Web Appendix 1. Theoretical Prediction

W1.1 Main Model

From our main theoretical model, we derive the impact of price and unemployment rates on the frequency, intensity, and total consumption of alcohol.

Proposition 1. *Intensity and total alcohol consumption decrease in price. The effect of a price increase on consumption frequency is ambiguous.*

Proof. From (3b) and (3c),

$$\frac{dn}{dp} = \frac{-1}{\Delta}\begin{vmatrix} F_p & F_c \\ G_p & G_c \end{vmatrix} = \frac{-F_pG_c + F_cG_p}{\Delta}$$

$$= \frac{-(-cf' + nc(pc+s)f'')(nu'' + n^2p^2f'') + np(pc+s)f''(-nf' + n^2pcf'')}{\Delta}$$

$$= \frac{ncu''(f' - n(pc+s)f'') - n^2psf'f''}{\Delta} >=< 0$$

$$\frac{dc}{dp} = \frac{-1}{\Delta}\begin{vmatrix} F_n & F_p \\ G_n & G_p \end{vmatrix} = \frac{-F_nG_p + F_pG_n}{\Delta}$$

$$= \frac{-(pc+s)^2f''(-nf' + n^2pcf'') + (-cf' + nc(pc+s)f'')np(pc+s)f''}{\Delta}$$

$$= \frac{ns(pc+s)f'f''}{\Delta} < 0$$

$$\frac{d(nc)}{dp} = c\frac{dn}{dp} + n\frac{dc}{dp} = \frac{nc^2u''(f' - n(pc+s)f'') + n^2s^2f'f''}{\Delta} < 0$$

Proposition 2. *If the drinking threshold function is strictly increasing, frequency decreases in unemployment rate and intensity increases in unemployment rate, and the effect of unemployment increase on total alcohol consumption is ambiguous. On the other hand, if the drinking threshold function is strictly decreasing, frequency increases in unemployment rate and intensity decreases in unemployment rate, and the effect of unemployment increase on total alcohol consumption is ambiguous.*

Proof. From (3b) and (3c), if $g'(\omega) > 0$,

$$\frac{dn}{d\omega} = \frac{-1}{\Delta}\begin{vmatrix} F_\omega & F_c \\ G_\omega & G_c \end{vmatrix} = \frac{-F_\omega G_c + F_cG_\omega}{\Delta}$$

$$= \frac{-(-g')(nu'' + n^2p^2f'') + np(pc+s)f''(0)}{\Delta} = \frac{nu'' + n^2p^2f''}{\Delta}g'$$

< 0 (W1a)

$$\frac{dc}{d\omega} = \frac{-1}{\Delta}\begin{vmatrix} F_n & F_\omega \\ G_n & G_\omega \end{vmatrix} = \frac{-F_nG_\omega + F_\omega G_n}{\Delta}$$

$$= \frac{-(pc+s)^2f''(0) + (-g')np(pc+s)f''}{\Delta} = \frac{-np(pc+s)f''}{\Delta}g'$$

> 0 (W1b)

$$\frac{d(nc)}{d\omega} = c\frac{dn}{d\omega} + n\frac{dc}{d\omega} = \frac{n(cu'' - npsf'')}{\Delta}g' >=< 0 \quad \text{(W1c)}$$

On the other hand, if $g'(\omega) < 0$,

$$\frac{dn}{d\omega} = \frac{(nu'' + n^2p^2f'')}{\Delta}g' > 0$$

$$\frac{dc}{d\omega} = \frac{-np(pc+s)f''}{\Delta}g' < 0$$

$$\frac{d(nc)}{d\omega} = \frac{n(cu'' - npsf'')}{\Delta}g' >=< 0$$

Proposition 3. *Frequency and total alcohol consumption increase in income and intensity is independent of income.*

Proof. From (3b) and (3c), if $g'(\omega) > 0$,

$$\frac{dn}{dy} = \frac{-1}{\Delta}\begin{vmatrix} F_y & F_c \\ G_y & G_c \end{vmatrix} = \frac{-F_yG_c + F_cG_y}{\Delta}$$

$$= \frac{(pc+s)f''(nu'' + n^2p^2f'') + (np(pc+s)f'')(-npf'')}{\Delta} = \frac{n(pc+s)u''f''}{\Delta} > 0$$

$$\frac{dc}{dy} = \frac{-1}{\Delta}\begin{vmatrix} F_n & F_y \\ G_n & G_y \end{vmatrix} = \frac{-F_nG_y + F_yG_n}{\Delta}$$

$$= \frac{-(pc+s)^2f''(-npf'') + (-(pc+s)f'')np(pc+s)f''}{\Delta} = 0$$

$$\frac{d(nc)}{dy} = c\frac{dn}{dy} + n\frac{dc}{dy} = \frac{nc(pc+s)u''f''}{\Delta} > 0$$

W1.2 Alternative Specification of the Set-up Cost

Assume that the set-up cost is a function of consumption intensity c (i.e., $s(c)$). Then, the profit maximization problem, first-order conditions, and proof for Proposition 2 (i.e., the proposition regarding unemployment rates) become as follows: Substituting the budget constraint $e = y - n\big(pc + s(c)\big)$ into the objective function, a consumer maximizes his/her utility by choosing n and c as follows:

[Profit maximization]

$$\max_{n,c} \quad n\big(u(c) - g(\omega)\big) + f\left(y - n\big(pc + s(c)\big)\right), \tag{W2a}$$

[First-order conditions with respect to n and c]

$$F(n, c; y, p, \omega) \equiv u - g - (pc + s)f' = 0, \tag{W2b}$$

$$G(n, c; y, p, \omega) \equiv nu' - npf' - ns'f' = 0. \tag{W2c}$$

Let the partial derivatives of functions F and G be denoted by F_j and G_j, where $j = n, c, p$, and ω. Note that by assuming $s' > 0$ and $s'' > 0$, the second-order conditions for the total utility maximization are satisfied, because

$$F_n = (pc + s)^2 f'' < 0 \tag{W3a}$$

$$\Delta \equiv \begin{vmatrix} F_n & F_c \\ G_n & G_c \end{vmatrix} = n(pc + s)^2(u'' - s''f')f'' > 0. \tag{W3b}$$

Proposition 2. *If the drinking threshold function is strictly increasing, frequency decreases in unemployment rate and intensity increases in unemployment rate, and the effect of unemployment increase on total alcohol consumption is ambiguous. On the other hand, if the drinking threshold function is strictly decreasing, frequency increases in unemployment rate and intensity decreases in unemployment rate, and the effect of unemployment increase on total alcohol consumption is ambiguous.*

Proof. From (W2b) and (W2c), if $g'(\omega) > 0$,

$$\frac{dn}{d\omega} = \frac{-1}{\Delta}\begin{vmatrix} F_\omega & F_c \\ G_\omega & G_c \end{vmatrix} = \frac{-F_\omega G_c + F_c G_\omega}{\Delta}$$

$$= \frac{-(-g')(nu'' - ns''f' + n^2(p + s')^2 f'') + n(p + s')(pc + s)f''(0)}{\Delta}$$

$$= \frac{nu'' - ns''f' + n^2(p + s')^2 f''}{\Delta} g' < 0$$

$$\frac{dc}{d\omega} = \frac{-1}{\Delta}\begin{vmatrix} F_n & F_\omega \\ G_n & G_\omega \end{vmatrix} = \frac{-F_n G_\omega + F_\omega G_n}{\Delta}$$

$$= \frac{-(pc+s)^2 f''(0) + (-g')n(p+s')(pc+s)f''}{\Delta}$$

$$= \frac{-n(p+s')(pc+s)f''}{\Delta} g' > 0$$

$$\frac{d(nc)}{d\omega} = c\frac{dn}{d\omega} + n\frac{dc}{d\omega}$$

$$= \frac{n(cu'' - cs''f' + ncs'(p+s')f'' - ns(p+s')f'')}{\Delta} g' >=< 0$$

On the other hand, if $g'(\omega) < 0$,

$$\frac{dn}{d\omega} = \frac{nu'' - ns''f' + n^2(p+s')^2 f''}{\Delta} g' > 0$$

$$\frac{dc}{d\omega} = \frac{-n(p+s')(pc+s)f''}{\Delta} g' < 0$$

$$\frac{d(nc)}{d\omega} = \frac{n(cu'' - cs''f' + ncs'(p+s')f'' - ns(p+s')f'')}{\Delta} g' >=< 0.$$

