Journal of Beer Economics

Volume 1, Number 1, 2023

Douglas ***Mitchell*** Econometric Consulting, SP

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Publisher

*Douglas**Mitchell*** Econometric Consulting, SP
Laramie, WY USA

ISSN: 2993-2521

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Journal of Beer Economics, Vol. 1, No. 1, 2023, 1-18.

State-Level Impacts on New Brewery Location Choices: The Beer-Snob Effect

Mitch Kunce[1]

Abstract
This paper examines new brewery location choice, across U.S. states for the resurgent facility growth period post 2009, purposed to better understand the regional clustering observed in the industry. A conditional logit model of brewery location choice is used to show how time-varying interstate differences in supply and demand factors effect small-beer location odds. Primarily, a state's demand factors are found to increase the likelihood of securing a new brewing facility. Specifically, states that have higher wages (incomes), have supportive populations of suitable demographics, are award winning in the eyes of the connoisseur and lean democrat politically possess the highest location probabilities.

Keywords: Firm location, conditional logit, small-beer industry
JEL Classifications: C25, R12, R30

Introduction
Brewing in, what is now, the United States dates back to the mid-seventeenth century when English and Dutch settlers farmed ingredients and honed their craft. Production and consumption was strictly a local affair, far reaching distribution was costly and the end product simply did not travel well (Baron, 2007). By the early 1800s, a budding industry touting over 100 commercial breweries ensued. Production remained small scale and local, but the industry was on the rise. The brewery count rose to a high of just over 4,100 by the end of 1873 − while in the shadows the industry was teetering towards a more mass-production model post civil war (Gallus, 1909). Technological and scientific advancements in production and packaging processes, rail travel, refrigeration and pasteurization all lead to the emergence of "shipping" breweries (Stack, 2000). The post civil war, pre-prohibition beer market resembled a colonial period dance among regional shipping breweries and their locally-oriented counterparts. Scale economies paired with the advancements mentioned consolidated the brewery count to roughly 1,100 just prior to prohibition.

Post repeal of the Volstead Act, the industry struggled to regain its pre-prohibition status. New legislation banned alcohol manufacturers from owning retail outlets (taverns), requiring them to sell to wholesale distributors (Acitelli, 2013).[2] Hundreds of the locally-oriented breweries either never reopened or quickly exited the market. Ten years after repeal, 491 breweries remained. Many of the remaining breweries, not surprisingly, were the shippers. Anheuser-Busch and Pabst, the largest shippers, doubled their annual

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https://douglasmitchellconsulting.eu5.org/Journal.html (journal website)
[2] The beginnings of the 'three-tiered-system' in beer distribution. All states eventually adopted some form of the three-tiered model.

production from the years 1934 to 1940 compared to overall industry growth of roughly 25 percent over the same period (Stack, 2000). By the beginning of World War II, industry production was at pre-prohibition levels with roughly half the number of breweries in operation. The period following World War II is best characterized as the great consolidation. Post-war to 1982, industry output more than doubled but the number of breweries decreased more than 4 fold. Scale economies, advanced technologies, vertical integration and the way beer was being packaged and sold are cited as some of the main factors leading to this concentration (Greer, 1981). Prior to prohibition, roughly 90 percent of beer sold was out of a tap in a saloon. By the end of 1982, roughly 90 percent of the beer sold in the U.S. was bottled or canned.[3] In January of 1983, 80 breweries comprised the entire industry in the U.S (Acitelli, 2013).

In 1981, for the first time since prohibition, a brewery opened in the U.S. selling and even serving its' products on-premises. Bert Grant's Yakima Brewing and Malting Company, a so-called brewpub, inadvertently violated the state of Washington's three-tiered-distribution laws by selling food and in-house produced beer on-site (Acitelli, 2013). Washington state legalized on-premises sales the following year and, perhaps unwittingly, started the surge of new locally-oriented (micro) brewing facilities − something not seen in the country since the 1800s. By 1999, all U.S. states and the District of Columbia adopted on-premises sales in some form (Elzinga et al., 2015). Figure 1 depicts the trajectory of TTB reporting brewing facilities and their production from 1980 to 2021.

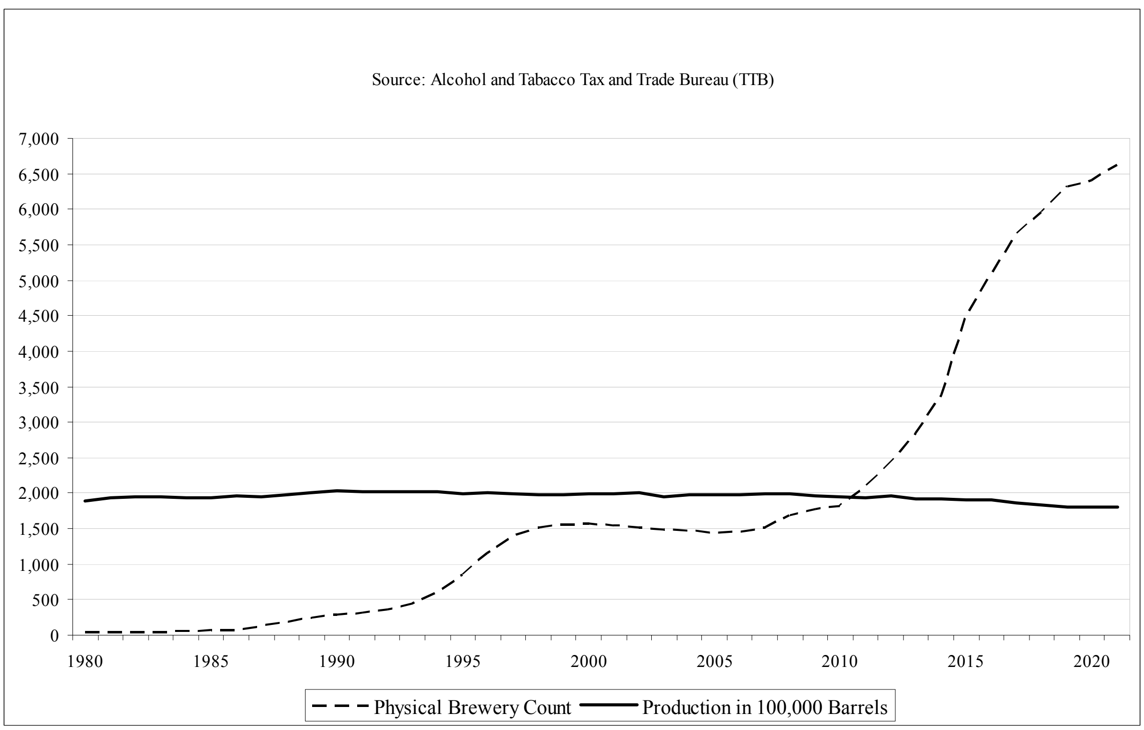

Figure 1. U.S. TTB reporting brewery count and production, 1980-2021

[3] Over 190 million 31 gallon barrels was produced in the U.S. in 1982 (TTB data). Interestingly, as shown in Figure 1, production has hovered around 190 million barrels each year, to date.

With all states now adopting on-premise retail sales and most allowing self distribution, small brewing enterprises now can capture all tiers of potential revenue thus increasing the likelihood of profitability (Kunce, 2021a). Post the shakeout period from the late 1990s to the mid to late 2000s,[4] the brewery count has accelerated. Both entrepreneurs and enthusiastic hobbyists have built thousands of new breweries to date. The vast majority of these new facilities, however, are very small and contribute little to overall industry production − 68 percent of all breweries in 2008 produced 1,000 barrels or less, 75 percent in 2021. This large number of 'small-beer' facilities are reliant on local consumption, much like those in the 1800s (Apardian et al., 2022). Concentration in the industry persists, in 2008, 57 brewing facilities accounted for 97% of total production − 91 breweries accounted for 93 percent in 2021 (TTB data).

It is increasingly more evident that the current expansion of small-beer in the U.S. is akin to a specialty act − fulfilling a niche, yet for reasons vastly different from why beer was local pre-prohibition. Today, for some, the fizzy corn and rice water offerings from big-beer are simply passé. A small-beer subculture has emerged, comparable to wine, centered on the tenets of neolocalism and consumer identity construction (Flack, 1997; Thurnell-Read, 2018). Small-beer consumers are of adequate means, like it local, desire product differentiation, quest for authenticity, favor sustainable practices and demand the experience at the production facility (Schnell and Reese, 2003; Clark, 2012; Schnell and Reese, 2014; Carr et al., 2017; Apardian et al., 2022). Merriam-Webster defines snob: "3b: one who has an air of superiority in matters of knowledge or taste." Determined not to be accused of generalization, we fondly coin the typical small-beer connoisseur: a beer-snob.

Figure 2 shows the proliferation of brewing facilities across the lower 48. Each colored dot represents an additional local clustering. For example, the black arrow in the center-

[4] See Schnell and Reese (2003), Tremblay and Tremblay (2005) and Acitelli (2013), all addressing the basis for this shakeout period.

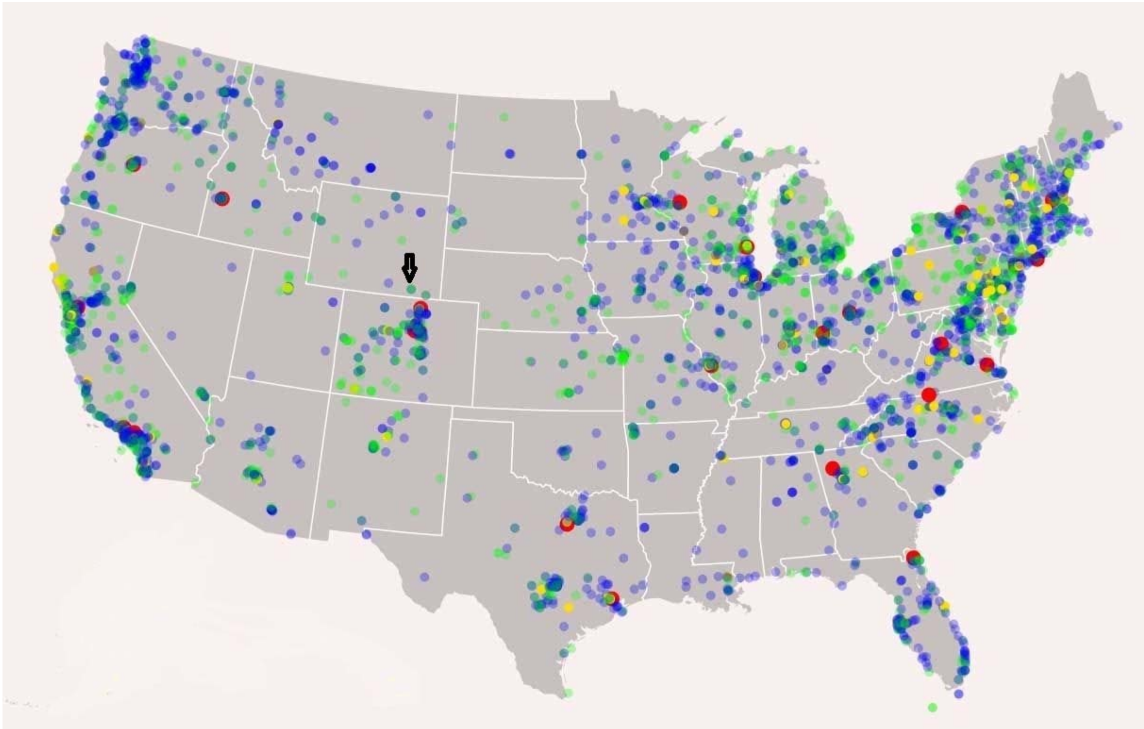

Figure 2. Map of brewery locations in the U.S. 2019

left of the map points to a dot that represents 5 brewing facilities within a 30 mile radius of Laramie, WY. In 2019, 98.7 percent of the facilities depicted produced 100,000 barrels or less for the year, 75 percent produced 1,000 barrels or less. The spatial distribution of these production facilities appears regionally clustered not random. This paper examines brewery location choice, across U.S. states for the resurgent growth period post 2009, purposed to better understand this regional clustering phenomenon. A budding international literature is developing regarding entry into the brewing industry. See Pokrivčák et al. (2022), Barajas et al. (2017), McLaughlin et al. (2016) and Moore et al. (2016) for helpful reviews. Herein, the analysis is more like Pokrivčák et al. (2022) in method and Elzinga et al. (2015) in its broader regional focus.

Data

Table 1 describes, provides sources and descriptive statistics for both left-hand-side (LHS) and RHS variables used in the conditional logit analysis below. Referring back to Figure 1, two time intervals will be examined. First, the period from 2009 to 2012 reflecting the beginning of the steep upward slope of facility counts and the interval 2016 to 2019, a period of more recent growth. The dependent variable takes the value 1 for the location-state chosen by a brewery, 0 otherwise. Data on supply and demand factors along with other state attributes were collected for the two years 2009 and 2016. The data are divided into the two time intervals to better reflect the economic conditions under

Table 1. Data descriptions, sources, descriptive statistics

New breweries. Dependent variable. New, producing, tax paying, reporting brewery premises appearing in the federal tax rolls at the end of 2012 (not in any previous year) and similarly for 2019. Location choices include the 48 contiguous U.S. states and the District of Columbia. Source, U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau (TTB) and the Beer Institute. 2012 new breweries 612, number of observations 29,988 (612 x 49 choices). 2019 new breweries 745, number of observations 36,505 (745 x 49 choices).
Agglomeration. Reporting brewery counts per million in population by state for 2009 and 2016. Source, U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau. Population by state and year sourced from the U.S. Census Bureau. 2009 Mean 9.59, STD 8.86 2016 Mean 28.80, STD 21.76
Cumulative GABF medals. Cumulative GABF Medal count by breweries' location-state, from 1983 to year-end 2009 and then to year-end 2016, divided by the number of physical breweries in the state for 2009 and 2016. Source, Brewer's Association (GABF 2023) and the TTB. 2009 Mean 1.49, STD 1.08 2016 Mean 0.70, STD 0.62
Electric rates. Average commercial electric rates by state in 2009 and then 2016 cents per kilowatt hour. Source, U.S. Energy Information Administration, State Electricity Profiles. 2009 Mean 9.75, STD 2.51 2016 Mean 10.54, STD 2.21
Politics. Based on state-specific, midyear legislative partisan composition. Calculated as Democrat held seats minus Republican seats as a share of total state legislative seats, in percent. National Conference of State Legislatures, 2009 and 2016. 2009 Mean 9.94, STD 30.74. 2016 Mean -14.13, STD 36.89
Population density. Population of a state per square mile of bordered land area. United States Census Bureau, 2009 and 2016. 2009 Mean 395.75, STD 1,390.02 2016 Mean 430.29, STD 1,547.70
Taxes. Beer-specific excise tax burden by state in 2009 and then 2016 dollars per 31 gallon barrel. Generally, this rate includes state and local brewery production and specific sales taxes and fees aimed at malt based products. Interestingly, in some states (e.g. Pennsylvania), separate on-brewery-premise sales taxes are imposed. Source, The Brewer's Almanac 2019, the Beer Institute. https://www.beerinstitute.org 2009 Mean 7.65, STD 6.06 2016 Mean 8.26, STD 5.96
Wages. Mean annual wage in a state in 1,000s of 2009 and then 2016 dollars. Source, U.S. Bureau of Labor Statistics. 2009 Mean 46.34, STD 7.42 2016 Mean 49.66, STD 8.07

Water and sewer rates. Marginal water and wastewater rates for each state presented in 2009 and then 2016 dollars per 1000 gallons of usage. Surveys of commercial/industrial customers, 2008-2017. Source, The Pacific Northwest National Laboratory conducts this study for the U.S. Department of Energy's Federal Energy Management Program to identify trends in annual water and wastewater price escalation rates across the United States. 2009 Mean 5.96, STD 2.37 2016 Mean 7.23, STD 2.85	
Means for regional dummies. Northwest 0.082, Southwest 0.061, Rockies 0.081, Central 0.102, Great Lakes 0.184, Southcentral 0.122, Northeast 0.285, Southeast 0.083.[5]	

which the location decisions were made. Moreover, time variation of state factors helps identify heterogeneity issues. The presumption is that the characteristics of a state in 2009 sway the location decision of a new brewery appearing on the tax rolls in 2012. In other words, there is a planning and building phase to account for and the economic conditions of a state two to three years prior to the facility operating were those most relevant to the location decision. In 2012, 612 new reporting facilities appeared in the TTB's tax record, 745 appeared in 2019. Choice location-states are limited to the lower 48 and the District of Columbia.

Place-based RHS variables included in the analysis are typical, with some exceptions, of those found in other studies of industry location: measures of or proxies for, agglomeration forces, labor market conditions, local tax and regulatory climate, utility costs, market size and consumer income.[6] In addition to conventional covariates, we include two unique state-level characteristics influencing brewery location decisions. First, each fall of the year since 1982, one of the industry's trade associations − the Brewers Association (BA) − puts on the Great American Beer Festival (GABF) in Colorado. The beer competition began in 1983 where winners were decided by a consumer poll. In 1987 the competition changed to a judged event − 38 medals were awarded over 13 style categories. In 2016, the competition boasted 7,227 entries from 1,752 breweries awarding 286 medals (GABF 2023). According to the Brewers Association,

> "The professional judge panel awards gold, silver or bronze medals that are recognized around the world as symbols of brewing excellence. These awards are among the most coveted in the industry and heralded by the winning brewers in their national advertising." (GABF 2023)

From 1983 to 2016, brewing facilities in California have accumulated the most medals, 965 (roughly 1.3 medals per brewery located in the state at the time), while all breweries in the state of West Virginia have cumulatively collected one. Additionally, Texas garnered an impressive 4.62 cumulative medals to breweries in 2009. The cumulative GABF medals variable has two main interpretations. First, it is a measure of the perceived beer

[5] See the Appendix for a map of states by region.

[6] Early in the development of this study we wanted to include an age variable reflecting the proportion of millennials in a state (aged 25-44) to the total state population. The age and politics (see Table 1) variables are highly correlated (0.89) hence we dropped age share from the sample favoring the more unusual and all encompassing political leanings attribute.

market quality in a state. High quality also acts as a definitive price signal (Kunce, 2021b). Second, the medals variable proxies as a location's knowledge base. Breweries in areas accumulating these awards must be doing something right, at least in the connoisseurs' judgment. Paraphrasing George Fix (1999), clean beer comes from a brewery that is either skilled or lucky and you don't want to be just lucky.

The second, somewhat non-conventional RHS variable is a state's perceived politics. We derive a jurisdictional political 'attitudes' proxy using the partisan composition of each state's legislature. Within-state composition of the local legislative body best represents the diverse political ideology stemming from 'all-corners' of a state's borders. The politics variable is derived for 2009 and 2016 as follows,

$$\frac{\text{Democrats (State House and Senate)} - \text{Republicans (State House and Senate)}}{\text{Total Seats (State House and Senate)}} \otimes 100\,. \qquad (1)$$

The partisan makeup of each state's legislature reflects the midyear (around June) seats held. An increasing politics percentage reflects a more Democrat leaning attitude of a particular state. The District of Columbia, Rhode Island and Massachusetts were the most Democrat leaning in 2009 and 2016 while Wyoming, South Dakota and Idaho were the most Republican. This political attitudes variable proxies for a myriad of perceived or latent state factors. Most noteworthy − regulatory environment, sustainability practices, religious convictions, gentrification attitudes, government grant and funding opportunities, population age demographics and cultural affinities.[7]

Tables 2 and 3 present the correlation coefficients of the RHS variables for 2009 and 2016. While multicollinearity problems are certainly a matter of degree, the strong positive correlation (over 0.7) between population density and mean wage, in both samples, suggests the two variables may be somewhat measuring the same phenomenon. Accordingly, in the econometric estimates below, we examine three models: Model 1 includes all RHS covariates, Model 2 drops population density and Model 3 drops wage.

Table 2. RHS correlation matrix, 2009

	AGGLOM	CUMGABF	ELECTRIC	POLITICS	POPDEN	TAX	WAGE
CUMGABF	0.232						
ELECTRIC	0.031	0.111					
POLITICS	0.031	0.064	0.494				
POPDEN	-0.094	-0.090	0.332	0.435			
TAX	-0.215	-0.224	-0.120	-0.182	-0.146		
WAGE	0.062	0.257	0.498	0.466	**0.751**	-0.299	
WATER	0.202	0.292	0.309	0.391	0.233	-0.055	0.483

[7] See Lehnert et al. (2020) for insight on the local regulatory environment impacting small-beer and the role played by political institutions. Additionally, see Schnell and Reese (2014) and Carr et al. (2017) for more on the political leanings of small-beer connoisseurs. Lastly, see Pew Research (2010) for more on the millennial cohort.

Table 3. RHS correlation matrix, 2016

	AGGLOM	CUMGABF	ELECTRIC	POLITICS	POPDEN	TAX	WAGE
CUMGABF	0.180						
ELECTRIC	0.162	0.147					
POLITICS	0.112	0.229	0.467				
POPDEN	-0.126	-0.089	0.170	0.501			
TAX	-0.163	-0.213	-0.040	-0.229	-0.133		
WAGE	0.053	0.239	0.433	0.472	**0.735**	-0.314	
WATER	0.032	0.236	0.196	0.434	0.306	-0.115	0.479

The conditional logit model

Following the conventional firm location literature [8], each brewery (i) possesses a latent profit function that depends on the attributes (X) of the state (j) in which it locates,

$$\pi_{ij} = F(X_j), \tag{2}$$

where X_j is a vector of state-specific factors influencing a brewery's location choice. Given these assumptions, the probability that brewery i chooses state j follows,

$$\text{Prob}[\pi_{ij} > \pi_{im}] \ \forall\, m \neq j, \tag{3}$$

where m indexes the alternative states not chosen. We can represent a brewery's location choice econometrically with McFadden's (1974) conditional logit specification. Equation (2) can be restated as,

$$\pi_{ij} = X_j^{\prime}\beta + \nu_{ij}, \tag{4}$$

where β denotes a vector of estimated parameters and ν_{ij} is the independently and identically distributed (IID) disturbance. Each ν_{ij} has the same type 1 extreme value distribution,

$$F(\nu_{ij}) = \exp(\text{-}\exp(\text{-}\nu_{ij})).^{9} \tag{5}$$

For independent extreme value (Gumbel) distributions, the probability that state j maximizes profits for brewery i becomes,

$$\text{Prob}(Y_i = j | X_j) = P_{ij} = \frac{\exp(X_j^{\prime}\beta)}{\sum_{m=1}^{J}\exp(X_m^{\prime}\beta)}, \tag{6}$$

[8] See Bartik (1988), McConnell and Schwab (1990), Levinson (1996), List and Co (2000). For a more recent review see Pokrivčák et al. (2022).
[9] See Greene (2018, p. 733).

where Y_i takes on a value of one for the state chosen, zero otherwise and J denotes the total number of state choices. The parameter vector β is estimated using maximum likelihood.

The stringent model assumptions regarding the error term in Equation (4) unfortunately lead to the *independence from irrelevant alternatives* (IIA) property in the conditional logit specification. With 49 broad choices herein, IIA may pose as problematic. If IIA is met, estimates will be consistent even if the decision to locate is partly endogenous.[10] One measure of IIA mitigation, suggested by McFadden (1974), Levinson (1996) and others, is to include regional dummy variables thereby controlling for most heterogeneity and cross-space error correlation. This correction is akin to the *nested* multinomial logit construct. Moreover, Hausman and McFadden (1984) suggested a structural test for IIA that involves restricting the choice set then comparing structurally to the unrestricted specification. If a subset of the full choice set is indeed irrelevant, then restricting it from the full model will not change the parameter estimates systematically. Excluding seemingly irrelevant choice states and the breweries that choose them will lead to inefficiency but not inconsistency. However, if the remaining probabilities are not independent from these alternatives, the estimator will be inconsistent. The familiar Hausman (1978) specification results in,

$$\chi_k^2 = (\hat{\beta}_r - \hat{\beta}_u)'[\hat{V}_r - \hat{V}_u]^{-1}(\hat{\beta}_r - \hat{\beta}_u), \tag{7}$$

where r and u indicate the restricted and unrestricted models and V is the estimated covariance matrices. This statistic is distributed chi-squared with k, equal to the number of regessors, degrees of freedom. A statistically sufficient statistic that rejects the null of IIA suggests that the two models do differ systematically.

Estimation results

Conditional on the decision to open a new brewery, the likelihood of constructing the facility in a particular state depends on characteristic factors of that state relative to other potential location-states. Tables 4 and 5 present the three-model conditional logit results and relevant summary statistics for new facilities appearing in both 2012 and 2019. The clustering computation for robust covariance matrices is used throughout. While results in the upper panels of both tables provide raw coefficient estimates and their statistical significance, these estimates do not represent marginal effects. Hensher (1991) suggested that reporting the elasticities of the probabilities provides a more straight forward interpretation. The effect of attribute k of choice j on P_{ij} then becomes,

$$\frac{\partial \ln P_{ij}}{\partial \ln X_{jk}}, \tag{8}$$

[10] See Long (2004) and Pokrivčák et al. (2022) for further discussion.

where X_{jk} is the k element of the attribute vector X_j . As such, elasticities, evaluated at the sample means, are shown in the lower panels of both Tables 4 and 5 for the statistically significant variables only.

Table 4 shows the estimation results for new firms appearing in 2012. Regional dummies were included in all three models and in all three test significantly (jointly) different from zero at the less than 1 percent level.[11] The importance of including regional dummies is reinforced by the Hausman-McFadden tests. The chi-squared statistics reported compared a restricted model that omitted the 'central' region choices to the full model specification.[12] The three statistics shown fail to reject IIA at the less than 5 percent level.

Table 4. Conditional logit results, 2012

	MODEL1	MODEL2	MODEL3
AGGLOMERATION	-0.011	-0.018	-0.031
CUMGABF	0.004***	0.005***	0.005***
ELECTRIC	-0.021	-0.002	-0.047
POLITICS	0.008***	0.008***	0.003
POPDENSITY	0.0007***	–	0.004**
TAX	-0.015	0.002	-0.005
WAGE	0.039***	0.026**	–
WATER	0.044	0.084	0.106
Log Likelihood	-2772	-2797	-2793
χ^2 (p-value)	430 (0.00)	381 (0.00)	390 (0.00)
Regional Wald Test	116.2***	109.7***	105.1***
Hausman-McFadden	13.4*	12.4*	12.0
p-value (df)	0.0988 (8)	0.0881 (7)	0.1006 (7)
Elasticities, computed at sample means			
	MODEL1	MODEL2	MODEL3
AGGLOMERATION	–	–	–
CUMGABF	0.237	0.348	0.354
ELECTRIC	–	–	–
POLITICS	0.077	0.079	–
POPDENSITY	0.272	–	1.392
TAX	–	–	–
WAGE	1.790	1.159	–
WATER	–	–	–

- significance at the < 1% (***), < 5% (**), < 10% (*) levels.

[11] States were also regionally grouped by United States Census Bureau divisions, estimation results were predictably similar to what is presented herein.

[12] Again, see the Appendix for the regional map used. Alternative tests were constructed by dropping other regions, forming the restricted models. Statistics presented in Tables 4 and 5 represent the 'best-case' for rejecting the null of IIA.

Models 1 and 2 reject the null at the less imperious 10 percent level, indicating perhaps slight structural difference. Significant (all positive) impact coefficients include, cumulative GABF medals, political leanings, population density and mean wage. The positive sign on the wage variable indicates that the odds of a brewery locating to a state with higher mean wages, at the margin, increase. This may first appear counterintuitive, but two associations are likely occurring. First, perhaps, is a confounding demand effect, higher mean wages strongly correlated with higher consumer income. Second, higher mean wages may also reflect skill effects (Cirillo, 2017). That is, higher wages proxy the availability of skills in a state which may attract small-beer. In Models 1 and 2, mean wages have the strongest impact on location odds. For example, a 1 percent increase in the average state's mean wage increases the probability of a brewery locating there by 1.79 percent, an elastic response in Model 1. Predictably, by dropping the wage variable in Model 3, the correlated population density covariate picks up the strong positive effect. Thus far, brewing facilities are attracted to densely populated states with higher mean wages (or incomes). These results align with previous examinations, chiefly Elzinga et al. (2015), Barajas et al. (2017) and Pokrivčák et al. (2022).

