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Bart J. Bronnenberg, Jean-Pierre Dubé and Joonhwi Joo

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Bart J. Bronnenberg, *CentER, Tilburg University and CEPR*

Jean-Pierre Dubé, *University of Chicago Booth School of Business and NBER*

Joonhwi Joo, *University of Texas at Dallas, Naveen Jindal School of Management*

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Abstract

We conduct an empirical case study of the U.S. beer industry to analyze the disruptive effects of locally-manufactured, craft brands on market structure, an increasingly common phenomenon in CPG industries typically attributed to the emerging generation of adult Millennial consumers. We document a *generational share gap*: Millennials buy more craft beer than earlier generations. We test between two competing mechanisms: (i) persistent generational differences in tastes and (ii) differences in past experiences, or, *consumption capital*. Our test exploits a novel database tracking the geographic differences in the diffusion of craft breweries across the U.S.. Using a structural model of demand with endogenous consumption capital stock formation, we find that heterogeneous consumption capital accounts for 85% of the generational share gap between Millennials and Baby Boomers, with the remainder explained by intrinsic generational differences in preferences. We predict the beer market structure will continue to fragment over the next decade, over-turning a nearly century-old structure dominated by a small number of national brands. The attribution of the share gap to consumption capital shaped through availability on the supply side of the market highlights how barriers to entry, such as regulation and high traditional marketing costs, sustained a concentrated market structure.

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1 Introduction

> "The weakness in the received theory of choice, then, is the extent to which it relies on differences in tastes to 'explain' behavior when it can neither explain how tastes are formed nor predict their effects."(Becker, 1976, p. 133)

Concentration and markups in the U.S. manufacturing sector have been rising for the past two decades (e.g., Autor et al., 2017; Ganapati, 2018; Berry et al., 2019). However, the U.S. consumer packaged goods (CPG) industry has emerged as an exception, with the dominance of large, established national CPG brands over the past half century (e.g., Bronnenberg et al., 2007, 2009) eroding in recent years with falling sales and market shares (eMarketer eMarketer Editors, 2019):

> "In 2016, the top 20 consumer packaged goods companies saw flat sales, while smaller firms averaged 2.9% growth. This follows four years, 2011 to 2015, in which large CPG companies lost an estimated $18 billion in market share to craft manufacturers."(13D Research, 2017)

By 2018, 16,000 smaller CPG manufacturers accounted for 19% of all U.S. CPG sales, an increase of 2 percentage points ($2 billion) over the previous year. That same year, the 16 largest CPG manufacturers accounted for 31% of CPG sales, down from 33% five years earlier (eMarketer eMarketer Editors, 2019). This rapid growth of smaller brands represents a striking, structural break in the historically high and persistent concentration of CPG categories and the dominance by large, national brands.

Industry experts routinely point to a demand-side explanation for this shift, identifying the generation of *Millennials* – consumers born after 1980[1] – as the leading cause of this decline in the sales of established brands:

[1] We use the Pew Research Center definition at https://www.pewresearch.org/politics/2015/09/03/the-whys-and-hows-of-generations-research/generations_2/ accessed on 12/2/2020.

> "They want to purchase brands that better align with their own values, whether it be their dietary nutrition preferences, sustainability, philanthropy, etc." (Howe, 2018; Yue, 2019)

Surveys routinely find that Millennials seek smaller brands with more authentic products: "Natural, simpler, more local and if possible small, as small as you can."(Daneshkhu, 2018) As a result, industry experts associate these declines with a *generational share gap* fueled by Millennials with fundamentally different intrinsic preferences. A short-coming of this theory is the lack of a mechanism for understanding why Millennials might form intrinsically different tastes from older generations.

We propose an alternative *consumption capital* theory (Stigler and Becker, 1977) for these generational differences in CPG purchase behavior and the disproportionate preference for emerging craft and artisanal goods amongst Millennials. Maintaining the neoclassical assumption of stable tastes, we hypothesize that generational differences in behavior reflect heterogeneity in the accumulation of consumption and brand capital (Bronnenberg et al., 2012). Older generations of consumers had already accumulated decades of consumption capital with established, national brands by the time that new craft and artisanal CPG products started to enter. In contrast, the younger Millennial generation of consumers often had access to both craft- and established national brands as they started to form their shopping habits.

We conduct an empirical case study of the take-home segment in the U.S. beer industry, one of the leading examples of an industry disrupted by the sudden emergence of craft brands, which grew from $10 billion to $29.3 billion between 2010 and 2019.[2] Surveys indeed find a striking generational share gap with half (50%) of older Millennials (25-34 year olds) drinking craft beer, in contrast with 36% of U.S. consumers overall (e.g., Herz, 2016). As with other CPGs, Millennials may value the perception of higher quality for craft beer: 43% of Millennial generation and Generation X consumers (born between 1965 and 1980) state that craft beer tastes better than national brands, in contrast with only 32% of Baby Boomers (born between 1946 and 1964) (e.g., Mintel, 2013). Unlike earlier generations that only had access to large, established national beer brands, Millennials have had access to a wide array of craft beers since their early adulthoods,

[2] See Statista: https://www.statista.com/statistics/267737/retail-dollar-sales-of-craft-beer-in-the-us/ referenced on 12/2/2020.

leading to different lifetime consumption experiences with nationally-branded and craft beer. The recency of the availability of craft beers reflects, in part, deregulation, lower entry costs due to the automation of the brewing process, the emergence of cheaper digital advertising formats and the scalability of organic, online word-of-mouth marketing.

To test between the two theories – inherently heterogeneous generational preferences versus heterogeneous consumption capital – we exploit the geographic differences in the timing and speed of diffusion of new craft beer brewers and local *availability* of craft beer. We manually assembled a novel database from various industry sources that tracks the history of all the craft beer brands sold in the U.S. with a unique universal product code (UPC) in the take-home market. For each UPC, we observe the product attributes, including beer style and alcohol content, the launch date and location of the brewer, and the eligibility of each brewery for official "craft" designation going back to the 1970s, when the first craft brewers entered the market. We match this beer census with the Nielsen-Kilts Homescan database (HMS), containing the 2004-2018 purchase activity for a nationally representative shopping panel of over 100,000 U.S. households. During the sample period, the craft beer segment collectively increased from 5.3% in 2004 to 20% in 2018 based on revenues, and from 5% to 12% based on volume. In 2018, Millennials accounted for 20% of total craft beer sales and allocated 34% of their beer expenditures to craft brands, in contrast with 20% for the much larger group of Baby Boomers.

The endogeneity of craft brewer entry into markets combined with the potential self-selection of consumer types across markets complicates the determination of a causal effect of craft beer availability. Our empirical strategy combines the panel structure of our data, to control for persistent differences between markets, and two sets of instrumental variables that have been shown in previous work to be drivers of brewer entry decisions: current and historic local population and local time since the state-level legalization of brew pubs. Both instruments explain a substantial portion of the variation in availability across markets and time. A series of suggestive placebo tests support the hypothesized exogeneity of these instruments.

To disentangle persistent generational differences in tastes and consumption capital, we extend the brand capital stock model of Bronnenberg et al. (2012). Reduced-form analysis of the model reveals an important role for local availability in consumers' craft versus nationally-branded beers. After additionally controlling for historic availability when a consumer turned 21 and started to accumulate consumption capital, the persistent generational differences in tastes become small and statistically insignificant even though we still detect heterogeneity along other socio-economic dimensions.

The structural analysis of craft beer purchases confirms a dominant role for past experiences to drive current purchase behavior through brand capital. We estimate a slow rate of depreciation of consumption capital, indicating persistence in the effects of past experiences. In our full model, we fail to detect significant differences in persistent preferences between, for instance, Millennials and Baby Boomers. Even in a version of our structural model that restricts the availability effect to be zero, generation effects alone account for at most 34% of the generational share gap at the 5% significance level. In spite of the lack of generational heterogeneity, our structural estimates reveal heterogeneity in intrinsic preferences driven by other socio-economic traits than generation. Education moderates craft beer demand, consistent with past research on product knowledge and objective product quality (Bronnenberg et al., 2015). We also find a non-trivial income effect, likely due to the price premium typically charged for craft brands.

To quantify the role of consumption capital in driving the observed generational share gap, we conduct a series of counterfactual simulations with the model that equalize past craft brand availability across generations. We find that 85.3% of the generational share gap is explained by consumption capital. Therefore, Millennials buy craft beer at higher rates than older consumer generations; but the differences in intrinsic preferences cannot account for the disruption to the market structure of established beer brands. Instead, generational differences in craft beer demand are mostly an artifact of generational differences in the historic availability of brands during early adulthood.

To analyze the implications of consumption capital for the evolution of the market structure of the U.S. beer category, we use our estimates to predict the cross-household average annual craft beer share through 2030. Our estimates imply sustained growth in the craft beer share, reaching almost 30% of the market by 2030. This growth primarily reflects the changing composition of beer consumers as older generations die and a new generation of new adults – Generation Z – enters the market and forms beer preferences.

Our findings add to the growing literature on consumption capital accumulation and the evolution of brand tastes (e.g., Bronnenberg et al., 2009, 2012; Sudhir and Tewari, 2015). These findings bolster the important role of past experiences in our understanding of heterogeneous preferences across consumers, confirming the critical role of availability as a barrier to entry into consumer goods markets.

Our findings also illustrate how consumer preferences can be shaped over time by the supply side of the market, in this case through entry and availability. This finding suggests an important role for the literature on industry dynamics (e.g., Ericson and Pakes, 1995; Pakes and Ericson, 1998; Doraszelski and Pakes, 2006) to incorporate the inter-dependence between supply and demand on the formation of preferences and the impact on the long-term market structure.

Due to its size and history, the beer category has generated a literature unto itself (e.g., Adams, 2006; Garavaglia and Swinnen, 2017) with recent attention paid to the disruptive effects of craft brands on the industrial market structure (e.g., Elzinga et al., 2015; Elzinga and McGlothlin, 2019). We contribute to this literature by testing for and measuring consumption capital which introduces a barrier to entry for new products. We also show that the dominance of established national brands will likely continue to erode as more young consumers reach adulthood with access to a broader variety of beer products from which to choose. However, a recent wave of craft brewer acquisitions by the leading national brand manufacturers may reverse the trends in firm, as opposed to brand, concentration.

The remainder of the paper is structured as follows. We provide a brief summary of the evolution of the U.S. beer market structure and the impact of craft brewing in section 2. We describe the data in section 3. Section 4 documents the generational share gap and section 5 develops a model of consumer demand with consumption capital formation. We present our empirical strategy and results in section 6, and our counterfactual analysis of availability and its effect on the generational share gap and market structure in section 7. We conclude in section 8.

2 The Craft Beer Market

A detailed history of the beer market structure and the evolution of the craft movement is beyond the scope of this paper. We refer the interested reader to Adams (2006) for a detailed account of the U.S. beer market, to Garavaglia and Swinnen (2018) for the economic impact of the craft beer movement, and to Hindy (2014) for an industry insider's account.

Prior to the emergence of craft brewers, the beer industry was highly concentrated by the 1970s, dominated by Anheuser-Busch, Miller, Schlitz and a small group of other macrobreweries. Technological innovation in brewing and packaging coupled with mass advertising, especially on television, established high barriers to entry (Adams, 2006; Noel, 2009; Garavaglia and Swinnen, 2018). To generate scale economies, U.S. brewers mostly supplied lager beers[3] described by expert Michael Jackson as "lacking hop character and generally bland in palate," (Alworth, 2015, p. 29) making "the beer landscape blander and more boring." 99% of beer consumed in the U.S. was pale lager beer (Elzinga et al., 2015).

The timing of the start of craft brewing coincided with the elimination of a legal barrier to entry.[4] In February 1979 (e.g., Elzinga et al., 2015), President Carter repealed prohibition-era restrictions on home brewing, with H.R. 1337 legalizing home brewing federally and allowing states to begin implementing their own laws. This repeal was not in response to changing beer demand, but rather part of Carter's broader agenda to deregulate and "reduce excessive government intrusion into the private affairs of American citizens."[5] While many craft brewers started off as home brewers, it was not until 1982 that Washington became the first state to legalize commercial brewpubs, triggering a series of state-level laws across the U.S. that legalized commercial sale of craft beer and modified the corresponding licensing fees and taxes. By 1990, over half the states had legalized brewpubs, and by 1999, all states had legalized brewpubs (Elzinga et al., 2015).

The take-off of the craft beer market share was initially slow due to poor pricing practices, high costs and a quasi-monopoly over distribution by the incumbent macrobreweries that led to waves of shakeouts in the 1980s and 1990s (e.g., Hindy, 2014; Noel, 2018). With the exception of the Boston Beer Company, few craft brewers had the financial resources to rely on traditional media – television and radio advertising – to generate awareness and build brands. The legalization of brewpubs "provided perhaps millions of Americans with their first encounters with craft beer." (Acitelli, 2017, p.217) The rise of the internet in the early 1990s is widely believed to have catalyzed growth in the craft market share: "The internet has arguably been the greatest ally of

[3]Scale economies are even more pronounced for lager beers that incur higher fixed costs from the need for more artificial cooling and longer fermentation times than other beer styles, like ales (Garavaglia and Swinnen, 2018).

[4]The brewing trade press times the debut of the U.S. craft beer movement to 1965, when Fritz Maytag took over the Anchor Steam Beer Company and focused operations on traditional beer flavors produced in small scale and emphasizing its local "made in San Francisco since 1896" image (Acitelli, 2017).

[5]This statement comes from Carter's debate with Reagan on October 28, 1980. Accessed on 8/22/2020 at https://www.debates.org/voter-education/debate-transcripts/october-28-1980-debate-transcript/.

the craft beer revolution. [...] Today nearly every craft brewer has a website and someone to talk directly to its customers and fans through social media." (Hindy, 2014, p.144). The disruptive force of the internet is not exclusive to the beer industry. It has also disrupted numerous CPG categories by facilitating successful start-ups like Dollar Shave Club, for razors, and Barkbox, for pet supplies.[6] In addition, "Associations of craft consumers, craft brewers, and homebrewers helped expand the market by spreading information and experiences, and being a vehicle for new forms of marketing (often via the internet, social media, and special events)."(Garavaglia and Swinnen, 2017, p. 43). The merger of the Association of Brewers and the Brewers' Association of America in January of 2005 allowed small brewers to organize to compete more effectively (Hindy, 2014), leading to a take-off in the segment that reached 3,490 U.S. craft breweries by 2015, in contrast with only 249 in 1990.

