Online Appendix to "One Markup to Rule Them All: Taxation by Liquor Pricing Regulation"

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Appendix

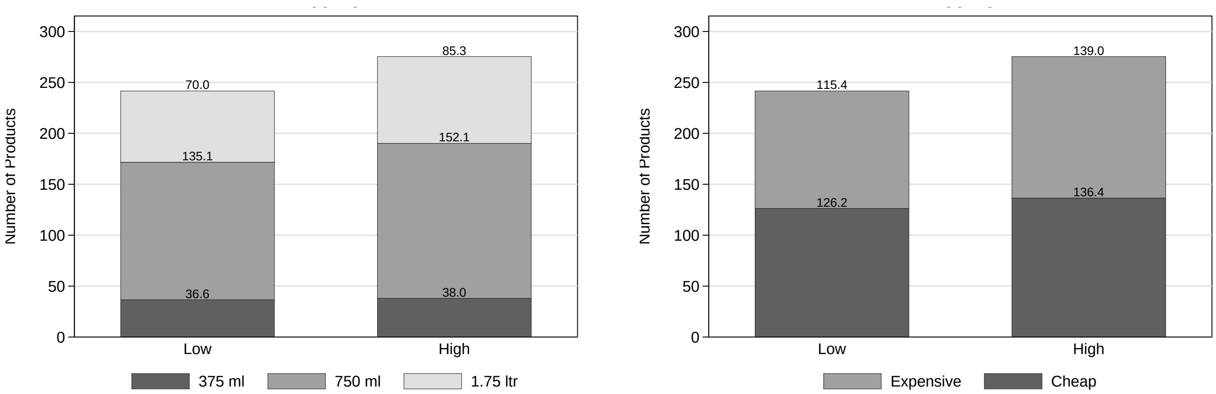
A Data

In this section we discuss the data in more detail. We begin with a discussion of how we aggregate the initial daily, store-level *PLCB* data and how we define market areas served by each store. We also address the possibility of stock-outs and how we link the available demographic information to our geographic market definition.

To reduce the size of the estimation sample, we consider the periodicity with which we observe price changes in the data. *PLCB* regulation in place during our sample period allows price to change only for two reasons: permanent and temporary wholesale price changes. Both follow set timing requirements. Permanent price changes can take effect on the first day of one of the *PLCB*'s four-week long accounting reporting periods. Temporary sales, on the other hand, begin on the last Monday of each month and last for either four or five weeks until the day before the last Monday of the following month. Reporting periods and temporary sales periods thus align largely, but not perfectly. To recognize that temporary price reductions are more prevalent than permanent ones (89.7% of price changes in the sample are temporary in nature) and avoid having multiple very short periods, we use sales periods as our time interval. In case of permanent price changes that take effect at the beginning of a reporting period that bisects two sales periods, we assume that the price change takes effect in the sales period that most overlaps with the given reporting period. This results in 22 "pricing periods" during which prices remain constant. In aggregating our daily sales data to the level of sales during a pricing period, we treat a product as being available in a store if we observe a sale at least once during a given pricing period. The length of the pricing period alleviates concern about distinguishing product availability from lack of sales in the period.

Product Set Variation Across Stores. Stores exhibit significant variation in the product composition of purchases but little variation in their product offering. These differences reflect heterogeneity in consumer preferences more than differences in the availability of products across stores: Of the 100 best selling products statewide in 2003, the median store carried 98.0%, while a store at the fifth percentile carried 72.0% of these products. Similarly, of the 1000 best selling products statewide in 2003, the median store carried 82.0%, while a store at the fifth percentile carried 44.2% of the products. The product availability at designated "premium" stores is somewhat better than the average, with the median premium store carrying all of the top 100 products and 95.1% of the top 1000 products. In addition, a consumer can request to have any regular product in the *PLCB*'s product catalog shipped to his local store for free, should that store not carry the product. In Figure A.1 we demonstrate the product set available to consumers in wealthier markets is greater for 1.75 L and EXPENSIVE products though the difference is small and consumers in poor neighborhoods clearly have access to a large set of these products. Further, the products purchased more often in high-income markets are all in the far right-tail of the sales distribution so it is reasonable to assume any bias they may introduce into our demand estimates are very small.

Figure A.1: Product Availability and Income



(a) Bottle Size (b) Price

Notes: A product is considered in the product set of a geographic market if it is ever sold during 2003-2004. Numbers reflect the average number of products in each category (e.g., 1.75 L products) carried by stores in the relevant income group.

The fact that most stores carry most popular products and can provide access to all products in the catalog easily, together with the absence of price differences across stores, supports an important assumption underlying our demand model: Differences in product availability do not drive consumers' store choices to a significant degree and as a result, consumers visit the store closest to them. In making this assumption, which allows us to focus on the consumer's choice between different liquor products available at the chosen store, we follow previous studies using scanner data such as Chintagunta, Dubé and Singh (2003).[1]

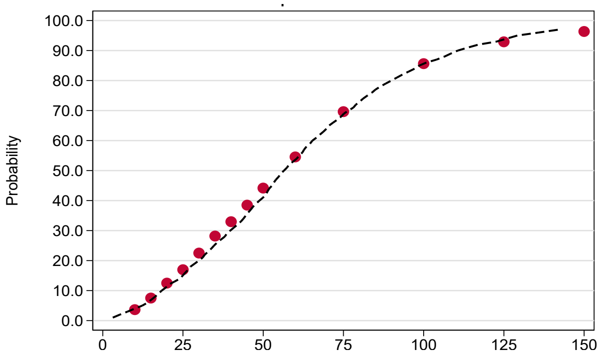
Simulating Consumers. To define the population served by each store, we calculate the straight-line distance to each store from each of Pennsylvania's 10,351 regular block groups and assign consumers to the closest open store for each pricing period. In instances where the *PLCB* operates more than one store within a ZIP code, we aggregate sales across stores to the ZIP code level; there are 114 such ZIP codes out of a total of 1,775. Note that these instances include both store relocations, where a store moved from one location in a ZIP code to another during 2003, but the data contain separate records for the store in the two locations, and instances where the *PLCB* operates two stores simultaneously within a ZIP code.[2] We consider the resulting block group zones as separate markets.

We derive consumer demographics for the stores' market areas by calculating the total population and population-weighted average demographics. We obtained detailed information on each block group's discrete income distribution by racial identity of the head of household, with household income divided into one of 16 categories. We aggregate across racial groups and across

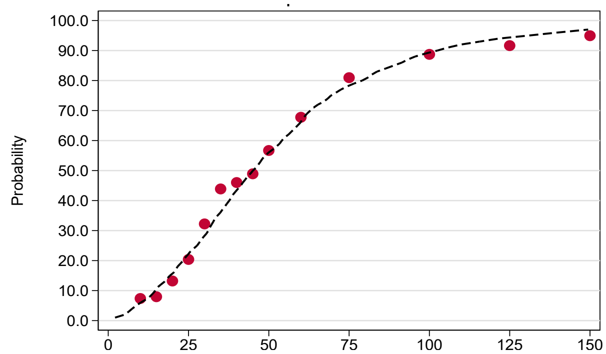
[1] Near the state's borders, the *PLCB* runs seven outlet stores that sell products, such as multi-packs, not available in regular stores to reduce the so-called 'border bleed' of consumers' shopping in lower-priced neighboring states. The addition of these stores to the sample has little qualitative or quantitative effects on the results. See Appendix D

[2] We drop wholesale stores, administrative locations, and stores without valid address information, for a total of 13 stores.