W1.3 Alternative Specification on the Utility Function

The modification of the objective function into $nu(c;\omega) + f(e)$ requires a revision on assumptions as follows: $u_{cc} \equiv \frac{\partial^2 u}{\partial c^2} < 0$, $f_e \equiv \frac{df}{de} > 0$, $f_{ee} \equiv \frac{d^2 f}{\partial e^2} < 0$, $u_\omega \equiv \frac{\partial u}{\partial \omega} >< 0$ (i.e., the sign of the impact of unemployment rates is undetermined), and $u_{c\omega} \equiv \frac{\partial^2 u}{\partial c \partial \omega}$. We relax the condition that the cross partial be equal to 0 by assuming that $\frac{u_{c\omega}}{u_\omega} < \frac{u_{cc}+p^2}{p(pc+s)}$. This gives us the same theoretical results. The details regarding the profit maximization, first-order conditions, and proof for Proposition 2 (i.e., the proposition for unemployment rates) are as follows: Substituting the budget constraint $e = y - n(pc+s)$ into the objective function, a consumer maximizes his/her utility by choosing n and c as follows:

[Profit maximization]

$$\max_{n,c} \; nu(c;\omega) + f\big(y - n(pc+s)\big), \tag{W4a}$$

[First-order conditions with respect to n and c]

$$F(n, c; y, p, \omega) \equiv u - (pc + s)f_e = 0, \tag{W4b}$$

$$G(n, c; y, p, \omega) \equiv nu_c - npf_e = 0. \tag{W4c}$$

Let the partial derivatives of functions F and G be denoted by F_j and G_j, where $j = n, c, p,$ and ω. Note that by assuming $s' > 0$ and $s'' > 0$, the second-order conditions for the total utility maximization are satisfied, because

$$F_n = (pc + s)^2 f_{ee} < 0 \tag{W5a}$$

$$\Delta \equiv \begin{vmatrix} F_n & F_c \\ G_n & G_c \end{vmatrix} = n(pc + s)^2 u_{cc} f_{cc} > 0. \tag{W5b}$$

Proposition 2. *If the utility is a strictly decreasing function of unemployment rate, frequency decreases in unemployment rate and intensity increases in unemployment rate, and the effect of unemployment increase on total alcohol consumption is ambiguous. On the other hand, if the utility is a strictly increasing function of unemployment rate, frequency increases in unemployment rate and intensity decreases in unemployment rate, and the effect of unemployment increase on total alcohol consumption is ambiguous.*

Proof. From (W4b) and (W4c), if $u_\omega < 0$,

$$\begin{aligned}
\frac{dn}{d\omega} = \frac{-1}{\Delta}\begin{vmatrix} F_\omega & F_c \\ G_\omega & G_c \end{vmatrix} &= \frac{-F_\omega G_c + F_c G_\omega}{\Delta} \\
&= \frac{-(u_\omega)\cdot(nu_{cc} + n^2p^2 f_{ee}) + (np(pc + s)f_{ee})\cdot(nu_{c\omega})}{\Delta} \\
&< \frac{-u_\omega(nu_{cc} + n^2p^2 f_{ee}) - np(pc + s)f_{ee}\left(n\left(-u_\omega \dfrac{u_{cc} + p^2}{p(pc + s)}\right)\right)}{\Delta} \\
&= \frac{nu_{cc}(1 - nf_{ee})}{\Delta}(-u_\omega) < 0
\end{aligned}$$

$$\begin{aligned}
\frac{dc}{d\omega} = \frac{-1}{\Delta}\begin{vmatrix} F_n & F_\omega \\ G_n & G_\omega \end{vmatrix} &= \frac{-F_n G_\omega + F_\omega G_n}{\Delta} \\
&= \frac{-((pc + s)^2 f_{ee})\cdot(nu_{c\omega}) + (u_\omega)\cdot(np(pc + s)f_{ee})}{\Delta}
\end{aligned}$$

$$> \quad \frac{-(pc+s)^2 f_{ee}\left(n\left(u_\omega \dfrac{u_{cc}+p^2}{p(pc+s)}\right)\right)+np(pc+s)f_{ee}u_\omega}{\Delta}$$

$$= \frac{-n(pc+s)u_{cc}f_{ee}}{\Delta}u_\omega > 0$$

$$\frac{d(nc)}{d\omega} = c\frac{dn}{d\omega} + n\frac{dc}{d\omega}$$

$$= \frac{-n(cu_{cc} - npsf_{ee})u_\omega - n^2(pc+s)sf_{ee}u_{c\omega}}{\Delta}$$

$$< \frac{-n\left(cu_{cc} + \dfrac{n}{p}su_{cc}f_{ee}\right)u_\omega}{\Delta} >=< 0.$$

On the other hand, if $u_\omega > 0$,

$$\frac{dn}{d\omega} > \frac{nu_{cc}(1-nf_{ee})}{\Delta}(-u_\omega) > 0$$

$$\frac{dc}{d\omega} < \frac{-n(pc+s)u_{cc}f_{ee}}{\Delta}u_\omega < 0 \frac{d(nc)}{d\omega} < \frac{-n\left(cu_{cc} + \dfrac{n}{p}su_{cc}f_{ee}\right)u_\omega}{\Delta} >=< 0.$$

W1.4 Alternative Function for the Unemployment Rate

Assume that the utility function is $nu(c)$ and the budget constraint is $n\big(pc+s(\omega)\big)+e=y$. Then, the profit maximization problem, first-order conditions, and proof for Proposition 2 (i.e., the proposition regarding unemployment rates) are as follows: Substituting the budget constraint $e = y - n\big(pc+s(\omega)\big)$ into the objective function, a consumer maximizes his or her utility by choosing n and c as follows:

[Profit maximization]

$$\max_{n,c} \quad nu(c) + f\left(y - n\big(pc+s(\omega)\big)\right), \tag{W6a}$$

[First-order conditions with respect to n and c]:

$$F(n,c;y,p,\omega) \equiv u - (pc+s)f' = 0, \tag{W6b}$$

$$G(n,c;y,p,\omega) \equiv nu' - npf' = 0. \tag{W6c}$$

Let the partial derivatives of functions F and G be denoted by F_j and G_j, where $j = n, c, p,$ and ω. Note that the second-order conditions for the total utility maximization are satisfied, because

$$F_n = (pc+s)^2 f'' < 0 \tag{W7a}$$

$$\Delta \equiv \begin{vmatrix} F_n & F_c \\ G_n & G_c \end{vmatrix} = n(pc+s)^2 u'' f'' > 0. \tag{W7b}$$

Proposition 2. *If the set up cost function is strictly increasing, frequency decreases in the unemployment rate and intensity increases in unemployment rate; the effect of an increase in unemployment on total alcohol consumption is ambiguous. On the other hand, if the set up cost function is strictly decreasing, frequency increases in unemployment rate and intensity decreases in unemployment rate, and the effect of an increase in unemployment on total alcohol consumption is ambiguous.*

