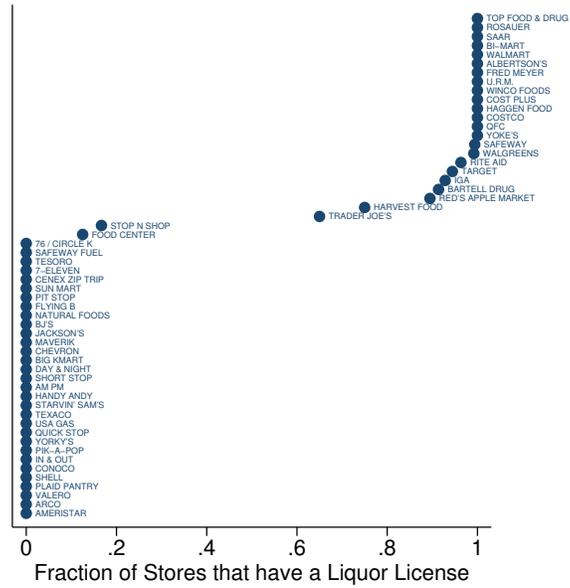


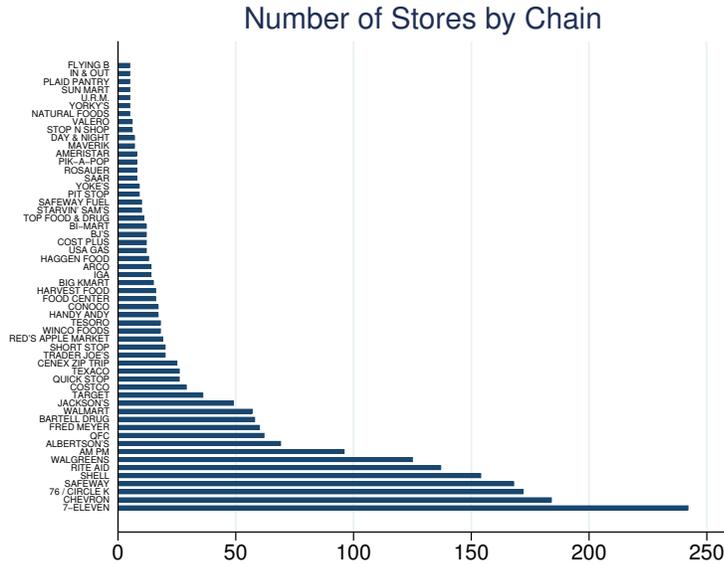
A. Appendix Figures and Tables (For Online Publication)

Figure A1: Chain Licensure



Notes: For each chain with 5 or more outlets in the WSLCB beer and wine licensure data, this figure plots the fraction of outlets that obtain a liquor license at liberalization.

Figure A2: Chain Sizes



Notes: This figure plots the number of retail outlets by chain for all chains with more than 5 outlets in the WSCLB beer and wine licensure data.

Table A1: Regression Discontinuity Estimates of the Effect of License Eligibility on Entry

	RD Estimates of the Effect of Licensure on Entry			
	(1)	(2)	(3)	(4)
	All Stores	Independent Stores	Chain Stores	Large Chains (10+ Stores)
Licensure Discontinuity	0.256 (0.112)	-0.033 (0.133)	0.862 (0.153)	0.879 (0.160)
Observations	4605	2599	2006	1870
Effective Observations – Below	194	102	103	23
Effective Observations – Above	130	87	55	40
Bandwidth	4149.9	3634.8	3397.6	2867.5
McCrary Test P-Value	0.379	0.620	0.545	0.981

Notes: This table presents results of a local polynomial regression-discontinuity design model with robust bias-corrected confidence intervals and a MSE-optimal bandwidth, estimated in Stata via the "rdrobust" command using techniques in Calonico, Cattaneo and Titiunik (2014), Calonico, Cattaneo and Farrell (2016) and Calonico, Cattaneo, Farrell and Titiunik (2016). Licensure Discontinuity denotes the estimated change in licensure probability at the 10,000 square foot cutoff. Column 1 reports this estimated quantity for all stores in our sample. Column 2 considers only non-chain stores, while column 3 only considers chain stores and Column 4 considers only chain stores for chains with 10 stores or more. The row labelled "McCrary Test p-value" presents the p-value of a McCrary test of the density of the running value around the 10,000 square foot cutoff. Robust, bias-corrected standard errors in parentheses.

Table A2: First Stage Regressions

	# All Liquor Outlets				# Nielsen	# MM
	Linear	Quadratic	Linear	Quadratic	Linear	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
# Marginally License-Eligible Stores	1.265 (0.174)	20.339 (2.695)	1.247 (0.181)	20.118 (2.754)	0.857 (0.205)	0.003 (0.011)
# Stores in the Bandwidth FE	X	X	X	X	X	X
FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Chain FE			X	X		
Observations	4630	4630	4630	4630	4630	4630
Kleibergen-Paap F-stat		9.3		11.1	45.9	8.28

Notes: Data are store-month level observations for 2015. Outcome in column 6 is the number of Nielsen outlets in the mass merchandizer channel. Standard errors clustered by ZIP code. Instruments also include a full set of interactions between the number of marginally eligible firms and the number of stores above 15,000 ft².

Table A3: Effect of Market Configuration on Type of Product Carried

	Store		ZIP Code		Household	
	# 1.75L Bottles	# High Proof	# 1.75L Bottles	# High Proof	# 1.75L Bottles	# High Proof
	(1)	(2)	(3)	(4)	(5)	(6)
# Liquor Outlets	3.343 (2.475)	6.45 (3.586)	30.21 (7.647)	40.833 (9.736)	0.057 (0.015)	0.027 (0.010)
# Liquor Outlets ²	-0.318 (0.186)	-0.498 (0.281)	-1.788 (0.622)	-2.659 (0.794)	-0.004 (0.001)	-0.002 (0.001)
# Stores in the Bandwidth FE	X	X	X	X	X	X
# Stores Above the Bandwidth FE	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
Chain FE	X	X	X	X		
Observations	4,630	4,630	1,377	1,377	31,875	31,875
Mean	59.91	47.23	83.13	67.68	0.05	0.016

Notes: Standard errors are clustered at the ZIP code level in columns 1, 2, 5 & 6. Columns 3 & 4 employ heteroskedasticity-robust standard errors. Instruments in are interactions between the number of marginally eligible firms and the number of stores above 15,000 ft².

Table A4: Effect of License-Eligibility on Price (\$)

	Store			Household	
	(1)	(2)	(3)	(4)	(5)
# Marginally License-Eligible Stores	0.023 (0.328)	0.306 (0.243)	0.018 (0.023)	0.363 (0.957)	0.872 (0.842)
# Marginally License-Eligible Stores × # Stores above the Bandwidth	-0.058 (0.035)	-0.052 (0.026)	-0.002 (0.003)	-0.012 (0.121)	-0.012 (0.096)
# Stores in the Bandwidth FE	X	X	X	X	X
# Stores above the Bandwidth FE	X	X	X	X	X
Month FE	X	X	X	X	X
Chain FE		X	X		
UPC FE			X		X
Observations	1,104,659	1,104,659	1,104,461	6046	6046

Notes: Standard errors clustered by ZIP code and reported in parentheses. Columns 1-3 use data on Nielsen scanner store sales in 2015. Columns 4&5 use data from the Consumer Panel from 2012-2015. The bandwidth is 5,000-15,000ft². The instruments include the interactions between the number of marginally license-eligible stores and a full set of indicators for the number of stores above 15,000ft². The mean pre-tax price of a liquor product (UPC) in 2015 was \$18.82.

Table A5: Effect of License-Eligibility on Volumes (L)

	Store		ZIP Code	Household
	(1)	(2)	(3)	(4)
# Marginally License-Eligible Stores	-349.348 (227.891)	47.149 (165.845)	-184.221 (432.229)	0.208 (0.091)
# Marginally License-Eligible Stores × # Stores above the Bandwidth	7.723 (21.841)	-7.808 (17.423)	0.591 (46.073)	-0.015 (0.007)
# Stores in the Bandwidth FE	X	X	X	X
# Stores above the Bandwidth FE	X	X	X	X
Month FE	X	X	X	X
Chain FE		X		
Observations	4,630	4,630	1,377	31,875

Notes: Standard errors clustered at the ZIP-level and reported in parentheses. Columns 1-3 use data on Nielsen scanner store sales in 2015 at the monthly level. Column 4 uses data from the Consumer Panel from 2012-2015.

