Manufacturer-Retailer Relationships and the Distribution of New Products

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Abstract

Manufacturer-retailer relationships are often cited as an important determinant in product distribution. They lead to the non-independence of retailers as intermediaries, contributing to major manufacturers' long-term dominance and high market concentration. However, characterizing relationships and establishing their causal effect are empirically challenging, because relationships often involve secret deals and lack exogenous variation. In this paper, I show mutual preferential treatments between manufacturers and retailers on assortments and wholesale prices in a new market of alcoholic beverages and interpret the results as relationship effects sustained through repeated interactions. The relationships are linked to the existing pair-specific beer sales performance and not driven by monetary transfer due to regulations. I estimate a multi-stage, theoretically founded structural model to characterize the coordination and asymmetry between manufacturers and retailers in relationships. The results show relationships overall increase Anheuser-Busch InBev's and MillerCoors' new cider availability by 17.3% and 5.1%, respectively. The reduction in double marginalization, the degree of assortment sub-optimality, and the externality on other manufacturers jointly determine the payoff of each party.

Keywords: product distribution, vertical relationships, alcoholic beverage markets, product assortment, market structure

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1 Introduction

Most consumer packaged goods (CPG) categories are dominated by a few leading manufacturers. Their dominance is persistent (Bronnenberg et al., 2007, 2009) and often carried over to new product segments and categories (Benkard et al., 2021). Examples for cross-category spillover include Frito Lay's Doritos tortilla chips, Pepsi's Pure Leaf tea drinks, and Anheuser-Busch InBev's Bud Light Seltzer. On the other hand, manufacturers often cite relationships with retailers as of paramount importance for their business, especially in securing product distribution, as this quote goes from a leading national manufacturer: *"So we have such good relationships with our retailers that we're able to have really great conversations and get more placement on shelves. And that really drives our brick-and-mortar distribution."* Because distribution has a crucial role in new product sales and long-term brand performance (Ataman et al., 2008, 2010), the relationships with retailers can contribute to major manufacturers' persistent dominance in CPG markets.

In this paper, I study the effect of manufacturer-retailer relationships on the distribution of new products. Relationships often arise as implicit contracts between long-term, top business partners. They can help a pair of manufacturer and retailer generate a larger profit pie than static optimal. One can formalize relationships with a repeated game framework, and a better relationship means a higher coordination level. In this paper, I focus on preferential treatments in assortment and wholesale prices between manufacturers and retailers in relationships. Through collaborating on assortment and wholesale prices, a pair can achieve partially integrated profit, even in markets with heavy regulations restricting vertical practices such as fixed transfers, private labels, and long-term contracts (e.g., Joskow, 1985).[1]

In practice, the relationship effect on product distribution can take the form of assortment recommendation from a manufacturer based on the joint profit with the retailer. In return for the retailer's adoption, the manufacturer can offer wholesale discounts. A win-win collaboration relies on both parties' collaborative spirit and transparency in communication. Anecdotally, retailers have regular meetings with major manufacturers to discuss how to generate incremental profits and

[1] The repeated game framework can incorporate the "trust" and "power" concepts of relationships. The cooperation is implicitly contingent on future profits—they cooperate in the current interaction with the belief that otherwise, they will lose the cooperation benefits from the next interaction. One can think of the belief that the partner would cooperate as "trust," and the potential punishment for the partner if the partner deviates as "power." In the earlier examples of Frito Lay, Pepsi, and Anheuser-Busch InBev, "power" can be interpreted as the leading manufacturers leveraging their dominance in existing categories to threaten the retailers (yet the threat not necessarily realized).

category growth. Due to limited shelf space, a good manufacturer-retailer relationship might reduce the availability of other manufacturers' products through the retailer.

Although vertical relationship is an important topic in the marketing and economics literature, empirical evidence of manufacturer-retailer relationships from field data with multiple firms on each side is scarce. Most papers either have a different focus and center around non-linear contracts (e.g., Hristakeva, 2020; Conlon and Mortimer, 2021) or use survey data (e.g., Kaufman et al., 2006), which typically source from one firm. This paper infers relationships from field data and quantifies the relationship impact on various market outcomes. But field data can bring in new challenges. First, relationships often involve secret deals such as slotting fees and wholesale price discounts that are hard to be characterized and separated from each other. Second, omitted variable bias might arise if a brand has an unobserved demand that drives both the distribution and the relationship, especially for the well-known brands.

I exploit a unique setting of the U.S. hard cider market to overcome the empirical challenges. New hard cider brands are launched by large beer manufacturers like Anheuser-Busch InBev and MillerCoors, as the category explodes and becomes the first successful "hard" adaptation to non-alcoholic beverages. The brewers leverage their existing relationships with retailers to promote new ciders. Although the cider brands they introduce are completely new and not related to their existing products and lager beer and hard cider cater to different consumer segments, the brewers' new ciders still receive a broad distribution from retailers.

I leverage industry regulations to disentangle mechanisms and rule out alternative explanations. First, Federal law prohibits offering things of value to retailers (e.g., slotting fees and services), tie-in sale (i.e., requiring a retailer to buy one product in order to buy another), and other types of complex contracts.[2] Second, a manufacturer's logistics quality is usually the same within a geographic region because distributors are assigned with exclusive territories. Third, regulations on wholesale pricing vary across states, with some states explicitly requiring linear posted prices, but others not. Thus, the only possible preferential treatments between manufacturers and retailers in this market will be related to assortment and wholesale discounts (in certain states). Further, the ownership changes of incumbent brands provide a different variation to identify the relationships' effect on distribution.

[2]Title 27 of USC and CFR

I find that Anheuser-Busch InBev and MillerCoors are able to place their ciders in more stores than the manufacturers with similar cider sales performance. Across retailers (i.e., chains), heavy Budweiser sellers tend to carry ciders made by Anheuser-Busch InBev, and heavy Miller and Coors sellers tend to carry ciders made by MillerCoors. As close collaborations usually occur for pairs with more business, the patterns are consistent with good relationships helping the brewers' cider distribution. While the adoption timing of each brand is consistent across stores within a retailer, suggesting the adoption decisions are largely made at the retailer level, there is considerable variation in adoption timing and level across retailers.

I present evidence on a strong and positive cross-sectional relationship between a brewer's past beer share by retailer and the retailer's adoption of the brewer's ciders. The past beer share is a good proxy for a relationship, because it is a persistent measure that reflects the business collaboration and communication they have been engaging in. I interpret the finding as a relationship effect and rely on regulations and high-dimensional fixed effects to show the result is not driven by slotting fees, local product preferences, or synergy in transportation and distribution. The finding is confirmed by the additional evidence utilizing ownership changes of incumbent cider brands.

I further show that the brewers offer wholesale discounts to retailers with good relationships in states without explicit wholesale pricing regulations. The preferential wholesale discounts compensate the retailers for their loss from sub-optimal assortments. The distribution effect, on the other hand, exists in all states because most retailers are multi-state retailers.

I develop and estimate a structural model of consumer demand, retail pricing, wholesale pricing, and retail assortment to characterize the relationships and the hard cider market. The relationship part is adopted from Fan and Sullivan (2018) and theoretically founded on repeated games. The parameters reflect the coordination level and player asymmetry in relationships. Demand is characterized by a random coefficient logit model with rich fixed effects that captures the substitution between similar products and retailer-specific consumer taste. Consistent with the descriptive findings, manufacturers can offer wholesale discounts to retailers with good relationships in states without explicit wholesale pricing regulations. Retailers can incorporate the relationships with manufacturers in assortment choices, identified by how the assortments vary with the manufacturers' equilibrium and deviating profits.

The structural results show manufacturer-retailer relationships play a significant role in both retail assortment and wholesale pricing decisions. The coordination in a relationship increases with the past beer share. The estimates reveal a moderate but imperfect coordination between retailers and the two leading brewers, Anheuser-Busch InBev and MillerCoors, which together account for more than half of the beer market and have been doing business with retailers for many decades. They offer an average wholesale discount of 7.6% and 5.5% in states without explicit regulations.

Using the model estimates, I quantify the importance of manufacturer-retailer relationships in product distribution and profits. I compare the current scenario with a counterfactual scenario of no relationships, in which both sides maximize their static profits. The comparison informs us the potential impact of implementing posted wholesale prices in all states. The relationships increase Anheuser-Busch InBev's and MillerCoors' cider availability by 17.3% and 5.1% and cider profits by 9.7% (\$0.5m) and 1% (\$0.1m), respectively. Despite the loss from sub-optimal assortments, retailers have a 1% (\$2.1m) profit increase due to wholesale discounts. Thus, the relationships present a double win to both sides, at the expense of 1.9% (−\$2.1m) profits of the remaining manufacturers. Consumers see a welfare increase of 1.1% (\$2.3m) due to reduced product markups despite worse assortments, although alcohol consumption is not always good.

The findings imply that manufacturers should maintain close relationships with retailers. Large manufacturers face growing challenges from small innovative brands in the increasing availability of small-scale production and new advertising channels. However, large manufacturers still hold comparative advantages in product distribution, contributed by their close relationships with retailers. One way to go is to combine the distribution advantages with an active acquisition and new product strategy (e.g., to acquire under-distributed but high-quality products, such as craft beer). On the other hand, P&G has been collecting novel product designs through its "Connect + Develop" program and promoting the complete products with its distribution power (Taneja, 2018). These are promising strategies to keep growing a large CPG business.

The strong impact of manufacturer-retailer relationships on new product distribution contributes to the persistent high concentration in CPG markets. The leading manufacturers are able to maintain their dominant positions with the success of new and acquired products, even if their main products decline slowly over time. The evolving consumer trends do not necessarily drive much new blood coming up and challenging existing manufacturers' shares. Instead, we see the established manufacturers thrive in new markets with strong cross-category spillover.

The findings also have important implications for regulations on vertical practices. The regulatory discussion has largely focused on the efficiency and anti-competitive effect of slotting allowance and contractual vertical restraints. However, assortments can still be distorted without slotting allowance or exclusive contracts. The heavy amount of regulations in the alcoholic beverages industry might not be as effective as they seem. On the other hand, wholesale price discrimination is shown to have an additional role of facilitating manufacturer-retailer relationships. Thus, a stricter regulation for wholesale pricing will lead to less coordination and fewer leading manufacturers' products being carried, not just higher prices, resulting in a combined impact on profits and welfare.

Literature review. This paper fits into the empirical literature on vertical relationships (e.g., Conlon and Mortimer, 2021; Ellickson et al., 2018; Draganska et al., 2010; Sudhir and Rao, 2006; Gross, 2019; Atalay et al., 2014) and category captaincy (Viswanathan et al., 2020). It provides new empirical evidence of manufacturer-retailer relationships and brings the relationship perspective to the literature. The paper is different from a close paper by Hristakeva (2020) in that it emphasizes cross-category spillover and characterizes the relationship impact in a heavily regulated setting with different underlying mechanisms and policy implications. The paper also relates to the literature on relational contracts (e.g., Brown et al. (2004) for lab evidence), yet most theoretical work assumes one party on each side, and an extensive marketing strategy literature on relationship marketing (e.g., Dwyer et al., 1987; Heide, 1994; Weitz and Jap, 1995; Zhang et al., 2014, 2016).

Second, the paper is closely related to the literature on new product distribution and retail adoption (e.g., Montgomery, 1975; Rao and McLaughlin, 1989). Most papers in this literature rely on retail surveys and acceptance records to analyze factors that affect new product acceptance. Kaufman et al. (2006) find that relationships matter most when new product attractiveness is moderate. Among papers that use retail scanner data, Bronnenberg and Mela (2004) study the geographic and temporal rollout of new brands, Hwang et al. (2010) examine assortment similarities across U.S. supermarkets, and Misra (2008) provides a model for optimal assortment. This paper combines field data with regulations and examines the impact of manufacturer-retailer relationships on new product distribution.

Third, the paper adds to the growing empirical literature on firm conduct (Fan and Sullivan, 2018; Sullivan, 2017; Miller and Weinberg, 2017; Miller et al., 2019; Villas-Boas, 2007; Nevo, 2001).

Fan and Sullivan (2018) provide a theoretically founded empirical model that links to supergames to understand firm competition and estimate markups. This paper adopts their model to a vertical setting. Crawford et al. (2018) study the imperfect internalization between a distributor and its vertically integrated content provider. This paper emphasizes the long-term collaborative relationship between two independent firms. Finally, this paper relates to the recent research on craft beer (Fan and Yang, 2020b; Bronnenberg et al., 2021).

The rest of the paper is organized as follows. Section 2 describes the hard cider market, regulations, and data. Section 3 presents the descriptive evidence of the relationship effect on cider distribution and wholesale discounts. Section 4 presents the structural model that characterize the relationships. Model estimation and identification are discussed in Section 5. Section 6 provides the structural results. Section 7 presents the counterfactual analysis that quantifies the importance of the relationships. Section 8 concludes.

2 Industry Background and Data

This section provides the industry background of hard cider and describes the data for analysis. It discusses the regulations for alcoholic beverages and presents important patterns in data.

