Post and Hold Regulation and Competitive Conduct: Evidence from the U.S. Beer Industry*

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Abstract

The literature argues that Post and Hold (PH) laws facilitate tacit collusive price-setting behavior among suppliers of alcoholic beverages. Yet there is no explicit empirical test of this claim. We specify and estimate a structural model designed to identify the extent to which PH laws induce tacit collusive price-setting behavior among beer suppliers. Our estimates reveal evidence of PH law-induced collusive behavior that causes higher prices and lower consumption. Furthermore, we find that an alcohol content tax as a replacement for PH regulation yields the highest surplus to consumers compared to a sales tax or the PH regulation.

Keywords: Post and Hold Regulation; Competitive Conduct; US Beer Industry; Externality; Corrective Tax Policy

JEL classification codes: I18; K00; L13; L40; L66; H21; H23

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*Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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1 Introduction

An externality occurs when an economic transaction affects a third party not directly involved in that transaction. This externality is positive if the third party benefits from the transaction but negative if the third party is adversely affected by the transaction. Some individuals' consumption of certain goods (e.g., cigarettes, sugary foods, alcohol, etc.,) generate negative externalities, i.e., generate social and economic costs borne by others who neither shared in the consumption nor provided the relevant goods. For example, alcohol consumption beyond a threshold rate significantly burdens public resources through alcohol-related health costs, such as liver cirrhosis, heart disease, and cancer, as well as social costs related to non-fatal and fatal vehicle accidents, violent crimes, and unemployment. Policy intervention is necessary to reduce the consumption of goods associated with negative consumption externalities since the reduced consumption is expected to in turn reduce the negative externalities caused by consuming the good. Policymakers often draw upon regulations and incentive-based policy instruments to mitigate negative externalities. Designing an optimal policy is challenging as there is rarely a one-size-fits-all solution. Accordingly, there is a growing interest among researchers in comparing the effectiveness and implications of alternative policy instruments to mitigate negative externalities [e.g., see Gruber and Koszegi (2004), Bonnet and Réquillart (2013), Heutel (2015), and O'Connell and Smith (forthcoming)].

A state-level regulation in the U.S. known as *Post and Hold* (PH) is intended to reduce the consumption of alcoholic beverages and in turn mitigate the associated negative consumption externalities. The PH laws require distributors to share future prices of their alcoholic beverages with the state regulator and hold those prices fixed for a certain period depending on the state's required number of hold-days prescribed by its PH laws. The PH laws often allow all rival distributors to observe each other's submitted menu of prices prior to any transaction occurring at the prices. In addition, the posted prices that will consummate transactions must remain in effect until the next PH cycle for posting future prices, implying that no seller has an opportunity to "steal" customers by secretly undercutting its competitors' price.

The motivation for adopting PH regulation is to mitigate the social and health costs associated with the consumption of alcoholic beverages (beer, wine, and distilled spirits) by indirectly reducing consumption through directly raising prices. Economic theory suggests that the PH laws will restrain price competition and therefore result in prices being higher than they would be otherwise. By requiring distributors to effectively make common knowledge among all rivals their future prices and the period over which these prices must remain fixed while transactions occur at the prices, the law softens price competition by offering distributors unilateral incentives to avoid price reduction for an extended period and providing them with a credible price coordination mechanism to maintain high prices.

PH laws in concentrated markets are particularly concerning because of their likelihood of playing an instrumental role in entrenching non-competitive behavior. The U.S. beer industry is categorized as one of the most concentrated industries in the U.S.[1] Market dominance of leading brewers (Anheuser-Busch InBev (ABI), SABMiller, and MillerCoors) has already alarmed researchers regarding the potential for anticompetitive behavior [Miller and Weinberg (2017)]. Yet there is no study on the separate additional role PH laws play in facilitating tacit collusive price-setting behavior among suppliers of beer.

This study empirically investigates the presence of tacit collusive behavior among beer suppliers in the U.S. caused by states' PH laws. The investigation is done by using a structural econometric model to explicitly capture and measure the impact of PH laws on the price-setting behavior among beer suppliers. Drawing on the modeling frameworks in Miller and Weinberg (2017) and Ciliberto and Williams (2014), we estimate a parameter that facilitates measuring the extent to which suppliers internalize pricing externalities across separately owned firms. To identify the collusive behavior parameter, we exploit the fact that identical beer products are sold across states that vary in whether they have PH laws, as well as vary in the stringency of PH laws implemented among the states with these laws. Variation in the stringency of PH laws is measured by the number of hold-days required by the state's PH laws. In our data, the stringency spectrum begins with the least stringent being 0 hold-days among states without PH laws, with the stringency progression being states adopting PH laws that require either 5, 7, 10, 30, 180, or the most stringent 360 hold-days. Using states' two-letter postal code, Table 1 lists PH and non-PH states with their corresponding number of hold-days shown in parenthesis required by the given state's PH laws.

Our research methodology begins with estimating a discrete choice model of demand using retail scanner data on beer purchases over the period 2011 through 2019. With demand estimates in hand but without observing brewers' and retailers' costs, we specify the supply-side of the model with an embedded function that determines how number of required hold-days influence price-setting conduct, i.e., the extent to which suppliers internalize pricing externalities across separately owned firms caused by the number

[1] Since 1950; the beer industry has experienced over 200 mergers [Trembley and Tremblay (2005)]. Past mergers were broadly considered consolidation exercises in response to changing technology and marketing success in the industry. However, the most recent waves of mergers that occurred during the last decade have raised concerns about greater market power and concentration in the industry [Ascher (2012)].

of hold-days required by the state's PH laws. Unlike Conlon and Rao (2023), our study explicitly estimates how the stringency of states' PH regulations influences the price-setting conduct of firms.

Table 1: List of States by whether they had Post-and-Hold (PH) Laws for beer during any subset of the period, 2011 through 2019.

States with PH laws (hold-days)	DE† (5); IN(7); SD* (10); NJ(30); OK††(30); CT(30); MA(30); GA(180); TN(360)
States without PH laws	AZ(0); AR(0); CO(0); IL(0); KS(0); KY(0); LA(0); MD(0); MN(0); MO(0); NE(0); NV(0); NM(0); NY(0); ND(0); RI(0); SC(0); TX(0); VA(0); WI(0)

Notes: The states designated as "control" states with respect to any alcoholic beverage (either beer, wine, or distilled spirits), i.e., states that have monopoly control over the distribution of any alcoholic beverage are not covered in our analysis. † For the period 2005-2016 it followed PH and then changed it to post only for the period 2016-2019. †† For the period 2005-2017 it followed PH and then changed it to post only for the period 2018-2019. * Data available only for 2019.

The modeling framework we use in this study for measuring the price-setting conduct of firms is tantamount to a conduct-parameter approach. As correctly argued in Corts (1999), a potential challenge with implementing the conduct-parameter approach is to accurately identify measures of firm conduct. To overcome this challenge, we follow the modeling framework in Ciliberto and Williams (2014) and specify that firms' price-setting conduct is a function of a market-varying factor. As discussed on page 778 of Ciliberto and Williams (2014), when firms' price-setting conduct is explicitly modeled in this way there is no need to address the critique of Corts (1999). In addition, Berry and Haile (2014) rigorously show that changes in "market environment" can be used to distinguish between competing oligopoly models of firm conduct. In our setting, changes in the "market environment" are measured by state-level variations in number of hold-days required by states' PH laws, which is the measure used for identifying firms' price-setting conduct. The intuition underlying identification of market-specific differences in firms' price-setting conduct is that changes in beer demand and cost conditions that are similar across markets will cause the equilibrium prices of any given set of beer products to change differently across markets that differ with respect to the required number of hold-days. Accordingly, once the impacts of changes in demand and cost conditions are controlled for, the remaining differential changes in beer prices across markets that differ in the stringency of their PH laws can only be attributed to differences in the price-setting conduct of the beer suppliers.

Our analysis shows evidence that PH laws facilitate tacit collusive pricing behavior in the U.S. beer industry. Our findings are consistent with Conlon and Rao (2023), who found evidence consistent with anticompetitive pricing behavior caused by PH laws in their analysis of Connecticut's distilled spirits market. Like Conlon and Rao, we consider alternative types of tax policy instruments to achieve the level of alcohol consumption obtained by the PH policy adopted in states with PH laws. However, unlike Conlon and Rao, we find that an alcohol content-specific tax policy outperforms a sales tax policy as a replacement for PH regulation. We believe a key reason for this different policy finding in our study compared to Conlon and Rao is that there is variation in the alcohol content across the beer products in our data sample, while there is little to no variation in alcohol content across the distilled spirt products (e.g., Gin, Rum, Tequila, Vodka, Whiskey, etc.) in the data sample used by Conlon and Rao. Based on the variation in alcohol content of different beer products, our counterfactual analysis shows that an alcohol content-specific tax will cause consumers to optimally substitute high alcohol-content beer products with lower alcohol-content products and experience welfare improvement as the states switch from PH regulation to an alcohol content-specific tax policy. Unlike our findings for the alcohol content-specific tax as a replacement for PH regulation, we show that using instead a sales tax on beer products to replace PH regulation will not result in welfare-improving consumption substitution across beer products with different alcohol contents.

The rest of the paper is organized as follows: Section 2 briefly describes the U.S. beer industry's profile; Section 3 reviews relevant literature; Section 4 describes the data and discusses evidence from descriptive linear price regressions; Section 5 outlines the structural econometric model of beer demand and supply; Section 6 discusses the estimation procedure; Estimation results are discussed in Section 7; Section 8 discusses counterfactual analyses and associated results; and Section 9 offers concluding remarks.

2 Profile of the U.S. beer industry[2]

While beer consumption per adult in the U.S. has been falling gradually between 1994 and 2016, it still ranks as the second-largest beer market after Germany.[3] In 2016, beer consumption per adult stood at 100 liters in the U.S. (with a total beer consumption of 24.1 billion liters) and was worth approximately \$100 billion. Almost 85 percent of the beer consumed is produced domestically in the U.S. In 2016, large breweries commanded over 90 percent market share in volume and sales, whereas craft breweries accounted for only 6% in volume and 9% share in total sales.[4] Almost three-fourths of beer sales occur

[2] The majority of this section is drawn from Tremblay and Tremblay (2005), Warner (2010) and Ascher (2012)
[3] The Economist June 13, 2017
[4] Brewers Association; America's Beer Distributors

through supermarkets and grocery stores, implying that most U.S. beer is consumed in home-settings (and not in restaurants or pubs). The relatively large size of the U.S. beer market in the world warrants questions about the structure and performance of its domestic market, which is shaped by various state regulations as well as merger and acquisition activities.[5]

The last two decades have seen two disparate industry trends. On the one hand, the industry is experiencing the re-emergence of small breweries (craft brewers)[6], but on the other hand, brewing is increasingly being controlled by a small number of large brewers. The extent of concentration is dramatic when viewed in terms of the market share of the top four breweries. From the year 1947 to the year 2007, the combined market share of the top four breweries grew from 19 percent to 92 percent.[7] In the wake of mergers between 2001 and 2008, the few large brewers that dominate the U.S. beer industry are Anheuser-Bush InBev (ABI), SABMiller, Molson Coors, Heineken, and Constellation Brands (brewers with imported brands).

The states' regulatory framework plays a significant role in shaping alcohol markets. For example, most states follow a three-tier structure in alcoholic markets where producers/brewers are located at the top tier and sell alcohol to retailers through distributors.[8] States are categorized as being either "control", "open", or "franchise" states based on the nature of their regulations governing the distribution tier. "Open" states are at one end of the spectrum of supply chain structure, in which distributors are privately-owned businesses that buy and sell alcohol and offer promotion services per state laws, and brewers have flexibility in terminating agreements with distributors. "Control" states are at the other end of the spectrum of supply chain structure, in which brewers sell alcohol directly to the state regulator, and the state-run monopoly carries out alcohol distribution. Recent empirical studies [see Seim and Waldfogel (2013); Miravete et al. (2018); Miravete et al. (2020);] have analyzed the behavior and welfare consequences of state-run monopolies in alcohol distribution. Last, in the case of "franchise" states, distributors are privately-owned businesses but the state dictates the terms of the brewer-distributor agreement through

[5] Historically, the U.S. beer industry evolved from being fragmented into a highly concentrated industry due to various waves of mergers and acquisitions.[5] From 421 breweries in 1947, the number of breweries declined to 92 in the year 1981 as mostly failing breweries merged and were acquired by successful brewers. Consequently, an increase in minimum efficient scale due to technological development and price competition allowed large brewers to benefit from large-scale production and sent small and regional brewers out of business.

[6] The Brewers Association statistics show that the total count of breweries stands at over 4,548 in the 2015, out of which only 30 were large non-craft breweries and 14 were other non-craft breweries.

[7] Gokhaley and Trembley (2012)

[8] The regulation forbids vertical integration, which takes away one mechanism that vertically related firms often use to resolve the double marginalization problem.

franchise laws. These states require brewers to show a cause for termination of the contractual relationship with their distributors. In franchise states brewers rarely switch distributors.

The three-tier system and franchise laws increase the cost of supplying beer to consumers as it prohibits brewers from directly selling to consumers. As discussed above, the upstream market of brewers is highly concentrated. Industry reports also suggest that the distributor and retail markets downstream are concentrated. [9] Much of the beer distribution network is directly or indirectly controlled by large brewers, e.g., ABI and MillerCoors, where distributors carry either brands of ABI or MillerCoors, but not both. Miller and Weinberg (2017) argue that the brewers effectively determine per unit retail prices, and distributors/retailers behave passively in setting retail prices paid by consumers.

Many states also regulate interactions between wholesalers and retailers through non-price restrictions by limiting wholesalers' ability to provide credit to retailers and banning wholesalers from offering volume discounts to retailers. These restrictions potentially affect beer prices indirectly by influencing the retail costs across the relevant states. For example, a state that bans volume discounts effectively restricts the ability of wholesalers to negotiate lower prices with large retailers in exchange for large volume purchases from wholesalers. A key objective of banning volume discount is to protect small retailers from related predatory marketing practices of large retailers, but a potential consequence of the ban is that it causes the retail costs for large retailers to be higher than they would be otherwise.

Similarly, the states that restrict the ability of wholesalers to provide credit to retailers aim to limit the influence of wholesalers on retailer behavior. When a retailer relies on wholesalers' credit, either in the form of direct loans or deferred payment of invoices, the retailer is likely to promote the products of the credit-extending wholesaler over rival wholesalers' products, as well as agree to the demands of the credit-extending wholesaler in terms of pricing and product placement. However, the states that enforce such restriction may increase retailers' costs as retailers may have to rely on more expensive alternative financing options to support their businesses.

In addition to the regulations described above, numerous states regulate beer prices through PH laws to indirectly control beer consumption. These laws require distributors to post future beer prices with the state agency and hold posted prices fixed for a specific period, which it is argued limits price competition between distributors. The hold-period requirement on prices varies across PH states, ranging from 5 days to 360 days. The posted prices are widely accessible to competitors. Over a dozen states currently impose PH laws on beer products, covering a substantial portion of the U.S. population.

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[9] Ascher (2012)

3 Related Literature

This paper fits into a body of literature that studies firms' incentives and ability to collude and the market features, some of which may be institutional, that facilitate collusion [e.g., see Porter (1983, 2020), Green and Porter (1984), Rotemberg and Saloner (1986), Bresnahan (1987), Slade (1987, 1992), Bernheim and Whinston (1990), Haltiwanger and Harrington (1991), Ellison (1994), Genesove and Mullin (1998), Porter and Zona (2008), and Igami and Sugaya (2022)]. The institutional market feature that is the focus of our study is PH regulation of the distribution of alcoholic beverages in several US states, and we empirically examine the extent to which this institutional feature facilitates tacit collusive price-setting behavior among suppliers of beer.

This paper also fits into the body of literature that examines alternative incentive-based policies designed for addressing negative consumption externalities [e.g., see Diamond (1973), Delipalla and O'Donnell (2001), Gruber and Koszegi (2004), Gruber and Mullainathan (2005), Kuchler et al. (2005), O'Donoghue and Rabin (2005, 2006), Bonnet and Réquillart (2013), Heutel (2015), and O'Connell and Smith (forthcoming)]. Like alcoholic beverages, the consumption of certain goods, e.g., cigarettes, sugary foods, etc., generate negative externalities that require policy intervention to address the consumption externalities. Similar in spirit to several issues explored in this body of literature, a key objective in our study is to compare the potential externality-mitigating outcomes in beer markets that are induced by PH regulation with beer market outcomes that could have been reached using alternate incentive-based policies such as an alcohol content-specific tax or a sales tax.

Economic theory suggests that PH laws soften price competition among firms through two channels: (1) by offering unilateral incentives to avoid price reduction for an extended period; and (2) by providing a price coordination mechanism to maintain high prices. The following discussion highlights each channel and the existing evidence on the impact of PH laws on alcoholic beverage markets.

Unilateral pricing incentives under PH regulation – price reduction/competition is expensive.

