Online Appendix: Preferences for Firearms

By Sarah Moshary, Bradley T. Shapiro and Sara Drango*

Appendix A – Additional Tables & Figures

Table A.1 enumerates the models included in our conjoint survey.

Figure A.1 shows a histogram of the number of firearms per household from our pilot survey. About 35% of firearm-owning households have only one firearm. About 7% of firearm-owning households have ten or more guns.

Figure A.1. : Distribution of Firearms per Household

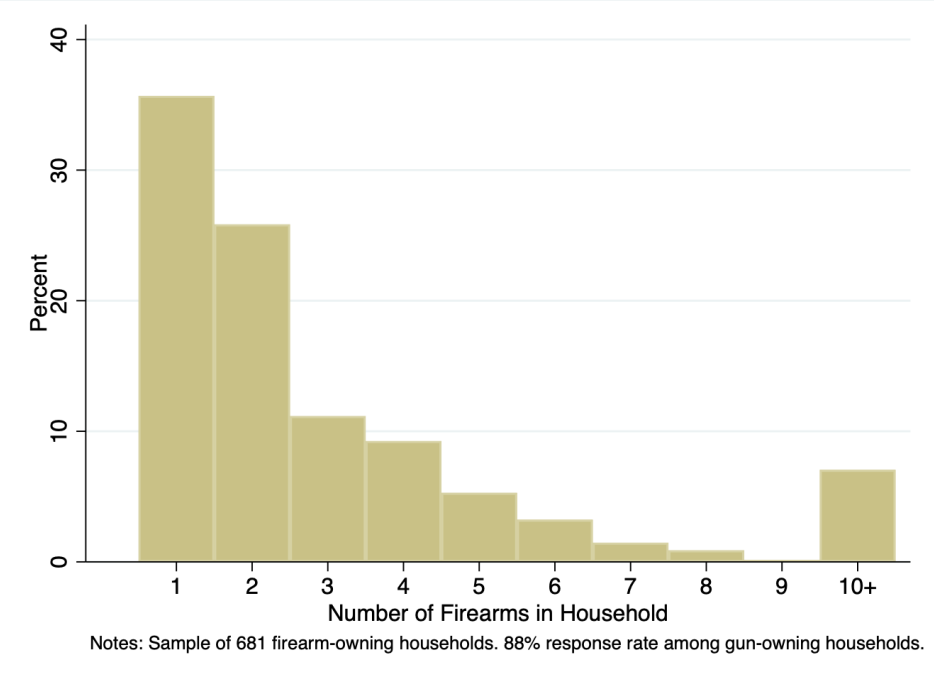


Table A.2 provides information by demographic group about the likelihood that respondents show interest in firearms or own a firearm such that they get selected into the final conjoint survey. Women are considerably less likely to report an interest in firearms, and conditional on interest, they are more likely to be new buyers. Respondents from the South have the highest rate of current gun ownership, but also show considerable interest from new buyers. The Northeast is the region with the lowest rate of current ownership as well as the lowest rate of new buyer interest.

Figure A.2 shows the geographic distribution of prices for the Glock 43, a popular pistol. Roughly 87% of stores have an identical price. In contrast, there is substantial variation in the prevalence of firearm dealerships across states, as shown by Figure A.3.

Table A.1—: 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

Figure A.4 plots ATF traces per NICS background check. Because the average gun that is traced