In addition to the erosion of barriers to entry, demand-side factors also likely contributed to the recent take-off in craft beers supplied to the market. Rising incomes enabled beer consumers to pay the price premium associated with a craft product supplied at a higher marginal production costs. Consumers may also genuinely perceive a superior-quality taste from beers brewed using traditional, small-scale methods. Alternatively, consumers may value the authenticity of a local, small-scale product. Macro brewers also attempted to counteract craft brewers by launching their own traditional-beer-style brands such as Blue Moon, by Coors, and Budweiser American Ale, by Anheuser-Busch. Thus far, such corporate launches have not been successful at dominating craft brewers outside the pale lager style category. However, the recent wave of acquisitions of successful craft brewers by Anheuser-Busch, Miller-Coors and other large macrobreweries does not appear to have decreased demand for those brands even after losing their craft status (Elzinga and McGlothlin, 2019). None of these demand-side factors suggest why Millennials per se would be the drivers of craft beer market share growth.

Since craft brewers represented mostly a fringe of the U.S. beer market until the early 2000s, most generations of consumers reached the legal drinking age of 21 facing a choice set comprising primarily large macrobreweries selling established brands of pale lager beers. Only the youngest

[6]According to the 2019 Online Consumer Packaged Goods Report, 34 CPG companies appeared in the top-1000 internet retailers, 19 of which sell and manufacture consumer brands. Just like the recent wave of acquisitions of craft brewers by Anheuser-Busch, many established CPG conglomerates in other product categories have begun acquiring digital start-ups such as Unilever's $1billion acquisition of Dollar Shave Club and Campbell Soup's recent $10million investment in Chef'd.

Generation X and Millennial consumers had access to craft brands on the shelves at the moment they reached the legal age to drink. Our focus herein is to test for such a timing effect on demand and to measure its relative magnitude compared to persistent generational differences and other socio-economic drivers of demand.

3 Data

3.1 Beer Characteristics

We manually assemble a census of bar coded, non-draught beers available in the U.S. using the digital repositories at three industry associations: the Brewers' Association (BA), the American Breweriana Association (ABA), and the website ratebeer.com. For each Universal Product Code (UPC), we observe the corresponding brewer, style (e.g., ale, lager, stout, etc.), alcohol by volume (ABV), quality ratings (on a 1-5 scale) and, most importantly, craft status. In total, we observe 36,214 unique UPCs.

We classify a brewer, and by association each of its UPCs, as *craft* if it meets either of the following criteria: (i) ratebeer.com classifies the brewer as a "Microbrewery", "Brew Pub" or "Brew Pub/Brewery" in 2018; or (ii) the BA has classified the brewer as "independent craft brewer" in 2018. We assume that any brand that is classified as craft in 2018 has always been a craft beer since its launch.[7] This classification includes many well-known craft brewers, including those that have expanded across states and to the national level, like Yuengling or the Boston Beer Company (widely known for its Sam Adams brand). In total, 63% of the UPCs (22,130) satisfy our craft definition.

While our craft classification scheme reflects the criteria of the leading beer association, the BA, it nevertheless excludes a few former craft brewers, such as Goose Island in Chicago, that were acquired by macro brewers like Anheuser-Busch during the sample period, even though consumers may continue to perceive their brands as craft. This exclusion affects the craft share in 2018 by only 0.6%.

We classify all other UPCs in our data as national brands produced by macro brewers. While

[7]Neither the BA nor ratebeer.com reports historic time-series data on past, annual craft designations.

this set includes many, often small, foreign brewers, macro brewer volume is highly concentrated amongst the largest brewers such as Anheuser-Busch, Heineken, and Miller-Coors.[8]

As expected, national brands are differentiated from craft brands along several dimensions. We observe a quality rating for 92% of the UPCs. On average, national brands are lower quality than craft beers with average ratebeer.com ratings of 2.4 and 3.3 (out of 5), respectively. National brands also tend to have a lower alcohol content, with an average ABV of 5.3% compared to 6.5% for craft beers. Some of these quality differences may reflect differences in beer styles. National brands are most likely to be lager style, whereas craft brands are most likely to be Indian Pale Ale (IPA), Pale Ale, or Amber Ale. For instance, the average quality rating of a national brand is 2.1 out of 5 in the lager category and 3.3 in the IPA category. But, even after residualizing on beer style and alcohol content, national brands are still significantly lower quality than craft beers with average ratings of 2.35 and 2.84, respectively (F-stat 7,570). This quality difference is consistent with the standard perception that craft beers have better flavor due to their production methods and ingredients. Therefore, for the remainder of the analysis, we focus on the differences in demand for craft versus national brand beers rather than focusing more granularly on demand for specific beer styles.

3.2 Household Panel Data

We use the Nielsen Homescan Panel (HMS) of U.S. households between 2004 and 2018 to measure households' beer purchases in the take-home market. The take-home market consists of prepackaged, bar-coded beer products sold for home consumption in retail outlets such as supermarkets, mass merchants, convenience stores, drug stores and liquor stores. The database contains 186,233 unique households during the sample period, with an average of about 39,000 households per year from 2004-2006 and 61,000 households per year from 2007-2018. For each household, we observe the date of each trip to a store selling beer along with the specific products purchased, as designated by their unique UPC, and the corresponding quantities and prices paid net of discounts. For each year, we retain those households that purchase beer at least once using the Nielsen product modules "Beer," "Near Beer," "Stout and Porter," "Light Beer," and "Ale" (i.e., module codes

[8]Using our Nielsen HMS data from 2004-2018, the top 10 macro brewers combined represent 88% of total beer volume purchased by our HMS panelists and 95% of macro brewer volume.

5000, 5001, 5005, 5010, and 5015, respectively). Our HMS data contain beer purchases from 104,115 unique households.

We match the HMS data with Nielsen's annual demographic survey of panelists to determine a household's income and size (# members). We also use the age (in years) and education attainment of the head of household, defined as the oldest head of household reported in the Nielsen demographic survey. Education attainment takes on one of six categorical values: Grade School, Some High School, High School Diploma, Some College, 4-year College degree, and Post College Degree. For household income, we use the mid-point of each of the 16 income brackets reported in the survey, top-coding the "above $100,000" category at $150,000.

We classify each household into a generation based on the year of birth of the oldest current head of household. We use the Pew Research Center's generation definitions as follows[9]:

- Millennial Generation: born between 1981 and 1996
- Generation X (hereafter GenX): born between 1965 and 1980
- Baby Boom Generation (hereafter BB): born between 1946 and 1964
- Silent Generation (hereafter SG): born between 1928 and 1945
- Greatest Generation (hereafter GG): born before 1928.

Since our sample period ends in 2018, we have a very small number of adults born after 1996 who are technically part of Generation Z (born after 1996). For our empirical analysis, we combine these households with the Millennials.

Each HMS household is assigned to a Nielsen Scantrack based on its geographic location. Most Scantracks represent a large metropolitan area (e.g., San Diego) or a part of a state (e.g., West Texas). However, 20% of beer buying HMS households live in rural areas that are not covered by a Scantrack definition and, hence, are classified as "Remaining U.S.." We cannot assign historic information regarding craft brand availability to these households, and therefore these households are discarded from our analysis. This leaves us with 83,187 households, which we use as our final sample.

[9] https://www.pewresearch.org/fact-tank/2019/01/17/where-Millennials-end-and-generation-z-begins/ accessed on 12/15/2020

We match the remaining HMS households' beer purchases with the beer characteristics database using UPCs and brand names. We successfully match over 95% of the UPCs purchased by our HMS panelists, accounting for 97% of the total beer volume purchased during the sample period. HMS panelists purchase 20,816 unique beer UPCs, or 57% of all UPCs available in our beer characteristics file. Recall that our original beer attribute file tracks an approximate census of all beer sold in the U.S. take-home market during the sample period, whereas the HMS sample only tracks those beers purchased by the panelists.

Our final HMS beer sample consists of 2.6 million unique beer transactions from 83,187 unique households. Table 1 describes the sample. The average household remains in our sample for 4 years, with the 5th and 95th percentile tenure of 1 year and 13 years, respectively. On average, a household conducts 6.8 transactions per year; with the 5th and 95th percentile frequency of 0.7 and 29.0, respectively. The average household purchases 166.9 ounces of beer per trip (slightly more than a 12-pack of 12-oz bottles or cans). Of all sizes, 12-pack cases constitute the most frequently-chosen pack size, accounting for 25.2% of all transactions. Finally, households spend an average of $11.94 per trip, with the 5th and 95th percentile expenditure levels of $4.28 and $22.38, respectively.

For the analysis below, we collapse the HMS transaction panel to 270,347 household-year observations. For each household, we compute the annual craft share of beer volume purchased. Table 1 describes the sample. While the average annual household craft purchase share is 14.2%, we observe a large degree of heterogeneity with 10th and 90th percentile shares of 0% and 67%, respectively.

We also observe a diverse set of households in the sample. Across households and years, the average age of household heads in our purchase data is 54 years with 90% of the household-years between 32 and 78. The average number of years of education is 15, with 90% of the households between 12 and 18 years. The average annual household income is $65K, with 90% between $17.5K and $120K. Finally, the average household size is 2.6 members, with 90% of households having between 1 and 5 members.

Finally, across households and years, 4% of our observations are Millennials, 18% GenX, 52% BB, 23% SG and 3% GG. The share of Millennials in our sample grows from 0.1% in 2004 to 11.2% in 2018 (or to 19.6% in 2018 if we use Nielsen's projection factors to re-weight households for national representativeness). Even though Millennials are the youngest panelists in our sample, they have completed more years of education than older generations and have comparable incomes. For instance, the average Millennial has 16 years of education in 2018 and earns an average income of \$73K. In comparison, the average years of education and average income in 2018 is 15 and \$74K, respectively, for BBs and 16 and \$81K, respectively, for GenXs.

—– include Table 1 here —–

3.3 A Measure of Local Craft Beer Availability

Even though our HMS purchase data reflect retail beer sales, we expect consumer awareness for craft beer to be influenced by local craft entrepreneurship more broadly, including brew pubs and other craft beer establishments with on-premise sales. We use the BA, ABA, and ratebeer.com digital archives to assemble an annual census of U.S. brewers by market from 1979 to 2018.

To determine the number of local craft brewers, we use the ABA's census of U.S. brewers, which contains each brewery's geographic location along with its opening and, when applicable, closing date. We match the brewer census with the ratebeer.com and the BA databases, retaining only those brewers satisfying the craft criteria defined in section 3.1 above. Since many of the brewers in this broader sample do not sell beer with a unique UPC, we use a fuzzy matching scheme to determine their craft status. See Appendix A for details regarding the matching criteria.

To verify that our craft census did not admit any macro brewers, we processed the remaining brewer names against a pre-determined list of substrings like "Anheuser," "Miller," and "Molson" from the largest non-craft brewers representing 99% of the non-craft beer volume in our HMS sample. After removing all additional matches, we classify all the remaining brewers as craft.

We normalize the craft beer availability in each market using the annual census of U.S. macro brewers compiled in the Elzinga-Tremblay-Tremblay database (Elzinga et al., 2015) spanning the period from 1979 to 2012. While the census ends in 2012, the total number of macro brewers was quite small and stable with 19 brewers between 2007 and 2012. Therefore, we assume the number of macro brewers remained stable at 19 through 2018. Finally, we assume macro brewers' products were available in all markets.

To measure availability, let N^C_{mt} denote the number of craft brewers in market m during year

t. As explained in section 2, craft brewers first emerged in 1979 with the legalization of home brewing. Therefore, $N^C_{mt} = 0 \; \forall t < 1979$. Since we assume that macro brewers are available in all markets, we let N^{NB}_t denote the count of macro brewers in year t. We use the local share of craft brewers in each market m and year t as our availability index: $D_{mt} = \frac{N^C_{mt}}{N^C_{mt}+N^{NB}_t}$.

We observe rapid growth in the number of local craft brewers, N^C_{mt}, during our sample period. The cross-Scantrack average grew from 20 in 2004 to 67 in 2018. In 2004, the cross-Scantrack minimum, maximum, and standard deviation of N^C_{mt} were 2 (Birmingham, AL), 79 (Portland, OR) and 18. For 2018, these numbers were 6 (Memphis, TN), 300 (Denver, CO), and 61.

The whisker plot in Figure 1 displays the corresponding two-year, cross-Scantrack distribution of our availability index, D_{mt}, between 1978 and 2018. Two patterns emerge. First, we observe substantial cross-market heterogeneity in the availability of craft brewers and the rate of growth. Not only do we observe growth in the median availability, we also observe growth in the inter-quartile range across markets. Second, we observe two national, industry-wide waves of craft brewer entry, first in the early 1990s and later in the 2010s. Interestingly, the lower bound of the centered 90% quantile interval grows most rapidly in the final years of the sample as the laggard markets *catch up* with their craft beer availability.

—– include Figure 1 here —–

This heterogeneous evolution in availability across markets generates useful variation in the extent of craft beer available when our panelists turned 21 and were legally able to buy beer. Figure 2 displays the distribution of D_{mt} at 21 years old by generation. Since the craft beer movement did not start until 1979, D_{mt} is mechanically zero for our two oldest generations: Greatest Generation and Silent Generation. Even for the Baby Boomers (the youngest of whom turned 21 in 1985), the average availability is quite low, less than 0.1, due to the fact that the average number of local craft brewers for this generation in the year they turned 21 is 1. For GenX, the average is approximately 0.18. But, for Millennials, the average availability of local craft brewers in the year they turned 21 is almost 0.4, more than double the availability for GenX.

—– include Figure 2 here —–

3.4 Population Data

To determine each Scantrack's population from 1969 through to 2018, we use the regional population data provided by the National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) Program.[10] The SEER data track annual, county-level population. We then use Nielsen's mapping between FIPS codes and Scantracks to determine the Scantrack populations.

3.5 State-Level Brewpub Laws

We use Elzinga et al. (2015, Table 2) to determine the exact year each U.S. state legalized commercial brewpubs, enabling local home brewers to sell their beer at a small scale while by-passing the three-tier distribution system required for larger brewers. Even though homebrewing was federally legalized in 1978, only in 1982 did Washington become the first state to legalize brewpubs, and it was not until 1999 that Mississippi and Montana became the last two states to legalize brewpubs. Due to the nature of diffusion, we expect the number of years since state legalization to be predictive of the diffusion of brewpubs and, accordingly, to predict some of the cross-state differences in craft beer availability.

3.6 Census Data

To determine the rate at which new Millennial and Generation-Z consumers reach adulthood and enter the beer market after the sample period, we use the Census projections for 2019-2030.[11] For each year, these projections include total U.S. population with a breakdown by age. We also use these projections to determine the mortality rates for our older generations of beer consumers.