2.1 U.S. Hard Cider Market

The hard cider market saw a nine-fold growth in the early 2010s and was the fastest-growing segment in the U.S. alcoholic beverage industry.[3] Its total sales reached $1.2 billion in 2018, including both on- and off-premise sales. Consumer interests in gluten-free, healthy products fuel the growth.

Hard cider is made from fermented apple juice and has a typical ABV (alcohol by volume) from 4.5% to 7%, with some up to 12%. While some niche, high ABV ciders cater to wine drinkers, most cider products are carbonated and designed as refreshing, beer-like drinks. The latter is the focus of this paper. As premium as craft beer, hard cider has a sweeter taste, is gluten-free, and caters to a gender-balanced and younger profile. Ciders are usually sold next to craft beer in stores.

[3] Source: IBISWorld Industry Report and Nielsen Report `https://ciderassociation.org/wp-content/uploads/2019/02/Nielsen-Presn-at-CiderCon-2019_2-7-2019.pdf`. Cider was popular among Americans before Prohibition in 1919, yet it had a low profile after Prohibition until the recent growth. It is popular and has a long consumption history in many places in the world. In the U.K., hard cider accounts for 19% share of the beer market.

To participate in the growth of hard cider, major brewing companies introduce many new brands into the market, including Angry Orchard (by Boston Beer in 2012), Smith & Forge (by MillerCoors in 2014), and Johnny Appleseed (by Anheuser-Busch InBev in 2014). In addition to introducing new brands, the brewers acquire incumbent brands to expand their presence in this rising category. Retailers, on the other hand, expand their cider assortments to cater to increasing customer demand. As shelf space is always limited, they need to choose which new ciders to adopt. Manufacturer-retailer relationships can play an important role in these decisions.

2.2 Industry Regulations

Cider, as well as other alcoholic beverages, is heavily regulated in the U.S. Policies are established at the Federal and State level to tax and regulate the sales and distribution of alcoholic beverages.[4] The goal of these policies is to encourage fair competition and maintain retailer independence. As a result, store brands are rare, and the tools manufacturers can employ to promote their products are limited. In particular, they need to follow restrictions on trade and wholesale pricing practices.

In general, it is illegal for alcohol manufacturers to provide things of value, such as slotting fees to retailers (Gundlach and Bloom, 1998). The Federal level policies, enforced by the Alcohol and Tobacco Tax and Trade Bureau (TTB), cover tax, licenses, and trade practices prohibited between industry members (i.e., producers, importers, and wholesalers) and retailers.[5] Specifically, industry members cannot pay or provide things of value, including slotting fees and services, to retailers for better product placement, distribution, and advertising. Category management is included as services of value. Tie-in sale, defined as an industry member requiring a retailer to purchase one product in order to obtain another product, is not permitted. These practices may result in the exclusion of competitors' products, and hence TTB actively enforce the regulations. For example, Kroger's plan to implement slotting fees for its beer category was shut down by TTB in 2016.[6]

Regulations regarding wholesale pricing practices are established at the State level. States have

[4]Some local governments establish regulations for alcoholic beverages with their jurisdictions, which are not considered in this paper.

[5]The policies are established by the Federal Alcohol Administration (FAA) Act (Title 27 U.S. Code) and Title 27 of the Code of Federal Regulations (CFR). The FAA Act prohibits the following four categories of trade practices: exclusive outlet, tied house, commercial bribery, and consignment sales. The law applies to producers of distilled spirits and wine. It also applies to producers of malt beverages if there is a similar State law, and 48 States have similar trade practice laws.

[6]See the TTB website for a full list of recent enforcement actions.

broad power and more detailed policies than the Federal to regulate alcohol sales and distribution within their borders. The wholesale pricing regulations fall into two types: Post & Hold and volume discount restrictions. Post & Hold requires wholesale prices to be posted and held for a certain period so that all retailers have the chance to buy at the same prices. The Post part usually requires filing price schedules at the State office, but sometimes requires posting price online (e.g., Connecticut) or maintaining a price list at the licensed location for inspection (e.g., Oregon). Volume discount restrictions require the same wholesale price per unit to be charged regardless of the quantity purchased. Based on the alcoholic beverage classification in each state, 16 states require Post & Hold (or just Post) for cider, 14 states ban volume discounts, and 10 of them overlap. Since wholesale discounts are feasible only in states without these restrictions, the difference between restricted and non-restricted states can provide information on the wholesale discounts.

Due to exclusive territories, stores in the same geographic region are usually served by the same wholesaler of a manufacturer (Burgdorf, 2019). Thus, the distributor quality of a manufacturer is the same within a region, and the manufacturer-location fixed effects should fully capture its variation. Although most states have a "three-tier system" that requires the separate operation of producers, wholesalers, and retailers, wholesalers can be seen as representing the interests of manufacturers. Most wholesalers serve one main account only (Anheuser-Busch InBev or MillerCoors) along with some craft brands. They do not have much power compared to the other two tiers (Asker, 2016). The wholesale market is fragmented and has more than 2,000 wholesalers in total, according to the National Beer Wholesaler's Association (NBWA), and Anheuser-Busch InBev alone has 500. The "three-tier system" prohibits private labels because a retailer cannot operate as a manufacturer.

In summary, first, offering things of value to retailers, including slotting fees, services, and payments for retail advertising and display, is prohibited by Federal laws. Thus, these trade practices do not affect cider distribution. Second, wholesale pricing regulations are different across states, which can be used to examine wholesale discounts. Third, the exclusive territory feature implies that manufacturer-location fixed effects can capture the variation in distribution network quality. Last, wholesalers can be seen as representing the interests of manufacturers.

2.3 Data

The main dataset comes from Kilts Center Nielsen Datasets.[7] I use weekly UPC-level hard cider store sales and prices for 2011 to 2016 from Retail Scanner Data. Distribution and store assortment are inferred from the sales data. A store is seen as carrying a product in a given period if the quantity sold is greater than zero, i.e., conditional on the product has any sales.[8] Feature and display information is available for 16% of the stores in the data.[9] I also use Nielsen AdIntel Data for brand-level advertising exposures because marketing supports can greatly affect new product demand.

I use the beer sales data to construct a proxy for manufacturer-retailer relationships. The measure I use is the manufacturer's beer share by retailer in 2010, which is the year before the cider data sample. The past beer share is an outcome of both the relationship itself and the retailer's customers' persistent taste for lager beer. The taste has motivated the pair to collaborate and maintain a good relationship. The past beer share reflects the collaboration level and is thus a good proxy for relationships when studying ciders. Since the past beer share is persistent over time (average serial correlation 0.996), I use the beer shares in 2010 to avoid the direct effect of contemporaneous beer shares.

Table 1 presents the summary statistics of the beer share. Anheuser-Busch InBev and Miller-Coors are the leading brewers, together accounting for more than half of the market. Cider remains as a small category relative to beer ($< 2\%$) throughout the sample.

I collect Federal level and state level regulations for alcoholic beverages. The Federal regulations on trade practices are drawn from the Federal Alcohol Administration (FAA) Act (Title 27 U.S.

[7] I own analyses calculated (or derived) based in part on (i) retail measurement/consumer data from Nielsen Consumer LLC ("NielsenIQ"); (ii) media data from The Nielsen Company (US), LLC ("Nielsen Media"); and (iii) marketing databases provided through the respective NielsenIQ and the Nielsen Media Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are my own and do not reflect the views of NielsenIQ or Nielsen Media. Neither NielsenIQ nor Nielsen Media is responsible for, had any role in, or was involved in analyzing and preparing the results reported herein.

[8] A limitation of this definition is that if a store carries a product but does not sell any in a period, it would be seen as not carrying the product in that period. To mitigate the concern, 1) in the descriptive analysis, I fill in potentially missing carrying observation if a non-seasonal product's sales is positive in the three weeks before and in the three weeks after the focal week; 2) in the structural estimation, I aggregate the data to the monthly level instead of using the weekly level.

[9] Although the selection criteria of the 16% of the stores are unknown, I have checked 1) they cover almost all retail chains, i.e., the selection is on stores, not on chains; 2) the average prices and shares of the products are very similar between those with the information and those without for each chain; 3) descriptive analysis results are close when the sample is a subset to those with the information.

Table 1: Manufacturer Beer Share by Retailer, 2010

Statistic	N	Mean	St. Dev.	Min	Median	Max
Anheuser-Busch InBev	61	0.36	0.12	0.12	0.35	0.59
Boston Beer	61	0.02	0.02	0.001	0.02	0.08
Heineken	61	0.07	0.04	0.01	0.06	0.18
MillerCoors	61	0.27	0.09	0.11	0.25	0.57

Code), Title 27 of the Code of Federal Regulations, and the Alcohol and Tobacco Tax and Trade Bureau (TTB). The State regulations on wholesale pricing practices are collected from the National Institute on Alcohol Abuse and Alcoholism (NIAAA) and the State Statutes and Regulations.

I manually collect cider product attributes from their package, nutrition labels, and websites, including alcohol content, sugar content (correlated with calorie), and whether the product is seasonal.

2.4 Market and Data Summary

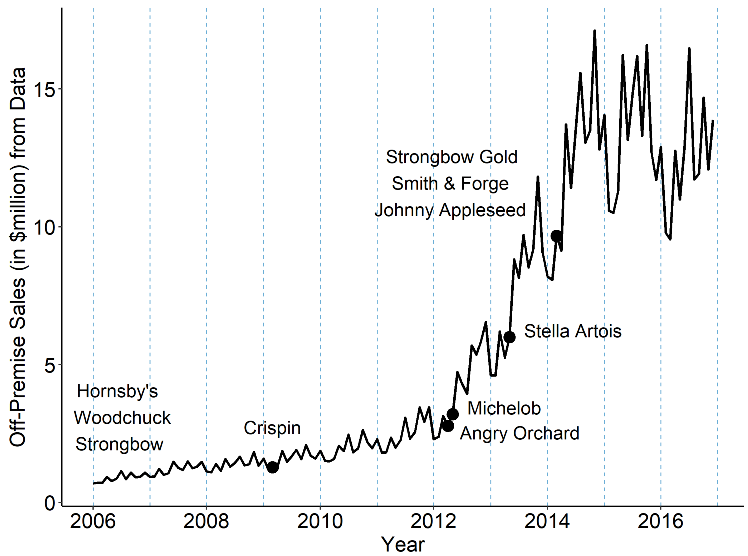
Figure 1 plots the overall cider sales in data from 2006 to 2016. As we can see, the category gradually expanded before 2010 and took off around 2011-2012. Since 2012, six new brands were nationally launched by big brewers, which fundamentally changed the market structure. The market has reached its peak around 2015 and remained stable after that. The category has a strong seasonality, with more sales in summer and fall and less in winter.

Table 2 provides a summary of shares, distribution, and prices of major cider brands. The upper part of the table lists the new cider brands launched by brewers, and the lower part lists the top incumbent brands before the launches. Columns (3) and (4) present two measures of cider distribution, the % product category volume (PCV), defined as the total beer sales in stores that carry the cider brand over all stores, and the percentage of stores that carry the cider brand of all stores. The statistics are based on the last quarter of 2014, when all the expansion, launches, and acquisitions are complete and the stable period starts.[10]

Table 2 provides several key observations of the market. First, large brewers show great interest in this growing category and the market is fairly concentrated. The top five manufacturers (and

[10]Some changes since 2015: Johnny Appleseed and Hornsby's exit the market in the second half of 2016. Regional craft brands (e.g., Bold Rock, 2 Towns Ciderhouse, Austin Eastciders) have been growing in recent years.

Figure 1: Hard Cider Sales and Launch Timing



Notes: Dots indicate the time the brands were launched. The three brands on the left were in the market before the sample starts.

Table 2: Summary Statistics

Brand (1)	Share (2)	% PCV (3)	% Stores (4)	Price (5)	Manufacturer/Importer (6)
New Brands					
Angry Orchard	54.8%	95.1%	70.4%	$8.82	Boston Beer
Strongbow Gold	5.3%	61.8%	30.6%	$9.28	Heineken USA
Smith & Forge	5.1%	76.3%	44.3%	$8.62	MillerCoors
Johnny Appleseed	4%	81.2%	46.9%	$8.37	Anheuser-Busch InBev
Stella Artois	3.5%	62.7%	32%	$10.82	Anheuser-Busch InBev
Michelob	1.5%	39.3%	19.9%	$7.68	Anheuser-Busch InBev
Incumbent Brands					
Woodchuck	10%	69.4%	37.4%	$8.74	C&C Group PLC
Crispin	3.7%	51.5%	23.7%	$10.53	MillerCoors
Hornsby's	1.7%	33.4%	14.2%	$8.08	C&C Group PLC
Strongbow	1.6%	25.4%	12.5%	$9.33	Heineken USA

importers) account for 91.3% of the market share, as we can see from the dollar shares in column (2) and manufacturers in column (6). Angry Orchard from Boston Beer is the absolute leader and takes half of the market. Most brands have fairly high market penetration (columns (3) and (4)), even their shares much smaller than Angry Orchard. Large stores are more likely to carry ciders than small stores, as evidenced by the higher % PCV than % Stores. As the market grows, the top incumbent brands have become big companies' acquisition targets. All four incumbent brands listed here have been changed hands.

