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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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Capital financing and allocation
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History
Industrial organization
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Are Hobby Breweries Part of the Recent Surge in U.S. Reporting Facility Counts?

Mitch Kunce[1]

Abstract

The vibrant U.S. homebrewing community of the 1970s and forward encouraged many impassioned artisans to pursue commercial endeavors. Are these ventures of passion or profit? This article establishes a conservative share-estimate of how many 'hobby' breweries are, potentially, in recent TTB counts. The underlying purpose is to shed much needed light on the hundreds, perhaps thousands, of licensed reporting breweries that are clearly not 'stand-alone' viable without ardent owners' financial support.

Keywords: Beer production, firm size, government reporting
JEL Classifications: L78, L79, R38

Introduction

The counter-culture environment of the 1960s and 1970s in the U.S. brought about landmark changes to post-prohibition beer consumption. Fed up with the homogenous fizzy corn and rice water offerings of the time[2], many of these early revolutionaries began their quest for authenticity by brewing at home. Inspired by the likes of author Fred Eckhart (1965; 1970), home brewing flourished through the 1970s and forward (Tremblay and Tremblay, 2005). In 1978, the U.S. Congress decriminalized home brewing making the already immensely popular hobby legitimate (Acitelli, 2013).[3] In this same year, Boulder, Colorado elementary school teacher, Charles Papazian, founded both the American Homebrewers Association (AHA) and the Association of Brewers, a U.S. trade organization (Shaer, 2020).[4] Both U.S. House Bill 1337 and the formation of the AHA launched a mania. Self-proclaimed Braumeisters around the country honed their craft and impressed their friends with artisan, kitchen-made ales and lagers. Homebrewing acquainted the many with old-world beer styles, influencing preferences away from mass produced adjunct lager.

This burgeoning community empowered a few to leap into their own commercial production and bottle/keg-distribution ventures. This was no easy task; fewer than 45 breweries were federally permitted in the U.S. in 1979. (Alcohol and Tobacco Tax and Trade Bureau (TTB), 2024). Noteworthy trailblazers include 'Fritz' Maytag (Anchor Brewing resurrection, 1965), Jack McAuliffe, Suzy (Denison) Stern and Jane Zimmerman (New Albion Brewing, 1976), David Hummer, 'Stick' Ware and Alvin

[1] *Douglas**Mitchell*** Econometric Consulting, Laramie, WY USA. Published January 2025.

[2] Tom Acitelli (2013) cites comments from Suzy Stern of New Albion Brewing, made to the Associated Press in 1977, indicating that the state of beer in America is "a national disgrace . . . a blizzard of chemicals, stabilizers, and all sorts of things that hide beer's true and ancient nature."

[3] 95th Congress, HR 1337. Public Law 95-458 − 92 STAT. 1255-1261. Enacted October 14, 1978 by President Jimmy Carter.

[4] In 2005, the Association of Brewers and the 63-year-old Brewer's Association of America merged forming the Brewers Association (BA) where the American Homebrewers Association is now an affiliate.

Nelson (Boulder Brewing, 1979) and Ken Grossman and Paul Camusi (Sierra Nevada Brewing, 1979).[5] In 1981, Herbert 'Bert' Grant's Yakima Brewing and Malting Company

Figure 1. Boulder Brewing's David Hummer, Randolph 'Stick' Ware and Alvin Nelson (Casey, 2019).

broke the post-prohibition mold. Bert's initial business model involved selling in-house manufactured ales *on-premises* or to-go in patrons' sanitary containers (Grant and Spector, 1998). At the time, on-premises consumption violated the state of Washington's three-tiered distribution laws (Acitelli, 2013). 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). Other states quickly followed suit with their own forms of on-premises legislation (Elzinga et al., 2015). Relaxation of local on-premises sales restrictions in the 1980s and forward handed, effectively, any fervent homebrewer the keys to starting a commercial endeavor. Rather than give your beer away by the glass to family and friends, you could now charge them for it, with proper federal and local permitting of course. Costly packaging equipment and materials, scaled production methods and off-premises distribution channels were no longer necessary.

[5] Years depicted are dates of formation, not dates of first sales. The first three of the four breweries mentioned have ceased operations. In a new development, billionaire Hamdi Ulukaya purchased what remained of Anchor Brewing in the summer of 2024 with the intention to revive it once again (Valinsky, 2024).

For instance, at the base of Sheep Mountain in Albany County Wyoming[6], longtime brewer Todd Adams licensed Sheep Mountain Brewery, LLC in January of 2014. The brewery was housed in an existing steel out-building on Adams' homestead property where it continues to reside today. Chilton Tippin (2014), representing the Associated Press at the time, described the brewery's layout,

> "The front room seems normal enough, with bikes on racks, an ATV and a Medicine Bow map pinned to the wall. Hook right into the next room, though, and you'll note a drum set alongside ceremonial 'Nyabinghi' bongos; a portrait of Jah, Rastafarian for God; and a bar built by Adams – three brews on tap; frothy beer mug lights festooning the ceiling; a chandelier fashioned of a metal keg; deejay equipment; a walk-in fermenting room; big black speakers nestled in corners; and, of course, the room's centerpiece: a gravity-fed brewing tree, laden with a tank, mash tun and brew kettle."

Figure 2. Sheep Mountain logo.

In the same Tippin article, Adams mentioned his other small businesses: Wyoming Sew Works, where he fashioned teepees and his oil and gas environmental consulting firm, which he considered his "real job". Adams goes on to state that he started Sheep Mountain Brewery because he "loves" beer chemistry, the process and "sharing" his beer with people. This motivation reveals passion for a hobby, not the pursuit of profit.

The purpose of this article is to establish a conservative share-estimate of how many 'hobby' breweries are, potentially, in recent TTB counts. This is not a simple task; public records do not divulge founders' motivations or personal finances. What we do have is what brewery owners must report to the TTB – periodic production and removals, in 31-gallon barrels, for tax purposes. Quantities reported year after year are very telling and because most breweries in the U.S. are very small,[7] their stand-alone viability can be fairly assessed by barrelage produced. We consider a brewery a hobby if potential revenues generated for barrelage reported could not possibly support all attributed costs of a standard, stand-alone, operation. This definition is slightly more restrictive than

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[6] 26 miles southwest of Laramie, Wyoming.

[7] In 2023, 79.2 percent of total reporting breweries produced 1,000 barrels or less for the year – 11.7 percent (924 breweries) reported no production for the year (TTB, 2024).

Internal Revenue Service directives (Jones, 2015).[8] In order to determine the shape of the frequency distribution of these small breweries, those producing 1,000 barrels or less annually, we lean on production surveys conducted by the Brewers Association (BA). The self-reported and imputed brewery specific data, gathered in the 2012 BA survey, provided a means to estimate and then forecast the far-left tail of the distribution. In the next section, we describe the production data used and the rather elementary statistical methodology applied.

Data and discussion

Each year, the Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau (TTB), publishes a public report entitled 'Number of Brewers by Production Size' for the entire industry.[9] Every brewery in the U.S. is licensed (Brewer's Notice) to operate by the 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.[10] 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 no production occurred or no taxes were due for the month or quarter.[11] The TTB relies on these individual premises reports for tax compliance and as the source for aggregated public reporting. The TTB groups the data for the 'Number of Brewers by Production Size' report by annual production, in 31-gallon barrels, splitting the counts into ten production size strata. Herein, we focus on the most recent compliance-audited data from 2012 to 2023 for the ten bins: BIN1) reporting no production for the year; BIN2) reporting greater than zero to 1,000 barrels for the year; BIN3 reporting greater than 1,000 to 7,500 barrels for the year and BINS4-10) reporting greater than 7,500 barrels.

Clearly, the TTB data lacks individual brewery detail due to federal taxpayer disclosure limitations. Annually, the Brewers Association (BA) surveys licensed breweries regarding operations including a section requesting taxed production for the year.[12] This brewery specific data is published in the May/June issue of *The New Brewer*, a BA print periodical. If a brewery does not respond to the survey, the BA will report an estimate. Breweries must respond to the survey (or contact the BA directly) to indicate ‘do not publish’ if they do not want their taxed production data, or an estimate, public. While not ideal, due to the presumably large number of non-responses and requested censoring, this surveyed data does provide a useful level of detail. Digital panel spreadsheets of the data, however, are only made available to select BA members.[13] Advantageously, the supplementary materials accompanying the prominent Elzinga, et al. (2015) paper provided BA panel spreadsheets for the years 1989 to 2012.[14] This data delivers an auspicious starting point. For 2012, conveniently the start of the compliance-audited

[8] See IRS Tax Reg. 1.183-2(b) for specifics.
[9] For example, see Appendix A to this paper for the 2012 report.
[10] 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.
[11] 27 Code of Federal Regulations 25.297
[12] See Appendix B for the 2024 survey form.
[13] Our requests (academic) for digital spreadsheets were first ignored then denied. As it turned out, the Elzinga, et al. (2015) data proved sufficient for our purpose here.
[14] See Appendix C for their description of this data.

TTB data, BA surveyed production for 2,080 breweries is provided.[15] Of the 2,080, 1,438 (69 percent) reported production of greater than zero to 1,000 barrels. The Elzinga data did not present breweries reporting no production for the year 2012. Figure 3 (below) shows a histogram of the 2012 surveyed data along with key descriptive statistics for the BIN2 stratum. The asymmetric shape (positive skewness) of the distribution is important to note. Roughly 57 percent of the count lies to the left of the mean. Moving one standard deviation left of the mean lands on 72 barrels reported for the year. Again, around 19 percent of the count is left of the one standard deviation shift. This equates to 271 breweries. Of the 271 breweries, 95 (35 percent) had a direct restaurant affiliation.[16] This reduces our potential hobby pool to 176, roughly *12 percent* of the surveyed BIN2 stratum.

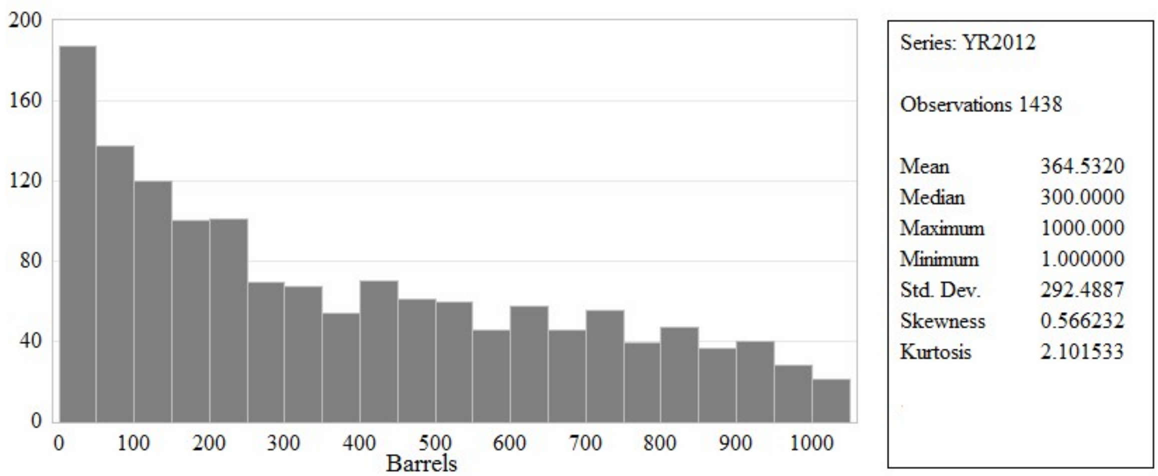

Figure 3. Histogram and descriptive statistics

To assign a current sales value (price) on a barrel of small brewery production, we start with the national 'craft' metrics. According to the BA (2024), craft sales in the U.S. were $28.9 billion on 23.4 million barrels in 2023. That comes to $1,235 per barrel[17] – roughly $89,000 of beer revenue for a small brewery producing at our hobby upper limit of 72 barrels. The national numbers, however, will tend to understate the revenue potential for a smaller brewery. Strict on-premises sales should yield a higher average price. Our own unscientific survey of 12 nano-breweries in 12 different states yielded a mean 2023 sales price of $1,587 per barrel or 40 cents per ounce.[18] Upper limit revenue now becomes approximately $114,000. Without getting into the specifics of the total costs involved in producing and dispensing beer,[19] this potential revenue unlikely supports even a one-man stand-alone venture, over-time, without owner subsidy of some kind. In the case of

[15] Likely examples of the BA inserting their production estimates: 26 breweries in the 2012 Elzinga data reported exactly 10 barrels produced for the year; 18 reported exactly 1,000 barrels.
[16] Restaurants with auxiliary breweries do not meet our stand-alone requirement. The 35 percent share is in line with Brewers' Association estimates (BA, 2024).
[17] Brewers tend to refer to metrics by the ounce, in this case 31 cents per ounce.
[18] A phone survey conducted for those brewers that would take the call and were willing to participate. We asked them to take their total beer sales from 2023 and divide by barrels sold. Interestingly, many knew the ratio without referring to any accounting notes.
[19] Bell (2024) inventories the myriad of hamstringing costs faced by small brewers today. He portrays labor costs, triple net lease arrangements and alcohol related liability insurance as "not only out of our control, they are simply out of control."

Sheep Mountain Brewery, seemingly all facilities, utilities and insurance are offset by the homeowner. Revenues generated from production may cover direct variable costs with very little remaining.

Critics could argue that these nano-ventures are simply start-ups, poised for growth. Table 1 below breaks down counts for the 2012 Elzinga data matched with the TTB's strata from the 'Number of Brewers by Production Size', May 2024 reports. Columns 2 through 5 reflect BIN1, BIN2, BIN3 and BINS4-10 described above. The last row of the

Table 1. Brewery counts

Report and Year	Reporting Zero bbls BIN1	Reporting > 0 to 1,000 bbls BIN2	Reporting >1000 to 7,500 bbls BIN3	Reporting > 7,500 bbls BINS4-10
BA Survey 2012	0	1,438	485	157
TTB 2012	325	1,620	576	261
TTB 2013	386	1,958	661	281
TTB 2014	441	2,380	752	331
TTB 2015	473	2,858	891	370
TTB 2016	572	3,402	957	403
TTB 2017	728	3,895	1,100	444
TTB 2018	740	4,448	1,205	459
TTB 2019	780	4,836	1,255	460
TTB 2020	932	5,097	1,103	467
TTB 2021[a]	1,014	5,089	1,275	503
TTB 2022[a]	950	5,375	1,247	485
TTB 2023[a]	924	5,351	1,191	459
Compound Growth	10.0%	11.5%	6.8%	5.3%

[a] Count totals updated from the TTB's 'Monthly National Statistical Report' dated 1/3/2025

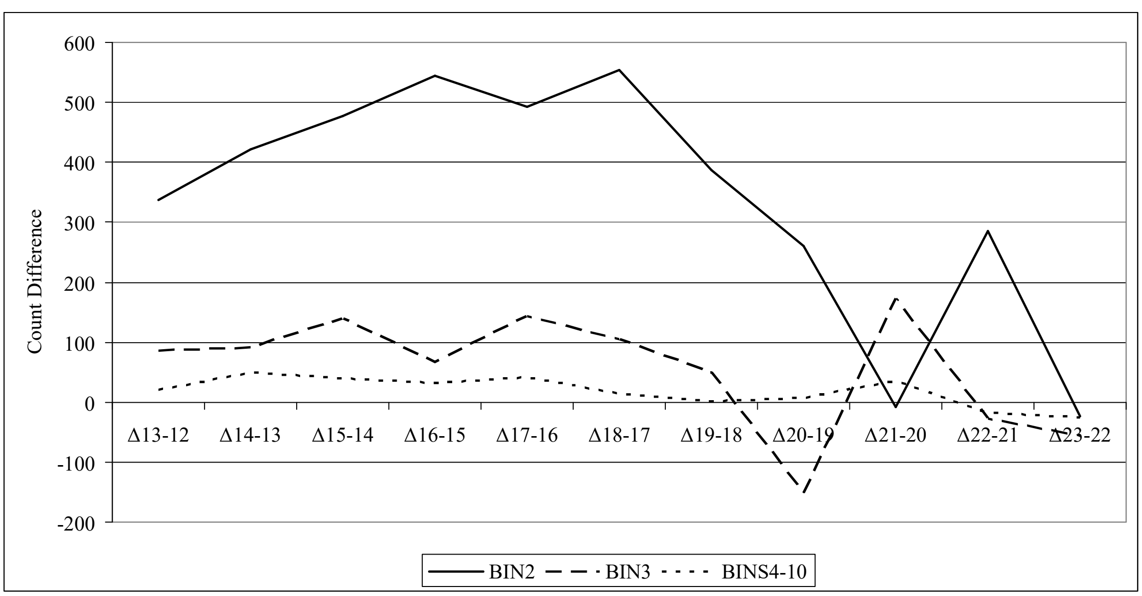

Figure 4. First-differenced count trends

table depicts annual compounded TTB count growth from 2012 to 2023 for each bin presented. What is evident from the Table 1 time-series presentation is just how many breweries have failed to move beyond BIN2. Figure 4 plots the first-differenced counts for the last three columns of Table 1. Note how the large year-to-year BIN2 count changes, prior to the post-pandemic spiked volatility, do not progress into the higher production strata. This implies that these breweries remain in the stratum or stop reporting production. In a somewhat related examination, Kunce (2023) used Markov evolutions to evaluate the probabilities of small brewery growth. Projected odds were not favorable for growth, a 2.3 percent chance in the long-run steady-state to make the 15,000 barrel mark, a 0.2 percent chance of reaching 500,000 barrels. Attainable growth then, for a nano, is perhaps reaching the right tail of the distribution shown in Figure 3. If this type of growth is trending, we would expect the shape of the BIN2 distribution to shift right. Table 2 presents the BIN2 mean trend coupled with the proportional share of breweries in the stratum. To make the shares comparable to the BA survey data, we exclude zero report counts from the totals. Again, the last row of the table depicts annual compounded growth (decline) from 2012 to 2023. Clearly, proportional counts in this stratum are growing and, if anything, the distribution is shifting more to the left. The average BIN2 brewery is getting slightly smaller, not larger, with time.

Table 2. BIN2 mean production and count share

Report and Year	Mean Prod. (bbls)	Count Share %
BA Survey 2012	364.5	69.1
TTB 2012	320.4	65.9
TTB 2013	313.1	67.5
TTB 2014	305.1	68.7
TTB 2015	299.4	69.4
TTB 2016	300.7	71.4
TTB 2017	292.4	71.6
TTB 2018	292.8	72.8
TTB 2019	287.7	73.8
TTB 2020	246.1	76.4
TTB 2021	291.1	74.1
TTB 2022	303.6	75.6
TTB 2023	306.0	76.4
Compound Growth	-0.4%	1.4%

Nothing in the presentation so far repudiates the shape of the production-size frequency distribution for roughly three-fourths of reporting breweries in the U.S. The estimated 12 percent 'hobby-share' for BIN2 breweries equates to over 640 licensed facilities in 2023. Interestingly, the share of breweries reporting zero production to the TTB has remained relatively stable from 2012 to 2023. Figure 5 below presents this data. The bulk of breweries reporting no production for a given year are newly formed entrants, those exiting the market or simply brewers that took the year off. Many of these breweries could be considered hobbies, under our definition, but are not part of the 12 percent, quite conservative, share. Frankly, we are just scratching the surface with this estimate. The one standard deviation shift left is, to some extent, arbitrary and simply highlights the size proportion of the BIN2 far left tail. At any rate, our underlying purpose here was to shed light on the hundreds, perhaps thousands, of reporting breweries that are clearly not 'stand-alone' viable without a passionate owner's subsidy. The question going forward is, when does the shine wear off? [20]

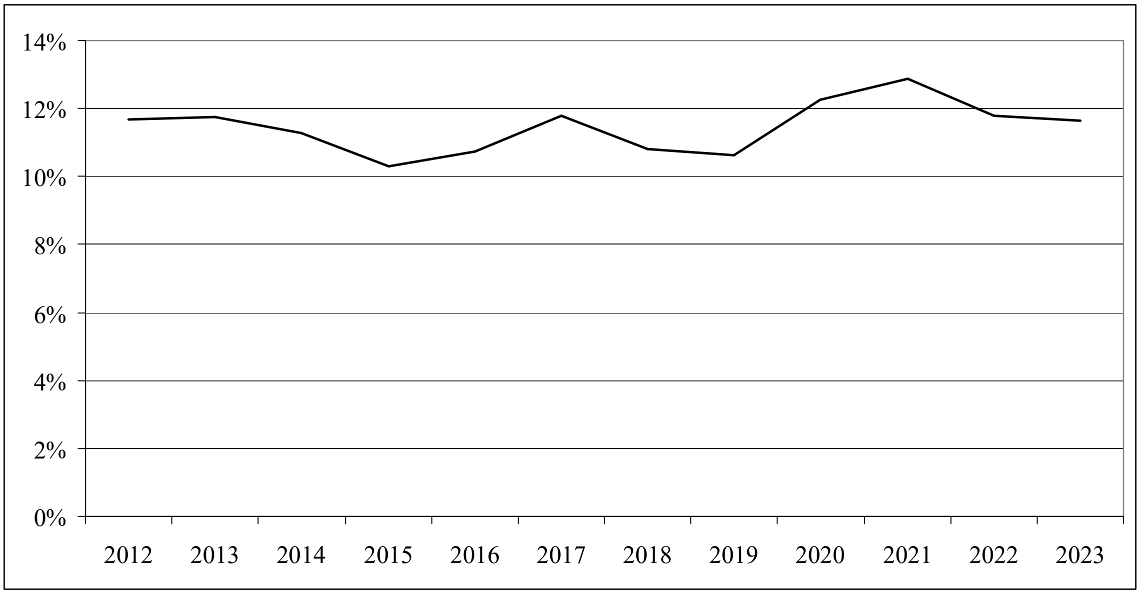

Figure 5. Share of breweries reporting zero production

In parting

In March of 2014, certified public accountant Cody Pisacka and software engineer Jimmy Vanderweide opened 1933 Brewing Company in Fort Collins, Colorado, the 12th brewery to open in the area. The strip-mall like space a block west of College Drive was small and so was the brewing equipment, a used 4-hectoliter system. Brewer Zach Wilson and taproom coordinator Laura (Sickles) Wilson ran the day-to-day operations. In December of 2016, the brewery was sold to Zach and Laura with plans to change the concept of the company "quite significantly, to focus more on personal passions and dreams" (Brewbound, 2016). Moving into 2017, Peter Bouckaert announced to executives and co-workers at New Belgium Brewing, in Fort Collins, that he was stepping-down from his 21-year post as Braumeister (Laxen, 2017).[21] Bouckaert had partnered with the Wilson's to start a new venture, Purpose Brewing and Cellars, in the old 1933 Brewing space. By August of 2017, the walls of the small South Mason Street location were lined with dozens of oak barrels for beer aging. Bouckaert, you see, is credited with introducing wood-aged sours to America. His beer travels around the world inspired him to write a book on wood-aging. He has headed research projects at two Colorado Universities examining foreign wood flavors. The logo for Purpose Brewing is an acorn; you get the point. Peter Bouckaert's transition from New Belgium was about rekindling his passion for artisan beer. Rather than focusing on scale, continuous growth or profit, "Purpose Brewing is wholly dedicated to the celebration of beauty" (Wilmes, 2018). In late 2018, Zach and Laura Wilson left Purpose Brewing. Zach joined Bing

[20] See Appendix D for data depicting the apparent decline in reporting brewery counts 2021-2024.

[21] Interestingly, New Belgium's CEO resigned in November of 2016. New Belgium Brewing was acquired by a subsidiary of Japan's Kirin Holdings Company in December of 2019 for a rumored $400 million (Reidy, 2019).

Capital in early 2021 pursuing a career as a real estate investor. The couple's beer passions, dreams and celebration of beauty were cast aside for a family and a steady paycheck.

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Appendix A

Table A1. Number of brewers by production size, 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

Appendix B

BREWERS ASSOCIATION

Beer Industry Production Survey

PLEASE FILL OUT ONLINE FORM BY JANUARY 31, 2025 AT **www.BrewersAssociation.org/BIPS**
OR RETURN FORM BY MAIL OR EMAIL TO bips@brewersassociation.org

Dear Brewer,

The Brewers Association is preparing our annual review of the U.S. brewing industry. The data we get from you helps us provide the most accurate brewing industry statistics to brewers like you. As the craft market develops and evolves, ***these data are more critical than ever***. Please assist us by responding to the questions below regarding your company's 2024 production. The more survey participation we have, the better data we can provide in our annual brewery industry review featured in the May/June 2025 issue of *The New Brewer*. There is also an option to provide the data, but not have your company's production published (check box below).

Please fill out this form by **January 31, 2025.** You can fill out the survey online at **www.BrewersAssociation.org/BIPS** or return this form to PO Box 1679, Boulder, CO 80306 (it's postage paid). You may also **email** your responses to **bips@brewersassociation.org**.

Thank you very much, in advance, for your assistance. Hope you had a great holiday season, and best wishes for a successful 2025!

Matt Gacioch
Staff Economist

Note: questions refer to taxable beer sold or produced during the 2024 calendar year.
To avoid double counting, are you filling out this form for **your entire company** ☐ **or just this location** ☐
If you do **not** want your company's data published in *The New Brewer* May/June 2025 annual industry review, check here: ☐ *Do Not Publish*

Beer Only

1. Please enter beer volume *produced by* and sold for your company, or *taxable beer production*. (Beer produced under an alternating proprietorship should be entered on question 2.)

______ **BBLS for 2024** ______ **BBLS for 2023**

2. Alternating Proprietorships: If applicable, please enter beer volume sold for your company produced via alternating proprietorship:

______ **BBLS for 2024** ___0___ **BBLS for 2023**

3. Total volume of taxable contract-brewed beer *you sold* that was produced for you by another company?

______ **BBLS for 2024** ___0___ **BBLS for 2023**

Thanks for filling out this survey! If you have questions about how to answer any of the items, please email bips@brewersassociation.org, or find detailed guidance on the web at brewersassociation.org/BIPS

NONE of the following information will be published

4. Please enter taxable production of non-beer beverage alcohol volume sold for your company-owned brewery (FMBs, hard seltzer, cider, RTD liquor, etc.). Enter 0 if none.