Proof. From (W6b) and (W6c), $s'(\omega) > 0$,

$$\frac{dn}{d\omega} = \frac{-1}{\Delta}\begin{vmatrix} F_\omega & F_c \\ G_\omega & G_c \end{vmatrix} = \frac{-F_\omega G_c + F_c G_\omega}{\Delta}$$

$$= \frac{-(-s'f' + n(pc+s)s'f'')(nu'' + n^2p^2f'') + np(pc+s)f''(n^2ps'f'')}{\Delta}$$

$$= \frac{nu''f' + n^2p^2f'f'' - n^2(pc+s)u''f''}{\Delta}s' < 0$$

$$\frac{dc}{d\omega} = \frac{-1}{\Delta}\begin{vmatrix} F_n & F_\omega \\ G_n & G_\omega \end{vmatrix} = \frac{-F_n G_\omega + F_\omega G_n}{\Delta}$$

$$= \frac{-(pc+s)^2f''(-n^2ps'f'') + (-s'f' + n(pc+s)s'f'')np(pc+s)f''}{\Delta}$$

$$= \frac{-np(pc+s)f'f''}{\Delta}s' > 0$$

$$\frac{d(nc)}{d\omega} = c\frac{dn}{d\omega} + n\frac{dc}{d\omega} = \frac{ncu''f' - n^2c(pc+s)u''f'' - n^2psf'f''}{\Delta}s' >=< 0$$

On the other hand, if $s'(\omega) < 0$,

$$\frac{dn}{d\omega} = \frac{nu''f' + n^2p^2f'f'' - n^2(pc+s)u''f''}{\Delta}s' > 0$$

$$\frac{dc}{d\omega} = \frac{-np(pc+s)f'f''}{\Delta}s' < 0$$

$$\frac{d(nc)}{d\omega} = c\frac{dn}{d\omega} + n\frac{dc}{d\omega} = \frac{ncu''f' - n^2c(pc+s)u''f'' - n^2psf'f''}{\Delta}s' >=< 0.$$

Web Appendix 2. Further Discussion on the RI Panel Data

W2.1 Demographic Distribution

Each quarter, approximately 6,000 panelists are selected randomly to ensure that the demographic distribution of the respondents is consistent with both local and national statistics. During the sample period, the quarterly demographic composition (e.g., age, gender, race) stays the same, as shown in Table W1:

Table W1. Quarterly Demographic Composition in the RI Dataset

	03Q1	03Q2	03Q3	03Q4	04Q1	04Q2	04Q3	04Q4	05Q1	05Q2
Age	43.13	43.23	43.26	43.09	43.20	43.42	43.35	43.48	43.42	43.38
Male	0.711	0.708	0.701	0.696	0.692	0.700	0.690	0.694	0.677	0.677
White	0.737	0.742	0.742	0.742	0.733	0.732	0.734	0.734	0.732	0.730

	05Q3	05Q4	06Q1	06Q2	06Q3	06Q4	07Q1	07Q2	07Q3	07Q4
Age	43.36	43.41	43.43	43.34	43.40	43.43	43.47	44.04	44.00	43.97
Male	0.674	0.676	0.676	0.675	0.675	0.676	0.673	0.698	0.698	0.696
White	0.729	0.733	0.731	0.729	0.728	0.730	0.726	0.689	0.701	0.688

W2.2 County-Level Unemployment Rates and Panelist Distribution

Table W2 provides the means of unemployment rates and the distribution of panelists at the county level. The unit for both variables is a percentage (%).

Table W2. Unemployment Rates and Distribution of Panelists by County

County	Unemp	Dist.	County	Unemp	Dist.	County	Unemp	Dist.
Akron, OH	5.74	0.812	Green Bay, WI	4.72	0.909	Plano, TX	4.65	0.003
Albany, GA	5.84	0.274	Greensboro, NC	5.18	0.633	Pompton Lakes, NJ	5.14	0.001
Albany, NY	4.04	0.757	Greensburg, PA	5.32	0.695	Port Saint Lucie, FL	5.38	0.104
Albuquerque, NM	4.39	0.958	Greenville, SC	5.41	0.404	Portland, ME	3.47	0.639
Alexandria, VA	2.62	0.625	Gulfport, MS	6.12	0.080	Portland, OR	5.92	1.242
Alhambra, CA	5.92	0.315	Hartford, CT	5.29	0.597	Providence, RI	5.60	0.452
Anchorage, AK	5.40	0.187	Harvester, MO	4.19	0.339	Racine, WI	6.10	0.692
Ann Arbor, MI	4.38	0.354	Honolulu, HI	2.81	0.694	Raleigh, NC	4.18	0.659
Arlington Hts, IL	6.15	0.632	Houston, TX	5.58	1.332	Reading, PA	4.98	1.108
Asheville, NC	4.12	0.228	Huntington, NY	4.39	0.335	Reno, NV	4.28	0.283
Atlanta, GA	4.98	0.930	Huntsville, AL	3.55	0.386	Richmond, VA	2.90	0.486
Atlantic City, NJ	5.75	0.269	Indianapolis, IN	4.71	0.577	Ridgewood, NY	5.05	0.008
Augusta, GA	5.19	0.651	Jackson, MS	5.24	0.336	Rochester, MN	3.89	0.459
Austin, TX	4.64	0.518	Jackson, TN	5.51	0.126	Rochester, NY	4.83	0.649
Bakersfield, CA	8.66	0.288	Jacksonville, FL	4.02	0.377	Rockford, IL	6.72	0.594
Baltimore, MD	3.73	1.189	Jersey City, NJ	5.87	0.389	Rockville, MD	2.98	0.960
Baton Rouge, LA	5.06	0.438	Kansas City, KS	8.86	0.383	Roseville, MI	6.93	0.275
Beaumont, TX	7.13	0.318	Kansas City, MO	6.00	0.639	Royal Oak, MI	5.73	0.360
Belleville, IL	6.58	0.693	Kirkland, WA	4.69	0.245	Sacramento, CA	5.28	0.474
Billings, MT	2.99	0.533	Knoxville, TN	3.92	0.260	Saginaw, MI	7.93	0.506
Binghamton, NY	5.08	0.400	Lakeland, FL	4.45	0.193	Saint Cloud, MN	4.61	0.452
Birmingham, AL	3.69	0.512	Lancaster, PA	3.68	0.635	Saint Louis, MO	4.15	1.490
Boise, ID	3.47	0.619	Laredo, TX	6.17	0.465	Saint Paul, MN	3.88	0.585