Figure A.2: Income Distributions Conditional on Race



(a) White Consumers (92.2%)



(b) Minority Consumers (7.8%)

Notes: In each panel we compare estimated income distribution (dashed line) and the block group discrete income distribution (dots). Income distributions are organized by racial identity of the head of household where panel (a) corresponds to white consumers and panel (b) corresponds to non-white (minority) consumers. In parentheses we present the share of consumers each racial category represents in the market. Results correspond to a store located in Reading, Pennsylvania.

block groups in a store's market area to derive the discrete income distribution separately for white and non-white households. We construct two income measures. First, we calculate the share of high-income households by minority status, defined as households with incomes above \$50,000. We use this measure in constructing the figures and descriptive statistics in the text. Second, we fit continuous market-specific distributions to the discrete distributions of income conditional on minority status. We use this measure in estimating the model and conducting counterfactual experiments. We employ generalized beta distributions of the second kind to fit the empirical income distribution for each market l. McDonald (1984) highlights that the beta distribution provides a good fit to empirical income data relative to other parametric distributions. In Figure A.2 we compare the estimated cumulative distribution functions for income conditional on minority status for a store located in Reading, PA. We observe that in this location the income distribution for white consumers first-order stochastically dominates the income distribution for minority consumer.

We also used a generalized beta distribution to estimate the continuous market-specific age distribution though due to data census limitations we could not condition this on race or income. We also obtained information on educational attainment by minority status and aggregated across several categories of educational attainment to derive the share of the population above the age of 25 with at least some college education, by minority status and market. Any correlation between educational attainment and income is therefore captured through the correlation between education and minority status and then minority status and income.

We construct the sample of simulated consumers for each market by relying on the empirical distributions of the demographic attributes considered above – whether a consumer is young, non-white, college-educated, and their income level – incorporating correlations between demographic attributes where possible. Conditional on a realization of a consumer's minority status, we take random draws from the corresponding income and educational attainment distributions and assign the consumer to an age bin based on the unconditional distribution of age above 21 years in the relevant location. Since the ambient population of stores changes with store openings and closings over the course of the year, the simulated set of agents changes in each pricing period. Lastly, we account for the unobserved preferences (ν_{il}) via scrambled Halton draws. As demonstrated by Train (2009), using Halton draws enables us to more efficiently cover the space of unobserved preferences (ν_{il}).

To summarize:

1. We use census data to construct a joint distribution of demographics for each market l.
    - We use census data for each market l to estimate the joint income distribution conditional on racial status (minority, non-minority). This yields L-by-2 estimated generalized beta distributions.
    - We complement this with census data on educational attainment conditional on racial status (minority, non-minority) by market l.
    - We include consumer age using the unconditional age distribution for each market l.
2. We simulate market l agents by drawing from the corresponding market l joint distribution, adding unobserved preferences (ν_{il}) via scrambled Halton draws.
3. In order to ensure we adequately cover the space of consumer characteristics, we chose a large number of simulated agents (1,000).

Price Instruments. Our price instruments come from two sources. First, the data on retail prices in other liquor control states consists of monthly product-level shelf prices by liquor control state. We assign a month to our Pennsylvania pricing periods to facilitate a match between the two data sets. Second, we attained historical commodity prices for corn and sugar from Quandl, a data aggregator. The prices are the monthly price of a "continuous contract" for each commodity where a "continuous contract" is defined as a hypothetical chained composite of a variety of futures contracts and is intended to represent a the spot market price of the given commodity. We also attained prices for rice, sorghum, wheat, barley, oats, and glass (as a cost input for bottle size) but found these input costs provided little additional explanatory power.

B Additional Descriptive Statistics

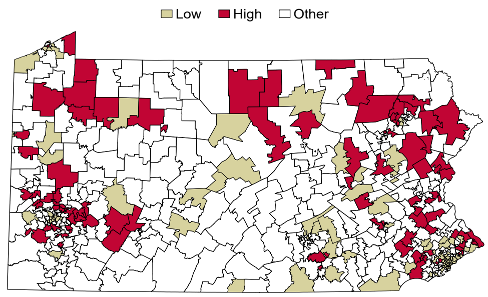
Table B.1 presents the distribution of bottle prices contained in our sample of 312 products. Average price is increasing across bottle sizes both within a category and for the whole sample. Vodkas are the most expensive products on average, while rums are least expensive. Figure B.1 documents the demographic diversity of Pennsylvania. Although correlated, the spatial distribution of demographics are not perfectly aligned.

Table B.1: Average Price and Market Shares by Type and Size

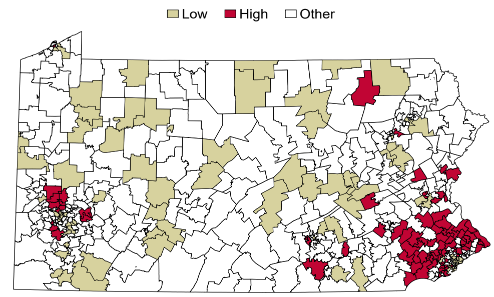
			Share of Market	
	Products	Avg. Price	By Quantity	By Revenue
BRANDY	26	14.41	7.26	6.75
375 ml	7	8.54	1.75	1.09
750 ml	13	15.56	4.28	4.13
1.75 L	6	18.76	1.22	1.52
CORDIALS	62	14.08	13.59	13.71
375 ml	13	10.76	2.11	1.49
750 ml	46	14.16	10.80	11.05
1.75 L	3	27.34	0.67	1.17
GIN	28	15.15	6.72	7.04
375 ml	4	7.80	0.62	0.33
750 ml	46	12.40	3.19	2.92
1.75 L	3	21.06	2.91	3.79
RUM	40	13.72	16.31	15.70
375 ml	5	6.59	1.65	0.73
750 ml	23	12.66	9.56	8.11
1.75 L	12	18.71	5.11	6.86
VODKA	66	16.82	32.10	29.80
375 ml	8	8.14	6.76	2.34
750 ml	33	15.54	10.85	11.08
1.75 L	25	21.29	14.50	16.37
WHISKEY	90	16.77	24.03	27.01
375 ml	11	9.12	2.33	1.37
750 ml	42	15.50	11.61	11.70
1.75 L	37	20.49	10.10	13.94
ALL PRODUCTS	312	16.35	100.00	100.00

Notes: "Quantity" market share is based on bottles while "Revenue" is based on dollar values.

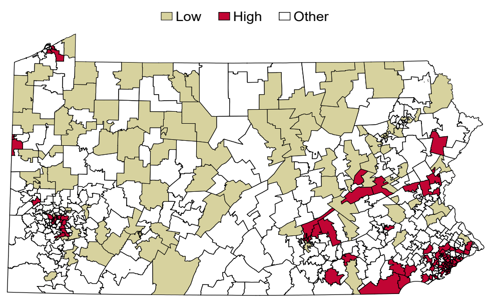
Figure B.1: Spatial Distribution of Consumer Characteristics



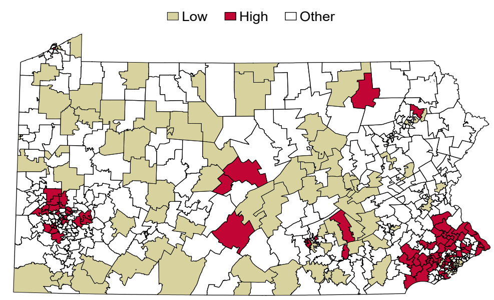
(a) Age



(b) Income



(c) Minority



(d) Education

Notes: Maps correspond to the spatial distribution of characteristics in Pennsylvania during the sample. Outlined polygons correspond to geographic markets (i.e., "stores" in the text). Dark shaded regions correspond to markets in the top quintile of the demographic attribute ("High" in the text). Lightly shaded regions correspond to markets in the bottom 20% for the corresponding demographic attribute ("Other" in the text). Remaining markets ("Other" in the figures) are not shaded.