______ **BBLS for 2024** ______ **BBLS for 2023**

5. Percent of taxable beer volume sold onsite at your brewery/ brewpub (draught or packaged):

______ **BBLS for 2024 OR** ______ **% for 2024**

6. If you sell 25%+ onsite, would you define yourself as a:

Taproom ______ **OR Brewpub** ______

7. Annual production capacity in BBLS (estimate): ______

8. Employees (brewpubs, include all staff):
Total number of full-time employees ______
Total number of part-time employees ______

Record Number: ______
Company Name: ______
Address: ______
City, State Zip+4 ______

Form completed by: ______
Title: ______
Signature: ______
Email address: ______

Sharing this information with the Brewers Association allows us to compile industry sales volume production totals.
NOTE: Non-responding breweries will have estimated totals published. If you do not wish to have an estimated total published, please select "Do Not Publish" above or email us at bips@brewersassociation.org.
If your brewery is still in its planning stages, please provide an estimated opening date: ______

Appendix C

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 D

Table D1. Reporting brewery counts by month

	2021	2022	2023	2024
January	756	746	713	696
February	760	734	718	681
March	7,017	7,258	7,120	6,562
April	762	727	724	
May	757	718	714	
June	7,035	7,255	7,098	
July	752	722	698	
August	751	713	699	
September	7,090	7,250	7,009	
October	750	727	701	
November	745	726	698	
December	7,211	7,240	6,949	

Source: TTB 'Monthly National Statistical Report - Beer' dated 1/3/2025

Journal of Beer Economics, Vol. 3, No. 1, 2025, 15-29.

Legal Cannabis Affects on U.S. State-Level Beer Consumption: A Principal-Components Dynamic Panel Approach

Mitch Kunce[1]

Abstract
This paper debits the inventory of applied literature focusing on the progression of recreational cannabis legalization in the U.S. and its impacts on alcohol consumption – specifically beer and other malt-based beverages. A complete U.S. dynamic panel specification (2008-2022) is developed allowing for comparisons of substance use between states that have enacted recreational legislation and those that have not, along with pre- and post-legalization time-trend evaluation. Herein, with a properly controlled basic demand specification for beer, we find evidence of a small state-level legalization policy substitution effect. However, when income non-linearity is introduced, the significant negative impact of cannabis legalization on beer consumption vanishes. Current, state-level, assessments of recreational cannabis affects on alcohol use remain provisional due to spatial data limitations.

Keywords: Recreational cannabis legalization, beer demand, dynamic panel estimation
JEL Classifications: C22, D12, L60

Introduction
Prior to 1913, marijuana was legal across the U.S. under both state and federal canon. California was the first state to outlaw the substance in that same year. By 1930, thirty states had adopted forms of marijuana prohibition. In 1937, the U.S. congress passed the Marijuana Tax Act which effectively banned legal use across the country by imposing a prohibitive tax. More draconian, criminal federal statutes soon followed (Musto, 1991). Despite this history of increasing federal enforcement, many states began to back-off from criminalization in the early 1970s. Liberalization on a local level, such as home possession and medical use, spread widely. In 2012, Washington and Colorado legalized recreational cannabis by ballot initiatives – commercial distribution in both states was authorized in 2014. By the end of 2024, 22 more states and the District of Columbia followed suit (Marijuana Policy Project, 2024). Moreover, a groundswell for federal decriminalization has been mounting (Rozo, 2025).

A rather multi-disciplined literature is developing regarding wide-spread cannabis legalization and its ancillary effects. In particular, what are the effects of legalization on the consumption of other intoxicating substances? Of course, top of mind is alcohol. Without question, alcohol and marijuana are the two most commonly used intoxicants in the U.S. (Guttmannova et al., 2016). The focus of a large part of this literature is whether marijuana and alcohol are 'substitutes' or have a 'complementary' relationship. Regarding the latter, concurrent use of alcohol and cannabis has been shown to intensify health harms over individual use of these substances (Subbaraman, 2016). From public policy and public health perspectives, understanding the effects of cannabis legalization on alcohol use is imperative.

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Existing evidence on the impact of recreational cannabis legalization on alcohol use is, at best, mixed (Anderson and Rees, 2023). A few economic based studies support a substitute relationship while the public health and sociological literatures are more inconclusive (Pacula et al., 2022). What is lacking in the extant literature, particularly U.S. centered, is full panel treatments. U.S. panel specifications allow for comparisons of substance use between states that have enacted pro-marijuana legislation and those that have not, along with pre- and post-legalization time-trend assessments (Guttmannova et al., 2016). Moreover, full U.S. panel data estimation provides controls for latent state- and time-specific characteristics and generally does not suffer sample selection biases. Grounded in economic demand theory, this paper debits the inventory of applied literature focusing on the progression of recreational cannabis legalization in the U.S. and its impacts on alcohol consumption – specifically beer and other malt-based beverages. Over the period 2008-2022, beer consumption lead the industry comprising, roughly, a 49 percent share of the alcoholic beverage sector (Beer Institute, 2024). In the sections that follow, we describe the data used and its particulars, fully develop the dynamic panel data model, present and discuss estimation results and offer concluding remarks.

Data

Data comprise a 15 year (2008-2022), all 50 state and District of Columbia panel. Table 1 describes all beer demand variables, provides sources and key descriptive statistics. The Beer Institute's consumption data have been examined in previous studies, notably Freeman (2011), Yakovlev and Guessford (2013) and Kunce (2024). Sources for aggregate own and substitute price proxies, state excise tax data, follow Freeman (2011) for beer and Fogary and Voon (2018) and Hart and Alston (2020) for wine.[2] Within the

Table 1. Data descriptions, sources and descriptive statistics

Beer consumption (C_{it}). Apparent beer consumption for all 50 states and D.C. by year in gallons per legal drinking age (LDA) population (i = 1 . . 51; t = 1. . 15). 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, teas, ranch waters, etc.). Population numbers (denominator) are aggregated by state (drinking age laws may differ by state) by the U.S. Bureau of the Census. No distinction is made in this ratio for variation of alcohol content in beer. Mean 28.910, STD 5.363.
Beer excise taxes (P_{it}). Beer-specific excise tax burden by state in 2020 dollars per gallon. Generally, this rate includes state and local brewery production and specific sales taxes and fees aimed at malt-based products. Interestingly, in some states (e.g. Pennsylvania), separate on-brewery-premise sales taxes are imposed. Source: The Brewer's Almanac, published periodically by The Beer Institute. Mean 0.301, STD 0.263.

[2] Wine taxes are compiled by the Tax Foundation. For some control states (where government controls all sales) data were missing. Data absent states included MS, NH, PA, UT and WY. In each incident we relied on the state's statutory markup (e.g. 17.6 percent in Wyoming, Wyoming Statute § 12-2-303) to compute specific tax revenue from state sales of wine − then converted the total to per gallon of apparent consumption per state, per year.

Disposable personal income (I_{it}). Defined as per capita personal income by state available to people for spending or saving (after-tax income), in thousands of 2020 dollars. U.S. Source: Bureau of Economic Analysis, Personal Income and Outlays release. Mean 48.709, STD 7.939.
Wine excise taxes (Ps_{it}). Wine-specific excise tax burden by state in 2020 dollars per gallon. Generally, this rate includes state and local production and specific sales taxes and fees aimed at fermented fruit-based products. Sources; Tax Foundation, Alcohol and Tobacco Tax and Trade Bureau. Mean 0.855, STD 0.561.
Legal Cannabis (d_{it}). Dummy variable taking the value of 1 in a state/year (2008 - 2022) where both recreational use *and* commercial distribution of marijuana was legal for more than one month of the year, 0 otherwise. Source: State-by-state marijuana laws. Marijuana Policy Project. Mean 0.113, STD 0.340.

time span represented in our panel, 17 states legalized recreational use *and* commercial distribution of marijuana.[3] Pioneering states include Colorado, Oregon and Washington.[4] Accessible aggregate cannabis price or proxy tax data, for states where commercial distribution is legal, is incomplete for our 15 year time span.[5] Moreover, for the 36 states where commercial distribution is either not authorized or still illegal, aggregate price proxies would have to reflect imputed values of hypothesized interstate bootlegging (Hansen et al., 2020a). Herein, we model legalization and distribution with an overall policy-effect dummy variable rather than introduce an inadequate cannabis price or proxy.[6] This dummy will act as a shifter when year-specific effects are included among the regressors. A negative (positive) coefficient would indicate that the combined legalization policies decreased (increased) beer consumption – a policy substitution (complementary) effect. Following research reviewed by Fogarty (2010), it is reasonable to model beer demand as,

$$C_{it} = f(P_{it}, I_{it}, Ps_{it}, d_{it}, \mu_i, \lambda_t), \tag{1}$$

using the variables described in Table 1. Moreover, μ_i denotes a vector of state-specific effects that are time-invariant while λ_t denotes the vector of year-specific effects that are state-invariant. Again, the legal cannabis dummy variable, d_{it}, will act as a policy shift-effect on beer consumption. All continuous variables are transformed into natural logarithms yielding estimated coefficients that are readily interpreted as elasticities. Interpretation of dummy variables follows Hardy (1993).

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[3] Two of the 17 states, New York and Rhode Island did not authorize commercial distribution until December of 2022 (Marijuana Policy Project, 2024). The legal cannabis dummy for these states takes a value of zero for 2022.

[4] Colorado was the second state to legalize, four days after Washington state – December 10, 2012, and the first to begin commercial distribution in January 2014 (Ingold, 2014).

[5] Interestingly, *High Times* magazine has been used as a key source for state-level cannabis pricing.

[6] To be fair, the beer and wine state-aggregate price proxies have also been considered inadequate (Hart and Alston, 2020; Kunce, 2024).

In addition to the variable particulars denoted in Table 1, Table 2 depicts the variable correlations and variance inflation factors (VIF). The diagnostic tools shown in Table 2

Table 2. Correlation matrix and centered variance inflation factors

	P_{it}	I_{it}	Ps_{it}	VIF
P_{it}	1.00	-		1.51
I_{it}	-0.18	1.00		1.04
Ps_{it}	0.47	-0.12	1.00	1.48
d_{it}	-0.08	0.39	-0.02	-

are standard in detecting multicollinearity. While multicollinearity problems are certainly a matter of degree, the risk of deleterious issues herein appears small.

Model

Following certain treatments found in Waters and Sloan (1995), Tremblay and Tremblay (2005), Freeman (2011) and Colen and Swinnen (2016), we assume that beer consumption is governed by a partial adjustment or persistence model. The use of panel data, in this context, allows for a better understanding of the dynamics of adjustment. This relationship is characterized by the inclusion of a first-order lagged dependent variable among the regressors,

$$C_{it} = \alpha C_{i,t-1} + x'_{it}\beta + \lambda_t + u_{it}\,, \tag{2}$$

where the error term is comprised of two orthogonal components, state effects and idiosyncratic shocks,

$$u_{it} = \mu_i + v_{it}\,. \tag{3}$$

As described above, the time dimension of our data is relatively short, limiting proper scrutiny of time-series asymptotics such as non-stationarity. As such, we rely on more standard short-panel treatments and include period dummies λ_t, in the right-hand-side (Roodman, 2009b). The dynamic regression shown in Equation (1) holds two sources of persistence: Autocorrelation due to the inclusion of the lagged dependent variable *and* state/year components characterizing heterogeneity.

A common problem in the estimation of panels with a relatively large number of cross-sectional group units, is cointegrating relationships among the units (Baltagi et al., 2007). Presuming that errors are cross-sectionally independent can lead to incorrect inference and inconsistent estimates. Pesaran (2004; 2015; 2021) proposed the following test statistic,

$$\vec{CD} = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right), \tag{4}$$

where $\hat{\rho}_{ij}$ denotes the pair-wise correlation coefficients from regression residuals (i = 1, . . . , N; t = 1, . . . , T). This $\overleftrightarrow{CD}$ statistic is distributed, generally, asymptotically standard normal and the null hypothesis depends on the relative expansion rates of N and T. Under general conditions, even when T is small, the appropriate null is weak dependence (Pesaran, 2015).[7] In many cases, an easy correction for cross-section dependence is the fixed effects or within estimator. However, Juodis and Reese (2022) revealed that the Pesaran $\overleftrightarrow{CD}$ test, when applied to residuals from a model correcting with fixed effects (FE), tends to diverge in favor of the null hypothesis.[8] The authors forward a weighted form of pair-wise correlation,

$$\hat{\rho}_{ij} = \sum_{t=1}^{T} w_i \hat{v}_{it} w_j \hat{v}_{jt}\,, \tag{5}$$

where $\hat{v}_{it}$ denotes the regression residuals and the weights, w_i , are iid Rademacher. Under the null, the statistic is again asymptotically normal. We will apply the weighted form in formal residual testing below.

Including a lagged dependent variable in the right-hand-side (RHS) of Equation (1) is problematic. Because C_{it} is a function of the state and year components in Equation (2), $C_{i,t-1}$ will be correlated with the residual v_{it} . This correlation renders ordinary least squares (OLS) and the within or FE estimators inconsistent (Nickell, 1981). Moreover, the random effects generalized least squares (GLS) estimator, when applied to dynamic panels, is also inconsistent. The weighted demeaning in GLS does not eliminate the correlation with the demeaned error. Anderson and Hsiao (1981; 1982) proposed first-differencing (FD) to eliminate the μ_i and then using differences, $\Delta C_{i,t-2}$, or levels, $C_{i,t-2}$, as an instrument for $\Delta C_{i,t-1}$. These instruments are not correlated with Δv_{it} as long as the v_{it} are not serially correlated. As an aside, Arellano (1989) recommended, for simple dynamic panel treatments, levels instruments over differenced due to singularities and large variances in the latter. Moreover, instrumenting with lagged levels maximizes the overall sample size. The seminal Anderson and Hsiao (1982) instrumental variable (IV) method was shown to be consistent but not fully efficient because it does not incorporate all available moment conditions (Holtz-Eakin, et al., 1988).[9] Even for panels with short time horizons, many moments (instruments) are available to improve asymptotic efficiency. The works of Arellano and Bond (1991), Arellano and Bover (1995), Ahn and Schmidt (1995) and Blundell and Bond (1998) extended generalized method of moments (GMM) estimation for dynamic panels. In addition to moment related efficiency improvements, these estimators handle endogeneity of regressors, heteroskedasticity and autocorrelation 'within' indexed groups (e.g. states), [10] and unbalanced panels.

[7] In Monte Carlo simulations, Pesaran (2015) shows the *CD* test holds correct size for all combinations of N and T, irrespective of whether the panel includes lags of the dependent variable.

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

[9] The use of GMM in this context originated with Holtz-Eakin, Newey and Rosen (1988).

[10] Cross-sectional (group) correlation is a violation.

Two estimators have been generalized in the literature, difference and system GMM. Difference GMM initiates by simply first-differencing the data in order to eliminate the group (state) effects.[11] Instrumenting proceeds using lags of variables, within the data set, at levels. System GMM claims efficiency gains over difference GMM by differencing instruments assuming that first-differenced instruments are uncorrelated with the group effects.[12] This provides a system of two equations, differenced and at levels, distinctly instrumented and estimated simultaneously (Blundell and Bond, 1998). Highly persistent (autoregressive) panels are prime candidates for system GMM estimation.[13] The progression of dynamic panel GMM estimation appears to promote more moment conditions to enhance performance. However, a proliferation of moments does not necessarily lead to the 'best' estimator (Bun and Kiviet, 2006; Roodman, 2009a; Okui, 2009). When *all* lags of variables are drawn on, the instrument count expands with T and x'. Table 3 provides an illustration of the full expansion for a lagged dependent variable and one regressor when $T = 15$.

Table 3. Instrument expansion

Year	**Lagged Dependent Variable $C_{i,t-1}$**	**Independent Variable x_{it}**
1	0	0
2	0	1
3	1	2
4	2	3
5	3	4
6	4	5
7	5	6
8	6	7
9	7	8
10	8	9
11	9	10
12	10	11
13	11	12
14	12	13
15	13	14
Total	**91**	**105**

The tradeoff now becomes efficiency for overfitting bias as the number of moment conditions expand (Newey and Smith, 2004). Moreover, moment expansion impacts the

[11] Unbalanced panels and gaps in data motivated a second transformation method, 'orthogonal deviations' (Arellano and Bover, 1995).
[12] This assumption is not trivial, it holds when the fixed effect and the autoregressive term α essentially offset each other in expectation across the complete panel (Roodman, 2009b). Moreover, including dummy variables in system GMM that are mostly zero, or mostly one, can introduce bias, particularly when T is small. This latter point influences our model choice below.
[13] From Equation (2), α close to unity.

weighting matrix[14] which may weaken the Hansen (1982) test for over-identifying restrictions and introduce downward bias in the standard errors (Windmeijer, 2005). Unfortunately, the theoretical literature extends no optimal number of moment conditions. Applied procedures to reduce the number of instruments have been forwarded, but generally rely on the discretion of the practitioner. An example would be selecting only certain lags to be included in the instrument set. Seemingly, a more attractive transformation would be at least statistically grounded and at best data driven (Mehrhoff, 2009; Liao, 2013). Bontempi and Mammi (2015) advocate the use of principal components analysis (PCA) of the instrument matrix in order to reduce instruments into a set of linear combinations of the original variables.[15] These combinations are purely data driven and maintain specific features of the data. The authors label the procedure 'principal components instrumental variables reduction' (PCIVR).[16] The aim of PCIVR is to reduce the dimension of the GMM instrument matrix $\boldsymbol{z}$ which is defined with p columns. To do so, q principal components corresponding to the eigenvalues of $\boldsymbol{z}$ are retained based on either 'average' or 'variance' criterion. The adopted rule follows,

$$(m+1) \leq q < p, \tag{6}$$

where m is the number of endogenous regressors other than the lagged dependent variable. The transformed instrument matrix is made up of q corresponding score vectors.

Estimation results

Table 4 presents results for the basic linear demand function represented by Equation (2) for a range of estimators. We start with ordinary least squares (OLS) in the second column then modify, step by step, to the right ending with the PCIVR estimates. Without accounting for state and year effects, pooled OLS appears to yield an upwards biased estimate of the coefficient on lagged consumption. This coefficient reflects predictive power that is actually part of the state/year effects. Moreover, covariate estimates are plagued by cross-state dependence indicated by the highly significant Pesaran statistic. Column 3 depicts the two-way fixed effects adjustment. Strong significance of the cross-state and year F-statistics confirm the importance of controlling for these effects. The weighted Pesaran statistic now fails to reject the null of weak cross-state dependence. Inclusion of state and year controls temper cross-sectional dependence biases. Note that the highly significant Hausman statistic confirms misspecification of the random effects GLS estimator. Interestingly, the lagged beer consumption coefficient reflects a downwards biased estimate. Credible estimates should lie between the OLS (0.990) and two-way FE (0.649) values (Bond, 2002).

The two-way FE specification provides certain necessary controls but does not directly address dynamic panel bias. Instrumental variable estimation does, while GMM methods improve efficiency. The choice between difference and system GMM is not trivial.[17]

[14] The weighting matrix is the inverse of the estimate of var[$\boldsymbol{z}'u$] where $\boldsymbol{z}$ is the instrument matrix.

[15] Interestingly, Kloek and Mennes (1960) and Amemiya (1966) first proposed the use of PCA in instrumental variable estimation.

[16] This procedure is available in the Stata® software package.

[17] See Chandra and Doshi (2025) for an in context use of these same methods. Using a 'unicorn' 15 year (1911-1925) panel of 25 districts within Bengal, India, where marijuana and opium were legal, evidence of substitution between cannabis bud and alcohol was established using complete price and wage data.

Herein, we apply difference GMM based on two overriding concerns. First, the point of this examination is to see if our cannabis policy-effect matters. Because roughly 89 percent of the data takes the value of zero for this variable (see Table 1), bias may be introduced using the system GMM specification (Roodman, 2009b, p. 115). Second, the validity of additional instruments in system GMM relies on specific assumptions about the initial conditions of the data generating process. Notably, because you are instrumenting levels with differences, the differences must be orthogonal to the levels error, which contains the state effect. Highly persistent data is said to benefit from this estimator (Blundell and Bond, 1998).

Column 4 of Table 4 shows the Windmeijer (2005) corrected, two-step, fully instrumented with lags from levels, difference GMM estimates. The coefficient of the lagged dependent variable falls within the credible range. Estimates of short-run price (excise taxes) and income elasticities are in line with the literature surveyed by Fogarty (2010) and results found in Freeman (2011) and Colen and Swinnen (2016).[18] The coefficient of the legal cannabis dummy is negative and significant, at the less than 5 percent level, indicating a substitute relationship between recreational marijuana and beer. The standard specification check for two-step GMM is the Hansen (1982) *J*-test. With a p-value of 0.611, the null of joint validity of the instruments is not rejected. The Arellano-Bond test for first-order serial correlation rejects the null of no first-order correlation but fails to reject the null of no second-order correlation. This result is expected from a first-differenced equation when the untransformed errors are assumed not serially correlated. When reassessing the over-identifying restrictions, the high p-value of the Hansen test appears suspicious. This test statistic is vulnerable to instrument proliferation (Roodman, 2009a). To mitigate potential size problems with this test, the set of instruments should be reduced.

The last column of Table 4 shows the results for the same difference GMM estimator using as IVs the PCA scores relative to the principal components, of the full lag matrix, retained by average criterion. The average criterion selects only those components (eigenvectors) whose corresponding eigenvalues are above the average of eigenvalues extracted. We let the nature of the data decide the composition of the transformed instrument matrix. This 'light touch' PCIVR method reduced the instrument count by over one-third. Note the significant decline of the Hansen p-value, though the null hypothesis still holds. The coefficients on own price (excise tax) and the cannabis dummy increased, in absolute value, by 50 percent over column 4 estimates. Again, marijuana and beer appear to be substitutes, though the magnitude of substitution is diminutive in the aggregate.[19]

Table 4. Basic demand function results

	OLS	**Two-Way FE**[a]	**DIFGMM**[a]	**PCIVR**[a]
$\ln C_{t-1}$	0.990***	0.649***	0.783***	0.753***
$\ln P$	0.002*	-0.002	-0.015*	-0.022**
$\ln I$	-0.017**	0.242**	0.457**	0.411**

[18] From Equation (2), the long-run multiplier becomes $1/(1-\alpha)$.
[19] Less than 1 percent, $e^{0.009} - 1$, of LDA population beer consumption (Hardy, 1993).

lnPs	-0.001	0.007	0.017	0.014
Cannabis Dummy	0.005*	-0.001	-0.006**	-0.009**
R^2	0.981	0.987	-	-
Pesaran $\overleftrightarrow{CD}$	17.08***	1.29[b]	-	-
Cross-State F-test	-	3.08***	-	-
Year F-test	-	6.53***	-	-
Hausman	-	25.28***	-	-
Hansen P-value	-	-	0.611	0.232
Arellano-Bond, AR(1) P-value	-	-	0.002	0.000
Arellano-Bond, AR(2) P-value	-	-	0.272	0.408

Windmeijer corrected significance: (***) < 1%, (**) < 5%, (*) < 10% .
[a] Year dummies included.
[b]Juodis and Reese (2022) weighted Pesaran statistic.

Much of the empirical literature on beer demand follows the basic linear model examined above (see Fogarty, 2010 for a review). Recently, particularly in long-run treatments, the focus has shifted to modeling income as polynomial non-linear (Gil and Molina, 2009; Colen and Swinnen, 2016; Kunce, 2024). Statistical representations in these studies, for countries and jurisdictions within, clearly suggest that per-capita beer consumption initially increases with rising income but at higher income levels consumption falls with continued income growth. Reasons for this inverted-U relationship presume increased demand for health at higher income levels and substitution to more expensive alcoholic beverages as incomes rise, including pricey beer, purchased in lower quantities (Swinnen, 2017). Figure 2 graphically represents trends in beer consumption against income in three states revealing an inverted-U shape. The cannabis-legal states shown, Alaska, New York and Maine have the highest real-income growth within our sample. Herein, we extend the basic demand model to include a second-order (squared) term for income.

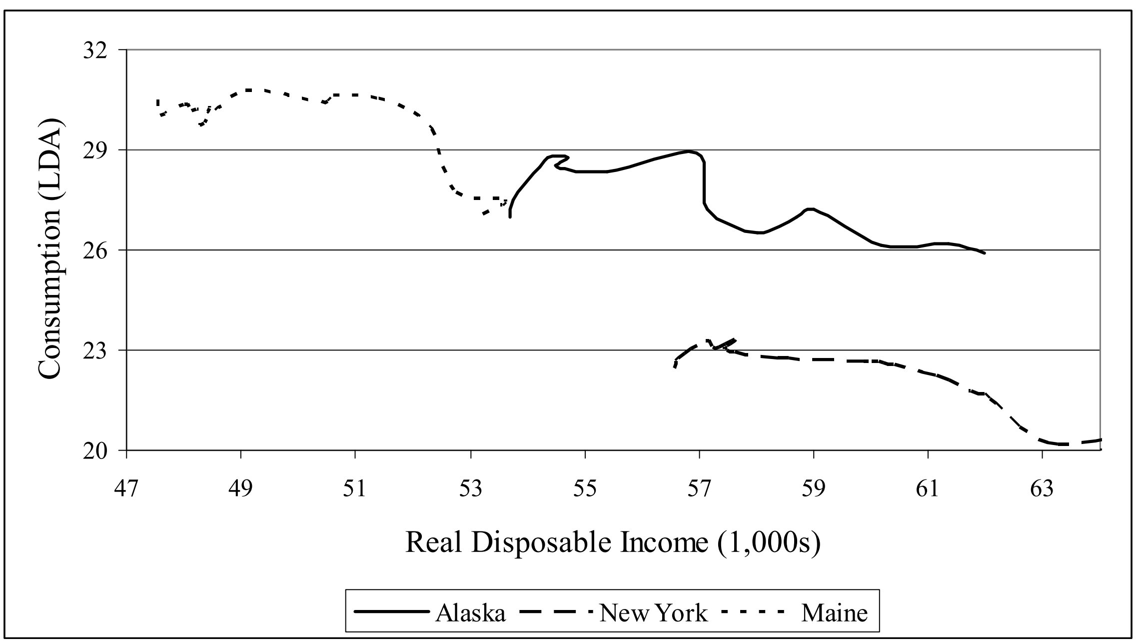

Figure 1. Beer consumption vs income for select states (2008-2022)

Table 5 presents the augmented results, following the same estimator progression implemented in Table 4.[20] Focusing on the PCIVR column, the first- and second-order income coefficients are highly significant and confirm the inverted-U non-linearity. These estimates are in line with the short-run American continent results of Colen and Swinnen (2016) and the U.S. state-level coefficients found in Kunce (2024). Interestingly, the cannabis dummy coefficient is now positive and highly insignificant. Inclusion of the second-order income term negates the 'substitution' result found in Table 4. This suggests that the policy dummy in the basic demand model was 'picking-up' the negative effect of higher real income growth on beer consumption. Lastly, note that the own price coefficient is only slightly smaller than the Table 4 estimate and the wine price proxy has changed signs but continues to be insignificant at conventional levels.