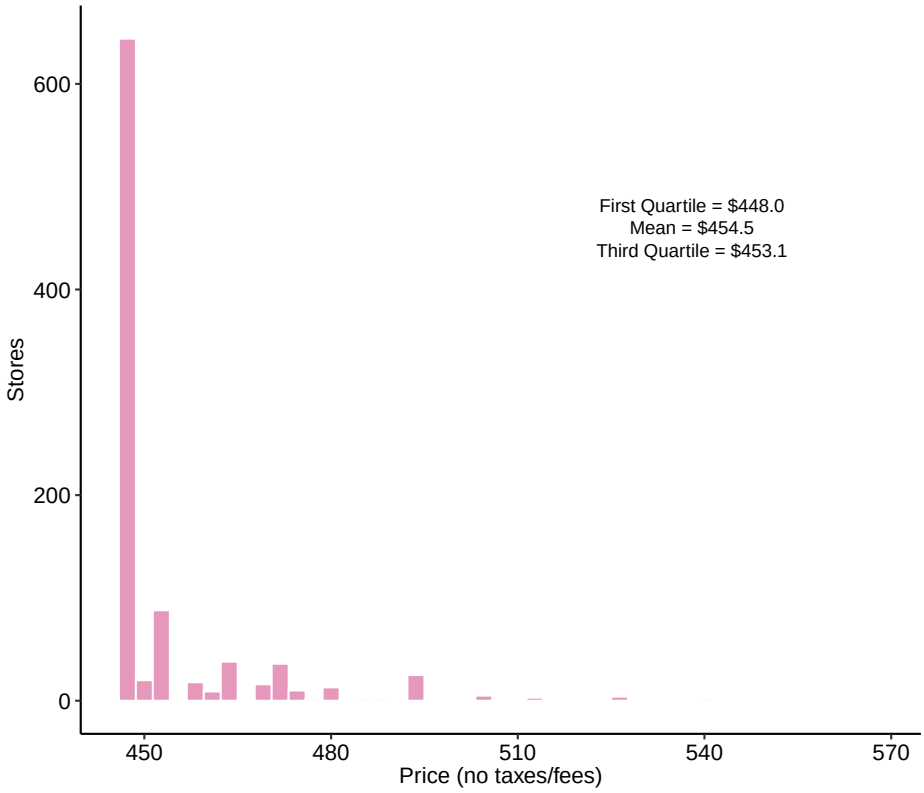
* Moshary: University of California, Berkeley, moshary@berkeley.edu. Shapiro: University of Chicago, bradley.shapiro@chicagobooth.edu. Drango: University of Chicago, sdrango1@chicagobooth.edu.

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

	Share of *Full* Sample (%)		
Group	In Conjoint	Existing Owners	New Buyers
Gender			
Female	14.67	7.67	6.27
Male	23.26	17.64	5.22
Region			
South	20.67	13.84	6.22
West	16.52	10.05	6.02
Northeast	12.43	7.52	4.37
Midwest	18.88	11.56	6.54
Obs.	4,018	2,557	1,325

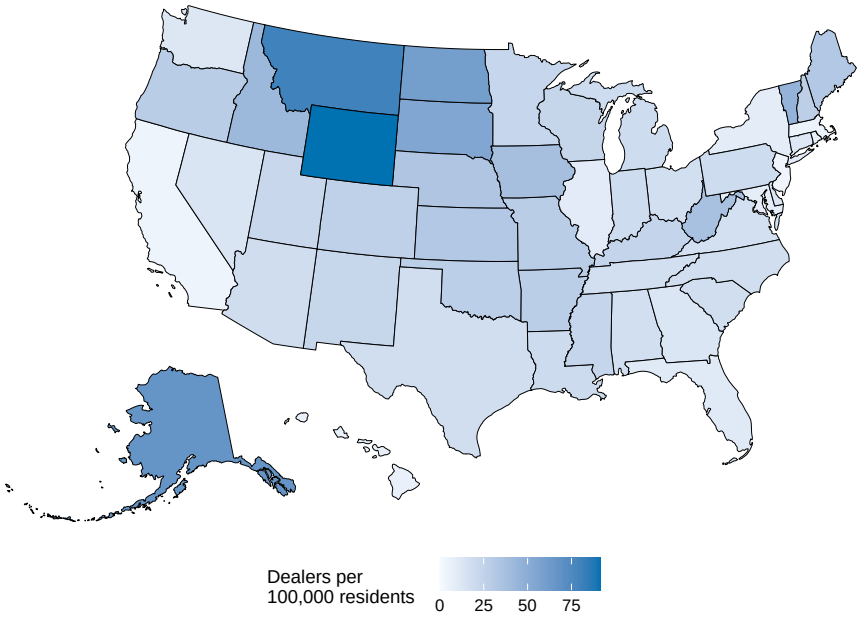
Notes: Data from the final survey. Conjoint-takers (N=4,018) comprise individuals who indicated that they own or are interested in owning a firearm. Of this group, 61 did not disclose their ownership status, 66 later indicated that they neither owned nor were interested in owning, and nine non-owners provided no information on future purchases.

