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About This Journal

The *Journal of Beer Economics* is an international, peer-reviewed, free, open-access journal focusing on the economics of the beer industry and related supporting industries. We publish reviews, theoretical and empirical research papers, and select industry communications. Our aim is to encourage a further understanding of industry issues in a scholarly manner.

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From 'Can or Die' to 'Can and Die'? A Structural ARDL Model of Small-Beer Packaging Trends

Mitch Kunce[1]

Abstract
Prohibition and its repercussions ended most small breweries that had a chance to be profitable prior to 1920. By 1982, roughly 50 breweries were operating in the U.S. The relaxation of devolved post-prohibition on-premises restrictions, in the 1980s and 1990s, is observably responsible for the unprecedented growth in small brewery counts to date. When veering from this refreshed on-premises model, to a more outside distribution form, the future of these small breweries is placed into question. Herein, we examine trends in keg and package (cans and bottles) removals data from the Alcohol and Tobacco Tax and Trade Bureau (TTB). Structural autoregressive distributed lag (ARDL) estimation links reporting brewery growth as long-run forcing to declines in proportional keg removals. For package removals, we find a significant upward structural shift and more volatility in the package share, post 2019. Small-beer's role in this shift is implied but not statistically imperious.

Keywords: Beer industry, production reporting, ARDL regression with breakpoints
JEL Classifications: C22, C49, L60

Introduction
In 1981, Herbert 'Bert' Grant started the makings of the Yakima Brewing and Malting Company in Yakima, Washington. Bert's initial business model involved selling in-house manufactured ales on-premises or to-go (Grant and Spector, 1998). Contrarily, Bert's on-premises business plan violated the state's three-tiered distribution laws (Acitelli, 2013). You see, post repeal of the Volstead Act in December of 1933, legislation was enacted nationwide leading to the creation of the devolved tiered regulation of beer sales by each state. Three tiers, in fact, as the standard – manufacturer to distributor, distributor to retailer, retailer to the customer. The goal of the separation was to prohibit alcohol manufacturers from owning saloons, distributorships, or serving on-premises, tempering the excesses that lead to the calls for prohibition in the first place (Stack, 2000). Prior to 1920, what Bert Grant wanted to do was somewhat common industry practice. Prohibition and its repercussions ended most small breweries that had a chance to be profitable prior to its ratification. From 1935 to 1980, brewery counts in the U.S. declined by roughly 8 fold (Stack, 2003). While Bert cobbled together his brewery in the confines of the old North Yakima Opera House, the state of Washington's Senate took up Bill 3206 aimed at making Yakama Brewing's proposed business model legal (WSL, 1981). When Bert Grant officially opened his permitted brewery in July of 1982, his was one of roughly 50 still active in the U.S.[2]

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[2] Total reported domestic production in 1982 was 194 million barrels – brewed, chiefly, in 37 large facilities (TTB, 2024). In his book, Bert recalled giving out 'free' beer for many months prior to his permitted opening (Grant and Spector, 1998). Later in the 1980s, Yakama Brewing began to bottle and

Prohibition led to another important industry change that serves as the motivation for this paper – how beer is sold. Prior to 1920, nearly all beer was sold on-tap (draft) in saloons and other establishments, many owned by the manufacturers. Buy the early 1980s, 90 percent of beer sold in the U.S. was bottled or canned (Stack and Gartland, 2011). Post-prohibition devolved dispensing and distribution regulations and the costs involved in properly packaging beer in bottles or cans for distribution contributed to industry concentration.[3] The larger "shipping" breweries benefited from technological and scale economies gained from investments made, even before prohibition (Stack, 2003). In addition, the larger breweries worked with legislatures to enact new law that favored their production and distribution forms while, in chorus, marketing their packaged beer extensively with massive advertising campaigns (Fogarty, 1985; LaForge, 1987; Stack and Gartland, 2011). Bert Grant's initial defiance of this post-prohibition distribution model influenced the passage of Senate Bill 3206. Other states quickly followed suit with their own forms of on-premises legislation – 28 in the 1980s and the balance in the 1990s (Elzinga et al., 2015).

Now that all states have adopted on-premise retail sales and many allowing self distribution, very small brewing enterprises can capture all tiers of potential revenue thus increasing the likelihood of profitability (Kunce, 2021). Granting beer manufacturers this direct line to the consumer was central to the 140 fold increase in facilities from 1982 to 2022.[4] Predictably, most of these new breweries are very small – 75 percent of those reporting operations in 2022 produced less than 1,000 barrels for the year (TTB, 2024). A sort of Bert Grant pre-prohibition model is now in play, reliance on over the bar (on-premises or take home) revenues coupled with, perhaps, a very small proportion of outside distribution. Current breweries following this model may be very familiar to the reader. Yet for some small brewers, on-premises sales were not an option or just not enough. Seeing their bottles and cans in liquor stores throughout or their logo on a tap handle in a neighboring state was an itch that needed to be scratched. Early on, there were many packaging success stories, bottles and, later on, cans of Sierra Nevada, Samuel Adams (Boston Beer) and New Belgium abundant in liquor store coolers. Role models to those that followed.

In 1995, Twisted Pine Brewing opened in Boulder, Colorado. A little over one year later the brewery sold to Bob Baile who merged Peak to Peak Brewing and Twisted Pine under the Twisted Pine moniker. The brewery's initial focus was to package and distribute, following the lead of Colorado's trailblazer, Boulder Brewing Company.[5] In

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distribute, breaking from the founding tenet. Bert sold the company in 1995 and subsequently died in 2001. Sadly, the brewery shuttered all operations in 2005.

[3] See Stack and Gartland (2011) for an excellent treatise on the triumph of packaged beer in the U.S. The authors, in great detail, discuss the myriad of factors contributing to packaging dominance and how this dominance contributed to the consolidation of the industry into the early 1980s.

[4] See Tremblay and Tremblay (2005) and Elzinga et al. (2015) for an examination of the many factors that influenced this unprecedented growth.

[5] Sadly, Boulder Brewing shuttered all facilities in January of 2020 after 40 years of operation. Sleeping Giant, a Colorado contract brewer, was engaged at the time to keep a few brands on shelves (Shikes, 2020). As of the date of publication of this paper, we could only find a single brand, Buffalo Gold, being brewed by a new brewery, Boulder Social, under a new arrangement (https://www.besocialcolorado.com).

2003 Baile moved the brewery to a larger facility on Walnut Street, just east of downtown Boulder. The Walnut Street location allowed for the expansion of the bottling and canning operations along with a large taproom for on-premises sales. A small kitchen was added in 2010 with an even larger expansion planned for 2012. Post expansion, Twisted Pine's outside distribution covered, at one point, 13 states. Citing cost

Figure 1. Twisted Pine's cans

issues, shelf space battles and the necessity to focus on taproom sales where profit margins were higher, Twisted Pine ceased outside distribution in the spring of 2016 (Wallace, 2016). Twisted Pine's Bob Baile told Westword magizine in 2016 "It's (retail) a different business model, but one that works. . . The wholesaling end took up a lot of time and capital, and the return wasn't as good as the retail end" (Shikes, 2016). The brewpub survived the pandemic and remains open today. Some, however, were not so fortunate.

In 2013, Mike Isley opened Isley Brewing Company in the Scott's Addition area of Richmond, Virginia. Under a Bert Grant type model, the brewery became a local favorite. In June of 2019, the brewery began a canning operation. Four-packs of sixteen ounce cans were being distributed to seven city locations across the state of Virginia (Dickerson,

Figure 2. Isley Brewing's cans

2019). Isley's Choosy Mother peanut butter porter was gaining popularity across the state. On October 29, 2023 the brewery abruptly closed (Cantor, 2023). Material costs and lease issues were cited as reasons, but details were scant. The following month, Isley sold its rights to Choosy Mother to nearby Callao Brewing in Callao, Virginia (Platania, 2023). Callao's plans for its newly acquired brand were not disclosed.

The tales of these three enterprises are representative and highlight the import of how beer is sold. The relaxation of devolved post-prohibition on-premises restrictions is observably responsible for the unprecedented growth in small brewery counts in the U.S. Without the direct retail outlet, viability of these small enterprises wanes. For instance, the COVID-19 pandemic restrictions impacted small scale breweries disproportionately, compared to big-beer, by shutting down then limiting most on-premises sales. The rallying cry in the spring of 2020 was 'can or die' (Levy, 2020). With \$5 to \$8 draft pints off the table (or bar), on-site and mobile canning operations increased. Many of the new canning breweries, at the time, did not fully endorse an outside distribution campaign, rather, an on-premises take-out model that became a short-run lifeline.[6] In late spring of 2020, the Brewers Association surveyed over 500 small scale breweries regarding COVID-19 impacts. In response to the question, "Given current costs, revenues, and the current level of State and Federal aid, how long do you project you can sustain your current business if social distance measures stay where they are now?", 60% responded 3 months or less (Watson, 2020). Full retail appears to be linked with small scale viability.

In an openly transparent world, an investigation of this *on-premises – viability* hypothesis would involve a time-series examination of each individual brewery's size, sales mix and profitability – a unicorn data set. Alternatively, every brewery in the U.S. is licensed to operate and is taxed by the Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau (TTB). Each permitted brewery is assigned a unique BR number and is required to complete a Brewer's Report of Operations either monthly or quarterly depending on taxed annual barrelage.[7] These TTB reports detail removals from produced inventory by category, for example, in bottles or cans (packaged), in kegs, on-premises sales, spoilage, for foreign export, etc. Aggregation of these individual reports are made public, periodically, in the form of a report entitled 'Monthly National Statistical Report - Beer'. This report breaks down removals into taxed or untaxed by the TTB. Untaxed removals are proportionately small and mostly represent foreign exports by larger scale brewers (see Table 1 below). Herein, we focus on taxed removals.

Small-scale breweries, with a tavern on-premises, move beer from fermentation to serving vessels or kegs in order to dispense. Beer is sold over the bar by the glass, pitcher or in some from of sealed to-go container (e.g. growlers, bottles or cans).[8] Additionally, depending on local regulations, small breweries may container (bottle, can or keg) their beer for wholesale distribution where the end user is an unaffiliated tavern,

[6] Canning accounts for roughly 2/3 of the packaging mix of late (Beer Institute, 2024).
[7] 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. While some small breweries file monthly regardless, most are below this threshold and choose to file quarterly.
[8] In many states, breweries may retail kegged beer directly to the consumer.

restaurant or retail liquor outlet. Many states allow small breweries to be their own distributors within the confines of the state's borders. Interstate arrangements typically involve brokered distribution (TTB, 2024). In theory, these are two distinct types of removals that should be reported separately.[9] In practice, many smaller scale producers simply lump the two together as reported on-premises sales. With this context, the unprecedented growth in brewery counts, particularly over the last 15 years, should be long-run forcing to increases in on-premises reported activities and declines in both package and keg proportional removals. In other words, with the addition of thousands of very small breweries reliant on direct retail activities, overall on-premises shares should cut into both aggregate package and keg shares, the latter two reported as offsite distribution. While not perfect, due to the inseparable inclusion of large brewery activities, an examination of this removals data should provide some insight into the output mix trends of small-beer. If package and keg shares are indeed rising with increases in reporting brewery counts, long-term viability of these forming small enterprises should be questioned. In the next section, we detail the TTB data.

Data

The data comprise a 142 month series of taxed removals reported in three categories: packaged in cans or bottles, kegged and on-premises sales. Our aim is to investigate the linkages between reporting brewery growth and outside distribution trends. Table 1 details the data, provides source particulars and presents relevant descriptive statistics. Note, the variation about the mean, in the reporting brewery and on-premises series is relatively high while variation in the package and keg share series appears less scattered.

Table 1. Data descriptions, monthly January 2012 through October 2023

Reporting member count. This is the count of unique (separate BR numbered) industry members who submitted any operational report for a reporting period ending in a given calendar month. Reports representing quarterly accrual are counted in the last month of their reporting period (March, June, September, December). Source: U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau, Monthly National Statistical Report - Beer, updated 1/22/2024. Mean 2,168, STD 2,329, Minimum 499, Maximum 7,103, Coefficient of variation 1.07, Observations 142.
Package share in percent. The proportion of canned or bottled taxed removals to the total, in percent. Few circumstances allow breweries to remove product that is not taxed by the TTB. Noteworthy exceptions include foreign exports and spoilage. Taxed removals represent 94 percent of reported production in the sample. Taxed removals and reported production share a correlation coefficient of 0.97. Canning beer dominates bottling in the U.S. roughly 2 to 1. Sources: U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau, Monthly National Statistical Report - Beer; The Beer Institute (2024). Mean 89.80, STD 3.16, Minimum 82.87, Maximum 99.86, Coefficient of variation 0.04, Observations 142.

[9] Both are taxed at the same per barrel rate by the TTB.

Keg share in percent. The proportion of kegged taxed removals to the total, in percent. Source: U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau, Monthly National Statistical Report - Beer. Mean 8.70, STD 2.06, Minimum 0.13, Maximum 11.92, Coefficient of variation 0.24, Observations 142.
On-premises share in percent. The proportion of on-premises taxed removals to the total, in percent. Source: U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau, Monthly National Statistical Report - Beer. Mean 1.50, STD 2.60, Minimum 0.01, Maximum 8.84, Coefficient of variation 1.73, Observations 142.

Less variation in the latter two series reflects the rather consistent reporting from large scale breweries. Figures 4 and 5 below depict the keg and on-premises shares, in percent, over the 142 month period. With the exception of the Covid-19 shock, shares in both plots trend as expected – falling for keg shares and increasing for on-premises removals.[10] Conversely, package share trends, shown in Figure 3, appear to be trending upward. Figure 6 below stacks the monthly reported shares in an area graph summing to 100 percent. The white and grey stalactite formations indicate quarterly reporting. The black and grey stalagmite formations represent non-quarter-end monthly reporting. Clearly, the keg area has declined with time and the on-premises area has increased. Oddly though, the on-premises share growth seems tempered, perhaps an indication of how small the new entries are. In any case, the package share area appears to be declining until late 2019 – followed by an area growth burst then more volatility.

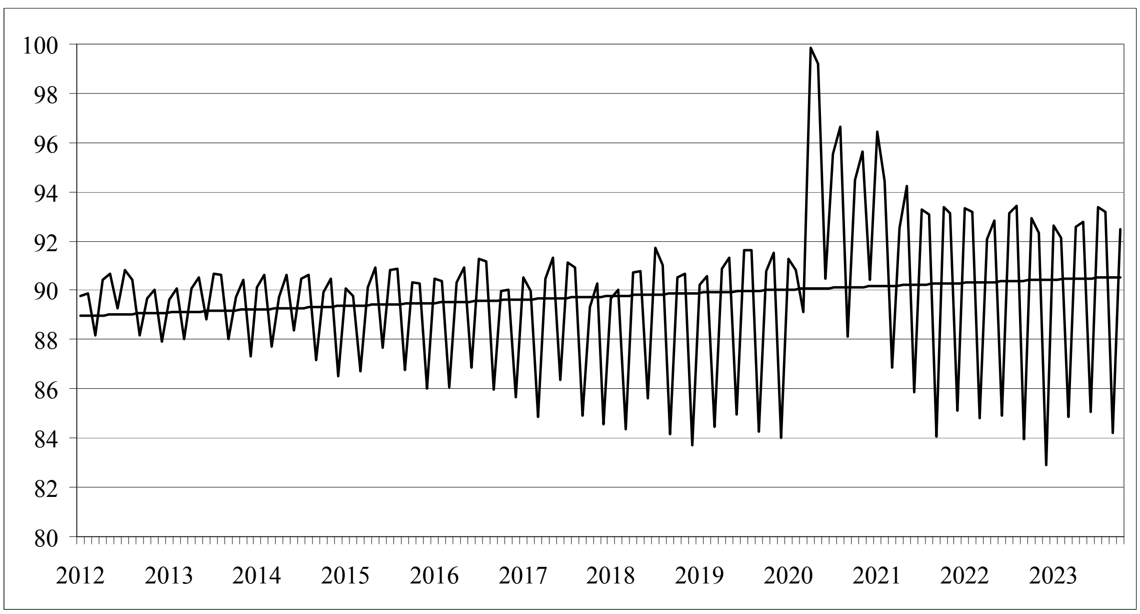

Figure 3. Monthly package share in percent with non-linear trend line

[10] See Figure A1 in the appendix to this paper for the graph of reporting members. Note how on-premises share trends and the growth in reporting breweries move together. Interestingly, the count of reporting breweries has declined from its peak of 7,103 in March of 2022.

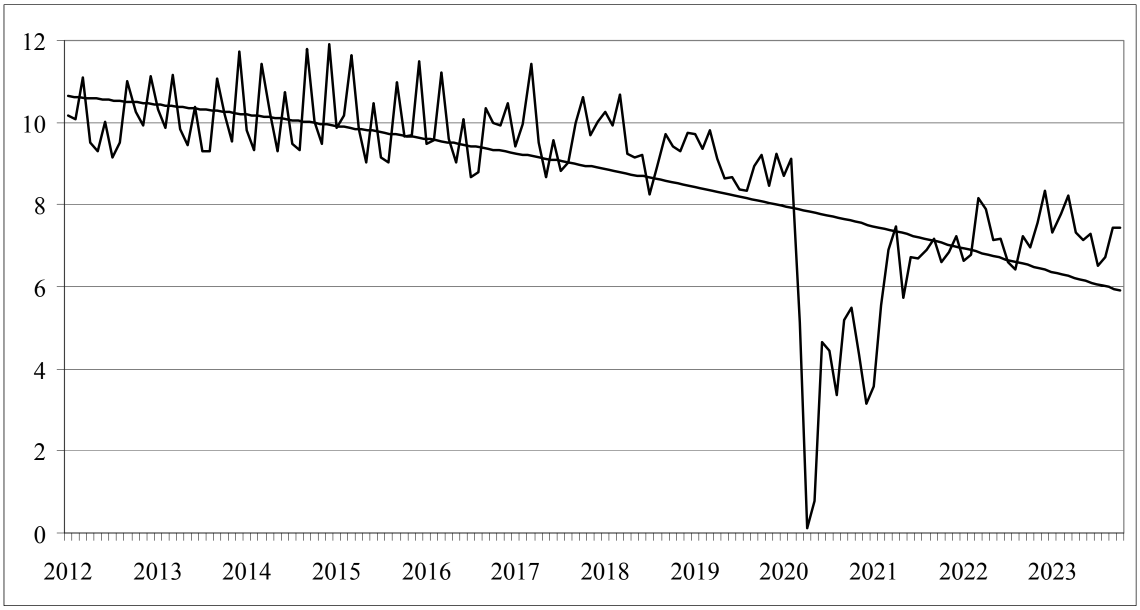

Figure 4. Monthly keg share in percent with non-linear trend line

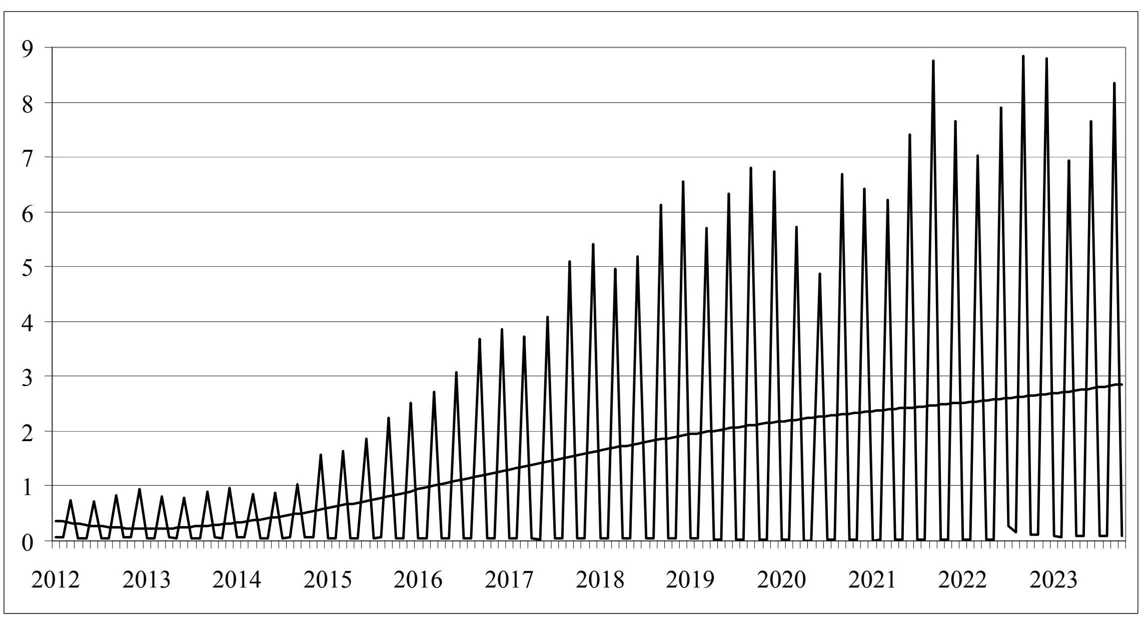

Figure 5. Monthly on-premises share in percent with non-linear trend line

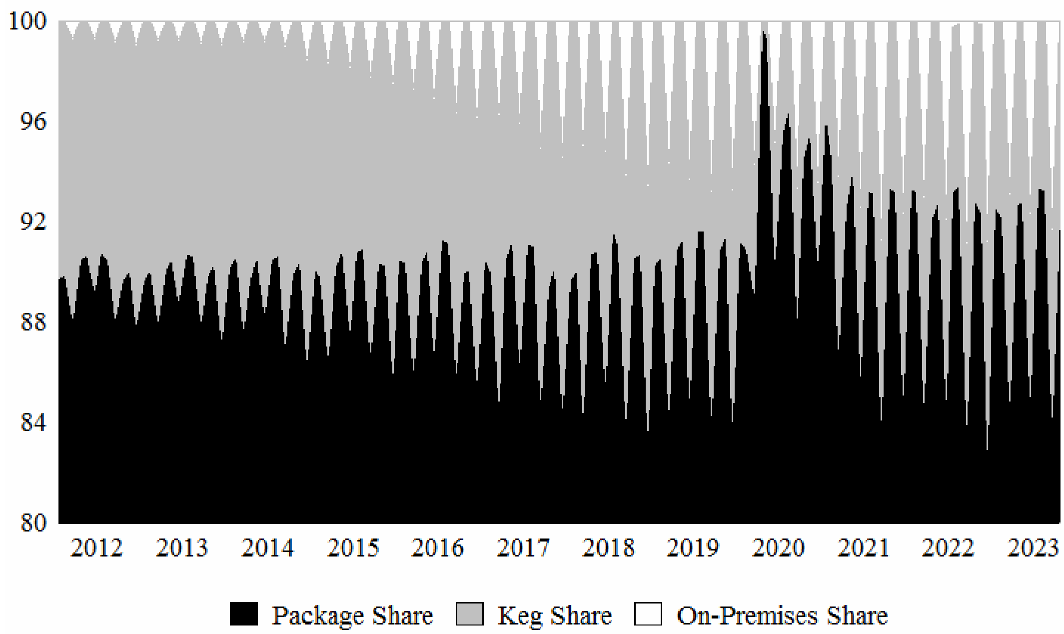

Figure 6. Monthly taxed removals stacked by category, in percent

Accordingly, the focus of this examination will center on the existence of short- and long-run associations running from the sharp rise in small-beer enterprises to beer package shares. We lean on the autoregressive distributed lag (ARDL) methods forwarded by Pesaran and Shin (1999) and Pesaran et al. (2001). The ARDL approach to time series modeling has the advantage of yielding consistent estimates regardless of whether the variables are level, I(0), or first-difference, I(1), stationary. Structural augmentations to the model, in light of the Covid-19 shock, were inspired by Zivot and Andrews (2002), Perron (2006) and Acar et al. (2023). The next section considers the more conventional ARDL bounds test methodology which forms the basis of the extended structural examination.

Conventional model

A general ARDL(p, q_1, . . . , q_k) dynamic model is defined,

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} C_i y_{t-i} + \sum_{j=1}^{k} \sum_{l_j=0}^{q_j} B_{j,l_j} x_{j,t-l_j} + \varepsilon_t \, , \tag{1}$$

where y_t is the dependent variable, α_0 is an unrestricted constant, $\alpha_1 t$ is an unrestricted deterministic trend [11], p denotes the lag selection for the dependent variable, C_i are the coefficients of the dependent variable lags, k is the number of $x_{j,t}$ explanatory variables[12], q_j denotes the lag selections for the explanatory variables, B_j are the coefficients of said

[11] With this form, deterministics will not contribute to the error correction (*EC*) term described below. Accompanying t-bounds testing applies to this unrestricted form (Banerjee et al., 1998; Pesaran et al., 2001).

[12] Variables y_t and x_t can be any combination of I(0) and/or I(1).

regressors and associated lags and, lastly, ε_t are the usual White noise. When k = 1, Equation (1) simplifies to,

$$y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} C_i y_{t-i} + \sum_{j=0}^{q} B_j x_{t-j} + \varepsilon_t \,. \tag{2}$$

This form of the model is an expedient starting point for determining appropriate lag lengths (p, q_j), dependent variable lag coefficients, proper error structure and whether a deterministic trend is requisite.[13] The long-run form and bounds test requires,

$$\Delta y_t = \alpha_0 + \alpha_1 t + \phi_0 y_{t-1} + \phi_1 x_{t-1} + \sum_{i=1}^{p-1} c_i \Delta y_{t-i} + \sum_{j=0}^{q-1} b_i \Delta x_{t-j} + u_t \,, \tag{3}$$

which is the conditional error correction specification. Testing for the existence of a long-run form involves the null,

$$H_0 : \phi_0 = \phi_1 = 0 \,. \tag{4}$$

Upon the rejection of Equation (4), the long-run parameter is defined by the ratio,

$$\hat{\theta} = \frac{\phi_1}{C(1)} = \frac{\hat{\phi}_1}{1 - \sum_{i=1}^{p} \hat{C}_i} \,, \tag{5}$$

with C_i as defined in Equation (1) (Pesaran and Shin, 1999). Computation of valid long-run standard errors follow either the *delta* method or Bewely's (1979) approach. Lastly, the conventional error correction model takes the form,

$$\Delta y_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p-1} c_i \Delta y_{t-i} + \sum_{j=0}^{q-1} b_i \Delta x_{t-j} + EC_{t-1} + u_t \,, \tag{6}$$

where EC stems from the long-run residual devoid of deterministics,

$$y_t - \hat{\theta}\, x_t \,. \tag{7}$$

The error correction term, EC, represents the speed of adjustment to the long-run.

Standard estimation

A natural first step in the analysis is to establish the underlying stochastic processes that generated each variable series. Initial, standard unit root tests are shown in Table 2. Phillips and Perron (1988) suggested a nonparametric method for controlling serial

[13] EViews 12® initiates the bounds test routine with this form.

correlation when testing for a unit root. This method modifies the conventional Dickey and Fuller (1979) statistic so that ordered serial correlation does not affect the asymptotic distribution of the test. The null hypothesis is the series has a unit root. Results indicate

Table 2. Standard unit root testing

	Package Share	Keg Share	On-premises Share	Reporting Breweries
Phillips-Perron				
Level, Intercept	-5.162***	-3.423**	-5.561***	-0.847
Level, Intercept & Trend	-5.098***	-4.848***	-6.742***	-2.489
1st Diff., Intercept	-	-	-	-4.169***
1st Diff., Intercept & Trend	-	-	-	-7.660***

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

that all share series are integrated of order zero, I(0), and the reporting brewery series is integrated of order one, I(1).[14] The ARDL framework, used in econometrics for decades, is particularly valuable as a method for examining cointegrating relationships between variables. ARDL-based estimators are "super-consistent" and exhibit strong small sample properties (Pesaran and Shin, 1999; Ghatak and Siddiki, 2001). An additional advantage of the ARDL process is the flexibility to assign different optimal lag-lengths to different series. In our case, we use the model selection algorithm found in the EViews® software package to determine appropriate lag-lengths. As described above, our focus is to model the package share series as the dependent variable. Because the shares are computed from reported production data, the issue of endogeneity must be addressed. A computed Durbin-Wu-Hausman difference statistic of 3.587, distributed chi-squared with one degree of freedom, fails to reject the null of exogeneity at the < 5 percent level (see Davidson and MacKinnon, 2021, 338-340). However, exogeneity is rejected at the less imperious 10 percent level. Deleterious inconsistencies should not be an issue moving forward. Two intertemporal dynamic models were first evaluated – with or without a deterministic linear trend. Tables 3 and 4 present these results. By minimizing Akaike's (1987) information (AIC), models where p = 1 and q = 3 were selected irrespective of including a deterministic trend. The Table 3 estimate for the trend coefficient is highly insignificant (pv > 0.5). In Table 4 below, the AIC for this *no trend* model is slightly lower and tests for both serial correlation and heteroscedasticy fail to reject the null of no

Table 3. ARDL(1,3) Intertemporal dynamics regression with trend

Model Selection Criteria: AIC, 20 models evaluated, 4 lag upper limits.			
Unrestricted Constant and *Trend*			
HAC standard errors and covariance (Newey and West, 1987)			
Variable	**Coefficient**		
Constant	16.2219***	R-squared	0.92

[14] The aforementioned Dickey-Fuller test yields the same conclusion. Share series stationary at level, I(0). report series stationary at first difference, I(1).

Trend	0.0066	Durbin-Watson	1.84
PShare(-1)	0.8177***	Log likelihood	-183.04
Report	0.0016*	AIC	2.734
Report(-1)	0.00101***	F-Serial correlation[a]	0.829
Report(-2)	0.00005	F-Heteroscedasticity[b]	1.657
Report(-3)	-0.0029***		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[a] Up to 3 lags. Attributed to Breusch (1978) and Godfrey (1988). See also Bergmeir, et. al. (2018).
[b] Godfrey (1978) and Breusch and Pagan (1979).