Cooper and Wright (2012) argue that PH laws create conditions for wholesalers that make engaging in price competition with rival firms expensive. In such states, offering price discounts for extended periods exposes wholesalers to the risk of supply and demand changes. As noted in Cooper and Wright, "Wholesalers also may have less incentive to offer discounts when their competitors can match them instantaneously. The gain from offering a discount to a retailer is increased sales of that brand. When discounts are made public and are announced to all rivals before going into effect, competing wholesalers can offer the same discount, diluting market share gains from price cuts." In short, PH laws requiring wholesalers to commit to a price for a specific period through its price-holding requirement make price reductions more expensive for wholesalers and therefore incentivizes them to maintain high prices. Effectively, PH laws make the gains to price cuts diffuse (the quantity increase accrues to all price matching wholesalers).

Coordination mechanism

The PH laws also provide a price coordination mechanism through which wholesalers/distributors may have implicit price agreements. First, the law solves the coordination problem and facilitates implicit price agreements among wholesalers by requiring wholesalers to announce future prices under the PH law. Second, by constraining wholesalers to hold prices fix for a certain period, the law makes announced prices credible commitments by increasing the probability of sustaining announced prices as collusive prices. Therefore, collusive behavior is likely to prevail in PH states as the regulation offers a platform to solve price coordination problems and signals announced prices to rivals as credible commitments.

Existing evidence on the impact of PH laws

The empirical evidence on the impact of PH laws on alcohol consumption and prices is mixed. On the one hand, Saffer and Gehrsitz (2016) argue that PH laws do not reduce consumption or raise prices using state-level consumption data from 1983-2012. The study documents that taxes are more effective than PH laws in driving up alcohol prices and reducing consumption. On the other hand, Cooper and Wright (2012) and Conlon and Rao (2023) find evidence consistent with PH laws weakening price competition by facilitating distributors to coordinate over prices. Cooper and Wright (2012) evaluate the impact of PH laws on alcohol consumption using state-level alcohol consumption data from 1983-2004.

Conlon and Rao (2023) argue that PH laws provide a coordination mechanism for wholesalers to maintain a monopoly price. The study finds that distilled spirit distributors' markup ranges from 30-40%, which is the level of markup consistent with the distributor of each product behaving like a single-product monopolist. In contrast to the methodological approach of our study, their study does not directly estimate the conduct behavior of distilled spirit sellers but instead compares the actual price-cost markup under assumed alternative market structures.

Competitive behavior in the U.S. beer industry

The growing concentration in the U.S. beer industry due to mergers and acquisitions has also weakened price competition [Treasury Department (2022); Ashenfelter, Hosken, and Weinberg (2015); Rojas (2008)]. As argued and shown in Miller and Weinberg (2017), the year 2008 merger between SABMiller and Molson Coors is considered a blow to the industry's competitive behavior in the form of increased market power and the emergence of collusive behavior during the post-merger period. Using retail scanner data for the years 2005-2011 and focusing on 13 flagship beer brands owned by ABI, SABMiller, Molson, Heineken, and Crown Imports, Miller and Weinberg (2017) provide evidence of tacit collusive behavior between MillerCoors and ABI during the post-merger period. Similar in spirit to the methodological approach of our study, their study estimates a structural econometric model that nests a parameter capturing potential coordinated price-setting behavior between separately owned ABI and MillerCoors during the periods after the SABMiller-Molson Coors merger. The key outcomes of their study are that retailers make low retail markup, the merger increased total surplus, but consumer surplus is lost due to merger-induced coordinated effects between ABI and MillerCoors.

Our study contributes to the literature in several ways. Both the Miller and Weinberg (2017) study in case of the beer industry, and the Igami and Sugaya (2022) study in case of the vitamins industry consider how a merger influences firms' incentive to collude after the merger. Methodologically similar to Miller and Weinberg (2017) in their study of the 2008 merger, we investigate how separately owned firms internalize pricing externalities or collude over prices induced by PH laws instead of a merger. In addition, we compare the effectiveness of the PH regulation against alternative incentives-based policies when dealing with market outcomes of the beer market. Specifically, we analyze the changes in beer prices and consumption that would result from counterfactually eliminating PH laws; and the welfare effects of replacing PH laws with a sales tax versus an alcohol-content tax.

4 Data and Descriptive Analysis

4.1 Retail Scanner Data and Other Data sets

To perform the empirical analysis in this paper we use longitudinal data drawn from the Nielsen Retail Scanner Database.[10] The database offers weekly prices and sales information by Universal Product Code (UPC) of products sold at over 35,000 participating stores such as grocery, drug stores, mass

[10] The dataset is available through the Kilts-Nielsen Data Center at The University of Chicago Booth School of Business. Information on availability and access to the data is available at http://research.chicagobooth.edu/nielsen.

merchandise and a small amount of the volume for convenience and liquor stores located across different U.S. states during the period 2006 through 2019. The database tracks the sales of over 1,000 products belonging to 115 groups (e.g., wine, beer, cheese, etc.). Our focus in this study is on the sales of beer products for the period 2011 through 2019.

The beer group consists of 6 different types of products: beer, light beer, malt beverages, stout and porter, ale, and light liquor. The beer and light beer products account for over 80% of unit sales and 90% of beverage volume sales across the beer group in the year 2013. [11] This sales pattern by product type is consistent for all other years.

Generally, beer, like other alcoholic products, is sold to consumers through retail outlets that can be distinguished based on where the consumption of the purchased beverage is expected to occur: off-premises versus on-premises of the retail outlet. Off-premises retail outlets are typically liquor stores, convenience stores, supermarkets, and grocery stores, whereas on-premises retail outlets are typically restaurants and bars. As mentioned earlier, almost three-fourths of beer sales occur off-premises through supermarkets and grocery stores, implying that most U.S. beer is consumed in home-settings (and not in restaurants or bars). The Nielsen scanner data only accounts for off-premises alcohol purchases in channels such as grocery, drug stores, mass merchandise and a small amount of the volume for convenience and liquor stores. Neither on-premises sales (e.g., restaurant and bars) nor e-commerce sales are covered by Nielsen scanner data. In summary, it is reasonable to argue that Nielsen scanner data are representative of the U.S. beer industry.

The scanner data cover a wide range of different package sizes of beer brands sold in retail stores. Consistent with the popular package sizes in the beer industry, most of the sales are concentrated in 6, 12, and 24-pack products, with each item in a pack containing 12 ounces of the beverage. These package sizes have the greatest unit sales (48.74% of total beer/light beer unit sales in 2013) as well as the greatest volume sales (51.77% of total beer/light beer volume sales in 2013). Our analysis focuses on these package sizes with individual 12 oz beverage containers: 6-pack products (total, 72 ounces of beverage); 12-pack products (total, 144 ounces of beverage); and 24-pack products (total, 288 ounces of beverage). Since our data include products of different package sizes, following other empirical studies on the beer industry [e.g., Miller and Weinberg (2017); Ashenfelter, Hosken, and Weinberg (2015] we calculate equivalent

[11] Unit sale is described as the physical volume of product sold at retail expressed in packages. This is the unit that the shopper buys in the store, and it is useful when comparing products of the same size. Volume sale is described as the physical volume of a product sold at retail expressed in a common unit (ounces, gallons, etc.) relevant to the category and useful when comparing products of different sizes. [for more detail see: http://www.cpgdatainsights.com]

prices for each packaged product by dividing dollar sales of a package by equivalent sales to 144 oz. The equivalent sales are computed by multiplying the number of units sold with the equivalent volume to 144 oz.[12]

Our sample selection methodology follows Ashenfelter, Hosken, and Weinberg (2015). For example, we limit our sample to the top selling 39 beer brands (see Table A1 in the appendix). The list of top selling brands in our data is identical to the brands analyzed in Ashenfelter, Hosken, and Weinberg (2015). Across different package sizes with individual 12 oz containers, these 39 brands account for more than half of the unit sales and volume sales. Our study focuses on these brands for the years 2011 through 2019. The focus brands are the best-performing brands of Anheuser-Busch InBev, Boston, MillerCoors, Pabst Blue Ribbon, Yuengling, Heineken, and Groupo Modelo. The coverage of domestic and imported brands makes these data representative of the U.S. beer industry. To reduce the computational burden during econometric estimation, we aggregate the weekly data to monthly unit sales and revenue for the select brands.

Following Miller and Weinberg (2017), we define the potential market size to be ten percent greater than the maximum observed unit sales for each geographical location. Note that this definition of potential market size does not imply that alcohol consumption is fixed, or potential market size is the same, across different markets. In fact, the definition implies quite the opposite. An advantage of using this method to measure the potential size of each market is that this method captures the variation across local markets in their populations' propensity to consume alcohol. For example, two local markets with the same number of individuals (same size populations) may have very different propensities to consume alcohol based on differences across the markets with respect to their populations' unobserved preferences and demographic characteristics such as income, etc. If one market historically has a larger maximum consumption of beer compared to the other market, then defining the potential market sizes as 10% greater than the maximum observed unit sales for each geographical location will ensure that the potential market size measure is larger for the market with the higher historical maximum consumption even in the case where the two markets have equal size populations.

[12] Equivalent units = units * equivalent vol. For example, if a firm sells 10 units of a 6-pack of 12 oz (each package having 72 oz of beverage), the firm's equivalent sales is 10*0.5 = 5 equivalent units of 144 oz. Similarly, if a firm sells 20 units of 24-packs of 12 oz (each package having 288 oz of beverage), the firm's equivalent sales is 20*2.0 = 40 equivalent units of 144 oz. Accordingly, we compute the equivalent price by dividing the total dollar sales (price * units) with equivalent sales as follows: $Price_{eq} = \frac{dollar\ sales}{equivalent\ unit\ sales} = \frac{Units*price}{Units*equivalent\ vol}$.

We define a market as the period-location combination, where a period is a year-month combination and geographic locations are delineated by states. A distinct product in a market is defined as a combination of brand and package size. In other words, Bud Light sold in 6-packs and 12-packs are considered two distinct products that may be sold within a market. Likewise, a 6-pack of Corona Light and a 6-pack of Corona Extra are considered two distinct products that may be sold within a market.

Our product-level data sample includes the following monthly variables: product share (computed as product quantity sold divided by our measure of potential market size discussed above); product prices; and measures of non-price product characteristics of the 39 brands with package sizes 6, 12, and 24-packs. Based on our definitions of markets and products discussed above, the data sample consists of 254,968 observations.

The information on brand characteristics is collected from labels available on the brands of beer. Our sales data cover only products available at grocery stores and superstores. We collected information on the characteristics of these products from the websites of superstores. Panel A in Table 2 provides summary statistics on price and various non-price characteristics of the beer products in our data sample, while Table A1 in the Appendix provides a listing of these brands with their corresponding measures of non-price characteristics. The beer brands contain an average alcohol content of 4.47% and 124 calories per 12 oz container.

Using data from the Alcohol Policy Information System (APIS), we supplement the product-level data with information on state-level regulations for beer that include: (*i*) PH law requirements; (*ii*) whether wholesalers are banned from offering volume discounts to retailers; and (*iii*) whether wholesalers are restricted from extending credit to retailers. The APIS provides information about the number of hold days required by the active PH laws for beer, spirit, and wine. We restrict our analysis to 29 states (out of which 9 states followed PH laws) for which the data are available for all the years 2011 through 2019. The reader is reminded that the list of PH and non-PH states included in our final data sample is given in Table 1. Panel B in Table 2 provides summary statistics on the three state-level regulatory variables. The notes of Table 2 list the states that ban wholesalers from offering volume discounts to retailers and states that restrict wholesalers from extending credit to retailers, respectively. A comparison of the list of PH and non-PH states in Table 1 with the list of states in the notes of Table 2 that ban volume discounts and have retail credit restrictions, respectively, reveal that states' adoption of any one of the three regulatory restrictions considered (PH laws, ban on volume discounts, and retail credit restrictions) does not seem a strong predictor of states' adoption of the other two regulatory restrictions. In other words, a PH state may or may not implement a ban on volume discounts or enforce retail credit restrictions.

Table 2: Summary statistics on characteristics of the beer products and state-level regulatory policy variables in our data sample

Panel A: **Summary Statistics on Price and non-price characteristics of the Beer Products**				
	Mean	Standard Deviation	Minimum	Maximum
Price ($ per 144 oz equivalent package)	12.02	3.25	1.74	30.25
Products' quantity sold (144 oz equivalent package)	3891	12767	1	590246
Products' market share (%)	1.08	2.10	0.00	30.73
Alcohol Content per 12 oz container (%)	4.47	0.61	2.80	5.90
Calorie Counts per 12 oz container	124	26.69	64	175
Imported (zero-one dummy = 1 if product imported)	0.26	0.44	0	1
Panel B: **State-level Regulatory Policy variables**				
	Mean	Standard Deviation	Minimum	Maximum
Hold Days (number of required hold-days)	25.59	76.18	0	360
Volume Discount Ban† (zero-one dummy = 1 if wholesalers are banned from offering volume discounts to retailers)	0.15	0.36	0	1
Retail Credit†† (zero-one dummy = 1 if wholesalers are restricted from extending credit to retailers)	0.35	0.48	0	1

Notes: Panel A in the table shows summary statistics on price and non-price product characteristics across the 39 beer brands included in our data sample. The price is measured in dollars per 144 oz equivalent package. The alcohol content and calorie counts are based on per 12 oz container. *Imported* is a zero-one dummy variable that takes the value one for imported brands and zero otherwise. Panel B in the table provides state-level regulatory treatment towards Hold Days, Volume Discount Ban, and Retail Credit. †The states banning volume discounts include: KS, LA, CT, OK, TN. ††The following states impose retail credit restrictions: CO, MO, NV, NM, NY, WI, DE, MA, NJ, CT.

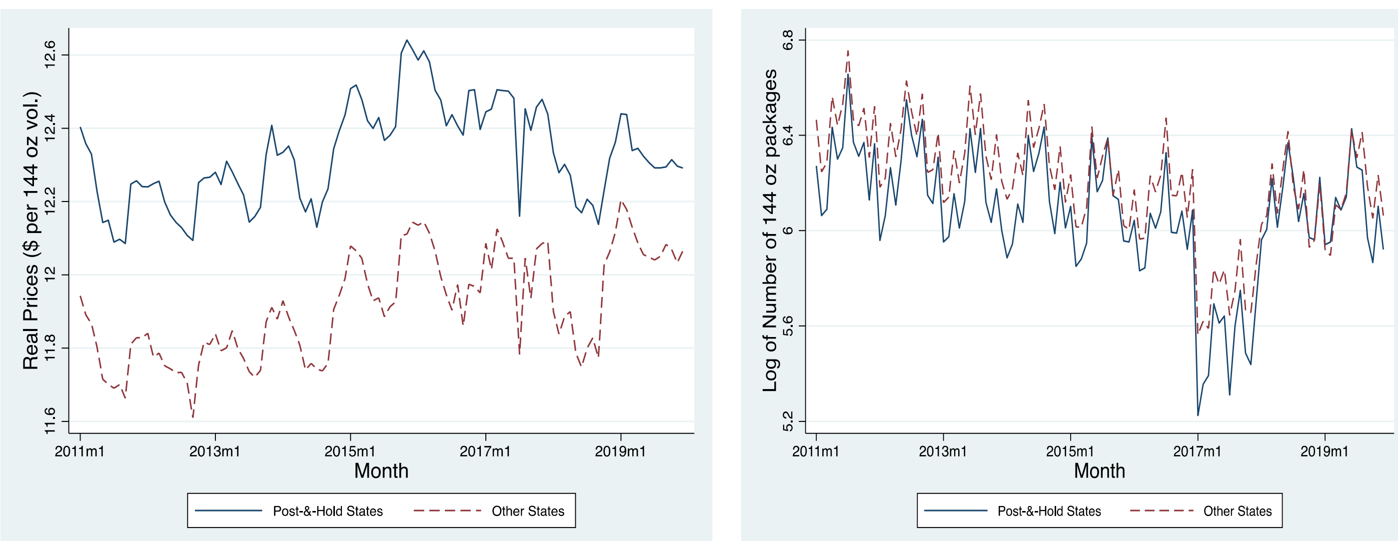
Furthermore, we exclude from our data states designated as "control" states with respect to any alcoholic beverage (either beer, wine, or distilled spirits), i.e., states that have monopoly control over the distribution of any alcoholic beverage. For example, even though Michigan follows PH laws in beer, it is excluded from the sample as it maintains a monopoly over the wholesaling of distilled spirits. The rationale for excluding such states from our data sample used for the analysis is to avoid confounding the true effects of states' PH regulation on beer with potential spillover effects from a state-run monopoly distribution system in other alcoholic beverages.

We also supplement product-level data with state-level income data. State-level income data are collected from the Public Microdata Sample (PUMS) database in which each state is partitioned into several non-overlapping Public Use Microdata Areas (PUMAs) each containing about 100,000 residents. The PUMS data provide useful demographic information for estimating demand. The data identifies household-level information across different PUMAs in a state. We draw data on consumers' income from the PUMS dataset for the period 2011 through 2019.