Second, the brewers introduce new brands for cider that are not associated with their signature lagers, except for Stella Artois and Michelob. Cider is on the premium side, and the brewers believe their beer brand image may not be "crafty" enough. Consumers are unlikely to recognize the association with the parent brewers, because the new brands have separate labels and websites that do not mention the parent brewers. Thus, umbrella brand spillover is not the reason why retailers favor a particular new brand over others.

Third, Anheuser-Busch InBev and MillerCoors are able to place their products in more stores than other manufacturers with similar sales performance, as shown in columns (3) and (4). For example, Johnny Appleseed and Smith & Forge have a broader distribution than Strongbow Gold and Woodchuck, and more stores carry Michelob than Hornsby's and Strongbow. Thus, Anheuser-Busch InBev and MillerCoors have a better cider distribution than other manufacturers, despite lower shares.

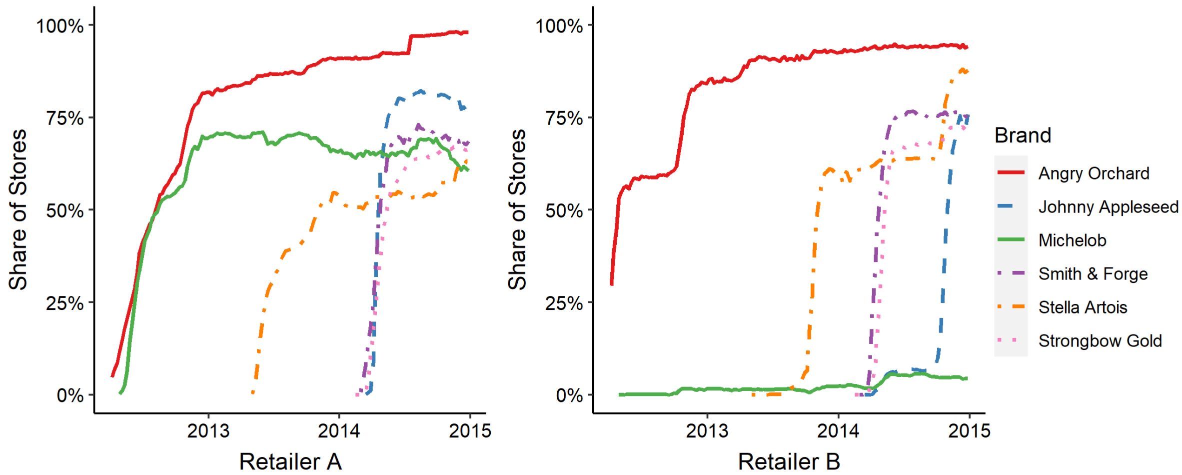
Last, cider brands have similar price positioning. A 6-pack (72oz) cider's price (column (5)) is close to craft beer's price, with half falling between \$8.5 and \$9.5.

2.5 Retailer Cider Adoption

To demonstrate the new cider retail adoption pattern, Figure 2 plots the top 2 grocery retailers in the sample for illustration.[11] The retailers quickly adopted the brewers' new ciders after their launches. The lines on the figure are nearly vertical and suggest that the adoption decisions are centralized at the chain rather than localized at the store because the stores all moved around the same time. In Appendix A.1, I show that retailer factors explain more variation in distribution than location factors, while the opposite is true for sales and prices, suggesting the relationships with retailers could play an important role in cider distribution. The adoption level and timing are different across retailers for some brands. For example, Michelob was well adopted by Retailer A but not by Retailer B. Johnny Appleseed was not immediately adopted by Retailer B. Retailer B has adjusted its adoption of Angry Orchard over time. Such adoption differences could be driven by the differences in their relationships with the brewers.

[11] Angry Orchard is the only brand that uses test markets (a few months in New England) before the national launch. The other brands were launched nationally without test marketing. I ignore the test market period of Angry Orchard in my analysis.

Figure 2: Adoption of Major Brewers' New Ciders: Top 2 Grocery Retailers



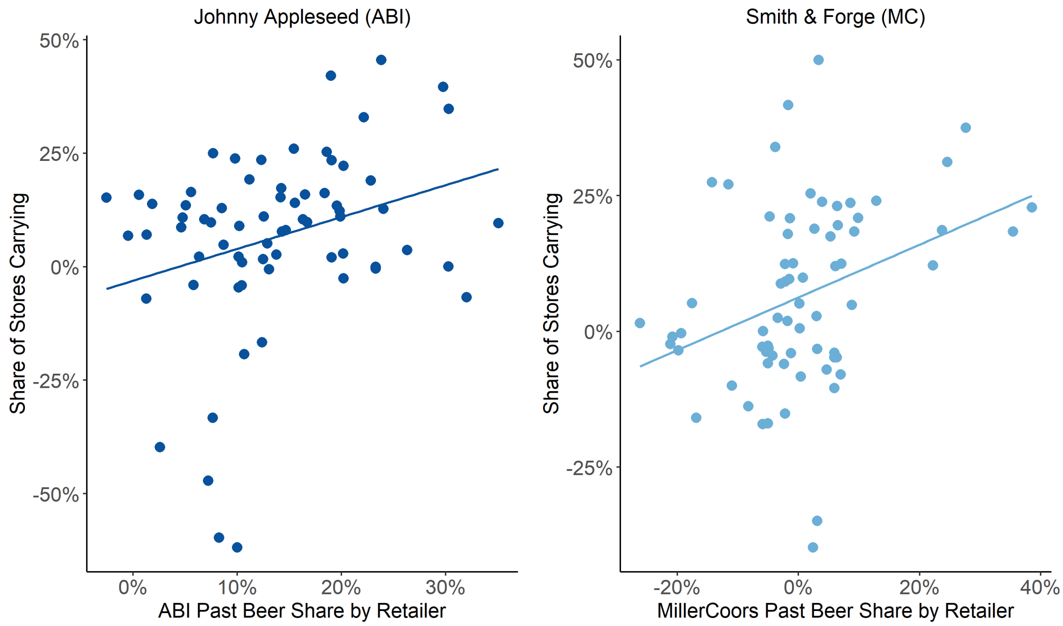
3 Descriptive Evidence

In this section, I present descriptive evidence of the relationship effect on new cider distribution and wholesale discounts. I start with data plots and fixed effects regressions to show a strong and positive association between a manufacturer's past beer share by retailer and the retailer's adoption of the manufacturer's new cider. I interpret the result as a relationship effect and show it is not driven by slotting fee and alternative explanations using a combination of regulations and high-dimensional fixed effects. I exploit the difference in wholesale pricing regulations across states to show manufacturers offer relationships-related wholesale discounts to retailers in states without explicit regulations. Finally, as additional evidence, I use ownership changes to show relationships help place the brewers' acquired craft ciders on the retailers' shelves.

3.1 New Cider Distribution and Manufacturer Past Beer Shares

Plots. If manufacturer-retailer relationships increase new product distribution, the manufacturer's past beer share by retailer should positively correlate with the pair-specific new cider distribution. Figure 3 plots the distribution for two new cider brands introduced by Anheuser-Busch InBev and MillerCoors, respectively. The x-axis is the past beer share, and the y-axis is the share of stores that carry the cider brands. Because hard ciders are in general more popular in retailers that sell less domestic lager beer, I partial out retailer fixed effects to remove the category-level popularity. The plots are based on October 2014 and reflect the cider distribution in the stable period.

Figure 3: New Cider Distribution and Manufacturer Past Beer Share by Retailer



Notes: The plot shows the percentage of stores that carry the cider by retailer in October, 2014 against the manufacturer's beer share by retailer in 2010. The negative numbers are due to retailer fixed effects (across brands) being removed.

As Figure 3 shows, a higher percentage of stores of a retailer carry the new cider brand if the manufacturer has a larger beer share and a stronger presence in the retailer. In other words, heavy Budweiser sellers tend to carry Johnny Appleseed, and heavy Miller and Coors sellers tend to carry Smith & Forge. A 10 percentage points increase in Anheuser-Busch InBev's beer share corresponds to a 7.0 percentage points increase in the share of stores carrying Johnny Appleseed (slope = 0.70), and a 10 percentage points increase in MillerCoors' beer share corresponds to a 4.9 percentage points increase in the share of stores carrying Smith & Forge (slope = 0.49). Both slopes are statistically different from zero. As there is no obvious association between the cider brands and the manufacturers' beer profile, the pattern is consistent with the story that the pair relationships improve the new cider distribution.

Regression analysis. To formally show the pattern and to control for more confounds, I conduct fixed effects regressions of new cider distribution on the past beer share. I focus on the six brands introduced by brewers during the period they were launched (2012-2014). The analysis is at the brand-store-week level:

$$cider\_distribution_{bst} = beer\_share^{2010}_{m(b)r(s)} \times \beta_1 + s^{u,2010}_{br(s)} \times \beta_2 + \lambda_{bc(s)t} + \lambda_{st} + \epsilon_{bst}, \tag{1}$$

where $beer\_share^{2010}_{m(b)r(s)}$ is the aggregate share of manufacturer m's beer products in retailer r in 2010, $s^{u,2010}_{br(s)}$ is the umbrella brand b's beer share in retailer r in 2010, $\lambda_{bc(s)t}$ and λ_{st} are brand-county-week and store-week fixed effects, respectively. I consider two distribution variables: 1) a binary variable that equals one if store s carries brand b in week t (extensive margin), and 2) the log number of products of brand b carried by store s in week t, conditional on the store carries the brand (intensive margin). The coefficient of interest β_1 captures the extent to which the manufacturer past beer share predicts its new cider distribution through the retailer.

The main variations used to estimate β_1 consist of the within-brand, across-retailer variations and the within-retailer, across-brand variations, net of the high-dimensional fixed effects. As the focus is on across-pair differences and the relationships and beer shares are time-persistent, across-time variations are not included in the proxy variable $beer\_share^{2010}_{m(b)r(s)}$. The brand-county-week fixed effects λ_{bct} control for several important factors that could potentially bias the result. First, the brand-week part absorbs the seasonality and category expansion over time, including each brand's different entry and growth time. Second, the brand-county part controls for the possible geographic proximity between production plants and stores, which could lower transportation costs and increase both beer share and cider distribution. Third, the fixed effects capture variations associated with wholesalers (e.g., wholesaler quality) due to the exclusive territory feature, as discussed in Section 2.2. Fourth, they control for the local consumer taste and the TV advertising (which is at the brand-DMA-week level). The store-week fixed effects λ_{st} control for the store and retailer level variations over time, including the gradual expansion of the cider section and the consumer preference for the whole category. The umbrella share variable $s^{u,2010}_{br(s)}$ controls for the popularity of the umbrella brands (Stella Artois and Michelob) among the retailer's customers. I include these two brands and an umbrella beer share control instead of dropping them because the manufacturer's past beer share is mostly driven by other beer brands (e.g., Budweiser).

Results and discussion. Table 3 presents the regression results on the positive association between the brewers' past beer shares in retailers and their new cider adoption. Columns (1)-(3)

Table 3: New Cider Distribution and Manufacturer Past Beer Share by Retailer

	carry	carry	carry	log(#UPC)
	(1)	(2)	(3)	(4)
Mfr. Past Beer Share by Retailer	0.45***	0.50***	0.48***	1.49***
	(0.17)	(0.15)	(0.15)	(0.53)
Umbrella Brand Share by Retailer		6.75***	5.65***	−2.91
		(1.23)	(1.11)	(2.28)
Brand-County-Week FE	Y		Y	Y
Brand-Week FE		Y		
Store-Week FE	Y	Y	Y	Y
Observations	10,499,897	10,499,897	10,499,897	3,325,976
R^2	0.70	0.64	0.70	0.88

Notes: Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

report the result for the binary dependent variable "carry," with column (3) as the preferred model. In the preferred model, a 10 percentage points increase in the past beer share is associated with a 4.8 percentage points increase in new cider brand availability. The results confirm the pattern in Figure 3. The estimate is robust when the umbrella brand share is not controlled (column (1)), or when only brand-week fixed effects are used instead of brand-county-week fixed effects (column (2)). The latter implies that brand-county specific factors, such as the store's distances to brewers and the wholesaler quality, are not the key confounders.

Given a cider brand is carried by a store, the past beer share in the retailer is positively associated with the cider brand presence in the store. Column (4) shows a 10 percentage points increase in the past beer share is associated with a 14.9% increase in the number of products being carried.

