Essays on vertical price restraint, merger and competitive conduct

by

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AN ABSTRACT OF A DISSERTATION

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Abstract

The dissertation investigates the two-fold impact on the competitive conduct of U.S. brewers of a) changes in the legal approach towards vertical price restraint and b) recent mergers and acquisition activities of leading brewers. These changes may have profound repercussions for the level of competition in the highly concentrated US beer industry.

The first essay analyzes the impact of change in legal environment toward vertical price restraint on the competitive behavior of brewers in the US beer industry. Resale price maintenance (RPM) is the practice whereby upstream firms in an industry, e.g. manufacturers, make an agreement with downstream firms, e.g. retailers, that the downstream firms will sell the manufacturer's product at certain prices. The 2007 US Supreme Court's decision in the *Leegin* case resulted in a legal paradigm shift in which the legality of a given RPM agreement is based on a "rule of reason" approach instead of being "per se illegal", i.e. the new approach calls for a ruling on the legality of an agreement in question based on weighing benefits and harms. This essay provides evidence on whether market data outcomes in the US beer industry are consistent with the use of RPM prior to and subsequent to the *Leegin* decision, and if so, whether RPM equilibrium outcomes are on net anticompetitive. We find that vertical relationships between brewers and retailers are best approximated by brewers using nonlinear, instead of linear, wholesale price contracts when selling to retailers, and brewers using RPM with retailers during *post-Leegin* periods but no RPM during *pre-Leegin* periods. Furthermore, our findings do not support that RPM agreements are on net anticompetitive in the US beer market.

The second essay explores the impact of the recent merger in the US beer industry. Using structural econometric models of demand and supply, this essay analyzes competitive conduct of national brewers in the US beer market. The analysis focuses on the recent merger between ABI and SABMiller in the US beer industry. We model supply behavior of ABI and MillerCoors by specifying a parameter measuring the extent to which these brewers internalize price externalities. Contrary to past findings, our empirical analysis reveals that the leading domestic brewers' price setting behavior is best approximated by Bertrand Nash model in the both pre-merger and post-merger periods.

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Chapter 1

Resale Price Maintenance: Evidence from the US Beer Industry in light of the US Supreme Court's Decision in the Leegin Case

1.1 Introduction

Resale price maintenance (RPM) is the practice whereby upstream firms in an industry, e.g. manufacturers, make an agreement with downstream firms, e.g. distributors or retailers, that the downstream firms will sell the manufacturer's product at certain prices. RPM is a form of vertical price restraint. In year 1911 the US courts, in *Dr. Miles* case, held RPM agreements "per se illegal". However, the 2007 US Supreme Court's decision in *Leegin Creative Leather Products, Inc. v. PSKS Inc.* (*Leegin)* overruled its nearly century-old per se approach towards RPM agreements. In the landmark verdict on *Leegin*, the US Supreme Court held that RPM contracts should be subject to "rule of reason" instead of being "per se illegal", i.e. the legality of an agreement in question should be based on weighing benefits and harms. The *Leegin* verdict did not imply that subsequent RPM agreements are automatically lawful, but the verdict was tantamount to enabling a friendly legal environment toward RPM agreements. This became possible as the *Leegin* decision reduced the legal risk involved in RPM related contracts [Lindsay (2007)].

In reaching this decision, the court heavily relied on procompetitive economic theories of RPM. Theoretical literature suggests that RPM agreements can be used to eliminate the double marginalization problem that often exists between two or more vertically related firms. The double marginalization problem emerges when two or more vertically related firms in the supply chain have market power and each of these firms non-cooperatively chooses to charge a markup on the commodity they sell. In such cases, the markups are set at levels that may maximize each firms' profit, but not maximize the combined profit across the firms. RPM agreements are also useful in enhancing demand of a product by encouraging retailers to adequately supply required services/sales efforts and shifting focus from price to non-price aspects of a product. However, RPM contracts may also harm competition among firms in two ways: 1) facilitating cartel/coordination among suppliers, retailers or both; and 2) foreclosing rival suppliers to access effective distribution channels when used by suppliers or foreclosing cost-efficient retailers [Asker and Ba-Isaac (2014); and Cheng (2018)]. In summary, the motivations and effects of these contracts may be procompetitive or anticompetitive, depending upon the context in which they are used.[1]

Despite the widespread presence of RPM contracts, the dearth of empirical evidence on the existence and effects of RPM agreement hinders our comprehensive understanding about RPM contracts [MacKay and Smith (2017)]. The emergence of the rule of reason approach toward RPM agreements further reinforces the need for more empirical evidence. To our best knowledge, there are two empirical studies [MacKay and Smith (2014) and Bailey and Leonard (2010)] which analyze the effects of RPM agreement during the *post-Leegin* period using a reduced-form econometric approach. These studies analyze the effects of RPM under the presumption of the presence of RPM agreements in the *post-Leegin* period. However, these studies ignore whether behavior of suppliers is consistent with predicted equilibrium behavior when RPM contracts are used. The present study models supplier behavior with RPM and analyzes empirically the consistency of supplier behavior with RPM agreements in a structural framework using data on the US beer market.

There are at least three reasons the US beer market offers a natural setting for the investigation of whether firms' behaviors are consistent with the use of RPM agreements. First, historically, beer market players have been criticized and charged for price-fixing and utilizing vertical price and non-prices restraints on retailers.[2] Second, Klein and Murphy (1988) cite beer as an example of a product requiring special retail services: constant refrigeration, strict product rotation, and stocking of limited inventory to maintain the freshness of the product. A retailer which does not adequately provide these services exerts an external cost on the manufacturer of the product. In this scenario, RPM agreements can be used to incentivize retailers to optimally supply retail services.[3] Third, US beer production is categorized as one of the most concentrated

[1] See Motta (2006), Rey and Verge (2008) and Gundlach (2014) for comprehensive surveys of studies on vertical price restraints.

[2] "…The Supreme Court's decision in 1975 upheld a Federal Trade Commission ruling, which found Coors guilty of restraint of trade. The F.T.C. charged that the company engaged in price-fixing and attempted to limit distribution to its 11-state area after the beer left its dealers, refusing to allow certain retail chains to carry its beer, parceling out exclusive distributorships and intimidating distributors and retailers. For example, some bars were told they wouldn't get any Coors unless they used Coors exclusively on tap..." available at https://www.nytimes.com/1975/12/28/archives/article-4-no-title-sold-only-in-the-west-coors-beer-is-smuggled-to.html. See also Chen (2014) and Klein and Murphy (1988).

[3] See chapter 6 in Motta (2006) for a detailed discussion of how RPM contracts can be used to incentivize retailers to provide optimal level of services.

industries in the US, an industry feature that better facilitates the use of RPM. In 2008, the second largest brewer, SABMiller, and third largest brewer, Molson Coors, merged to form a new firm known as Miller-Coors. With this merger, the market structure can effectively be characterized as a duopoly, with the two largest brewers, Anheuser-Busch InBev (ABI) and Miller-Coors, having a combined market share of almost 80 percent.

Market dominance of ABI and Miller-Coors has already alarmed researchers with regards to the potential for anticompetitive behavior in the industry [Miller and Weinberg (2017)]. The relatively high market concentration at the brewer level (upstream) of the industry combined with evidence of co-movement of prices across brands of beer produced by leading brewers further supports arguments of collusive behavior. However, there is little discussion and analysis of the mechanisms used by firms to sustain collusive behavior. As mentioned above, RPM is a mechanism that can be used to sustain collusive outcomes. The empirical analysis in this paper does provide evidence on whether market data outcomes in the US beer industry are consistent with the use of RPM, and if so, whether the RPM equilibrium outcomes are collusive.

Competition analysis in the US beer industry demands a better understanding of the strategic relationship between upstream and downstream firms, along with an analysis of competition at upstream and downstream levels. This paper analyzes the nature of competition in the US beer industry by explicitly modeling vertical relationships with and without RPM between brewers upstream and retailers downstream. Specifically, we analyze potential changes in vertical relationships and relative market power between brewers and retailers of beer against the backdrop of the *Leegin* decision.

We first estimate a discrete choice model of demand using retail scanner data on beer purchases over the period 2005-2012. With the demand estimates in hand, but without observing brewers' and retailers' costs, we specify and use alternate models of supply to compute price-cost margins for brewers and retailers under each supply model. The various models of supply considered allow for linear and nonlinear price-setting behavior of vertically related firms, brewers and retailers of beer. To model supply behavior we follow the empirical framework of Villas-Boas (2007) and Bonnet and Dubois (2010), which is rooted in recent theoretical work on vertical price restraints [Rey and Verge (2010), Jullien and Rey (2007)]. Similar to empirical methodologies in Villas-Boas (2007), Bonnet and Dubois (2010) and Bonnet et al (2013), we use non-nested statistical tests to assess which of the eight distinct supply models best approximates price-setting behavior of brewers and retailers of beer.

Demand estimates of beer suggest that income is an important determinant of beer demand consistent with Miller and Weinberg (2017). Our demand estimates also suggest that consumer's choice of beer is substantially influenced by price along with several non-price characteristics such as alcoholic content, calories, carbohydrates, whether the beer is imported versus produced domestically, and style of beer (Lager, Pilsner, Malt, Bock and Hefeweizen).

Consistent with empirical findings on price-setting behavior in other industries [Villas-Boas (2007), Bonnet and Dubois (2010) and Bonnet et. al (2013)], we find that supply models that allow brewers to use nonlinear, instead of linear, wholesale price contracts when selling to retailers best fit the data in both *pre-Leegin* and *post-Leegin* periods. Furthermore, the supply-side model analysis has not found any evidence that collusive pricing exists prior to, or subsequent to, the *Leegin* decision. Slade (2004) and Rojas (2008) also did not find evidence of collusive pricing in their analysis of the U.K. and U.S. brewing industries respectively. Among supply models that allow brewers to use nonlinear wholesale pricing, specifically, two-part tariff pricing (per-unit wholesale price and fixed fee), the model that does not allow brewers to impose RPM (resale price maintenance) best fits *pre-Leegin* period data. However, the supply model that allows brewers to use two-part tariff pricing as well as impose RPM to limit retail markup best fits the data during the *post-Leegin* period. In summary, in the *post-Leegin* period, the empirical findings suggest that brewers enjoy relatively more bargaining power and control over setting retail prices and extracting downstream profit without colluding with rival brewers.

The rest of the chapter is organized as follows: Section 1.2 briefly describes the profile of the US beer industry; Section 1.3 reviews the literature; Section 1.4 provides description of the data; Section 1.5 outlines the structural econometric modelling of beer demand and supply; Section 1.6 discusses the estimation procedure; Results are discussed in Section 1.7; Counterfactual analyses in Section 1.8, and Section 1.9 offers concluding remarks.

1.2 Profile of US beer industry[4]

While beer consumption per adult in the US has been falling gradually between 1994 and 2016, it still ranks as the second largest beer market after Germany.[5] In year 2016, beer consumption per adult stood at 100 liters in the US (with 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 US. In year 2016, large breweries command over 90 percent market share both in volume and sales, whereas craft breweries account for only 6% share in volume and 9% share in total sales.[6]

Historically, the US beer industry evolved from being fragmented into a highly concentrated industry due to various waves of mergers and acquisitions. From 421 breweries in year 1947, the number of breweries declined to 92 in year 1981[7] as mostly failing breweries merged and were acquired by successful brewers.[8] 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.

The last two decades have seen two disparate trends in US brewers' industry. On the one hand, the industry is experiencing the re-emergence of small breweries (craft brewers), but on the other hand, brewing is increasingly being controlled by a small number of large brewers. As Brewers Association statistics show that the total count of breweries stands at over 4548 in the year 2015, out of which only 30 were large non-craft breweries and 14 were other non-craft breweries.

The extent of concentration is dramatic when viewed in terms of market share of the top four breweries. From year 1947 to year 2007, the combined market share of the top four breweries grew from 19 percent to 92 percent.[9] In the wake of mergers between years 2001 and 2008, the few large brewers that dominate the US beer industry are: Anheuser-Bush InBev (ABI), SABMiller, Molson Coors, Heineken, and Crown Importers/Groupo Modelo (brewers with imported brands). ABI is the largest brewer in the US selling over 200 brands. SABMiller and

[4] Majority of this section is drawn from Tremblay and Tremblay (2005) and Ascher (2012)
[5] The Economist June 13 2017
[6] Brewers Association; America's Beer Distributors
[7] https://www.brewersassociation.org/statistics/number-of-breweries/
[8] Tremblay and Tremblay (2005)
[9] Gokhale and Tremblay (2012)

Molson Coors are the second and third-largest brewers in the US producing hundreds of different brands. The year 2008 merger between SABMiller and Molson Coors (forming the new firm, MillerCoors) resulted in increased concentration in the US beer industry. The recent structure of the industry is effectively characterized as a duopoly with ABI and Miller-Coors accounting for a combined 80 percent share of the market, as depicted in Table 1.1.

Table 1.1:Market share by Vol. (%) of US leading Brewers in years 1971 and 2010

Name of Brewer\Importer	Percentage Market Shares in year 1971	Name of Brewer\Importer	Percentage Market Shares in year 2010
Anheuser-Busch	29	Anheuser-Busch InBev	49.3
Schlitz	19	Miller-Coors	30.2
Fallstaf	13	Crown Imports (e.g Corona)	5.3
Schaefer	8	Heineken USA	4.0
All others	31	All others	11.2

Sources: Ascher (2012)

Since 1935, the law has prohibited US breweries (except small breweries) from selling beer directly to end consumers. The beer industry follows a three-tier-structure where brewers are located at the top tier, and sell beer to retailers through distributors. The Three-tier system increases the cost of supplying beer to the consumers as it prohibits brewers from directly selling to consumers. Regulation forbids vertical integration, which takes away one mechanism that vertically related firms often use to resolve the double marginalization problem. Brewers may use price and non-price vertical restraints to increase efficiency and relative market power in the industry.

As discussed above, the upstream market of brewers is highly concentrated. Industry reports[10] suggest that the market for distributors, as well as the retail (downstream) market are concentrated. Much of the beer distribution network is owned and controlled by ABI and Miller-Coors, where distributors carry either brands of ABI or Miller-Coors, but not both. Almost three fourth of beer sales takes place through supermarkets and grocery stores, implying that most of the US beer consumption takes place at home (and not in restaurants or pubs).

[10] Ascher (2012)

US beer manufacturers' conduct is best explained by advertising expenditure, pricing strategy, mergers & acquisition, the proliferation of beer products, and packaging, which often are aimed at a specific demographic group. To soften direct price competition and to grab market share from regional sellers, leading brewers offer a full line of differentiated products, varying along characteristics like calories, carbohydrate, alcoholic content. About 13000 brands are available to US consumers. These brands are classified as premium, sub-premium, super-premium, crafts, and import. The price competition among premium brands is very different from competition among other beer categories. Tremblay and Tremblay (2005) argue that "a firm that discounts the price of a premium brand to boost sales temporarily or to punish uncooperative rivals risk losing its premium image if the discounting goes on too long". There is less fluctuation in prices of premium brand in comparison to other brands.

1.3 Literature Review

US Supreme Court's 2007 *Leegin* decision has reduced the legal risk of adopting RPM agreements for the US business community. After the *Leegin* decision, the discussion on vertical price restrains has attracted interests from both lawyers and economists for their potential welfare effects. The ambiguous economic theories on vertical price restraints identifies both procompetitive and anticompetitive effects of RPM agreements. The evolution of these theories may have contributed to the change in legal perspective on RPM agreements. In the following discussion, we briefly review the evolution of the legal approach as well as economic theories on vertical price restraints.

RPM agreements have enjoyed a 'rule of reason' legal status since the 2007 Supreme Court's landmark decision in the *Leegin vs. PSKS* case.[11] In the year 1911, the Supreme Court held that vertical price restraints violate Section 1 of the Sherman Act and are per se illegal in its judgement on the *Dr. Miles* case.[12] The Supreme Court reversed its nearly century old position on the matter from being 'per se illegal' to 'rule of reason' in the *Leegin* case. The Court's verdict hints that RPM contracts may help firms to provide better retail services to consumers. Indirectly, these contracts may enhance inter-brand competition among firms in serving consumers.

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[11] Leegin Creative Leather Prods., Inc. v. PSKS, Inc., 127 S. Ct. 2705 (2007).
[12] Dr. Miles Med. Co. v. John D. Park & Sons, 220 U.S. 373 (1911)

The shift in the legal approach towards RPM is not spontaneous. Between *Dr. Miles* and *Leegin*, three important cases show a gradual change in the approach. After eight years of *Dr. Miles*, the Supreme Court ruled in the *Colgate* case[13] that a manufacturer's suggested retail prices (MSRP) are legal as long as retail prices are not enforced through a contract/agreement. In other words, manufacturers may suggest retail prices and can disband supply to retailers if a retailer fails to comply MSRP. This policy is also famously known as *Colgate* policy. In the 1977 *Sylvania* case[14], the Supreme Court upheld rule of reason for non-price vertical restraints. In the 1997 *Kahn* case[15], the court held that maximum RPM contracts should be evaluated under rule of reason than the per se rule. These three legal developments paved the way for RPM contracts to enjoy a friendlier legal environment than in the past. The change in the legal treatment towards RPM contracts serves as a milestone as manufacturers/retailers may rely more on them for distinct economic objectives.

The economics of vertical relationship unfolds the motivations for vertical price restraints. The vertical relationship between an upstream (manufacturer) and downstream (retailer) depends upon a number of variables including retail prices, sales, wholesale prices and other demand enhancing factors (sales efforts, services, promotion etc.). Since an upstream firm is unable to observe and directly control these variables, the retailers' inefficient actions or decision[16] may exert negative externality upon upstream firms. To overcome such inefficiency, manufacturers use (price or non-price) vertical restraints. However, these vertical restraints are often criticized as they may lead to anticompetitive behavior. Many studies discuss the effects of vertical restraints in a market. Motta (2006), Rey and Verge (2008) and Gundlach (2014) offer comprehensive surveys of studies on vertical price restraints.

The welfare effects of RPM are theoretically ambiguous as the economic literature on RPM contracts identifies both procompetitive and anticompetitive effects of RPM. The procompetitive effects are often driven by demand enhancing and/or the elimination of double marginalization.

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[13] United States v. Colgate & Co., 250 U.S. 300 (1919)
[14] Continental T.V., Inc. v. GTE Sylvania Inc., 433 U.S. 36 (1977)
[15] State Oil Co. v. Kahn, 522 U.S. 3(1997)
[16] A retailer's marketing and pricing behavior (sales efforts and services, promotion and display of the products etc.) not only affect its own sales and profit but also manufacturers' incentives. Inclusion of such efforts/services in a private contract between manufacturer and retailer is challenging due to non-verifiability of retailers' behavior. In other words, vertical contracts cannot encompass all vertical relationship specific contingencies for given demand/cost uncertainties. The alignment of retailers and manufacturers behavior is inevitable to increase efficiency of vertical relationship.

However, RPM contracts may harm competition among firms in two ways: 1) facilitating cartel/coordination among suppliers, retailers or both; and 2) foreclosing rival suppliers access to effective distribution channels when used by suppliers/upstream firms, or foreclosing more cost-efficient retailers [Asker and Ba-Isaac (2014); and Cheng (2018)]. In other words, depending upon who initiates RPM contracts - a retailer or a manufacturer, RPM contracts may forestall competition by limiting rival supplier access to effective distribution channel or sabotaging cost-effective retailers. For example, a retailer may offer RPM contracts to suppliers/upstream firms in order to hinder price competition from low-cost rival retailers or to facilitate cartel arrangement among the retailers. Therefore, RPM can serve as a tool to exercise market power or increase prices by limiting intra-brand and inter-brand competition.

In a vertical structure, decentralized choice behavior may create externalities since benefits from actions taken by a given firm are often dispersed across vertically-related firms rather that fully captured by the firm that bears the full cost of the relevant actions. Therefore, non-cooperative choice behavior among vertically-related firms can result in suboptimal provision of retail sales efforts and services from the perspective of what is best for the joint vertical structure. In particular, a lack of coordination between a retailer and manufacturer can result in the double marginalization problem [Telser (1960)] as well as under provision of retail services and/or sales efforts [Spengler (1950)]. The under provision of services is even more acute when the product of the upstream firm is available through multiple retailers. The double marginalization problem among vertically-related firms is another example in which non-cooperative actions, in this case price-setting actions, of vertically-related firms are suboptimal from the perspective of price-setting actions that maximize the joint profit of the vertical structure.

Vertical price restraints such as RPM may correct the externalities described above by mitigating double markup and free-riding problems, incentivize demand enhancing efforts, and preserve the retail margin by discouraging discounters [Mathewson and Winter (1998)]. With RPM contracts, a manufacturer can reduce retail price and eliminate double markup. RPM contracts can also be used to reduce price competition and shift focus from price to non-price features (sales efforts, services, promotional activities) of the products to enhance provision of services and discourage free riding by rival retailers, which directly benefit consumers. A manufacturer not only assures the provision of essential services and efforts for marketing of the products, but enhances the network of retailers by offering certain retail margins through RPM

[Klein (2009)]. RPM contracts can also be used to incentivize retailers to carry adequate inventories under uncertain demand conditions [Marval (1994)].

Manufacturers or retailers may use RPM contracts to avoid competition. In such contracts, RPM acts as an instrument in suppressing competition by facilitating cartel and coordination among suppliers/retailers [Jullien and Rey (2007); and Rey and Verge (2010)]. Contrary to the Nash bargaining game of Dobson and Waterson (2007), Jullien and Rey (2007) and Rey and Verge (2010) show that RPM can soften inter-brand competition and may help producers collude[17] on retail prices by developing a theoretical model in nonlinear prices with and without RPM.[18] They find two distinct equilibria for contracts consisting of a two-part tariff with RPM: 1) Two-part tariff contracts with RPM can be used to eliminate both upstream and downstream competition, resulting in collusive behavior under the assumption of setting upstream wholesale prices equal to marginal cost of production; and 2) Two-part tariff contracts with RPM may result in below monopoly prices if producers set wholesale prices greater than marginal cost of production.

A powerful supplier may use RPM to incentivize downstream retailer to not carry rival suppliers' brands. Asker and Ba-Isaac (2014) analyze the exclusionary effects of RPM contracts as such contracts can allow upstream firms to offer rents to downstream firm for not carrying rival firms' products. A powerful retailer may also suppress price competition and foreclose innovation [Cheng (2018)]. The following describes how such a situation may arise. Without RPM agreements, an efficient retailer may undercut prices of other retailers, and pass benefits to consumers. A powerful but inefficient retailer may negotiate RPM contracts with supplier to avoid price competition, which keeps the inefficient retailer in business with less incentive to become more efficient by innovating.

The Supreme Court's *Leegin* decision has raised concerns about anticompetitive effects arising from RPM agreements. To our knowledge, only one study [MacKay and Smith (2014)] has investigated the impact of the *Leegin* decision on prices and quantities for a wide range of products.

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[17] Verge (2008) discusses the intuition of the argument: "since the terms of contracts accepted by retailers affect the nature of competition between these retailers, they will indirectly affect the behavior of rival producers when they set the terms of contracts with their own retailers. A manufacturer can thus credibly commit not to behave aggressively (e.g. to keep the price high) by engaging early in the use of particular vertical restraints.''

[18] The basic idea is that producers can more easily observe variability in retail prices than in wholesale prices. Contrary to other vertical restraints such as quantity quotas and exclusive territories, RPM makes retail prices rigid in response to retail demand shocks, and makes deviations from a collusive outcome more easily detectable, thus making collusive behavior an attainable task.

MacKay and Smith (2014) analyze the *Leegin* effect on prices and quantities of 1.4 million products at the state-level using Nielson Consumer panel data during years 2004-2009. The study finds that states with a friendly legal environment for RPM experience an increase in prices in contrast to states with strict legal environments for RPM. The study associates the increase in prices to the *Leegin* decision by the US Supreme Court.

In the *pre-Leegin* period, empirical evidence is in favor of the procompetitive role of RPM contracts. Cooper et al (2005) review the empirical literature on vertical restraints and provide strong support in favor of welfare enhancing role of vertical restraints as they solve double markup problem and/or reduce cost. Ippolito (1991) reviews 203 litigated RPM-related cases from 1976 to 1982. Among the reviewed cases, Ippolito (1991) finds a few cases alleging other firms using RPM contracts for horizontal price fixing whereas a majority of the cases offered facts suggesting the procompetitive use of RPM. The study concludes that RPM is procompetitive as it is instrumental in enhancing demand and hence treating RPM as per se illegal does little to deter collusion.

Like *Leegin* in US, the 1996 *Loi Galland Act*[19] in France is criticized for suppressing industry-wide competition. Biscourp et. al (2013) empirically analyze this regulation that legalized industry-wide price floor by facilitating retail price alignment in France. They use retail prices of 190 products collected from 200 stores during years 1994-1999. While empirically testing the possibility that the regulation facilitated manufacturers in imposing a price floor, Biscourp et. al (2013) find a positive correlation between retail prices and the concentration index in 199 products before the enactment of the regulation. Prices were 15% higher in monopolized market than competitive markets. The correlation between retail price and concentration was not significant in year 1999. In other words, an interpretation of this empirical finding is that the enactment of *Loi Galland Act* facilitated firms in coordinating and increasing retail prices across different industries in France. The results support the idea that overall prices increased in the year 1999, eliminating intra-brand competition attributed to RPM.

To our knowledge Bonnet and Dubois (2010) is the only study which analyzes the impact of 1996 Gallant Act using a structural econometric model. Similar to our study, their study lays out several empirical models of vertical contracting between manufacturers and retailers, and

[19] The motivation behind *Leegin* and *Loi Galland Act* is somewhat similar in the sense that the focus was to encourage small businesses.

estimate these models using micro-level data of the highly concentrated French bottled water market during the 1998-2000 period. Their analysis constitutes a direct empirical test of theoretical outcomes provided in Rey and Verge (2010). Specifically, the models analyzed by Bonnet and Dubois (2010) allow manufacturers and retailers to use linear as well as nonlinear pricing with and without RPM, and with or without collusion upstream and/or downstream. They find that manufacturers use two-part tariff with RPM, rejecting other supply models in favor of this model. They show that retail prices will drop by 7% under two-part tariff if RPM is banned.