Table A6: Effect of License-Eligibility on Liquor Revenues

	Store		ZIP Code		Household
	(1)	(2)	Nielsen (3)	All (4)	
# Marginally License-Eligible Stores	-0.383 (0.392)	0.199 (0.299)	1.192 (1.522)	10.146 (7.589)	4.013 (1.640)
# Marginally License-Eligible Stores × # Stores above the Bandwidth	-0.006 (0.038)	-0.023 (0.032)	0.001 (0.18)	-1.542 (1.174)	-0.460 (0.155)
# Stores in the Bandwidth FE	X	X	X	X	X
# Stores above the Bandwidth FE	X	X	X	X	X
Month/Quarter FE	X	X	X	X	X
Chain FE		X			
Observations	4,630	4,630	1,377	846	31,875

Notes: Standard errors clustered at ZIP-level. Columns 1-3 use data on Nielsen scanner store sales in 2015 at the monthly level. Column 4 uses quarterly revenue data from the WSLCB from Q3 2012 - Q4 2013. Columns 1-4 are measured in \$10,000's. Column 5 uses data from the Consumer Panel from 2012-2015 and is measured in dollars.

Table A7: Effect of License-Eligibility on Adverse Behaviors

	Household Level (Monthly)					Zip Code Level		
	Buy Alcohol		Drink ≥		Beer & Wine Consumption (Gallons)	Accidents 06/2012-12/2015		Bars Operating January 2013
	All	Heavy Drinkers	Non- Drinkers	2.66 L Alcohol		All	Severe	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
# Marginally License-Eligible Stores	0.058 (0.016)	0.127 (0.042)	0.014 (0.009)	0.045 (0.012)	0.194 (0.199)	-0.011 (0.115)	0.009 (0.020)	5.426 (6.129)
# Marginally License-Eligible Stores × # Stores Above the Bandwidth	-0.007 (0.002)	-0.015 (0.004)	-0.002 (0.001)	-0.005 (0.001)	-0.000 (0.018)	-0.007 (0.014)	-0.000 (0.002)	-0.795 (0.931)
# Stores in the Bandwidth FE	X	X	X	X	X	X	X	X
# Stores Above the Bandwidth FE	X	X	X	X	X	X	X	X
Month FE	X	X	X	X	X			
Observations	31,875	8,024	17,810	31,875	31,875	141	141	141

Notes: Observations in column 1-5 are at the panelist-month level for May 2012 - January 2015, and standard errors are clustered at the zip code level. Observations in columns 5-7 are at the zip code level, and standard errors are heteroskedasticity-robust. Severe accidents include: "Dead at Scene," "Dead on Arrival," "Died in Hospital" or "Suspected Serious Injury." 2.66L of alcohol is the CDC definition of heavy drinking for men. "Heavy" in column 2 refers to households above the 75th percentile in average per-person consumption January 2010-May 2012.

B. Google Maps Square Footage Calculations (For Online Publication)

This appendix section presents further details on our square footage calculations using Google Maps Developers' Square Footage Calculator and Amazon Mechanical Turk. Google Maps Developers' Square Footage Calculator allows us to overlay a tool for calculating square footage on top of Google Maps, as shown in Figure B1. Over an 2 week period in May, 2017, we hired workers on Amazon Mechanical Turk to perform this calculation for each store in our sample.

Figure B1: Example of a Square Footage Calculation



We hired workers on a per-task basis. To ensure high quality responses, we screened out workers whose acceptance rate for previous work was lower than 98%, and required them to have performed at least 1,000 tasks in the past. Furthermore, workers had to pass a qualification test, where they were asked to calculate the square footage of a set of 5 stores that we had previously done ourselves and found to require attention to detail. Finally, we announced (and paid out) bonuses for the 10 most accurate workers.

A task consists of calculating the square footage of a given store. Upon accepting a task, workers clicked-through to the Google Map Developers' Area Calculator website and inputted the store address. Then, they had to zoom in to an appropriate distance from the store, check that the store name appeared in the map, calculate the area, and enter the square footage into a text box. In cases where the store name did not appear on the map, workers could click-through to a new instance of the square footage calculator website where the store name had been inputted into the search box. If the store was still not found, the workers returned to the address-based search and calculated square footage for the given address.

The instructions used for the qualification test are found at the end of this Appendix section. Instructions for other stores were mostly the same, but sometimes tailored to the specific characteristics of the store type. For example, we added instructions not to consider the pumps for calculating gas station square footage.

To ensure data quality, we hired multiple workers to calculate square footage for each store and use the average across their reports. After collecting data from MTurk, we also double-checked each store with recorded square footage between 5,000 – 15,000ft², to ensure accurate responses around the licensure threshold. Despite these checks, some measurement error remains: 36 out of the 3,292 stores we code to be below 10,000ft² are licensed to sell liquor. Based on our conversations with the WSLCB, we are confident that we have mismeasured square footage for these stores (in reality, they exceed 10,000ft²). Miscategorizing a store below (above) the threshold as above (below) weakly lowers (raises) the average entry probability above (below) 10,000ft². We therefore expect measurement error to bias our regression discontinuity estimates downwards, as in Pei and Shen (2017)).

The MTurk dataset contains square footage for 94% of our sample (303 firms are missing). Since we measure square footage using the Google Maps in 2017, stores may be absent if they closed between 2012 and 2017. Missing data is therefore correlated with survival and other associated store characteristics: 12% of former state liquor stores are missing data, compared to 5% of the rest of the sample; 1% of chain stores, compared to 7% of independents. This measurement error is unlikely to be classical. If selling spirits is profitable, then survival should discontinuously increase at the licensure threshold. In that case, our discontinuity estimates are

conservative, as we are missing more stores below the threshold (that do not sell liquor) than stores above it. However, the low incidence of missing stores allays our concerns that measurement error affects our estimates in section III, particularly as we focus on chain stores, which have near complete coverage.

Figure B2: Sample Instructions

Website data collection - Instructions (Click to collapse)

Click the link below to review the Website. Collect the following information if it's available:

- Go to the link below
- Copy and paste the Address, then click "Go!"
- Zoom into the pin and confirm the label matches the Store Name
- Outline the store by clicking on the corners.
- Corners can be rearranged with the white and grey circles.
- Record the area in square feet as it appears below the address bar

Store Name	Address
STAMPEDE MINI MARKET	111 RIVERSIDE DR OMAH WA 98841

Address: 111 RIVERSIDE DR OMAH WA 98841 [Go!](#) [Zoom to Fit](#) [Clear Last Point](#)
 Area: 0 meters², 0 feet², 0.00 acres, 0.000 miles², 0.000 km²
 Perimeter: 0 meters, 0 feet, 0.000 miles, 0.000 km



Address: 111 RIVERSIDE DR OMAH WA 98841 [Go!](#) [Zoom to Fit](#) [Clear Last Point](#)
 Area: 313 meters², 3360 feet², 0.08 acres, 0.000 miles², 0.000 km²
 Perimeter: 73 meters, 79 feet, 0.001 miles, 0.001 km



The store can sometimes be away from the pin:

Store Name	Address
HAROLD'S GENERAL MERCHANDISE	4080 HARRAH RD HARRAH WA 98933

Address: 4080 HARRAH RD HARRAH WA 98933 [Go!](#) [Zoom to Fit](#) [Clear Last Point](#)
 Area: 1650 meters², 17830 feet², 0.41 acres, 0.001 miles², 0.001 km²
 Perimeter: 169 meters, 184 feet, 0.004 acres, 0.004 km



Stores can sometimes share a building. Use Streetview (the yellow person icon) to approximate the store size:

Figure B3: Sample Instructions (cont.)



C. Sample Restrictions (For Online Publication)

III.A. Corelogic Tax Records

This subsection describes the sample restrictions and variable definitions used to create Table D2, which studies covariate balance across the 10,000 square foot licensure threshold using CoreLogic data. We access the 2015-04-22 version of the CoreLogic Tax Records dataset, which contains parcel-level property tax records for the entire United States. This dataset includes information regarding building square footage ("Universal Building Square Feet"), the construction year of the original building ("Year Built") and the first year the building was assessed with its current components ("Effective Year Built"). We code a parcel as "Ever Renovated" if the first year the building was assessed with its current components is greater than the construction year of the original building.