The results suggest manufacturer-retailer relationships have a positive effect on new cider availability and presence. As mentioned before, the past beer share is a good proxy for relationships, because it is proportional to the potential gain from the relationship, and retailers often communicate with brewers that have a large share. Further, the main confounding factors are ruled out, including transportation costs and wholesaler quality (captured by fixed effects), and slotting fees and tie-in sales (prohibited by regulations).[12] In Appendix C.7, I show that the manufacturers'

[12] An efficiency gain in shipping costs is unlikely to explain the result in Table 3 for three reasons. First, the manufacturers focused are all large brewers, so their beers need to be shipped to stores regularly anyway, and cider shipping is just a small part of it. Second, the brand-county-week fixed effects control for the shipping costs from cidery to the county, which is the major part of the shipping. Third, I show the results are robust when only focusing

relationships are established with retailers, instead of stores, by including the manufacturer's past beer share by store to the regression. In Appendix C.5, I show that the manufacturer's current beer share does not decrease as the retailer carries its cider, suggesting the results are not due to direct replacement of the manufacturer's beer.[13]

The notion of relationships is related to category captaincy because being selected as a captain reflects a very close relationship with the retailer. However, the captains of alcoholic beverages are different from the usual ones because the things they can do for the retailers are limited (e.g., no free shelving services), although they can still provide assortment recommendations. Further, to show it is not just category captaincy, I run a robustness test without each retailer's highest share manufacturer and find the results robust (see Appendix C.6).

3.2 Wholesale Discounts and Manufacturer Past Beer Shares

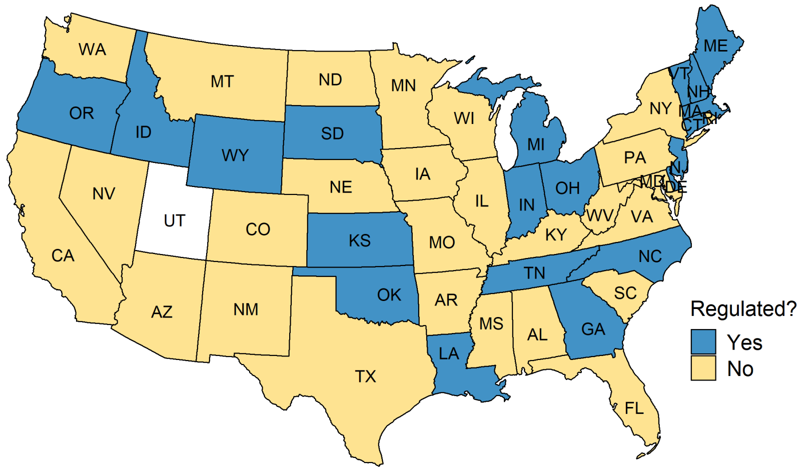
Manufacturers might offer wholesale discounts to retailers with good relationships in states that they are allowed to compensate the retailers. This subsection explores whether there are relationship-related wholesale discounts by leveraging the variation in wholesale pricing regulations across states. I call the states that require Post & Hold or ban volume discount, as discussed in Section 2.2, as "regulated" states, and the states that do not have such requirements as "unregulated" states. I combine states with either or both of the rules because both rules significantly restrict the retailer-specific discounts manufacturers can offer. Figure 4 plots the two types of states.

To explore the possibility of relationship-related wholesale discounts, I examine if the association between cider retail prices and past beer shares is different across the two types of states. I construct an interaction term of past beer share and a dummy for whether a store is in a regulated state (D_s). If the association is negative in unregulated states but close to zero in regulated states, then it suggests the association is between past beer shares and wholesale markups rather than retail markups. It further suggests relationship-related wholesale discounts exist in unregulated states.

on brand-store pairs with positive manufacturer past beer share at the store (see Appendix C.4), so it is not driven by last-mile shipping efficiency.

[13] There is usually a separate shelf for cider next to craft beer in stores. So focal brewers' beers are mainly on a different shelf, and direct exchange is very unlikely. Most cider products have single facing. One might worry that even tie-in sale is illegal, brewers can still offer a wholesale discount for their beer to induce retailers to buy their cider. Appendix C.3 shows the results are robust for states with strict beer wholesale pricing regulations.

Figure 4: Map of Regulated and Unregulated States for Wholesale Pricing



I run the following product-store-week level regression for products being carried:

$$\begin{aligned}\log(cider\_price_{jst}) = {} & beer\_share^{2010}_{m(b)r(s)} \times \beta_1 + beer\_share^{2010}_{m(b)r(s)} \times D_s \times \beta_1' + \\ & s^{u,2010}_{br(s)} \times \beta_2 + s^{u,2010}_{br(s)} \times D_s \times \beta_2' + \lambda_{jc(s)t} + \lambda_{st} + \epsilon_{jst}, \end{aligned} \tag{2}$$

where j indexes products, D_s is a dummy for whether store s is in a regulated state, and the other variables follow the same definition as in equation (1). The coefficient β_1 captures the association of past beer share and cider retail price in unregulated states, and $\beta_1 + \beta_1'$ captures such association in regulated states.

The result in Table 4 shows there are wholesale discounts in unregulated states. Conditional on the same product-county-week, cider prices are low when past beer shares are high, only in unregulated states (-0.09) but not in regulated states (-0.009). The difference is statistically significant. This suggests manufacturers offer wholesale discounts to retailers with good relationships in states they are allowed to compensate the retailers.

Note that the wholesale price result is different from what a bargaining model would imply. A bargaining model would predict high wholesale prices for pairs with high beer shares because beer shares should be positively related to manufacturer bargaining power. The difference is due to the fact that product assortment is taken into account here. Once assortment is taken into account, persuading retailers to carry its product is more important for a manufacturer than giving up some

Table 4: Retail Price and Manufacturer Past Beer Share by Retailer

	log(Price)	
	(1)	(2)
Mfr. Past Beer Share by Retailer	-0.071^{**}	-0.090^{***}
	(0.029)	(0.034)
$\times$ **1**{P&H or Ban Q.D.}		0.081^{**}
		(0.034)
Umbrella Control?	Y	Y
Product-County-Week FE	Y	Y
Store-Week FE	Y	Y
Observations	8,077,969	8,077,969
R^2	0.987	0.987

Notes: Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

margin. Lowering margin and gaining distribution is a better solution for both. The structural model in Section 4 will separately estimate the coordination level and asymmetry of a pair using variations in on-equilibrium profits and deviating profits.

3.3 Distribution Effect in Regulated and Unregulated States

We have so far seen relationships affect both cider distribution and cider wholesale prices. A natural question is whether the distribution effect exists only in unregulated states but not regulated states. Note that almost all retailers in the sample are multi-state retailers operating in both types of states. If the distribution effect appears in both types of states, that suggests the wholesale discounts compensating retailers for carrying the manufactures' ciders in all states and not just the states with discounts.

To this end, I add an interaction term of past beer share and the regulated dummy to the distribution regression in equation (1). The results in Table 5 show that the distribution effect exists in both types of states. The interaction term is negative and statistically insignificant (-0.24) for the binary variable "carry" and positive and statistically insignificant (0.29) for the log number of products carried. The distribution effect is not significantly different across the two types of states, suggesting the wholesale discounts compensate for all states or the relationships include

Table 5: Relationships by the Types of States the Stores in

	carry	log(#UPC)
	(1)	(2)
Mfr. Past Beer Share by Retailer	0.54***	1.41***
	(0.16)	(0.51)
$\times$ $\mathbf{1}\{$P&H or Ban Q.D.$\}$	−0.24	0.29
	(0.14)	(0.56)
Umbrella Control?	Y	Y
Brand-County-Week FE	Y	Y
Store-Week FE	Y	Y
Observations	10,499,897	3,325,976
R^2	0.70	0.88

Notes: Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

other aspects not covered in this paper (e.g., information exchange as in Atalay et al. (2014)).[14]

3.4 Distribution of Incumbent Brands after Acquisition

As additional evidence and a validity check to the main finding of beer share and cider distribution, I look at the incumbent cider brands' acquisitions by major brewers. Specifically, Crispin was acquired by MillerCoors in 2012. Strongbow's importation right was transitioned to Heineken USA as of 2013 to facilitate C&C's acquisition of Vermont Hard Cider Company and gain antitrust approval. Woodchuck and Hornsby's were acquired by Irish cider company C&C (which does not sell any beer in the U.S.). The brewers' acquisitions significantly increased the distribution of Crispin and Strongbow (see Figure 9 in Appendix A.2).

These ownership changes provide within-brand variations to identify the relationships' effect. The idea is that if a brewer has an established relationship with a retailer, the brewer should be able to increase the acquired cider's distribution after the acquisition. Thus, the new owners' past beer shares should be positively associated with the acquired brands' distribution *after* the ownership changes, but not *before* (so it is not that the brewers selectively acquire ciders that cater to their beer drinkers). I estimate equation (1) with data from 2011 to 2014 before and after the ownership changes, respectively.

[14]In Appendix C.2, I present an alternative specification with an interaction of past beer share and the retailer's share of stores in regulated states. The interaction term is also insignificant there.

Table 6: Incumbent Brand Availability, before/after Ownership Change

	Before	After
	(1)	(2)
New Owner's Past Beer Share by Retailer	0.02	0.90***
	(0.31)	(0.33)
Brand-County-Week FE	Y	Y
Store-Week FE	Y	Y
Observations	3,472,499	5,273,256
R^2	0.82	0.77

Notes: The incumbent brands have a single product most of the time. Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

Table 6 presents the results. In column (2), there is a positive association between the new owners' past beer shares and the incumbent cider brands' availability (0.90) after the acquisitions. In the placebo test before the acquisitions (column (1)), the estimate is small and statistically insignificant (0.02). This additional finding supports the main distribution result.

4 Model

In this section, I develop a structural model based on repeated games to characterize manufacturer-retailer relationships. I adopt the pricing supergame in Fan and Sullivan (2018) to a vertical setting. Fan and Sullivan (2018) derive an empirical static model that is theoretically founded and consistent with an infinitely repeated game model. The model differs from the common profit-weight model in an extra term that takes into account how a firm's action affects its partner's incentive compatibility. The model parameters are interpretable as the extent of collaboration and asymmetry between firms. They are related to the repeated game equilibrium and the gains from relaxing the incentive compatibility constraints.

The model has four stages - demand, retail pricing, wholesale pricing, and assortment choice. As shown in the descriptive evidence section, relationships influence manufacturer wholesale pricing and retail assortment choices. The model accounts for demand-side factors in assortments including retailer-specific brand preferences and the substitution between similar products. The model predicts the counterfactual demand and prices, had the stores carried a different set of products.

4.1 Relation to a Repeated Game

I first show the model is consistent with an infinitely repeated game, then later present the details of each stage of the model. The derivation is adapted from Fan and Sullivan (2018) to a vertical setting. Consider an infinitely repeated game between a pair of manufacturer-retailer with grim trigger strategies (i.e., indefinite reversion to Nash equilibrium punishment). Let δ be the discount factor. Each period has four stages:

- Stage 1 (assortment choice): Retailer chooses assortment
- Stage 2 (wholesale pricing): Manufacturer sets wholesale prices
- Stage 3 (retail pricing): Retailer sets retail prices
- Stage 4 (purchase): Consumers make purchases

In stages 1 and 2, the discounted sum of profits $\sum_{t=0}^{\infty} \delta^t \pi_{rt}$ and $\sum_{t=0}^{\infty} \delta^t \pi_{mt}$ are maximized. In stages 3 and 4, the static objectives are maximized. Because the past beer shares are not correlated with retail prices in regulated states, I assume the retailer does not take into account the relationship when setting retail prices. Negotiation over retail prices between manufacturers and retailers was considered per se illegal before Leegin (2007) and still involves a lot of risk nowadays. The timeline of the stage game follows Villas-Boas (2007), Hristakeva (2020) and Fan and Yang (2020a). I assume retailer make separate decisions on assortment and prices because they are in charge by different units within a retail firm.

I assume any deviation from an equilibrium will not be detected by partner until the next period. That is, manufacturers will still charge equilibrium wholesale prices in this period even when retailers choose off-equilibrium assortments, and the punishment starts from the next period. Thus, although this sequential timeline is different from the simultaneous setting in Fan and Sullivan (2018), the equilibrium conditions remain the same.