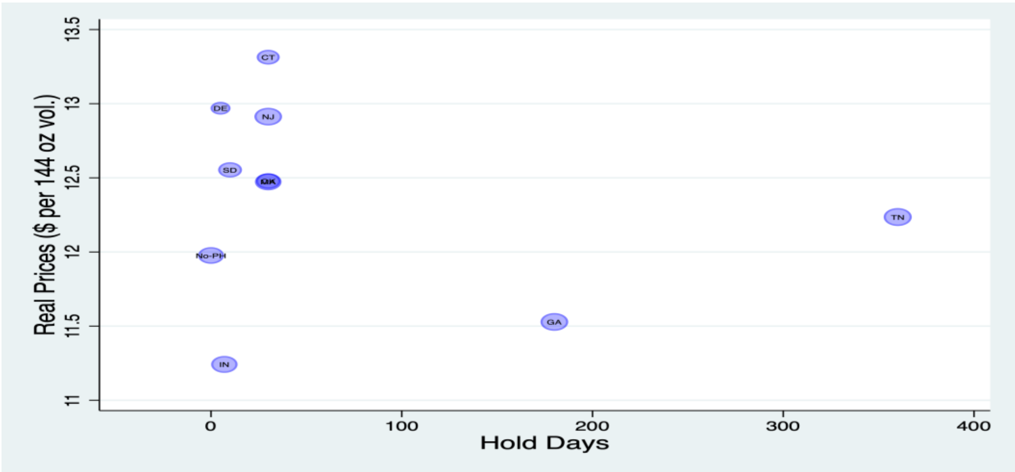
Panel A and Panel B in Figure 1 show time series plots of mean real prices and consumption, respectively, across the beer brands in our sample in PH states and non-PH states, respectively, from 2011 through 2019. It is noticeable from the figure that the prices of the beer brands in PH states are consistently higher than the prices of the same brands in non-PH states. Conversely, beer consumption in the PH states is consistently either lower or equal to the beer consumption in the non-PH states.

The bubble plot in Panel C of Figure 1 shows mean price in combination with number of required hold-days for each state, with the size of the bubble for each state corresponding to the state's relative beer consumption size in the sample. For ease of comparison, the bubble representing non-PH states is obtained by averaging across the non-PH states. The bubble plot in Panel C suggests that, on average, PH states tend to have relatively higher prices, with their consumption being either equal to or lower than non-PH states. Therefore, the plots in Figure 1 are consistent with the conjecture that PH laws are associated with relatively higher prices and often relatively lower consumption of alcoholic beverages.

Figure 1: Average Real Prices and Consumption in PH and Non-PH States



Panel A *Panel B*



Panel C

4.2 Descriptive Linear Regression Analysis

This section uses descriptive linear regressions to compare price differences and consumption differences, respectively, across states with varying stringency of PH laws for the purpose of measuring the price and consumption differences, respectively, that can be attributed to the PH laws. We specify and estimate the following regression equation:

$$Y_{jht} = \pi_0 + f(HD_{ht}; \boldsymbol{\pi}_1) + \pi_2 Income_{ht} + \eta_j + \tau_t + \epsilon_{jht} \quad (1)$$

where the dependent variable, Y_{jht}, measures either the logarithm of price or the logarithm of consumption of brand j in state h during period t; $f(\cdot)$ is a function of the policy variable, HD_{ht}, which is a count of the number of hold-days required by the relevant state's PH laws; and $\boldsymbol{\pi}_1$ is a vector of parameters associated with variable HD_{ht}. We explore various specifications for function $f(\cdot)$. Note that HD_{ht} takes a value of zero for non-PH states, and non-zero values ranging from 5 days to 360 days among states with PH laws. The control variable, $Income_{ht}$, is the mean income across individuals located in state h during period t. η_j and τ_t represent brand-pack size and period (year and month) fixed effects, respectively; and ϵ_{jht} is an error term capturing a composite of unobserved shocks to prices/consumption. The parameters to be estimated are, π_0, $\boldsymbol{\pi}_1$, and π_2.

Our key parameters of interest are contained in vector $\boldsymbol{\pi}_1$. The parameters in vector $\boldsymbol{\pi}_1$ measure the average percent differences across states in prices/consumption of beer brands that can be attributed to the states' PH laws. Table 3 reports the results of estimating equation (1) when the logarithm of beer price is the dependent variable. Note that the policy function, $f(\cdot)$, takes on a subset of the following functional forms in each column of the table:

$$f(\cdot)=\begin{cases}\pi_1^a \times PH\ Dum_{ht}, & where\ PH\ Dum_{ht}=1\ \ if\ HD_{ht}>0, otherwise\ PH\ Dum_{ht}=0\\ \pi_1^b \times HD\ Dum\ 1_{ht}, & where\ HD\ Dum\ 1_{ht}=1\ if\ 0<HD_{ht}<30,\ \ otherwise\ HD\ Dum\ 1_{ht}=0\\ \pi_1^c \times HD\ Dum\ 2_{ht}, & where\ HD\ Dum\ 2_{ht}=1\ if\ HD_{ht}=30,\ \ otherwise\ HD\ Dum\ 2_{ht}=0\\ \pi_1^d \times HD\ Dum\ 3_{ht}, & where\ HD\ Dum\ 3_{ht}=1\ if\ HD_{ht}>30,\ \ otherwise\ HD\ Dum\ 3_{ht}=0\\ \pi_1^e \times HD_{ht} & \\ \pi_1^f \times HD_{ht}^2 & \\ \pi_1^g \times log(1+HD_{ht}) & \end{cases}$$

The collection of specifications of $f(\cdot)$ shown above reveal the parameters in vector $\boldsymbol{\pi}_1$, i.e., $\boldsymbol{\pi}_1 = \left(\pi_1^a, \pi_1^b, \pi_1^c, \pi_1^d, \pi_1^e, \pi_1^f, \pi_1^g\right)$.

	Table 3: Differences in Beer Prices associated with PH Regulation						
	Dependent variable: $log\ (p_{jht})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PH Dum	0.0154*** (0.00044)				0.00096* (0.00054)		-0.032*** (0.001)
HD Dum 1 (=1 if $0 < HD_{ht} <$ 30)		-0.0211*** (0.00077)					
HD Dum 2 (=1 if $HD_{ht} = 30$)		0.0285*** (0.0006)					
HD Dum 3 (=1 if $HD_{ht} > 30$)		0.0252*** (0.0006)					
Hold Days (HD_{ht})			0.0001*** (0.000002)	-0.000087*** (0.000008)	0.00014*** (0.000002)		
HD_{ht}^2				0.0000007*** (0.00000003)			
log (1+ HD_{ht})						0.0052*** (0.0001)	0.0125*** (0.0003)
log ($Income_{ht}$)	0.0671*** (0.0013)	0.0466*** (0.0014)	0.0831*** (0.0013)	0.0905*** (0.0013)	0.0824*** (0.0013)	0.0669*** (0.0012)	0.0730*** (0.0013)
Constant	2.149*** (0.0134)	2.366*** (0.0148)	1.982*** (0.0132)	1.905*** (0.0135)	1.989*** (0.0138)	2.150*** (0.013)	2.088*** (0.0134)
No. of Observations	254,968	254,968	254,968	254,968	254,968	254,968	254,968

Notes: Observations are at the brand-size-state-year-month level. Each regression includes fixed effects controls for brand-size, year, and month even though these parameter estimates are not reported in the table. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The coefficient estimate on variable $PH\ Dum_{ht}$ in column (1) of Table 3 is positive and statistically significant, suggesting that, on average, prices in PH states are 1.5% higher than prices in non-PH states if we do not control for the impact of the varying stringency of PH laws across states. In column (2) we decompose variable, $PH\ Dum_{ht}$, based on the hold days stringency of PH laws across states using variables, $HD\ Dum\ 1_{ht}$, $HD\ Dum\ 2_{ht}$, and $HD\ Dum\ 3_{ht}$, respectively. The coefficient estimate on $HD\ Dum\ 1_{ht}$ is negative and statistically significant, suggesting that prices are lower in states with PH laws that require less than 30 hold days compared to prices in non-PH states. In contrast, the coefficient estimates on $HD\ Dum\ 2_{ht}$ and $HD\ Dum\ 3_{ht}$ are each positive and statistically significant, suggesting that prices are higher in states with PH laws that require 30 or more hold days compared to prices in non-PH states. Specifically, the coefficient estimate on $HD\ Dum\ 2_{ht}$ suggests that beer prices in states with PH laws that require 30 hold days are approximately 3% higher compared to the prices of similar beer products in non-PH states. Second, the coefficient estimate on $HD\ Dum\ 3_{ht}$ suggests that beer prices in states with PH laws that require more than 30 hold days are approximately 2.5% higher compared to the prices of similar beer products in non-PH states. Accordingly, the evidence suggests that PH laws only have an upward pressure on prices when they require 30 or more hold days.

The specifications in columns (3) and (4) use instead the actual number of required hold days variable in its linear and quadratic forms, respectively. In column (3), which only allows the required number of hold days variable, HD_{ht}, to impact prices linearly, the coefficient estimate on HD_{ht} is positive and statistically significant, suggesting that required number of hold days positively impact price. However, in column (4) where the required number of hold days is allowed to have a quadratic impact on prices, the coefficient estimate on HD_{ht}^2 is positive but the coefficient estimate on HD_{ht} is negative. Evidently, the results in column (4) reveal that the average positive effect that required number of hold days has on price in column (3) is driven by the PH states that require relatively larger number of hold days. Therefore, the takeaway lesson from the specifications in columns (3) and (4) is qualitatively similar to that in column (2), i.e., PH laws have an upward pressure on prices when the required number of hold days is larger than a threshold number of days. Furthermore, the alternate specifications in columns (5), (6), and (7) do not overturn this takeaway message.

Table 4 reports the results of estimating equation (1) when the logarithm of beer consumption is the dependent variable. Interestingly, the coefficient estimate on $PH\ Dum_{ht}$ in column (1) is positive and statistically significant, suggesting that, on average, beer consumption is 2.4% higher in PH states compared to non-PH states. In column (2) the coefficient estimates on $HD\ Dum\ 1_{ht}$ and $HD\ Dum\ 2_{ht}$ are negative and statistically significant, suggesting that beer consumption is lower in states with PH laws that require 30 or less hold days compared to consumption in non-PH states. However, interestingly and counter to expectations, the coefficient estimate on $HD\ Dum\ 3_{ht}$ is positive and statistically significant, suggesting that beer consumption is substantially higher, approximately two times higher, in PH states that require more than 30 hold days compared to consumption in non-PH states. Overall, the results in Table 4 suggest that PH regulation does not have the intended effect of reducing beer consumption.

	Table 4: Differences in Beer Consumption associated with PH Policy						
	Dependent variable: $log\ (consumption_{jht})$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PH Dum	0.0239*** (0.0086)				-0.6012*** (0.0108)		-2.166*** (0.0227)
HD Dum 1 (=1 if $0 < HD_{ht} < 30$)		-0.7223*** (0.0182)					
HD Dum 2 (=1 if $HD_{ht} = 30$)		-0.4182*** (0.0126)					
HD Dum 3 (=1 if $HD_{ht} > 30$)		1.105*** (0.0097)					
Hold Days (HD_{ht})			0.0039*** (0.00004)	0.0037*** (0.0002)	0.0059*** (0.00005)		
HD_{ht}^2				0.000001 (0.0000004)			
$log\ (1+HD_{ht})$						0.0868*** (0.0019)	0.5756*** (0.005)
$log\ (Income_{ht})$	0.6323*** (0.0234)	1.191*** (0.0256)	0.8350*** (0.0233)	0.8404*** (0.0237)	1.291*** (0.0235)	0.4909*** (0.0236)	0.9027*** (0.0235)
Constant	-2.104*** (0.2475)	-7.948*** (0.2699)	-4.331*** (0.2464)	-4.387*** (0.2506)	-9.005*** (0.2482)	-0.7026*** (0.2496)	-4.916*** (0.2483)
No. of Observations	254,968	254,968	254,968	254,968	254,968	254,968	254,968

Notes: Observations are at the brand-size-state-year-month level. Each regression includes fixed effects controls for brand-size, year, and month even though these parameter estimates are not reported in the table. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The statistically significant results in the descriptive linear price regression models in Table 3 give reason to pursue a structural econometric model for investigating the extent to which PH laws cause higher beer prices through impacting the price-setting conduct of beer firms. In other words, to what extent are the relatively higher price in PH states the result of these laws facilitating tacit collusive pricing among separately owned beer firms?

5 The Econometric Model

We begin by describing the demand-side of the model, followed by a description of the supply-side of the model.

5.1 Demand

We model the demand for beer using a random coefficients logit model. As previously discussed, a market is defined as the unique combination of a state and period, while a product in a market is defined as the unique combination of beer brand and package size. Let markets be indexed by m and products by j. In each market, consumer i has $J_m + 1$ alternative options, i.e., the consumer can choose among the J_m ($j = 1,2, \ldots J_m$) differentiated beer products in a market or the outside option $j = 0$, where the outside option includes alternative beverages that are substitutes for beer which include: non-beer beverages such as wine, spirits, beer sold outside grocery/superstore channels, and other beer brands such as craft beer.

Assume consumer i receives indirect utility V_{ijm} from product j in market m and solves the following discrete choice optimization problem:

$$\max_{j \in \{0,1,\ldots J_m\}} \{V_{ijm} = x_{jm}\beta_i + \alpha_i p_{jm} + \xi_{jm} + \Delta\xi_{jm} + \varepsilon_{ijm}\} \tag{2}$$

where $x_{jm}$is a $k \times 1$ vector of observed non-price product characteristics; p_{jm} is the price of product j; ξ_{jm} is a composite measure of product characteristics that are unobserved by the researchers, but observed by consumers and firms; $\Delta\xi_{jm}$ is a market–specific deviation from ξ_{jm}; and ε_{ijm} is an individual-specific random component of utility that accounts for deviation of the individual's preference from the mean utility.

Examples of measurable non-price product characteristics we control for are calorie counts, alcoholic content, and a zero-one indicator variable that takes the value one only if the product is imported. Product characteristics unobserved to us may include various vertical and horizontal aspects of product differentiation. Unknown vertical components in ξ_{jm} imply that a researcher may not have knowledge if a beer brand, or set of beer brands, is perceived superior to others in terms of their quality and tastes by all consumers. We control for vertical components in ξ_{jm} by including brand dummy variables in the estimation of demand. The market-specific unobserved product characteristics included in $\Delta\xi_{jm}$ are left as the error term.

The unknown random coefficients β_i and α_i, respectively, vary across consumers, where β_i is a vector of consumer-specific taste parameters associated with different non-price product characteristics in x_{jm}, while α_i represents consumer-specific marginal disutility of price. Following the notation in Nevo (2000), the variation in individual-specific parameters is explained by a known *m*-dimensional column vector of demographic information (D_i), and a k-dimensional column vector of unobserved consumer taste shocks (v_i), i.e.:

$$\binom{\alpha_i}{\beta_i} = \binom{\alpha}{\beta} + \Psi D_i + \Upsilon v_i, \tag{3}$$

where Ψ is a $k \times m$ matrix of parameters measuring how taste characteristics vary with demographics; and Υ is a $k \times k$ diagonal matrix measuring the variation in consumers' tastes due to random taste shocks, v_i.[13] The demographic variables are included in the form of deviation from their respective means, implying that the mean of each demographic variable in D_i is zero. We assume v_i follows the standard normal distribution ($v_i \sim N(0, I)$). Since the means of v_i and D_i are each zero, then α and β measure the mean of the random coefficients. Therefore, the mean utility level obtained from each of the J_m products, δ_{jm}, is given by:

$$\delta_{jm} = x_{jm}\beta + \alpha p_{jm} + \xi_{jm} + \Delta\xi_{jm} \tag{4}$$

The mean utility obtained from the outside option, denote δ_{0m}, is normalized to zero, i.e., $\delta_{0m} = 0$.

Let $\theta_d = (\theta_1, \theta_2)$ be parameters of the demand model, where $\theta_1 = (\alpha, \beta)$ is the vector of demand parameters that enters the demand model linearly, whereas $\theta_2 = (\Psi, \Upsilon)$ is the vector of demand parameters that enters the demand model non-linearly. Furthermore, let

$$\mu_{ijm}(x_{jm}, p_{jm}, v_i, D_i; \theta_2) = [p_{jm}, x_{jm}](\Psi D_i + \Upsilon v_i) \tag{5}$$

Using equations (2) through (5) allow us to express the indirect utility from consuming product j as:

$$V_{ijm} = \delta_{jm}(x_{jm}, p_{jm}, \rho_j, \delta_r, \tau_t, \xi_{jm}; \theta_1) + \mu_{ijm}(x_{jm}, p_{jm}, D_i, v_i; \theta_2) + \varepsilon_{ijm} \tag{6}$$

The indirect utility is expressed as the mean utility (δ_{jm}) and a consumer-specific mean-zero-deviation $(\mu_{ijm} + \varepsilon_{ijm})$ from the mean utility.

