surplus from a handgun ban. Meanwhile, the median consumer who chooses an assault weapon at their mean parameters loses \$6,342 in surplus from an assault weapons ban. Thus while a handgun ban leads to a greater reduction in aggregate consumer surplus, an assault weapons ban has a greater impact *per affected purchaser.*. This result suggests that more handgun owners are marginal in the sense that they individually lose less from missing out on their favorite firearm. These surplus numbers are relevant to a hypothetical gun buyback program. On a per gun basis, it would be much more expensive to buy back assault weapons than it would be to buy back handguns.

Table 6: Market Shares and Consumer Surplus under Alternative Policy Proposals

		Market Share (%)			Consumer Surplus Loss (\$)	
		Handgun	Long Gun	None	Est. 1	Est. 2
All	Assault Weapons Ban	57.25	22.47	20.27	-1,649	-1,507
	Handgun Ban	0	49.45	50.54	-7,405	-4,184
	+10% Prices Increase for All Guns	51.60	27.67	20.73	-51	-44
New Buyers	Assault Weapons Ban	61.27	17.28	21.45	-1,111	-946
	Handgun Ban	0	40.46	59.54	-8,452	-4,801
	+10% Price Increase for All Guns	56.39	21.4	22.21	-48	-40

Notes: Estimates 1 and 2 show the mean consumer surplus loss across individuals in our sample relative to the status quo. Estimate 1 calculates consumer surplus incorporating the logit draws (the logsum scaled by the inverse price coefficient); estimate 2 ignores the logit draws following but draws from the full posterior distribution of the preference parameters instead of using only their posterior means.

[39] For this analysis, we use the consumer surplus numbers ignoring logit shocks. The table which includes the logit shocks is in Appendix A Table 8. While the absolute numbers are higher, the relative numbers are similar.

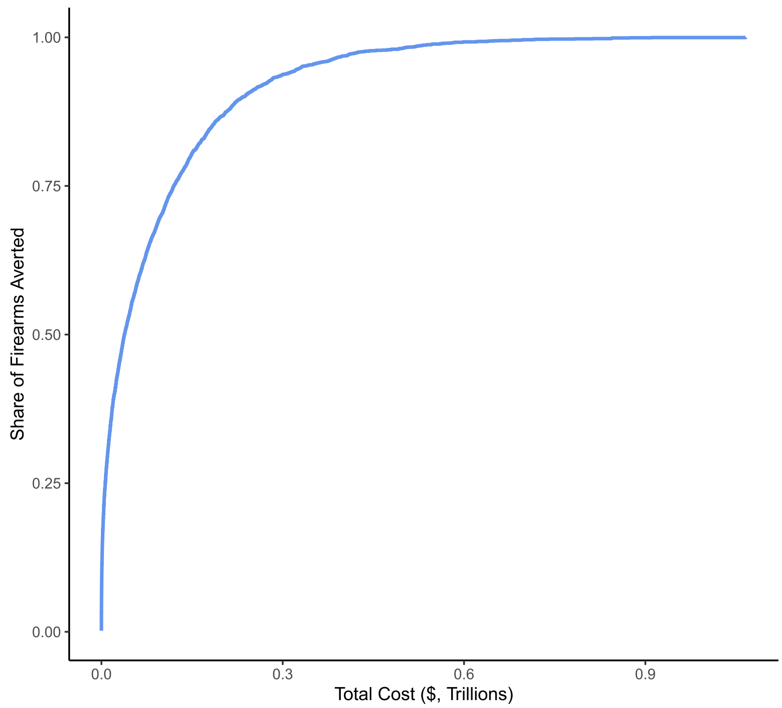
Table 7: Consumer Surplus

	Distribution of Consumer Surplus ($)						
	Median	Mean	Min.	1st Qu.	3rd Qu.	Max.	Mean MSRP
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 suprlus 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 paratmeter 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 statisfy $B = b \cdot F(b) \cdot 40$ million (recall that approximately 40 million guns were sold in the US in 2020). Figure 5 below plots the share of firearm purchases averted as a function of the budget B. To reduce 50% of gun sales over a one-year horizon would cost an estimated \$1,902 per gun, which implies a total cost of approximately \$38.0 billion. Reducing one-year purchases by 90% would require a much higher payment of \$6,499 per gun (\$234.0 billion in total). 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. This type of policy could further be targeted to reduce the sales of specific guns, for instance, those with higher mortality risk.