Table 5. Polynomial income results

	OLS	Two-Way FE[c]	DIFFGMM[c]	PCIVR[c]
$\ln C_{t-1}$	0.991***	0.627***	0.753***	0.705***
$\ln P$	-0.002	-0.005	-0.012*	-0.017*
$\ln I$	0.817**	0.651***	0.782***	0.714***
$(\ln I)^2$	-0.105**	-0.079***	-0.098***	-0.086***
$\ln Ps$	-0.002	-0.009**	-0.014	-0.011
Cannabis Dummy	0.003	0.006	0.004	0.008[d]
R^2	0.982	0.987	-	-
Pesaran $\overleftarrow{C}\overrightarrow{D}$	16.64***	1.16[e]	-	-
Cross-State F-test	-	3.56***	-	-
Period F-test	-	6.64***	-	-
Hausman	-	34.63***	-	-
Hansen P-value	-	-	0.684	0.211
Arellano-Bond, AR(1) P-value	-	-	0.000	0.002
Arellano-Bond, AR(2) P-value	-	-	0.449	0.291

Windmeijer corrected significance: (***) < 1%, (**) < 5%, (*) < 10% .
[c]Year dummies included.
[d]P-value 0.354.
[e]Judis and Reese (2022) weighted Pesaran statistic.

Since the mid 1990s, beer's consumption-share of the U.S. alcohol market has been declining (Hart and Alston, 2020). For example, in our sample, the overall U.S. share was 52 percent in 2008 falling to 42 percent by 2022 (Beer Institute, 2024). The bulk of this lost share has moved to the spirits sector. Moreover, consumption per legal aged adult is also in decline. Figure 2 below shows consumption trends for all 50 states and the District of Columbia from 2008 to 2022. Recreational cannabis legalization is occurring in a time when beer (in volume) is already falling out of favor with U.S. consumers. Teasing out any role legal cannabis has played in these state-level differences will be challenging. What we have forcefully confirmed is the non-linear link running

[20] With one exception regarding use of the full instrument set, we did not include lags of the second order income term in z due to potential rank reduction (see Kiviet et al., 2017).

from mean state-level disposable income to beer consumption. Income non-linearity, however, is not unique to beer demand, Colen and Swinnen (2016) find evidence of the inverted-U relationship when *total* alcohol consumption per-capita is the dependent variable.

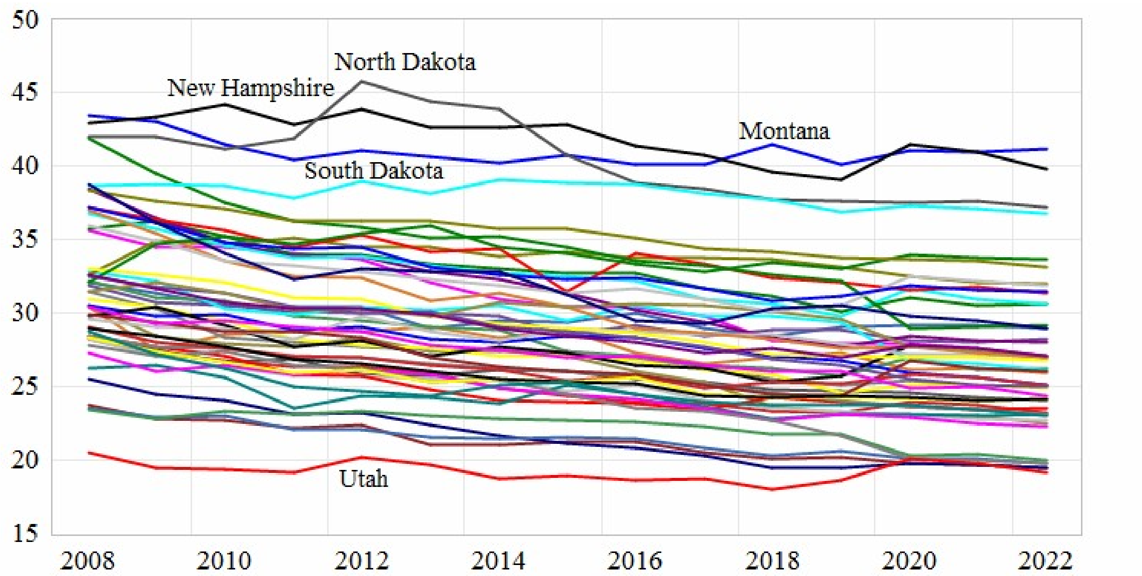

Figure 2. Beer consumption, gallons per LDA population, state trends

Concluding remarks

U.S. states are well over 10 years into the recreational cannabis experiment. One of the key topics of debate leading up to the origin ballot measures in 2012 and commercial dispensing in 2014 was the relationship between cannabis and alcohol. To date, a burgeoning literature is rather unclear regarding what impact legal recreational marijuana has had on alcohol consumption. Within the economic based examinations, a paucity of evidence supports a substitute relationship in the U.S. (e.g. Hansen et al., 2020b; Miller and Seo, 2021). Herein, with a properly controlled basic demand specification for beer, we find evidence of a small state-level policy substitution effect. However, when income non-linearity is included in the right-hand-side, the significant impact of cannabis legalization vanishes. Within our sample period (2008-2022), recreational cannabis legalization has been enacted, primarily, in high mean-income and higher income-growth states. Only two, Nevada and Montana, were below sample means in both metrics. It is not surprising then that the legalization dummy, taking the value of one in mostly the latter years of the sample period, forces a confounding relationship with the negative second order income effect. Perhaps the remedy for the lack of clarity shown herein, and in the extant literature, is time. More states are moving toward recreational legalization. Expanding legalization will provide additional and perhaps even better data, particularly farther-reaching cannabis price data. Efforts examining the potential substitution (complementary) effects between marijuana and alcohol, at the jurisdictional level, need to capture both between and within variation in the *legal* marijuana price (Guttmannova et al., 2016). In any case, existing work still provides a useful perspective on what appears to be imminent, wide-spread, legal use of cannabis in the U.S.

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U.S. Small Brewery Tipping Behavior: Evidence from a Brewpub POS Records

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Abstract

In small breweries across the U.S., on premises patrons leave voluntary payments to the serving staff who waited on them. Understanding the motivation behind and variation of gratuity payments, in general, is the subject of a growing literature. Using 6,655 guest checks, from a combined brewery-restaurant in the western U.S., we case study predictors of actual tipping behavior. When controls for tip ~ bill simultaneity and server-specific effects are in place, we can account for only 7 percent of the variation in tip percentage. Perhaps the most revealing observation from the data is that over 82 percent of patrons tipped in integer amounts. Results suggest that acceptance of social norms and a bit of apathy play important roles in actual tipping behavior.

Keywords: Small breweries, specialty restaurants, tipping
JEL Classifications: J10, J30, L83

Introduction

In 2024, roughly 7,500 U.S. brewing operations reported their activities to the federal government (TTB, 2025).[2] The majority of these breweries are very small – around 80 percent produced 1,000 barrels or less for the year. Promoting on-premises sales is vital to a small brewery's longevity (Kunce, 2024). Accordingly, most small breweries have a direct association with a restaurant or tavern. As a result, all employ taproom sales help, servers or tavern bartenders. Akin to serving staff in most restaurants and bars in the U.S., small brewery front-of-the-house employees generally rely on tips for additional or in some cases all of their take-home income. Interestingly, the origins of tipping may have roots in 16th century English public houses. Brenner (2001) describes brass urns with the inscription 'To Insure Promptitude (TIP)' placed in old English pubs to collect fractional farthings from patrons enjoying local ale.

Plausible reasons for tipping in eating and drinking establishments follow more a social predicate rather than economic consideration (Azar, 2010). Normative multiples for U.S. restaurants have evolved from around 10 percent of the bill to 20 percent over the last 10 decades or so (Azar, 2020; Norris et al., 2023; Lynn, 2025). This suggests that patrons of U.S. restaurants derive social benefit by acceptance of this costly evolving norm (Azar, 2004; 2005). Enough said then, restaurant and bar tipping today is simply a normative calculation, tab × 0.20. Notwithstanding, there exists a burgeoning literature attempting to explain tipping behavior that deviates from the accepted arithmetic (see reviews by Lynn, 2006; Azar, 2007; Banks et al., 2018; Fernandez et al., 2024). Empirical efforts generally derive data through surveys of customers or servers. Hard observables such as bill size, payment method, party size, patronage frequency, sex and ethnicity are commonly gathered. Soft or impressionistic variables can include constructed scales for

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[2] 2024 Monthly National Statistical Report-Beer, dated 2/24/2025.

service quality, fare quality and server personality. The evidence that any of these predictors, other than bill amount, explain a meaningful share of the variation in tipping is mixed at best (Banks et al., 2018).

Herein, we throw our hat in the tipping literature ring. Our empirical examination aims to contribute in three important ways. First, we draw data from a rather unique source, a combined brewery-restaurant establishment in the western U.S.[3] By doing so, we tap into the small-beer neo-local subculture to explore postmodern consumption influences on tipping behavior (Long et al, 2018; Thurnell-Read, 2018). Second, we exploit actual point-of-sale (POS), not surveyed, data.[4] Lastly, the nature and individual detail of the POS data allows for controls of unobserved server-specific and period effects.[5] Simple cross-section methods are deficient in controlling for anticipated two-way heterogeneity biases. The balance of this examination is divided into three sections. The next section describes the data, presents descriptive statistics and data particulars. The third section describes the empirical models, discusses the econometric issues and presents estimation results. Conclusions and implications are drawn in the last section.

Data

The extant literature empirically examining tipping behavior has relied, generally, on experience surveys of either patrons or servers (Lynn, 2006; Azar, 2007; Banks et al., 2018; Fernandez et al., 2024). Herein, we exploit a truly unique data set of actual (proprietary) tip claims from a single brewery-restaurant located on the front range of the U.S. Rocky Mountains. Along with in-house crafted beer the pub offers wine, spirits and bar-casual dining fare (appetizers, salads, wings, sandwiches, burgers, pizza). The data follows eight servers/bartenders over the years 2023-2024. The initial random sampling captured 10,128 ticket records generated from an Aloha® POS Payment Report for the eight employees over the three-year period.[6] Each electronic ticket record was backed-up by the Merchant Copy presented at the transaction closing. Three filters were applied to the raw data set. First, cash payments were excluded because the system record and back-up documents provided no evidence of a cash tip. Second, large party tickets generating an automatic gratuity were dropped. One of the special features of this data is that the paying customer had to calculate and then enter the tip amount on the Merchant Copy of the bill. Lastly, the name on the credit card, read by the system, was presumed to indicate whether the signing patron was male or female.[7] Post filtering, 6,655 ticket records remained.

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[3] Though not representative of the entire U.S. population, this establishment-level analysis provides a level of individual detail that would likely be redacted in a broader public data set.

[4] Ali et al., (2023; 2025) also use a large sample of POS guest checks stratified by restaurant brand, location, date and time.

[5] Norris et al., (2023) emphasizes the importance of focusing on the server's role in the service exchange relationship.

[6] Aloha® POS is a product of NCR VOYIX Corporation.

[7] Of course, this indication is based on researcher judgment. For example, Susan Jones was considered to be a female. John Smith was considered to be a male. Close calls were dropped from the sample. As it happened, in the models estimated below, whether the signing customer was male or female did not matter statistically.

The ticket records provided the following variables: sever name, date and time of the closing transaction, signing customer name, bill amount, tip amount, total and credit card type. The POS system also supplied a field for the server to identify the location of the customer party within the facility. Table or seat numbers were a common entry, some servers entered amusing descriptions of patrons or ticket guest counts, but overall this field did not yield a consistent usable variable.[8] All monetary variables were converted to 2022 real dollars using the Consumer Price Index. Ticket times provided an intraday meal-shift variable.[9] In addition to the signing customer name, the credit card field also indicated whether the card swiped was associated with a named business or a division of government.[10] Signing customers that appeared twelve or more times in the data, per year, were designated as 'regulars'.[11] Table 1 provides the variable descriptive statistics, most means are category proportional. All categorical characteristics in the rows below tip percentage will be modeled with dummy variables.

Table 1. Descriptive statistics

Variable	Mean	STD
Tip (in \$2022)	8.22	6.54
Bill (in \$2022)	39.87	31.25
Tip% (Tip ÷ Bill)	23.87	16.15
Server Sex (Female=1)	0.759	0.428
Signing Customer Sex (Male=1)	0.659	0.474
Business or Government Card = 1	0.026	0.160
Lunch Shift	0.289	0.453
Dinner Shift	0.483	0.499
Late Night	0.228	0.419
2022	0.348	0.482
2023	0.346	0.487
2024	0.306	0.431
Server/Bartender 1 (Female)	0.125	0.331
Server/Bartender 2 (Male, Hispanic)	0.117	0.319
Server 3 (Male)	0.126	0.331
Server 4 (Female)	0.119	0.322
Server/Bartender 5 (Female)	0.134	0.341
Server/Bartender 6 (Female)	0.126	0.333
Server 7 (Female)	0.129	0.336
Server 8 (Female)	0.124	0.329

[8] The lack of more customer related characteristics, for example a ticket-specific party count variable, influenced the choice of empirical method presented below.

[9] Three categories, lunch shift: 11am to 3:30pm; dinner shift: 3:30pm to 9:00pm; late night: 9:00pm to close. A late-night food menu was available until close.

[10] Total observations in this category were 175, 32 of which swiped a state or local government card. The largest employer in the brewpub's surrounding jurisdiction is the state government.

[11] Other thresholds were modeled, results were analogous to those shown below.

Regular Patrons = 1	0.212	0.198
Observations	6,655	-
Correlation Tip and Bill	0.862	-
Correlation Tip% and Bill	-0.229	-

In quantitative reviews of the restaurant tipping literature, Lynn and McCall (2000) and Lynn (2006) found that roughly 70 percent of the variation in tip amount is explained by simply the bill size. Moreover, these reviews suggest that tip amounts increase with bill size, perhaps at a decreasing rate, but overall tip percentages decline. To test this, we regress tips in 2022 dollars on the bill amount and then on the bill and its square. Results are shown in Table 2. Interestingly, we find that the bill size explains 74 percent of the variation in tips and a slight negative second order non-linearity in bill amount. Referencing Table 1, the simple correlation between tip and bill is 0.86. Figure 1 below

Table 2. Preliminary regression results

	Linear	**Second Order**
Intercept	1.136***	0.931***
Bill	0.180***	0.189***
$Bill^2$	-	-0.0001*
$\overline{R}^2$	0.743	0.745
Durbin-Watson	1.98	1.97

Huber-White-Hinkley (HC1) corrected standard errors.
(***) < 1%, (**) < 5%, (*) < 10% level of significance.

depicts the Table 2 predicted relationships for tip percentage and tips (in 2022 dollars) when varying bill amounts. The negative impact on the tip amount from the second-order square term is very small, only a decrease of 64 cents on a predicted 80 dollar bill. This result bolsters the so-called 'Magnitude Effect' in tipping (Lynn and Sturman, 2003).

Integer or 'flat dollar' tipping was prevalent in the sample, over 82 percent of the 6,655 recorded actual tips were flat dollar. Past national surveys show only a 20 percent frequency of integer tipping (Lynn and Sturman, 2003). This considerable gap is noteworthy. Figure 2 below plots the frequency of integer tips; 10, 5, 3 and 2 dollar tips were most common. No tip was indicated on 105 (1.6 percent) recorded bills. This either represents 'stiffing' or a cash tip was left leaving the tip field blank on the Merchant Copy. This cluster of zeros in the dependent variable, though small, could be problematic. We will address this potential lower limit censoring below. Lastly, the nature of the POS data allows for controls of server-specific heterogeneity and period-specific fixed effects. Many of these two-way characteristics are generally immeasurable and omitted in simple cross-section specifications.

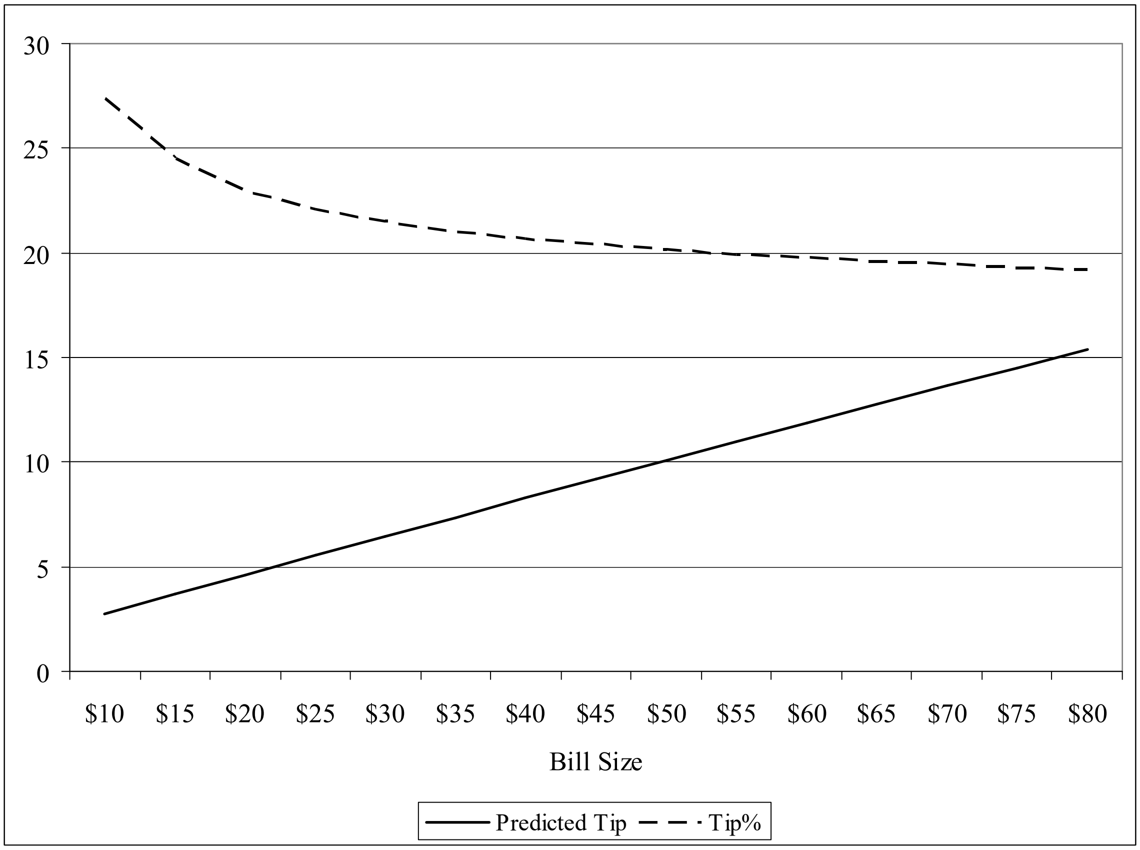

Figure 1. Predicted simulation

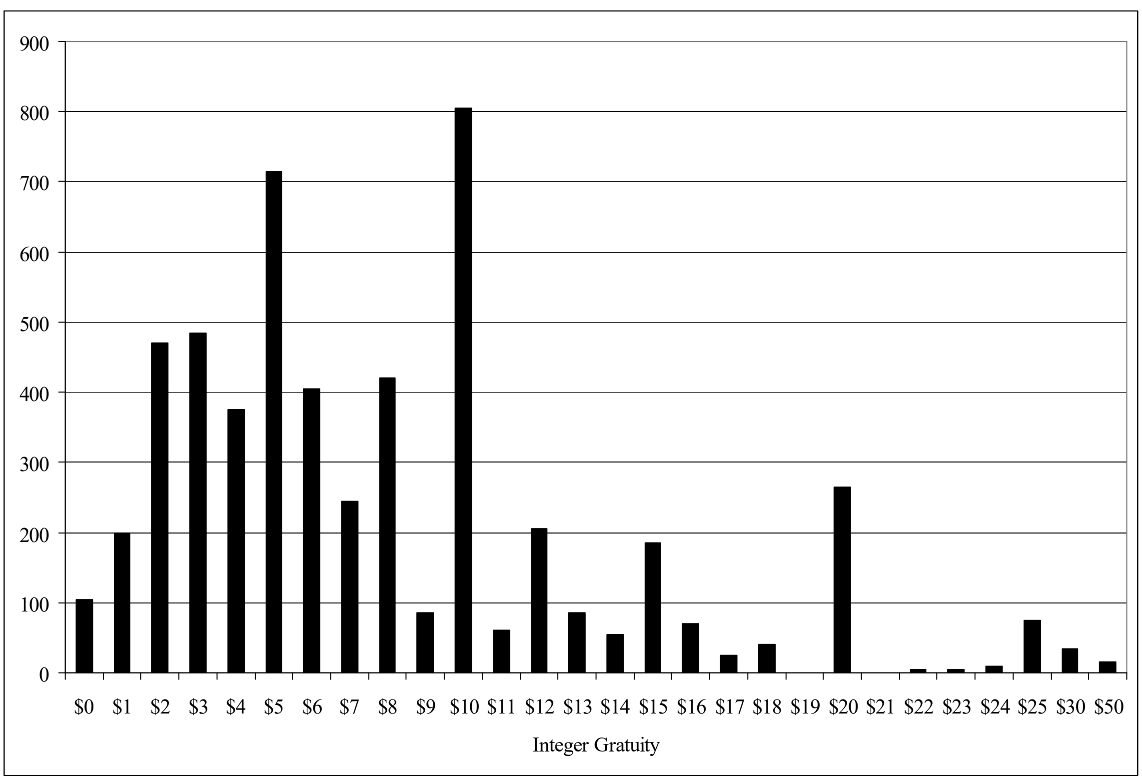

Figure 2. Frequency of integer tips

Regression modeling

Our initial model follows the general literature as emphasized by Fernandez et al., (2024) where the tip amount is regressed on various factors that could explain the variation in tip size. Herein,

> *Real tip amount = f (signing customer's sex, credit card type, meal shift, year fixed effects, server fixed effects, patronage, real bill amount, bill*^{2}) *+ error.* (1)

In Equation (1), observation subscripts have been suppressed to economize on notation. The dependent variable denotes the real tip amount in 2022 dollars, *signing customer's sex* is a dummy variable indicating the sex of the person who signed the Merchant Copy of the brewpub tab, *credit card type* is a dummy variable denoting whether the card used was business or government issued, *meal shift* is a categorical dummy indicating the intraday timing of the ticket, *year fixed effects* for 2022-2024 account for factors such as local regulation changes or Covid19 pandemic impacts, *server fixed effects* capture unobserved heterogeneity in tip amounts among the eight servers followed in the sample, *patronage* is a dummy variable denoting frequent or regular patrons, *real bill amount* is the bill presented before the tip is added in 2022 dollars, *bill*^{2} denotes the second-order non-linearity, and *error* reflects the net effect on tip amount of all factors not otherwise controlled.

As described in the data section above, the dependent variable takes the value of zero in 1.6 percent of the sample. Situations involving expenditures with values close to the lower limit of zero are typical. Conventional regression methods (ordinary least squares, OLS) fail to account for the qualitative difference between limit (zero) observations and non-limit continuous observations. The Tobit model may be appropriate here to improve fit (Tobin, 1958; Wooldridge, 2009). The simplest version of the Tobit model is,

$$\begin{aligned} &Y^* = \beta' X + \varepsilon, \\ &Y = Y^* \text{ if } Y^* > 0;\; Y = 0 \text{ otherwise.} \end{aligned} \tag{2}$$

For fully parametric specifications, maximum likelihood estimation (MLE) is convention. Coefficients from Tobit MLE are not directly marginal effects. The adjustment for continuous regressors follows,

$$\frac{\partial \mathrm{E}[Y^* \mid X]}{\partial X} = \beta\left(\Phi\left(\frac{\beta' X}{\sigma}\right)\right) = \beta \times \text{probability of a nonlimit observation} . \tag{3}$$

For dummy variables, marginal effects become,

$$\mathrm{E}[Y \mid X^1] - \mathrm{E}[Y \mid X^0], \tag{4}$$

where superscripts 1 and 0 indicate that in the computation the dummy variable in the vector X takes the values 1 and 0.[12] Lastly, a robust covariance matrix is obtainable by using the ordinary 'sandwich' estimator.

Table 3 presents both OLS and Tobit Limdep® estimates for Equation (1). The marginal effects of both models are roughly analogous, perhaps due to the low percentage of zeros on the left-hand-side. A Wald test of joint significance of the server fixed-effects fails to reject the null hypothesis that they are jointly zero. This result was unexpected as it counters a growing literature stressing the importance of server-specific characteristics impacting tipped amounts (Lynn, 2006; Banks et al., 2018; Norris et al., 2023). Controlling for year fixed-effects tests marginally significant in both models (p-value < 10 percent). This latter result is likely due to the phasing out of the Covid19 pandemic restrictions of 2020 - 2022. In addition to marginally significant year effects, only Bill, $Bill^2$ and whether the tab was paid with a business or government card mattered statistically. On their face, Table 2 and 3 results seem spurious. Moreover, most of the slight improvement in fit, 0.743 to 0.764, can be attributed to one regressor, payment with business or government card. All other, more conventional, explanatory variables added to the Table 2 specification had little impact. Pragmatically, the act of tipping is

Table 3. Regression results, dependent variable Tip

Variable	OLS[a]	Tobit[b]
Intercept	0.571	0.515
Signing Customer Sex (Male=1)	0.283	0.285
Business or Government Card = 1	4.343***	4.334***
Dinner Shift	-0.086	-0.087
Late Night	0.451	0.474*
2023	0.482**	0.454**
2024	0.096	0.088
Server 2	-0.407	-0.389
Server 3	-0.608	-0.615*
Server 4	-0.591	-0.602
Server 5	-0.061	-0.078
Server 6	-0.183	-0.226
Server 7	-0.231	-0.243
Server 8	-0.724*	-0.728*
Regular Patrons = 1	0.442	0.458
Bill	0.194***	0.195***
$Bill^2$	-0.0001**	-0.0001***
$\overline{R}^2$	0.764	c
Sigma	-	3.156***
Log Likelihood	-	-3,389

[12] See Greene (2018) Chapter 19 for more detail.