Interestingly, the simple agglomeration of breweries in a state (per capita) does not have a statistically significant impact on location odds. This result is contrary to extant findings in the literature (e.g. Pokrivčák et al., 2022). Apparently what does matter, herein, is where award winning breweries are clustering. Though the response is inelastic, a 1 percent increase in cumulative GABF medals per location-state brewery count, increases the location odds by 0.24 to 0.35 percent, for the average state. New facilities are forming where perceived beer quality is high and the potential for technological and knowledge spillovers is seemingly rich − typical economic integration impacts under a different hat. Moreover, the perceived quality signal may also impact location price determination. Though anecdotal, the price of a pint of WYO HazE IPA at the 28 year-old Library Brewery in Laramie, WY runs $5, while just 60 miles south in medal rich Fort Collins, CO, Snowbank Brewing charges $7 for a pint of their Snow Juice IPA.[13]

The significance and positive sign of the politics variable in Models 1 and 2 implies that small-beer likely chooses to locate in states that lean more democrat. Recall, this political attitudes variable is highly correlated with the population proportion of millennials in a state as well. Though the significant response is very inelastic, blue-state policies, population composition and cultural affinities appear to favorably tilt small-beer location odds. Interestingly, states' place-based tax climate, electric energy costs and water-sewer utility fees in 2009 did not significantly influence location odds. This result is quite surprising and may suggest that small-beer is ignoring crucial fiscal, production and input cost differences in favor of a location's demand attributes − reinforcing the neolocalism tenant discussed above. Then again, aggregation of these cost data to the state level may be simply masking more influential devolved detail. In contrast, Elzinga et al. (2015) found that federal combined with state excise taxes negatively impacted brewery counts

[13] Personal experience and a phone conversation on January 13, 2023. Obviously we are ignoring structural cost differences between the two locations.

in the average state. No previous examinations have looked at energy and water-sewer utility cost impacts on small brewery entry.[14]

Table 5 presents the estimation results for breweries appearing in 2019. This allowance for time variation in the state variables had little impact on coefficient estimates with the exception of electric costs. Average commercial electricity rates now impact location odds in model 1. A 1 percent increase in electric rates per kilowatt hour *decrease* location

Table 5. Conditional logit results, 2019

	MODEL1	MODEL2	MODEL3
AGGLOMERATION	-0.002	-0.001	-0.005
CUMGABF	0.003***	0.003***	0.003***
ELECTRIC	-0.044*	-0.019	-0.019
POLITICS	0.007***	0.009***	0.003
POPDENSITY	0.0005***	–	0.003**
TAX	-0.001	0.004	-0.002
WAGE	0.042***	0.024**	–
WATER	0.007	0.031	0.038
Log Likelihood	-3464	-3484	-3480
χ^2 (p-value)	346 (0.00)	305 (0.00)	314 (0.00)
Regional Wald Test	124.3***	126.2***	125.3***
Hausman/McFadden	12.9	12.2*	11.9
p-value (df)	0.1153 (8)	0.0942 (7)	0.1039 (7)
Elasticities, computed at sample means.			
	MODEL1	MODEL2	MODEL3
AGGLOMERATION	–	–	–
CUMGABF	0.286	0.351	0.344
ELECTRIC	-0.455	–	–
POLITICS	0.100	0.137	–
POPDENSITY	0.202	–	1.271
TAX	–	–	–
WAGE	2.026	1.149	–
WATER	–	–	–

- significance at the < 1% (***), < 5% (**), < 10% (*) levels.

odds by 0.46 percent, for the average state. This finding is new to the brewery entry literature yet fairly common to the more general firm location empirical work (see Levinson, 1996; Mani et al., 1997).

[14] Kunce (2021a) finds that rising commercial electric and water-sewer rates significantly decrease aggregate state-level production of beer.

While the estimated elasticities provide information on how changes in state factors affect the likelihood of a state being chosen for a new small brewery, examining the relative position of a state in the location decision is of particular import in this regional context. Using the estimates for Model 1, in both time settings evaluated at appropriate variable means, we derive the overall location odds for a state. Table 6 presents these likelihoods in descending order. California garners the highest location probabilities with

Table 6. Ranked state predicted probabilities, in %, evaluated at sample means

	2012		2019
California	8.45	California	7.03
Washington	6.75	Virginia	4.13
Texas	5.53	Texas	3.91
Colorado	5.23	Colorado	3.88
Wisconsin	5.16	Pennsylvania	3.85
Illinois	4.42	North Carolina	3.82
Oregon	4.21	Wisconsin	3.80
Minnesota	3.61	Washington	3.78
Missouri	3.40	Georgia	3.78
New York	3.32	Illinois	3.42
Georgia	3.08	New York	3.22
Ohio	2.88	Minnesota	3.17
Virginia	2.68	Missouri	3.16
Michigan	2.60	Florida	3.10
Maryland	2.42	Ohio	2.79
Florida	2.31	Michigan	2.57
Massachusetts	2.24	Maryland	2.40
Tennessee	2.12	South Carolina	2.32
Pennsylvania	2.04	Indiana	2.30
Indiana	2.04	Oregon	2.27
North Carolina	2.01	Connecticut	2.12
Iowa	1.69	Massachusetts	2.10
Kentucky	1.50	Iowa	1.83
Idaho	1.47	Delaware	1.82
South Carolina	1.42	Tennessee	1.75
Connecticut	1.40	New Hampshire	1.69
Louisiana	1.26	Kentucky	1.66
New Hampshire	1.18	New Jersey	1.44
New Jersey	1.17	Arkansas	1.36
Delaware	1.09	West Virginia	1.34
Wyoming	0.97	Alabama	1.22
Montana	0.96	Louisiana	1.17

Utah	0.96	Maine	1.14
Alabama	0.95	Vermont	1.06
Mississippi	0.92	Idaho	1.03
Arizona	0.82	Mississippi	0.93
Arkansas	0.81	North Dakota	0.88
Vermont	0.71	Utah	0.82
North Dakota	0.55	Wyoming	0.74
Rhode Island	0.55	Rhode Island	0.73
Maine	0.52	Montana	0.71
West Virginia	0.43	Oklahoma	0.70
Kansas	0.43	Arizona	0.62
Nebraska	0.42	Nebraska	0.57
Nevada	0.37	Kansas	0.57
New Mexico	0.35	South Dakota	0.50
Oklahoma	0.31	Nevada	0.40
South Dakota	0.25	New Mexico	0.33
DistCol	0.03	DistCol	0.06

the District of Columbia being the least likely location choice. To be fair, the District had only one brewery appear on the rolls in the two time period samples examined. Of the 49 choices in the 2009-2012 period, California had the sixth highest mean wage, ranked twelfth in population density (while being the most populated state), was the fourteenth most partisan democrat and ranked seventeenth in GABF medals per 2009 brewery count (the most medals won overall however). California is the purported genesis of this small-beer expansion (Elzinga et al., 2015) and appears to be the odds on favorite location for new ventures post 2019.

Concluding remarks

You can learn a lot about a state's people by looking at the small-beer that state produces and consumes. The counter-culture connoisseurs in states like California, Colorado and Washington have served to fuel and influence the growth trajectory of small-beer facilities. In a rather glib portrayal of the culture, Cassidy (1993) writes,

> "See, these beers, lovingly created at small breweries and pubs that make no more than 60,000 barrels a year, are not brewskis, cold ones or suds. They do not travel down your throat on the direct path well-worn by years of Coors, Miller and Bud. They bounce around your mouth, hitting spots that no beer has hit before. You do not chug them, shotgun them or otherwise defile them.You don't even drink them, really. You taste them. Sometimes with 'beer cuisine', which in no way involves peanuts or pretzels."

While being driven primarily by demand factors, the location empirics presented in this paper echo the importance of cultural forces. States that gained new small-beer facilities, post 2009, had higher wages-incomes, had supportive populations[15], were award winning

[15] Ample and proportioned with the millennial demographic.

in the eyes of the connoisseur and leaned blue politically, affectionately the beer-snob effect.

However, in the sample period 2016-2019, commercial electric rates emerged as a significant negative impact to location odds. This result perhaps signals the rising importance of supply factors to future location decisions. In the decade represented by the data herein, average commercial electric rates increased by over 20 percent in the U.S. while water-sewer fees jumped by over 40 percent. The outlook regarding future rate increases for these two crucial utility inputs to the small-beer industry appears uncertain to bleak. For example, recent data from the U.S. Energy Information Administration show that average commercial electric rates (in cents per kilowatt hour) for the state of California increased from 20.25 in 2021 to 22.78 in 2022, an increase of over 12 percent for the *year*. In Pennsylvania, mean rates increased by over 21 percent over the same time period (EIA, 2022). An aging power grid, increasing demand, fierce political battles over generation and broad inflationary pressures lead to the uncertainty in electric rate stability. Projections on place-based rates for water and sewer paint a more dire picture for small breweries. Water use and discharge is critical in all stages of the brewing process. In the U.S., it is estimated that, on average, it takes roughly seven gallons of water to produce one gallon of finished beer (Brewers Association, 2013). Moreover, U.S. breweries discharge around 70% of the incoming water as effluent. In most states, wastewater marginal costs are much higher than fresh water supply costs. A study by McKinsey and Company (2009) projects water and sewer fees to more than double in the U.S. from 2021 to 2030. Reasons cited included increasing demand, drought, aging pipe infrastructure, costly treatment technologies and certain degrees of price discrimination. While demand and cultural factors have certainly dominated the developing brewery location literature to date, future examinations would benefit from considering potential interjurisdictional impacts of supply-side forces where costs are on the rise.

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Appendix

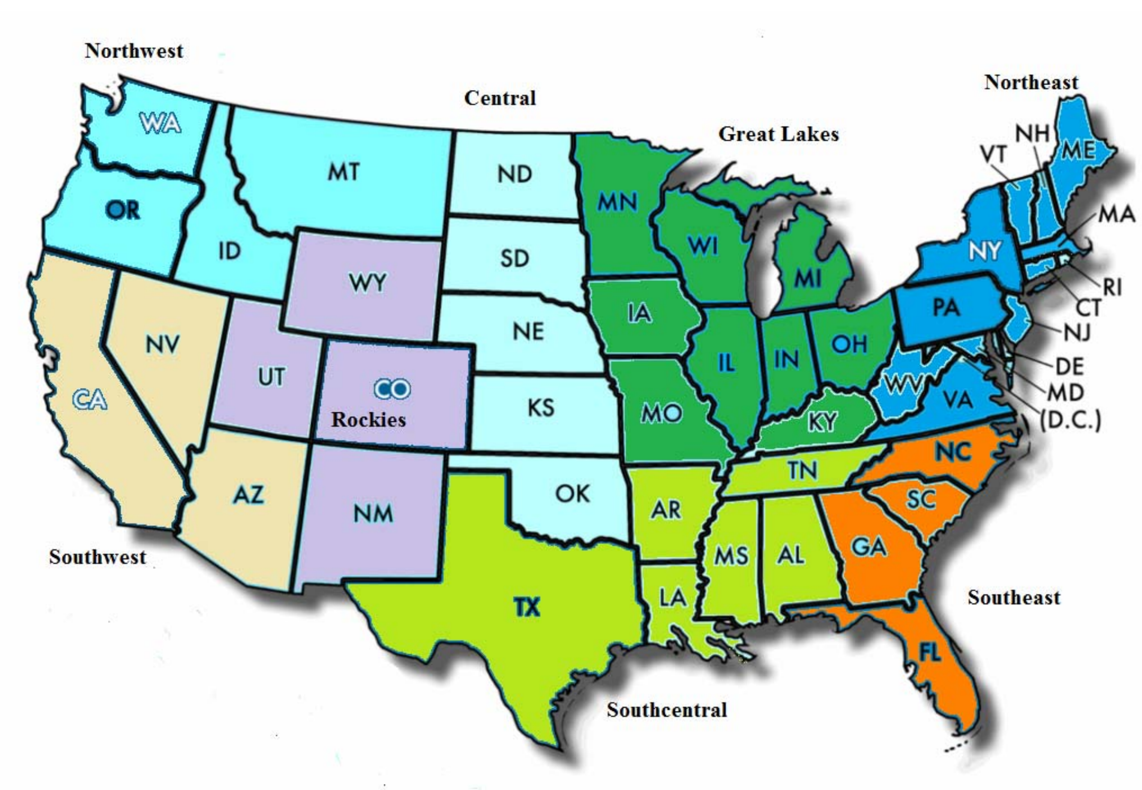

Figure A1. Map of regions

Journal of Beer Economics, Vol. 1, No. 1, 2023, 19-22.

A 17 Year Look at the Brewers Association

Mitch Kunce[1]

Abstract
This communication looks back at 17 years of financials of the Brewers Association. The organization appears endowed and poised for the future of small-beer and beyond.

Keywords: Trade organization, Finances
JEL Classifications: D71, J51, L44

Introduction
In the same year of the authorization of H.R. 1337[2], an amendment enacted in 1978 allowing the production of beer and wine for personal use, a Boulder, Colorado elementary school teacher, Charles Papazian, founded both the American Homebrewers Association and the Association of Brewers, a U.S. trade organization (Shaer, 2020). In 2005, the Association of Brewers and the 63 year old Brewer's Association of America merged forming the Brewers Association (BA) where the American Homebrewers Association is now an affiliate. The Brewers Association is a 501(c)(6) not-for-profit trade organization. The stated purpose of the association is to promote and protect American craft brewers, their beers, and the community of brewing enthusiasts. Craft brewers, as defined by the BA:

- produce less than 6 million barrels annually,
- are less than 25 percent owned or controlled by a non-craft brewer.

As of the date of publication of this paper, the BA touted membership of nearly 6,000 U.S. breweries (BA, 2023a).

Select financials
Table 1 depicts select financials of the association for the 17 years 2005 to 2021.[3] Note that membership dues comprise less than 20 percent, on average, of the association's revenue each year. Publications, conferences, advertising, sponsorships, investment income and event revenues make up the lion's share of the total annually. Key revenue generating events for the BA include the Great American Beer Festival and the World Beer Cup. For the years 2008 to 2019 (where employee counts were available), annual compensation plus benefits averaged over $80,000 per employee and yearly travel expenses averaged around $16,000 per employee. In all but two of the years depicted, revenues surpassed functional expenses. Net revenues are retained by the association as assets. The last row of Table 1 shows the change in net assets year to year. Generally, this change is simply the addition (subtraction) of net revenues to net assets. On occasion, these numbers do not coincide and where the differences are around $200,000 or more, the reason given for the discrepancy is denoted in a footnote to the table.

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[1] Douglas**Mitchell** Econometric Consulting SP, Laramie, WY USA
[2] Public Law 95-458 − 92 STAT. 1255-1261. Enacted October 14, 1978 by president Jimmy Carter.
[3] To cast these financials in the proper context, see the Appendix to this paper for a 2019 comparison to a like trade association, The Beer Institute (BI).

Table 1. Select financials, in millions of U.S. dollars [a]

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Total Revenue	3.5	4.7	5.4	6.9	7.5	8.8	10.5	13.0	17.2	20.7	23.8	28.2	27.7	30.2	28.1	13.1	19.9
Member Dues	0.6	0.9	1.1	1.2	1.3	1.6	1.9	2.5	3.1	3.6	4.2	4.6	4.9	5.0	5.1	4.8	4.5
Total Functional Expenses	3.3	4.1	4.8	6.0	6.8	8.1	10.3	12.1	14.7	16.5	19.2	24.2	26.0	30.3	26.9	14.1	16.1
Compensation and Benefits	1.3	1.5	1.8	2.0	2.1	2.4	3.5	3.6	4.1	4.7	5.2	6.3	7.3	7.6	7.7	6.7	7.1
Travel	0.2	0.3	0.2	0.4	0.3	0.5	0.6	0.8	0.8	1.1	1.1	1.7	1.3	1.7	1.1	0.2	0.3
Employees	n/a	n/a	n/a	31	33	40	47	49	51	62	63	69	74	79	77	n/a	n/a
Net Revenue	0.2	0.6	0.6	0.9	0.7	0.7	0.2	0.9	2.5	4.2	4.6	4.0	1.7	-0.1	1.2	-1.0	3.8
Total Assets	1.6	2.1	2.9	3.9	5.1	6.0	7.2	9.6	14.1	19.4	24.9	28.4	33.3	33.1	36.5	28.9	36.7
Cash and Equivalents	0.3	0.3	0.2	0.1	0.5	0.4	5.4	7.0	10.7	11.0	16.4	20.0	24.6	23.4	28.0	12.4	18.1
Net Land, Building and Equipment	0.2	0.3	0.1	0.1	0.1	0.2	0.4	0.4	0.4	5.3	5.2	5.1	5.1	5.1	4.9	4.7	4.7
Long Term Investments [b]	0.4	0.9	1.8	2.7	3.2	3.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.0	10.6
Total Liabilities [c]	1.0	0.9	1.3	1.5	2.0	2.2	3.3	4.8	6.7	7.7	8.9	8.4	11.3	11.8	12.4	5.9	9.9
Net Assets	0.6	1.2	1.6	2.4	3.1	3.8	3.9	4.8	7.4	11.7	16.0	20.0	22.0	21.3	24.1	23.0	26.8
Change in Net Assets	0.2	0.6	0.4[d]	0.8	0.7	0.7	0.1	0.9	2.6	4.3	4.3[e]	4.0	2.0[f]	-0.7[g]	2.8[e]	-1.1	3.8

[a] Sources, IRS form 990 and audit reports from CliftonLarsonAllen, LLP.
[b] Equities and fixed income.
[c] The vast majority of total liabilities each year is deferred revenue, 87% in 2005 and 2021. Deferred revenue is comprised of payments received in advance to be recognized as revenue at a future date.
[d] Audit adjustment affecting cost of goods sold.
[e] Unrealized investment loss adjustment.
[f] Unrealized investment gain adjustment.
[g] Unrealized investment loss adjustment.
[e] Large unrealized investment gain adjustment.

As Table 1 shows, total assets of the association have increased roughly 23 fold over the 17 years depicted. On average, over 80 percent of total assets are comprised of cash and equivalents, net land-buildings-equipment and long-term investments in equities and fixed-income securities. For some context, each year the BA puts out a top 50 producing craft brewing companies list. In 2019, Boston Beer Company (BBC, a.k.a. Sam Adams) was number two behind D.G. Yuengling and Son, Incorporated. In that year, Boston Beer (a public corporation) reported just under $37 million dollars in cash and equivalents on their collective corporate balance sheet (BBC, 2020). As shown above, the BA reported $28 million.

Parting remarks

What this 17 year review of the BA reveals is the financial strength of the association going forward. The Brewers Association appears endowed and poised for the future. Interestingly, the future may be beyond small-beer. The January/February 2023 volume of The New Brewer, the Journal of the Brewers Association, explores emerging products beyond craft beer (BA, 2023b). Non-alcohol beers, mocktails, kombucha, THC products, hop teas, flavored malt beverages and non-barley gluten-free offerings are featured. Consumer preferences are reaching farther and changing faster it seems and the BA appears adaptable to lead and capitalize on these trends.

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Appendix

The Beer Institute is a not-for-profit national trade association based in the District of Columbia, U.S. The organization represents big and small-beer along with industry suppliers and importers. Founded in 1862 as the U.S. Brewers Association, the association reorganized in 1986 forming the now Beer Institute. The stated mission of the organization is to serve the brewing industry with representation before congress, state legislatures and public forums across the country. The institute also promotes industry self-regulation, responsible consumption habits and moderation by working with governmental entities, distributors and retailers to educate and inform consumers (BI, 2023). Table A1 provides a comparison of select financials for the Beer Institute and the Brewers Association.

Table A1. Financial comparison 2019, in millions of U.S. dollars

	2019 BI	2019 BA
Total Revenue	5.3	28.1
Member Dues	5.3	5.1
Total Functional Expenses	5.1	26.9
Compensation, Salaries and Benefits	2.5	7.7
Travel	0.1	1.1
Employees	12	77
Net Revenue	0.2	1.2
Total Assets	1.2	36.5
Cash, Saving, Short Term Investments	0.7	28.0
Net Land, Building and Equipment	0.3	4.9
Long Term Investments (Equities, Fixed Income)	0.0	0.0
Total Liabilities	0.9	12.4
Net Assets	0.3	24.1
Change in Net Assets	0.2	2.8

- Source, 2019 IRS Form 990.

Journal of Beer Economics, Vol. 1, No. 1, 2023, 23-40 .

U.S. Interstate Impacts on Beer Consumption, 2008-2020: A Hausman-Taylor Approach

Mitch Kunce[1]

Abstract

Since roughly 1980, per capita beer consumption has declined in the U.S. Conversely, a historic growth trajectory of breweries continues with no end in site. Herein we exploit a United States panel, covering the brewery growth period 2008 to 2020, in an attempt to better understand demand characteristics influencing this contrasting relationship. Results suggest that states with a larger population share age 20-35 whose demographic is more white, non-religious with better than average incomes are consuming higher quality beer (as perceived by connoisseurs) in less quantities. Advantageously, small-beer entrepreneurs are chasing this demographic in hope of carving out their share of the declining market dominance of big-beer.

Keywords: Demand models, beer consumption, panel data, Hausman-Taylor
JEL Classifications: C23, D12, L66

Introduction

The United States is a beer drinking nation,[2] but domestic production and per capita consumption are on the decline. Beer production hit a peak in the early 1990s (TTB, 2023) while consumption started its downward trajectory around a decade earlier (Freeman, 2011). Interestingly, subsequent to the start of these downward trends, the largest expansion of separate brewing facilities the nation has ever seen − began. Figure 1 depicts production and reporting brewery count expansion from 1980 to 2020.[3] The majority of facilities being constructed are considered small (micro) in the sense that annual barrelage produced, at most, is in the thousands not millions.[4] From 1985 to 1996 the number of small-beer facilities grew at an annualized growth rate of more than 16 percent (Elzinga et al., 2015). As Figure 1 shows, facility growth ceased in the late 1990s and resurged around 2008.[5] The resurgent expansion of small-beer has been nothing short of tremendous − from 2008 to 2020 the brewery count increased by well over 4 fold.[6] Conversely, during the same period, domestic production is down roughly 10 percent (TTB, 2023) and adult consumption per capita is down by over 13 percent (The Beer Institute, 2021). Figure 2 shows the trends in beer consumption from 2008 for the highest and lowest consuming states as well as the U.S. in total. Overall, beer consumption has declined from just over 30 gallons per legal age population to around 26

[1] *Douglas**Mitchell*** Econometric Consulting, Laramie, WY USA
[2] In 2020, beer accounted for more than 46 percent of alcoholic beverage consumption in the U.S. (The Beer Institute, 2021).
[3] The expansion appears to have no end in site. In 2020, the TTB reported that well over 12,000 Brewer's Notices (permits) were active indicating new producing facilities on the horizon.
[4] Anheuser-Bush reached the 50 million barrel mark (annual production) in 1980.
[5] See Tremblay and Tremblay (2005) and Elzinga et al. (2015) for explanations of this shakeout period.
[6] Note that 77 percent of all breweries in 2020 produced 1,000 barrels or less, for the year.

gallons. Only one state, Vermont, experienced an increase in consumption over this period.

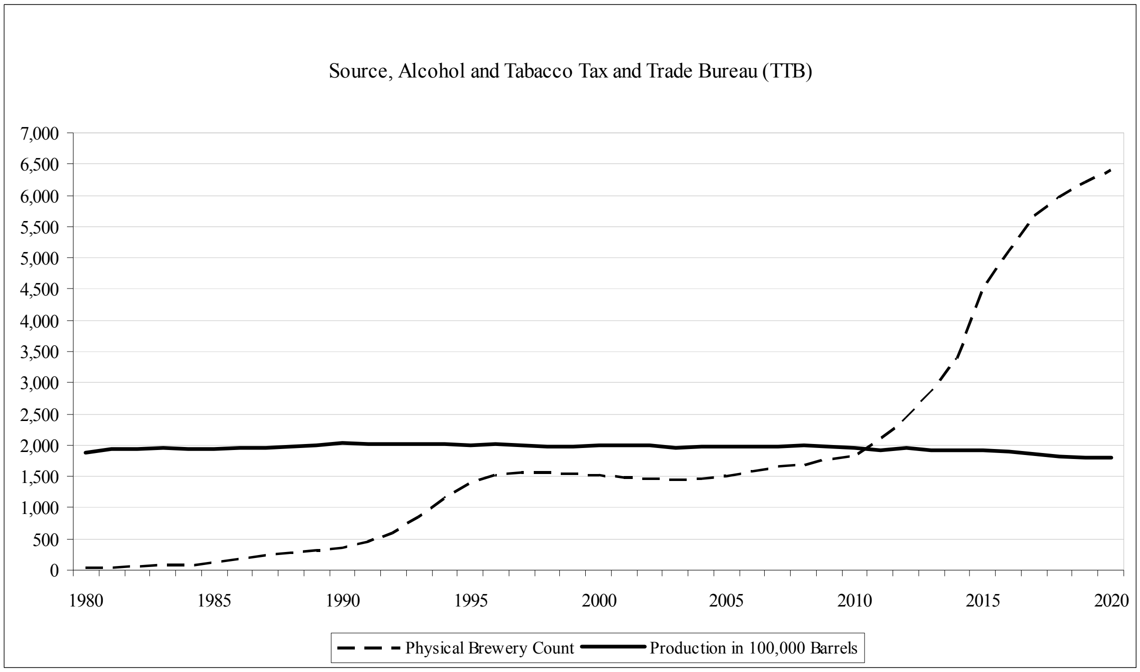

Figure 1. U.S. beer production and reporting brewery count, 1980 - 2020

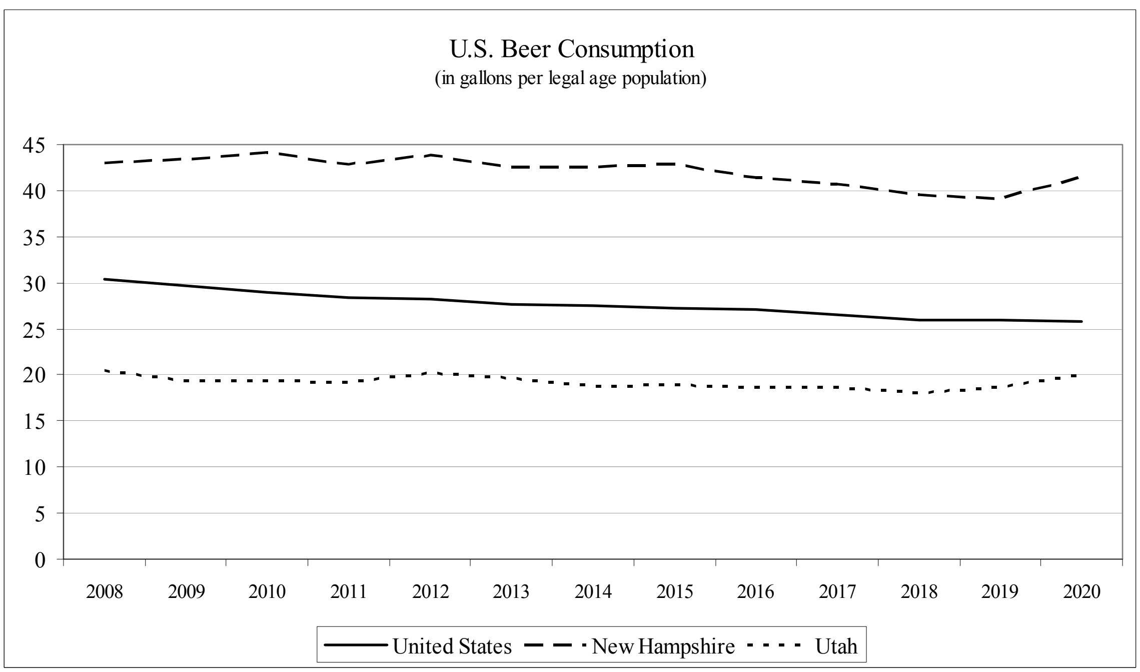

Figure 2. U.S. beer consumption, 2008 - 2020

Given the proper back-drop regarding these trends, a salient question arises: What do entrepreneurs and enthusiastic hobbyists see in these relationships that justifies the largest (ongoing) brewery count expansion the nation has ever experienced? Perhaps an examination of this country's beer demand for the resurgent period to 2020 will shed some much needed light. Alcohol consumption is the subject of a vast literature. Socioeconomic determinants of consumption, generally, are examined using aggregate jurisdictional data (e.g. countries or cantons). Analyses of disaggregated or individual level behavior are rare due to data availability and focus mainly on smaller market segments, case studies or ad hoc consumer surveys (see Hart and Alston, 2020 for a recent example). Following the conventional path cleared by Ogwang and Cho (2009), Freeman (2011) and Yakovlev and Guessford (2013) we exploit a United States panel, covering the resurgent growth period to 2020, in an attempt to better understand demand characteristics impacting per capita consumption. Results suggest that states with a larger population share age 20-35 whose demographic is more white, non-religious with better than average incomes are consuming higher quality beer (as perceived by connoisseurs) in lesser volume. The beer drinking demographic in the U.S. appears to have reached an upper limit to utility derived from consuming *suitcases* of big-beers' traditional products. Entrepreneurs and enthusiastic hobbyists are constructing their small facilities in areas of the country exhibiting these deterministic characteristics in hope of carving out their small (localized) share of big-beers' declining market dominance. See Moore et al. (2016), McLaughlin et al. (2016), Barajas et al. (2017), Pokrivčák et al. (2022) and Kunce (2023) for examinations of factors affecting entry and location choice of new breweries. Jurisdictional attributes such as higher incomes, larger populations filled with millennials and agglomeration economies run as a common thread through the budding brewery entry literature.