The theoretical literature largely focuses on the motivation for the use of vertical restraints. These studies offer theoretical framework for the use of resale price maintenance and their potential welfare impacts. On the other side, empirical studies often focus on measuring how market outcomes change when the market and legal environments are more or less conducive for use of RPM. However, the empirical studies largely ignore whether observed outcomes in the data are consistent with firms optimally using RPM in a market equilibrium to achieve the observed outcomes. Considering the change in the US legal framework towards RPM captured by the US Supreme Court's decision in the *Leegin* case, the present study fills this gap in the empirical literature using real-world data drawn from the highly concentrated US beer industry.

1.4 Sources of Data

1.4.1 Retail Scanner Data

Our primary source of data is retail scanner data from the IRI Academic Database.[20] The data offer weekly sales and revenue information by Universal Product Code (UPC) of beer products sold at 2000 grocery/superstores for the period 2001-2012. The selected stores are located within 49 distinct IRI defined geographic regions covering the entire US. The sales trends are uneven among different brands of a company. There are over 10 million weekly observations for each year covering approximately 1500 brands. Three-fourth of the brands are categorized as domestic brands. The coverage of domestic and imported brands makes this data representative of the US beer industry.

[20] Bronnenberg, Kruger and Mela (2008) provide a detailed description of the data.

Overall, there are 75 brands that account for approximately 80% of the sales in the data. This study focuses on these brands for years 2005 to 2012. The focus brands are the best performing brands of their respective companies. The list of the brands are given in Appendix A.

The data cover information on more than 500 breweries. We focus on leading breweries widely discussed in the literature.[21] In the beer industry, 12-pack size has the greatest unit sales, while 24-pack size has the greatest volume sales[22]. Both sizes are considered as two distinct products. The scanner data covers a wide range of different sizes of brands sold in superstores. About 64 percent of the beer sales are concentrated in 12-packs (144 ounces) and 24-packs (288 ounces). Our analysis focuses on 12-packs (144 ounces) products only.

Revenue share estimates from the retail scanner data confirm the high concentration in the US beer industry for the period 2001-2012. Table 1.2 and Table 1.3 display the revenue share of eight leading breweries for select brands. The estimates suggest that our select breweries and their brands account for over 90 percent revenue share among 24-pack products, and over 80 percent revenue share among 12-pack products. Among the select breweries, ABI, Molson Coors, and SABMiller account for much of the revenue share. The share of these four brewers is consistent when evaluated using unit sales of the 75 brands.

Table 1.2: Select Brewers' Revenue Share (12-packs) across 75 beer brands

	ABI	BOS	DGY	GM	HEIN	MOLS	SABM	MillerCo	GAMB	Total
2001	36.76	1.71	0.11	12.42	7.23	11.09	19.38	…	0.85	89.54
2004	34.28	2.29	0.69	14.23	9.03	8.42	16.56	…	0.68	86.19
2006	29.39	3.07	0.98	17.54	10.95	7.64	14.46	…	0.84	84.88
2008	31.20	3.77	1.61	18.09	9.72	8.83	14.33	23.15	0.87	88.42
2010	29.20	4.53	2.11	17.34	9.51	9.83	13.20	23.03	0.94	86.66
2012	27.17	4.85	2.76	18.52	9.59	10.80	10.74	21.54	0.98	85.41

Note: Anheuser-Bush InBev (ABI); Boston (BOS); DG Yuengling (DGY); Groupo Modelo (GM); Heineken (HEIN); Molson Coors (MOLS); SABMiller (SABM); MillerCoor (MIllerCo); The Gambrinus (GAMB)

[21] Ascher (2012)
[22] Unit sales 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 sales is described as physical volume of 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]

Table 1.3: Select Brewers' Revenue Share (24-packs) across 75 beer brands

Years	ABI	BOS	DGY	GM	HEIN	MOLS	SABM	MillerCo	Total
2001	52.22	0.07	0.04	0.07	0.28	11.88	29.41	..	93.96
2004	51.84	0.10	0.25	2.02	0.40	11.33	29.06	…	95.01
2006	49.69	0.10	0.54	4.57	0.99	10.94	28.79	..	95.61
2008	47.63	0.26	1.08	7.48	1.64	11.77	27.75	39.53	97.61
2010	45.66	0.27	1.75	8.50	2.38	13.55	25.06	38.60	97.17
2012	45.89	0.22	2.72	8.38	2.55	14.76	22.17	36.93	96.70

Note: Anheuser-Bush InBev (ABI), Boston (BOS), DG Yuengling (DGY): Heineken (HEIN); Molson Coors (MOLS); SABMiller (SABM); MillerCoor (MIllerCo); Groupo Modelo (GM)

To reduce the computational burden during econometric estimation, we further aggregate the weekly data up to monthly unit sales and revenue separately for each beer size. Following the standard approach, we compute average price by dividing the monthly sales revenue by monthly unit sales. Figure 1 displays trends of the log of real prices from 2005 to 2012. The *post-Leegin* period begins in year 2008 after the *Leegin* decision was enacted. Panels a, b and d in Figure 1.1 reveal upward price trends of select domestic brands during the *post-Leegin* period. However, panel c in Figure 1 shows downward price trends of select imported brands, Heineken (Heink) and Corona Extra (Corona_E), during *pre-Leegin* and *post-Leegin* periods.

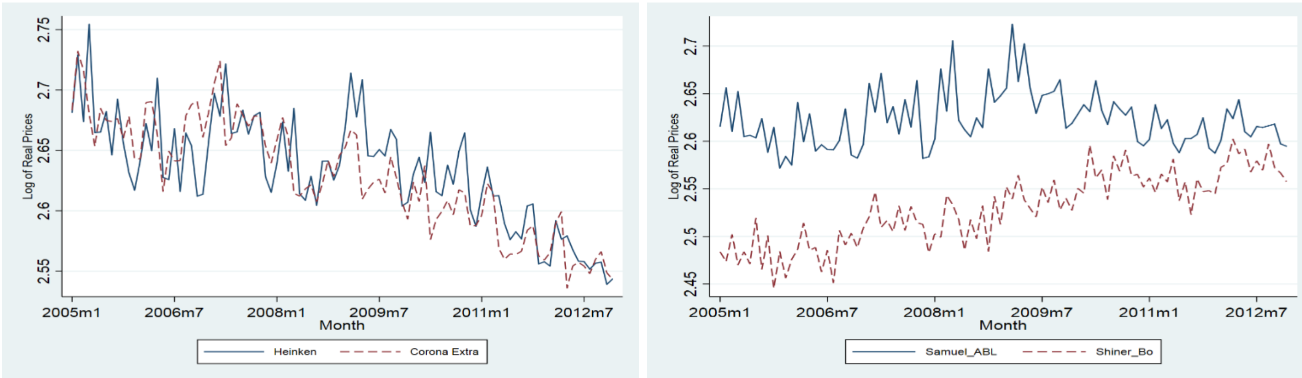
Figure 1.1: Log of Real Prices of Major Beer brands (12-pack)

Panel (a)

Panel (b)

Panel (c)

Panel (d)



Following Miller and Weinberg (2017), we define the total potential market size to be ten percent greater than the maximum observed unit sales for each geographical location market. We define a market as the period-location combination, while a distinct product in a market is defined as a combination of brand and retailer (stores). In other words, Bud Light sold at two different retailers within the same defined IRI geographic region during the same time period is considered two distinct products within a market.

1.4.2Product characteristics data

We supplement the sales data with brand characteristics and brand style information. The information on characteristics is collected from labels available on the brands of beer. The sales data covers only products available at grocery and superstores. We collected information on characteristics of these products from websites of grocery and superstores. Our selected brands can be classified into 20 different beer styles.[23] The list of the beer styles is given in Appendix A. Table 1.4 shows descriptive statistics of the non-price characteristics across the brands. On average, our selected brands contain an average alcohol content of 4.6%, 10.25 grams of carbohydrates, and 137 calories.

[23]. There are different beer guides available. We follow styles given at www.beeradvocate.com/beer/style/

Table 1.4: Average non-price Product Characteristics

Characteristics	Mean	Min	Max
Alcohol (%)	4.62 (0.97)	0.4	8.1
Carbohydrates (grams)	10.25 (4.47)	2.6	21
Calories	136.54 (30.21)	58	222

Note: Standard deviations are reported in parentheses.

1.4.3 Demographic data set

We supplement the IRI scanner data (sales and product characteristics) with market consumer income data drawn from the Public Microdata Sample (PUMS) database. The PUMS data are useful in estimating demand. In PUMS data, household are identified as living in a geographical location containing at least 100,000 people. Data on consumers' income are drawn from the PUMS for the period 2005-2012. The PUMS data are yearly.

Table 1.5 shows income variation of random draws of 200 individuals for each IRI Market, for the years 2007 and 2009. Variation in income distribution within and across the select IRI Markets, corresponding to national levels, is observed. For example, out of a random draw of 200 individuals for New York, 53.5% of the individuals have personal income less than or equal to $50,000, and 5.5% of them have income above $200,000 in the year 2007. For the same year, a random draw of 200 individuals for Roanoke shows 79% of the individuals have income less than or equal to $50,000, and 1.5% of the individuals have income more than $200,000. The income distributions for the years 2007 and 2009 are similar. For example, in both years slightly more than two-thirds of the individuals have income less than $50,000, while 2.2% and 1.6% of the individuals have income more than $200,000 in years 2007 and 2009 respectively.

1.4.4 Transportation Cost

Transportation cost is a major component of the total cost of providing beer to consumers. The uneven ownership structure of breweries in the US beer industry suggests that brewers with the largest number of breweries enjoy a cost advantage[24] over rival brewers with fewer breweries. ABI with 12 breweries and Miller-Coors with 9 breweries own the largest number of breweries in the industry. The merger between SABMiller and Molson Coors was proposed with the premise that it will help reduce transportation costs. Following Miller and Weinberg (2017), we compute transportation cost at brand level by calculating the distance between the IRI geographic locations and nearest brewery using Google Map. During the *pre-Leegin/*merger period, the transportation costs of brands owned by SABMiller and Molson Coors only consider breweries owned by the respective firms separately, while in the *post-Leegin/*merger period transportation cost is computed considering a single firm (Miller-Coors) owning all 9 breweries.

[24] The merger between SABMiller and Molson Coors was approved by antitrust authorities under the premise that the cost advantage of the merger will outweigh the anticompetitive effects of increased concentration in the industry.

Table 1.5: Percentage of individuals in each IRI Market who fall into specified income categories based on random draws of 200 individuals for each IRI Market for the years 2007 and 2009

	Income Categories: Year 2007						Income Categories: Year 2009					
IRI Market	**≤$50K**	**$50K<& ≤$$100K**	**$100K<& ≤$150K**	**$150K<& ≤$200K**	**>$200K**	Total (%)	**≤$50K**	**$50K<& ≤$100K**	**$100K<& ≤$150K**	**$150K<& ≤$200K**	**>$200K**	Total (%)
New York	53.5	29.5	9.5	2.0	5.5	100	57.5	28.5	7.5	2.5	4.0	100
Oklahoma City	75.5	18.5	1.5	1.5	3.0	100	68.5	24.5	4.0	0.5	2.5	100
Omaha	71.0	20.0	6.0	2.0	1.0	100	75.5	17.5	3.5	2.0	1.5	100
Peoria/Springfield	75.0	21.5	2.5	1.0	0.0	100	74.0	19.5	3.5	1.0	2.0	100
Philadelphia	65.0	27.5	5.0	1.0	1.5	100	61.0	29.5	6.0	1.5	2.0	100
Phoenix, AZ	66.5	23.5	4.5	3.0	2.5	100	67.5	22.5	4.5	2.0	3.5	100
Pittsfield	75.5	19.0	2.0	1.5	2.0	100	78.5	14.5	2.5	2.5	2.0	100
Portland, OR	74.5	18.5	3.0	3.5	0.5	100	65.5	29.0	4.5	0.5	0.5	100
Raleigh/Durham	67.5	25.5	4.5	1.0	1.5	100	71.0	19.0	6.0	2.0	2.0	100
Richmond/Norfolk	71.5	23.0	4.0	1.0	0.5	100	71.5	23.0	5.0	0.0	0.5	100
Roanoke	79.0	16.5	1.0	2.0	1.5	100	81.0	16.5	2.0	0.5	0.0	100
Sacramento	62.0	27.5	7.5	2.5	0.5	100	64.0	27.5	6.0	1.5	1.0	100
Salt Lake City	72.0	23.0	1.5	1.5	2.0	100	65.0	27.5	3.5	1.0	3.0	100
San Diego	61.5	31.0	5.0	0.0	2.5	100	56.0	34.5	4.5	3.0	2.0	100
San Francisco	47.0	31.0	9.0	5.0	8.0	100	44.5	35.0	12.0	5.5	3.0	100
Seattle/Tacoma	59.0	31.0	4.0	1.5	4.5	100	53.5	35.5	7.0	0.5	3.5	100
South Carolina	79.5	17.0	2.0	0.0	1.5	100	78.0	19.0	3.0	0.0	0.0	100
Spokane	75.0	21.0	3.0	0.5	0.5	100	78.5	19.5	0.5	0.5	1.0	100
St. Louis	69.5	24.5	4.5	1.0	0.5	100	70.5	22.0	5.5	2.0	0.0	100
Syracuse	75.5	20.5	2.5	0.5	1.0	100	73.5	24.0	2.0	0.5	0.0	100
Toledo	78.0	17.5	1.0	1.0	2.5	100	77.5	19.0	3.0	0.0	0.5	100
Tulsa, OK	73.5	22.0	1.0	1.5	2.0	100	75.0	21.5	2.0	1.0	0.5	100
Washington, DC	52.0	30.5	8.0	4.0	5.5	100	50.5	32.0	11.0	3.0	3.5	100
West Tex/New Mex	75.0	19.5	2.0	0.5	3.0	100	74.0	21.0	2.5	1.5	1.0	100
Percentage of total individuals drawn across all markets	68.9	23.3	3.9	1.6	2.2	100	68.0	24.3	4.6	1.5	1.6	100

1.4.5 Sample Size

Our data sample includes the following monthly variables during the period 2005-2012: product share (computed as product quantity sold divided by our measure of potential market size discussed above), product prices, measures of non-price product characteristics discussed above, and transportation costs of 75 brands of 12-packs (144 ounces). The brands in the data sample are produced by 8 different brewers, and these brands are sold through various retailers located across the 49 IRI geographical regions. Based on our definitions of markets and products discussed above, the data sample has 3.85 million observations. These many observations are substantially too large for the computationally intensive structural econometric model we estimate. As such, we proceed by randomly selecting 24 of the 49 IRI markets to use in the empirical analysis. We further divide the sample into *pre-Leegin* period and *post-Leegin* period subsamples. The number of observations in the data sample used in the empirical analysis is 1.91 million observations. Further, our *pre-Leegin* period subsample span the years 2005 and 2006 while the *post-Leegin* period subsample span the years 2008 to 2012.

1.5 The Econometric Model

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

1.5.1 Demand

We use a random coefficients logit model to model the demand for beer. As previously discussed, a market is defined as the unique combination of an IRI geographic region and time-period, while a product in a market is defined as the unique combination of beer brand and retailer. Let markets be indexed by *m* and products by *j*. In each market, consumer i has $J+1$ alternative options, i.e., the consumer can choose among the J ($j = 1,2, \dots J$) differentiated beer products in a market or the outside option $j = 0$, where the outside option includes alternative beverages that are substitutes for beer.

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

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

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 measure of the mean product characteristics that are unobserved by the researchers, but observed by consumers and firms; $\Delta\xi_{jm}$ is a market–specific deviation from this mean; and ε_{ijm} is a mean-zero individual-specific random component of utility that accounts for deviation of the individual's preferences from the mean utility.

Examples of non-price product characteristics we control for are: calorie counts, amount of carbohydrates, alcoholic content, a zero-one indicator variable that takes the value one only if the product is imported, and various zero-one indicator variables indicating different styles of beer. 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 potential consumers in the relevant market. 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 vary across consumers, where β_i is a vector of consumer-specific taste parameter associated with different non-price product characteristics in x_{jm}, while α_i represents consumer-specific marginal disutility of price. The variation in individual-specific parameters is explained by a known *m*-dimensional column vector of demographic information (D_i), where *m* represents the number of distinct demographic variables, and a k-dimensional column vector of unobserved consumer characteristics (v_i), where k represents the number of distinct random coefficients. As such, the following linear equation captures how the random taste parameters vary across potential consumers:

$$\begin{pmatrix}\beta_i\\ \alpha_i\end{pmatrix} = \begin{pmatrix}\beta\\ \alpha\end{pmatrix} + \Gamma D_i + \Upsilon v_i, \tag{2}$$

where Γ is the $k \times m$ matrix of parameters measuring how taste characteristics vary with demographics; Υ is the $k \times k$ diagonal matrix measuring the variation in taste due to random shocks v_i. 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 probability distribution, i.e., $v_i \sim N(0, I)$. Since the mean of v_i and the mean of D_i are zero, then α and β measure the mean of the random coefficients. Therefore, the mean utility level across all potential consumers of product j, δ_{jm}, is given by:

$$\delta_{jm} = x_{jm}\beta + \alpha p_{jm} + \xi_{jm} + \Delta\xi_{jm} \tag{3}$$

The mean utility obtained from the outside option is normalized to zero.

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

$$\mu_{ijm}\left(x_{jm}, p_{jm}, v_i, D_i; \theta_2\right) = \left[x_{jm}, p_{jm}\right](\Gamma D_i + \Upsilon v_i) \tag{4}$$

Using equations (1) to (3) allow us to express the indirect utility from consuming product j as:

$$V_{ijm} = \delta_{jm}\left(x_{jm}, p_{jm}, \xi_{jm}; \theta_1\right) + \mu_{ijm}\left(x_{jm}, p_{jm}, D_i, v_i; \theta_2\right) + \varepsilon_{ijm} \tag{5}$$

The indirect utility is expressed as the mean utility $\left(\delta_{jm}\right)$ 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 share of product j, or the choice probability of product j is given by:

$$s_{jm} = \int \frac{e^{\delta_{jm} + \mu_{ijm}}}{1 + \sum_{l=1}^{J} e^{\delta_{lm} + \mu_{ilm}}} \widehat{dF}(D) dF(v), \tag{6}$$

where $\hat{F}(D)$ is the empirical distribution of demographic variables; and $F(v)$ is the multivariate standard normal distribution. No closed-form solution exists for the integral problem in equation (6), thus the right-hand-side of the equation must be approximated numerically using random draws from $\hat{F}(D)$ and $F(v)$.

We computed the total unit sales in each geographical market. On finding the maximum unit sales in each market, we define the potential market size (M_m) as 10% higher than the observed maximum unit sales in a market m. Finally, the demand for product j is given by:

$$d_{jm} = M_m * s_{jm}(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \theta_d) \tag{7}$$

where M_m is the potential size of market m; $s_{jm}(\cdot)$ is the predicted product share from equation (6); $\mathbf{x}$ and $\mathbf{p}$ are vectors of observed non-price product characteristics and price, respectively; $\boldsymbol{\xi}$ is a vector of unobserved product characteristics; and $\theta_d = (\alpha, \beta, \Gamma, \Upsilon)$ is the vector of demand parameters to be estimated.

1.5.2 Supply

In this section, we outline different supply models based on various assumptions about linear and non-linear vertical price-setting behavior between upstream (brewers) and downstream (retailers) firms involved in the supply of beer. In these supply models, brewers first set their per unit wholesale prices for the menu of beer products they produce and offer to retailers, and then retailers follow by choosing per unit retail prices for these products to maximize their profit. We first describe retailer's profit maximizing behavior when setting the retail prices that consumers pay, then we describe brewer's profit maximizing behavior in setting the prices they charge retailers to carry their products. Five of the eight distinct models of vertical price-setting behavior we discuss below restrict firms (brewers and retailers) to use only linear pricing, i.e., each firm can only set per unit prices for products, while the other three models allow brewers to charge retailers nonlinear prices, i.e., a combination of per unit wholesale prices and lump sum fixed fees that are unrelated to quantity sold.

1.5.2.1 Linear Pricing

Model A: Active brewers – brewers competing with other brewers at the upstream level
Active retailers – retailers compete at the downstream level

In Model A, we assume retailers compete in the downstream market by simultaneously and non-cooperatively choosing per unit retail prices (Bertrand Nash fashion) for the menu of differentiated beer products they sell to consumers. Similarly, brewers compete amongst themselves in the upstream market by simultaneously and non-cooperatively choosing per unit wholesale prices (Bertrand Nash fashion) for the menu of differentiated beer products they sell to retailers. Since retailers and brewers independently choose their prices to maximize individual firm-level profits, this model yields double marginalization, i.e., positive price-cost margins upstream and downstream, within the vertical structure of US beer market.

Retailers Optimization Problem

Concerning retailer's behavior, we assume retailer r sells a set of S_m^r products, where S_m^r is a subset of the J_m beer products available to consumers in market *m*. As previously discussed, a market is defined by a geographic location during a given time period. Retailer r considers the following profit function to maximize its profit in market *m*:

$$\Pi^r = \sum_{j \in S_m^r} (p_{jm} - w_{jm} - c_{jm}) \times q_{jm} \tag{8}$$

where p_{jm} denotes the retail price of product j; w_{jm} denotes the wholesale price paid to the brewer (upstream firm) of product j; c_{jm} denotes per unit retail cost incurred that is unrelated to the wholesale price paid to the brewer; and q_{jm} is the quantity of product j sold in market *m*. Market equilibrium requires $q_{jm} = d_{jm} = M_m \times s_{jm}(p)$. Each retailer therefore solves the following profit maximization problem:

$$\max_{p_{jm} \forall j \in S_m^r} \left[\sum_{j \in S_m^r} (p_{jm} - w_{jm} - c_{jm}) \times M_m \times s_{jm}(p) \right] \tag{9}$$

Since we assume that brewers determine their optimal wholesale prices prior to retailer setting retail prices, then w_{jm} is predetermined when retailers solve their profit maximization problem.

The first-order conditions that yield a pure strategy Bertrand Nash equilibrium in retail prices are:

$$s_j + \sum_{k \in S^r} (p_k - w_k - c_k) \left(\frac{\partial s_k}{\partial p_j} \right) = 0 \quad \forall\, j \in S^r \tag{10}$$

Market subscripts are suppressed in equation (10) and many subsequent equations only to avoid a clutter of notation. We can conveniently recover the set of retail markups by re-writing the above equation in matrix form. To do so we define a $J \times J$ matrix, T_r, that characterizes retailers' ownership structure of the *J* products in the market. Matrix T_r has general element $T_r(i, j)$ equal to 1 if products i and j are sold by the same retailer, and 0 otherwise. Let Δ_r be the $J \times J$ matrix that captures the response of product share to retail prices. Matrix Δ_r contains first-order partial derivatives of product shares with respect to all retail prices:

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

In vector notation, the first-order conditions characterized by equation (10) implies that the $J \times 1$ vector of retail markups (γ) is given by the following expression:

$$\gamma \equiv p - w - c = -[T_r * \Delta_r]^{-1} \times s(p) \tag{11}$$

where p, w, c, and $s(\cdot)$ are $J \times 1$ vectors of retail prices, wholesale prices, retail marginal costs, and product shares respectively; while $T_r * \Delta_r$ represents element-by-element multiplication of the two matrices.

Brewers' Optimization Problem

Prior to retailers solving their profit maximization problem, we assume that brewers simultaneously and non-cooperatively choosing per unit wholesale prices for the menu of differentiated beer products they sell to retailers. Let the set of products brewer *b* sells to retailers in market *m* be denoted by S_m^b, where S_m^b is a subset of the J_m beer products available to consumers in market *m*. Brewer *b* solves the following profit maximization problem:

$$\max_{w_{jm} \forall j \in S_m^b} \left[\sum_{j \in S_m^b} \left(w_{jm} - \mu_{jm}\right) \times M_m \times s_{jm}\left(p(w)\right) \right] \tag{12}$$

where μ_{jm} is the brewer's marginal cost of producing product j. The first-order conditions that yield a pure strategy Bertrand Nash equilibrium in wholesale prices are:

$$s_j + \sum_{k \in S^b} (w_k - \mu_k) \left(\frac{\partial s_k(p(w))}{\partial w_j} \right) = 0 \quad \forall\, j \in S^b \tag{13}$$

where $\frac{\partial s_k(p(w))}{\partial w_j} = \sum_{l \in J} \frac{\partial s_k(p(w))}{\partial p_l} \frac{\partial p_l}{\partial w_j}$. Note that $\sum_{l \in J} \frac{\partial s_k(p(w))}{\partial p_l} \frac{\partial p_l}{\partial w_j}$ reveals that the wholesale price of product *j* marginally impacts the share of product *k* (demand for product *k*) indirectly through marginally influencing the retail prices of all *J* products in the market. In other words, in choosing the optimal wholesale price for product *j* (w_j), the brewer takes into account how the chosen level of this wholesale price impacts the level of retail prices $\left(\frac{\partial p_1}{\partial w_j}, \frac{\partial p_2}{\partial w_j}, \frac{\partial p_3}{\partial w_j}, \ldots, \frac{\partial p_J}{\partial w_j}\right)$ for all competing products in the market.

Let Δ_p denote a $J \times J$ matrix of partial derivatives of retail prices with respect to wholesale prices, i.e.,

$$\Delta_p = \begin{pmatrix} \frac{\partial p_1}{\partial w_1} & \cdots & \frac{\partial p_J}{\partial w_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial p_1}{\partial w_J} & \cdots & \frac{\partial p_J}{\partial w_J} \end{pmatrix}$$

As shown in Villas-Boas (2007), the matrix that captures the response of all product shares with respect to marginal changes in wholesale prices can be computed using the product of matrices Δ_p and Δ_r as follows: $\Delta_b = \Delta_\mathrm{p}^{/}\Delta_r$.