Our goal is to extract from these records a subset of parcels that contains the set of potential liquor retailers, and to study whether there is any significant variation in observables across the licensure threshold. To do so, we rely on three additional variables from the CoreLogic dataset: "Property Indicator Code", described as a "CoreLogic general code used to easily recognize specific property types (e.g. Residential, Condominium, Commercial)."; "Land Use Code", described as a "CoreLogic established land use code converted from various county land use codes to aid in search and extract functions"; and "Building Code", described as "the primary building type (e.g. Bowling Alley, Supermarket)." Using different restrictions on the values of these variables, we construct three samples: "All Potential Alcohol Retail Records", "Selected Land Use Codes" and "Selected Building Codes".

Table C1 describes on the sample restrictions used to create the first sample, "All Potential Alcohol Retail Records", from the full set of Corelogic records. For each code described in the previous paragraph, we exclude all parcels with non-commercial code values, as well as parcels with commercial code values that are not associated with alcohol sales. We also exclude parcels with no square footage records and parcels that were built after 2012. This reduces the sample from 2,538,477 records to the 19,902 records that make up the "All Potential Alcohol Retail Records" sample.

Table C1: CoreLogic Sample Restrictions

Restriction	CoreLogic Sample Restrictions	
	Observations	Excluded Values
Number of Records for Washington	2,538,477	
Excluding Non-Commercial Property Indicator Codes	190,268	Miscellaneous, Single Family Residence, Condominium, Industrial, Industrial Light, Industrial Heavy, Transport, Utilities, Agricultural, Vacant, Exempt
Excluding Selected Commercial Property Indicator Codes	155,704	Hotel/Motel, Service, Office Building, Warehouse, Financial Institution, Hospital, Parking, Amusement/Recreation
Excluding Non-Commercial Land Use Codes	77,137	Apartment/Hotel, Apartment, Duplex, Residence Hall/Dormitories, Multi Family 10 Units Plus, Multi Family 10 Units Less, Multi Family Dwelling, Mixed Complex, Mobile Home Park, Quadruplex, Group Quarters, Triplex, Time Share
Excluding Selected Commercial Land Use Codes	67,396	Auto Equipment, Auto Repair, Auto Sales, Condotel, Salvage Imprvr, Auto Wrecking, Business Park, Cemetery, Convention Center, Department Store, Greenhouse, Kennel, Medical Building, Medical Condo, Laboratory, Office Condo, Public Storage, Store Franchise, Misc. Improvements
Excluding Non-Commercial Building Codes	28,484	Type Unknown, Agricultural, Fruit, Building, House, Storage, Out Building, Equipment Building, Equipment Shed, Barn, Barn Pole, Creamery, Storage Building, Shed, Utility, Utility Storage, Farm, Cocktail Lounge, Caf, Fast Food, Club, Lounge/Nite Club, Fraternal, Tavern, Bar, Bar Cocktail Lounge, Basketball Court, Clubhouse, Country Club, Convention Center, Fitness Center, Recreation, Restaurant, Theater, Theater/Cinema, Gymnasium, Health Club, Skating Rink, Arcade, Government, City Club, Fire Station, Community Center, Community Service, Post Office, Elderly/Senior Housing, Loading Dock, Multi Family, Multi Family Low Rise, Multi-Plex, Apartment, Apartment Low Rise, Condo Apartment, Duplex, Rooming/Boarding House, Triplex, Residential, Manufactured Home, Cabin/Cottage, Cabin/Apartment, Mobile Home, Mobile Home Single Wide, Mobile Home Double Wide, Single Family, Hangar, Hangar Maintenance, Truck Terminal, Truck Stop, Distribution, Cold Storage, Industrial Light, Industrial Office, Processing, Industrial Condo, Bulk Storage, Food Storage, Manufacturing, Manufacturing Heavy, Manufacturing Light, Other, Research & Development, Warehouse, Warehouse Distribution, Mini Warehouse, Warehouse Storage, Mixed Type, Group Home, Auditorium/Gymnasium, Classrooms, Center, Convalescent, Dental, Museum, University, Veterinarian, Medical, Surgical Center, Office Medical, Office Dental, College, Church/Synagogue, Day Care Center, Hospital, Hospital Convalescent, Hospital Public, Veterinary Hospital, Dormitory, Kennel, Kennel Veterinary, Fraternity, Library, Library Museum, Nursing Home, Retirement Home, Mortuary, School, School Classroom, Elementary School, Clinic Dental, Dispensary, Dispensary Medical, Ymca/Ywca, Telephone, Mixed Use, Condo & Single Family Residenc, Miscellaneous Industrial, Office/Shop, Apartments & Residential
Excluding Selected Commercial Building Codes	22,287	Storage, Commercial Greenhouse, Lumber Store, Lumber Storage, Office, Medical Office, Auto, Auto Agency, Auto Showroom, Auto Sales, Auto Sales & Service, Auto Service, Laundromat/Dry Cleaners, Bank, Garage, Repair Garage, Barber Shop, Barber & Beauty Shop, Shop Office, Retail Office, Car Wash, Car Wash Drive Thru, Car Wash Automatic, Car Wash Self Service, Parking, Parking Garage, Marina, Hotel, Hotel/Motel, Motel, Department Store, Auto Repair, Garage Service
Excluding Parcels with Missing Square Footage or Missing Year Built	18,451	
Excluding Parcels Built After 2011	18,224	

Table C2 presents the values for the Property Indicator Code, Land Use Code, and Building Code variables in the "All Potential Alcohol Retail Records" sample. As is discussed in the main text, this sample aims to include the full set of potential liquor-selling outlets, perhaps erring on the side of including too many outlets but without including any values that can be immediately dismissed, such as auto sales or department stores. The "Selected Land Use Codes" sample further restricts the "All Potential Alcohol Retail Records" sample by using only parcels with "Supermarket", "Food Store" or "Wholesale" land use code values. Finally, the "Selected Building Code" sample further restricts the "All Potential Alcohol Retail Records" sample by using only parcels with "Market", "Supermarket", "Food Stand", "Convenience Market", "Convenience Store", "Pharmacy" or "Warehouse Store" building code values. These two sets of restrictions aim to generate a sample of parcels for which

the probability of selling alcohol is high, and who may have the greatest incentive to game their square footage in order to become license-eligible.

III.B. Nielsen Consumer Panel

Nielsen’s Consumer Panel tracks household purchases of a wide array of products (including both food and non-food items), and it contains an entire product module labeled “liquor.” Unfortunately, the liquor module corresponds only loosely to the WSLCB definition of spirits. For our principal analysis, we are interested in products formerly sold exclusively by the state monopoly. We therefore restrict our sample based on the following three criteria:

Coolers

Products that Nielsen describes as coolers (*product_module_descr = “COOLERS—REMAINING”*) are not included, some 1,627 UPCs. 99.8% of these observations were not sold by WSLCB stores under the state monopoly, and none have an associated proof. 51% of cooler purchases before liberalization correspond to stores with 2-digit zip codes within Washington state, so it appears that Washington households purchased these goods at non-state stores before deregulation. Further, purchases by panelists in border and interior counties were equally likely to fall under the cooler category under the WSLCB (t-stat of 0.108). We therefore conclude these are products that were legally sold by Washington state supermarkets before liberalization.