Figure A.2. : Distribution of Prices for the Glock 43 across Federally Licensed Dealers



Notes: Prices exclude state and local taxes and fees.

Figure A.3. : Locations of Federally Licensed Gun Retailers



Notes: This map shows the density of federally licensed dealers operating as of January 2022.

by the ATF is purchased some nine years earlier, we divide traces in year t by background checks in year $t-9$ to compute this number. We exclude data from the nineteen states that serve as partial or full "point-of-contact" states for NICS reporting purposes.

Table A.3 shows the MSRPs for the firearms included in the conjoint survey, as scraped from GalleryofGuns.com.

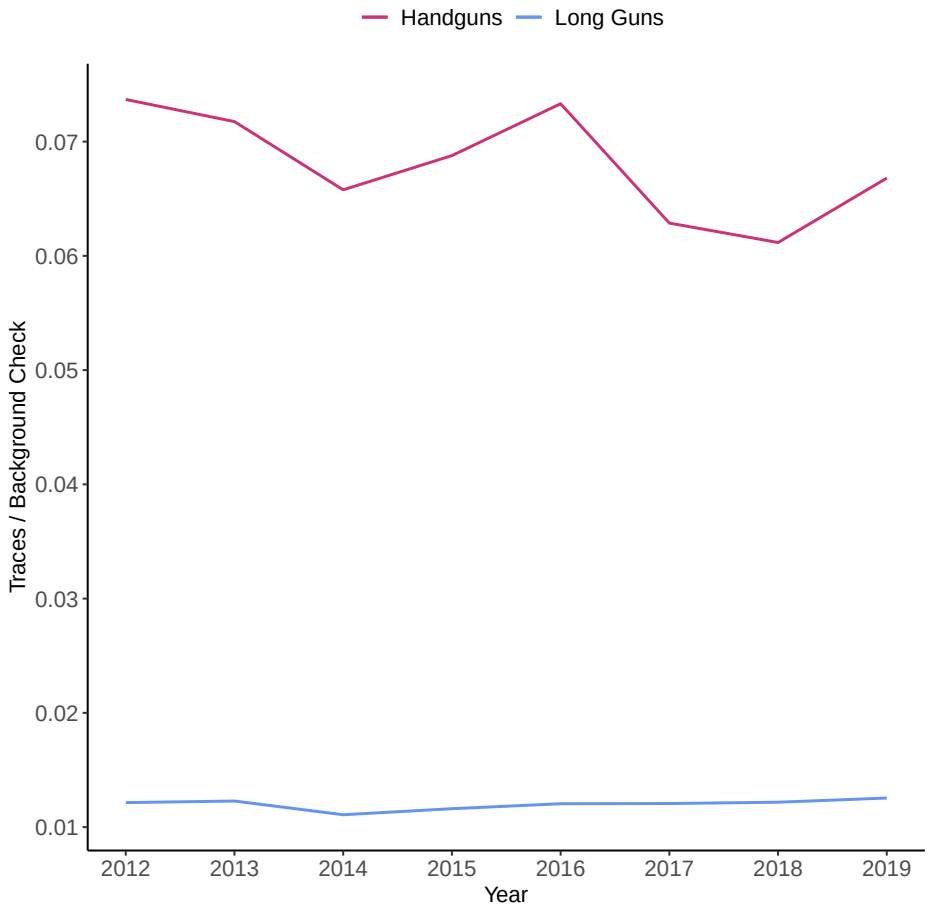
Table A.3—: Distribution of Firearm MSRPs ($) in the Conjoint Survey

	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 survey, 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 advertised on the manufacturer website.

Recall that our demand model allows for the price coefficient, brand intercepts, and gun-type intercepts to differ across individuals .Table A.4 illustrates how this flexibility translates to differences in estimated market shares across groups. One salient difference between men and women is interest

Figure A.4. : ATF Traces per NICS Background Check



in assault weapons; at current market prices, the share of men who would purchase an assault weapon 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 condition on the market definition (i.e., the share among gun owners and those interested in buying a gun). Thus, Table A.4 shows that conditional on being in the market, demand is relatively similar across region, education, and income. Where we 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.