4 Craft Beer and the Generational Share Gap

We begin by using the HMS sample to document the generational differences in craft beer purchase behavior. Due to their smaller production scale and emphasis on higher-quality ingredients, craft and artisanal consumer products tend to be more expensive. Therefore, we also anticipate that

[10]https://seer.cancer.gov/popdata/ accessed on 8/16/2020.

[11]https://www2.census.gov/programs-surveys/popproj/datasets/2017/2017-popproj/np2017_d1_mid.csv accessed on 12/10/2020

demand for craft products will depend, in part, on socioeconomic status (SES). Since SES likely correlates with generations, we control for SES in our analyses. In particular, we use household income, household size, and household education to control for SES and factors correlated with SES.

Craft beer has disrupted the long-established dominance of macro brewers and their established brands. The left panel of Figure 3 plots the annual national craft share both in volume and dollars. The craft share of volume grew from approximately 5%, in 2004, to approximately 12%, in 2018. The revenue share grew even faster, largely due to the craft price premium, reaching nearly 20% of beer sales in 2018. The 2018 HMS craft volume and revenue shares are close to the 13.2% and 24.1% reported by the BA for the entire U.S. market.[12] Even amongst the largest macro brewers, overall revenues have increasingly fragmented over time as acquired craft brewers represent an increasing portion of their sales. In Figure 4, we show that AB-InBev's HHI across its owned breweries has decreased from 0.986 in 2004 to 0.852 in 2018. This decline largely reflects the declining share of AB-InBev revenues coming from its two top brands, Budweiser and Bud Light, for which the share fell from 49.1% in 2004 to 40.9% in 2018. By 2018, 33% of the craft beer volume sold was supplied by brewers that had been acquired by a macro brewer. In sum, the recent growth in craft beer has fragmented both the category as well as some of the largest firms' revenue sources.

—– include Figure 3 here —–

—– include Figure 4 here —–

During this same period, we also observe rapid growth in the number craft UPCs purchased by HMS panelists. The total annual count increased from 1,008 (32% of all UPCs purchased by panelists), in 2004, to 4,961 (67% of all UPCs purchased by panelists), in 2018. In contrast, the total number of macro brew UPCs purchased by HMS panelists remained quite stable with 2,185 in 2004 and 2,460 in 2018. These findings are consistent with the escalation in craft brewer entry and stable macro brewer presence during our sample period, as described in section 3.3. These patterns are suggestive of a role for availability and variety in the growth of the craft beer segment.

[12]https://www.brewersassociation.org/press-releases/brewers-association-releases-annual-growth-report/#:~:text=In%202018%2C%20small%20and%20independent,7%20percent%20growth%20over%202017 accessed on 9/8/2020.

Our main interest is in the role of Millennial consumers in driving the growth of craft beer. The right panel of Figure 3 displays the evolution of each generation's share of craft beer purchased. Due to their young age, Millennials represented less than 1% of craft volume in 2004. By 2018, Millennials accounted for almost 20% of craft volume sold in spite of the much larger number of Baby Boomer households in the U.S.. With the exception of Millennials, every other generation's share of craft volume sold decreased between 2004 and 2018. Therefore, even though all generations are purchasing craft beer, Millennials are driving most of the growth.

Figure 5 displays our key stylized fact: the *generational share gap*. The bars indicate each generation's mean annual craft share of beer volume sold across households and years. The diamonds indicate the analogous mean craft share for each generation, residual of our SES controls. Households belonging to the Greatest Generation have a low craft beer share at 6%. In contrast, Millennials have a 19% share, 11.5 percentage points higher than Baby Boomers and 7 percentage points higher than GenXers. These pooled differences may confound the changing composition of household generations through our sample period. Focusing on 2018, our most recent sample year, the generational share gap is even larger with Millennials purchasing 34% craft beer versus 13% for the Greatest Generation and 20% for Baby Boomers. This share gap is robust to SES controls, even though each generation's mean annual share decreases after residualizing on SES. The remainder of the paper seeks to explain the 12 percentage-point generational share gap between Millennials and Baby Boomers. In the next section, we test and quantify the relative roles of intrinsic generational differences in preferences and generational differences in historic brand experiences that generate the accumulation of consumption capital for craft beer brands.

—– include Figure 5 here —–

5 A Consumption Capital Stock Model of Demand

To quantify the extent to which differences in craft beer purchases across generations reflects intrinsically different preferences versus consumption capital accumulation, we use the consumption capital stock model from Bronnenberg et al. (2012). Unlike the rational addiction literature which treats consumption capital as a habit (e.g., Becker and Murphy, 1988), we think of consumption capital herein as the component of a consumer's preference for craft beer due to past consumption experiences. The model allows us to disentangle the extent to which a consumer's craft purchase behavior is driven by persistently different preferences versus different historic consumption experiences and availability.

We model each consumer's choices between craft brands (CB) and national brands (NB). On a given purchase occasion, a consumer derives the following incremental utility from choosing a craft beer instead of a national brand:

$$\Delta U = \alpha \mu (D, X, \xi) + (1 - \alpha) k - \nu$$

where $\mu (D, X, \xi)$ represents the consumer's baseline utility, which depends on the observed availability of craft brands, D, on the consumer's generation and SES, X, and on other unobserved consumer-specific factors of that year, ξ. $\mu (D, X, \xi)$ captures the treatment effect of the contemporaneous choice environment. The variable $k \in (0, 1)$ denotes the consumer's *consumption capital* stock at the start of the year and $\alpha \in (0, 1]$ determines the relative importance of accumulated consumption capital on current choices. Finally, $\nu \sim \text{Uniform}(0, 1)$ is an i.i.d. random utility shock drawn at each purchase occasion.

If the consumer makes beer brand purchases to maximize her conditional indirect utility then she chooses CB if $\Delta U \geq 0$. The corresponding expected CB share of beer purchases is

$$y = \alpha \mu (D, X, \xi) + (1 - \alpha) k, \tag{1}$$

which is the linear probability model of demand (e.g., Heckman and Snyder, 1997).

The consumer's stock of consumption capital evolves as a discounted average of her past consumption:

$$k_A = \frac{\sum_{a=21}^{A-1} \delta^{A-a} y_a}{\sum_{a=21}^{A-1} \delta^{A-a}} \tag{2}$$

where $A \geq 22$ is the consumer's current age and y_a is the consumer's CB purchase share at age a. To initialize consumption capital, we assume $k_{21} = \mu (D_{21}, X, \xi_{21})$. The degree of persistence in past consumption on current beer choices is determined by the parameter $\delta \geq 0$. Therefore, evolution in the availability of craft brands not only changes a consumer's contemporaneous choices through

(1), it also influences her subsequent consumption capital accumulation through (2).

To see the connection between this model and the traditional human capital stock accumulation models (e.g., Becker, 1967), we can re-write the consumption capital stock (2) recursively as follows:

$$k_A = k_{A-1}\left(1-\rho_A\right) + y_{A-1}\rho_A \tag{3}$$

where

$$\rho_A = \frac{1-\delta}{1-\delta^{A-21}}. \tag{4}$$

See Appendix B.1 for the proof. Conceptually, the net contribution to consumption capital at the end of each period, $k_A - k_{A-1}$, depends on the gross investment, $\rho_A y_{A-1}$, and depreciation, $\rho_A \in [0,1]$. At age 22, $\rho_{22} = 1$ and a consumer only responds to current availability and marketing, $\mu\left(D_{22}, X, \xi_{22}\right)$. In contrast, as a consumer ages, her consumption capital becomes less sensitive to recent choices and the recent choice environment. The persistence parameter, δ, governs the relative role of current versus past experiences on consumption capital. Note that $\lim_{\delta\to 0}\rho_A = 1$, $\lim_{\delta\to 1}\rho_A = \frac{1}{A-21}$, and $\lim_{\delta\to\infty}\rho_A = 0$. Consequently, when $\delta < 1$, consumption capital is affected more by consumers' most recent experiences, and when $\delta > 1$, consumption capital is affected more by their earliest experiences during adulthood than recent experiences. Unlike the literatures on investment in education and health capital (e.g., Grossman, 2000), we assume consumers are myopic about their consumption capital (i.e., consumers do not plan ahead for future years' craft beer consumption and associated consumption capital accumulation).

To derive our empirical formulation, we can re-write expected demand at age $A \geq 21$ as a weighted sum of the consumer's experiences with past choice environment:

$$y_A = \sum_{a=21}^{A} \omega_{A,a}\mu\left(D_a, X, \xi_a\right) \tag{5}$$

where

$$\sum_{a=21}^{A} \omega_{A,a} = 1, \omega_{A,a} \geq 0\ \forall A, a.$$

See Appendix C for the proof. Therefore, demand is a distributed lag over a consumer's entire history of access to craft beer brands during her adult life (i.e., since 21). At the heart of our empirical test for whether differences in craft purchase propensities reflect intrinsic differences in preferences versus differences in past brand experiences is the relative importance of differences between consumer generations in $\mu\left(D_a, X, \xi_a\right)$ versus $\left\{D_a\right\}_{a=21}^{A}$.

For our empirical implementation of the consumption capital model above, we re-cast the model in calendar time. We define the contemporaneous choice environment in year t for a consumer h living in market $m(h)$ as follows:

$$\mu\left(D_{m(h)t}, X_h, \xi_{ht}\right) = \phi\left(X_h;\Lambda\right)\mathbb{I}_{\left\{D_{m(h)t}>0\right\}} + \gamma D_{m(h)t} + \xi_{ht} \tag{6}$$

where

$$\begin{aligned}\phi\left(X_h;\Lambda\right) \quad = \quad & \beta_0 + \sum_{g\in\mathscr{G}}\mathbb{I}_{\{gen_h=g\}}\beta_g^{gen} + \sum_{e\in\mathscr{E}}\mathbb{I}_{\{educ_h=e\}}\beta_e^{educ} + \\ & \beta^{inc}\text{Income}_h + \beta^{size}\text{HouseholdSize}_h + \sum_{m\in\mathscr{M}}\mathbb{I}_{\{mkt_{ht}=m\}}\lambda^{mkt}\end{aligned}$$

represents a consumer's time-invariant taste for craft beer and $\Lambda = \left(\beta', \lambda'\right)$ is the vector of intrinsic preference parameters, and X_h contains a household's generation and SES variables. $\mathscr{G}$, $\mathscr{E}$ and $\mathscr{M}$ are the sets of observed generations, education levels, and Scantrack markets, and $\mathbb{I}_{\{\cdot\}}$is the indicator function. The interaction with the indicator $\mathbb{I}_{\left\{D_{m(h)t}>0\right\}}$ ensures that expected craft demand is only positive when craft beer is available. ξ_{ht} is a mean-zero, unobserved (to the econometrician) contemporaneous demand shock.

Using (5), we can therefore write consumer h's craft beer share in year t as a distributed lag over her adult life experiences with craft beer:

$$y_{ht} = \phi\left(X_h;\Lambda\right)\varpi_{ht}\left(\delta,\alpha\right) + \sum_{\tau=t-A_{ht}+21}^{t}\omega_{A_{ht},A_{h\tau}}\left(\delta,\alpha\right)\left(\gamma D_{m(h),\tau}\right) + \tilde{\xi}_{ht} \tag{7}$$

where the weights $\omega_{A_{ht},A_{h\tau}}\left(\delta,\alpha\right)$ depend on the consumer's age in the current year t and past year τ respectively, as well as the non-linear parameters $\left(\delta,\alpha\right)$, and $\varpi_{ht}\left(\delta,\alpha\right) = \sum_{\tau=t-A_{ht}+21}^{t}\omega_{A_{ht},a_{h\tau}}\left(\delta,\alpha\right)\mathbb{I}_{\left\{D_{m(h)\tau}>0\right\}}$ is the sum of the weights over those adult years during which craft beer was available. Thus, for a consumer that has always had craft beer available during her adult years (e.g., younger Millennials), $\varpi_{ht}\left(\delta,\alpha\right) = 1$. $\tilde{\xi}_{ht} = \sum_{\tau=t-A_{ht}+21}^{t}\omega_{A_{ht},a_{h\tau}}\left(\delta,\alpha\right)\xi_{h\tau}$ is the composite error term, a weighted average of historic demand shocks and therefore $\mathbb{E}\left(\tilde{\xi}_{ht}\right) = 0$ and $\text{var}\left(\tilde{\xi}_{ht}\right) < \infty$ since

$\sum_{\tau=t-A_{ht}+21}^{t} \omega_{A_{ht},a_{h\tau}}(\delta,\alpha) = 1$ and $A_{ht}\ (\geq 21)$ is finite.

6 Structural Analysis of Demand

6.1 Endogeneity of Availability

There is good reason to expect craft beer availability to be exogenous to individual consumer demand. As recently as 2009, Charlie Papazian, founder and president of the BA, explained: "I'd say over 90 percent of small brewers I talk to today have roots in home brewing,"(Beato, 2009) such that most craft brewers did not originate with the intention to generate profits per se. Since our analysis controls for persistent between-market differences, the endogeneity would need to arise from differential cross-market trends in unobserved demand. We envision two potential sources of endogeneity bias. First, to the extent that craft brewers endogenously time their entry into a market based, in part, on unobserved aspects (to the researcher) of demand, $\tilde{\xi}_{ht}$, this simultaneity could bias NLLS estimation of equation (7). In addition, there is potential measurement error in our availability variable.

One potential source of measurement error arises if local brewers serves as an imperfect proxy for perceived availability. Since the direction of the simultaneity bias from endogenous availability is difficult to determine without a full-blown model of entry, it is difficult a priori to determine the net effect of measurement error and simultaneity on a NLLS estimator that treats availability as exogenous. A potential source of measurement error in historical availability rates arises from households moving between markets prior to the sample period. We conduct two robustness checks to rule out a bias due to unobserved moves. First, for the $3,521$ moves that are observed during the sample period we observe the correct availability history and, although not reported herein, our findings do not change if we assume these households always lived in their most recent market. In a separate analysis, we used only those HMS panelists who responded to Bronnenberg et al. (2012)'s Panelviews migration survey, allowing us to determine the correct availability history prior to the sample period. Appendix Table 2 reports almost identical OLS estimates of the current and lagged availability effects in reduced-form versions of (7) that correct versus do not correct for moves prior to the sample period.