C Estimation Procedure

In this Appendix, we lay out the three-stage estimation procedure we adopt to estimate contributions to the consumer's mean utility from a given product, δ_{jlt}, and individual-specific contributions to utility, μ_{ijlt}. We discuss each stage in turn, highlighting the variation in the data that allows us to identify the relevant parameters in each stage.

Stage 1: Random Coefficients and Demographic Interactions. In the first of the three stages, we estimate the contributions of unobserved (Σ) and observed (Π) demographic interactions to deviations from mean utility, μ_{ijlt}, controlling for location and product by time fixed effects. We decompose the unobserved product valuations, ξ_{jlt}, as follows

$$\xi_{jlt} = \zeta_l^1 + \xi_{jt} + \Delta\xi_{jlt} \, . \tag{C.1}$$

In equation (C.1), ζ_l^1 is a market fixed effect that captures systematic variation across locations in the preference for spirits consumption, relative to beer and wine.[3] We control for systematic variation in preferences for a given product over time via ξ_{jt}, to reflect the fact that across the state, a product's mean demand varies over the course of the year. The remaining structural error $\Delta\xi_{jlt}$ represents deviations in unobserved product valuations within a store from these mean product-time valuations, controlling for the average taste for spirits in market l.

This decomposition of ξ_{jlt} simplifies the mean utility of product j, δ_{jlt} in equation (5a), to

$$\delta_{jlt} = \zeta_l^1 + \zeta_{jt}^2 + \Delta\xi_{jlt} \, , \tag{C.2}$$

where the product and time specific fixed effect ζ_{jt}^2 comprises the effect of product characteristics $(x_j\beta)$, seasonal buying $(H_t\gamma)$, price (αp_{jt}^r), and ξ_{jt} on a product's mean utility.

Equation (C.2) highlights an advantage to our setting: since price does not vary across locations l, we are able to control for its mean contribution to utility via product by time fixed effects, which we then use in a second stage estimation to isolate α.

Given a guess at $\theta_A = \{\Sigma, \Pi\}$, we solve for the structural error $\Delta\xi_{jlt}(\theta_A)$ using the following algorithm. We first find the mean-utility levels $\delta_{jlt}(S_{jlt}; \theta_A)$ that set the predicted market share of each product, s_{jlt} in equation (7), equal to the market share observed in the data, S_{jlt}.[4] To evaluate the integral in equation (7) we simulate for each market l the purchase probabilities of 1000 randomly drawn heterogeneous consumers who vary in their demographics.

Given mean utility levels that equate predicted and actual market shares, we then follow Somaini and Wolak (2015) and use a within transformation of δ to remove the store and product-

[3] This accounts for the fact that the potential market is defined based on the average Pennsylvanian's consumption as disaggregated per-capita consumption of alcoholic beverages is not available.

[4] We make use of the contraction mapping procedure outlined in Appendix I of *BLP*, imposing a tolerance level for the contraction mapping of 1e-14 as advised by Dubé, Fox and Su (2012, §4.2) to ensure convergence to consistent stable estimates.

period fixed effects ζ_l^1 and ζ_{jt}^2, leaving only $\Delta\xi_{jlt}$. We follow the earlier literature in using a generalized method of moments (GMM) estimator that interacts $\Delta\xi$ with within-transformations of suitable instruments Z. We include in Z the following information: the number of products of the same type and price category, the root mean square distance in spirit product scores, plus interactions between these variables and demographics (see Section 4 for further detail). Define Z^+ as the within transformation of the instruments matrix; e.g., for instrument k, $Z_{jlt}^{+,k} = Z_{jlt}^k - \overline{Z_{jt}^k} - \overline{Z_l^k}$.

The GMM estimator exploits the fact that at the true value of parameters $\theta^\star = (\Sigma^\star, \Pi^\star)$, the instruments Z^+ are orthogonal to the structural errors $\Delta\xi(\theta^\star)$, i.e., $E\left[Z^{+'}\Delta\xi(\theta^\star)\right] = 0$, so that the GMM estimates solve

$$\hat{\theta}_A = \underset{\theta_A}{\operatorname{argmin}} \left\{\Delta\xi(\theta_A)' Z^+ W^+ Z^{+'} \Delta\xi(\theta_A)\right\}, \tag{C.3}$$

where W^+ is the weighting matrix, representing a consistent estimate of $E[Z^{+'}\Delta\xi\Delta\xi' Z^+]$.[5] To increase the likelihood of achieving a global minimum, we employed the Knitro Interior/ Direct algorithm suggested by Dubé et al. (2012) starting from several different initial conditions.

Stage 2: Mean Utility – Price and Seasonality Coefficients. In the second of the three stages of the estimation procedure, we decompose the mean utility implied by the estimated first-stage coefficients $\hat{\theta}_A$, $\delta_{jlt}(\hat{\theta}_A)$, into the associated location and product by type fixed effects, $\zeta_l^1(\hat{\theta}_A)$ and $\zeta_{jt}^2(\hat{\theta}_A)$. We then project ζ_{jt}^2 onto price and the seasonal indicators, controlling for product fixed effects ζ_j,

$$\zeta_{jt}^2 = H_t\gamma + \alpha p_{jt} + \zeta_j + \xi_{jt}\,. \tag{C.4}$$

Equation (C.4) highlights the potential for price endogeneity, to the extent that price responds to time varying preference variation for a given product that is common across locations, in the form of, for example, category-specific seasonal variation in consumption. The $PLCB$ pricing cannot respond to unobserved demand shocks. However, the predictable link between wholesale and retail prices opens the possibility to spirit prices being endogenous because of the pricing behavior of distillers whose wholesale prices reflect, through their products' market shares, the unobserved common tastes for product characteristics of spirits, ξ_{jt}. Recall the pricing optimality conditions in equation (13).

In principle, such endogeneity concerns are mitigated by the fact that distillers need to request both temporary and permanent changes to their wholesale price a number of months before the new price takes effect. Prices thus only respond to predictable variation in a product's demand over time. At the same time, none of the available product characteristics vary across time, limiting our ability to flexibly represent such time varying preference heterogeneity at the level of the product. We therefore use instrumental variables techniques to estimate the parameters in

[5] In constructing our optimal weighting matrix, we first assume homoscedastic errors and use $W^+ = [Z^{+'}Z^+]^{-1}$ to derive initial parameter estimates. Given these estimates, we solve for the structural error $\Delta\xi$ and construct $E[Z^{+'}\Delta\xi\Delta\xi' Z^+]^{-1}$ as a consistent estimate for W^+.

equation (C.4) using the contemporaneous average price of a given product from liquor control states outside of the Northeast and Mid-Atlantic regions (Alabama, Iowa, Idaho, Michigan, Mississippi, North Carolina, Oregon, Utah, and Wyoming) as an instrument for price denoted as Z_B. Our identifying assumption is that cost shocks are national (since products are often produced in a single facility) but demand shocks are at most regional, perhaps due to differences in demographics or climate.[6] We add to this instrument changes in input prices, sugar and corn, interacted with spirit-type dummies to account for exogenous cost shifts across spirit types. For instance, a major input for rums is sugar while corn is an input to gins, vodkas, and whiskeys. We found that contemporaneous futures prices worked best while including price-type interactions for barley, glass, oats, rice, rye, sorghum, and wheat does not improve our estimates. Collapsing the second stage parameters into vector θ_B, this implies the following parameter estimates

$$\hat{\theta}_B = (\hat{X}_B'\hat{X}_B)^{-1}\hat{X}_B'\zeta^2\,, \tag{C.5}$$

where $\hat{X}_B = Z_B(Z_B'Z_B)^{-1}Z_B'X_B$, with $X_B = [H_t \quad p_{jt} \quad \zeta_j]$. The price coefficient is identified by variation in prices over time, benefiting from the fact that distillers do not change the wholesale prices p^w for all products simultaneously.