We focus next on the comparison between prospective first-time gun owners and current owners in Table A.5. Prospective first-time gun owners are defined as respondents who do not already own a firearm. We find that this group is more price sensitive and has a higher relative preference for handguns compared to current owners. 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 A.6 provides more information on how heterogeneity in estimated parameters is correlated

Table A.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%.

Table A.5—: Estimates of Demand Parameters, Elasticities & Market Shares for First-Time Buyers and Current Owners

	Estimated Parameters				Estimated Model Implied	
	Posterior Mean	SD	2.5%	97.5%	Own-Price Elasticity	Market Share
			New Buyers			
Price	-0.013	0.022	-0.077	-0.000	–	–
Revolver	0.872	1.222	-1.509	3.161	-1.177	17.585
Pistol	1.997	1.187	-0.537	4.107	-1.064	41.177
Rifle	0.903	1.045	-1.405	2.714	-0.779	8.525
Shotgun	0.285	1.001	-1.845	2.142	-0.874	5.734
Assault Weapons	1.169	1.177	-0.914	3.475	-1.068	7.663
Outside Option	–	–	–	–	–	19.316
			Current Owners			
Price	-0.012	0.022	-0.074	-0.000	–	–
Revolver	0.813	1.214	-1.632	3.108	-1.098	13.965
Pistol	1.840	1.222	-0.697	4.038	-1.035	35.920
Rifle	0.888	1.041	-1.197	2.746	-0.735	13.078
Shotgun	0.382	0.977	-1.623	2.191	-0.850	8.447
Assault Weapons	1.170	1.245	-0.968	3.486	-0.933	10.114
Outside Option	–	–	–	–	–	18.476

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.

with observables. None of these estimates is critical to our underlying analysis and interpretation, but are provided in the interest of transparency.

Table A.6—: 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 $1,000$.

Figure A.5 displays estimated cross-price elasticities from the demand model. 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 so that substitution from a category with a small share does not move the pistol share much.

Table A.7 reports the credible intervals for the diversion ratios presented in Figure 3.

Table A.7—: Diversion Ratios — Credible Intervals

		Substitute From				
		Pistol	Revolver	Assault Weapon	Rifle	Shotgun
Substitute To	Pistol	[0.729, 0.763]	[0.130, 0.153]	[0.172, 0.202]	[0.130, 0.162]	[0.128, 0.156]
	Revolver	[0.049, 0.062]	[0.579, 0.620]	[0.073, 0.095]	[0.083, 0.108]	[0.063, 0.085]
	Assault Weapon	[0.030, 0.045]	[0.038, 0.054]	[0.317, 0.382]	[0.157, 0.212]	[0.070, 0.101]
	Rifle	[0.021, 0.030]	[0.034, 0.049]	[0.119, 0.160]	[0.321, 0.388]	[0.054, 0.078]
	Shotgun	[0.033, 0.043]	[0.041, 0.056]	[0.164, 0.199]	[0.094, 0.123]	[0.429, 0.495]
	Outside Option	[0.086, 0.113]	[0.109, 0.138]	[0.050, 0.076]	[0.095, 0.132]	[0.151, 0.192]

Appendix B – Conjoint Details

This section provides more details about our conjoint survey.

B1. 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

Figure A.5. : Cross Price Elasticities for Firearms

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

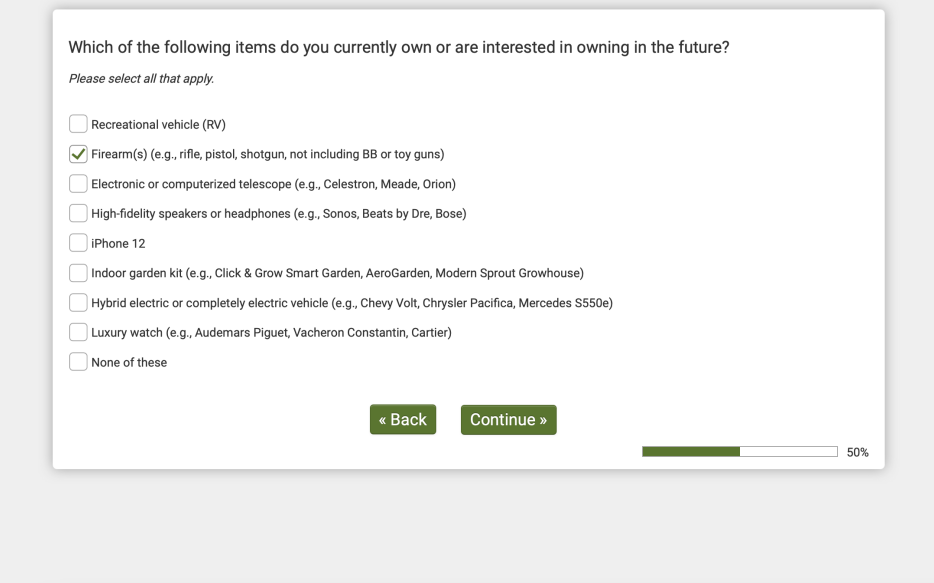
three surveys begin by drawing from the pool of survey respondents maintained by Harris Poll and its partners. A disadvantage of working with their sample is that we do not know their exact procedure for recruiting participants to the pool. However, we see two advantages of working with their respondents: 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 a question 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.