Table 4. ARDL(1,3) Intertemporal dynamics regression without trend

Model Selection Criteria: AIC, 20 models evaluated, 4 lag upper limits.			
Unrestricted Constant and *No Trend*			
HAC standard errors and covariance			
Variable	**Coefficient**		
Constant	15.8297***	R-squared	0.92
PShare(-1)	0.8176***	Durbin-Watson	1.85
Report	0.0012*	Log likelihood	-183.12
Report(-1)	0.00114***	AIC	2.720
Report(-2)	0.00018***	F-Serial correlation	0.862
Report(-3)	-0.00227**	F-Heteroscedasticity	1.660

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

presence. Proceeding with the no trend specification, Table 5 shows the results of estimating Equation (3) dropping the α_1 term. The values of the F- and t-statistics shown are sufficient to reject the null of no long-run association (see Equation (4)). Though small in magnitude, the long-run coefficient for reporting breweries is positive and significant at the less than 10 percent level. Simply, as the count of reporting breweries

Table 5. ARDL(1,3) Conditional error correction regression

Unrestricted Constant and No Trend[15]			
HAC standard errors and covariance			
Variable	**Coefficient**		
Constant	15.8297***	R-squared	0.96
PShare(-1)	-0.18245***	Durbin-Watson	1.85
Report(-1)	0.00023*	Log likelihood	-183.12
Δ Report	0.00118*	Bounds F-test[c]	6.658**
Δ Report(-1)	0.00209**	Bounds t-test[c]	-3.581**
Δ Report(-2)	0.00227**		

[15] With a restricted constant and no trend, the levels equation becomes:

PShare = 86.8197*** + 0.00126*(Report).

Levels equation, long-run			
Report	0.00126*		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[c] Critical values from Pesaran et al. (2001).

increases, the package proportion of taxed removals rises. This result is contrary to expectations, yet, may be confounded by structural shifts and large brewery behavior. Lastly, Table 6 presents the more familiar short-run error correction model (see Equation (6)). The cointegrating error correction (*EC*) term is negative and highly significant as anticipated. This coefficient represents the speed of adjustment to the long-run equilibrium each period. Smaller relative magnitudes of this coefficient imply a slower adjustment process. Results from the short-run Wald test indicates a positive, significant short-run association running from reporting breweries to the package share, again contrary to supposition.

Table 6. ARDL(1,3) Error correction regression

Unrestricted Constant and No Trend			
HAC standard errors and covariance			
Variable	**Coefficient**		
Constant	15.8297***	R-squared	0.96
Δ Report	0.00118*	Durbin-Watson	1.85
Δ Report(-1)	0.00209**	Log likelihood	-183.12
Δ Report(-2)	0.00227**	Wald: Short-run[d]	106.951***
Coint*EC*(-1)	-0.18245***		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[d] H_0: Δ Report = Δ Report(-1) = Δ Report(-2) = 0. See Engle and Granger (1987).

The standard bounds test results appear to support the existence of positive short- and long-run associations with relatively short lag lengths selected and when the statistically insignificant deterministic trend is excluded from the models. However, the low level of statistical significance for the long-run coefficient (pv = 0.077) raises certain flags. Coupled with the apparent structural break in the dependent series (see Figures 3 and 8) further scrutiny is warranted. Functional form misspecification is rejected at the 5 percent level inferring that non-linearities or asymmetries are not the issue (Ramsey, 1969)). Recursive estimation of the dynamic model, without trend, suggests that the coefficients are not stable over the sample period. Figure 7 below plots the cumulative sum of recursive residuals (CUSUM) along with critical bounds at the 5 percent significance level (Brown et al., 1975). Note that the plot shows statistically significant breaks – becoming more prominent moving into the 2000s on the horizontal axis. An examination of this structural instability is necessary and will follow in the next section.

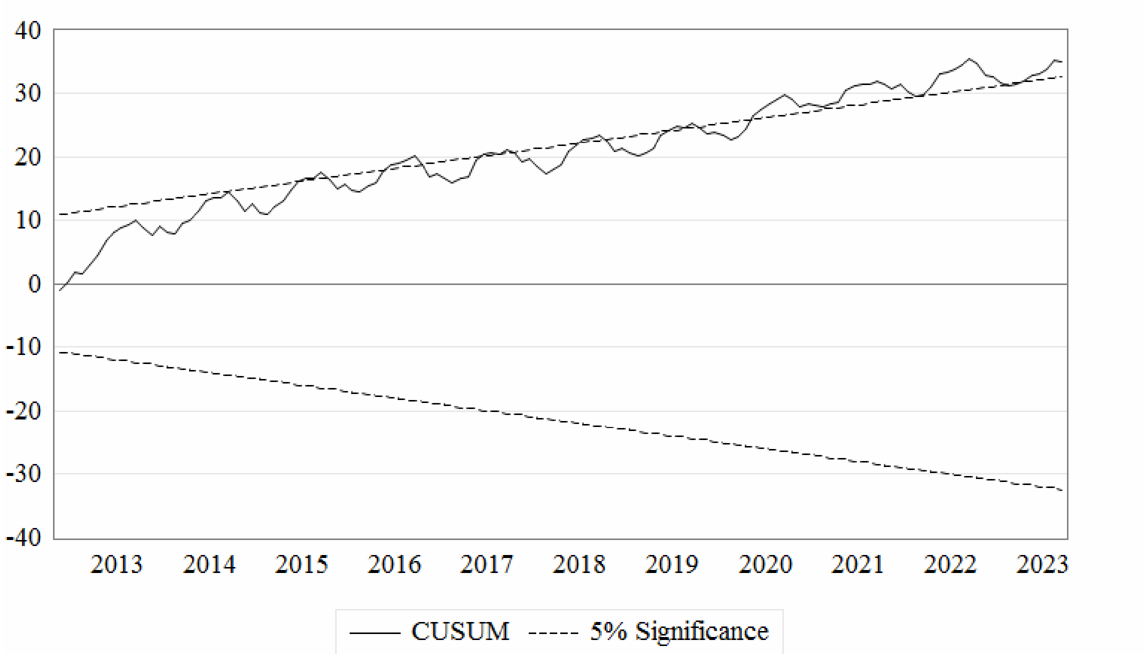

Figure 7. Cumulative sum of recursive residuals

Structural estimation

Perron (1989) observed that structural change in a series is closely related to unit root. A large literature has developed outlining various unit root tests that remain valid in the presence of structural breaks (see Hansen, 2001 for a review). We endogenously determine break dates from the data, following Zivot and Andrews (1992), by minimizing the Dickey-Fuller t-statistic. Table 7 shows the breakpoint unit root test results for the left- and right-hand side series. Both are stationary at first difference with the selected single break-date for the package share series estimated to be September, 2019. We will

Table 7. Breakpoint unit root testing[16]

	Package Share	Reporting Breweries
Dickey-Fuller minimum t-stat		
Level, Intercept, AIC	-3.281*	-3.194
Level, Intercept & Trend, AIC	-3.582*	-3.607
1st Diff., Intercept, AIC	-4.585***	-4.919**
1st Diff., Intercept & Trend, AIC	-4.619***	-5.147**
Break-date	2019M09	2014M02

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

proceed with the September, 2019 external shock.[17] In order to capture this structural change in the standard ARDL bounds model detailed above, we include a dummy

[16] The keg share series is stationary at first difference with an estimated breakpoint of 2019M11. The on-premises share series is stationary at level with an estimated break point of 2013M02.
[17] A Quandt-Andrews unknown breakpoint test yields analogous results (see Andrews, 1993).

variable for the 2019 breakpoint[18] and an interaction term representing the product of the breakpoint dummy and the reporting brewery series. This addition allows for structural change in both the intercept and slope.

Following previous conventional steps, two intertemporal dynamic models were evaluated – with or without a deterministic linear trend. As before, the trend variable is highly insignificant and dropped from the analysis. Model selection criteria indicates that $p = 1$, $q_1 = 4$ and $q_2 = 0$ (no lag for the interaction term). The structural dummy is simply an intercept shifter. Table 8 presents the relevant estimates for the short-run error correction model and the long-run levels equation. Veering from the standard estimation above, we integrate the deterministic terms (intercept and shifter) into the cointegrating vector by restricting the parameters (Pesaran et al., 2001). First, the short-run error correction regression estimates suggest a somewhat complicated dynamic running from reporting breweries to package shares. Two of the report coefficients are significant but with differing signs. Lag selection picks up the larger negative association, though the two center negative lag coefficients are not statistically different from zero. The cointegrating error correction (*EC*) term is negative and highly significant as expected. The diagnostic tests for serial correlation and heteroscedasticity fail to reject the null of no presence.

Table 8. ARDL(1,4,0) Error correction regression and long-run form

Model Selection Criteria: AIC, 180 models evaluated, 5 lag upper limits.			
Restricted Constant and No Trend			
HAC standard errors and covariance			
Variable	**Coefficient**		
Δ Report	0.00145*	R-squared	0.97
Δ Report(-1)	-0.00026	Durbin-Watson	1.83
Δ Report(-2)	-0.00020	Log likelihood	-175.77
Δ Report(-3)	-0.00286**	Bounds F-test[e]	4.471**
Coint*EC*(-1)	-0.21772***	F-Serial correlation	0.760
		F-Heteroscedasticity	1.442
Levels equation, long-run			
Constant	89.7491***		
Structural dummy	2.5501**		
Report	-0.00071		
Interaction term	-0.0001		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[e] Critical values from Pesaran et al. (2001). Bounds t-statistic does not apply in the restricted version.

Regarding the long-run equation, the bounds F-test is sufficient to reject the null hypothesis of no long-run associations. Interestingly, the reporting breweries and interaction coefficients are negative but not statistically different from zero. The entirety

[18] Months from September, 2019 to October, 2023 take a value of 1, 0 otherwise.

of the long-run structural model reduces to a constant, reflective of the package share mean, and the structural shifter. Recursive estimation now suggests that the coefficients are stable. Figure 8 shows the cumulative sum plot, based on the structural recursive residuals, indicating no statistically significant breaks post 2019. While the ascent of small reporting breweries now appears to have no significant long-run link to the packaging share, the lack of significance for the negative signed report and interaction variables coupled with the significant 2.6 percentage point upward shift, post 2019, is still concerning. Aggregation of the reporting data may be masking linkages smaller breweries have to the variation in packaging proportions. To illustrate, Table 9 below shows the long-run results for the keg share series. A significant negative association running from reporting breweries to keg shares is established. Interestingly, the structural coefficients are not statistically significant. This suggests that a statistically significant portion of the decline in keg shares is due to the rise in small brewery counts, and their on-premises activities, not simply larger breweries switching to more packaging. As a result, small brewery activity must be supporting the relatively horizontal packaging trend and significant upward structural shift. The lack of more convincing evidence that the rise in small-beer counts did indeed reduced industry packaging proportions is telling and provides a sound basis for further, suitably disaggregated, research.

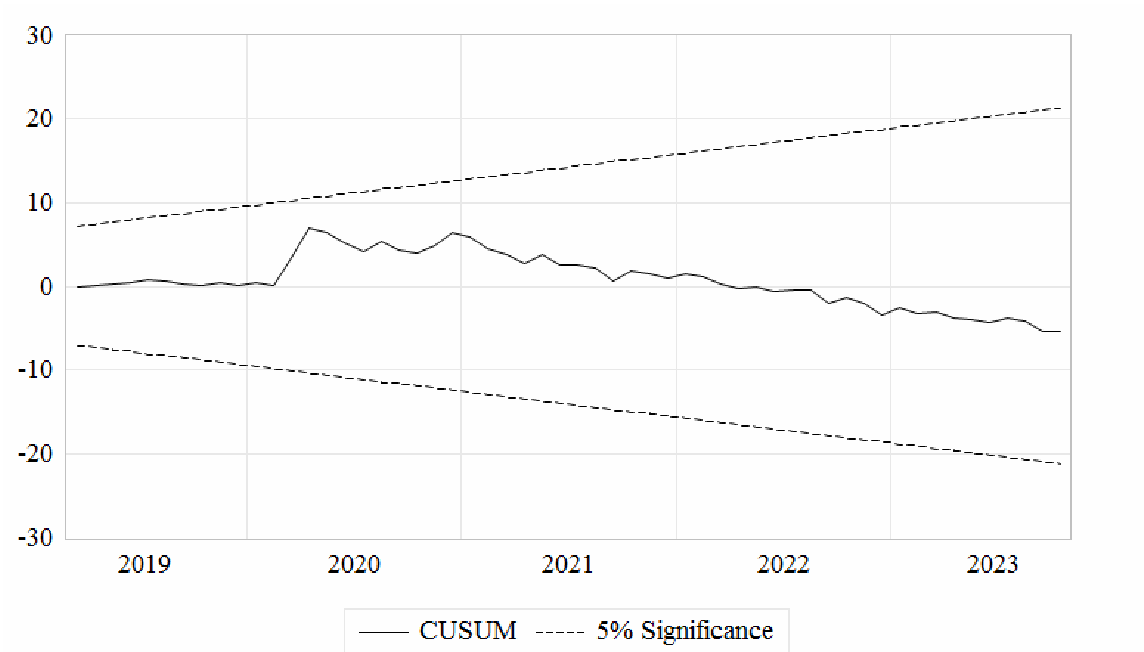

Figure 8. Cumulative sum of structural recursive residuals

Table 9. ARDL(4,5,4) Keg share, long-run structural equation

Model Selection Criteria: AIC, 2,058 models evaluated, 6 lag upper limits.			
Restricted Constant and Restricted Trend			
HAC standard errors and covariance			
Variable	**Coefficient**		
Constant	11.7148***	Bounds F-test[f]	4.895**

Trend	0.1173**	F-Serial correlation	0.112
Structural dummy	-3.9794	F-Heteroscedasticity	1.401
Report	-0.00685***	Durbin-Wu-Hausman endogeneity	3.523*
Interaction term	-0.00074		

Significance at the < 1% (***), < 5% (**), < 10% (*) levels.
[f] Critical values from Pesaran et al. (2001). Bounds t-statistic does not apply in the restricted version.

Concluding remarks

In the latter part of 2021, Ball Corporation, the world's largest metal can manufacturer, disclosed the following to its customers worldwide:

> "To more effectively serve our non-contracted customer base, effective January 1, 2022[19], where supply is available, we will require a minimum order of five truckloads per SKU for printed cans, and we will no longer be able to warehouse inventory on behalf of our customers. . . Demand for sustainable aluminum beverage packaging continues to grow at an accelerated pace. Ball is making investments to bring additional capacity online, and in the meantime we remain in a tightly constrained environment for the foreseeable future." (Shikes, 2021)

This decision has forced small breweries, that have committed to more of an outside distribution model, to find other outlets for aluminum canning materials. Patrick Crawford, co-founder of Denver Beer Company, was quoted in Westword magazine, "it (Ball's decision) triples our expenses" (Shikes, 2021). American Canning, one of Ball's largest distributors in Austin, Texas, offers a single truckload order of 6,419 case equivalent materials for $8.00 to $10.00 per 24/12 ounce count depending on shipping distance.[20] Upward of $10.00 per 24 can case just for the packaging materials, no beer, no shipping to wholesalers. To put this cost in a competitive perspective, DaveCo, the self-proclaimed world's largest liquor store, north of Denver, Colorado, retails a case of 12 ounce cans of New Belgium's, Mountain Time Lager for $23.00 before tax.[21] It appears that the more appropriate mantra for small-beer post-pandemic should be 'can and die' (Kunce, 2023; Vorel, 2023).

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[19] Ball delayed the start date to March, 2022 (BA, 2024).
[20] Case equivalent materials includes, 24/12 ounce printed cans, 24 ends, 4 PakTech® holders, one cardboard case tray, prorated artwork fees and shipping, see Table A1 in the Appendix to this paper, https://americancanning.com. Alternative vendors may offer single pallet orders but at a higher per unit price, e.g. https://wwww.cancraftsolutions.com. Many of these single pallet vendors will label cans with shrink-wrap art at a lower cost, however, this addition makes the cans non-recyclable (Shikes, 2021).
[21] https://www.daveco-liquors.com

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Appendix

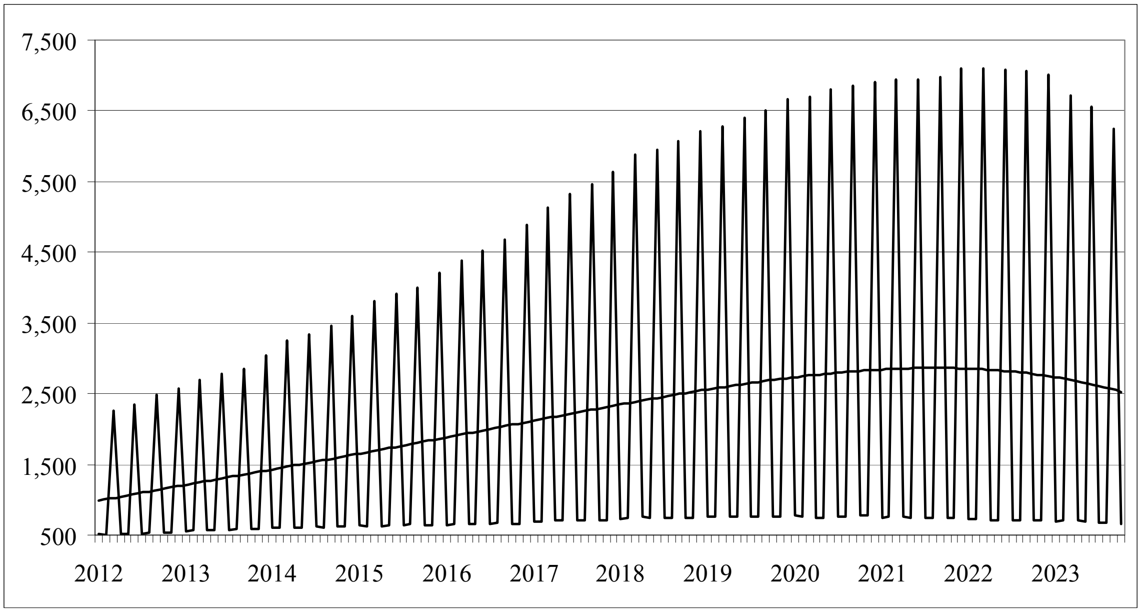

Figure A1. Reporting members with non-linear trend

Note the decline in reporting members from the peak in March 2022 – 7,103 to 6,248.

Table A1. American Canning order example, minimum order for printed cans

	In 24 Can Cases	Units Ordered	Cost Quote	Per Unit Cost
12 Ounce Printed Cans	6,419	154,044	$30,809.00	$0.200
Ends, 552 per sleeve	6,419	153,456	$5,859.00	$0.038
6PakTech, 510 per box	25,676	26,010	$4,641.00	$0.178
Case Trays, 100 per bundle	6,419	6,400	$4,080.00	$0.638
Shipping estimate: Austin to Denver w/liftgate			$8,000.00	
Artwork fees			$1,000.00	
		Total	$54,389.00	
	Per 24 Can Case		$8.47	

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Local Subsidies and Tax Incentives and the Small-Beer Industry

Mitch Kunce[1]

Abstract

Herein, we review and extend the theoretical tax competition model in an effort to defend place-based tax incentives. The standard argument in the literature is that subsidizing or lowering taxes to lure mobile capital leads to inefficient provision of local public goods. Firm-specific subsidies are shown to be socially efficient under certain augmentative assumptions. The small-beer industry, of late, has been a target of these locally driven incentive strategies. We forward the recent expansion of Wyoming's Melvin Brewing as a case study.

Keywords: Beer industry, tax competition, local economic incentives
JEL Classifications: H29, H41, L60

Introduction

In 2009, Wu inspired hopheads Jeremy Tofte and Kirk McHale started Thai Me Up Brewing in the small confines of a popular Thai restaurant, of the same name, in Jackson, Wyoming.[2] Their goal was to develop then produce the most audacious and bold India Pale Ales (IPAs) with dreams of global domination (Roadhouse Brewery Presser, 2022). In 2012, the pair's efforts were rewarded – two gold and one silver (medals) at the Great American Beer Festival and the coveted Alpha King award in the same year. Plans for expansion soon followed – early out of state target sites and markets for the newly named Melvin Brewing included Colorado, Washington and Idaho (Brewbound, 2015). In 2014 the search ended, the state of Wyoming awarded the small town of Alpine, roughly 37 miles southwest of Jackson, a $3 million dollar Business Committed grant for the infrastructure and expansion of Melvin. The town of Alpine provided a local match of $600 thousand.[3] The grants were set to pay for the construction of a 20,000 square-foot building on 6 acres and all necessary utility extensions (Wyoming Business Council (WBC), 2023).[4] The brewery would occupy the facility under a 15 year recapture arrangement with the town – interest free if the brewery met employment targets and repayment schedules. Melvin's initial plan was to produce and can their beer with distribution to, primarily, Colorado, Washington and Wyoming markets. An onsite taproom was also in the works. As an aside, the state of Wyoming exempts in-state beer

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[1] *Douglas* ***Mitchell*** Econometric Consulting, Laramie, WY USA
[2] Referencing Wu Zetian or perhaps the Wu-Tang Clan.
[3] Alpine, Wyoming population 1,300, located roughly 10 miles from the southern most border of Teton County. We thank the town of Alpine and the Wyoming Business Council for providing 10 years of council and board minutes that served as key sources for much of this introduction and part of the concluding remarks below.
[4] See the appendix to this paper for a working summary of community grant programs offered by the Wyoming Business Council.

production from excise taxes on exports outside of the state's borders.[5] Moreover, the state does not tax personal or corporate income.

Figure 1. Brewery photo 2022

The resulting relationship between the town of Alpine and Melvin may best be described as turbulent. Production commenced in December of 2015 and within the next few months the town was facing a sewer and waste water treatment dilemma. The small town was simply not prepared for the amount of solids and sewage sludge generated from the IPA brewing process. Early on the sludge was captured in local digesters, but as brewery production increased the sludge had to be hauled to surrounding towns. Volumes of 30 to 50 thousand gallons per month being trucked at a substantial cost shared by the town and Melvin. In 2019, Alpine was awarded another grant from the Wyoming Business Council (WBC), totaling $2.3 million, to construct a pre-treatment sludge handling facility. The required matching funds were to be sourced by a concurrent Environmental Protection Agency (EPA) grant. The EPA grant was denied and the town could not come up with the required matching funds on their own. The WBC urged Alpine to reapply for consideration in 2022.

In addition to the sewage turmoil, Melvin fell behind on their recapture payments and defaulted on the original 15 year contract. Several agreement addendums were made over the years, even extending the recapture period to 2035, but the brewery continued behind on payments. In early 2022, Melvin retained GLC Advisors & Company, out of Denver, Colorado, to search for a 'strategic partner' or negotiate the sale of the brewery (Gribbons, 2022). In December of 2022 Roadhouse Brewery Group, co-founded by Jackson Hole restaurateur Gavin Fine, publicly announced their purchase of Melvin

[5] Wyoming Statute § 12-3-101

Brewing for an undisclosed amount (Roadhouse Brewery Presser, 2022).[6] The Roadhouse group assumed the recapture agreement with the town of Alpine and planned to negotiate a contract revision in the coming months. In April of 2023, the newly formed brewing company was re-branded – Pure Madness Brewery Group (Brew Public, 2023).

Placed-based fiscal incentives to attract small breweries like Melvin, while a relatively new phenomenon, appear to be common practice among communities across the United States (Farzan, 2016).[7] Interestingly, these incentives are not offered across the board, only to a select number of breweries (Infante, 2023). Why did the state of Wyoming and the town of Alpine offer Melvin Brewing taxpayer granted land and facilities to expand there? Are arrangements like this "efficiency enhancing or distortion inducing" (Oates and Schwab, 1988)? The literature on decentralized (local) competition for firms and capital is vast. Bartik (2017), Slattery and Zidar (2020) and Patrick and Partridge (2022) provide roughly 20 pages of references capturing a more recent overview of this literature. Edward Glaeser (2001) summarized five theories on why local incentives occur. Influenced by Austin, Glaeser and Summers (2018) and Layser (2020), we added a sixth. First, attracting new firms to a community generates surpluses (consumer and producer) to current residents. New firms participate in local input (chiefly labor) and output markets thereby enhancing welfare. In other words, welfare enhancement comes from hiring current residents or providing goods or services the community desires. The next theory centers on the idea of ex post appropriation. Firms recognize that once they decide on a location, it will be difficult to pick up and leave so they require up-front payments to compensate for possible future exploitation. Firms that end up paying the most ex-post will receive the largest incentives ex ante. Third, jurisdictions will offer larger incentives to firms that are on the location margin. This theory is akin to the price discrimination behaviors of a monopolist. Firms that are strongly interested in a location would be offered little to no stimulus. The fourth theory involves corruption and influence. This behavior is not representative of local welfare enhancement, instead it reflects the ability of firms to coerce local authority. Our addition to the list is jurisdictional equity. Locations will use place-based fiscal incentives to encourage capital investment in lagging areas in order to level geographic equity. Lastly, jurisdictions use incentives to attract firms that generate spillovers. The accumulation of firms (capital) in a location augments the productivity of all firms in the area by way of concentration externalities. Such externalities would include supply linkages, skills, information, technology and many pecuniary impacts.

The state of Wyoming, through the Wyoming Business Council, appears to promote the last theory listed above most prominently. Promotional literature from the council touts that when state backed local incentives work, "the ripple effect is felt throughout the community" (WBC, 2023). To address this more normative question regarding welfare

[6] Gavin Fine, and others, started the Fine Dining Restaurant Group in 2001 and currently operate 7 restaurants in the area of Jackson, Wyoming. http:/jhfinedining.com Roadhouse Brewery was co-founded in 2012 by Fine and brewer Colby Cox in Jackson.

[7] A 'new phenomenon' refers to the accelerated growth in brewery counts, in the U.S., beginning in the mid to late 2000s (Kunce, 2023)

impacts to the community, we provide a working review and detailed extension of the theoretical tax competition model in the next section. The focus is on structuring the conventional model to include concentration externalities, then examine the welfare implications of tax incentives or subsidies. Can a case be made for firm-specific incentives that are welfare enhancing or are states like Wyoming just inefficiently picking winners?

Theoretical underpinnings

To begin, we build on the inter-jurisdictional tax competition seminal foundation laid by Oates (1972), Zodrow and Mieszowski (1986), Wilson (1986) and Wildasin (1989). Much of this work is familiar so we will keep it brief. Consider an economy made up of a large number of 'small' symmetric jurisdictions, $j = 1 \ldots \bar{J}$. Competitive firms in each jurisdiction produce a numeraire output. In equilibrium, firms are of indeterminate size earning zero economic profits. There are two primary, private factors of production − an immobile factor, L, and mobile capital, K. A jurisdiction's fixed supply of the immobile factor is owned entirely and equally by the jurisdiction's identical residents and is provided to production inelastically. Convention focuses on efficiency over equity concerns.[8] Capital is perfectly mobile both within and across jurisdictions (at least in the long run), but fixed in supply ($\bar{K}$) in the broader economy. New capital formation is not considered as the model concentrates on location choices of the existing capital stock. Jurisdictional output is produced by a constant returns to scale technology,

$$F(L,K) = F = F_L L + F_K K \,, \tag{1}$$

where subscripts denote partial derivatives. Marginal products are assumed positive and diminishing, e.g. $F_K > 0$, $F_{KK} < 0$. Capital will move between jurisdictions until all face the same after-tax return, r. Competitive firms and 'small' jurisdictions view r as a parameter. The profit maximizing condition for capital becomes,

$$r = F_K - t \,, \tag{2}$$

where t is a source-based unit tax on capital. Local governments believe that private production is sufficiently capital intensive, hence t becomes a crucial policy instrument. Jurisdictions provide a Samuelsonian public good, G, where each unit provided is consumed jointly by all residents of a jurisdiction (Wilson, 1986). The public budget constraint then becomes,

$$G = tK \,, \tag{3}$$

[8] The presumption of symmetric jurisdictions and identical residents allows us to avoid the potential inefficiencies in which Tiebout (1956) type regions are inefficiently organized or incongruously stratified by class, information, wealth or size. Moreover, if inefficiencies arise in a symmetric setting, they are likely to be exacerbated in an asymmetric construct. For more on equity concerns and modeling see Layser (2020), Austin, Glaeser and Summers (2018) and Slattery and Zidar (2020).

where G is constrained to an interior solution, thus $t > 0$.[9] Jurisdictional residents' income consists of returns to the fixed factor and any returns from equal capital ownership. For convenience, the population of a given jurisdiction is normalized to equal one. When using Equations (1) and (2), a representative resident's income-consumption is equal to,

$$C = F - (r+t)K + \frac{r\overline{K}}{\overline{J}}\,. \tag{4}$$

The resident of a jurisdiction receives utility from consumption and local public goods, Jurisdictional utility takes the form, $U(C,G)$, where U_C and $U_G > 0$. In keeping with the Arrow-Debreu (Wilson, 1999) separation assumption for general equilibrium constructs, residents have two distinct roles in the model. First, as consumers, they seek to maximize utility over a bundle of goods and public services. Second, they supply fixed factor inputs to production and in return receiving income for consumption. More of the mobile factor enhances local production and can provide residents with higher incomes hence more consumption. However, in order to attract the mobile factor, jurisdictions' may lower taxes on, or subsidize, capital effecting the provision of G thus setting up a characteristic economic tradeoff.