Joint Meal Shift Wald Test, χ^2	3.921	3.831
Joint Period Wald Test, χ^2	5.963*	5.330*
Joint Server Wald Test, χ^2	7.572	7.533

(***) < 1%, (**) < 5%, (*) < 10% level of significance.
[a]Huber-White-Hinkley (HC1) corrected standard errors.
[b]Sandwich covariance matrix used. Marginal effects reported.
[c]Pseudo fit measures are not directly comparable to R^2.

simultaneous with bill amount. As discussed above, recent accepted norms profess a 20 percent multiple (Norris et al., 2024). This suspected endogeneity may be affecting estimate consistency. An approach to overcome the simultaneity involves instrumental variable (IV) estimation within two-stage least squares. The object of IV estimation is to find a set of secondary predictors that are strongly correlated with the bill amount but not with the error term in Equation (1). Not an easy task. As noted in the data section above, the lack of patron-specific characteristics in the POS data hampers construction and use of IV estimation. Moreover, simply testing for endogeneity in the specification involves instrumenting the suspected regressor (Hausman, 1978; Spencer and Berk, 1981).[13]

Perhaps the cleanest way to circumvent the suspected simultaneity bias is to eliminate bill amount from the right-hand-side (RHS) and use *Tip Percentage* as the dependent variable (e.g. Jahan et al., 2023).[14] Table 4 presents descriptive statistics for the new dependent variable stratified by category. Noteworthy are the high mean tip percentages for customers paying with a business or government card and who frequent the pub after the

Table 4. Tip percentage stratified descriptive statistics

Variable	Tip%, Stratified Mean	STD
Server (Female)	24.17	16.28
Server (Male)	22.94	15.73
Signing Customer (Female)	23.69	17.58
Signing Customer (Male)	23.97	15.36
Business or Government Card	31.61	25.33
Personal Card	23.39	12.05
Lunch Shift	22.02	13.21
Dinner Shift	22.52	12.82
Late Night	29.01	23.27
2022	22.85	14.15
2023	24.41	17.85
2024	24.58	16.11

[13] We attempted to instrument *Bill* for two-stage least squares with specifications including patron dummies on the RHS. In every case, the difference in J-statistic test rejected the null of *Bill* being exogenous. Not surprisingly, the instrument attempts pre-tested as weak. The null hypothesis of weak instruments was not rejected, under differing bias distortions, for each specification modeled (Stock and Yogo, 2005).
[14] For comparison, see the appendix to this paper for results from a model that adds *Bill* and $Bill^2$ to the RHS.

Server/Bartender 1 (Female)	27.56	19.28
Server/Bartender 2 (Male, Hispanic)	22.75	11.39
Server 3 (Male)	23.13	18.89
Server 4 (Female)	20.74	8.29
Server/Bartender 5 (Female)	26.98	20.63
Server/Bartender 6 (Female)	24.72	19.64
Server 7 (Female)	25.14	15.18
Server 8 (Female)	19.38	5.85
Regular Patrons	24.62	17.01
Other Patrons	23.17	15.89

dinner period. Table 5 depicts the regression results with tip percentage as the dependent variable. The intercept term in both hedonic like models can be interpreted as the average tip percentage for server 1, during lunch shifts in 2022, with female, non-frequent signing customers using a personal credit card. Without the influence of suspected endogeneity in the bill amount variables, server-specific effects now test jointly significant at the less than the 1 percent level. These effects are intended to control for a myriad of server idiosyncrasies. This highly significant result is more in line with extant literature (Lynn, 2006; Banks et al., 2018). While yearly fixed-effects were marginally significant above

Table 5. Regression results, dependent variable Tip Percentage

Variable	OLS[a]	Tobit[b]
Intercept	23.390***	22.699***
Signing Customer Sex (Male=1)	-0.564	-0.493
Business or Government Card = 1	10.179***	9.544***
Dinner Shift	0.667	0.626
Late Night	6.321***	5.993***
2023	1.062	0.853
2024	1.354	1.217
Server 2	-2.922*	-2.624*
Server 3	-2.813*	-2.608*
Server 4	-4.501**	-4.221**
Server 5	0.702	0.618
Server 6	-0.351	-0.454
Server 7	-1.963	-1.818
Server 8	-5.614***	-5.182***
Regular Patrons = 1	1.012	0.968
$\overline{R}^2$	0.073	c
Sigma	-	15.675***
Log Likelihood	-	-5,490

Joint Meal Shift Wald Test, χ^2	29.101***	28.422***
Joint Period Wald Test, χ^2	1.672	1.401
Joint Server Wald Test, χ^2	22.620***	21.330***

(***) < 1%, (**) < 5%, (*) < 10% level of significance.
[a]Huber-White-Hinkley (HC1) corrected standard errors.
[b]Sandwich covariance matrix used. Marginal effects reported.
[c]Pseudo fit measures are not directly comparable to R^2.

(see Table 3), their impact is jointly insignificant on tip percentage. Year to year, sampled mean tip percentage varied only modestly. Meal timing tests jointly significant at the less than 1 percent level with late night patrons tipping roughly 6 percentage points more on average.[15] One factor that could explain part of this behavior is smaller tabs for late night patrons – on average more than 10 dollars less than the overall bill mean (see the relationship in Figure 1). Another explanation, expressed by brewpub management after a review of these findings, is 'service sweethearting'. This is the act of servers' giving away food and drinks to encourage larger tips (Brady et al., 2012). Brewpub management has been aware of and is addressing this, alleged, late night theft issue.[16] Interestingly, in a survey of roughly 700 U.S. restaurant servers, 30 percent admitted to sometimes giving away items to increase tips (Lynn, 2017). Patrons paying tabs with business or government cards were very generous tippers – roughly 10 percentage points more on average. As described above, business cards were more frequently swiped within this category and the ability to expense a business-related outing is the likely explanation for this significant generosity.

Overall, the categorical predictors modeled explained very little of the variation in tip percentage, $\overline{R}^2 = 0.07$. Server-specific attributes were jointly significant, at the less than 1 percent level, but not as statistically impressive as anticipated. The two additional key findings were rather unconventional – business boasters and suspected late night conspirators. The small, adjusted coefficient of determination, when tip percentage is the dependent variable, is not unique to this study. In the more nationally representative efforts of Jahan et al., (2023), Ali et al., (2023) and Ali et al., (2025), all estimate fit ranging from 0.05 to 0.09.[17] File this examination, with numerous others, under the tab 'weak or some' evidence that any factor other than bill size simultaneity explains a meaningful part of tipping variation.

Concluding remarks

Contrary to those promoting a small-beer neo-local subculture, we did not find that brewpub consumers have intrinsically different tipping habits. The postmodern conscious consumer, that is said to frequent small breweries, appears to operate no differently than the professed rabble who would frequent an Applebee's®. Perhaps one of the most revealing observations from our sample is that out of 6,655 actual guest tabs, 5,485 signing customers tipped in integer amounts. Of these flat tippers, 1,529 left 5 or 10 dollars (see Figure 2). With all due respect, little learned evaluation goes into looking at

[15] Ali et al., (2025) also found a highly significant late-night effect, roughly 1.5 percentage points higher.
[16] See the appendix of this paper for a cross-tabulation exercise provided to management.
[17] A note of interpretive caution, a low R^2 is routine in cross-sections.

a 45 dollar tab and leaving 10 bucks. More likely, it exposes consumer apathy and the wholesale acceptance of the normative cost of going out to eat and drink in the U.S.

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Appendix

Table A1. Regression results, dependent variable Tip Percentage

Variable	OLS[a]	Tobit[b]
Intercept	30.677***	30.454***
Signing Customer Sex (Male=1)	-0.038	-0.009
Business or Government Card = 1	11.718***	10.604***
Dinner Shift	0.091	0.101
Late Night	4.102***	3.977***
2023	0.554	0.402
2024	0.084	0.056
Server 2	-2.329	-2.099
Server 3	-0.731	-0.693
Server 4	-2.933	-2.793
Server 5	1.090	0.991
Server 6	-0.358	-0.436
Server 7	-0.509	-0.476
Server 8	-2.449	-2.286
Regular Patrons = 1	0.531	0.456
Bill	-0.244***	-0.225***
$Bill^2$	0.0008	0.0007
$\overline{R}^2$	0.135	c
Sigma	-	15.136***
Log Likelihood	-	-5,446
Joint Meal Shift Wald Text χ^2	14.133***	14.662***
Joint Period Wald Text χ^2	0.371	0.220
Joint Server Wald Text χ^2	9.358	8.863

(***) < 1%, (**) < 5%, (*) < 10% level of significance.
[a]Huber-White-Hinkley (HC1) corrected standard errors.
[b]Sandwich covariance matrix used. Marginal effects reported.
[c]Pseudo fit measures are not directly comparable to R^2.

Note how the inclusion of Bill and $Bill^2$ render the server-specific effects insignificant.

Table A2. Late night tip percentage cross-tabulations

Variable	Tip% Overall Mean	Tip% Late Night Mean	Late Night Tab Share
Server/Bartender 1 (Female)	27.56	31.09	25.56%
Server/Bartender 2 (Male)	22.75	26.39	6.71%
Server 3 (Male)	23.13	33.34	10.22%
Server 4 (Female)	20.74	17.50	4.47%
Server/Bartender 5 (Female)	26.98	27.00	15.97%
Server/Bartender 6 (Female)	24.72	48.64	7.99%
Server 7 (Female)	25.14	28.56	23.32%
Server 8 (Female)	19.38	16.63	5.75%

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U.S. Hop Industry Economics

Mitch Kunce[1]

Abstract
In the last 15 years, reporting brewery counts in the U.S. have increased four-fold. These new micro-breweries sought to differentiate their products from macro-beer by touting production authenticity – which included the innovative use of hops. Recognizing the potential early on, U.S. hop grower/dealers began comprehensive breeding programs to develop then market proprietary varietals to the entrant breweries. This paper examines the many time series dynamics of these unprecedented industry changes. Using standard, structural and Bayesian vector autoregression, we explore the significance of the many influences on U.S. hop acreage responses. Interestingly, contracted forward pricing emerges as the key forcing variable.

Keywords: Hop acreage, agricultural marketing, vector autoregression
JEL Classifications: C32, Q11, Q15

Introduction
Hops (*Humulus lupulus* of the *Cannabaceae* family) are a key input to world-wide beer production. Competing commercial uses for hop products comprise merely 2 percent of global production (Almaguer et al., 2014). This perennial vining plant will climb nearby trellis-like structures – growing as high as 25 feet in a single season (see Figure 1 below). Hops are generally unisexual, producing either male or female flowers (cones). The pollen-producing male plants are removed from commercial acreage in order to limit seed growth in the desired female cone. Hops brewing value comes from the resins and essential oils found in the lupulin glands of the cones. Resulting brewing products include cones, powder, pellets and liquid extract. Resins provide balancing bitterness to malty sweet beer while essential oils promote aroma. Accordingly, hop production is generally categorized as either *alpha* (bittering) or aroma.[2]

In 2024, 137 thousand acres worldwide produced 251 million pounds of hop product.[3] Figures 2 and 3 below highlight the top 4 countries in acreage and production. Aroma varieties comprised roughly 60 percent of the world acreage (HGA, 2024; IHGC, 2024). As shown, the U.S. is a major producer in the world hop market. U.S. growers harvested roughly 45,000 acres in 2024 yielding 87 million pounds of hop product.[4] Interestingly, current U.S. acreage and production are down from 2017-2023 levels. Figure 4 below shows historical trends of U.S. hop acreage and production. The rise in U.S. acreage and production, starting in the late 2000s, is attributed to the small-beer revolution (MacKinnon and Pavlovič, 2020).

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[1] *Douglas**Mitchell*** Econometric Consulting, Laramie, WY USA. Published August 2025.

[2] Alpha refers to measured α-acid in the resins. Many aroma varieties are considered dual purpose.

[3] For reported metrics, a hop crop year starts September 1.

[4] The state of Washington leads with roughly three fourths of 2024 U.S. acreage and harvest (HGA, 2024). The U.S. Pacific Northwest (PNW) provides optimal conditions for hop plant health and flowering (Henning et al., 2015).

Figure 1. Hop yard in Yakima, Washington.

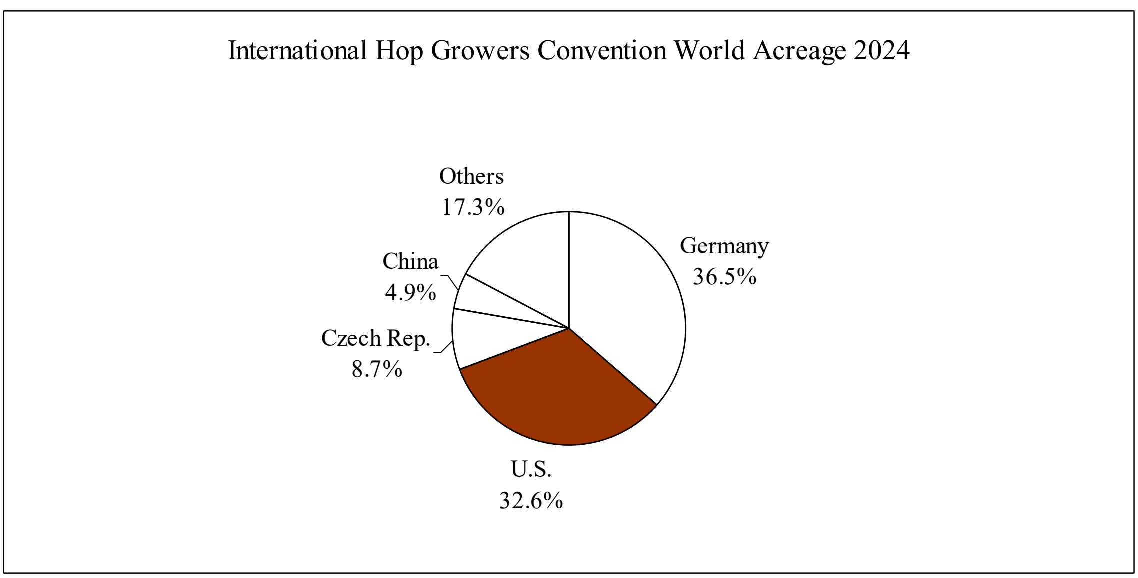

Figure 2. World hop acreage shares, source Hop Growers Association of America (HGA).

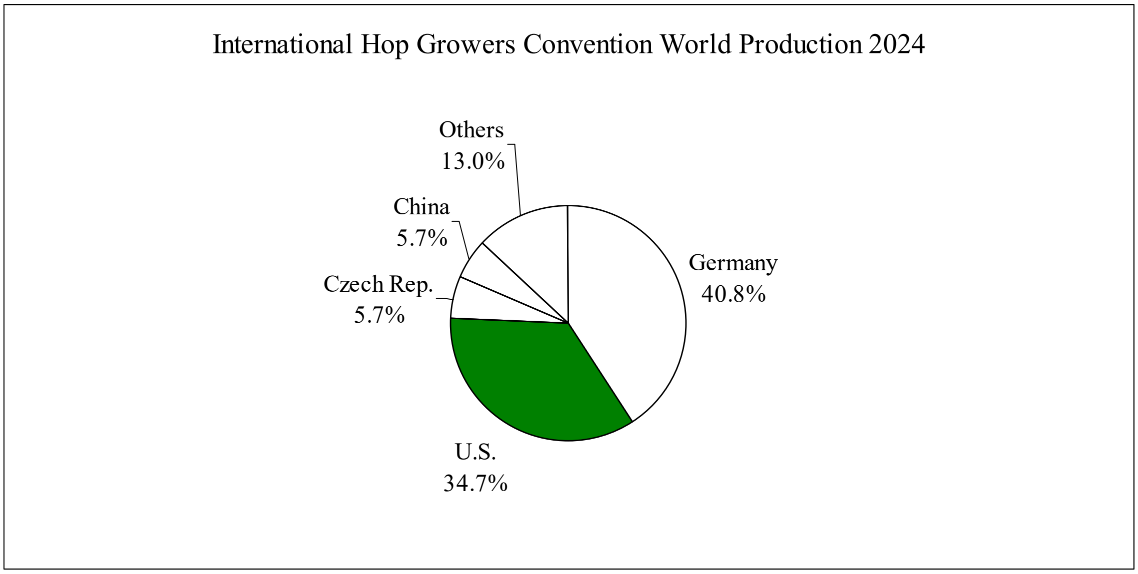

Figure 3. World hop production shares, source HGA.

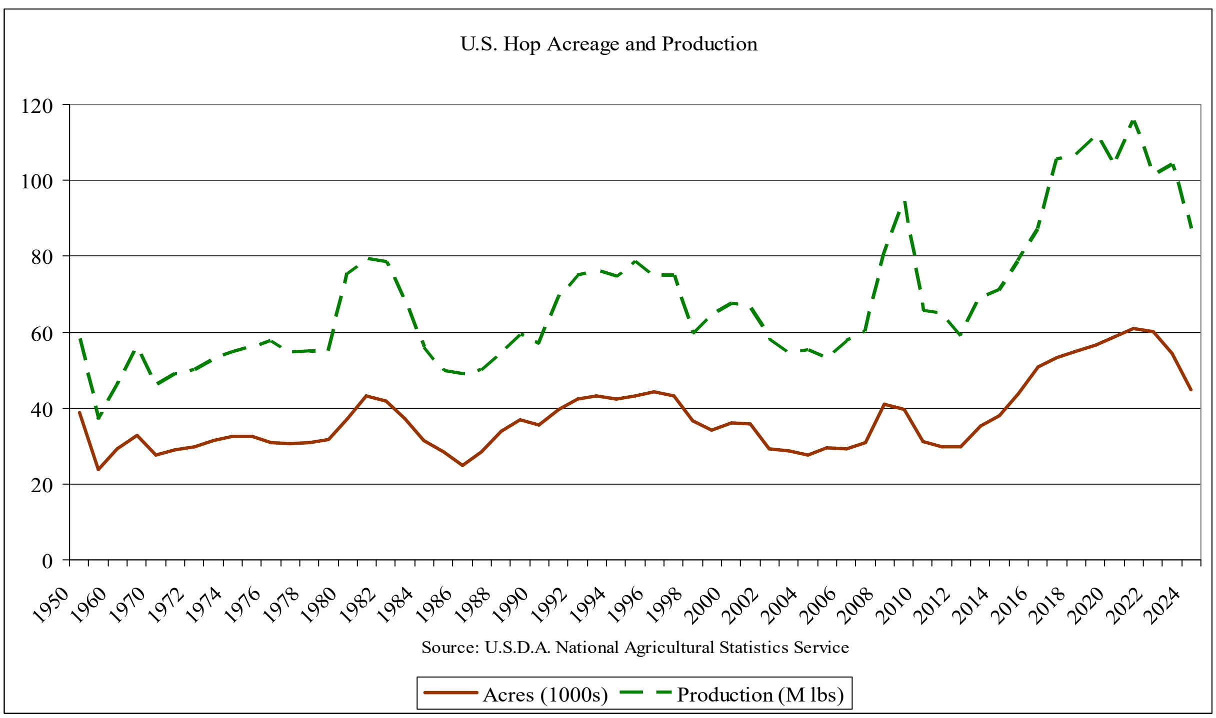

Figure 4. Historical U.S. hop acreage and production

Figure 5 below shows the growth trajectory of reporting U.S. breweries from 1950 to 2024. Providing context, 80.3 percent of breweries (over 6,100) reporting operations to the TTB in 2024 produced 1,000 barrels or less for the year, hence the idiom small-beer. Conversely, 96.3 percent of 2024 U.S. beer production comes from less than 4 percent of the reporting count (roughly 300 breweries). Figure 6 depicts reported U.S. beer production from 1950 to 2024. Notable are the declines in U.S. beer production in the last decade.[5]

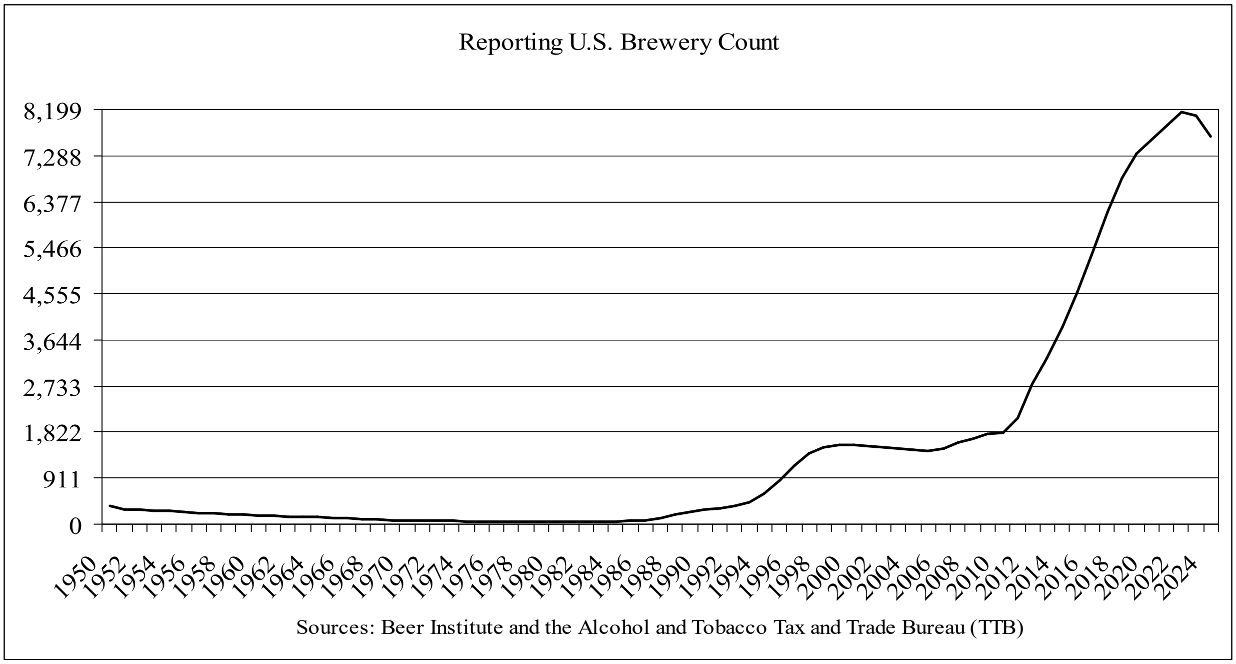

Figure 5. Historical U.S. TTB brewery counts.

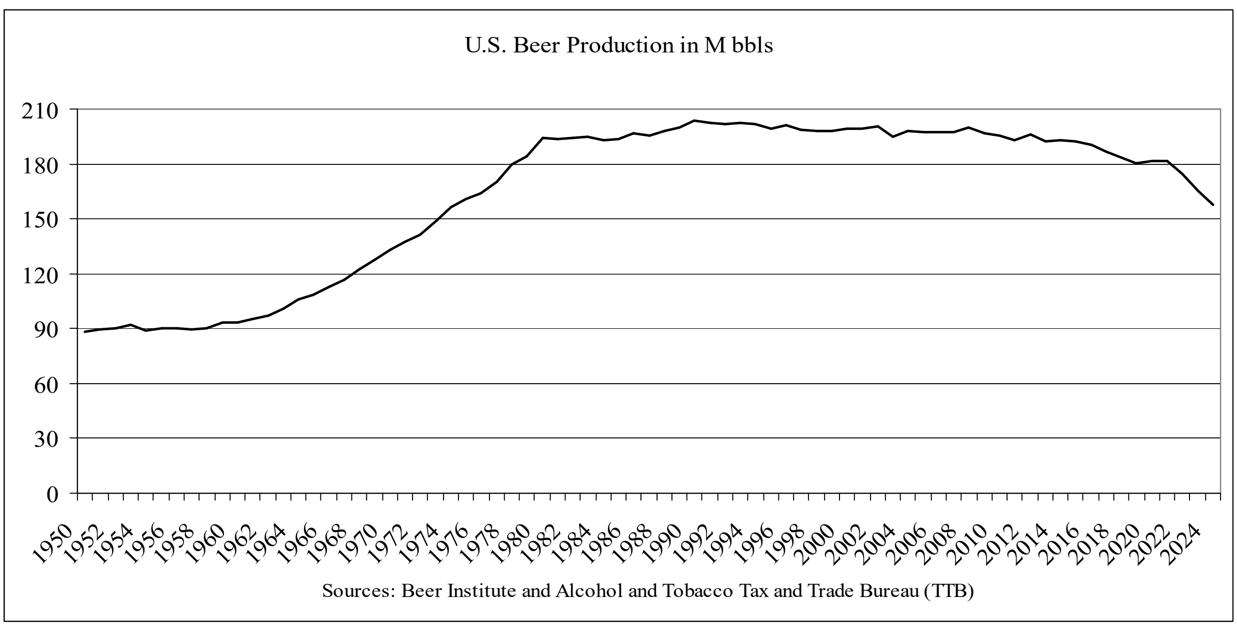

Figure 6. Historical U.S. beer production

[5] Traditional hopped beer production is falling faster than portrayed. Flavored malt beverage (FMB) production is propping up the declining trend. FMB is the industry vernacular for fermented seltzers, teas, lemonades, ranch waters, etc. In 2024, barrelage of FMBs was roughly 18 million (IRI, 2024).

The new, amassing, smaller brewers were fixated on differentiating from big-beer, and each other, with highly hopped products.[6] As such, advanced and innovative hop breeding programs began and variety in the U.S. changed markedly (Darby, 2013). Table 1 below shows the leading varieties in acreage and production from 1984 to 2024.[7] Table 2 highlights the move to more aroma varieties from the late 1980s to 2024. For example

Table 1. Leading variety U.S. share.

Year	Leading Variety	Acreage Share
1984	Cluster	19.3%
1994	Galena	21.1%
2004	Columbus/Tomahawk®/Zeus	21.9%
2014	Cascade	17.0%
2024	Citra®	15.1%
	Leading Variety	**Production Share**
1984	Cluster	31.5%
1994	Galena	23.3%
2004	Columbus/Tomahawk®/Zeus	30.4%
2014	Columbus/Tomahawk®/Zeus	22.5%
2024	Columbus/Tomahawk®/Zeus	16.4%

Source: U.S.D.A. National Agricultural Statistics Service

Table 2. Category comparison 1988, 2024

Year	Category	Acreage Share	Production Share
1988	Alpha	59.8%	71.1%
1988	Aroma	40.2%	28.9%
2024	Alpha	18.7%	39.7%
2024	Aroma	81.3%	60.3%

Source: U.S.D.A. National Agricultural Statistics Service

in 1990, the beginnings of the Hop Breeding Company (HBC) developed the Citra®, HBC 394 variety – arguably the most predominant pale ale hop in the U.S. to date. Citra® is well known for its tropical aroma and fruity flavors, best used in late boil additions or right in the fermenter. Patented in 2009, Citra® acreage in the PNW rose to number one in 2018, surpassing the once celebrated Cascade variety.