Stage 3: Mean Utility – Product Characteristics Coefficients. In the third and final estimation stage, we recover product fixed effects ζ_j from equation (C.5) and project them onto observable product characteristics x_j, resulting in

$$\hat{\theta}_C = (x'x)^{-1}x'\zeta\,. \tag{C.6}$$

where mean preferences for these product characteristics are identified by variation in market shares of spirits of differing characteristics, e.g., proof or spirit type.

[6] For example, whiskey consumption, more so than the consumption of other spirits, peaks during the colder fall and winter months. Whiskey consumption also varies significantly across demographic groups; for example, African American households consume larger amounts of whiskey than other racial groups relative to their baseline levels of spirit consumption.

D Robustness

In this Appendix, we present the results of several alternative demand specifications.

In Table D.1 we demonstrate the robustness of our demand results to alternative samples using a simple OLS multinomial logit demand system. For each model, we regress the logged ratio of product to outside share on product-period and store fixed effects, including interactions between mean demographics and product characteristics (e.g., % minority-X-rum dummy). In Column (i) we presents results using the sample in the main text. This model generates product elasticities that are similar to our preferred mixed-logit model while the elasticity for spirits as a category is more elastic reflecting the IIA problem of logit demand systems (see *BLP*). In Columns (ii)-(iv) we vary the number of markets to show that including markets with premium (i.e., large stores) and border stores (i.e., stores located within five miles of the PA border) as well as the holiday period has little effect on our estimated price coefficient and elasticities. This indicates that restricting the sample has little effect on our results.

Table D.1: OLS Demand Estimates Based on Different Samples (Multinomial Logit Demand)

	(i)	(ii)	(iii)	(iv)
PRICE	−0.2396	−0.2469	−0.2238	−0.2341
	(0.0032)	(0.0033)	(0.0032)	(0.0028)
Product FEs	Y	Y	Y	Y
Premium Stores	Y	N	Y	Y
Border Stores	Y	Y	N	Y
Holiday Period	Y	Y	Y	N
Statistics:				
R^2	0.9584	0.9589	0.9564	0.9736
N	6,852	6,852	6,852	5,606
Elasticities:				
Average	−3.7454	−3.8610	−3.4916	−3.6618
% Inelastic	0.7353	0.3626	0.7477	0.7389
Spirits	−3.3936	−3.5374	−3.1225	−3.3134

Notes: The dependent variable for all models is the estimated product-period fixed effect from a first-stage regression of $\ln(S_{jmt})-\ln(S_{0mt})$ onto product-period fixed effects and demographic-product interactions. Robust standard errors in parentheses. "% Inelastic" is the percentage of products with inelastic demand. "Spirits" is the price elasticity of total *PLCB* off-premise (i.e., sold in a state-run store) spirit sales. "Premium Stores" are a *PLCB* designation. These stores typically carry greater number of products. "Border Stores" are stores located within five miles of the Pennsylvania border.

In Table D.2, we show that our estimation approach based on disaggregated data provides superior identification. In Model (i) we deviate from our multi-step approach and estimate the model in a single step, regressing the logged ratio of product share to outside share on price, brand fixed effects, bottle size fixed effects, pricing period fixed effects, market fixed effects, and mean demographic interactions, where brand refers to all bottle sizes of a particular "brand name", e.g., "Absolut Vodka". Demand becomes steeper relative to the Model (i) in Table D.1 when following this alternative approach leading to less elastic demand. We see even steeper effects when aggregating product demand across the state (Models iii and iv).

Interestingly, we see that not conducting the estimation via the steps outlined in the text leads to price elasticity estimates found by Leung and Phelps (1993) as well as other studies. Less elastic product demands increase estimated dollar markups for upstream firms, ultimately driving down estimated distiller marginal costs. Miravete, Seim and Thurk, 2018 show using similar data that spirit category elasticities presented in the health literature (e.g., Leung and Phelps, 1993) imply negative marginal costs for these firms. Table D.2 therefore suggests that such studies may suffer from an aggregation bias that leads to less elastic estimated demand.

Table D.2: OLS Demand Estimates Using Different Approaches (Multinomial Logit Demand)

	(i)	(ii)	(iii)	(iv)
PRICE	−0.1224	−0.0513	−0.0822	−0.0103
	(0.0004)	(0.0003)	(0.0022)	(0.0016)
Brand FEs	Y	N	Y	N
Statistics:				
R^2	0.5129	0.2420	0.8218	0.1441
N	2,237,937	2,237,937	6,852	6,852
Elasticities:				
Average	−1.9133	−0.8028	−1.2853	−0.1610
% Inelastic	12.9738	77.7657	39.1113	100.0000
Spirits	−1.7512	−0.7393	−1.1805	−0.1488

Notes: The dependent variable for models (i)-(ii) is $\ln(S_{jmt}) - \ln(S_{0mt})$ while it is $\ln(S_{jt}) - \ln(S_{0t})$ for models (iii)-(iv). Robust standard errors in parentheses. "% Inelastic" is the percentage of products with inelastic demand. "Spirits" is the price elasticity of total *PLCB* off-premise (i.e., sold in a state-run store) spirit sales.

In Model (ii) we replace the product fixed effects with observable characteristics (e.g., dummies for spirit type, imported). Demand becomes even steeper and demand becomes more inelastic due the coarseness of our observable characteristics. For example, two brands of imported rum could have different unobservable quality to consumers thereby leading different product shares and firms choosing to charge different prices but in this specification, the estimation wrongly correlates differences in price with the differences in shares (quantity sold). In Models (iii)-(iv) we aggregate consumption to the state-level requiring us to drop the demographic interactions but otherwise using the same controls as Models (ii)-(iii). Again, we see the inclusion of brand fixed effects is important to absorbing differences in unobservable (to the econometrician) characteristics across brands. We further see that aggregation drives the elasticity of off-premise spirits to become more inelastic, well within the set of estimates included in Leung and Phelps (1993).

As discussed in Section C, we use the contemporaneous average price in distant control states as an instrument for price in the second step. In Table D.3, we consider the sensitivity of our results to the particular instrumentation strategy. We compare the estimated price coefficient from alternative two-stage least squares regression models of the estimated first stage product-period fixed effects underlying the estimates in Table 4 projected onto price, seasonal dummies, and product fixed effects.

Relative to $IV1$, our preferred specification, the estimated price coefficients are stable across alternative instruments, and, as expected, entail larger price responses than an uninstrumented OLS specification. Each estimated price coefficient is significant at the 95% level and the sets of IVs generate significant F-statistics for all specifications. Removing the average price in other states decreases the price coefficient but also decreases the F-Statistic.