Let T_b be a $J \times J$ matrix of zeros and ones that captures the product ownership structure across brewers. Specifically, general element in the brewer's ownership matrix $T_b(l, k)$ is equal to 1 if products l and k are produced by the same brewer, and 0 otherwise. We can now use matrix notation to represent the system of first-order condition equations generated by the brewer's profit maximization as follows:

$$s(p) + (T_b * \Delta_b) \times (w - \mu) = 0 \tag{14}$$

where w and μ are $J \times 1$ vectors of wholesale prices and brewers marginal costs respectively; while $T_b * \Delta_b$ represents element-by-element multiplication of the two matrices. Equation (14) can be re-arranged to recover brewers' equilibrium product markups:

$$\Gamma \equiv w - \mu = -[T_b * \Delta_b]^{-1} \times s(p) \tag{15}$$

The markup expressions for retailer and brewers described above can be exploited to recover expressions for a variety of alternate supply models for the beer market.

Model B: Collusive behavior among brewers – all domestic brewers collude at the upstream level. Active retailers – retailers compete at the downstream level

Contrary to Model A, in Model B we assume that all domestic brewers cooperatively choose wholesale prices to maximize joint profit. The brewers' markup expression given in equation (15) is still relevant except the product ownership matrix needs to be appropriately modified. The appropriate modification of the brewers' ownership structure matrix is to convert from zero to one elements in T_b where the row and column products are produced by distinct domestic brewers. Effectively, the modified brewers' product ownership structure matrix, denoted $T_b^{collude}$, treats all brands owned by domestic brewers as if they were jointly owned by a single firm. Therefore, the equation that determines brewer markups in Model B is:

$$w - \mu = -\left[T_b^{collude} * \Delta_b\right]^{-1} \times s(p) \quad (16)$$

The retailer's markup expression given in Model A will remain unchanged for Model B.

Model C: Select brewers collude with each other – ABI and Miller-Coors Collude
Active retailers – retailers compete at the downstream level

Model C assumes that major players like ABI, SABMiller and Molson Coors (Miller-Coors *post-Leegin*) collude on setting wholesale prices of their brands. The rest of the brewers act independently in setting their wholesale prices. The appropriate modification of the brewers' ownership structure matrix is to convert from zero to one elements in T_b where the row and column products are produced by the select brewers (ABI, SABMiller and Molson Coors (Miller-Coors *post-Leegin*)) we assume are jointly setting their wholesale prices. Effectively, the modified brewers' product ownership structure matrix, denoted $T_b^{collude\_select}$, treats all brands owned by select brewers as if they were jointly owned by a single firm. Therefore, the equation that determines brewer markups in Model C is:

$$w - \mu = -\left[T_b^{collude\_select} * \Delta_b\right]^{-1} \times s(p) \quad (17)$$

The retailers' markup expression given in Model A will remain unchanged for Model C.

Model D: Collusive behavior among brewers – all domestic brewers collude at the upstream level. Passive retailers – retailers earn zero markup at the downstream level

Like Model B, Model D assumes collusive behavior among domestic brewers. However, Model D assumes retailers behave as passive players in passing wholesale prices along with the retail cost to consumers in the form of a final price. In other words, retailers charge final retail prices in a manner that yield zero retail markup over their effective marginal cost: $p = w + c$ or $p - w - c = 0$. The product ownership structure matrix $T_b^{collude}$ treats all brands owned by domestic brewers as if a single firm jointly owned them. The markups for brewers are determine by the following equation:

$$w - \mu = -\left[T_b^{collude} * \Delta_r\right]^{-1} \times s(p) \tag{18}$$

Model E: Select brewers collude with each other – ABI & Miller-Coors Collude

Passive retailers – retailers earn zero markup at the downstream level

Instead of assuming collusive behavior among all domestic brewers, Model E assumes collusive behavior among select brewers (*pre-Leegin* ABI collude with SABMiller and Molson Coors, and *post-Leegin* ABI collude with Miller-Coors). Effectively, the modified brewers' product ownership structure matrix, denoted $T_b^{collude\_select}$, treats all brands owned by select brewers as if they were jointly owned by a single firm. Therefore, the equation that determines brewer markups in Model E is:

$$w - \mu = -\left[T_b^{collude\_select} * \Delta_r\right]^{-1} \times s(p) \tag{19}$$

Similar to Model D, retailer markups in Model E are assumed to be zero. Therefore, total markup in this case is equal to upstream markup.

1.5.2.2 Nonlinear Pricing: Two- Part tariff with and without RPM

Following Bonnet and Dubois (2010), we consider supply behavior when upstream firms (brewers) charge downstream firms (retailers) non-linear prices – two-part tariff with and without retail pricing maintenance (RPM). In the following discussion, we first derive markups for upstream firms under two-part pricing with RPM. Under two-part pricing strategy, a brewer can write a contract with a retailer specifying a per unit wholesale price along with a fixed lump sum fee that is independent of quantity sold. If a brewer imposes RPM, perhaps due to substantial bargaining power with retailers, then this means that the brewer directly chooses the retail price charged to consumers. Rey and Verge (2010) argue that multiple equilibria are possible in such a multiple common agency game. However, they suggest that under certain assumptions, we can focus on two possible equilibria: (1) the case when wholesale price is equal to marginal costs; 2) the case when retail markup is equal to zero.

Even though we assume that brewers set their prices prior to retailers setting their price, we describe retailers profit maximization problem before describing brewers profit maximization problem. In the case of two-part tariff pricing, retailer r pays the per unit wholesale price w_{jm}

along with a fixed fee F_j^r for the right to sell product j. The profit function of retailer r is given by:

$$\Pi^r = \sum_{j\in S^r} \left[\left(p_j - w_j - c_j\right) \times M \times s_j^r(p) - F_j^r \right] \tag{20}$$

Market subscript, m, is omitted from profit equations only to avoid a clutter of notation.

We assume brewer b produces and offers to retailers a subset of the J competing products in a market, and the subset of products is denoted by S_b. A brewer sets per unit wholesale price w_{km} along with fixed fee F_k^b to maximize the following profit function:

$$\Pi^b = \sum_{j\in S^b} \left(w_j - \mu_j \right) \times M \times s_j^b + \sum_{j\in S^b} F_j^b \tag{21}$$

A brewer maximizes profit subject to the retailer's participatory constraint: $\Pi^r \geq \overline{\Pi^r}$, where $\overline{\Pi^r}$ represents a lower bound of retail profit below which the retailer will choose not to participate in the market. As such, $\overline{\Pi^r}$ is retailer r's outside option profit. The retailer's participatory constraint is binding, i.e. $\Pi^r = \overline{\Pi^r}$, otherwise the manufacturer can increase its profit by increasing the fixed fee. To simplify the model, we normalize the outside option profit as follows: $\Pi^r = \overline{\Pi^r} = 0$, which implies that $\sum_{j=1}^J F_j = \sum_{j=1}^J \left(p_j - w_j - c_j\right) \times M \times s_j$. Furthermore, note that $\sum_{j\in S^b} F_j = \sum_{j=1}^J F_j - \sum_{j\notin S^b} F_j$, which can be re-written as follows after substituting for $\sum_{j=1}^J F_j$ on the right-hand-side:

$$\sum_{j\in S^b} F_j^b = \sum_{j=1}^{J} \left(p_j - w_j - c_j\right) \times M \times s_j - \sum_{j\notin S^b} F_j \tag{22}$$

Substituting for $\sum_{j\in S^b} F_j^b$ on the right-hand-side of equation (21) allows us to re-write the brewer's profit function as follows:

$$\Pi^b = \sum_{j\in S^b} \left(w_j - \mu_j \right) \times M \times s_j^b + \sum_{j=1}^{J} \left(p_j - w_j - c_j\right) \times M \times s_j - \sum_{j\notin S^b} F_j \tag{23}$$

The above expression suggests that a brewer maximizes profit by choosing per unit wholesale prices and retail prices (in case of RPM) for its products conditional on the retail prices, wholesale prices, and fixed fees charged by rival brewers. Since the last term in brewer b's profit function, $\sum_{j \notin S^b} F_j$, is not influenced by marginal changes in brewer b's retail and wholesale prices, then this term can be omitted from brewer b's profit function when it chooses its profit maximizing levels of wholesale and retail prices. In addition, if brewers can directly determine the level of retail prices for their products through imposing RPM, and can extract retailers' profit by imposing a fixed fee, then there is no need to use wholesale prices as an indirect instrument to influence its retail prices and maximize profit. Rey and Verge (2010) use a theoretical model to show that the upstream firm always finds it optimal to set retail prices instead of wholesale prices when contracting with retailers. The preceding arguments suggest that brewer b's profit maximization problem can be written as:

$$\max_{\{p_j\} \forall j \in S^b} \left\{ \sum_{j \in S^b} (w_j - \mu_j) \times M \times s_j^b + \sum_{j=1}^{J} (p_j - w_j - c_j) \times M \times s_j \right\} \tag{24}$$

The profit maximization problem in (24) can be re-written as:

$$\max_{\{p_j\} \forall j \in S^b} \left\{ \sum_{j \in S^b} (p_j - \mu_j - c_j) \times M \times s_j^b(p) + \sum_{j \notin S^b} (p_j - w_j - c_j) \times M \times s_j(p) \right\} \tag{25}$$

Even though upstream firms that use RPM are unlikely to use wholesale price as a direct instrument to maximize their profit, the level of wholesale price(s) they set prior to setting retail price(s) via RPM is of strategic importance. The profit function in (25) reveals that a brewer's wholesale price influences rival brewers' profits through the channel of indirectly influencing optimal levels of retail prices and product shares. In a theoretical analysis, Rey and Verge (2010) shows there exist multiple equilibria with one for each set of predetermined wholesale prices that affect rival upstream firms' strategic behavior. Bonnet and Dubois (2010) point out that "… for each wholesale price vector w^*, there exists a symmetric subgame perfect equilibria in which retailers earn zero profit and manufacturer set retail prices to $p(w^*)$, where $p(w^*)$ is a decreasing function of w^* equal to the monopoly price when the wholesale prices are equal to the marginal cost of production".

The set of first-order conditions that results from the brewer's profit maximization problem in equation (25) is:

$$s_j^b(p) + \sum_{k \in S^b} (p_k \ - \mu_k - c_k) \frac{\partial s_k^b(p)}{\partial p_j} + \sum_{k \notin S^b} (p_k^* - w_k^* - c_k) \frac{\partial s_k^b(p)}{\partial p_j} = 0 \ \forall \ j \in S^b \qquad (26)$$

Using the system of first-order conditions in equation (26), we proceed under two assumptions: (1) The brewers charge wholesale price equal to their marginal cost of production, i.e. $w_k^b = \mu_k$; and (2) The brewers leave zero markup with the retailers, which implies $p_{jm} - w_{jm} - c_{jm} = 0$. However, in both cases the brewer decides the retailer price charged at the retail level, i.e. brewers utilize RPM with retailers. We recover the expression for total markup under these two assumptions in models F and G, respectively.

Model F: Two-part Tariff with RPM – wholesale prices set equal to brewers' marginal cost.

In view of the strategic importance of the wholesale price, we assume in Model F that each brewer sets their wholesale prices equal to their marginal cost of production.

$$s_j^b(p) + \sum_{k=1 \ldots J} (p_k - \mu_k - c_k) \frac{\partial s_k^b(p)}{\partial p_j} = 0. \ \forall \ j = 1 \ldots \ldots J \qquad (27)$$

The system of first-order conditions in (27) can be represented using matrix notation as follows:

$$s(p) + \Delta_r \times (p - \mu - c) = 0 \qquad (28)$$

Total markup (the sum of brewers and retailers markup) can be recovered from equation (28) as follows:

$$\Gamma + \gamma \equiv p - \mu - c = -[\Delta_r]^{-1} \times s(p) \qquad (29)$$

The total markup retrieved in the above expression is equivalent to the scenario in which the industry is vertically integrated and horizontally collusive, i.e. all active firms fully coordinate their price-setting such that joint profit is maximized. The implied total markup can also be achieved using either equations (11) or (18) in the event that product ownership structure matrix $T_b = T_r = T_1$, where T_1 is a matrix of ones.

Model G: Two-part Tariff with RPM – Retail markup equal to zero

Model G assumes that retail markup is equal to zero, implying that $p_k^* - w_k^* - c_k = 0$ or $p_k^* = w_k^* + c_k$. Under the zero-retail markup assumption, the first-order condition in (26) reduces to:

$$s_j(p) + \sum_{k \in S^b} (p_k \ - \mu_k - c_k) \frac{\partial s_k^b(p)}{\partial p_j} = 0 \ \forall j \in S^b \tag{30}$$

The system of first-order conditions in (30) can be represented using matrix notation:

$$s(p) + \ (T_b * \Delta_r) \times (p - \mu - c) = 0 \tag{31}$$

Total markup (the sum of brewers and retailers markup) can be recovered from equation (31) as follows:

$$\Gamma + \gamma \equiv p - \mu - c = -[T_b * \Delta_r]^{-1} \times s(p) \tag{32}$$

The implied total markup is equivalent to the scenario in which brewers actively compete in wholesale prices with rival brewers, leaving zero markup with retailers.

Two-part Tariff without RPM

We now assume each brewer can only charge retailers per unit wholesale prices and fixed fees for the products retailers stock and sell, but brewers cannot directly control the price retailers charge consumers. Each retailer sets their profit maximizing final prices charged to consumers. However, each brewer can capture the entire retailer surplus via the fixed fee charged to the retailer. Formally, brewer b sets wholesale prices along with the fixed fees to maximize the following profit function:

$$\max_{\{w_j\} \forall j \in S^b} \left\{ \sum_{j \in S^b} \left(p_j(w) - \mu_j - c_j\right) \times M \times s_j^b\big(p(w)\big) \ + \sum_{j \notin S^b} \left(p_j(w) - w_j - c_j\right) \times M \times s_j\big(p(w)\big) \right\} \tag{33}$$

The profit maximization problem in (33) yields the following set of first-order conditions:

$$\sum_{k \in S^b} \frac{\partial p_k}{\partial w_j} s_k\big(p(w)\big) + \left(p_j - \mu_j - c_j\right) \sum_{i \in S^b} \frac{\partial s_j\big(p(w)\big)}{\partial p_i} \frac{\partial p_i}{\partial w_j} + \sum_{k \notin j} (p_k - w_k - c_k) \left[\sum_{i \in S^b} \frac{\partial s_k\big(p(w)\big)}{\partial p_i} \frac{\partial p_i}{\partial w_j} \right] = 0 \ \forall j = 1 \ldots J \tag{34}$$

Model H: Two- part tariff without RPM

The assumed supply behavior of brewers in Model H is that brewers offer two-part tariff contracts to retailers without using RPM. The system of first-order conditions that results from brewers profit maximization problem yield the following total markup:

$$\Gamma_b + \gamma_b = -\left[I * \left(\Delta_p \times \Delta_r\ \right)\right]^{-1} \times \left[\Delta_p \times s(p) + \Big(\left(1 - I\right) * \left(\Delta_p \times \Delta_r\right)\Big) \times \gamma\ \right] \tag{35}$$

In the equation above, $*$ means element-by-element multiplication whereas $\times$ means regular matrices multiplication. I is a $J \times J$ identity matrix. The above equation allows us to estimate the total markup using retail markup derived in equation (11).

1.5.2.3 General Supply Equation and Marginal Cost Specification

Let the alternate supply models be indexed by l, i.e. $l = A, B, C, \dots, H$. Consistent with the notation above, γ^l represents a vector of markups by retailers in supply model l, i.e., $\gamma^l = p - w - c$, while Γ^l represents a vector of markups by brewers in supply model l, i.e., $\Gamma^l = w - \mu$. As such, total markups (brewers plus retailers) generated by supply model l is:

$$\Gamma^l + \gamma^l = p - \mu - c \qquad (36)$$

where μ represents brewers marginal costs; and c represents retailers marginal costs. Note that for a subset of our supply models retailers have markup equal to zero, i.e., $\gamma^l = 0$ for $l = D, E, G$.

Equation (36) can be re-written as:

$$p - \left[\, \Gamma^l\left(\hat{\theta}_d\right) + \gamma^l\left(\hat{\theta}_d\right)\right] = \mu + c \qquad (37)$$

Note that the markup terms, $\Gamma^l\left(\hat{\theta}_d\right)$ and $\gamma^l\left(\hat{\theta}_d\right)$, are a function of demand parameter estimates. So with the demand parameter estimates in hand, we can compute markups based on any of the previously discussed supply models. Furthermore, since p is observed data on retail price, the left-hand side of equation (37) 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 (37) by specifying and estimating a marginal cost function.

Consider the following specification of the marginal cost function:

$$\mu_{jm} + c_{jm} = W_{jm}\phi + f^b + f^r + a_m + \varepsilon_{jm} \qquad (38)$$

where W_j is a vector of variables that shift marginal costs for brewers, retailers or both; ϕ is the vector of parameters associated with the variables in W_j; f^b, f^r and a_m are brewer-specific, retailer-specific and market-specific fixed effects, respectively; and ε_{jm} is a mean-zero, random error term that captures determinants of marginal cost that are unobserved to us the researchers. In the subsequent section we discuss variables included in W_j.

Combining equations (37) and (38) yields an estimable supply regression equation:

$$p_{jm} - \left[\Gamma^l_{jm}\left(\hat{\theta}_d\right) + \gamma^l_{jm}\left(\hat{\theta}_d\right)\right] = W_{jm}\phi + f^b + f^r + a_m + \varepsilon_{jm} \qquad (39)$$

Equation (39) is estimated under each of the alternate supply models, $l = A, B, C, \dots, H$. We then use non-nested statistical tests developed by Vuong (1989) to determine which supply model(s) best approximate price-setting behavior among brewers and retailers of beer during *pre-Leegin* and *post-Leegin* periods respectively.

1.6 Estimation

We estimate the demand and supply sides of the model separately. We begin by describing how we estimate demand, and then briefly discus how the supply equations are estimated.

1.6.1 Demand Estimation

Following the 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 is the composite of geographic area-time period-specific deviations of non-price product characteristics that are unobserved to us the researchers ($\Delta\xi_{jm}$), 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 non-price product characteristics ξ_j. 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.

Since price (p_{jm}) is correlated with the structural demand error term ($\Delta\xi_{jm}$), i.e., price is endogenous in the demand model; we need to find reasonable instruments for price when estimating demand. We now describe the instruments used when estimating demand.

1.6.2 Instruments

The production cost of beer is influenced by changes in the prices of key ingredients (barley, corn, wheat, rice and hop) used in the manufacture of beer. Since various brands of beer use these ingredients with differential levels of intensities, then a change in the price of a given ingredient will differentially influence production costs across the brands, and consequently influence the final retail prices differentially across the brands. As such, one set of instruments we use for beer price is the interaction of key ingredient prices with brand dummy variables. The prices of beer ingredients listed above are determined in markets sufficiently broad such that beer industry shocks only have relatively small influences on these broader markets for the ingredients. For example, it is unlikely that beer industry shocks have a substantial influence on the equilibrium prices of wheat, rice, barley and corn since these products are used in so many ways other than beer production. In summary, the prices of these key ingredients of beer are in principle valid instruments for beer price in the demand model since they are likely to be correlated with beer price through the production cost of beer, but uncorrelated to beer demand shocks.

The distribution cost of beer is mainly dominated by transportation (driving) costs to ship a product from the brewery to a particular region or IRI market. We compute the physical distance from the relevant brewer to the designated IRI market in which the product is retailed to consumers, which facilitates computing the travel cost for a beer brand. We then multiply the travel distance by the relevant fuel price in order to compute the driving or shipment cost for a brand. In principle, this approximation of beer brand travel cost is a valid instrument we use for beer price in the demand model since the components of the travel cost (distance of brewer to market; and fuel price) are predetermined, and often exogenous, to beer demand shocks, but influence beer price via the distribution cost.

1.6.3 Supply Estimation

We estimate the supply equation (39) after recovering product markups from different supply models. As described in the previous section, W is a vector of cost shifters which explain the exogenous variation in the marginal cost function. We can recover consistent estimates of parameters of marginal cost function using simple Ordinary Least Square (OLS) method. We estimate eight different marginal cost function using different sets of recovered markups.

1.7 Results

1.7.1 Results from Demand Estimation

We report demand estimation results for both the standard logit model and the random coefficients logit model in Table 1.6. However, the subsequent discussion focuses on the random coefficients logit model since it allows for richer heterogeneity in consumer taste. 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 us the researchers for various product characteristics. The effects are insignificant both economically and statistically, suggesting the included demographic variable (income) captures well the consumer heterogeneity.

The estimated coefficients of price and non-price attributes vary across individuals in random coefficient 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, an increase in price reduces utility for individuals.

The estimated coefficient on the "imported" dummy variable is negative, suggesting that the average consumer obtains relatively lower utility from consuming imported beer brands. In other words, after controlling for price, the average consumer seems to prefer domestic beer brands to imported brands.

The fourth column displays the coefficient estimate on the interaction variable of imported beer with income. This coefficient estimate is positive and statistically significant, implying that individuals with higher income are more likely to choose imported beer over domestic beer compared to lower income individuals. This finding is quite consistent with the trend of real prices of domestic and imported beers. Imported beer brands are often more expensive than domestic beer brands.

Beer brands differ in terms of the range of alcohol content from 0.4% to 8%. For the average consumer, higher alcohol content is preferable as the coefficient of alcohol content is positive and statistically significant at 1% level of significance. In other words, alcohol content is positively related to the average individual's utility from consuming beer.

On average, consumers dislike calorie-intensive and carbohydrate-intensive beer brands as implied by the negative sign of the coefficient estimates on these two variables. The carbohydrate adds sweetness to the beer taste, but increased sweetness is typically associated with more calories. There is a general perception that carbohydrates and calories make beer an unhealthy drink relative to other alcoholic drinks[25]. Research on exploring the relationship between obesity and beer reinforces the positive relationship between obesity and beer consumption[26]. In line with this finding, our results show that for the average consumer both carbohydrates and calories decrease the utility.

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

Beer style describes overall the character of a beer, which is shaped by various factors including the origin of the beer. A specific style given to a beer is an outcome of centuries of brewing, trial and error, marketing, and consumer acceptance.[27] Our selected brands fall into 20 different styles. The coefficient estimates on dummy variables of different beer styles are statistically significant, and reported in Appendix A.

Table 1.6: Demand Model Parameter Estimates using Broader Categories of Beer Type

	Standard logit model		Random coefficient logit model		
	OLS (Means)	2SLS (Mean)	RCM (Means)	Standard Deviations	Interactions with Income
Variable	α, β	α, β	α, β	Υ	Γ
Price	-2.387**	-1.807**	-1.888**	0.067	…
	(0.007)	(0.027)	(0.033)	(0.065)	
Constant	-7.465** [a]	-9.424** [a]	-9.793** [a]	0.018	-4.753**
	(0.012)	(0.013)	(0.021)	(0.187)	(0.531)
Imported	-0.010** [a]	-0.258** [a]	-1.181** [a]	-0.029	11.831**
	(0.002)	(0.002)	(0.014)	(0.291)	(1.024)
Alcohol	0.236** [a]	0.309** [a]	0.270** [a]	…	…
	(0.002)	(0.002)	(0.002)	…	…
Calories	-0.010** [a]	-0.012** [a]	-0.010** [a]	…	…
	(0.000)	(0.000)	(0.000)	…	…
Carbohydrates	0.009** [a]	0.005** [a]	-0.008** [a]	…	…
	(0.000)	(0.000)	(0.000)	…	…
Lager	0.208** [a]	0.349** [a]	0.326** [a]	…	…
	(0.003)	(0.003)	(0.003)	…	…
Pilsner	0.267** [a]	0.305** [a]	0.221** [a]	…	…
	(0.005)	(0.005)	(0.005)	…	…
Hefeweizen	0.133** [a]	0.204** [a]	0.188** [a]	…	…
	(0.012)	(0.012)	(0.009)	…	…
Malt	-0.272** [a]	-0.113** [a]	-0.206** [a]	…	…
	(0.008)	(0.008)	(0.007)	…	…
Bock	-0.379** [a]	-0.410** [a]	-0.365** [a]	…	…
	(0.011)	(0.011)	(0.011)	…	…
GMM Objective			25551.6	…	…

Based on 1.91 million observations. All regressions include time, market and brand dummies. Asymptotically robust standard errors are given in parentheses. ** indicates statistical significance at the 1% level.
[a] Estimates from a Minimum Distance Procedure.

[27] https://www.beeradvocate.com/beer/style/

We summarize 20 different beer styles into 6 broad categories of beer types: Ale, Lager, Pilsner, Malt beverages, Hafeweizen, and Bock. We then constructed beer-type dummy variables accordingly. These types can be considered as a broader classification of beer brands in characteristics space. The estimated coefficients on different beer-type dummy variables provides a ranking of consumers' preference over the 6 types of beer. Note that among the 6 types of beer, Ale is the type excluded from the regression model. As such, the sign of the estimated coefficients suggests that, on average, consumers prefer Lager, Pilsner and Hefeweizen over Ale, while Malt and Bock are less preferred to Ale. Furthermore, the coefficient estimates suggest that consumers most preferred beer type is Larger, followed by Pilsner, Hefeweizen, Ale, Malt and Bock, respectively.

1.7.2 Demand Elasticities

We now discuss elasticity estimates generated from the demand model. We report and discuss elasticity estimates at the brewer and beer brand levels of aggregation during *pre* and *post-Leegin* periods. Our discussion of elasticity estimates begins with the brewer level of aggregation.