Consider a Pareto optimal equilibrium of the infinitely repeated game. An equilibrium is Pareto optimal if one cannot increase a party's profit without decreasing another one's. Following Bernheim and Whinston (1990) and Fan and Sullivan (2018), I assume deviations in one market s will be punished by reversing to static Nash equilibrium in all markets $\mathcal{S}$. In this conceptual model, I further assume assortment choice is continuous and a_{st} represents the probability a product is available in market s. With the assumption of Pareto optimality, an equilibrium of assortment a^*

and wholesale prices w^* of the repeated game can be represented as the solution to the following maximization problem with incentive compatibility constraints:

$$\max_{a_{st}, w_{st}, s \in \mathcal{S}} \sum_s \omega_r \pi_r(a_{st}, w_{st}, z_{st}) + \omega_m \pi_m(a_{st}, w_{st}, z_{st}) \tag{3}$$

$$\text{s.t. } \sum_s \left[\pi_r(a_{st}, w_{st}, z_{st}) + \sum_{\tau=1}^{\infty} \delta^\tau E\{\pi_r(a^*(z_{st+\tau}), w^*(z_{st+\tau}), z_{st+\tau})|z_{st}\} \right]$$
$$\geq \sum_s \left[\pi_r^d(w_{st}, z_{st}) + \sum_{\tau=1}^{\infty} \delta^\tau E\{\pi_r(a^{NE}(z_{st+\tau}), w^{NE}(z_{st+\tau}), z_{st+\tau})|z_{st}\} \right] \tag{4}$$

$$\sum_s \left[\pi_m(a_{st}, w_{st}, z_{st}) + \sum_{\tau=1}^{\infty} \delta^\tau E\{\pi_m(a^*(z_{st+\tau}), w^*(z_{st+\tau}), z_{st+\tau})|z_{st}\} \right]$$
$$\geq \sum_s \left[\pi_m^d(a_{st}, z_{st}) + \sum_{\tau=1}^{\infty} \delta^\tau E\{\pi_m(a^{NE}(z_{st+\tau}), w^{NE}(z_{st+\tau}), z_{st+\tau})|z_{st}\} \right] \tag{5}$$

where ω_r and ω_m are the weights of the Pareto optimal equilibrium outcome (up to normalization), z_{st} is the demand shifter, and the superscripts d and NE represent the most profitable deviation and the Nash equilibrium strategy, respectively.

We then obtain the first-order conditions of the above constrained optimization problem:

$$\omega_r \frac{\partial \pi_{rst}}{\partial a_{st}} + \omega_m \frac{\partial \pi_{mst}}{\partial a_{st}} + \gamma_{rt} \frac{\partial \pi_{rst}}{\partial a_{st}} + \gamma_{mt} \left(\frac{\partial \pi_{mst}}{\partial a_{st}} - \frac{\partial \pi_{mst}^d}{\partial a_{st}} \right) = 0 \tag{6}$$
$$\omega_r \frac{\partial \pi_{rst}}{\partial w_{st}} + \omega_m \frac{\partial \pi_{mst}}{\partial w_{st}} + \gamma_{rt} \left(\frac{\partial \pi_{rst}}{\partial w_{st}} - \frac{\partial \pi_{rst}^d}{\partial w_{st}} \right) + \gamma_{mt} \frac{\partial \pi_{mst}}{\partial w_{st}} = 0 \tag{7}$$

where γ_{rt} and γ_{mt} are the Karush-Kuhn-Tucker (KKT) multipliers of the retailer's and the manufacturer's incentive compatibility constraints, respectively. The multipliers are non-negative and exactly zero if the constraint is a strict inequality. They can be interpreted as the change of the pie when the corresponding constraint is relaxed. The multipliers do not have the s subscript because the constraints are pooled across markets.

The above conditions can be rewritten as the following:

$$\frac{\partial \pi_{rst}}{\partial a_{st}} + \theta_{rmt} \frac{\partial \pi_{mst}}{\partial a_{st}} - \rho_{mt} \theta_{rmt} \frac{\partial \pi_{mst}^d}{\partial a_{st}} = 0 \tag{8}$$
$$\frac{\partial \pi_{mst}}{\partial w_{st}} + \theta_{mrt} \frac{\partial \pi_{rst}}{\partial w_{st}} - \rho_{rt} \theta_{mrt} \frac{\partial \pi_{rst}^d}{\partial w_{st}} = 0 \tag{9}$$

where $\theta_{rmt} = \frac{\omega_m+\gamma_{mt}}{\omega_r+\gamma_{rt}}$, $\theta_{mrt} = 1/\theta_{rmt}$, $\rho_{mt} = \frac{\gamma_{mt}}{\omega_m+\gamma_{mt}}$, and $\rho_{rt} = \frac{\gamma_{rt}}{\omega_r+\gamma_{rt}}$. These conditions are equivalent to the first-order conditions of the following static profit maximization problem:

$$\max \pi^r(a_{st}, w_{st}, z_{st}) + \theta_{rmt}\pi_m(a_{st}, w_{st}, z_{st}) - \rho_{mt}\theta_{rmt}\pi_m^d(a_{st}, z_{st}) \tag{10}$$

$$\max \pi^m(a_{st}, w_{st}, z_{st}) + \theta_{mrt}\pi_r(a_{st}, w_{st}, z_{st}) - \rho_{rt}\theta_{mrt}\pi_r^d(w_{st}, z_{st}) \tag{11}$$

Compared to the common profit weight approach, the key difference is in the last term that accounts for how the player's action would affect its partner's deviation profit. I will estimate θ and ρ and calculate ratios of ω and γ. The parameter $\rho \in [0, 1]$ is inversely related to the coordination level, while θ captures the asymmetry of the two players. When $\rho = 1$, the outcome approaches a static Nash equilibrium. When $\rho = 0$, $\gamma = 0$, the incentive constraints are not binding, and (3) becomes an unconstrained optimization. Further, if $\theta = 1$, the outcome corresponds to vertical integration. If $\frac{\gamma_m}{\gamma_r} = \frac{\rho_m}{\rho_r}\theta_{rm} > 1$, relaxing m's incentive constraint would yield a higher objective value of (3) than relaxing r's. More details about the mapping from an infinitely repeated game to a static maximization problem can be found in Fan and Sullivan (2018) and will not be repeated here. Although time-specific θ_t and ρ_t in principle can be estimated with data from each period, I assume time-invariant θ and ρ due to persistence of beer shares.

4.2 Demand

I start with the last stage to present the details of the model. The demand is characterized by a random coefficient logit model (Berry et al., 1995). Consumer i derives the following utility from the purchase of cider j in store s and month t:

$$u_{ijst} = x_{jst}^1\beta_i + \alpha_i p_{jst} + x_{jst}^2\gamma + \xi_{jst} + \epsilon_{ijst}, \tag{12}$$

where p_{jst} is the price, x_{jst}^1 is a vector of product characteristics, x_{jst}^2 is a vector of marketing mix variables, ξ_{jst} is the product-store-month specific shocks, and ϵ_{ijst} is a type 1 extreme value error. The random coefficients (α_i, β_i) follow a multivariate normal distribution with mean ($\bar{\alpha}$, $\bar{\beta}$) and variance $\Sigma = \begin{pmatrix} \sigma_\alpha^2 & 0 \\ 0 & \sigma_\beta^2 \end{pmatrix}$. The vector x_{jst}^1 consists of three variables: *abv*, the alcohol by volume, *sugar*, the amount of sugar per serving, and *seasonal*, whether the product is seasonal. These variables could vary across time and stores because the data is aggregated to the brand-size level. The vector x^2_{jst} consists of four variables: F_{jst}, whether product j is on feature, D_{jst}, whether j is on display, $\log(Ads_{jdt})$, TV advertising level measured by the number of impressions per capita for j in DMA d, and $\log(Ads, all_{dt})$, TV advertising level for the whole cider category in DMA d. I include these marketing mix variables because in-store promotion and advertising are often used for launch support. The consumers in store s and month t choose among cider products $j \in a_{st}$ and the outside option of no purchase, where a_{st} is the set of products offered.

To construct a realistic counterfactual demand and to capture the growth and seasonality of hard cider, I include four types of fixed effects. Specifically, $\xi_{jst} = \xi_{jt} + \xi_{b(j)r(s)} + \xi_{b(j)d(s)} + \xi_s + \Delta\xi_{jst}$. The product-month fixed effects ξ_{jt} absorb the category expansion, seasonality, and each brand's entry time and growing path. The brand-retailer fixed effects ξ_{br} absorb the different brand preferences across retailers. The brand-DMA fixed effects ξ_{bd} capture the local taste and the local advertising intensity. The store fixed effects ξ_s capture the store-specific preferences for the whole category, which shape the substitution towards the outside option. These fixed effects capture the majority of variations in the data and are important for the identification of (α, β, γ).

The share of cider j in store s and month t is given as follows:

$$s_{jst} = \int \frac{\exp(x^1_{jst}\beta_i + \alpha_i p_{jst} + x^2_{jst}\gamma + \xi_{jst})}{1 + \sum_k \exp(x^1_{kst}\beta_i + \alpha_i p_{kst} + x^2_{kst}\gamma + \xi_{kst})} dF(\alpha_i, \beta_i) \tag{13}$$

4.3 Supply

4.3.1 Retail Pricing

In the retail pricing stage, retailer r sets monopolist retail prices for products in store s to maximize the store profit:

$$\max_{p_{jst}, j \in \mathcal{J}_{st}} \quad \pi_{rst} = \sum_{j \in \mathcal{J}_{st}} (p_{jst} - w_{jst}) s_{jst} N_s, \tag{14}$$

where $\mathcal{J}_{st}$ is the set of products carried by store s in month t, w_{jst} is the wholesale price charged by the manufacturer, and N_s is the market size. I assume retailers are monopolist and they know the demand shocks $\Delta\xi_{jst}$ when setting retail prices. w_{jst} includes prices of the goods and transportation costs to the store. The effective wholesale prices are therefore different across stores, even in states where the distributors are required to sell at non-discriminatory prices.

Based on the descriptive evidence of no correlation between past beer shares and retail prices in regulated states, I assume retailers maximize static profits and do not take into account relationships in retail pricing stage. Further, negotiation over retail prices between manufacturers and retailers was considered per se illegal before Leegin (2007) and still involves a lot of uncertainty today. I focus on the firms' decisions on cider and do not model beer. I find a manufacturer's cider does not particularly substitute away its own beer in Appendix C.5, although beer and cider are substitutes in general.

Using the first-order condition of the retail profit function (14), I can invert out the wholesale price vector w_{st}:

$$w_{st} = p_{st} + \left[\Delta^r_{st}\right]^{-1} s_{st}, \tag{15}$$

where Δ^r_{st} is a $|\mathcal{J}_{st}|$ by $|\mathcal{J}_{st}|$ matrix with the (j, j') term equal to $\frac{\partial s_{j'st}}{\partial p_{jst}}$, p_{st} and s_{st} are vectors of retail prices and market shares, respectively.

4.3.2 Wholesale Pricing

In the wholesale pricing stage, manufacturers set wholesale prices based on relationships and institutional constraints. In regulated states (i.e., states that have the Post & Hold law or ban volume discount), manufacturers engage in a static Nash-Bertrand game and do not offer retailer-specific discounts. In unregulated states, manufacturers set prices according to (11), taking into account relationships. They solve the following maximization problem:

$$\begin{aligned} &\max_{w_{jst}, j \in \mathcal{J}_{mst}} \quad \pi_{mst} + \theta^w_{mr} d_s \pi_{rst} - \rho^w_r \theta^w_{mr} d_s \pi^d_{rst} \qquad (16) \\ &= \sum_{j \in \mathcal{J}_{mst}} (w_{jst} - mc_{jst}) s_{jst} N_s + \theta^w_{mr} d_s \sum_{j \in \mathcal{J}_{st}} (p_{jst} - w_{jst}) s_{jst} N_s - \rho^w_r \theta^w_{mr} d_s \sum_{j \in \mathcal{J}^d_{st}} (p^d_{jst} - w^d_{jst}) s^d_{jst} N_s, \end{aligned}$$

where $\mathcal{J}_{mst}$ is the set of products offered by manufacturer m in store s and month t, mc_{jst} is the marginal cost of the manufacturer, and d_s is a dummy variable that equals to one if store s is in an unregulated state. The model assumes that manufacturers know about own and competitors' demand shocks $\Delta\xi_{jst}$ and take into account how retail prices would be set in the following stage. The parameters θ^w_{mr} and ρ^w_r capture the asymmetry and coordination level (inversely) of the manufacturer-retailer pair, respectively.

The marginal costs mc_{jst} include production costs, transportation costs, store-specific supply costs, and cost shocks. I use product-month fixed effects λ_{jt} to capture production costs, which depend on apple prices and could fluctuate over time. I use product-county fixed effects λ_{jc} to capture transportation costs, which depend on manufacturer-to-store distances. I also include store fixed effects λ_s to capture the costs to sell at the stores.

$$mc_{jst} = \lambda_{jt} + \lambda_{jc(s)} + \lambda_s + \eta_{jst}. \tag{17}$$

Using the first-order condition of the manufacturer profit function (16), I can invert out the marginal cost vector mc_{st} as a function of θ^w_{mr} and ρ^w_r:

$$mc_{st} = w_{st} + [\Omega_{st}\Delta^w_{st}]^{-1}\left[s_{st} - \theta^w_{mr} d_s s_{st} + \rho^w_r \theta^w_{mr} d_s s^d_{st}\right], \tag{18}$$

where Δ^w_{st} is a $|\mathcal{J}_{st}|$ by $|\mathcal{J}_{st}|$ matrix with the (j, j') term equal to $\frac{\partial s_{j'st}}{\partial w_{jst}} = \sum_{j'' \in J_{st}} \frac{\partial s_{j'st}}{\partial p_{j''st}} \frac{\partial p_{j''st}}{\partial w_{jst}}$, Ω_{st} is an ownership matrix of the same size with the (j, j') term equal to 1 if j and j' are produced by the same manufacturer and zero otherwise.[15]

The wholesale markup increases in ρ^w_r and decreases in θ^w_{mr} in most cases. Intuitively, when ρ^w_r is lower, m and r are more coordinated, and hence the wholesale markup would be lower to reduce double marginalization. When θ^w_{mr} is higher, r has more bargaining power, or the gain from relaxing r's (m's) incentive constraint is higher (lower), so m's wholesale markup would be lower. If a product is currently being carried but would be dropped had the retailer deviated, θ^w_{mr} also reflects the discount m gives to r for it to be carried. When $\rho^w_r = 1$, the repeated game approaches the static Nash equilibrium and $s^d_{st} = s_{st}$. Equation (18) reduces to the static Nash-Bertrand pricing. When $\rho^w_r = 0$, r's deviation profit does not matter. The markup depends only on θ^w_{mr}, and a weighted sum of m's and r's profits will be maximized. θ^w_{mr} should be less than 1 in this case, otherwise the wholesale markup would be negative.