Boston, MA	5.47	0.820
Bowling Green, KY	4.91	0.338
Brooklyn, NY	5.41	1.999
Bryan, TX	4.20	0.169
Buffalo, NY	5.33	1.190
Burlington, VT	3.39	0.320
Champaign, IL	4.37	0.403
Charleston, SC	5.29	0.719
Charlotte, NC	5.01	0.613
Chattanooga, TN	4.48	0.260
Cheyenne, WY	4.23	0.361
Chicago, IL	6.06	1.729
Chico, CA	6.90	0.400
Cincinnati, OH	5.27	1.039
Cleveland, OH	6.06	1.138
Colorado Springs, CO	5.24	0.438
Columbia, SC	4.58	0.848
Columbus, OH	4.95	0.607
Conroe, TX	4.84	0.108
Corpus Christi, TX	5.47	0.379
Dallas, TX	5.40	1.322
Dayton, OH	6.03	0.799
Daytona Beach, FL	3.98	0.194
Denver, CO	5.29	1.917
Des Moines, IA	3.87	0.351
Detroit, MI	7.39	0.965
Doylestown, PA	3.86	0.023
Duluth, MN	5.50	0.344
El Paso, TX	7.41	0.701
El Toro, CA	4.13	0.150
Erie, PA	5.50	0.734
Eugene, OR	6.63	0.566
Evansville, IN	4.86	0.324
Exton, PA	3.38	0.032
Fargo, ND	2.70	0.475
Flint, MI	8.08	0.262
Fort Lauderdale, FL	4.01	0.431
Fort Worth, TX	5.32	0.538
Fresno, CA	9.68	0.601
Ft Collins, CO	4.36	0.539
Gainesville, FL	3.03	0.292
Gaithersburg, MD	3.03	0.024
Gary, IN	5.83	0.425
Grand Rapids, MI	6.17	0.505
Las Vegas, NV	4.52	0.273
Lexington, KY	4.37	0.241
Little Rock, AR	4.88	0.282
Long Beach, CA	5.78	0.334
Los Angeles, CA	5.70	1.315
Louisville, KY	5.81	0.738
Lowell, MA	4.33	0.421
Lubbock, TX	4.28	0.222
Lynbrook, NY	4.21	0.290
Lynn, MA	5.57	0.415
Macon, GA	5.22	0.201
Madison, WI	3.36	0.693
Manchester, NH	3.82	0.412
Melbourne, FL	4.29	0.133
Memphis, TN	5.83	0.552
Mesa, AZ	3.96	0.401
Miami, FL	4.71	0.786
Milwaukee, WI	6.08	1.433
Minneapolis, MN	4.24	0.717
Mobile, AL	4.40	0.183
Modesto, CA	8.82	0.446
Montgomery, AL	4.19	0.397
Moorestown, NJ	4.15	0.318
Muncie, IN	5.98	0.314
Murrieta, CA	5.52	0.177
Naperville, IL	4.89	0.503
Naples, FL	3.73	0.110
Nashville, TN	4.38	0.588
New Haven, CT	5.24	0.529
New Orleans, LA	5.03	0.515
New York, NY	5.29	0.471
Northboro, MA	5.50	0.013
Oak Park, IL	6.16	0.535
Oakland, CA	5.31	0.822
Ogden, UT	4.53	0.290
Oklahoma City, OK	4.57	0.320
Omaha, NE	3.90	0.546
Orlando, FL	4.08	0.378
Peoria, IL	5.74	0.320
Philadelphia, PA	5.59	1.020
Phoenix, AZ	3.80	0.554
Pikesville, MD	3.86	0.036
Pittsburgh, PA	4.88	0.579
Plainfield, NJ	3.59	0.251
Saint Petersburg, FL	4.15	0.265
San Bernardino, CA	5.61	0.598
San Diego, CA	4.54	0.578
San Francisco, CA	4.98	0.309
San Jose, CA	5.77	0.421
San Mateo, CA	4.32	0.189
Santa Ana, CA	4.10	0.435
Santa Barbara, CA	4.45	0.377
Santa Cruz, CA	6.66	0.209
Santa Rosa, CA	4.52	0.347
Sarasota, FL	3.74	0.211
Savannah, GA	4.18	0.220
Scranton, PA	5.28	0.646
Seattle, WA	4.92	0.651
Shreveport, LA	5.66	0.473
Sioux Falls, SD	2.96	0.394
Spokane, WA	6.11	0.803
Spring Valley, NY	4.13	0.440
Springfield, MA	6.00	0.343
Springfield, MO	4.16	0.170
Syracuse, NY	4.68	0.885
Tacoma, WA	5.80	0.305
Tallahassee, FL	3.33	0.387
Tampa, FL	4.12	0.408
Toledo, OH	6.59	0.800
Toms River, NJ	4.96	0.385
Topeka, KS	5.14	0.291
Tucson, AZ	4.30	0.546
Tulsa, OK	4.71	0.293
Tupelo, MS	6.13	0.406
Tyler, TX	5.06	0.277
Van Nuys, CA	5.83	0.349
Vancouver, WA	6.90	0.512
Virginia Beach, VA	3.18	0.691
Vista, CA	4.57	0.450
Waco, TX	5.28	0.265
Walnut Creek, CA	5.05	0.219
Washington, DC	6.44	0.347
Wauconda, IL	5.02	0.003
West Palm Beach, FL	4.47	0.323
Wichita, KS	5.36	0.254
Wilmington, DE	4.04	0.261
Worcester, MA	5.42	0.571
Yonkers, NY	4.12	0.220

Note: The unit of unemployment rates is a percentage (%).

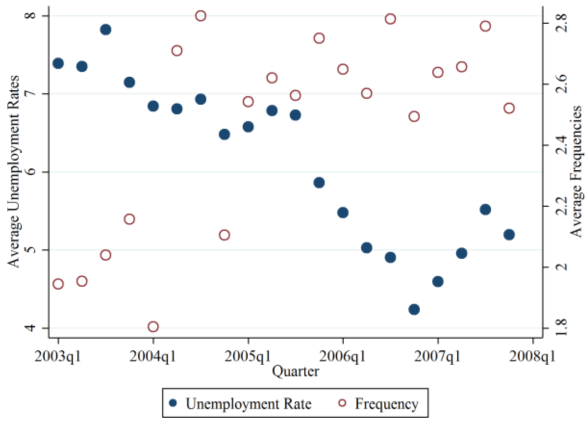
Figure W1 presents the quarter-over-quarter changes in unemployment rates, frequencies, and intensities by quarter in a few major counties with many panelists.

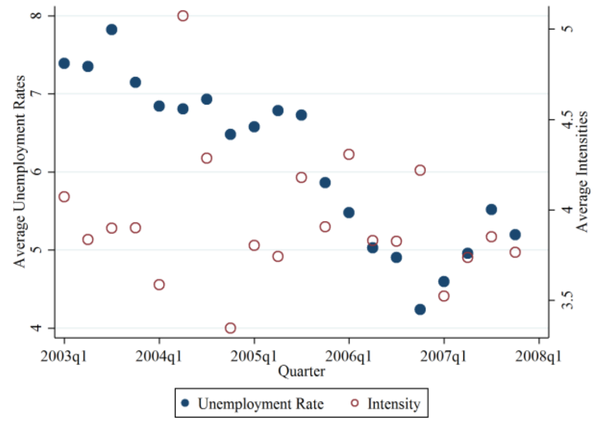
Figure W1. Unemployment Rate, Frequency, and Intensity: Major Counties