1.7.2.1 Brewer's Own and Cross Price Elasticity

Overall, the elasticity estimates in the *pre-Leegin* period are different from *post-Leegin* period as shown in Table 1.7 and Table 1.8. However, both own and cross elasticity estimates vary across brewers. Table 1.7 and Table 1.8 show that brewers selling imported beer brands, e.g. brands by Grupo-Modelo and Heineken, have the highest own price elasticity estimates for *pre-Leegin* and *post-Leegin* periods. In Table 1.7, for example, the mean own price elasticity of all brands sold by Heineken is -4.9, implying on average that increasing the price of Heineken brands by 1% reduces consumers' quantity demanded for these brands by 4.9%. As discussed above, imported beer brands are often relatively more expensive compared to domestic beer brands. As such, the finding that imported brands are more price-elastic relative to domestic brands is quite intuitive, suggesting consumers are more sensitive to changes in the price of imported beer brands than that of domestic beer brands.

There is also variation in mean cross price elasticity across brewers. The mean cross elasticity between ABI and Boston suggests that if the price of ABI's beer brands increased by 1%, on average, the quantity demanded for Boston's beer brands will increase by 0.003%. ABI's brands experience higher cross price elasticity with other brewers' brands in the *pre-Leegin* period compared to the *post-Leegin* period. In other words, consumers perceive ABI's beer brands as closer substitutes to other brewers' beer brands prior to the *Leegin* court decision we consider.

Table 1.7: Brewer's mean own and cross price elasticity for all brands Pre-Leegin 2005-2006

	ABI	Boston	DGY	Groupo	Heineken	Molson	SABMiller	Gambrinus
ABI	-4.124	0.004	0.003	0.004	0.004	0.003	0.003	0.004
	(1.1e-3)	(4.7e-6)	(3.4e-6)	(5.6e-6)	(5.5e-6)	(4.9e-6)	(4.6e-6)	(4.9e-6)
Boston	0.003	-4.74	0.001	0.001	0.001	0.001	0.001	0.001
	(3.7e-6)	(1.5e-3)	(1.6e-6)	(4.8e-6)	(4.7e-6)	(4.3e-6)	(1.1e-6)	(1.1e-6)
DGY	0.003	0.001	-4.148	0.002	0.002	0.002	0.002	0.002
	(3.0e-6)	(1.3e-6)	(1.1e-3)	(1.3e-5)	(1.1e-5)	(1.1e-5)	(1.0e-5)	(1.2e-5)
Groupo	0.003	0.001	0.002	-5.018	0.005	0.004	0.004	0.005
	(3.8e-6)	(1.4e-6)	(8.1e-6)	(9.7e-4)	(1.2e-5)	(1.0e-5)	(9.4e-6)	(7.9e-6)
Heineken	0.003	0.001	0.002	0.004	-4.945	0.002	0.002	0.002
	(3.6e-6)	(1.4e-6)	(9.2e-6)	(9.1e-6)	(1.2e-3)	(4.5e-6)	(4.2e-6)	(2.7e-6)
Molson	0.003	0.001	0.002	0.003	0.002	-4.214	0.002	0.002
	(3.0e-6)	(1.3e-6)	(7.2e-6)	(7.5e-6)	(3.7e-6)	(1.6e-3)	(5.2e-6)	(7.0e-6)
SABMiller	0.002	0.001	0.001	0.003	0.002	0.001	-3.935	0.002
	(2.8e-6)	(1.2e-6)	(7.5e-6)	(6.7e-6)	(3.3e-6)	(2.9e-6)	(1.3e-3)	(3.5e-6)
Gambrinus	0.003	0.001	0.002	0.004	0.002	0.001	0.002	-4.650
	(3.3e-6)	(1.4e-6)	(7.2e-6)	(9.0e-6)	(4.2e-6)	(5.0e-6)	(3.6e-6)	(2.5e-3)

Notes: Standard errors in parentheses.

Table 1.8: Brewer's mean own and cross price elasticity for all brands Post-Leegin 2008-2012

	ABI	Boston	DGY	Groupo	Heineken	Molson	SABMiller	Gambrinus
ABI	-4.154	0.003	0.002	0.003	0.003	0.003	0.002	0.003
	(6.4e-4)	(2.2e-6)	(1.8e-6)	(2.3e-6)	(2.2e-6)	(2.1e-6)	(1.9e-6)	(2.1e-6)
Boston	0.002	-4.794	0.001	0.001	0.001	0.001	0.001	0.001
	(2.1e-6)	(7.5e-4)	(2.2e-6)	(2.9e-6)	(2.9e-6)	(2.9e-6)	(2.7e-6)	(8.7e-7)
DGY	0.002	0.001	-4.153	0.002	0.002	0.002	0.002	0.002
	(1.7e-6)	(1.9e-6)	(7.5e-4)	(1.1e-5)	(1.2e-5)	(1.0e-5)	(9.9e-6)	(1.8e-5)
Groupo	0.002	0.001	0.002	-4.926	0.004	0.003	0.002	0.003
	(1.9e-6)	(2.2e-6)	(8.8e-6)	(5.23E-4)	(6.9e-6))	(6.0e-6)	(5.4e-6)	(4.8e-6)
Heineken	0.002	0.001	0.002	0.003	-4.886	0.002	0.002	0.002
	(1.9e-6)	(2.1e-6)	(9.5e-6)	(9.28E-6)	(6.6e-4)	(2.9e-6)	(2.7e-6)	(2.3e-6)
Molson	0.002	0.001	0.002	0.002	0.001	-4.315	0.002	0.002
	(1.8e-6)	(1.9e-6)	(9.4e-6)	(8.23E-6)	(3.6e-6)	(9.8e-4)	(2.)	(2.1e-6)
SABMiller	0.002	0.001	0.002	0.002	0.001	0.001	-3.966	0.002
	(1.6e-6)	(1.8e-6)	(7.7e-6)	(7.27E-6)	(3.2e-6)	(3.9e-6)	(8.5e-4)	(2.3e-6)
Gambrinus	0.002	0.001	0.002	0.003	0.001	0.001	0.002	-4.653
	(1.9e-6)	(2.6e-6)	(1.0e-5)	(8.65E-6)	(3.8e-6)	(4.0e-6)	(3.0e-6)	(1.3e-3)

Notes: Standard errors in parentheses.

1.7.3 Select Brands' Own and Cross Price Elasticity:

Beer demand is sensitive to changes in price. Own and cross price elasticities do vary across beer brands. Table 1.9 and Table 1.10 display own and cross price elasticities for select beer brands in the *pre-Leegin* and the *post-Leegin* periods. Contrary to mean cross price elasticity, on average, the select beer brands have elastic demand as evident from own price elasticity estimates. However, imported beer brands (Corona extra, Corona light, Heineken and Heineken Premium Light Lager) have higher own price elasticity estimates compared to other beer brands. For example, the own price elasticity estimate of Bud Light, a domestic beer brand, is -4.172, suggesting that a 1% increase in price of Bud Light causes, on average, a 4.172% reduction in quantity demanded of Bud Light. However, the own price elasticity estimate of Corona Light, an imported brand, is -5.041, suggesting that a 1% increase in price of Corona Light causes, on average, a 5.041% reduction in quantity demanded of Corona Light.

The cross price elasticity between Bud Light and Budweiser is 0.008, which implies that if the price of Bud Light increases by 1%, then on average the quantity demand for Budweiser will increase by 0.008%. The cross-price elasticity estimates in the *pre-Leegin* period are slightly higher compared to the *post-Leegin* period.

In general, the mean brand level own and cross price elasticities are similar to those reported in other studies [Miller and Weinberg (2017), Rojas and Peterson (2008), and Slade (2004)]. Rojas and Peterson (2008) find median own price elasticities range from −3.726 to −3.20 and cross price elasticity from 0.001 to 1.08. Slade (2004) finds median own prices elasticity -4.1 and cross price elasticity 0.009. Miller and Weinberg (2017) shows own price elasticities range from -3.81 to -6.10 and cross price elasticity from 0.001 to 0.351. Table 1.9 shows that our estimates are in the ballpark of the elasticity estimates reported by these studies.

1.7.4 Computed Markups and Marginal cost under each Supply Model

Table 1.11 reports summary statistics on prices, computed markup and recovered marginal costs during *pre-Leegin* and *post-Leegin* periods. Each reported sample mean in Table 1.11 has an associated sample standard error reported in parentheses. The reported sample means of prices, markup, and marginal costs are statistically significant at the 1% level, implying that each sample mean is statistically different from zero at the 1% level of significance.

Table 1.9: Selected Brands' Own and Cross Price Elasticity – *Pre-Leegin* period 2005-2006

	Bud Light	Budweiser	Coors	Coors Light	Corona Extra	Corona Light	Heineken	Heineken Premium Light Lager	Miller Genuine Draft	Miller High Life	Miller Lite
Bud Light	-4.172	0.008	0.005	0.007	0.010	0.006	0.007	0.005	0.006	0.006	0.007
	(1.3e-3)	(1.8e-05)	(1.4e-05)	(2.0e-05)	(1.9e-05)	(1.6e-05)	(1.5e-05)	(1.4e-05)	(1.4e-05)	(1.4e-05)	(1.9e-05)
Budweiser	0.008	-4.17	0.003	0.005	0.007	0.004	0.005	0.003	0.003	0.004	0.005
	(1.7e-5)	(1.3e-3)	(1.1e-05)	(1.4e-05)	(1.6e-05)	(1.1e-05)	(1.2e-05)	(9.1e-06)	(1.1e-05)	(8.0e-06)	(1.5e-05)
Coors	0.005	0.003	-4.197	0.003	0.005	0.002	0.003	0.001	0.001	0.002	0.003
	(1.2e-5)	(6.1e-6)	(1.5e-3)	(1.3e-05)	(1.4e-05)	(6.6e-06)	(8.6e-06)	(4.1e-06)	(2.3e-06)	(2.5e-06)	(1.3e-05)
Coors Light	0.007	0.005	0.003	-4.176	0.007	0.004	0.005	0.003	0.003	0.004	0.005
	(1.8e-5)	(1.8e-5)	(1.2e-5)	(1.3e-3)	(1.8e-05)	(1.3e-05)	(1.3e-05)	(1.3e-05)	(1.2e-05)	(1.2e-05)	(1.8e-05)
Corona Extra	0.009	0.007	0.005	0.007	-5.04	0.007	0.008	0.006	0.006	0.006	0.007
	(1.9e-5)	(1.82e-5)	(1.3e-5)	(1.9e-5)	(1.5e-3)	(1.9e-05)	(1.8e-05)	(1.4e-05)	(1.4e-05)	(1.2e-05)	(1.8e-05)
Corona Light	0.006	0.004	0.002	0.004	0.007	-5.041	0.004	0.002	0.002	0.003	0.003
	(1.4e-5)	(1.0e-5)	(5.4e-6)	(1.5e-5)	(1.6e-5)	(1.6e-3)	(1.2e-05)	(7.0e-06)	(6.1e-06)	(5.8e-06)	(1.3e-05)
Heineken	0.007	0.005	0.003	0.005	0.008	0.004	-5.024	0.003	0.003	0.004	0.005
	(1.5e-5)	(1.2e-5)	(7.1e-6)	(1.7e-5)	(1.9e-5)	(1.1e-5)	(1.5e-3)	(7.5e-06)	(7.8e-06)	(6.5e-06)	(1.4e-05)
Heineken Premium Light Lager	0.005	0.003	0.001	0.003	0.006	0.002	0.004	-5.014	0.001	0.002	0.003
	(1.3e-5)	(9.0e-6)	(2.8e-6)	(1.3e-5)	(1.3e-5)	(8.9e-6)	(1.2e-5)	(2.9e-3)	(4.0e-06)	(3.3e-06)	(1.3e-05)
Miller Genuine Draft	0.006	0.003	0.001	0.003	0.006	0.002	0.003	0.001	-4.186	0.002	0.003
	(1.2e-5)	(6.7e-6)	(2.3e-6)	(1.3e-5)	(1.3e-5)	(6.2e-6)	(8.2e-6)	(3.5e-6)	(1.3e-3)	(3.1e-06)	(1.1e-05)
Miller High Life	0.006	0.004	0.002	0.004	0.006	0.003	0.004	0.002	0.002	-3.675	0.003
	(1.3e-5)	(1.0e-5)	(2.6e-6)	(1.3e-5)	(1.5e-5)	(7.5e-6)	(9.1e-6)	(4.2e-6)	(3.1e-6)	(1.8e-3)	(1.4e-05)
Miller Lite	0.007	0.005	0.003	0.005	0.007	0.004	0.005	0.003	0.003	0.003	-4.17
	(1.8e-5)	(1.6e-5)	(1.0e-5)	(1.7e-5)	(1.7e-5)	(1.3e-5)	(1.4e-5)	(1.1e-5)	(1.3e-5)	(1.0e-5)	(1.3e-3)

Notes: Standard errors in parentheses.

Table 1.10: Selected Brands Own and Cross Price Elasticity – Post-Leegin period 2008-2012

	Bud Light	Budweiser	Coors	Coors Light	Corona Extra	Corona Light	Heineken	Heineken Premium Light Lager	Miller Genuine Draft	Miller High Life	Miller Lite
Bud Light	-4.233	0.006	0.004	0.006	0.007	0.005	0.006	0.004	0.005	0.005	0.006
	(8.8e-4)	(6.1e-6)	(4.8e-6)	(7.3e-6)	(7.9e-6)	(5.8e-6)	(6.2e-6)	(4.9e-6)	(5.0e-6)	(5.2e-6)	(7.0e-6)
Budweiser	0.006	-4.236	0.002	0.004	0.005	0.003	0.004	0.002	0.002	0.003	0.004
	(6.0e-6)	(8.8e-4)	(2.7e-6)	(5.7e-6)	(6.5e-6)	(3.9e-6)	(4.5e-6)	(3.0e-6)	(2.8e-6)	(3.0e-6)	(5.0e-6)
Coors	0.004	0.002	4.257	0.003	0.004	0.002	0.002	0.001	0.001	0.001	0.002
	(4.5e-6)	(2.6e-6)	(1.2e-3)	(4.6e-6)	(5.9e-6)	(3.0e-6)	(3.6e-6)	(1.7e-6)	(8.1e-7)	(1.1e-6)	(4.5e-6)
Coors Light	0.006	0.004	0.003	-4.248	0.006	0.004	0.004	0.003	0.003	0.003	0.004
	(7.2e-6)	(6.0e-6)	(4.9e-6)	(9.1e-4)	(8.5e-6)	(5.8e-6)	(6.2e-6)	(4.7e-6)	(4.3e-6)	(4.5e-6)	(7.0e-6)
Corona Extra	0.007	0.005	0.004	0.006	-4.935	0.005	0.006	0.004	0.004	0.004	0.005
	(7.8e-6)	(7.0e-6)	(5.7e-6)	(7.8e-6)	(9.7e-4)	(8.0e-6)	(8.5e-6)	(6.8e-6)	(5.5e-6)	(6.0e-6)	(8.0e-6)
Corona Light	0.005	0.003	0.002	0.004	0.005	-4.938	0.004	0.002	0.002	0.002	0.003

	(5.5e-6)	(4.2e-6)	(2.8e-6)	(5.9e-6)	(7.5e-6)	(9.8e-4)	(5.8e-6)	(3.7e-6)	(2.8e-6)	(3.0e-6)	(5.6e-6)
Heineken	0.006	0.004	0.002	0.004	0.006	0.003	-4.954	0.003	0.002	0.003	0.004
	(6.0e-6)	(5.0e-6)	(3.7e-6)	(6.5e-6)	(8.1e-6)	(5.5e-6)	(9.7e-4)	(4.5e-6)	(3.6e-6)	(3.7e-6)	(5.9e-6)
Heineken Premium Light Lager	0.004	0.002	0.001	0.003	0.004	0.002	0.003	-4.955	0.001	0.002	0.002
	(4.6e-6)	(3.1e-6)	(1.4e-6)	(5.1e-6)	(6.8e-6)	(3.9e-6)	(4.7e-6)	(1.0e-3)	(1.6e-6)	(1.9e-6)	(4.5e-6)
Miller Genuine Draft	0.005	0.002	0.001	0.003	0.004	0.002	0.002	0.001	-4.233	0.002	0.002
	(4.8e-6)	(2.9e-6)	(8.1e-7)	(5.2e-6)	(5.5e-6)	(3.2e-6)	(3.9e-6)	(1.6e-6)	(1.0e-3)	(1.2e-6)	(4.0e-6)
Miller High Life	0.005	0.003	0.001	0.003	0.004	0.002	0.003	0.002	0.002	-3.728	0.003
	(4.7e-6)	(2.8e-6)	(1.1e-6)	(5.0e-6)	(5.8e-6)	(3.0e-6)	(3.9e-6)	(1.6e-6)	(1.2e-6)	(1.1e-3)	(4.2e-6)
Miller Lite	0.006	0.004	0.002	0.004	0.005	0.003	0.004	0.002	0.002	0.003	-4.221
	(7.1e-6)	(6.0e-6)	(4.4e-6)	(7.2e-6)	(7.6e-6)	(5.6e-6)	(6.3e-6)	(4.8e-6)	(4.9e-6)	(5.0e-6)	(9.4e-4)

Notes: Standard errors in parentheses.

On average, the mean real price of beer is higher in the *post-Leegin* period than *pre-Leegin* period. The mean beer prices vary quite a bit across firms and brands (See Table A2 and A4 in Appendix A). Second, mean computed markup from each supply model is lower in the *post-Leegin* period than *pre-Leegin* period. However, mean marginal costs recovered from these supply models are higher during the *post-Leegin* period compared to the *pre-Leegin* period. Therefore, the increase in mean price of beer products over the *pre-Leegin* and *post-Leegin* periods is likely due to cost factors as evidenced by recovered marginal cost in the last two columns of the table.

Not surprisingly, mean predicted markups are largest from the supply models that assume collusive behavior, Models B and C, as well as Model F, a supply model that assumes brewers use two-part tariff pricing and impose RPM. For example, the mean markup retrieved from Model F during the *pre-Leegin* period is the largest ($5.72), which is not surprising since the market equilibrium outcome from this model is equivalent to the market outcome with industry-wide collusive behavior. An industry-wide collusive behavior market outcome can be achieved through two-part tariff pricing with RPM [Rey and Verge (2010)].

Table 1.11: Mean Price, Product Markup and Recovered Marginal Cost (in $ per 12 pack)

	Price & Total Markup		Total Marginal Costs ($\mu + c$)	
	Pre-Leegin	*Post-Leegin*	*Pre-Leegin*	*Post-Leegin*
Price	10.53**	10.91**	…	…
	(0.00414)	(0.00253)		
			…	…
Total Markup=brewer markup ($\boldsymbol{\Gamma}$) +retailer markup ($\boldsymbol{\gamma}$)				
Model A	3.299**	3.226**	7.229**	7.684**
(All Compete)	(0.000540)	(0.00022)	(0.00432)	(0.00263)

Model B (Collude)	4.984** (0.00479)	3.935** (0.00105)	5.545** (0.00700)	6.975** (0.00305)
Model C (Select Collude)	4.543** (0.00352)	3.677** (0.00078)	5.986** (0.00615)	7.233** (0.00294)
Model D (Collude & Passive retailers)	2.722** (0.00195)	2.227** (0.000519)	7.806** (0.00502)	8.683** (0.00275)
Model E (Select Collude & Passive retailers)	2.514** (0.00152)	2.096** (0.00039)	8.014** (0.00485)	8.814** (0.00272)
Model F (TPT w/ RPM ($Wholesal\ price = \mu$))	5.722** (0.0162)	3.149** (0.00365)	4.807** (0.0168)	7.761** (0.00451)
Model G (TPT w/ RPM & $Wholesal\ price \neq \mu$)	1.896** (0.000268)	1.859** (0.00010)	8.633** (0.00422)	9.051** (0.00258)
Model H (TPT w/o RPM)	4.037** (0.000388)	3.772** (0.00028)	6.492** (0.00423)	7.138** (0.00259)

Notes: Standard errors in parentheses; ** indicates statistical significant at the 1% level; TPT is the abbreviation for Two-Part-tariff; μ is the brewer's marginal cost; c is the retailer's marginal cost.

Table 1.11only provides mean markups and associated marginal costs generated by alternate supply models of vertical price-setting behavior without suggesting which, among the models, is better supported by the data. To investigate which among the specified supply models best approximates price-setting behavior in the beer industry, we turn to a formal non-nested statistical test for model selection.

1.7.5 Statistical Non-nested test for Model Selection

We consider eight different supply model specifications, which are captured by the regression model specification in equation (39). Markups are computed and marginal costs recovered under each of the supply model specifications. To determine which among the set of supply models best explains the data, we rely on a likelihood-based non-nested statistical test developed by Vuong (1989). The non-nested statistical test is a modification of the well-known likelihood ratio test.

To begin, recall equation (39), which is the regression equation that captures the alternate supply models, and is specified as:

$$p_{jm} - \left[\Gamma_{jm}^{l}(\hat{\theta}_d) + \gamma_{jm}^{l}(\hat{\theta}_d)\right] = W_{jm}\phi + \varepsilon_{jm}$$

Equation (39) is estimated under each of the alternate supply models, $l = A, B, C, \dots, H$. Let a pair of alternate supply models be denoted by l and l'. Based on regression equation (39), the likelihood ratio test statistic for comparing $Model\ l$ and $Model\ l'$ is given by:

$$LR = \sum_{n=1}^{N}\left(LL_n^{l} - LL_n^{l'}\right) \tag{40}$$

where n denotes the observation, which in the case of equation (39) is a unique j and m combination; N represents the sample size; and LL_n^{l} is the optimal value of the log likelihood function evaluated at observation n for $Model\ l$. Assuming the residuals of supply $Model\ l$ follows a normal distribution, the log likelihood values for $Model\ l$ is:

$$LL_n^{l} = \log\left[\varphi\left(\frac{p_n - markup_n - W_n\hat{\phi}_l}{\hat{\sigma}_l}\right)\right]$$

where $\varphi(\cdot)$ is the standard normal distribution; $markup_n = \Gamma_n^{l}(\hat{\theta}_d) + \gamma_n^{l}(\hat{\theta}_d)$ is the total markup (brewer and retailer) on a product; $\hat{\phi}_l$ is the vector of marginal cost function parameter estimates for $Model\ l$; and $\hat{\sigma}_l$ is the estimate of the standard deviation of the residuals from $Model\ l$. We compute $LL_n^{l'}$ analogously for alternative supply Model l' under consideration.

Vuong (1989) shows that the likelihood ratio statistic in (40) can be normalized by its variance:

$$v^2 = \frac{1}{N}\sum_{n=1}^{N}\left(LL_n^{l} - LL_n^{l'}\right)^2 - \left[\frac{1}{N}\sum_{n=1}^{N}\left(LL_n^{l} - LL_n^{l'}\right)\right]^2 \tag{41}$$

The resulting test statistic is given by:

$$Q = N^{-0.5}\frac{LR}{v} \tag{42}$$

The value of Q is asymptotically distributed standard normal under the null hypothesis that the two models being compared by the test are asymptotically equivalent. For a one-tail test, $Q > 1.64$ implies that the supply model l' is statistically rejected in favor of supply model l; and $Q < -1.64$ implies that supply model l is statistically rejected in favor of supply model l'. For $-1.64 < Q < 1.64$, we cannot statistically distinguish between two models being compared.

1.7.6 Results from Statistical Model Selection

Using the Vuong (1989) non-nested likelihood ratio statistical test, we compare the eight different supply models described above to discern which supply model(s) best approximate price-setting behavior among brewers and retailers of beer during *pre-Leegin* and *post-Leegin* periods respectively.

Table 1.12 and Table 1.13 report non-nested likelihood ratio test statistics, i.e. the values of Q from equation (42), for pairwise comparisons of the alternate models. Table 1.12 compares the models during *pre-Leegin* periods, while Table 1.13 compares the models during *post-Leegin* periods. Test statistic values that are positive and greater than 1.64 imply that the model in the row is statistically rejected in favor of the model in the column, i.e., the column model better approximates price-setting behavior when compared to the relevant row model. On the other hand, test statistic values that are negative and less than -1.64 imply that the model in the column is statistically rejected in favor of the model in the row, i.e., the row model better approximates price-setting behavior when compared to the relevant column model.

In Table 1.12, the values of test statistics given in the first column compares how Model A fares in comparison to the other seven models during the *pre-Leegin* period. Under the null hypothesis that two models are equivalent to each other, in comparing Model A to Model B, the test statistic of 182.62 is greater than 1.64 and implies that Model B is statistically rejected in favor Model A. In fact, the test statistics in the same column reveal that Model A is only outperformed by Model G and Model H. Recall that models F, G and H are the only models that allow upstream brewers to charge downstream retailers nonlinear prices in the form of two-part tariffs. Therefore, Model A best approximates price-setting behavior among the models that restrict firms to charge linear prices. It is also important to recall that Model A does not allow collusive pricing among firms, but the set of models it outperforms assume some extent of collusive pricing among brewers. The only nonlinear pricing model that Model A outperforms is Model F, and interestingly, among the three nonlinear pricing models considered, Model F is the one that yields the maximum collusive outcome. It is therefore reasonable to conclude from the results in Table 1.12 that price-setting behavior during the *pre-Leegin* period is not characterized by RPM or collusive pricing among brewers.

In Table 1.12, the negative test statistic values in the rows for Model G and Model H reveal that these models that allow brewers to charge retailers nonlinear prices without colluding, outperform all other models considered. In other words, it is reasonable to conclude from the results in Table 1.12 that price-setting behavior during the *pre-Leegin* period is best characterized by non-collusive, nonlinear pricing among brewers. Furthermore, the test statistic of -97.43 is less than -1.64 and implies that Model G is statistically rejected in favor Model H. Recall that the key distinction between Model G and Model H is that Model G assumes brewers impose RPM on retailers, while Model H does not. In summary, the model that best approximates price-setting behavior during the *pre-Leegin* period is the model that assumes brewers non-cooperatively charge retailers nonlinear prices (two-part tariffs: per unit wholesale price and fixed fee) without imposing RPM. In addition, the best performing model during the *pre-Leegin* period (Model H) assumes that retailers freely, and non-cooperatively, choose the final prices consumers pay, resulting in a positive retail markup.