[15] The derivative of retailer profit π_{rst} with respect to wholesale price w_{st} is $-s_{st} + \Delta^w_{st}(p_{st} - w_{st}) + \Delta^p_{st} s_{st} = -s_{st} + \Delta^p_{st}\Delta^r_{st}\left(-[\Delta^r_{st}]^{-1} s_{st}\right) + \Delta^p_{st} s_{st} = -s_{st}$, where $\Delta^w_{st} = \Delta^p_{st}\Delta^r_{st}$ and Δ^p_{st} is a $|\mathcal{J}_{st}|$ by $|\mathcal{J}_{st}|$ matrix with the (j, j') term equal to $\frac{\partial p_{j'st}}{\partial w_{jst}}$. Similarly, the derivative of π^d_{rst} to w_{st} is $-s^d_{st}$.

Combining equations (17) and (18) gives the following equation:

$$w_{jst} + \Delta^{w}_{jst} = \theta^{w}_{mr} d_s \Delta^{w}_{jst} - \rho^{w}_{r} \theta^{w}_{mr} d_s \Delta^{w,d}_{jst} + \lambda_{jt} + \lambda_{jc} + \lambda_s + \eta_{jst}, \tag{19}$$

where $\Delta^{w}_{jst} = \left([\Omega_{st} \Delta^{w}_{st}]^{-1} s_{st} \right)_j$ is the static Nash-Bertrand wholesale markup and $\Delta^{w,d}_{jst} = \left([\Omega_{st} \Delta^{w}_{st}]^{-1} s^{d}_{st} \right)_j$. Based on the descriptive findings, I assume ρ^{w}_{r} as a function of past beer share. Specifically:

$$\theta^{w}_{mr} = \theta^{w}; \qquad \rho^{w}_{r} \theta^{w} = (\rho^{w}_{0} + \rho^{w}_{1} \times beer\_share^{2010}_{mr}) \theta^{w}. \tag{20}$$

ρ^{w}_{1} is expected to be negative because ρ^{w}_{r} is negatively related to the coordination level.

4.3.3 Assortment Choices

In the assortment stage, retailers choose assortment for each store with the following objective:

$$\max_{\mathcal{J}_{st} \subseteq \mathcal{J}_t} \quad \pi_r(\mathcal{J}_{st}) + \sum_{m} \theta^{a}_{rm} \pi_m(\mathcal{J}_{st}) - \sum_{m} \rho^{a}_{m} \theta^{a}_{rm} \pi^{d}_{m}(\mathcal{J}_{st}) - R_{st}, \tag{21}$$

where R_{st} is the shadow cost to retailer for stocking a cider assortment of size $|\mathcal{J}_{st}|$ in store s and month t, and $\mathcal{J}_t$ is the set of products that are available in month t.

The probability r carries m's products decreases in ρ^{a}_{r} and increases in θ^{a}_{rm} in most cases. If $\rho^{a}_{m} = 1$, the outcome approaches a static Nash equilibrium and $\pi^{d}_{mst} = \pi_{mst}$. Retailer r then chooses assortment based on its static profit π_{rst}. If $\rho^{a}_{m} = 0$, the assortment depends only on θ^{a}_{rm}: r is more likely to carry m's products if m has a larger bargaining power or the gain from relaxing m's (r's) incentive constraint is higher (lower). A close relationship between m and r could yield a negative externality on m's competitors by excluding the competitors' products. In practice, close partners of retailers offer assortment recommendations via shelf plans built on both sides' interests. Retailers decide whether to and the extent to which adopt the plans.

I use a revealed preference approach and assume the observed assortment maximizes the retailer's objective function. Consider a one-step deviation from the observed assortment by replacing a product in the set with a same size alternative. Let $\mathcal{A}_{st}$ denote the set of assortments that include the observed one and all such deviations. The observed assortment $\mathcal{J}_{st}$ satisfies:

$$\mathcal{J}_{st} = \arg \max_{\mathcal{J}'_{st} \in \mathcal{A}_{st}} \left[\pi_r(\mathcal{J}'_{st}) + \sum_m \theta^a_{rm} \pi_m(\mathcal{J}'_{st}) - \sum_m \rho^a_m \theta^a_{rm} \pi^d_m(\mathcal{J}'_{st}) \right]. \tag{22}$$

That is, $\mathcal{J}_{st}$ is optimal, and any one-step replacement deviation does not yield a higher objective value. The shadow shelf cost R_{st} is dropped in equation (22) because the assortment size remains the same in the deviations. The choice over assortment is assumed to be made before the demand shocks $\Delta\xi_{jst}$ and the cost shocks η_{jst} are realized.

Based on the descriptive findings, I assume ρ^a_m and θ^a_{rm} as functions of past beer shares:

$$\theta^a_{rm} = 1/(\theta^a_0 + \theta^a_1 \times beer\_share^{2010}_{mr}); \quad \rho^a_m = \rho^a_0 + \rho^a_1 \times beer\_share^{2010}_{mr}. \tag{23}$$

Specifically, θ^a_{rm} is parameterized in a way that is consistent with $\theta^a \theta^m = 1$. ρ^a_1 is expected to be negative because ρ^a_m is negatively related to a relationship.

5 Estimation and Identification

5.1 Demand

The demand side estimation follows Berry et al. (1995). The analysis is at the product-store-month level, and a product is defined as a brand-size combination. A market includes all potential cider drinkers that visit the store, measured by the monthly average of the beer and cider sold in the store. The sample for structural estimation consists of stores with feature and display information, excluding the small ones (i.e., average quantity sold less than 10 per product per month) due to imprecision in share computation. I include the top 42 products that account for 90% of the sales in the data. The final sample consists of 1,410 stores and 433,210 observations. All volumes and prices are normalized to the 6-pack 12oz equivalent. The key parameters to estimate are $\{\alpha, \beta, \gamma, \Sigma\}$.

The identification follows the standard discussion of a random coefficient logit model estimated with aggregate demand data and generalized method of moments. The rich set of fixed effects captures the majority of variation in data and has an important role in estimating the parameters. The marketing mix variables are assumed exogenous conditional on the fixed effects. Specifically, the advertising effects are identified by the variations within brand-DMA across time, and the feature and display effects are identified within brand-retailer across stores and time.

To handle potential price endogeneity caused by firm knowledge of demand shocks $\Delta\xi_{jst}$ when setting prices, I use the average price of the same product in other retailers in other counties within the state as an instrument. This instrument and the price variable share the same local costs, such as the state excise tax and local transportation costs.

To estimate random coefficients, I use instruments that capture how much competition a product faces in a market, namely, the counts of products with similar characteristics. The characteristics include 1) the same pack size (e.g., 6-pack), 2) overall average price difference within fifty cents and the same pack size, 3) overall average price difference within one dollar and the same pack size, 4) abv difference within 0.5% and same pack size, 5) sugar difference within 2 grams and the same pack size, and 6) seasonal cider. These instruments are likely to be exogenous because, given the rich fixed effects, the remaining demand shocks $\Delta\xi_{jst}$ are unlikely to be realized before the assortment is chosen. The changes in market shares, as the counts of products with similar characteristics change, identify the random coefficients.

5.2 Supply

The supply model is estimated sequentially in reverse order starting from the retail pricing stage. I first back out wholesale prices using first-order conditions of the retail profit function in equation (15). Then, I estimate the wholesale pricing parameters θ^w_{mr} and ρ^w_r in equation (19) with a linear instrumental variable approach. Finally, I estimate the assortment parameters θ^a_{mr} and ρ^a_m via maximum likelihood. I take the demand estimates and the results in previous steps as given throughout the three steps.

Wholesale pricing. I use an instrumental variable approach to estimate θ^w, $\rho^w_0\theta^w$, and $\rho^w_1\theta^w$ in equation (19). The terms Δ^w_{jst} and $\Delta^{w,d}_{jst}$ are endogenous because both the derivative matrix Δ^w_{st} and market shares s_{st}, s^d_{st} depend on prices, which are affected by cost shocks η_{jst}. To solve this endogeneity problem, I use demand shifters (Berry and Haile, 2014) and past beer shares as instruments to identify the supply parameters. Based on the suggestions in Fan and Sullivan (2018), I use the market size, unobserved characteristics $\Delta\xi_{jst}$, and the number of seasonal products by rivals in the market as demand shifters, all interacted with the unregulated dummy d_s. Standard errors are clustered at the product-store level. The first stage p-values of the F-statistics of the excluded instruments are 0.00 for all three variables.

To compute s^d_{st}, I first estimate the model using the profit weight approach (i.e., without the last term in equation (16)), which is an approximation to the micro-founded model in equation (16)). Then I use the estimates to simulate the deviation scenario. I assume products in the observed assortment charge the same wholesale prices, and products not in the observed set charge the profit maximizing prices. I repeat the above steps with the new estimates and find the results very close.

Assortment choices. I use a revealed preference approach with maximum likelihood to estimate θ^a_0, θ^a_1, ρ^a_0, and ρ^a_1. Denote $\hat{\pi}_r(\mathcal{J}_{st})+\sum_m \theta^a_{rm}\hat{\pi}_m(\mathcal{J}_{st})-\sum_m \rho^a_m\theta^a_{rm}\hat{\pi}^d_m(\mathcal{J}_{st})$ as r's true objective value associated with assortment $\mathcal{J}_{st}$. Assume the observed assortment $\mathcal{J}_{st}$ maximizes the objective. Hence, for any alternative assortment $\mathcal{J}'_{st} \in \mathcal{A}_{st}$,

$$\left[\hat{\pi}_r(\mathcal{J}_{st}) + \sum_m \left(\theta^a_{rm}\hat{\pi}_m(\mathcal{J}_{st}) - \rho^a_m\theta^a_{rm}\hat{\pi}^d_m(\mathcal{J}_{st})\right)\right] - \left[\hat{\pi}_r(\mathcal{J}'_{st}) + \sum_m \left(\theta^a_{rm}\hat{\pi}_m(\mathcal{J}'_{st}) - \rho^a_m\theta^a_{rm}\hat{\pi}^d_m(\mathcal{J}'_{st})\right)\right] \geq 0. \tag{24}$$

As described in Section 4.3.3, $\mathcal{A}_{st}$ consists of the observed assortment and all one-step deviations of replacing a product in the set with a same size alternative. Thus, there is no changes in shelf space requirements. Further, to minimize the concern that the replacement product is not currently carried due to the product not being available in the region at all instead of due to the retailer's assortment choice, I restrict the replacement set to products available in the same county (i.e., sold in other stores within the county).[16] In total, I construct 591,170 one-step replacement deviations from the 46,830 observed assortments at the store-month level.[17]

Following Crawford et al. (2018), I assume $\omega(\mathcal{J}_{st})$ to be the measurement error of the true objective associated with assortment $\mathcal{J}_{st}$. That is,

$$\omega(\mathcal{J}_{st}) = \left[\hat{\pi}_r(\mathcal{J}_{st}) + \sum_m \left(\theta^a_{rm}\hat{\pi}_m(\mathcal{J}_{st}) - \rho^a_m\theta^a_{rm}\hat{\pi}^d_m(\mathcal{J}_{st})\right)\right] - \left[\pi_r(\mathcal{J}_{st}) + \sum_m \left(\theta^a_{rm}\pi_m(\mathcal{J}_{st}) - \rho^a_m\theta^a_{rm}\pi^d_m(\mathcal{J}_{st})\right)\right], \tag{25}$$

where $\omega(\mathcal{J}_{st})$ is type 1 extreme value distributed with scale parameter σ^ω and i.i.d. across assortment-

[16] To sell its hard cider in a state, a manufacturer needs to contract with a licensed beer distributor in the state. The manufacturer may find it better not to sell in the state/region at all if it cannot reach the economies of scale. The manufacturers' contracting decision with distributors is beyond the scope of the paper.