The balance of this examination is divided into four sections. The next section describes the data, provides sources, presents descriptive statistics and relevant inference testing. The third section presents the empirical model and discusses the complex econometric issues. Section four presents and interprets the empirical results with conclusions and implications drawn in the last section.

Data

Data comprise a 13 year (2008-2020), all 50 state and District of Columbia panel. As shown in figure 1, the late 2000s time frame is the start of the tremendous growth in brewing facilities across the country. Table 1 describes all variables, provides sources and

Table 1. Data descriptions, sources and descriptive statistics

Beer consumption. Apparent beer consumption for all 50 states and D.C. by year in gallons per legal drinking age population. Compiled by The Beer Institute (Brewer's Almanac) based on reporting from individual states. The numerator reflects shipments and/or sales determined by local tax payments and/or state reports of malt beverage shipments. Mean 29.23, STD 5.32; Natural Log Mean 3.36, STD 0.18.
Unemployment rate. Average annual rates for all 50 states and D.C., in percent of labor force. U.S. Bureau of Labor Statistics, 2008-2020. Mean 6.08, STD 2.29.

Disposable personal income. Defined as per capita personal income by state available to persons for spending or saving (after-tax income), in thousands of 2020 dollars. U.S. Bureau of Economic Analysis, Personal Income and Outlays release. Mean 48.189, STD 7.844.
Taxes. Beer-specific excise tax burden by state in 2020 dollars per gallon. Generally, this rate includes state and local brewery production and specific sales taxes and fees aimed at malt based products. Interestingly, in some states (e.g. Pennsylvania), separate on-brewery-premise sales taxes are imposed. The Brewer's Almanac, published periodically by The Beer Institute. Mean 0.30, STD 0.26.
Age 20-35. Percent of a state's population aged 20 to 35. U.S. Bureau of the Census. Mean 21.11, STD 1.88.
Cumulative GABF medals. Aggregate Great American Brew Fest (GABF) medal count by breweries' location state from 1983 to each successive year 2008 to 2020 divided by that years total physical brewery count. Brewers Association and U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau (TTB). Mean 0.96. STD 0.84.
Politics. Based on state-specific, midyear legislative (state house and senate) partisan composition. Calculated as Democrat held seats minus Republican seats as a share of total state legislative seats, in percent. National Conference of State Legislatures, 2008-2020. Mean -1.59, STD 36.15.
Non-White. Percent of a state's population that is non-white alone. U.S. Bureau of the Census. Mean 31.73, STD 15.88.
Church attendance. Percent of a state's population that attends church at least once per week. Gallup polling began tracking state-level church attendance in 2008. State percentages are calculated from polling surveys. Mean 29.23, STD 5.32.

key descriptive statistics. Analogous to Freeman (2011) and Yakovlev and Guessford (2013), the dependent variable examined is apparent personal beer consumption (by state) compiled periodically by The Beer Institute (a non-profit trade association).[7] Although there is little in the alcohol consumption literature that prescribes functional form, previous examinations have explored linear, semilog, log-log and other non-linear specifications (see Ogwang and Cho, 2009; Hart and Alston, 2020 for reviews). On a priori grounds, the semilog functional form has considerable appeal relative to the more conventional linear form. By taking the natural logarithm of the dependent variable, adult per capita consumption, estimates of right-hand-side (RHS) coefficients vary proportionately (at the margin) with consumption rather than affect the overall level as in the linear construct. Moreover, semilog form can lessen the effects of vertical outliers on coefficient estimates (see the application in Verardi and Wagner, 2011). This monotonic

[7] No distinction is made in this variable for variation in alcohol content in beer. This is a state-level, aggregate metric.

transformation of the left-hand-side also corrects for a common form of error variance heteroscedasticity in which the standard error is correlated with the conditional expectation of the dependent variable (Glejser, 1969). The natural log transformation of the dependent variable is used herein.

Strict demand theory envisions consumption as a function of own price, prices of substitutes and compliments, income, product characteristics and consumer preferences. Generally, panel data efforts in the alcohol consumption literature attempt to model demand theory by focusing on jurisdictional right-hand-side (RHS) determinants of beer demand. Following this rich literature, we include unemployment (Freeman, 2011; Yakovlev and Guessford, 2013; Sadik-Zada and Niklas, 2021), income, excise taxes (Ogwang and Cho, 2009; Freeman, 2011), population age-group 20-35 (Freeman, 2011) [8], political ideology (Yakovlev and Guessford, 2013; Hart and Alston, 2020), population racial makeup (Yakovlev and Guessford, 2013) and religion adherence (Yakovlev and Guessford, 2013; Colen and Swinnen, 2016; Hart and Alston, 2020). In addition to conventional covariates, we add one unique state-level characteristic influencing beer consumption. Each fall of the year since 1982, one of the industry's trade associations − the Brewers Association (BA) − puts on the Great American Beer Festival (GABF) in Colorado. The beer competition began in 1983 where winners were decided by a consumer poll. In 1987 the competition changed to a judged event − 38 medals were awarded over 13 style categories. In 2020, the competition boasted 8,806 entries from 1,720 breweries awarding 272 medals (GABF, 2023). The vast majority of these competing breweries are relatively small and rely on local consumption, though big-beer has certainly won a fair share of medals.[9] According to the Brewers Association,

> "The professional judge panel awards gold, silver or bronze medals that are recognized around the world as symbols of brewing excellence. These awards are among the most coveted in the industry and heralded by the winning brewers in their national advertising" (GABF, 2023).

From 1983 to 2008, brewing facilities in California had accumulated the most medals, 539 (rougly 1.8 medals per brewery located in the state at the time), while all breweries in the state of West Virginia had cumulatively collected one. From 1983 to 2020, California remained first, accumulating 1,226 or 1.1 medals per producing brewery. Additionally, Texas garnered an impressive 4.2 cumulative medals to breweries in 2008. Utah had the most medals to breweries in 2020, 2.2.

The cumulative GABF medals variable has two main interpretations herein. First, it is a measure of perceived beer quality in a state, accumulating GABF medals is viewed as an efficacious default and sale-independent quality signal (Kunce, 2021b).[10] In allied support, a small subset of the signaling literature focuses on expert review effects on

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[8] Freeman (2011) uses this same grouping. Yakovlev and Guessford (2013) include in the RHS, share of the population aged 20-24.

[9] Recall that in 2020, 77 percent of all producing breweries brewed 1,000 barrels or less for the year (TTB, 2023). The king of big-beer, Anheuser-Bush InBev took home four (a gold and three bronze) medals in 2020, four in 2021 and four more in 2022 (Anheuser-Bush InBev, 2023). These award winning beers were brewed in AB InBev facilities from California to North Carolina.

[10] Entering the GABF competition requires more than nominal upfront expenditures by breweries, see Kunce (2021b) for an analysis.

consumer demand. Most noteworthy and fairly related to the interpretation herein is a study by Friberg and Grönqvist (2012) involving the wine industry. They found evidence that favorable expert reviews increase wine sales from the Swedish state-owned liquor monopoly, Systembolaget. Interestingly, the authors revealed no significant negative effects from unfavorable reviews. Second, prices are generally not observable in the aggregated jurisdictional panel treatments reviewed above, hence perceived quality can proxy price. The empirical literature on the perceived quality − price relationship is substantial (see Kirmani and Rao, 2000; Connelly et al., 2011 for extensive reviews).

In addition to the variable particulars denoted in Table 1, Table 2 depicts the variable correlation matrix for all RHS regressors. While multicollinearity problems are certainly a matter of degree, the risk of detrimental issues herein appears small. Careful pre-testing

Table 2. RHS correlation matrix

	Unemployment	Income	Taxes	Age 20-35	Medals	Politics	NonWhite
Unemployment	1.000						
Income	0.002	1.000					
Taxes	-0.018	-0.186	1.000				
Age 20-35	0.047	0.453	-0.092	1.000			
Medals	0.228	0.025	-0.131	0.251	1.000		
Politics	0.322	0.456	-0.140	**0.553**	0.026	1.000	
Non-White	0.179	0.396	0.284	0.366	0.103	0.398	1.000
Church	0.153	-0.335	0.269	0.095	0.071	-0.363	0.010

inference presented in Table 3 initially rejects the null hypothesis of homoscedastic disturbances in the pooled sample White statistic at the < 10 percent level, but fail to reject the null at any level when controls are included for cross-section (c-s likelihood ratio test) and period-specific effects. The Pesaran CD test for the pooled OLS sample rejects the null of cross-sectional independence at the < 5 percent level, however fails to reject at the < 5 percent level after controlling for cross-sectioned effects (Pesaran, 2015, 2021). Results suggest weak cross-sectional error correlation in the panel. Panel corrected standard error (PCSE) covariance structures will be explored in the models estimated below (Beck and Katz, 1995). Lastly, the pooled OLS Durbin-Watson statistic of 1.740 lies just to the left of the lower critical value of the test. After controlling for cross-sectioned effects, the test statistic is sufficient to retain the null of no first-order serial correlation (Bartels and Goodhew, 1981).

Table 3. Initial test statistics

	Pooled OLS (POLS)	With Effects
White Test (df)	13.86* (8)	
C-S Heteroscedasticity LR Test		63.16
Period Heteroscedasticity LR Test		2.51
Peseran CD	2.51**	1.77*
Durbin-Watson	1.740	1.902

Significance at < 5% (**), < 10% (*)

Generally, non-stationary variables should not be used in conventional regression models. However, within conventional panel analysis, the time dimension, T , is characteristically too short for proper scrutiny. As a result, the time-series asymptotics are often cast aside and given little attention. Being thorough, we address cointegration of the variable suite − fully aware of the diagnostic limitations when T is short. Cointegrating combinations of variables require resulting regression errors to be integrated of order zero, I(0). Analogous to panel unit root analysis, cross-section dependence plays an important role in panel cointegration testing. Diagnostic results from Table 3 suggest weak cross-sectional error correlation in our variable suite, therefore we proceed to test the panel for cointegration following Pedroni (1999, 2004) and Kao (1999).[11] Testing particulars, detailed in the appendix, are sufficient to reject the null of the no cointegration.

Model

Consider the conventional two-way time-series and cross-section model,

$$Y_{it} = X_{it}\beta + Z_i\gamma + \varepsilon_{it} \qquad (i = 1, \ldots, N;\ t = 1, \ldots, T;\ n = NT), \tag{1}$$

where Y_{it} is the dependent variable, X_{it} are observable variables that vary across states i and over years t, Z_i are observable time-invariant variables, β and γ are k and f vectors of estimated coefficients and ε_{it} denotes the overall error term.[12] The error term is comprised of three components,

$$\varepsilon_{it} = \mu_i + \lambda_t + \nu_{it}, \tag{2}$$

where μ_i denotes the unobservable state-specific effects, λ_t is the latent year-specific effects and ν_{it} is the remainder stochastic disturbance. The component μ_i is time-invariant and will account for state-specific effects not included in the RHS. The year-specific effect, λ_t, is state-invariant and will account for any time-specific effects not included in

[11] Pedroni (1999, 2004) and Kao (1999) rely on cross-sectional independence or weak dependence (Pesaran, 2015).

[12] Many presentations of this familiar model may include a scalar constant term, α.

the regression.[13] The remainder disturbance v_{it} varies with groups and time and is assumed orthogonal to X, Z, μ and λ with a mean of zero and a constant variance σ_v^2.

Generally, two specifications of Equation (1) are considered and differ based on their treatment of the specific effects. First, fixed effects (FE) treats μ_i and λ_t as fixed but unknown constants differing across states and time. This specification is easily estimated by including dummy variables in the RHS (Least Squares Dummy Variable (LSDV) estimator). However, as in our case (N = 51, T = 13), LSDV suffers from the loss of precious degrees of freedom. Alternatively, estimates can be obtained by transforming the data into deviations from respective state-means (within estimator) and by including T - 1 year dummies. The two fixed effects estimation methods described reveal two crucial defects: (i) time-invariant variables are eliminated so γ cannot be estimated, and (ii) the estimator is not fully efficient because, in certain cases, it ignores variation across states and/or time.

Second, random effects (RE) assumes that the μ_i are random variables, distributed independently across groups with variance σ_μ^2. When T is short, including year dummies for λ_t facilitates a two-way model. Estimates of this specification are based on transformations of the data into deviations from weighted respective state-means where the weights are based on, generally, the estimated variances of the components in equation (2) and T (Feasible General Least Squares (FGLS) estimator). Specifically, the weight on the state-means takes the form,

$$\hat{\theta} = 1 - \frac{\hat{\sigma}_v}{\sqrt{T\hat{\sigma}_\mu^2 + \hat{\sigma}_v^2}}. \qquad (3)$$

Note, if $\hat{\theta} = 1$, random effects is the within fixed effects estimator. Unbiased robust estimates of the variance components are best obtained from pooled OLS and LSDV estimators. The potential correlation of the specific effects with the variables in X_{it} and Z_i is a defect of the random effects construct. If these correlations are present, random effects estimation yields biased and inconsistent estimates of β and γ Conversely, by transforming the data into deviations from the simple state-means the fixed effects estimator is not impacted by this lack of orthogonality.

Hausman (1978) and Kang (1985) outlined specification tests of the null hypotheses of orthogonality between the effects and the regressors. By failing to reject the null, both fixed effects and random effects are unbiased and consistent, but fixed effects is less efficient. When the null is rejected, fixed effects is unbiased and consistent but random effects is not. The random effects specification requires exogeneity of all regressors and the components in equation (2). Conversely, the fixed effects model allows for endogeneity of all the regressors and the specific effects, but ignores observable variables

[13] The model is presented in the most general form. Herein, the natural log of the dependent variable will be used. As careful trial will show below, year-effects test jointly zero in all specifications therefore the one-way model is estimated and presented.

Z_i. In order to avoid this all or nothing choice of exogeneity and accommodate the estimation of γ, Hausman and Taylor (1981) (HT) propose a third specification (instrumental variable random effects) for estimating equation (1) where the RHS is split into two main categories of variables, those presumed uncorrelated (exogenous) with the effects and v_{it}, and those correlated (endogenous) with the effects, but not v_{it}. Table 4 shows the four possible sets of observable variables for Equation (1).

Table 4. Hausman-Taylor variable sets

	Exogenous	Endogenous
Time varying	X_1 is n x k_1	X_2 is n x k_2
Time invariant	Z_1 is n x f_1	Z_2 is n x f_2

The exogenous category identified serves two functions, (i) using state-mean deviations, unbiased estimates of the respective elements of β are produced, and (ii) the exogenous set and state-means provide valid instruments for the unbiased and efficient estimation of β and γ. An advantage of panel data is the formulation of instruments from *within* the model construct. The order condition for identification requires that k_1 (the number of regressors in X_1) is greater than or equal to f_2 (the number of regressors in Z_2). When $k_1 > f_2$, the model is over-identified and HT is more efficient than within fixed effects.

The complex HT estimator requires prior knowledge that certain RHS variables in Equation (1) are uncorrelated with the effects. Following the pretest procedure suggested by Kunce (2021), we sort the regressors into the categories presented in Table 4. The variable pretest proposed builds on the pretest estimator suggested by Baltagi et al. (2003) by providing the necessary foundation for regressor identification. As a first step, estimate Equation (1) with both fixed (within) and random effects (FGLS) specifications and subsequently construct the chi-squared distributed Hausman test statistic. This initial statistic becomes the base of comparison. As a side note, if the Hausman null hypothesis of orthogonality is not rejected, FGLS is unbiased, efficient and commonly the correct specification. If the null is rejected (as it is in our case, $\chi^2_8 = 47.13$), identifying the RHS variables that contribute to the size of the Hausman statistic estimated from Equation (1) is of primary concern. Second, estimate succeeding Hausman statistics from re-specified models by dropping one sequential regressor each iteration. Table 5 contains these results.

Row one of Table 5 shows the Hausman statistic when the unemployment variable is dropped from the RHS and all others remain. Row two of Table 5 shows the Hausman statistic when the income variable is dropped from the RHS and the other 7 remain − and so on. Note that the Hausman test statistic reduces to 38.46 from 47.13 when the unemployment variable is dropped from the specification. The unemployment variable appears to be a significant 'correlation contributor' therefore pretests as likely endogenous. The same is true for the income, age 20-35 and church variables. Recall that the necessary condition for identification and efficient estimation of β and γ is that $k_1 > f_2$ and

Table 5. μ_i correlation tests*

	χ^2_7
Unemployment	38.46
Income	39.81
State Taxes	45.88
Age 20-35	38.48
Medals	46.29
Politics	45.89
Non-White	45.19
Church	33.59

* χ^2_8 = 47.13, base of comparison.

f_2 may be empty (Hausman and Taylor, (1981), pp. 1385-1387). Thus, a natural sorting from Tables 4 and 5 follows,

X_1: State taxes, Medals, Politics, Non-white,
X_2: Unemployment, Income, Age 20-35, Church,
Z_1: Constant term,
Z_2: Empty.

Estimation and results

Table 6 shows the results of the three one-way error component models estimated.[14] The RE and FE models are estimated using the PCSE robust covariance structure. The large F-statistic shown in the second to last row (center) rejects the null of cross-section homogeneity at the < 1 percent level. F-test results shown in the last row (center) indicate that year-effects, jointly, are not significantly different from zero thus favoring the one-way model. The first column depicts the RE estimates, included only for comparison. The second column of Table 6 presents the within FE estimates. Comparing FE and RE estimates using the Hausman test rejects the null hypothesis of orthogonality confirming that the RE model is misspecified. This initial Hausman test outcome justifies the use of the HT instrumental variable random effects method. Given the variable pretest results from above, the last column of Table 6 shows the estimates using the HT routine in *LIMDEP 11*®. A subsequent Hausman test based on the difference between FE and the HT estimators fails to reject the null hypothesis of orthogonality. There are four degrees of freedom in this chi-squared test since there are four over-identifying conditions (the number of X_1 regressors minus the number of Z_2 regressors, see Baltagi et al., (2003)). The variable pretest herein is shown to be valid, we

[14] Not shown are Arellano-Bond-Bover Generalized Method of Moments (GMM) results estimated with the dependent variable lagged one period on the RHS (Arellano and Bond, 1991; Arellano and Bover, 1995). The lagged dependent variable was significant at the < 10 percent level. The remaining GMM coefficient estimates were not substantially different from the HT results presented.

Table 6. Estimation results

	One-Way RE	One-Way FE	One-Way HT
Unemployment	-0.119*	0.069	0.068
Income	-0.846***	-0.696***	-0.738**
State Taxes	-0.464	-0.552	-0.165
Age 20-35	1.330***	1.254***	1.714**
Medals	0.847*	0.491	0.803*
Politics	0.0163	0.0025	0.0052
Non-White	-0.505***	-0.708***	-0.810***
Church	-0.441***	-0.527***	-0.604***
R^2	a	0.972	a
Hausman (df)	47.13*** (8)	−	7.03 (4)
One-Way vs. POLS	−	F(50,604) 234.14***	−
Two-Way vs. One-Way	−	F(12,592) 1.55	−

[a] No precise counterpart to OLS R^2 in these constructs.
Significance at < 1% (***), < 5% (**), < 10% (*)

cannot reject that the set of instruments are appropriate. Because of the over identification described above, the HT specification is more efficient and favored over FE. Additionally, between state variation of the data is certainly considerable but within state temporal variation is thin for some variables (e.g. Taxes, Church). This lack of time variation in some of the data negatively impacts the FE specification − bolstering the use of the HT random effects estimator.

Coefficient estimates shown in Table 6 are displayed in percentage terms. Focusing on the last column of Table 6, significant variables include disposable personal income, population share aged 20-35, cumulative GABF medals, share of the non-white population and church attendance. A marginal increase in disposable personal income for the average state decreases individual beer consumption by roughly 0.7 percent. Beer is a slightly inferior good for the resurgent facility growth period. This result is consistent with the one-way and two-way fixed effects interstate models in Freeman (2011) and the long-run cross-country fixed effects specifications in Colen and Swinnen (2016). In the latter study, the authors show that when income rises above a certain level,[15] these now richer countries experience a decrease in beer consumption with further increases in income. Reasons cited first presume that higher levels of income increase the demand for good health and then demonstrate that higher incomes induce preference shifts to other beverages. For example, Swinnen (2017) points out that while higher income jurisdictions may be drinking less beer, they are in turn drinking more expensive beer. Preferences are shifting within market-segment to perceived higher quality in less overall volume. Coupled results herein, to some extent, support this finding. The positive cumulative GABF medals to breweries coefficient implies that

[15] The authors find an inverse U nonlinearity. The threshold levels cited are GDP per capita of $21,000 to $33,000, in 2005 dollars, depending on the particular specification. The U.S. surpassed these levels in the 1970s.

states' perceived beer quality matters to consumption and perhaps high income state consumers prefer lesser quantities of higher priced beers.

The control for the age 20-35 population share across states has the largest proportional impact on the consumption of beer for the resurgent brewery growth period. A marginal increase in the share of a states' population aged 20-35 increases consumption by roughly 1.7 percent. This result concurs with age cohort findings by Freeman (2011) and Yakovlev and Guessford (2013). In addition to the single age group control, Freeman (2011) incorporated the entire age distribution in separate models arguing that the proportions of ages older or younger than typical beer-drinking age may affect the consumption of the typical age group. After controlling for all age group proportions using polynomial distributed lag covariates, coefficient magnitudes were indeed impacted[16] and Freeman estimated that per capita beer consumption peaked at roughly age 40 for the average state. In a related vein Tremblay and Tremblay (2005), examining market research data, found that the prevalence of beer consumption is highest (roughly 50 percent of the group) for those age 25-34.

Yakovlev and Guessford (2013) estimated a beer consumption to white-population elasticity of 2.72. We find an analogous result (though lesser magnitude) of beer consumption declining by 0.8 percent when the proportion of non-whites, in the average state, increases marginally. Not surprisingly, religion adherence plays an important role in determining personal beer consumption from 2008 to 2020. As overall church attendance for the population increases in the average state, beer consumption falls. Many religions simply abstain and even more promote a non-alcohol lifestyle. This result mimics those found in Colen and Swinnen (2016) for the Muslim faith and Hart and Alston (2020) for Mormons and Evangelicals. Turning to the insignificant variables, a relationship between unemployment and beer consumption is not supported herein. This result is not unique to this paper, Freeman's (2011) two-way fixed effects estimates and Sadik-Zada and Niklas' (2021) short-run nonlinear panel ARDL assessment show no statistically significant relationship running from unemployment to consumption. Moving on, Ogwang and Cho (2009) found that beer excise taxes were not effective at curtailing the consumption of beer, insignificant results herein correspond. Lastly, our political ideology covariate is statistically insignificant. Moderate positive correlation (0.553) with the age 20-35 variable, highlighted in Table 2, may be confounding significance. This result is contrary to extant findings in the literature − both Yakovlev and Guessford (2013) and Hart and Alston (2020)[17] found that states that lean more liberal, consume more beer per capita.

Conclusion

When baby boomers in the U.S. (born between the mid 1940s to mid 1960s) were introduced to beer for the first time, they likely choked down a Budweiser or Miller High Life. For those that latched on to beer as their go-to alcoholic beverage, these national big-beer brands carried historic weight in preference formation. Gen-Xers, those born in the mid to late 1960s, experienced the start of the small-beer expansion − experimenting

[16] The Z_1 Age PDL coefficients appear oversized, particularly in the common correlated effects models.
[17] Hart and Alston (2020) show this result using 1997 to 2016 data.

with, perhaps, Sierra Nevada Pale Ale or Sam Adams Boston Lager when they were not drinking Coors Light. Millennials, on the other hand, had full access to small-beer alongside the established national brands early on in their preference formation. Moreover, consumer surveys find that millennials perceive small-beer as authentic and of higher quality, a product more aligned with their cultural values (see Daneshkhu, 2018; Howe, 2018; Yue, 2019). Our findings bolster contemporary beer consumer sentiment. Falling consumption quantities with rising incomes indicate a shift in generational composition of beer consumers. Younger gen-Xers and millennials are buying more small-beer than older generations − beer they perceive as top quality offered at a premium price hence purchased in lower volume.

Entrepreneurs and enthusiastic homebrewers have built thousands of small breweries[18], to date, in hope of securing their piece of the eroding big-beer market dominance. New entrants recognize the generational shift of the beer consumer and his/her long shaped acceptance of small-beer and its neo-local sub-culture. One has to wonder though, how is big-beer fighting back? Elzinga and McGlothlin (2022) examine one response − big-beer is buying back portions of lost market share. Beginning around 2011, Molson Coors, Heineken USA, and Anheuser-Busch InBev began acquiring smaller breweries.[19] Most notable are Terrapin (Molson Coors), Lagunitas (Heineken) and Goose Island (AB InBev). The authors examine the AB InBev - Goose Island acquisition finding that consumers were not worse off in terms of price and output metrics but perhaps lose the utility of localism. What the authors do not fully address is the asymmetry of information. How many beer consumers actually know that Budweiser is now a part of a Belgian conglomerate while, in turn, have a clue that this conglomerate acquired Goose Island? The March 2019 British Craft Beer Report, released by the Society of Independent Brewers (SIBA), cites an awkwardly worded consumer survey implying − 2 percent − as an answer to the latter question posed. The survey finds that 98 percent of respondents do not believe global firms, such as AB InBev or Molson Coors, make craft beer. Mike Benner, SIBA's CEO at the time was quoted "This new research shows that if consumers were fully aware of what they were buying, then they wouldn't consider any beers from the global beer companies as craft" (SIBA, 2019). Advantageously, the resurgent brewery expansion is largely made up of small facilities that rely on local (on-premise) consumption and appear to be growing at a more rapid rate than big-beer, collectively, can buy them up (Elzinga and McGlothlin, 2022). A parting thought, when Jeff Lebesch and his wife at the time, Kim Jordan, were brewing and bottling Fat Tire out of their Fort Collins, CO basement in 1991, do you think a $400 million (Reidy, 2019) purchase price for New Belgium,[20] somewhere down the line, even entered their minds? Is a future buyout on the minds of each small-beer owner?

[18] The TTB reports close to 13,000 active Brewer's Notices in late 2022.
[19] Not intended as an inclusive list.
[20] In December of 2019, a craft beer unit of Japan's Kirin Holdings Company purchased New Belgium Brewing for a rumored $400 million.

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Appendix

Both Pedroni's (2004) and Kao's (1999) panel methodology is Engle and Granger (1987) based examining the residuals of a spurious regression using non-stationary variables. If the suite of variables are cointegrated the residuals should be stationary. Ensuring broad applicability, Pedroni proposes several tests that allow for heterogeneous intercepts and coefficients across cross-sections. This heterogeniety attribute separates Pedroni from Kao. Pedroni (2004) defines five specific test statistics, three within-dimension panel and two between-dimension group mean. The first three statistics: *panel rho*, *panel t* and *panel variance ratio (v)* are analogous to the semiparametric treatments examined by Phillips and Perron (1988) and Phillips and Ouliaris (1990) for conventional time-series data. The two grouped mean statistics, *group rho* and *group t* were also adapted from Phillips and Ouliaris (1990). Additionally, we will include parametric ADF versions of the panel and group mean statistics for reinforcement (see Pedroni 1999). Table A1 presents the testing results.