Prior Purchases

Products purchased by households before liberalization that were not sold by the WSLCB state monopolist are not included in the sample. The WSLCB provides monthly price lists for products sold in state liquor stores from February 2010 – May 2012. These lists include 3,973 unique products (UPCs). We merge WSLCB prices with the Nielsen panelist dataset on UPC. Observations without WSLCB prices either correspond to spirits bought out-of-state or to products the WSLCB does not classify as spirits (and therefore potentially bought in-state). In the latter case, these products experience no regulatory changes and therefore ought to be excluded from

Table C2: CoreLogic Codes for “All Potential Alcohol Retail Records” Sample

CoreLogic Code Values – All Potential Alcohol Retail Records Sample			
Panel A: Property Indicator Code			
Type	Frequency	Percentage	
Commercial	5,583	30.64%	
Commercial Condominium	203	1.11%	
Retail	12,438	68.25%	
Panel B: Land Use Code			
Type	Frequency	Percentage	
Commercial (NEC)	3,542	19.44%	
Multiple Uses	10	0.05%	
Commercial Building	391	2.15%	
Commercial Condominium	203	1.11%	
Misc. Building	103	0.57%	
Misc. Commercial Services	1,398	7.67%	
Shopping Center	590	3.24%	
Strip Commercial Center	297	1.63%	
Store Building	755	4.14%	
Retail Trade	9,742	53.46%	
Supermarket	167	0.92%	
Food Stores	887	4.87%	
Wholesale	139	0.76%	
Panel C: Building Code			
Type	Frequency	Percentage	
Commercial	7,078	38.84%	
Market	309	1.70%	
Supermarket	247	1.36%	
Commercial Condo	96	0.53%	
Store	17	0.09%	
Food Stand	56	0.31%	
Service	1	0.01%	
Service Station	13	0.07%	
Service Garage	180	0.99%	
Shops	185	1.02%	
Retail	4,445	24.39%	
Retail Store	3,821	20.97%	
Convenience Market	408	2.24%	
Convenience Store	260	1.43%	
Shopping Center	345	1.89%	
Discount	339	1.86%	
Discount Store	269	1.48%	
Pharmacy	15	0.08%	
Retail & Warehouse	12	0.07%	
Warehouse Store	128	0.70%	

our principal analysis. In the former case, we would tend to lose power by excluding part of the sample. To differentiate these theories, we check whether any of these products were purchased at retailers with non-Washington 3-digit zip codes: none do.

However, Nielsen notes that store zip codes are sometimes imputed from a panelist's home zip code, so we cannot rule out inter-state shopping trips. In total, 78.52% of purchases are matched to WSLCB prices - 86.67% have matches before liberalization 69.94% have matches after liberalization. This pattern is consistent with the introduction of new products in the private market post-liberalization.

Proof

We use regular expressions to extract proof from the Nielsen *upc_descr* string. We exclude 4,067 observations that correspond to product that are less than 48 proof, as per the state definition of spirits.

D. Covariate Balance (For Online Publication)

IV.A. Covariate Balance for Stores Around the Licensure Threshold

This Appendix presents results from a battery of covariate balance tests that study whether store observables vary around the 10,000 square foot threshold. To begin, we estimate equation (1) using store characteristics reported by the WSLCB as outcome variables, and present results in Table (D1). For example, the first row reports the discontinuity at 10,000ft² in the probability that we can geolocate a store using the address provided by the WSLCB. We consider as store covariates whether the store is geolocated, the earliest date it receives any kind of beer or wine license, the total amount of alcohol-related fines paid in 2010, 2011 and for the pre-liberalization months of 2012, a series of zip code demographics, and the number of competitors within 0.5 miles that are either below 5,000 square feet, between 5,000 and 15,000 square feet, between 10,000 and 15,000 square feet, and above 15,000 square feet. The only significant discontinuity for the full sample is on poverty rate, as stores just above the threshold are more likely to be located in zip codes with higher poverty rates. This result is driven by independent stores, as for chain stores the discontinuity is statistically insignificant. Moreover, independent stores just above the threshold are also located in zip codes with lower median household income. Despite this, independent stores are balanced across all metrics related to the number of competitors. That is, these differences in zip code income are not correlated with differences in neighbor configuration, alleviating concerns about differences in demand around the threshold. As for chain stores, there is a discontinuity in total fines paid in 2011, but not in 2010 or 2012, and stores just above the threshold appear to have more competitors nearby. If anything, a systematic difference in the number of competitors ought to generate downward bias in our estimate of the causal effect of license eligibility on liquor licensure. Particularly as the estimate of uptake for chain stores is already close to one, this difference in competitors does not appear economically significant.

As an additional test for gaming the threshold, we leverage auxiliary data from CoreLogic to test for store expansions. While the distribution of stores around 10,000ft² is smooth, it is possible that small stores undergo large-scale expansions

Table D1: Covariate Balance Across Licensure Threshold

Covariate Balance of Store Characteristics Around the Licensure Threshold			
	(1)	(2)	(3)
	All Stores	Independent Stores	Chain Stores
Is Geolocated	-0.05 (0.088)	0.00 (0.102)	-0.01 (0.150)
Earliest Privilege Date (Days)	269.14 (550.8)	172.76 (631.7)	1,347.73 (1670.4)
Total Fines Paid in 2010 (\$)	-10.97 (34.1)	-28.72 (60.4)	36.11 (40.8)
Total Fines Paid in 2011 (\$)	-184.92 (150.7)	-49.43 (166.0)	-795.52** (337.2)
Total Fines Paid in 2012, Before June (\$)	2.06 (9.4)	13.39 (16.1)	-2.37 (5.4)
Zip Code Population	-968.15 (4667.6)	-5,339.74 (5747.6)	-3,986.55 (7919.5)
Zip Code Population Over 21	-809.60 (3438.3)	-4,004.47 (3995.3)	-1,907.31 (5576.2)
Zip Code African American Population	122.97 (459.3)	406.81 (459.6)	-2,531.51 (2313.9)
Zip Code Hispanic Population	-255.49 (1187.0)	280.56 (1682.2)	-4,539.33 (3849.1)
Zip Code Median Age	-3.62 (3.3)	-2.83 (4.5)	-3.02 (4.1)
Zip Code Unemployment Rate	1.55 (1.7)	2.22 (2.1)	1.19 (3.8)
Zip Code Median Household Income	-11,440.53 (8677.3)	-23,472.87** (9328.7)	-5,930.57 (18721.8)
Zip Code Percentage of Population with Less than High School Education	1.09 (3.5)	5.89 (4.6)	-10.19 (9.1)
Zip Code Percentage of Population with High School Education	-4.00 (2.9)	1.13 (3.5)	-14.16 (11.2)
Zip Code Percentage of Population with BA or Higher	5.90 (7.2)	-6.16 (8.1)	24.69 (21.2)
Zip Code Percentage of Population in Poverty	11.28** (4.54)	16.33*** (5.43)	5.14 (7.30)
Number of Neighbors within 0.5 Miles with Square Footage between 5,000 and 15,000	-0.13 (0.229)	-0.20 (0.290)	0.37 (0.235)
Number of Neighbors within 0.5 Miles with Square Footage between 10,000 and 15,000	0.16 (0.121)	0.05 (0.172)	0.39** (0.159)
Number of Neighbors within 0.5 Miles with Square Footage below 5,000	1.12 (1.469)	-0.62 (1.138)	6.53* (3.760)
Number of Neighbors within 0.5 Miles with Square Footage above 15,000	-0.22 (0.822)	0.02 (0.420)	-2.14 (1.498)

Notes: This table presents results of a local polynomial regression-discontinuity design model with robust bias-corrected confidence intervals and a MSE-optimal bandwidth, estimated in Stata via the "rdrobust" command using techniques in Calonico, Cattaneo and Titiunik (2014), Calonico, Cattaneo and Farrell (2016) and Calonico, Cattaneo, Farrell and Titiunik (2016). Each row uses a different store characteristic as the dependent variable. Column 1 reports, for each dependent variable, the discontinuity at 10,000 square feet using our full sample. Column 2 considers only independent stores, and Column 3 considers only chain stores. Robust, bias-corrected standard errors in parentheses. Coefficients are significant at the * 10%, ** 5% and *** 1% levels.

in response to I-1193. This type of manipulation might put stores far above the threshold, and would be consistent with large fixed costs and small marginal costs of renovation. We use CoreLogic to test whether retailers just below 10,000ft² are more likely to renovate between 2012-2015 than those just above. CoreLogic pools County Assessor tax records for each parcel of land registered in the United States as of May 2015. It contains square footage, year of construction, and year of initial assessment with current configuration. Renovations are classified based on the difference in the date of initial assessment and construction. Unfortunately, we cannot accurately match CoreLogic and WSLCB records, precluding use of CoreLogic size measures in a regression on licensure (our main specification). We attempted a match based on trade names, addresses, latitude and longitude, but had little success. We restrict attention to stores likely to sell beer or wine using Property Indicator Codes, Land Use Codes, and Building Codes, three variables created by CoreLogic to describe the economic activity on a given parcel. For example, we exclude commercial parcels marked as “Hotel/Motel” or “Hospital”. See appendix C for sample construction details. The final sample contains 18,224 commercial parcels in the state of Washington built prior to 2012. Table D2 presents summary statistics for this sample. While roughly 37% of these parcels have been renovated at least once, only 0.04% have been renovated after 2011. Selective renovation therefore seems unlikely to be important in this setting.