[17] There are other types of deviations, such as adding or removing a product, which will lead to changes in shelf space for the category and involve comparisons with products outside the category. I do not consider those deviations, and shelf space allocation across categories is beyond the scope of the paper. On the other hand, the set $\mathcal{A}_{st}$ could be expanded to include multi-step deviations that are combinations of the one-step replacement deviations.

store-month. The probability that $\mathcal{J}_{st}$ is the observed assortment is thus:

$$\Pr(\mathcal{J}_{st}) = \frac{\exp\left[\left(\pi_r(\mathcal{J}_{st}) + \sum_m \left(\theta^a_{rm}\pi_m(\mathcal{J}_{st}) - \rho^a_m\theta^a_{rm}\pi^d_m(\mathcal{J}_{st})\right)\right)/\sigma^\omega\right]}{\sum_{\mathcal{J}'_{st}\in\mathcal{A}_{st}}\exp\left[\left(\pi_r(\mathcal{J}'_{st}) + \sum_m \left(\theta^a_{rm}\pi_m(\mathcal{J}'_{st}) - \sum_m \rho^a_m\theta^a_{rm}\pi^d_m(\mathcal{J}'_{st})\right)\right)/\sigma^\omega\right]}. \quad (26)$$

To compute the profits π_{rst}, π_{mst}, and π^d_{mst} for each deviation $\mathcal{J}'_{st}$, I construct demand and supply variables for the replacement product j' and solve for the new equilibrium wholesale and retail prices for all products in $\mathcal{J}'_{st}$. Specifically, the advertising variables are directly observed at the brand-DMA-month level. Feature and display variables are extrapolated to be the same retailer-month average because retailers often use the same promotion strategy across stores. Product characteristics are extrapolated to be the same state-retailer-month average. The various fixed effects follow the model estimates. To compute π^d_{mst}, I simulate wholesale prices that maximize the deviating manufacturer's current period profit, keeping other manufacturers unchanged.

With θ^a_{rm} and ρ^a_m being functions of past beer shares, the log-likelihood is then:

$$LL(\theta^a_0, \theta^a_1, \rho^a_0, \rho^a_1, \sigma^\omega) = \sum_{st} \log(\Pr(\mathcal{J}_{st})). \quad (27)$$

I normalize the weight on retailers' own profits to one and estimate the scale of the measurement error σ^ω instead.

The identifying variation of θ^a and ρ^a comes from how retail assortments respond to changes in manufacturers' and retailers' profits. As ρ^a decreases (i.e., coordination level increases), assortments respond less negatively to manufacturers' deviating profits. As θ^a increases, assortments respond more strongly to manufacturers' profits than retailers' profits. For example, if a retailer prefers a relatively low π_{rst} and high π_{mst} over a relatively high π_{rst} and low π_{mst} and responds more strongly to π_{mst} than π^d_{mst}, then θ^a_{mr} (θ^a_0) would be high (low) and ρ^a_0 would be low (in magnitude). The correlation between the assortment response and past beer shares identifies θ^a_1 and ρ^a_1.

6 Results

6.1 Demand Estimates

Table 7 reports the demand estimates. The first column presents the logit specification following Berry (1994). The second and third columns present the main specification with random coefficients on price and alcohol content following Berry et al. (1995).[18] Both specifications include product-month, brand-retailer, brand-DMA, and store fixed effects.

In the main specification (2), the mean price coefficient is negative and significant (-0.632), and implying that consumers buy less cider as the price increases. The price random coefficient is large and marginally significant (0.187), suggesting a sizable heterogeneity in consumer price sensitivity. These estimates translate to an average own price elasticity of -3.89. The magnitude of the elasticity is slightly smaller than lager beer in the literature (Miller and Weinberg, 2017), which is reasonable because hard cider is on the premium side of alcoholic drinks.

There is also significant heterogeneity in alcohol content preference. While the average consumer prefers low alcohol ciders (-0.808), a portion of consumers like high alcohol drinks (sd = 0.558) and they buy more cider than others. Without this random coefficient, one could reach the wrong conclusion that consumers on average prefer high alcohol cider (0.227) as in specification (1). Consumers also like seasonal ciders (0.476) and ciders with less sugar (-0.014). The substitution between similar ciders is accounted for in retailers' assortment choices.

For marketing support, own advertising has a positive and statistically insignificant effect on utility (0.023), with an average elasticity of 0.02. Category advertising has a negative and insignificant effect (-0.003), with an average elasticity of -0.002. Fixed effects absorb most of the variation in these variables. Display has a positive and significant role in purchases (0.427). The effect is comparable to a \$1 decrease in price (average \$9.55), showing that display is important for a new category. The estimate for feature is negative and significant (-0.051). One should take this result with a grain of salt because there might not be enough variation to separate feature from display after controlling for brand-retailer fixed effects.

[18] An alternative specification that includes four random coefficients on price, alcohol content, sugar, and seasonal yields nearly identical estimates with insignificant random coefficients of the latter two.

Table 7: Demand Estimates

	(1) logit	(2) random coef. logit mean	sd
Price	−0.391***	−0.632***	0.187*
	(0.013)	(0.179)	(0.098)
Abv	0.227***	−0.808***	0.558***
	(0.012)	(0.361)	(0.085)
Seasonal	0.426***	0.476***	
	(0.013)	(0.017)	
Sugar (g)	−0.013***	−0.014***	
	(0.001)	(0.002)	
log(Ads)	0.016	0.023	
	(0.017)	(0.024)	
log(Ads, all)	0.001	−0.003	
	(0.009)	(0.010)	
Feature	−0.006	−0.051***	
	(0.014)	(0.017)	
Display	0.401***	0.427***	
	(0.006)	(0.012)	
Avg Own Price Elasticity	−3.73	−3.89	
Product-Month FE	Y	Y	
Brand-Retailer FE	Y	Y	
Brand-DMA FE	Y	Y	
Store FE	Y	Y	
Observations	432,210	432,210	

Notes: The observation unit is brand-size-store-month. The price instrument is the average price of the same product in other retailers in other counties within the state, and has a first stage t-stat of 73. Advertising variables are measured by the number of impressions per capita. *p<0.1; **p<0.05; ***p<0.01

6.2 Supply Estimates

Pricing. Table 8 reports the parameter estimates for wholesale pricing and the average recovered margins.[19] Based on the estimates, Figure 5 plots how the coordination parameter ρ^w changes with past beer shares. As past beer shares increase, ρ^w decreases, implying a higher coordination level. For brewers with low market shares (e.g., Heineken, Boston Beer), ρ^w is close to 1, suggesting no coordination between them and the retailers. For brewers with high market shares (e.g.,

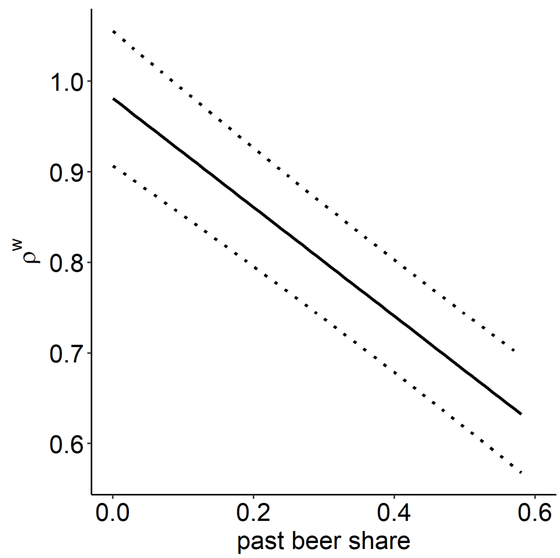
[19] Ohio is excluded from supply estimation because of its minimum markup requirement on alcoholic beverages. Two retailers that were not in the data in 2010 are excluded.

Table 8: Pricing Estimates

θ^w	0.67***
	(0.05)
$\rho_0^w \times \theta^w$	0.66***
	(0.03)
$\rho_1^w \times \theta^w$	−0.40***
	(0.09)
Average retail margin	35.9%
Average wholesale margin	34.3%
Average wholesale price (6-pack)	$6.26

Notes: Standard errors are clustered at the product-store level. *p<0.1; **p<0.05; ***p<0.01

Figure 5: ρ^w and past beer share



Anheuser-Busch InBev, MillerCoors), ρ^w is different from either 0 or 1, suggesting a moderate level of coordination. The asymmetry parameter θ^w is estimated to be 0.67, meaning the sum of the weight ω and KKT multiplier γ is higher for manufacturers than for retailers.

The estimates suggest Anheuser-Busch InBev and MillerCoors on average provide a 7.6% and 5.5% discount in wholesale prices to retailers in unregulated states. The discounts compensate retailers for the help with assortment and mitigate double marginalization. The results are consistent with the finding in Table 4.

As for the margins, the average recovered retail margin ($\frac{p-w}{p}$) is 35.9%, matching up with the 35% based on beer industry studies in Tremblay and Tremblay (2005). The implied average wholesale price is $6.26 per 6-pack. The average recovered wholesale margin ($\frac{w-mc}{w}$) is 34.3%, accounting for 21.7% of retail prices. Less than 0.06% of the recovered marginal costs are below zero.

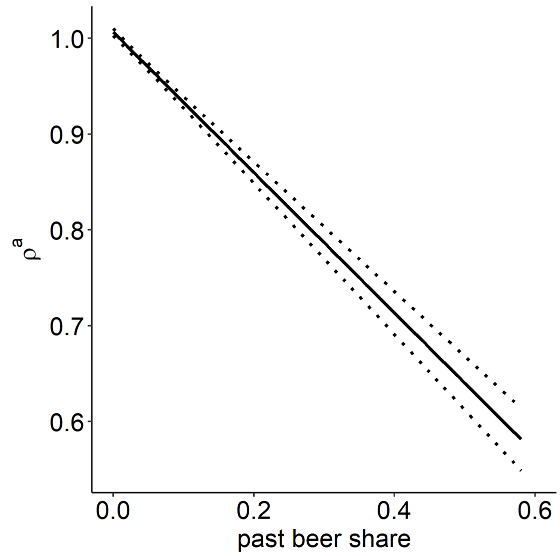
Assortment Choice. Table 9 reports the parameter estimates for assortment choices. Figure 6 provides the corresponding plot of ρ_a against past beer shares. We can see as past beer shares increase, ρ_a decreases, and the coordination level goes up. There is almost no coordination for Heineken and Boston Beer (low market shares). On the contrary, there is some but imperfect coordination for Anheuser-Busch InBev and MillerCoors. Retailers carry more of Anheuser-Busch

Table 9: Assortment Estimates

θ^a_0	0.16***
	(0.003)
θ^a_1	-0.004
	(0.03)
ρ^a_0	1.01***
	(0.002)
ρ^a_1	-0.73***
	(0.03)
σ^ω	0.04***
	(0.0004)

Notes: Standard errors in parentheses are based on the assortment stage only. *p<0.1; **p<0.05; ***p<0.01

Figure 6: ρ^a and past beer share



InBev's and MillerCoors' ciders than what profits imply.[20]

The estimates of θ^a_0 and θ^a_1 suggest the sum of weight ω and KKT multiplier γ is higher for manufacturers than for retailers, because $\theta^a_{rm} = 1/(\theta^a_0 + \theta^a_1 \times beer\_share^{2010}_{mr})$. Since $\theta^a_{rm} = 1/\theta^w_{mr}$, the θ estimates in both stages theoretically should be equivalent. Empirically, I find both estimates have the same direction but different magnitude.

6.3 Ratios γ_r/γ_m, ω_r/ω_m, γ/ω and Implications for Policies

The estimates of θ and ρ contain information of the underlying weight parameters ω and KKT multipliers γ. Specifically, the following ratios can be backed out from the model estimates:

$$\frac{\gamma_r}{\gamma_m} = \theta_{mr}\frac{\rho_r}{\rho_m}; \qquad \frac{\omega_r}{\omega_m} = \theta_{mr}\frac{1-\rho_r}{1-\rho_m}; \qquad \frac{\gamma_r}{\omega_r} = \frac{\rho_r}{1-\rho_r}; \qquad \frac{\gamma_m}{\omega_m} = \frac{\rho_m}{1-\rho_m}.$$

[20]A natural question is whether the results are driven by the ex-ante trust placed in Anheuser-Busch InBev's and MillerCoors' products, yet they do not perform well compared to Boston Beer's Angry Orchard and Heineken's Strongbow Gold. Such a situation may not be foreseen by the retailers when they first decided to carry the products. To answer this question, I have done a robustness check and restricted the sample to October 2014 onward, when all major brands have entered for at least six months and demand has been stable. The results are close.