Table A1. Pedroni and Kao residual cointegration tests

Included observations: 663		
Cross-sections included: 51		
Null hypothesis: No cointegration		
Trend assumption: Deterministic intercept and trend		
Alternative hypothesis: common AR coefs. (within-dimension)		
Panel v-Statistic	-3.33	
Panel rho-Statistic	10.83	
Panel t-Statistic	-16.42***	
Panel ADF-Statistic	-4.89***	
Alternative hypothesis: individual AR coefs. (between-dimension)		
Group rho-Statistic	12.94	
Group t-Statistic	-44.63***	
Group ADF-Statistic	-8.37***	
Kao residual cointegration test		
Included observations: 663		
Null hypothesis: No cointegration		
Trend assumption: Deterministic intercept		
ADF-Statistic	2.081**	

Significance at < 1% (***), < 5% (**)

In a Monte Carlo experiment of the small sample properties of the statistics, Pedroni (2004, pp. 609-617) finds, for T in the range of 10 to 50, that the *panel rho*, *panel v* and *group rho* statistics suffer size distortions that lead to persistent failure to reject the null in simulation. This was the case for all specifications we tested. Pedroni makes the point, for short panels, "if the *group rho* statistic rejects the null, one can be relatively confident of the conclusion". Conversely, the two t-statistics were size distorted such as to over reject the null of no-cointegration in simulation.[21] Again, our results reflect this. Both parametric ADF tests along with Kao's ADF test reject the null of no cointegration. In light of the Pedroni Monte Carlo results, we are on the inference fence − leaning toward a conclusion of variable cointegration.

[21] Pedroni shows that when the T dimension reaches 150, the size distortion of the statistics wane.

Journal of Beer Economics, Vol. 1, No. 1, 2023, 41-50.

In Hope of a Big-Beer Buyout: An Application of Markov Processes

Mitch Kunce[1]

Abstract
In an effort to recoup lost market share, big-beer in the U.S. has been acquiring mid-sized to larger breweries. We examine the likelihood of breweries reaching target production characteristics common to recent acquisitions. Using Markov evolutions, projected probabilities of attaining the production characteristics desired by big-beer are small and declining as the industry premises count rises. New entrants start small and are predicted to remain small serving a niche, carve-out market.

Keywords: Markov chains, industrial organization, brewing industry
JEL Classifications: C53, L11, L20

Introduction
The Scribner-Bantam dictionary defines *Golden Road* as a form of expression reflecting the yellow brick road mentality with emphasis on the good things waiting to be discovered at the path's end. In 2011, four partners, including Meg Gill, started Golden Road Brewing in Los Angeles, CA. In March of the same year, Anheuser-Busch InBev (AB InBev) acquired Goose Island Brewing, out of the Chicago, IL area, for an alleged $39 million (Elzinga and McGlothlin, 2022). After, roughly, four years of remarkable growth, Meg Gill reached out to AB InBev in search of a similar buyout for Golden Road − somewhat inspired by the Goose Island arrangement (Verve, 2015). The deal was completed by the end of September, 2015 − the selling price was not disclosed. At the time of their acquisitions, Golden Road was producing around 45,000 barrels (bbls) per year − Goose Island was producing well over 125,000 barrels. As suggested by Elzinga and McGlothlin (2022), Golden Road and Goose Island were *natural candidates* for acquisition.

AB InBev is not a lone actor in the acquisition pursuit, other large brewers have participated.[2] But the brewing behemoth, through its High End Brands unit takes, what appears to be, a more formulated approach. Elzinga and McGlothlin (2022) detail 10 AB InBev acquisitions, made from 2011 to 2017, highlighting the age and barrelage of the breweries at the time of sale. Looking at the averages over the 10 breweries, AB InBev appears to have a type − local prominence, around 14 years old and producing roughly 60,000 barrels annually. Regarding the acquisition targets, the authors suggest that the prospect of being bought out, at a premium price, can induce entry into the industry from aspiring entrepreneurs and hobbyists. Figure 1 depicts net brewery entry since 1980. This growth has been attributed to relaxed barriers to entry, mostly centered around state-

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[2] For example, in 2016 Molson Coors acquired Terrapin Beer Company, Revolver Brewing and Hop Valley Brewing. Terrapin was a 15 year old company brewing 100,000 barrels at the time of acquisition, Revolver was 5 years in and brewing 24,000 barrels, and Hop Valley was 8 years old brewing close to 60,000 barrels.

level on-premise sales legislation (Elzinga et al., 2015). From the late 2000s to date, U.S. brewery growth is unprecedented.[3] Of these thousands of new entrants, how many were inspired by the prospect of a buyout? If so, the salient question then becomes, what is the likelihood a new brewery befits the natural candidate type for acquisition? The purpose

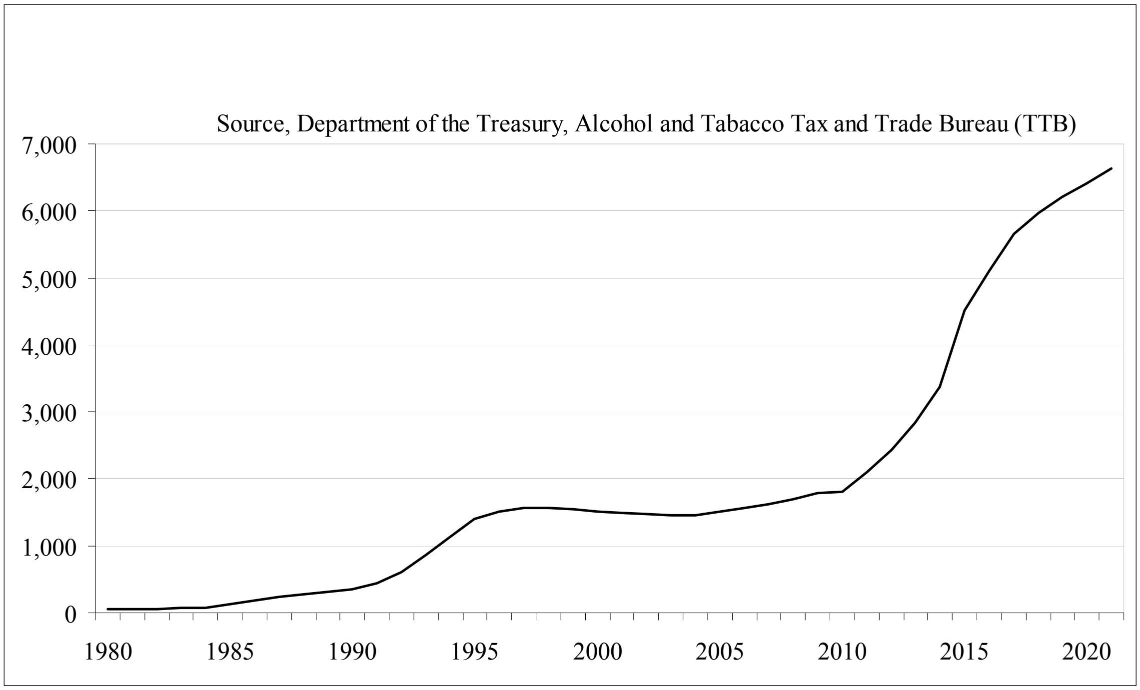

Figure 1. Reporting brewery count by year, 1980 - 2021[4]

of this examination is to explore the probabilities that breweries, allowing for industry entry, movement and exit, fall within specific production categories over time. One of these categories will include our natural candidates for acquisition. To make these calculations, we do not use entry, exit, merger or barrelage growth at the individual brewery level − data that is very difficult, if not impossible, to obtain. Instead, we use an aggregate Markov evolution − splitting the entire industry distribution into barrelage production categories (data available publicly) that can capture net temporal movements within the industry. The data reflects firms entering, remaining in their current category, moving to a different category or exiting the industry. Probabilities of moving between these categories are summarized with a Markov, or transition, matrix.[5] Lastly, using these transition probabilities, we can make predictions and estimate a unique long-run steady-state distribution. The next section describes this industry data.

Data

Each year, the Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau (TTB), publishes a public report entitled 'Number of Brewers by Production Size' for the

[3] The availability of *plug and play* brewing systems also contributed to this staggering growth.
[4] The TTB refers to reporting breweries as 'Industry Members'. We interchange 'premises' and 'facilities'.
[5] Analyses of firm size dynamics based on Markov transition probabilities are credited to Hart and Prais (1956) and Adelman (1958).

entire industry. Every brewery in the U.S. is licensed (Brewer's Notice) to operate by the TTB. Each permitted brewery is assigned a BR number and is required to complete a Brewer's Report of Operations either monthly or quarterly depending on taxed annual barrelage. The TTB relies on these individual premises reports as the source for the aggregated public report. Generally, the TTB groups the data by annual production, in 31 gallon barrels, splitting the counts into ten categories. Herein, we focus on the data from 2007 to 2021 capturing the tremendous growth period for the industry as shown in Figure 1. Figure 2 depicts the reporting premises count data that we have purposely collapsed

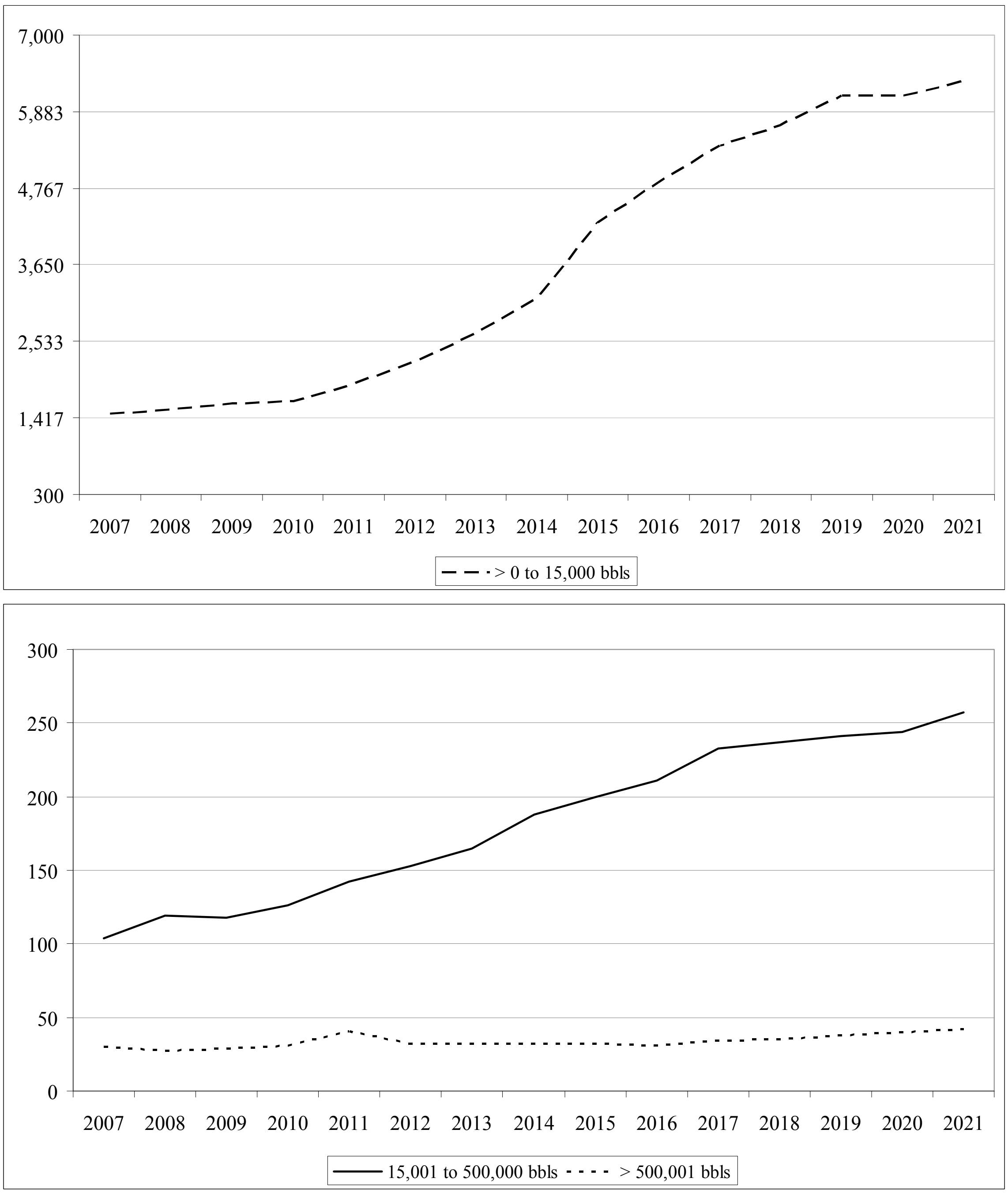

Figure 2. Brewery net reporting premises counts over time by grouping

down to three production groupings.[6] The mid-interval, 15,001 to 500,000 barrels, captures the production target range for acquisitions described above. We presume breweries that land in this interval are likely candidates for a buyout. The > 0 to 15,000 barrels category has grown by well over 4 fold from 2007. The bulk of net new entrants land in this interval. The acquisition target interval has grown from 104 facilities in 2007 to 257 in 2021. Interestingly, the largest production category has experienced the least change. Placing these growth trajectories in proper context, Figure 3 shows each interval

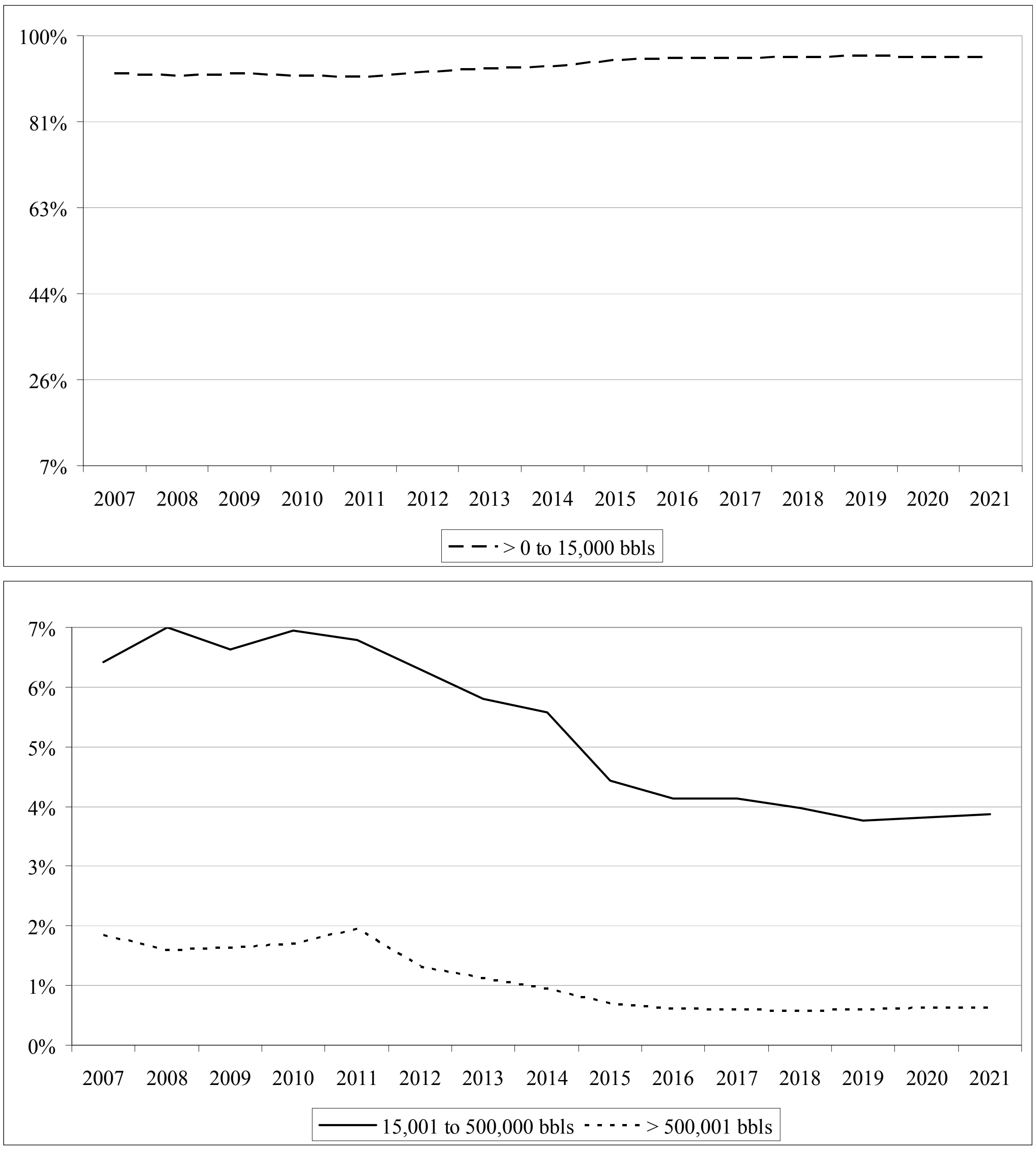

Figure 3. Brewery net premises count shares in percent

[6] See Tables A1 and A2 in the appendix for the expanded TTB detail. Collapsing to three categories simplifies the matrix manipulations below without loss of specificity.

as a proportional share of the industry count totals. Well over 90 percent of all premises in the industry produce 15,000 barrels or less. Our proposed acquisition interval dropped from around 7 percent of the industry total to under 4 percent by 2021. Lastly, Table 1 provides a nice end-point summary of the TTB data. Two important points are brought to light from this table, first, big-beers' production dominance is in decline. In 2021, 42 large scale facilities produced roughly 87 percent of total TTB reported production − down from 95 percent produced by 30 breweries in 2007. Second, it is somewhat surprising how small the new net entrants are. In 2021, 6,332 facilities landed in our first interval producing, on average, 1,005 barrels per brewery (less than in 2007). Given the range of this interval, > 0 to 15,000 barrels, a vast number of these facilities must be very small. In fact, roughly 5,000 produced 1,000 barrels or less. Granted, many of these small breweries are associated with restaurants (brewpubs)[7] while a growing share could be categorized as hobbies.[8] In any case, what is clear from this preliminary temporal analysis is that movement into the mid and top production intervals is very unlikely within this industry.

Table 1. Industry data by production groupings, 2007 and 2021

2007	Brewery Premises Count Share (%)	Production Share (%)	Average Production per Brewery (bbls)
> 0 to 15,000 bbls	91.723	0.824	1,095
15,001 to 500,000 bbls	6.424	4.291	81,407
> 500,001 bbls	1.853	94.885	6,240,264
2021			
> 0 to 15,000 bbls	95.491	3.519	1,005
15,001 to 500,000 bbls	3.876	9.717	68,390
> 500,001 bbls	0.633	86.764	3,736,822

Markov processes

The existence of the Jordan form provides for certain types of matrices known as Markov matrices or transition matrices.[9] An $n \times n$ matrix $P = (a_{ij})$ is a transition matrix if all elements of the matrix follow,

$$\begin{aligned}&a_{ij} \geq 0,\\ &\text{either } \textstyle\sum_i a_{ij} = 1 \text{ or } \sum_j a_{ij} = 1,\\ &\text{the distinct eigenvalues of } P \text{ are } \{1, \lambda_2, \ldots, \lambda_n\} \text{ where each } |\lambda| < 1.\end{aligned} \tag{1}$$

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[7] The Brewers Association (2023), an industry trade association, estimated that 36 percent of all breweries in 2021 were directly associated with a restaurant (0.36 x 6,631 = 2,387).

[8] This idea of hobbyist breweries is worthy topic for future research.

[9] Camille Jordan. (1875). Essay on the geometry of *n* dimensions. *Bulletin de la Société Mathématique*, *3*, 103-174. English translation, http://www.umiacs.umd.edu/_stewart/Jord75.pdf

A transition matrix is denoted *regular* if powers of P comprise all positive elements. Moreover, a vector $\tilde{v} \in \mathrm{R}^n$ is considered a steady-state if $P\tilde{v} = \tilde{v}$.[10] Consider our three TTB brewery groupings by barrels produced in a specific year. In 2007 (see Table 1): 91.723 percent of breweries produced 15,000 barrels or less, 6.424 percent produced 15,001 to 500,000 barrels and 1.853 percent produced over 500,000 barrels. The initial state vector becomes,

$$v_{07} = \begin{bmatrix} 0.91723 \\ 0.06424 \\ 0.01853 \end{bmatrix}. \tag{2}$$

In 2021: 95.491 percent of breweries landed in the first category, 3.876 percent entered or migrated to the crucial buyout target range and 0.633 percent produced over 500,000 barrels for the year. The future state vector becomes,

$$v_{21} = \begin{bmatrix} 0.95491 \\ 0.03876 \\ 0.00633 \end{bmatrix}. \tag{3}$$

Capturing net brewery temporal movements,[11] the transformation matrix is the solution to the following,

$$v_{21} = Pv_{07}, \tag{4}$$

where P is 3×3 and through numerical methods becomes,

$$P = \begin{bmatrix} 0.97877 & 0.88970 & 0 \\ 0.02123 & 0.02154 & 0.96611 \\ 0 & 0.08876 & 0.03389 \end{bmatrix}, \tag{5}$$

with eigenvalues {1, 0.30718, -0.27298}. The following Markov Chain facilitates a projection of probabilities out to 2035 by squaring P,

$$v_{35} = P^2 v_{07} = \begin{bmatrix} 0.96912 \\ 0.02722 \\ 0.00366 \end{bmatrix}. \tag{6}$$

---

[10] In order to ensure a unique steady-state, P must be an ergodic unichain (see Gallager, 2013). Regular transition matrices generally satisfy this constraint.

[11] Net involving entries, exits, group migration or mergers. These movements are baked into the data, so to speak.

Note, the likelihood a brewery lands into the buyout production range falls to 2.722 percent of all facilities by 2035.

Now consider the steady-state of this system. From above, P is shown to be a regular Markov matrix. The steady-state of proportion probabilities, $\tilde{v}$, is therefore solution to the following,

$$P\tilde{v} = \tilde{v};\ (P\text{-I})\tilde{v} = 0, \tag{7}$$

where I is the 3×3 identity matrix. Equations (7) yield the following system,

$$\begin{aligned} &-0.02123x + 0.8897y = 0 \\ &0.02123x - 0.97846y + 0.96611z = 0 \\ &0.08876y - 0.96611z = 0 \\ &x + y + z = 1, \end{aligned} \tag{8}$$

where x, y, and z are the unknowns in the column vector $\tilde{v}$.[12] The resulting steady-state vector becomes,

$$\tilde{v} = \begin{bmatrix} 0.97461 \\ 0.02326 \\ 0.00213 \end{bmatrix}. \tag{9}$$

The vector in (9) is also the solution to,

$$P^{\phi} v_{07} = \tilde{v};\ \phi \to \infty. \tag{10}$$

Table 2 summarizes our Markov chain results. Projections do not favor our buyout hopefuls. The probability of attaining the production characteristics desired by big-beer is small and projected to fall − 2.3 percent in the long-run steady-state.

Table 2. Proportions of breweries landing in each production grouping

			Projected	
	2007	**2021**	**2035**	**Steady-State**
> 0 to 15,000 bbls	91.723	95.491	96.912	97.461
15,001 to 500,000 bbls	6.424	3.876	2.722	2.326
> 500,001 bbls	1.853	0.633	0.366	0.213

Concluding remarks

Since the mid-1980s, brewery counts in the U.S. have been on the rise. Most of this growth is attributed to legislation allowing on-premise retail sales and, secondly, overt

[12] Such that $\tilde{v}$ is the right eigenvector of P associated to the eigenvalue of one.

changes in beer demand through product differentiation. The lion's share of these new breweries are small in terms of annual output − 75 percent of the industry count in 2021 produced 1,000 barrels or less per facility. Why open a small brewery today? As shown herein, your prospect for growth is very small and the likelihood of a potential buyout is even less. To be fair, many of these micro facilities opening of late are simply part of the product mix offered by accompanying restaurants. In fact, today's small-beer model bears a striking resemblance to the local specialty restaurant industry. Common neo-local attributes include strong community ties, atmosphere, authenticity and differentiated products. Visitors to communities across the country not only seek out the local fare, they often frequent the towns' breweries. This paper's predictions of sustained smallness bolsters this neo-localism tenet. In the end, perhaps only Dorothy was lucky enough to find riches on the Golden Road.

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Appendix

Table A1. Number of brewers by production size, 2007-2021

	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
> 0 to 1,000 bbls	1088	1142	1232	1178	1334	1604	1923	2321	3288	3771	4199	4405	4779	4961	4968
1,001 to 7,500 bbls	356	360	357	428	513	564	645	730	851	935	1030	1132	1183	1005	1186
7,501 to 15,000 bbls	41	40	42	51	63	77	81	102	133	148	152	155	159	156	178
15,001 to 30,000 bbls	26	43	40	40	42	44	51	62	71	75	99	102	102	103	102
30,001 to 60,000 bbls	34	26	32	38	43	50	52	62	56	53	53	53	64	67	76
60,001 to 100,000 bbls	20	20	19	16	16	20	24	20	24	38	41	40	33	30	30
100,001 to 500,000 bbls	24	30	27	32	41	39	38	44	49	45	40	42	42	44	49
500,001 to 1,000,000 bbls	10	7	7	9	11	7	7	6	7	6	10	10	12	12	14
1,000,001 to 6,000,000 bbls	3	9	4	5	14	8	8	11	10	11	9	10	11	14	13
> 6,000,001 bbls	17	11	18	17	16	17	17	15	15	14	15	15	15	14	15
Total	**1619**	**1688**	**1778**	**1814**	**2093**	**2430**	**2846**	**3373**	**4504**	**5096**	**5648**	**5964**	**6400**	**6406**	**6631**

Source: Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau

Count of industry members assigned a BR number reporting any production operations during the denoted calendar year.

Table A2. Total barrels produced by category, 2007-2021, in millions

	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
> 0 to 1,000 bbls	0.36	0.38	0.40	0.43	0.46	0.52	0.60	0.70
1,001 to 7,500 bbls	0.82	0.85	0.86	1.06	1.26	1.40	1.69	1.96
7,501 to 15,000 bbls	0.45	0.42	0.44	0.56	0.66	0.82	0.84	1.04
15,001 to 30,000 bbls	0.54	0.90	0.90	0.91	0.89	0.92	1.09	1.31
30,001 to 60,000 bbls	1.44	1.16	1.41	1.54	1.75	2.18	2.27	2.64
60,001 to 100,000 bbls	1.51	1.59	1.50	1.23	1.16	1.47	1.82	1.55
100,001 to 500,000 bbls	4.97	7.07	5.42	6.12	7.93	7.81	7.64	9.09
500,001 to 1,000,000 bbls	6.64	4.88	4.83	7.14	8.45	4.65	4.80	3.84
1,000,001 to 6,000,000 bbls	13.01	60.82	9.97	15.45	31.23	18.60	18.22	31.21
> 6,000,001 bbls	167.56	121.64	171.24	160.77	138.96	157.78	153.02	138.68
Total	**197.30**	**199.71**	**196.97**	**195.21**	**192.75**	**196.15**	**191.99**	**192.02**
	2015	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	
> 0 to 1,000 bbls	0.84	0.99	1.07	1.24	1.32	1.16	1.30	
1,001 to 7,500 bbls	2.24	2.46	2.66	3.06	3.15	2.66	3.19	
7,501 to 15,000 bbls	1.43	1.55	1.57	1.62	1.68	1.63	1.88	
15,001 to 30,000 bbls	1.51	1.58	2.06	2.12	2.17	2.15	2.20	
30,001 to 60,000 bbls	2.45	2.33	2.23	2.17	2.68	2.77	3.13	
60,001 to 100,000 bbls	1.89	3.05	3.18	3.12	2.58	2.35	2.29	
100,001 to 500,000 bbls	10.65	10.47	8.79	8.78	8.37	9.41	9.96	
500,001 to 1,000,000 bbls	5.05	4.29	6.25	5.86	7.59	8.38	9.73	
1,000,001 to 6,000,000 bbls	28.93	31.46	22.16	23.48	24.40	32.63	22.94	
> 6,000,001 bbls	136.12	131.66	135.61	131.34	125.78	116.82	124.27	
Total	**191.11**	**189.84**	**185.58**	**182.79**	**179.72**	**179.96**	**180.89**	

Source: Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau
Aggregation of Brewer's Report of Operations.