Benchmark social efficiency requires the maximization of the jurisdictional residents' utility subject to (i) utility in all other jurisdictions is equalized to a fixed level, (ii) aggregate production and consumption clear, and (iii) the mobile capital stock is allocated entirely among jurisdictions (clears). The resulting social optimum conditions from this standard model are well known (see Wilson 1999) therefore derivation and discussion here is keep to a minimum. Social efficiency becomes,

$$MRS(G,C) = \frac{U_G}{U_C} = 1 \quad \forall \text{ jurisdictions}\,. \tag{5}$$

Equation (5) represents the familiar 'Samuelson condition' for the provision of public goods (Wilson 1986). This optimality condition suggests that the jurisdictional marginal rate of substitution ($MRS(G,C)$) between the public good and consumption equals the marginal cost of providing an incremental increase in the public good. Given Equations (3) and (4), the marginal rate of transformation, dC/dG, in this context is one for one.

Jurisdictional authority, acting as a benevolent dictator, maximizes jurisdictional utility subject to constraint Equations (2), (3) and (4) by choosing policy variables θ, here $\theta = t$. The first order condition, with respect to t, takes the differential form,

$$U_G \frac{\partial G}{\partial t} + U_C \frac{\partial C}{\partial t} = 0\,, \tag{6}$$

[9] An interior solution requires G to be positive, no corner solutions. Imagine a two-good world with G on the horizontal axis. Optimality requires a tangency where the marginal rate of substitution, $MRS(G,C)$, equals the marginal rate of transformation, dC/dG.

with,

$$\frac{\partial G}{\partial t} = t\frac{\partial K}{\partial t} + K\,, \tag{7}$$

and,

$$\frac{\partial C}{\partial t} = F_K\frac{\partial K}{\partial t} - r\frac{\partial K}{\partial t} - t\frac{\partial K}{\partial t} - K = -K\,. \tag{8}$$

Substituting Equations (7) and (8) into (6), with suitable rearrangement, yields the optimality condition,

$$\frac{U_G}{U_C} = \frac{K}{t\dfrac{\partial K}{\partial t} + K}\,. \tag{9}$$

Efficiency in public good provision requires that capital movement is not influenced by changes in t, $\partial K/\partial t = 0$. To explore this, we examine Equation (2) using the Implicit Function Theorem,

$$\begin{aligned} &I : F_K - r - t = 0,\\ &\frac{\partial K}{\partial t} = -\frac{I_t}{I_K} = \frac{1}{F_{KK}} < 0. \end{aligned} \tag{10}$$

This comparative static implies that capital unambiguously responds to tax rates inversely and that the first term in the left-side denominator of Equation (9) is negative, not zero. With K sufficient in magnitude, U_G/U_C , becomes greater than one indicating public goods are underprovided. This is the standard equilibrium in the inter-jurisdictional tax competition literature. Because jurisdictions finance public goods with capital taxation, alone, they possess incentives to use taxation as a policy lever to stimulate capital investment. However, the social cost of local public goods differs from the private cost, in this context, due to capital movement externalities. These externalities are overlooked and jurisdictions choose an inefficiently low level of public services as a result (Wildasin, 1989). This argument certainly does not support the use of tax incentives or subsidies to attract capital in a socially efficient manner.

It is straightforward to show that the inefficient outcome presented in Equation (9) vanishes if jurisdictions have access to other tax instruments, namely, a fixed factor tax (Kunce, 2000). Assume each jurisdiction taxes the immobile factor at a free-to-vary rate h. The governments' budget constraint now becomes

$$G = tK + hL\,. \tag{11}$$

The representative resident's income changes to,

$$C = F - (r+t)K - hL + \frac{r\overline{K}}{\overline{J}}, \tag{12}$$

where,

$$\frac{\partial C}{\partial h} = -L \text{ and } \frac{\partial G}{\partial h} = L. \tag{13}$$

The first order condition with respect to the additional policy variable, *h*, becomes,

$$\frac{U_G}{U_C} L - L = 0 \text{ or } \frac{U_G}{U_C} = 1. \tag{14}$$

Solving Equations (9) and (14) simultaneously forces $t = 0$. The fixed factor tax emerges as the efficient policy instrument for all jurisdictions even when capital taxes are available. Again, this result does not favor place-based subsidies or tax incentives.

As listed in the introduction, one compelling theory explaining why jurisdictions may offer local incentives, efficiently, is that luring more capital to a jurisdiction will provide copious spillovers that improve overall commerce and welfare (Slattery and Zidar, 2020). Following Garcia-Milà and McGuire (2002)[10], we augment regional productivity with capital concentration economies, $S(K) = S$, $S > 1$, $S_K > 0$, where production now becomes,

$$S(K)F(L,K) = SF = S(F_L L + F_K K). \tag{15}$$

A greater concentration of capital in a jurisdiction now has multiplicative spillover impacts to productivity. The profit maximizing condition for capital follows,

$$r = SF_K - t. \tag{16}$$

When making decisions regarding inputs and output, firms treat *S* as a parameter. Moreover, firms operate under constant returns to scale, yet, an increase in capital has jurisdictional productivity impacts. The representative resident's income-consumption is defined,

$$C = SF - (r+t)K - hL + \frac{r\overline{K}}{\overline{J}}, \tag{17}$$

and the government's budget constraint continues to follow Equation (11). Jurisdictional authority may take two views when choosing policy variables $\theta = \{h, t\}$: i) overlook the concentration effects or ii) use this information when maximizing utility. If jurisdictions ignore spillovers, the first order conditions become,

[10] Garcia-Milà and McGuire (2002) give this spillover function specific form, we opt for generality.

$$h: \frac{U_G}{U_C} L - L = 0, \tag{18}$$

$$t: \frac{U_G}{U_C}\left(t\frac{\partial K}{\partial t} + K\right) - K = 0\,. \tag{19}$$

We have seen these optimal conditions before and quickly show that they reduce to,

$$\frac{U_G}{U_C} = 1\,, \tag{20}$$

$$t^* = 0\,, \tag{21}$$

$$r^* = SF_K\,. \tag{22}$$

When the jurisdictional authority recognizes the spillover impacts, first order conditions become,

$$h: \frac{U_G}{U_C} L - L = 0, \tag{23}$$

$$t: \frac{U_G}{U_C}\left(t\frac{\partial K}{\partial t} + K\right) + FS_K\frac{\partial K}{\partial t} - K = 0\,, \tag{24}$$

and reduce to,

$$\frac{U_G}{U_C} = 1\,, \tag{25}$$

$$t^{**} = -FS_K\,, \tag{26}$$

$$r^{**} = SF_K + FS_K\,. \tag{27}$$

Now, recognizing capital concentration spillovers allows jurisdictions to subsidize mobile capital in a socially efficient manner. The subsidy in Equation (26) is equal to the marginal concentration benefit of additional capital. Welfare implications rest on the tradeoff of higher fixed factor taxes covering the subsidies for increases in capital investment and its many externalities. This result, however, hinges on two key elements – a free-to-vary fixed factor tax and the magnitude of S_K. If fixed factor taxes are subject to some type of cap or ceiling, public goods will be underprovided as before. Regarding the intensity of S_K, consider the following marginal effect,

$$\frac{\partial}{\partial K}\left[SF_K\right] = SF_{KK} + F_K S_K\,. \tag{28}$$

The change in the spillover impacts with respect increases in capital, S_K, must be sufficiently small so that SF_{KK} dominates $F_K S_K$ hence Equation (28) is negative.[11] Recall the derivation of $\partial K/\partial t$ found in Equation (10). In this latter form of the model the comparison becomes,

$$\begin{aligned} &I : SF_K - r - t = 0, \\ &\frac{\partial K}{\partial t} = -\frac{I_t}{I_K} = \frac{1}{SF_{KK} + F_K S_K}\,. \end{aligned} \tag{29}$$

If S_K is not sufficiently small and Equation (29) is not negative, outermost corner solutions will result (refer to Equations (26) and (27)).[12]

To this point, firms have played no role in the provision of public services, which they certainly benefit from. Following Oates and Schwab (1991) and Garcia-Milà and McGuire (2002), we redefine production as,

$$S(K)F(L,K,X) = SF = S(F_L L + F_K K + F_X X)\,, \tag{30}$$

where X is a publicly provided input to production purchased at a price p_X. Moreover, X is subject to the same degree of rivalry in use as L and K and curvature assumptions $F_X > 0$, $F_{XX} < 0$ remain (Feehan, 1989). We ration this public input to firms proportionate to their capital stock. Equilibrium public input provision and equilibrium jurisdictional capital stock will determine the ration ratio X/K. These aggregate levels in the jurisdiction are treated as exogenous by firms. In addition to the marginal product of capital, a marginal capital investment generates an additional return $R = (SF_X X)/K$, therefore,

$$r = SF_K + R - t\,. \tag{31}$$

For consistency, we assign a price, p_G , for the Samuelsonian public good G. This assumption is analogous to Oates and Schwab (1991) and Garcia-Milà and McGuire (2002) and provides a bit more generality.[13] The public budget constraint, now including the public input becomes,

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[11] Garcia-Milà and McGuire (2002) argue that this assumption is "reasonable".

[12] This is reminiscent of the core-periphery equilibrium found in the new economic geography (NEG) literature (see Baldwin and Krugman, 2004). For more recent empirical evidence on spillover magnitudes, see Patrick and Partridge (2022).

[13] Socially efficient provision of G now requires $U_G/U_C = p_G$.

$$p_G G + p_X X = tK + hL \,. \tag{32}$$

Income-consumption continues to follow Equation (17) with production as defined in Equation (30). Moving quickly to the optimal conditions, Table 1 provides a comparison of when jurisdictions account for concentration spillovers to when they do not.[14]

Table 1. Optimal conditions summary

	Recognize *S*(*K*)	**Overlook *S*(*K*)**
Provision of *G*	$U_G / U_C = p_G$	$U_G / U_C = p_G$
Price of public input	$p_X = SF_X$	$p_X = SF_X$
Capital taxation *t*	$t^{**} = R - FS_K$	$t^{*} = R$
Return to capital *r*	$r^{**} = SF_K + FS_K$	$r^{*} = SF_K$

When concentration spillovers are taken into account by jurisdictions, optimal tax rates on capital are lower than the in case where spillovers are overlooked. The tax rate t^{**} is equal to marginal public input rents minus the subsidy term found previously. As before, marginal spillover impacts, S_K, need to be sufficiently small in order to avoid corner solutions and free-to-vary fixed factor taxation is needed to cover the subsidies. Welfare will be higher in the recognize $S(K)$ case because the latter is a restricted solution to the more general problem that recognizes the externality and produces an equilibrium that internalizes it impacts. Locals will pay higher fixed factor taxes but their utility is maximized when firms are marginally subsidized to invest in higher, optimal levels of capital for the jurisdiction.

This derived general theory implies that incentives are offered to *all* firms in a jurisdiction. Garcia-Milà and McGuire (2002) provide specific extensions to the general theory that allow jurisdictions and more importantly firms to differ in concentration externalities and consequence. To illustrate the efficiency of selective tax incentives, they fashion a two jurisdiction game. The two players differ by capital type, jurisdiction 1 uses capital that generates spillovers and jurisdiction 2 employs capital that does not. Optimal tax types become,

$$t_1 = R_1 - F_1 S_{K_1} - F_2 S_{K_1} \,, \tag{33}$$

$$t_2 = R_2 \,, \tag{34}$$

where the tax on capital in jurisdiction 2 equals the marginal benefit, to the firm, of the public input while the optimal tax in jurisdiction 1 is set to the marginal benefit of the public input minus the marginal spillover benefit to both jurisdictions of capital concentration in jurisdiction 1. The last two terms in Equation (33), combined, reflect the

[14] Table 1 optimal conditions are analogous to those derived in Garcia-Milà and McGuire (2002). Table 1, column 1 results, derived using Garcia-Milà and McGuire's method, can be found in the Appendix to this paper.

subsidy required to internalize the externality generated by concentration economies. In equilibrium, following magnitude assumptions on S_{K_1}, firms generating spillovers are taxed less than firms generating no externalities, thus, it is optimal for jurisdictions to offer firm-specific tax incentives.

Concluding discussion

Wyoming's economic development mission, to provide incentives to commerce that produces a "ripple effect", appears to be supported by economic theory. The daunting task now becomes finding firms that foster the desired externalities. The small-beer industry, with its unprecedented growth over the last 20+ years, has become a popular target for place-based efforts (Farzan, 2016). Attracting the brewery 'scene' is viewed as a cultural and economic enhancement for local communities (Brewers Association, 2020). In Melvin's case, the initial negative externalities were overlooked by the town of Alpine for the promise of long-run benefit. Perhaps this benefit will be achieved with the Roadhouse buyout.

Conversely, there are those that view, generally, Wyoming's efforts to expand Melvin more a cautionary tale (Woodward, 2012; Parilla and Liu, 2018). While the empirical literature does find moderate employment gains from incentive strategies, little evidence supports firm-specific incentives enhancing local growth or overall welfare (see the review by Slattery and Zidar, 2020).[15] Moreover, landing the copious positive spillover firm is much like bagging the unicorn (Patrick and Partridge, 2022). More broadly, the regional science literature finds that agglomeration forces stand out as the key determinant of firm location and local growth (Krugman, 1991; Woodward, 2012). It is the concentration of commerce and its' spillovers that attracts and retains the firm, not the incentive bait. Subsidies and tax incentives are viewed as vain compensation for weak local external economies.

Melvin Brewing started in Jackson, Wyoming – the seat of Teton County. Teton is by far the wealthiest county in the United States, matched with unique economic integration (Jean, 2022). Melvin had deep roots in the city and would likely have expanded in the area without the aid of the Wyoming taxpayers. On November 15, 2022, the Alpine town council heard from Colby Cox, one of the co-founders of the Roadhouse Brewing Group, on the acceleration (discount) of the newly acquired Melvin recapture agreement. Cox proposed discounting the remaining contracted payments, through 2035, to their present value and made the offer of $1.28 million for the 6 acre property and building. One town councilman touted the benefits, to the town, of taking a lump sum for the property and countered with a $1.55 million figure. The town attorney halted the negotiation by explaining the actual process Alpine would have to adhere to when selling a public property outright – a formal offer must be received, public notice of the proposed sale and offer, an appraisal of the property completed followed by public hearings. With this clarification, the Roadhouse Group appeared satisfied to simply assume the recapture arrangement and perhaps address the outright purchase at a future date. A fair question

[15] Courant (1994) forcefully makes the point that employment increases do not necessarily translate to increases in welfare.

arises, did Roadhouse buy a going-concern brewery or simply want the town's property, including a specialized facility, at a deep discount? In any case, perhaps the moniker 'pure madness' more pointedly describes the distortions induced by the Wyoming Business Council, regardless of intent.

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Appendix

Wyoming Business Council
The Wyoming Business Council (WBC) is the state government's economic development arm. Quoting their website, "The Wyoming Business Council's approach to economic development focuses on identifying problems and breaking down barriers obstructing a more resilient economy. Collaboratively, we test, adapt, and repeat the process to develop locally crafted solutions." In keeping with local solutions, the WBC founded the Business Ready Community (BRC) program in 2002. The BRC provides state funded grants and loans to local communities within the state so they can direct their own economic futures. Again quoting the WBC, "when BRC investments work, the ripple effect is felt throughout the community." Through 2023, the program touts grants and loans totaling roughly \$450 million creating well over 5,000 jobs. Revenue recaptured back to the BRC fund is reported to be around \$15 million.

Alternative derivation
The jurisdictional authority, acting as a benevolent dictator, maximizes the representative resident's utility subject to text constraint Equations (17), (31) and (32) forming the Lagrangian,

$$\begin{aligned}\text{Max}_{C,G,K,X,t,h} \quad & U(C,G) + \lambda_1\left[SF_K + R - t - r\right] + \lambda_2\left[tK + hL - p_G G - p_X X\right] + \\ & \lambda_3\left[SF - (r+t)K - hL + \frac{r\overline{K}}{\overline{J}} - C\right]. \end{aligned} \tag{A1}$$

First-order-conditions, recognizing S become,

$$C: \quad U_C - \lambda_3 = 0, \tag{A2}$$

$$G: \quad U_G - \lambda_2 p_G = 0\,, \tag{A3}$$

$$K: \quad \lambda_1(F_K S_K + SF_{KK} + R_K) + \lambda_2 t + \lambda_3(FS_K + \underbrace{SF_K - r - t}_{-R}) = 0\,, \tag{A4}$$

$$X: \quad \lambda_1(SF_{KX} + R_X) - \lambda_2 p_X + \lambda_3 SF_X = 0\,, \tag{A5}$$

$$t: \quad -\lambda_1 + \lambda_2 K - \lambda_3 K = 0\,, \tag{A6}$$

$$h: \quad \lambda_2 L - \lambda_3 L = 0\,. \tag{A7}$$

Solving equations (A2), (A3) and (A6) for the Lagrange multipliers yields,

$$\lambda_1 = K(\lambda_2 - \lambda_3)\,, \tag{A8}$$

$$\lambda_2 = \frac{U_G}{p_G}\,, \tag{A9}$$

$$\lambda_3 = U_C\,. \tag{A10}$$

Note that Lagrange multipliers measure the sensitivity of the optimally valued utility function to changes in the constraints. Binding equality constraints generally require non-zero multipliers. Kuhn and Tucker (1951) conditions are the exception. The multiplier λ_1 is associated with the price for (returns to) capital, λ_2 measures the effect of changes in public expenditures, lastly, λ_3 reflects changes in income-consumption. The condition found in Equation (A7) forces $\lambda_2 = \lambda_3$ implying efficient provision of G. However, this equality drives $\lambda_1 = 0$ (see Equation (A8)) implying that the price of capital constraint may be nonbinding, a contradiction. Though in fact, the price of capital constraint is redundant. Consider the expansion of Equation (31) from the text,

$$r = \quad SF_K + \frac{SF_X X}{K} - t \quad = \quad \frac{SF_K K}{K} + \frac{SF_X X}{K} - t\,, \tag{A11}$$

where,

$$(r + t)K = SF_K K + SF_X X\,. \tag{A12}$$

By linear homogeneity of production, the price of capital constraint is imbedded into the income-consumption constraint in Equation (A1), that indeed binds. Equations (A2) - (A7) now reduce to,

$$\frac{U_G}{p_G} t + U_C (FS_K + \underbrace{SF_K - r - t}_{-R}) = 0\,, \tag{A13}$$

$$U_C SF_X - \frac{U_G}{p_G} p_X = 0\,, \tag{A14}$$

$$\frac{U_G}{p_G} K - U_C K = 0\,, \tag{A15}$$

when solved simultaneously yields the results in column 1 of Table 1 in the text.

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Beer Income Elasticities in the U.S.: An Autometric, Cross-Sectionally Dependent, Dynamic Panel Approach

Mitch Kunce[1]

Abstract

Per capita consumption of macro-adjunct lager is declining in the U.S. Rising real incomes and the expansion of small-beer appear as key factors. This paper explores the beer consumption – income link using four decades of state-level data that coincide with recent growth in brewery counts (1985-2022). Results from cross-sectionally augmented distributed lag models (CS-DL) show that income elasticities are continuing to trend downward for the beer sector. Moreover, we draw on automatic model selection, Autometrics, to improve our CS-DL estimation with specification selection based on incorporating structural breaks, outliers, and nonlinearities. Automatic selection finds non-linearity in the income variable, approximating a polynomial form, suggesting even deeper declines in U.S. beer consumption as real incomes rise.

Keywords: Beer consumption, panel data, cross-section dependency, Autometrics
JEL Classifications: C23, D12, L66

Introduction

The consumption of beer is the topic of a vast, multidiscipline literature. In economics, studies of demand patterns and relationships are forefront. The last four decades of declining beer consumption in the U.S. has coincided with the largest expansion of reporting brewing facilities the nation has ever seen. Figure 1 depicts this brewery growth trend (Alcohol and Tobacco Tax and Trade Bureau (TTB), 2024). Conversely, adult consumption per capita is down by roughly 25 percent from its peak in the early 1980s (The Beer Institute, 2024). Figure 2 shows the trends in beer consumption, in gallons per legal drinking aged adult (LDA), for all states and the District of Columbia. What this figure highlights is the persistent differences in consumption of beer across states and over time. What drives these differences – are the thousands of new breweries a factor? In economics, strict demand theory envisions consumption as a function of own price, prices of substitutes and compliments, income, product characteristics and consumer preferences. With regard to alcohol demand, influences like government regulation, culture and addictive behavior may also affect spatial patterns (Tremblay and Tremblay, 2005; Kunce, 2021).

In the extensive economic literature on the understanding of alcohol demand, most of the attention centers on the estimation of price and income elasticities. Fogarty (2010) and Nelson (2014) provide surveys of 141 and 114 papers, respectively, that reported estimated elasticities. Both surveys revealed that a large portion of this elasticity based literature has focused on single jurisdiction data, grocery store scanner data, market case studies and/or ad hoc consumer surveys. Complete panel data approaches, able to capture

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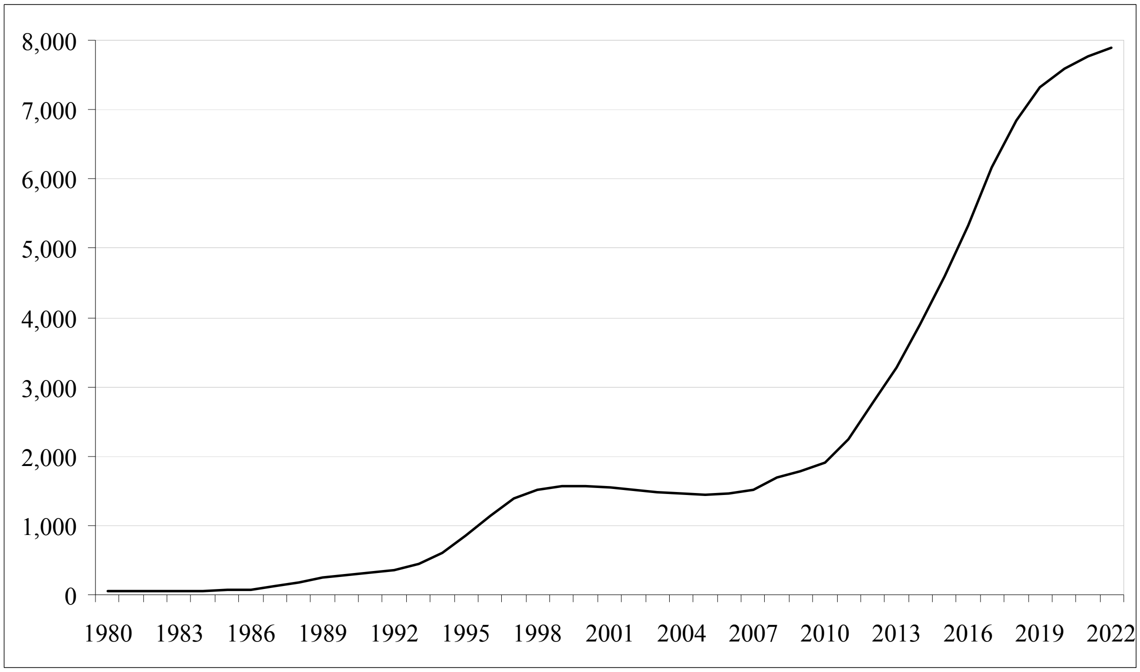

Figure 1. U.S. TTB reporting brewery count, 1980 - 2022

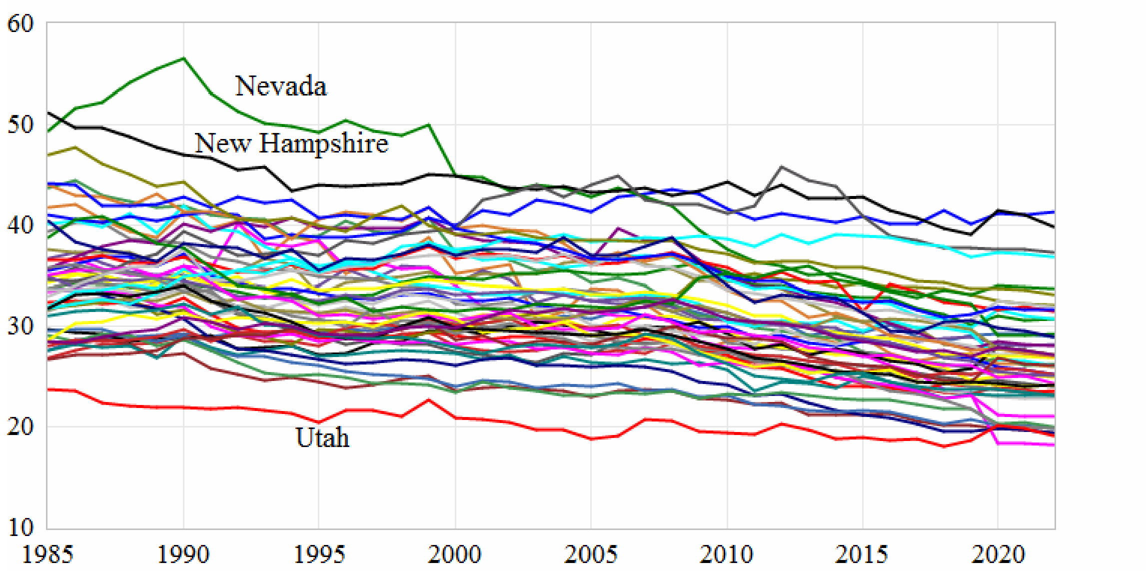

Figure 2. U.S. beer consumption in gallons per LDA, all states and D.C., 1985 - 2022

cross-section and time trend effects, were a rarity due to data availability at the individual level (Fogarty, 2010). Of late, macro aggregate panel treatments are gaining interest, most noteworthy are Ogwang and Cho (2009), Freeman (2011), Colen and Swinnen (2016), Holmes and Anderson (2017), Clements et al. (2020), Hart and Alston (2020) and Sadik-Zada and Niklas (2021).

In the aggregate, price proxies are judged, fairly, as inadequate (Hart and Alston, 2020). Cross-country studies tend to impute a value to volume calculation for price. U.S. state-level examinations incorporate excise tax data which does vary interstate but exhibits little variation within state over time. Sufficient within jurisdiction variation in other right-hand-side demand factors or socioeconomic variables is also lacking with few exceptions. The more micro-oriented attempts, while benefiting from more precise price data, suffer from inadequate income proxies and weighty sample selection issues (Nelson, 2014). Perhaps the most intriguing across and within forcing relationship found in the more recent macro aggregate examinations involves the beer consumption – income linkage. Colen and Swinnen (2016), in an 81 country 31 year panel, found that beer consumption increased with per capita GDP but at a decreasing rate. Countries with high GDP levels, on average, consumed less beer per capita over time. In a U.S. state-level analysis, Hart and Alston (2020) revealed that household income elasticities for beer have declined over the period 1970 to 2016. Sadik-Zada and Niklas (2021), with a 24 country 54 year panel, estimated an asymmetric ARDL consumption model. Increases in average GDP per capita were found to increase beer consumption (though inelastically around 0.1) while decreases had very little impact indicating a persistence of beer consumption as GDP declines. Herein, we elect to isolate the analysis on the U.S. beer consumption – disposable income relationship (long-run) and model the other relatively time invariant, or unobservable, demand factors with state and time specific controls. By doing so we veer from strict demand theory and purpose the analysis more on adventurous statistical methods. At any rate, our results are certainly plausible and in line with previous efforts.

With few exceptions (e.g. Freeman, 2011), the macro aggregate examinations have ignored cross-jurisdictional dependence. Wrongly assuming that errors are cross-jurisdictionally independent leads to faulty inference and case specific inconsistent estimation. In addition to accommodating error dependence at every step, we extend efforts in long-run modeling using cross-sectional dependent dynamic panel estimation with U.S. state-level data that begins in 1985, the genesis of the now four decade long U.S. brewery expansion (see Figure 1). We first estimate beer income elasticities, in this new brewery landscape, with a rather novel insight from Chudik et al. (2016), cross-sectionally augmented distributed lag modeling (CS-DL). Moving from this baseline, we use automatic model selection, Autometrics, to improve our CS-DL estimation with specification selection based on incorporating structural breaks, outliers, and nonlinearities.[2] The balance of this examination is divided into six sections. The next section describes the data, provides sources, presents descriptive statistics and undertakes extensive cross-sectional dependence testing. In the third section we examine the underlying stochastic process generating each variable's series through unit root testing. Section four focuses on cointegration structures and tests for them. First we assess the

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[2] We thank the staff at Timberlake Consultants Limited for their help adapting our input code to comply with their search algorithm. Autometrics is a part of the OxMetrics 9 software package.

import of cross-section dependence along with structural stability on any cointegrating relationship. The fifth section presents the CS-DL empirical model and shows the baseline results. Section six presents and interprets the Autometric selected results. Conclusions and implications are drawn in the last section.

Data

Data comprise a 38 (T) year (1985-2022), 50 state and District of Columbia (N) panel. As shown in Figure 1, the early to mid 1980s time frame is the start of the tremendous growth in TTB reporting brewing facilities across the country. Table 1 describes all variables, provides sources and key descriptive statistics. Natural logarithmic transformations are used as a means to remove potential growth in variance over time and of course coefficients on income are interpreted as elasticities. Analogous to other state

Table 1. Data descriptions, sources and descriptive statistics

Beer consumption. Apparent total 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 (includes malt-based seltzers, ranch waters, etc.).[3] Population numbers (denominator) are aggregated by state (drinking age laws may differ by state) by the U.S. Bureau of the Census. Mean 31.58, STD 5.89; Natural Log Mean 3.44, STD 0.19. Pooled Peseran CD 132.34***
Disposable personal income. Defined as per capita personal income by state available to persons for spending or saving (after-tax income), in thousands of 2017 dollars. U.S. Bureau of Economic Analysis, Personal Income and Outlays release. Mean 41.830, STD 9.593. Natural Log Mean 3.709, STD 0.222. Pooled Peseran CD 219.59***

Significance at < 1% (***).

panel examinations of beer demand (e.g. Freeman, 2011; Yakovlev and Guessford, 2013) the dependent variable examined is apparent personal beer consumption compiled periodically by The Beer Institute (a non-profit trade association).[4] Rather than use state domestic product per capita as an income proxy, we rely on real disposable personal income akin to Yakovlev and Guessford (2013).