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[6] Big-beers' rather homogeneous adjunct lagers are not considered hop forward. Their hop extract use is focused on alpha bittering for balanced taste.

[7] The early 1980s were indeed pioneering. In 1981, for the first time since prohibition, a brewery in the U.S. planned to serve its' products on-premises. Bert Grant's Yakima Brewing and Malting Company, a so-called brewpub, inadvertently violated the state of Washington's three-tiered-distribution laws by offering food and in-house produced beer on-site (Acitelli, 2013). Washington state legalized on-premises sales the following year and, perhaps unwittingly, started the nationwide surge of new locally-oriented small brewing facilities − something not seen in the country since the 1800s (Grant and Spector, 1998).

U.S. grown hop demand is world-wide. Figure 7 tracks U.S. hop exports and imports over the last decade. Quantities shown represent pounds of extract and solid products shipped, not imputed dried hop cone weight equivalent. Providing perspective, the 2018 export total is, comparatively, over 60 percent of U.S. hop production in that same crop year. In 2024 the main importer of U.S. grown hops was Belgium-Luxemburg. The U.S. imports mainly German grown hops.

Figure 7. U.S. hop exports and imports

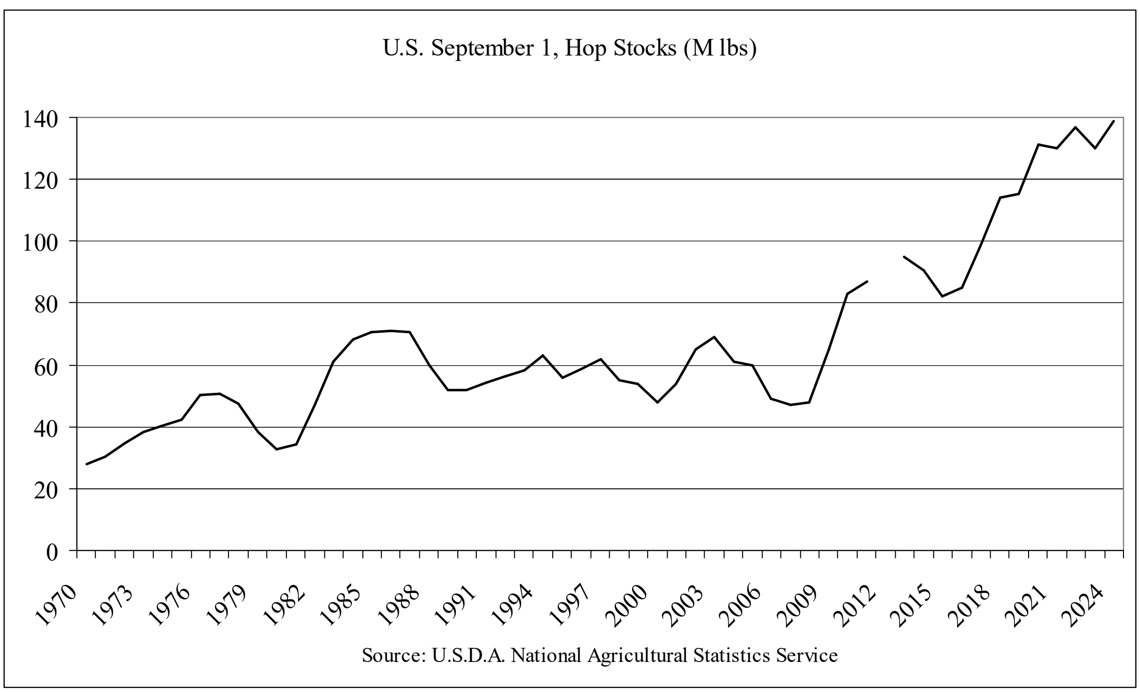

Figure 8. U.S. warehoused hop inventory

Perhaps the most intriguing trend in the U.S. hop industry is the rise in inventory (stock). Figure 8 above shows this trend. U.S. hop stock levels represent *surveyed* inventories in brewer, grower and dealer warehouses as of September 1 of a given year.[8] In 2024, grower/dealers held 83 percent of the contracted inventory. Rising stocks have persisted over the last decade. Noticeable reductions in acreage, production and real price have occurred only recently (see Figures 4 and 9).[9] This apparent delayed response to declining demand is due to the stickiness of vital hop acreage and grower/dealers locking brewers into long-term forward contracts (MacKinnon and Pavlovič, 2022). Focusing on

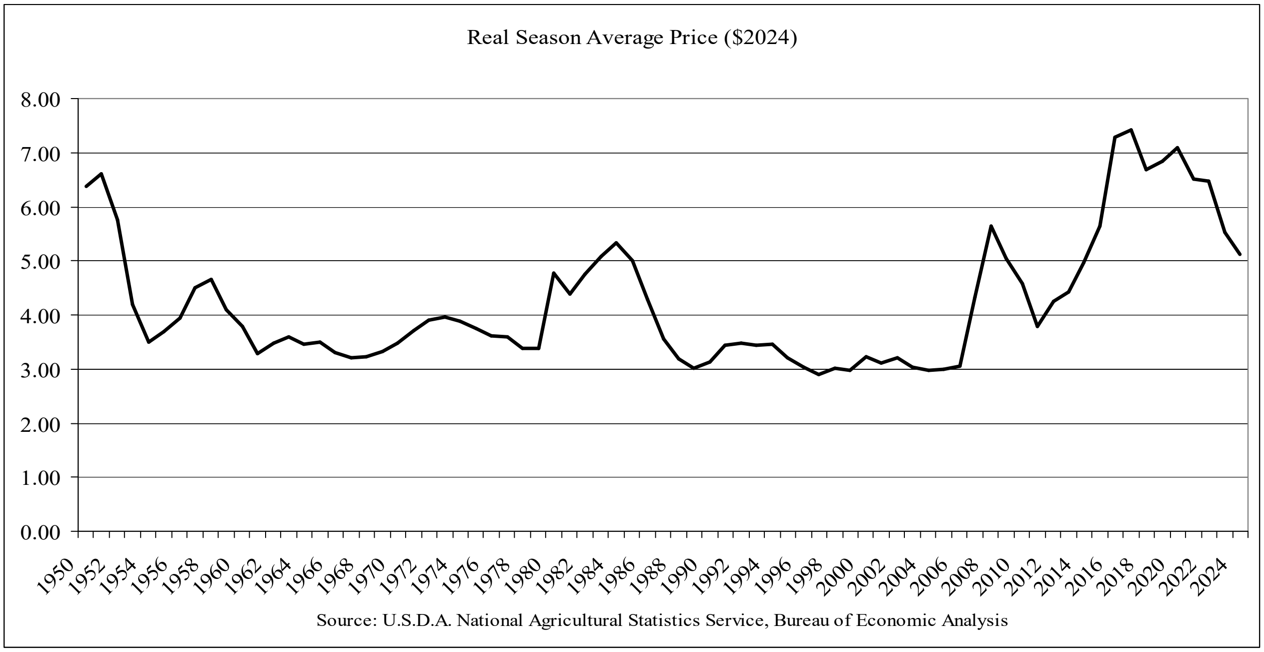

Figure 9. U.S. season average price per pound in $2024

U.S. markets, declines in demand are expected to continue. Through June of 2025, U.S. taxable removals of beer are down 5.2 percent year over year (Beer Institute, 2025). Moreover, net reporting brewery counts have been declining since mid 2022, more on this key point in what follows.

Each month, the Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau (TTB), publishes an aggregated public report entitled 'Monthly National Statistical Report - Beer'. Every brewery in the U.S. is licensed (i.e. Brewer's Notice) to operate by the TTB. Each permitted brewery is assigned a BR number and is required to complete a Brewer's Report of Operations either monthly or quarterly depending on taxed annual barrelage.[10] There is no annual filing option and reports must be submitted even if

[8] The line between farmer and dealer has blurred over the last two decades. Most of the 70 or so hop farms left in the PNW also operate as dealers (MacKinnon, 2025).

[9] U.S. 2025 strung acreage is down 6 percent from acreage harvested in 2024 (BarthHaas, 2025). The bulk of the reduction was in high alpha varieties. See the appendix to this paper for a nominal price graph.

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

there was no activity during the period.[11] Reports are due the 15th day following the close of the reporting period. The TTB relies on these individual premises reports of production and removals as the source for the aggregated public report. Table 3 shows a section of the report for the month of December, 2024.[12] Number of industry members

Table 3. Monthly National Statistical Report, December 2024

Units: Beer Barrels (1 Barrel = 31 Gallons)	December 2024
Number of Industry Members	6,564
Production	11,962,791
Taxable Removals	11,432,663
Tax Free Removals for Export	186,240
Stocks on Hand End-of-Period	9,732,399

refers to the count of unique BR numbers with any operational report filed for the month, or quarter ending, December 2024. Monthly data are available publicly from 2012.[13] Figure 10 depicts the reporting trends for the 2012-2025 data. Each horizontal tick represents a monthly count. The, somewhat, uniform shorter teeth of this comb-like graphic illustrates the rather consistent count of larger breweries reporting monthly. Unique reports peaked in the second quarter of 2022 and quarterly counts have declined thereafter. From the peak, quarterly reports have declined by 19 percent – roughly 1,400 fewer BR numbers reporting in March 2025.[14] Interestingly, 1,009 breweries submitted reports showing *no* production for the year 2024. Non-producing permitted breweries,[15] falling aggregate domestic beer production and moderate reductions of acreage in 2025 does not bode well for the depletion of the aging U.S. hop stock going forward.

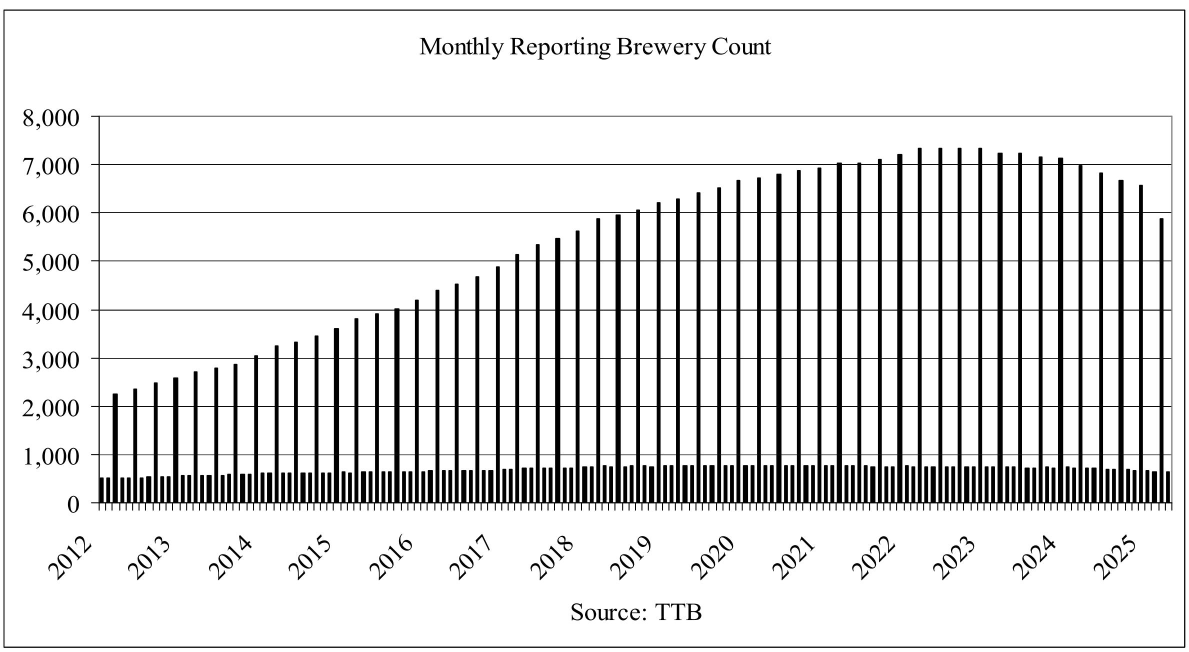

Figure 10. Reporting brewery count by month

[11] 27 Code of Federal Regulations 25.297
[12] Report dated July 14, 2025.
[13] Historical brewery counts never reached the peak levels depicted in this most recent data (TTB, 2025).
[14] The TTB notes that reporting counts may change due to late operational reporting (see Kunce, 2024).
[15] TTB reports show that over 15,000 breweries were permitted as of December 2024.

Investigation of paired structural dynamics

In the last decade or so, with the sharp rise in small brewery counts in the U.S., more attention has been given to the dynamics of hop metrics and trends (Kerckhoven, 2020). Stocks – price, acreage – price, and industry concentration – price linkages have been examined recently in the Agricultural Economics literature (e.g., MacKinnon and Pavlovič, 2020; 2022; 2023). These studies connect, using simple Bayesian inference, the forming duopoly in the U.S. hop industry *to* undue influence over hop pricing, even beyond the farmgate.[16] Herein, we choose to explore, econometrically, possible structural linkage of the many time series laid out in the introduction. The dynamic nature of agricultural production is well suited for vector autoregression (VAR) modeling (Sims, 1980). A standard VAR expresses each time series as a linear function of its own past values, the past values of all other time series included in the model and a *serially* uncorrelated error term. How far back in the past (lag) is determined by specific information criteria (e.g. Akaike). Error terms or innovations are typically correlated *across* equations in this reduced form.

We proceed, initially, by exploring the 55 year time series data set described in Table 4 below. To address the industry market power dynamics, a subset of the data will be constructed – more on this in sections that follow. All series are converted to natural logarithms as a means to reduce growth in variance over the 55 year time horizon. Many of the time series described in Table 4 and presented graphically in Figures above exhibit nonstationary characteristics. For example, an augmented Dickey-Fuller unit root test on the natural log acreage series (at level) fails to reject the null of a unit root.[17] Nonetheless, unit root and cointegration tests are not without low power limitations. Rather than pre-test and possibly transform each series unnecessarily, we choose to follow the practical recommendations of Gospodinov et al., (2013) and estimate all specified VARs in levels.[18] In some cases, however, it may be necessary to impose certain structural restrictions when identifying variable responses.

To begin, we will explore a few paired series dynamics. Convention in VAR analysis leans on reporting Granger-causality tests, error variance decompositions and impulse responses (Stock and Watson, 2001). Table 5 below presents the VAR results for the hop acreage (lnA) hop production (lnHP) pair. As shown, Granger-causality goes one way, hop acreage to hop production. Variance decomposition for a series shows the percentage of the variance of the error in forecasting a variable attributed to a one standard deviation innovation in another variable at a given time horizon. For example, at the one step ahead horizon, 60.1 percent of the error in projected hop production is attributed to acreage innovations. Due to the dominate one-way forcing relationship of hop acreage to production, we limit the estimated impulse responses presented to hop production.[19] An innovation in hop acreage increases production by 7.8 percent in year one, 11.8 percent in

[16] Two entities, Hop Breeding Company, LLC and S. S. Steiner, Inc. controlled roughly two thirds of the 2024 hop acreage in the U.S. (USDA NASS, 2025)

[17] See Table A1 in the appendix to this paper for unit root testing of all series shown in Table 4.

[18] Sims et al., (1990) also show that transforming models to stationary form, in many cases, is unnecessary.

[19] Table 5 below presents full detail of the impulse response of hop production to innovations in acreage, including +/- asymptotic standard error confidence bands (Lütkepohl, 1990). Point estimates are statistically significant when all of the confidence region is on the same side of zero as the estimate. As we proceed, we will limit the presentations to what is statistically significant and expositionally relevant.

Table 4. Data descriptions, sources and descriptive statistics

Hop acreage. Hop acreage harvested in the U.S. by crop year in 1,000s. Source: Surveys conducted by the USDA NASS, 1970-2024. Mean 37.909, STD 9.309.
Hop production. U.S. hop production by crop year in millions of pounds. Source: Surveys conducted by the USDA NASS, 1970-2024. Mean 69.746, STD 18.234.
Season average hop price. Average price per pound received by U.S. grower/dealers in a given crop year. Inflation adjusted to $2024. Five year forward contracting is convention. Sources: Surveys conducted by the USDA NASS, 1970-2024; Bureau of Economic Analysis for GDP deflator data (Hausman et al, 2012). Mean $4.28, STD 1.28.
Hop stock. All hop inventories held by growers, dealers and brewers in the U.S. as of September 1 of a given crop year in millions of pounds. Source: Surveys conducted by the USDA NASS, 1970-2024. Mean 67.557, STD 28.775.
Hop utilization. Calculated as: beginning stock + production - ending stock for each crop year in millions of pounds. This represents the net disposition (utilization) of hops for a given crop year (Zepp et al., 1995). Mean 67.890, STD 16.614.
Hop utilization ratio. Calculated as: hop utilization ÷ production. This ratio approximates net demand to supply (equilibrium) in a given crop year (MacKinnon and Pavlovič, 2020). A ratio of greater than unity represents stock depletion for a crop year. Mean 0.982, STD 0.102.
U.S. brewery counts. This is the count of unique industry members (BR identification numbers) submitting any operational report for a given calendar year. Source: TTB. Mean 1.984, STD 2.572. (in 1000s)
U.S. beer production. Total production, in millions of 31 gallon barrels, reported to the TTB in a given calendar year via monthly or quarterly Brewer's Report of Operations. Mean 186.959, STD 17.875

Table 5. Hop acreage - hop production VAR results (2 lags selected, all criteria)[a]

Granger-Causality F-test, P-values	**Dependent Variable**		
Regressor	lnA	lnHP	
lnA	0.00	0.00	
lnHP	0.90	0.00	
Variance Decomposition of lnA			
Horizon(years)	Standard Error (se)	lnA	lnHP
1	0.09	100.0%	0.0%
5	0.23	99.9%	0.1%
10	0.24	99.5%	0.5%
Variance Decomposition of lnHP			
Horizon(years)	Standard Error (se)	lnA	lnHP
1	0.10	60.1%	39.9%
5	0.23	88.6%	11.4%
10	0.24	87.8%	12.2%

Impulse Response of lnHP to one STD Innovation in:			
Horizon(years)	**lnA** Est. (se) (Est./se)[b]	(- 2 se)	(+ 2 se)
1	0.078 (0.012) (6.8)	0.0549	0.1011
2	0.118 (0.018) (6.7)	0.0829	0.1534
3	0.115 (0.024) (4.7)	0.0659	0.1637
4	0.097 (0.028) (3.4)	0.0403	0.1541
5	0.072 (0.030) (2.4)	0.0115	0.1333
6	0.049 (0.032) (1.6)	-0.0141	0.1124
7	0.029 (0.032) (0.9)	-0.0341	0.0938
8	0.016 (0.031) (0.5)	-0.0459	0.0776
9	0.007 (0.028) (0.2)	-0.0495	0.0627
10	0.001 (0.024) (0.1)	-0.0466	0.0491

[a]All VAR diagnostic and stability checks are satisfied for this pair.

[b]The ratio of (Est./se) is not calculated from rounded estimates shown.

year 2 then decays to statistically zero after the 5th year. The strength of the forcing relationship of acreage to production should not be surprising. VAR diagnostic and stability checks include serial correlation, residual normality and characteristic root testing. For the hop acreage - production pair, no serial correlation is detected for the 2 selected lags. Tests fail to reject the null of residual normality and no characteristic polynomial root lies outside the unit circle. This levels VAR appears stable.

Table 6 presents the VAR results for the brewery count (lnC) beer production (lnBP) pair. Block Wald F-tests shows that Granger-causality goes one way at the < 5 percent level, brewery count to production, but the variance decomposition reveals this relationship is weak. Over 91 percent of the variance of the error, even ten steps ahead, comes from unobserved variables. Moreover, the impulse responses of beer production to innovations in brewery counts are statistically insignificant and not presented. Only beer production innovations and responses are shown. All VAR diagnostics are satisfied for the pair.[20] To the casual observer, this weak linkage may appear counterintuitive. In fact, VAR results bolster past findings suggesting that most of the 1000s of breweries in the U.S., built in the last 4 decades, are significantly small and contribute little to overall industry output, at the margin (Kunce, 2023).

Table 6. Brewery count - beer production VAR results (2 lags selected, all criteria)[a]

Granger-Causality F-test, P-values	**Dependent Variable**		
Regressor	lnC	lnBP	
lnC	0.00	0.00	
lnBP	0.09	0.00	
Variance Decomposition of lnC			
Horizon (years)	Standard Error (se)	lnC	lnBP
1	0.08	100.0%	0.0%
5	0.35	99.8%	0.2%
10	0.56	96.7%	3.3%

[20] Failure to reject the null of residual normality was at the < 10 percent significance level.

Variance Decomposition of lnBP			
Horizon (years)	Standard Error (se)	lnC	lnBP
1	0.02	1.2%	98.8%
5	0.04	1.7%	98.3%
10	0.05	8.5%	91.5%
Impulse Response of lnBP to one STD Innovation in:			
Horizon (years)	**lnBP** Est. (se) (Est./se)		
1	0.016 (0.002) (10.3)		
4	0.018 (0.004) (4.1)		
7	0.014 (0.004) (3.3)		
10	0.008 (0.005) (1.7)		

[a]All VAR diagnostic and stability checks are satisfied for this pair.

Tables 7 - 9 below focus on total hop acreage dynamics. First, Table 7 presents the VAR results for the brewery count (lnC) hop acreage (lnA) pair. Results provide scant evidence that U.S. brewery counts predict total hop acreage. Innovations in brewery counts produce marginally significant acreage responses in out years 6 through 8, then decay. Rising brewery counts alone have affected little change in *total* U.S. hop acreage.

Table 7. Brewery count - hop acreage VAR results (2 lags selected, all criteria)[a]

Granger-Causality F-test, P-values	**Dependent Variable**		
Regressor	lnC	lnA	
lnC	0.00	0.11	
lnA	0.25	0.00	
Variance Decomposition of lnC			
Horizon (years)	Standard Error (se)	lnC	lnA
1	0.08	97.3%	2.7%
5	0.44	99.2%	0.8%
10	0.82	99.0%	1.0%
Variance Decomposition of lnA			
Horizon (years)	Standard Error (se)	lnC	lnA
1	0.09	0.0%	100.0%
5	0.20	8.6%	91.4%
10	0.22	19.7%	80.3%
Impulse Response of lnA to one S.D. Innovation in:			
Horizon (years)	**lnC** Est. (se) (Est./se)	**lnA** Est. (se) (Est./se)	
1	0.00	0.087 (0.008) (10.3)	
4	0.035 (0.022) (1.6)	0.071 (0.026) (2.7)	
6	0.041 (0.023) (1.8)	0.013 (0.028) (0.5)	
7	0.038 (0.021) (1.8)	-	
8	0.034 (0.019) (1.8)	-	
10	0.025 (0.016) (1.5)	-	

[a]All VAR diagnostic and stability checks are satisfied for this pair.

Table 8 below presents the VAR results for the September 1 hop stock (lnS) hop acreage (lnA) pair. Granger-causality is bi-directional at the < 5 percent level. Innovations in hop stocks produce, generally, insignificant responses in hop acreage.[21] This result reinforces the 'sticky acreage' proposition forwarded by MacKinnon and Pavlovič, (2022). As shown in Table 8, a one standard deviation innovation in acreage produces increases in hop stocks that peak in horizon year five, at 10 percent, then decay.

Table 8. Hop stock - hop acreage VAR results (2 lags selected, all criteria)[a]

Granger-Causality F-test, P-values	**Dependent Variable**		
Regressor	lnS	lnA	
lnS	0.00	0.03	
lnA	0.00	0.00	
Variance Decomposition of lnS			
Horizon (years)	Standard Error (se)	lnS	lnA
1	0.10	100.0%	0.0%
5	0.26	66.2%	33.8%
10	0.31	50.9%	49.1%
Variance Decomposition of lnA			
Horizon (years)	Standard Error (se)	lnS	lnA
1	0.08	3.1%	96.9%
5	0.18	10.0%	90.0%
10	0.20	21.5%	78.5%
Impulse Response of lnS to one S.D. Innovation in:			
Horizon (years)	**lnS** Est. (se) (Est./se)	**lnA** Est. (se) (Est./se)	
1	0.096 (0.009) (10.3)	0.0	
2	0.124 (0.017) (7.1)	0.027 (0.012) (2.2)	
4	0.077 (0.031) (2.5)	0.089 (0.027) (3.4)	
5	0.048 (0.034) (1.4)	0.100 (0.029) (3.4)	
10	-	0.049 (0.027) (1.9)	

[a]All VAR diagnostic and stability checks are satisfied for this pair.

Table 9 presents the VAR results for the real hop price (lnP) hop acreage (lnA) pair. Real price helps predict hop acreage at the < 1 percent significance level. Innovations in real price increase hop acreage, one step ahead, by 2.5 percent. This significant effect lasts two additional periods then fades. Responses of real price to hop acreage innovations are statistically insignificant. Real hop price appears to be more influential on *total* acreage decisions than either brewery counts or September 1 hop inventories.

Table 9. Real hop price - hop acreage VAR results (3 lags selected, Akaike criteria)[a]

Granger-Causality F-test, P-values	**Dependent Variable**		
Regressor	lnP	lnA	
lnP	0.00	0.00	
lnA	0.69	0.00	
Variance Decomposition of lnP			
Horizon (years)	Standard Error (se)	lnP	lnA
1	0.11	100.0%	0.0%
5	0.27	97.7%	2.3%
10	0.29	97.4%	2.6%

[21] The exception is the outer horizon year 8 estimate.

Variance Decomposition of lnA			
Horizon (years)	Standard Error (se)	lnP	lnA
1	0.08	10.0%	90.0%
5	0.21	24.3%	75.7%
10	0.23	33.9%	66.1%
Impulse Response of lnA to one S.D. Innovation in:			
Horizon (years)	**lnP** Est. (se) (Est./se)		
1	0.025 (0.011) (2.3)		
2	0.072 (0.020) (3.6)		
3	0.056 (0.026) (2.2)		
4	0.035 (0.029) (1.2)		

[a]All VAR diagnostic and stability checks are satisfied for this pair.