We now discus results in Table 1.13, which focuses on pairwise statistical comparisons of the models during *post-Leegin* periods. The test statistics given in the row labeled Model G are all negative and less than -1.64, revealing that we fail to reject Model G in comparison to models A, B, C, D, E, and F. Furthermore, the test statistic in the column labeled Model G is positive and greater than 1.64, revealing that Model H is statistically rejected in favor of Model G. In other words, the test statistics in Table 1.13 reveal that during *post-Leegin* periods Model G best approximates price-setting behavior in comparison to each of the other seven models considered.

Model G being the best performing model during *post-Leegin* period suggests that brewers use two-part tariff pricing when selling to retailers, as well as impose direct control on retail pricing (impose RPM on retailers) in a manner that leaves zero markup with retailers. In spite of finding that each brewer during the *pre-Leegin* period faces competition from rival brewers in determining wholesale prices, and retailers freely, and non-cooperatively set retail prices in a manner that leaves them with positive markup, the *post-Leegin* period puts brewers in-charge of retail prices and net claimant of industry profit. This result is quite in accordance with the change in legal treatment towards RPM agreements/contracts in the *post-Leegin* period. With the provision of friendly legal environment for RPM contracts, upstream firms in the concentrated markets like the US beer market gain more control and perhaps market power in the *post-Leegin* period.

Collectively, the best performing models (Model H *pre-Leegin*; but Model G *post-Leegin*) suggest the following three implications. First, consistent with findings in other industries [Villas-Boas (2007); Bonnet and Dubois (2010); and Bonnet et. al (2013)], we find in the US beer industry that the vertical relationship between brewers and retailers is equivalent to brewers using efficient nonlinear wholesale price contracts when selling to retailers. Second, the supply-side model analysis has not found any evidence that collusive pricing exists prior to, or subsequent to, the *Leegin* decision we study. Slade (2004) and Rojas (2008) also did not find evidence of collusive pricing in their analysis of the U.K. and U.S. brewing industries respectively. Third, in the *post-Leegin* period, concentrated markets like US beer market, brewers enjoy higher bargaining power in negotiating beer prices and share of industry profit.

Table 1.12: Non-nested Likelihood Ratio Test Statistics for Pairwise Comparisons of Alternate Supply Models during the Pre-Leegin Period

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H
Model A	NA							
Model B	182.62	NA						
Model C	170.82	-122.15	NA					
Model D	173.89	-197.17	0.61	NA				
Model E	162.87	-190.74	-187.00	-118.71	NA			
Model F	300.73	302.98	325.23	350.45	357.40	NA		
Model G	-38.94	-171.91	-160.23	-163.22	-152.36	-281.35	NA	
Model H	-89.90	-174.13	-163.03	-166.79	-156.60	-276.10	-97.43	NA

Table 1.13: Non-nested Likelihood Ratio Test Statistics for Pairwise Comparisons of Alternate Supply Models during the Post-Leegin Period

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H
Model A	NA							
Model B	345.28	NA						
Model C	301.31	-224.78	NA					
Model D	310.91	-186.36	110.77	NA				
Model E	284.45	-298.32	-189.85	-207.33	NA			
Model F	385.36	272.90	306.86	304.24	329.77	NA		
Model G	-61.09	-340.84	-299.27	-312.27	-287.59	-384.93	NA	
Model H	-6.31	-325.70	-268.16	-289.34	-248.20	-388.24	13.23	NA

1.8 Counterfactual Analyses

It is reasonable to conjecture that consolidation among upstream firms is likely to increase market power among these upstream firms, which may in turn better enable them to impose RPM in their wholesale agreements with downstream retailers. The merger between SABMiller, the second largest brewer, and Molson Coors, third largest brewer, is a specific example of consolidation among upstream firms in the US Beer industry. The merger produced a new firm known as Miller-Coors. With this merger, the market structure can effectively be characterized as a duopoly, with the two largest brewers, Anheuser-Busch InBev (ABI) and Miller-Coors, having a combined market share of almost 80 percent. Since this merger occurred in year 2008, this consolidation of upstream firms' event approximately coincided with the *Leegin* decision. The approximate coincidence of these two events makes it empirically challenging to disentangle the contribution of each event to our empirical result suggesting RPM being used during the *post-Leegin* period, but not used during the *pre-Leegin* period. One type of counterfactual analysis we implement in this section is designed to help us better understand the role these two events play in incentivizing brewers to use RPM agreement during *post-Leegin* periods, but not use these agreements during *pre-Leegin* periods.

1.8.1 Experiments to Assess the Impact of a Merger on the use of RPM

A useful feature of the data used in this paper is that we are able to identify beer products that separately belong to SABMiller and Molson Coors even after these two brewers merged. This feature of the data allows us to perform counterfactual merger and demerger price-setting scenarios prior to and subsequent to the actual merger of these brewers. Effectively, this feature of the data allows us to write down supply models during post-merger periods that are based on the counterfactual assumption that beer products that were produced by SABMiller prior to the merger continue to be priced non-cooperatively with beer products that were produced by Molson Coors. We also can write down supply models during pre-merger periods that are based on the counterfactual assumption that beer products that are produced by SABMiller prior to the merger are priced cooperatively with beer products that are produced by Molson Coors. In summary, during pre-merger periods we can construct counterfactual cooperative price-setting behavior (counterfactual merger) across products owned by the firms that subsequently merge, while during post-merger periods we can construct counterfactual non-cooperative price-setting behavior (counterfactual demerger) across products owned by the merged firm.

Recall our results above suggest that during *pre-Leegin* periods the best performing supply model assumes brewers do not use RPM agreements (Model H). If consolidation among upstream firms better enables, and incentivizes, them to use RPM agreements, then a relevant counterfactual question is: If SABMiller and Molson Coors had merged prior to the *pre-Leegin* periods in our data, would this merger better enable, and sufficiently incentivize brewers to use RPM during the *pre-Leegin* periods in our data? To test this hypothesis we consider the following counterfactual supply model during *pre-Leegin* periods: Assume SABMiller and Molson Coors have already merged, and brewers use two-part tariff contracts with RPM (Model G^{merger}). For completeness, during *pre-Leegin* periods we also consider a counterfactual model that assumes SABMiller and Molson Coors have already merged, and brewers use two-part tariff contracts without RPM (Model H^{merger}). If the SABMiller and Molson Coors merger better enables, and sufficiently incentivizes brewers to use RPM, then had these brewers merged prior to *pre-Leegin* periods in our data we should find that Model G^{merger} statistically outperforms Model H and Model H^{merger}. Statistical comparisons of these models using non-nested statistical tests are reported in Table 1.14. Non-nested test statistic values in the table reveal that Model G^{merger} is statistically outperformed by Model H and Model H^{merger}. In summary, evidence from the counterfactual analysis suggests that even if the SABMiller and Molson Coors merger had taken place prior to the *pre-Leegin* periods in our sample, this merger would not sufficiently incentivize brewers to use RPM agreements during the *pre-Leegin* periods in our sample.

Table 1.14: Non-nested Likelihood Ratio Test Statistics for Pairwise Comparisons of Alternate Supply and Counterfactual Models during the *Pre-Leegin* Period (2005-06)

	Model G	Model H	Model G^{merger}	Model H^{merger}
Model G	…	…	…	…
Model H	-97.43	…	…	…
Model G^{merger}	18.51	99.14	…	…
Model H^{merger}	-97.43	3.03	-99.14	…

Note: Model G - TPT with RPM $(w \neq p)$; Model H: TPT without RPM; Model G^{merger} - TPT with RPM $(w \neq p)$ assuming merger between SABMiller and Miller Coors; Model H^{merger} TPT without RPM assuming merger between SABMiller and Miller Coors.

We now consider counterfactual supply models during *post-Leegin* periods to better assess the extent to which the merger between SABMiller and Molson Coors may have contributed to brewers choosing to use RPM during *post-Leegin* periods in our data. Recall our results above suggest that during *post-Leegin* periods the best performing supply model assumes brewers do use RPM agreements (Model G). If consolidation among upstream firms better enables, and incentivizes, them to use RPM agreements, then a relevant counterfactual question is: If SABMiller and Molson Coors had not merged, would the *Leegin* decision cause brewers to be sufficiently incentivized to use RPM during *post-Leegin* periods in our data? To test this hypothesis we consider the following counterfactual supply model during *post-Leegin* periods: Assume SABMiller and Molson Coors had not merged, and brewers use two-part tariff contracts with RPM (Model $G^{demerger}$). For completeness, during *post-Leegin* periods we also consider a counterfactual model that assumes SABMiller and Molson Coors had not merged, and brewers use two-part tariff contracts without RPM (Model $H^{demerger}$). If the *Leegin* decision caused brewers to be sufficiently incentivized to use RPM during *post-Leegin* periods in our data, then assuming SABMiller and Molson Coors did not merge, we should find that Model $G^{demerger}$ statistically outperforms Model $H^{demerger}$. In the event that Model $G^{demerger}$ also outperforms Model G, we may interpret this as suggesting that the merger did not reinforce brewers' incentive to use RPM, and may even have served to dis-incentivize the use of RPM. Statistical comparisons of these models using non-nested statistical tests are reported in Table 1.15. Non-nested test statistic values in the table reveal that Model $G^{demerger}$ statistically outperforms Model $H^{demerger}$ and Model G. In summary, evidence from the counterfactual analysis suggests that even if the SABMiller and Molson Coors merger had not taken place, the *Leegin* decision sufficiently incentivized brewers to use RPM agreements during *post-Leegin* periods in our sample. Furthermore, the evidence suggests that the merger did not reinforce brewers' incentive to use RPM, and may have even served to dis-incentivize the use of RPM.

Table 1.15: Non-nested Likelihood Ratio Test Statistics for Pairwise Comparisons of Alternate Supply and Counterfactual Models during the *Post-Leegin*/Merger Period (2009-12)

	Model G	Model H	Model $\mathrm{G}^{\mathrm{demerger}}$	Model $\mathrm{H}^{\mathrm{demerger}}$
Model G	…	…	…	…
Model H	12.06	…	…	…
Model $\mathrm{G}^{\mathrm{demerger}}$	-37.79	-19.21	…	…
Model $\mathrm{H}^{\mathrm{demerger}}$	12.06	-0. 69	19.21	…

Note: Model G: TPT with RPM $(w \neq p)$; Model H: TPT without RPM; Model $\mathrm{G}^{\mathrm{demerger}}$-TPT with RPM $(w \neq p)$ assuming demerger between SABMiller and Miller Coors; Model $\mathrm{H}^{\mathrm{demerger}}$ TPT without RPM assuming demerger between SABMiller and Miller Coors.

1.8.2 Experiment to Assess the Impact of RPM on Equilibrium Prices

We now implement another counterfactual experiment, but this experiment is designed to measure market impacts associated with the change in pricing-setting behavior of beer brewers, i.e. their apparent adoption of pricing-strategies tantamount to RPM, which is consistent with a change in the legal stance towards RPM captured by the 2007 US Supreme Court's decision in the *Leegin* case. The essence of the counterfactual experiment is to use the estimated structural demand-supply model to simulate equilibrium beer prices assuming brewers' pricing strategy during the *post-Leegin* period is the same as their pricing strategy in the *pre-Leegin* period. In other words, we simulate equilibrium prices assuming brewers counterfactually use two-part tariff pricing without RPM during the *post-Leegin* period.

The previous estimation allows us to recover a vector of marginal costs from the preferred model for the *post-Leegin* period. Let $C = C_1 \cdots C_J$ represent the vector of marginal costs for all products during the *post-Leegin* period, which we recover using the preferred model for that period of two-part tariff pricing with RPM. For the factual product ownership structure across upstream and downstream firms, estimated structural parameters and vector of recovered marginal costs during the *post-Leegin* period, our policy experiment is to simulate equilibrium outcomes of a supply model in which upstream firms counterfactually use two-part tariff pricing without RPM.

Specifically, the predicted equilibrium vector of prices p^* should satisfy the following first-order condition:

$$p^* + \left[I * \left(\Delta_p \times \Delta_r\right)\right]^{-1} \times \left[\Delta_p \times s(p^*) + \left((1 - I) * \left(\Delta_p \times \Delta_r\right)\right) \times \gamma\right] = C$$

The solution algorithm we use to obtain p^* is tantamount to solving the following optimization problem:

$$\min_{p^*} \left\| p^* + \left[I * \left(\Delta_p \times \Delta_r\right)\right]^{-1} \times \left[\Delta_p \times s(p^*) + \left((1 - I) * \left(\Delta_p \times \Delta_r\right)\right) \times \gamma\right] - C \right\|$$

Figure 1.2 shows actual *post-Leegin* product prices as well as simulated predicted prices for the same products based on the counterfactual supply model of two-part tariff without RPM. It is notable that the simulated prices are consistently higher than the actual prices for all brands. Specifically, Table 1.16 shows that, on average, the simulated prices are 13% higher than actual prices across all beer products. In summary, the level and trend of simulated prices compared to actual prices shown in Figure 1.2 reveal that brewers' prices would have been higher without them using RPM, suggesting that RPM was predominantly used in a pro-competitive manner during the *post-Leegin* period.

Figure 1.2: Mean actual price and counterfactual prices of brands during the *post-Leegin* period.

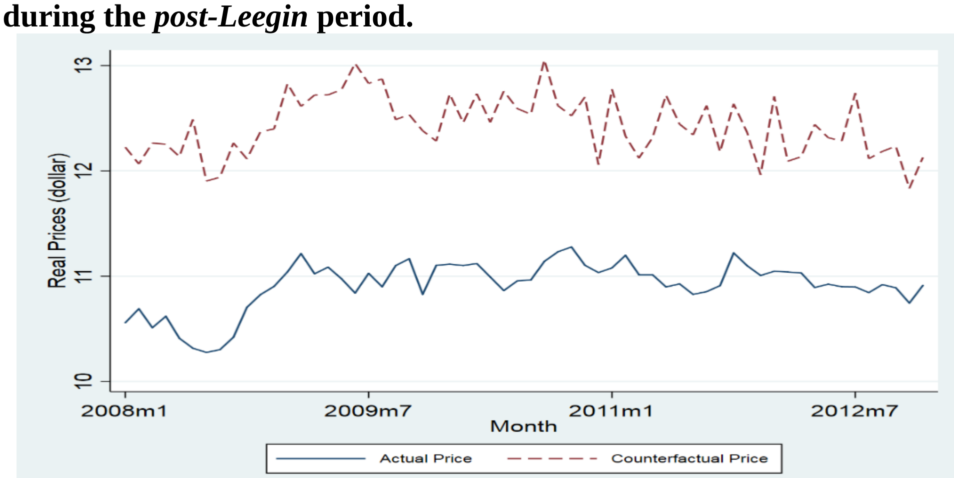


Table 1.16: Comparison of mean actual and counterfactual price (dollar/12- pack) by brewery/brands

Brewery	Actual Price (P)	Counterfactual Price (P^*)	% Change: $[\frac{P^*-P}{P} \times 100]$
ABI	9.958	10.993	10.390
Boston	14.004	17.044	21.705
DGY	9.747	11.881	21.897
Groupo	13.562	15.573	14.828
Heineken	13.278	15.703	18.264
Miller-Coors	9.805	10.988	12.060
Gambrinus	12.370	14.913	20.563
Across all breweries	**10.920**	**12.429**	**13.823**
Select brands			
Bud light	10.368	11.483	10.756
Budweiser	10.361	11.469	10.695
Coors	10.432	11.710	12.252
Coors light	10.456	11.747	12.339
Corona extra	13.604	15.723	15.576
Corona light	13.598	15.701	15.466
Heineken	13.774	16.288	18.253
Heineken premium light	13.770	16.284	18.258
Miller genuine draft	10.333	11.589	12.160
Miller high life	7.912	8.862	12.009
Miller lite	10.271	11.546	12.422

Note: The highlighted brands are owned by Miller-Coors. The above table is based on 984,028 observations. The price denoted by P is the actual price whereas the price P^* is the price computed by assuming two-part tariff without RPM.

1.9 Conclusion

The 2007 US Supreme Court's decision in the *Leegin* case resulted in a legal paradigm shift in which the legality of a given RPM agreement is based on a "rule of reason" approach instead of being "per se illegal". The change in the legal approach is consistent with the growing economic theory literature that suggests RPM contracts may have pro-competitive as well as anti-competitive effects. This *Leegin* decision facilitated a friendlier and accommodating legal environment for firms wanting to engage in RPM agreements. In light of the *Leegin* decision, the empirical analysis in this paper provides evidence on whether market data outcomes in the US beer industry are consistent with the use of RPM prior to and subsequent to the *Leegin* decision, and if so, whether the RPM equilibrium outcomes are on net procompetitive or anticompetitive/collusive.

Alternative empirical supply models with or without RPM are tested to determine whether brewers at the upstream level exhibit anticompetitive (collusive) behavior while writing contracts with beer retailers at the downstream level. These supply models cover a wide range of possible vertical contracts in linear and nonlinear pricing.

For the set of markets analyzed in this paper, we find supply models in nonlinear prices fit the data best. This finding is consistent with studies of other industries [Villas-Boas (2007); Bonnet and Dubois (2010); and Bonnet et. al (2013)] suggesting that upstream firms rely on more efficient and sophisticated nonlinear pricing wholesale contracts rather than inefficient linear pricing wholesale contracts. Our findings suggest that price-setting behavior is different across the *pre-Leegin* and *post-Leegin* periods respectively. In particular, the supply model with two-part tariff pricing, but without brewers imposing RPM, best explains the *pre-Leegin* data, while the model with two-part tariff pricing with brewers imposing RPM best fits the *post-Leegin* period data. However, for both periods, we do not find evidence of collusive price-setting behavior. Our findings do not support that RPM facilitates anticompetitive behavior in the US beer market.

We used the preferred estimated models to perform a counterfactual experiment designed to measure market impacts associated with the change in pricing-setting behavior of beer brewers, i.e. their apparent adoption of pricing-strategies tantamount to RPM, which is consistent with a change in the legal stance towards RPM captured by the 2007 US Supreme Court's decision in the *Leegin* case. The counterfactual analysis reveals that brewers' prices would have been, on average, 13% higher without them using RPM, suggesting that RPM was predominantly used in a pro-competitive manner during the *post-Leegin* period.

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Chapter 2
Mergers and Competitive Conduct: Evidence from US Beer Industry

2.1 Introduction

Concentrated industries are frequently targeted by antitrust authorities and industrial economists in their inquiries concerning abuse of dominance either by a single firm or group of firms. In such industries, the unilateral and coordinated effects of mergers and acquisitions are often scrutinized. The US beer industry is categorized as one of the most concentrated industries in the US. Since 1950, the beer industry has experienced over 200 mergers [Trembley and Tremblay (2005)]. Past mergers were broadly considered as 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)]. In 2008, the second largest beer brewer, SABMiller, and third largest brewer, Molson Coors, merged to form a new firm known as MillerCoors. In 2016, the largest brewer Anheuser-Busch InBev (ABI) merged with SABMiller after divestiture of SABMiller business interest in MillerCoors[28]. With this recent merger, the market structure can effectively be characterized as a duopoly, with the two largest brewers, ABI and MillerCoors, having a combined market share of almost 80 percent.

Market dominance of leading brewers (ABI, SABMiller, and MillerCoors) has already alarmed researchers with regards to the potential for anticompetitive behavior in the industry. The merger between SABMiller and Molson Coors in year 2008 raised interesting questions about the presence of unilateral and coordinated effects of the merger. Interestingly, recent studies report little or no evidence of unilateral effects, but find evidence on the presence of abuse of joint dominance. The most recent empirical evidence on the merger [Aschenfelter et. al (2015); Gokhale and Tremblay (2012)] suggests that it has caused a modest increase in beer prices along with gains in terms of cost efficiency, while industry profits have remained low. Overall gains in efficiency

[28] There is no change in the name of the MillerCoors even after the de-merger between SABMiller and Molson Coors in 2016. However, Molson Coors solely owns MillerCoors in the post-merger.

mitigate the increase in prices. In short, unilateral effects of the merger are not considered substantially damaging to competition.

While evidence suggests minimal averse unilateral effects, there is also empirical evidence consistent with coordinated effects of the merger [Miller & Weinberg (2017)], suggesting that the merger between SABMiller and Molson Coors may have facilitated collusion between leading players like ABI and Miller Coors over prices. The relatively high market concentration at the brewer level (upstream) of the industry combined with evidence of co-movement of prices across brands of beer produced by leading brewers further supports arguments in favor of collusive behavior.

The recent merger between ABI and SABMiller in year 2016 may or may not be helpful in facilitating collusive behavior between newly merged firms, ABI-SABMiller and MillerCoors. Competition analysis in the US beer industry demands a better understanding of the strategic relationship among national brewers. This paper analyzes the nature of competition in the US beer industry by explicitly modeling collusive behavior in the pre-merger and post-merger periods. Following Miller and Weinberg (2017), we estimate potential collusive behavior, and analyze if there exists evidence of internalization of price externalities between ABI and MillerCoors.

We first estimate a discrete choice model of demand using retail scanner data on beer purchases over the period 2013-2017. With demand estimates in hand, but without observing brewers' and retailers' costs, we specify supply models with parameters of internalizing price externalities in the pre-merger and post-merger periods. Demand estimates of beer suggest income is an important determinant of beer demand consistent with Miller and Weinberg (2017). Our demand estimates also suggest that consumers' choice of beer is substantially influenced by price along with several non-price characteristics such as alcoholic content, calories, and import versus domestic. Contrary to Miller and Weinberg (2017), the supply-side model analysis does not provide any evidence that collusive pricing exists prior to, or subsequent to, the merger we study. Our findings are consistent with Slade (2004) and Rojas (2008), which did not find evidence of collusive pricing in their analysis of the U.K. and U.S. brewing industries respectively.

The rest of the chapter is organized as follows: Section 2.2 reviews relevant literature; Section 2.3 provides description of the data; Section 2.4 outlines the structural econometric model of beer demand and supply; Section 2.5 discusses the estimation procedure; Results are discussed in Section 2.6, and Section 2.7 offers concluding remarks.

2.2 Literature Review

Growing concentration in the US beer industry[29] due to mergers and acquisitions, has received mixed evaluation from researchers in recent years. On the one hand, recent studies [Tremblay & Tremblay (2005); Gokhale, Jayendra and Tremblay (2012); and Aschenfelter et. al (2015)] find procompetitive effects of growing consolidation in the form of an increase in minimum efficient scale, lower shipping/transportation cost, lower prices, and improved quality. On the other hand, the year 2008 merger between SABMiller and Molson Coors is considered as a blow to the industry's competitive behavior in the form of an increase in market power and the emergence of collusive behavior in the post-merger period [Miller and Weinberg (2017]. In the discussion below, we review these two different conclusions on competitive behavior in the US beer industry.

As noted by Tremblay and Tremblay (2005), national brewers were successful in capturing market share primarily due to technological development and advertising. Gokhale and Tremblay (2012) argue that the recent merger waves are different from mergers prior.[30] They find empirical evidence of a small increase in market power during the period 1997-2008 using annual data that spans 1977 to 2008 for 11 national brewers. Their findings support the conclusion that despite an increase in market power, industry prices and profits remain relatively low during this period. The study does not cover the post-merger period to enable a comparison between market outcomes of the pre-merger and post-merger periods. Iwasaki et al (2008) also suggest that the profits are low in US brewing despite an increase in concentration in the industry due to continuing war of attrition.

The most recent study by Aschenfelter et. al (2015) analyzes the merger between SABMiller & Molson Coors using retail scanner data on 40 top selling brands of 8 breweries from 2007-2011. The study documents indirect evidence on the effect of merger-specific efficiencies on pricing using reduced-form regression analysis. They find that the post-merger increase in price is offset by gains due to the reduction in shipping/transportation cost. They show a positive

[29] Empirical evidence from merger evaluation of UK beer industry has similarities to the US beer industry. In the 1990s UK beer industry dominated with 6 national brewers (Bass, Allied Lyons, Scottish & Newcastle Grand Metropolitan, Courage and Whitbread) covering about 75% of the market share.

[30] In the last two decades some notable mergers took place in the US beer industry. For example, Miller was purchased by South African Breweries to form SABMiller in year 2002; and Anheuser– Busch was purchased by Belgium's InBev to form Anheuser–Busch InBev in year 2008.

relationship between prices and concentration implying that "price increases occurred in regions where merger increased concentration more". Nevertheless, the efficiency gains as a result of MillerCoors merger act as a countervailing force on prices, resulting in price decreases in the average market.

In theory, mergers in concentrated industries can lead to anticompetitive (e.g. collusive) behavior despite an increase in cost efficiency. There is a dearth of empirical evidence to support this argument, especially with regards to the US beer industry. Slade (2004) emphasizes the importance of coordinated effects by highlighting the differences between the UK and North American competition authorities' approaches toward unilateral and coordinated effects of merger cases. These differences explain why mergers are evaluated differently in these regions. More specifically, North American merger policy tends to be based on unilateral effects whereas European authorities tend to base their policy on the notion of single or group of firms dominance. Merger evaluation based on joint dominance leads to scrutiny of coordinated effects or tacit collusion that may be facilitated by the merger. Evaluating the merger between Courage and Scottish & Newcastle, Slade (2004) did not find coordinating effects or abuse of dominant position of UK brewers in the industry.

Evidence on collusive behavior in the US beer industry is limited and inconclusive. We found two studies [Rojas (2008); and Miller and Weinberg (2017)] analyzing the possibility of collusive behavior in the industry. Rojas (2008) rules out collusive behavior among brewers by testing alternative price-setting (Bertrand-Nash, leadership and collusion) models using quarterly data on 64 brands from years 1988-1992, covering 58 major metropolitan areas of the US. A potential concern with this study's finding relates to the time period studied. The industry structure in years 1988-92 is very different from its structure in 2008.