Pesaran (2004; 2015; 2021) proposed a test statistic that can be adapted to test individual variable series cross-section dependence,

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right), \tag{1}$$

[3] See the appendix to this paper for a more detailed description of the Brewer's Almanac data provided by The Beer Institute.

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

where, following Pesaran (2007), $\hat{\rho}_{ij}$ denotes the pair-wise correlation coefficients from the residuals of cross-sectioned (i = 1, . . , N; t = 1, . . , T) Augmented Dickey and Fuller (1979, 1981) ADF regressions.[5] This *CD* statistic is distributed, generally, asymptotically standard normal and the null hypothesis depends on the relative expansion rates of N and T. In the case of large panels (both N and T tend to infinity at the same rate), the appropriate null is defined as weak cross-sectional dependence (Pesaran, 2015). In most panel estimations, only strong cross-sectional error dependence can pose deleterious effects on estimation and inference. Table 1 presents the uncorrected pooled statistics for each series and suggest sufficiency to reject the implicit null hypothesis of weak cross-sectional dependence at the < 1% level.[6]

In many cases, an easy correction for cross-section dependence is the inclusion of fixed effects. However, Juodis and Reese (2022) show that the Pesaran *CD* test, when applied to residuals from a model correcting with fixed effects, tends to diverge in favor of the null hypothesis.[7] The authors forward a weighted form of pair-wise correlation,

$$\hat{\rho}_{ij} = \sum_{t=1}^{T} w_i \hat{u}_{it} w_j \hat{u}_{jt}\,, \tag{2}$$

where $\hat{u}_{it}$ denotes the regression residuals and the weights w_i are iid Rademacher. Under the null, the statistic is again asymptotically normal. Table 2 presents six corrected then weighted *CD* test forms for our two series. For both *individual* series, we test residuals from two specifications. First, we regress on a constant, one-way state effects and a linear trend. Second, we apply a state and time effects two-way model. The last pair form tests the residuals of regressing lnConsumption on lnIncome with the same right-hand-side specifications just mentioned. While the corrected and weighted *CD* statistics are substantially lower than those presented in Table 1, all specifications continue to reject

Table 2. Corrected then weighted cross-sectional dependence testing

	One-way fixed effects	**Two-way fixed effects**
lnConsumption panel series		
Intercept	3.569***	3.435***
Trend	-0.007***	-
R^2	0.86	0.88
AIC	-2.462	-2.549
Weighted CD statistic	**33.76*** **	**3.09***
lnIncome panel series		
Intercept	3.424***	3.709***
Trend	0.015***	-

[5] For convenience, we may duplicate the use of some equation variable symbols as the paper proceeds. While there will be some overlap, consider similar symbols and definitions equation specific.

[6] CD tests based on uncorrected panel least squares are more robust to slope and error-variance heterogeneity.

[7] Juodis and Reese (2022) also look at other correction forms such as common-correlated effects (CCE) models.

R^2	0.97	0.98
AIC	-3.875	-6.369
Weighted CD statistic	**26.77*** **	**2.56** **
lnConsumption on lnIncome		
Intercept	1.585***	3.588***
lnIncome	0.579***	-0.041
Trend	-0.016***	-
AIC	-2.547	-2.548
R^2	0.87	0.88
Weighted CD statistic	**7.76*** **	**3.11** **

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

the null at the < 5 percent level. Interestingly, the last pair form test discloses income elasticity estimates for both test specifications. In the one-way with trend model, a significant positive income elasticity of 0.58 is found. The two-way fixed effects model estimates a negative but insignificant coefficient.

Panel unit root testing

The next step in the analysis is to establish the non-stationary characteristics of each panel series. Panel unit root testing benefits from increased power through the exploitation of cross-sectional information. However, conventional panel unit root tests have been criticized, of late, for assuming that cross-section cointegrating relationships are not present (Westerlund and Breitung 2013). Presuming cross-sectional independence, when perhaps strong error dependence is in play, tends to distort the size of the estimated test statistics that reject the null of non-stationarity too often. Faced with relatively strong cross-sectional dependence detected above − we opt for Bai and Ng's (2004, 2010), Panel Analysis of Non-stationarity in Idiosyncratic and Common components (PANIC), method for panel unit root testing.[8] The PANIC unit root test is based on a factor model in which non-stationarity can arise from common factors, idiosyncratic components, or both. Consider the following stochastic process for a series S_{it},

$$S_{it} = D_{it} + \lambda_i' F_t + \eta_{it}, \tag{3}$$

where the series is the sum of a deterministic component D_{it}, a common component $\lambda_i' F_t$, and an error η_{it} that is idiosyncratic. Because we only observe S_{it}, the components cannot be identified from single time series data, therefore a large panel is requisite. The deterministic component is comprised of cross-section intercepts c_i and can include a linear trend $\beta_i t$.[9] The r x 1 vector of common factors is denoted F_t where λ_i is an r x 1 vector of factor loadings. Factor estimation follows the information criteria proposed by Bai and Ng (2002) and is based on the method of principal components. PANIC avoids inconsistent estimation of the components by applying the method to the first-differenced

[8] This approach is arguably the workhorse in panel unit root testing, however, can suffer from small sample distortion particularly when the number of cross-sections N is 'small'.

[9] Results from the single series regressions in Table 2 indicate significance of the trend variables at the < 1 percent level.

data. Relative to the number of cross-sections (N), the number of common factors (r) are usually small.

Multivariate common factors ($r > 1$) from Equation (3) are tested, herein, using the modified version of the, more general, *Qc* test developed by Stock and Watson (1988) denoted *MQc* by Bai and Ng (2004).[10] The *MQc* test, which corrects for serial correlation of arbitrary form through non-parametric estimation, parallels the multivariate procedure suggested by Phillips (1987). Testing proceeds using a successive procedure for determining the number of stochastic trends underlying the r common factors. The null hypothesis states that r common factors have at most r common stochastic trends, against the alternative that they have less than r common trends. The test first derives a *MQc* for $r = m$, the number of common stochastic trends. If the null is not rejected at the onset, we conclude that all $r = m$ common factors are non-stationary. If the null is rejected, decrement m by 1 and repeat until we fail to reject the null or only one trend remains. If the null is rejected when one trend remains, we conclude that all r are stationary.

Removing the common components from the observed data facilitates the construction of a valid pooled test. For each idiosyncratic component $\hat{\eta}_{it}$, the Augmented Dickey-Fuller test is applied to each cross-section. Accordingly, a pooled panel unit root statistic (distributed $N(0,1)$) for the idiosyncratic terms can be constructed,

$$P_{\hat{\eta}} = \frac{-2\sum_{i=1}^{N} \ln\left(p_{\hat{\eta}_i}\right) - 2N}{2\sqrt{N}}, \tag{4}$$

where $p_{\hat{\eta}_i}$ denotes the probability values from the cross-sectioned Augmented Dickey-Fuller tests. Higher cross-section p-values will generate a smaller test statistic. Pooling of p-values has broad appeal and allows more heterogeneity in the cross-sections. The null hypothesis of this test is all cross-sections, jointly, have a unit root (non-stationary). As such, the pooled test mirrors a panel test for no cointegration among all cross-sections for each variable separately. If cross-section correlation can be represented by common factors, idiosyncratic error independence is then assumed in developing the pooled test even though univariate testing permits weak cross-sectional correlation.[11] Moreover, tests on the idiosyncratic components are asymptotically independent of tests on the common factors. Lastly, a series with a factor structure is non-stationary (unit root) if one or more of the common factors are non-stationary, or the idiosyncratic error is non-stationary, or both. Table 3 provides the PANIC results for the natural log series of each variable separately.

[10] When $r = 1$, PANIC suggests an Augmented Dickey-Fuller test for unit root in the common factor.
[11] The behavior of this pooled test holds up against other PANIC residual based tests involving pooled autoregressive coefficients and sample moments (Bai and Ng, 2010).

Table 3. PANIC results

	lnConsumption		lnIncome	
	Lags	**Statistic**	**Lags**	**Statistic**
Alabama	0	-1.81	3	-1.60
Alaska	0	-1.04	0	-1.42
Arizona	0	-1.96	3	-1.02
Arkansas	0	-0.88	0	**-4.38*** **
California	0	-0.76	8	-1.45
Colorado	3	-1.73	1	-0.16
Connecticut	6	-1.72	4	**-2.79** **
DC	6	-1.17	0	-0.72
Delaware	0	-1.36	7	-1.59
Florida	2	**-3.62*** **	9	-0.98
Georgia	7	-1.80	0	-0.95
Hawaii	0	-1.84	4	-1.31
Idaho	4	-1.33	5	**-3.50*** **
Illinois	7	-2.14	4	-2.01
Indiana	0	-1.49	6	**-3.01** **
Iowa	0	-0.91	1	-0.88
Kansas	1	-1.37	0	-0.77
Kentucky	1	-1.49	0	-2.05
Louisiana	3	-1.06	9	-0.70
Maine	9	**-3.58*** **	4	-1.15
Maryland	6	**-3.20** **	7	-1.53
Massachusetts	6	**-2.67** **	9	-1.23
Michigan	6	-1.07	4	-1.87
Minnesota	0	-2.11	0	**-4.19*** **
Mississippi	9	-2.27	5	-0.45
Missouri	0	-0.91	2	-0.67
Montana	8	-1.62	4	-1.22
Nebraska	1	-2.17	2	-1.02
Nevada	3	-2.30	0	-1.81
New Hampshire	0	-1.49	9	-0.52
New Jersey	0	-0.87	4	0.55
New Mexico	1	-0.89	3	-1.79
New York	7	-2.08	9	-1.12
North Carolina	0	-1.23	1	-1.98
North Dakota	0	-1.07	0	-1.34
Ohio	2	-0.82	8	-0.99
Oklahoma	0	-1.06	0	-2.11
Oregon	0	-1.84	6	-2.01
Pennsylvania	0	-1.68	8	-0.54
Rhode Island	2	-1.28	3	-0.93
South Carolina	5	-1.02	0	-0.82
South Dakota	5	-1.00	7	-1.10
Tennessee	2	-1.38	8	-1.03

Texas	1	-1.48	7	-0.64
Utah	1	-0.89	6	-0.11
Vermont	3	-1.59	1	-1.32
Virginia	0	-1.63	0	-1.54
Washington	0	-2.16	9	2.98
West Virginia	0	-0.81	2	-0.83
Wisconsin	7	-2.14	1	-1.22
Wyoming	3	-2.57	1	-1.11
Cross-Section Rejections		**4**		**5**
Common Factors | MQc | ADF	**2**	**62.91**	**1**	**-1.77**
Pooled Idiosyncratic		**1.10**		**0.56**
Deterministics: Constant and Trend. Series are demeaned and standardized.				
Significance (***) < 1%, (**) < 5%.				

As depicted near the bottom of Table 3, the Bai and Ng (2002) criterion determines 2 common factors in the consumption series and 1 in the income series. The two factors in the consumption series possess the largest eigenvalues and explain 88 percent of the variations in the data. The single factor in the income series explains 98 percent of the variations. For the consumption series, the *MQc* fails to reject the null at the onset indicating that both of the common factors are non-stationary.[12] In the income series, the ADF test fails to reject the null of unit root at the < 5 percent significance level but does reject unit root at < 10 percent (*p*-value 0.06). This indicates some evidence of a stationary common factor in the disposable income series.[13]

Regarding the idiosyncratic components, individual cross-section unit root tests show null hypothesis (unit root) rejections in 4 states for beer consumption and in 5 states for disposable income. The last row of Table 3 shows the pooled idiosyncratic component test (Equation (4)) for each panel variable. The pooled statistic fails to reject joint unit root in both series.[14] Overall, PANIC results are consistent with non-stationarity (I(1)) in both series, pervasive in the idiosyncratic components and somewhat mixed in the common factors.

Cointegration

Generally, testing for cointegration is a necessary third step prior to estimating long-run variable relationships. As in the unit root analysis above, cross-section dependence plays an important role in cointegration testing. Popular testing methods such as Kao (1999) and Pedroni (1999, 2004) assume cross-section independence among the grouped units of a panel series. Herein, panel cointegration testing must account for the presence of cross-sectional dependence. In keeping with the factor-based unit root testing above, cointegration testing will follow the companion factor-based procedure developed by Banerjee and Carrion-i-Silvestre (2015) which relaxes the assumption of cross-section

[12] Critical values for *MQc* are found in Bai and Ng (2004) p. 1136. Here the 0.05 critical value when $m = 2$ is -31.356.

[13] When $D_{it} = c_i$ only, the *MQc* is 19.01 and the ADF is -3.24 which is sufficient to reject unit root in the single common factor for the disposable income series at < 5 percent.

[14] When $D_{it} = c_i$ only, the pooled statistic is 1.49 for the consumption series and 1.17 for the income series. Both fail to reject the null at the < 5 percent level.

independence and addresses the structural stability of any cointegrating relationship. Advantages of this method include the ability to paint a more complete picture of the stochastic properties of all variables and components impacting the model. Assessing the properties of the common factors is of particular import because it allows for cointegration among the variables of interest (beer consumption and disposable income) alone or helps specify whether any non-stationary common factors are needed to form a cointegrating relationship. Following a similar set of assumptions of Bai and Ng (2004), we now define $Y_{it} = (y_{it}, x'_{it})'$ as a vector of stochastic processes including a dependent variable y_{it} with regressors x_{it} where,

$$Y_{it} = D_{it} + \pi_i F_t + u_{it} . \tag{5}$$

The deterministic component D_{it} can be empty, include cross-section intercepts and/or linear time trends. The F_t component denotes a vector of common factors, π_i is a matrix of factor loadings and u_{it} is the idiosyncratic disturbance. The dependent variable y_{it} on stochastic regressors x_{it} are assumed relationally cross-section dependent with the dependence determined by the common factors F_t. Interestingly, Banerjee and Carrion-i-Silvestre (2015) (BCIS) show that the set of common factors affecting the dependent variable can be different from those impacting the regressors by defining π_i as block-diagonal.

The BCIS framework is very flexible and implies a broader definition of cointegration. Generally, cointegration among $Y_{it} = (y_{it}, x'_{it})'$ requires F_t to be integrated of order zero, I(0), so that the observables capture all the common trends. However, BCIS allows F_t to be I(0), I(1) or a combination of both. Specifically, the general model that relates the dependent variable and the regressors becomes,

$$y_{it} = D_{it} + x'_{it}\beta_{it} + \pi_i F_t + u_{it} , \tag{6}$$

where β_{it} denotes the vector of parameters.[15] To this point, cross-section dependence has been presumed to be the result of observable common factors which is not feasible in practice where unobservable factors must be estimated. BCIS follows Bai and Ng (2002, 2004) using principal components to estimate the common factors and panel information criteria to determine the number of factors. In order to derive idiosyncratic disturbance test statistics, BCIS proposes six model specifications by varying the deterministic components and the cointegrating vector. Using any specification, they suggest testing the null hypothesis of no cointegration using ADF type regression results. The performance-preferred, pooled, panel statistic (between dimension) then becomes,

$$N^{-1/2} Z_{\hat{t}}(\hat{\lambda}) = N^{-1/2} \sum_{i=1}^{N} t_{\hat{\rho}_i}(\hat{\lambda}_i) , \tag{7}$$

where $t_{\hat{\rho}_i}(\hat{\lambda}_i)$ are the t-ratios from the model specific ADF-type regressions on the recovered estimated residuals from the model specific version of equation (6). Note that

[15] Banerjee and Carrion-i-Silvestre (2015) denote the deterministic component as $f_i(t)$.

Bai and Ng (2004) prefer to combine p-values (see equation (4)). The notation ($\hat{\lambda}_i$) refers to the break fraction parameters, which (if exist) are generally unknown. Unidentified break points are determined as the dates that minimize the sequence of the ADF t-ratio test statistics. This panel test statistic allows for a large degree of heterogeneity and is shown to converge to standard normal post standardization (Pedroni, 1999, 2004; Banerjee and Carrion-i-Silvestre, 2015).

Herein, our application centers on the estimation of disposable income impacts to legal age beer consumption. This data allows a balanced panel of 51 jurisdictions over the time dimension of 38 years (see Table 1). Recall from Table 2 the weighted CD test statistics reject the null hypothesis of weak cross-sectional dependence at the < 5% level. Table 4 reports the results of the BCIS factor-based cointegration testing.

Table 4. BCIS panel cointegration test

	Transformed
Common Factors	1
ADF statistic	-3.98*
State Rejections	16
Pooled Z_t	-3.23**
-Schwert Criteria Max Common Factors: 5	
-Significant at the < 5% (**), < 10%(*) for all D_{it} . See BCIS (2015) for tables containing critical values.	
-Results for one unknown break point shown.	
-Allowance for structural change in level and trend.	

Results presented rely on the transformed variables in ratio to their standard deviations when using principal components. With transformation, Bai and Ng (2002) criteria selects one common factor. The ADF statistic rejects the null of unit root at the < 10 percent level (p-value 0.064) weakly favoring stationarity in the single common factor. The calculated structural break modestly impacts the test results. The pooled idiosyncratic test rejects the null for all D_{it} specifications with one unknown break modeled at the < 5% level. To conclude, the variables (in the vector $Y_{it} = (y_{it}, x'_{it})'$) natural log consumption and natural log income are interpreted as cointegrated, not needing the common factor for a long-run relationship.

Cross-sectionally augmented panel models

Accommodating cross-sectional dependence in panels begins with Pesaran (2006). These so called common-correlated effects models have been extended to the dynamic macro-panel universe by relying on autoregressive distributed lag (ARDL) specifications. Specifically, panel CS-ARDL models are augmented with cross-section averages in order to control for the unobserved common factors which approximate the cross-sectional dependence (Chudik and Pesaran, 2015; Chudik et al., 2016). The main downside to CS-ARDL modeling is the requisite time horizon for each cross-section group series. The CS-ARDL approach does not perform well when T is not long (< 50) coined the 'small T bias'. An alternative specification proposed by Chudik et al. (2016) relies on a cross-section augmented distributed lag model (CS-DL) that does *not* include lags of the dependent variable.[16] Monte Carlo simulations show that the CS-DL approach, even when ignoring dependent variable feedback effects, outperforms when T is moderately large ($30 < T < 50$).[17]

The CS-DL model follows the auxiliary regressions,

$$y_{i,t} = \theta_{0,i} + \theta_{1,i} x_{i,t} + \sum_{l=0}^{p-1} \delta_{i,l} \Delta x_{i,t-l} + \sum_{l=0}^{p_{\bar{y}}} \gamma_{y,i,l} \bar{y}_{i,t-l} + \sum_{l=0}^{p_{\bar{x}}} \gamma_{x,i,l} \bar{x}_{i,t-l} + \varepsilon_{i,t}, \tag{8}$$

where $\bar{y}_{i,t-l}$ and $\bar{x}_{i,t-l}$ denote the cross-section averages, $p = p_{\bar{x}}$ which is equal to the integer part of $\sqrt[3]{T}$ and $p_{\bar{y}} = 0$. We consider the mean group estimator for $\hat{\theta}_1$ and variances (Pesaran et al., 1999). The mean group estimator produces consistent estimates under long-run slope heterogeneity and will not suffer lagged dependent variable bias under CS-DL.

Table 5 shows the mean group estimates of the long-run effect of disposable income on beer consumption for $p = p_{\bar{x}} = 3, 2, 1$. Schwarz (1978) information criterion (SIC) and non-weighted cross-section dependence test statistics are also depicted.[18] Focusing on the

Table 5. CS-DL long-run estimates

$p = p_{\bar{x}} = 3, p_{\bar{y}} = 0$	
lnIncome	0.064***
SIC	-4.779
CD	0.313
$p = p_{\bar{x}} = 2, p_{\bar{y}} = 0$	
lnIncome	0.255***
SIC	-4.654
CD	0.483
$p = p_{\bar{x}} = 1, p_{\bar{y}} = 0$	
lnIncome	0.493***
SIC	-4.569
CD	1.027
Significance (***) < 1%.	

[16] Unlike CS-ARDL, CS-DL is sensitive to endogeneity. However, strict exogeneity is not necessarily requisite due to the allowed correlations in the reduced form errors. In any case, any potential endogeneity issues are more than offset by the estimator's small sample performance (Chudik et al., 2016).

[17] In addition to the time dimension merits, CS-DL is robust to unit roots in regressors and factors, lag order misspecification, serial correlation in the errors and factors, and possible breaks in the errors. See Cao and Zhou (2022) for more on unit root in the common factors.

[18] We report SIC over other criterion to be compatible with Hendry (2000) and Doornik (2009) below. Schwarz criterion leans toward a more parsimonious specification. Non-weighted CD statistics tend to favor rejection of the implicit null.

SIC selected model with $p = \sqrt[3]{38} = 3.362 \Rightarrow 3$ lags, the income elasticity (0.064) estimated is significant at the < 1 percent level and, of course, very inelastic. This result is comparable to both the single- and system-model, split time horizon estimates of Hart and Alston (2020).[19] As incomes rise, adult beer consumption in the U.S. increases only slightly and these slight increases have markedly declined over time, in the aggregate.

Autometric selection

The appendix to this paper (see Figure A1) presents 51, state plus DC, graphs of LDA beer consumption in gallons against real disposable income, in 1,000s, where 39 suggest a non-linear relationship between the variables. Moreover, these paired graphic representations along with the series trends shown in Figure 2 highlight four potential sources of outliers in the panel (data for DC, Nevada, New Hampshire and Utah). In order to investigate these data issues further, we adopt the automatic model selection methods featured in the Autometrics algorithm. Autometrics follows the Hendry 'general-to-specific' method that starts with a broad, user specified, unrestricted specification (Hendry, 2000; Doornik, 2009; Doornik and Hendry, 2018). It then applies a sequence of reductions, weighed by diagnostic testing and information criterion, and selects the optimal, terminal specification. In order to capture outliers and breaks, Autometrics 'saturates' each observation with impulse and step indicators. Regarding non-linear-in-variable forms, the possible terminal function approximations are considerable. Castle and Hendry (2010; 2011) suggest refinement starting with an index test where principle components of the set of possible linear regressors are computed then tested jointly with their non-linear forms. Herein, testing suggests polynomial approximations for parsimony in our model. Generally, dynamics and lags are incorporated into Autometric selection, however in our specification the dynamic rigidity of the CS-DL framework limits this feature. Lastly, the algorithm allows certain variables to be 'fixed' and not eliminated from the terminal model. We will apply this feature to the consumption and income cross-section averages and lags.

The search algorithm is used to estimate the auxiliary regressions as defined in Equation 8. We set the lag orders to $p = p_{\bar{x}} = 3, p_{\bar{y}} = 0$. The candidate variable for polynomial approximation is disposable income and we limit expansion to the third-degree. All cross-section averages and lags are fixed and will follow through to the terminal model. The algorithm rejected linearity in 40 states, the cubic was rejected in all auxiliary equations. Impulse and step indicators did not prevent discovering these non-linearities. The algorithm removed all large outliers and failed to detect any meaningful structural shifts. Table 6 presents two sets of long-run results. The first reflects the selection from the Autometrics algorithm. Mean group estimates are derived from the 40 non-linear auxiliary equations. The second offers a comparison to simply modeling a quadratic form to the entire sample. Interestingly, the contrasts are subtle. Both sets show that beer consumption in the U.S. increases with real disposable income but at a decreasing rate. The Autometric selected model estimates an over two times larger second-degree effect.

[19] Hart and Alston (2020) estimated single equation beer income elasticities of 0.211 for the 1970-1996 period and 0.046 for the 1997-2016 period.

Table 6. Selected long-run results

Autometric Terminal Mean Group	
lnIncome	0.636***
$lnIncome^2$	-0.059**
SIC	-4.806
CD	-0.227
General Quadratic Mean Group	
lnIncome	0.764**
$lnIncome^2$	-0.027**
SIC	-4.798
CD	0.405
Significance (***) < 1%, (**) < 5%.	

Our results are somewhat analogous to the American continent findings of Colen and Swinnen (2016). They explain this inverse-U form by presuming that higher levels of income increase the demand for good health over alcohol and then demonstrate that higher incomes induce certain preference shifts to other alcohol sectors. For example, Swinnen (2017) pointed out that while higher income jurisdictions may be drinking less beer, they are in turn drinking more expensive beer. Preferences are shifting to perceived higher quality segments – a four-pack of Hazy IPA over a suitcase of Keystone Light (Elzinga et al., 2015).

Conclusion

While beer is a widely consumed good across the U.S., quantities enjoyed per adult are in decline. Rising real incomes appear to play a role in the volume descent. The homogenous adjunct lagers, that were prevalent at the consumption peak in the early 1980s, comprise the greater part of the four decade volume loss. With roughly 8,000 breweries reporting operations in 2022[20], variety beyond Bud Light and Coors Light prevails. Moreover, the beer shipments data, generated by the Beer Institute, includes flavored malt based beverages (FMBs) in their apparent beer consumption accounting. FMB is the industry vernacular for fermented seltzers, teas, lemonades, ranch waters, etc. In 2022, barrelage of FMBs reached roughly 11 percent of total domestic beer consumption and represented the only domestic beer segment with any noticeable volume growth over the previous year (Kunce, 2023). While FMB sales appear to be propping up U.S. LDA beer consumption, small-beer's vast product differentiation and perceived higher quality effects a downward force on beer sector income elasticities. Is our father's (or grandfather's) beer trending toward demand inferiority in the U.S.?

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[20] Where 78 percent reported production of 0 to 1,000 barrels for the year (TTB, 2024).

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Appendix

Glossary

User's Guide to the *Brewers Almanac*

The following section will help you better understand the nature and origin of the statistics used for the *Brewer's Almanac*. These terms and concepts will enable the user to realize what different statistical series should (and, more important, should not) be used for, and improve data analysis and research. Any questions should be directed to Matthew Hein at the Beer Institute.

BEER:
Production is measured at the time the beer reaches the settling tank of the brewery. Beer is fermented after removal from the settling tank. It is barreled, canned or bottled before its removal from the brewery. Once in the settling tank, it does not mean that the beer is ready for consumption.

TAXPAID WITHDRAWALS (sometimes called taxable removals):
This figure gives the number of barrels shipped from U. S. brewers to wholesalers/branches for the period shown. TAXPAID WITHDRAWALS GIVE THE BEST MEASURE OF BREWER ACTIVITY AND THE AMOUNT OF BEER SHIPPED FROM DOMESTIC BREWING OPERATIONS INTO THE U. S. MARKET. The Bureau of Alcohol, Tobacco, and Firearms (BATF), U. S. Department of the Treasury, publishes these figures.

This figure does NOT include non-alcoholic brews, but DOES include malt-based coolers (both terms described more fully below).

TAX-FREE WITHDRAWALS:
These barrels of beer are manufactured and sold (like taxpaid withdrawals), but are not included in domestic shipments. Tax-free shipments are designated for the following four key markets: 1.) For production of cereal beverages; 2.) For export overseas; 3.) For Puerto Rico and other U. S. possessions (U. S. Virgin Islands, Guam, etc.); and 4.) For the U. S. military overseas (domestic shipments to the military are included in taxpaid withdrawals).

Separate statistics for the first three categories are obtainable from disparate sources. [Exports Overseas appear in Table 51], Puerto Rico statistics, although not published in the *Almanac*, are available through Beer Institute. Using these independent sources does NOT give reliable measurements of the military market's size, due to inventory build and drawdowns. Therefore, please contact the Beer Institute for answers to questions about the composition of the various components in this category.

BARREL:
The standard English term for measuring containers of beer. Each barrel holds 31 gallons.

The standard metric measurement for beer is the HECTOLITER. 1.1734 hectoliters of beer comprise one barrel (conversely, 0.8522 barrels of beer are in one hectoliter).

24/12 OUNCE CASES:
This is the other standard measure (besides barrels) used to measure beer shipments. A barrel contains 3,968 ounces of beer (31 gallons x 128 ounces per gallon). To convert barrels to a case of 24 12-ounce containers, multiply by 13.777777.

NON-ALCOHOLIC BREWS (also known as cereal beverages):
These are malt-based products containing less than 0.5 percent alcohol. In 1998, this segment accounted for only about 1 percent of total malt beverage shipments.

COOLERS:
These products can be made from a malt base, a wine base, or a spirit base. Wine and spirit-based coolers are <u>not</u> included in the taxpaid withdrawal and shipment reports, but malt-based coolers <u>are</u> included.

PACKAGED BEER:
This includes beer shipped in canned, one-way (also called nonreturnable) bottles, and refillable bottles. The first beer can was manufactured in 1935.

DRAUGHT BEER:
This includes beer shipped in kegs. Kegs are most often shipped in one-half and one-quarter barrel sizes. In 1947, draught beer shipments accounted for about one-third of all domestic taxpaid withdrawals; in 1998 that figure stood just below 10 percent.

SHIPMENTS:

Data represents shipments from brewers to wholesalers within the state or entire United States, as applicable. SHIPMENTS ARE THE BEST AVAILABLE PROXY FOR "CONSUMPTION," WHICH CAN ONLY BE MEASURED AT THE RETAIL LEVEL. Shifts in inventory levels can distort the rate that shipments flow from brewer to wholesaler to retailer to consumer. In addition, a case (or barrel or keg) of beer shipped late in a calendar year from a brewer to a wholesaler may not necessarily be consumed by the end user until the next calendar year; this last factor should not affect the figures much. Most states include shipments to military facilities within their state shipment reports.

A common mistake is to cumulate taxpaid withdrawals and import figures to arrive at a "consumption" figure. Although conceptually correct, the "shipment," taxpaid withdrawal and import figures come from different sources: Shipment figures are based on reports from each of the fifty states and the District of Columbia. Taxpaid withdrawal figures come from the Bureau of Alcohol, Tobacco and Firearms, and the U. S. Commerce Department publishes the import figures. None of these three sources coordinate their figures in any way with each other. Given the possible effect of inventory adjustments (noted immediately above), the "shipments" figure should be used as the best available measure of "consumption."