Journal of Beer Economics, Vol. 1, No. 1, 2023, 51-59 .

Impacts to U.S. State-Level Beer, Wine and Spirits Consumption Shares: An Application of Compositional Regressions

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Abstract

With few exceptions, alcohol related demand studies tend to ignore consumption share modeling. Because of the constraints on compositional data, the application of usual multivariate statistical methods is severely limited. Herein, we present a recent alternative application using the attraction form of the compositional model (CODA) adapted and proposed by Morais et al., (2018a). The attraction CODA model offers several advantages over its counterparts − it captures all cross-effects with relative parsimony, it accommodates a variety of explanatory variables including compositions, it is not bounded by the restrictive 'Independence from Irrelevant Alternatives' property, and it is easily implemented using the **R** software package. Application results presented herein are comparable to those in the standing literature where conventional systems models were used.

Keywords: Alcohol consumption shares, Compositional dependent variables, Compositional regressions

JEL Classifications: D12, C59, L66

Introduction

Alcoholic beverage consumption is the subject of a vast international literature. In the United States, alcohol consumption and production provide substantial economic throughput. Sector sales in 2021 were estimated at $247.3B, second only to China.[2] The understanding of factors affecting consumption patterns is the topic of a considerable portion of the literature inventory (see Fogarty and Voon, 2018; Hart and Alston, 2020 for reviews). The bulk of these impact studies rely on aggregate data − canton or country-level. Analyses of disaggregated or individual level behavior are less frequent due to data availability and focus mainly on smaller market segments, case studies or consumer surveys (e.g. Kerr et al., 2004). Convention, regarding the aggregate studies, groups the industry data into three components − beer, wine and spirits. Methods to analyze consumption patterns rely, generally, on single equation models for each component (e.g. Yakovlev and Guessford, 2013; Kunce, 2023). Regrettably, single equation estimation tends to ignore important cross-effects of the D - 1 components and determinates. In response, a few studies propose modeling a system of equations that would allow for cross-equation interactions (see Selvanathan and Selvanathan, 2004; Freeman, 2011; Hart and Alston, 2020). These exceptions have been based, mainly, on Barten (1964) and Theil's (1965) Rotterdam framework of differential demand analysis. The Rotterdam approach is not free from criticism (Clements and Gao, 2015) and optimal

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[2] Euromonitor Global Marketing Database. https://www.euromonitor.com

performance demands extensive price data that is generally ad hoc in the aggregate (Freeman, 2011).

Herein, we propose something a bit different when examining the complete system is of particular import. The three components − beer, wine and spirits − form an industry composition. Rather than isolate component consumption (sales) we could *close* the entire industry by formulating consumption or market-shares. Even in the case where we only analyze one component share, we are in fact implicitly relating it either to a predefined total or to another complementary proportion. It seems unconsidered to isolate consumption share data. Modeling shares of the total, rather than per capita sales for example, has the advantage of exploiting relative competitive information implicit in the compositional vector. By *relative competitive information* we mean the complex pattern of interplay within a market or industry. The aggregate concept of market-share simply captures the collective of individual choice probability. A '*D*' composition (simplex) of shares are all positive and sum to one. In our case, the simplex can be represented in a triangle. These constraints, however, severely limit the application of usual multivariate statistical methods. Early work on specific compositional data analysis is credited to Aitchison (1986).

More recently, two types of statistical models have been adapted to handle market-share dependent variables − the Dirichlet covariate model and the Compositional Data Analysis (CODA) model. Both have been shown to outperform earlier specifications when derived in the conventional *attraction* form (Morais et al., 2018a). Attraction models are analogous to the utility concept in discrete choice modeling. Simply, consumer attraction to a component is modeled as a function of determinates impacting its proportional share (e.g., component taxation and consumer income herein). The market-share of the component is defined as its relative attraction to other competing components (Cooper, 1993). Morais et al. (2018a) strongly advocate for their adaptation of the CODA model when: i) cross effects are important to consider and ii) the property of Independence from Irrelevant Alternatives (IIA) becomes too restrictive. CODA models follow the subcompositional coherence property which does not imply IIA (van den Boogaart and Tolosana-Delgado, 2013).

Herein, we propose the use of the attraction CODA framework to model impacts to state-level consumption shares of the U.S. alcoholic beverage industry for the years 2008 - 2020. Alcohol consumption data are provided by the Beer Institute annually and published for public view in *The Brewer's Almanac*.[3] Table 1 shows the consumption shares derived for each state, the District of Columbia and the United States overall for the bookend years 2008 and 2020. These state comparisons reveal considerable variation among the states. Overall, wine and spirits shares have increased over the 13 year period as the U.S. beer component exhibits decline. Table 1 shares are analogous to those found in other state-level examinations, namely Hart and Alston (2020).

[3] These are volume not value shares. Brewer's Almanac, September 20, 2021 revised version used herein.

Table 1. Shares of Beer, Wine and Spirits consumption for the years 2008 and 2020

		2008			2020	
State	**Beer**	**Wine**	**Spirits**	**Beer**	**Wine**	**Spirits**
Alabama	0.6479	0.0948	0.2573	0.5756	0.1060	0.3184
Alaska	0.4753	0.1498	0.3749	0.4002	0.1575	0.4424
Arizona	0.5693	0.1403	0.2904	0.4844	0.1397	0.3759
Arkansas	0.6152	0.0780	0.3068	0.5391	0.0852	0.3757
California	0.5078	0.2109	0.2813	0.4459	0.2340	0.3201
Colorado	0.5131	0.1290	0.3579	0.4387	0.1103	0.4510
Connecticut	0.4343	0.2162	0.3495	0.3383	0.2233	0.4384
Delaware	0.4661	0.1614	0.3725	0.3263	0.1323	0.5414
DC	0.3589	0.2482	0.3928	0.2432	0.2733	0.4835
Florida	0.5119	0.1662	0.3220	0.4266	0.1633	0.4101
Georgia	0.5903	0.1113	0.2985	0.5247	0.1175	0.3578
Hawaii	0.5475	0.1825	0.2700	0.4774	0.2166	0.3061
Idaho	0.5782	0.1341	0.2877	0.4763	0.1270	0.3967
Illinois	0.5571	0.1484	0.2945	0.4790	0.1799	0.3411
Indiana	0.5706	0.1022	0.3272	0.4563	0.1026	0.4410
Iowa	0.6494	0.0669	0.2837	0.5325	0.0735	0.3940
Kansas	0.6296	0.0644	0.3060	0.5481	0.0600	0.3920
Kentucky	0.5979	0.0780	0.3241	0.4815	0.0730	0.4455
Louisiana	0.6145	0.0886	0.2969	0.5099	0.0965	0.3935
Maine	0.5454	0.1478	0.3069	0.4501	0.1244	0.4254
Maryland	0.4913	0.1443	0.3644	0.4021	0.1591	0.4388
Massachusetts	0.4623	0.2249	0.3128	0.3473	0.2394	0.4132
Michigan	0.5495	0.1235	0.3270	0.4342	0.1243	0.4414
Minnesota	0.4998	0.1159	0.3843	0.4300	0.1166	0.4534
Mississippi	0.6677	0.0459	0.2864	0.5655	0.0482	0.3864
Missouri	0.5814	0.1060	0.3126	0.4517	0.1065	0.4418
Montana	0.6206	0.1050	0.2745	0.5636	0.1005	0.3359
Nebraska	0.6288	0.0738	0.2974	0.5084	0.0721	0.4195
Nevada	0.5002	0.1543	0.3456	0.4559	0.1891	0.3550
New Hampshire	0.4383	0.1593	0.4024	0.3989	0.1580	0.4431
New Jersey	0.4327	0.2180	0.3493	0.3356	0.2252	0.4392
New Mexico	0.6020	0.0952	0.3028	0.5708	0.1317	0.2975
New York	0.4904	0.1998	0.3098	0.4100	0.2219	0.3681
North Carolina	0.6121	0.1205	0.2674	0.5349	0.1117	0.3535
North Dakota	0.5847	0.0612	0.3541	0.4778	0.0605	0.4617
Ohio	0.6390	0.1082	0.2528	0.4979	0.1256	0.3766
Oklahoma	0.6572	0.0823	0.2605	0.5409	0.0822	0.3770

Oregon	0.5274	0.1711	0.3015	0.4627	0.1638	0.3736
Pennsylvania	0.6247	0.1015	0.2738	0.5636	0.1144	0.3220
Rhode Island	0.4781	0.1967	0.3252	0.3146	0.1931	0.4923
South Carolina	0.6180	0.0887	0.2933	0.5962	0.0925	0.3113
South Dakota	0.6258	0.0653	0.3089	0.6067	0.0756	0.3176
Tennessee	0.6192	0.0936	0.2872	0.4735	0.0896	0.4369
Texas	0.6760	0.0859	0.2381	0.5861	0.0796	0.3344
Utah	0.6042	0.0912	0.3046	0.5427	0.0794	0.3780
Vermont	0.5273	0.2148	0.2579	0.5004	0.2318	0.2678
Virginia	0.5773	0.1653	0.2574	0.4790	0.1848	0.3362
Washington	0.5137	0.1892	0.2971	0.4648	0.2030	0.3322
West Virginia	0.6955	0.0577	0.2468	0.6571	0.0542	0.2887
Wisconsin	0.5560	0.1029	0.3411	0.4627	0.1100	0.4274
Wyoming	0.5669	0.0705	0.3626	0.4525	0.0775	0.4700
United States	**0.5584**	**0.1423**	**0.2993**	**0.4598**	**0.1687**	**0.3715**

With state-level volume consumption shares on the left-hand-side (LHS) of our application example, RHS covariates include state-level excise taxation unique to each alcohol component by state and year and personal disposable income unique to each state by year. State and time dummies are included to mitigate heterogeneity and autocorrelation issues. Elasticities are then computed to provide straight forward interpretations of underlying coefficient marginal effects. All models are estimated in **R** (van den Boogaart et al., 2014). The balance of this examination is divided into four sections. The next section describes the data, provides sources and presents descriptive statistics. The third section presents the empirical model and discusses the complex econometric issues. Section four presents and interprets the empirical results with conclusions and implications drawn in the last section.

Data

Data comprise a 13 year (2008-2020), all 50 state and District of Columbia panel. Table 2 describes all variables, provides sources and key descriptive statistics. The Beer Institute's consumption data have been examined in previous studies, notably Freeman (2011), Yakovlev and Guessford (2013) and Kunce (2023). Each observation on the LHS is comprised of 3 components, summing to one, for each jurisdiction per year (51 x 13 = 663). Sources for excise tax data follow Freeman (2011) for beer and Fogary and Voon (2018) and Hart and Alston (2020) for both wine and spirits.[4] Each LHS share carries a component specific tax rate on the RHS. Income is only state and year (observation) specific. It is important to illustrate that the CODA attraction model can accommodate both types of explanatory variables described. Moreover, the RHS can

[4] Wine and spirits taxes are compiled by the Tax Foundation. For some control states (where government controls all sales) data were missing. For wine, data absent states included MS, NH, PA, UT and WY. For spirits, NH and WY were missing data. In each incident we relied on the state's statutory markup (e.g. 17.6 percent in Wyoming) to compute specific tax revenue from state sales of wine and spirits − then converted the total to per gallon of apparent consumption per state, per year.

Table 2. Data descriptions, sources and descriptive statistics

Beer, wine and spirits consumption shares. Apparent beer, wine and spirits consumption for all 50 states and D.C. by year in drink equivalent volumes as a proportional share of the total. Aggregate shares of drink equivalents are calculated using 12 ounces of beer, 5 ounces of wine and 1.5 ounces of spirits. Compiled by The Beer Institute (Brewer's Almanac) based on reporting from individual states. Data reflect shipments and/or sales volumes determined by local tax payments and/or state reports of malt, wine and spirits beverage shipments. Beer mean 0.4882, STD 0.0735; Wine mean 0.1407, STD 0.0534; Spirits mean 0.3710, STD 0.0567.
Beer taxes. Beer-specific excise tax burden by state in 2020 dollars per gallon. Generally, this rate includes state and local brewery production and specific sales taxes and fees aimed at malt based products. Interestingly, in some states (e.g. Pennsylvania), separate on-brewery-premise sales taxes are imposed. Source; The Brewer's Almanac, published annually by The Beer Institute. Mean 0.297, STD 0.259.
Wine taxes. Wine-specific excise tax burden by state in 2020 dollars per gallon. Generally, this rate includes state and local brewery production and specific sales taxes and fees aimed at fermented fruit based products. Sources; Tax Foundation, Alcohol and Tobacco Tax and Trade Bureau. Mean 0.858, STD 0.569.
Spirits taxes. Spirits-specific excise tax burden by state in 2020 dollars per gallon. Generally, this rate includes state and local production and specific sales taxes and fees aimed at distilled products. Sources; Tax Foundation, Distilled Spirits Council of the United States, Alcohol and Tobacco Tax and Trade Bureau. Mean 4.197, STD 2.236.
Disposable personal income. Defined as per capita personal income by state available to persons for spending or saving (after-tax income), in thousands of 2020 dollars. U.S. Bureau of Economic Analysis, Personal Income and Outlays release. Mean 48.189, STD 7.844.

include compositional and numerous dummy variables. Table 3 contains variable notations and indices used to develop the general empirical model presented in the next section.

Table 3. Model notations

Observations, indexed $i = 1, \ldots, N$ ($N = 51$ states x 13 years = 663) Components, indexed $j, l, m = 1, \ldots, D$
Dependent shares variable, $S_{j,i}$, $S_j > 0$, $\sum_j^D S_j = 1$
Explanatory variables that vary over components and observations, $X_{j,i}$ Index of type X variables, $k = 1, \ldots, K_X$ Estimated coefficients of the X type, β_k
Explanatory variables that vary over observation only, W_i Index of type W variables, $\kappa = 1, \ldots, K_W$ Estimated coefficients of the W type, β_κ
$E^{\oplus}$, expected value in the simplex. α, model intercepts.

Compositional model

The CODA specification belongs to a class of transformation models. The dependent variable is a vector of shares which are distributed Gaussian in the simplex. Traditional expected values are not computable in the CODA framework. Therefore, the model relies on 'expectations in the simplex' which means that the expected value in the simplex of the composition of shares corresponds with the inverse transformation of expected values of the random coordinates (Pawlowsky-Glahn et al., 2015). The literature proposes several transformation methods (van den Boogaart et al., 2013). The isometric log-ratio transformation is preferred for compositional regression specifications. Composition in general terms of expected shares in the simplex becomes,

$$E^{\oplus} S_{j,i} = \frac{\alpha_j \cdot \prod_{l=1}^{D} \prod_{k=1}^{K_X} X_{k,l,i}^{\beta_{k,j,l}} \cdot \prod_{\kappa=1}^{K_W} \beta_{\kappa,j}^{W_{\kappa,i}}}{\sum_{m=1}^{D} \alpha_m \cdot \prod_{l=1}^{D} \prod_{k=1}^{K_X} X_{k,l,i}^{\beta_{k,m,l}} \cdot \prod_{\kappa=1}^{K_W} \beta_{\kappa,m}^{W_{\kappa,i}}}. \tag{1}$$

Note that in this specification attraction depends on all alternative characteristics, including component-specific and cross-effect parameters.[5] When including numerous state and year dummy variables in the specification (in effect splitting the intercepts), fitted shares remain centered on the data via geometric means. This property of simplex geometry bolsters the use of the CODA framework for market-share applications. The 'compositions' package in **R** was used in the estimation of Equation (1).[6]

Results

The aim of this examination is to illustrate the usefulness of attraction-based compositional regressions in explaining the evolution of alcohol industry consumption shares. In effect, data presented represent the aggregation of individual choices for the 51 canton jurisdictions in the U.S. from 2008 to 2020. Consumption shares ($S_{j,i}$) are modeled as a function of state-specific alcohol component taxation ($X_{j,i}$) and overall state-level per capita disposable income (W_i). State and year dummy variables are included to

[5] Adapted from Morais et al. (2018a), p. 14.
[6] See van den Boogaart et al. (2014).

control for state and temporal heterogeneity and correlation. While **R** estimation results provide raw coefficient estimates and their statistical significance, these estimates do not represent marginal effects. Convention suggests that reporting the elasticities, direct and cross, provides a more straight forward interpretation. As such, elasticities, centered on the geometric means, are shown in Table 4.[7]

Table 4. Elasticities

	Beer Tax	Wine Tax	Spirits Tax	Income
Beer Share	-0.0142*	0.0041	0.0474*	-0.2497*
Wine Share	0.0055	-0.0204**	0.0335*	0.9617***
Spirits Share	0.0017	0.0118**	-0.0744**	0.3960**

- Underlying coefficients significant at (*) < 10%, (**) < 5%, (***) < 1% levels.

All own-tax elasticities (on the diagonal of the first 3 columns in Table 4) are negative and statistically significant at conventional levels. As shown, a 1 percent increase in state beer excise taxes per gallon decrease beer's consumption share by 0.0142 percent. Interestingly, three cross-tax elasticities are statistically significant and all positive. For example, a 1 percent increase in the wine tax increases the spirits consumption share by 0.0118 percent. These cross-component results highlight one of the many strengths of the attraction CODA framework. Table 4 tax elasticities are comparable to those found in previous state-level per capita consumption examinations, namely Yakovlev and Guessford (2013).

All income elasticities are statistically significant at conventional levels. A 1 percent increase in disposable personal income decreases the beer consumption share by roughly 0.25 percent. Beer shares have been negatively impacted by income increases over the 2008 - 2020 period. This result is consistent with the American continent beer share model in Colen and Swinnen (2016).[8] In this study, the authors show that when income rises above a certain level,[9] the American continent experiences a decrease in beer consumption share with further increases in income. They demonstrate that higher incomes induce preference shifts to other beverages. For example, Swinnen (2017) points out that while higher income jurisdictions may be drinking relatively less beer, they are in turn drinking more expensive beer. Preferences are shifting within component to perceived higher quality in less overall volume. The CODA framework herein reveals and bolsters this finding. Wine and spirits shares are shown to increase with increases in disposable personal income, though the impacts are inelastic. These results align with previous wine and spirits consumption examinations (see the survey by Fogarty, 2010).

Conclusion

It is of value to understand the evolution and patterns of alcohol consumption by interrelated components. With few exceptions, alcohol related demand studies tend to

[7] See Morais et al. (2018b), pp. 7-11, for derivation details.
[8] See Table 4 in Colen and Swinnen (2016).
[9] The authors find an inverse U nonlinearity. The threshold levels cited are GDP per capita of $21,000 to $33,000, in 2005 dollars, depending on the particular specification. The U.S. surpassed these levels in the 1970s.

ignore consumption share examination. Because of the constraints on compositional data, conventional regression models cannot be used directly to model market component shares. Herein, we present a recent alternative approach using the attraction compositional model (CODA) adapted and proposed by Morais et al., (2018a). The attraction CODA model offers several advantages − it captures all cross-effects with relative parsimony, it accommodates a variety of explanatory variables, it is not bounded by the restrictive IIA property, and it is easily implemented using the **R** software package. Application results shown are certainly comparable to those in the standing literature where conventional systems models are used. This adapted CODA framework appears to be a useful alternative for analyzing impacts to aggregate alcohol consumption trends.

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Journal of Beer Economics, Vol. 1, No. 1, 2023, 60-74 .

Place-based Characteristics Impacting the Chance of Winning a GABF Medal

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Abstract
The record of the Great American Beer Festival (GABF) is the history of small-beer in the U.S. Winning a GABF award is an aspiration for many brewers across the country. Given the apparent perceived importance of these awards what, if any, place-based factors influence the probability of winning? Herein, we combine brewery medal winning with state-level location characteristics that may follow through and impact the chance at one of these awards. Results from zero-inflated negative binomial panel specifications highlight state-level medal accumulation (legacy), general economic conditions and the proliferation of very small breweries in the U.S. as important place-based characteristics impacting medal awards.

Keywords: Zero-inflated negative binomial regressions, panel data, socio-economic characteristics, Great American Beer Festival
JEL Classifications: C14, C23, C25

Introduction
Each fall of the year since 1982, one of the brewing industry's trade associations − the Brewers Association (BA) − puts on the Great American Beer Festival in Colorado. The beer competition began in 1983 where winners were decided by a consumer poll. In 1987 the competition changed to a judged event − 38 medals were awarded over 13 style categories. In those early days of the festival, less than 100 breweries were operating in the U.S. (see Figure 1). By 2022, there were well over 7,000 reporting industry members producing and paying taxes and thousands more permitted to operate. Last year (2022), the competition boasted just under 10,000 entries from 2,151 U.S. breweries awarding just over 300 medals (GABF, 2023). These medals are much sought after by brewers and according to the Brewers Association,

> "The professional judge panel awards gold, silver or bronze medals that are recognized around the world as symbols of brewing excellence. These awards are among the most coveted in the industry and heralded by the winning brewers in their national advertising" (GABF, 2023).

Participation in this premier competition is not costless to the breweries and there are certain barriers to entry. Each style entry requires a specific fee[2] along with the cost of properly transporting (over one month before the event) the packaged beer to the competition's location, Denver, CO. Interestingly, breweries can ensure entry by becoming a 'Featured Sponsor' making a lump sum donation to the BA based on their annual production (Kunce, 2021). Given the unprecedented growth of brewery counts in

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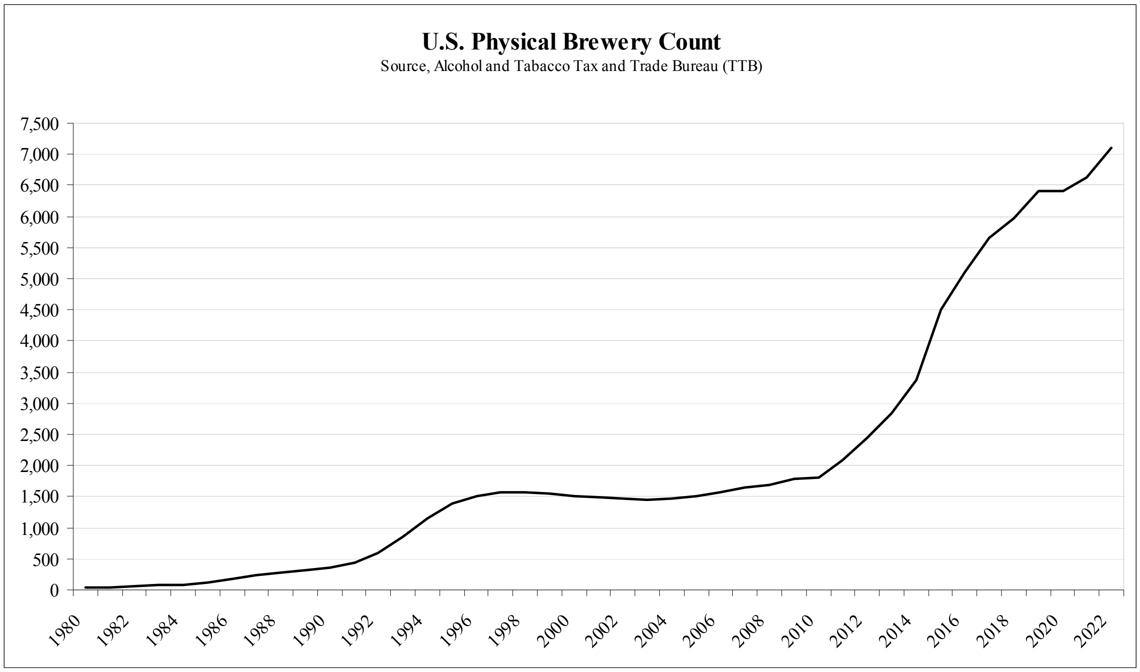
[2] If brewers are not members of the BA, fees are more than doubled. In most cases, becoming a dues paying member of the BA lowers specific entry cost. As of the date of publication of this paper, the BA touted membership of over 6,000 U.S. breweries.

the U.S. to date, there is a surplus of fervent entrants yearning to compete. The GABF online[3] entry registration has been characterized as a spirited game of chance (Meyer, 2019).

Figure 1. U.S. reporting brewery count 1980-2022



Given the obvious perceived importance of these awards[4] what, if any, factors influence the probability of winning? Unfortunately, access to broad data on individual breweries is limited. The BA may retain certain information on their member brewers, but access to this data is guarded. Nevertheless, some descriptive and location data of the winners is publicly available. Herein, we marry medal winning with state-level location characteristics that may impact the chance at one of these awards. The idea being that place-based characteristics of a brewery's location generally follow through and influence entry and the odds of winning. Today's small-beer segment[5] is said to originate in California and these legacy roots have influenced the overall geography of beer in the U.S. (Elzinga et al., 2015). Elzinga and the Tremblays found that constructed spatial-lag variables confirm the significance of agglomeration forces impacting brewery location choices. They also describe an *exuberance* effect of having like, successful, brewers near by. Do these origin, location and exuberance forces also affect medal winning?

In order to test this hypothesis, we treat medal winning, or not, by breweries in a state over time as a panel count variable. A count is an outcome in non-negative integers typically littered with zeros. Models for count data have been forefront in many strands

[3] The competitive online registration was incrementally introduced from the mid to late 2000s.
[4] Little if any empirical evidence exists regarding any measurable economic benefit to breweries from winning these medals. Kunce (2021) found no significant relationship between winning a GABF medal or medals and changes in a brewery's output.
[5] What the BA refers to as the craft beer segment, though all beer manufacture is certainly a craft.

of the recent applied literature (see Winkelmann, 2008 for a review). The preparatory building block in this modeling is the Poisson regression framework. The Poisson model, however, restricts the distribution of observed counts where the variance of the random variable is equal to its mean. More general specifications have been suggested − the negative binomial (NB) model rises to the top (Hilbe, 2011). There are also many applications that extend NB models to accommodate special features of the data generating process, such as zero inflation (ZINB). Models for panel data, fixed and random effects, are natural extensions. Herein, results from ZINB panel specifications highlight state-level medal accumulation (legacy), general economic conditions and the proliferation of very small breweries as important place-based factors impacting medal awards.

The balance of this examination is divided into four sections. The next section describes the data, provides sources, presents descriptive statistics and relevant context. The third section presents the empirical model and discusses the complex econometric issues. Section four presents and interprets the empirical results with conclusions and implications drawn in the last section.

Data

Data comprise a 15 year (2008-2022), all 50 state and District of Columbia panel. As shown in Figure 1, the late 2000s time frame is the start of the tremendous growth in brewing facilities across the country. Table 1 describes all variables, provides sources and key descriptive statistics. The dependent variable is the count of medals awarded to participating U.S. brewing facilities located within a specific state by event-year. As

Table 1. Data descriptions, sources and descriptive statistics

GABF medal count. Event-year Great American Beer Festival all-medal count by breweries' location state, 2008 to 2022. All-medal count includes pro-am and collaboration awards. State/event-years = 51 x 15 = 765. Source, Brewers Association. Mean 5.36, STD 9.97.
Cumulative GABF medals. Aggregate Great American Beer Festival all-medal count by breweries' location state from 1983 to each successive year 2008 to 2022. Source, Brewers Association. Mean 95.96. STD 166.86.
Unemployment rate. Average annual rates for all 50 states and D.C., in percent of labor force. Source, U.S. Bureau of Labor Statistics, 2008-2022. Mean 5.83, STD 2.28.
Politics. Based on state-specific, midyear legislative (state house and senate) partisan composition. Calculated as Democrat held seats minus Republican seats as a share of total state legislative seats, in percent. Source, National Conference of State Legislatures, 2008- 2022. Mean -2.37, STD 36.63.
Non-white. Percent of a state's population that is non-white alone. Source, U.S. Bureau of the Census. Mean 32.15, STD 15.87.