For completeness, we run a battery of other tests using the CoreLogic data. Panel B of table D2 reports estimates for discontinuities in other variables. We do not find a significant differences in year built, year renovated (conditional on renovation), or renovation after 2011. We repeat this exercise for smaller CoreLogic subsamples for which we assign a high probability of selling alcohol, such that the incentive to renovate is strongest. Again, the overall probability of renovating post-2012 is minute, and we cannot detect a discontinuity at the licensure threshold. The final row of this table reports the estimate from a McCrary test for bunching (in the number of stores) at 10,000ft². Again, we find no evidence of this behavior. Overall, the information from this auxiliary dataset makes us confident that our setting satisfies the exclusion restriction required for valid regression discontinuity inference.

Table D2: Corelogic Covariate Balance

Covariate Balance of Store Characteristics Around the Licensure Threshold – Corelogic Sample			
	(1)	(2)	(3)
<i>Panel A: Descriptive Statistics</i>			
	All Potential Alcohol Retail Records	Selected Land Use Codes	Selected Building Codes
Number of Records	18,224	1,193	1,423
Square Footage, 10 th Percentile	960	1,641	1,650
Square Footage, 50 th Percentile	3,749	4,151	3,438
Square Footage, 90 th Percentile	19,664	46,821	51,300
Year Built, 10 th Percentile	1923	1929	1945
Year Built, 50 th Percentile	1974	1974	1980
Year Built, 90 th Percentile	2003	2000	2001
Percentage Ever Renovated	37.04%	57.67%	49.05%
Year Renovated, 10 th Percentile	1964	1964	1970
Year Renovated, 50 th Percentile	1982	1985	1988
Year Renovated, 90 th Percentile	1997	2000	2000
Percentage Renovated Post 2012	0.04%	0.08%	0.00%
% Renovated Post 2012, If Ever Renova	0.10%	0.15%	0.00%
<i>Panel B: Discontinuity at Licensure Cutoff</i>			
	All Potential Alcohol Retail Records	Selected Land Use Codes	Selected Building Codes
Year Built	-0.559 (3.119)	-35.309** (16.441)	-13.309 (13.602)
Ever Renovated	0.096** (0.046)	0.307 (0.221)	-0.204 (0.218)
Year Renovated, If Ever Renovated	1.073 (1.918)	-5.280 (7.923)	-2.794 (6.809)
Renovated Post 2012	-0.001 (0.001)	0.010 (0.010)	- -
Renovated Post 2012, If Ever Renovated	0.000 (0.000)	- -	- -
McCrary Test P-Value	0.30	0.48	0.26
<p>Notes: This table presents results of a local polynomial regression-discontinuity design model with robust bias-corrected confidence intervals and an optimal bandwidth, estimated in Stata via the "rdrobust" command using techniques in Calonico, Cattaneo and Titiunik (2014), Calonico, Cattaneo and Farrell (2016) and Calonico, Cattaneo, Farrell and Titiunik (2016). The relevant sample is the set of Corelogic property tax records of potential alcohol retailers, as defined in Appendix B. Column 2 further restricts the sample to selected Corelogic "Land Use Codes" that are associated with retail sale of food (supermarket/food store/wholesale). Column 3 further restricts the sample to selected Corelogic "Building Codes" that are associated with retail sale of food (market/supermarket/food stand/convenience market, convenience store). For each sample, the dependent variable is different store record characteristics. More details regarding variable definitions and sample construction are in Appendix B. Robust, bias-corrected standard errors in parentheses. Coefficients are significant at the * 10%, ** 5% and *** 1% levels.</p>			

Table D3: Zip Code Covariate Balance

Covariate Balance of Zip Code Characteristics by Store Eligibility								
	# Households	# Stores	# WSLCB Stores	Log Population	% White	Log Median Income	Median Age	# Accidents per Month
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of Marginally License-Eligible Firms	2.194 (4.309)	0.760 (1.610)	-0.039 (0.060)	0.074 (0.157)	1.169 (2.003)	0.011 (0.055)	1.587** (0.790)	-0.092 (0.079)
Number of Stores in the Bandwidth FE	X	X	X	X	X	X	X	X
Mean	32.113	18.163	0.156	9.802	82.526	10.933	37.349	1.820
Observations	141	141	141	141	141	141	141	141

Notes: Sample includes zip codes with at least one chain store sized 5,000-15,000 ft². # households is the number of Nielsen Panel households in the zip code 2010-2012. # stores is the number of beer/wine licensees as of 12/2011. Demographic data come from the 2010 US Census. Coefficients are statistically significant at the *10%, **5%, and ***1% level.

IV.B. Covariate Balance for Zip Codes with Stores Around the Licensure Threshold

We estimate the reduced-form equation

$$y_{ut} = \beta_0 + \beta_1 \cdot N_{z(u,t)}^{10-15} + \beta_2 \cdot N_{z(u,t)}^{10-15} \times N_{z(u,t)}^{15+} + \sum_k \lambda_k \cdot 1 \left[N_{z(u,t)}^{5-15} = k \right] + \sum_j \gamma_j \cdot 1 \left[N_{z(u,t)}^{15+} = j \right] + \epsilon_{ut} \quad (4)$$

employing the following characteristics from the 2010 census as dependent variables: log population, percent white, log median income, and log median age. Results are reported in table D3. As an example, the coefficient in column (6) implies that treatment zip codes boast 1.1% higher median income than control zip codes, but this difference is not statistically significant at the 10% level. Covariates are balanced across treatment and control zip codes, except for median age, as residents are 1.59 years older in treatment zip codes. Although this difference is statistically significant, it is economically small (a less than 5% difference). Zip codes are also similar in terms of representation in the Nielsen Panel (the number of households residing in the zip code), the number of beer and wine licensees in 2011, and the number of WSLCB stores pre-liberalization, which correspond to columns 1, 2, and 3 respectively. While we cannot test whether zip codes differ on unobservable characteristics, it is reassuring that they look similar both in terms of census population demographics and beer and wine market configurations before deregulation.

We next examine whether the panelists residing in treatment and control zip

codes appear similar on observables. Panel A of table D4 shows comparisons between households that live in zip codes with the same number of stores in the bandwidth, but different numbers of stores just above the cutoff, pooled across the entire sample period (2010-2015). Point estimates are small and statistically insignificant for differences in income levels and race, although heads of household in treated zip codes are 13.8% less likely to be married, a difference that is significant at the 5 level. This difference in marital status threatens our identification strategy if it indicates differences in demand across treatment and control zipcodes. Fortunately, we can examine pre-liberalization alcohol consumption directly using data from January 2010 - May 2012. We find no statistically significant differences in the annual number of shopping trips (for any product), liquor purchase probabilities, or total liquor expenditures (Panel B). As an example, treated panelists engage in 0.45 more shopping trips per month (for any grocery item), a less than 5% difference¹⁵. Overall, households do not appear different in their shopping behavior across zip codes with stores just-above versus just-below the licensure threshold.

¹⁵To be precise, Panel B contains a proper subset of the households in Panel A, as some households included in Panel A enter the dataset after 2012 and have no pre-liberalization data.

Table D4: Covariate Balance for Panelists

Covariate Balance of Panelist Characteristics by Local Store Eligibility					
<i>Panel A: Full Sample Covariates (N=1,426)</i>					
	(1)	(2)	(3)	(4)	(5)
				Income	
	Married	White	<25k	50k-100k	100k+
Number of Marginally License-Eligible Firms in Zip Code	-0.138*** (0.023)	-0.018 (0.018)	0.018 (0.017)	-0.010 (0.017)	-0.012 (0.018)
Number of Stores in the Bandwidth FE	X	X	X	X	X
Mean	0.610	0.832	0.162	0.187	0.162
<i>Panel B: Pre-Liberalization Covariates (N=1,092)</i>					
	(6)	(7)	(8)		
	# Shopping Trips	Purchase Probability	Liquor Expenditures		
Number of Marginally License-Eligible Firms in Zip Code	0.450 (0.525)	0.035 (0.025)	0.425 (0.945)		
Number of Stores in the Bandwidth FE	X	X	X		
Mean	12.813	0.269	3.465		

Notes: Panel A includes households in Washington State in the Nielsen sample from 2010-2015. Panel B includes households in Washington State in the sample from 2010-2012. Both samples exclude households that switch zip codes during this six year period (5.71% of households). The sample includes only those residing in a zip code with at least one chain store 5,000-15,000 ft².