PER CAPITA CONSUMPTION:

Figures are based on total population in the United States or in the individual state, as applicable. These figures are truly a measure of per capita *shipments*, as explained immediately above. The population figures used come from the U. S. Bureau of the Census.

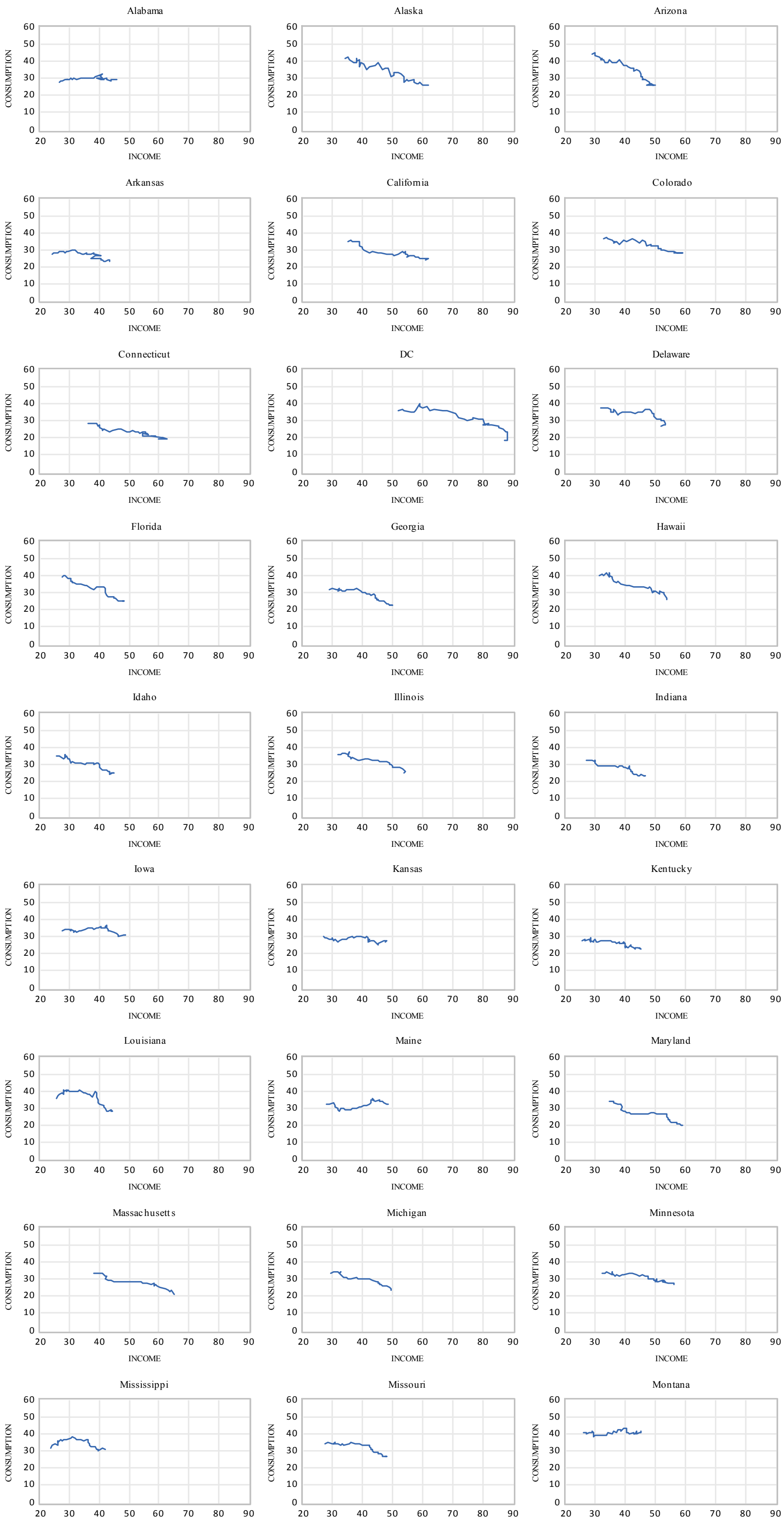
EXCISE TAXES:

These taxes are levied at both the federal level and in all fifty states and the District of Columbia. In addition, some counties and cities also levy malt beverage excise taxes. Since revenue is involved in the sale and shipment of malt beverages, excise tax collection statistics can be helpful in discerning total shipments within a state. Some states have different levies for packaged and draught beer, or for malt beverages above or below specified alcohol content levels.

For brewers brewing less than 2 million barrels of beer a year, up to and including the first 60,000 barrels, each barrel is taxed by the federal government at $7 per barrel, rather than the usual $18 per barrel. Some states also provide an excise tax differential for small brewers.

STOCKS:

Data represents barrels of beer housed in brewery inventory on the last day of the month of the reported period (since 1976, this date has been September 30, the last day of the government's fiscal year).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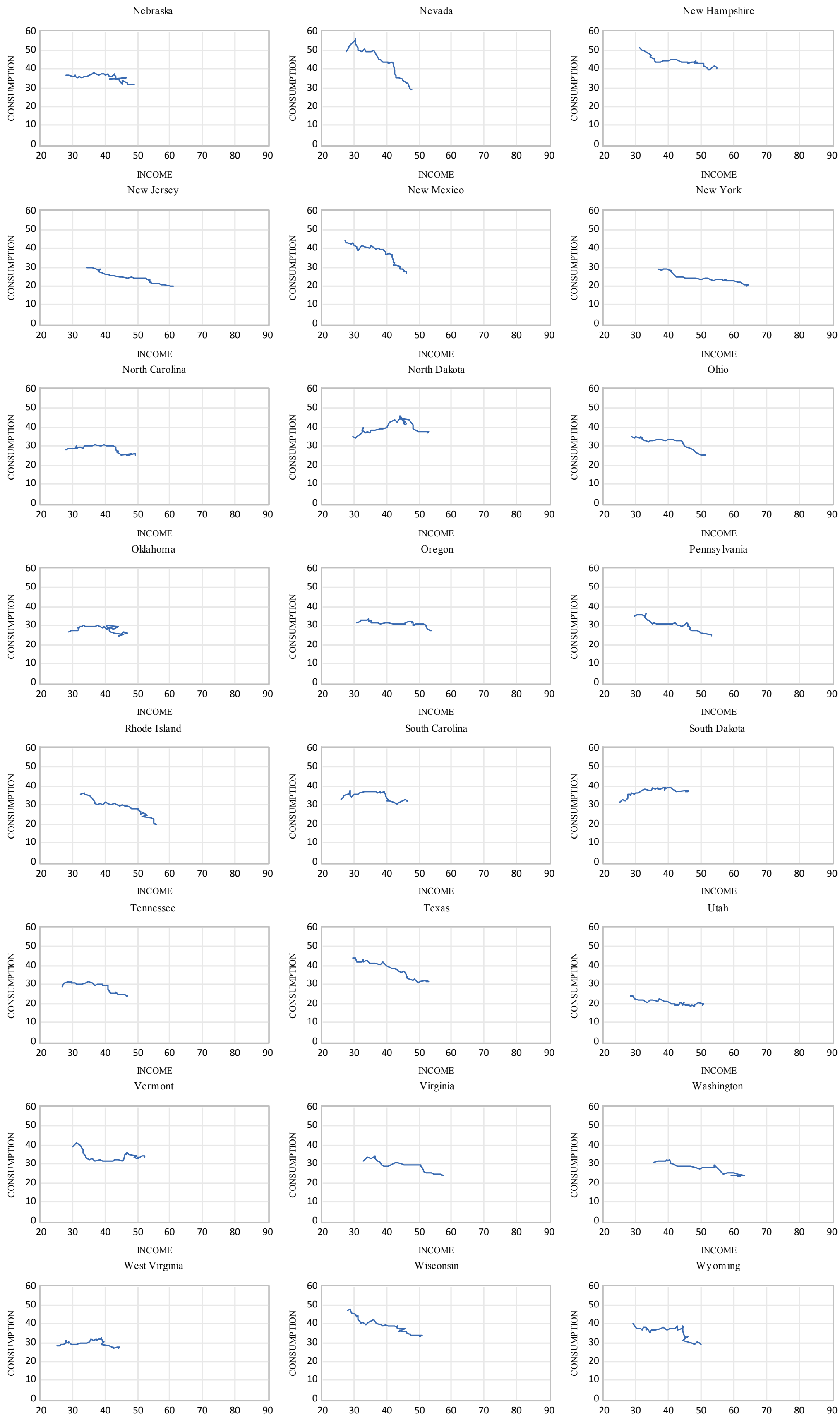

Figure A1. Adult beer consumption against disposable income by state and DC

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Conflicts in U.S. Small-Beer Reporting: A Comparison of Recent TTB Data

Mitch Kunce[1]

Abstract

In the latter part of 2022, the Alcohol and Tobacco Tax and Trade Bureau (http://www.ttb.gov) took down many of the bureau's aggregated beer industry reports for compliance purposes. Recently (May, 2024), many of these public reports were reinstated. This paper examines the compliance differences and, not surprisingly, finds that most of the conflicts, from previous reporting, can be attributed to very small breweries, those producing 1,000 barrels or less per annum.

Keywords: Beer production, tax compliance, government reporting
JEL Classifications: L78, L79, R38

Introduction

The Alcohol and Tobacco Tax and Trade Bureau (TTB) derives its aggregated beer statistics directly from industry member reporting of operations. The monthly or quarterly submitted 'Brewer's Report of Operations' is mandatory for each permitted production facility. This report forms the basis for brewery federal excise tax compliance. One of the key public reports compiled from this operations data is the 'Number of Brewers by Production Size'. This report provides a count of premises reporting any operations in a given calendar year, categorized by annual production size. On April 26, 2022, the report for calendar year 2021 was compiled then posted on the TTB's website. Generally, end-of-year statistical releases are generated roughly 60 days after the December filing due date of January 15. Later that same year, all production size annual reports were taken down from the website replaced with the message "under review for compliance purposes and not available at this time". In May of 2024 the reports reappeared on the TTB's website. This paper examines the differences and highlights the new data.

Data description and comparison

Table 1 presents a ten year comparison (2012-2021) of the report, 'Number of Brewers by Production Size'.[2] Prior releases and the May 6, 2024 aggregations are contrasted. The TTB (2024) lists production size strata of breweries based on the total volume of beer, in 31 gallon barrels, produced then reported by each brewery member during the calendar year. Each permitted brewery in the U.S. is assigned a unique BR number and is required to complete a Brewer's Report of Operations either monthly or quarterly depending on taxed annual barrelage.[3] The due date is the 15th day of the month following the reporting period. There is no annual filing option and reports must be submitted even if

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[2] The appendix to this paper shows the May 6, 2024 reports for the calendar years 2022 and 2023.

[3] 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. While some small breweries file monthly regardless, most are below this threshold and choose to file quarterly.

Table 1. Report comparisons

2012	**Report Date 9/13/2016**		**Report Date 5/6/2024**	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	25	176,380,080	25	176,380,080
>500,000 to 1,000,000	7	4,654,831	7	4,654,831
>100,000 to 500,000	39	7,810,357	39	7,821,769
>60,000 to 100,000	20	1,468,172	20	1,468,172
>30,000 to 60,000	50	2,179,430	50	2,179,430
>15,000 to 30,000	44	913,884	43	899,309
>7,500 to 15,000	77	821,101	77	817,793
>1,000 to 7,500	564	1,402,601	576	1,433,837
>0 to 1,000	1,604	516,746	1,620	519,058
0 Production Reported	-	-	325	0
Total	2,430	196,147,202	2,782	196,174,279
2013	**Report Date 9/13/2016**		**Report Date 5/6/2024**	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	25	171,239,158	25	171,239,158
>500,000 to 1,000,000	7	4,797,758	7	4,797,786
>100,000 to 500,000	38	7,637,584	38	7,663,969
>60,000 to 100,000	24	1,824,548	24	1,835,454
>30,000 to 60,000	52	2,271,815	52	2,282,130
>15,000 to 30,000	51	1,087,971	53	1,121,014
>7,500 to 15,000	81	842,820	82	844,490
>1,000 to 7,500	645	1,693,580	661	1,732,201
>0 to 1,000	1,923	602,141	1,958	613,126
0 Production Reported	-	-	386	0
Total	2,846	191,997,375	3,286	192,129,328
2014	**Report Date 9/13/2016**		**Report Date 5/6/2024**	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	26	169,885,120	26	169,885,120
>500,000 to 1,000,000	6	3,836,841	7	4,427,383
>100,000 to 500,000	44	9,093,515	44	9,116,595
>60,000 to 100,000	20	1,548,669	20	1,548,679
>30,000 to 60,000	62	2,639,562	62	2,670,877
>15,000 to 30,000	62	1,310,960	67	1,420,204
>7,500 to 15,000	102	1,042,199	105	1,071,407
>1,000 to 7,500	730	1,959,534	752	2,012,257
>0 to 1,000	2,321	698,738	2,380	726,998
0 Production Reported	-	-	441	0
Total	3,373	192,015,138	3,904	192,879,520

Table 1. continued

2015	**Report Date 10/25/2017**		**Report Date 5/6/2024**	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	26	165,059,434	26	166,061,014
>500,000 to 1,000,000	7	5,050,717	7	5,045,091
>100,000 to 500,000	49	10,645,528	51	11,103,223
>60,000 to 100,000	24	1,887,856	23	1,799,390
>30,000 to 60,000	56	2,453,623	57	2,514,576
>15,000 to 30,000	71	1,509,411	71	1,495,773
>7,500 to 15,000	133	1,427,754	135	1,442,945
>1,000 to 7,500	850	2,242,859	891	2,317,753
>0 to 1,000	2,812	835,836	2,855	855,541
0 Production Reported	476	0	476	0
Total	4,504	191,113,018	4,592	192,635,306
2016	**Report Date 10/25/2017**		**Report Date 5/6/2024**	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	25	163,111,389	25	163,111,389
>500,000 to 1,000,000	6	4,293,997	6	4,293,252
>100,000 to 500,000	45	10,469,048	46	10,961,394
>60,000 to 100,000	38	3,052,311	37	2,961,546
>30,000 to 60,000	53	2,329,947	56	2,481,320
>15,000 to 30,000	75	1,577,515	79	1,661,993
>7,500 to 15,000	148	1,550,640	154	1,611,109
>1,000 to 7,500	935	2,461,723	957	2,526,671
>0 to 1,000	3,291	993,344	3,402	1,023,118
0 Production Reported	480	0	572	0
Total	5,096	189,839,914	5,334	190,631,792
2017	**Report Date 3/21/2018**		**Report Date 5/6/2024**	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	24	157,771,814	24	157,771,815
>500,000 to 1,000,000	10	6,253,029	10	6,287,408
>100,000 to 500,000	40	8,792,844	41	8,984,860
>60,000 to 100,000	41	3,175,933	42	3,266,711
>30,000 to 60,000	53	2,230,145	57	2,397,456
>15,000 to 30,000	99	2,062,332	106	2,206,502
>7,500 to 15,000	152	1,565,336	164	1,699,972
>1,000 to 7,500	1,030	2,656,419	1,100	2,825,122
>0 to 1,000	3,656	1,073,985	3,895	1,138,808
0 Production Reported	543	0	728	0
Total	5,648	185,581,837	6,167	186,578,654

Table 1. continued

2018	**Report Date 4/4/2019**		**Report Date 5/6/2024**	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	25	154,824,114	25	154,823,365
>500,000 to 1,000,000	10	5,859,956	10	5,862,622
>100,000 to 500,000	42	8,777,286	43	8,832,838
>60,000 to 100,000	40	3,120,045	42	3,255,303
>30,000 to 60,000	53	2,170,405	58	2,377,842
>15,000 to 30,000	102	2,124,239	111	2,333,965
>7,500 to 15,000	155	1,618,340	170	1,748,346
>1,000 to 7,500	1,132	3,058,298	1,205	3,252,409
>0 to 1,000	4,252	1,238,277	4,448	1,302,278
0 Production Reported	153	0	740	0
Total	5,964	182,790,960	6,852	183,788,968
2019	**Report Date 3/11/2020**		**Report Date 5/6/2024**	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	26	150,190,673	26	150,190,234
>500,000 to 1,000,000	12	7,585,072	12	7,585,072
>100,000 to 500,000	42	8,373,875	41	8,135,417
>60,000 to 100,000	33	2,575,066	34	2,678,254
>30,000 to 60,000	64	2,675,606	70	2,941,703
>15,000 to 30,000	102	2,166,278	107	2,290,400
>7,500 to 15,000	159	1,680,545	170	1,804,671
>1,000 to 7,500	1,183	3,151,130	1,255	3,398,469
>0 to 1,000	4,605	1,321,919	4,834	1,391,336
0 Production Reported	174	0	780	0
Total	6,400	179,720,164	7,329	180,415,556
2020	**Report Date 3/31/2021**		**Report Date 5/6/2024**	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	28	149,443,768	27	148,644,021
>500,000 to 1,000,000	12	8,384,634	13	9,319,741
>100,000 to 500,000	44	9,409,404	46	10,243,515
>60,000 to 100,000	30	2,347,353	32	2,476,876
>30,000 to 60,000	67	2,772,031	71	2,924,981
>15,000 to 30,000	103	2,154,377	106	2,250,414
>7,500 to 15,000	156	1,626,497	172	1,796,147
>1,000 to 7,500	1,005	2,659,987	1,103	2,925,265
>0 to 1,000	4,741	1,162,426	5,092	1,254,583
0 Production Reported	220	0	932	0
Total	6,406	179,960,477	7,594	181,835,543

Table 1. continued

2021	Report Date 4/26/2022		Report Date 5/6/2024	
Production Size in Barrels	**Number of Breweries**	**Barrels Reported**	**Number of Breweries**	**Barrels Reported**
>1,000,000	28	147,212,213	28	147,212,213
>500,000 to 1,000,000	14	9,734,290	14	9,734,291
>100,000 to 500,000	49	9,959,373	50	9,976,249
>60,000 to 100,000	30	2,287,025	30	2,292,664
>30,000 to 60,000	76	3,129,899	80	3,314,868
>15,000 to 30,000	102	2,199,955	103	2,227,769
>7,500 to 15,000	178	1,882,822	198	2,098,841
>1,000 to 7,500	1,186	3,187,010	1,275	3,418,343
>0 to 1,000	4,728	1,295,879	5,026	1,385,610
0 Production Reported	240	0	1014	0
Total	6,631	180,888,466	7,818	181,660,848

no production occurred or no taxes were due for the month or quarter.[4] Regarding the number of brewers, prior releases defined the counts as those brewery premises reporting operations *and* paying taxes in a given calendar year. The May 6, 2024 reporting defines counts as those permitted breweries submitting any report for the given calendar year, payment of taxes is not mentioned. As shown in the last column of Table 2 below, the majority of reporting conflicts in counts are attributed to small-beer. Herein, we define small-beer as breweries producing 1,000 barrels or less in a calendar year. Big-beer is defined by combining the top 3 stratum, breweries producing more than 100,000 barrels per annum. Midsize breweries comprise the balance. What the Table 2 percentages reflect are proportional shares of the count reporting difference within the categories denoted. For example, in 2012 the reporting difference is calculated as 2,782 - 2,403 = 352 breweries. The corresponding percentage in the last column of Table 2 reflects the share 341/352 = 0.969, where 341 more breweries were counted in the 5/6/2024 data within the small-beer stratum.

Figure 1 below depicts, graphically, the number of breweries by year for the two reporting treatments (prior releases against 5/6/2024 reporting). Again, Table 2 presents the sources of treatment differences in brewery counts. As shown in Table 2, much of the difference stems from the TTB, previously, not including breweries in the overall count that filed reports but paid no taxes.[5] Column four of Table 2 indicates the likely sources of the balance of the treatment differences.[6] Late reporting occurs frequently with small breweries, particularly new small breweries. Moreover, audits of and amendments to submitted reports are just as frequent for small-beer. We have included TTB Forms 5130.9 and 5130.26 in the Appendix to this paper to illustrate reporting complexities. Form 5130.26 is streamlined and designed for smaller breweries that only sell beer on-

[4] 27 Code of Federal Regulations 25.297

[5] When would a brewery file a report indicating no production and have a tax liability for the period? In most cases, the breweries are working off prior or intra-company transferred inventory.

[6] We are extending gracious credit to the TTB, regarding this category, by not attributing their own errors and omissions. It appears that enforcement of reporting due dates, for small breweries, is a bit lenient.

premises. Novice brewers appear to struggle with this mandated reporting and more importantly, filing dates.

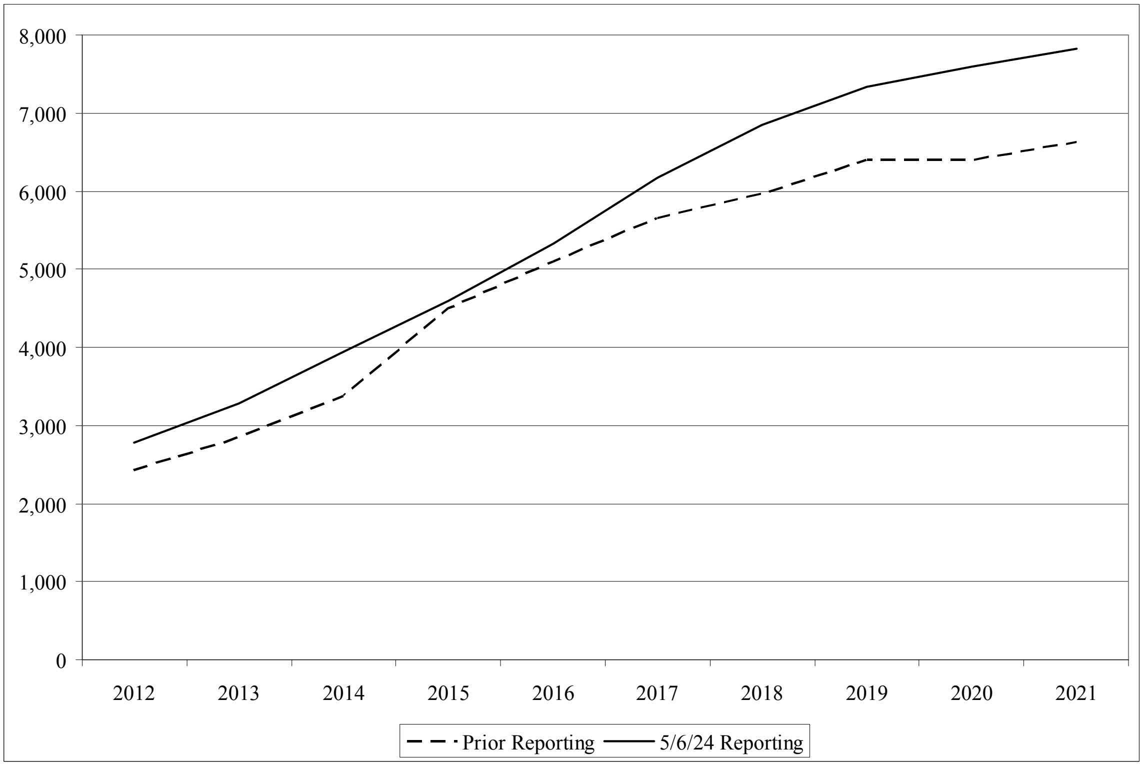

Figure 1. Brewery count comparison

Table 2. Sources of count differences

Year	Difference in Counts (%)	0 Production Reported No Taxes Paid	Late, Amended or Audited Reports	Attributed to Small-Beer
2012	352 (14.5%)	92.3%	7.7%	96.9%
2013	440 (15.5%)	87.7%	12.3%	95.7%
2014	531 (16.8%)	83.1%	16.9%	94.2%
2015	88 (2.0%)	0.0%	100.0%	48.9%
2016	238 (4.7%)	38.7%	61.3%	85.3%
2017	519 (9.2%)	35.6%	64.4%	81.7%
2018	888 (14.9%)	66.1%	33.9%	88.2%
2019	929 (14.5%)	65.2%	34.8%	89.9%
2020	1,188 (18.5%)	59.9%	40.1%	89.5%
2021	1,187 (17.9%)	65.2%	34.8%	90.3%

Figure 2 below shows aggregated production for the two treatments. Proportionately, the differences are markedly smaller than the count differences discussed above. Table 3 reflects the strata sources of these differences. As one would expect, the bulk of the reported production differences lie with larger breweries. Large brewery audits and report amendments are the key sources of these compliance differences. Overall, it appears that accurate and timely count and production reporting is a target difficult to hit.

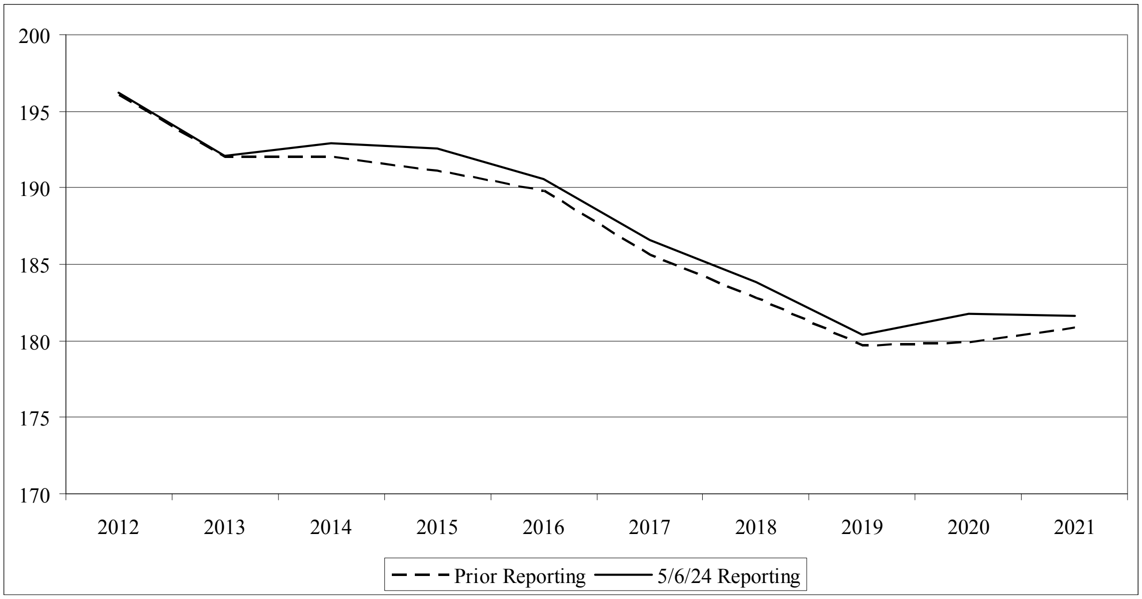

Figure 2. Production comparison

Table 3. Production differences

Year	Difference in Production (%)	Attributed to Big-Beer	Attributed to Midsize-Beer	Attributed to Small-Beer
2012	27,077 (0.01%)	42.2%	49.3%	8.5%
2013	131,953 (0.07%)	20.0%	71.7%	8.3%
2014	864,382 (0.45%)	71.0%	25.7%	3.3%
2015	1,522,288 (0.80%)	95.5%	3.2%	1.3%
2016	791,878 (0.42%)	62.1%	34.2%	3.7%
2017	996,817 (0.54%)	22.7%	70.8%	6.5%
2018	998,008 (0.55%)	5.8%	87.8%	6.4%
2019	695,392 (0.39%)	0.0%	90.1%	9.9%
2020	1,875,066 (1.04%)	51.7%	43.4%	4.9%
2021	772,382 (0.43%)	2.2%	86.2%	11.6%

Examination of the new 5/6/2024 data

The newly released data provides some important insights for the industry. Figure 3 highlights, graphically, these trends. First, over the period 2012 to 2023, industry reported production has declined 16.1 percent or by roughly 32 million barrels per annum. Understanding U.S. beer production and consumption declines has become an important topic in the current literature (Fogarty and Voon, 2018; Hart and Alston, 2020; Kunce, 2021). Secondly, reporting brewery counts appear to be leveling off or perhaps starting to decline. The most recent, June 3, 2024, TTB National Statistical Report–Beer shows under 6,000 breweries timely reporting operations for March 2024. As discussed above, this current count is likely to change due to late and/or amended reports but appears to support the premise that active U.S. brewery counts are beginning to fall (Kunce, 2023).

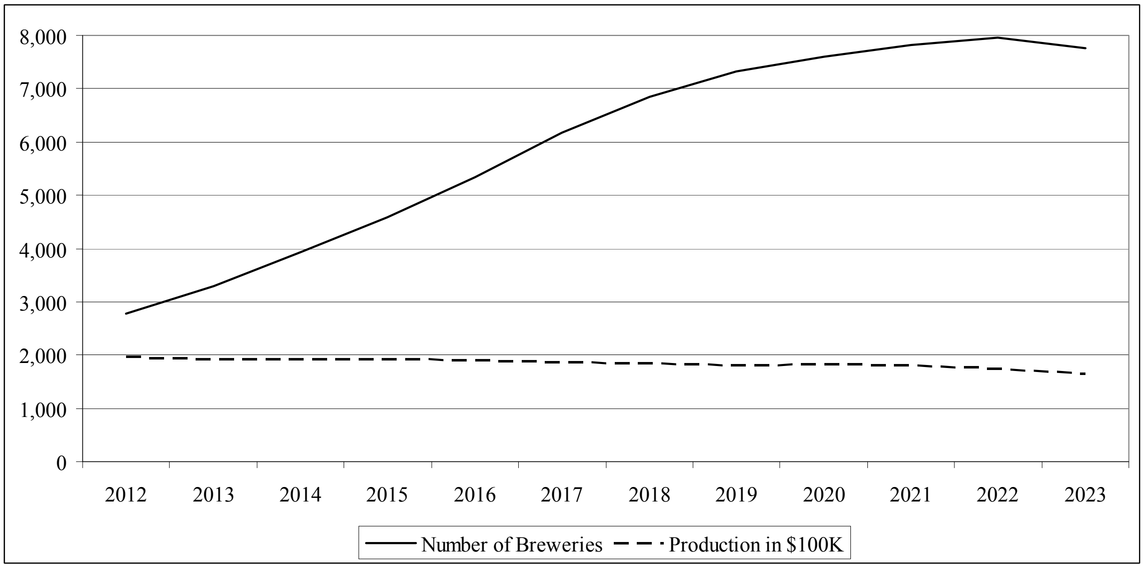

Figure 3. New count and production data, 2012 - 2023

Table 4 illustrates the growing count majority for small-beer and of course production dominance by the 70 to 90 (depending on the year) larger breweries in the country. The last column of Table 4 is very telling and may hold the explanation to why attention to timely and accurate counts, in TTB public reporting, was arguably not a bureau priority.