In contrast to findings by Rojas (2008), Miller and Weinberg (2017) provide empirical evidence on tacit collusive behavior between Miller Coors and ABI in the post-merger period. They use retail scanner data from years 2005-2011, focusing on 13 flagship beer brands owned by ABI, SABMiller, Molson, Heineken and Crown Imports. The study estimates a structural econometric model that nests a parameter capturing potential coordinated price-setting behavior during the post-merger period of ABI and Miller Coors. The key outcome of the study suggests that retailers make low retail markup, total surplus increased, but consumer surplus is lost due to coordinated effects between Miller Coors and ABI.

Following Miller and Weinberg (2017), we investigate whether ABI and MillerCoors internalize price externality or collude over prices in the pre-merger as well as in the post-merge period using Nielson scanner retail data. Our paper contributes to the existing set of empirical evidence on coordinated effect in highly concentrated industries like the US beer market.

2.3 Sources of Data

2.3.1 Retail Scanner Data

To perform empirical analysis in this paper, we use longitudinal data: Nielson Retail Scanner Data.[31] The data offer weekly prices, and sales information by Universal Product Code (UPC) of products sold at over 35000 participating stores located in 210 Designated Market Areas (DMA) across the US for the period 2006-2017. The data have over 1000 products belonging to 115 groups (e.g. wine, beer, cheese etc.). Our focus is on the sales of beer products for the period 2013-2017. The beer group consists of 6 different types of products: beer, light beer, malt beverages, stout & porter, ale, and light liquor. The beer and light beer products account for over 80% unit sales and 90% volume sales across all products in year 2013 (Table 2.1).[32] The pattern is consistent for all other years.

Table 2.1: Unit Sales, Vol. Sales, and Revenue of Major Beer Products for year 2013

Beer Categories	Unit Sale (%)	Volume Sales (%)	Revenue (%)
Ale	13.29	7.99	12.50
Beer	44.63	39.27	40.47
Light beer (low calorie)	37.10	50.46	44.25
Malt liquor	1.71	0.56	0.48
Near beer/malt beverages	1.65	0.87	0.88
Stout and porter	1.61	0.84	1.41

Note: For year 2013, there are total 37,902,777 weekly observations.

[31] 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.

[32] Unit sales 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 sales is described as physical volume of 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]

There are over 37 million weekly observations for each year covering both domestic and imported brands. The coverage of domestic and imported brands makes this data representative of the US beer industry. The scanner data covers a wide range of different sizes of brands sold in stores. Most of the sales are concentrated in 6,12 and 24 packs with each item containing 12 oz in a pack. Consistent with the popular package sizes in the beer industry, 12-pack size has the greatest unit sales as well as the greatest volume sales. Our analysis focuses on 12-packs (144 ounces) products. Across different package sizes in 12 oz, there are 16 brands account for approximately 40% of the unit sales and over 50% volume sales. This study focuses on these brands for years 2013 to 2017. The focus brands are the best performing brands of ABI, MillerCoors, Heineken, and Modelo. The list of the brands is given in Appendix B.

To reduce the computational burden during econometric estimation, we aggregate the weekly data up to monthly unit sales and revenue for the 12-pack size. Figure 1a and Figure 1b display trends of the log of real prices of regular and light beer brands from 2013 to 2017, where the vertical line serves to delineate the pre-merger and post-merger periods for the year 2016 merger between ABI and SABMiller. The price trends of select brands suggest a slight upward trend after the merger but later a downward trend in prices. The prices of imported brands follow the same trend during pre-merger and post-merger periods (Figure given in Appendix B).

Figure 2.1: Log of Real Prices of Major Beer brands (12-pack)

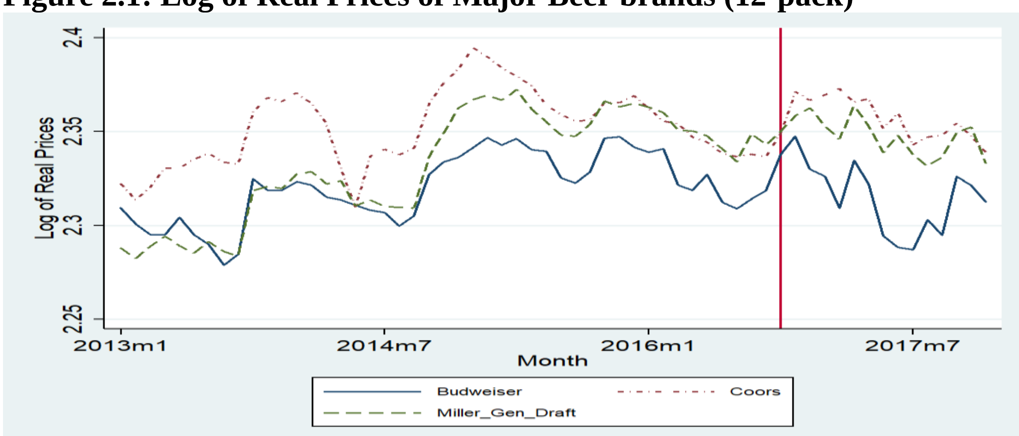
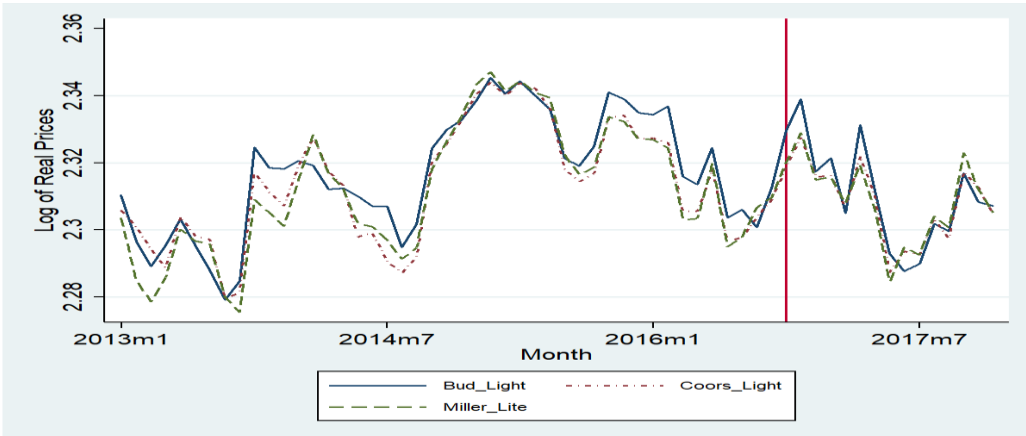


Figure 2.2: Log of Real Prices of Major Light Beer brands (12-pack)



Further, we also restrict our analysis to randomly selected geographic locations - 20 DMA (5 from each four regions of US) to reduce the computational burden during econometric estimation. We drop 3 out of 20 selected DMA which do not have sales data for all the years. The list of randomly selected 17 DMAs is given in Table 2.2. Following Miller and Weinberg (2017), we define the total potential market size to be ten percent greater than the maximum observed unit sales for each geographical location market. We define a market as the period-location combination, while a distinct product in a market is defined as a combination of brand and retailer (stores). In other words, Bud Light sold at two different retailers is considered two distinct products within a market.

We supplement the sales data with brand characteristics. The information on characteristics is collected from labels available on the brands of beer. The sales data covers only products available at grocery and superstores. We collected information on characteristics of these products from websites of grocery and superstores. On average, the selected brands contain an average alcohol content of 4.41%, and 122 calories.

2.3.2 Demographic data set

We supplement the Nielson retail scanner data with market consumer income data drawn from the Public Microdata Sample (PUMS) database. The PUMS data are useful in estimating demand. In PUMS data household are identified as living in a geographical location containing at least 100,000 people. Data on consumers' income are drawn from the PUMS for the time period 2013-17.

Table 2.2 shows income variation of random draws of 200 individuals for each DMA, for the years 2013 and 2016. Variation in income distribution within and across the select DMA, corresponding to national levels, is observed. For example, out of a random draw of 200 individuals for Binghamton, NY, 64.5% of the individuals have personal income less than or equal to $50,000, and 2.0% of them have income above $200,000 in the year 2013. For the same year, a random draw of 200 individuals for Louisville, KY shows 72% of the individuals have income less than or equal to $50,000, and 1.0% of the individuals have income more than $200,000. The income distributions for the years 2013 and 2016 are similar. For example, in both years more than two-thirds of the individuals have income less than $50,000, while 1.5% and 2.53% of the individuals have income more than $200,000 in years 2013 and 2016 respectively.

Table 2.2: Percentage of individuals in each IRI Market who fall into specified income categories based on random draws of 200 individuals for each Designated Market Area (DMA) for the years 2013 and 2016

	Income 2013 (%)						Income 2016 (%)					
Designated market area (DMA)	Mean ($)	**≤$50K**	**$50K<& ≤$$100K**	**$100K<& ≤$150K**	**$150K<& ≤$200K**	**>$200K**	Mean ($)	**≤$50K**	**$50K<& ≤$$100K**	**$100K<& ≤$150K**	**$150K<& ≤$200K**	**>$200K**
Binghamton, NY	52369	64.5	25.5	7.5	0.5	2	51165	67	24	5	2	2
Philadelphia, PA	62399	57	31	6.5	2	3.5	57719	58.5	31	6.5	1	3
Indianapolis, IN	44644	73.5	20.5	4.5	…	1.5	43346	73.5	20.5	5	0.5	0.5
Louisville, KY	43191	72	24	2.5	1	0.5	47720	72.5	21	4	0.5	2
Rochester, NY	40398	75.5	19.5	4.5	…	0.5	50443	70.5	20.5	3.5	3.5	2
Traverse City-Cadillac, MI	40629	76.5	20	2	1	0.5	53925	68.5	24.5	2.5	1	3.5
Norfolk, VA	46929	73.5	20	4	1.5	1	47169	71.5	22.5	3.5	0.5	2
Presque Isle, ME	42928	77	19	2.5	0.5	1	50361	75.5	17	2.5	0.5	4.5
Charleston-Huntington, WY	38401	76	21.5	1.5	1	…	48318	64.5	29.5	2.5	1.5	2
Salisbury, MD	43930	74	21	3	0.5	1.5	52831	69.5	22.5	3.5	2	2.5
Gainesville, FL	58527	61	24.5	8.5	3.5	2.5	63720	64	21.5	7.5	3	4
Rockford, IL	50508	66	26	5.5	1.5	1	55105	70.5	22	4	3.5	
Dallas-Worth, TX	42095	71	25.5	2	1	0.5	45622	73	18.5	5	2	1.5
Omaha, NE	48375	71	22.5	3.5	…	3	50989	65	25.5	5.5	2	2
Colorado Springs-Pueblo, CO	62817	54.5	29.5	11.5	2	2.5	65484	54.5	33.5	5.5	2	4.5
Idaho Falls-Pocatello, ID	42353	75.5	21.5	1	1	1	50061	66	27.5	3	1.5	2
Medford-Klamath Falls, OR	43375	68	22	6	2	2.5	44587	77	17	4.5		1.5
Percentage of total individuals drawn across all markets	46943	70.65	22.55	4.17	1.13	1.5	51463	68.32	23.44	4.32	1.38	2.53

2.3.3 Transportation Cost

Transportation cost is a major component of the total cost of providing beer to consumers. The uneven ownership structure of breweries in the US beer industry suggests that brewers with the largest number of breweries enjoy a cost advantage over rival brewers with fewer breweries. For example, ABI with 12 breweries and Miller Coors with 9 breweries own the largest number of breweries in the industry during the pre-merger period. Out of 9 breweries owned by MillerCoors, SABMiller owns 7 breweries. Collectively ABI-SABMiller owns 19 breweries after the merger. In year 2008, the merger between SABMiller and Molson Coors was proposed with the premise that it will help reduce transportation costs. Following Miller and Weinberg (2017), we compute transportation cost at brand level by calculating the distance between the DMA geographic locations and nearest brewery using Google Map.

During the pre-merger period, the transportation costs of brands owned by ABI consider the minimum distance from 12 breweries to DMA, while in the post-merger period transportation cost is computed considering a single firm (ABI-SABMiller) owning 19 breweries in the US. The transportation cost for the imported brands is calculated considering the minimum distance from a port to a DMA.

2.3.4 Sample Size

Our data sample includes the following monthly variables during the period 2013-2017: product share (computed as product quantity sold divided by our measure of potential market size discussed above), product prices, measures of non-price product characteristics discussed above, and transportation costs of 16 brands of 12-packs (144 ounces). Since the ABI and SABMiller merger was approved in September 2016, we omit the sales data from January 2016 to October 2016 from the sample. The brands in the data sample are produced by 4 different brewers, and these brands are sold through various retailers located across the 17 geographical regions/ DMA. Based on our definitions of markets and products discussed above, the data sample consists of 1.18 million observations.

2.4 The Econometric Model

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

2.4.1 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 Nielson Designated Market Area (DMA) and time-period, while a product in a market is defined as the unique combination of beer brand and retailer. Let markets be indexed by m and products by j. In each market, consumer i has $J+1$ alternative options, i.e., the consumer can choose among the J ($j = 1,2, \ldots J$) differentiated beer products in a market or the outside option $j = 0$, where the outside option includes alternative beverages that are substitutes for beer.

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

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

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 measure of the mean product characteristics that are unobserved by the researchers, but observed by consumers and firms; $\Delta\xi_{jm}$ is a market–specific deviation from this mean; and ε_{ijm} is an individual-specific random component of utility that accounts for deviation of the individual's preferences from the mean utility.

Examples of 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 research 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 and markets. 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 (non-price and price) coefficients β_i, α_i 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 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 characteristics (v_i), i.e.:

$$\binom{\alpha_i}{\beta_i} = \binom{\alpha}{\beta} + \Gamma D_i + \Upsilon v_i, \qquad (2)$$

where Γ is the $k \times m$ matrix of parameters measuring how taste characteristics vary with demographics; Υ is the $k \times k$ diagonal matrix measuring the variation in taste due to random shocks v_i.[33] 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 mean of v_i and D_i are zero, then α and β measure the mean of the random coefficients. The mean utility level obtained from each of the J products, δ_{jm} is given by:

$$\delta_{jm} = x_{jm} - \alpha p_{jm} + \xi_{jm} + \Delta\xi_{jm} \qquad (3)$$

The mean utility obtained from the outside option is normalized to zero.

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 $\theta_2 = (\Gamma, \Upsilon)$ is the vector of demand parameters that enters the demand model non-linearly. Further, let

$$\mu_{ijm}(x_{jm}, p_{jm}, v_i, D_i; \theta_2) = [-p_{jm}, x_{jm}](\Gamma D_i + \Upsilon v_i) \qquad (4)$$

Using equations (1) to (3) allow us to express the indirect utility from consuming product j as:

$$V_{ijm} = \delta_{jm}(x_{jm}, p_{jm}, \rho_j, \delta_r, \tau_t, \xi_{jm}; \theta_1) + \mu_{ijm}(x_{jm}, p_{jm}, D_i, v_i; \theta_2) + \epsilon_{ijm} \qquad (5)$$

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

Following the literature [Berry, Levinsohn and Pakes (1995) here after 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 share of product j, or the choice probability of product j is given by:

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

$$s_{jm} = \int \frac{e^{\delta_{jm}+\mu_{ijm}}}{1+\sum_{l=1}^{J} e^{\delta_{lm}+\mu_{ilm}}} \widehat{dF}(D)dF(v), \tag{6}$$

where $\hat{F}(D)$ is the empirical distribution of demographic variables; and $F(v)$ is the multivariate standard normal distribution. The integral problem in equation (6) 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 $F(v)$.

The potential market size is defined in terms of 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 a market m. Finally, the demand for product j is given by:

$$d_{jm} = M_m * s_{jm}(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}; \theta_d) \tag{7}$$

where M_m is the size of market m; $s_{jm}(\cdot)$ is the predicted product share from equation (6); **x** and **p** are vectors of observed non-price product characteristics and price, respectively; $\boldsymbol{\xi}$ is a vector of unobserved product characteristics; and $\theta_d = (\alpha, \beta, \Gamma, \Upsilon)$ is the vector of demand parameters to be estimated.

2.4.2 Supply

In this section, we outline supply model of differentiated price competition in which brewers partially or fully internalize price externalities of beer products. In other words, we specify supply models assuming partial or full collusive behavior among the select brewers. We assume brewers set per unit retail prices whereas retailers behave passively and pass on retail prices to consumers. We describe brewer's profit maximizing behavior when setting the retail prices that consumers pay.

Brewers' Optimization Problem

Concerning brewer's behavior, we assume brewer b sells a set of S_m^b products, where S_m^b is a subset of the J_m beer products available to consumers in market m. As previously discussed, a market m is defined by a geographic location during a given time period. We assume ABI and MillerCoors in the pre-merger and ABI-SABMiller and MillerCoors in the post-merger partially or fully internalize price externalities choosing per unit retail prices (Bertrand Nash fashion) for the menu of differentiated beer products they sell to consumers. Brewer b considers the following profit function to maximize its profit in market *m*:

$$\Pi^b = \sum_{j \in S_m^b} \left(p_{jm} - \mu_{jm} - c_{jm}\right) \times q_{jm} + \kappa_{tm} \sum_{j \notin S_m^b} \left(p_{jm} - \mu_{jm} - c_{jm}\right) \times q_{jm} \qquad (8)$$

where p_{jm} denotes the retail price of product j; μ_{jm} denotes per unit wholesale cost of product j; c_{jm} denotes per unit retail cost that is unrelated to the wholesale cost incurred by the brewer; and q_{jm} is the quantity of product j sold in market *m*. The parameter $\kappa_{tm} \in [0,1]$ denotes the extent to which brewers internalize price externality in the pre-merger period $t = 1$ and the post-merger period $t = 2$. The parameter κ_{tm} implies Bertrand Nash competition if $\kappa_{tm} = 0$ and joint profit maximization or perfect collusion if $\kappa_{tm} = 1$. We may infer partial collusion or internalization of price externalities if $0 < \kappa_{tm} < 1$. For example, if $\kappa_{tm} = 0.5$ implies that ABI-SABMiller/MillerCoors internalize about 50% effects of their prices on each other's profit in period t and market m.

Market equilibrium requires $q_{jm} = d_{jm} = M_m \times s_{jm}(p)$.

Each brewer therefore solves the following profit maximization problem:

$$\max_{p_{jm} \forall j \in S_m^b} \left[\sum_{j \in S_m^b} \left(p_{jm} - \mu_{jm} - c_{jm}\right) \times M_m \times s_{jm}(p) + \kappa_{tm} \sum_{j \notin S_m^b} \left(p_{jm} - \mu_{jm} - c_{jm}\right) \times M_m \times s_{jm}(p)\right] \qquad (9)$$

The first-order conditions that yield a pure strategy Bertrand Nash equilibrium in retail prices are:

$$s_j + \sum_{l \in S^b} (p_l - \mu_l - c_l)\left(\frac{\partial s_l}{\partial p_j}\right) + \kappa_t \sum_{l \notin S^b} (p_l - \mu_l - c_l)\left(\frac{\partial s_l}{\partial p_j}\right) = 0 \quad \forall\, j \in S^b \qquad (10)$$

Market subscripts are suppressed in equation (10) and many subsequent equations only to avoid a clutter of notation. We can conveniently recover total markup (Γ) and re-write the above equation in matrix form. To do so we define a $J \times J$ matrix, T_b, that characterizes brewers' ownership as well as internalization of price externality structure of the *J* products in the market. Matrix T_b has general element $T_b(h, j)$ equal to 1 if products h and j are sold by the same brewer, equal to κ if product h and product j are sold by different brewers, but these brewers internalize pricing externalities across the products they sell, and 0 otherwise. Let Δ_r be the $J \times J$ matrix that captures the response of product share to retail prices. Matrix Δ_r contains first-order partial derivatives of product shares with respect to all retail prices:

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

In vector notation, the first-order conditions characterized by equation (10) implies that the $J \times 1$ vector of total markups (Γ) is given by the following expression:

$$\Gamma = p - \mu - c = -[T_b(\kappa) * \Delta_r]^{-1} \times s(p) \tag{11}$$

where p, μ, c, and $s(\cdot)$ are $J \times 1$ vectors of retail prices, wholesale marginal costs, retail marginal costs, and product shares respectively; while $T_b(\kappa) * \Delta_r$ represents element-by-element multiplication of the two matrices. The vector of equilibrium prices for each market satisfies the following first order condition.

$$p = \mu + c + \Gamma\left(\hat{\theta}_d, \kappa\right) \tag{12}$$

Note that the markup terms, $\Gamma\left(\hat{\theta}_d, \kappa\right)$ is a function of κ and demand parameter estimates. Furthermore, since p is observed data on retail price, the left-hand side of equation (12) 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 (12) by specifying and estimating a marginal cost function.

Consider the following specification of the marginal cost function:

$$\mu_{jm} + c_{jm} = W_{jm}\phi + f^b + f^r + a_m + \varepsilon_{jm} \tag{13}$$

where W_j is a vector of variables that shift marginal costs for brewers, retailers or both; ϕ is the vector of parameters associated with the variables in W_j; f^b, f^r and a_m are brewer-specific, retailer-specific and market-specific fixed effects, respectively; and ε_{jm} is a mean-zero, random error term that captures determinants of marginal cost that are unobserved to us the researchers.

From equations (12) and (13), the error term as function of demand and supply parameters is given as:

$$\varepsilon_{jm}\left(\hat{\theta}_d, \theta_s\right) = p_{jm} - W_{jm}\phi - f^b - f^r - a_m - \Gamma\left(\hat{\theta}_d, \kappa\right) \tag{14}$$

where $\theta_s = (\phi, \kappa)$ denotes the vector of supply side parameters. So, with the demand parameter estimates $\hat{\theta}_d$ in hand, we can estimate supply side parameter θ_s by minimizing the error terms (ε_{jm}).

2.5 Estimation

We estimate the demand and supply sides of the model separately. We begin by describing how we estimate demand, and then briefly discus how the supply equations are estimated.

2.5.1 Demand Estimation

Following the 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 ($\Delta\xi_{jm}$) from the demand model is the composite of geographic area-time 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 non-price product characteristics ξ_j. 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.

Since price (p_{jm}) is correlated with the structural demand error term ($\Delta\xi_{jm}$), i.e., price is endogenous in the demand model; we need to find reasonable instruments for price when estimating demand. We now describe the instruments used when estimating demand.

The production cost of beer is influenced by changes in the prices of key ingredients (barley, corn, wheat, and hop) used in the manufacture of beer. Since various brands of beer use these ingredients with differential levels of intensities, then a change in the price of a given ingredient will differentially influence production costs across the brands, and consequently influence the final retail prices differentially across the brands. As such, one set of instruments we use for beer price is the interaction of key ingredient prices with brand dummy variables. The prices of beer ingredients listed above are determined in markets sufficiently broad such that beer industry shocks only have relatively small influences on these broader markets for the ingredients. For example, it is unlikely that beer industry shocks have a substantial influence on the equilibrium prices of wheat, barley and corn since these products are used in so many ways other than beer production. In summary, the prices of these key ingredients of beer are in principle valid instruments for beer price in the demand model since they are likely to be correlated with beer price through the production cost of beer, but uncorrelated to beer demand shocks.

The distribution cost of beer is mainly dominated by transportation (driving) costs to ship a product from the brewery to a particular region or Nielson DMA. We compute the physical distance from the relevant brewer to the DMA in which the product is retailed to consumers, which facilitates computing the travel cost for a beer brand. We then multiply the travel distance by the relevant fuel price in order to compute the driving or shipment cost for a brand. In principle, this approximation of beer brand travel cost is a valid instrument for a beer price in the demand model since the components of the travel cost (distance of brewer to market; and fuel price) are predetermined, and often exogenous, to beer demand shocks, but influence beer price via the distribution cost.

2.5.2 Supply Estimation

We estimate the supply side of the model using Generalized Method of Moment (GMM). The vector of supply side parameters to be estimated is given by $\theta_s = (\phi, \kappa)$. For each candidate supply side parameters, we compute markup and observed marginal costs to compute error terms as function of parameters given in (14). Based on the instruments discussed in the previous section, the identification of the model rests on the population moment condition is $E[z'\varepsilon] = 0$ where z is a matrix of instruments (discussed above) that are assumed to be orthogonal to the error vector ε. Using population moment condition, the GMM optimization problem is given by:

$$\min_{\theta_s} \varepsilon' z \, \psi z' \varepsilon \tag{15}$$

where ψ is an optimal weighing matrix given by $[z'z]^{-1}$.

Since parameters ϕ enter the error term linearly, we can restructure the GMM optimization problem in (15) such that the search to minimize the objective function, $\varepsilon' z \, \psi z' \varepsilon$, is done exclusively over parameter vector κ, i.e., the GMM optimization problem reduces to $\min_{\kappa} \varepsilon' z \, \psi z' \varepsilon$. Once the optimization over κ is complete, we can recover estimates of ϕ.

2.6 Results

2.6.1 Results from Demand Estimation

We report demand estimation results for both the standard logit model and the random coefficients logit model in Table 2.3. However, the subsequent discussion focuses on the random coefficients logit model since it allows for richer heterogeneity in consumer taste. 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 us the researchers for various product characteristics. The effects are insignificant both economically and statistically, suggesting the included demographic variable (income) captures well the consumer heterogeneity.

The estimated coefficients of price and non-price attributes vary across individuals in random coefficient 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, an increase in price reduces utility for individuals.

The estimated coefficient on the "imported" dummy variable is negative, suggesting that the average consumer obtains relatively lower utility from consuming imported beer brands. In other words, after controlling for price, the average consumer seems to prefer domestic beer brands to imported brands.

The fourth column displays the coefficient estimate on the interaction variable of imported beer with income. This coefficient estimate is positive and statistically significant, implying that individuals with higher income are more likely to choose imported beer over domestic beer compared to lower income individuals. This finding is quite consistent with the trend of real prices of domestic and imported beers. Imported beer brands are often more expensive than domestic beer brands.