E. Proofs (For Online Publication)

To establish the causal effect of market structure on outcomes of interest, in section III we estimate equation (3) at both the retail outlet- and market-level. For expositional clarity, consider how an increase in the number of liquor retailers affects product assortment, measured as the number of unique UPCs. Intuitively, the retail outlet-level regression yields the expected change in the number of UPCs carried by a retail outlet when the number of firms in its ZIP code increases from N to $N + 1$. Note that these estimates speak to the effect of competition in complier markets—markets where the marginally-eligible retailer would choose to sell liquor—and to effects on the prices and assortments of retailers that partner with Nielsen. In some complier markets, the marginally-eligible firm is observed in our data (if the chain partners with Nielsen), but in others, it is not. Proposition 1 below shows that our estimates average across instances when we do/do not observe the marginally-eligible firm in the Nielsen data, where the weights depend on the licensure probabilities in each type of market. Analogously, the market-level regression estimates the expected change in the total number of unique products sold in complier markets when the number of firms increases from N to $N + 1$.

Let m denote a market, \bar{T}_m the number of firms in the bandwidth (i.e. between 5,000 and 15,000 square feet), and T_m the number of firms in the bandwidth and above the 10,000 square foot threshold. Let A_m denote the number of firms above the bandwidth, and assume that all of these firms sell liquor regardless of the entry decisions of the stores in the bandwidth. Each market is treated by the number of entrants $E_m(T_m) \in \{0, \dots, T_m\}$; these are the stores that are in the bandwidth and above the threshold who decide to enter.

We assume that firms respond to the number of competitors in their market. That is, when E_m stores enter, each a of the A_m firms offers the set of products $S_a^A(A_m + E_m)$. Analogously, each e of the E_m firms offers the set of products $S_e^E(A_m + E_m)$. Denote a feature of these sets by $f(S_a^A(A_m + E_m))$ and $f(S_e^E(A_m + E_m))$, respectively.

As mentioned earlier, not all stores that sell liquor appear in the Nielsen RMS dataset. Denote the number of A_m stores that are in the dataset by A_m^N . Additionally,

if firm $t_m \in 1, \dots, \bar{T}_m$ is in Nielsen, we say $t_m \in N$.

Assumption 1. Independence:

$[\{\{S_a^A(A_m + E, T); \forall a = 1, \dots, A_m\}; \forall E, T\}, \{E_m(T) \forall T\}]$ and T_m are independent conditional on \bar{T}_m, A_m

$[\{\{S_e^E(A_m + E, T); \forall e = 1, \dots, E_m\}; \forall E, T\}, \{E_m(T) \forall T\}]$ and T_m are independent conditional on \bar{T}_m, A_m

Assumption 2. Exclusion:

$\{S_a^A(N, T) = S_a^A(N, T') \forall T, T'\}$ and $\{S_e^E(N, T) = S_e^E(N, T') \forall T, T'\}$

Assumption 3. Monotonicity:

$E(T) \geq E(T')$ if $T \geq T'$

Assumption 4. Licensure restriction binds:

$E(T) \leq T \forall T$

Then in the case where $\bar{T}_m = 1$ and for arbitrary A_m the following proposition holds:

Proposition 1. Conditional on $\bar{T}_m = 1$ and $A_m = \bar{A}$, the store level regression yields

$$\begin{aligned} \hat{\beta}^{Store} = & E_m \left[\frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f(S_a^A(\bar{A} + 1)) - f(S_a^A(\bar{A})) \middle| E_m(1) = 1, t_m \notin N \right] \omega_m \\ & + E_m \left[\frac{1}{A_m^N + 1} \left(\sum_{a=1}^{A_m^N} f(S_a^A(\bar{A} + 1)) + f(S_e^E(\bar{A} + 1)) \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f(S_a^A(\bar{A})) \middle| E_m(1) = 1, t_m \in N \right] (1 - \omega_m). \end{aligned} \quad (5)$$

The market level regression yields

$$\begin{aligned} \hat{\beta}^{Market} = & E_m \left[f \left(\left\{ S_a^A(\bar{A} + 1) \right\}_{a=1}^{A_m^N} \right) - f \left(\left\{ S_a^A(\bar{A}) \right\}_{a=1}^{A_m^N} \right) \middle| E_m(1) = 1, t_m \notin N \right] \omega_m \\ & + E_m \left[f \left(\left\{ \left\{ S_a^A(\bar{A} + 1) \right\}_{a=1}^{A_m^N}, S_e^E(\bar{A} + 1) \right\} \right) - f \left(\left\{ S_a^A(\bar{A}) \right\}_{a=1}^{A_m^N} \right) \middle| E_m(1) = 1, t_m \in N \right] (1 - \omega_m). \end{aligned} \quad (6)$$

And their difference is

$$\begin{aligned} \hat{\beta}^{Market} - \hat{\beta}^{Store} = & \omega_m \left\{ E_m \left[f \left(\left\{ S_a^A(\bar{A} + 1) \right\}_{a=1}^{A_m^N} \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f(S_a^A(\bar{A} + 1)) \middle| E_m(1) = 1, t_m \notin N \right] \right\} \end{aligned} \quad (7)$$

$$\begin{aligned}
& - E_m \left[f \left(\left\{ S_a^A(\bar{A}) \right\}_{a=1}^{A_m^N} \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f \left(S_a^A(\bar{A}) \right) \middle| E_m(1) = 1, t_m \notin N \right] \Bigg\} \\
& + (1 - \omega_m) \left\{ E_m \left[f \left(\left\{ \left\{ S_a^A(\bar{A} + 1) \right\}_{a=1}^{A_m^N}, S_e^E(\bar{A} + 1) \right\} \right) - \frac{1}{A_m^N + 1} \left(\sum_{a=1}^{A_m^N} f \left(S_a^A(\bar{A} + 1) \right) + f \left(S_e^E(\bar{A} + 1) \right) \right) \right] \middle| E_m(1) = 1, t_m \in N \right. \\
& \quad \left. - E_m \left[f \left(\left\{ S_a^A(\bar{A}) \right\}_{a=1}^{A_m^N} \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f \left(S_a^A(\bar{A}) \right) \right] \middle| E_m(1) = 1, t_m \in N \right] \Bigg\}
\end{aligned}$$

$$\text{where } \omega_m = \frac{\Pr[E_m(1)=1, t_m \notin N]}{\Pr[E_m(1)=1]}.$$

Proof. Across both regressions, the first stage is:

$$\Pr[E_m(1) = 1 | T_m = 1] - \Pr[E_m(1) = 1 | T_m = 0] = \Pr[E_m(1) = 1 | T_m = 1].$$

For the store level regression, the reduced form yields:

$$\begin{aligned}
& E_m [f(S(\bar{A} + e)) | T_m = 1] - E_m [f(S(\bar{A} + e)) | T_m = 0] \\
& = E_m \left[1[t_m \notin N] \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f(S_a^A(\bar{A})) + 1[E_m(1) = 1] \left(f(S_a^A(\bar{A} + 1)) - f(S_a^A(\bar{A})) \right) \right] \\
& + E_m \left[1[t_m \in N] \left\{ 1[E_m(1) = 0] \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f(S_a^A(\bar{A})) + 1[E_m(1) = 1] \frac{1}{A_m^N + 1} \left(\sum_{a=1}^{A_m^N} f(S_a^A(\bar{A} + 1)) + f(S_e^E(\bar{A} + 1)) \right) \right\} \right] \\
& - E_m \left[\frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f(S_a^A(\bar{A})) \right] \\
& = E_m \left[1[E_m(1) = 1] 1[t_m \notin N] \frac{1}{A_m^N} \left(\sum_{a=1}^{A_m^N} f(S_a^A(\bar{A} + 1)) - f(S_a^A(\bar{A})) \right) \right] \\
& + E_m \left[1[E_m(1) = 1] 1[t_m \in N] \left\{ \frac{1}{A_m^N + 1} \left(\sum_{a=1}^{A_m^N} f(S_a^A(\bar{A} + 1)) + f(S_e^E(\bar{A} + 1)) \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f(S_a^A(\bar{A})) \right\} \right] \\
& = E_m \left[\frac{1}{A_m^N} \left(\sum_{a=1}^{A_m^N} f(S_a^A(\bar{A} + 1)) - f(S_a^A(\bar{A})) \right) \middle| E_m(1) = 1, t_m \notin N \right] \Pr[E_m(1) = 1, t_m \notin N] \\
& + E_m \left[\frac{1}{A_m^N + 1} \left(\sum_{a=1}^{A_m^N} f(S_a^A(\bar{A} + 1)) + f(S_e^E(\bar{A} + 1)) \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f(S_a^A(\bar{A})) \middle| E_m(1) = 1, t_m \in N \right] \Pr[E_m(1) = 1, t_m \in N].
\end{aligned}$$