Table 10 presents the final paired series VAR results, real hop price (lnP) and hop stock (lnS). Interestingly, Granger-causality runs from price to stocks. Impulse responses of price to innovations in hop inventories are statistically insignificant. Conversely, innovations to real price contributed to a rather large share of the variance of the forecast error in hop stocks in the outer horizon years. Effects of price innovations on stock response peak in year six at 12 percent and remain persistent thereafter. A possible explanation for this persistence is false demand signals generated by long-term forward contracts hop grower/dealers require from brewers (MacKinnon and Pavlovič, 2020). In

Table 10. Real hop price - hop stock VAR results (2 lags selected, all criteria)[a]

Granger-Causality F-test, P-values	**Dependent Variable**		
Regressor	lnP	lnS	
lnP	0.00	0.00	
lnS	0.13	0.00	
Variance Decomposition of lnP			
Horizon (years)	Standard Error (se)	lnP	lnS
1	0.11	100.0%	0.0%
5	0.25	94.6%	5.4%
10	0.27	95.3%	4.7%
Variance Decomposition of lnS			
Horizon (years)	Standard Error (se)	lnP	lnS
1	0.09	0.1%	99.9%
5	0.24	44.6%	55.4%
10	0.34	72.8%	27.2%
Impulse Response of lnS to one STD Innovation in:			
Horizon (years)	**lnP** Est. (se) (Est./se)	**lnS** Est. (se) (Est./se)	
1	0.001 (0.013) (0.1)	0.094 (0.009) (10.3)	
4	0.092 (0.025) (3.7)	0.055 (0.022) (2.5)	
6	0.120 (0.031) (3.8)	-	
10	0.090 (0.039) (2.3)	-	

[a]All VAR diagnostic and stability checks are satisfied for this pair.

fact, forward pricing within these contracts is shown to be the key forcing variable in the select price paired dynamics examined.

Structural identification

Variance decompositions of the paired VARs, above, reveal a weakness of two variable specifications – a large portion of the variation of the error can be attributed to unobserved variables (Hausman et al., 2012). In other words, each pair is part of a larger VAR. A structural VAR should provide a more comprehensive sorting of the dynamic linkages. In this structural setting, we will use a system of equations to explain the relationship between hop acreage, average real prices, September 1 hop inventories, and net supply and demand equilibrium forces. Hop grower/dealers are assumed to make their acreage decisions based on forward prices, current inventories held and market equilibrium expectations. Accordingly, the variable vector becomes,

$$y_t = \begin{bmatrix} \ln\text{A} \rightarrow \text{hop acreage}_t \\ \ln\text{P} \rightarrow \text{real hop price}_t \\ \ln\text{S} \rightarrow \text{September 1 stocks}_t \\ \ln\text{UR} \rightarrow \text{utilization ratio}_t \end{bmatrix}. \tag{1}$$

The VAR with potential exogenous variables x_t is specified,

$$Ay_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + Cx_t + Bu_t, \tag{2}$$

where A and C are the structural coefficients and the u_t are orthonormal structural innovations. In our case, the exogenous variable is an overall constant term. Short-run identifying restrictions follow the *A-B* feedback model as suggested in Rubio-Ramirez et al., (2010). Moreover, careful attention is paid to the moment restrictions in this structural VAR specification. Table 11 presents the p-values from the *unrestricted* block exogeneity Wald tests for Granger-causality. All selection criteria chooses two lags for each variable. Interestingly, real price is not predicted by lagged values of acreage, stocks or market equilibrium expectations. Price impacts emerge as leading.

Table 11. Granger-causality, Wald F-test, p-values

	Dependent Variable			
Regressor	lnA	lnP	lnS	lnUR
lnA	0.00	0.97	0.02	0.06
lnP	0.01	0.00	0.12	0.01
lnS	0.11	0.68	0.00	0.04
lnUR	0.04	0.35	0.00	0.00

Table 12 below presents the percentage of variance due to orthogonal innovations. All VAR diagnostic and stability checks are satisfied for these equations. Innovations to real price explain 3.1 percent of the one-step ahead forecast error in hop acreage. The outer horizon years show a larger price impact to acreage forecast error. In fact, price is the largest cross contributor to the forecast error in all decompositions. Table 13 below shows relevant and statistically significant impulse responses to specific innovations. A one standard deviation innovation in real price is shown to increase hop acreage from 2.2 to 4.1 percent over the first three horizon years then decline to statistically zero. Affects

Table 12. Variance decompositions (2 lags)

Variance Decomposition of **lnA**					
Horizon	Standard Error	lnA	lnP	lnS	lnUR
1	0.07	96.9%	3.1%	0.0%	0.0%
5	0.17	74.3%	19.5%	2.3%	3.9%
10	0.19	64.9%	25.1%	3.9%	6.1%
Variance Decomposition of **lnP**					
Horizon	Standard Error	lnA	lnP	lnS	lnUR
1	0.11	0.0%	100.0%	0.0%	0.0%
5	0.25	2.5%	94.6%	1.1%	1.8%
10	0.28	3.2%	92.4%	2.0%	2.4%
Variance Decomposition of **lnS**					
Horizon	Standard Error	lnA	lnP	lnS	lnUR
1	0.02	0.0%	5.9%	94.1%	0.0%
5	0.25	18.2%	37.0%	6.7%	38.1%
10	0.32	20.0%	51.3%	5.7%	23.0%
Variance Decomposition of **lnUR**					
Horizon	Standard Error	lnA	lnP	lnS	lnUR
1	0.08	0.0%	5.2%	1.3%	93.5%
5	0.11	11.2%	23.6%	1.5%	63.7%
10	0.11	13.0%	24.5%	1.5%	61.0%

Table 13. Impulse responses (2 lags)

Impulse Response of lnA to one STD Innovation in:			
Horizon (years)	**lnP** Est. (se) (Est./se)		
1	0.022 (0.011) (2.0)		
2	0.033 (0.012) (2.8)		
3	0.041 (0.019) (2.2)		
Impulse Response of lnS to one STD Innovation in:			
Horizon	**lnA** Est. (se) (Est./se)	**lnP** Est. (se) (Est./se)	**lnUR** Est. (se) (Est./se)
1	0.0	0.006 (0.003) (1.8)	0.0
2	0.006 (0.013) (0.4)	0.010 (0.005) (2.0)	-0.085 (0.009) (-9.4)
3	0.042 (0.019) (2.1)	0.055 (0.019) (2.8)	-0.089 (0.017) (-5.4)
4	0.064 (0.026) (2.5)	0.091 (0.025) (3.6)	-0.078 (0.023) (-3.4)
5	0.073 (0.030) (2.4)	0.106 (0.029) (3.6)	-
6	0.066 (0.032) (2.0)	0.102 (0.034) (3.0)	-
7	-	0.088 (0.036) (2.4)	-
8	-	0.073 (0.038) (1.9)	-
Impulse Response of lnUR to one STD Innovation in:			
Horizon	**lnA** Est. (se) (Est./se)	**lnP** Est. (se) (Est./se)	
1	0.0	-0.019 (0.011) (1.7)	
2	-0.029 (0.012) (-2.5)	-0.037 (0.012) (3.1)	
3	-0.022 (0.010) (-2.1)	-0.029 (0.011) (2.7)	

from acreage and price innovations on hop inventories peak in horizon year 5 then decay to statistically zero. The price impact to hop stocks is markedly persistent. Hop grower/dealer long-term contracting would appear to explain this persistence (MacKinnon and Pavlovič, 2020; 2022; 2023). Innovations to the utilization ratio produce, as expected, declines in hop inventories to horizon year 4 then ascend to statistically zero. Lastly, innovations to both acreage and price negatively impact the utilization ratio, likely through denominator (demand/supply) forces. Analogous to the select paired dynamics above, price innovations dominate the structural responses.

Market power dynamics

Changes in U.S. states' on-premise consumption laws, beginning in the early 1980s, started the small-beer revolution (see Figure 5 and Footnote 7 above). New industry entrants sought to differentiate their products from big-beer by touting production authenticity – which included the creative use of hops. Recognizing the potential early on, U.S. hop grower/dealers began comprehensive breeding programs to develop then market proprietary varietals to the new breweries. By the late 1990s, acreage and production of proprietary hops started to appear in USDA publications (MacKinnon and Pavlovič, 2023). The new varieties, for example Citra® and Mosiac®, were quickly coveted by the new breweries. In 2024, roughly 70 percent of the U.S. hop acreage grows patented plants. Two development companies dominate the acreage decisions (see footnote 16 above). Following MacKinnon and Pavlovič (2023), we constructed a 28 year time series of the percentage of acreage in the U.S. attributed to proprietary hops. The mean of the series is 38 percent with a standard deviation of 20 percent.

To examine the effects of the move to more proprietary hop varieties, consider the following 28 year VAR vector,

$$y_t = \begin{bmatrix} \text{lnC} \rightarrow \text{reporting brewery count}_t \\ \text{lnPAS} \rightarrow \text{proprietary acreage share}_t \\ \text{lnP} \rightarrow \text{real hop price}_t \end{bmatrix}, \tag{3}$$

where the identification strategy exploits the sequence: small-beer revolution – rise of proprietary acreage – price impacts.[22] Table 14 presents the p-values from the unrestricted block exogeneity Wald tests for Granger-causality. All selection criteria chooses two lags for each variable. Reporting brewery counts Granger-cause both proprietary acreage share and real price at the ≤ 5 percent significance level. Proprietary

Table 14. Granger-causality, Wald F-test, p-values

	Dependent Variable		
Regressor	lnC	lnPAS	lnP
lnC	0.00	0.05	0.03
lnPAS	0.17	0.00	0.22
lnP	0.43	0.01	0.00

[22] Mean of the 28 year brewery count series (in 1000s) is 3.611 with a standard deviation of 2.630. Mean of the shortened real price series is $4.66 per pound with a standard deviation of $1.57.

acreage share does not help predict real price but real price helps predict acreage shares.[23] Tables 15 and 16 present the balance of innovation results. All VAR diagnostic and stability checks are satisfied for this system. Noteworthy are the significant and persistent impulse responses of both proprietary acreage and real price to innovations in brewery counts.

Table 15. Variance decompositions (2 lags)

Variance Decomposition of **lnC**				
Horizon	Standard Error	lnC	lnPAS	lnP
1	0.04	100.0%	0.0%	0.0%
5	0.22	95.9%	3.2%	0.9%
10	0.37	94.5%	3.5%	2.0%
Variance Decomposition of **lnPAS**				
Horizon	Standard Error	lnC	lnPAS	lnP
1	0.08	9.4%	90.6%	0.0%
5	0.14	32.9%	46.9%	20.2%
10	0.20	53.3%	32.1%	14.6%
Variance Decomposition of **lnP**				
Horizon	Standard Error	lnC	lnPAS	lnP
1	0.10	5.8%	0.0%	94.2%
5	0.21	39.7%	5.4%	54.9%
10	0.23	41.4%	7.5%	51.1%

Table 16. Impulse responses (2 lags)

Impulse Response of lnPAS to one STD Innovation in:		
Horizon	**lnC** Est. (se) (Est./se)	**lnP** Est. (se) (Est./se)
1	0.019 (0.015) (1.2)	0.0
2	0.023 (0.014) (1.6)	0.044 (0.016) (2.7)
3	0.032 (0.015) (2.1)	0.036 (0.018) (2.0)
4	0.047 (0.017) (2.8)	-
5	0.054 (0.019) (2.9)	-
6	0.059 (0.020) (2.9)	-
7	0.058 (0.022) (2.6)	-
8	0.057 (0.024) (2.3)	-
9	0.054 (0.025) (2.1)	-
10	0.049 (0.027) (1.8)	-
Impulse Response of lnP to one STD Innovation in:		
Horizon	**lnC** Est. (se) (Est./se)	
1	0.026 (0.020) (1.3)	
2	0.052 (0.025) (2.1)	
3	0.071 (0.026) (2.7)	
4	0.071 (0.028) (2.5)	
5	0.061 (0.028) (2.2)	

[23] See Tables A2 – A4 in the appendix for results of three robustness checks.

Concluding remarks

Public data and empirical dynamics presented herein support the following corollary. The rise in small brewery counts in the U.S., starting in the 1980s, fostered both the development of proprietary hop varieties and the method to market them to the, somewhat naive, amassing industry entrants.[24] The brewing factor-market power dynamic was about to shift.[25] Moving into the late 2000s, grower/dealers convinced entrant brewers that the new patented varieties would set them apart and, in order to ensure a steady supply well into the future, long term contracting was necessary.[26] Resulting forward prices within these contracts emerge as the forcing variable. With prices and quantities, by and large, contractually set, the new hop development companies made their acreage decisions. Aging inventories and market equilibrium expectations had little influence on acreage responses.

A few caveats need mentioning. First, what the USDA NASS seasonal average price survey is, actually, attempting to measure is not clear. Do spot market prices play any role? Publicly documented details of the survey methodology are lacking in this regard. Uncertainty about this metric is warranted. Second, any time series data on hop contracting would be valuable. Our conflation of contract and price seems reasonable, but is not empirically hardened. Lastly, our examination tends to ignore interrelated world hop market effects. Efforting an analysis of, for example, any U.S. and German cooperation in acreage decisions could prove useful. Results of the 2025 hop harvest will certainly be interesting.

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[24] See Kunce (2025) for an examination of this notion of naiveté.

[25] For decades, the conglomerate breweries behaved as alpha oligopsonists (MacKinnon and Pavlovič, 2020). Hops were viewed as a basic input commodity (alpha) prior to the small beer boom.

[26] Long time Executive Director of the Hop Growers Association of America and hop merchant, Douglas MacKinnon, coined this tactic as creating the 'perception of scarcity' (MacKinnon, 2025).

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Appendix

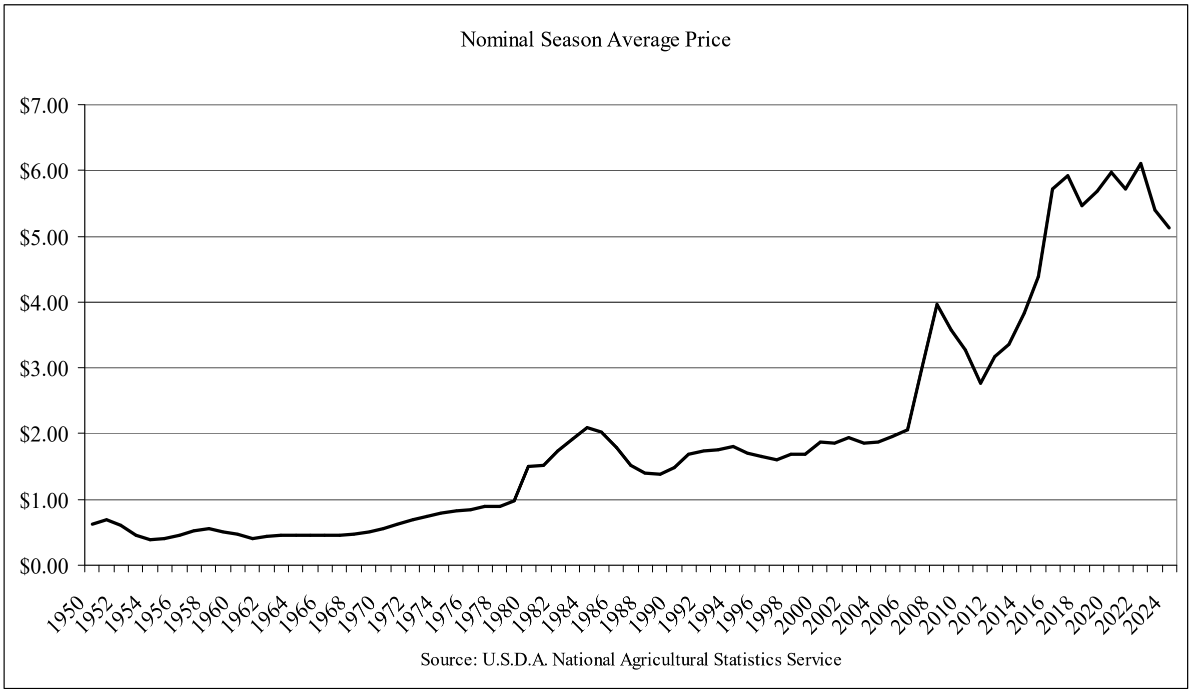

Figure A1. Nominal U.S. hop season average price per pound, 1950 - 2024

Table A1. Unit root testing

		Phillips-Perron Test Null: Series has a Unit Root	**Kwiatkowski, Phillips, Schmidt, and Shin Test** Null: Series is Stationary
ln(HOP ACREAGE)			
At Level	Constant	Fail to Reject	Reject < 10% Level
At Level	Constant & Trend	Fail to Reject	Fail to Reject
1st Difference	Constant	Reject < 1% Level	Fail to Reject
1st Difference	Constant & Trend	Reject < 5% Level	Fail to Reject
ln(HOP PRODUCTION)			
At Level	Constant	Fail to Reject	Reject < 5% Level
At Level	Constant & Trend	Fail to Reject	Fail to Reject
1st Difference	Constant	Reject < 1% Level	Fail to Reject
1st Difference	Constant & Trend	Reject < 1% Level	Fail to Reject
ln(HOP PRICE)			
At Level	Constant	Fail to Reject	Reject < 10% Level
At Level	Constant & Trend	Fail to Reject	Reject < 5% Level
1st Difference	Constant	Reject < 1% Level	Fail to Reject
1st Difference	Constant & Trend	Reject < 1% Level	Fail to Reject

ln(HOP STOCK)			
At Level	Constant	Fail to Reject	Reject < 1% Level
At Level	Constant & Trend	Fail to Reject	Reject < 10% Level
1st Difference	Constant	Reject < 1% Level	Fail to Reject
1st Difference	Constant & Trend	Reject < 5% Level	Fail to Reject
ln(HOP UTILIZATION)			
At Level	Constant	Fail to Reject	Reject < 5% Level
At Level	Constant & Trend	Fail to Reject	Fail to Reject
1st Difference	Constant	Reject < 1% Level	Fail to Reject
1st Difference	Constant & Trend	Reject < 1% Level	Fail to Reject
ln(UTILIZATION RATIO)			
At Level	Constant	Reject < 5% Level	Fail to Reject
At Level	Constant & Trend	Reject < 5% Level	Fail to Reject
1st Difference	Constant	Reject < 1% Level	Fail to Reject
1st Difference	Constant & Trend	Reject < 1% Level	Reject < 1% Level
ln(BREWERY COUNT)			
At Level	Constant	Fail to Reject	Reject < 1% Level
At Level	Constant & Trend	Fail to Reject	Fail to Reject
1st Difference	Constant	Reject < 10% Level	Fail to Reject
1st Difference	Constant & Trend	Fail to Reject	Reject < 10% Level
ln(BEER PRODUCTION)			
At Level	Constant	Fail to Reject	Fail to Reject
At Level	Constant & Trend	Fail to Reject	Reject < 1% Level
1st Difference	Constant	Reject < 5% Level	Reject < 1% Level
1st Difference	Constant & Trend	Reject < 1% Level	Fail to Reject

Robustness checks

MacKinnon and Pavlovič (2020) used season average price data unadjusted for inflation (see Figure A1 above) for their Bayesian inference. Table A2 presents the unrestricted Granger-causality results for Equation (3) above using nominal prices (lnNP). Results are analogous to those found in text Table 14. Table A3 below presents unrestricted Granger-

Table A2. Reduced form Granger-causality, Wald F-test, p-values, 2 lags selected

	Dependent Variable		
Regressor	lnC	lnPAS	lnNP
lnC	0.00	0.02	0.03
lnPAS	0.28	0.00	0.20
lnNP	0.57	0.00	0.00

causality results for Equation (3) using the first differenced natural log of each series. Two differences from the levels model are noteworthy. Brewery count helps predict real price at the <10 percent level and real price helps predict proprietary acreage shares at the

Table A3. First differenced Granger-causality, Wald F-test, p-values, 1 lag selected

	Dependent Variable		
Regressor	lnC	lnPAS	lnP
lnC	0.00	0.03	0.09
lnPAS	0.15	0.00	0.27
lnP	0.36	0.08	0.00

< 10 percent significance level. Lastly, Table A4 shows the variance decomposition of Equation (3) estimated with a Bayesian VAR at levels (Sims et al., 1990). Results are similar to those in text Table 15 though explained variation is tempered, particularly in outer horizon years.

Table A4. Levels Bayesian VAR, variance decomposition, 2 lags selected[a]

Variance Decomposition of **lnC**				
Horizon	Standard Error	lnC	lnPAS	lnP
1	0.07	100.0%	0.0%	0.0%
5	0.17	98.3%	0.5%	1.2%
10	0.24	94.1%	1.2%	4.7%
Variance Decomposition of **lnPAS**				
Horizon	Standard Error	lnC	lnPAS	lnP
1	0.09	1.2%	98.8%	0.0%
5	0.16	12.7%	85.8%	1.5%
10	0.19	33.0%	61.6%	5.4%
Variance Decomposition of **lnP**				
Horizon	Standard Error	lnC	lnPAS	lnP
1	0.12	14.7%	0.1%	85.2%
5	0.23	19.9%	0.4%	79.7%
10	0.28	25.5%	0.5%	74.0%

[a]Litterman/Minnesota priors (Litterman, 1986).

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No Pliny in Sonoma County?

Mitch Kunce[1,2]

Abstract

Competitive price theory posits that standard or lower quality goods are more heavily consumed within the vicinity of production as opposed to farther away. Alchian and Allen's (1964) "shipping the good apples out" theorem captures this observed occurrence. This 'casual empiricism' has been established with many examples including those found in the U.S. beer industry. More broad empirical work, confirming the proposition, has centered in international trade treatments (Hummels and Skiba, 2004; Hummels and Klenow, 2005). This paper explores, theoretically, perceived-quality relative consumption for the U.S. beer industry. A more general, utility based, exposition is forwarded.

Keywords: Perceived quality, consumer theory, transportation cost
JEL Classifications: C02, D11, L15

Introduction

Pliny the Elder, the creation of Vinnie Cilurzo of Russian River Brewing Company, is arguably the most celebrated India Pale Ale (IPA) in the U.S. since its inception 25 years ago.[3] In September of 2024, Forbes magazine placed Pliny first in their hall-of-fame list of top-rated IPAs in America (Micallef, 2024). The Beer Advocate, one of the oldest and largest online beer-geek communities, has logged close to 16,000 member ratings of Pliny, more than any other IPA.[4] Piling on, Pliny was voted 'Best Beer in America', by members of the Homebrewers Association, an unprecedented eight years in a row, 2009-2016 (Zymurgy, 2017). Unsurprisingly, Pliny has earned cult status.

On a trip last year to the Santa Rosa, California area, I found myself with a few colleagues in the Beer Baron Bar on 4th Street in Santa Rosa. Without hesitation, I was eager to order a proper pint of Pliny. However, one in our crew, a local, set me straight. Apparently, other than at the two Russian River locations, finding Pliny (even in a bottle) at any given restaurant or bar in Sonoma County is not guaranteed. Well, that seems odd, I just had a draft of Pliny at the Choice City Deli in Fort Collins, Colorado (1,200 miles from Sonoma, paying $11.50 for a shaker) about a month before this trip. Somewhat disappointed, I settled for a pint of Blind Pig IPA, a Vinnie Cilurzo carryover from his days at Blind Pig Brewing in Temecula, California. Russian River's Blind Pig is special, but it is not Pliny.[5] Interestingly, my Sonoma experience is not uncommon (Curtis, 2020).

---

[1] *Douglas**Mitchell*** Econometric Consulting, Laramie, WY USA. Published November 2025.
[2] To a great mentor, John T. Tschirhart.
[3] At the time of publication of this paper, Russian River Brewing operated two locations (Santa Rosa and Windsor) both in Sonoma County, California.
[4] Ratings average 4.65 out of 5.00 which is considered world class by members (Beer Advocate, 2025).
[5] Blind Pig is roughly one percent lower in alcohol by volume compared to Pliny. Regardless, the two beers drink as if they were relatively close substitutes.

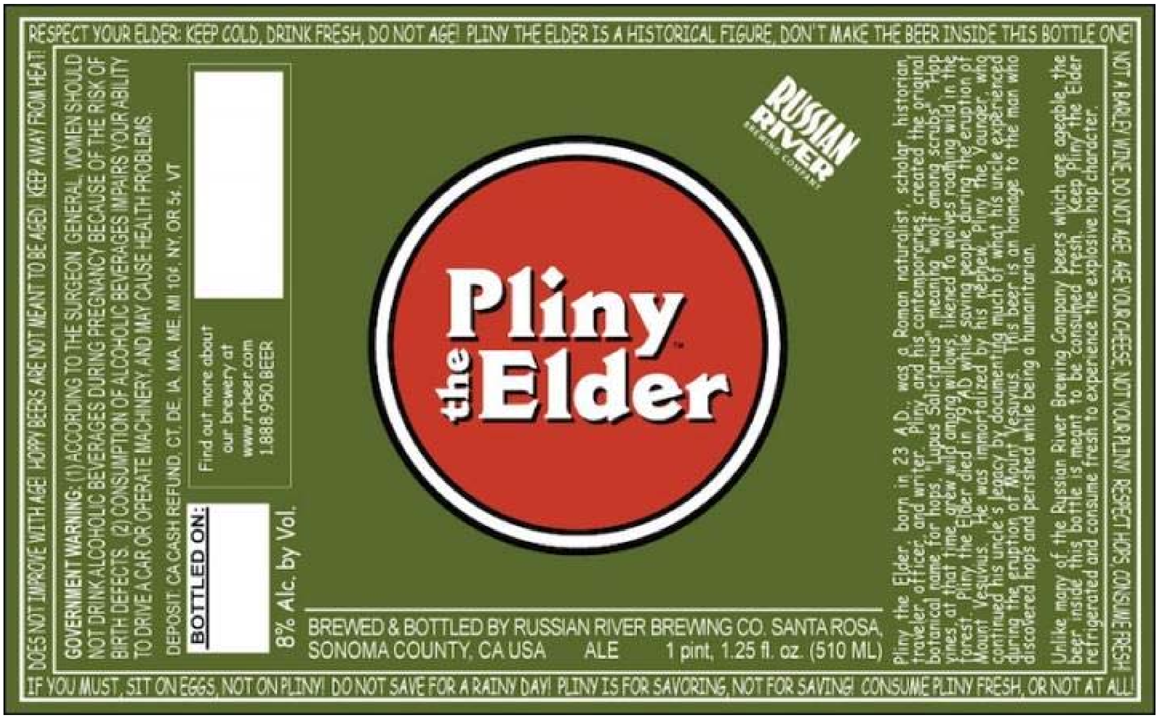

Figure 1. Pliny bottle label

Are the previous two paragraphs a lead-in to some economic proposition? Indeed. The hypothesis suggests that a fixed charge *t* (e.g. a transportation charge) added to the price of two similar goods (high (*H*) and standard or lower (*L*) quality IPAs) leads to a relative increase in consumption of the high quality good (Alchian and Allen, 1964). Hence, no Pliny in Sonoma County because it is being shipped away. The Alchian and Allen proposition has additional caveats. First, transportation is essential for access and has no affect on the two goods (e.g., beer is refrigerated in transport). Second, *t* is not considered a good, meaning it has no separable value (Umbeck, 1980). Lastly, the proposition focuses on individual choice not the collective. The next section rigorously explores the theory.