A. Cook County, IL

(a) Unemployment rate and frequency

(b) Unemployment rate and intensity

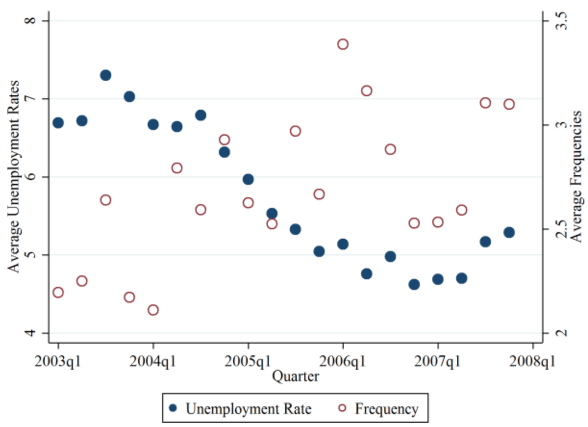


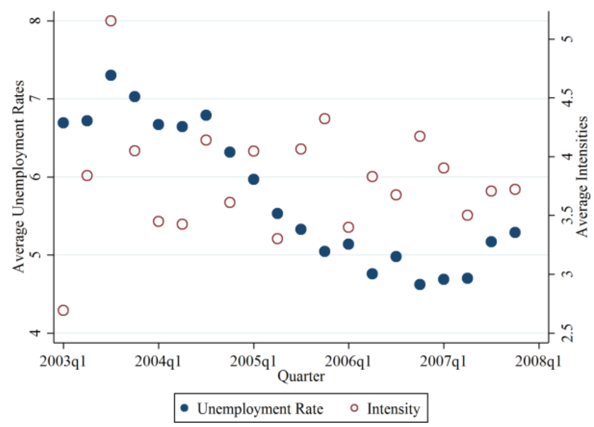


B. Los Angeles County, CA

(a) Unemployment rate and frequency

(b) Unemployment rate and intensity

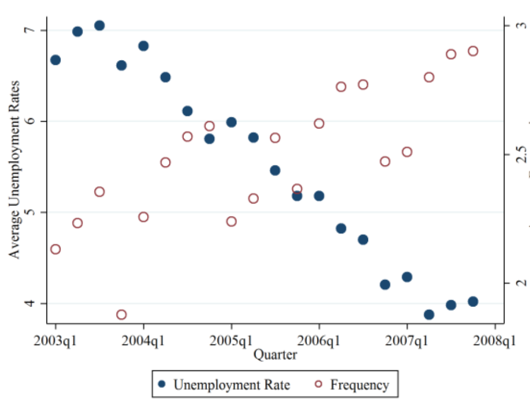




C. City and County of Denver, CO

(a) Unemployment rate and frequency

(b) Unemployment rate and intensity



W2.3 Baseline Consumption Levels by Group

Table W3 presents the mean levels of frequency, intensity, and total consumption across demographic groups and a few selected counties, as well as over national holiday weeks.

Table W3. Baseline Consumption

A. Demographic groups

	Mean		
	Frequency	Intensity	Total
White	2.637	3.361	9.090
Male	2.732	3.695	10.284
Age 41–60	2.706	3.363	9.566
Age 61+	3.111	2.441	8.122
Married	2.628	3.229	8.675
Employed	2.551	3.606	9.445
Urban	2.625	3.502	9.620
All	2.623	3.505	9.465

B. Selected counties

	Mean		
	Frequency	Intensity	Total
Cook County, IL	2.473	3.927	9.961
Los Angeles County, CA	2.710	3.805	10.777
City and County of Denver, CO	2.526	2.969	7.784
All	2.623	3.505	9.465

C. Specific weeks

	Mean		
	Frequency	Intensity	Total
New Year's Day	2.727	3.725	10.449
Martin Luther King Jr. Day	2.352	3.319	8.357
Memorial Day	2.781	3.510	9.956
Independence Day	2.936	3.959	11.951
Labor Day	2.795	3.365	9.688
Thanksgiving	2.537	3.647	9.664
Christmas Day	2.571	4.205	11.122
All	2.623	3.505	9.465

We also found in the raw data that drinking patterns per week are quite consistent within individuals across weeks. For instance, the correlation between previous frequency and current frequency is 0.584, and that between previous intensity and current intensity is 0.523.

Web Appendix 3. Data Analysis with the Nielsen Data

W3.1 Model-Free Plots from the Nielsen Data

From the Nielsen data, we obtained several model-free plots. Figure W2 illustrates the trend in purchasing alcoholic beverages. The proportions of beer in the total alcoholic beverage purchase volumes are stable over time.

Figure W2. Trend in Purchasing Alcoholic Beverages

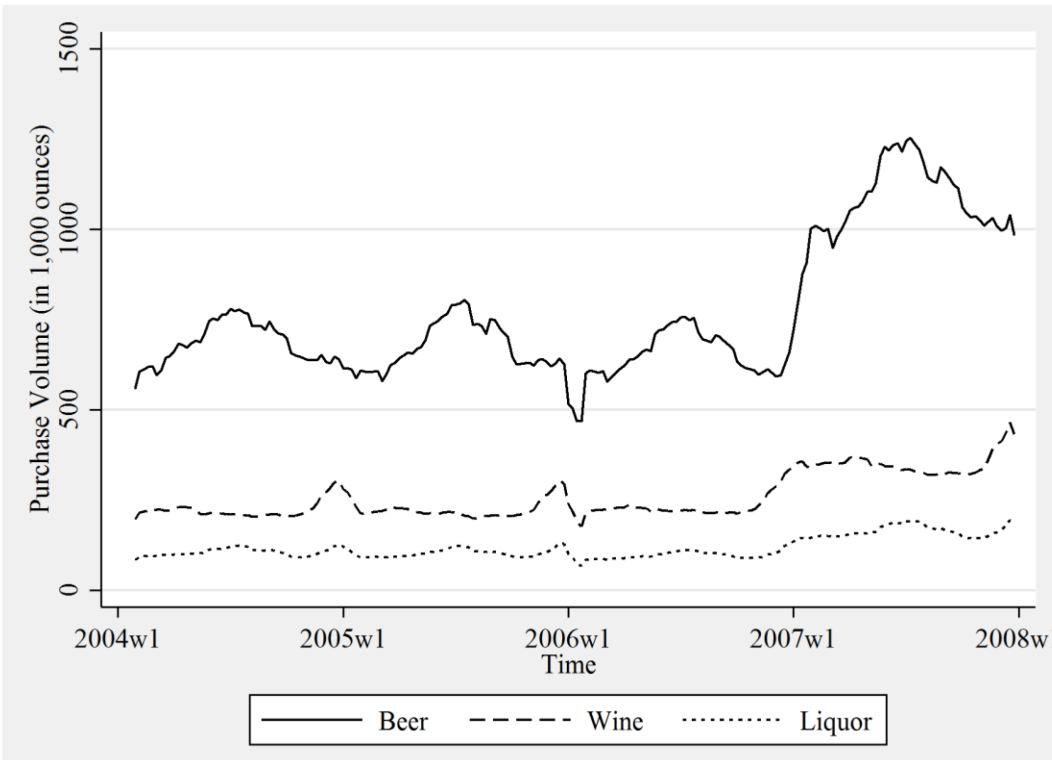
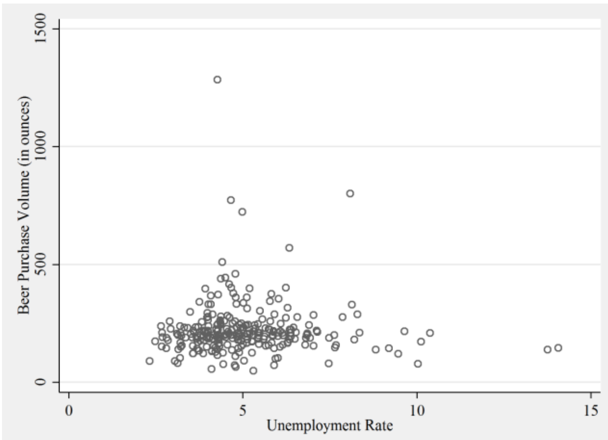


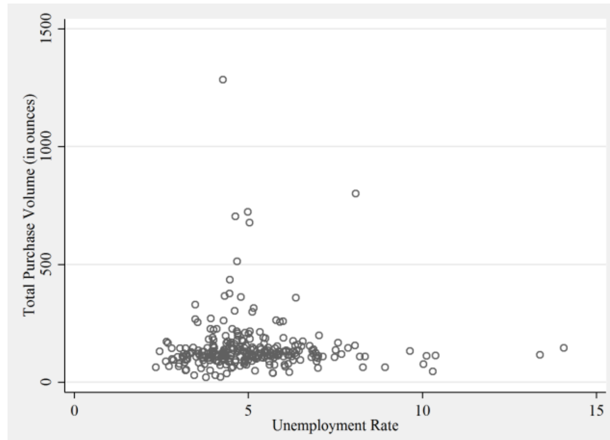
Figure W3 portrays the relationship between beer purchases and unemployment rates, as well as that between overall alcoholic beverage purchases and unemployment rates at the county level. Both show similar patterns. However, because beer purchase volumes are based on household levels and potentially include stockpiling, they are larger compared to individual beer consumption volumes in the RI data.