At the store level, the IV estimator then gives:

$$\begin{aligned}\hat{\beta}^{\text{store}} = & E_m \left[\frac{1}{A_m^N} \left(\sum_{a=1}^{A_m^N} f(S_a^A(\bar{A}+1)) - f(S_a^A(\bar{A})) \right) \middle| E_m(1) = 1, t_m \notin N \right] \omega_m \\ & + E_m \left[\frac{1}{A_m^N + 1} \left(\sum_{a=1}^{A_m^N} f(S_a^A(\bar{A}+1)) + f(S_e^E(\bar{A}+1)) \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f(S_a^A(\bar{A})) \middle| E_m(1) = 1, t_m \in N \right] (1 - \omega_m).\end{aligned}$$

For the market level regression, the reduced form yields:

$$\begin{aligned}& E_m \left[f \left(\{S_i(\bar{A} + e)\}_{i \in m} \right) \middle| T_m = 1 \right] - E_m \left[f \left(\{S_i(\bar{A} + e)\}_{i \in m} \right) \middle| T_m = 0 \right] \\ & = E_m \left[1[t_m \notin N] \cdot f \left(\{S_a^A(\bar{A})\}_{a=1}^{A_m^N} \right) + 1[E_m(1) = 1] \cdot \left(f \left(\{S_a^A(\bar{A}+1)\}_{a=1}^{A_m^N} \right) - f \left(\{S_a^A(\bar{A})\}_{a=1}^{A_m^N} \right) \right) \right] \\ & + E_m \left[1[t_m \in N] \cdot 1[E_m(1) = 0] \cdot f \left(\{S_a^A(\bar{A})\}_{a=1}^{A_m^N} \right) + 1[E_m(1) = 1] \cdot f \left(\left\{ \{S_a^A(\bar{A}+1)\}_{a=1}^{A_m^N}, S_e^E(\bar{A}+1) \right\} \right) \right] \\ & - E_m \left[f \left(\{S_i(\bar{A})\}_{i \in m} \right) \right] \\ & = E_m \left[1[E_m(1) = 1] 1[t_m \notin N] \left(f \left(\{S_a^A(\bar{A}+1)\}_{a=1}^{A_m^N} \right) - f \left(\{S_a^A(\bar{A})\}_{a=1}^{A_m^N} \right) \right) \right] \\ & + E_m \left[1[E_m(1) = 1] \cdot 1[t_m \in N] \left(f \left(\left\{ \{S_a^A(\bar{A}+1)\}_{a=1}^{A_m^N}, S_e^E(\bar{A}+1) \right\} \right) - f \left(\{S_a^A(\bar{A})\}_{a=1}^{A_m^N} \right) \right) \right] \\ & = E_m \left[f \left(\{S_a^A(\bar{A}+1)\}_{a=1}^{A_m^N} \right) - f \left(\{S_a^A(\bar{A})\}_{a=1}^{A_m^N} \right) \middle| E_m(1) = 1, t_m \notin N \right] \Pr[E_m(1) = 1, t_m \notin N] \\ & + E_m \left[f \left(\left\{ \{S_a^A(\bar{A}+1)\}_{a=1}^{A_m^N}, S_e^E(\bar{A}+1) \right\} \right) - f \left(\{S_a^A(\bar{A})\}_{a=1}^{A_m^N} \right) \middle| E_m(1) = 1, t_m \in N \right] \Pr[E_m(1) = 1, t_m \in N].\end{aligned}$$

And the IV estimator yields:

$$\begin{aligned}\hat{\beta}^{\text{Market}} = & E_m \left[f \left(\{S_a^A(\bar{A}+1)\}_{a=1}^{A_m^N} \right) - f \left(\{S_a^A(\bar{A})\}_{a=1}^{A_m^N} \right) \middle| E_m(1) = 1, t_m \notin N \right] \omega_m \\ & + E_m \left[f \left(\left\{ \{S_a^A(\bar{A}+1)\}_{a=1}^{A_m^N}, S_e^E(\bar{A}+1) \right\} \right) - f \left(\{S_a^A(\bar{A})\}_{a=1}^{A_m^N} \right) \middle| E_m(1) = 1, t_m \in N \right] (1 - \omega_m).\end{aligned}$$

Subtracting the two coefficients and rearranging terms gives

$$\begin{aligned}\hat{\beta}^{\text{Market}} - \hat{\beta}^{\text{Store}} = & \omega_m \left\{ E_m \left[f \left(\{S_a^A(\bar{A}+1)\}_{a=1}^{A_m^N} \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f \left(S_a^A(\bar{A}+1) \right) \middle| E_m(1) = 1, t_m \notin N \right] \right\}\end{aligned}$$

$$\begin{aligned}
& - E_m \left[f \left(\left\{ S_a^A(\bar{A}) \right\}_{a=1}^{A_m^N} \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f \left(S_a^A(\bar{A}) \right) \middle| E_m(1) = 1, t_m \notin N \right] \Bigg\} \\
& + (1 - \omega_m) \left\{ E_m \left[f \left(\left\{ \left\{ S_a^A(\bar{A} + 1) \right\}_{a=1}^{A_m^N}, S_e^E(\bar{A} + 1) \right\} \right) - \frac{1}{A_m^N + 1} \left(\sum_{a=1}^{A_m^N} f \left(S_a^A(\bar{A} + 1) \right) + f \left(S_e^E(\bar{A} + 1) \right) \right) \right] \middle| E_m(1) = 1, t_m \in N \right. \\
& \quad \left. - E_m \left[f \left(\left\{ S_a^A(\bar{A} + 1) \right\}_{a=1}^{A_m^N} \right) - \frac{1}{A_m^N} \sum_{a=1}^{A_m^N} f \left(S_a^A(\bar{A}) \right) \middle| E_m(1) = 1, t_m \in N \right] \right\}.
\end{aligned}$$

□

Corollary 1. Denote the marginal effect of moving from 1 to 2 stores on the number of unique products offered by a store by \hat{m}^{Store} , on the number of unique products offered in a market by \hat{m}^{Union} , and on the intersection of product offerings across stores in a market by \hat{m}^{Int} . Under the null hypothesis that the incumbent does not change its product assortment, $\frac{\hat{m}^{Union} + \hat{m}^{Int}}{2\hat{m}^{Store}} = 1$

Proof. Under the null, $S_a^A(2) = S_a^A(1)$ for all a . The store level regression then yields:

$$\begin{aligned}
\hat{\beta}^{store} &= E_m \left[\frac{1}{2} \left(f(S_a^A(1)) + f(S_e^E(2)) \right) - f(S_a^A(1)) \middle| E_m(1) = 1, t_m \in N \right] (1 - \omega_m) \\
&= E_m \left[\frac{1}{2} \left(f(S_e^E(2)) - f(S_a^A(1)) \right) \middle| E_m(1) = 1, t_m \in N \right] (1 - \omega_m).
\end{aligned}$$

Where $f(\cdot)$ measures the cardinality of the set. The market level regression of the union of product assortment sets yields:

$$\begin{aligned}
\hat{\beta}^{Union} &= E_m \left[f \left(S_a^A(1) \cup S_e^E(2) \right) - f \left(S_a^A(1) \right) \middle| E_m(1) = 1, t_m \in N \right] (1 - \omega_m) \\
&= E_m \left[f \left(S_e^E(2) \right) - f \left(\left(S_a^A(1) \cap S_e^E(2) \right) \right) \middle| E_m(1) = 1, t_m \in N \right].
\end{aligned}$$