Following the literature [Berry, Levinsohn, and Pakes (1995) hereafter BLP (1995), and Nevo (2000)] on discrete choice models, the random utility term ε_{ijm} is assumed to be governed by an independent and identically distributed extreme value density. The implied predicted market share of product j, or the choice probability of product j is given by:

[13] As previously noted, *k* corresponds to the number of measured non-price product characteristics.

$$s_{jm}(\boldsymbol{x}, \boldsymbol{p}, \boldsymbol{\xi}; \theta_d) = \int \frac{e^{\delta_{jm}+\mu_{ijm}}}{1 + \sum_{l=1}^{J_m} e^{\delta_{lm}+\mu_{ilm}}} \, \widehat{dF}(D) dF(v), \tag{7}$$

where $\hat{F}(D)$ is the empirical distribution of demographic variables; and $F(v)$ is the multivariate standard normal distribution. It is well-known that the integral problem in equation (7) does not have a closed-form solution; thus, the right-hand side of the equation must be approximated numerically using random draws from $\hat{F}(D)$ and $F(v)$.[14]

The potential market size is defined in terms of the maximum unit sales in each geographical market. We follow Miller and Weinberg (2017) and define the potential market size, M_m, as 10% higher than the observed maximum unit sales in the relevant geographic location. Accordingly, the demand for product j is given by:

$$d_{jm} = M_m \times s_{jm}(\boldsymbol{x}, \boldsymbol{p}, \boldsymbol{\xi}; \theta_d) \tag{8}$$

where $s_{jm}(\cdot)$ is the model-predicted product share from equation (7); $\boldsymbol{x}$ and $\boldsymbol{p}$ are vectors of observed non-price product characteristics and prices, respectively; $\boldsymbol{\xi}$ is a vector of product characteristics unobserved by researchers but observed by firms and consumers; and $\theta_d = (\alpha, \beta, \Psi, \Upsilon)$ is the vector of demand parameters to be estimated.

5.2 Supply

We now outline the supply-side of the model. The PH laws of a state directly apply to the local distributors of alcohol. Information on local distributors that is of particular importance for the objectives of our analysis include their identity, the menu of products they sell, distributors' unit sales of these products, and the prices they set for these products. Unfortunately, a limitation of our study is that we do not have information on local distributors. Accordingly, we assume that PH laws indirectly impact the price-setting behavior of brewers when pricing their products for sale in states with PH laws. Specifically, we assume that PH laws cause brewers to, partially or fully, internalize pricing externalities across beer products owned by separate brewers in each PH state. In other words, we specify a supply-side framework adapted from Miller and Weinberg (2017), allowing for varying degrees of collusive price-setting behavior - conditional upon the number of permitted post and hold days policy - among brewers selling

[14] Accordingly, s_{jm} in equation (7) is numerically approximated as follows: $s_{jm} = \frac{1}{ns}\sum_{i=1}^{ns} s_{ijm}(\boldsymbol{x}, \boldsymbol{p}, \boldsymbol{\xi}; \theta_d)$ with $s_{ijm}(\boldsymbol{x}, \boldsymbol{p}, \boldsymbol{\xi}; \theta_d) = \frac{exp(\delta_{jm}+\mu_{ijmt})}{1+\sum_{l=1}^{J_{mt}} exp(\delta_{lm}+\mu_{ilmt})}$ where $ns = 500$, which is the number of individual random draws from $\hat{F}(D)$ and $F(v)$ used for the approximation.

beer products in each PH state. Like Miller and Weinberg (2017), we make the simplifying assumption that brewers effectively determine per-unit retail prices, and retailers behave passively in setting retail beer prices paid by consumers.

Studies have argued that PH policy facilitates non-competitive pricing behavior among alcoholic beverage suppliers in a state. For example, Conlon and Rao (2023) show theoretically that PH policy facilitates coordination in price-setting behavior among separately owned firms, and use data drawn from Connecticut's distilled spirits market to estimate impacts and policy implications of such coordinated price-setting behavior. In addition, Cooper and Wright (2012) argue that the drop in alcohol consumption in PH states is consistent with higher prices driven by collusive behavior among alcoholic beverage wholesalers. Accordingly, unlike in non-PH states, we assume that in a PH state brewers may internalize pricing externalities across their separately owned menus of differentiated beer products when setting per-unit retail prices for these products.

Concerning brewers' behavior, we assume brewer b sells a set of B_m^b products, where B_m^b is a subset of the J_m beer products available to consumers in market m. Therefore, brewer b considers the following profit function when setting prices for its products to maximize its profit in market m:

$$\Pi^b = \sum_{j \in B_m^b} \left(p_{jm} - mc_{jm}\right) \times q_{jm} + \kappa_h \sum_{r \in \left(J_{m \setminus B_m^b}\right)} (p_{rm} - mc_{rm}) \times q_{rm} \qquad (9)$$

where p_{jm} denotes the retail price of product j in market m; mc_{jm} denotes per unit marginal cost that is a composite of the wholesale and retail costs incurred by the brewer and the retailer; q_{jm} is the quantity of product j sold in market m; $\sum_{j \in B_m^b} \left(p_{jm} - mc_{jm}\right) \times q_{jm}$ is the joint variable profit earned by brewer b in selling its set of products, B_m^b; while $\sum_{r \in \left(J_{m \setminus B_m^b}\right)} (p_{rm} - mc_{rm}) \times q_{rm}$ is the joint variable profit earned by other brewers selling products that are substitutes for brewer $b's$ products. Collusive price-setting behavior implies that brewer b cares how pricing of its products impacts $\sum_{r \in \left(J_{m \setminus B_m^b}\right)} (p_{rm} - mc_{rm}) \times q_{rm}$. Accordingly, κ_h is an index measure of the extent to which each brewer in state h cares about how pricing of its products impacts the joint variable profit of other "competing" brewers in the state, which effectively means that κ_h is an index measure of the extent to which brewers in state h tacitly coordinate over pricing, where $\kappa_h \in [0,1]$.

Each brewer, therefore, solves the following profit maximization problem:

$$\max_{p_{jm}\forall j\in B_m^b}\left[\sum_{j\in B_m^b}(p_{jm}-mc_{jm})\times M_m\times s_{jm}(p)+\kappa_h\sum_{r\in(J_m\backslash B_m^b)}(p_{rm}-mc_{rm})\times M_m\times s_{rm}(p)\right] \quad (10)$$

where market equilibrium requires $q_{jm} = d_{jm} = M_m \times s_{jm}(p)$. The system of first-order conditions from the optimization problem in (10) that yields a pure strategy Nash equilibrium in retail prices is:

$$s_j + \sum_{l\in B^b}(p_l - mc_l)\left(\frac{\partial s_l}{\partial p_j}\right) + \kappa_h \sum_{r\in(J\backslash B^b)}(p_r - mc_r)\left(\frac{\partial s_r}{\partial p_j}\right) = 0 \quad \forall\, j \in B^b \quad (11)$$

How κ_h enters the system of first-order conditions in equation (11) makes it clearer that κ_h measures the extent to which each brewer incorporates the marginal impact of its pricing on the profits of rival brewers. At one end of the price-setting behavior spectrum, $\kappa_h = 0$, which implies that price-setting behavior is equivalent to Bertrand Nash competition, i.e., no collusive pricing; while at the other end of the price-setting behavior spectrum, $\kappa_h = 1$, which implies that price-setting behavior is equivalent to joint profit maximization across separately owned firms, i.e., perfect collusion. Therefore, $0 < \kappa_h < 1$ correspond to partial collusion or partial internalization of pricing externalities.

Guided by the theoretical prediction and the empirical evidence consistent with non-competitive pricing behavior attributed to PH laws provided in prior studies, as well as the linear regression evidence provided in Table 3 of this study revealing that PH laws have an upward pressure on prices when the required number of hold days is larger than a threshold number of days, we specify that the index measure κ_h is a function of the stringency of the relevant state's PH policy, measured by variable, $\overline{HD}_h$. Variable, $\overline{HD}_h$, is a modified PH policy variable that takes a value of zero for non-PH states and states with PH laws that require less than 30 hold days but takes a value of the number of hold days for states with PH laws that require 30 or more hold days. Accordingly, we specify that the extent of tacit price-setting collusion that occurs in state h is determined by the following equation:

$$\kappa_h = \lambda \times \overline{HD}_h \quad (12)$$

where λ is an estimable parameter.

The modeling of firms' price-setting conduct here, captured by $\kappa_h = f\left(\overline{HD}_h\right)$, is similar in spirit to that in Ciliberto and Williams (2014) where they specify that price-setting conduct between a given pair of airlines is a function of the pair's number of multimarket contacts, i.e., $f(mmc_{kh})$, where mmc_{kh} is a measure of the number of distinct air travel markets in which airline pair (k, h) "compete" for passengers. On page 778 of Ciliberto and Williams (2014), they point out that when firms' price-setting conduct is explicitly modeled in this way there is no need to address the critique of Corts (1999). The reason is that Corts (1999) points out that inference regarding conduct parameters is invalid if the researcher does not stipulate "the true nature of the behavior underlying the observed equilibrium." Like in Ciliberto and Williams (2014), our analysis explicitly stipulates a Bertrand-Nash pricing model and identifies price-setting conduct measures conditional on this behavioral assumption. Furthermore, Berry and Haile (2014) show that changes in "market environment" can be used to distinguish between competing oligopoly models of firm conduct. In our setting, changes in the "market environment" is measured by state-level variations in number of required hold-days, which is used for identifying firms' price-setting conduct.

We argue that required number of hold-days is exogenous, or at least predetermined, to the price-setting oligopoly model since once a state sets its required number of hold-days this requirement rarely ever changes. For example, over the 9-year time span of our data sample it is only the state of Michigan that changed its required number of hold-days in 2016 from 180 to 90 days. Accordingly, the required number of hold-days in each state is unlikely to change with shocks to beer demand or cost. Therefore, for changes in beer demand and cost conditions that are similar across markets, equilibrium prices of beer products will change differently across markets that differ with respect to the required number of hold-days allowing for the identification of market-specific differences in firms' price-setting conduct since such differential changes in prices can only be attributed to differences in the firms' price-setting conduct.

For further analytical purposes it is more convenient to represent the system of first-order conditions in (11) using matrix notation. Market subscripts are suppressed in many subsequent equations only to avoid a clutter of notation. To represent the system of first-order conditions using matrix notation we first need to define a few matrices.

First, let $\mathbf{\Omega}$ be a $J \times J$ matrix, with each element taking a value of either 1 or κ_h in a pattern that characterizes brewers' product ownership structure as well as the structure of internalization of pricing externalities across brewers among the J products in the market. Specifically, matrix $\mathbf{\Omega}$ has general element $\Omega(g, j)$ equal to 1 if $g = j$ or if distinct products g and j are sold by the same brewer; but equal to κ_h if product g and product j are sold by different brewers.

Second, let Δ be a $J \times J$ matrix that captures the marginal responses of model-predicted product market shares to marginal changes in retail prices. Therefore, matrix Δ contains first-order partial derivatives of product shares with respect to retail prices:

$$\Delta = \begin{pmatrix} \frac{\partial s_1}{\partial p_1} & \cdots & \frac{\partial s_J}{\partial p_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial s_1}{\partial p_J} & \cdots & \frac{\partial s_J}{\partial p_J} \end{pmatrix}$$

The system of first-order conditions characterized by equation (11) can now be represented in matrix notation as follows:

$$s(p) + \left[\mathbf{\Omega}\left(1, \kappa_h(\overline{HD}_h; \lambda)\right) * \Delta\right] \times (p - mc) = \mathbf{0} \qquad (13)$$

where $s(\cdot)$, p, and mc are $J \times 1$ vectors of product shares, retail prices, and full (wholesale plus retail) marginal costs, respectively; $\mathbf{\Omega}(\cdot) * \Delta$ is an element-by-element multiplication of the two matrices; and the functional form specification of $\kappa_h(\overline{HD}_h; \lambda)$ is given in equation (12).

A Simple Hypothetical Example for Illustrative Purposes

Consider a simple hypothetical market with only two rival brewers, each offering a single beer product for sale, with the two beer products being differentiated imperfect substitutes for each other. In this two-product-two-firm example, $\mathbf{\Omega}\left(1, \kappa_h(\overline{HD}_h; \lambda)\right) = \begin{pmatrix} 1 & \kappa_h \\ \kappa_h & 1 \end{pmatrix}$; and $\Delta = \begin{pmatrix} \frac{\partial s_1}{\partial p_1} & \frac{\partial s_2}{\partial p_1} \\ \frac{\partial s_1}{\partial p_2} & \frac{\partial s_2}{\partial p_2} \end{pmatrix}$. Therefore, equation (13) yields the following two-equation system:

$$\begin{pmatrix} s_1 \\ s_2 \end{pmatrix} + \begin{pmatrix} \frac{\partial s_1}{\partial p_1} & \kappa_h * \frac{\partial s_2}{\partial p_1} \\ \kappa_h * \frac{\partial s_1}{\partial p_2} & \frac{\partial s_2}{\partial p_2} \end{pmatrix} \times \begin{pmatrix} p_1 - mc_1 \\ p_2 - mc_2 \end{pmatrix} = \mathbf{0}$$

which implies the following first-order condition for the brewer offering product j:

$$\underbrace{s_j(p) + \frac{\partial s_j}{\partial p_j}\left(p_j - mc_j\right)}_{Bertrand\ Nash\ F.O.C\ with\ no\ collusion} + \underbrace{(\lambda \times \overline{HD}_h) * \frac{\partial s_{-j}}{\partial p_j}\left(p_{-j} - mc_{-j}\right)}_{Collusive\ effect} = 0 \quad \text{for } j = 1, 2 \qquad (14)$$

where $-j$ denotes the product that is an imperfect substitute for product j; and $\lambda \times \overline{HD}_h = \kappa_h$. Similar in spirit to the collusive price-setting framework in Ciliberto and Williams (2014),[15] equation (14) here reveals that the *collusive effect* comprises an interaction between the coordination price-setting conduct measure of the firms, $(\lambda \times \overline{HD}_h)$, and the cross-price demand elasticity between the substitute products, $\frac{\partial s_{-j}}{\partial p_j}$. If the market is in a non-PH state, or in a PH state with PH laws that require less than 30 hold-days,

[15] See equation (9) on page 778 in Ciliberto and Williams (2014).

then $\overline{HD}_h = 0$ and the collusive effect labeled in equation (14) goes to zero. Assuming parameter $\lambda > 0$ as we anticipate, then for states with PH laws that require 30 or more hold-days the coordination price-setting conduct measure of the firms, $(\lambda \times \overline{HD}_h)$, will be positive and the magnitude of the collusive effect shown in equation (14) depends on the size of the cross-price demand elasticity between the substitute products. In other words, conditional on a given positive coordination price-setting conduct measure, the extent to which the corresponding collusive price-setting behavior drives up prices depends on the size of cross-price demand elasticities between the relevant substitute products.

Specifying the structural empirical supply-side equation

The general system of first-order conditions in equation (13) can be rearranged to recover the $J \times 1$ vector of total product-level markups, denoted as Γ:

$$\Gamma = p - mc = -[\mathbf{\Omega}(\cdot) * \Delta]^{-1} \times s(p) \tag{15}$$

Therefore, the following supply equation helps determine the vector of equilibrium prices for each market:

$$p = \Gamma\left(\hat{\theta}_d, \lambda\right) + mc \tag{16}$$

Note that the markup term, $\Gamma\left(\hat{\theta}_d, \lambda\right)$, is a function of λ and demand parameter estimates, $\hat{\theta}_d$. Furthermore, since p is observed data on retail price, the left-hand side of equation (16) is completely known. However, we, the researchers, do not have direct data on marginal costs, and therefore at best, we can only approximate the right-hand side of equation (16) by specifying and estimating a marginal cost function.

Consider the following specification of the marginal cost function:

$$mc_j = \phi W_j + \varepsilon_j^{mc} \tag{17}$$

where W_j is a vector of variables that shift the marginal costs and ϕ is the associated vector of parameters; and ε_j^{mc} is a mean-zero, random error term that captures determinants of the marginal cost unobserved to us, the researchers. In W_j we include a couple state-level regulation variables for volume discount ban and retail credit restrictions, respectively, as well as period (year-month) dummies, and brand-size dummies. The variables in W_j are assumed exogenous and therefore serve as valid instruments for themselves.

Together, equations (16) and (17) yield the following structural empirical supply-side equation:

$$p = \Gamma\left(\hat{\theta}_d, \lambda\right) + \phi W_j + \varepsilon_j^{mc} \tag{18}$$

The error term in equation (18) as a function of demand and supply parameters is given as:

$$\varepsilon_{jm}^{mc}\left(\hat{\theta}_d, \theta_s\right) = p_{jm} - \phi W_j - \Gamma\left(\hat{\theta}_d, \lambda\right) \tag{19}$$

where $\theta_s = (\phi, \lambda)$ denotes the vector of supply-side parameters. So, with the demand parameter estimates $\hat{\theta}_d$ in hand, we can estimate supply-side parameters in θ_s using generalized methods of moments (GMM), where moment conditions are constructed by interacting the error term (ε_{jm}^{mc}) with appropriate instrument variables.

6 Estimation

We estimate the demand and supply sides of the model separately. This section begins with describing how we estimate the demand parameters, and then briefly discuss how the supply parameters are estimated.

6.1 Demand Estimation

Following much of the empirical industrial organization literature [Berry (1994), BLP (1995), and Nevo (2000)], we estimate the demand parameters using Generalized Methods of Moments (GMM). Moments and the GMM objective function are constructed by interacting instruments with the structural error term from the demand model. The structural error term from the demand model, $\Delta\xi_{jm}$, is the composite of geographic area-period-specific deviations of non-price product characteristics that are unobserved to us, the researchers, but observable to firms and consumers.