Table D.3: Price Endogeneity

	OLS	*IV1*	*IV2*	*IV3*	*IV4*
PRICE	-0.2412	-0.2763	-0.2781	-0.2775	-0.3145
	(0.0038)	(0.0046)	(0.0046)	(0.0046)	(0.0051)
Instruments:					
Input Prices		Y	Y	Y	Y
Alabama		Y		Y	
Iowa		Y	Y		
Idaho		Y	Y	Y	
Michigan		Y			
Mississippi		Y	Y		
North Carolina		Y	Y		
Oregon		Y	Y	Y	
Utah		Y	Y		
Wyoming		Y	Y	Y	
F-Statistic		1,280.2	1,235.1	1,235.8	920.79
N	6,852	6,852	6,852	6,852	6,852

Notes: Specifications include the same covariates as in Table 4. "Input Prices" is the interaction of spirit type and commodity prices. This amounts to nine interactions: corn-x-gin, corn-x-vodka, corn-x-whiskey, sugar-x-brandy, sugar-x-cordials, sugar-x-gin, sugar-x-rum, sugar-x-whiskey, and sugar-x-vodka where "corn" and "sugar" corresponds to the futures price of corn and sugar during the period. In models 1-4 we also include contemporaneous average price in distant control states as an instrument for price but vary the states used to compute the average.

E Confidence Intervals for Counterfactual Experiments

For each counterfactual exercise, we constructed 95% confidence intervals via bootstrap simulation based on the multivariate empirical distribution implied by the estimated demand parameters (Table 4). The confidence intervals are based on $n = 1, \dots, 100$ random samples of the demand parameters where we restricted the draws to be over the nonlinear parameters $\{\Sigma, \Pi\}$ and the linear price coefficient (α). This both increases tractability of the bootstrap procedure and focuses the analysis on the parameters, especially the mean price coefficient α and the income-price interaction (in Π), which drive the own and cross-price elasticities and, ultimately, redistribution due to the uniform markup.

A counterfactual simulation proceeds as follows. Define $\theta_n = \{\alpha_n, \Sigma_n, \Pi_n\}$ as the bootstrap parameters for sample n. We use $\{\Sigma_n, \Pi_n\}$ and the observed vector of product market shares s_j to recover the mean utility $\delta(\theta_n; s_j)$ following the solution method outlined in Section C of this Appendix. Estimates of firm-level marginal costs then follow using the observed product-ownership matrix and equation (13) as discussed in section 4.3. By using this procedure, we guarantee that each bootstrap simulation n generates predicted market shares which match the data and marginal costs estimates which are consistent with upstream Bertrand–Nash pricing. Thus, each counterfactual equilibrium generated from a bootstrap simulation generates the data under the 30% markup rule, or, equivalently, starts from the same place.

Define $\overline{\xi}_n = \delta(\theta; s_j) - \alpha_n p^r$ where p^r is the vector of observed retail prices in the data. We then use $\{\alpha_n, \Sigma_n, \Pi_n, c_n, \overline{\xi}_n\}$ to solve for each of the counterfactual equilibria in the main text (e.g., "Profit") where changes in the markup rule lead to a new set of equilibrium upstream firm prices (p_n^w) and retail prices (p_n^r). The retail prices impact consumer mean utility since $\delta_n = \alpha_n p_n^r + \overline{\xi}_n$, and ultimately lead to changes in consumer demand via equation 6.

For each bootstrap simulation and counterfactual equilibrium, we compute the descriptive statistics presented in the text (e.g., aggregate tax revenue in Table 7). To compute compensating variation in each simulation, we compare consumer surplus (up to an additive constant) given observed prices and θ_n (i.e., consumer surplus in the observed equilibrium conditional on θ_n) to the consumer surplus generated in the counterfactual Stackelberg equilibrium.

Most of our analysis compares summary statistics from the current equilibrium to summary statistics from counterfactual Stackelberg equilibria using the point-estimates from our demand estimation ($\hat{\theta}$). Where possible, we also include the 95% confidence intervals from the bootstrap simulations in order to demonstrate the robustness of our conclusions. The 95% confidence intervals presented in the text correspond to the range of bootstrap simulation-counterfactual equilibria for the given statistic which fall between the 2.5% and 97.5% quartiles, i.e., the middle 95%.

F Additional Results and Figures

Table F.1: Estimated Marginal Costs (Select Firms)

	All	Diageo	Bacardi	Beam	Jacquin	Sazerac
By Spirit Type:						
BRANDY	5.34	-	-	-	3.66	-
CORDIALS	6.16	7.18	15.00	3.21	1.98	5.08
GIN	6.43	7.72	12.51	4.90	4.29	2.67
RUM	5.66	7.05	5.48	4.47	3.45	-
VODKA	6.37	6.07	-	4.64	4.24	3.83
WHISKEY	7.11	8.17	14.82	6.05	4.67	4.88
By Price:						
CHEAP	3.67	3.66	3.67	3.62	3.59	3.70
EXPENSIVE	9.04	8.53	10.46	8.08	-	7.78
By Bottle Size:						
375 ml	2.39	2.13	1.45	1.02	0.23	2.89
750 ml	5.81	6.13	5.83	3.51	2.02	2.97
1.75 L	8.24	11.28	11.84	7.54	5.00	4.68
ALL PRODUCTS	6.33	6.33	6.89	5.14	3.59	4.14

Notes: Estimated upstream marginal costs weighted by sales.

Table F.2: Retail and Wholesale Prices by Product Category

		Wholesale Price (p^w)			Retail Price (p^r)		
	Elast.	Current	Single	Profit	Current	Single	Profit
By Spirit Type:							
brandy	-3.64	8.09	8.19 [8.09, 8.3]	7.25 [7.24, 7.3]	13.85	13.50 [13.18, 13.83]	15.70 [15.64, 15.85]
cordials	-3.46	8.88	8.98 [8.88, 9.08]	8.72 [8.66, 8.73]	15.03	14.63 [14.25, 15]	15.00 [14.96, 15.29]
gin	-3.9	9.14	9.24 [9.15, 9.35]	8.83 [8.78, 8.85]	15.61	15.19 [14.8, 15.58]	16.15 [16.12, 16.44]
rum	-3.38	8.35	8.45 [8.36, 8.55]	8.13 [8.07, 8.16]	14.34	13.97 [13.63, 14.32]	14.57 [14.47, 14.83]
vodka	-3.95	7.99	8.09 [7.99, 8.19]	7.62 [7.55, 7.64]	13.82	13.48 [13.15, 13.8]	13.79 [13.77, 14.14]
whiskey	-3.98	9.89	9.99 [9.89, 10.1]	9.69 [9.63, 9.71]	16.74	16.28 [15.85, 16.71]	16.68 [16.63, 17.06]
By Price:							
cheap	-2.81	5.85	5.95 [5.85, 6.05]	5.26 [5.24, 5.29]	10.50	10.28 [10.08, 10.48]	11.46 [11.41, 11.56]
expensive	-4.74	11.94	12.04 [11.94, 12.15]	11.95 [11.86, 11.96]	19.85	19.27 [18.72, 19.82]	19.15 [19.1, 19.72]
By Bottle Size:							
375 ml	-2.36	3.89	3.99 [3.89, 4.09]	2.94 [2.94, 3.02]	7.20	7.11 [7.02, 7.2]	7.87 [7.75, 7.92]
750 ml	-3.58	8.53	8.64 [8.54, 8.74]	8.24 [8.18, 8.26]	14.51	14.13 [13.78, 14.49]	15.08 [15.03, 15.34]
1.75 L	-4.74	11.09	11.19 [11.09, 11.3]	11.05 [10.96, 11.06]	18.84	18.31 [17.81, 18.81]	18.24 [18.21, 18.79]
all products	-3.75	8.71	8.81 [8.71, 8.92]	8.40 [8.35, 8.43]	14.89	14.50 [14.14, 14.87]	15.07 [15.03, 15.39]