The market level regression of the intersection of product assortment sets yields:

$$\hat{\beta}^{Int} = E_m \left[f \left(S_a^A(1) \cap S_e^E(2) \right) - f \left(S_a^A(1) \right) \middle| E_m(1) = 1, t_m \in N \right] (1 - \omega_m).$$

Then if $\omega_m > 0$,

$$\frac{\hat{m}^{Union} + \hat{m}^{Int}}{2\hat{m}^{Store}} = \frac{E_m \left[f \left(S_e^E(2) \right) - f \left(S_a^A(1) \right) \middle| E_m(1) = 1, t_m \in N \right]}{2E_m \left[\frac{1}{2} \left(f \left(S_e^E(2) \right) - f \left(S_a^A(1) \right) \right) \middle| E_m(1) = 1, t_m \in N \right]} = 1.$$

We then test the null hypothesis that

$$\hat{m}^{\text{Union}} + \hat{m}^{\text{Int}} - 2\hat{m}^{\text{Store}} = 0.$$

□

F. Toy Model (For Online Publication)

Assume that there are two stores, A and B , and two products of varying quality H (high) and L (low) so that $q^H > q^L$ (q^j denotes product quality). The marginal cost associated with product j is c^j . Assume there is a unit mass of consumers. Let a fraction λ of these consumers have a low valuation for quality (θ^L) and the remaining $1 - \lambda$ have a high valuation for quality (θ^H). Assume that utility is given by $u^i = \theta^i q^j - p^j$ for $i \in \{H, L\}$.

We assume that prices and costs are taken by each firm as given, perhaps by a regional manager. This modeling choice is motivated by the price regressions presented in section III and by a recent literature documenting the use of zone pricing by US grocery chains. Costs is done for expositional clarity; we want to focus on a setting where firms only decide which products to carry.

Assume that low valuation consumers do not purchase the high quality product, $\theta^L q^H - p^H < 0$, and that high valuation types prefer the high quality product to the low quality product, but would buy the low quality product if it were the only option ($\theta^H q^H - p^H > \theta^H q^L - p^L > 0$).

Monopoly profits are as follows:

$$\pi = \begin{cases} (1 - \lambda)(p^H - c^H) & \text{if it offers only the high quality product} \\ (1 - \lambda)(p^H - c^H) + \lambda(p^L - c^L) & \text{if it offers both products} \\ p^L - c^L & \text{if it offers only the low quality product} \end{cases}$$

Observe that carrying both products dominates only carrying the high quality product, and the monopolist prefers to carry both if $\frac{p^H - c^H}{p^L - c^L} > 1$.

Under duopoly, the normal form of the game is:

		FIRM A		
		$\{H, L\}$	H	L
Firm B	$\{H, L\}$	$\frac{1}{2}\pi(\{H, L\}), \frac{1}{2}\pi(\{H, L\})$	$\frac{1}{2}\pi(H) + \lambda\pi(L), \frac{1}{2}\pi(H)$	$\pi(H) + \frac{1}{2}\lambda\pi(L), \frac{1}{2}\lambda\pi(L)$
	H	$\frac{1}{2}\pi(H), \frac{1}{2}\pi(H) + \lambda\pi(L)$	$\frac{1}{2}\pi(H), \frac{1}{2}\pi(H)$	$\pi^H, \lambda\pi^L$
	L	$\frac{1}{2}\lambda\pi^L, \pi^H + \frac{1}{2}\lambda\pi^L$	$\lambda\pi^L, \pi^H$	$\frac{1}{2}\pi^L, \frac{1}{2}\pi^H$

Note that offering H is strictly dominated by offering $\{H, L\}$. L is also strictly dominated by $\{H, L\}$ if $\frac{p^H - c^H}{p^L - c^L} > \frac{1}{2}$. As a result, if $\frac{p^H - c^H}{p^L - c^L} > \frac{1}{2}$ the unique equilibrium is $(\{H, L\}, \{H, L\})$. Otherwise, the equilibria are $(\{H, L\}, \{H, L\})$, (L, L) , and mixing between these two strategies.

Then if $\frac{1}{2} < \frac{p^H - c^H}{p^L - c^L} < 1$, the duopoly offers a wider product assortment than the monopoly. The monopolist has revenue p^L , and each of the duopolists has revenue $\frac{\lambda p^L + (1-\lambda)p^H}{2}$. Revenue increases if $\frac{p^H}{p^L} > 1 + \frac{1}{1-\lambda}$.

G. Demand (For Online Publication)

To estimate demand, we focus on mass merchandisers, and assume that each individual's choice set consists of either purchasing liquor, beer, or wine at the mass merchandiser where they shop. We divide liquor products into exhaustive and mutually exclusive nests, and assume that indirect utility can be written as:

$$u_{ijst} = \alpha_0 + \alpha_1 \cdot p_{jst} + \gamma_j + X'_{jst}\beta + \xi_{jst} + \zeta_{ig(j)} + (1 - \sigma) \cdot \epsilon_{ijst} \quad (8)$$

where γ_j is a product fixed effect, ξ_{jst} is a product-store-time structural error which is unobserved to the econometrician, $\zeta_{ig(j)}$ is a nest-level unobservable, and ϵ_{ijst} is a logit error.

Berry (1994) shows that one can invert the market share function derived from this indirect utility function, recovering the following linear estimating equation:

$$\ln(s_{jst}) - \ln(s_{0st}) = \alpha_0 + \alpha_1 \cdot p_{jst} + X'_{jst}\beta + \sigma \cdot \ln(\bar{s}_{j|g}) + \gamma_j + \xi_{jst} \quad (9)$$

where $\bar{s}_{j|g}$ is product j 's market share within its nest, and s_{0st} is the share of the outside good.

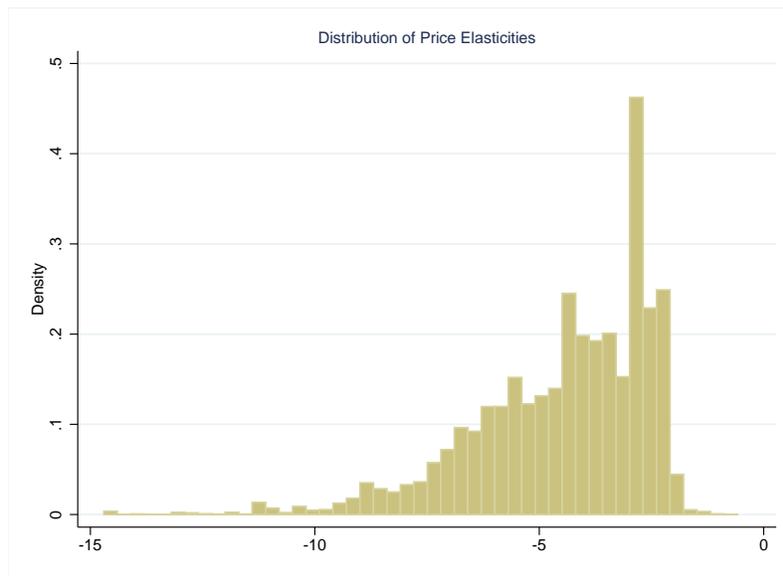
To estimate this model, we assume that the outside good is beer or wine, calculate quantity shares in milliliters, and include fixed effects for the number of stores in the bandwidth and the number of stores above the bandwidth in store s 's ZIP code. This allows us to use as instruments dummy variables for the number of stores in the bandwidth and above the threshold, as well as interactions between this variable and the number of stores above the cutoff. We also use the input prices of corn and sugar as additional instruments, following Miravete et al. (2020). Finally, the nests are (1) beer & wine, (2) Bourbon, Whiskey, & Scotch, (3) Rum, (4) Tequila, (5) Vodka and (6) other liquor (such as Gin). Coefficient estimates are presented in table G1, while the distribution of estimated own-price elasticity is presented in figure G1.

Table G1: Product Variety Effects of Market Configuration on Consumer Welfare

	(1)
Nest Share	0.452 (0.112)
Price	-0.124 (0.0435)
<i>N</i>	54,977

Notes: Clustered standard errors in parentheses, clustered at the week-store level.

Figure G1: Distribution of Price Elasticities



Notes: This figure presents the distribution of own-price elasticities for 245 products in 19 mass merchandizers the 2015 Nielsen RMS data, estimated using a nested logit with six nests for spirit type. The outside option is beer/wine.