Figure W3. Alcoholic Beverage Purchases/Consumption and Unemployment Rates

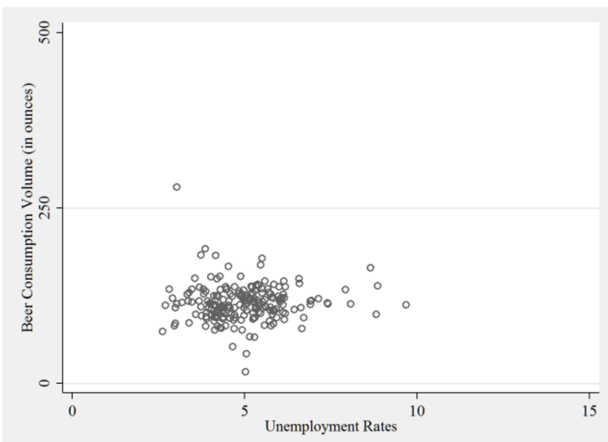
A. Beer purchases (Nielsen)



B. Total alcohol purchases (Nielsen)



C. Beer consumption (RI)



W3.2 Limitations in the Nielsen Data

Among other things, the most important limitation of the Nielsen data for the purpose of our paper is that the Nielsen data do not have any information on *consumption,* only purchases at the household level. Even if we convert such purchase data to consumption data, it is not possible either to assign household purchases to each individual or to assign purchased alcohol to particular drinking events. In addition, we do not know whether the purchased alcoholic beverages are actually consumed, stockpiled, or wasted.

To push this argument further, we did the following:

(i) We focused on single-adult households in the Nielsen Homescan panel so as to resolve the issue of whom to ascribe the purchases to.

(i) We used the total quantity of beer purchased from 2004 to 2007.

(ii) For each panelist, we took the dates of first and last purchases in the data period and computed a time horizon in days for each household to obtain an average consumption rate per person per day (this follows previous research that has used Nielsen data on other packaged goods).

(iii) We checked to see how many adults qualify as having consumed heavily in the Nielsen data.

(iv) Since the above might represent a conservative measure, we also singled out the "above median" purchase quantities for each household (based on that household's median quantity), took the time till the next purchase, and computed a consumption rate per day for each household and, hence, each adult in the data.

(v) We checked to see how many adult-purchase occasions satisfied the heavy drinking criterion.

(vi) The results of these computations are provided in the table below.

(vii) Note that all this assumes that adults who purchase also consume all the alcohol, that is, we are ruling out things such as parties, celebrations, etc.

Table W4. Converting Purchase to Consumption: Single-Adult Households

A. Average consumption rate per person per day in ounces

			Percentiles					
	Mean	SD	5th	25th	50th	75th	95th	Obs
Consumption	9.50	21.71	0.50	1.61	3.60	9.00	36.41	6,044

B. Average consumption rate per person per day excluding the above median

			Percentiles					
	Mean	SD	5th	25th	50th	75th	95th	Obs
Consumption	8.38	20.31	0.45	1.43	3.18	7.84	32.54	6,044

C. Average consumption rate per person per day excluding the below median

			Percentiles					
	Mean	SD	5th	25th	50th	75th	95th	Obs
Consumption	11.27	24.50	0.51	1.71	4.12	10.59	44.08	6,044

Note: The unit is an ounce.

As seen from Table W4, the best we can do with the Nielsen data is figure out heavy purchase sub-durations for each panelist. Even with this information, we can only obtain an average consumption rate per day without assuming heavy drinking occurred in the data. This seems like an arbitrary way of studying heavy drinking by individuals, especially when the consumption panel data are available us. About 3% of people appear to drink more than four bottles (48 ounces) of beer per day, which seems too low compared to the 30% in the literature (e.g., Naimi et al., 2003) and the 25% in the RI data. This route is not very promising for our specific purposes.

We then apply a similar framework to all the households. For example, let us assume constant daily consumption for the duration between two consecutive purchases. If someone buys 24 bottles of 12 ounces, there are two adults in the family, and the next purchase happens after seven days, the per day consumption is 24/2/7 per occasion. Based on this assumption, the average drinking intensity is computed to be around 0.5 bottles of 12 ounces per the Nielsen data from 2004 to 2007 (see Table W5). About 4.3% of people appear to drink more than two bottles (24 ounces) per day. This indicates that converting purchase information to consumption information based on this assumption does not capture intensive drinking behaviors. Unlike with our consumption data, one would have to assume heavy drinking in order to observe heavy drinking in the data, which renders the subsequent analysis vacuous.

Table W5. Converting Purchase to Daily Consumption Per Person: All Households

			Percentiles					
	Mean	SD	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}	Obs.
Consumption	5.69	14.37	0.33	1.01	2.21	5.28	21.95	28,343

Note: The unit is an ounce.

Concerning the counterfactual condition to consider within-household effects or exploit the more granular heterogeneity offered by the data, modeling at the household level is of potential interest but beyond the scope of this study.

W3.3 Substitution of Beer for Other Alcoholic Beverages

Since our focus is on intensive drinking, the total amount of alcohol *consumed* each day by the individuals in our sample is of most value. Regarding the extent to which consumers might substitute beer for wine or other alcoholic beverages, our measure of intensive drinking may underestimate or overestimate the actual amount of consumption. We address this issue in several different ways.

1) First, we examine the weekly average quantity of beer and other alcoholic beverages *purchased* per the Nielsen data from 2004 to 2007 (even though, as shown later, this is not a plausible dataset to measure actual consumption). We also examine the weekly average quantity of beer *consumed* per our Research International (RI) consumption panel during the same period. These numbers (in ounces) are provided in Table W6.

Table W6. Weekly Average Purchasing & Consumption Behaviors

A. Nielsen data

	Mean	SD	Min	Max
Purchase volume per *household*				
Beer	145.44	15.94	98.21	186.83
Wine	48.90	3.96	40.73	59.46
Liquor	22.09	1.81	17.57	28.32

B. RI data

	Mean	SD	Min	Max
Consumption volume per *drinker*				
Beer	116.86	14.21	71.65	162.38
Conjectured consumption volume per *drinker*				
Wine	*8.50**	*1.04**	*6.26**	*11.98**
Liquor	*2.79**	*0.52**	*1.94**	*5.17**

Note: The unit is an ounce.

*: From the 4th quarter of 2005, the RI data surveyed how many servings of each alcoholic beverage a panelist consumes in a typical week. We converted 1 serving of beer, wine, and liquor into 12, 5, and 1.5 ounces, respectively. Then, we scaled the beer number by actual consumption and applied that scale to the other beverages.

There are several important takeaways from Table W6. First, the numbers from the two datasets are roughly comparable if one considers that purchasing data is at the household level and often reflects stockpiling, while consumption data does not. Further, stockpiling is more likely to occur with purchases of wine and liquor. In terms of household-level purchases, we see that wine purchases reach only 33% of the level of beer purchases. From this, we can conclude that the majority of the opportunities for intensive drinking come from beer and not from wine. Next, we convert the above metrics to equivalent drinks following the guideline of National Institute on Alcohol Abuse and Alcoholism (i.e., the standard serving sizes for beer, wine, and spirit are respectively 12, 5, and 1.5 ounces, respectively). Because of the storability of wine, the proportion of purchasing beers to all alcoholic beverages is about one-third at the household level, but that of consuming beers is dominant at the individual level. Once again, we see a similar pattern in consumption.

2) If we are concerned about substitution taking place over time, we can split the data into two time periods (from 2004 to 2005 and from 2006 to 2007) in the Nielsen data and look at the above statistics again. If substitution is a concern, it could be that wine (and other liquors) occupy a larger percentage of total purchasing in the latter half of the data. However, as we can see from Table W7, this is not actually a concern.