To instrument for availability, we turn to the industrial organization literature on entry and market structure in the U.S. beer industry to determine the exogenous influences on the local entry of craft brewers into a market. A full-fledged analysis of the industry dynamics of entry and exit in the U.S. beer market is beyond the scope of this paper.[13] However, the recent empirical literature studying the endogenous formation of the industrial market structure has routinely found population, a proxy for potential market size, to be a critical determinant of market structure (Sutton, 1991; Bresnahan and Reiss, 1991), including in the U.S. beer industry specifically where population predicts the historic number of local competing brewers (Manuszak, 2002; Elzinga et al., 2015). We use each Scantrack market's annual population as our proxy for market size. We also use the number of years elapsed since each U.S. state legalized commercial brewpubs, allowing for differential timing of diffusion across states. Although not reported herein, we also collected a detailed database tracking changes in state and federal craft brewing laws related to permits and fees; but these instruments had no power in explaining availability variation.

Figure 6 visualizes the correlation between the population instrument and the differential rate of diffusion in craft beer availability across geographic markets and time. Each panel corresponds to a year, $t \in \{1980, 1985, 1990, 1995, 2000, 2005, 2010, 2015\}$. Within each panel, we plot a circle for each of our 53 Scantrack markets, with diameter proportional to that year's availability, D_{mt}. We also use shading of each circle to represent that year's population.

—– include Figure 6 here —–

To quantify the power of the two instruments, we analyze the first stage of a linear version of an IV estimator that includes current availability along with generation, SES and market-specific effects and clusters standard errors on Scantrack-year combinations. We obtain an incremental F-statistic for contemporaneous population of 468.83.[14] Adding every 5th lag in population as far back as 35 years prior to the current year generates a joint incremental F-statistic (current and lagged population) of 110.14. Adding years since the state legalized brewpubs further increases the power of the incremental F-statistic to 312.9. Persistent Scantrack differences explain 65% of

[13]A related literature has also studied the role of recent large-scale mergers, acquisitions and joint ventures on the industrial market structure of beer (e.g., Tremblay et al., 2005; Ashenfelter et al., 2015; Miller and Weinberg, 2017; Elzinga and McGlothlin, 2019).

[14]If we instead pool all 2,120 unique Scantrack-years from 1979 (start of craft brewing) to 2018 and regress availability on contemporaneous population, we obtain an incremental F-statistic of 2,255.11.

the variation in availability, D_{mt}. Adding our excluded population instruments explains 80% of the variation in D_{mt} and adding years since the state legalization of brewpubs explains 89%. In all these specifications, the effect of both current population and years since the state legalization of brewpubs are positive and statistically significant.

Formally, our key identifying assumption is that in any year s,

$$\mathbb{E}\left(\xi_{hs}q_{m(h,s)s}\right) \quad = \quad 0$$

where $q_{m(h,s)s}$ is the population in year s and the market, $m(h,s)$, where household h lived in year s. We have an analogous moment for the number of years since the state legalized brewpubs. We cannot formally test these assumption. However, even after residualizing on market fixed effects, the scantrack population is uncorrelated with the prevalence of beer drinkers (i.e., share of HMS panelists with positive beer expenditures in a market-year) and also uncorrelated with the prevalence of Craft beer drinkers (i.e., the share of HMS panelists with positive expenditures on craft beer in a market-year), generating correlations of –0.020 (0.035) and 0.038 (0.034), respectively, where standard errors are in parentheses.[15] Therefore, areas with higher population growth are not systematically attracting more beer drinkers or more craft beer drinkers, factors that could indicate strong local beer-drinking trends.

We also conduct two placebo tests. First, we test whether markets and years where contemporaneous local panelist SES variables predict high craft share also tend to have higher populations. We predict household-year craft shares using market fixed effects and SES variables. We use these estimates to predict the Scantrack-year level expected share. We find that population and years since the state legalization of brewpubs are both negatively associated with this predicted Scantrack-year share, so that if anything, population and the elapsed time since legalization both tend to be smaller in markets with higher craft brand shares.

We also test whether markets and years where contemporaneous craft beer availability is high also tend to have higher populations or tend to be markets that were earliest to legalize brewpubs. In this case, we predict Scantrack-year availability using SES variables and Scantrack fixed-effects. Once again, we find negative associations between predicted availability and population and years

[15] We use the Nielsen projection factors to ensure our Scantrack panelists are representative of the actual population

since state brewpub legalization, respectively.

6.2 A GMM Estimator

We now derive the GMM estimator of the structural demand equation (7). The reduced form of the demand model (7) consists of a high-dimensional distributed lag over each annual level of craft availability during a consumer's entire adult life, with the weights on each lagged availability dependent on the consumer's current age. However, as shown in Appendix C, the structural form of the model mechanically imposes restrictions over the weights on each lagged availability level, reducing the estimation problem to three parameters (δ, α, γ) in addition to the linear parameters on generation and SES, Λ. These restrictions reduce the number of necessary identifying moments required for identification.

We construct a set of moment conditions based on the econometric errors, $\tilde{\xi}_{ht}$, to estimate our key model parameters:

$$\begin{aligned} &\mathbb{E}\left(\tilde{\xi}_{ht}\mathbf{q}_{m(h,t-s),t-s}\right) = 0,\ s \in \{0, ..., 35\} \\ &\mathbb{E}\left(\tilde{\xi}_{ht}\mathbf{B}\right) = 0,\ \forall h \end{aligned} \tag{8}$$

where

$$\tilde{\xi}_{ht} = y_{ht} - \varpi_{ht}\left(\delta, \alpha\right)\left(X_h\beta + \lambda_{m(h)}\right) - \sum_{\tau=t-A_{ht}+21}^{t} \omega_{A_{ht},a_{h\tau}}\left(\delta, \alpha\right)\left(\gamma D_{m(h),\tau}\right),$$

$\mathbf{B}$ is a matrix of household characteristics, including generation and SES, and $\lambda_{m(h)}$ is the Scantrack-market fixed effect. The excluded instruments, $\mathbf{q}_{m,t-s}$, consist of contemporaneous and lagged values of population in the corresponding market m in year $t-s$. Recall that the reduced-form of demand (7) has age-specific coefficients on each of the lagged values of historic availability. We therefore also use interactions between historic population and a consumer's current age as instruments in $\mathbf{q}$. Since we only observe population data as far back 1969, we cannot include lags beyond 35 years prior to the sample period. Finally, we also include the number of years since the state for market m legalized brewpubs.

We can define our GMM estimator as follows

$$(\delta,\alpha,\gamma,\Lambda)^{GMM} = \underset{(\delta,\alpha,\gamma,\Lambda)}{\operatorname{argmin}}\, \mathbf{g}(\delta,\alpha,\gamma,\Lambda)'\,\mathbf{\Phi}\mathbf{g}(\delta,\alpha,\gamma,\Lambda) \tag{9}$$

where $\mathbf{\Phi}$ is a weight matrix and $\mathbf{g}(\delta,\alpha,\gamma,\Lambda)$ is the vector of mean sample moments (8) with k^{th} element $\mathbf{g}_k(\delta,\alpha,\gamma,\Lambda) = \sum_h \sum_t g_{hkt} \equiv \sum_h \sum_t \tilde{\xi}_{ht} q_{m(h)kt}$. Appendix D provides technical details on the implementation of the GMM estimator. In particular, we exploit the linearity of the model in $\phi(X_h;\Lambda)$ to derive analytic expressions for Λ^{GMM}, allowing us to reduce the numerical optimization of (9) to a nonlinear search over the three parameters (δ,α,γ).

The identification of the structural parameters $(\delta,\alpha,\gamma,\Lambda)$ is straightforward. The linear parameters, Λ, are identified off the persistent differences in shares across panelists. The nonlinear parameters, (δ,α,γ), are identified off the variation in current and historic values of the population instruments, $\mathbf{q}$. The reduced-form of demand (7) has age-specific coefficients on each of the lagged values of historic availability. We therefore also use interactions between historic population and a consumer's current age as instruments. The separate identification of the multiplicative effects of α and γ comes from the fact that the weights in the distributed lag sum to one: $\sum_{a=21}^{A} \omega_{A,a}(\delta,\alpha) = 1,\ \forall A$.

6.3 Reduced-Form Estimates

We begin the empirical analysis with descriptive evidence that the supply-side variable availability, current and historic D_{mt}, have a material impact on demand. As explained above, even the reduced-form of our demand model is a high-dimensional distributed lag with interactions between age and lagged availability. To make the evidence more transparent, we estimate a quasi-reduced-form that includes only current availability and historic availability during the Scantrack-year when the primary shopper turned 21 to assess the role of historic experiences. In Table 2, we report the results of six specifications. All standard errors are clustered at the Scantrack-year level. In the first specification, we include only our intrinsic preferences: $\phi(X_h;\Lambda)$. This specification corresponds to the structural model with the restrictions $\alpha = 1$ and $\gamma = 0$. In the third specification, we add the effect of current availability, instrumented using current population. This specification corresponds to the structural model with the restrictions $\alpha = 1$ and $\delta = 0$; although technically δ could take on any value since it no longer affects choices in this specification. In the fourth specification, we also add availability at age 21, instrumented using the population in the corresponding Scantrack-year, as a proxy for consumption capital stock. The second specification reports the OLS analog of specification four, treating both current and lagged availability as exogenous. Finally, specifications five and six assess the robustness of our IV estimates in specifications three and four to an alternative instrument: "years since state legalization of brewpubs."[16] Our estimates are almost identical with the two sets of instruments, an important robustness check since the timing of state brewpub legalization could plausibly reflect evolving demand for craft beer.

—– include Table 2 here —–

When we ignore the role of availability, we find a large generational share gap of 17 percentage points between Millennials and the Greatest Generation (our base generation), and 15 percentage points between Millennials and Baby Boomers. However, controlling for availability reduces the generational gap between Millennials and Baby Boomers to 11 percentage points. If we control for both current availability and availability at age 21, the gap between Millennials and Baby Boomers falls to 6 percentage points. Interestingly, our other SES variables appear to be robust to the inclusion of controls for availability. We also find that IV generates a larger effect of current availability on demand and a slightly smaller gap between Millennial and Baby Boomers. As explained in section 6.1, the smaller OLS estimate of the availability effect most likely reflects attenuation bias from measurement error in our availability measure, which overwhelms any simultaneity bias from endogenous craft brewer entry. That said, to determine the direction of bias on the OLS coefficients for availability, we would need to determine the equilibrium relationship between craft brewer entry and unobserved demand shocks, requiring an entry model that is beyond the scope of this paper. Using column 6 of Table 2, we fail to reject that the Millennial craft beer share based purely on intrinsic preferences would be as high as 6.7% at the 5% significance level. In 2018, Millennials accounted for 11% of our households and craft volume accounted for 12% of beer sold. Therefore, Millennials' intrinsic preferences account for at most 0.7% of the 2018 craft share. Even if every

[16]As established in section 6.1, the instruments are not under-powered. The incremental F-statistics for the excluded "population" instruments in the first-stage regressions are 491.88 and 373.69 for availability and availability at age 21, respectively (i.e., specification four). The incremental F-statistics for the excluded "years since brewpub legalization" instruments in the first-stage regressions are 965.78 and 1995.79 for availability and availability at age 21, respectively (i.e., specification six).

household had Millennials' intrinsic preferences, we would still only account for 56% of the craft beer share in 2018. In Table 1 of Appendix F, we show that our reduced-form results are robust to the inclusion of annual fixed-effects for each of our sample years.

In sum, the reduced-form analysis demonstrates that controlling for historic availability of craft beer leads to a lower generational share gap, suggestive of our brand capital theory. In the next section, we use our consumption capital model to account for a household's entire adult history of experiences and to quantify the role of consumption capital as a driver of the generational share gap and of the growth in craft beer.

6.4 Structural Estimates

Turning to our structural analysis, Table 3 summarizes the results from several specifications that compare the GMM results to a standard NLLS estimator, and which also assess robustness to the inclusion of SES variables.[17] Each GMM specification uses every 5th lag of availability to construct the moments $\mathbb{E}\left(\tilde{\xi}_{ht}\mathbf{q}_{m(h,t-s),t-s}\right)$. In Table 3 of Appendix F, we show that our results are robust to the inclusion of more lags in the instrument matrix. Columns 5 and 6 of Table 3 also include "years since state legalization of craft breweries" as an instrument. All standard errors are clustered at the Scantrack-year level, which corresponds to the frequency of our availability variables. Interestingly, most of our GMM and NLLS estimates are qualitatively similar, especially two of our three key structural parameters: δ and α. However, our GMM point estimate of γ is larger than our NLLS estimate, a difference that is statistically significant. Once again, the differences in magnitude between GMM and NLLS likely reflect bias in the latter due to measurement error in availability. In a series of Monte Carlo simulations (available upon request) we indeed find that measurement error in the historic availability variables would attenuate γ, with only small effects on δ and α. Although, as discussed above, the direction of bias also requires determining the equilibrium relationship between craft brewer entry and unobserved demand shocks, which is beyond the scope of this paper.

—– include Table 3 here —–

[17]GMM and NLLS were both implemented in Matlab using IPOPT with analytic gradients. For each specification, the optimization was conducted with 100 independently and randomly generated starting values for (δ, α, γ). The global optimization was assessed by selecting the run with the minimum criterion value across those runs that generated an exit flag indicating a local optimum.

For the remainder of our analysis, we focus on our main GMM specification in column 4 of Table 3, which controls for market fixed effects and SES variables but does not include "years since state legalization of brewpubs" as an instrument. Our results are very similar regardless of whether we use column 4 or column 6 as our preferred specification; but we view the orthogonality of demand shocks and the state law instrument as less defensible than population, for instance if the timing of legislative change was influenced by a consumer lobby. In the model, α ultimately determines the relative importance of consumption capital stock versus preferences in driving craft share. δ determines the relative importance of recent versus historic brand experiences and γ determines the relative importance of availability versus SES in the determination of preferences. As anticipated, local craft beer availability contributes to the relative preferences consumers exhibit for craft brands versus national brands: $\gamma > 0$. The relatively high value of δ implies a high degree of persistence in the impact of historic availability (i.e., past experiences) in the determination of the consumption capital stock. Our point estimates of δ are slightly higher than those in (Bronnenberg et al., 2012), allowing for the possibility that the earliest beer experiences in an adult's life weigh more heavily than more recent experiences, a finding that potentially reflects the habit-forming nature of alcoholic beverages. The high value of δ also suggests that differences in past experiences across generations lead to differing amounts of consumption capital, especially when we consider the large fraction of adult years with no craft beer for Baby Boomers or Silent Generation consumers. Finally, the estimate of α close to 0.5 indicates that consumers' craft purchase propensities are almost equally driven by consumption capital and current point-of-sale factors.