Table 4. New count and production shares

	Big-Beer Count Share	Small-Beer Count Share	Big-Beer Production Share	Small-Beer Production Share
2012	2.6%	70.0%	96.3%	0.3%
2013	2.1%	71.3%	95.6%	0.3%
2014	2.0%	72.3%	95.1%	0.4%
2015	1.8%	72.5%	94.6%	0.4%
2016	1.4%	74.5%	93.6%	0.5%
2017	1.2%	75.0%	92.7%	0.6%
2018	1.1%	75.7%	92.2%	0.7%
2019	1.1%	76.6%	92.0%	0.8%
2020	1.1%	79.3%	92.5%	0.7%
2021	1.2%	77.3%	91.9%	0.8%
2022	1.1%	78.2%	91.9%	0.8%
2023	1.1%	78.7%	92.1%	0.8%

References

Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau (TTB). (2024). http://www.ttb.gov

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Appendix

Table A1. 2022 TTB Report

Department of the Treasury

Alcohol and Tobacco Tax and Trade Bureau

National Revenue Center - 550 Main Street - Suite 8002 - Cincinnati, OH 45202-5215

1-877-882-3277

NUMBER OF BREWERS BY PRODUCTION SIZE - CY 2022

Reporting Period: 2022

Report Date: 6- May - 2024

Production Size [1]	Number of Breweries [2]	Total Barrels [3]	Taxable Removals [4]
Greater Than 1,000,000 Barrels	26	140,171,400	130,683,509
Greater Than 500,000 to 1,000,000 Barrels	14	9,610,584	9,391,087
Greater Than 100,000 to 500,000 Barrels	46	10,246,202	8,569,559
Greater Than 60,000 to 100,000 Barrels	24	1,869,996	1,594,858
Greater Than 30,000 to 60,000 Barrels	77	3,244,101	2,906,627
Greater Than 15,000 to 30,000 Barrels	110	2,337,252	2,089,524
Greater Than 7,500 to 15,000 Barrels	188	1,972,727	2,111,003
Greater Than 1,000 to 7,500 Barrels	1,247	3,406,066	3,144,654
Greater Than 0 to 1,000 Barrels	5,280	1,431,909	1,396,359
0 Barrels	950	0	342,312
Total	**7,962**	**174,290,237**	**162,229,493**

Notes:

1. Size - Based on Annual Production - The listed strata of breweries is based on the total amount of beer, in barrels, produced during the calendar year by each brewer.
2. Number of Breweries - Count of brewery permits that submitted an Operational Report for the calendar year 2022, including reports showing no production activity.
3. Barrels Produced - Total barrels of beer produced by the breweries comprising the named strata of data. Totals from each brewer are drawn from Lines 2 and 3, column (g), of TTB Form 5130.9 - Brewer's Report of Operations, and Line 2 of TTB Form 5130.26 - Quarterly Brewer's Report of Operations submitted by brewer for operations during the calendar year.

4. Taxable Removals - Total barrels removed subject to tax by the breweries comprising the named strata of data. Totals from each brewer are from Lines 14 and 15, column (g) of TTB Form 5130.9 - Brewer's Report of Operations, less the totals from Line 7, column (g), (returns of this breweries' beer to the brewery during the reporting period), plus Lines 10 and 11 of TTB Form 5130.26 - Quarterly Brewer's Report of Operations submitted by breweries for operations during the calendar year, less the amounts on Line 4 (returns of this breweries' beer to the brewery).

http://www.ttb.gov

Table A2. 2023 TTB Reports

Department of the Treasury

Alcohol and Tobacco Tax and Trade Bureau

National Revenue Center - 550 Main Street - Suite 8002 - Cincinnati, OH 45202-5215

1-877-882-3277

NUMBER OF BREWERS BY PRODUCTION SIZE - CY 2023

Reporting Period: 2023

Report Date: 6- May - 2024

Production Size [1]	Number of Breweries [2]	Total Barrels [3]	Taxable Removals [4]
Greater Than 1,000,000 Barrels	24	130,742,976	120,926,152
Greater Than 500,000 to 1,000,000 Barrels	16	10,799,523	9,738,786
Greater Than 100,000 to 500,000 Barrels	49	10,037,091	8,760,634
Greater Than 60,000 to 100,000 Barrels	19	1,463,471	1,255,686
Greater Than 30,000 to 60,000 Barrels	70	2,907,860	2,542,827
Greater Than 15,000 to 30,000 Barrels	122	2,488,206	2,549,785
Greater Than 7,500 to 15,000 Barrels	159	1,655,712	1,436,690
Greater Than 1,000 to 7,500 Barrels	1,191	3,132,830	2,845,090
Greater Than 0 to 1,000 Barrels	5,178	1,337,489	1,367,325
0 Barrels	924	0	232,871
Total	**7,752**	**164,565,158**	**151,655,846**

Notes:

1. Size - Based on Annual Production - The listed strata of breweries is based on the total amount of beer, in barrels, produced during the calendar year by each brewer.
2. Number of Breweries - Count of brewery permits that submitted an Operational Report for the calendar year 2023, including reports showing no production activity.
3. Barrels Produced - Total barrels of beer produced by the breweries comprising the named strata of data. Totals from each brewer are drawn from Lines 2 and 3, column (g), of TTB Form 5130.9 - Brewer's Report of Operations, and Line 2 of TTB Form 5130.26 - Quarterly Brewer's Report of Operations submitted by brewer for operations during the calendar year.
4. Taxable Removals - Total barrels removed subject to tax by the breweries comprising the named strata of data. Totals from each brewer are from Lines 14 and 15, column (g) of TTB Form 5130.9 - Brewer's Report of Operations, less the totals from Line 7, column (g), (returns of this breweries' beer to the brewery during the reporting period), plus Lines 10 and 11 of TTB Form 5130.26 - Quarterly Brewer's Report of Operations submitted by breweries for operations during the calendar year, less the amounts on Line 4 (returns of this breweries' beer to the brewery).

http://www.ttb.gov

Table A3. TTB Form 5130.9

OMB No. 1513-0007 (04/30/2015)

DEPARTMENT OF THE TREASURY
ALCOHOL AND TOBACCO TAX AND TRADE BUREAU (TTB)

BREWER'S REPORT OF OPERATIONS

Our Brewery EIN is:

Our TTB Brewery Number is:
BR-

TTB can reach the brewery by calling:
(   )

What is the name of your brewery?

What is the location of your brewery?

(Number & Street) (City) (County) (State) (ZIP Code)

Reporting Period (enter year)

Monthly Report for (enter month) ______ OR Quarterly Report for: ☐ January - March ☐ April - June ☐ July - September ☐ October - December

Part 1 - Beer Summary

Operations	Cellar	Racking		Bottling		Totals
		Bulk	Keg	Bulk	Case	
(a)	(b)	(c)	(d)	(e)	(f)	(g)
Additions to Beer Inventory (*round your entries to the nearest second decimal*)						
1. On hand beginning of this report period (*see line 33 totals from last monthly report or line 17 from last quarterly report*)						
2. Beer produced by fermentation						
3. Addition of water and other liquids						
4. Beer received from racking and bottling						
5. Beer received in bond (*see Instruction #10*)						
6. Beer received from cellars						
7. Beer returned to this brewery after removal from this brewery (*see Instruction #11*)						
8. Beer returned to the brewery after removal from another brewery of same ownership (*see Instruction #11*)						
9. Racked						
10. Bottled						
11. Physical inventory disclosed an overage						
12.						
13. Total additions to inventory, plus beer on hand (*add all columns in lines 1 through 12*)						
Removals from Beer Inventory (*round your entries to the nearest second decimal*)						
14. Removed for consumption or sale (*see Instruction #7*)						
15. Removed tax-determined for consumption or sale to tavern on brewery premises (*see Instruction #12*)						
16. Removed without payment of tax for export						
17. Removed without payment of tax for use as supplies (vessels/aircraft)						
18. Removed without payment of tax for use in research and development						
19. Removed without payment of tax to other breweries and pilot brewing plants of same ownership						
20. Removed without payment of tax as beer unfit for sale removed for use in manufacturing						
21. Beer consumed on premises (*see Instruction #12*)						
22. Beer transferred for racking						
23. Beer transferred for bottling						
24. Beer returned to cellars						
25. Beer racked						
26. Beer bottled						
27. Laboratory samples						
28. Beer destroyed at brewery (*see Instruction #13*)						
29. Beer transferred to a distilled spirits plant						
30. Losses, including theft (*see Instruction #14*)						
31. Physical inventory disclosed a shortage (*see Instruction #14*)						
32.						
33. Total amount of beer on hand at the end of this period (*see Instruction #15*)						
34. Total beer (*see Instruction #16*)						

TTB F 5130.9 (01/2015) Page 1 of 2
See instructions and Paperwork Reduction Act Notice on TTB F 5130.9i.

Table A3. TTB Form 5130.9 (continued)

Prior Period Adjustments *(see instruction #16)*

35. Additions to beer inventory	(+)	(-)	36. Removals from beer inventory	(+)	(-)

Under penalties of perjury I declare that this report is supported by true, complete, and correct records that are available for inspection at my brewery. I have examined this report and to the best of my knowledge and belief it is true, complete, and correct.

Signature | Title | Date

Part 2 - Cereal Beverage Summary
(products that are less than 0.5% alcohol by volume)

1. Produced	Bbls.	4. Loss and wastage	Bbls.
2. Removed	Bbls.	5.	Bbls.
3. Received	Bbls.	6. Total on hand end of period	Bbls.

Part 3 – Remarks
(Add remarks below or on a separate piece of paper attached to this form)

TTB F 5130.9 (01/2015) Page 2 of 2
See instructions and Paperwork Reduction Act Notice on TTB F 5130.9i.

Table A4. TTB Form 5130.26

OMB No. 1513–0007

DEPARTMENT OF THE TREASURY ALCOHOL AND TOBACCO TAX AND TRADE BUREAU (TTB) QUARTERLY BREWER'S REPORT OF OPERATIONS	Our brewery's EIN is:
	Our TTB brewery number is: BR-
	TTB can reach the brewery by calling:

What is the name of your brewery?

What is the location of your brewery?

(Number and Street) *(City)* *(County)* *(State)* *(Zip Code)*

Reporting Period (enter year)

This quarterly report is for: ☐ **January–March** ☐ **April–June** ☐ **July–September** ☐ **October–December**

Part 1 – Beer Summary

Additions to Beer Inventory	Number of Barrels (round to the nearest second decimal)		Removals from Beer Inventory	Number of Barrels (round to the nearest second decimal)	
1. Total amount of beer on hand at beginning of quarter *(see #17 from last quarterly report or #33 from TTB F 5130.9. If this is the first report for this brewery, enter "0".)*			10. Beer removed for consumption or sale including beer removed tax determined for consumption or sale in a tavern on brewery premises		
2. Total amount of beer produced by fermentation, plus total amount of water or other liquids added			11. Beer removed without payment of tax as outlined under Subpart L of 27 CFR part 25 *(see Instruction #12)*		
3. Beer received in bond *(see Instruction #10)*			12. Beer consumed on premises *(see Instruction #13)*		
4. Beer returned to the brewery after removal from the brewery *(see Instruction #11)*			13. Beer destroyed on premises *(see Instruction #14)*		
5. Physical inventory disclosed an overage			14. Losses, including theft *(see Instruction #15)*		
6.			15. Physical inventory disclosed a shortage *(see Instruction #15)*		
7.			16.		
8. Total additions to inventory, plus beer on hand *(add lines 1 through 7)*	0.00		**17. Total amount of beer on hand at end of quarter** *(see Instruction #16)*		
9. *Adjustments to additions from a prior reporting period (see Instruction #17)*	(+)	(-)	18. *Adjustments to removals from a prior reporting period (see Instruction #17)*	(+)	(-)
			19. Total beer *(see Instruction #18)*	0.00	

Part 2 - Cereal Beverage Summary (products that are less than 0.5% alcohol by volume)

1. Produced	Bbls.	4. Received	Bbls.
2. Removed	Bbls.	5.	Bbls.
3. Loss and wastage	Bbls.	6. Total on hand at end of quarter	0.00 Bbls.

Part 3 – Remarks

(Add remarks below or on a separate piece of paper attached to this form)

Under penalties of perjury, I declare that this report is supported by true, complete, and correct records that are available for inspection at my brewery. I have examined this report and to the best of my knowledge and belief it is true, complete, and correct.

Signature	Title	Date

TTB F 5130.26sm (10/2014) Page 1 of 1

See Instructions and Paperwork Reduction Act Notice on TTB F 5130.26i.

Does Winning GABF Medals Reduce the Likelihood of Firm Exit in the U.S. Beer Industry?

Mitch Kunce[1]

Abstract

In order to test the hypothesis that winning Great American Beer Festival (GABF) medals impacts small brewery operations, we incorporate medaling into a standard firm exit model. Industry exit would seem to be the quintessential economic consequence. Along with conventional determinants, GABF medaling is modeled as a factor potentially influencing the likelihood of firm exit. Results from a dichotomous qualitative response model demonstrate that local economic conditions and the age of the brewery had the largest impacts on the likelihood of exit. Brewery agglomeration, per capita, produced a significant competition pressure while joint restaurant ownership added management complexities that also influenced exit. Contrary to widely held perceptions, GABF medaling had no significant impact on the likelihood of firm exit. Exits of smaller firms have not been sufficiently examined in the literature, this study was aimed to offset this deficiency.

Keywords: Small firm exit, brewing industry, industrial dynamics
JEL Classifications: L10, L22, D22

"A win at the Great American Beer Festival (GABF) competition is a big deal. Taking a gold, silver or bronze medal can put a new brewery on the map..." *American Craft Beer.*

"The GABF is the most prestigious U.S. beer contest..." *Axios-Denver.*

"The Great American Beer Festival (GABF) is the Super Bowl of beer events. Award-winning breweries often see a tangible impact on their bottom line." *Craft Beer Times.*

"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." *Brewers Association*.

"But to keep up with increasing demand, especially after a gold medal win, a brewery expansion may be necessary." *Brewbound*.

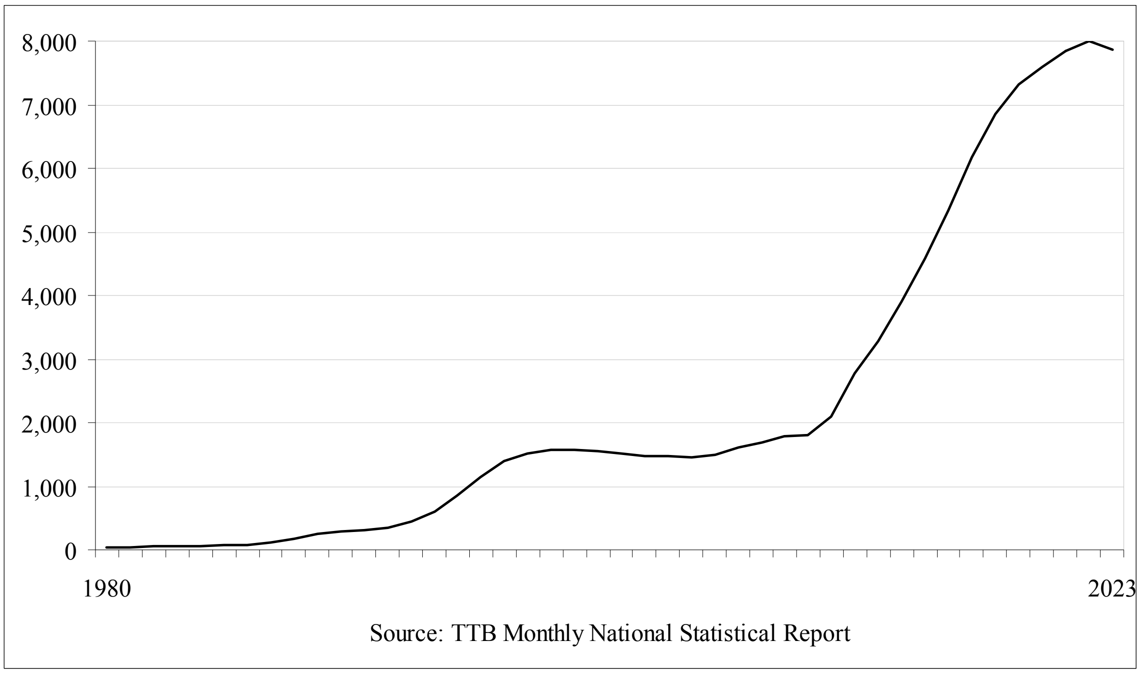
Introduction

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 the peoples' choice. 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

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

the U.S. (see Figure 1). Last year, 2023, the competition boasted just under 9,300 entries from 2,033 breweries awarding just over 300 medals (GABF, 2024). As revealed by the trade media quotes above, GABF medals are much sought after and carry a weighty perception of success (Kunce, 2021a). 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 (generally over one month before the event) the packaged beer to the competition's location, Denver, CO. Given the unprecedented growth of brewery counts in the U.S. to date (see Figure 1), there is a surplus of entrants wanting to compete. The GABF online[3] entry registration has been characterized in the past as a spirited game of chance (Kunce, 2023). As such, a majority of breweries have not participated in the judged competition of late.

Figure 1. U.S. reporting brewery count, 1980-2023



In 2012, home-brewer and auto technician Sean Nook and his wife Erin opened Black Bottle Brewery in Fort Collins, Colorado. The brewery quickly gained the reputation of being irreverent but creative. In early 2013, Nook began the *Cerealiously* beer campaign which involved using sugary breakfast cereals in the malt mash (Shikes, 2014). Styles using Golden Grahams, Cinnamon Toast Crunch, Lucky Charms and Count Chocula became taproom favorites. In the fall of 2015, Black Bottle won its first GABF medal after two previous attempts, a bronze for a Kölsch named after his father who passed away earlier in the year. "This medal was to honor him" Nook said in an interview with the Fort Collins newspaper, the Coloradoan (Sexton, 2015). Nook reflected on his father's support, the importance of this medal and the future of the brewery. In 2016 and 2017 Black Bottle followed up by winning 3 silver medals – on the face of it, the

[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.
[3] The competitive online registration was incrementally introduced from the mid to late 2000s.

brewery's future looked bright. Regrettably, in a brief note on social media in November of 2023, Sean and Erin Nook announced the closure of the brewery and the sale of all assets (Ricciardi, 2023). The note reads, in part, "running a small business is no skate in the park..." The Nooks did not elaborate on the specific circumstances of the closure. Despite the medals and expectations, Black Bottle did not survive.

The perception around winning GABF medals seems clear, event popularity and thousands of entries each year is a testament. But to what extent does winning actually impact a brewery's operations? Little, if any, empirical evidence exists regarding any measurable economic benefit to breweries from winning these medals.[4] In order to test the hypothesis that winning matters, economically, we incorporate medaling into a standard firm exit model. Industry exit would seem to be the epitome of economic consequence. A vast literature exists regarding determinants of firm entry and survival. Firm entry has received most of the attention over the years, but an interest in firm exit is expanding (DeTienne and Wennberg, 2016). Herein, we follow the seminal work of Schary (1991) but focus on exit as a dichotomous outcome due to certain data limitations. Along with conventional determinants, GABF medaling is modeled as a factor potentially influencing the likelihood of firm exit. Studies which assess the influence or effect of a specific factor on exit are fairly common in the literature (Cefis et al., 2022).

The rest of paper is structured as follows. The next section discusses the data, its generation, limitations and descriptive statistics. Section three provides details of qualitative response econometric models. Section four provides the empirical results for the baseline sample. Section five investigates structural differences between large and small producing firms. The last section concludes.

Data

Supplementary materials accompanying the prominent Elzinga, et al. (2015) paper provide an expansive data set of firm level annual production for U.S., so called, craft breweries for the years 1989 to 2012.[5] As described in Appendix A to this paper, the data was originally sourced from *The New Brewer*, a periodical published regularly by the Brewers Association (BA).[6] After merging the twelve spreadsheets provided, the raw data set supplied 23,360 observations of annual production – including firm name, categorization type (regional brewery, brewpub, etc.) and location details for just under 2,600 breweries. This data delivers an auspicious starting point. First, we define exits, simply, as breweries who ceased all operations under the firm's name and brand on or before the year 2012, the endpoint of the Elzinga data. We do not consider mergers or acquisitions of a going concern firm name, facilities and brands as industry exits. Moreover, we do not examine exit modes, intentions or specific strategies (Wennberg and DeTienne, 2014). Within the raw data, if production reporting stopped for a given brewery, further investigation followed.[7] For example, Theo Debroen founded the

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[4] Kunce (2021a) and (2021b) found no significant relationship between winning GABF medals and changes in a brewery's output.

[5] The term 'craft' is vernacular of the Brewers Association.

[6] This data is generally guarded and only made available to select BA member requests.

[7] Sources used included the Brewers Association, The Beer Institute, breweries' websites, local media articles, beer industry websites such as Beer Advocate, Alcohol and Tobacco Tax and Trade Bureau (TTB) permitting data and Secretary of States' listings.

Baltimore Beer Company in 1989. The Elzinga data shows production reported by Baltimore Beer, to the BA, for the years 1990 through 2004. As suspected, Debroen ceased all operations of the brewery in 2005 (Kasper, 2012). Clearly an industry exit under our definition ($Y = 1$). Alternatively, reported production data for Goose Island Beer Company stopped in 2009. Notably, the going concern brewery name, facilities and brands were acquired by Anheuser-Busch InBev in 2011 (Elzinga and McGlothlin, 2022). AB InBev planned to keep the operation running as is under the same name and brands ($Y = 0$). Accordingly, breweries lacking consistent production reporting were dropped from the raw data set. Missing production data is not a result of censoring and simply appears to be random. Post filtering, left-hand-side (LHS) exits comprise 657 of 2,405 total breweries spanning all 50 states and the District of Columbia for the time period ending in 2012.

Regarding the right-hand-side (RHS) and our focal determinate, the Brewers Association maintains a searchable database for all GABF medals awarded from 1983 to date at the website http://www.greatamericanbeerfestival.com.[8] Information available for query is brewery by name, brewery location by city and state, name of winning beer, style category and medal(s) awarded by year. Medals awarded by brewery and year were merged with the production data described above. For example, Tables 1 and 2 list medals awarded to the aforementioned Baltimore Beer Company and Goose Island Beer Company through 2012.

Table 1. GABF medals, Baltimore Beer Company

1994	Silver	1998	Bronze
1994	Silver	1999	Gold
1995	Gold	2000	Gold
1996	Gold	2002	Gold
1998	Bronze	2003	Silver

Table 2. GABF medals, Goose Island Beer Company

1989	Silver	2001	Bronze	2006	Gold	2009	Silver
1992	Gold	2002	Gold	2007	Gold	2010	Gold
1992	Bronze	2002	Silver	2007	Silver	2010	Bronze
1997	Gold	2003	Gold	2007	Bronze	2011	Bronze
1998	Silver	2004	Silver	2008	Bronze	2011	Bronze
1999	Gold	2004	Bronze	2009	Silver		
2000	Gold	2005	Gold	2009	Silver		

There is a special consideration for RHS variables in the binary dependent variable model. For a large portion of our forming data, breweries did not win GABF medals in any year nor did they exit the industry. In these cases the firm's LHS variable is the same as the RHS each year – a perfect predictor. Regretfully, this defect negates the use of the data's firm-specific panel structure. As an alternative, we simply collapsed the data into a

[8] Pro-Am and Collaboration Brewing medals included.

cross-section of 2,405 breweries. To capture GABF medaling over time on the RHS, we define two separate dummy variables. The first reflects breweries awarded a medal or medals in only one year of the firm's tenure to 2012. Second, breweries with multiple year wins were identified reflecting consistent excellence in the eyes, or more fittingly tastes, of the GABF judges.

Continuing on, more conventional factors that influence firms' exit are easily included in the RHS. The 'liability of newness' (Stinchcombe, 1965; Freeman et al., 1983) is captured by age of the brewery, in years, to closure or the end of 2012. Moreover, the 'liability of smallness' (Evans, 1987; Baum, 1996) is represented by average annual production size, in 31 gallon barrels, calculated using the Elzinga, et al. (2015) data. Interestingly, 71.7 percent of the breweries in our data produced, on average, 1,000 barrels or less annually – smallness is count dominant in the U.S. beer industry (Kunce, 2024). County-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. Unemployment rates for the county location of a specific brewery are averaged over relevant time periods.[9] For example, Baltimore county partly surrounds the city of Baltimore which was the location of the Baltimore Beer Company. County annual unemployment rates for the years 1989 - 2005 were averaged to form our unemployment RHS variable. In a few cases, going concern breweries actually moved physical locations. For example, the Flying Dog Brewpub opened in Aspen, Colorado (Pitkin county) in 1990. Outgrowing the Aspen location, the brewery moved operations to Denver (Denver county) in 1994. In 2006 the brewery moved to Fredrick, Maryland (Fredrick county), purchasing the Fredrick Brewing Company and its' facilities (Terry, 2007). Period specific unemployment data from the three counties were averaged to form our unemployment metric for Flying Dog. Using the same method, limited to the breweries in our 2,405 count, we can capture the average number of breweries, per capita, in a county forming an agglomeration proxy.[10] Spatial concentration has been shown to impact the likelihood of firms' exit (Weterings and Marsili, 2015; Basile et al., 2017). Lastly, the Elzinga, et al. (2015) data indicates whether a brewery is part of a restaurant concept (brewpub) having a jointly owned restaurant on the physical location. Management of these combined businesses adds a complexity that may impact industry exit.

Table 3 provides the descriptive statistics for the variables just defined. A firm's location

Table 3. Descriptive statistics

Variable, $N = 2{,}405$	**Mean**	**STD**
Exit - dependent variable, exit = 1, 0 otherwise.	0.273	0.446
Medal - brewery awarded a medal or medals in only one year = 1, 0 otherwise.	0.121	0.326
MYMedals - brewery awarded medals in multiple years = 1, 0 otherwise.	0.150	0.359

[9] U.S. county level time series data from the Department of Labor is more readily accessible than city or town specific metrics.

[10] County population for 1989 - 2012 sourced through the Census Bureau.

Age - age of the brewery in years from opening to closure or 2012.	10.916	5.385
Size - time series average in 1,000s of 31 gallon barrels.	2.907	21.110
Unemployment - county-level time series average rate in percent.	6.001	0.908
Agglomeration - time series average number of breweries, per 100,000 in population, in a location county.	2.942	9.687
Restaurant - jointly operating restaurant = 1, 0 otherwise.	0.537	0.495

allows for the consideration of controlling for unobservable (unattainable) location specific effects. Devolution of these effects, unfortunately, results in the same perfect predictor problem identified above with respect to certain RHS dummy variables. Consequently, we group the breweries into the more aggregated nine U.S. Census Bureau designated divisions (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific) and include them as RHS dummy variable fixed-effects.

Mindful of multicollinearity in the data, attention is paid to the orthogonality of covariates entered in the RHS. A correlation matrix for the focus determinants is provided in Table 4. Moreover, variance inflation factors (VIF) are estimated for each regressor and shown in the far-right column of Table 4.[11] Multicollinearity, as a matter of degree, does not appear problematic with this suite of covariates. Descriptive data on

Table 4. RHS correlation, variance inflation factors

	Medal	MYMedals	Age	Size	Unemployment	VIF
Medal	1.000					1.063
MYMedals	-0.157	1.000				1.316
Age	0.075	0.408	1.000			1.308
Size	0.006	0.178	0.218	1.000		1.066
Unemployment	0.007	-0.001	-0.043	0.010	1.000	1.094
Agglomeration	0.045	0.124	0.089	0.214	-0.099	1.125
Restaurant	0.029	-0.030	-0.017	-0.077	-0.052	1.018

the breweries that met our exit definition compared to breweries still operating at the end of 2012 revealed that exiting breweries were, on average: 1) four years younger, 2) roughly one-third the size, 3) faced with higher local unemployment, 4) located in a county with a higher brewery concentration, 5) more likely operating jointly with a restaurant and lastly 6) medaling in roughly the same frequency.

Model

Within the confines of the Elzinga, et al. (2015) data detailed above, we consider a process with a binary outcome, Exit = 1, 0 otherwise. Generally, the likelihood of an outcome is impacted by an index function, $\beta' x + \varepsilon$, where β is a vector of parameters to be estimated for variables x (including a constant term) and ε is the random error. Formally,

[11] Centered VIFs, including a constant, are shown.

$$\text{Prob}(\text{Exit} = 1 \mid x) = F(\beta' x), \tag{1}$$

where F denotes the cumulative distribution function of the random variable, ε. Using the logistic distribution function,

$$\text{Prob}(\text{Exit} = 1 \mid x) = \frac{\exp(\beta' x)}{1 + \exp(\beta' x)} = \Lambda(\beta' x), \tag{2}$$

or the standard normal cumulative distribution yields,

$$\text{Prob}(\text{Exit} = 1 \mid x) = \int_{-\infty}^{\beta' x} \frac{\exp(-t^2/2)}{\sqrt{2\pi}} dt = \Phi(\beta' x). \tag{3}$$

The former is the Logit model, the latter the Probit model. We estimate both as the choice of one distribution over the other is an issue rather unresolved (Amemiya, 1981).