Table W7. Purchase Volume Per Household in Two Sub-Periods (Nielsen)

	2004−2005		2006−2007	
	Mean	SD	Mean	SD
Beer	144.79	16.81	146.09	15.06
Wine	48.07	3.82	49.73	3.95
Liquor	22.28	1.87	21.89	1.75

Note: The unit is an ounce.

3) An alternative measure of intensive drinking would be to take the *total* amount of alcoholic drinks purchased (and/or consumed). If this measure does not correlate highly with the measure using only beer data, then using only beer data in the analysis might be of concern. To safeguard against this, we compute the time series both for beer alone and for all alcoholic beverages in the Nielsen data. The correlations are 0.98 for these purchases. Once again, this indicates that using only beer data does not seriously compromise the variation in the data that identifies our parameters.

4) To assess the extent of substitution between beer and wine at the *individual* level, we look at both purchase and consumption data. We regress the wine metrics on the beer metrics after controlling for individual and time fixed effects. In doing so, we get the following results:

Table W8. Regression of the Wine Metrics on the Beer Metrics

	Dependent variables: Wine (in ounces)		
	Purchase (Nielsen)		Consumption (RI)
	Monthly	Quarterly	Weekly
Variable	(1)	(2)	(3)
Beer (in ounces)	0.027**	0.104***	0.006***
	(0.005)	(0.007)	(0.001)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj. R-squared	0.663	0.693	0.577

Note: ** and *** indicate significance at the 5% and 1% levels, respectively.

We see from Table W8 that beer and wine metrics are not *negatively* correlated *after* accounting for individual and time differences. Thus, substitution seems unlikely in the data. Combined with all the previous data, this provides further justification for focusing our attention on beer alone.

Web Appendix 4. Elasticities

W4.1 Equations for Elasticities

The elasticities of frequency, intensity, and total consumption with respect to price are computed as follows:

$$\begin{aligned}\frac{dn}{dp}\cdot\frac{p}{n} &= \frac{ncu''(f'-n(pc+s)f'')-n^2psf'f''}{n(pc+s)^2u''f''}\cdot\frac{p}{n}\\ &= \frac{ncu''f'}{n(pc+s)^2u''f''}\cdot\frac{p}{n}-\frac{n^2cu''(pc+s)f''}{n(pc+s)^2u''f''}\cdot\frac{p}{n}-\frac{n^2psf'f''}{n(pc+s)^2u''f''}\cdot\frac{p}{n}\\ &= \frac{cpf'}{n(pc+s)^2f''}-\frac{pc}{pc+s}-\frac{p^2sf'}{(pc+s)^2u''}.\end{aligned}$$

$$\frac{dc}{dp}\cdot\frac{p}{c}=\frac{ns(pc+s)f'f''}{n(pc+s)^2u''f''}\cdot\frac{p}{c}=\frac{psf'}{c(pc+s)u''}.$$

$$\begin{aligned}\frac{d(nc)}{dp}\cdot\frac{p}{nc} &= \left(c\frac{dn}{dp}+n\frac{dc}{dp}\right)\frac{p}{nc}=\frac{dn}{dp}\cdot\frac{p}{n}+\frac{dc}{dp}\cdot\frac{p}{c}\\ &= \frac{cpf'}{n(pc+s)^2f''}-\frac{pc}{pc+s}-\frac{p^2sf'}{(pc+s)^2u''}+\frac{psf'}{c(pc+s)u''}\\ &= \frac{cpf'}{n(pc+s)^2f''}-\frac{pc}{pc+s}-\frac{ps^2f'}{(pc+s)^2u''c}.\end{aligned}$$

The three elasticities with respect to unemployment are computed by:

$$\begin{aligned}\frac{dn}{d\omega}\cdot\frac{\omega}{n} &= \frac{(nu''+n^2p^2f'')g'}{n(pc+s)^2u''f''}\cdot\frac{\omega}{n}=\frac{nu''g'}{n(pc+s)^2u''f''}\cdot\frac{\omega}{n}+\frac{n^2p^2f''g'}{n(pc+s)^2u''f''}\cdot\frac{\omega}{n}\\ &= \frac{\omega g'}{n(pc+s)^2f''}+\frac{p^2\omega g'}{(pc+s)^2u''}\end{aligned}$$

$$\frac{dc}{d\omega}\cdot\frac{\omega}{c}=\frac{-np(pc+s)f''g'}{n(pc+s)^2u''f''}\cdot\frac{\omega}{c}=-\frac{p\omega g'}{c(pc+s)u''}$$

$$\begin{aligned}\frac{d(nc)}{d\omega}\cdot\frac{\omega}{nc} &= \left(c\frac{dn}{d\omega}+n\frac{dc}{d\omega}\right)\frac{\omega}{nc}=\frac{dn}{d\omega}\cdot\frac{\omega}{n}+\frac{dc}{d\omega}\cdot\frac{\omega}{c}\\ &= \frac{\omega g'}{n(pc+s)^2f''}+\frac{p^2\omega g'}{(pc+s)^2u''}-\frac{p\omega g'}{c(pc+s)u''}\\ &= \frac{\omega g'}{n(pc+s)^2f''}-\frac{ps\omega g'}{(pc+s)^2u''c}.\end{aligned}$$

W4.2 Elasticities Excluding Observed Heterogeneity

As shown in Table 4, incorporating individual observed heterogeneity into the model (i.e., column (c)) does affect the estimated elasticities, especially price. To the extent that we can show that the elasticities have implications for policy, incorporating heterogeneity is of value. To show how variation across different demographic groups delivers different policy implications, for example, we present the price elasticities with and without heterogeneity in both the utility function for beer consumption and the set-up cost. As shown in Table W9, there is a significant difference in price elasticities regarding intensity and total consumption. This means that a tax policy would not affect the different consumer groups in a uniform way.

Table W9. Individuals' Elasticities Regarding Observed Heterogeneity

A. Price

	Specification regarding observed heterogeneity			
	Excluded[a]		Included[b]	
	Mean (S.E.)	S.D.	Mean (S.E.)	S.D.
Frequency	−0.055*** (0.008)	0.140	−0.058*** (0.007)	0.133
Intensity	−0.839*** (0.138)	2.210	−1.326*** (0.147)	2.150
Total consumption	−0.894*** (0.138)	2.208	−1.384*** (0.146)	2.130

B. Unemployment rates

	Specification regarding observed heterogeneity			
	Excluded[a]		Included[b]	
	Mean (S.E.)	S.D.	Mean (S.E.)	S.D.
Frequency	−0.052*** (0.003)	0.056	−0.051*** (0.003)	0.057
Intensity	0.039*** (0.002)	0.034	0.040*** (0.002)	0.034
Total consumption	−0.013*** (0.002)	0.047	−0.011*** (0.002)	0.050

Note: *** indicates significance at the 1% level.

a. The elasticities are computed with the parameter values from Table 4(a), which exclude the observed heterogeneities in both the utility function for beer consumption and set-up cost.

b. The elasticities are computed with the parameter values from Table 4(c), which include all observed heterogeneities.

We further check how the price elasticities on intensity and total consumption vary across age and income groups. As seen in Table W10, compared to younger and high-income consumers, consumers in the older and low-income groups exhibit much stronger negative elasticities.