Real median income. Median household income by state and year in thousands of 2021 dollars. Source, U.S. Census Bureau, Current Population Survey. Mean 66.303, STD 11.321.
Breweries. Number of physical breweries in a state, by year, per million population. Source, U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau. Population by state and year sourced from the U.S. Census Bureau. Mean 23.84, STD 23.34.
Production. Production, in 1000s of 31 gallon barrels, per brewery by location state and year. Source, U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau. Mean 32.87, STD 83.93.

Table 2 illustrates not all states have participating breweries each year, though the incidence of aggregated non-participation is rather infrequent given the historic growth trajectory (post 2008) of member counts in the U.S. (see Figure 1). Obviously, states lacking a participating brewery have a zero medal count. On the other hand, GABF participation does not always generate a non-zero outcome for breweries within a state.

Table 2. Jurisdictional participation

Year	U.S. Breweries Participating	Source Jurisdictions
2008	472	47 States + DC
2009	495	48 States + DC
2010	516	48 States + DC
2011[6]	525	48 States
2012	665	48 States + DC
2013	732	49 States + DC
2014	1,309	50 States + DC
2015	1,552	50 States + DC
2016	1,752	50 States + DC
2017	2,217	50 States + DC
2018	2,404	49 States + DC
2019	2,292	50 States + DC
2020	1,720	50 States + DC
2021	2,190	50 States + DC
2022	2,151	50 States + DC

Fitting a typical count model with this two part regime data may *inflate* the theoretical probability of zero medals. Table 3 depicts the frequency of state/event-year medal outcomes. Interestingly, the preponderance of zeros stem from simply not winning in a

[6] Starting in 2011, breweries located in the unincorporated, organized U.S. Territories of Guam, Northern Mariana Islands, Puerto Rico and U.S. Virgin Islands are eligible to enter the GABF. Such entries have been few through 2022 and are not included in the analysis herein.

given event-year. Zero medals occurred in 202 state/event-year observations, 26.41 percent of the total. As shown towards the bottom of Table 3, breweries in the state of California won 76 medals in 2022.

Table 3. Outcome frequency

State/Medals/Year	Frequency	Proportion	Cumulative
0	202	26.41%	26.41%
1	124	16.21%	42.61%
2	80	10.46%	53.07%
3	65	8.50%	61.57%
4	56	7.32%	68.89%
5	36	4.71%	73.59%
6	30	3.92%	77.52%
7	30	3.92%	81.44%
8	19	2.48%	83.92%
9	13	1.70%	85.62%
10	20	2.61%	88.24%
11	4	0.52%	88.76%
12	9	1.18%	89.93%
13	7	0.92%	90.85%
14	8	1.05%	91.90%
15	6	0.78%	92.68%
16	6	0.78%	93.46%
17	4	0.52%	93.99%
18	2	0.26%	94.25%
19	4	0.52%	94.77%
21	4	0.52%	95.29%
22	4	0.52%	95.82%
24	2	0.26%	96.08%
25	2	0.26%	96.34%
26	1	0.13%	96.47%
33	1	0.13%	96.60%
34	1	0.13%	96.73%
36	1	0.13%	96.86%
38	3	0.39%	97.25%
39	2	0.26%	97.52%
40	1	0.13%	97.65%
41	1	0.13%	97.78%
42	1	0.13%	97.91%
45	1	0.13%	98.04%
46	1	0.13%	98.17%

47	1	0.13%	98.30%
48	1	0.13%	98.43%
49	1	0.13%	98.56%
51	1	0.13%	98.69%
52	1	0.13%	98.82%
53	1	0.13%	98.95%
57	1	0.13%	99.08%
60	1	0.13%	99.22%
63	1	0.13%	99.35%
67	1	0.13%	99.48%
68	2	0.26%	99.74%
73	1	0.13%	99.87%
76	1	0.13%	100.00%
-	765	100.00%	-

Regarding regressors, *cumulative medals* awarded proxies the legacy effect noted above. One common criticism of the competition is that breweries from the same states[7] seem to win the bulk of the medals year after year (Rich, 2015; Alworth, 2017). However, including cumulative counts in the right-hand-side (RHS) suite may raise endogeneity issues. This form of potential simultaneity will be addressed in the estimation and results section below. State-level *unemployment* provides wide reaching controls for local economic conditions. Hatzius and Stehn (2012) referred to the unemployment rate as their "desert island economic indicator", the one they would choose if they had to choose only one indicator to provide information about an economy. A somewhat non-conventional covariate is a state's perceived *politics*. We derive a state-level political 'attitudes' proxy using the partisan composition of each state's legislature. Within-state composition of the local legislative body best represents the diverse political ideology stemming from 'all-corners' of a state's borders. The politics variable is derived as follows,

$$\frac{\text{Democrats (State House and Senate)} - \text{Republicans (State House and Senate)}}{\text{Total Seats (State House and Senate)}} \otimes 100\,. \qquad (1)$$

The partisan makeup of each state's legislature reflects the midyear (around June) seats held. An increasing politics percentage reflects a more Democrat leaning attitude of a particular state. A state's ethnic diversity is represented in the *non-white* population share while real median *income* controls for a state's average wealth. The *breweries* variable proxies relative industry agglomeration. Given the rapid, nation-wide, growth in brewery counts of late, states with smaller populations are generating larger breweries per capita ratios.[8] Lastly, the *production* variable controls for average brewery size, in terms of

[7] The top 3 cumulative medal states are California (1,362), Colorado (885) and Oregon (454).
[8] Vermont, Maine, Montana and Alaska have the highest ratios.

output, in a state. Obviously, states with large macro-facilities skew the averages.[9] The vast majority of competing breweries are relatively small, though big-beer has certainly won a fair share of medals.[10]

In addition to the variable particulars denoted in Table 1, Table 4 depicts the variable correlation matrix for all RHS regressors. While multicollinearity problems are certainly a matter of degree, the risk of detrimental issues herein appears small.

Table 4. RHS correlation matrix

	Cum. Medals	Unemploy	Politics	Non-White	Income	Breweries
Cum. Medals	1.000	-	-	-	-	-
Unemploy	0.026	1.000	-	-	-	-
Politics	0.131	0.329	1.000	-	-	-
Non-White	0.226	0.169	0.406	1.000	-	-
Income	0.246	-0.267	0.327	0.162	1.000	-
Breweries	0.221	-0.368	-0.028	-0.256	0.311	1.000
Production	0.075	0.201	-0.066	0.084	-0.046	-0.186

Model

Relaxing the equi-dispersion constraint imposed by Poisson, the NB2 form distribution becomes,

$$\text{Prob}(y_{it}) = \frac{\Gamma\left(\frac{1}{\alpha} + y_{it}\right)}{\Gamma\left(\frac{1}{\alpha}\right)\Gamma\left(y_{it}+1\right)}\left(\frac{\frac{1}{\alpha}}{\frac{1}{\alpha}+\lambda_{it}}\right)^{\frac{1}{\alpha}}\left(\frac{\lambda_{it}}{\frac{1}{\alpha}+\lambda_{it}}\right)^{y_{it}}, \tag{2}$$

where Γ is the factorial function, y_{it} is the count of medals won by breweries in state i during event year t and $\lambda_{it} = \text{E}[y_{it} \mid x_{it}]$ where x_{it} are the explanatory covariates.[11] This model has an additional estimable parameter, α, such that $\text{Var}[y_{it}] = \text{E}[y_{it}](1 + \alpha\text{E}[y_{it}])$. Regarding panel estimation treatments, for the fixed effects case,

$$\log \lambda_{it} = \mu_i + \gamma_t + \beta' x_{it} + \varepsilon_{it}, \tag{3}$$

where μ_i and γ_t are the latent effects, β is the vector of estimated coefficients and ε_{it} is the residual disturbance. Following Allison and Waterman's (2002) critique of Hausman, et al. (1984) we use the unconditional estimator or *brute-force* direct maximum log

[9] Largest production per brewery states include Georgia, Texas, Missouri and Virginia. Anheuser-Bush InBev has large facilities in the first three, Molson Coors dominates the production in Virginia.

[10] In 2022, 75 percent of all producing breweries in the U.S. brewed 1,000 barrels or less for the year (TTB, 2023). The king of big-beer, Anheuser-Bush InBev (owned affiliates) took home four (a gold and three bronze) medals in 2020, four in 2021 and four more in 2022 (Anheuser-Bush InBev, 2023). Before 2018, big-beer dominated the American lager, light lager and cream ale categories of the GABF.

[11] The presentation and application of Cameron and Trivedi's (1986) standard model Negbin 2 is the result of careful specification pre-testing, as suggested by Greene (2008), giving confirmation to the quadratic form of λ_{it} in the conditional variance function. Indices follow $i = 1, \ldots, N$; $t = 1, \ldots, T$. Lastly, $\theta = 1/\alpha$.

likelihood. A virtue of the fixed effects approach is that it is not necessary to assume that the heterogeneity is uncorrelated with x_{it} .

The random effects model is,

$$\log \lambda_{it} = \beta' x_{it} + u_i + \gamma_t , \quad (4)$$

where u_i is a random effect (presumed independent of x_{it}) for the ith state such that $\exp(u_i)$ is distributed log gamma with parameters (θ_i, θ_i).[12] Additionally, $\theta_i /(1+\theta_i)$ is distributed beta with hyper-parameters (a, b). Adding time dummies, γ_t , makes the model two-way. Layering random state effects into the NB model, in this fashion, supposes that the over-dispersion parameter is randomly distributed across states. In both panel treatments, zero-inflation can be introduced. Given a binary indicator of regime type, if the regime indicator takes a zero value, then the observed y_{it} is zero regardless. If regime selection takes a value of one, y_{it} is as observed − which could still be zero (Lambert, 1992). The probabilities of the various outcomes are,

$$\text{Prob}[y_{it} = 0] = q_{it} + (1 - q_{it}) R_{it}(0) , \quad (5)$$

$$\text{Prob}[y_{it} = j > 0] = (1 - q_{it}) R_{it}(j) . \quad (6)$$

The NB probability is denoted $R_{it}(y_{it})$ and q_{it} represents the ancillary regime probability.

Estimation and results

Careful pre-testing inference presented in Table 5 first rejects the null hypothesis of homoscedastic disturbances at the < 10 percent level when controls are included for cross-sectioned effects. Regarding the period test in the second row, the null of homoscadasticity is retained. Alternative covariance structures have been suggested for the Poisson model due to the lack of heterogeneity in the mean (Greene, 2018). Generally, the NB specification will accommodate and temper these efficiency issues. The Pesaran CD test fails to reject the null of weak or no cross-sectional error correlation in the panel at conventional levels (Pesaran, 2015, 2021). The Durbin-Watson statistic of 1.87 lies in

Table 5. Initial test statistics

	With Effects
Cross-section Heteroscedasticity LR Test	64.56*
Period Heteroscedasticity LR Test	59.34
Peseran CD	1.53
Durbin-Watson	1.87
Kao Panel Cointegration	5.61***

Significance at <1% (***), < 5% (**), < 10% (*)

[12] One may presume normality rather than gamma for the distribution of the state random effects, herein both results are analogous nonetheless.

the inconclusive region of the test (1.86 - 1.90). This region appears in the test because the sequence of residuals are influenced by the movement of the independent variables in the equation. In this region, it is possible that the seeming correlation of the errors is due to the connection to the regressors, not the error terms. (Bartels and Goodhew, 1981).

Generally, non-stationary variables should not be used in regression models. Moreover, within conventional panel analysis, the time dimension, T, is characteristically too short for proper scrutiny. As a result, the time-series asymptotics are often cast aside and given little attention. Being thorough, we address cointegration of the variable suite − fully aware of the diagnostic limitations when T is short. Cointegrating combinations of variables require resulting regression errors to be integrated of order zero, I(0). Analogous to panel unit root analysis, cross-section dependence plays an important role in panel cointegration testing. Diagnostic results from Table 5 suggest weak to no cross-sectional error correlation in our variable suite, therefore we proceed to test the panel for cointegration following Kao (1999).[13] The test statistic of 5.61 is sufficient to reject the null of the no cointegration at the < 1 percent level.

Table 6 shows the unconditional fixed effect results adapted for zero inflation (ZINB).[14] First, the log-likelihood test statistic (distributed chi-squared with 14 df) shown in the last row (left) indicates that year-effects, jointly, are not significantly different from zero thus favoring the one-way model.[15] The first column depicts raw coefficient estimates and statistical significance. The second and third columns of Table 6 present partial effects and elasticities computed at the means of the covariates for significant variables only. The dispersion parameter, α, is significantly different from zero indicating that the NB is

Table 6. Fixed effects ZINB estimation results

	Coefficient	Partial Effect	Elasticity
Cumulative Medals	0.0004*	0.0022	0.0394
Unemployment	-0.0264**	-0.1543	-0.1677
Politics	0.0035**	0.0207	0.0092
Non-White	0.0073	-	-
Income	-0.0010	-	-
Breweries	-0.0039**	-0.0228	-0.1014
Production	-0.0013***	-0.0076	-0.0466
Log-likelihood	-1,392	-	-
Dispersion, α	0.0304**	-	-
Vuong ZINB v NB	-0.2187	-	-
Year-effects	7.7	-	-

Significance at < 1% (***), < 5% (**), < 10% (*)

[13] Kao (1999) relies on cross-sectional independence or weak dependence as shown in Pesaran (2015).

[14] *LIMDEP 11*® used for estimation of all models.

[15] The log likelihood without state effects is -1,763.

the appropriate specification. Vuong (1989) provides a non-nested test statistic suitable to determine whether the zero inflation splitting is favored over the unaltered NB model. The statistic is distributed standard normal and is directional (+1.96 ↔ -1.96). Larger positive values favor ZINB while more negative values favor the unaltered NB. The test statistic provided in Table 6 has been corrected using Bayesian (Schwarz, 1978) information criteria (BIC). In extensive Monte Carlo trials, Desmarais and Harden (2013) show that the uncorrected Vuong statistic suffers size distortions favoring the ZINB specification. Post BIC correction in the Monte Carlo trials, the simulated statistic selects the NB model with a p-value < 0.05. Herein, the BIC corrected statistic lands in the inconclusive zone of the distribution close to zero. Because there is no clear rejection of the zero-inflated model post correction, we choose *not* to ignore the import of the data-generating process.[16]

Significant placed-based characteristics that influenced medal wins include cumulative medals won by breweries in a state, the economic condition of the state measured by unemployment, the partisan makeup of each state's legislature, brewery agglomeration in a state and the average brewery size in a particular state. Accumulating more medals over time increased the chance of winning. As noted above, including medal accumulation in the RHS suite may give rise to simultaneity issues. A version of the Hausman specification test, as suggested by Spencer and Berk (1981), is appropriate here. This residuals based framework fails to reject the null of no simultaneity at the less than 5 percent level.[17] Inclusion of medal accumulation appears to have little impact on the efficiency and consistency of the parameter estimates shown. The elasticity computed for this variable indicates that a 1 percent increase in medals accumulated by the average state increased the mean medal count by 0.04 percent, a very inelastic response. The aggregation of the data to the state-level is the likely culprit for the small elasticity estimates shown in Table 6. The significant positive relationship between medal accumulation and event-year wins confirms the legacy notion mentioned earlier. In order to provide more context, Table 7 shows the eight states that comprise 60 percent of all

Table 7. Medal accumulation to 2022

State	Medals	Share
California	1,362	19.71%
Colorado	885	12.81%
Oregon	454	6.57%
Texas	342	4.95%
Washington	307	4.44%
Wisconsin	303	4.38%
Pennsylvania	274	3.97%
Illinois	224	3.24%
		60.07%

[16] See the Appendix to this paper for the results from the unaltered NB models.
[17] However, the null is rejected at less statistically imperious 10 percent level.

medals won since 1983. Odds of winning were certainly reduced if the entrant brewery was not part of this geographical club. One other significant positive relationship involves the political ideology of a state. As state legislatures leaned more democrat in composition, mean medal counts increased though the effect was very inelastic. This relationship likely reflects the importance of a location's cultural forces as influenced by political ideology (Yakovlev and Guessford, 2013; Hart and Alston, 2020).

The largest significant impact on medals won was the economic condition of a state as measured by unemployment. As unemployment increased, mean state medal counts declined. This result likely infers that poor economic conditions in a location, perhaps, limited entry and medaling odds by breweries from that ailing location.[18] Moving on, more breweries per capita in a state decreased the likelihood of winning medals. As noted in the data section above, states with the largest breweries per capita ratios are generally sparsely populated. New brewery growth to date has been dominated by the construction of very small facilities (see footnote 10). This combination of smallness appears to negatively impact entry and the odds of winning medals. Providing context, despite the competition's popularity, more than 70 percent of the active breweries in 2022 did *not* participate in the competition. Lastly, increasing average production per brewery in a state negatively affected mean medal wins. States with large production per brewery averages are generally dominated by big-beer facilities (see footnote 9). While big-beer has certainly won a fair share of medals over the years for their fizzy rice and corn water offerings, the growing number of GABF judged categories, subcategories and styles have clearly out flanked the behemoths' wheelhouse.[19]

The received literature, arguably, favors fixed effect estimators over random effects specifications (Greene, 2018). The random effects model requires exogeneity of all regressors and u_i from Equation (4), an obvious defect. With that, favoring completeness, we include random effects estimates in Table 8. Coefficient signs and significance are

Table 8. Random effects ZINB estimation results

	Coefficient	Partial Effect	Elasticity
Cumulative Medals	0.0008*	0.0044	0.0787
Unemployment	-0.0111*	-0.0595	-0.0647
Politics	0.0069***	0.0373	0.0165
Non-White	0.0029	-	-
Income	-0.0006	-	-
Breweries	-0.0064***	-0.0347	-0.1543
Production	-0.0012***	-0.0065	-0.0399
Log-likelihood	-1,502		
Beta Dist. Parameter, *a*	4.3291**		
Beta Dist. Parameter, *b*	0.8679***		

Significance at < 1% (***), < 5% (**), < 10% (*)

[18] Entries to the annual competition by state are not available publicly.
[19] In 2022, 177 different styles were judged.

relatively similar to the fixed effects estimates. Impact magnitudes, however, are quite different for some variables. For example, focusing on the elasticities, the cumulative medals impact roughly doubles and the affect of economic conditions (unemployment) is substantially reduced. While there is no standard method for choosing between the count model fixed and random effects specifications, the log likelihood from the random effects model is markedly smaller.

Conclusion

In their prominent article on the beer industry, Elzinga, et al. (2015) credited Fritz Maytag's purchase and resurrection of San Francisco's Anchor Brewing in 1965 as the Genesis of the small-beer (craft) segment. Maytag's pioneering influence was said to inspire many others to follow making San Francisco the "taproot" of this new industry sector. Hundreds of promising entrepreneurs, mostly from the Pacific states, contacted Maytag in those early days for advice and direction on opening new breweries (Elzinga, 2011; Tremblay and Tremblay, 2005). Maytag not only inspired other small commercial brewers, he reigned large over the influencers. After graduating from college in Virginia, Charles Papazian and a friend traveled to Wyoming and Colorado. He decided to relocate to Boulder, Colorado and found a job teaching in an elementary school (Shaer, 2020). Charlie was an avid homebrewer and was eager to share his skills and knowledge with the masses. The Colorado branch from the taproot was formed. In the same year of the authorization of H.R. 1337[20], an amendment enacted in 1978 allowing the production of beer and wine for personal use, Charlie founded both the American Homebrewers Association and the Association of Brewers, a U.S. trade organization (Shaer, 2020).[21] As part of the fourth annual National Homebrew and Microbrewery Conference in 1982, Charlie organized the first Great American Beer Festival. As established empirically herein, this taproot legacy, in the aggregate, matters when medals are awarded. This could be a consequence of economic geography, evolution and integration or, as some have argued, a good ole boys club.

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Appendix

Table A1. Unconditional fixed effects NB estimation results

	Coefficient	Partial Effect	Elasticity
Cumulative Medals	0.0005*	0.0029	0.0519
Unemployment	-0.0301**	-0.1618	-0.1759
Politics	0.0065***	0.0348	0.0154
Non-White	0.0035	-	-
Income	-0.0015	-	-
Breweries	-0.0041*	-0.0223	-0.0992
Production	-0.0015***	-0.0078	-0.0479
Log-likelihood	-1,396	-	-
Dispersion	0.0354***	-	-
Time Effects	16.6	-	-

Significance at < 1% (***), < 5% (**), < 10% (*)

Table A2. Random effects NB estimation results

	Coefficient	Partial Effect	Elasticity
Cumulative Medals	0.0009*	0.0049	0.0877
Unemployment	-0.0340*	-0.1823	-0.1981
Politics	0.0097***	0.0519	0.0230
Non-White	0.0036	-	-
Income	-0.0018	-	-
Breweries	-0.0044*	-0.0240	-0.1067
Production	-0.0014***	-0.0079	-0.0485
Log-likelihood	-1,508	-	-
Beta Dist. Parameter, *a*	4.2836*	-	-
Beta Dist. Parameter, *b*	0.8668***	-	-

Significance at < 1% (***), < 5% (**), < 10% (*)

Journal of Beer Economics, Vol. 1, No. 1, 2023, 75-90 .

Imported versus U.S. Domestic Beer Consumption: Asymmetric Lag Vector Autoregression Forecasts

Mitch Kunce[1]

Abstract

U.S. beer production for domestic consumption has declined by roughly 25 percent over the last two decades despite the concurrent 5 fold increase in local production facilities. Conversely, U.S. imports of beer for consumption, mostly from Mexico, have almost doubled over the same time period. Despite the conspicuous importance of rising imports, few studies were identified in the beer consumption literature that even mention U.S. imports in any part of the discussion or analysis. This paper seeks to fill the void by assessing the role future imports play on overall projected consumption patterns of beer in the U.S. Forecasts to 2033, of both imported and domestic beer consumption, are generated using vector autoregressions. Predictions suggest continued decline in domestically produced beer consumption and potential sharp increases in consumption of imports – particularly from Mexico.

Keywords: U.S. beer consumption, trade imports, vector autoregression forecasts
JEL Classifications: C32, C53, F10

Introduction

In the late 2000s, the resurgent period of brewery counts in the U.S. began (Elzinga et al., 2015). Since 2008, reporting brewery counts have increased by well over 4 fold (Kunce, 2023a). Interestingly, U.S. production for domestic consumption has declined by over 13 percent from 2008 despite the tremendous growth in local production facilities (Beer Institute, 2022).[2] In contrast, over the last two decades, U.S. imports of beer for consumption have roughly doubled (Beer Institute, 2023).[3] In 2022, imports reached just over 40 million barrels for the first time. Figure 1 depicts the exporting countries key to this most recent import consumption barrelage. Providing context, 2022 imports of Mexican produced beer far exceed the volume from the highly touted *craft* beer segment within the U.S. (Brewers Association, 2023).[4] Figure 2 shows the trends of U.S. consumption of both domestic and imported beer from 1946 to 2022. In this graph, total barrelage is converted to gallons consumed per legal drinking aged adult. The year 1980 appears to represent a structural break in both trends of U.S. consumption – more on this aspect in the examination below.

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[2] To be fair, 75 percent of breweries producing and paying taxes in 2022 brewed less than 1,000 barrels for the year (TTB, 2023). This small-beer segment best resembles the local specialty restaurant industry (Kunce, 2023b).

[3] Beer exported from the U.S. totaled 4.1 million barrels in 2008 and 3.8 million barrels in 2022 (TTB, 2023). The focus herein is on U.S. consumption as the potential export market appears limited.

[4] In 2022, 32.1 million barrels from Mexico versus 24.5 million barrels domestic craft.

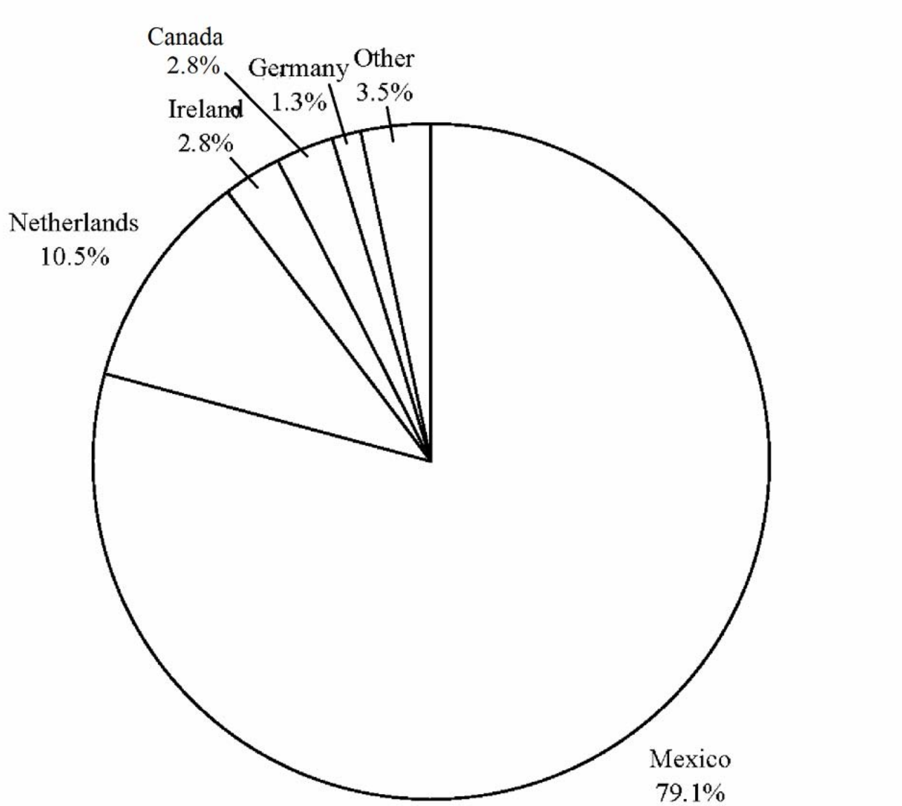

Figure 1. Share of beer imports by exporting country, 2022

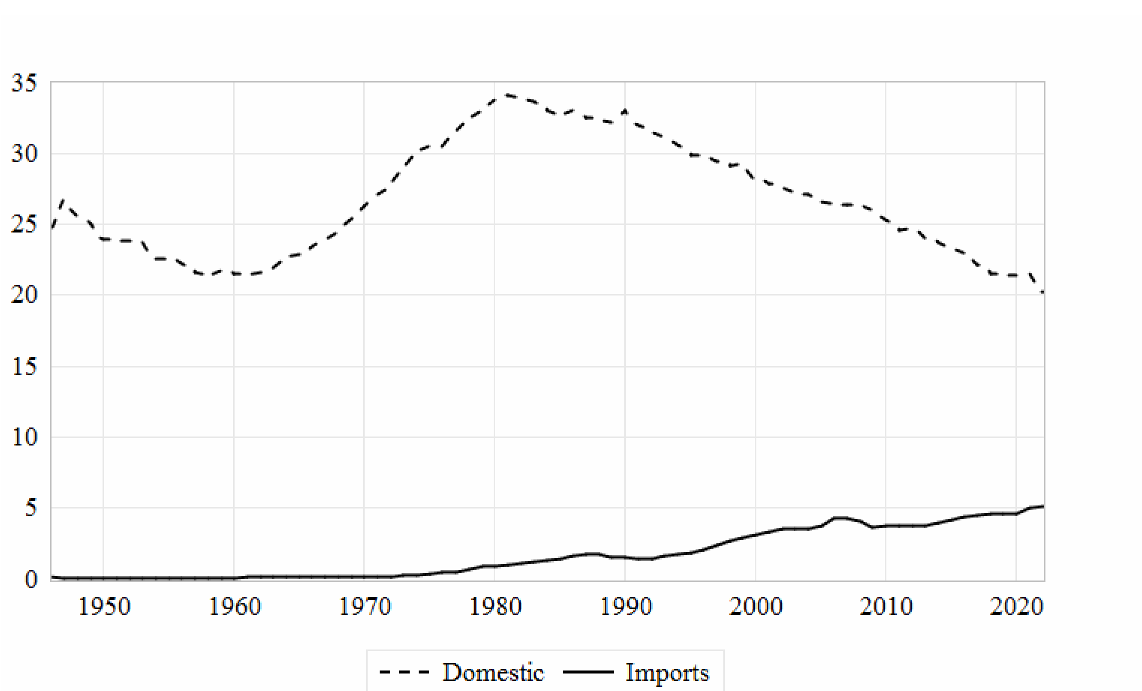

Figure 2. Consumption trends in gallons per legal drinking aged adults, 1949-2022

Despite the conspicuous importance of rising beer imports, few studies were identified in the literature that even mention U.S. imports in any part of the discussion or analysis. This paper seeks to fill the void by assessing the role future imports play on overall projected consumption patterns of beer in the U.S. Forecasts of both imported and domestic beer consumption are generated using vector autoregressions (VARs). A VAR is a multiple equation, multiple variable linear model where each variable is treated as endogenous and is explained by its own lagged values along with the lagged values of all other variables (Sims, 1980). Variable series lag selection is an important component of the VAR specification. Longer lag orders (over-fitting) can impact degrees of freedom and forecast error while under-fitting the lag lengths can generate error autocorrelation (Lütkepohl, 2007). Convention calls for symmetric lag length selected by minimizing Akaike (1987) (AIC) or Schwartz (1978) (SIC) statistical criterion. Herein, we follow Ozcicek and McMillin (1999) and Keating (2000) and attempt to improve upon symmetric lag selection by allowing for lag asymmetry by variable. Resulting predictions suggest continued decline in domestically produced beer consumption and, depending on the timeliness of the data used, potential sharp increases in consumption of imports – particularly from Mexico.