Following Nevo (2000), we use a full set of brand dummy variables as regressors to capture both observed ($x_{jm}\beta$) and unobserved (ξ_j) non-price product characteristics. We then use a minimum distance estimator to recover β. Since Nevo (2000) describes in great detail both the GMM estimation algorithm for the random coefficients logit demand model and the minimum distance estimator to recover β, we refer the reader to that paper for a description of the demand estimation procedures we use.

Firms set prices based on product characteristics and market-specific consumer valuations. As such, price (p_{jm}) is likely to be correlated with the structural demand error term ($\Delta\xi_{jm}$), i.e., price is endogenous in the demand model. It is, therefore, necessary to find instruments for price when estimating the demand parameters.

Instruments for demand estimation

One set of instruments for prices we use are BLP-style instruments. These instruments are constructed using distinct non-price product attributes like alcohol content, calories, and package sizes. A BLP-style instrument is obtained by computing for each product the average package sizes across rival products in the relevant market. Another BLP-style instrument is obtained by interacting for each product the average calories and average alcoholic contents across its rival products in each relevant market. Last, another BLP-style instrument is obtained by summing for each product the alcohol content of the rival products and interacting this variable with the average package size of the rival products.

Another type of instrument for beer price we use in demand estimation is a variable expected to shift the marginal cost of providing beer. Specifically, we use monthly regional diesel prices as an instrument.[16] As discussed in Miller and Wienberg (2017), transportation cost is an important component of beer production cost due to differences in the location proximity of breweries relative to the local markets they serve. Accordingly, changes in diesel prices should shift the marginal cost of providing beer products to local markets. Shifts in marginal cost will be reflected in prices but should not be correlated with demand-side shocks, making marginal cost-shifting variables valid instruments for price in demand estimation.

Following Gandhi and Houde (2020), we supplement the BLP-style and marginal cost-shifting instruments described above with product differentiation instruments that capture the relative isolation of products in characteristics space.[17] We use different differentiation instruments that help identify the standard deviations of the random coefficients on price, the alcohol content variable, and the constant term. To help identify the standard deviation preference parameter on price, we compute the Euclidian distance between a product's predicted price and predicted prices of rival products, where the predicted prices are generated from an ordinary least square (OLS) estimated reduced-form price regression.[18] Second, another differentiation instrument that helps identify the standard deviation preference parameter on price is the square of the summation of the interaction of an indicator variable with the predicted price differences between the product's and rival products' predicted prices. Here, the indicator variable identifies rival products with the same attribute (imported or domestically produced) as the given product.[19]

[16] The data on monthly diesel prices is downloaded from https://www.eia.gov.

[17] For the construction of these differentiation instruments, we refer the reader to Table 12 in Gandhi and Houde (2020). The predicted prices are obtained from a reduced-form regression of prices on all the non-price product characteristics as well as the exogenous cost-shifters and fixed effects previously discussed.

[18] As discussed in Gandhi and Houde (2020), the Euclidian distance instrument for prices is defined as: $\sqrt{\sum_{j' \neq j \in J_t} \left(\hat{P}_{j't} - \hat{P}_{jt}\right)^2}$.

[19] The differentiation instrument for the discrete product attribute of whether or not the relevant product in question is imported is defined as: $\left(\sum_{j' \neq j \in J_t} 1\{x_{j't,import} = x_{jt,import}\}\left(\hat{P}_{j't} - \hat{P}_{jt}\right)\right)^2$.

According to Gandhi and Houde (2020), differentiation instruments, like those described above, are intended to improve empirical performance and avoid the weak instrument challenge.[20] The variations in these differentiation instruments capture consumers' substitution choice behavior along the dimensions measured by these instruments. For example, the differentiation instruments constructed from the predicted prices described above capture the fact that low-priced products are closer substitutes with the outside option than higher-priced beer products.

6.2 Supply Estimation

We estimate the supply side of the model using GMM. The vector of supply-side parameters to be estimated is given by $\theta_s = (\phi, \lambda)$. The parameters in vector ϕ are identified by the cost-shifting variables and fixed effects. Second, as revealed in Figure 1, PH states have higher prices than non-PH states for the same set of beer products. In addition, the linear price regression results in Table 3 show that the number of hold-days required by states PH laws impacts prices positively. Therefore, parameter λ is identified by the variation of number of hold-days across states.

7 Estimation Results

7.1 Results from Demand Estimation

We report demand estimation results for both the standard logit model and the random coefficients logit model in Table 5. Comparing ordinary least squares (OLS) estimates without instrumentation with the other columns of estimates when price instruments are used, it is noticeable that the coefficient estimate for price increases in absolute value with instrumentation. The Wu-Hausman test statistic reported in Table 5 confirms the endogeneity of price by rejecting the exogeneity of the price at the 1% level, suggesting that the OLS estimation produces a biased and inconsistent estimate of the price coefficient. Furthermore, the Stock and Yogo (2005) weak instrument test statistic, also reported in the table, rejects the null hypothesis that the instruments used for price are weak.

Gandhi and Houde (2020) argue that the differentiation instruments help to avoid the weak instruments challenge that may arise in demand estimation. We perform the Independence of Irrelevant Alternatives (IIA) hypothesis test to investigate the possibility of weak (differentiation) instruments problems.[21] The IIA joint test statistic reported in Table 5 confirms the relevance of our product

[20] See also Gandhi and Nevo (2021).
[21] See Gandhi and Houde (2020) for details of how to test for weak identification issues in random coefficients demand models.

differentiation instruments to identify deviations of the random coefficients from the standard logit preferences.

The subsequent discussion focuses on the random coefficients logit model since it allows for richer heterogeneity in consumers' tastes. Furthermore, the IIA statistical test reported in the table clearly rejects the standard logit model in favor of the random coefficients logit model. Estimation results from the random coefficients logit demand model are presented in columns 3, 4, and 5. The column labeled "Standard Deviations" captures taste variation unobserved by the researchers for various product characteristics.

Table 5: Demand Model Parameter Estimates

	Standard Logit Model		**Random Coefficient Logit Model**		
	OLS (1)	2SLS (2)	Means (3)	Standard Deviation (4)	Interaction with Income (5)
Variables	α, β	α, β	α, β	Υ	Ψ
Price	-0.20^{***}	-1.58^{***}	-1.64^{***}	0.004	-1.39
	(0.003)	(0.05)	(0.32)	(0.01)	(1.52)
Constant	-3.85^{***a}	-4.23^{***a}	2.07^{***a}	6.31^{***}	…
	(0.03)	(0.04)	(0.13)	(0.26)	…
Alcohol	0.30^{***a}	0.35^{***a}	1.32^{***a}	0.32^{***}	-1.12
	(0.01)	(0.01)	(0.01)	(0.01)	(3.98)
Imported	0.21^{***a}	0.13^{***a}	0.54^{***a}	…	…
	(0.01)	(0.01)	(0.01)	…	…
Calories	-0.01^{***a}	-0.01^{***a}	-0.02^{***a}	…	…
	(0.00019)	(0.00027)	(0.00028)	…	…
Year & Month Fixed Effects	Yes	Yes	Yes		
Brand× pack size Fixed Effects	Yes	Yes	Yes		
State Fixed Effects	Yes	Yes	Yes		
Stock and Yogo Weak Instrument Test (F-statistic)		337.97^{***}			
Wu-Hausman (F-statistic)		1743.76^{***}			
IIA Test (Chi2)		1474.96^{***}			
GMM Objective			5659.97		

Notes: Standard errors are given in parentheses. * indicates statistical significance at the 10% level, ** indicates statistical significance at the 5% level, and *** indicates statistical significance at the 1% level. The above results are based on 254,968 observations. All regression includes year, month, brand×pack size dummies, and state dummies.
[a] Estimates from a Minimum Distance Procedure.

The estimated consumer sensitivities to changes in price and non-price attributes vary across individuals in the random coefficients logit model. For the average consumer, the disutility of price is statistically significant as the mean price coefficient estimate (α) is negative and statistically significant.

As such, on average, a price increase reduces utility for individuals and will cause less purchases of the product that sustained a price increase, *ceteris paribus*. In addition, the estimated standard deviation coefficient on the constant is statistically significant, suggesting that consumers are heterogeneous with respect to their preference for the outside option. The fifth column displays the coefficient estimate on the interaction variable of price with income, which in contrast to the evidence in Miller and Weinberg (2017) is not statistically different from zero at conventional levels of statistical significance, suggesting that consumers' sensitivities to price changes do not vary by their income level when it comes to beer. Perhaps a reason for this finding is that beer likely takes up a relatively small portion of the budget of a typical consumer.

The estimated coefficient on the "Imported" dummy variable is positive, suggesting that the average consumer obtains relatively higher utility from consuming imported beer brands than domestic brands. In other words, after controlling for price and other non-price beer attributes, the average consumer seems to prefer imported beer brands to domestic brands.

Beer products differ in terms of the range of alcohol content from 2.8% to 5.9%. For the average consumer, the higher alcohol content is preferable as the coefficient of alcohol content is positive and statistically significant at the 1% level of significance. In other words, the alcohol content is positively related to the average individual's utility from consuming beer. In addition, the estimated standard deviation coefficient on the alcohol content variable is statistically significant, suggesting that consumers are heterogeneous with respect to their preference for the alcoholic content attribute of beer. There is no evidence that the heterogeneity in preference for the alcoholic content attribute of beer is correlated with consumers' income level since the coefficient estimate on the interaction variable of alcohol content with income is not statistically different from zero at conventional levels of statistical significance.

Apparently, consumers dislike calorie-intensive beer brands, as implied by the negative sign of the coefficient estimate on the *Calories* variable. There is a general perception that carbohydrates and calories make beer an unhealthy drink relative to other alcoholic drinks.[22] Research on the relationship between obesity and beer supports a positive relationship between obesity and beer consumption.[23] Consistent with this finding, our results show that for the average consumer, calories decrease their utility.

[22] http://www.npr.org/sections/thesalt/2014/12/31/374187472/if-youre-toasting-for-health-beer-may-be-a-good-bet
[23] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4338356/

Given the demand parameter estimates in Table 5, we use the demand model to compute own- and cross-price demand elasticities.[24] As our discussion of equation (14) above reveals, the magnitude of cross-price demand elasticities does influence the size of any collusive effect, *ceteris paribus*. Specifically, the magnitude of cross-price demand elasticities between products of independently owned firms does influence the extent to which collusive price-setting conduct among the firms will increase equilibrium prices. Accordingly, it is instructive to get a sense of the estimates of demand elasticities generated by our model and compared them to others obtained in the literature.

The mean of own-price demand elasticities across the 39 beer brands in our sample is -19.59, while the mean of cross-price demand elasticities is 0.16. For comparison, we report in Table 6, mean own- and cross-price demand elasticities generated by our demand model for the 13 beer brands studied in Miller and Weinberg (2017). It is evident from comparing the estimates in our Table 6 with the estimates in Table V on page 1778 in Miller and Weinberg (2017) that both studies find estimates of cross-price demand elasticities of a similar order of magnitude. However, our estimates of own-price demand elasticities are an order of magnitude higher compared to those reported in Miller and Weinberg (2017). A likely reason for our demand model generating larger estimates of own-price demand elasticities is that our study covers 39 beer brands, while Miller and Weinberg (2017) focus on only 13 beer brands. Accordingly, our demand model accommodates a wider range of substitute choice alternatives faced by the average consumer, and therefore is likely to capture greater consumption substitutability that is reflected in the higher own-price demand elasticities in our study.

7.2 Results from Supply Estimation

Table 7 provides estimates of the structural parameters in the supply equation, $\theta_s = (\phi, \lambda)$, where ϕ is the vector of parameters associated with marginal cost-shifting variables and λ is the parameter that is interacted with the hold-days policy variable, $\overline{HD}_h$, based on equation (12), which enables generating the coordination price-setting conduct measure among brewers selling in the relevant state. We begin by discussing the estimates of key marginal cost parameters in vector ϕ.

[24] The price elasticities of demand are computed using, $\eta_{jrm} = \frac{\partial s_{jm}}{\partial p_{rm}} \frac{p_{rm}}{s_{jm}} =$

$$\begin{cases} -\frac{p_{rm}}{s_{jm}} \frac{1}{ns} \sum_{i=1}^{ns} \alpha_i s_{ijm}\left(1 - s_{ijm}\right) & if \quad j = r, \text{ i.e., own-price elasticity} \\ \frac{p_{rm}}{s_{jm}} \frac{1}{ns} \sum_{i=1}^{ns} \alpha_i s_{ijm} s_{irm} & \text{otherwise, i.e., cross-price elasticity} \end{cases}.$$

Table 6: Select Beer Brands' Own- and Cross-Price Demand Elasticities

Brands	Bud Light	Budweiser	Coors Banquet	Coors Light	Corona Extra	Corona Light	Heineken	Heineken Light	Michelob Light	Michelob Ultra Light	Miller Genuine Draft	Miller High Life	Miller Lite
Bud Light	-17.48	…	…	…	…	…	…	…	…	…	…	…	…
Budweiser	0.61	-18.11	…	…	…	…	…	…	…	…	…	…	…
Coors Banquet	0.45	0.23	-18.42	…	…	…	…	…	…	…	…	…	…
Coors Light	0.66	0.42	0.24	-17.81	…	…	…	…	…	…	…	…	…
Corona Extra	0.75	0.52	0.36	0.53	-24.14	…	…	…	…	…	…	…	…
Corona Light	0.59	0.31	0.13	0.35	0.44	-24.48	…	…	…	…	…	…	…
Heineken	0.67	0.46	0.29	0.47	0.58	0.37	-24.35	…	…	…	…	…	…
Heineken Light	0.48	0.23	0.07	0.29	0.39	0.18	0.30	-25.06	…	…	…	…	…
Michelob Light	0.46	0.22	0.05	0.25	0.35	0.15	0.28	0.08	-22.36	…	…	…	…
Michelob Ultra Light	0.58	0.35	0.18	0.38	0.47	0.29	0.40	0.21	0.19	-20.30	…	…	…
Miller Genuine Draft	0.43	0.22	0.04	0.24	0.34	0.13	0.28	0.07	0.04	0.18	-18.54	…	…
Miller High Life	0.43	0.20	0.03	0.24	0.31	0.12	0.25	0.07	0.04	0.17	0.03	-13.81	…
Miller Lite	0.63	0.40	0.23	0.45	0.54	0.35	0.46	0.28	0.25	0.37	0.23	0.23	-17.87

As we discussed in Section 2, several states regulate the interaction between wholesalers and retailers through non-price restrictions by limiting wholesalers' ability to provide credit to retailers and banning wholesalers from offering volume discounts to retailers. It is expected that these restrictions indirectly affect beer prices by influencing retail costs across the relevant states. Accordingly, we construct two variables to control for the impacts of these non-price regulatory restrictions on marginal cost. One of the two variables is *Volume Discount Ban*, which is a zero-one dummy variable that takes the value 1 if the relevant state enforces a ban on wholesalers offering volume discounts to retailers. The other regulatory restriction variable, *Retail Credit*, is a zero-one dummy variable that takes the value 1 if the relevant state enforces restrictions on wholesalers extending credit to retailers. As expected, the coefficient estimate on *Volume Discount Ban* is positive and statistically significant, suggesting that the states that ban volume discounts to retailers are likely to experience higher retail costs than states which do not have this restriction. Also expected, the estimated coefficient on *Retail Credit* is positive and statistically significant, suggesting that restrictions on wholesalers extending credit to retailers is associated with higher retail costs.

Table 7: Supply Equation Parameter Estimates

	Estimates
Estimates of Collusive Pricing Parameters	
Collusive Pricing Parameter (λ)	0.00056*** (0.000018)
Estimates of Marginal Cost Function Parameters	
Volume Discount Ban (zero-one dummy = 1 if wholesalers are banned from offering volume discounts to retailers)	0.3149*** (0.0065)
Retail Credit (zero-one dummy = 1 if wholesalers are restricted from extending credit to retailers)	0.1844*** (0.0051)
Constant	16.6017*** (0.0234)
Brand-Size Fixed Effects	Yes
Diesel prices interacted with Brewer Fixed Effects	Yes
Time Fixed Effects	Yes
GMM Objective	6.24×10^{-13}

Notes: Standard errors are given in parentheses. *** indicates statistical significance at the 1% level. Observations are at brand-pack size-state-year-month level. The marginal cost function parameter estimates associated with brand-pack size and time fixed effects as well as diesel prices interacted with brewer fixed effects are not reported here but can be made available upon request.

The estimated value of λ is statistically significant and equal to 0.00056, providing evidence consistent with tacit collusive price-setting behavior among beer firms that operate in PH states that require 30 or more hold days. The estimate of λ suggests that for each hold-day required by these states' PH laws, a beer firm internalizes approximately 0.056% of the impact of the pricing of each of its products on the profitability of beer products supplied by other firms operating in the state.

We then use the estimated value of λ along with equation (12) to generate state-level estimates of $\hat{\kappa}_h$ for PH states with PH laws that require 30 or more hold days. The state-level estimates of $\hat{\kappa}_h$ are reported in Table 8. The implied estimates of $\hat{\kappa}_h$ reported in Table 8 vary quite a bit across PH states from 1.68% in Connecticut to 20.16% in Tennessee. In other words, Connecticut's PH laws cause a beer firm to internalize only 1.68% of the impact of the pricing of each of its products on the profitability of beer products supplied by other firms operating in the state. However, Tennessee's PH laws cause a beer firm to internalize as much as 20.16% of the impact of the pricing of each of its products on the profitability of beer products supplied by other firms operating in the state.