B2. 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:

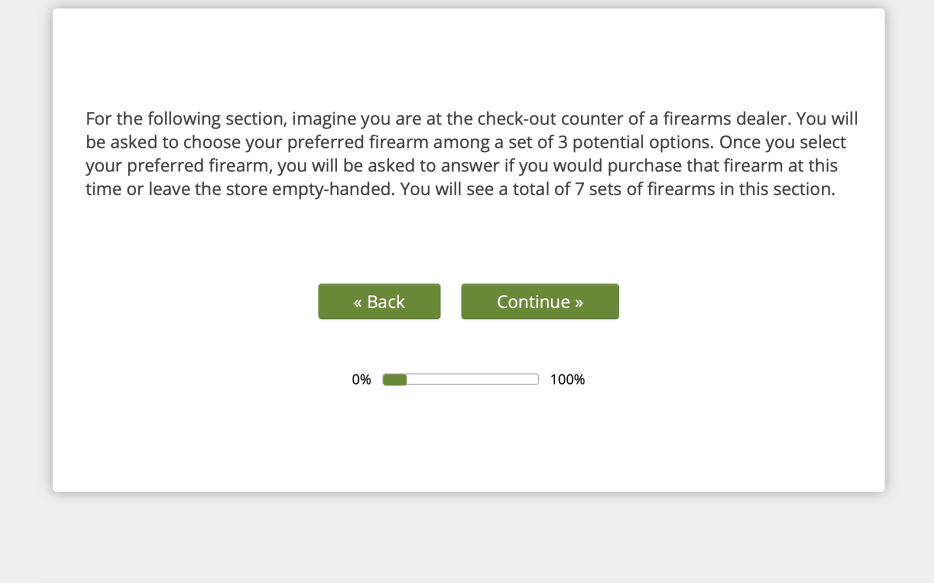
Note that the order of the options in this screener question is randomized (and changes across respondents), except for "None of these," which is always displayed last. All respondents who

Figure B.1. : Initial Screen Question



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 B.2. : Conjoint Instructions



And an example task is shown below:

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

Once respondents choose their most preferred firearm, they are shown the second part of the task:

Figure B.3. : Example Conjoint Question

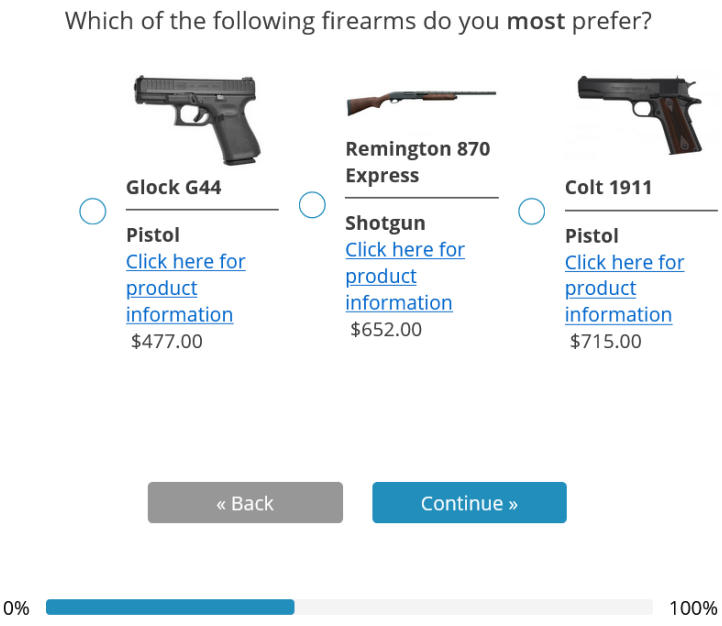


Figure B.4. : Example Conjoint Question

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

B3. Other Attributes

In addition to the product's price, the X_j vector of product characteristics in our demand system includes gun-type and brand intercepts. Each product is classified into its gun and brand category according to Table B.1, where the intercept for products in the 'Other' brand category is excluded to avoid multicollinearity.

Appendix C – Demand Model with Endogenous Consideration Sets

In this section, we augment our base demand model by modeling consideration sets as the outcome of a consumer search process. This modification allows customers to consider alternative firearm categories if characteristics of the market change (e.g., if certain firearms become relatively more/less expensive than others). The details of this model and estimation are provided in the online appendix, but the results are not substantially altered from our base model. We adopt an

Figure B.5. : Example Conjoint Question

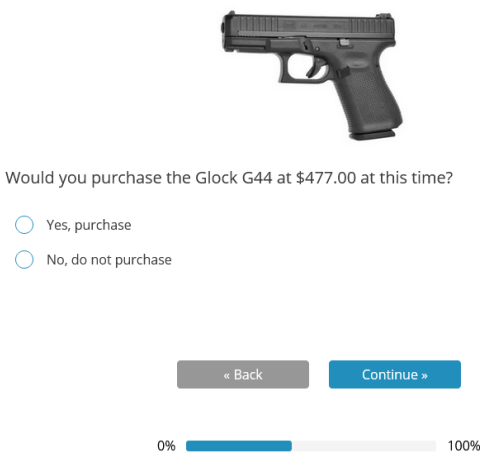


Table B.1—: X_j Product Characteristics

Gun-Type Intercepts	Brand Intercepts
Semi-Automatic Pistol	Glock
Inexpensive Revolver	Smith & Wesson
Mid-Tier Revolver	Ruger
Expensive Revolver	Colt
Semi-Automatic Rifle	Mossberg
Bolt Rifle	Springfield
Pump Rifle	Taurus
Lever Rifle	Benelli
Single-Shot Rifle	Sig Sauer
Semi-Automatic Shotgun	Other
Pump Shotgun	
Over-Under Shotgun	
Side-by-Side Shotgun	
Single-Shot Shotgun	

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.[1]

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:

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

It follows that each consumer that participates in the in the market will choose one of the following 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:

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

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

$$\min_{c \in l} \ln \left[\sum_{k \in c} exp(X_k' \beta_i - \alpha_i \cdot \bar{p}_k) \right] \geq \max_{\tilde{c} \notin l} \ln \left[\sum_{\tilde{k} \in \tilde{c}} exp(X_{\tilde{k}}' \beta_i - \alpha_i \cdot \bar{p}_{\tilde{k}}) \right] \tag{3}$$

Inequalities (1) and (2) stem from revealed preference: the respondent who elects to consider n categories must do weakly worse if they consider one more/fewer categories. Inequality (3) 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.

Then, to construct the likelihood, we modify equation 3 to include an indicator that inequalities (1) - (3) hold:

$$Pr\{y_{it} | \theta_i\} = s_{ijt} \cdot Pr\{C_t | l_i\} \cdot 1\{l_i | \theta_i\} \tag{4}$$

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

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

would not consider multiple categories, the alternatives from different non-considered categories are introduced in different tasks. We must therefore make an additional adjustment to the likelihood function to account for the inclusion of non-considered alternatives. The conditional probability that task t for respondent i comprises choice set C_{it} given stated consideration set l_i is then:

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

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

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:

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

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

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

C1. Search Cost Model Estimates

We present estimates of search costs in dollars in Figure C.1. The median search cost is \$100, which is approximately 16% of the cost of the median gun purchase predicted by the model.