Data

Table 1 describes the data particulars for the two consumption series examined. Domestically produced beer consumption has declined by roughly 14 gallons per adult in the U.S. since 1980. Conversely, consumption of imported beer has increased by over 4

Table 1. Data descriptions, sources and descriptive statistics

Domestically produced consumption. Apparent U.S. beer consumption from domestic breweries by year (1946 - 2022) in gallons per legal drinking age population. Compiled by The Beer Institute (Brewer's Almanac) based on shipments and other reporting from individual states. The numerator reflects aggregated shipments and/or volume sales determined by local tax payments and/or state reports of malt beverage shipments (including malt-based seltzers, ranch waters, etc.) Population numbers (denominator) are aggregated by state (drinking laws may differ) by the U.S. Bureau of the Census. Sources: Beer Institute, Alcohol and Tobacco Tax and Trade Bureau (TTB), U.S. Bureau of the Census. Total barrelage (in millions of 31 gallon barrels): Mean 146.23, STD 39.77. Gallons per legal drinking aged adult: Mean 26.75, STD 4.12, lnMean 3.28, STD 0.15.
Imported for consumption. Imported malt-based alcoholic beverages for consumption in the U.S. in gallons per legal drinking age by year (1946 - 2022). Sources, Beer Institute, U.S. Department of Commerce, U.S. Bureau of the Census. Total barrelage (in millions of 31 gallon barrels): Mean 11.65, STD 12.74. Gallons per legal drinking aged adult: Mean 1.73, STD 1.69, lnMean -0.40, STD 1.71.

gallons per adult over the same time period (see Figure 2). Herein, both series are converted to natural logarithms as a means to reduce growth in variance over the 77 year time horizon. As we proceed, it is necessary to determine whether the underlying stochastic processes that generated the two data series are invariant with time. VARs require that the two series are stationary at level or first difference. Table 2 presents unit root testing for both series in natural log. Results verify that the two series are integrated

Table 2. Unit root testing, null is unit root

	lnDomestic	Lags/ Bandwidth	lnImports	Lags/ Bandwidth	Exogenous
At Level:					
Augmented Dickey-Fuller	-1.497	4, AIC	-2.130	4, AIC	Constant, Trend
Phillips-Perron	-0.096	5, Newey-West	-1.833	1, Newey-West	Constant, Trend
At First Difference:					
Augmented Dickey-Fuller	-3.284*	2, AIC	-3.186*	3, AIC	Constant, Trend
Phillips-Perron	-6.836***	4, Newey-West	-5.807***	7, Newey-West	Constant, Trend

Significance at: (***) < 1%, (**) < 5%, (*) < 10%.

of order one, I(1).[5] Structural change and unit roots are closely related (Perron, 1989). We determine break dates in the two series endogenously from the data by using break-date unit root methodology. Results find a break at the year 1981 for the lnDomestic series and 1979 for the lnImports series. An examination of the significance of these structural breaks follows in the *estimation results and forecasts* section below.

Model

Following Ozcicek and McMillin (1999) and Keating (2000), a bivariate, asymmetric lag VAR becomes,

$$\begin{aligned} \ln IMP_t &= \alpha_1 + \sum_{i=1}^{k} \beta_{1i} \ln IMP_{t-i} + \sum_{j=1}^{l} \phi_{1j} \ln DOM_{t-j} + \varepsilon_{1t} \\ \ln DOM_t &= \alpha_2 + \sum_{i=1}^{k} \beta_{2i} \ln IMP_{t-i} + \sum_{j=1}^{l} \phi_{2j} \ln DOM_{t-j} + \varepsilon_{2t} \ , \end{aligned} \tag{1}$$

where α, β, ϕ are estimated parameters and lag lengths k and l can differ. The ε represents white noise innovation processes that are assumed uncorrelated with the leads and lags of the innovations and uncorrelated with all of the right-hand-side (RHS) variables. Given the type of lag structure defined in Equation (1), variable lag combinations are then simulated in order to choose the minimum AIC model coupled with the minimum forecast (within sample) root mean squared error (RMSE). AIC and similar forms consistently outperformed other criteria in both lag selection and forecast performance in

[5] VARs do not require cointegration of I(1) series. For completeness, Appendix Table A1 shows the results of Johansen cointegration testing. Results present weak support of a cointegrated pair.

Monte Carlo simulations conducted by Ozcicek and McMillin (1999).[6] In contrast, SIC imposes too many constraints on reduced form dynamics that may lead to inconsistent estimates (Keating, 2000). Bergmeir et al., (2018) pointed out that the use of RMSE is most common in evaluating time series prediction as it operates on the same scale as the data.

Estimation results and forecasts

First we estimate and predict, conservatively, with the full sample model, then explore any significant differences resulting from the series' structural deviations.

Full sample

Standard symmetric lag selection methods, as suggested by Lütkepohl (2007), choose 5 lags for both series.[7] The resulting AIC for the symmetric model is -7.59. Static within sample forecasting (one-step ahead) evaluation computes a RMSE of 0.0147 for the lnDomestic series and 0.0658 for the lnImports series. Asymmetric lag selection methods choose a model with $l = 5$ lags for lnDomestic and $k = 3$ lags for lnImports. The AIC for the asymmetric model is -7.68. Forecast RMSEs are calculated as 0.0146 (lnDomestic) and 0.0647 (lnImports). The asymmetric model appears to provide modest improvement over conventional estimation methods. Table 3 presents the coefficient estimates for the asymmetric specification. Interestingly, 11 of 18 coefficients are statistically significant

Table 3. Asymmetric vector autoregression estimates

	lnDomestic	**lnImports**
Constant	0.061	-0.056
lnImports(-1)	-0.039*	1.186***
lnImports(-2)	0.083**	0.017
lnImports(-3)	-0.046**	-0.218**
lnDomestic(-1)	1.171***	-1.042*
lnDomestic(-2)	-0.135	1.784**
lnDomestic(-3)	0.198	-1.319
lnDomestic(-4)	0.057	1.778**
lnDomestic(-5)	-0.309***	-1.173***
R-squared	0.98	
Log likelihood	293.95	
Akaike information criterion	-7.68	

Significance at: (***) < 1%, (**) < 5%, (*) < 10%.

at conventional levels. Keating (2000) found that asymmetric VARs generally lead to a higher percentage of significant coefficients over the standard model.[8] Model stability and residual diagnostics, presented in the Appendix to this paper (see Figure A1 and

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[6] For example, Keating (2000) fashioned his own version of AIC.
[7] Eviews software is used for all model estimation.
[8] In the symmetric 5 lag model estimated for comparison, 10 of 22 coefficients were significant.

Table A2), confirm VAR stability conditions and no autocorrelation resulting from lag selection.

Customary practice in VAR analysis is to report Granger-causality tests and forecast error variance decompositions (Stock and Watson, 2001).[9] Granger-causality examines whether lagged values of one variable aid in the prediction of another. Table 4 summarizes the results for our two variable VAR. It shows p-values associated with block exogeneity Wald tests. Neither variable helps predict the other at the 5 percent level. Both are significant at the less statistically imperious 10 percent confidence. The

Table 4. Granger-causality

	Dependent Variables	
RHS	**lnDomestic**	**lnImports**
lnImports	0.064	0
lnDomestic	0	0.085

forecast error decomposition is the percentage of the variance of the error made in forecasting a variable due to an innovation in another variable at a given future period. Table 5 shows the decompositions for one-step ahead forecasts to 1, 5 and 10 years. For example, at the 10 year horizon, 40 percent of the error in the forecast of lnImports is attributed to innovations in the lnDomestic series.

Table 5. Variance decompositons ordered as lnDomestic, lnImports

Variance Decomposition of lnImports (in percent)			
Forecast Horizon	**s.e.**	**VD lnImports**	**VD lnDomestic**
1	0.072	100	0
5	0.219	96	4
10	0.413	60	40
Variance Decomposition of lnDomestic (in percent)			
Forecast Horizon	**s.e.**	**VD lnImports**	**VD lnDomestic**
1	0.016	0	100
5	0.048	0	100
10	0.128	1	99

Figures 3 and 4 illustrate the VAR within sample forecast accuracy for the lnDomestic series. Figure 4 depicts the forecast with plus or minus 2 standard error intervals. Figures 5 and 6 depict the same for the lnImports series. Our asymmetric VAR appears to be a powerful tool for describing and predicting the beer consumption data.

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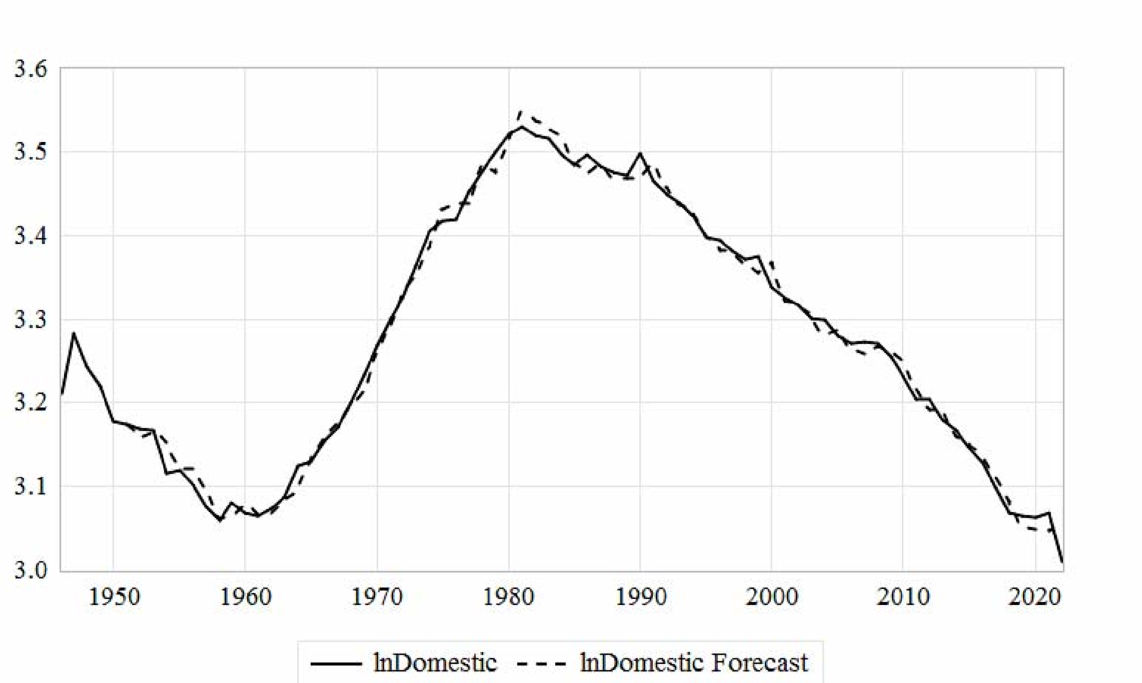
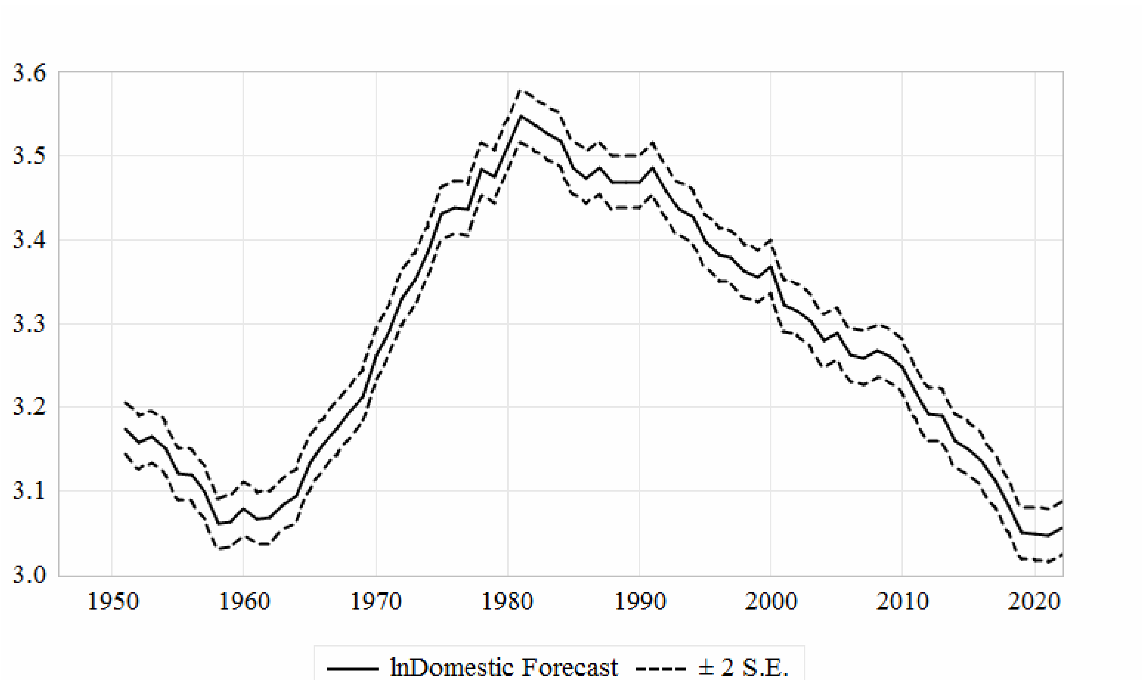
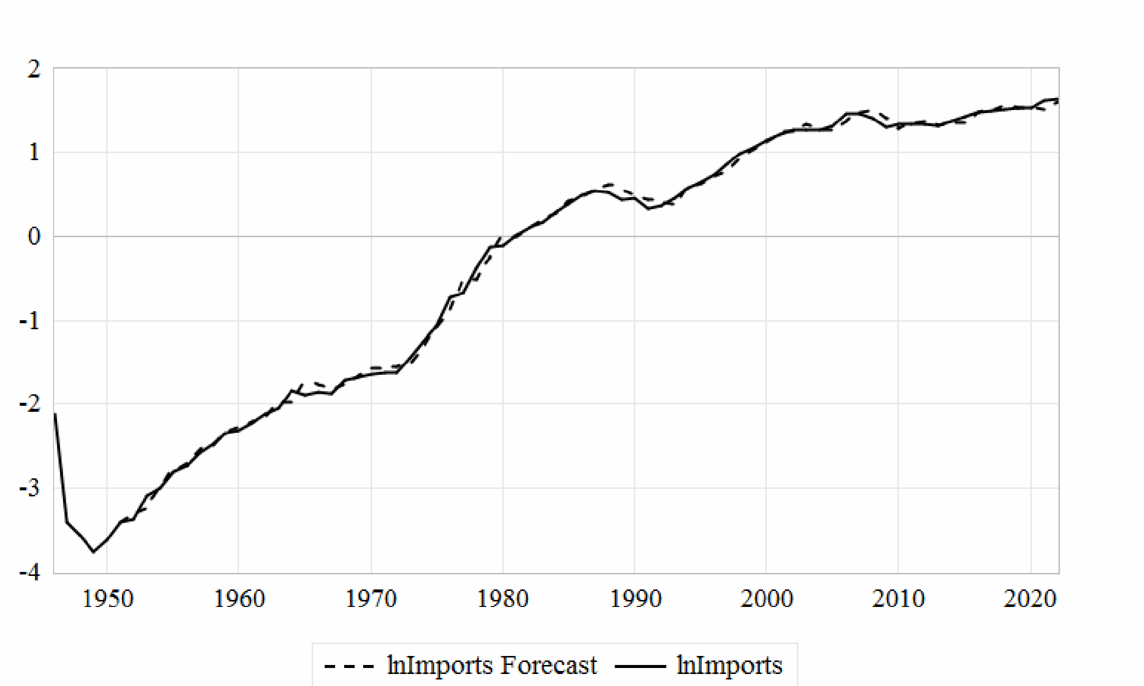
[9] Impulse responses are also listed – we are less interested in the impacts of unexpected shocks and more interested in reliable forecasting of the two series.



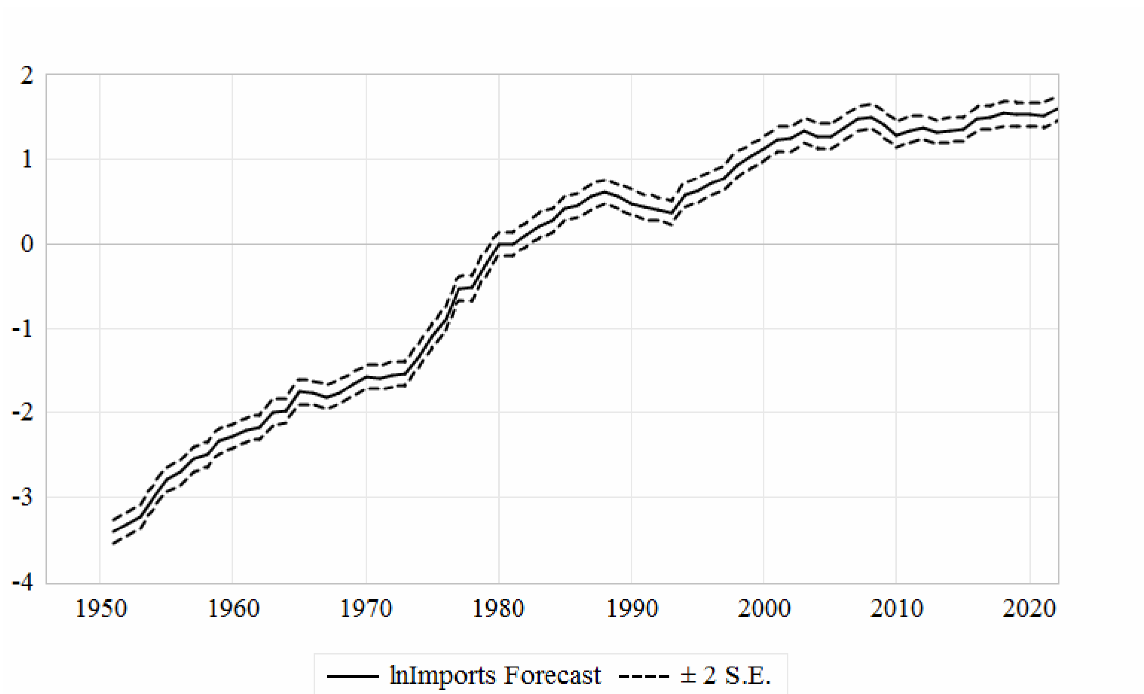
Fiqure 3. Within sample lnDomestic forecast



Fiqure 4. lnDomestic forecast with confidence bands



Fiqure 5. Within sample lnImports forecast



Fiqure 6. lnImports forecast with confidence bands

Regarding out of sample forecasts, Figures 7 and 8 focus on predictions for the years 2023 to 2033. The forecast steps ahead one year using the estimates in Table 3, then re-estimates the VAR including the new forecasted series points, then makes the next year forecast and so on through the year 2033. For exposition purposes, we converted the forecasted series back to gallons consumed per legal aged adult. Moreover, plus or minus 2 standard error confidence bands are shown as high and low predictions. To add historic

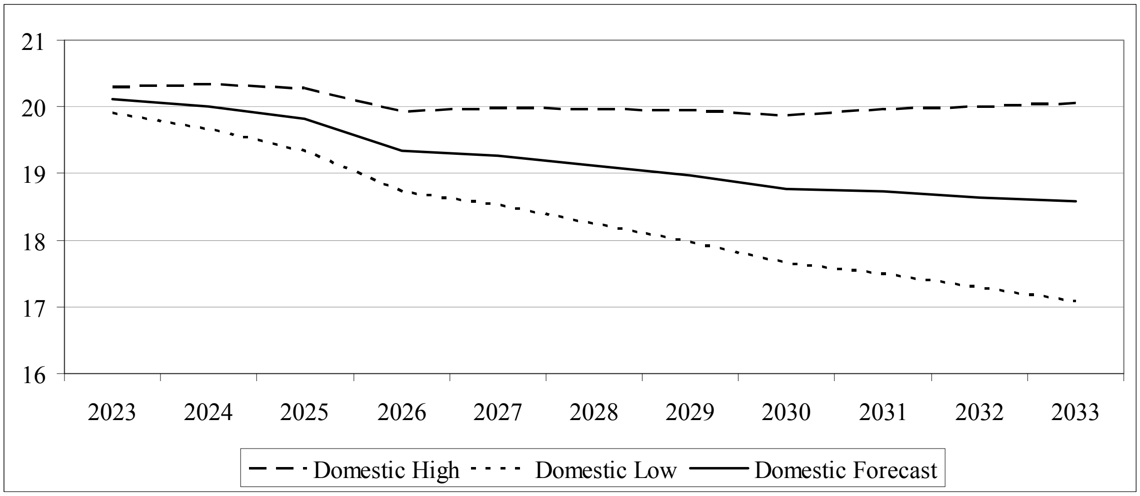


Figure 7. Domestic beer consumption future forecast and confidence bands

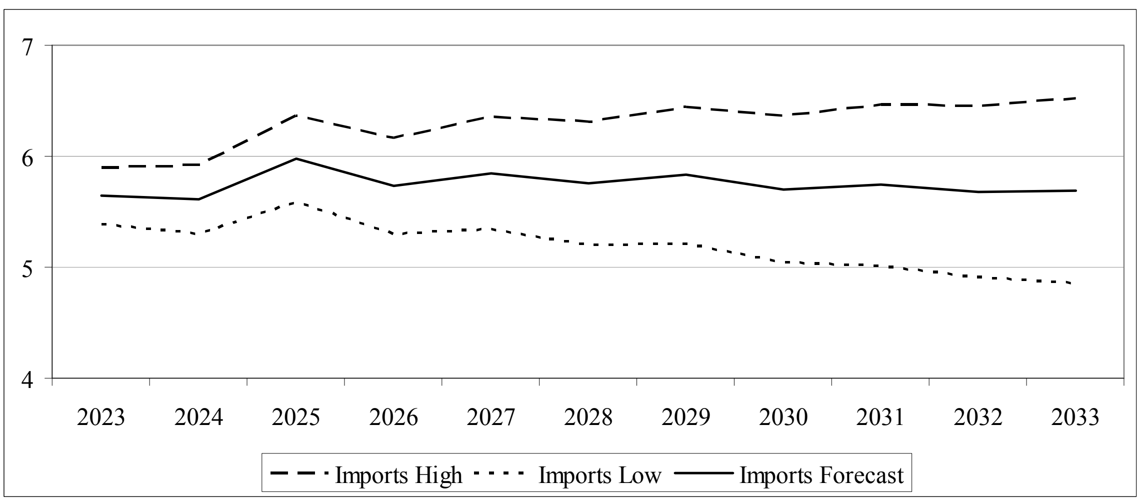


Figure 8. Imported beer consumption future forecast and confidence bands

context, Figure 9 marries 1946 to 2022 actuals with the future forecasts separated by the bold vertical line. Conservative predications suggest continued decline in domestic produced consumption. From 2022 to 2033, domestic consumption is projected to decline by roughly 8 percent to 18.58 gallons per legal aged adult. Projections for imports, on the other hand, initially rise sharply then level off to an overall increase of just above 10 percent from 2022 to 5.69 gallons per adult in 2033.

Post breakpoint sample

In the discussion above, unit root analysis identified structural breaks in both consumption series–1981 for lnDomestic and 1979 for lnImports. In this section, we split the difference in estimated break points and analyze data from 1980 to 2022. Both series

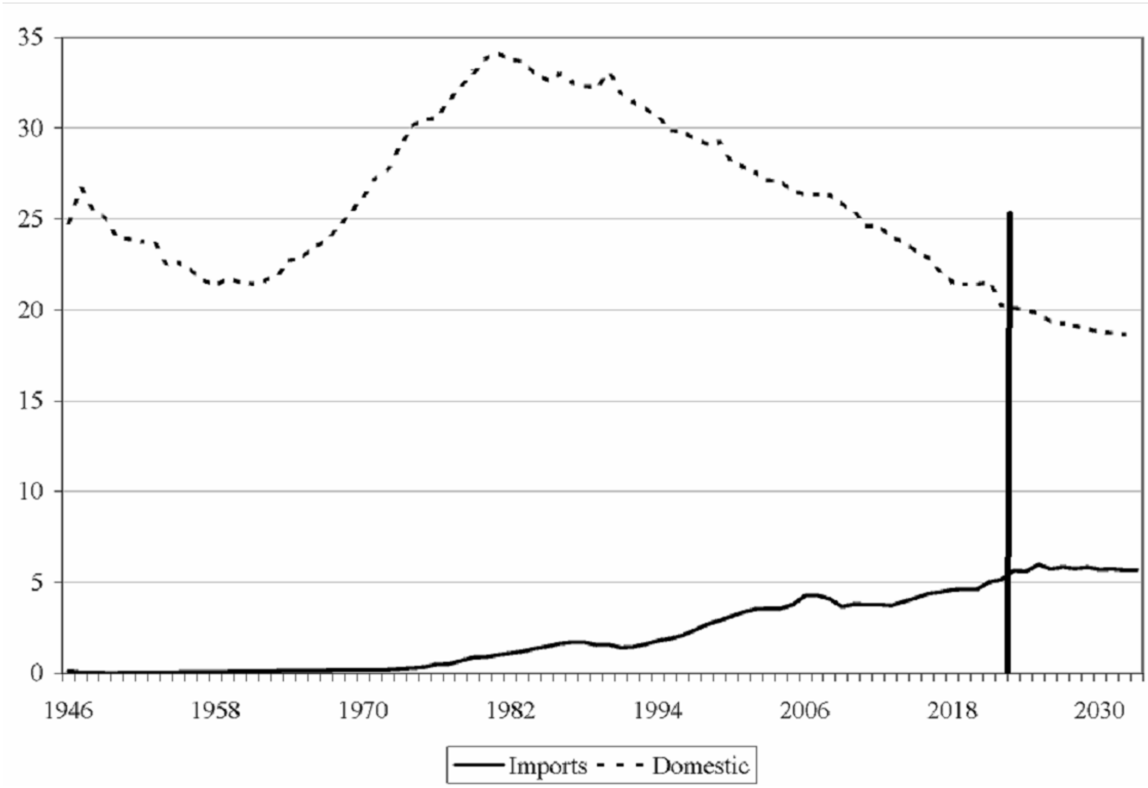


Figure 9. U.S. beer consumption by source, 1946 to 2022, projected to 2033.

exhibit strong linear trends from 1980 forward (see Figure 2) which may lead to zealous predictions. Following the same methods preformed on the full sample above, a symmetric VAR with 3 lags for each variable was chosen based on analogous criterion. The minimum AIC was -8.65 for the (3,3) model. This specification also provided the lowest within sample forecast RMSE for both lnDomestic (0.0119) and lnImports (0.0457). Lag asymmetry did not improve the fit or forecast performance of the post breakpoint model. Figures 10-12 depict these 11 year forecasts.