Importantly, the results in Table 8 reveal that, while PH policy facilitates tacit collusive price-setting behavior in beer markets, it does not result in perfect/full price collusion since $\hat{\kappa}_h < 100\%$. This implies that imposing a structural model that assumes the PH laws in a state induce perfect collusion or monopoly pricing behavior among firms will likely overstate the collusive impact of these laws in beer markets. Furthermore, based on the results in Table 8, the extent to which an imposed assumption of perfect collusion will bias model-predicted market effects varies across PH states.

Table 8: Extent of Collusive Behavior Across PH States.

Name of PH state	Number of required Hold-days	$\hat{\kappa}_h$ (%)
Connecticut	30	1.68
Massachusetts	30	1.68
New Jersey	30	1.68
Oklahoma	30	1.68
Georgia	180	10.08
Tennessee	360	20.16
Overall mean		6.16

Note: $\hat{\kappa}_h = (0.00056 \times Hold\ Days) * 100$

In summary, evidence from the structural model analysis suggests that PH policy, which impacts the price-setting of alcohol beverages, facilitates tacit collusive behavior among beer brewers. Recall Figure 1 and the results from our descriptive linear price regression analysis suggest that, on average, beer prices in PH states are higher than in non-PH states. The results from our structural model reported in Table 8 underscore the market mechanisms driving the relatively higher prices attributed to the PH policy. Specifically, results from the structural model suggest that the relatively higher prices in PH states is driven by tacit collusive price-setting conduct induced by the PH policy.

8 Counterfactual Policy Analyses

This section presents two counterfactual experiments designed to examine the impact of PH policy on beer prices, consumption, and consumer surplus, as well as assess the market impacts if a state's PH policy were to be replaced with one of two alternate tax policies. Specifically, *Experiment 1* aims to determine the effect on beer prices and consumption from counterfactually eliminating the PH policy, while *Experiment 2* examines the market impacts of two distinct tax policies as an alternative to the PH policy such that aggregate volume of alcohol consumed from beer in a state is equal to the level achieved under its PH policy.

Experiment 1: Assessing Market Impacts of Eliminating Post & Hold Policy

We evaluate a counterfactual scenario in which each state eliminates its PH policy. To assess the impact on beer prices and consumption, we first recover product-level marginal costs using the system of first-order conditions for products sold in PH states:

$$\widehat{mc} = P_{ph} - \left[- \left[\Omega\left(1, \hat{\kappa}_h\left(\overline{HD}_h; \hat{\lambda}\right)\right) * \Delta\left(P_{ph}; \hat{\theta}_d\right)\right]^{-1} \times s\left(P_{ph}; \hat{\theta}_d\right)\right] \tag{20}$$

where $\widehat{mc}$ is a $J \times 1$ vector of recovered product-level marginal costs. As previously discussed, matrices Ω and Δ are each of dimension $J \times J$, with $\Omega * \Delta$ being an element-by-element multiplication of the two matrices. $s(\cdot)$ and P_{ph} are each $J \times 1$ vectors of model-predicted product market shares and observed post-and-hold prices, respectively.

With $\widehat{mc}$ in hand, we solve the following system of first-order conditions for the new equilibrium vector of prices, P^*, associated with counterfactual elimination of the PH policy in the relevant state:

$$P^* - \left[- \left[\Omega\left(1, \hat{\kappa}_h\left(\widetilde{HD}_h; \hat{\lambda}\right)\right) * \Delta(P^*; \hat{\theta}_d)\right]^{-1} \times s(P^*; \hat{\theta}_d)\right] - \widehat{mc} = 0 \tag{21}$$

where $\widetilde{HD}_h$ represents a counterfactual number of hold days of our choosing, with $\widetilde{HD}_h = 0$ being equivalent to counterfactual elimination of the PH policy. Note that $\widetilde{HD}_h = 0$ implies that $\hat{\kappa}_h = 0$ based on equation (12). Accordingly, with the counterfactual elimination of the PH policy, each element in matrix Ω is either 1 or 0. A comparison of P^* with P_{ph} reveals the extent to which the policy impacts prices. Second, with the counterfactual vector of prices in hand, P^*, we compute the extent to which the policy impacts the consumption of each beer product:

$$q_{jm}^*(P^*) = M_m \times s_{jm}(P^*) \tag{22}$$

where $s_{jm}(P^*)$ is the model-predicted share function from the demand model evaluated at the relevant counterfactual prices, and M_m is the potential market size of market m.

Experiment 2: Evaluating Two Tax Policies as an Alternative to PH Policy

Following Conlon and Rao (2023), we evaluate two tax policies as an alternative to PH policy. First, we evaluate various implications of states replacing their PH policy with a tax on the alcoholic content of the beverage such that aggregate volume of alcohol consumed from beer in each state is equal to the level achieved under its PH policy. Second, we also evaluate the implication of states replacing their PH policy with a sales tax such that aggregate volume of alcohol consumed from beer is equal to the level achieved under the relevant state's PH policy. Note that the tax policies evaluated in the experiment are separate from any taxes that may already be in effect.

Conlon and Rao (2023) find that there is no difference between using an alcohol content tax versus using a sales tax to limit alcohol consumption. A key reason for this finding is the insufficient variation of alcoholic content across the distilled spirits products analyzed in their study (e.g., Gin, Rum, Tequila, Vodka, Whiskey, etc.). However, the beer products included in our sample have considerable variation in alcohol content. Given the variation in the alcohol content across beer products, we anticipate that an alcohol content tax will impact alcohol consumption differently than a sales tax. It is essential to note that this analysis is not an attempt to determine the optimal policy; it is merely an attempt to compare equilibrium outcomes resulting from distinct policies designed to achieve a specified level of alcohol volume consumed from beer products.

Let ac represent the $J \times 1$ vector of alcoholic contents, measured in ounces of ethanol in the beverage, that correspond to the $J \times 1$ vector of products in our data. We solve the following equation (23) and equation (24) for the level of alcohol content tax, $t_h^{alcohol}$, and sales tax, t_h^{sales}, respectively, in each PH state such that aggregate volume of alcohol consumed from beer given in equation (25) is held fixed at the level achieved under the state's post-and-hold policy:

$$P_{tax}\left(t_h^{alcohol}\right) = \widehat{mc} + mkp\left[P_{tax}\left(t_h^{alcohol}\right)\right] + t_h^{alcohol} ac \qquad (23)$$

$$P_{tax}\left(t_h^{sales}\right) = \left[\widehat{mc} + mkp\left[P_{tax}\left(t_h^{sales}\right)\right]\right](1 + t_h^{sales}) \qquad (24)$$

$$\mathrm{ac} \cdot q_{tax}\left(P_{tax}(t_h)\right) = ac \cdot q_{ph} \qquad (25)$$

where $mkp(P_{tax}) = \left[-\left(\Omega(\hat{\kappa}_h|_{\widetilde{HD}_h=0}) * \Delta(P_{tax})\right)^{-1} \times s(P_{tax})\right]$ is the $J \times 1$ vector of endogenously determined Nash equilibrium product-level markups induced by the counterfactual implementation of a given tax policy as a replacement for the PH policy. Note that in the right-hand expression for $mkp(P_{tax})$, the number of hold-days is counterfactually set equal to zero, i.e., $\widetilde{HD}_h = 0$. In the equations above, $P_{tax}\left(t_h^{alcohol}\right)$ and $P_{tax}\left(t_h^{sales}\right)$ are the model-predicted equilibrium price vectors with alcohol content tax and sales tax, respectively; q_{ph} is the $J \times 1$ vector of observed beer product-level consumption levels in the relevant PH state; and q_{tax} is the model-predicted $J \times 1$ vector of equilibrium beer product-level consumption levels under the relevant tax policy. Accordingly, the right-hand side of equation (25), $ac \cdot q_{ph}$, is a dot product of vectors ac and q_{ph} that yields a scalar measure of the aggregate volume of alcohol, in ounces of ethanol, consumed from beer under the relevant state's PH policy. It is important to note that equation (25) is holding fix the aggregate volume of alcohol consumed from beer rather than aggregate volume of beer consumed. The aggregate volume of beer consumed will be an equilibrium outcome of the model in response to the counterfactual taxes (alcohol content-specific tax or sales tax) imposed.[25]

Once $t_h^{alcohol}$ and t_h^{sales} are computed for each state, we can recover $q_{tax}\left(P_{tax}\left(t_h^{alcohol}\right)\right)$ and $q_{tax}\left(P_{tax}\left(t_h^{sales}\right)\right)$, which may be different than q_{ph}, i.e., compared to the post-and-hold policy environment, consumers may optimally choose different beer volume consumption levels among the menu

[25] The algorithm to solve for the required level of each tax rate ($t_h^{alcohol}$ or t_h^{sales}) works like a nested fixed-point algorithm with an inner loop and an outer loop. The objective of the outer loop is to solve for the relevant tax rate t_h that yields aggregate alcohol consumed from beer in the state equal to the level achieved under its PH policy. However, for each tax rate, t_h, that is tried in the outer loop iteration, an inner loop must be solved for the new vector of equilibrium prices that satisfy equation (23) in the case of the alcohol content tax policy, but instead satisfy equation (24) in the case of the sales tax policy. In case of the algorithm solving for the alcohol content tax rate, using the P_{tax} vector that solves equation (23) in the inner loop for a given $t_h^{alcohol}$, the iteration is completed in the outer loop by computing $q_{tax}(P_{tax})$ and then $\mathrm{ac} \cdot q_{tax}(P_{tax})$ on the left-hand side of equation (25), with the objective of minimizing the distance between $\mathrm{ac} \cdot q_{tax}(P_{tax})$ and $\mathrm{ac} \cdot q_{ph}$. Analogously, in case of the algorithm solving for the sales tax rate, using the P_{tax} vector that solves equation (24) in the inner loop for a given t_h^{sales}, the iteration is completed in the outer loop by computing $q_{tax}(P_{tax})$ and then $\mathrm{ac} \cdot q_{tax}(P_{tax})$ on the left-hand side of equation (25), with the objective of minimizing the distance between $\mathrm{ac} \cdot q_{tax}(P_{tax})$ and $\mathrm{ac} \cdot q_{ph}$.

of alcoholic beverages under the tax policies, respectively. Accordingly, compared to the PH policy environment, consumer surplus may be different under each tax policy. Using the predicted equilibrium outcomes from the structural model, we compute the surplus for the average consumer under the tax policies, $CS\left(P_{tax}\left(t_h^{alcohol}\right); \widehat{\Theta}\right)$ and $CS\left(P_{tax}\left(t_h^{sales}\right); \widehat{\Theta}\right)$, respectively, and compare each of them with the surplus obtained by the average consumer under the status quo PH policy, $CS\left(P_{ph}; \widehat{\Theta}\right)$.[26]

8.1 Results from the Counterfactual Policy Experiments

The results of *Experiment 1* and *Experiment 2* are given in Figures 2 through 6 and Table 9. Below we discuss the results from both experiments, respectively.

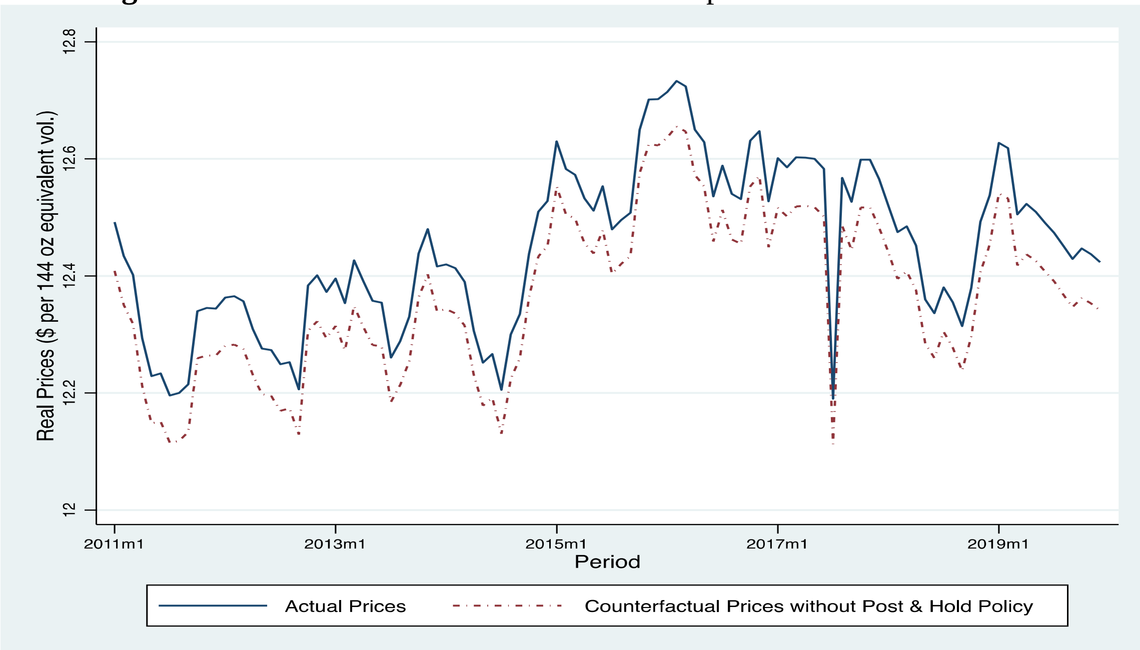
Impact of Post-&-Hold Policy on Beer Price and Consumption

With the counterfactual elimination of the PH policy in each state, Figure 2 shows that our model predicts a mean decrease in beer prices in these states throughout the sample period. The difference between the counterfactual and corresponding actual prices in *Experiment 1* is driven by tacit collusive price-setting behavior among brewers caused by the PH policy.

Column (1) of Table 9 reports the mean percentage changes in counterfactual prices relative to actual prices by state over the sample period. The summary statistics in the table show mean decreases in counterfactual prices relative to corresponding actual prices in each state. On average, the drop in counterfactual price ranges from -0.104% in Connecticut and Massachusetts, each with PH laws that require 30 hold days, to -2.08% in Tennessee with PH laws that require 360 hold days. Note that the percentage drop in counterfactual prices is positively associated with the number of hold-days required by the states' PH policy. In other words, the extent to which actual beer prices are higher than the level they would be in the absence of the state's PH policy tend to be greater in states with larger required number of hold-days. The results from our counterfactual price analysis are consistent with findings in the literature [Cooper and Wright (2012); and Conlon and Rao (2023)] showing that consumers pay higher prices for alcoholic beverages in PH states.

[26] $CS\left(\boldsymbol{P_{ph}}; \widehat{\Theta}\right) = \frac{1}{n}\sum_{i=1}^{n} \frac{\ln\left[1+\sum_{j=1}^{J} \exp\left(\delta_j(\boldsymbol{P_{ph}})+\mu_{ij}(\boldsymbol{P_{ph}})\right)\right]}{-\alpha_i}$ and $CS\left(\boldsymbol{P_{tax}}; \widehat{\Theta}\right) = \frac{1}{n}\sum_{i=1}^{n} \frac{\ln\left[1+\sum_{j=1}^{J} \exp\left(\delta_j(\boldsymbol{P_{tax}})+\mu_{ij}(\boldsymbol{P_{tax}})\right)\right]}{-\alpha_i}$

Figure 2: Actual vs. Counterfactual mean Beer product Prices in PH States



The plots in Figure 3 reveal that the impact of lower counterfactual prices in turn results in higher counterfactual consumption of beer relative to actual consumption. The mean increases in counterfactual consumption range from 0.064% to 1.21% across the different PH states as shown in column (2) of Table 9. Consistent with the percentage decreases in counterfactual prices, the counterfactual increases in consumption tend to be larger in states with PH laws that require a larger number of hold-days.

In summary, the counterfactual results of *Experiment 1* reveal that the PH policy in each state results in higher prices and lower consumption of beer due to the tacit collusive price-setting behavior of beer suppliers induced by the PH policy. Furthermore, the extent to which the PH policy causes beer prices to be higher and consumption lower is greater the larger the number of hold-days required by the state's PH laws.