Theoretical models

We begin in Alchian and Allen's two good world.[6] Goods include *H* (high quality) and *L* (standard or lower grade) where the high quality good sells at a premium price. We focus on the dual of the standard consumer problem to avoid pesky income effect issues (Gould and Segall, 1969, p. 131).[7] The consumer's goal is to minimize expenditure on quantities *H* and *L*,

$$E = p^H(t)H + p^L(t)L\,, \tag{1}$$

with prices defined as,

[6] Because we are modeling the interjurisdictional shipment of alcoholic beverages, we assume, for simplicity, the distribution laws in the exporting and importing jurisdictions are the same.
[7] See the Appendix to this paper for the standard approach that illuminates the income effect issues.

$$p^H(t) = p^H + t \;>\; p^L(t) = p^L + t\,, \tag{2}$$

where t denotes the per unit transportation cost. We constrain the problem to a constant level of utility represented by the 'well-behaved' function,

$$\overline{U} = U(H, L)\,. \tag{3}$$

The appropriate Lagrangian becomes,

$$\mathcal{L} = p^H(t)H + p^L(t)L + \lambda(\overline{U} - U(H, L))\,, \tag{4}$$

where the consumer chooses quantities of H and L based on the first-order conditions,[8]

$$\mathcal{L}_\lambda = \overline{U} - U(H, L,) = 0\,, \tag{5}$$
$$\mathcal{L}_H = p^H(t) - \lambda U_H = 0\,, \tag{6}$$
$$\mathcal{L}_L = p^L(t) - \lambda U_L = 0\,. \tag{7}$$

The sufficient second-order conditions for a constrained minimum are conditioned on the bordered Hessian or Jacobian determinant, [9]

$$\begin{gathered}|J| = \begin{vmatrix} 0 & -U_H & -U_L \\ -U_H & -\lambda U_{HH} & -\lambda U_{HL} \\ -U_L & -\lambda U_{LH} & -\lambda U_{LL} \end{vmatrix} = \lambda\left(-2U_H U_L U_{HL} + U_{HH}\left(U_L\right)^2 + U_{LL}\left(U_H\right)^2\right) < 0, \\ |J| = \lambda(Q) < 0. \end{gathered} \tag{8}$$

Under the conditions of the implicit function theorem, Equations (5) - (7) provide the optimal solutions,

$$\lambda = \lambda^*(p^H(t), p^L(t), \overline{U})\,, \tag{9}$$
$$H = H^*(p^H(t), p^L(t), \overline{U})\,, \tag{10}$$
$$L = L^*(p^H(t), p^L(t), \overline{U})\,, \tag{11}$$

where Equations (10) and (11) represent Hicksian demand functions and Equation (9) is the positive marginal cost of utility (Hicks, 1946). Under the assertion that only relative prices matter, Hicksian demands are homogeneous of degree zero in prices only. Using Euler's theorem, we can restate Equation (10) as,

$$\frac{\partial H^*}{\partial p^H(t)} p^H(t) + \frac{\partial H^*}{\partial p^L(t)} p^L(t) = H^*_{p^H} p^H + H^*_{p^L} p^L = 0\,, \tag{12}$$

---

[8] Subscripts denote partial derivatives, letter superscripts reflect commodity designation.

[9] Young's theorem and symmetry of J shows $U_{HL} = U_{LH}$.

which establishes that H and L must be net substitutes, which is natural prevalence in a two-good world.[10]

In order to examine 'no Pliny in Sonoma County', the ratio of the consumption of the high quality good to the lower quality good must increase with an increase in transportation cost (Alchian and Allen, 1964; Borcherding and Silberberg, 1978) or,

$$\frac{\partial\left(\frac{H^*}{L^*}\right)}{\partial t} > 0, \tag{13}$$

holding real income (utility) constant. Using the quotient rule,

$$\frac{\partial\left(\frac{H^*}{L^*}\right)}{\partial t} = \frac{\left(L^* H_t^* - H^* L_t^*\right)}{\left(L^*\right)^2} > 0\,. \tag{14}$$

In order to evaluate the sign of Equation (14) we need to find tractable solutions for the expressions H_t^* and L_t^*. Differentiating Equations (5) - (7), evaluated at the optimum Equations (9) - (11), with respect to λ^*, H^*, L^* and t yields the comparative static matrix system,

$$\begin{pmatrix} 0 & -U_H & -U_L \\ -U_H & -\lambda^* U_{HH} & -\lambda^* U_{HL} \\ -U_L & -\lambda^* U_{LH} & -\lambda^* U_{LL} \end{pmatrix} \begin{pmatrix} \lambda_t^* \\ H_t^* \\ L_t^* \end{pmatrix} = -\begin{pmatrix} 0 \\ p_t^H = 1 \\ p_t^L = 1 \end{pmatrix}, \tag{15}$$

where,

$$H_t^* = \frac{(U_L)^2 - U_H U_L}{\lambda^* Q}, \tag{16}$$

$$L_t^* = \frac{(U_H)^2 - U_H U_L}{\lambda^* Q}. \tag{17}$$

Substituting Equations (16) and (17) into (14) yields,

$$\frac{L^*}{\left(L^*\right)^2}\left(\frac{(U_L)^2 - U_H U_L}{\lambda^* Q}\right) - \frac{H^*}{\left(L^*\right)^2}\left(\frac{(U_H)^2 - U_H U_L}{\lambda^* Q}\right) = \frac{(U_H - U_L)\left(H^* U_H + L^* U_L\right)}{-\left(L^*\right)^2 \lambda^* Q}. \tag{18}$$

From Equations (2), (6) and (7),

[10] See the Appendix to this paper for how Equation (12) relates to utility.

$$\lambda^{*}U_{H} > \lambda^{*}U_{L}, \tag{19}$$

which results in an unambiguously positive Equation (18) at the sufficient optimum. In this two good, real income compensated case, the higher quality good will be shipped away in greater amounts than the lower quality good.

What about expanding to a n good world? The expenditure minimization problem for n goods becomes,

$$\min \; E = p^{H}(t)H + p^{L}(t)L + \sum\nolimits_{i=3}^{n} p^{i}x^{i}, \tag{20}$$

$$\text{s.t.} \quad \overline{U} = U(H, L, \ldots. x^{n}). \tag{21}$$

The two beers H (good 1) and L (good 2) are transported from another location, Edgeworth utility is well-behaved and dependent on all goods, and the far-right summation term in Equation (20) represents a Hicksian composite commodity 'C', denoting all other goods (Hicks, 1946).[11] The composite good is produced locally. First-order conditions from the Lagrangian become,

$$\mathcal{L}_{\lambda} = \overline{U} - U(H, L, C) = 0, \tag{22}$$

$$\mathcal{L}_{H} = p^{H}(t) - \lambda U_{H} = 0, \tag{23}$$

$$\mathcal{L}_{L} = p^{L}(t) - \lambda U_{L} = 0, \tag{24}$$

$$\mathcal{L}_{C} = p^{C} - \lambda U_{C} = 0. \tag{25}$$

Sufficient second-order conditions for a minimum can be established by evaluating the signs of the leading principal minors of the bordered Hessian,

$$\left|\overline{H}\right| = \begin{vmatrix} 0 & -U_{H} & -U_{L} & -U_{C} \\ -U_{H} & -\lambda U_{HH} & -\lambda U_{HL} & -\lambda U_{HC} \\ -U_{L} & -\lambda U_{LH} & -\lambda U_{LL} & -\lambda U_{LC} \\ -U_{C} & -\lambda U_{CH} & -\lambda U_{CL} & -\lambda U_{CC} \end{vmatrix} = \lambda^{2}(\Omega) < 0, \tag{26}$$

$$\begin{aligned} \Omega = (U_{L}U_{HC} - U_{H}U_{LC})^{2} - U_{CC}(Q) + (U_{C})^{2}\left((U_{HL})^{2} - U_{HH}U_{LL}\right) - \\ 2U_{C}U_{LC}\left(U_{H}U_{HL} - U_{L}U_{HH}\right) - 2U_{C}U_{HC}\left(U_{L}U_{HL} - U_{H}U_{LL}\right) < 0, \end{aligned}$$

where the 3 x 3 leading minor is reflected in Equation (8) above. Hicksian compensated demands are represented implicitly and take the general form,

$$\lambda = \lambda^{*}(p^{H}, p^{L}, p^{C}, \overline{U}), \tag{27}$$

$$H = H^{*}(p^{H}, p^{L}, p^{C}, \overline{U}), \tag{28}$$

[11] See the Appendix to this paper for a more general treatment of 'all other goods'.

$$L = L^*(p^H, p^L, p^C, \overline{U}), \tag{29}$$

$$C = C^*(p^H, p^L, p^C, \overline{U}), \tag{30}$$

where the prices of H and L are still functions of t following Equation (2) above. Homogeneity of compensated demand allows the restatement of Equations (28) and (29) using Euler's theorem as,

$$H^*_{p^H} p^H + H^*_{p^L} p^L + H^*_{p^C} p^C = 0, \tag{31}$$

$$L^*_{p^H} p^H + L^*_{p^L} p^L + L^*_{p^C} p^C = 0. \tag{32}$$

The composite commodity may have a net substitute or net complementary relationship with the two qualities of beer, though it is more than reasonable to assume that both beers will interact with C in a similar manner.

Again, in order to evaluate the sign of Equation (14) above we need to find tractable solutions for the expressions H^*_t and L^*_t. Differentiating Equations (22) - (25), evaluated at the optimum demand Equations (27) - (30), with respect to λ^*, H^*, L^*, C^* and t yields the comparative static matrix system,

$$\begin{pmatrix} 0 & -U_H & -U_L & -U_C \\ -U_H & -\lambda^* U_{HH} & -\lambda^* U_{HL} & -\lambda^* U_{HC} \\ -U_L & -\lambda^* U_{LH} & -\lambda^* U_{LL} & -\lambda^* U_{LC} \\ -U_C & -\lambda^* U_{CH} & -\lambda^* U_{CL} & -\lambda^* U_{LL} \end{pmatrix} \begin{pmatrix} \lambda^*_t \\ H^*_t \\ L^*_t \\ C^*_t \end{pmatrix} = - \begin{pmatrix} 0 \\ p^H_t = 1 \\ p^L_t = 1 \\ 0 \end{pmatrix}, \tag{33}$$

where,

$$H^*_t = \frac{\left[2U_L U_C U_{LC} - (U_L)^2 U_{CC} - (U_C)^2 U_{LL}\right] + \left[U_H U_L U_{CC} - U_C (U_H U_{LC} + U_L U_{HC}) + (U_C)^2 U_{HL}\right]}{\lambda^* \Omega} \tag{34}$$

$$L^*_t = \frac{\left[2U_H U_C U_{HC} - (U_H)^2 U_{CC} - (U_C)^2 U_{HH}\right] + \left[U_H U_L U_{CC} - U_C (U_H U_{LC} + U_L U_{HC}) + (U_C)^2 U_{HL}\right]}{\lambda^* \Omega}. \tag{35}$$

With a 4 x 4 Jacobian, we find ourselves swimming in a mass of utility function partial derivatives. Let's avoid drowning. Upon inspection, the right-side of Equations (34) and (35) are simply a summation (separated by brackets) of the respective optimal compensated demands' slope and cross-effect,

$$H^*_t = H^*_{p^H} + H^*_{p^L}, \tag{36}$$

$$L_t^* = L_{p^L}^* + L_{p^H}^* , \tag{37}$$

where $H_{p^L}^* = L_{p^H}^*$. This observation is supported by differentiating Equations (28) and (29), via the chain rule, with respect to *t*. Substituting Equations (36) and (37) into (14) yields,

$$\frac{L^*}{\left(L^*\right)^2}\left(H_{p^H}^* + H_{p^L}^*\right) - \frac{H^*}{\left(L^*\right)^2}\left(L_{p^L}^* + L_{p^H}^*\right), \tag{38}$$

where the signs of each term (e.g., $H_{p^H}^* < 0, L_{p^H}^* > 0$) stem from demand theory or postulate. Assigning a priori magnitudes to these terms, however, originates more from one's imagination (see Equations (34) and (35)). Regardless, Equation (38) is going to require a bit of manipulation in order to sign. One initial obstacle in the way of signing of Equation (38) is the presence of the optimal quantity choices of the two beers. Borcherding and Silberberg (1978) recognized this in their 'apples' specification and offered a suitable rearrangement that centers the focus on demand responses and prices. Consider this restatement of Equation (38),

$$\begin{gathered}\left(\frac{H_{p^H}^*}{L^*}\frac{H^*}{H^*}\frac{p^H}{p^H}\right) + \left(\frac{H_{p^L}^*}{L^*}\frac{H^*}{H^*}\frac{p^L}{p^L}\right) - \left(\frac{H^*}{L^*}\frac{L_{p^L}^*}{L^*}\frac{p^L}{p^L}\right) - \left(\frac{H^*}{L^*}\frac{L_{p^H}^*}{L^*}\frac{p^H}{p^H}\right) = \\ \frac{H^*}{L^*}\left(\frac{\varepsilon^*(H^*,p^H)}{p^H} + \frac{\varepsilon^*(H^*,p^L)}{p^L} - \frac{\varepsilon^*(L^*,p^L)}{p^L} - \frac{\varepsilon^*(L^*,p^H)}{p^H}\right)\end{gathered}, \tag{39}$$

where $\varepsilon^*(*)$ indicates the optimal compensated own and cross price elasticities. Explicit quantity choices are now factored out of the meaningful (bracketed) part of the lower expression.

To place emphasis on the requisite explicit interactions of H^* and L^* with C^*, consider the following restatement of Euler demand Equations (31) and (32). First, divide both sides of Equation (31) by H^*, divide both sides of Equation (32) by L^* and set the two equal to each other,

$$\varepsilon^*(H^*,p^H) + \varepsilon^*(H^*,p^L) + \varepsilon^*(H^*,p^C) = \varepsilon^*(L^*,p^H) + \varepsilon^*(L^*,p^L) + \varepsilon^*(L^*,p^C). \tag{40}$$

Solving Equation (40) for $\varepsilon^*(H^*, p^L)$ then substituting the rearrangement into Equation (39) yields a tractable expression[12] for Equation (38),

$$\frac{H^*}{L^*}\left(\frac{p^H\left(\varepsilon^*(L^*,p^C) - \varepsilon^*(H^*,p^C)\right) + \left(p^H - p^L\right)\left(\varepsilon^*(L^*,p^H) - \varepsilon^*(H^*,p^H)\right)}{p^H p^L}\right). \tag{41}$$

[12] Algebra is our friend.

The sign of Equation (41) depends on the term ($\varepsilon^*(L^*, p^C) - \varepsilon^*(H^*, p^C)$). To relate this expression to utility, use the comparative static system,

$$\begin{pmatrix} 0 & -U_H & -U_L & -U_C \\ -U_H & -\lambda^* U_{HH} & -\lambda^* U_{HL} & -\lambda^* U_{HC} \\ -U_L & -\lambda^* U_{LH} & -\lambda^* U_{LL} & -\lambda^* U_{LC} \\ -U_C & -\lambda^* U_{CH} & -\lambda^* U_{CL} & -\lambda^* U_{LL} \end{pmatrix} \begin{pmatrix} \lambda^*_{p^C} \\ H^*_{p^C} \\ L^*_{p^C} \\ C^*_{p^C} \end{pmatrix} = -\begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix}, \tag{42}$$

and Equations (23) - (25), (28), (29), (31), (32), and (39) to yield,

$$\varepsilon^*(H^*, p^C) = \frac{U_H U_{LL} (U_C)^2 + U_C U_{HC} (U_L)^2 - U_L U_{HL} (U_C)^2 - U_H U_L U_C U_{LC}}{\lambda^* \Omega H^*}, \tag{43}$$

$$\varepsilon^*(L^*, p^C) = \frac{U_L U_{HH} (U_C)^2 + U_C U_{LC} (U_H)^2 - U_H U_{HL} (U_C)^2 - U_H U_L U_C U_{HC}}{\lambda^* \Omega L^*}. \tag{44}$$

If the two qualities of beer interact with the composite commodity in a like fashion, $\varepsilon^*(L^*, p^C) = \varepsilon^*(H^*, p^C)$, Equation (41) is unambiguously positive at the sufficient optimum. If the demand interactions differ (e.g., $\varepsilon^*(L^*, p^C) < \varepsilon^*(H^*, p^C)$ as net substitutes) Equation (41) may become indeterminate, reliant on creative magnitude scenarios.

Concluding remarks

Many California breweries ship their beer across the U.S. and abroad. Regardless of perceived-quality, shipping beer to, for example, Colorado should cost the same. As shown herein, relatively more high quality beer will be shipped away because the fixed cost of transportation lowers the relative price of the higher quality substitute. Interestingly, while it is common to find Pliny in establishments in Colorado or Oregon, a state like Wyoming is by and large a Pliny desert.[13] In other words, do importing location attributes play a role in tilting consumption towards higher quality? The theoretical literature addressing asymmetries, in this context, is lacking (Bastos and Silva, 2010). Of course, more specificity is usually accompanied by more complexity. Introducing asymmetries makes obtaining closed-form solutions and general analysis more difficult. One seemingly obvious direction for future treatments would be a move to general equilibrium modeling. Initial endowment asymmetries of importing locations would meaningfully augment the standard neoclassical model of production in tandem with local utility maximization.

[13] With the exception of Jackson, Wyoming.

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Appendix

The standard maximization problem seeks to $\max_{H,L}\, U(H, L)$ subject to text Equations (1) and (2) forming the Lagrangian,

$$\mathcal{L} = U(H,L) + \mu(E - p^H(t)H - p^L(t)L)\,, \tag{A1}$$

where the first-order-conditions are,

$$\mathcal{L}_\mu = E - p^H(t)H - p^L(t)L = 0\,, \tag{A2}$$
$$\mathcal{L}_H = U_H - \mu\, p^H(t) = 0\,, \tag{A3}$$
$$\mathcal{L}_L = U_L - \mu\, p^L(t) = 0\,. \tag{A4}$$

The sufficient second-order conditions for a constrained maximum are conditioned on a bordered Hessian, substituting a rearrangement of Equations (A3) and (A4) in the border,

$$\left|\overline{H}\right| = \begin{vmatrix} 0 & -U_H/\mu & -U_L/\mu \\ -U_H/\mu & U_{HH} & U_{HL} \\ -U_L/\mu & U_{LH} & U_{LL} \end{vmatrix} = -\frac{1}{\mu^2}(Q) > 0\,, \tag{A5}$$

where $Q < 0$ is from text Equation (8). Under the conditions of the implicit function theorem, Equations (A2) - (A4) provide the simultaneous solutions,

$$\mu = \mu^*(p^H(t), p^L(t), E)\,, \tag{A6}$$
$$H = H^*(p^H(t), p^L(t), E)\,, \tag{A7}$$
$$L = L^*(p^H(t), p^L(t), E)\,, \tag{A8}$$

where Equations (A7) and (A8) represent Marshallian demand functions and Equation (A6) is the positive marginal utility of income. Marshallian demands are homogeneous of degree zero in prices and income. Using Euler's theorem, we can restate Equations (A7) and (A8) as,

$$H^*_{p^H} p^H + H^*_{p^L} p^L + H^*_E E = 0\,, \tag{A9}$$
$$L^*_{p^H} p^H + L^*_{p^L} p^L + L^*_E E = 0\,, \tag{A10}$$

which establishes income (expenditure) effects and the possibility of an inferior good (e.g., $L^*_E < 0$).

Again, our interest is to find solutions for H^*_t and L^*_t in order to evaluate text Equation (14). Differentiating Equations (A2) - (A4), evaluated at the optimums, with respect to μ^*, H^*, L^* and t yields the comparative static matrix system,

$$\begin{pmatrix} 0 & -U_H/\mu^* & -U_L/\mu^* \\ -U_H/\mu^* & U_{HH} & U_{HL} \\ -U_L/\mu^* & U_{LH} & U_{LL} \end{pmatrix} \begin{pmatrix} \mu_t^* \\ H_t^* \\ L_t^* \end{pmatrix} = -\begin{pmatrix} -H^* - L^* \\ -\mu^* \\ -\mu^* \end{pmatrix}, \tag{A11}$$

where,

$$H_t^* = \frac{\mu^*\left(U_L^2 - U_H U_L + (H^* + L^*)(U_L U_{HL} - U_H U_{LL})\right)}{Q}, \tag{A12}$$

$$L_t^* = \frac{\mu^*\left(U_H^2 - U_H U_L + (H^* + L^*)(U_H U_{HL} - U_L U_{HH})\right)}{Q}. \tag{A13}$$

Equations (A9), (A12) and (A13) differ materially from text Equations (12), (16) and (17) by the income effect terms. The following system yields these terms,

$$\begin{pmatrix} 0 & -U_H/\mu^* & -U_L/\mu^* \\ -U_H/\mu^* & U_{HH} & U_{HL} \\ -U_L/\mu^* & U_{LH} & U_{LL} \end{pmatrix} \begin{pmatrix} \mu_E^* \\ H_E^* \\ L_E^* \end{pmatrix} = -\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \tag{A14}$$

where,

$$H_E^* = \frac{-\mu^*(U_L U_{HL} - U_H U_{LL})}{Q}, \tag{A15}$$

$$L_E^* = \frac{-\mu^*(U_H U_{HL} - U_L U_{HH})}{Q}. \tag{A16}$$

Equations (A15) and (A16) have no definitive sign. Curvature properties of the utility function do not rule out inferior goods. These effects, along with the obvious accumulation of utility function partial derivatives, complicate efforts in signing text Equation (14). Upon inspection, the right-side of Equations (A12) and (A13) are simply a summation of the respective optimal Marshallian demands' slope and cross-effect,

$$H_t^* = H_{p^H}^* + H_{p^L}^*, \tag{A17}$$

$$L_t^* = L_{p^L}^* + L_{p^H}^*, \tag{A18}$$

where $H^*_{p^L} = L^*_{p^H}$. This observation is supported by differentiating Equations (A7) and (A8), via the chain rule, with respect to t. Substituting Equations (A17) and (A18) into text Equation (14) yields,

$$\frac{L^*}{\left(L^*\right)^2}\left(H^*_{p^H} + H^*_{p^L}\right) - \frac{H^*}{\left(L^*\right)^2}\left(L^*_{p^L} + L^*_{p^H}\right), \tag{A19}$$

where the signs of each term (e.g., $H^*_{p^H} < 0, L^*_{p^H} > 0$) stem from demand theory or postulate. Consider this restatement of Equation (A19),

$$\begin{aligned}&\left(\frac{H^*_{p^H}}{L^*}\frac{H^*}{H^*}\frac{p^H}{p^H}\right) + \left(\frac{H^*_{p^L}}{L^*}\frac{H^*}{H^*}\frac{p^L}{p^L}\right) - \left(\frac{H^*}{L^*}\frac{L^*_{p^L}}{L^*}\frac{p^L}{p^L}\right) - \left(\frac{H^*}{L^*}\frac{L^*_{p^H}}{L^*}\frac{p^H}{p^H}\right) = \\ &\frac{H^*}{L^*}\left(\frac{\varepsilon^*(H^*, p^H)}{p^H} + \frac{\varepsilon^*(H^*, p^L)}{p^L} - \frac{\varepsilon^*(L^*, p^L)}{p^L} - \frac{\varepsilon^*(L^*, p^H)}{p^H}\right)\end{aligned}, \tag{A20}$$

where $\varepsilon^*(*)$ indicates the optimal own, cross price and potential income elasticities.

Consider the following restatement of Euler demand Equations (A9) and (A10). First, divide both sides of Equation (A9) by H^*, divide both sides of Equation (A10) by L^* and set the two equal to each other,

$$\varepsilon^*(H^*, p^H) + \varepsilon^*(H^*, p^L) + \varepsilon^*(H^*, E) = \varepsilon^*(L^*, p^H) + \varepsilon^*(L^*, p^L) + \varepsilon^*(L^*, E). \tag{A21}$$

Solving Equation (A21) for $\varepsilon^*(H^*, p^L)$ then substituting the rearrangement into Equation (A20) yields, after suitable rearrangement,

$$\frac{H^*}{L^*}\left(\frac{p^H\left(\varepsilon^*(L^*, E) - \varepsilon^*(H^*, E)\right) + \left(p^H - p^L\right)\left(\varepsilon^*(L^*, p^H) - \varepsilon^*(H^*, p^H)\right)}{p^H p^L}\right). \tag{A22}$$

The income elasticity terms, $\varepsilon^*(L^*, E)$ and $\varepsilon^*(H^*, E)$ frustrate the signing of Equation (A22). This task is more manageable if real income (utility) is held constant (the dual problem as shown in the text).