Table W10. OLS Estimation for Heterogeneous Price Elasticities

	Dependent variables: Individual price elasticities on:			
	Intensity		Total Consumption	
	Est.	S.E.	Est.	S.E.
Age 41–60	−0.404***	0.019	−0.452***	0.019
Age 61+	−1.084***	0.028	−1.163***	0.029
Low income	−3.579***	0.028	−3.415***	0.029
Mid income	−2.383***	0.023	−2.313***	0.023
Constant	1.138***	0.022	1.171***	0.023
Adj. R-squared	0.4176		0.3868	

Regarding the positive price elasticity in the baseline consumer group (young and high income), we note that this group is small and accounts for only a small proportion of the sample (7%). Further, other studies that have allowed for heterogeneity in price effects have also found the support of the distribution (be it for observable or unobservable reasons) to spill over into the positive domain (see, e.g., Dubé et al. (2009, 2010) with the panel data from AC Nielsen). Of course, researchers have suggested techniques that minimize this problem, such as imposing constrained priors, as in Boatwright et al. (1999), or theory-based priors, as in Montgomery and Rossi (1999). However, those approaches are beyond the scope of the current paper. Nevertheless, we cannot fully rule out the possibility of measurement error due to aggregation across products. For example, a certain group of consumers could switch to cheaper beer during the economic downturn and consequently increase their total amount of alcohol consumption.[1]

[1] We ran the individual FE regression of the ratio of premium beer consumption to total beer consumption in a given week on the unemployment rate and individual fixed effects. We found that the ratio of premium beer consumption does not vary by the unemployment rate; the coefficient estimate is -0.001 (p-value = 0.499). We also ran the same regression using the ratio of light beer consumption to total beer consumption in a given week as a dependent variable. We found that, while people do substitute light beers with regular ones when the unemployment rate is higher, the magnitude of the substitution is not large.

Web Appendix 5. Auxiliary Reduced-Form Analyses

In this section, we conduct auxiliary reduced-from analyses regarding (i) a consumer's daily decision to drink and (ii) level of beer consumption conditional on decision, *without* aggregating daily consumption data to the weekly level.

As seen in Table W11, the estimation results are consistent with our main findings. Moreover, they are robust across model specifications, i.e., Linear Probability Model (LPM) vs. Probit in columns (1) and (2) and OLS vs. Poisson in columns (3) and (4). Specifically, the effect of the unemployment rate on drinking decision is negative in both columns (1) and (2). This means that frequency decreases during the economic downturn. Additionally, as presented in columns (3) and (4), the consumption volume of beer increases as the unemployment rate increases, implying that intensity increases during a recession.

Table W11. Reduced-Form Analyses Based on Consumers' Daily Decisions

	Dependent Variables:			
	Dummy for drinking incidence (1 = drink, 0 = not drink)		Beer consumption in ounces *conditional on drinking*	
	LPM (1)	Probit (2)	OLS (3)	Truncated Poisson (4)
Unemployment rate	-0.008***	-0.008***	0.516***	0.012***
	(5×10^{-4})	(5×10^{-4})	(0.066)	(2×10^{-4})
White	0.003**	0.003**	-2.231***	-0.046***
	(0.001)	(0.002)	(0.205)	(0.001)
Male	0.054***	0.056***	9.996***	0.234***
	(0.001)	(0.001)	(0.201)	(0.001)
Age 41–60	0.059***	0.062***	-7.674***	-0.161***
	(0.001)	(0.001)	(0.199)	(0.001)
Age 61+	0.104***	0.110***	-21.781***	-0.528***
	(0.002)	(0.002)	(0.290)	(0.001)
Married	0.001	0.001	-3.940***	-0.086***
	(0.001)	(0.001)	(0.203)	(0.001)
Employed	-0.012***	-0.013***	-1.258***	-0.028***
	(0.002)	(0.002)	(0.228)	(0.001)
Urban	0.004***	0.004***	-1.079***	-0.024***
	(0.001)	(0.001)	(0.186)	(0.001)
Income	-0.015***	-0.015***	-7.095***	-0.167***
	(0.001)	(0.001)	(0.144)	(0.001)
Obs.	593,075	593,075	223,130	223,130
R-squared	0.050	-	0.065	-
Log-likelihood	-	-377,852	-	-3,590,570

Note: Model specifications are the LPM for columns (1) and (3), Probit for column (2) and Truncated Poisson for (4). The days of the week are controlled in all columns. Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Furthermore, we conducted the same analyses as those in Table W11 distinguishing weekdays and weekends (see Table W12). We found the results to be consistent with our structural results. Among the social economic variables, we found qualitatively similar results between weekdays and weekends except for the coefficients for White regarding drinking incidence.[2]

Table W12. Separate Analyses on Weekends and Weekdays

A. Drinking incidence

	Dependent Variables: Dummy for drinking incidence (1 = drink, 0 = not drink)			
	Weekends		Weekdays	
	LPM	Probit	LPM	Probit
	(1)	(2)	(3)	(4)
Unemployment rate	-0.007**	-0.008***	-0.008***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
White	-0.012**	-0.012**	0.008***	0.009***
	(0.003)	(0.003)	(0.002)	(0.002)
Male	0.057**	0.058**	0.052***	0.055***
	(0.003)	(0.003)	(0.002)	(0.002)
Age 41–60	0.080**	0.083**	0.050***	0.053***
	(0.003)	(0.003)	(0.002)	(0.002)
Age 61+	0.129**	0.134**	0.094***	0.100***
	(0.004)	(0.004)	(0.002)	(0.003)
Married	0.016**	0.016**	-0.005***	-0.005***
	(0.003)	(0.003)	(0.002)	(0.002)
Employed	-0.013**	-0.013**	-0.012***	-0.012***
	(0.003)	(0.003)	(0.002)	(0.002)
Urban	0.007**	0.007**	0.003*	0.003*
	(0.002)	(0.003)	(0.002)	(0.002)
Income	-0.011**	-0.011**	-0.016***	-0.017***
	(0.002)	(0.002)	(0.001)	(0.001)
Obs.	169,450	169,450	423,625	423,625
R-squared	0.031	-	0.058	-
Log-likelihood	-	-109,015	-	-268,735

[2] Frone (2016) claimed that employed adults may decrease the frequency and typical number of drinks consumed (i.e., intensity) during the workday due to job insecurity whereas increasing the frequency and quantity of alcohol use after work to reduce stress. Although we cannot explicitly contextualize our findings due to the lack of information on workday and after-work use in Frone (2016), the results from the Truncated Poisson model partially support Frone (2016) in the sense that the intensity increases slightly more during weekends.

B. Beer consumption

	Dependent Variables: Beer consumption in ounces *conditional on drinking*			
	Weekends		Weekdays	
	OLS	Truncated Poisson	OLS	Truncated Poisson
	(1)	(2)	(3)	(4)
Unemployment rate	0.594***	0.014***	0.483***	0.011***
	(0.122)	(4×10^{-4})	(0.078)	(3×10^{-4})
White	-3.762***	-0.080***	-1.632***	-0.033***
	(0.379)	(0.001)	(0.243)	(0.001)
Male	10.189***	0.243***	9.921***	0.231***
	(0.376)	(0.001)	(0.238)	(0.001)
Age 41–60	-6.210***	-0.132***	-8.214***	-0.172***
	(0.375)	(0.001)	(0.235)	(0.001)
Age 61+	-20.092***	-0.490***	-22.419***	-0.542***
	(0.542)	(0.002)	(0.344)	(0.001)
Married	-3.064***	-0.069***	-4.272***	-0.093***
	(0.382)	(0.001)	(0.240)	(0.001)
Employed	-1.059***	-0.024***	-1.344***	-0.030***
	(0.425)	(0.002)	(0.271)	(0.001)
Urban	-0.642***	-0.015***	-1.243***	-0.028***
	(0.346)	(0.001)	(0.220)	(0.001)
Income	-7.599***	-0.180***	-6.901***	-0.161***
	(0.268)	(0.001)	(0.171)	(0.001)
Obs.	62,805	62,805	160,325	160,325
R-squared	0.060	-	0.067	-
Log-likelihood	-	-1,001,213	-	-2,588,198

Note: Model specifications in panel A are the LPM for columns (1) and (3) and Probit for columns (2) and (4), while those in panel B are the OLS for columns (1) and (3) and Truncated Poisson for columns (2) and (4). The days of the week are controlled in all columns. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$