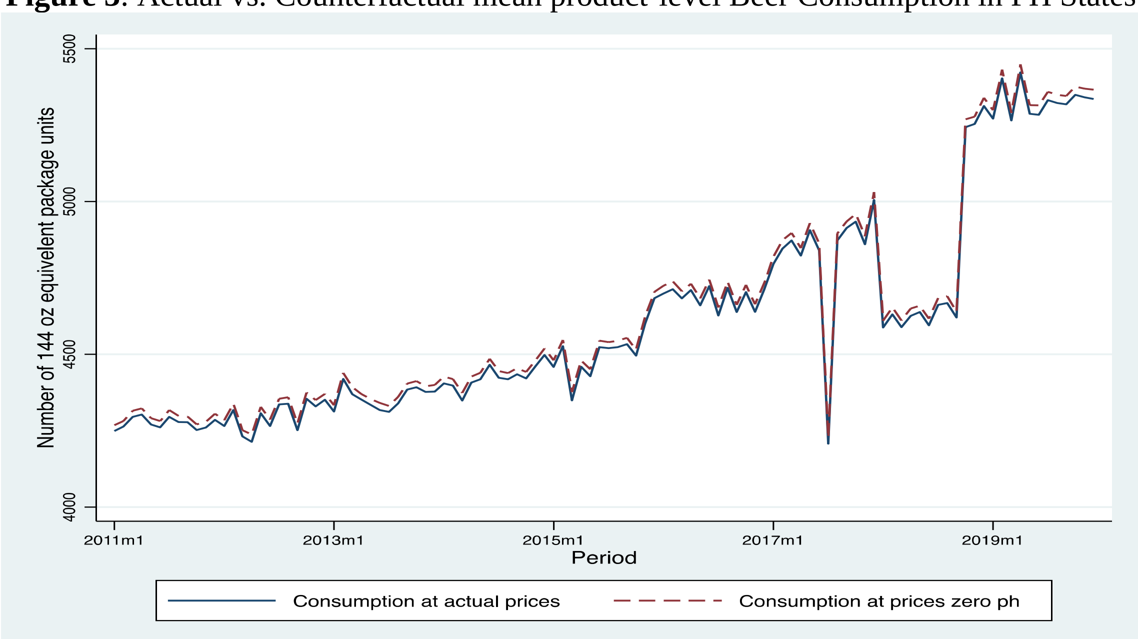
Considering Alcohol Content Tax and Sales Tax as an Alternative to Post-&-Hold Policy

Experiment 2 evaluates the market effects of counterfactual tax policies replacing the PH policy in each state. As discussed above, the experiment considers two distinct tax policies: (*i*) an alcohol content-specific tax; and (*ii*) a sales tax. Columns (3) and (4) of Table 9 report the model-predicted alcoholic content-specific taxes and sales taxes, respectively, that result in the aggregate volume of alcohol consumed from beer in the relevant state being equal to the aggregate volume observed under the state's PH policy.

Table 9: Model-predicted Taxes and Percent Changes in Prices, Consumption, and Consumer Surplus by Post & Hold States.

Post & Hold (PH) States	Changes in Prices if the PH Policy is Counterfactually Eliminated in the given State (%)	Changes in Beer Consumption if the PH Policy is Counterfactually Eliminated in the given State (%)	Mean Alcohol Content Taxes ($ per oz of alcohol in 144 oz equivalent vol. packages) if the PH Policy is Counterfactually Replaced with an Alcohol Content Tax Policy in the given State	Mean Sales Taxes ($ amount of tax per $ of before-tax price) if the PH Policy is Counterfactually Replaced with a Sales Tax Policy in the given State	Changes in Consumer Surplus if the PH Policy is Counterfactually Replaced with an Alcohol Content Tax Policy (%)	Changes in Consumer Surplus if the PH Policy is Counterfactually Replaced with a Sales Tax Policy in the given State (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Connecticut	-0.104	0.069	0.002	0.001	0.025	-0.047
Georgia	-0.988	0.536	0.015	0.010	0.279	0.010
Massachusetts	-0.104	0.064	0.002	0.001	0.034	-0.067
New Jersey	-0.106	0.065	0.002	0.001	0.021	-0.034
Oklahoma	-0.177	0.095	0.003	0.002	0.002	0.013
Tennessee	-2.077	1.206	0.029	0.022	1.085	-0.109
Overall mean	-0.593	0.339	0.009	0.006	0.241	-0.039

Figure 3: Actual vs. Counterfactual mean product-level Beer Consumption in PH States

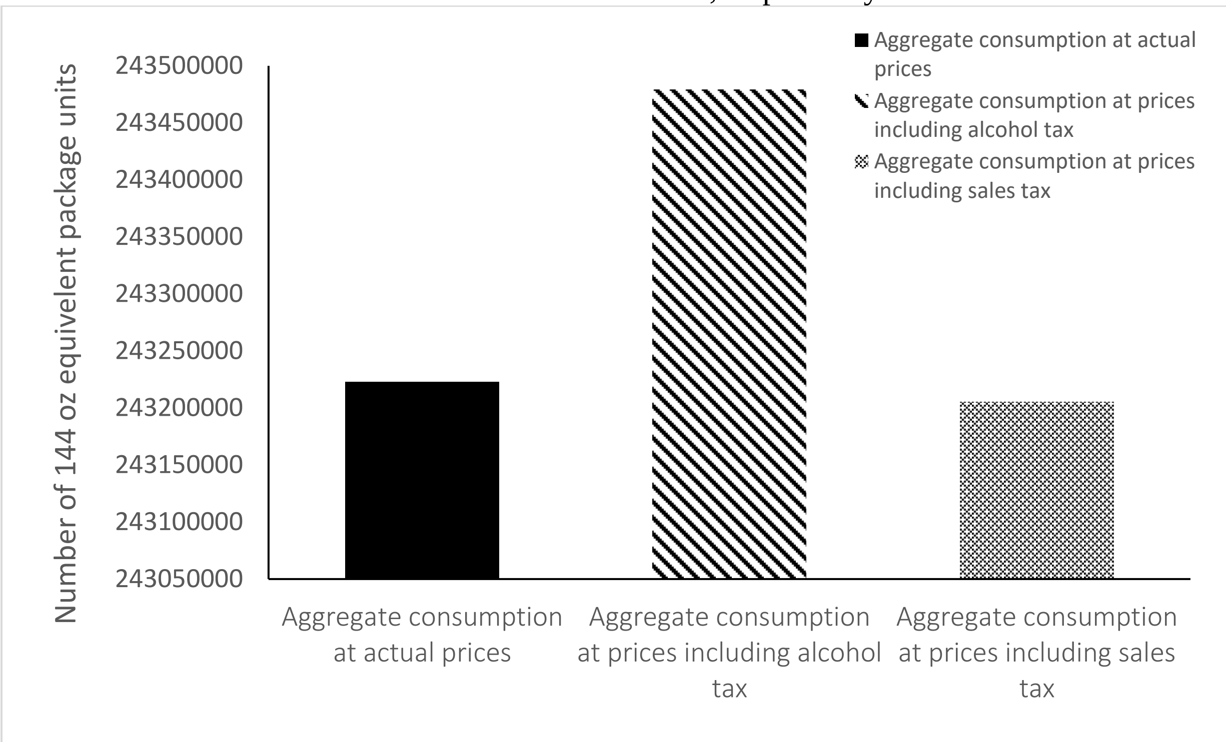


Column (3) shows that the average alcohol content tax rate on a 144 oz equivalent volume package (e.g., a 12-pack with 12 oz cans) of beer ranges from \$0.002 to \$0.029 per oz of alcohol contained in the beverage package. For example, Connecticut could eliminate its PH policy and raise alcohol content taxes on beer by an additional \$0.002 per oz of alcohol in the beer. In other words, for a package of 144 oz equivalent volume containing 4% alcohol, Connecticut could replace its PH policy by imposing an additional alcohol content tax of \$0.012 (=144*0.04*\$0.002) on the 144 oz beer package, whereas Tennessee could replace its PH policy by imposing an additional alcohol content tax of \$0.17 (=144*0.04*\$0.029) for the same package.

Column (4) shows that the average sales tax rate ranges from \$0.001 to \$0.022 per \$, which is equivalent to ranging from 0.1% to 2.2% of the before-the-new-tax product price. Figure 2 shows that the 144 oz equivalent volume before-the-new-tax price absent the PH policy (i.e., the mean counterfactual price in Figure 2) hovers around \$12, which implies a new sales tax in dollar amount of \$0.012 using the lowest sales tax rate of 0.1% versus a new sales tax in dollar amount of \$0.26 using the highest sales tax rate of 2.2%. Therefore, measured in comparable dollar amounts of a new tax on a 144 oz package of beer, it is evident that the model-predicted new sales taxes are different from the new alcoholic content-specific taxes. The reader is again reminded that the estimated tax rates are not derived as optimal taxes. Instead, these taxes are calculated merely to compare equilibrium outcomes resulting from two distinct tax policies designed to achieve a specified level of alcohol volume (not beer volume) consumption when they are each used as replacements for the PH policy in the relevant state.

Figure 4 shows that aggregate beer volume consumption evaluated at prices with the alcoholic content-specific tax will be higher than aggregate beer volume consumption under the PH policy, even though volume of alcohol consumed from beer is the same under the two policies. However, it is noticeable that beer volume consumption at prices with the sales tax is lower relative to beer volume consumption under the PH policy. Two reasons explain the unambiguous increase in beer volume consumption when an alcohol content-specific tax policy replaces PH policy. First, the elimination of PH policy removes firms' incentives to tacitly collude, yielding more competitively set prices in the beer market. Second, with alcohol content-specific taxes, consumers optimally substitute their consumption of beer products containing high alcoholic content with beer products containing lower alcoholic content to minimize the amount they pay in taxes. Figure 5 illustrates this optimal consumption substitution in response to a change in policy from PH policy to the alcohol content-specific tax policy.

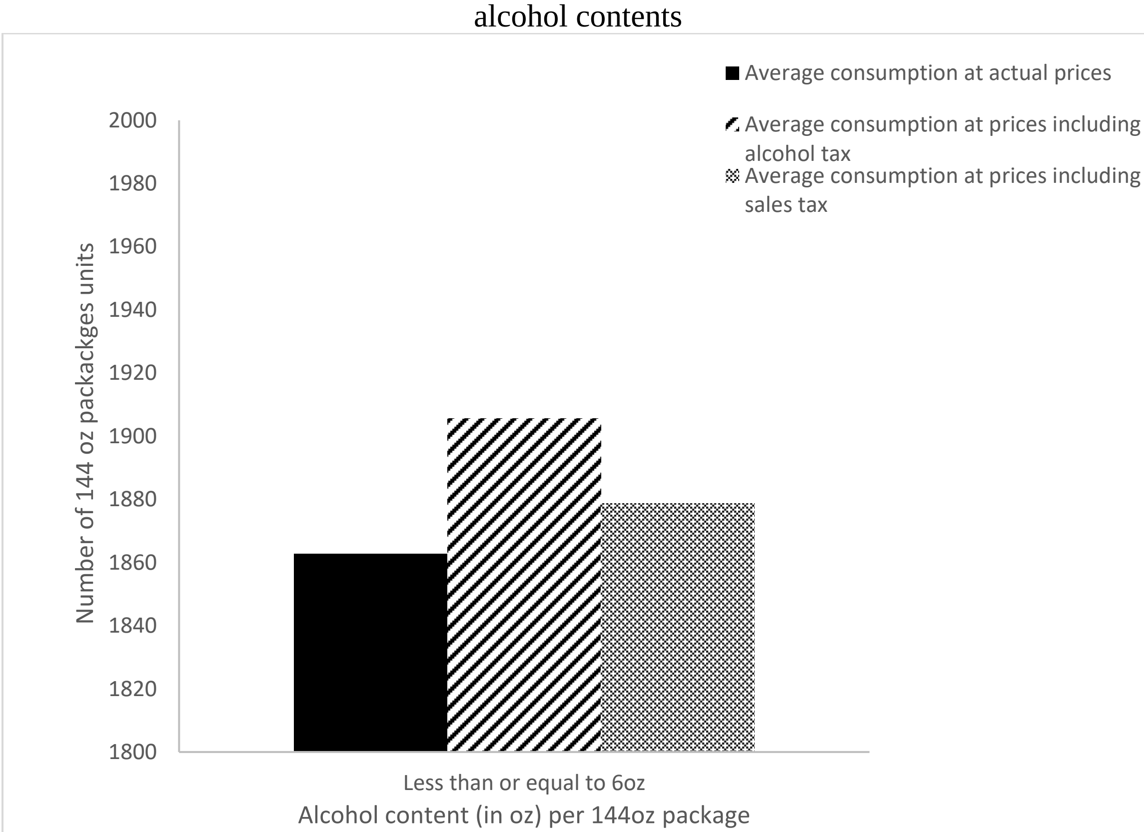
Figure 4: Actual and Counterfactual U.S. Domestic Market Aggregate Beer Consumption Levels under alternate Tax Policies, respectively.



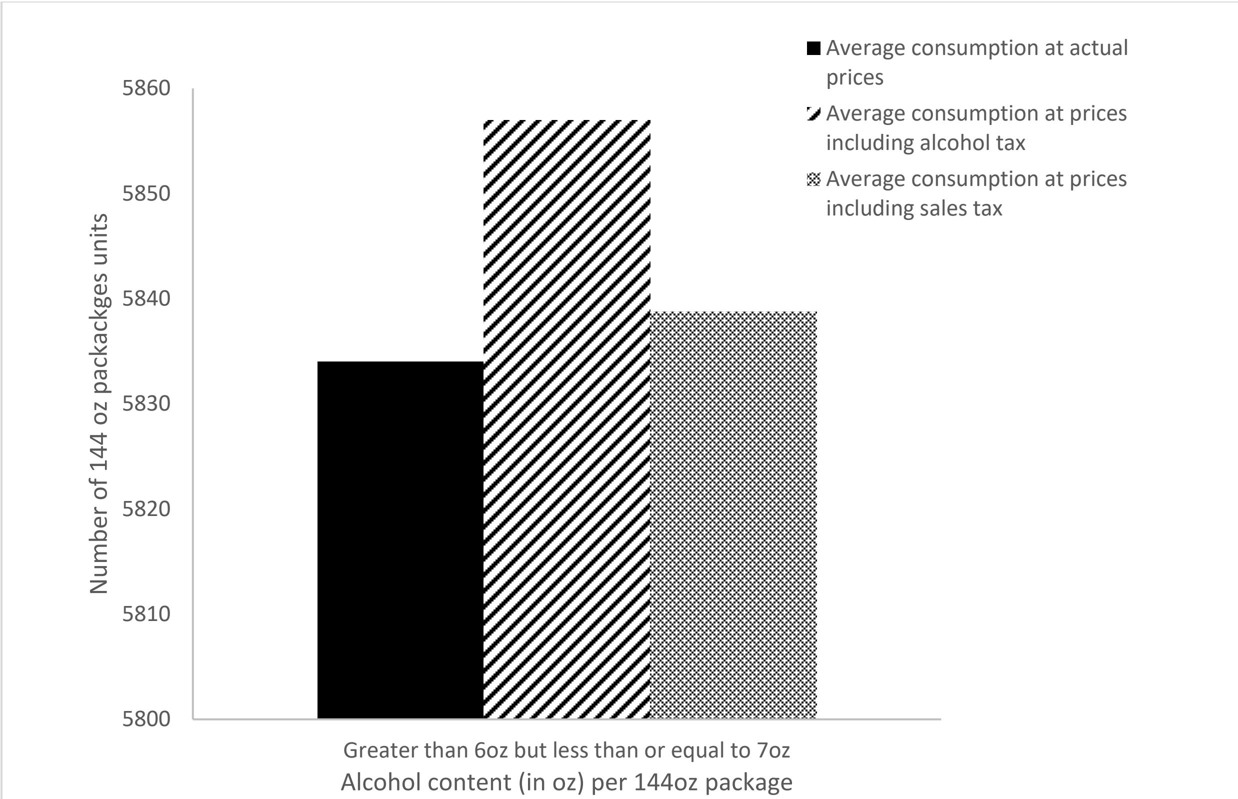
Each panel in Figure 5 shows mean product-level beer consumption under the PH policy, alcohol content-specific tax policy, and sales tax policy across products that fall within specific categories of alcohol content. The alcoholic content of the beer products in our sample ranges from a minimum of 4.032oz to a maximum of 8.50oz per 144oz beer volume package, which correspond to a 2.8% minimum to a 5.9% maximum product-level alcoholic content. In constructing Figure 5, we decompose this product-level alcoholic content range into three non-overlapping categories to generate panel (a), panel (b), and panel (c) in the figure, respectively. The horizontal axis in each panel of the figure represents a specific alcoholic content category: panel (a) focuses on products with alcohol content equal to or less than 6oz of alcohol in a 144oz beer volume package; panel (b) focuses on products with alcohol content greater than 6oz but less than or equal to 7oz of alcohol in a 144oz beer volume package; and panel (c) focuses on products with alcohol content greater than 7oz of alcohol in a 144oz beer volume package. The vertical axis in each panel of Figure 5 measures beer consumption levels among the products that fall within the specific alcoholic content category.

The evidence in Figure 5 reveals that beer consumption of high-alcoholic-content products shown in panel (c) of the figure is lower under the alcohol content-specific tax policy compared to the PH policy and sales tax policy, respectively; whereas the consumption of low-alcoholic-content products shown in panel (a) of the figure is higher under the alcohol content-specific tax policy compared to the PH policy and sales tax policy, respectively. Therefore, unlike sales tax, an alcohol content-specific tax incentivizes consumers to substitute their consumption of high-alcoholic-content beer products with consuming low-alcoholic-content beer products. The sales tax increases all products' prices without regard for the alcoholic content of the product and therefore does not incentivize consumers to substitute their consumption across products with different alcoholic content. Accordingly, consumers respond to the sales tax by reducing their beer consumption more than is necessary to achieve the alcohol volume consumption target. The reader is again reminded that aggregate volume of alcohol consumed from beer is the same across all three policies, the PH policy, the alcohol content-specific tax policy, and the sales tax policy, even though the aggregate volume of beer consumption differ across the three policies.