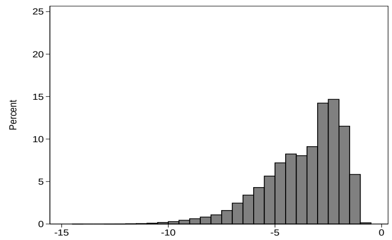
Notes: "Elast." corresponds to the average estimated demand elasticities from Table 5. Other reported statistics are average wholesale and retail price ($). "Cheap" ("Expensive") products are those products whose mean price is below (above) the mean price of other spirits in the same spirit type and bottle size. "Single" indicates the counterfactual where the *PLCB* chooses the revenue-maximizing markup ("Maximizing" in the main text). The *PLCB* employs 312 product-specific markups to maximize tax revenue ("Profit" in the main text).

Table F.3: Best Substitutes

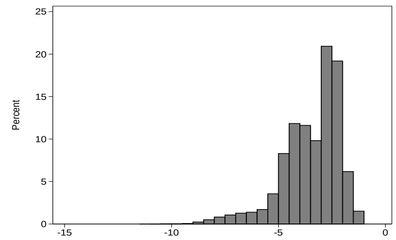
Product	Type	Closest Substitute: Product	Type	ϵ_{ji}
HENNESSY V. S. COGNAC - 375 ML	BRANDY	COURVOISIER V. S. COGNAC - 375 ML	BRANDY	0.2522
E & J CAL. BRANDY - 375 ML	BRANDY	E & J CAL. V.S.O.P. BRANDY - 375 ML	BRANDY	0.1005
THE CHRISTIAN BROS. CAL. BRANDY - 375 ML	BRANDY	E & J CAL. V.S.O.P. BRANDY - 375 ML	BRANDY	0.0547
E & J CAL. BRANDY - 750 ML	BRANDY	PAUL MASSON GRANDE AMBER BRANDY - 750 ML	BRANDY	0.1503
HENNESSY V. S. COGNAC - 750 ML	BRANDY	MARTELL V. S. COGNAC - 750 ML	BRANDY	0.3900
THE CHRISTIAN BROS. CAL. BRANDY - 750 ML	BRANDY	THE CHRISTIAN BROS. CAL. BRANDY - PET BOTTLE - 750 ML	BRANDY	0.1114
E & J CAL. BRANDY - 1.75 LTR	BRANDY	E & J CAL. V.S.O.P. BRANDY - 1.75 LTR	BRANDY	0.1216
THE CHRISTIAN BROS. CAL. BRANDY - 1.75 LTR	BRANDY	E & J CAL. BRANDY - 1.75 LTR	BRANDY	0.1118
JACQUIN'S BLACKBERRY FLAV. BRANDY - 1.75 LTR	BRANDY	JACQUIN'S APRICOT FLAV. BRANDY - 1.75 LTR	BRANDY	0.1261
BAILEYS ORIGINAL IRISH CREAM LIQUEUR - 375 ML	CORDIALS	GREY GOOSE IMP. VODKA - 375 ML	VODKA	0.0073
JAGERMEISTER IMP. HERB LIQUEUR - 375 ML	CORDIALS	YUKON JACK CANADIAN LIQUEUR - 375 ML	CORDIALS	0.0292
KAHLUA IMP. COFFEE LIQUEUR - 375 ML	CORDIALS	DI SARONNO AMARETTO IMP. LIQUEUR - 375 ML	CORDIALS	0.0095
KAHLUA IMP. COFFEE LIQUEUR - 750 ML	CORDIALS	ABSOLUT IMP. VODKA - 100 PROOF - 750 ML	VODKA	0.0147
SOUTHERN COMFORT - 76 PROOF - 750 ML	CORDIALS	FIRE WATER HOT CINNAMON SCHNAPPS - 750 ML	CORDIALS	0.0297
HPNOTIQ IMP. LIQUEUR - 750 ML	CORDIALS	BELVEDERE IMP. VODKA - 750 ML	VODKA	0.0112
SOUTHERN COMFORT - 76 PROOF - 1.75 LTR	CORDIALS	WILD TURKEY STR. BOURBON WKY. - 101 PROOF - 750 ML	WHISKEY	0.0272
DEKUYPER PEACHTREE SCHNAPPS - 1.75 LTR	CORDIALS	KAHLUA IMP. COFFEE LIQUEUR - 1.75 LTR	CORDIALS	0.0018
KAHLUA IMP. COFFEE LIQUEUR - 1.75 LTR	CORDIALS	GREY GOOSE IMP. FRENCH VODKA - 1.75 LTR	VODKA	0.0078
SEAGRAM'S EXTRA DRY GIN - 375 ML	GIN	BANKER'S CLUB DRY GIN - 375 ML	GIN	0.0164
TANQUERAY IMP. DRY GIN - 375 ML	GIN	BANKER'S CLUB DRY GIN - 375 ML	GIN	0.0141
GORDON'S DRY GIN - PET - 375 ML	GIN	BANKER'S CLUB DRY GIN - 375 ML	GIN	0.0083
TANQUERAY IMP. DRY GIN - 750 ML	GIN	BOMBAY IMP. SAPPHIRE GIN - 750 ML	GIN	0.0610
SEAGRAM'S EXTRA DRY GIN - 750 ML	GIN	FIVE O'CLOCK EXTRA DRY GIN - 750 ML	GIN	0.0136
GORDON'S DRY GIN - 750 ML	GIN	BEEFEATER IMP. DRY GIN - 750 ML	GIN	0.0078