Relation of text Equation (12) to utility

To establish the slope terms of text Equation (12), consider the following comparative static systems,

$$\begin{pmatrix} 0 & -U_H & -U_L \\ -U_H & -\lambda^* U_{HH} & -\lambda^* U_{HL} \\ -U_L & -\lambda^* U_{LH} & -\lambda^* U_{LL} \end{pmatrix}\begin{pmatrix} \lambda^*_{p^H} \\ H^*_{p^H} \\ L^*_{p^H} \end{pmatrix} = -\begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}, \tag{A23}$$

where,

$$H^*_{p^H} = \frac{(U_L)^2}{\lambda^* Q}, \tag{A24}$$

which is unambiguously negative from the denominator and,

$$\begin{pmatrix} 0 & -U_H & -U_L \\ -U_H & -\lambda^* U_{HH} & -\lambda^* U_{HL} \\ -U_L & -\lambda^* U_{LH} & -\lambda^* U_{LL} \end{pmatrix} \begin{pmatrix} \lambda^*_{p^L} \\ H^*_{p^L} \\ L^*_{p^L} \end{pmatrix} = -\begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}, \tag{A25}$$

where,

$$H^*_{p^L} = \frac{-U_H U_L}{\lambda^* Q}. \tag{A26}$$

which is unambiguously positive indicating a net substitute relationship. Substituting Equations (A24), (A26) and a rearrangement of text Equations (6) and (7) into text Equation (12) yields,

$$\frac{(U_L)^2}{\lambda^* Q}\lambda^* U_H - \frac{U_H U_L}{\lambda^* Q}\lambda^* U_L = \frac{(U_L)^2 U_H - U_H U_L U_L}{Q} = 0. \tag{A27}$$

This same exercise also succeeds for Euler Equations (A9) and (A10).

More generality in the *n* good world.

In a more broad n good world where H is good one and L is good two, text Equation (40) becomes,

$$\varepsilon^*(H^*, p^H) + \varepsilon^*(H^*, p^L) + \sum_{j=3}^{n} \varepsilon^*(H^*, p^j) = \varepsilon^*(L^*, p^H) + \varepsilon^*(L^*, p^L) + \sum_{j=3}^{n} \varepsilon^*(L^*, p^j). \tag{A28}$$

Solving Equation (A28) for $\varepsilon^*(H^*, p^L)$ then substituting the rearrangement into text Equation (39) yields,

$$\frac{H^*}{L^*}\left(\frac{p^H \sum_{j=3}^{n} \left(\varepsilon^*(L^*, p^j) - \varepsilon^*(H^*, p^j)\right) + \left(p^H - p^L\right)\left(\varepsilon^*(L^*, p^H) - \varepsilon^*(H^*, p^H)\right)}{p^H p^L} \right), \tag{A29}$$

where if we assume that the two IPAs interact with all other goods in the same manner, Equation (A29) is positive. One could argue that differences arise when the two IPAs are competing with all other IPAs, then a myriad of magnitude scenarios exist.

Using a different substitution and rearrangement of Equation (A29), Bauman (2004) shows that the two transported goods do not have to be substitutes for a positive sign. If the two goods are not close compliments, Bauman plays the magnitude game to make the case for a positive sign.

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Dissecting the U.S. Brewery Count

Mitch Kunce[1]

Abstract

What is the U.S. brewery count in any given year? It depends on your definition of a brewery and the motive of those that tally. This communication dissects the U.S. brewery count data from two key institutional sources, the Alcohol and Tobacco Tax and Trade Bureau and the Brewers Association. Our aim is to provide a better understanding of what this data represents. As it turns out, a periodic accurate count is a target, difficult to hit.

Keywords: Trade associations, government data, data analysis
JEL Classifications: C81, L60, M48

Introduction

In a recent New York Times article, spotlighting the state of the beer industry in the U.S., the author refers to the "more than 9,900" breweries operating in the country (Creswell, 2025). A similar article in Slate Magazine, when providing context, describes the over 14,000 breweries that were operating in the U.S. in 2023 (Sammon, 2025). A rather glaring difference in media reported counts. The Times number is sourced from the Brewers Association (BA), while the Slate count appears to come from the Beer Institute (BI).[2] The Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau (TTB) is another frequently cited source. In a 2024 blog entry, Oregon beer-geek Jeff Alworth describes his recent involvement with the Celebrate Oregon Beer project. His task was to assemble a complete list of Oregon breweries for a new website (Alworth, 2024). Armed with the "BA's official tally", Alworth began the daunting chore of confirming the existence of listed breweries. The compilation he ended up with was roughly 30 percent shy of what the BA touted for the state. A large portion of the wedge was made up of breweries that have ceased operations and those that are newly permitted but not producing beer. Jeff Alworth's experience is not unique; we tasked a similar effort for the state of Wyoming in 2024 and found a wedge of roughly 15 percent.[3] The purpose of this short industry communication is to dissect the publicly available data for brewery counts in the U.S. Our aim is to provide a better understanding of what the data represents. We focus on three sources, the TTB's 'Brewery Count by State', the TTB's 'Monthly National Statistical Report - Beer' and the BA's annual 'Beer Industry Production Survey'.

Dissection of the data

Quarterly, the TTB publishes the report 'Brewery Count by State'. This worksheet provides the count of *all* brewers, by state, that hold an active Brewer's Notice (permit/license). Every brewery in the U.S. is regulated and must be licensed to operate by the TTB. Each permitted brewery is assigned a unique BR reporting number. This

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[1] *Douglas**Mitchell*** Econometric Consulting, Laramie, WY USA. Published December 2025.
[2] Both the BA and BI are national, beer industry, trade organizations.
[3] See Appendix A to this paper for the BA's 2024 statistics for the state of Wyoming.

specific report, however, does not speak to whether the permitted facility is operational. The January 8, 2025 report shows a count of 14,597 active permits in the U.S. for the year 2023.[4] This is likely the BI's source in the Slate Magazine story referenced above.

Monthly, the aggregated public report entitled 'Monthly National Statistical Report - Beer' is published by the TTB. Each licensed brewer (BR number) is required to complete a 'Brewer's Report of Operations' either monthly or quarterly depending on taxed annual barrelage.[5] There is no annual filing option and reports must be submitted even if there is no activity during the period.[6] Reports are due on the 15th day following the close of the reporting period. The TTB relies on these individual premises reports of production and removals for taxing purposes and as the source for most aggregated public reports. Table 1 shows a section of the report for the year 2024. The December 2024 column with the row denoted 'Number of Industry Members' refers to the count of unique BR numbers with an operational report filed in December. The Annual Total column contains the count of all BR numbers with any report filed throughout the year. The two counts differ because of either late/amended reporting for the month of December[7] or breweries that filed previously in the year did not report in December.

Table 1. 2024 Monthly National Statistical Report - Beer (Dated, 18 SEP 2025)

Units: Beer Barrels (1 Barrel = 31 Gallons)	December 2024	Annual Total 2024
Number of Industry Members	6,671	7,723
Production	11,982,054	157,998,783
Taxable Removals	11,451,107	147,680,509
In Bottles & Cans	9,604,264	132,433,409
In Kegs	904,398	10,981,725
Removal Method not Specified	942,446	4,265,375
Tax Free Removals for Export	186,240	2,596,332
Stocks on Hand End-of-Period	9,762,766	126,226,930

Figure 1 below depicts the reporting brewery trends for 2012-2025. Each horizontal tick represents a monthly count. The, somewhat, uniform shorter teeth of this comb-like graphic illustrate the rather consistent count of larger breweries reporting monthly. Unique reports peaked in the third quarter of 2022 with quarterly counts declining thereafter. Interestingly, over 1,000 breweries submitted reports showing *no* production for the year 2024.

Annually, the Brewers Association surveys all, non-macro owned, properly permitted establishments regarding operations.[8] This brewery specific data is published in the May/June issue of *The New Brewer*, a BA print periodical. Aggregated reporting appears

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[4] See this January 8, 2025 report in Appendix B to this paper.
[5] Taxed annual barrelage triggers the liability threshold. If a brewery's tax liability is more than $50,000 in the current or prior year, monthly filing is required. Today, most breweries are below this threshold and file quarterly.
[6] 27 Code of Federal Regulations 25.297
[7] Small breweries in the U.S. filing quarterly are habitually late (see Kunce, 2024a).
[8] The count of large, non-craft, breweries in 2024 was 126. These 126 breweries produced roughly 94 percent of the 158 million barrels in 2024. See Appendix B for the mailed version of the 2024 survey form.

on the BA's website.[9] If an establishment does not respond to the survey, the BA will report their own assessment of operations. While not ideal, due to the presumably large number of non-responses, this surveyed data does provide a useful level of detail. In 2024, the BA count was 9,922 total U.S. breweries, far different from the TTB BR counts found in Figure 1.

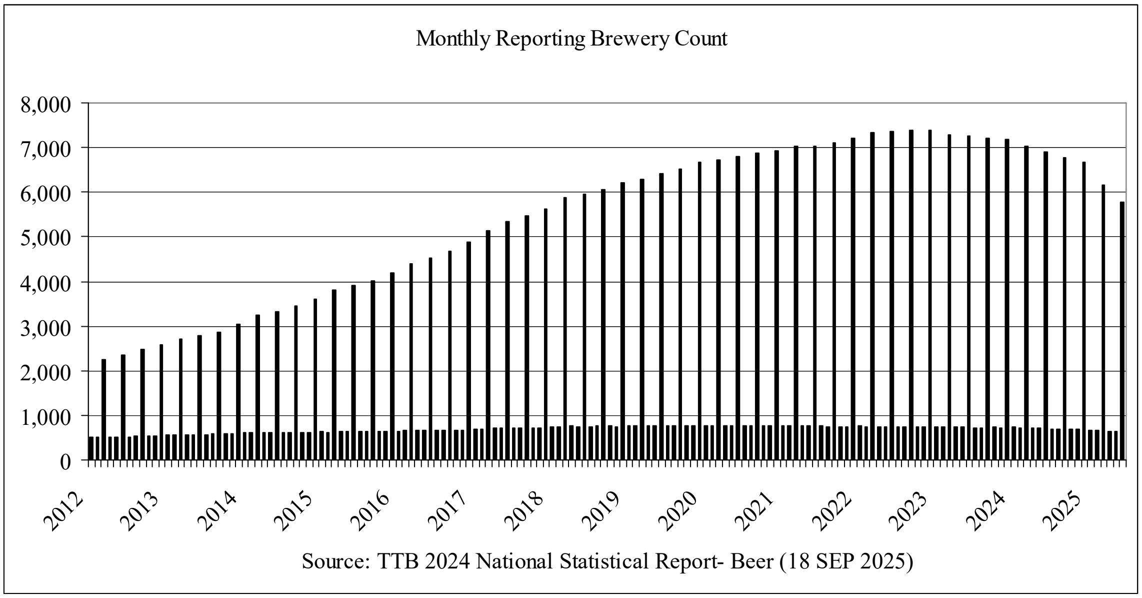

Figure 1. U.S. reporting brewery count by month

Figure 2 below shows recent time trends of all count sources referenced above. Interestingly, trends diverge around the year 2013. Of the 15,166 TTB permitted establishments in 2024, the BA claims 9,922 were operating yet only 6,671 have filed operation reports for the month of or quarter ending December 2024 (as of September 18, 2025). Clearly, a large portion of current active permits may never become operational breweries. We affectionately refer to this as the 'pipe-dream' count. Moreover, the BA appears reluctant to scrub its database. Remember, the BA is a non-profit trade organization that promotes small-beer. Funding for the association comes from membership dues and, more significantly, brewery participation in contests and conferences.[10] Positioning the industry in the best light is a self-serving function.

The TTB reported BR counts are also far from perfect. Table 2 below highlights the 'moving target' for reporting brewery counts for a select year, 2021. Parts of five versions of the 'Monthly National Statistical Report - Beer' for 2021 are listed by update date. An initial 2021 count was published on April 26, 2022. Recall, the statutory due date for December reporting was January 15, 2022. Moving down Table 2, it becomes apparent that the initial counts were incomplete. It takes more than three years for the counts to settle. The last two rows of Table 2 highlight the changes from 2022 to 2025. As shown, the bulk of the count difference comes from small breweries filing quarterly. In 2024, roughly 80 percent of all breweries in the U.S. produced 1,000 barrels or less for the year. It appears that many of these smaller establishments have trouble filing timely or accurate

[9] Visited 11-7-2025.
[10] For an in-depth look into the BA's financials, see Kunce (2023).

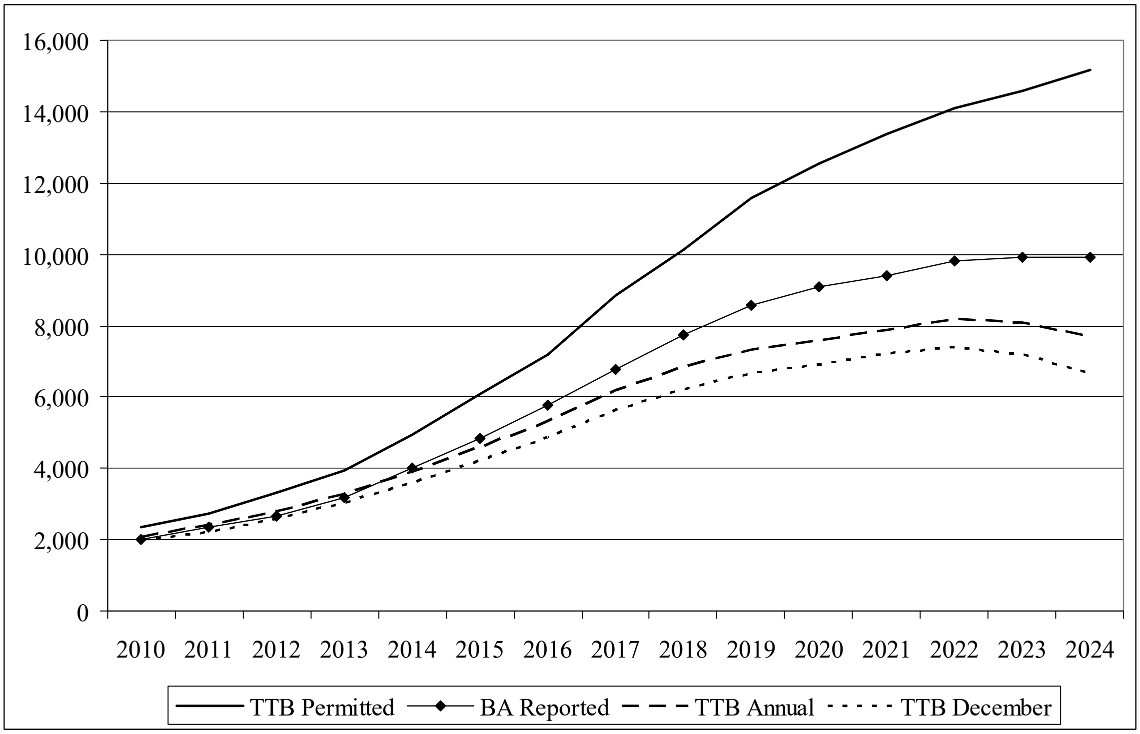

Figure 2. Brewery count trends, 2010-2024

operation reports (Kunce, 2024a). For taxable production, the relative changes from 2022 to 2025 are much smaller. Moreover, larger brewery amendments make up most of the production volume changes. It makes sense that the TTB would focus more on accurate reporting of large brewery production over chasing down the late paperwork of a few hundred very small breweries, many of which report no taxable production. What, then, was the brewery count in 2021? It depends on your definition of a brewery. The BA's compilation yielded 9,384. Kunce (2024b) refined the industry reach and reduced the 2021 *relevant* brewery count to roughly 700. All other establishments with small brewing

Table 2. 'Monthly National Statistical Report - Beer' (2021) five updates

April 26, 2022 Report	**November 2021**	**December 2021**	**Annual Total 2021**
Number of Industry Members	729	6,960	7,631
Production in BBLS	13,099,261	14,644,487	180,888,466
Taxable Removals in BBLS	12,471,970	13,887,754	169,202,051
November 6, 2023 Report			
Number of Industry Members	734	7,070	7,752
Production in BBLS	13,147,380	14,698,283	181,552,951
Taxable Removals in BBLS	12,520,508	13,941,802	169,860,545
October 3, 2024 Report			
Number of Industry Members	745	7,180	7,852
Production in BBLS	13,159,206	14,731,522	181,799,369
Taxable Removals in BBLS	12,531,505	13,970,363	170,076,860

May 22, 2025 Report			
Number of Industry Members	747	7,216	7,885
Production in BBLS	13,160,339	14,743,671	181,861,958
Taxable Removals in BBLS	12,532,538	13,981,197	170,129,070
September 18, 2025 Report			
Number of Industry Members	747	7,217	7,886
Production in BBLS	13,160,339	14,743,671	181,861,958
Taxable Removals in BBLS	12,532,538	13,981,197	170,131,461
Changes from 2022 to 2025			
Δ in BR Reports	18 (2.5%)	257 (3.7%)	255 (3.3%)
Δ in Taxable Removals (BBLS)	60,568 (0.5%)	93,443 (0.7%)	929,410 (0.5%)

capabilities were categorized as bars (taverns) or specialty restaurants. Alternatively, the TTB received reports from 7,886 unique BR numbers throughout the year (as of September of 2025), though 1,039 indicated no production for 2021. If your definition is framed by any sized establishment having taxed production activity at any time throughout the year, the answer is 6,847.

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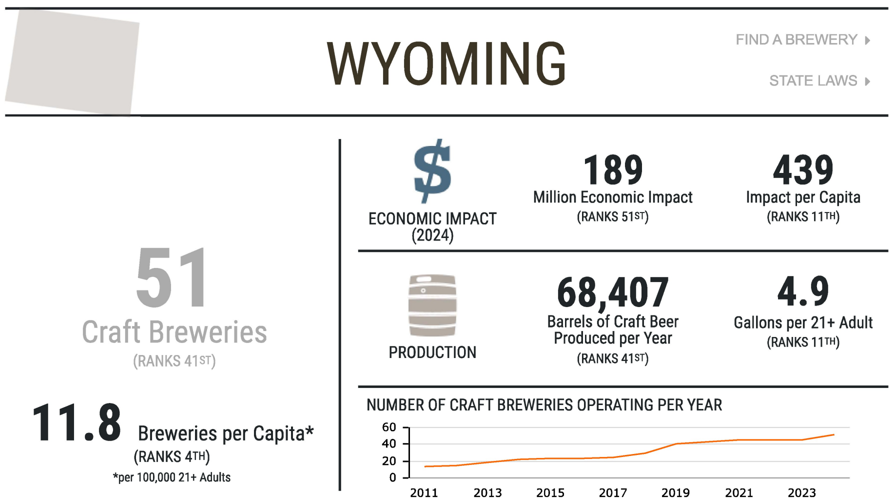
Appendix A

Wyoming's Craft Beer Sales & Production Statistics, 2024

Craft beer sales and production by state, breweries per capita, economic impact of craft breweries and other statistics as gathered and maintained by the Brewers Association.

SELECT A STATE



Wyoming does not have a macro-brewery.

Appendix B

BREWERS ASSOCIATION
Beer Industry Production Survey

PLEASE FILL OUT ONLINE FORM BY JANUARY 31, 2025 AT **www.BrewersAssociation.org/BIPS**
OR RETURN FORM BY MAIL OR EMAIL TO bips@brewersassociation.org

Dear Brewer,

The Brewers Association is preparing our annual review of the U.S. brewing industry. The data we get from you helps us provide the most accurate brewing industry statistics to brewers like you. As the craft market develops and evolves, ***these data are more critical than ever***. Please assist us by responding to the questions below regarding your company's 2024 production. The more survey participation we have, the better data we can provide in our annual brewery industry review featured in the May/June 2025 issue of *The New Brewer*. There is also an option to provide the data, but not have your company's production published (check box below).

Please fill out this form by **January 31, 2025.** You can fill out the survey online at **www.BrewersAssociation.org/BIPS** or return this form to PO Box 1679, Boulder, CO 80306 (it's postage paid). You may also **email** your responses to **bips@brewersassociation.org**.

Thank you very much, in advance, for your assistance. Hope you had a great holiday season, and best wishes for a successful 2025!

Matt Gacioch
Staff Economist

Note: questions refer to taxable beer sold or produced during the 2024 calendar year.
To avoid double counting, are you filling out this form for **your entire company** ☐ **or just this location** ☐
If you do **not** want your company's data published in *The New Brewer* May/June 2025 annual industry review, check here: ☐ *Do Not Publish*

Beer Only

1. Please enter beer volume *produced by* and sold for your company, or *taxable beer production*. (Beer produced under an alternating proprietorship should be entered on question 2.)

______ **BBLS for 2024** ______ **BBLS for 2023**

2. Alternating Proprietorships: If applicable, please enter beer volume sold for your company produced via alternating proprietorship:

______ **BBLS for 2024** ___0___ **BBLS for 2023**

3. Total volume of taxable contract-brewed beer *you sold* that was produced for you by another company?

______ **BBLS for 2024** ___0___ **BBLS for 2023**

Thanks for filling out this survey! If you have questions about how to answer any of the items, please email bips@brewersassociation.org, or find detailed guidance on the web at brewersassociation.org/BIPS

NONE of the following information will be published

4. Please enter taxable production of non-beer beverage alcohol volume sold for your company-owned brewery (FMBs, hard seltzer, cider, RTD liquor, etc.). Enter 0 if none.

______ **BBLS for 2024** ______ **BBLS for 2023**

5. Percent of taxable beer volume sold onsite at your brewery/ brewpub (draught or packaged):

______ **BBLS for 2024 OR** ______ **% for 2024**

6. If you sell 25%+ onsite, would you define yourself as a:

Taproom ______ **OR Brewpub** ______

7. Annual production capacity in BBLS (estimate):______

8. Employees (brewpubs, include all staff):
Total number of full-time employees______
Total number of part-time employees______

Record Number: ______
Company Name: ______
Address: ______
City, State Zip+4 ______

Form completed by: ______
Title: ______
Signature: ______
Email address: ______

Sharing this information with the Brewers Association allows us to compile industry sales volume production totals.
NOTE: Non-responding breweries will have estimated totals published. If you do not wish to have an estimated total published, please select "Do Not Publish" above or email us at bips@brewersassociation.org.
If your brewery is still in its planning stages, please provide an estimated opening date: ______

Appendix C

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

BREWERY COUNT BY STATE: 2010 - Dec 31, 2024«

Includes: All Continental United States

January 8, 2025

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
STATE	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT	COUNT
AK	20	23	25	25	28	35	36	45	51	59	66	72	75	79	80
AL	7	9	15	23	25	30	37	52	55	66	68	77	84	93	99
AR	5	7	13	18	23	29	34	44	53	58	70	76	82	90	94
AZ	37	45	55	59	77	91	110	130	146	157	170	179	184	186	197
CA	358	401	472	528	654	788	927	1,106	1,236	1,370	1,465	1,524	1,571	1,563	1,624
CO	129	149	185	234	300	352	386	448	500	544	561	586	614	619	641
CT	21	20	24	39	50	59	76	103	124	149	162	172	176	177	179
DC	4	6	5	11	12	13	13	13	13	15	17	19	21	21	22
DE	11	12	13	13	15	21	25	33	38	43	47	51	54	57	60
FL	60	71	89	113	158	205	264	338	386	464	500	531	571	598	618
GA	26	25	31	37	48	54	69	102	121	158	186	208	234	244	265
HI	11	12	15	17	20	26	23	28	38	43	44	50	52	52	53
IA	27	35	46	54	60	71	94	115	125	137	149	154	166	177	181
ID	25	33	39	42	51	57	67	76	87	101	118	120	129	136	138
IL	62	68	95	123	164	210	244	291	338	372	405	418	436	455	463
IN	43	59	72	95	116	151	163	213	234	261	277	288	295	305	311
KS	17	21	21	25	27	37	47	53	64	78	78	88	92	100	112
KY	14	21	25	25	38	48	60	73	86	105	118	128	138	147	152
LA	12	12	12	15	17	25	34	43	47	60	68	69	75	78	80
MA	48	52	65	82	98	124	146	189	230	268	293	321	340	355	367
MD	24	26	40	43	55	73	88	116	141	159	176	188	200	206	218
ME	44	49	53	60	71	84	102	131	165	186	197	212	227	235	241
MI	111	131	160	195	256	316	379	452	510	577	605	636	670	691	719
MN	42	56	70	75	113	142	165	214	239	267	286	301	314	322	331
MO	51	55	60	63	77	90	116	145	168	192	212	230	249	261	275
MS	3	*	4	7	10	14	14	16	19	22	25	32	33	35	38
MT	31	35	41	49	62	74	79	98	108	121	128	137	139	138	142
NC	61	71	94	125	155	207	260	330	387	443	491	544	578	597	613
ND	3	3	7	8	10	11	15	22	26	29	31	34	33	33	33
NE	16	18	20	25	35	39	47	53	60	67	73	78	82	81	87
NH	19	21	25	35	46	63	73	88	106	125	135	140	156	154	161
NJ	24	31	29	37	49	71	96	123	146	175	186	198	211	219	232
NM	26	30	38	48	60	71	86	110	124	143	151	155	161	159	169
NV	20	20	23	26	34	39	44	46	50	65	71	73	72	76	81
NY	100	123	150	193	255	329	394	471	532	618	666	720	762	788	822
OH	75	81	99	114	151	187	236	324	377	437	482	525	563	602	625
OK	10	10	13	17	18	21	26	43	55	76	88	95	102	108	114
OR	120	148	180	220	244	281	304	347	386	406	428	441	451	459	459
PA	118	146	162	183	233	278	333	411	472	560	619	712	761	819	854
RI	5	6	9	12	14	15	17	27	33	40	51	52	54	55	54
SC	16	17	23	30	37	51	59	84	94	115	131	149	164	172	178
SD	8	9	12	12	15	19	21	28	35	45	58	63	64	68	70
TN	26	31	45	51	69	88	101	120	140	174	196	205	220	232	243
TX	59	84	107	128	170	220	266	333	387	466	526	581	618	650	688
UT	18	18	22	24	27	29	34	39	46	54	54	55	61	65	66
VA	44	54	67	85	117	155	209	287	328	383	420	447	479	517	552
VT	32	34	39	45	51	66	73	84	90	100	106	111	117	118	118
WA	157	188	230	266	314	383	424	499	540	600	627	667	692	694	719
WI	119	126	146	146	168	189	217	261	303	346	365	374	391	407	419
WV	8	8	8	9	13	17	24	27	32	34	35	38	40	43	45
WY	16	15	19	25	28	32	33	39	44	51	51	56	59	61	64
Total	2,343	2,725	3,312	3,934	4,938	6,080	7,190	8,863	10,115	11,584	12,532	13,380	14,112	14,597	15,166

*** No reportable data**
«This list will be updated quarterly.

Data derived from TTB filesource: https://hwpsasmiddle01.ad.ttb.gov/SASStoredProcess/
Includes all breweries who hold an Active Brewer's Notice with TTB as of 10/24/2024.
Other breweries included in this count are those in a:
Bankrupt Status
Under a current Cease and Desist Order
HOLD Status due to a violation/violations
Pending Revocation Status