Figure 5: 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.

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 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 Tables & Figures

Figure 6: Distribution of Firearms per Household

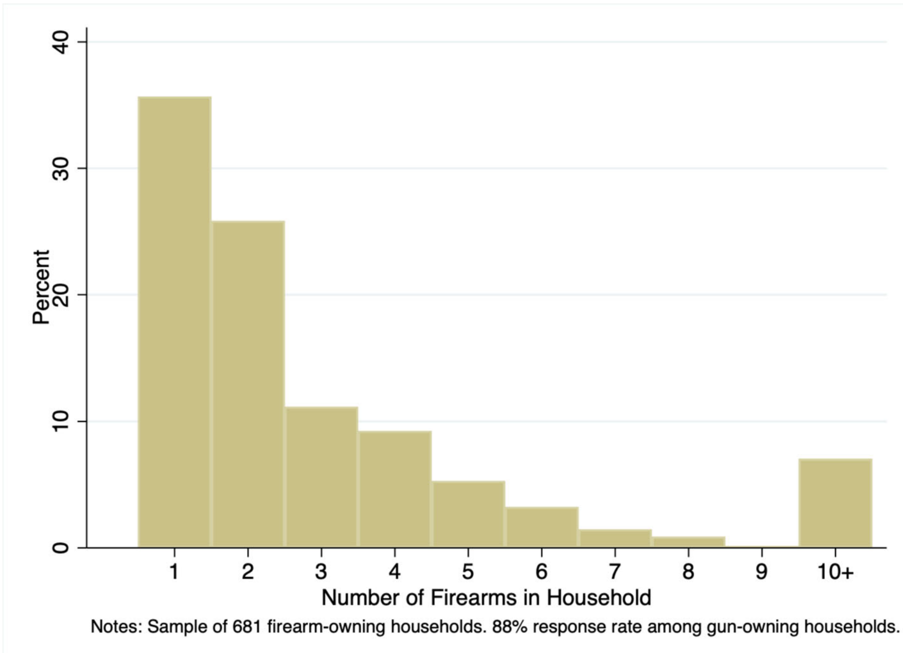


Table 8: Consumer Surplus (Logit Draws Included)

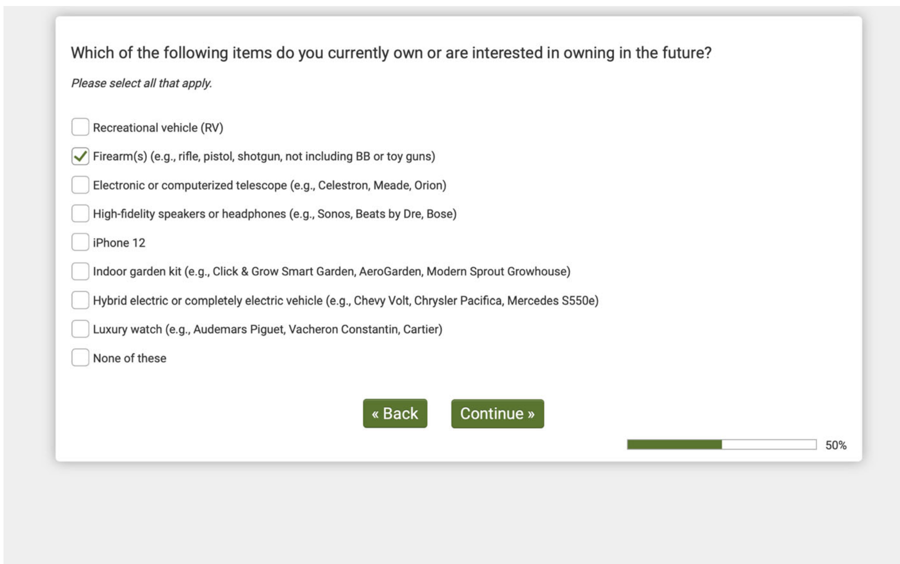
	Distribution of Consumer Surplus ($)						
	Median	Mean	Min.	1st Qu.	3rd Qu.	Max.	Mean MSRP
Assault Weapons Ban							
All	-110	-1,649	0	0	-1,254	-69,900	
If Considered	-776	-2,700	0	-193	-2,833	-69,900	1,066
If Chose	-6,089	-8,825	-124	-3,176	-11,873	-69,900	
Handgun Ban							
All	-2,821	-7,405	0	-368	-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 suprlus loss for those consumers who, at their mean posterior preference parameters, choose the gun category in question absent the hypothetical restriction.