GORDON'S DRY GIN - 1.75 LTR	GIN	BOMBAY IMP. SAPPHIRE GIN - 1.75 LTR	GIN	0.0319
BANKER'S CLUB DRY GIN - 1.75 LTR	GIN	BEEFEATER IMP. DRY GIN - 1.75 LTR	GIN	0.0136
SEAGRAM'S EXTRA DRY GIN - 1.75 LTR	GIN	TANQUERAY IMP. DRY GIN - 1.75 LTR	GIN	0.0174
BACARDI LIGHT-DRY P. R. RUM - 375 ML	RUM	SOUTHERN COMFORT - 100 PROOF - 375 ML	CORDIALS	0.0171
CAPTAIN MORGAN P. R. SPICED RUM - 375 ML	RUM	YUKON JACK CANADIAN LIQUEUR - 375 ML	CORDIALS	0.0130
BACARDI LIMON P. R. RUM - 375 ML	RUM	SOUTHERN COMFORT - 100 PROOF - 375 ML	CORDIALS	0.0051
CAPTAIN MORGAN P. R. SPICED RUM - 750 ML	RUM	CAPTAIN MORGAN PRIVATE STOCK P. R. SPICED RUM - 750 ML	RUM	0.0358
BACARDI LIGHT-DRY P. R. RUM - 750 ML	RUM	FIRE WATER HOT CINNAMON SCHNAPPS - 750 ML	CORDIALS	0.0207
CAPTAIN MORGAN P. R. SPICED RUM PET - 750 ML	RUM	CAPTAIN MORGAN PRIVATE STOCK P. R. SPICED RUM - 750 ML	RUM	0.0211
BACARDI LIGHT-DRY P. R. RUM - 1.75 LTR	RUM	WILD TURKEY STR. BOURBON WKY. - 101 PROOF - 750 ML	WHISKEY	0.0547
CAPTAIN MORGAN P. R. SPICED RUM - 1.75 LTR	RUM	SMIRNOFF VODKA - 100 PROOF - 1.75 LTR	VODKA	0.0512
JACQUIN'S WHITE RUM - 1.75 LTR	RUM	WILD TURKEY STR. BOURBON WKY. - 101 PROOF - 750 ML	WHISKEY	0.0204
NIKOLAI VODKA - 80 PROOF - 375 ML	VODKA	STOLICHNAYA IMP. VODKA - 80 PROOF - 375 ML	VODKA	0.0402
JACQUIN'S VODKA ROYALE - 80 PROOF - 375 ML	VODKA	NIKOLAI VODKA - 80 PROOF - 375 ML	VODKA	0.0287
SMIRNOFF VODKA - 80 PROOF - 375 ML	VODKA	STOLICHNAYA IMP. VODKA - 80 PROOF - 375 ML	VODKA	0.0199
ABSOLUT IMP. VODKA - 80 PROOF - 750 ML	VODKA	ABSOLUT IMP. VODKA - 100 PROOF - 750 ML	VODKA	0.0496
SMIRNOFF VODKA - 80 PF. PORTABLE - 750 ML	VODKA	ABSOLUT IMP. VODKA - 100 PROOF - 750 ML	VODKA	0.0220
SMIRNOFF VODKA - 80 PROOF - 750 ML	VODKA	ABSOLUT IMP. VODKA - 100 PROOF - 750 ML	VODKA	0.0154
JACQUIN'S VODKA ROYALE - 80 PROOF - 1.75 LTR	VODKA	BEEFEATER IMP. DRY GIN - 750 ML	GIN	0.0448
NIKOLAI VODKA - 80 PROOF - 1.75 LTR	VODKA	NIKOLAI VODKA - 100 PROOF - 1.75 LTR	VODKA	0.0375
VLADIMIR VODKA - 1.75 LTR	VODKA	BEEFEATER IMP. DRY GIN - 750 ML	GIN	0.0272
JACK DANIEL'S OLD NO. 7 BLACK LABEL WKY. - 375 ML	WHISKEY	WILD TURKEY STR. BOURBON WKY. - 101 PROOF - 375 ML	WHISKEY	0.0450
CROWN ROYAL CANADIAN WKY. - 375 ML	WHISKEY	TANQUERAY IMP. DRY GIN - 375 ML	GIN	0.0225
WINDSOR CANADIAN SUPREME WKY. - 375 ML	WHISKEY	TANQUERAY IMP. DRY GIN - 375 ML	GIN	0.0110
JACK DANIEL'S OLD NO. 7 BLACK LABEL WKY. - 750 ML	WHISKEY	WILD TURKEY STR. BOURBON WKY. - 101 PROOF - 750 ML	WHISKEY	0.0506
JIM BEAM STR. BOURBON WKY. - 750 ML	WHISKEY	WILD TURKEY STR. BOURBON WKY. - 101 PROOF - 750 ML	WHISKEY	0.0195
CROWN ROYAL CANADIAN WKY. - 750 ML	WHISKEY	TANQUERAY IMP. DRY GIN - 1.75 LTR	GIN	0.0348
WINDSOR CANADIAN SUPREME WKY. - 1.75 LTR	WHISKEY	BEEFEATER IMP. DRY GIN - 1.75 LTR	GIN	0.0462
JIM BEAM STR. BOURBON WKY. - 1.75 LTR	WHISKEY	CROWN ROYAL CANADIAN WKY. - 1.75 LTR	WHISKEY	0.0351
SEAGRAM'S 7 CROWN AMERICAN BLEND WKY. - 1.75 LTR	WHISKEY	BEEFEATER IMP. DRY GIN - 1.75 LTR	GIN	0.0233