To quantify the degree of persistence in consumption capital, Figure 7 reports the depreciation rate of consumption capital, ρ_A as in equation (4), for each age between 20 and 100. As expected, the depreciation rate drops as a consumer ages, so that consumption capital decays more slowly later in life. If we use the age profile of each of the generations in 2018, we can see that Greatest Generation, Silent Generation and Baby Boomer consumers have all reached nearly zero decay by 2018. However, we see a lot of heterogeneity amongst Millennials, with even the older Millennials exhibiting annual decay rates between 0.5 and 0.1. In sum, Millennials ultimately exhibit relatively malleable beer preferences even as late as 2018. In contrast, older generations' preferences exhibit persistent, established brand capital, formed during years with limited or no craft availability.

—– include Figure 7 here —–

Turning to the role of intrinsic preferences, we already saw in the reduced-form analysis that controlling for SES and availability (current and historic) decreases the differences between generations by more than 50%. Using the structural model to control for a consumer's entire availability history nearly eliminates all the generational differences in intrinsic preferences. We fail to reject that Millennials and Baby Boomers have the same intrinsic preferences for craft beer and we can reject differences larger than 5.8 percentage points, which is only 34% of the magnitude of the generational share gap in Table 2 when we restrict $\alpha = 1$ and $\gamma = 0$ (no availability effects) and only 55% of the magnitude when we restrict $\alpha = 1$ and $\delta = 0$ (only current availability effects).

Even though the generational differences shrink, we nevertheless detect several empirical regularities in the role of household SES variables on craft beer demand that have been echoed in the surveys and trade press surveyed earlier. Education is an important determinant of craft beer share: a college-educated primary shopper buying 10.8 percentage points more craft beer than primary shoppers that failed to complete high school; although we cannot rule out the difference is as low as 9.4 percentage points at the 5% significance level. Given the artisanal nature of craft beer, the education effect potentially captures the role of knowledge about quality and the health benefits of locally-produced, small-scale production goods (e.g., Bronnenberg et al., 2015).

We also observe a strong income effect, with each \$100,000 of annual household income contributing 7.7 additional percentage points of craft beer share; although we cannot rule increments as low as 6.8 percentage points at the 5% significance level. This finding follows logically from the price premium typically charged for craft beer.

We now quantify the relative importance of the various factors contributing to the intrinsic taste component of craft demand, $\phi(X_h;\Lambda)$. We define the total range of possible intrinsic preferences as: $\phi^{range} = \max_h (\phi(X_h;\Lambda)) - \min_h (\phi(X_h;\Lambda))$. To determine a given household trait's importance to intrinsic preferences, we look at the fraction of this range it represents. We compute the following importance weights for each of generation, education of household head, household income, household size and market:

$$
\begin{aligned}
\text{imp}^{gen} &= \frac{\text{range}\left\{\beta_g^{gen}, g \in \mathscr{G}\right\}}{\phi^{range}} \\
\text{imp}^{edu} &= \frac{\text{range}\left\{\beta_e^{edu}, e \in \mathscr{E}\right\}}{\phi^{range}} \\
\text{imp}^{inc} &= \frac{\beta^{Inc}\left(\max\limits_h(\text{income}_h) - \min\limits_h(\text{income}_h)\right)}{\phi^{range}} \quad . \qquad (10) \\
\text{imp}^{size} &= \frac{\beta^{size}\left(\max\limits_h(\text{hhSize}_h) - \min\limits_h(\text{hhSize}_h)\right)}{\phi^{range}} \\
\text{imp}^{mkt} &= \frac{\text{range}\left\{\beta_m^{mkt}, m \in \mathscr{M}\right\}}{\phi^{range}}
\end{aligned}
$$

Each importance weight indicates the fraction of the heterogeneity in intrinsic preferences accounted for by the corresponding underlying factors (i.e., generation, SES and market). Table 4 lists the parametric bootstrap estimates of the mean and standard errors for each importance weight. The importance of generation is 0.053, or merely 5% of the heterogeneity in intrinsic preferences. In contrast, the importance of education and market fixed effects are much higher at 0.271 and 0.453, respectively. Finally, the importance of income and family size are 0.142 and 0.145, respectively. The large relative importance of education relative to income is suggestive that knowledge-related factors might be more important than income in determining who buys craft beer. In sum, we find evidence of important differences between households' intrinsic preferences due to SES variables. However, contrary to the established wisdom amongst marketing practitioners and the trade press (e.g., Daneshkhu, 2018; Howe, 2018; Yue, 2019), we fail to detect large generational differences in intrinsic preferences for craft beer. It follows then that the generational share gap must arise from consumption capital, which we explore in the next section.

—– include Table 4 here —–

7 The Generational Share Gap and Market Structure

We now conduct two sets of counterfactual analyses. First, we quantify the extent to which consumption capital drives the generational share gap. Then we analyze the extent to which evolving consumption capital, especially amongst younger consumers, will continue to fragment the U.S. take-home beer industry.

7.1 Availability and the Generational Share Gap

We now use our structural estimates to assess our key research objective: the relative magnitude of preferences versus past experiences in driving the generational share gap in craft beer purchases. We conduct two counterfactuals. First, we predict each Millennial's purchase share when their birth year is counterfactually set to 1946, the first year of the Baby Boomer generation. Second, we predict each Millennial's purchase share when we additionally set their persistent generational preferences to those of Baby Boomers. For each scenario, we conduct a parametric bootstrap from the asymptotic distribution of our GMM estimates and report the corresponding mean and standard errors.

More formally, we begin by predicting the factual expected craft share for each generation $g \in \mathscr{G}$:

$$\mathbb{E}\left(y_{ht}|X_{ht},\mathbf{D}_{m(h)t},A=A_{ht}\right)=\phi\left(X_{ht}\right)\varpi_{ht}+\sum_{\tau=t-A+21}^{t}\omega_{A,\tau}\left(\gamma D_{m(h),\tau}\right),\ \forall h \text{ such that } \mathbb{I}_{\{gen_h=g\}}=1 \tag{11}$$

where A_{ht} is the current age of the primary shopper for household h in year t. The first column of Table 5 reports the cross-household mean of the fitted values for each generation in year $t = 2018$. As expected, we see large differences in the shares between each generation. In particular, the generational share gap between Millennials and Baby Boomers is 12.6 percentage points; although we cannot rule out a gap as small as 11.6 percentage points or as large as 13.6 percentage points at the 5% significance level.

—– include Table 5 here —–

To measure the generational share gap, we conduct a counterfactual prediction of the shares when we change each household's birth year to 1946 and their generation assignment to Baby Boomer, holding the SES variables at their true values:

$$\mathbb{E}\left(y_{ht}|X_{ht}^{BB},\mathbf{D}_{m(h)t},A=A_{ht}^{BB}\right) \tag{12}$$

where A_{ht}^{BB} sets the consumer's age to that of someone born in 1946 and X_{ht}^{BB} sets the element $\mathbb{I}_{\{gen_h=BB\}}=1$. Note that changing the age effectively changes the weights assigned to historic availability levels in past years τ to $\omega_{A_{ht}^{BB},\tau}$. Column two of Table 5 reports these counter-factual shares. By comparing columns one and two, we avoid the confounding effect of SES differences. For Millennials in particular, the mean craft beer share of their Baby Boomer analogs is 21% in 2018. We can then measure the generational share gap of interest as follows:

$$\Delta y^{BB} = \mathbb{E}\left(y_{ht}|X_{ht},\mathbf{D}_{m(h)t},A=A_{ht}\right) - \mathbb{E}\left(y_{ht}|X_{ht}^{BB},\mathbf{D}_{m(h)t},A=A_{ht}^{BB}\right),\ \forall h \text{ s.t. } \mathbb{I}_{\{gen_h=Millenial\}}=1. \tag{13}$$

We obtain a cross-Millennial-household mean generational share gap for Millennials of $\Delta y^{BB} = 12.4$ percentage points in 2018; although we fail to reject values as low as 11.4 percentage points and as high as 13.5 percentage points at the 5% significance level.

To isolate the effect of past experience, we run a second counterfactual that maintains each household's SES values and generation assignment, but only changes their birth year to A_{ht}^{BB}. Column three of Table 5 reports these counterfactual shares, $\mathbb{E}\left(y_{ht}|X_{ht},\mathbf{D}_{m(h)t},A=A_{ht}^{BB}\right)$, for 2018. We can then measure the partial generational share gap due to past experience:

$$\Delta\tilde{y}^{BB} = \mathbb{E}\left(y_{ht}|X_{ht},\mathbf{D}_{m(h)t},A=A_{ht}\right) - \mathbb{E}\left(y_{ht}|X_{ht},\mathbf{D}_{m(h)t},A=A_{ht}^{BB}\right),\ \forall h \text{ such that } \mathbb{I}_{\{gen_h=Millenial\}}=1. \tag{14}$$

We obtain a partial generational share gap due to experience for Millennials of $\Delta\tilde{y}^{BB} = 10.6$ percentage points; although we fail to reject values as low as 6.9 percentage points and as high as 13.9 percentage points at the 5% significance level.

We now turn to the main objective of the study, the measurement of the experience share:

$$\Gamma^{BB} = \frac{\Delta\tilde{y}^{BB}}{\Delta y^{BB}} \tag{15}$$

which measures the fraction of the generational share gap due to past experiences. We find a Millennial experience share of $\Gamma^{BB} = 0.853$; although we fail to reject experience shares as low as 0.562 and as high as 1.072 at the 5% significance level. The upper bound above 1 reflects the fact that our estimates cannot reject the possibility that that Millennials have a lower intrinsic taste for craft beer than Baby Boomers at the 5% significance level.

In sum, contrary to the widespread view in the trade press, the role of Millennials in driving craft beer growth is not due to a fundamentally different preference from older generations. We find that most of the generational share gap arises from differences in consumption experiences, especially when consumers reach the legal age to buy alcohol and start forming a strong brand preference. Only the youngest Generation X consumers and Millennials had access to a wide variety of craft beers from an early part of their adult lives. We find that this difference in availability is a major determinant of the relatively high craft beer share amongst Millennial consumers. Namely, established brands were afforded the early-mover advantage that helped them defend their shares amongst older generations; but not amongst younger generations. These findings are consistent with the view that the lower barriers to entry into the beer category due to low online marketing costs and the organizational benefits of the Brewers Association will likely help craft brands continue to erode the shares of established brands.

7.2 The Impact of Craft Beer on the Long-Term Market Structure

We now investigate the longer-term implications of craft beer for the on-going evolution in the U.S. beer market structure.

We use our demand estimates to conduct a simulation of the evolution of the craft beer market share relative to national macro brewers during the 12-year period immediately after our sample, 2019-2030. Our simulation predicts the expected household-level craft volume share, as opposed to the national craft beer share of volume sold that was reported in Figure 3. We use the 2018 sample of households, thinning the older-generation panelists subject to the mortality rates from the U.S. Census. We also use the Census data to adjust the sample for the emerging Generation Z population reaching 21 years old. Each new Generation Z adult consumer is assigned to a Scantrack in proportion to the population size of these Scantracks and endowed with the SES variables of a randomly chosen 2018 Millennial from that same Scantrack. See Appendix E for details.

We also investigate the role of the evolution of craft beer availability in our simulation. In our base simulation, we use the observed availability for the year up until 2018, holding availability fixed thereafter: $D_{mt} = D_{m,2018}, \forall t \in [2019, 2030]$. In a second simulation, we allow availability to evolve after 2018 using a forecast based on the observed availability index between 1978 and

2018. Again, see Appendix E for details.

Figure 8 summarizes the cross-household mean, annual volume share between 2004 and 2030. The solid line corresponds to the actual availability levels from 2004-2018, holding availability fixed at the 2018 levels from 2019-2030. The hatched line shows how the forecasted shares between 2019 and 2030 change when we allow availability to continue evolving. To assess the predictive fit of our forecasts, we also use the solid triangles to report the observed cross-household mean volume share, $\frac{1}{N_t}\sum_{h=1}^{N_t} y_{ht}$ where y_{ht} is the observed craft share for household h in year t. The share predictions fit well in-sample, i.e., between 2004 and 2018.

—– include Figure 8 here —–

The predicted craft beer share increases from 22.6%, in 2018, to 27.1%, in 2030, under the assumption of constant availability. Under constant availability, we therefore predict an additional 19.9% growth in the craft share relative to 2018, driven primarily by the changing composition of generations. See Appendix E for details. The increase in craft share is only in small part (9%) due to existing beer drinkers still changing their purchases in response to the 2018 levels of availability. In contrast, most of the increase (91%) stems from low-share Silent Generation consumers gradually being replaced by new Generation Z consumers who, like Millennials, are exposed to a large assortment of craft beer as soon as they reach 21 and start purchasing craft beer. When we allow availability to continue to evolve after 2018, we see slightly stronger growth with the craft share reaching 28.0% of the volume by 2030, a growth rate of 23.8% relative to 2018.

With the continued projected growth in craft beers through 2030, we also analyze whether we will see any convergence in Millennial and Baby Boomer craft purchasing behavior over the next 12 years. We compare the predicted, mean craft share across our sample of observed Millennials and our sample of observed Baby Boomers, respectively. In fact, our predictions suggest that the difference in expected craft shares for Millennials and Baby Boomers will slightly diverge over this time period, increasing from 17.3% in 2004 to 17.5% in 2030. The divergence reflects the fact that, while both Baby Boomers and Millennials continue to accumulate consumption capital for craft beer, Millennials accumulate capital more quickly. The faster Millennial capital growth reflects the lower rate of depreciation, ρ_A, especially for younger members of that generation (see Figure 7). Given the relatively low capital depreciation rate for Baby Boomers, it is unlikely that the generational share gap Δy^{BB} discussed in section 7.1 would converge, all else equal.

In summary, we predict a continued growth in the craft beer share over the next decade, fueled primarily by the emergence of new consumers with no prior history during the era of the macro-brewed-lager oligopoly. Even with no future growth in availability, we still anticipate craft beer reaching more than 27% of the market share.

8 Conclusions

Contrary to established wisdom in the trade press, we do not find that Millennial consumers have intrinsically different preferences for craft brands than older generations, at least for our case study of craft beer. Rather, we attribute most of the generational share gap to differences in historic experiences with craft beer availability. Older generations of consumers formed their preferences during a period when craft beers were not available. This consumption capital stock matches with other research showing how consumers form brand preferences over time (e.g., Bronnenberg et al., 2012; Sudhir and Tewari, 2015). With craft and artisanal brands emerging in other consumer goods categories, it will be interesting to test whether a similar consumption capital theory explains strong Millennial preferences more generally.