Estimation is based on the method of maximum likelihood. Because the first order conditions of the likelihood functions are non-linear, obtaining parameter estimates requires an iterative solution. Generally for both distribution assumptions, Newton's method will converge in just a few iterations (see Greene, 2018, 742-744).[12] As a consequence, raw estimates of β from Newton's method do not represent marginal effects. Therefore, using the chain rule,

$$\frac{\partial E[y \mid x]}{\partial x} = \frac{dF(\beta' x)}{d(\beta' x)} \beta = f(\beta' x)\beta, \tag{4}$$

where the vector of marginal effects is a scalar multiple of the coefficient vector. The scalar is the density function f, which is a function of x. Average partial effects (APE) are computed by averaging the function over the sample observations. When the variable of interest in x is a dummy variable d, applying Equation (4) is inappropriate. The NLogit software computes,

$$\Delta F_d = E[y \mid x, d = 1] - E[y \mid x, d = 0]. \tag{5}$$

Hensher (1991), however, suggested that reporting the elasticities of the probabilities provides a more straight forward interpretation. Rather than specify covariate units constantly, it is convenient to consider a unit-free measurement response. The elasticity of the probability becomes,

$$\frac{\partial \log E[y \mid x]}{\partial \log x_k} = \frac{\partial E[y \mid x]}{\partial x_k} \frac{x_k}{E[y \mid x]}, \tag{6}$$

[12] NLogit 6 ® used for all model estimation.

where x_k denotes a conventional covariate. For the effects of a dummy variable, NLogit computes APE function *arc* elasticities.

Regarding the covariance estimator, the concept of a *robust* covariance matrix attempts to account for possible unobserved model misspecification. An example would be unspecified latent heterogeneity. A frequent adjustment for this case is the so called *sandwich estimator* (White, 1982; Huber, 1987). In almost any case, the sandwich estimator provides an appropriate asymptotic covariance matrix for a model that may be biased in some unknown direction (Freedman, 2006). In our estimations below, robust standard errors are used and are slightly different when compared to the conventional errors.

Estimation results

Table 5 presents elasticity estimates for both distribution functions. Predictably, the two models yield similar estimates. A Wald test of the census division effects being jointly zero is rejected at the less than 1 percent level for both models. Two fit measures are shown, the McFadden (1974) pseudo R^2 based on the log likelihood and the Cramer (1999) R^2 based on the accuracy of model predictions. Medaling in only a single year of a brewery's tenure is statistically insignificant. This measure, indicating limited success at the GABF, had no impact on the likelihood of exit. Multiple year GABF medals show a negative inelastic effect but statistical insignificance at conventional levels. In light of certain perceptions, GABF medaling is not significantly related to exit. Operating jointly with a restaurant, on the other hand, had a positive, but inelastic, significant effect. Complexities of managing both, seemingly synergistic efforts, increased the likelihood of exit. The restaurant industry is notorious for its purportedly high level of firm exit (Muller and Woods, 1991; Parsa et al., 2005; Healy and Mac Con Iomaire, 2019).

Table 5. Elasticity estimates[a]

	Logit	Probit
Medal	0.106	0.139
MYMedals	-0.213[b]	-0.271[c]
Age	-1.992***	-2.351***
Size	-0.002	-0.001
Unemployment	2.459***	2.742***
Agglomeration	0.335*	0.346*
Restaurant	0.635***	0.673***
McFadden R^2	0.224	0.211
Cramer R^2	0.241	0.235
Log Likelihood	-1,122.22	-1,126.13
Census Divisions Wald, $\chi^2_{8\,\mathrm{df}}$	51.745***	51.116***

[a] Census division control estimates not included.
[b] P-value of 0.127.
[c] P-value of 0.119.
Significance at: (***) < 1%, (*) < 10%. Robust standard errors used.

Regarding the more conventional determinants, firm age and local economic conditions (unemployment) carried the largest-elastic significant impacts. The 'liability of newness' hypothesis is bolstered in this examination. Moreover, the state of the local economy, proxied by average county-level unemployment rates, affects the largest impact to the likelihood of brewery exit. This general result is consistent with other socioeconomic based studies in the exit literature (e.g., Buzzelli, 2005; Bhattacharjee et al., 2009). Concentration of breweries in a county positively impacts the likelihood of exit, though the effect is inelastic and statistical significance is weak. This result differs from Weterings and Marsili (2015) and is somewhat similar to Basile's et al. (2017) results for non-service industry sectors. It appears our agglomeration variable is picking up the effects of competition rather than economic integration. Lastly, it is interesting that our size proxy is highly insignificant. As mentioned above, roughly 72 percent of the breweries in our data set produced, on average, 1,000 barrels or less annually. The inclusion of the larger producers may be introducing structural biases that mask any 'liability of smallness' impacts.[13] We address this in the next section.

Small-beer focus

In specifying the model above, we presumed that assumptions apply to all observations in the sample. It is straightforward, however, to test the hypothesis that some or all of the covariate coefficients are different for different subsets of the data. Pooling large producing breweries with the numerous small producers is a warranted testable hypothesis. Because we are estimating with maximum likelihood, a likelihood ratio test is appropriate. This test of the pooling hypothesis is a counterpart to the Chow (1960) test of structural change. We split the data into two subsets, breweries producing, on average, 1,000 barrels or less per annum (small-beer) and otherwise. Test statistics for both distributions are shown in the last row of Table 7. The pooling hypothesis is rejected at the less than 1 percent level in both cases. We proceed by re-estimating both the Logit and Probit models for the small-beer sample. Descriptive statistics for the new sample are provided in Table 6. Generally, by *on average* comparison, small breweries are: 5 years younger than larger producers, 20 fold smaller in production, medaling roughly 3 times less often, two fold more likely to operate with a restaurant and exiting the industry 9 percent more often.

Table 6. Descriptive statistics

Variable, $N = 1{,}724$	**Mean**	**STD**
Exit	0.309	0.456
Medal	0.099	0.297
MYMedals	0.079	0.271
Age	9.485	4.423
Size	0.449	0.275
Unemployment	6.002	0.917
Agglomeration	2.917	9.842
Restaurant	0.583	0.498

[13] Ten breweries in the sample averaged over 100,000 barrels per annum between 1989 - 2012.

Table 7 presents elasticity estimates for the small-beer sample. Predictably, estimates are similar to those in Table 5 with the exception of the size variable. Size now matters, statistically, yielding an inelastic-negative effect on the likelihood of exit. This result is more in line with a vast literature showing a significant inverse relationship between firm

Table 7. Elasticity estimates[a]

	Logit	Probit
Medal	0.096	0.101
MYMedals	-0.299[b]	-0.283[c]
Age	-2.084***	-2.061***
Size	-0.288***	-0.302***
Unemployment	2.395***	2.469***
Agglomeration	0.384**	0.397**
Restaurant	0.774***	0.781***
McFadden R^2	0.229	0.219
Cramer R^2	0.252	0.246
Log Likelihood	-820.16	-822.06
Census Divisions Wald, $\chi^2_{8\,\mathrm{df}}$	27.91***	28.12***
Pooling, $\chi^2_{15\,\mathrm{df}}$	43.67***	45.65***

[a] Census division control estimates not included.
[b] P-value of 0.120.
[c] P-value of 0.129.
Significance at: (***) < 1%, (**) < 5%. Robust standard errors used.

size and the likelihood of exit (see Cefis et al., 2022 for a review). Inclusion of the larger, more established craft breweries in the sample cloaked the 'liability of smallness' impact for the numerous very small producers.

Conclusion

Roughly eight out of ten U.S. breweries, as of 2023, are small firms, producing 1,000 barrels or less annually (Kunce, 2024). Issues related to entries and exits in the industry are largely a small firm matter. Exits of smaller firms have not been sufficiently examined in the literature, partly due to data availability. As such, this paper looked at small-beer exit behavior using a unique data set sourced, mainly, from the Brewers Association. Results demonstrated that local economic conditions and the age of the brewery had the largest impacts on the likelihood of exit. More 'like' firms in the area, per capita, produced a competition pressure while joint restaurant ownership added management complexities that also influenced exit. Contrary to widely held perceptions, GABF medaling had no significant impact on the likelihood of firm exit. Black Bottle Brewery's Sean and Erin Nook were long-time dues paying members of the Brewers Association and frequent participants in their competitions and conferences. In 2022, the Brewers Association reported $16 million in event revenues, $24 million total revenues, $26 million in cash and equivalents, and $36 million in total assets (see select pages from

IRS Form 990 in Appendix B). In 2023, Sean and Erin sold their brewery assets and moved on to the next chapter.

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Appendix A

Directly quoted read-me file from supplements to Elzinga et al. (2015):

Database Documentation
"Craft Beer in the United States: History, Numbers, and Geography"
Kenneth Elzinga, Carol Horton Tremblay and Victor J. Tremblay
Journal of Wine Economics

The database for this paper consists of 3 files (one of which is in 2 formats):

Craft Brewer Capacity and Production-1979-1988.xlsx
Craft Brewer Production-1989-2012.xlsx
State Data on Craft Brewers-1979-2012.xlsx; State Data on Craft Brewers-1979-2012.dta

The production and number of firms data for figures, maps and regressions were aggregated from the first two data sets, which consist of micro firm-level data. Figures contain data aggregated to the national level for the U.S., and maps and regressions are based on data aggregated to the state level. In defining "craft brewer" we include brewpubs, microbreweries and craft regionals but do not include contract brewers, national brewers and large regional brewers that were in existence before 1965. Units of measurement for production and capacity are 31-gallon barrels except for the regression data where units of measurement are in 10,000 31-gallon barrels. The text, Table 3 and Appendix to the paper contain additional information regarding the data. The following describes each data set further.

Craft Brewer Capacity and Production-1979-1988.xlsx

This Excel file contains individual firm level data on craft beer company name, city, state abbreviation, zip code, capacity and production for 1979-1988. The file also contains state level data. Production for craft brewers is taken from data on the leading 100 firms produced by *The Office of R.S. Weinberg, St. Louis.* When production is missing for a particular brewer, it is estimated by: Production Estimate = capacity x mean capacity utilization rate. (Estimates are shown in the file in red.) The source for the capacity data is *Brewers Digest, Brewery Directory,* 1979-1989, which is published in January-February. The directory in year t (e.g., 1989) reflects capacity in year t-1 (1988).

Craft Brewer Production-1989-2012.xlsx

The source for this file is *The New Brewer* which contains individual firm level data on type of firm (micro, brewpub, regional), company name, state and production. The Excel file contains data for 1989-2012 which appears on multiple sheets, each sheet with data on 2 consecutive years. As mentioned above, contract brewers, national brewers, and large regional brewers that were in existence before 1965 have been deleted from the original source data.

State Data on Craft Brewers-1979-2012.xlsx; State Data on Craft Brewers-1979-2012.dta

The state-level data set is provided in both Excel and STATA formats. The dependent variables for the regressions, production and number of brewers, derive from the two craft brewer firm data sets listed above. The 50 states and the District of Columbia are included for a total of 1,683 observations. (Not all variables are available for 1979; the regression sample runs from 1980-2012). When Spatial-firms and Spatial-prod are used, the sample is limited to the continental U.S. and the number of observations is 1,617. These spatial variables are based on inverse distances between states, and Alaska and Hawaii are too distant from the other states to have reasonable values.

The Appendix in the paper contains source information for the regressors. The data set includes the state, state abbreviation, st, year, and the variables listed in Table 3 of the paper. All variables in the file are defined in Table 3 except for "st" which is a numeric value that identifies the state. The "st" variable does not correspond to any government designation but serves as a sort variable or numeric value for statements such as the "xtset" command in STATA.

August 22, 2015

Appendix B

efile GRAPHIC print | Submission Date - 2023-10-25 | DLN: 93493298011343

Form **990** — **Return of Organization Exempt From Income Tax**

Under section 501(c), 527, or 4947(a)(1) of the Internal Revenue Code (except private foundations)

▶ Do not enter social security numbers on this form as it may be made public.

▶ Go to www.irs.gov/Form990 for instructions and the latest information.

OMB No. 1545-0047 — **2022** — Open to Public Inspection

Department of the Treasury Internal Revenue Service

A For the 2022 calendar year, or tax year beginning 01-01-2022 , and ending 12-31-2022

B Check if applicable: ☐ Address change ☐ Name change ☐ Initial return ☐ Final return/terminated ☐ Amended return ☐ Application pending

C Name of organization: BREWERS ASSOCIATION INC

Doing business as

Number and street (or P.O. box if mail is not delivered to street address): 1327 SPRUCE STREET — Room/suite

City or town, state or province, country, and ZIP or foreign postal code: BOULDER, CO 80302

D Employer identification number: 84-0802918

E Telephone number: (303) 447-0816

G Gross receipts $ 25,017,812

F Name and address of principal officer: DREW ROSANOVA, 1327 SPRUCE STREET, BOULDER, CO 80302

H(a) Is this a group return for subordinates? ☐ Yes ☑ No

H(b) Are all subordinates included? ☐ Yes ☐ No — If "No," attach a list. See instructions.

H(c) Group exemption number ▶

I Tax-exempt status: ☐ 501(c)(3) ☑ 501(c) (6) ◀ (insert no.) ☐ 4947(a)(1) or ☐ 527

J Website: ▶ WWW.BREWERSASSOCIATION.ORG

K Form of organization: ☑ Corporation ☐ Trust ☐ Association ☐ Other ▶

L Year of formation: 1979 — M State of legal domicile: CO

Part I Summary

Activities & Governance

1 Briefly describe the organization's mission or most significant activities: TO PROMOTE SMALL & INDEPENDENT AMERICAN BREWERS, THEIR BEERS & THE COMMUNITY OF BREWING ENTHUSIASTS

2 Check this box ▶ ☐ if the organization discontinued its operations or disposed of more than 25% of its net assets.

3	Number of voting members of the governing body (Part VI, line 1a)	3	20
4	Number of independent voting members of the governing body (Part VI, line 1b)	4	20
5	Total number of individuals employed in calendar year 2022 (Part V, line 2a)	5	59
6	Total number of volunteers (estimate if necessary)	6	3,000
7a	Total unrelated business revenue from Part VIII, column (C), line 12	7a	1,458,703
b	Net unrelated business taxable income from Form 990-T, Part I, line 11	7b	84,865

			Prior Year	Current Year
Revenue	8	Contributions and grants (Part VIII, line 1h)	4,044,663	1,394,514
	9	Program service revenue (Part VIII, line 2g)	13,625,619	22,350,298
	10	Investment income (Part VIII, column (A), lines 3, 4, and 7d)	551,644	501,013
	11	Other revenue (Part VIII, column (A), lines 5, 6d, 8c, 9c, 10c, and 11e)	703,184	554,429
	12	Total revenue—add lines 8 through 11 (must equal Part VIII, column (A), line 12)	18,925,110	24,800,254
Expenses	13	Grants and similar amounts paid (Part IX, column (A), lines 1-3)	68,535	179,671
	14	Benefits paid to or for members (Part IX, column (A), line 4)	0	0
	15	Salaries, other compensation, employee benefits (Part IX, column (A), lines 5-10)	7,057,410	7,854,332
	16a	Professional fundraising fees (Part IX, column (A), line 11e)	0	0
	b	Total fundraising expenses (Part IX, column (D), line 25) ▶16,040		
	17	Other expenses (Part IX, column (A), lines 11a-11d, 11f-24e)	8,992,846	15,566,611
	18	Total expenses. Add lines 13-17 (must equal Part IX, column (A), line 25)	16,118,791	23,600,614
	19	Revenue less expenses. Subtract line 18 from line 12	2,806,319	1,199,640

			Beginning of Current Year	End of Year
Net Assets or Fund Balances	20	Total assets (Part X, line 16)	36,725,546	36,404,650
	21	Total liabilities (Part X, line 26)	9,919,075	11,976,195
	22	Net assets or fund balances. Subtract line 21 from line 20	26,806,471	24,428,455

Part II Signature Block

Under penalties of perjury, I declare that I have examined this return, including accompanying schedules and statements, and to the best of my knowledge and belief, it is true, correct, and complete. Declaration of preparer (other than officer) is based on all information of which preparer has any knowledge.

Sign Here — Signature of officer — Date: 2023-10-23

DREW ROSANOVA FINANCE DIRECTOR — Type or print name and title

Paid Preparer Use Only

Print/Type preparer's name — Preparer's signature — Date: 2023-10-19 — Check ☐ if self-employed — PTIN: P00492291

Firm's name ▶ CLIFTONLARSONALLEN LLP — Firm's EIN ▶ 41-0746749

Firm's address ▶ 8390 EAST CRESCENT PARKWAY SUITE 300, GREENWOOD VILLAGE, CO 80111 — Phone no. (303) 779-5710

May the IRS discuss this return with the preparer shown above? (see instructions) ☑ Yes ☐ No

For Paperwork Reduction Act Notice, see the separate instructions. — Cat. No. 11282Y — Form **990** (2022)

Form 990 (2022) Page **9**

Part VIII **Statement of Revenue**

Check if Schedule O contains a response or note to any line in this Part VIII . . . . ☐

Section	Line				(A) Total revenue	(B) Related or exempt function revenue	(C) Unrelated business revenue	(D) Revenue excluded from tax under sections 512 - 514
Contributions, gifts, grants, and other similar amounts	1a	Federated campaigns	1a					
	b	Membership dues	1b					
	c	Fundraising events	1c					
	d	Related organizations	1d					
	e	Government grants (contributions)	1e	1,394,514				
	f	All other contributions, gifts, grants, and similar amounts not included above	1f					
	g	Noncash contributions included in lines 1a - 1f:$	1g					
	h	**Total.** Add lines 1a-1f ▶			1,394,514			
Program Service Revenue				Business Code				
	2a	PROJECTS & SERVICES		541900	16,472,445	16,472,445		
	b	MEMBERSHIP DUES		611430	4,354,519	4,354,519		
	c	ADVERTISING		541800	1,458,703		1,458,703	
	d	BOOK DEVELOPMENT		513130	64,631	64,631		
	e							
	f	All other program service revenue.						
	g	**Total.** Add lines 2a–2f. ▶		22,350,298				
Other Revenue	3	Investment income (including dividends, interest, and other similar amounts) ▶			332,387			332,387
	4	Income from investment of tax-exempt bond proceeds ▶						
	5	Royalties ▶			34,780			34,780
				(i) Real / (ii) Personal				
	6a	Gross rents	6a					
	b	Less: rental expenses	6b					
	c	Rental income or (loss)	6c					
	d	Net rental income or (loss) ▶						
				(i) Securities / (ii) Other				
	7a	Gross amount from sales of assets other than inventory	7a	207,542 / 150				
	b	Less: cost or other basis and sales expenses	7b	39,066 / 0				
	c	Gain or (loss)	7c	168,476 / 150				
	d	Net gain or (loss) ▶			168,626			168,626
	8a	Gross income from fundraising events (not including $ of contributions reported on line 1c). See Part IV, line 18	8a					
	b	Less: direct expenses	8b					
	c	Net income or (loss) from fundraising events ▶						
	9a	Gross income from gaming activities. See Part IV, line 19	9a					
	b	Less: direct expenses	9b					
	c	Net income or (loss) from gaming activities ▶						
	10a	Gross sales of inventory, less returns and allowances	10a	698,141				
	b	Less: cost of goods sold	10b	178,492				
	c	Net income or (loss) from sales of inventory ▶			519,649	519,649		
		Miscellaneous Revenue		Business Code				
	11a							
	b							
	c							
	d	All other revenue						
	e	**Total.** Add lines 11a–11d ▶						
	12	**Total revenue.** See instructions ▶			24,800,254	21,411,244	1,458,703	535,793

Form **990** (2022)

Form 990 (2022) Page **11**

Part X Balance Sheet

Check if Schedule O contains a response or note to any line in this Part IX . . . ☐

				(A) Beginning of year		(B) End of year
Assets	1	Cash–non-interest-bearing		10,867,760	1	3,606,681
	2	Savings and temporary cash investments		17,764,498	2	23,010,805
	3	Pledges and grants receivable, net		556,794	3	884,774
	4	Accounts receivable, net		611,584	4	477,720
	5	Loans and other receivables from any current or former officer, director, trustee, key employee, creator or founder, substantial contributor, or 35% controlled entity or family member of any of these persons			5	
	6	Loans and other receivables from other disqualified persons (as defined under section 4958(f)(1)), and persons described in section 4958(c)(3)(B)			6	
	7	Notes and loans receivable, net			7	
	8	Inventories for sale or use		769,547	8	740,779
	9	Prepaid expenses and deferred charges		1,138,182	9	1,312,672
	10a	Land, buildings, and equipment: cost or other basis. Complete Part VI of Schedule D	10a 6,267,099			
	b	Less: accumulated depreciation	10b 1,828,013	4,478,817	10c	4,439,086
	11	Investments—publicly traded securities			11	
	12	Investments—other securities. See Part IV, line 11			12	
	13	Investments—program-related. See Part IV, line 11			13	
	14	Intangible assets		251,711	14	470,311
	15	Other assets. See Part IV, line 11		286,653	15	1,461,822
	16	**Total assets.** Add lines 1 through 15 (must equal line 33)		36,725,546	16	36,404,650
Liabilities	17	Accounts payable and accrued expenses		829,406	17	1,377,413
	18	Grants payable		167,000	18	0
	19	Deferred revenue		8,632,266	19	9,110,190
	20	Tax-exempt bond liabilities			20	
	21	Escrow or custodial account liability. Complete Part IV of Schedule D			21	
	22	Loans and other payables to any current or former officer, director, trustee, key employee, creator or founder, substantial contributor, or 35% controlled entity or family member of any of these persons			22	
	23	Secured mortgages and notes payable to unrelated third parties			23	
	24	Unsecured notes and loans payable to unrelated third parties			24	
	25	Other liabilities (including federal income tax, payables to related third parties, and other liabilities not included on lines 17 - 24). Complete Part X of Schedule D		290,403	25	1,488,592
	26	**Total liabilities.** Add lines 17 through 25		9,919,075	26	11,976,195
Net Assets or Fund Balances		**Organizations that follow FASB ASC 958, check here ▶ ☑ and complete lines 27, 28, 32, and 33.**				
	27	Net assets without donor restrictions		26,806,471	27	24,428,455
	28	Net assets with donor restrictions			28	
		Organizations that do not follow FASB ASC 958, check here ▶ ☐ and complete lines 29 through 33.				
	29	Capital stock or trust principal, or current funds			29	
	30	Paid-in or capital surplus, or land, building or equipment fund			30	
	31	Retained earnings, endowment, accumulated income, or other funds			31	
	32	Total net assets or fund balances		26,806,471	32	24,428,455
	33	Total liabilities and net assets/fund balances		36,725,546	33	36,404,650

Form **990** (2022)

Journal of Beer Economics, Vol. 2, No. 1, 2024, 90-104 .

Overcapacity in the U.S. Beer Industry? Insights from Domar's Conception of Capacity Utilization

Mitch Kunce[1]

Abstract

The last twenty years of expansive facility investment in the U.S. beer industry has many observers raising concerns of overcapacity. To the contrary, declining demand appears as the main culprit. With help from Evsey Domar's conception of dynamic capacity utilization, we narrow the definition of the U.S. beer industry to properly address overcapacity. The relevant industry represents roughly 6 percent of reporting facilities that produce over 97 percent of the barrelage. We maintain that the smaller reporting operations, encompassing the bulk of new investment, more resemble what Robert Gibart coined, 'competitive fringe'. Calls for an analytical separation of the extraneous faction are advanced.

Keywords: Overcapacity, Domar's coefficient of utilization, defining the U.S. brewing industry

JEL Classifications: D25, E22, O40

Introduction

At first glance, Figure 1 below depicts a beer (malt alcoholic beverage) industry that is booming.[2] At the least, it shows an industry investment boom. From 1980, reporting brewery counts have increased by 165 fold. As shown, the greater part of the expansion has occurred in the last 20 years or so. Reasons for this explosion of facility counts have been widely examined, but appear to center on the relaxation of state-level on-premises sales restrictions, left over from prohibition, that took place in the 1980s and 1990s (Elzinga et al., 2015; Kunce, 2024a). When digging a bit deeper, however, the throughput from this capital expansion has yet to materialize. Figure 2 below shows reported U.S. production, in millions of 31 gallon barrels, from 1980 to 2023. From 1980, annual production has decreased by just over 13 percent, 190 million barrels in 1980 to 165 million in 2023. From 2012, industry-wide annual production is down by over 16 percent with *real* annual revenues down by over 11 percent (Brewers Association, 2024).[3] Interestingly, while domestic beer production is in decline of late, imports (mainly from Mexico)[4] are on the rise. Figure 3 below shows the steep accent in import barrelage since

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[2] In the broadest terms, this industry markets fermented alcoholic beverages from producers permitted by the TTB. Distinguishing fermentable sugars are primarily sourced from malted grains, corn, rice and occasionally cane or beets.

[3] What Figure 2 does not show is that traditional U.S. beer production is falling faster than portrayed. Production of flavored malt beverages (FMBs) is propping up reported output totals in the latter years. FMB is the industry vernacular for fermented seltzers, teas, lemonades, ranch waters, etc. In 2023, the barrelage of these beer alternatives reached roughly 11 percent of total domestic beer consumption shipments (IRI, 2024).

[4] Roughly 80 percent of 2023 beer imports are from Mexico. Popular brands of corn adjunct lager in competition with U.S. brewed adjunct lagers. At the time of publication of this paper, Mexico's Modelo Especial was the number one selling beer in the U.S.

1980 and, represented more recently, the rather thin export market for U.S. produced beer. It would appear that the capital expansion shown has been misguided and that useless production capacity will result. Falling real revenues and rising capital-to-output ratios are generally telltale signs of detrimental overcapacity (Erturk, 2001).[5] Is the U.S. beer industry facing an overcapacity crisis?

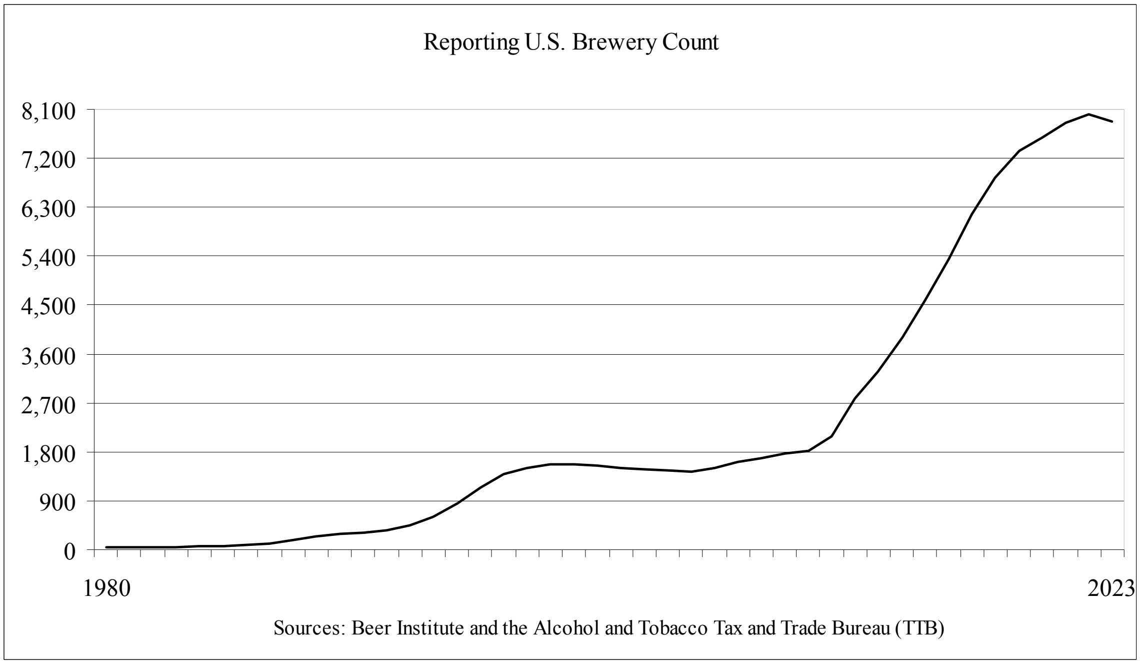

Figure 1. U.S. brewery count, 1980 to 2023

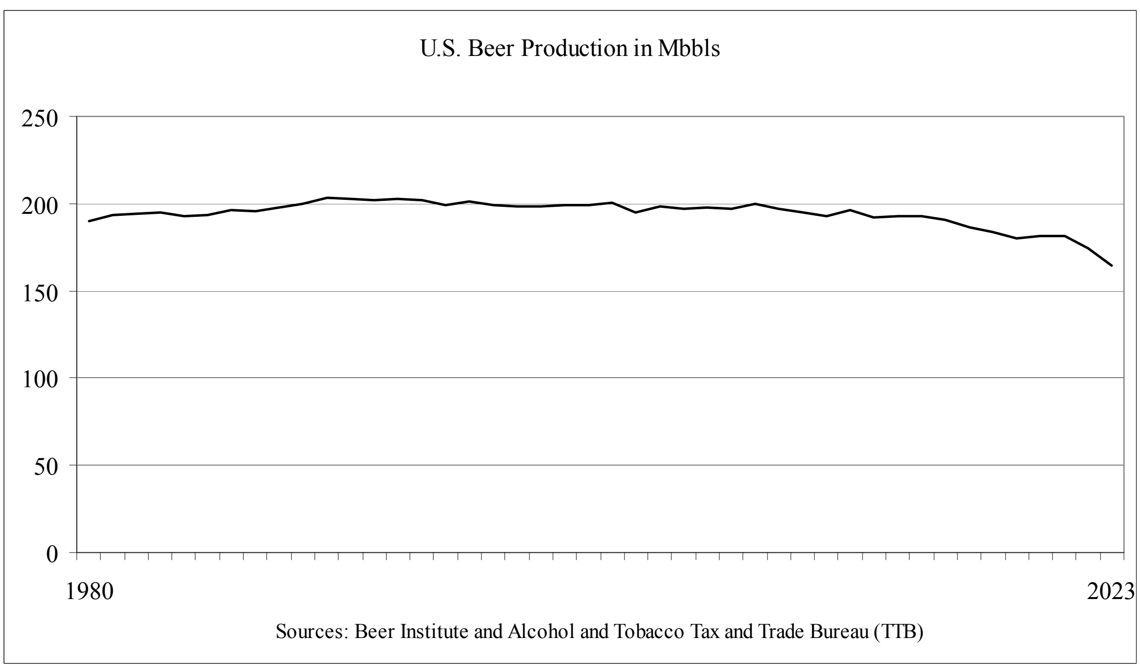

Figure 2. U.S. beer production, 1980 to 2023

[5] The economic literature on production does not make a clear distinction between *excess* capacity and *overcapacity*. Herein, excess capacity describes a more short-term, mean reverting phenomenon. Overcapacity, however, presents as more long-run and perhaps pernicious.