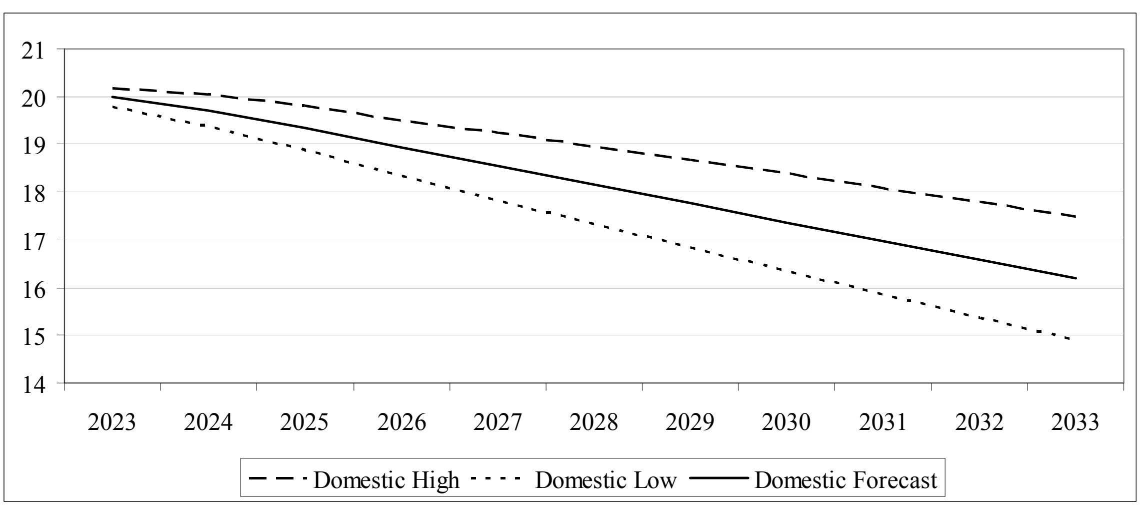


Figure 10. Domestic beer consumption future forecast and confidence bands

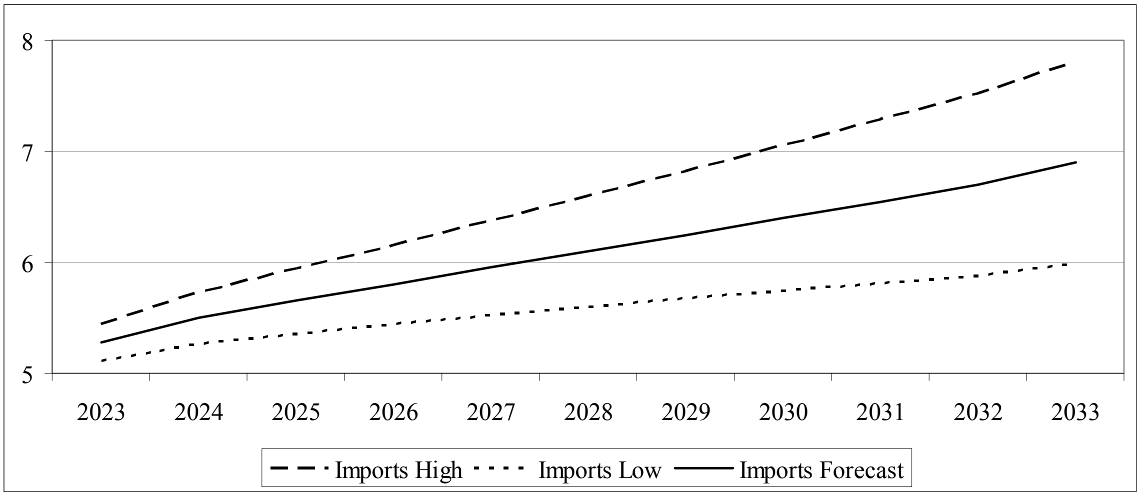


Figure 11. Imported beer consumption future forecast and confidence bands

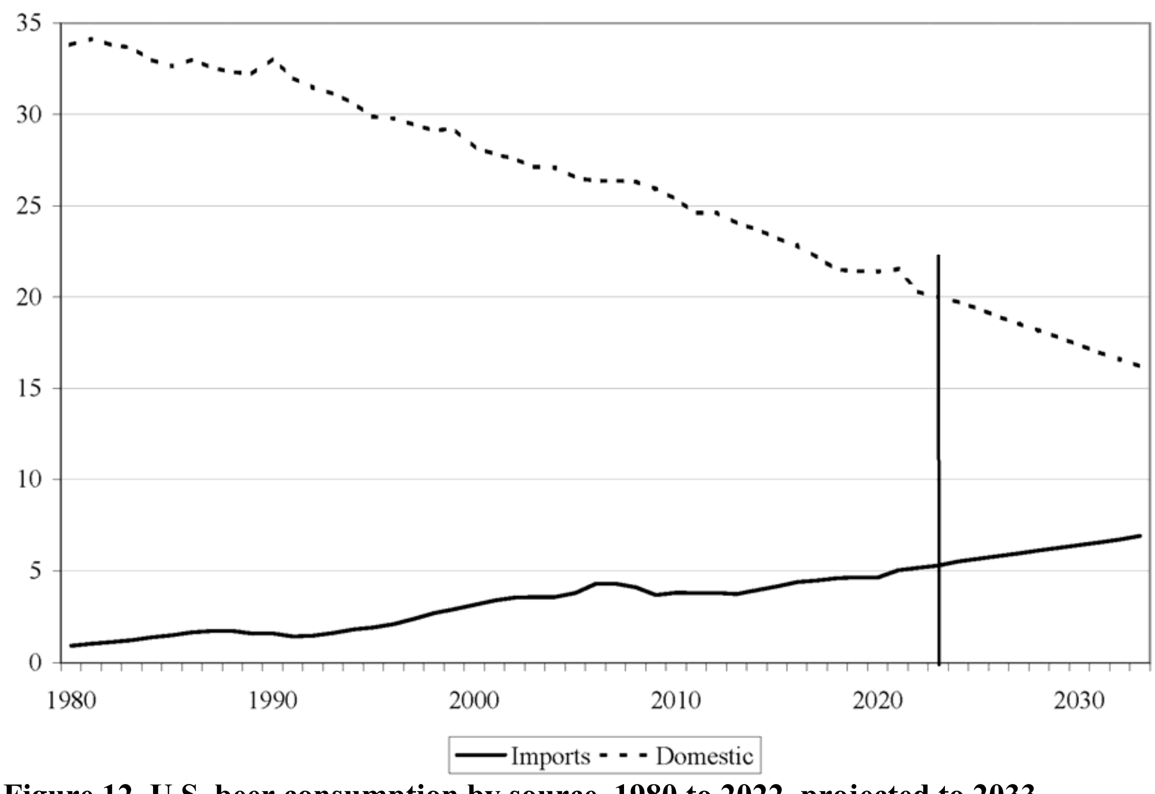


Figure 12. U.S. beer consumption by source, 1980 to 2022, projected to 2033

As expected, out of sample projections for this truncated model follow a strict linear trajectory. The more recent data projects a sharper decline in domestically produced beer consumption. From 2022 to 2033, domestic consumption is projected to decline by roughly 20 percent to 16.19 gallons per legal aged adult. Projections for imports show a continued rise to 6.90 gallons per adult in 2033, an over 30 percent increase from 2022. Interestingly, beer import volume data from the U.S. Department of Commerce, year-to-date September 2023, show imports on track to exceed those tallied in 2022 (Beer Institute, 2023). Additionally, domestic consumption tax collections through September of 2023 are down compared to the prior year indicating that domestic beer consumption is continuing to slide (Beer Institute, 2023).

Conclusion

The projected result of continued decline for domestically produced beer consumption in the U.S., as demonstrated herein, is shared by industry insiders and media (Infante, 2023; Stein, 2023). The buried lead in our analysis is that *actual* domestic beer consumption is falling faster than portrayed.[10] Recall that the Beer Institute's domestic consumption data includes shipments of flavored malt beverages (FMBs).[11] FMB is the industry vernacular for fermented seltzers, teas, lemonades, ranch waters, etc. In 2022, the barrelage of these beer alternatives reached roughly 11 percent of total domestic consumption shipments (IRI, 2023). Moreover, FMBs were the only domestic segment that gained noticeable volume in 2022 (Beverage Industry, 2023). Conversely, the future for Mexican imports looks *brillante* (Moreno, 2023). With Grupo Modelo and Constellation Brands leading the way, data herein project imported beer for consumption (per adult) to increase by 10 to, perhaps, 30 percent (in volume) over the next decade.[12]

As Figure 2 illustrates, domestically produced beer consumption has been falling for over 4 decades. In 2023, U.S. consumers enjoy the most diverse selection of alcoholic beverages ever. Choice is great for consumers, but what are the ramifications for the thousands of breweries already operating in the U.S. and the thousands more on the horizon? In the early 1980s, less than 100 breweries were producing in the U.S. In September of 2023, the TTB reported just under 15,000 active permits where roughly half are reporting production and paying taxes.[13] Moreover, there are likely hundreds more in the application pipeline. Let this sink in, rising domestic production capacity in a market where consumption of the domestic output is in decline, where competition from imports is fierce and the potential for export trade is thin. To be fair, the vast majority of these new breweries are very small (restaurant like) and, if they survive, will likely remain localized and small (Kunce, 2023b; Infante, 2023). Not to worry though, behemoths like Anheuser-Busch InBev and Molson Coors are adapting to the new trends and will certainly endure.

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[10] *Actual* meaning traditional malty, hopped, beer flavored beer.
[11] See Table 1.
[12] Anheuser-Busch InBev owns Grupo Modelo and the brands Modelo, Corona and Pacifico. Constellation Brands only owns U.S. rights to these brands (Moreno, 2023).
[13] In the U.S., all alcohol production is sanctioned by the Alcohol and Tobacco Tax and Trade Bureau (TTB).

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Appendix

Table A1. Johansen cointegration test

Trend assumption: Constant, Trend				
Lags interval (in first differences): 1 to 2				
Unrestricted Cointegration Rank Test (Trace)				
Cointegrating Relations		Eigenvalue	Statistic	P-Value
None		0.216	25.412	0.057
At most 1		0.095	7.412	0.304
-Trace test indicates no cointegration at the 5 percent level.				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Cointegrating Relations		Eigenvalue	Statistic	P-Value
None		0.216	18.000	0.079
At most 1		0.095	7.412	0.304
-Max-eigenvalue test indicates no cointegration at the 5 percent level.				
Varying Trend and Test Assumptions				
Selected (5 percent level) Number of Cointegrating Relations**				
Data Trend:	None	None	Linear	Linear
Test Type:	No Constant	Constant	Constant	Constant
	No Trend	No Trend	No Trend	Trend
Trace	1	0	0	0
Max-Eigenvalue	0	0	0	0

Cointegration is not rejected at the 10 percent level. Increasing lag intervals leads to rejecting the null of no cointegrating relations at the 5 percent level. This test specification suffers reduced power when sample sizes are relatively small.

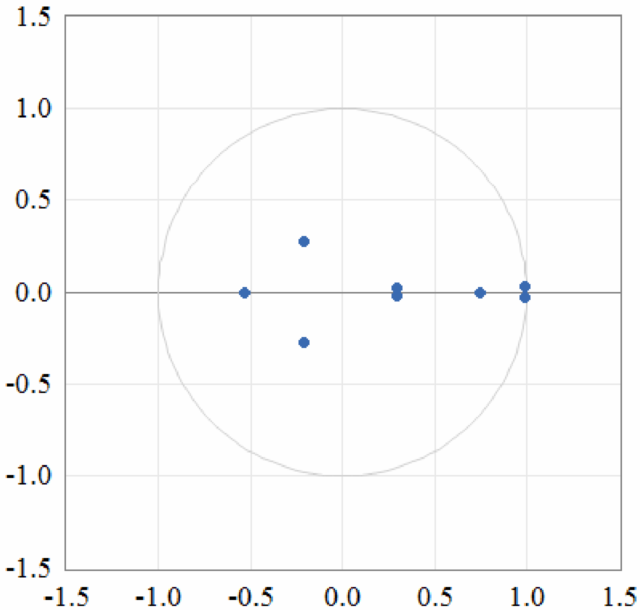

Figure A1. Inverse roots of the autoregressive characteristic polynomial

No root lies on or outside the unit circle. VAR satisfies the stability condition (Lütkepohl, 1990; 2007).

Table A2. VAR Residual Serial Correlation LM Tests

Null hypothesis: No serial correlation at lags 1 to 5				
Lag	**LRE statistic**	**P-value**	**Rao F-statistic**	**P-value**
1	1.601265	0.8086	0.399646	0.8086
2	4.005524	0.8566	0.496375	0.8567
3	5.269146	0.9484	0.429939	0.9485
4	8.981398	0.9142	0.548301	0.9146
5	9.842353	0.9709	0.473233	0.9713

Two tests of lag selection impacts. Both the LRE and Rao forms are attributed to Edgerton and Shukur (1999). Here, introduced lag structure does not induce autocorrelation (see Bartels and Goodhew, 1981).

Journal of Beer Economics, Vol. 1, No. 1, 2023, 91-97 .

The Canary in the Coal Mine: An Examination of Recent U.S. Small Brewery TTB Reporting

Mitch Kunce[1]

Abstract

The brewing industry in the U.S. is heavily regulated and each permitted facility is required to report production operations to the Federal government periodically. Generally, larger volume breweries report monthly and smaller facilities report quarterly. Recent aggregated data from the Alcohol and Tobacco Tax and Trade Bureau show a rather steep decline in reporting entities (members). From the peak in March of 2022, September 2023 reporting members have declined by 23 percent. Using this monthly data beginning in 2012, an estimate of what an incremental (marginal) brewery contributes to overall industry output is computed using autoregressive seasonal regression analysis. Maximum likelihood results indicate that an incremental brewery contributes only 200 to 250 barrels per month to total industry output. Is this the canary in the coal mine for small-beer?

Keywords: Beer industry, production reporting, seasonal regressions
JEL Classifications: C22, L60, L88

Introduction

Each month, the Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau (TTB), publishes an aggregated public report entitled 'Monthly National Statistical Report - Beer'. Every brewery in the U.S. is licensed (i.e. Brewer's Notice) to operate by the TTB. Each permitted brewery is assigned a BR number and is required to complete a Brewer's Report of Operations either monthly or quarterly depending on taxed annual barrelage.[2] There is no annual filing option and reports must be submitted even if there was no activity during the period.[3] Reports are due the 15th day following the close of the reporting period. The TTB relies on these individual premises reports of production and removals as the source for the aggregated public report. Table 1 shows a section of the report for the month of September, 2023.[4] Number of industry members

Table 1. Monthly National Statistical Report, September 2023

Units: Beer Barrels (1 Barrel = 31 Gallons)	September 2023
Number of Industry Members	5,454
Production	13,690,622
Taxable Removals	12,785,337
In Bottles & Cans	10,909,733

[1] *Douglas**Mitchell*** Econometric Consulting, Laramie, WY USA

[2] Taxed annual barrelage triggers the liability threshold. If a brewery's tax liability is more than $50,000 in the current or prior year, monthly filing is required. Today, most breweries are below this threshold and file quarterly.

[3] 27 Code of Federal Regulations 25.297

[4] Report dated November 6, 2023, updated on November 15, 2023.

In Kegs	938,536
Tax Determined, Premises Use	937,068
Tax Free Removals	262,276
For Export (includes Vessels & Aircraft)	239,720
Consumed on Brewery Premises	22,556
Stocks on Hand End-of-Month	10,600,777

refers to the count of unique BR numbers filing any operational report for the period ending September 2023. Monthly data are available publicly from 2012.[5] Table 2 describes the data particulars for reporting member counts and production.

Table 2. Data descriptive statistics, January 2012 through September 2023

Reporting Member Count. Mean 2,168, STD 2,316, Minimum 499 (February 2012), Maximum 7,073 (March 2022).
Production in millions of barrels. Mean 15.463, STD 1.549, Minimum 11.814 (February 2022), Maximum 18.450 (June 2012). Correlation coefficient with reporting member counts, 0.208.

Figure 1 graphically depicts the reporting trends for the 2012-2023 data. Each horizontal tick represents a monthly count. The somewhat uniform shorter teeth of this comb-like graphic illustrates the rather consistent count of larger breweries reporting monthly. Unique reports peaked in the first quarter of 2022 and quarterly counts have declined thereafter. From the peak, quarterly reports have declined by 23 percent, 1,619 fewer BR numbers reporting in September 2023.[6] Is this the canary in the coal mine for small-beer?

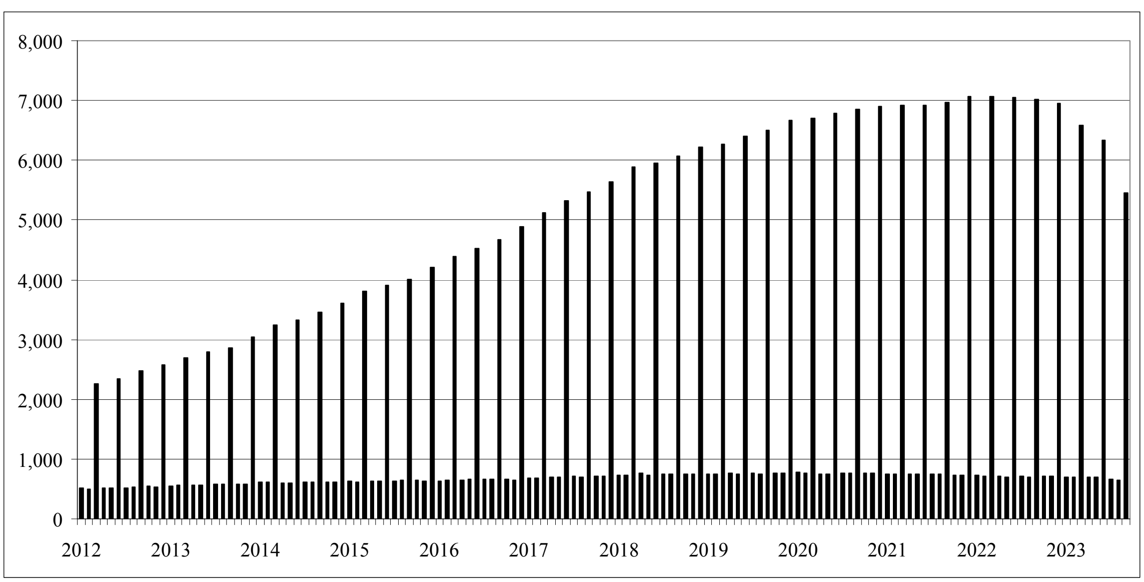

Figure 1. Reporting brewery count by month[7]

[5] Brewery counts prior to 2012 never reached the level depicted in this most recent data (Elzinga et al., 2015).
[6] The TTB notes that reporting counts may change due to late operational reporting.
[7] Shorter teeth mean, 676. Quarterly reporting mean, 5,153.

Figure 2 shows the monthly reported production in millions of 31 gallon barrels. Note the midyear seasonality (cycle) of the data and the evident downward time trend. This downward trend indicates that macro-facilities, in light of the recent loss of small brewery reporting, have been producing less over time. In the next section we estimate, using the TTB data, what an incremental (marginal) brewery contributes to overall U.S. monthly beer production.

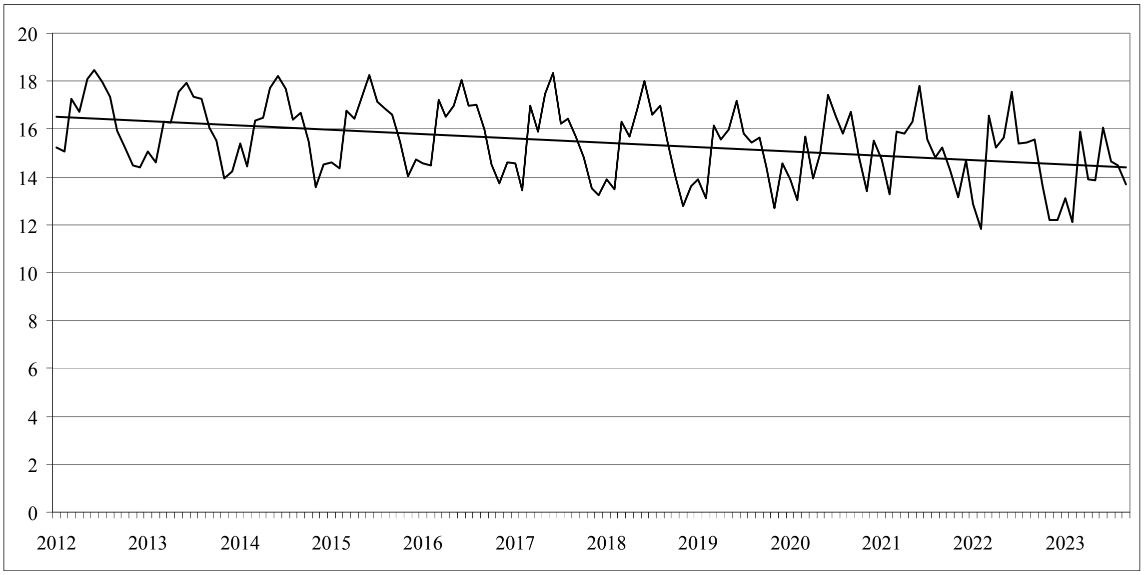

Figure 2. Reported production by month with trend, in millions of barrels

Estimation

As we proceed, it is necessary to test whether or not the underlying stochastic processes that generated the two data series are invariant with time. Standard and seasonal unit root testing confirm non-stationarity at level for both series.[8] Generally, non-stationary variable series should not be used in conventional regression models. However, if a linear combination of two is stationary, we can proceed in a rather stylized manner. Technically, the errors of this said combination are integrated of order zero, I(0). Series that satisfy this requirement are desired and defined as cointegrated (Engle and Granger, 1987). A natural first step in the analysis of cointegration is to establish that it is indeed a characteristic of the data. Table 3 shows the residual based cointegration test results based on Phillips and Ouliaris (1990). The null of no cointegration is rejected by both

Table 3. Cointegration testing

Long-run variance estimate (Pre-whitening with lags = 4 from Schwarz (1978) criterion).	
Phillips-Ouliaris tau-statistic	-3.708447**
Phillips-Ouliaris z-statistic	-23.40912**

**Significant at the < 5% level.

[8] Standard unit root testing based on Phillips and Perron (1988) and Perron (1989). Seasonal testing based on Hylleberg et al. (1990). Both series are stationary at first-difference.

statistics generated. As noted above, both series fluctuate cyclically – quarterly for reporting and midyear for production. If the cyclical fluctuations in the right-hand-side (RHS) fully accounted for the variability in the left-hand-side (LHS), precise coefficient estimation could result. However, seasonality appearing in the resulting residuals may pose problems. Figure 3 depicts the residuals of regressing production on reporting breweries and a constant term.

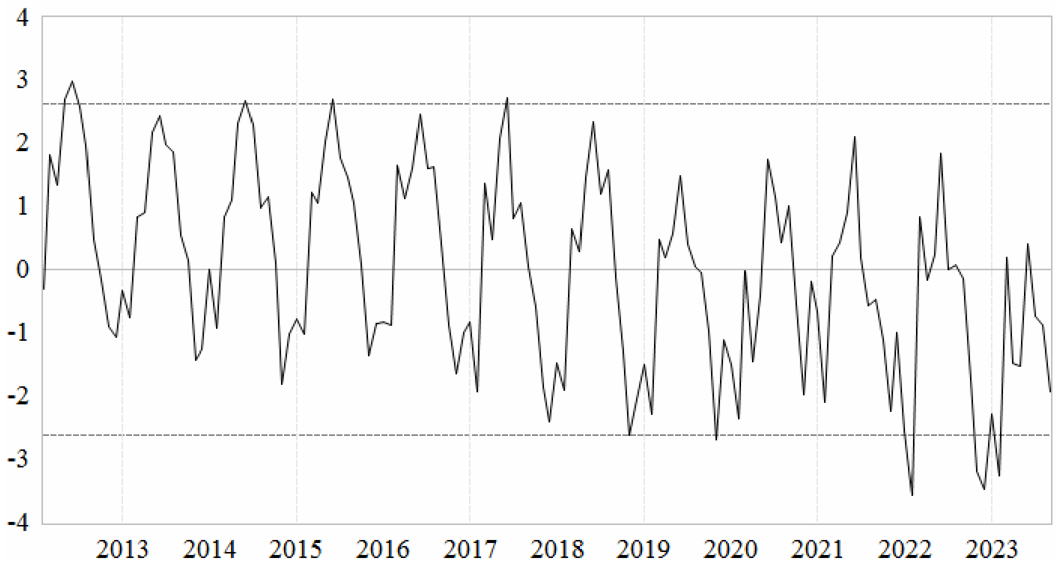

Figure 3. Base regression residuals

Clearly the regression errors indicate midyear seasonality. Many sophisticated techniques for deseasonalization have been suggested (see Lütkepohl, 2007 for a review), but the most basic is to simply include seasonal dummies in the RHS (Lovell, 1963). We propose the following basic seasonal specification,

$$\text{Prod}_t = \alpha + \text{Brew}_t\beta_1 + D_{it}\beta_2 + D_{it}\text{Brew}_t\beta_3 + \varepsilon_t , \tag{1}$$

where D_{it} is a scalar dummy equal to unity if period t is in the ith season, zero otherwise. The last term before the error represents an interaction between the season and the brewery count. Including the dummy variables alone presumes that the cyclical nature of data is separable and captured by the intercepts. The interaction term allows the slope to also vary with the cycles thus implying non-separable seasonality. The coefficient β_1 should provide a rough upper estimate of the marginal monthly production contribution of an incremental reporting brewery.[9]

Figure 3 also suggests serial correlation of the errors. The error term in Equation (1) then becomes,

$$\varepsilon_t = \rho_1\varepsilon_{t-1} + \rho_2\varepsilon_{t-2} + \ldots + \rho_p\varepsilon_{t-p} + u_t , \tag{2}$$

[9] Recall that smaller breweries are reporting 3 months of data, 4 times a year. Because of this aggregation, estimation of β_1 will be biased upward. Consider this aggregated monthly estimate a high-end limit. In an alternative ARDL framework estimated, marginal contributions were analogous to those found below.

allowing for higher order, more complex, autoregressive processes. Note that the ρ's represent the correlation coefficients between the errors over various time periods (p). Following Beach and MacKinnon (1978) we use maximum likelihood, initially addressing first-order serial correlation. Table 4 depicts monthly production regressed on two separate dummy variable specifications, midyear (June) and quarterly dummies. Note

Table 4. Maximum likelihood dummy variable only estimation results

	Midyear	**Quarterly**
Constant	15.327***	15.101***
Seasonal Dummy	1.378***	0.959***
ρ_1	0.607***	0.726***
Durbin-Watson	2.05	1.98
Log likelihood	-216.17	-203.18

Significance at: (***) < 1%, (**) < 5%, (*) < 10%.

the significant increases in reported production, peaking in the midyear. Table 5 shows the results for the two specifications of Equation 1. The interaction variables were highly insignificant and had little impact on other coefficient estimates. The estimated Durbin-Watson statistics suggest that more complex forms of residual correlation are unlikely (Bartels and Goodhew, 1981). Differenced transformed maximum likelihood results indicate that the marginal reporting brewery contributes, roughly, 200 to 250 barrels per month to total reported production. The core of production reported month to month is captured by the constant term then augmented by the seasonal adjustments. Think of the constant term as the production reporting by the *shorter teeth* of the comb-like graphic in Figure 1. Results herein bolster past findings suggesting that most of the 1000s of breweries built in the U.S. over the last two decades are significantly small and contribute little to overall industry output, at the margin (Kunce, 2023). Some industry insiders even advocate for small-beer to be set apart as a unique industry akin to restaurants (Beer Institute, 2023; Beverage Industry, 2023; Halter, 2023; Vorel, 2023).[10] How this all plays out over the next decade will be interesting.

Table 5. Maximum likelihood estimation results

	Midyear	**Quarterly**
Constant	14.9529***	14.9189***
Reporting Breweries	0.00020***	0.00025***
Seasonal Dummy	0.41704*	0.16568*
Interaction Term	a	a
ρ_1	0.75496***	0.76902***
Durbin-Watson	1.99	1.94
Log likelihood	-196.58	-197.77

[a]The interaction terms were highly insignificant and dropped from the final model.
Significance at: (***) < 1%, (**) < 5%, (*) < 10%.

[10] Halter (2023) quotes Bart Watson, chief economist for the Brewers Association (2023), "craft brewing has turned into a normal market like the restaurant industry."

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