Our findings also suggest that as craft brands continue to build awareness and distribution through the internet and other non-traditional channels, the entry barriers afforded to established brands through intensive television advertising will likely continue to erode over the next decades. Accordingly, we expect to see a decline in the persistence of dominance of the twentieth century's large CPG brands.

An interesting direction for future research consists of incorporating the formation of consumer preferences into a dynamic model of entry and exit to see how preferences may be shaped in tandem with the underlying market structure over time. Another related interesting direction for future research consists of studying the role of mergers and acquisitions in the persistence of dominance of established, incumbent CPG manufacturers. In the beer industry, large macro brewers are increasingly seeing their revenues fragment as they acquire craft brewers, as opposed to launching successful new products. Macro brewer revenues and overall market shares would be substantially lower but-for these recent craft brewer acquisitions.

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Tables

Table 1: Household demographics of beer purchasers.

Variable	Mean	Std.dev	Percentile 5^{th}	Percentile 95^{th}	N
Number of years in panel	3.975	3.892	1.000	13.000	83187
Number of purchases	31.188	101.611	1.000	134.000	83187
Number of purchases per year	6.847	15.755	0.667	29.000	83187
Volume purchased per year	166.941	256.285	49.778	360.000	83187
Dollars per year	11.942	9.748	4.280	22.380	83187
Age (years)	53.910	13.774	32.000	77.500	83187
Number of years education	15.102	1.976	12.000	18.000	83187
Household income ($1,000)	65.307	33.105	17.500	120.000	83187
Household size (#)	2.610	1.287	1.000	5.000	83187

Note: Age corresponds to the oldest household head. Number of years education corresponds to maximum number of years of education across household heads.

Table 2: Reduced-form analysis of craft beer demand

	OLS				IV				IV			
Variable	coeff.	(se)	coeff.	(se)	coeff.	(se)	coeff.	(se)	coeff.	(se)	coeff.	(se)
Greatest Generation	0.000		0.000		0.000		0.000		0.000		0.000	
Silent Generation	0.005	(0.003)	-0.007	(0.003)	-0.010	(0.003)	-0.010	(0.003)	-0.010	(0.003)	-0.010	(0.003)
Baby Boomers	0.021	(0.003)	-0.000	(0.003)	-0.004	(0.003)	-0.005	(0.003)	-0.004	(0.003)	-0.005	(0.003)
Generation X	0.064	(0.004)	0.018	(0.004)	0.030	(0.004)	0.005	(0.007)	0.030	(0.003)	0.005	(0.007)
Millennials	0.169	(0.006)	0.075	(0.006)	0.106	(0.006)	0.046	(0.016)	0.107	(0.005)	0.046	(0.016)
Availability share			0.284	(0.008)	0.354	(0.015)	0.345	(0.014)	0.351	(0.011)	0.345	(0.011)
Availability share at 21			0.102	(0.010)			0.143	(0.036)			0.144	(0.036)
Scantrack fixed effects	√		√		√		√		√		√	
Population IV					√		√		√		√	
Brewpub legalization IV									√		√	
R^2	0.080		0.093		0.059		0.060		0.059		0.060	
N	270347		270347		270347		270347		270347		270347	

Note: This table uses the 2004-2018 HMS beer sample at the household-year level. The dependent variable in each specification is the household's annual craft share of beer volume purchased. Availability measures the craft share of brewers using D_{mt} as in subsection 3.3. We use the Greatest Generation (the oldest in our sample) as our base generation cell. All regressions control for household SES (annual income, education years, and household size). Standard errors are clustered at the market-year level. The first set of IV estimates use annual scantrack population and population at 21 as instruments for availability and availability at 21, while the second set of IV estimates ads years since state legalization of brewpubs to the population instruments.

Table 3: Structural model estimates

	NLLS				GMM1				GMM2			
δ	0.929	(0.009)	0.944	(0.007)	0.995	(0.020)	1.006	(0.022)	0.998	(0.020)	1.007	(0.022)
α	0.472	(0.017)	0.475	(0.016)	0.485	(0.055)	0.497	(0.057)	0.490	(0.054)	0.499	(0.056)
γ	0.480	(0.010)	0.451	(0.009)	0.623	(0.063)	0.580	(0.059)	0.637	(0.062)	0.589	(0.057)
Greatest Generation	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-
Silent Generation	0.007	(0.004)	-0.010	(0.005)	0.005	(0.005)	-0.013	(0.005)	0.005	(0.005)	-0.014	(0.005)
Baby Boomers	0.022	(0.004)	-0.005	(0.005)	0.021	(0.005)	-0.009	(0.005)	0.021	(0.005)	-0.009	(0.005)
Generation X	0.039	(0.005)	0.004	(0.005)	0.020	(0.008)	-0.017	(0.010)	0.019	(0.007)	-0.017	(0.009)
Millennials	0.095	(0.006)	0.057	(0.006)	0.053	(0.019)	0.017	(0.021)	0.051	(0.019)	0.016	(0.020)
Grade School			0.000	-			0.000	-			0.000	-
Some High School			-0.021	(0.021)			-0.022	(0.017)			-0.022	(0.017)
High School			-0.008	(0.020)			-0.007	(0.017)			-0.007	(0.017)
Some College			0.027	(0.020)			0.032	(0.017)			0.032	(0.017)
College			0.078	(0.020)			0.087	(0.017)			0.087	(0.017)
Post College			0.138	(0.020)			0.151	(0.018)			0.151	(0.018)
Income ($100K)			0.073	(0.002)			0.077	(0.004)			0.076	(0.004)
Family Size			-0.011	(0.001)			-0.012	(0.001)			-0.011	(0.001)
Observations	270347		270347		270347		270347		270347		270347	
Parameters	60		67		60		67		60		67	
Function value	0.090		0.087		0.13e-03		0.18e-03		0.14e-03		0.18e-03	

Note: This table uses the 2004-2018 HMS beer sample at the household-year level. The dependent variable in each specification is the household's annual craft share of beer volume purchased. All specifications include market fixed effects. Standard errors clustered at the scantrack-year level and reported in parentheses. We use a two-step GMM estimator to obtain the efficient weights. In GMM1, to address the potential endogeneity of current and lagged availability, we include 16 moment conditions based on excluded instruments: current population, every 5th year of lagged population up to 35 years prior to the sample period and interactions of each of these 8 instruments with the primary shopper's current age. In GMM2, we add the number of years since legalization of brewpubs in each state as an additional instrument. Standard errors are clustered at the market-year level.

Table 4: Relative importance of generation, socio-economic status and market

	importance weight	standard error
Generation	0.053	(0.024)
Education	0.271	(0.013)
Income	0.142	(0.006)
Family size	0.145	(0.007)
Market effects	0.453	(0.025)

Note: This table reports the estimated importance weights, 10, for each of the factors driving intrinsic tastes. The reported point estimates and standard errors are based on 500 IID draws from the asymptotic distribution of our GMM estimates (column 4 of Table 3).

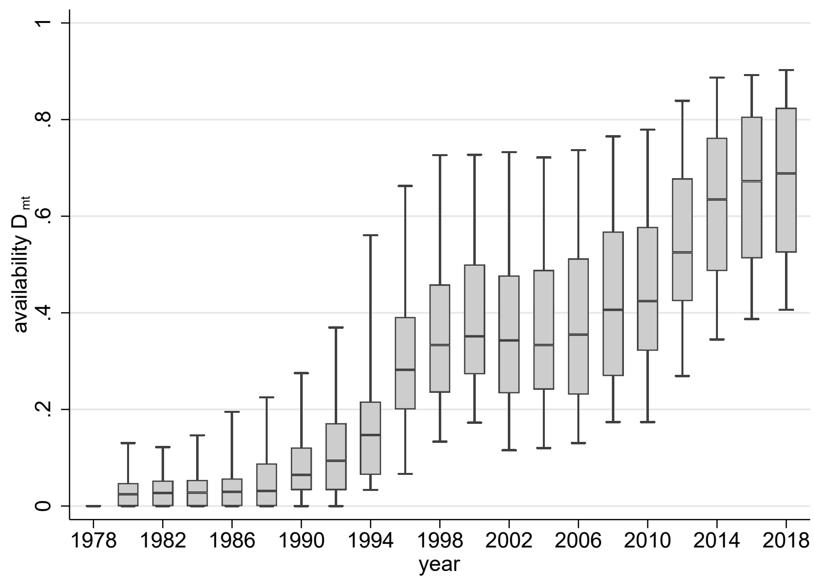
Table 5: Decomposing the generational share gap

	$\mathbb{E}\left(y_{ht}\|X_{ht},\mathbf{D}_{m(h)t},A_{ht}\right)$	$\mathbb{E}\left(y_{ht}\|X_{ht}^{BB},\mathbf{D}_{m(h)t},A_{ht}^{BB}\right)$	$\mathbb{E}\left(y_{ht}\|X_{ht},\mathbf{D}_{m(h)t},A_{ht}^{BB}\right)$
Greatest Generation	0.178	0.185	0.185
	(0.005)	(0.005)	(0.005)
Silent Generation	0.185	0.191	0.188
	(0.004)	(0.004)	(0.004)
Baby Boomers	0.205	0.199	0.199
	(0.003)	(0.004)	(0.004)
Generation X	0.249	0.202	0.197
	(0.004)	(0.004)	(0.006)
Millennials	0.331	0.207	0.225
	(0.006)	(0.004)	(0.015)

Note: This table reports the counterfactual predicted share levels of each generation as we eliminate heterogeneity in past experiences and intrinsic preferences. Standard errors in parentheses. The reported point estimates and standard errors are based on 500 IID draws from the asymptotic distribution of our GMM estimates (column 4 of Table 3).

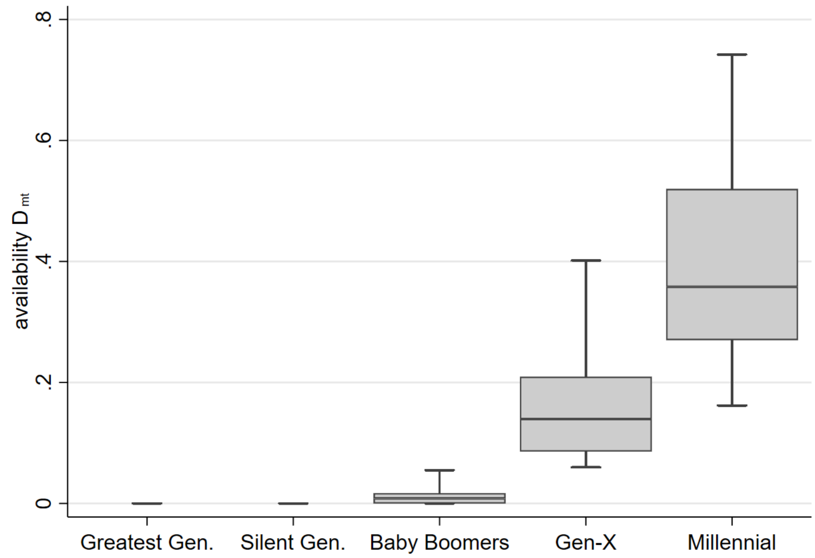
Figures

Figure 1: Craft beer availability across markets and years



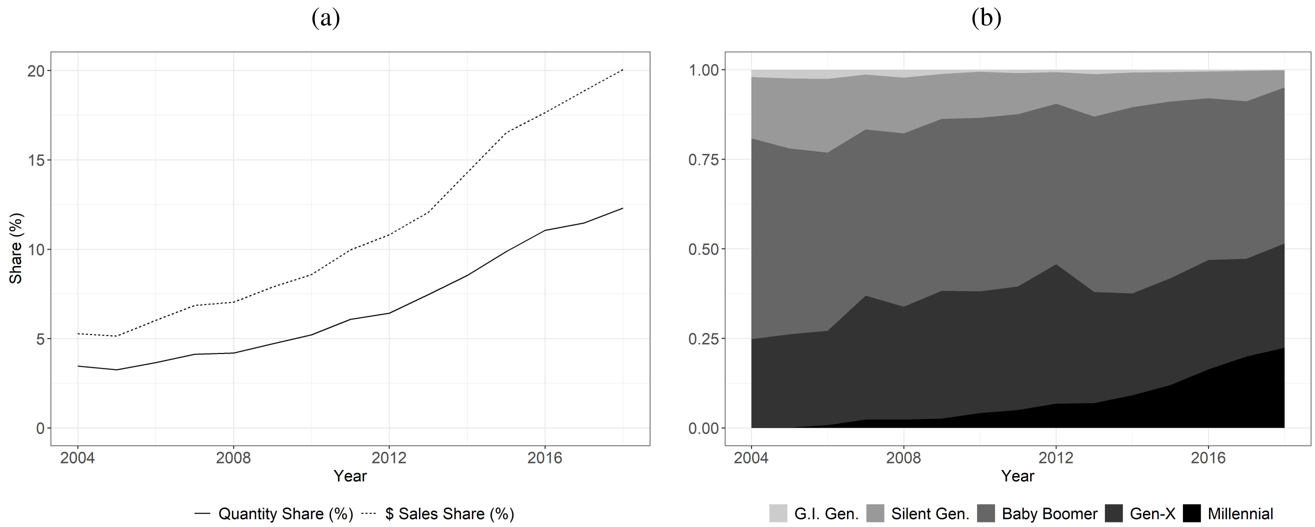
Note: This figure presents the annual, cross-market distribution of our availability measure, D_{mt}. The bars represent the inter-quartile range (IQR) across markets each year. The whiskers represent the interval between the upper and lower 5^{th} percentiles across markets each year and the center lines represent each year's median availability across markets.

Figure 2: Local craft beer availability when consumers turned 21



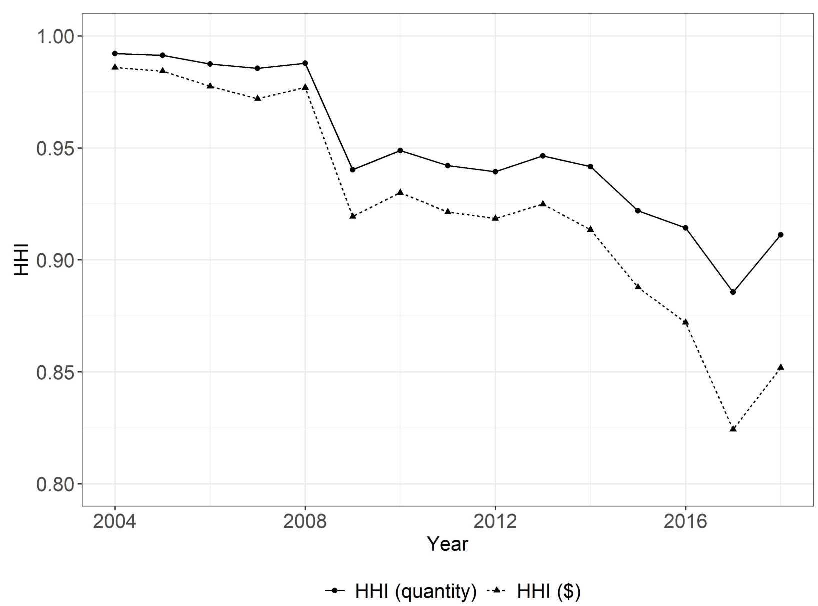
Note: This figure presents each generation's cross-household distribution of availability when a household's oldest shopper turned 21, $D_{m(h)\tau_{21}}$. The bars represent the inter-quartile range (IQR) across households. The whiskers represent the interval between the upper and lower 5^{th} percentiles across households and the center lines represent each generation's median availability at 21 across households.