B Conjoint Details

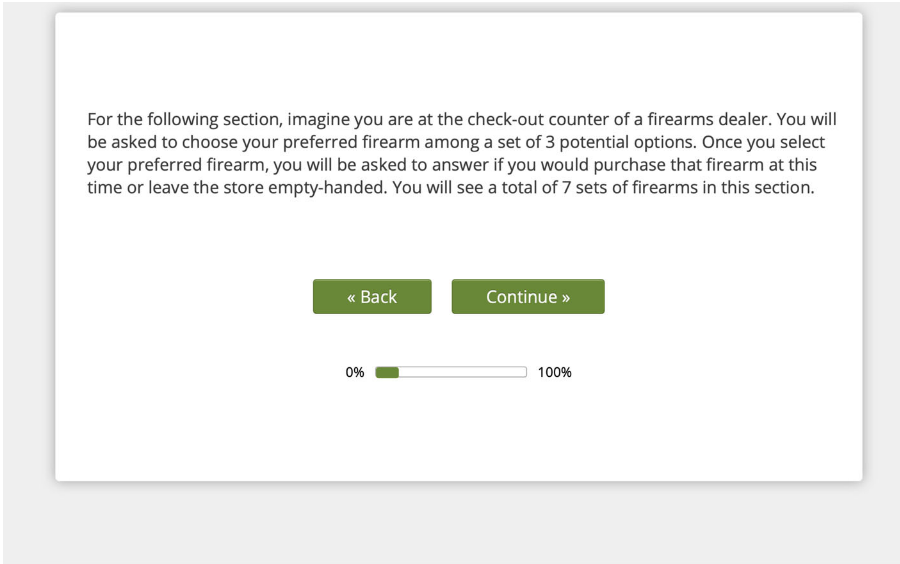
This section provides more details about our conjoint survey. The survey begins with Harris Poll's standard demographic questions. Respondents are then asked questions specific to our study, which begin with a question intended to select those who are in the market for firearms:

Figure 7: Initial Screen Question



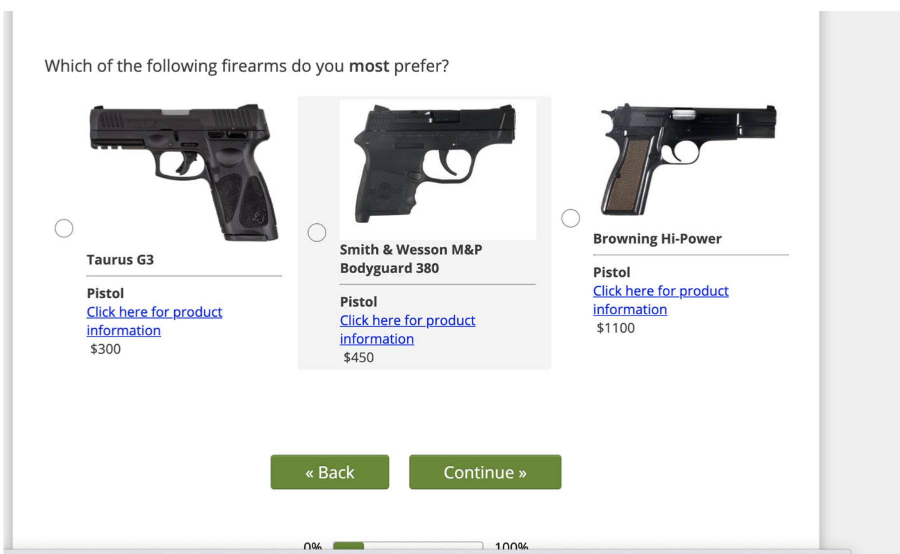
All respondents who indicate an interest in firearms are then asked to complete a series of hypothetical purchase decisions. The figure below displays the task description shown to respondents:

Figure 8: Conjoint Instructions



And an example task is shown below:

Figure 9: Example Conjoint Question



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

Figure 10: Example Conjoint Question

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

C Estimation Details

The estimation of our demand 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

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

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

   (b) Daw $u \sim U[0,1]$. 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:

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

Return to step (1).

We retain every 300th draw from a Markov Chain with 300,000 after a burn in of 30,000 draws.

Figure 11: Likelihood across Draws

D Demand Model with Endogenous Consideration Sets

These results will be forthcoming