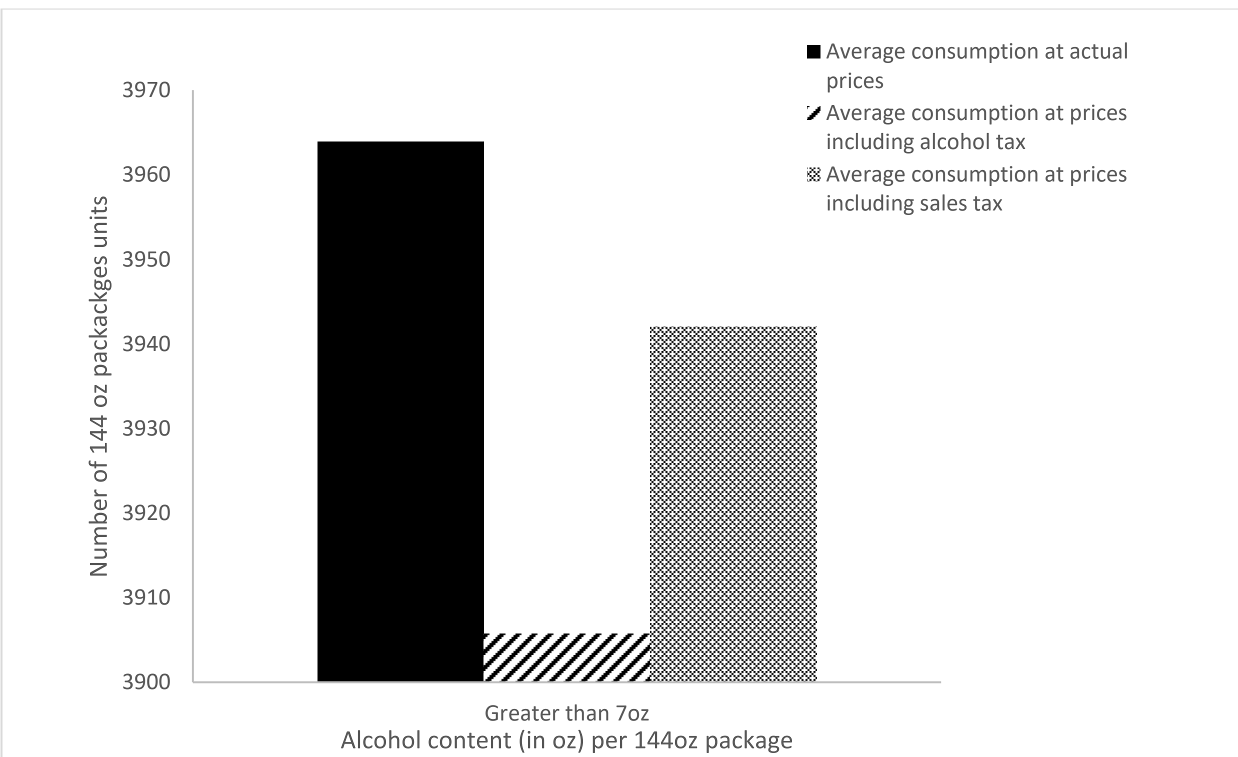
Figure 5: Actual and Counterfactual mean product-level Beer Consumption across different alcohol contents



Panel (a)



Panel (b)



Panel (c)

Consistent with the aggregate beer consumption analysis under the tax policies and PH policy discussed above, our consumer welfare analysis reveals that the alcoholic content-specific tax policy outperforms both the sales tax policy and the PH policy as a replacement for the PH policy. Figure 6 shows that consumer surplus under the alcohol content-specific tax policy is higher than that under the PH policy and the sales tax policy. This consumer welfare result is consistent with the unambiguous increase in aggregate beer volume consumption under the alcohol content-specific tax policy shown in Figure 4. Furthermore, consistent with the sales tax policy yielding the lowest aggregate beer consumption shown in Figure 4, consumer surplus under the sales tax policy is even lower than consumer surplus under the PH policy.

Column (5) and column (6) of Table 9 show the state-level changes in consumer surplus if the relevant state's PH policy is replaced with either an alcohol content-specific tax or a sales tax. On average, the average consumer experiences between a 0.002% to 1.08% increase in surplus as the relevant state switches from PH policy to an alcohol content-specific tax (see column (5) of Table 9). For example, consumers in Tennessee will experience a considerable improvement in surplus of 1.08% compared to other PH states if the state replaces its PH policy with an alcohol content-specific tax. However, the state-level changes in consumer surplus when a new sales tax replaces the PH policy in each state is noticeably lower, even a negative change for some states, than the corresponding state-level changes in consumer surplus when a new alcoholic content-specific tax policy replaces the PH policy in each state (see column (6) in comparison to column (5) of Table 9).

In summary, the results of counterfactual *Experiment 2* suggest that beer consumers in PH states are better off if each of these states replaces its PH policy with an alcohol content-specific tax policy. With this transition, suppliers of beer will engage in more competitive price-setting and consumers will be incentivized to substitute their consumption of high-alcoholic-content beer products with low-alcoholic-content beer products. The comparative analysis of the sales tax and alcohol content-specific tax policies reveals that an alcohol content-specific tax is a superior policy instrument compared to the sales tax if the policy objective is to reduce the volume of alcohol consumed from beer beverages as opposed to reducing the volume of beer consumed.

Figure 6: Measures of Average Consumer Surplus under PH policy (actual), Alcohol Content Tax Policy, and Sales Tax Policy, respectively.

9 Conclusion

The social cost of alcoholic beverage consumption imposes a financial burden on states. Several states have imposed PH laws with the objective of directly raising the prices of alcoholic beverages to indirectly reduce their consumption. This study provides evidence that PH laws achieve these market outcomes by facilitating tacit collusive price-setting behavior among alcoholic beverage suppliers. The additional source of non-competitive behavior induced by PH laws is particularly concerning in concentrated industries like beer.

The study first specifies and estimates a structural model designed to identify the impact on tacit collusive price-setting behavior among firms that is caused by PH laws. Important for identifying this impact is the variation on the extensive margin as to whether a given state has PH laws, as well as variation on the intensive margin in terms of the stringency of PH laws adopted by the given state, with stringency measured by number of required hold-days prescribed by the PH laws. The parameter estimates from the structural model reveal that PH laws do facilitate price collusion, and the degree of price collusion is positively related to the number of hold-days prescribed by the laws.

We then use the estimated structural model to perform various counterfactual analyses. Results from the counterfactual analyses suggest that the tacit price collusion caused by PH laws drives beer prices to be higher by a mean 0.1% to 2% and beer consumption to be lower by a mean 0.06% to 1.2% depending on the stringency of the laws adopted by the given state. Results from the counterfactual experiments also suggest that beer consumers in PH states are better off if each of these states replaces its PH regulation with an alcohol content-specific tax policy. With this transition, suppliers of beer will engage in more competitive price-setting and consumers will be incentivized to substitute their consumption of high alcoholic content beer products with lower alcoholic content beer products. Furthermore, we show that these beneficial outcomes will not be achieved if the PH regulation is replaced with a sales tax policy.

A limitation of our study is that we do not have information on the local distributors of beer in a state and therefore cannot model how their price-setting behavior is directly influenced by PH laws. Using the supply-side framework laid out in this study, future studies with access to such data may more meticulously investigate the direct impact of PH laws on local beer distributors.

References

Ascher, B. (2012), "Global Beer: The Road to Monopoly," manuscript, *The American Antitrust Institute*.

Ashenfelter, O., D. S. Hosken, and M. C. Weinberg (2015), "Efficiencies brewed: Pricing and Consolidation in the U.S. beer industry," *Rand Journal of Economics*, Vol. 46, 328-361.

Bernheim, B. D. and Whinston, M. D. (1990), "Multimarket Contact and Collusive Behavior", *RAND Journal of Economics*, Vol. 21, 1–26.

Berry, S. (1994), "Estimating Discrete-Choice Models of Product Differentiation" *Rand Journal of Economics*, Vol. 25, No. 2, 242-262.

Berry, S., Levinsohn, J. and A. Pakes (1995), "Automobile Prices in Market Equilibrium", *Econometrica*, Vol 63, 841-890.

Berry, S. and P. Haile (2014). "Identification in Differentiated Products Markets Using Market Level Data." *Econometrica*, Vol. 82, No. 5 (September 2014), 1749–1797.

Bonnet, Céline and Vincent Réquillart (2013) "Tax incidence with strategic firms in the soft drink market," *Journal of Public Economics*, Vol. 106 (2013), 77-88.

Bresnahan, T. F. (1987), "Competition and Collusion in the American Automobile Industry: The 1955 Price War," *Journal of Industrial Economics*, Vol. 35, 457–482.

Ciliberto, F. and J. Williams (2014). "Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry," *Rand Journal of Economics*, Vol. 45, No. 4, Winter 2014, 764-791.

Conlon, Christopher T. & Nirupama Rao, (2023), "The Cost of Curbing Externalities with Market Power: Alcohol Regulations and Tax Alternatives," N.Y.U. Wagner Research Paper No. 2610118.

Cooper, James C. and Joshua D. Wright, (2012), "Alcohol, Antitrust, and the 21st Amendment: An Empirical Examination of Post and Hold Laws," International Review of Law and Economics, Vol 32, 379-388.

Corts, Kenneth S., (1999) “Conduct parameters and the measurement of market power,” *Journal of Econometrics*, Vol. 88, Issue 2, February 1999, pp. 227-250.

Delipalla, Sophia and Owen O’Donnell (2001), “Estimating tax incidence, market power and market conduct: The European cigarette industry,” *International Journal of Industrial Organization*, Vol. 19 (2001), 885–908.

Diamond, Peter A. (1973), “Consumption Externalities and Imperfect Corrective Pricing,” *The Bell Journal of Economics and Management Science*, Autumn, 1973, Vol. 4, No. 2 (Autumn, 1973), pp. 526-538.

Ellison, G. (1994), “Theories of Cartel Stability and the Joint Executive Committee”, *RAND Journal of Economics*, Vol. 25, 37–57.

Gandhi, A. and A. Nevo (2021), “Empirical Models of Demand and Supply in Differentiated Products Industries”, *NBER Working Paper*.

Gandhi, A. and J.-F. Houde (2020), “Measuring substitution patterns in differentiated products industries”, *NBER Working Paper*.

Genesove, D. and Mullin, W. P. (1998), “Testing Static Oligopoly Models: Conduct and Cost in the Sugar Industry, 1890-1914”, *RAND Journal of Economics*, Vol. 29, 355–377.

Gokhale, J. and V. J. Tremblay (2012), “Competition and Price Wars in the U.S. Brewing Industry,” *Journal of Wine Economics*, Vol. 7, 226–240.

Green, E. J. and Porter, R. H. (1984), “Noncooperative Collusion under Imperfect Price Information,” *Econometrica*, Vol. 52, 87–100.

Gruber, Jonathan and Botond Koszegi (2004), “Tax incidence when individuals are time-inconsistent: the case of cigarette excise taxes,” *Journal of Public Economics*, Vol. 88 (2004) 1959– 1987.

Gruber, Jonathan and Sendhil Mullainathan (2005) “Do Cigarette Taxes Make Smokers Happier,” *B.E. Journals: Advances in Economic Analysis & Policy*, Vol. 5, Issue 1, Article 4, 1-43.

Haltiwanger, J. and Harrington, Jr. J. E. (1991), “The Impact of Cyclical Demand Movements on Collusive Behavior,” *RAND Journal of Economics*, **22**, 89–106.

Heutel, Garth (2015), “Optimal policy instruments for externality-producing durable goods under present bias,” *Journal of Environmental Economics and Management*, Vol. 72 (2015), 54-70.

Igami, Mitsuru and Takuo Sugaya (2022), “Measuring the Incentive to Collude: The Vitamin Cartels, 1990-1999,” *Review of Economic Studies*, (2022) 89, 1460–1494.

Iwasaki, N., Seldon, B.J. and Tremblay, V.J. (2008), “Brewing wars of attrition for profit and concentration,” *Review of Industrial Organization*, Vol. 33, 263–279.

Kuchler, Fred, Abebayehu Tegene, and J. Michael Harris (2005) “Taxing Snack Foods: Manipulating Diet Quality or Financing Information Programs?” *Review of Agricultural Economics*, Spring, 2005, Vol. 27, No. 1 (Spring, 2005), pp. 4-20.

Miller, N. H. and M. C. Weinberg (2017), “Understanding the price effects of the MillerCoors joint venture,” *Econometrica*, Vol. 85, 1763–1791.

Miravete, E. J., K. Seim, and J. Thurk (2018): “Market Power and the Laffer Curve,” *Econometrica*, 86, 1651–1687.

Miravete, E. J., K. Seim, and J. Thurk (2020): “One Markup to Rule Them All: Taxation by Liquor Pricing Regulation,” *American Economic Journal: Microeconomics*, 12, 1–41.

Nevo, A. (2000), “A Practitioner's Guide to Estimation of Random Coefficients Logit Models of Demand,” *Journal of Economics and Management Strategy*, Vol. 9, 513-548.

O’Connell, Martin and Kate Smith (forthcoming) “Optimal sin taxation and market power,” *American Economic Journal: Applied Economics*, forthcoming.

O'Donoghue, Ted and Matthew Rabin (2005), "Optimal taxes for sin goods," *Swedish Economic Policy Review*, Vol. 12 (2005), 7-39.
O'Donoghue, Ted and Matthew Rabin (2006), "Optimal sin taxes," *Journal of Public Economics*, Vol. 90 (2006), 1825-1849.
Porter, R. H. (1983), "A Study of Cartel Stability: The Joint Executive Committee, 1880–1886", *Bell Journal of Economics*, Vol. 14, 301–314.
Porter, R. H. (2020), "Mergers and Coordinated Effects", *International Journal of Industrial Organization*, **73**, 1–14.
Porter, R. H. and Zona, J. D. (2008), "Collusion," *Antitrust Law Journal*, Vol. 2, 1069–1084.
Rojas, C. (2008), "Price Competition in U.S. Brewing," *The Journal of Industrial Economics*, Vol. (56), 1-31.
Rotemberg, J. J. and Saloner, G. (1986), "A Supergame-Theoretic Model of Price Wars During Booms," *American Economic Review*, **76**, 390–407.
Saffer, Henry and Markus Gehrsitz (2016), "The effect of post-and-hold laws on alcohol consumption," *International Review of Law and Economics*, Vol 45, 63-71.
Seim, K. and J. Waldfogel (2013): "Public Monopoly and Economic Efficiency: Evidence from the Pennsylvania Liquor Control Board's Entry Decisions," *American Economic Review*, 103,831–862.
Slade, M. E. (1987), "Interfirm Rivalry in a Repeated Game: An Empirical Test of Tacit Collusion," *Journal of Industrial Economics*, Vol. 35, 499–516.
Slade, M. E. (1992), "Vancouver's Gasoline-PriceWars: An Empirical Exercise in Uncovering Supergame Strategies," *Review of Economic Studies*, Vol. 59, 257–276.
Treasury Department. (2022). "*Competition in the markets for beer, wine, and spirits,"* https://home.treasury.gov/system/files/136/Competition-Report.pdf
Tremblay, V. J. and C. H. Tremblay (2005), "The U.S. Brewing Industry", *The MIT Press*.
Warner, A. G. (2010), "The Evolution of The American Brewing Industry," *Journal of Business Case Studies*, Vol. 6, 31-46.

Appendix

Table A1: List of Beer Brands covered in the data sample.

Brand	Alcohol (%)	Calories (count)	Imported (Yes= 1; No=0)
Amstel Light	3.5	95	1
Beck's	5	146	0
Bud Light	4.2	110	0
Bud Light Lime	4.2	116	0
Budweiser	5	145	0
Budweiser Select	4.3	99	0
Budweiser Select Light	4.3	99	0
Busch	4.3	114	0
Busch Light	4.5	95	0
Coors Banquet	5	147	0
Coors Light	4.2	102	0
Corona Extra	4.6	148	1
Corona Light	4.1	99	1
Dos Equis Especial Lager	4.3	130	1
George Killian's Irish Red Lgr	5.4	168	0
Heineken	5	150	1
Heineken Light	3.2	99	1
Icehouse	5.5	153	0
Keystone Light	4.1	104	0
Michelob Light	4.1	122	0
Michelob Ultra Light	4.2	95	0
Miller 64 Light	2.8	64	0
Miller Genuine Draft	4.6	143	0
Miller High Life Light	4.1	110	0
Miller Lite	4.2	96	0
Milwaukee's Best	4.3	127	0
Milwaukee's Best Ice	5.9	148	0
Milwaukee's Best Light	4.1	96	0
Modelo Especial	4.4	145	1
Natural Ice	5.9	130	0
Natural Light	4.2	95	0
Negra Modelo Dark	5.4	165	1
Pabst Blue Ribbon	4.7	145	0
Pacifico	4.4	146	1
Rolling Rock	4.5	130	0

Table A1 continued: List of Beer Brands covered in the data sample.

Brand	Alcohol (%)	Calories (count)	Imported (Yes= 1; No=0)
Samuel Adams Boston Lager	4.9	175	0
Samuel Adams Seasonal	5.3	165	0
Tecate	4.5	146	1
Yuengling	4.4	128	0