Figure 3: Craft beer share and its decomposition by generation



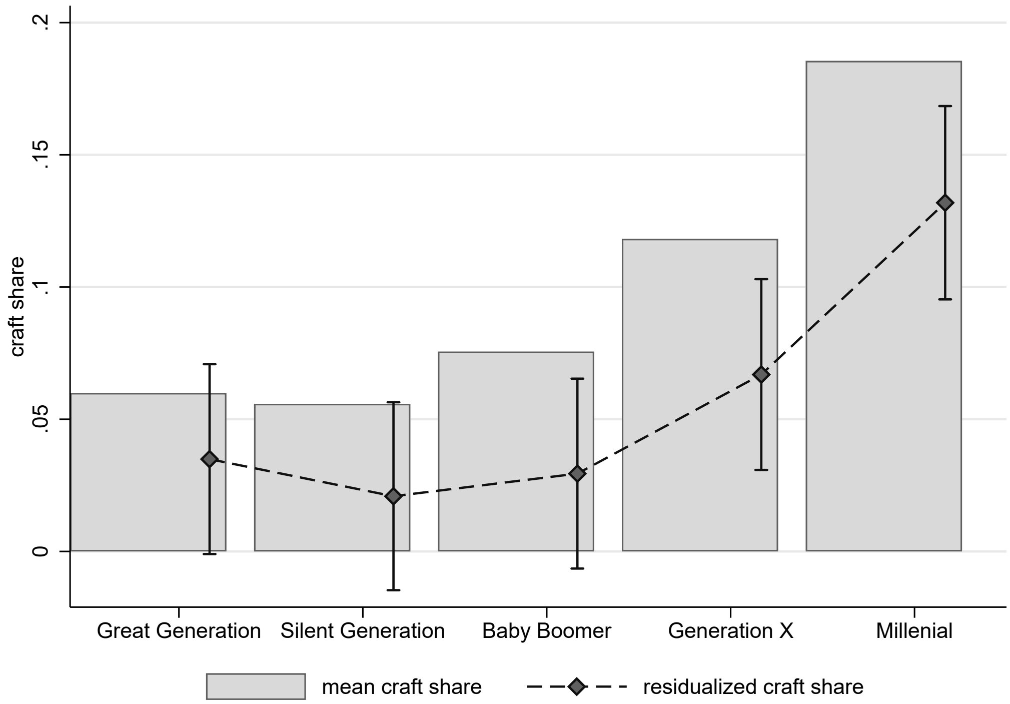
Note: This figure presents the HMS beer purchase sample between 2004 and 2018.Panel (a) plots the national craft beer share (by ounces and dollars) in the take-home market each year. Panel (b) decomposes the national annual craft sales in ounces across consumer generations. All observations are weighted using HMS's projection factors for national representativeness.

Figure 4: Concentration of Anheuser-Busch InBev sales across its owned breweries



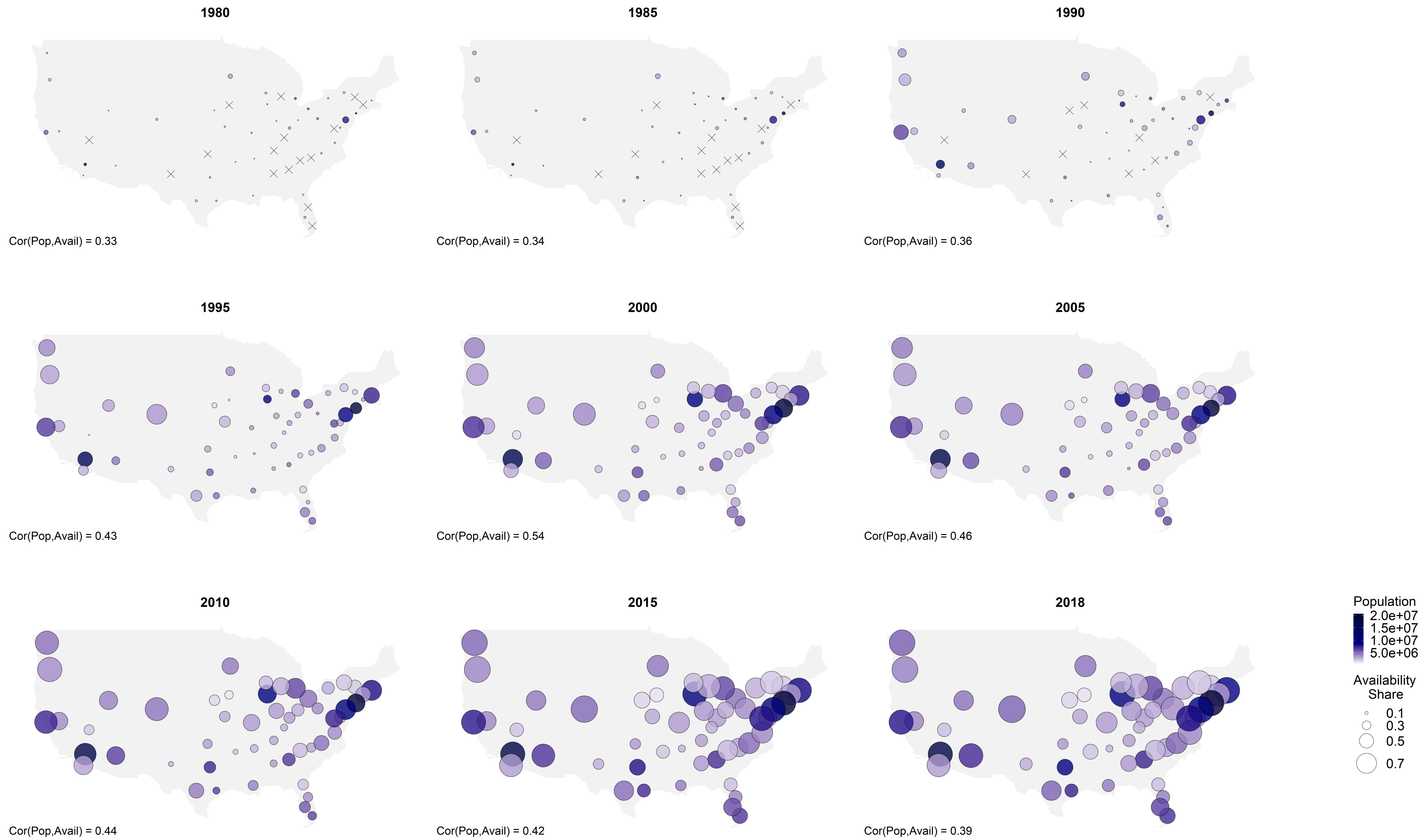
Note: This figure presents the annual U.S. HHI for sales revenues across Anheuser-Busch InBev.'s owned breweries.

Figure 5: Craft beer purchase shares and the generation gap



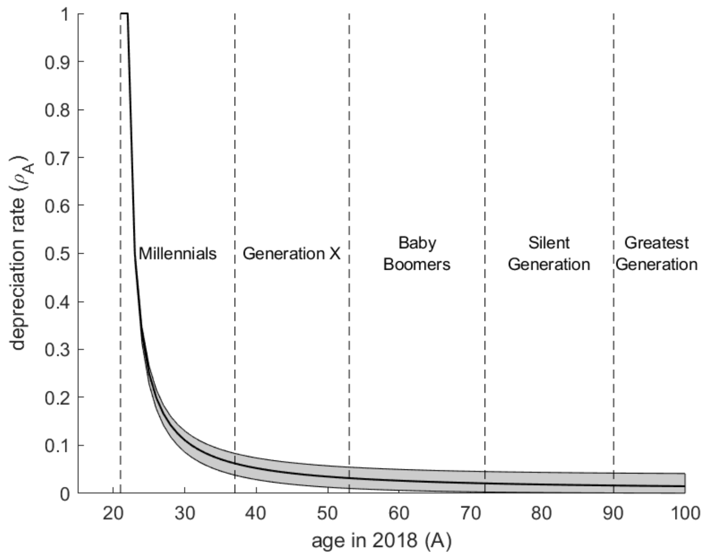
Note: This figure presents the HMS beer purchase sample between 2004 and 2018. The bars represent each generation's mean annual craft beer purchase share across households and years. The diamonds represent each generation's mean annual craft beer purchase share across households and years, residualized on SES (annual income, years of education, household size). The line segments represent the corresponding confidence intervals (clustered on Scantrack and calendar year). All observations are weighted using HMS's projection factors for national representativeness.

Figure 6: Geographic and temporal co-variation in U.S. craft availability and population: 1980 to 2018



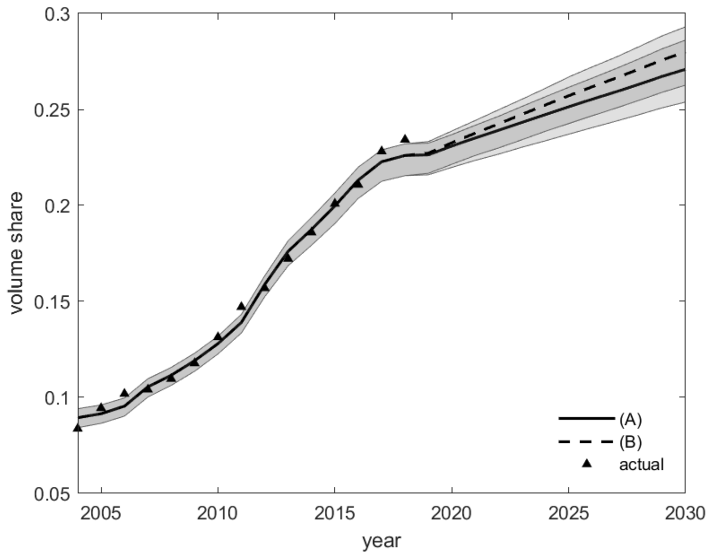
Note: The maps present the availability share, D_{mt}, and market population of the 53 Scantrack markets during the period between 1980 and 2018. Each circle represents the geographic location of a Scantrack market. The circle diameters are proportional to D_{mt}, and the shading intensities are proportional to the market population. We use $\times$ to indicate those market-years with $D_{mt} = 0$.

Figure 7: Depreciation of consumption capital, ρ_A, by age and generation



Note: This figure presents the depreciation rate of consumption capital for each age between 20 and 100. We use a parametric bootstrap from the asymptotic distribution of our GMM estimates and plot the mean (black line) and 95% confidence region (shaded region) at each age. The generations correspond to the ages in 2018.

Figure 8: Craft volume share forecast 2019-2030



Note: This figure reports forecasts of the average household volume share of craft beer. It also reports 95% confidence intervals computed over 500 draws of the distribution of the parameter estimates. Forecast (A) holds availability fixed at the observed 2018 level. Forecast (B) uses predictions of availability levels during the 2019-2030 period.

A The Brewer Database

We use STATA's fuzzy matching algorithm, *matchit*, to merge the ABA's census of brewers with the brewer attributes contained in our ratebeer.com and BA databases. In each database, we first purged stop words from the brewer names, such as "Brewery", "Brewing", "Pub", and "The". We then created a brewer identifier from the first 5 characters of the cleaned brewer name and the first 5 characters of the city of operation. We conducted the fuzzy match using these identifiers.

B Recursive Formulation of Consumption Capital Stock

We first derive the recursive formulation of consumption capital stock as in equation (3).

Proposition B.1. *For a consumer at age A, consumption capital evolves recursively as follows:*

$$k_A = (1-\rho_A)\,k_{A-1} + \rho_A y_{A-1}$$

with

$$\rho_A = \frac{1-\delta}{1-\delta^{A-21}}.$$

Proof: From equation (2) it follows that consumption capital can be expanded as follows:

$$\begin{aligned} k_A &= \frac{\sum_{a=21}^{A-2}\delta^{A-a}y_a+\delta y_{A-1}}{\sum_{a=21}^{A-2}\delta^{A-a}} \times \frac{\sum_{a=21}^{A-2}\delta^{A-a}}{\sum_{a=21}^{A-2}\delta^{A-a}+\delta} \\ &= \left(k_{A-1} + \frac{\delta y_{A-1}}{\sum_{a=21}^{A-2}\delta^{A-a}}\right) \times \frac{\sum_{a=21}^{A-2}\delta^{A-a}}{\sum_{a=21}^{A-2}\delta^{A-a}+\delta}. \end{aligned} \tag{16}$$

Using standard results on geometric series, $\frac{\delta}{\sum_{a=21}^{A-2}\delta^{A-a}} = \frac{1-\delta}{\delta\left(1-\delta^{A-22}\right)}$ and $\frac{\sum_{a=21}^{A-2}\delta^{A-a}}{\sum_{a=21}^{A-2}\delta^{A-a}+\delta} = \delta\frac{1-\delta^{A-22}}{1-\delta^{A-21}}$, we can re-write equation (16) as follows:

$$k_A = k_{A-1} \times \frac{\delta-\delta^{A-21}}{1-\delta^{A-21}} + y_{A-1} \times \frac{1-\delta}{1-\delta^{A-21}},$$

which can be written more compactly as:

$$k_A = (1-\rho_A)\,k_{A-1} + \rho_A y_{A-1}.$$

□

C Derivation of Demand

We now derive the formulation of demand as a distributed lag in historic availability.