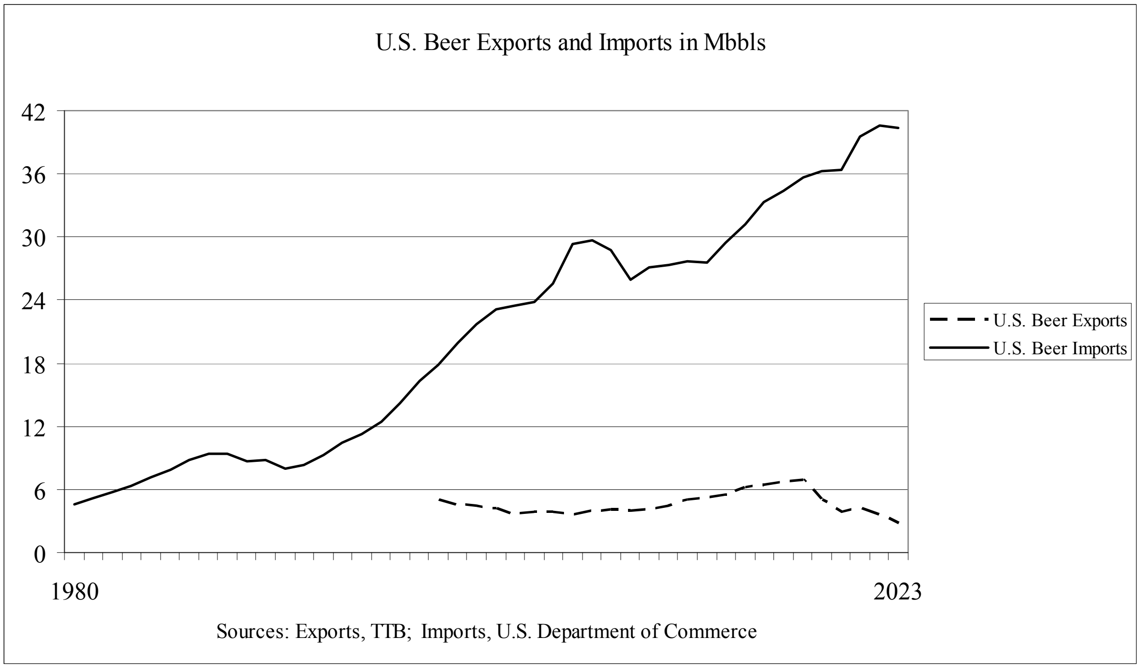

Figure 3. U.S. beer exports and imports

In an April, 2015 industry communication, Bart Watson of the Brewers Association (BA) addressed brewery capacity and presented estimates generated from a member survey.[6] Members of the BA represented roughly 70 percent of the total brewery count in 2015. Watson estimated a self-reported excess capacity share of 36 percent, for the average brewery. He went on to point out "that the gap between production and capacity is perfectly appropriate and healthy in an industry that is growing year over year". In a series of regressions, Watson showed that as brewery annual barrelage increases, the excess capacity gap narrows. For smaller breweries, on average, the excess capacity share was around 60 percent, for larger breweries, 24 percent. Watson went on to conclude that a 16 percent compound growth rate in demand uses up all excess industry capacity in three years and that "breweries appear to be managing their capacity very well". Since 2015, roughly 3,300 more breweries are reporting production to the TTB with 1,000s more currently permitted by the authority (TTB, 2024).[7] Moreover, as discussed above, industry throughput is in decline.

In this paper, we examine the question of beer industry overcapacity by first framing the issue as a balance between dynamic demand and capital accumulation. To do so, we rely on an unfortunately overlooked dynamic theoretical relationship, Evsey Domar's (1946) conception of capacity utilization. While Domar's model concentrated on conditions for economic growth, in the shadows of both Harrod (1939; 1948) and Solow (1956), his ratio (reworked herein) between the time derivatives of demand and productive capacity forms the "moving" theoretical backdrop for our examination (Boianovsky, 2017). First, we provide a brief derivation of a single industry level dynamic equilibrium condition and resulting capacity utilization ratio. Next, we examine model predictions as they

[6] 'Craft' beer is the pliable vernacular of the Brewers Association, generally signifying ownership independence from big-beer.
[7] Over 15,000 as of September, 2024.

pertain to the beer industry defined above and assess an evolving discord. A detailed discussion follows, focusing on what appears to be a distinct division within the broad industry as defined and calls for an analytical separation of the two factions.

Theoretical underpinnings

One intriguing part of Domar's modeling is the treatment of productive capacity. Critical of Keynes and his ilk, Domar insisted that investment had temporary effects on demand but permanent effects on capacity and that this *dual* characteristic had to be recognized. This insight benefits our purpose. Imagine a single industry economy with a large number of firms producing a numeraire output over time t. The level of output in a period, under the full employment of all productive factors, is determined by a simple linear function of the capital stock $K(t)$,

$$P(t) = sK(t) \text{ or } P = sK \text{ ,} \tag{1}$$

where P denotes productive capacity and s represents the marginal as well as average ratio of potential net productivity.[8] Industry investment advances at the rate I per period. Net annual output of investment is then equal to sI, forming the supply-side differential equation,

$$\frac{dP}{dt} = sI \text{ or } \dot{P} = sI \text{ .} \tag{2}$$

The increase in potential capacity s is assumed constant but does not imply that other production factors or technological progress remain constant. The magnitude of s reflects these forces. The demand-side relies on the multiplier theory where,

$$\dot{Y} = m\dot{I} \text{ .} \tag{3}$$

The economy's general income (Y) changes over time by a constant multiple (m) of the time differential of investment.[9] Here is where we change course. Domar was focused on the rate of growth required to retain economic equilibrium (see Appendix B).[10] We opt to concentrate our analysis on his general conception of capacity utilization.

Dynamic equilibrium is held when productive capacity is fully utilized. Therefore, aggregate demand must equal the potential output producible in a given period. Starting from equilibrium at time zero,

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[8] This simple production construct actually corresponds with the capital intensive nature of the brewing industry. Domar pointed out that productive capacity depends not only on physical and technical factors, but on other forces such as income distribution, consumers' preferences, wage rates, relative prices, and industry structure. Most of the criticism of Domar's framework centered on this production specification. Solow's (1956) seminal essay addressed these shortcomings (see Appendix A).

[9] Due to the fixed multiplier effect of investment $m\dot{I}$, Domar's 'knife-edge' produced the curious result that in order to eliminate excess capacity, more capital should be accumulated.

[10] Domar's rigid growth rate of I relies on the fixed proportions s and m. Adding to the long-standing 'Knife-Edge' debate is not our purpose. Instead, we exploit the intuitive simplicity of Equations (5) and (6) below.

$$Y(0) = P(0)\,, \tag{4}$$

where essentially the balancing of demand and supply must hold for each t yielding,

$$\dot{Y} = \dot{P}\,. \tag{5}$$

Any conclusions regarding capacity shortages or surpluses will actually apply to any period, not just as time approaches infinity (again see Appendix B). Therefore, the ratio of the two time derivatives in Equation (5) yields a stylized equilibrium of capacity utilization (u),

$$\frac{\dot{Y}}{\dot{P}} = u\,. \tag{6}$$

The numerator of the left-hand-side of Equation (6) is the *demand effect* while the denominator reflects the *capacity effect* (Chiang and Wainwright, 2005). When $u = 1$, capacity is fully utilized at full factor employment. When the ratio drifts from unity, dynamic forces will move the system back to convergence.

As described in the introduction, the demand effect in the U.S. beer industry is deficient and continues to reflect a downward trend. Through September of 2024, U.S. beer shipments are roughly 3.8 percent less than the same eight months of 2023 (Beer Institute, 2024). As a result, time dynamics would predict that some proportion of brewery capacity will be unused and factor unemployment will result.[11] The significant capital investment depicted in Figure 1 does not reasonably reflect the convergence proposition for this industry – leading many to suppose that the industry is heading toward an overcapacity crisis. The next section delves into this forming paradox.

Discussion

In order to understand the trajectories in Figures (1) and (2), we need to dissect brewery counts and production. Each year, the TTB produces the report 'Number of Brewers by Production Size'. This report provides a count of premises reporting any operations in a given calendar year, categorized by annual production size. Post audits for compliance, the May 2024 revised reports for 2012 - 2023 were available on TTB's website (Kunce, 2024b). For instance, Table 1 below provides the 2012 report. Table 2 below collapses the ten production categories to three for each report year 2012 - 2023: 0 to 7,500 barrels, greater than 7,500 to 1,000,000 barrels and greater than 1,000,000 barrels. These groupings are comparable to those found in Watson (2015). Interestingly, Watson considered breweries producing more than 5,000 barrels annually to have "clearly shifted into a production and distribution mode", away from a strict on-premises sales model. The first two columns in Table 2 show brewery counts for the group by year and the percent of the count to the industry total. Columns 3 and 4 show total production in millions of 31 gallon barrels for the year and the percent of annual group production to the total. The last column divides annual production by the count reflecting the average

[11] Domar referred to the reduction of productive capital as "junking'.

annual production per reporting brewery by year. Table 2 reveals a vast amount of useful information.

Table 1. Number of brewers by production size - CY 2012

Department of the Treasury

Alcohol and Tobacco Tax and Trade Bureau

National Revenue Center - 550 Main Street - Suite 8002 - Cincinnati, OH 45202-5215

1-877-882-3277

NUMBER OF BREWERS BY PRODUCTION SIZE - CY 2012

Reporting Period: 2012

Report Date: 6- May - 2024

Production Size [1]	Number of Breweries [2]	Total Barrels [3]	Taxable Removals [4]
Greater Than 1,000,000 Barrels	25	176,380,080	163,956,600
Greater Than 500,000 to 1,000,000 Barrels	7	4,654,831	3,842,587
Greater Than 100,000 to 500,000 Barrels	39	7,821,769	6,214,108
Greater Than 60,000 to 100,000 Barrels	20	1,468,172	1,265,128
Greater Than 30,000 to 60,000 Barrels	50	2,179,430	1,878,132
Greater Than 15,000 to 30,000 Barrels	43	899,309	757,469
Greater Than 7,500 to 15,000 Barrels	77	817,793	720,553
Greater Than 1,000 to 7,500 Barrels	576	1,433,837	1,283,964
Greater Than 0 to 1,000 Barrels	1,620	519,058	461,440
0 Barrels	325	0	23,088
Total	**2,782**	**196,174,279**	**180,403,067**

Notes:

1. Size - Based on Annual Production - The listed strata of breweries is based on the total amount of beer, in barrels, produced during the calendar year by each brewer.
2. Number of Breweries - Count of brewery permits that submitted an Operational Report for the calendar year 2012, including reports showing no production activity.
3. Barrels Produced - Total barrels of beer produced by the breweries comprising the named strata of data. Totals from each brewer are drawn from Lines 2 and 3, column (g), of TTB Form 5130.9 - Brewer's Report of Operations, and Line 2 of TTB Form 5130.26 - Quarterly Brewer's Report of Operations submitted by brewer for operations during the calendar year.

4. Taxable Removals - Total barrels removed subject to tax by the breweries comprising the named strata of data. Totals from each brewer are from Lines 14 and 15, column (g) of TTB Form 5130.9 - Brewer's Report of Operations, less the totals from Line 7, column (g), (returns of this breweries' beer to the brewery during the reporting period), plus Lines 10 and 11 of TTB Form 5130.26 - Quarterly Brewer's Report of Operations submitted by breweries for operations during the calendar year, less the amounts on Line 4 (returns of this breweries' beer to the brewery).

http://www.ttb.gov

First, the entirety of the steep count expansion shown in Figure 1 is captured in Group 1. Group 1 counts have increased 3 fold since 2012, representative of the overall trend. In 2023, over 94 percent of reporting breweries in the U.S. produced, on average, 629 barrels per-year for a group total of 2.8 percent of industry production. The 2023 group production average, because the upper limit of the group range is 7,500 barrels, is masking just how many *very* small breweries are in the group producing way below the 629 barrel average.[12] The time trend also supports this 'very small' notion, average annual per-brewery production in the group is down roughly 19 percent since 2012. Robert Gibrat (1931) would consider this group 'competitive fringe'.[13] Candidly, members of Group 1 are either restaurants permitted to produce beer or specialty taverns, generally flanked by a food truck, permitted to produce beer. On-premises retail and take-out dominates in the group, off-premises beer distribution is limited due to inefficient scale

[12]Actually, in 2023, 84 percent of the members in Group 1 reported under 1,000 barrels, averaging just 247 for the year.

[13] Gibrat's Law - Firm growth rates are independent of firm size. The statistical distribution of firm sizes is highly skewed to a few large players producing most of the output – an application of Pareto's (1896) so-called 80-20 rule.

Table 2. Brewery counts by production size

Group 1: Zero to 7,500 bbls					
	Brewery Count	% Total	Production (Mbbls)	% Total	Prod./Count (bbls)
2012	2,521	90.6%	1.953	1.0%	775
2013	3,005	91.4%	2.345	1.2%	780
2014	3,573	91.5%	2.739	1.4%	767
2015	4,222	91.9%	3.173	1.6%	752
2016	4,931	92.4%	3.550	1.9%	720
2017	5,723	92.8%	3.964	2.1%	693
2018	6,393	93.3%	4.555	2.5%	712
2019	6,869	93.7%	4.790	2.7%	697
2020	7,127	93.9%	4.180	2.3%	587
2021	7,349	93.6%	4.904	2.7%	667
2022	7,533	94.0%	5.038	2.9%	669
2023	7,419	94.2%	4.670	2.8%	629
Group 2: Greater than 7,500 bbls to 1,000,000 bbls					
	Brewery Count	% Total	Production (Mbbls)	% Total	Prod./Count (bbls)
2012	236	8.5%	17.841	9.1%	75,597
2013	256	7.8%	18.545	9.7%	72,441
2014	305	7.8%	20.255	10.5%	66,410
2015	344	7.5%	23.401	12.1%	68,026
2016	378	7.1%	23.971	12.6%	63,415
2017	420	6.8%	24.843	13.3%	59,150
2018	434	6.3%	24.411	13.3%	56,247
2019	434	5.9%	25.436	14.1%	58,608
2020	440	5.8%	29.012	16.0%	65,936
2021	475	6.0%	29.645	16.3%	62,411
2022	459	5.7%	29.281	16.8%	63,793
2023	435	5.5%	29.352	17.8%	67,476
Group 3: Greater than 1,000,000 bbls					
	Brewery Count	% Total	Production (Mbbls)	% Total	Prod./Count (bbls)
2012	25	0.9%	176.380	89.9%	7,055,200
2013	25	0.8%	171.239	89.1%	6,849,560
2014	26	0.7%	169.885	88.1%	6,534,038
2015	26	0.6%	166.061	86.2%	6,386,962
2016	25	0.5%	163.111	85.6%	6,524,440
2017	24	0.4%	157.772	84.6%	6,573,833
2018	25	0.4%	154.823	84.2%	6,192,920
2019	26	0.4%	150.190	83.2%	5,776,538
2020	27	0.4%	148.644	81.7%	5,505,333
2021	28	0.4%	147.212	81.0%	5,257,571
2022	26	0.3%	140.171	80.3%	5,391,192
2023	24	0.3%	130.743	79.4%	5,447,625

and cost structures. Moreover, the on-premises reliance of these firms severely limits their geographic reach making them simply localized entertainment spots. The supposition of beer industry overcapacity based on the expansion of reporting firms in this group is misguided. Members of Group 1, structurally, belong in the food services and drinking establishments sector.[14] A local sports bar and grill with a plug-and-play brewing operation is more like a neighborhood bistro touting their own mill-to-oven bakery than, say, Wisconsin's New Glarus Brewing Company. Plainly, the 'lines of business' are markedly different (Nightingale, 1978). The U.S. restaurant and bar industry promoted counts of roughly 850,000 establishments in 2023, down from well over one-million pre-pandemic (NRA, 2024; USBLS, 2024). A small percentage increase or decrease in this notoriously volatile industry count, due to entry and exit of members touting auxiliary brewing operations, hardly moves the analytic needle.

Members of Group 2, on the other hand, do not follow a strict on-premises model. Instead, as advanced by Watson (2015), they have scaled production to package for wide-reaching distribution.[15] Many may still promote restaurant affiliations or maintain tasting rooms, but by and large compete off-premises via substitution by product differentiation (Elzinga et al., 2015). That is, for example, California commons or American pale ales proficiently produced and distributed as opposed to homogeneous adjunct lager characteristic of Group 3 (big-beer). Seemingly, welcomed and more authentic product variety. We propose that Group 2 along with Group 3 form the relevant U.S. beer industry.[16] From Table 2, production trends for the two industry groups are negatively correlated (-0.93). As annual production increased in Group 2, Group 3 experienced a highly correlated downward trend – substitution by product differentiation due to flat then declining overall demand for U.S. produced beer. In other words, production growth in Group 2 was mostly generated from cultivating consumer preferences and the resulting substitution effect, not beer industry long-run growth.[17]

With our refined definition of the more relevant malt alcoholic beverage industry in place (Boyer, 1984), we can properly address the question of capacity utilization. From Equation (6), demand deficiency leads to unused capacity and factor unemployment. Regarding the numerator, per-capita consumption of U.S. produced beer has been declining since the early 1980s (Freeman, 2011; Kunce, 2023; Rogelberg, 2024). Reasons forwarded for the decline include an aging population, real disposable income trends, evolving preferences, substitution effects including impacts from expanding legal cannabis markets and alcohol related health concerns. In response, relevant industry producers have been restructuring capacity as theory would predict. Roughly two decades ago, capital combinations through high profile firm acquisitions and mergers

[14] North American Industry Classification System code 722. Of course the 7,500 barrel upper limit is analytically convenient, not a hard and fast threshold. Moreover, TTB permitting, common to all three groups, does not pose a strict entry barrier and should not be central in defining the relevant industry. For example, the Beer Institute (2024) estimated close to 17,000 active and pending brewer's notices for 2023.

[15] Packaging trends since 1980 have changed markedly. In 1980, draught (kegged) beer comprised 12 percent of the total, cans 53 percent. In 2023, draught fell to around 8 percent, cans increased to roughly 65 percent (Beer Institute, 2024).

[16] Going forward, fierce competition to the relevant industry comes from Mexican imports. Production trends for Group 2 and 3 against imports are negatively correlated (-0.91). Moreover, 'away-from-home consumption' has declined to merely 15 percent of total U.S. beer shipments (Beer Institute, 2024; NBWA, 2024). The relevant industry's bread and butter is sales to take-home retail outlets. This strong reliance bolsters our refined definition.

[17] Note that the trend in reported production for this group has flattened since 2020.

commenced (Elzinga and McGlothlin, 2022). Streamlined capacity efforts and connective distribution efficiencies, as a result of these combinations, were developing, but U.S. volume declines continued. Of late, internal efficiency restructuring, divestiture and shuttering facilities is becoming necessary. Examples of the predicted overhaul, within the relevant industry, are seemingly endless, below are a few of the more current actions.

In 2020, Molson Coors ceased production at its Irwindale, CA brewery. MC Irwindale produced roughly 5 million barrels in 2019 (Molson Coors, 2023). More recently, Molson Coors closed AC Golden Brewing (Colorado), two Leinenkugel breweries (Wisconsin) and sold-off its entire 10th and Blake craft unit (Frank, 2024; Rovito, 2024). Similarly, Anheuser-Busch InBev either sold or shuttered a substantial portion of its U.S. craft beer portfolio (Kendall and Licata, 2023). ABI's U.S. barrelage was down roughly 12 percent from 2022 to 2023 (Anheuser-Busch InBev, 2023) Strikingly, after only five years of operation, Diageo closed its Maryland brewery, a $90 million investment, in the spring of 2024 (Infante and Kendall, 2024). In 2022, Odell Brewing Company (Colorado) restructured brewing operations and laid off 5 percent of its workforce (Brewbound, 2024). Odell's 2022 production ranked in the craft top 20 according to the Brewers Association. Heineken's Lagunitas Brewing closed its massive Chicago facility in the summer of 2024 (Yee, 2024). There's more. In the last five years, Boston Beer Company (Samuel Adams and Dogfish Head) has been moving more production from third-party contract facilities to their three company-owned breweries. Roughly 60 percent of BBC's volume was produced in-house in 2019 compared to an expected 75 percent in 2024. As stated in their 2023 annual report, "At current production volume projections, the company believes that it will fall short of its future annual volume commitments at certain third-party production facilities and will incur shortfall fees" (Boston Beer, 2023).[18] It would appear that U.S. beer is aggressively realigning long-run capacity in lockstep with dynamic theory predictions ($u \rightarrow 1$).

Conclusion

The received paradigm of industrial organization economics forwards that accurately defining the relevant industry and addressing its behavior increases the welfare possibilities of the overall economy (Nightingale, 1978; Baumol et al., 1982). Herein, Domar's general conception of capacity utilization assisted in refining the definition of the relevant U.S. malt alcoholic beverage industry in order to properly address the issue of overcapacity. We maintain that the proliferation of restaurants and specialty taverns permitted to produce beer should be categorized as such. The more looming challenge to the relevant industry is declining domestic demand.[19] Unfortunately, the resulting overcapacity from forecasted demand deficiencies may lead to more long-run industry consolidation, reminiscent of the pre-1980s.[20]

[18] Shortfall fees of $41 million are expected to be incurred from 2024 moving forward (Boston Beer, 2023, p. 7).

[19] The re-election of Donald Trump introduces the possibility of high tariffs on Mexican imports. This action could steer beer consumers toward domestic products thereby reversing downward trends. Then again, tariffs on aluminum imports, reminiscent of 2018, could frustrate these potential domestic volume gains.

[20] In early summer of 2024, The Wall Street Journal reported that Boston Beer Company was in sale talks with multiple suitors (Thomas, 2024).

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Appendix A

Solow's (1956) alternative modeling begins by redefining production,

$$F(K,L), \tag{A1}$$

where L denotes a labor factor that can be combined with capital in varying proportions. The function F is linearly homogeneous where Euler's theorem establishes,

$$F(K,L) = F_K K + F_L L. \tag{A2}$$

The marginal products, F_K and F_L, are positive with subscripts denoting partial derivatives. Differentiating Equation (A2) with respect to each factor yields,

$$F_K = F_K + F_{KK}K + F_{LK}L, \tag{A3}$$

$$F_L = F_{KL}K + F_L + F_{LL}L. \tag{A4}$$

Equations (A3) and (A4) allow for marginal products to diminish (F_{KK} and $F_{LL} < 0$) as long as capital and labor are complements in production. Properties of F allow us to multiply both production factors by $1/L$ yielding,

$$F(K,L) = LF\left(\frac{K}{L},1\right) = Lf(r), \tag{A5}$$

where r denotes the capital/labor ratio, Solow's notation. Using,

$$\frac{\partial r}{\partial K} = \frac{1}{L}, \tag{A6}$$

and the chain rule on the far right side of Equations (A5),

$$L\frac{\mathrm{d}f(r)}{\mathrm{d}r}\frac{\partial r}{\partial K} = Lf_r\frac{1}{L} = f_r, \tag{A7}$$

showing that F_K is f_r and both are > 0. Using the same method on the right side of Equation (A7) yields $F_{KK} = f_{rr}/L$, both < 0. Solow assumes that capital changes over time by,

$$\dot{K} = sLf(r), \tag{A8}$$

where a constant proportion of equilibrium national income 's' is invested. Labor's differential equation is defined,

$$\dot{L} = nL, \tag{A9}$$

where n represents the constant growth rate of labor. Recognizing that $K = rL$, by the product rule,

$$\dot{K} = r\dot{L} + L\dot{r}, \tag{A10}$$

and using Equations (A8) and (A9),

$$sLf(r) = rnL + L\dot{r}, \text{ or, } \dot{r} = sf(r) - nr. \tag{A11}$$

Equation (A11) is Solow's fundamental equation, a differential equation in r. Using the broad properties of Equation (A1), Solow isolates, graphically, a capital/labor accumulation path replicated here in Figure (A1). The straight line from the origin is linear in r with slope n. Production $sf(r)$ follows $f_r > 0$ and $f_{rr} < 0$. In order to maintain the point of intersection, r^*, capital and labor will grow proportionately at rate n. Because production is linearly homogeneous, output will also grow at rate n, a steady state.

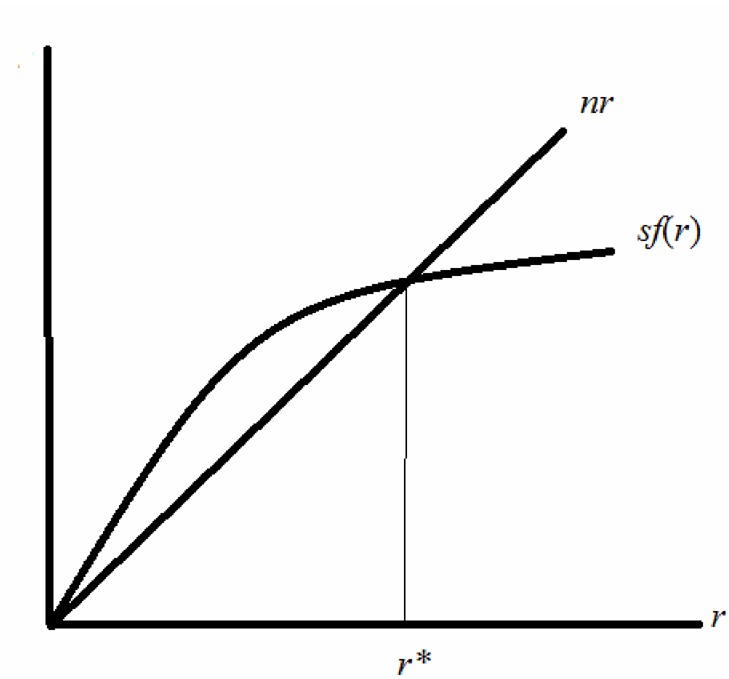

Figure A1. Solow's steady state

Appendix B

Starting with Domar's fundamental equation from the text above,

$$m\dot{I} = sI\ , \tag{B1}$$

rearranging to isolate I,

$$\frac{1}{I}\dot{I} = s/m\ , \tag{B2}$$

integrating both sides with respect to time yields,

$$\int \frac{1}{I}\dot{I}\,\mathrm{d}t = \int s/m\,\mathrm{d}t\ . \tag{B3}$$

Regarding the left side of Equation (B3), recall the substitution rule,

$$\int f(u)\frac{\mathrm{d}u}{\mathrm{d}x}\mathrm{d}x = \int f(u)\,\mathrm{d}u = F(u) + c\ , \tag{B4}$$

where integration of the left side becomes,

$$\int \frac{1}{I}\mathrm{d}I = \ln|I| + c\ . \tag{B5}$$

The right side of Equation (B3) is the integration of a constant therefore,

$$\ln I = (s/m)t + c\ , \tag{B6}$$

presuming investment is positive. Using the exponential yields,

$$e^{\ln I} = e^{(s/m)t}e^{c}\text{, or, } I(t) = e^{c}e^{(s/m)t}\ , \tag{B7}$$

and when $t = 0$, $I(0) = e^c$, thus,

$$I(t) = I(0)e^{(s/m)t}\ , \tag{B8}$$

which is Domar's growth rate solution. Domar goes on to define his *coefficient of utilization* as,

$$\theta = \lim_{t\to\infty}\frac{\dot{Y}}{\dot{P}}\ , \tag{B9}$$

where θ is a constant involving the fixed proportions of s and m. Domar allows s to differ between new and social investment and models growth rates that may differ from s/m denoted as r. Domar's 'knife edge' coefficient becomes,

$$\theta = \frac{rm}{s}\,. \tag{B10}$$

Chiang and Wainwright (2005) p.473 show that Equation (B9) will hold at any time t, not just as t approaches infinity. From Equation (B8), allowing the equilibrium growth rate to vary denoted by r,

$$\dot{I} = rI(0)e^{(r)t}\,. \tag{B10}$$

Using Equations (2) and (3) from the above text and Equation (B10),

$$\dot{Y} = m\dot{I} = rmI(0)e^{(r)t}\,, \tag{B11}$$

$$\dot{P} = sI = sI(0)e^{(r)t}\,, \tag{B12}$$

which forms the ratio,

$$\frac{\dot{Y}}{\dot{P}} = \frac{rm}{s} = \theta\,. \tag{B13}$$