Beer brands differ in terms of the range of alcohol content from 0.4% to 5%. For the average consumer, higher alcohol content is preferable as the coefficient of alcohol content is positive and statistically significant at 1% level of significance. In other words, alcohol content is positively related to the average individual's utility from consuming beer.

On average, consumers dislike calorie-intensive beer brands as implied by the negative sign of the coefficient estimates on these two variables. There is a general perception that carbohydrates and calories make beer an unhealthy drink relative to other alcoholic drinks.[34] Research on the relationship between obesity and beer reinforces the positive relationship between obesity and beer

[34] http://www.npr.org/sections/thesalt/2014/12/31/374187472/if-youre-toasting-for-health-beer-may-be-a-good-bet

consumption.[35] In line with this finding, our results show that for the average consumer calories decrease the utility.

Table 2.3: Demand Model Parameter Estimates

	Standard Logit Model		Random Coefficient Logit Model		
	OLS	2SLS	RCM (Means)	Standard Deviation	Interaction with Income
Variables	α, β	α, β	α, β	Υ	Γ
Price	-1.6184**	-2.5624**	-3.2614**	-0.2139	…
	(0.0139)	(0.1392)	(0.1848)	(0.1033)	…
Constant	-4.7321**[a]	-6.9610**[a]	-4.5137**[a]	-0.1023	-0.3342
	(0.0279)	(0.0339)	(0.0648)	(0.1204)	(0.3290)
Imported	0.1530**[a]	-0.1353**[a]	-0.3076**[a]	0.0707	13.1985**
	(0.0038)	(0.0046)	(0.0189)	(0.3431)	(0.7875)
Alcohol	0.3093**[a]	0.2764**[a]	0.4186**[a]	…	…
	(0.0049)	(0.0049	(0.0047)	…	…
Calories	-0.0101**[a]	-0.0088**[a]	-0.0122**[a]	…	…
	(0.0001)	(0.0001)	(0.0001)	…	…
Time Fixed Effects	Yes	Yes	Yes		
DMA Fixed Effects	Yes	Yes	Yes		
Brand Fixed Effects	Yes	Yes	Yes		
Store Fixed Effects	Yes	Yes	Yes		
GMM Objective	9159.4				

Above results are based on 118,149,6 observations. All regression includes time, market, and brand dummies. The price is instrumented using brand dummies × input prices and transportation costs for 2SLS and RCM models. Standard errors are given in parenthesis. ** indicates statistical significance at the 1% level.

[a] Estimates from a Minimum Distance Procedure.

2.6.2 Demand Elasticities

We now discuss elasticity estimates generated from the demand model. We report and discuss elasticity estimates at the beer brand levels of aggregation during pre and post-merger periods. Beer demand is sensitive to changes in price. Own and cross price elasticities do vary across beer brands. Table 2.4 and Table 2.5 display own and cross price elasticities for select beer brands in the pre-merger and the post-merger periods. Contrary to mean cross price elasticity, on average, the select

[35] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4338356/

beer brands have elastic demand as evident from own price elasticity estimates. However, imported beer brands (Corona Extra and Heineken) have higher own price elasticity estimates compared to domestic beer brands. For example, the own price elasticity estimate of Bud Light, a domestic beer brand, is -7.49, suggesting that a 1% increase in price of Bud Light causes, on average, a 7.49% reduction in quantity demanded of Bud Light. However, the own price elasticity estimates of Corona Extra, an imported brand, is -8.32, suggesting that a 1% increase in price of Corona Extra causes, on average, a 8.32% reduction in quantity demanded of Corona Extra.

The cross-price elasticity between Bud Light and Budweiser is 0.005, which implies that if the price of Bud Light increases by 1%, then on average the quantity demand for Budweiser will increase by 0.005%. The cross-price elasticity estimates in the pre-merger period are slightly higher compared to the post-merger period.

In general, the mean brand own price elasticities are higher than those reported in other studies [Miller and Weinberg (2017), Rojas and Peterson (2008), and Slade (2004)]. Rojas and Peterson (2008) find median own price elasticities range from −3.726 to −3.20 and cross price elasticity from 0.001 to 1.08. Slade (2004) finds median own prices elasticity -4.1 and cross price elasticity 0.009. Miller and Weinberg (2017) shows own price elasticities range from -3.81 to -6.10 and cross price elasticity from 0.001 to 0.351. Our own price elasticities estimates are higher than Miller and Weinberg (2017) since the geographic market is defined narrowly. The geographic (IRI) market in Miller and Weinberg (2017) is larger than the Nielson DMA. Our cross-price elasticity estimates reported in Table 2.5 are in the ballpark of the elasticity estimates reported by these studies.

Table 2.4: **Selected Brands' Own and Cross Price Elasticity – Pre-Merger period 2013-15**

	Bud Light	Budweiser	Coors Banquet	Coors Light	Corona Extra	Heineken	Miller G. Draft	Miller Lite
Bud Light	-7.4888	0.0151	0.0122	0.0218	0.0213	0.0163	0.0101	0.0186
	(0.0010)	(0.0009)	(0.0008)	(0.0018)	(0.0015)	(0.0010)	(0.0008)	(0.0015)
Budweiser	0.0051	-7.4977	0.0087	0.0180	0.0180	0.0127	0.0070	0.0151
	(0.0007)	(0.0010)	(0.0006)	(0.0017)	(0.0014)	(0.0008)	(0.0005)	(0.0013)
Coors Banquet	0.0046	0.0029	-7.6109	0.0149	0.0138	0.0101	0.0059	0.0122
	(0.0006)	(0.0004)	(0.0023)	(0.0015)	(0.0012)	(0.0007)	(0.0005)	(0.0012)
Coors Light	0.0087	0.0066	0.0059	-7.4801	0.0241	0.0187	0.0137	0.0215
	(0.0015)	(0.0013)	(0.0012)	(0.0011)	(0.0023)	(0.0016)	(0.0015)	(0.0022)
Corona Extra	0.0102	0.0084	0.0081	0.0119	-8.3173	0.0349	0.0134	0.0210
	(0.0016)	(0.0014)	(0.0015)	(0.0020)	(0.0011)	(0.0024)	(0.0015)	(0.0019)
Heineken	0.0063	0.0047	0.0041	0.0083	0.0100	-8.3278	0.0080	0.0162
	(0.0008)	(0.0007)	(0.0006)	(0.0014)	(0.0016)	(0.0010)	(0.0007)	(0.0014)
Miller G. Draft	0.0044	0.0029	0.0022	0.0052	0.0071	0.0038	-7.5153	0.0110
	(0.0006)	(0.0004)	(0.0003)	(0.0011)	(0.0013)	(0.0006)	(0.0026)	(0.0012)
Miller Lite	0.0076	0.0057	0.0052	0.0093	0.0107	0.0070	0.0051	-7.4779
	(0.0013)	(0.0011)	(0.0010)	(0.0018)	(0.0018)	(0.0011)	(0.0010)	(0.0011)

Note: Standard errors are given in parenthesis.

Table 2.5: Selected Brands' Own and Cross Price Elasticity – Post-Merger period 2016-17

	Bud Light	Budweiser	Coors Banquet	Coors Light	Corona Extra	Heineken	Miller G. Draft	Miller Lite
Bud Light	-7.4581	0.0152	0.0137	0.0208	0.0178	0.0145	0.0093	0.0180
	(0.0018)	(0.0018)	(0.0018)	(0.0029)	(0.0021)	(0.0016)	(0.0017	(0.0025
Budweiser	0.0039	-7.4766	0.0101	0.0166	0.0143	0.0106	0.0058	0.0150
	(0.0006)	(0.0021)	(0.0012)	(0.0023)	(0.0017)	(0.0009)	(0.0009)	(0.0022)
Coors Banquet	0.0035	0.0022	-7.6155	0.0153	0.0131	0.0096	0.0058	0.0132
	(0.0005)	(0.0004)	(0.0047)	(0.0024)	(0.0018)	(0.0011)	(0.0011)	(0.0021)
Coors Light	0.0061	0.0046	0.0039	-7.4539	0.0193	0.0163	0.0113	0.0204
	(0.0013)	(0.0011)	(0.0009)	(0.0021)	(0.0027)	(0.0023)	(0.0025)	(0.0033)
Corona Extra	0.0075	0.0062	0.0060	0.0085	-8.3565	0.0275	0.0078	0.0175
	(0.0013)	(0.0012)	(0.0012)	(0.0018)	(0.0015)	(0.0032)	(0.0016)	(0.0025)
Heineken	0.0048	0.0035	0.0030	0.0057	0.0074	-8.3286	0.0051	0.0145
	(0.0007)	(0.0006)	(0.0005)	(0.0011)	(0.0014)	(0.0018)	(0.0007)	(0.0020)
Miller G. Draft	0.0032	0.0020	0.0016	0.0031	0.0050	0.0027	-7.5864	0.0101
	(0.0005)	(0.0004)	(0.0003)	(0.0008)	(0.0010)	(0.0004)	(0.0069)	(0.0023)
Miller Lite	0.0054	0.0041	0.0035	0.0061	0.0074	0.0049	0.0033	-7.4550
	(0.0009)	(0.0011)	(0.0008)	(0.0008)	(0.0015)	(0.0012)	(0.0011)	(0.0022)

Note: Standard errors are given in parenthesis.

2.7 Supply Results

Following Miller and Weinberg (2017), we estimate the extent to which ABI and MillerCoors internalize price externalities or collude over prices in the pre-merger and post-merger periods. The supply model parameter κ_1 captures the extent to which ABI and MillerCoors internalize price externalities or collude over prices in the pre-merger period. After the merger between ABI and

SABMiller, we estimate the extent to which merged firms ABI-SABMiller and MillerCoors internalize price externalities or collude over prices by the supply model parameter κ_2. The estimated parameter implies Bertrand Nash competition if $\kappa_t = 0$ and joint profit maximization or perfect collusion if $\kappa_t = 1$. We may infer partial collusion or internalization of price externalities if $0 < \kappa_t < 1$.

Table 2.6 presents estimates of κ_t during pre-merger and post-merger periods respectively. The marginal cost function controls for brands, time, and region fixed effects. The estimated value of κ_1 is 0.1048 and statistically insignificant. Miller and Weinberg (2017) suggests that in the post-merger period ABI and MillerCoors internalize somewhat between a quarter and a third of their price effects on the other's profit. Contrary to their findings, we do not find empirical evidence of collusive behavior between ABI and MillerCoors. The estimated values of κ_2 is close to zero and statistically insignificant suggesting Bertrand Nash competition for the post-merger period. Since the estimated parameters are statistically insignificant, we fail to reject null hypothesis of Bertrand Nash competition in the pre-merger and post-merger periods. The supply side results suggest that brewers non-cooperatively choose beer prices in the pre-merger as well as post-merger periods.

Table 2.6: Internalization of Coalition Pricing Externalities[1]

	Estimates
Pre-Merger Collusive Parameter κ_1	0.1048
	(0.1879)
Post-Merger Collusive Parameter κ_2	2.7204×10^{-7}
	(0.1271)
GMM Objective	3.3470×10^{-9}

Note: Standard errors are given in parenthesis.
[1]The estimates of cost shifters and fixed effects in the marginal cost function for brand, time and region are not reported here, but can be made available upon request.

2.7.1 Alternative Supply Analysis

To further investigate the supply behavior of brewers, we assume two alternate supply models along with the supply model discussed in the previous section. We estimate marginal costs after recovering markup to confirm the best supply model for the beer market using Vuong (1988) test.

To assess the best performing supply model, we consider following three supply models. In Model A we assume domestic brewers simultaneously and non-cooperatively choosing per unit retail prices (Bertrand Nash fashion) for the menu of differentiated beer products they sell to consumers. In other words, ABI and MillerCoors in the pre-merger and ABI-SABMiller and MillerCoors in the post-merger choose retail prices non-cooperatively. Using equation (11), we recover the following markup under the assumption of $\kappa_t = 0$:

$$\Gamma^{\mathrm{A}} = p - \mu - c = -\left[T_b^{no\_collude} * \Delta_r\right]^{-1} \times s(p) \tag{16}$$

In Model B, we assume domestic brewers partially internalize price externalities or collude over retail prices. Considering the estimated values of $\hat{\kappa}_1 = 0.1048$ and $\hat{\kappa}_2 = 2.7204 \times 10^{-7}$, we recover the associated markup given below:

$$\Gamma^{\mathrm{B}} = p - \mu - c = -[T_b(\hat{\kappa}) * \Delta_r]^{-1} \times s(p) \tag{17}$$

We expect markup in equations (16) and (17) are slightly different from each other.

In Model C, we assume domestic brewers choose retail prices by jointly maximizing their profits. In other words, ABI and MillerCoors in the pre-merger and ABI-SABMiller and MillerCoors in the post-merger choose retail prices to jointly maximize profits. We recover the associated markup under the assumption of $\kappa_t = 1$:

$$\Gamma^{\mathrm{C}} = p - \mu - c = -\left[T_b^{collude\_select} * \Delta_r\right]^{-1} \times s(p) \tag{17}$$

Let the alternate supply models be indexed by l, i.e. $l = A, B, C$. Consistent with the notation above, Γ^l represents a vector of markups in supply model l, i.e., $\Gamma^l = p - \mu - c$ where μ represents brewers' marginal costs; and c represents retailers' marginal costs. Combining equations (12) and (13) yields an estimable supply regression equation:

$$p_{jm} - \left[\Gamma_{jm}^l\left(\hat{\theta}_d, \kappa\right)\right] = W_{jm}\phi + f^b + f^r + a_m + \varepsilon_{jm} \tag{19}$$

Note that the markup terms, $\Gamma^l\left(\hat{\theta}_d, \kappa\right)$ is a function of demand parameter estimates and κ. With the demand parameter estimates in hand and κ, we can compute markups based on any of the previously discussed supply models. Furthermore, since p is observed data on retail price, the left-hand side of equation (19) is completely known.

Equation (19) is estimated under each of the alternate supply models, $l = A, B, C$. We then use non-nested statistical tests developed by Vuong (1989) to determine which supply model(s) best approximate price-setting behavior among brewers during pre-merger and post-merger periods respectively.

2.7.2 Statistical Non-nested test for Model Selection

We consider three different supply model specifications, which are captured by the regression model specification in equation (19). Markups are computed, and marginal costs recovered under each of the supply model specifications. To determine which among the set of supply models best explains the data, we rely on a likelihood-based non-nested statistical test developed by Vuong (1989). The non-nested statistical test is a modification of the well-known likelihood ratio test.

To begin, recall equation (19), which is the regression equation that captures the alternate supply models, and is estimated under each of the alternate supply models, $l = A, B, C$. Let a pair of alternate supply models be denoted by l and l'. Based on regression equation (19), the likelihood ratio test statistic for comparing $Model\ l$ and $Model\ l'$ is given by:

$$LR = \sum_{n=1}^{N} \left(LL_n^l - LL_n^{l'}\right) \tag{20}$$

where n denotes the observation, which in the case of equation (19) is a unique j and m combination; N represents the sample size; and LL_n^l is the optimal value of the log likelihood function evaluated at observation n for $Model\ l$. Assuming the residuals of supply $Model\ l$ follows a normal distribution, the log likelihood values for $Model\ l$ is:

$$LL_n^l = \log\left[\varphi\left(\frac{p_n - markup_n - W_n\hat{\phi}_l}{\hat{\sigma}_l}\right)\right]$$

where $\varphi(\cdot)$ is the standard normal distribution; $markup_n = \Gamma_n^l\left(\hat{\theta}_d, \kappa\right)$ is the markup on a product; $\hat{\phi}_l$ is the vector of marginal cost function parameter estimates for $Model\ l$; and $\hat{\sigma}_l$ is the estimate of the standard deviation of the residuals from $Model\ l$. We compute $LL_n^{l'}$ analogously for alternative supply Model l' under consideration.

Vuong (1989) shows that the likelihood ratio statistic in (20) can be normalized by its variance:

$$v^2 = \frac{1}{N}\sum_{n=1}^{N}\left(LL_n^l - LL_n^{l'}\right)^2 - \left[\frac{1}{N}\sum_{n=1}^{N}\left(LL_n^l - LL_n^{l'}\right)\right]^2 \tag{21}$$

The resulting test statistic is given by:

$$Q = N^{-0.5} \frac{LR}{v} \tag{22}$$

The value of Q is asymptotically distributed standard normal under the null hypothesis that the two models being compared by the test are asymptotically equivalent. For a one-tail test, $Q > 1.64$ implies that the supply model l' is statistically rejected in favor of supply model l; and $Q < -1.64$ implies that supply model l is statistically rejected in favor of supply model l'. For $-1.64 < Q < 1.64$, we cannot statistically distinguish between two models being compared.

2.7.3 Results from Statistical Model Selection

Using the Vuong (1989) non-nested likelihood ratio statistical test, we compare the three different supply models described above to discern which supply model(s) best approximate price-setting behavior among brewers during pre-merger and post-merger periods respectively.

Table 2.7 and Table 2.8 report non-nested likelihood ratio test statistics, i.e. the values of Q from equation (22), for pairwise comparisons of the alternate models. Table 2.7 compare the models during pre-merger periods, while Table 2.8 compare the models during post-merger periods. Test statistic values that are positive and greater than 1.64 imply that the model in the row is statistically rejected in favor of the model in the column, i.e., the column model better approximates price-setting behavior when compared to the relevant row model. On the other hand, test statistic values that are negative and less than -1.64 imply that the model in the column is statistically rejected in favor of the model in the row, i.e., the row model better approximates price-setting behavior when compared to the relevant column model.

In Table 2.7, the values of test statistics given in the first column compares how Model A fares in comparison to the other two models during the pre-merger period. Under the null hypothesis that two models are equivalent to each other, in comparing Model A to Model B, the test statistic of 147.58 is greater than 1.64 and implies that Model B is statistically rejected in favor Model A. In fact, the test statistics in the same column reveal that Model A also outperforms Model C. The value of test statistics given in the second column suggests that Model C is rejected in favor of Model B. Therefore, Model A best approximates price-setting behavior in the pre-merger period. It is also important to recall that Model A does not allow collusive pricing among firms, but the set of models it outperforms assume partial (Model B) or full collusive pricing among brewers. It is therefore reasonable to conclude from the results in Table 2.7 that price-setting behavior during the pre-merger period is not characterized by collusive pricing between ABI and MillerCoors.

We now discus results in Table 2.8, which focuses on pairwise statistical comparisons of the models during post–merger periods. The test statistics given in the first column are positive and greater than 1.64 suggesting Model A outperforms Model B and Model C. Further, the value of test statistics given in the second column suggests that Model C is rejected in favor of Model B. In other words, the test statistics in Table 2.8 reveal that during post-merger periods Model A best approximates price-setting behavior in comparison to other two models considered.

Model A being the best performing model during post-merger period suggests ABI-SABMiller and MillerCoors choose non-cooperatively retail prices. Consistent with the pre-merger period findings, each brewer during the post-merger period faces competition from rival brewers in determining retail prices, and brewers freely, and non-cooperatively set retail prices.
This result is quite in accordance with the estimated $\hat{\kappa}_t \approx 0$ discussed in the previous section. As mergers leave less players to compete, the large brewers like ABI-SABMiller gain more control and perhaps market power. However, the selected model suggests that price-setting behavior during the post-merger period is not characterized by collusive pricing between ABI-SABMiller and MillerCoors.

Collectively, the best performing models (Model A pre-merger as well as post-merger) suggest that the supply-side model analysis has not found any evidence that collusive pricing exists prior to, or subsequent to, the upstream merger we study. Slade (2004) and Rojas (2008) also did not find evidence of collusive pricing in their analysis of the U.K. and U.S. brewing industries respectively.

Table 2.7: Non-nested Likelihood Ratio Test Statistics for Pairwise Comparisons of Alternate Supply Models during the Pre-merger Period

	Model A	Model B	Model C
Model A	NA		
Model B	147.577	NA	
Model C	387.0288	391.0055	NA

Table 2.8: Non-nested Likelihood Ratio Test Statistics for Pairwise Comparisons of Alternate Supply Models during the Post-merger Period

	Model A	Model B	Model C
Model A	NA		
Model B	18.48967	NA	
Model C	143.2107	143.2108	NA

2.8 Conclusion

In light of the ABI and SABMiller's recent merger, this paper analyzes horizontal relationships between brewers and draws inference on the changing nature of horizontal competition in the beer industry. We model supply behavior of ABI and MillerCoors by specifying a parameter measuring the extent to which these brewers internalize price externalities pre-merger and post-merger periods. Unlike Miller and Weinberg (2017), we do not find evidence of partial or full collusive between ABI and MillerCoors in the pre-merger and post-merger periods. However, our findings are consistent with other studies [Slade (2008), Rojas (2008)], rejecting coordinated effects in the beer industry.

Alternative empirical supply models are also estimated to determine the best supply model that fits the supply behavior of brewers. These supply models cover three different supply behavior between brewers: competition, partial collusive and perfect collusive. For the set of markets analyzed in this paper, we find supply models involving competition between ABI and MillerCoors in the pre-merger and post-merger periods best fits the data. In other words, our findings suggest that price-setting behavior is same for large brewers ABI and MillerCoors across the pre-merger and post-merger periods.

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Appendix A

Table A.1: Demand estimate from standard logit and random coefficient logit models

	Standard logit model		Random coefficient logit model		
	OLS (Means)	2SLS (Means)	RCM (Means)	Standard Deviations	Interaction with Income
Variable	α, β	α, β	α, β	Υ	Γ
Price	-2.387**	-1.807**	-1.888**	0.067	…
	(0.007)	(0.027)	(0.033)	(0.065)	
Constant	-6.426** [a]	-8.937** [a]	-9.147** [a]	0.018	-4.753**
	(0.019)	(0.021)	(0.026)	(0.187)	(0.531)
Imported	-0.075** [a]	-0.373** [a]	-1.186** [a]	-0.029	11.831**
	(0.002)	(0.003)	(0.014)	(0.291)	(1.024)
Alcohol	0.026** [a]	0.184** [a]	0.138** [a]	…	…
	(0.003)	(0.003)	(0.003)		
Calories	-0.005** [a]	-0.011** [a]	-0.007** [a]	…	…
	(0.000)	(0.000)	(0.000)		
Carbohydrates	0.021** [a]	0.017** [a]	0.004** [a]	…	…
	(0.000)	(0.000)	(0.000)		
American Amber/Red Ale	-0.128** [a]	0.251** [a]	0.171** [a]	…	…
	(0.006)	(0.006)	(0.006)		
American Indian Pale Ale	-0.184** [a]	0.183** [a]	0.086** [a]	…	…
	(0.021)	(0.021)	(0.018)		
American Pale Wheat Ale	-0.937** [a]	-0.662** [a]	-0.667** [a]	…	…
	(0.007)	(0.007)	(0.007)		
American Pale Ale	-0.432** [a]	0.008** [a]	-0.184** [a]	…	…
	(0.009)	(0.009)	(0.008)		
English Brown Ale	-1.013** [a]	-0.687** [a]	-0.802** [a]	…	…
	(0.009)	(0.009)	(0.009)		
English Pale Ale	-1.426** [a]	-1.309** [a]	-1.295** [a]	…	…
	(0.028)	(0.028)	(0.026)		
American Pale Lager	-0.109** [a]	0.228** [a]	0.146** [a]	…	…
	(0.009)	(0.009)	(0.008)		
Light Lager	-1.008** [a]	-0.912** [a]	-0.934** [a]	…	…
	(0.035)	(0.035)	(0.031)		
Red Lager	-1.150** [a]	-0.587** [a]	-0.532** [a]	…	…
	(0.013)	(0.013)	(0.013)		
Vienna Lager	-0.084** [a]	0.101** [a]	-0.063** [a]	…	…
	(0.007)	(0.007)	(0.007)		
Euro Pale Lager	0.327** [a]	0.490** [a]	0.399** [a]	…	…
	(0.098)	(0.098)	(0.055)		
Czech Pilsner	-0.813** [a]	-0.700** [a]	-0.691** [a]	…	…
	(0.012)	(0.012)	(0.012)		
German Pilsner	0.940** [a]	1.180** [a]	1.154** [a]	…	…
	(0.007)	(0.007)	(0.007)		
American Malt Liquor	-0.325** [a]	-0.265** [a]	-0.290** [a]	…	…
	0.015	(0.015)	(0.016)		
Black and Tan	-0.186** [a]	0.097** [a]	0.014 [a]	…	…
	(0.013)	(0.013)	(0.010)		

Table A.1: Demand estimate from standard logit and random coefficient logit models (Continues)

	Standard logit model		Random coefficient logit model		
	OLS (Means)	2SLS (Means)	RCM (Means)	Standard Deviations	Interaction with Income
Variable	α, β	α, β	α, β	Υ	Γ
Bock	-0.659** [a]	-0.339** [a]	-0.363** [a]	…	…
	(0.010)	(0.010)	(0.009)		
Kristalweizen	-0.457** [a]	-0.235** [a]	-0.269** [a]	…	…
	(0.007)	(0.008)	(0.008)		
Witbier	-0.464** [a]	-0.273** [a]	-0.304** [a]	…	…
	(0.006)	(0.006)	(0.006)		
Low alcohol beer	-0.015** [a]	0.158** [a]	0.137** [a]	…	…
	(0.007)	(0.007)	(0.007)		
GMM Objective			25551.6	…	…

Based on 1.9 million observations. All regressions include time, market and brand dummies. Asymptotically robust standard errors are given in parenthesis. ** indicates statistical significant at the 1% level.

[a] Estimates from a Minimum Distance Procedure.