Proposition C.1. *From (3), a consumer's consumption capital at age A is a distributed lag of the treatment effects of the choice environments she experienced for each age a,* μ_a*, since turning 21* *years old:*

$$k_A = \sum_{a=21}^{A-1} \omega_{A,a}\mu_a$$

where

$$\sum_{a=21}^{A-1} \tilde{\omega}_{A,a} = 1.$$

Proof: By induction.

$$\begin{aligned} k_{A+1} &= (1-\rho_{A+1})k_A + \rho_{A+1}y_A \\ &= (1-\rho_{A+1})k_A + \rho_{A+1}(\alpha\mu_A + (1-\alpha)k_A) \\ &= ((1-\rho_{A+1}) + (1-\alpha)\rho_{A+1})k_A + \rho_{A+1}\alpha\mu_A \\ &= (1-\alpha\rho_{A+1})k_A + \alpha\rho_{A+1}\mu_A \\ &= (1-\alpha\rho_{A+1})\sum_{a=21}^{A-1}\tilde{\omega}_{A,a}\mu_a + \alpha\rho_{A+1}\mu_A. \end{aligned}$$

Accordingly, $\tilde{\omega}_{A,a} = \begin{cases} \tilde{\omega}_{A-1,a}(1-\alpha\rho_A), & a < A-1 \\ \alpha\rho_A, & a = A-1 \end{cases}$. So, if $\sum_{a=21}^{A-1}\tilde{\omega}_{A-1,a} = 1$,then $\sum_{a=21}^{A}\tilde{\omega}_{A,a} = \alpha\rho_A + (1-\alpha\rho_A)\sum_{a=21}^{A-1}\tilde{\omega}_{A-1,a} = 1.$ □

Using Proposition C.1, we can write demand as follows

$$\begin{aligned} y_A &= \alpha\mu_A + (1-\alpha)k_A \\ &= \sum_{a=21}^{A}\omega_{A,a}\mu_A \end{aligned}$$

where $\omega_{A,a} = \begin{cases} \alpha, & a = A \\ (1-\alpha)\omega_{A,a}, & a < A \end{cases}$ and $\sum_{a=21}^{A}\omega_{A,a} = 1$.

D GMM Estimator

We can define our GMM estimator as follows

$$(\delta,\alpha,\gamma,\Lambda)^{GMM} = \underset{(\alpha,\delta,\gamma,\Lambda)}{\operatorname{argmin}} \left\{ \mathbf{g}(\delta,\alpha,\gamma,\Lambda)'\,\mathbf{\Phi}\mathbf{g}(\delta,\alpha,\gamma,\Lambda) \right\} \tag{17}$$

where $\mathbf{\Phi}$ is a weight matrix and $\mathbf{g}(\delta,\alpha,\gamma,\Lambda)$ is the vector of sample moments (8).

We can simplify the GMM estimation problem by concentrating out the linear parameters on the household SES variables and market fixed effects. Let the matrix $\mathbf{B}$ contain the SES, X_{ht}, and market dummies, $(\mathbb{I}_{h1},...,\mathbb{I}_{hM})$, weighted by $\varpi(\delta,\alpha,\gamma)$,where the weights depend only on the nonlinear parameters: $\mathbf{B}_{ht} = \varpi_{ht}(\delta,\alpha,\gamma)\left(X'_{ht},\mathbb{I}_{h1},...,\mathbb{I}_{hM}\right)$. Define the projection matrix $\Pr_{\mathbf{B}} = \left(\mathbf{B}'\mathbf{Q}\mathbf{Q}'\mathbf{B}\right)^{-1}\mathbf{B}'\mathbf{Q}\mathbf{Q}'$. We can compute the linear coefficients, Λ, analytically as follows:

$$\blacksquare(\delta,\alpha,\gamma) = \Pr_{\mathbf{B}}\left(y_{ht} - \sum_{\tau=t-A_{ht}+21}^{t} \omega_{A_{ht},\tau-t+A_{ht}}\gamma D_h \right). \tag{18}$$

Substituting (18) back into (17), we can re-define the GMM estimator over the remaining parameters as follows:

$$(\delta,\alpha,\gamma)^{GMM} = \underset{(\delta,\alpha,\gamma)}{\operatorname{argmin}} \left\{ \mathbf{g}(\delta,\alpha,\gamma)\, \mathbf{\Phi} \mathbf{g}(\delta,\alpha,\gamma) \right\}. \tag{19}$$

E Market Structure Simulation

Households To forecast future demand, we simulate Nielsen panel membership as follows. We start with the 2018 panelists. Each year thereafter, we adjust the cross-section with a mortality rate, causing attrition of incumbent households, and with a birth rate, causing the introduction of new, 21-year-old Generation Z households. We obtain the mortality and birth rates from the census population projections. The mortality rates increase from 0.00% for 21-year-olds to 0.78% for 65-year-olds and 6.50% for 85-year-olds (i.e., about 1 in 13 surviving 85-year-olds in a given year die during the next year). For each year between 2019 and 2030, we apply these mortality rates to a household based on the primary shopper's current age. Surviving panelists are assumed to retain their Scantrack of residence and SES.

According to the census, 21-year-old adults represent 1.6% of the U.S. adult population. Each year from 2019 to 2030, we introduce new 21-year-olds to maintain this 1.6% composition rate, after adjusting incumbent households for mortality. To simulate a new Generation Z consumer, we randomly draw one of our 2018 Millennials and assign the simulated consumer the same SES and Scantrack.

Evolving Availability To allow availability to evolve between 2019 and 2030, we assume that the number of local craft brewers in year t and market m, N^C_{mt}, follows a simple Scantrack-specific ARMA(r_m,s_m) model with a linear time trend that we estimate separately across each of our 53 Scantracks. Recall that for each Scantrack, we observe the complete history of availability from 1979 (the year of deregulation of home brewing) to 2018. We can therefore select the number of lags, r_m and s_m, for each market using the BIC criterion.[18] Across the 53 Scantracks, a pure AR(1) (i.e., ARMA(1,0)) produces the highest BIC, on average, and is the best-fitting specification for 36 of the 53 markets. On average, the incremental improvement to BIC from one additional lag to either the AR or MA is between 3.5 and 9.3 (log-likelihood) points. The simpler AR(1) also fits the sample data well with market-specific OLS regressions (assuming serially-independent errors) with a single lag in N^C_{mt} producing R^2 values ranging from 0.91 to 0.98.

For the simulation, we treat the AR(1) as deterministically known, ignoring parameter uncertainty and the random component of the model. We then use the estimated AR(1) model to forecast availability dynamically, initializing the process using 2018 as date 0: $N^C_{m\tau}$, $\tau = 1,...,12$ where $N^C_{m0} = N_{m2018}$.[19] We assume that the number of macrobreweries remains fixed throughout this period at the 2018 level: $N^{NB}_{\tau} = N^{NB}_{2018}, \tau = 1,...,12$. This assumption is consistent with the stability in N^{NB}_{t} throughout the latter years in our sample period. We then re-compute each simulated year's availability as follows: $D_{m\tau} = \frac{N^C_{m\tau}}{N^C_{m\tau}+N^{NB}_{\tau}}, \tau = 1,...,12$ corresponding to our forecast horizon

[18] We use STATA's *arima* function to estimate the model. We use the *esttab ic* command to produce the post-estimation model fit statistic.

[19] We use the STATA function *predict.*

between 2019 and 2030.

Decomposition of the share increase We decompose the difference in average shares, $\frac{1}{N_t}\sum_{h=1}^{N_t} y_{ht}$, between 2018 and 2030 as follows:

$$\Delta y = \frac{1}{N_{2030}}\sum_{h=1}^{N_{2030}} y_{h2030} - \frac{1}{N_{2018}}\sum_{h=1}^{N_{2018}} y_{h2018}.$$

We then classify panelists, h, into 3 groups: (1) new Generation Z households, (2) aging households, (3) expired households. We compute the total within-group shares, $y_{gt} = \frac{1}{N_t}\sum_{h\in g}^{N_{gt}} y_{ht}$, $g = 1,..3$. The corresponding group-specific share differences are:

$$\Delta y_g = \frac{1}{N_{2030}} y_{g,2030} - \frac{1}{N_{2018}} y_{g,2018}, g = 1,..,3$$

so that we can compute the decomposition of interest as follows: $\Delta y = \sum_{g=1}^{3} \Delta y_g$.

F Additional Tables

Appendix Table 1: Reduced-form analysis of craft beer demand with additional year fixed effects

	OLS				IV			
Variable	coeff.	(se)	coeff.	(se)	coeff.	(se)	coeff.	(se)
Greatest Generation	0.000		0.000		0.000		0.000	
Silent Generation	-0.009	(0.003)	-0.009	(0.003)	-0.010	(0.003)	-0.010	(0.003)
Baby Boomers	-0.003	(0.003)	-0.004	(0.003)	-0.003	(0.003)	-0.005	(0.003)
Generation X	0.031	(0.003)	0.015	(0.004)	0.030	(0.003)	0.005	(0.007)
Millennials	0.106	(0.005)	0.067	(0.006)	0.106	(0.005)	0.046	(0.016)
Availability share			0.043	(0.014)	0.308	(0.146)	0.338	(0.151)
Availability share at 21			0.091	(0.010)			0.143	(0.036)
Scantrack fixed effects	√		√		√		√	
Year fixed effects	√		√		√		√	
R^2	0.094		0.095		0.036		0.036	
N	270347		270347		270347		270347	

Note: This table uses the 2004-2018 HMS beer sample at the household-year level. The dependent variable in each specification is the household's annual craft share of beer volume purchased. Availability measures the craft share of brewers using D_{mt} as in subsection 3.3. We use the Greatest Generation (the oldest in our sample) as our base generation cell. All regressions control for household SES (education years, annual income, and household size). Standard errors are clustered at the market-year level. The IV estimates use annual scantrack population and population at 21 as instruments for availability and availability at 21. It is not possible to use years since state legalization of brewpubs as an instrument in the presence of year fixed effects since they are confounded.

Appendix Table 2: Robustness using 2008 Panelviews sample

	All moving information		Moving post 2004	
Variable	coeff.	(se)	coeff.	(se)
Greatest Generation	0.000		0.000	
Silent Generation	0.003	(0.006)	0.003	(0.006)
Baby Boomers	0.011	(0.006)	0.011	(0.006)
Generation X	0.025	(0.007)	0.024	(0.007)
Millennials	0.077	(0.020)	0.073	(0.020)
Availability share	0.300	(0.012)	0.300	(0.012)
Availability share at 21	0.079	(0.020)	0.092	(0.020)
Scantrack fixed effects	√		√	
R^2	0.082		0.082	
N	74191		74191	

Note: This table uses the subset of the 2004-2018 annual HMS beer sample for those panelists who completed the migration survey in Bronnenberg et al. (2012). The dependent variable in each specification is the household's annual craft share of beer volume purchased. Availability measures the craft share of brewers using D_{mt} as in subsection 3.3. We use the Greatest Generation (the oldest in our sample) as our base generation cell. All regressions control for household SES (education years, annual income, and household size). Standard errors are clustered at the market-year level. The first column reports OLS estimates when each household's complete migration history is used to determine historical availability at 21. The second column reports OLS estimates when only the observed migration information during the sample period is used, as in the main analysis in the paper.

Appendix Table 3: GMM estimates using different population lags in the instruments

Population lags	1yr gap		3yr gap		5yr gap		10yr gap		1yr gap		3yr gap		5yr gap		10yr gap	
δ	1.012	(0.021)	1.008	(0.023)	1.006	(0.022)	1.016	(0.030)	1.012	(0.021)	1.009	(0.023)	1.007	(0.022)	1.016	(0.030)
α	0.498	(0.049)	0.520	(0.057)	0.497	(0.057)	0.575	(0.065)	0.498	(0.048)	0.521	(0.056)	0.499	(0.056)	0.571	(0.064)
γ	0.593	(0.053)	0.569	(0.056)	0.580	(0.059)	0.531	(0.059)	0.600	(0.051)	0.574	(0.054)	0.589	(0.057)	0.541	(0.057)
Greatest Generation	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-
Silent Generation	-0.013	(0.005)	-0.013	(0.005)	-0.013	(0.005)	-0.012	(0.005)	-0.013	(0.005)	-0.013	(0.005)	-0.013	(0.005)	-0.013	(0.005)
Baby Boomers	-0.009	(0.005)	-0.009	(0.005)	-0.009	(0.005)	-0.008	(0.005)	-0.009	(0.005)	-0.009	(0.005)	-0.009	(0.005)	-0.008	(0.005)
Generation X	-0.018	(0.008)	-0.014	(0.009)	-0.017	(0.010)	-0.008	(0.009)	-0.018	(0.008)	-0.014	(0.009)	-0.017	(0.009)	-0.008	(0.009)
Millennials	0.013	(0.018)	0.022	(0.019)	0.017	(0.021)	0.036	(0.020)	0.012	(0.018)	0.022	(0.019)	0.016	(0.020)	0.034	(0.020)
Grade School	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-	0.000	-
Some High School	-0.022	(0.017)	-0.021	(0.017)	-0.022	(0.017)	-0.021	(0.017)	-0.022	(0.017)	-0.021	(0.017)	-0.022	(0.017)	-0.021	(0.017)
High School	-0.007	(0.016)	-0.007	(0.017)	-0.007	(0.017)	-0.008	(0.016)	-0.007	(0.016)	-0.007	(0.017)	-0.007	(0.017)	-0.008	(0.016)
Some College	0.033	(0.016)	0.031	(0.017)	0.032	(0.017)	0.029	(0.016)	0.033	(0.016)	0.031	(0.016)	0.032	(0.017)	0.030	(0.016)
College	0.088	(0.017)	0.086	(0.017)	0.087	(0.017)	0.083	(0.017)	0.088	(0.017)	0.086	(0.017)	0.087	(0.017)	0.083	(0.017)
Post College	0.152	(0.017)	0.149	(0.018)	0.151	(0.018)	0.145	(0.018)	0.152	(0.017)	0.149	(0.018)	0.151	(0.018)	0.145	(0.018)
Income ($100K)	0.077	(0.004)	0.076	(0.004)	0.077	(0.004)	0.074	(0.005)	0.077	(0.004)	0.075	(0.004)	0.076	(0.004)	0.074	(0.005)
Family Size	-0.012	(0.001)	-0.011	(0.001)	-0.012	(0.001)	-0.011	(0.001)	-0.011	(0.001)	-0.011	(0.001)	-0.011	(0.001)	-0.011	(0.001)
Brewpub Legalization									√		√		√		√	
Observations	270347		270347		270347		270347		270347		270347		270347		270347	
Parameters	67		67		67		67		67		67		67		67	

Note: This table uses the 2004-2018 HMS beer sample at the household-year level with different population lags included in the instruments. All the specifications are identical to GMM1 and GMM2 columns reported in Table 3 except for the construction of instruments. Estimates reported in the columns labeled "5yr gap" coincide exactly with GMM1 and GMM2 columns reported in Table 3, respectively.