Notes: Table presents the three best-selling products by number of bottles for each spirit type, bottle size pair, and the corresponding best substitute based on cross-price elasticity.

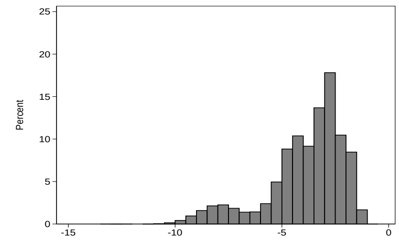
Figure F.1: Distribution of Demand Elasticities



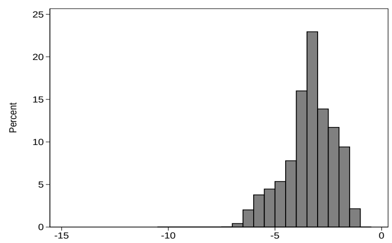
(a) Brandy



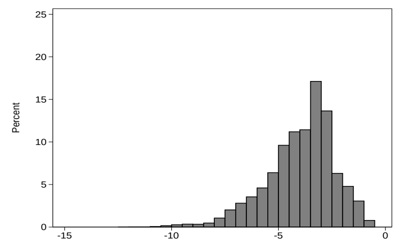
(b) Cordials



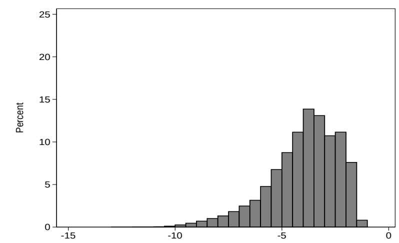
(c) Gin



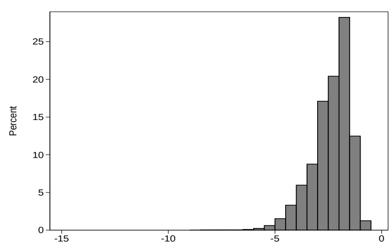
(d) Rum



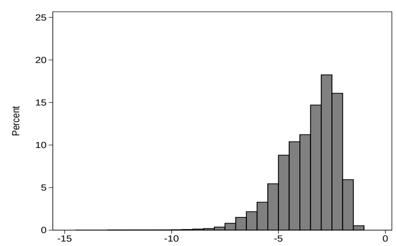
(e) Vodka



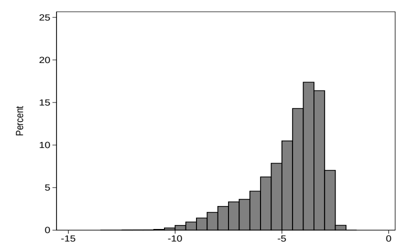
(f) Whiskey



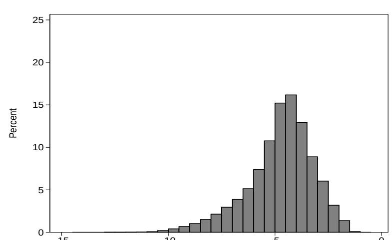
(g) 375 ml



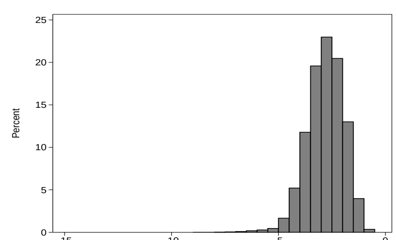
(h) 750 ml



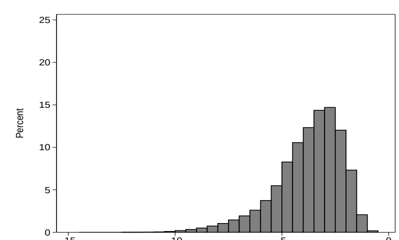
(i) 1.75 Ltr



(j) Expensive

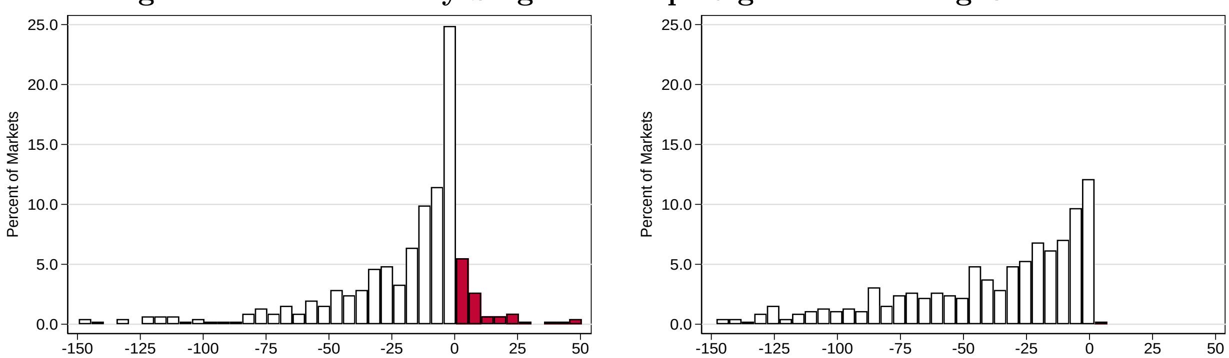


(k) Cheap



(l) All Products

Figure F.2: Taxation by Single Markup Regulation Among Consumers

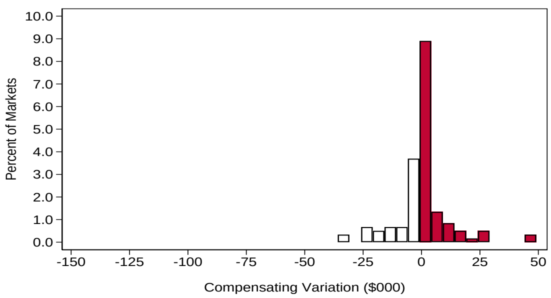


(a) Objective: Maximize Tax Revenue

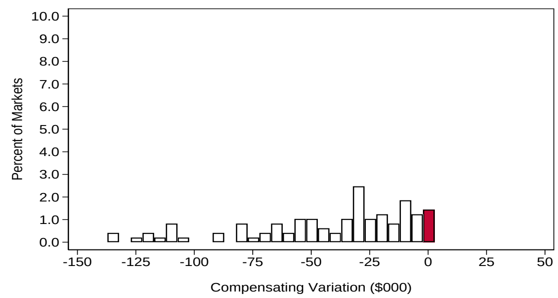
(b) Objective: Maximize Consumer Welfare

Notes: We present the distribution of compensating variation $\{CV_l\}_{l=1}^{454}$, denominated in thousands of dollars, calculated as the mean compensating variation in each market l using the Stackelberg equilibria under the alternative markup policy to the one observed under the current 30% markup policy.

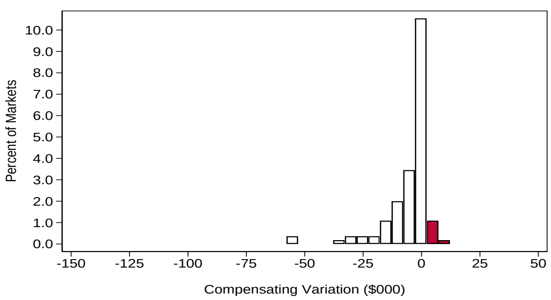
Figure F.3: Compensating Variation by Consumer Demographics



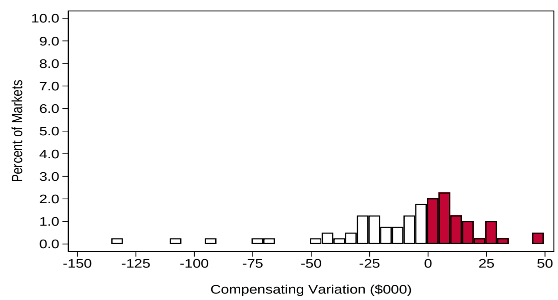
(a) Income - Low



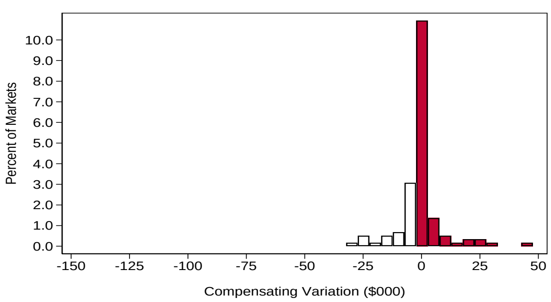
(b) Income - High



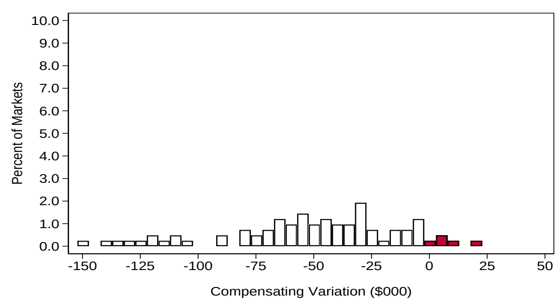
(c) Minority - Low



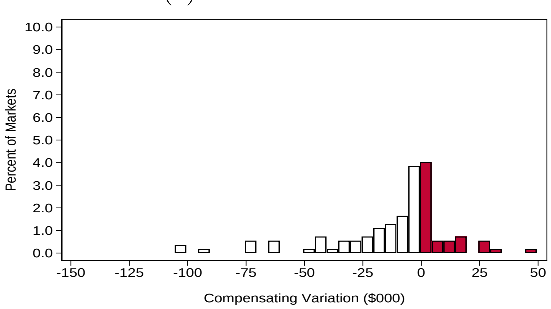
(d) Minority - High



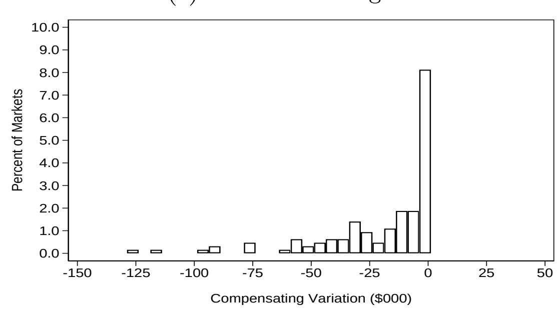
(e) Education - Low



(f) Education - High



(g) Age - Low



(h) Age - High

Notes: We present the distribution of compensating variation $\{CV_l\}_{l=1}^{454}$, denominated in thousands of dollars, calculated as the mean compensating variation in each market l using the Stackelberg equilibria under the alternative markup policy to the one observed under the current 30% markup policy. Average of markets with top and bottom 20% of AGE, MINORITY, EDUCATION, and INCOME as defined in Table 2.

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