Table A.2: Mean Price & Product Markup for Firm-specific brands:

	Price	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H
					Pre-Leegin				
		Total Markup=brewer markup(Γ) + retailer markup(γ)							
ABI	9.687**	3.587**	5.183**	4.862**	2.819**	2.673**	5.030**	2.044**	4.034**
	(0.00459)	(0.000879)	(0.00661)	(0.00488)	(0.00262)	(0.00206)	(0.0217)	(0.000436)	(0.000540)
BOS	13.69**	3.050**	4.983**	3.050**	2.714**	1.742**	4.738**	1.742**	4.060**
	(0.00922)	(0.000648)	(0.0144)	(0.000648)	(0.00619)	(0.0000816)	(0.0374)	(0.0000816)	(0.00164)
DGY	9.626**	3.056**	5.212**	3.056**	2.886**	1.754**	4.668**	1.754**	4.054**
	(0.00483)	(0.000562)	(0.0156)	(0.000562)	(0.00785)	(0.000105)	(0.0433)	(0.000105)	(0.00174)
GRO	14.46**	3.082**	3.082**	3.082**	1.804**	1.804**	4.594**	1.804**	3.868**
	(0.00550)	(0.000537)	(0.000537)	(0.000537)	(0.000261)	(0.000261)	(0.0277)	(0.000261)	(0.000886)
HEI	13.85**	2.995**	2.995**	2.995**	1.757**	1.757**	4.656**	1.757**	3.860**
	(0.00633)	(0.000405)	(0.000405)	(0.000405)	(0.000144)	(0.000144)	(0.0292)	(0.000144)	(0.000864)
MOL	10.18**	3.094**	5.134**	4.812**	2.797**	2.651**	4.947**	1.780**	4.012**
	(0.00705)	(0.000360)	(0.00995)	(0.00745)	(0.00401)	(0.00317)	(0.0310)	(0.0000952)	(0.000871)
SAB	8.769**	3.246**	5.151**	4.848**	2.819**	2.678**	5.044**	1.865**	4.025**
	(0.00547)	(0.000312)	(0.00651)	(0.00487)	(0.00265)	(0.00209)	(0.0210)	(0.000142)	(0.000560)
GAM	12.15**	2.940**	4.861**	2.940**	2.682**	1.713**	5.081**	1.713**	3.925**
	(0.0146)	(0.000979)	(0.0278)	(0.000979)	(0.0101)	(0.000233)	(0.102)	(0.000233)	(0.00216)
					Post-Leegin				
ABI	9.963**	3.368**	4.207**	3.990**	2.361**	2.253**	3.211**	1.928**	3.815**
	(0.00359)	(0.000411)	(0.00195)	(0.00143)	(0.000958)	(0.000714)	(0.00698)	(0.000199)	(0.000504)
BOS	14.09**	3.050**	4.217**	3.050**	2.345**	1.744**	3.254**	1.744**	3.856**
	(0.00631)	(0.000485)	(0.00532)	(0.000485)	(0.00249)	(0.0000561)	(0.0197)	(0.0000561)	(0.00143)
DGY	9.816**	3.078**	4.490**	3.078**	2.517**	1.766**	3.558**	1.766**	3.919**
	(0.00449)	(0.000691)	(0.00621)	(0.000691)	(0.00319)	(0.0000964)	(0.0243)	(0.0000964)	(0.00176)
GRO	13.62**	3.041**	3.041**	3.041**	1.786**	1.786**	2.919**	1.786**	3.626**
	(0.00391)	(0.000337)	(0.000337)	(0.000337)	(0.000142)	(0.000142)	(0.00889)	(0.000142)	(0.000707)
HEI	13.37**	2.966**	2.966**	2.966**	1.745**	1.745**	3.010**	1.745**	3.645**
	(0.00522)	(0.000331)	(0.000331)	(0.000331)	(0.000107)	(0.000107)	(0.00997)	(0.000107)	(0.000779)
MOL	10.92**	3.286**	4.166**	3.958**	2.336**	2.234**	3.147**	1.884**	3.801**
	(0.00604)	(0.000430)	(0.00283)	(0.00209)	(0.00138)	(0.00103)	(0.0100)	(0.000177)	(0.000767)
SAB	9.069**	3.297**	4.235**	4.018**	2.382**	2.272**	3.201**	1.893**	3.805**
	(0.00459)	(0.000307)	(0.00221)	(0.00163)	(0.00111)	(0.000819)	(0.00753)	(0.000137)	(0.000536)
GAM	12.33**	2.953**	3.859**	2.953**	2.205**	1.719**	2.848**	1.719**	3.676**
	(0.0106)	(0.000772)	(0.00573)	(0.000772)	(0.00278)	(0.000177)	(0.0214)	(0.000177)	(0.00196)

Notes: Standard errors in parentheses; ** indicates statistical significance at the 1% level.

Table A.3: Mean Marginal Cost retrieved from different models (in Dollars $/12 pack)

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H
				Pre-Leegin				
ABI	6.099**	4.503**	4.825**	6.868**	7.013**	4.656**	7.643**	5.653**
	(0.00476)	(0.00830)	(0.00694)	(0.00546)	(0.00518)	(0.0222)	(0.00465)	(0.00467)
BOS	10.64**	8.708**	10.64**	10.98**	11.95**	8.953**	11.95**	9.631**
	(0.00924)	(0.0173)	(0.00924)	(0.0113)	(0.00922)	(0.0391)	(0.00922)	(0.00946)
DGY	6.570**	4.414**	6.570**	6.740**	7.872**	4.958**	7.872**	5.572**
	(0.00491)	(0.0168)	(0.00491)	(0.00963)	(0.00484)	(0.0437)	(0.00484)	(0.00533)
GRO	11.38**	11.38**	11.38**	12.65**	12.65**	9.864**	12.65**	10.59**
	(0.00556)	(0.00556)	(0.00556)	(0.00554)	(0.00554)	(0.0287)	(0.00554)	(0.00565)
HEI	10.86**	10.86**	10.86**	12.10**	12.10**	9.199**	12.10**	9.995**
	(0.00629)	(0.00629)	(0.00629)	(0.00632)	(0.00632)	(0.0300)	(0.00632)	(0.00633)
MOL	7.085**	5.046**	5.368**	7.382**	7.529**	5.232**	8.400**	6.168**
	(0.00706)	(0.0125)	(0.0106)	(0.00835)	(0.00793)	(0.0318)	(0.00705)	(0.00712)
SAB	5.523**	3.619**	3.921**	5.951**	6.091**	3.725**	6.904**	4.744**
	(0.00555)	(0.00901)	(0.00778)	(0.00641)	(0.00612)	(0.0217)	(0.00550)	(0.00559)
GAM	9.211**	7.290**	9.211**	9.469**	10.44**	7.070**	10.44**	8.226**
	(0.0143)	(0.0317)	(0.0143)	(0.0181)	(0.0145)	(0.104)	(0.0145)	(0.0144)
				Post-Leegin				
ABI	6.595**	5.756**	5.973**	7.602**	7.710**	6.752**	8.035**	6.148**
	(0.00370)	(0.00437)	(0.00410)	(0.00387)	(0.00379)	(0.00798)	(0.00364)	(0.00370)
BOS	11.04**	9.872**	11.04**	11.74**	12.34**	10.83**	12.34**	10.23**
	(0.00634)	(0.00805)	(0.00634)	(0.00663)	(0.00631)	(0.0204)	(0.00631)	(0.00622)
DGY	6.737**	5.326**	6.737**	7.299**	8.050**	6.258**	8.050**	5.897**
	(0.00459)	(0.00833)	(0.00459)	(0.00593)	(0.00450)	(0.0247)	(0.00450)	(0.00489)
GRO	10.58**	10.58**	10.58**	11.83**	11.83**	10.70**	11.83**	9.995**
	(0.00387)	(0.00387)	(0.00387)	(0.00389)	(0.00389)	(0.00954)	(0.00389)	(0.00389)
HEI	10.40**	10.40**	10.40**	11.62**	11.62**	10.36**	11.62**	9.722**
	(0.00514)	(0.00514)	(0.00514)	(0.00519)	(0.00519)	(0.0110)	(0.00519)	(0.00512)
MOL	7.629**	6.749**	6.957**	8.579**	8.681**	7.768**	9.032**	7.115**
	(0.00607)	(0.00691)	(0.00661)	(0.00633)	(0.00624)	(0.0118)	(0.00605)	(0.00607)
SAB	5.772**	4.833**	5.051**	6.687**	6.796**	5.867**	7.176**	5.263**
	(0.00469)	(0.00556)	(0.00525)	(0.00498)	(0.00486)	(0.00905)	(0.00463)	(0.00473)
GAM	9.378**	8.472**	9.378**	10.13**	10.61**	9.483**	10.61**	8.655**
	(0.0103)	(0.0117)	(0.0103)	(0.0109)	(0.0105)	(0.0239)	(0.0105)	(0.0104)

Notes: Standard errors in parentheses; ** statistical significance at the 1% level.

Table A.4: Mean Price and Product Markup of selected brands (in Dollars $/12 pack)

					Pre-Leegin				
	Price	**Total Markup=brewer markup(Γ) + retailer markup(γ)**							
		Model A	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**	**Model G**	**Model H**
Bud Light	9.902**	3.589**	5.167**	4.848**	2.812**	2.667**	5.072**	2.043**	4.061**
	(0.00598)	(0.00273)	(0.0218)	(0.0159)	(0.00869)	(0.00678)	(0.0747)	(0.00138)	(0.00174)
Budweiser	9.877**	3.589**	5.169**	4.849**	2.809**	2.664**	5.065**	2.042**	4.053**
	(0.00605)	(0.00274)	(0.0219)	(0.0160)	(0.00867)	(0.00676)	(0.0745)	(0.00138)	(0.00171)
Coors	10.04**	3.121**	5.137**	4.830**	2.773**	2.639**	5.159**	1.786**	4.047**
	(0.00725)	(0.000703)	(0.0268)	(0.0194)	(0.0103)	(0.00796)	(0.0909)	(0.000176)	(0.00200)
Coors Light	9.913**	3.115**	5.158**	4.839**	2.803**	2.658**	5.063**	1.785**	4.052**
	(0.00605)	(0.000556)	(0.0220)	(0.0160)	(0.00865)	(0.00673)	(0.0752)	(0.000157)	(0.00171)
Corona Extra	14.63**	3.069**	3.069**	3.069**	1.796**	1.796**	4.721**	1.796**	3.879**
	(0.00883)	(0.000943)	(0.000943)	(0.000943)	(0.000450)	(0.000450)	(0.0637)	(0.000450)	(0.00165)
Corona Light	14.60**	3.073**	3.073**	3.073**	1.798**	1.798**	4.545**	1.798**	3.870**
	(0.00930)	(0.000997)	(0.000997)	(0.000997)	(0.000474)	(0.000474)	(0.0465)	(0.000474)	(0.00167)
Heineken	14.46**	2.992**	2.992**	2.992**	1.754**	1.754**	4.673**	1.754**	3.872**
	(0.00864)	(0.000729)	(0.000729)	(0.000729)	(0.000265)	(0.000265)	(0.0591)	(0.000265)	(0.00163)
Heineken-PLL	14.29**	2.991**	2.991**	2.991**	1.758**	1.758**	4.335**	1.758**	3.840**
	(0.0115)	(0.00105)	(0.00105)	(0.00105)	(0.000377)	(0.000377)	(0.0509)	(0.000377)	(0.00200)
Miller GD	9.917**	3.252**	5.148**	4.837**	2.791**	2.651**	5.049**	1.860**	4.048**
	(0.00607)	(0.000917)	(0.0224)	(0.0164)	(0.00873)	(0.00682)	(0.0740)	(0.000433)	(0.00174)
Miller HL	7.435**	3.244**	5.184**	4.863**	2.818**	2.673**	5.079**	1.860**	4.037**
	(0.00616)	(0.000880)	(0.0225)	(0.0164)	(0.00883)	(0.00689)	(0.0751)	(0.000418)	(0.00173)
Miller Light	9.847**	3.250**	5.175**	4.854**	2.811**	2.666**	5.084**	1.860**	4.052**
	(0.00601)	(0.000877)	(0.0223)	(0.0162)	(0.00876)	(0.00683)	(0.0755)	(0.000421)	(0.00172)
					Post-Leegin				
Bud Light	10.36**	3.358**	4.131**	3.932**	2.323**	2.224**	3.160**	1.921**	3.819**
	(0.00573)	(0.00114)	(0.00552)	(0.00404)	(0.00274)	(0.00204)	(0.0207)	(0.000571)	(0.00151)
Budweiser	10.36**	3.358**	4.130**	3.931**	2.321**	2.222**	3.160**	1.920**	3.815**
	(0.00578)	(0.00114)	(0.00553)	(0.00406)	(0.00273)	(0.00203)	(0.0208)	(0.000570)	(0.00150)
Coors	10.44**	3.315**	4.231**	4.022**	2.351**	2.254**	3.238**	1.890**	3.831**
	(0.00794)	(0.00118)	(0.00822)	(0.00597)	(0.00387)	(0.00291)	(0.0296)	(0.000468)	(0.00216)
Coors Light	10.44**	3.292**	4.128**	3.930**	2.320**	2.221**	3.162**	1.885**	3.817**
	(0.00598)	(0.000781)	(0.00551)	(0.00403)	(0.00272)	(0.00202)	(0.0209)	(0.000347)	(0.00151)
Corona Extra	13.70**	3.036**	3.036**	3.036**	1.783**	1.783**	3.001**	1.783**	3.645**
	(0.00744)	(0.000669)	(0.000669)	(0.000669)	(0.000279)	(0.000279)	(0.0182)	(0.000279)	(0.00145)
Corona Light	13.69**	3.039**	3.039**	3.039**	1.784**	1.784**	3.007**	1.784**	3.645**
	(0.00747)	(0.000694)	(0.000694)	(0.000694)	(0.000286)	(0.000286)	(0.0190)	(0.000286)	(0.00146)
Heineken	13.87**	2.969**	2.969**	2.969**	1.745**	1.745**	3.010**	1.745**	3.648**
	(0.00777)	(0.000581)	(0.000581)	(0.000581)	(0.000195)	(0.000195)	(0.0184)	(0.000195)	(0.00144)
Heineken-PLL	13.87**	2.973**	2.973**	2.973**	1.747**	1.747**	3.026**	1.747**	3.652**
	(0.00830)	(0.000637)	(0.000637)	(0.000637)	(0.000209)	(0.000209)	(0.0198)	(0.000209)	(0.00153)
Miller GD	10.33**	3.309**	4.189**	3.988**	2.341**	2.244**	3.190**	1.891**	3.825**
	(0.00665)	(0.000956)	(0.00671)	(0.00493)	(0.00323)	(0.00242)	(0.0239)	(0.000403)	(0.00175)
Miller HL	7.840**	3.286**	4.141**	3.940**	2.327**	2.228**	3.089**	1.884**	3.793**
	(0.00568)	(0.000839)	(0.00593)	(0.00433)	(0.00293)	(0.00218)	(0.0199)	(0.000367)	(0.00157)
Miller Light	10.27**	3.304**	4.194**	3.983**	2.352**	2.248**	3.210**	1.890**	3.831**

	(0.00614)	(0.000822)	(0.00595)	(0.00435)	(0.00295)	(0.00219)	(0.0221)	(0.000364)	(0.00157)

Notes: Standard errors in parentheses; ** indicates statistical significance at the 1% level.

Table A.5: Mean Marginal Costs for selected Brands (in Dollars $ /12 pack)

	Pre-Leegin							
	Model A	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**	**Model G**	**Model H**
Bud Light	6.313**	4.735**	5.055**	7.090**	7.235**	4.831**	7.859**	5.842**
	(0.00691)	(0.0233)	(0.0177)	(0.0113)	(0.00968)	(0.0751)	(0.00635)	(0.00637)
Budweiser	6.288**	4.709**	5.028**	7.068**	7.213**	4.812**	7.835**	5.824**
	(0.00697)	(0.0234)	(0.0178)	(0.0113)	(0.00972)	(0.0749)	(0.00641)	(0.00642)
Coors	6.919**	4.904**	5.210**	7.267**	7.401**	4.882**	8.254**	5.993**
	(0.00725)	(0.0287)	(0.0216)	(0.0135)	(0.0116)	(0.0914)	(0.00724)	(0.00765)
Coors Light	6.798**	4.756**	5.074**	7.111**	7.255**	4.850**	8.128**	5.862**
	(0.00602)	(0.0235)	(0.0179)	(0.0113)	(0.00975)	(0.0755)	(0.00603)	(0.00640)
Corona Extra	11.56**	11.56**	11.56**	12.83**	12.83**	9.906**	12.83**	10.75**
	(0.00899)	(0.00899)	(0.00899)	(0.00893)	(0.00893)	(0.0648)	(0.00893)	(0.00917)
Corona Light	11.53**	11.53**	11.53**	12.80**	12.80**	10.05**	12.80**	10.73**
	(0.00946)	(0.00946)	(0.00946)	(0.00940)	(0.00940)	(0.0483)	(0.00940)	(0.00964)
Heineken	11.47**	11.47**	11.47**	12.71**	12.71**	9.787**	12.71**	10.59**
	(0.00864)	(0.00864)	(0.00864)	(0.00866)	(0.00866)	(0.0598)	(0.00866)	(0.00875)
Heineken-PLL	11.30**	11.30**	11.30**	12.54**	12.54**	9.959**	12.54**	10.45**
	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0525)	(0.0114)	(0.0116)
Miller GD	6.665**	4.770**	5.081**	7.127**	7.266**	4.868**	8.057**	5.869**
	(0.00627)	(0.0237)	(0.0180)	(0.0112)	(0.00969)	(0.0743)	(0.00617)	(0.00639)
Miller HL	4.191**	2.251**	2.572**	4.617**	4.762**	2.356**	5.575**	3.398**
	(0.00631)	(0.0237)	(0.0179)	(0.0113)	(0.00970)	(0.0753)	(0.00626)	(0.00646)
Miller Light	6.597**	4.672**	4.993**	7.036**	7.181**	4.763**	7.987**	5.795**
	(0.00620)	(0.0236)	(0.0179)	(0.0113)	(0.00965)	(0.0757)	(0.00611)	(0.00634)
	Post-Leegin							
Bud Light	7.007**	6.234**	6.433**	8.041**	8.141**	7.204**	8.444**	6.545**
	(0.00622)	(0.00917)	(0.00805)	(0.00714)	(0.00672)	(0.0220)	(0.00597)	(0.00620)
Budweiser	7.001**	6.230**	6.428**	8.039**	8.138**	7.199**	8.439**	6.544**
	(0.00627)	(0.00920)	(0.00809)	(0.00717)	(0.00675)	(0.0220)	(0.00601)	(0.00623)
Coors	7.123**	6.207**	6.415**	8.086**	8.183**	7.200**	8.548**	6.606**
	(0.00835)	(0.0131)	(0.0114)	(0.00992)	(0.00933)	(0.0313)	(0.00811)	(0.00859)
Coors Light	7.151**	6.315**	6.513**	8.123**	8.222**	7.281**	8.558**	6.626**
	(0.00628)	(0.00941)	(0.00831)	(0.00739)	(0.00697)	(0.0222)	(0.00612)	(0.00643)
Corona Extra	10.66**	10.66**	10.66**	11.91**	11.91**	10.70**	11.91**	10.05**
	(0.00735)	(0.00735)	(0.00735)	(0.00739)	(0.00739)	(0.0192)	(0.00739)	(0.00735)
Corona Light	10.65**	10.65**	10.65**	11.90**	11.90**	10.68**	11.90**	10.04**
	(0.00738)	(0.00738)	(0.00738)	(0.00742)	(0.00742)	(0.0199)	(0.00742)	(0.00738)

Heineken	10.91**	10.91**	10.91**	12.13**	12.13**	10.86**	12.13**	10.23**
	(0.00764)	(0.00764)	(0.00764)	(0.00771)	(0.00771)	(0.0195)	(0.00771)	(0.00759)
Heineken-PLL	10.90**	10.90**	10.90**	12.12**	12.12**	10.84**	12.12**	10.22**
	(0.00816)	(0.00816)	(0.00816)	(0.00823)	(0.00823)	(0.0210)	(0.00823)	(0.00811)

Table A.5: Mean Marginal Costs for selected Brands (in Dollars $ /12 pack) (Continues)

	Post-Leegin							
	Model A	**Model B**	**Model C**	**Model D**	**Model E**	**Model F**	**Model G**	**Model H**
Miller GD	7.024**	6.144**	6.346**	7.992**	8.090**	7.144**	8.443**	6.508**
	(0.00701)	(0.0109)	(0.00951)	(0.00831)	(0.00783)	(0.0254)	(0.00681)	(0.00727)
Miller HL	4.553**	3.698**	3.899**	5.512**	5.612**	4.750**	5.956**	4.047**
	(0.00593)	(0.00936)	(0.00812)	(0.00721)	(0.00673)	(0.0212)	(0.00582)	(0.00625)
Miller Light	6.966**	6.076**	6.287**	7.918**	8.023**	7.060**	8.380**	6.439**
	(0.00644)	(0.00978)	(0.00859)	(0.00761)	(0.00717)	(0.0234)	(0.00629)	(0.00662)

Notes: Standard errors in parentheses; ** indicates statistical significance at the 1% level.

Table A.6: List of Selected Brands and their Styles

No.	Brands	Style	Style (Short Name)
1	Amstel light	Light Lager	Llager
2	Aspen edge	Light Lager	Llager
3	Becks	German Pilsner	GPilsner
4	Bluemoon belgium white ale	Witbier	Witbier
5	Bridgeport india pale ale	American Indian Pale Ale	Am_IPA
6	Bud light	Light Lager	Llager
7	Budweiser	American Adjunct Lager	Am_AL
8	Budweiser select	Light Lager	Llager
9	Busch	American Adjunct Lager	Am_AL
10	Busch light	Light Lager	Llager
11	Coors	American Adjunct Lager	Am_AL
12	Coors light	Light Lager	Llager
13	Corona extra	American Adjunct Lager	Am_AL
14	Corona light	Light Lager	Llager
15	Dos equis xx amber lager	Vienna Lager	Vlager
16	Dos equis xx special lager	American Adjunct Lager	Am_AL
17	Fosters lager	American Adjunct Lager	Am_AL
18	George killians irish red lag	Red Lager	Rlarger
19	Hamms	American Adjunct Lager	Am_AL
20	Heineken	Euro Pale Lager	Eplager
21	Heineken premium light lager	Light Lager	Llager
22	Henry weinhard amber ale ligh	American Amber/Red Ale	Am_RA
23	Henry weinhard honey hefeweiz	American Pale Wheat Ale	Am_WA
24	Henry weinhard pale ale	American Pale Ale	Am_PA
25	Henry weinhard private reserve	American Pale Ale	Am_PA
26	Henry wnhrd nrthwst trl blnd	American Pale Ale	Am_PA
27	Icehouse	American Adjunct Lager	Am_AL
28	Keystone ice	American Adjunct Lager	Am_AL
29	Keystone light	Light Lager	Llager
30	Labatt blue	American Adjunct Lager	Am_AL

31	Leinenkugel	American Adjunct Lager	Am_AL
32	Leinenkugel honey Weiss	Kristalweizen	Krista
33	Leinenkugel red	Vienna Lager	VLager
34	Michelob	American Pale Lager	Am_PL
35	Michelob light	Light Lager	Llager

Table A6: List of Selected Brands and their Styles (Continues)

No.	Brands	Style	Style (Short Name)
36	Michelob ultra	Light Lager	Llager
37	Mickeys malt liquor	American Malt Liquor	Am_ML
38	Miller genuine draft	American Adjunct Lager	Am_AL
39	Miller genuine draft light	Light Lager	Llager
40	Miller high life	American Adjunct Lager	Am_AL
41	Miller high life light	Light Lager	Llager
42	Miller lite	Light Lager	Llager
43	Milwaukees best	American Adjunct Lager	Am_AL
44	Milwaukees best ice	American Adjunct Lager	Am_AL
45	Milwaukees best light	Light Lager	Llager
46	Modelo especial	American Adjunct Lager	Am_AL
47	Molson Canadian	American Adjunct Lager	Am_AL
48	Molson canadian light	Light Lager	Llager
49	Molson golden	American Pale Lager	Am_PL
50	Molson ice	American Adjunct Lager	Am_AL
51	Moosehead	American Adjunct Lager	Am_AL
52	Natural ice	American Adjunct Lager	Am_AL
53	Natural light	Light Lager	Llager
54	Negra modelo	Vienna Lager	Vlager
55	Odouls	Low alcohol beer	Lbeer
56	Pacifico	American Adjunct Lager	Am_AL
57	Petes wicked ale	English Brown Ale	EBAle
58	Petes wicked seasonal ales	English Brown Ale	EBAle
59	Pilsner urquell	Czech Pilsner	Cpilsner
60	Red dog	American Adjunct Lager	Am_AL
61	Rolling rock extra pale	American Adjunct Lager	Am_AL
62	Samuel adams boston ale	English Pale Ale	EPAle
63	Samuel adams boston lager	Vienna Lager	Vlager
64	Samuel adams light	Light Lager	Llager
65	Sharps	Low alcohol beer	Lbeer
66	Shiner bock	Bock	bock
67	Shiner light	American Pale Lager	Am_PL
68	Sol	American Adjunct Lager	Am_AL
69	Southpaw light	Light Lager	Llager
70	Steel reserve high gravity la	American Malt Liquor	Am_ML
71	Tecate	American Adjunct Lager	Am_AL
72	Twisted tea	American Malt Liquor	Am_ML
73	Yuengling black and tan	Black and Tan	B&Tan
74	Yuengling light lager	Light Lager	Llager
75	Yuengling traditional lager	Red Lager	Rlager

Appendix B

Table B1: List of Brands

1	BUD LIGHT
2	BUDWEISER
3	BUSCH
4	BUSCH LIGHT
5	COORS BANQUET
6	COORS LIGHT
7	CORONA EXTRA
8	CORONA LIGHT
9	HEINEKEN
10	HEINEKEN LIGHT
11	MICHELOB
12	MICHELOB LIGHT
13	MICHELOB ULTRA LIGHT
14	MILLER GENUINE DRAFT
15	MILLER HIGH LIFE
16	MILLER LITE

Figure B1: Log of Real Prices of Imported Beer brands (12-pack)