Figure C.1. : Distribution of Search Costs

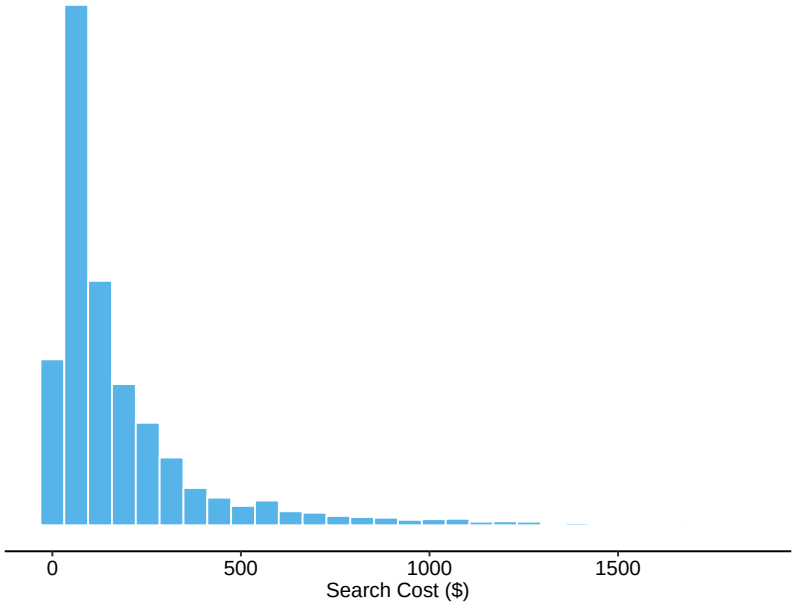


Table C.1 presents estimates from both the search cost and baseline demand models. The two models produce similar own-price elasticities (shown in columns 1 and 3), which hover around -1. Estimates from both models indicate that demand is more price elastic for handguns relative to long guns, with the 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. 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. Our intuition is that the model can fit such choices by increasing price sensitivity and model intercepts.

Table C.1—: 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

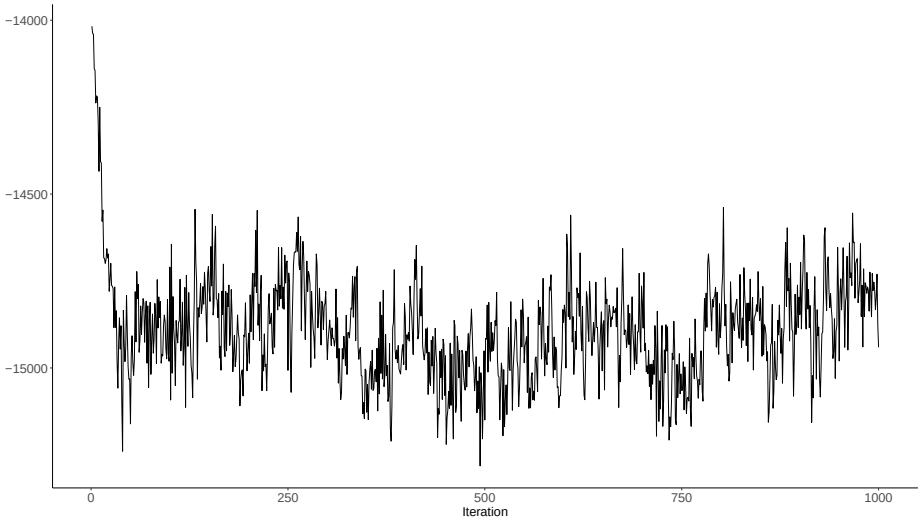
Appendix D – Estimation Details

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:

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

where $u_i \sim MVN(\mu, V_\theta)$. We use the package defaults for $\bar{\mu}, a_\mu^{-1}, \bar{\Delta}, \nu$, 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 draws after a burn in of 30,000 draws.

Figure D.1. : Log-Likelihood across Draws



D1. Search Cost Model

To estimate the search cost model, we write our own Metropolis-in-Gibbs 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 0.66. 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) 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:

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

Return to step (1).

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

REFERENCES

Honka, Elisabeth, "Quantifying search and switching costs in the US auto insurance industry," *The RAND Journal of Economics*, 2014, *45* (4), 847–884.

Rossi, P. E., G. M. Allenby, and R. McCulloch, *Bayesian Statistics and Marketing*, John Wiley & Sons, Ltd., 2005.