Figure 7: Ratios of γ and ω

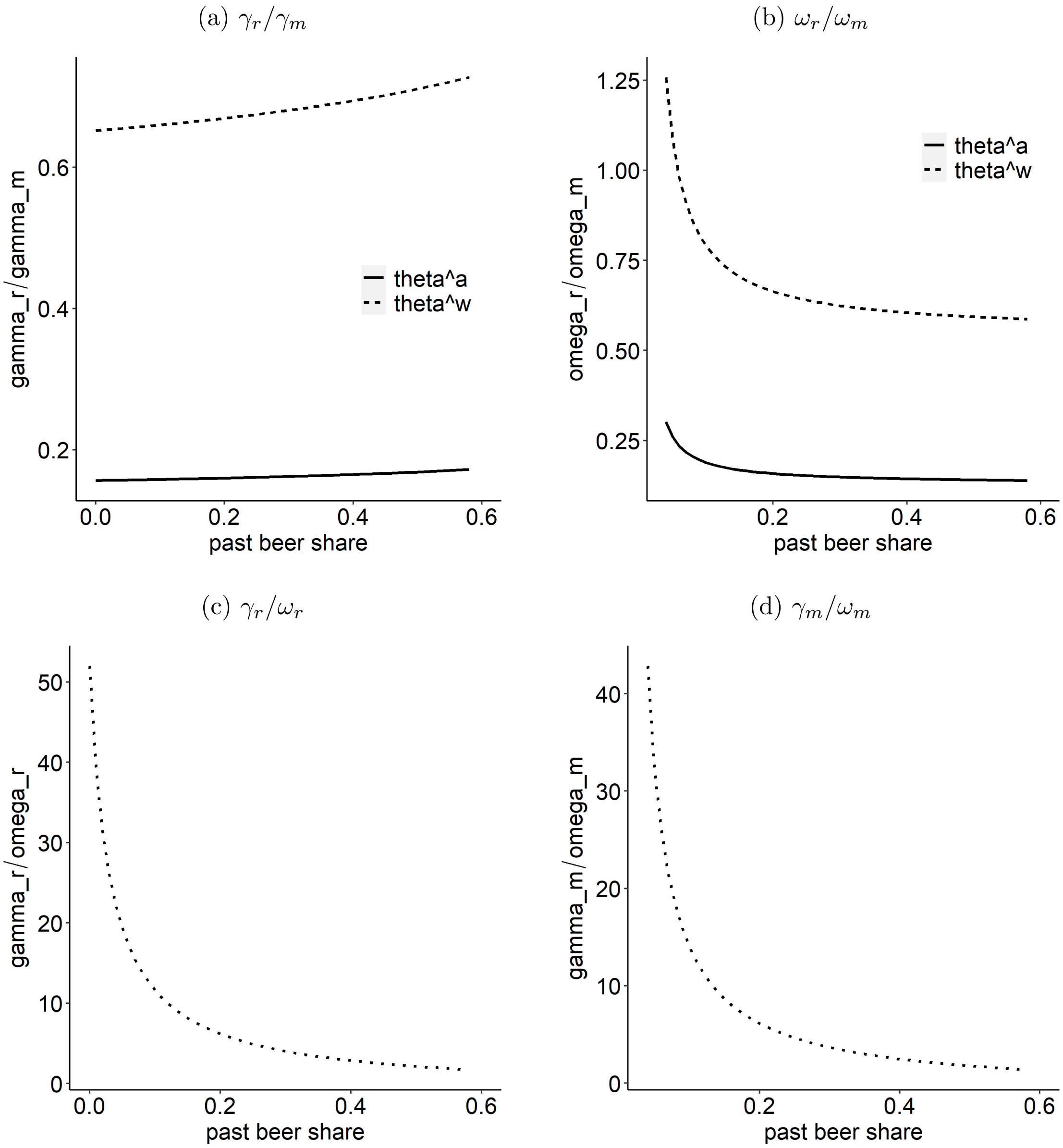


Figure 7 presents the ratios and how they change with past beer shares. If we fix the value of one of $\{\gamma_r, \gamma_m, \omega_r, \omega_m\}$, the other three can be recovered from the ratios.

The value of γ_r/γ_m (Figure 7 panel (a)) implies that the KKT multipliers of manufacturers' incentive constraints are greater than the retailers'. In other words, relaxing manufacturers' incentive compatibility constraints will yield a larger increase of the objective (3) than relaxing retailers' constraints. Although the two estimates (based on $\hat{\theta}^w$ and $\hat{\theta}^a$, respectively) are different, they both suggest $\gamma_m > \gamma_r$.

The value of ω_r/ω_m (Figure 7 panel (b)) shows how manufacturers' and retailers' profits are weighted in the objective (3). Retailers' weight becomes smaller as the past beer share increases. Big brewers Anheuser-Busch InBev and MillerCoors have a larger weight than retailers. Because manufacturers' profits are smaller than retailers' profits per store, percentage-wise retailers' profits are larger weighted.

The ratios γ_r/ω_r and γ_m/ω_m (Figure 7 panels (c) and (d)) capture the gain from relaxing incentive compatibility constraints normalized by the level of profit weights. As the past beer share increases, the coordination level increases, and the normalized gain decreases.

The values of the ratios have implications for policies. If policymakers relax regulations on vertical practices for alcoholic beverages, the ratios inform potential changes to profits. For example, if a regulation looses m's constraint by $\$x$ per period, the objective $\omega_m \pi_m + \omega_r \pi_r$ would go up by $\$\gamma_m \frac{1-\delta}{\delta} x$. A larger increase in the weighted sum implies a stronger relationship can be formed under the new policy. Practices such as slotting fees, rebates, and longer credit period can loose retailers' as well as manufacturers' constraints by giving them additional tools to coordinate on, so that they will not solely rely on assortment and wholesale discounts.

7 Counterfactual: Impact of Manufacturer-Retailer Relationships

In this section, I quantify the impact of manufacturer-retailer relationships with counterfactual simulations. I compare the current scenario with a counterfactual scenario in which all players maximize their static profits. The regulations for alcoholic beverages currently allow for only a limited set of vertical practices, namely wholesale discounts in certain states, assortment recommendation, and information exchange. Implementing posted wholesale prices in all states will significantly reduce retailer collaboration incentive and lead to a potential collapse of the relationship. The comparison of the two scenarios will inform us the value of relationships to manufacturers and retailers, as well as the potential impact of a fully tightened wholesale pricing law.

The simulations take the following steps. First, I construct the set of potential assortments from one-step replacement deviations. The replacement product has to be of the same size and available in the county. Second, for each possible assortment and for either scenario, I solve for the equilibrium wholesale and retail prices using equations (15) and (18) based on the structural estimates of costs and demand. I follow the same procedure to construct variables for products currently not being carried as in Section 5.2 and set $\Delta\xi_{jst} = 0$ and $\eta_{jst} = 0$ for tractability.[21] Finally, retailers select the objective maximizing assortment out of the set for each scenario.

Table 10 presents the simulation results. Overall, relationships provide a double win to both sides. The results are presented as percentage difference between the current scenario and the no-relationship scenario. Anheuser-Busch InBev and MillerCoors gain 17.3% and 5.1% in distribution and 9.7% (\$0.5m) and 1% (\$0.1m) in profits, respectively. Retailers have a profit increase of 1.1% (\$2.1m) due to wholesale discounts, despite the loss from compromised assortments. The compromises do not hurt the retailers much, since they prefer partners' products over other manufacturers' only if the profit differences are small. Such choices, however, could have a big impact on manufacturers, because it is an "in or out" difference. As a return, the manufacturers offer wholesale discounts, which mitigate the double marginalization problem. Together, Anheuser-Busch InBev, MillerCoors, and the retailers' profits increase by 1.4% (\$2.7m). The retailers as intermediaries are thus non-independent and can be seen as "partially integrated" with the largest brewers.

The gains of the largest brewers and retailers are at the expense of other cider manufacturers. They lose distribution and profit as a result of lacking relationships and being left out of coordination. Specifically, Heineken loses 7.8% (−\$0.6m), Boston Beer loses 0.9% (−\$0.6m), and craft ciders lose 2.7% (−\$0.9m). Together, they lose 1.9% (−\$2.1m) in profits.

The overall channel sees a slight profit increase of 0.2% (\$0.6m) from the combined impact of reduced double marginalization and sub-optimal assortments. Consumers' welfare goes up by 1.1% (\$2.3m) due to the reduced double marginalization, despite worse assortments. This result should be interpreted with caution because alcohol consumption is not always good.

The results highlight the strategic importance of relationships for promoting new products and maintaining market-dominant positions. As many CPG manufacturers face stagnation and decline in their main products in recent years, the distribution advantage from their close relationships with retailers can help them thrive in new product markets and categories. Relationships can thus have a profound impact on market structure and contributes to the concentration of CPG markets.

Policy-wise, the results demonstrate the potential impact of implementing posted wholesale

[21] The demand model explains 68% of the variations in $\log(s_{jst}) - \log(s_{0st})$ (i.e., $\Delta\xi_{jst}$ explains 32%). The R^2 is 0.95 in the estimation of θ^w and ρ^w.

Table 10: Impact of Relationships

		Relationship Impact (percentage change)	Absolute change ($m) (industry per year)
Anheuser−Busch InBev	Distribution	17.3%	
	Profit	9.7%	0.5
MillerCoors	Distribution	5.1%	
	Profit	1%	0.1
Heineken	Distribution	−7.5%	
	Profit	−7.8%	−0.6
Boston Beer	Distribution	−1.3%	
	Profit	−0.9%	−0.6
Craft Ciders	Distribution	−3.8%	
	Profit	−2.7%	−0.9
Retailers	Profit	1.1%	2.1
Retailers+ABI+MC	Profit	1.4%	2.7
HN+BB+Craft	Profit	−1.9%	−2.1
Channel (M+R)	Profit	0.2%	0.6
Consumer	Surplus	1.1%	2.3

Notes: The relationship impact is defined as the relative difference of the status quo and the no-relationship scenario. The distribution measure is averaged across products.

prices as a federal level policy. The results also shed light on the role of wholesale price discrimination in the presence of manufacturer-retailer relationships. Because retailers' gain from relationships relies on the discounts received, taking away wholesale discounts can lead to relationships collapse. Thus, implementing posted prices nationwide can lead to a shift in assortment and a decrease in large manufacturers' cross-category spillover ability. The welfare impact of such a policy hinges on the trade off between a decrease in double marginalization and a better assortment.

Finally, the generalizability of the results depends on market structure and regulations. Relationships will play a significant role in markets with high concentration. Regulations determine the set of tools available for both sides to collaborate on and form relationships. The relationship impact estimated in this paper would readily apply to duopoly markets with wholesale discounts being the main subsidy offered by manufacturers.

8 Conclusion

In this paper, I study the relationships between manufacturers and retailers in a unique setting. I provide empirical evidence of preferential treatments between manufacturers and retailers in assortment choice and wholesale pricing. I estimate a theoretically founded structural model to quantify the relationship impact and draw policy implications. The findings show the leading manufacturers are able to increase new product availability through the relationships with retailers even in a heavily regulated setting. The relationships contribute to large CPG manufacturers' long-run dominance and present a strong cross-category spillover. Implementing posted wholesale prices nationwide could break the relationships, resulting in increased double marginalization and better assortments.

The paper can be extended in two ways. First, the paper has focused on assortment and wholesale prices in relationships. Other types of vertical arrangements such as rebates, fixed transfers, information exchange, and their influence on relationships would be interesting to explore. Second, the paper has focused on characterizing the present relationships between manufacturers and retailers. Understanding how relationships are developed and changed over time through communication and relationship-specific investment is another important extension.

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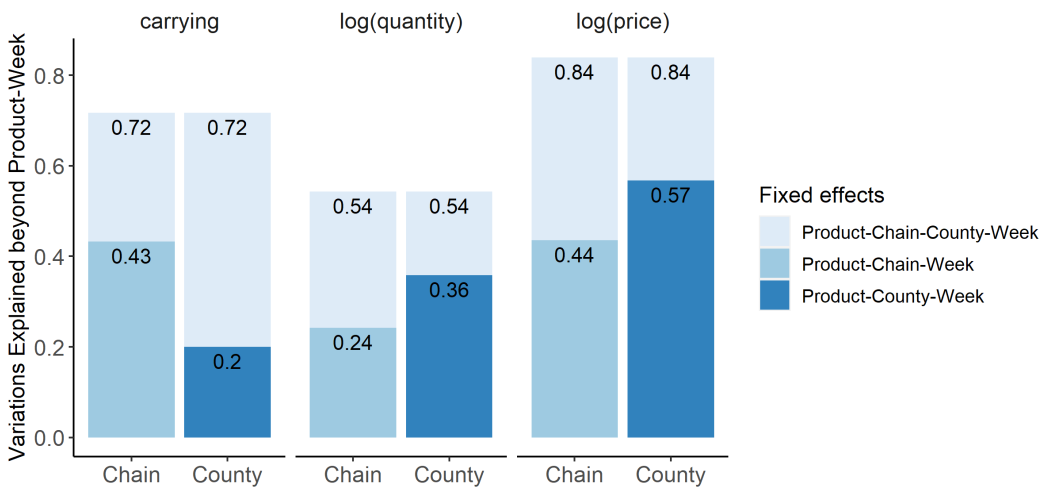
Appendix

A Additional Data Patterns

A.1 Analysis of Variance

This section examines the extent to which the variations in cider assortment, sales, and prices can be explained by retail chain factors versus location factors. I conduct an analysis of variance for 1) whether a store carries a product, 2) the log quantity sold, and 3) log price conditional on carrying. I include product-*chain*-week and product-*county*-week fixed effects separately in the regressions and compare their R^2.

Figure 8: Variations in Distribution, Sales, and Prices



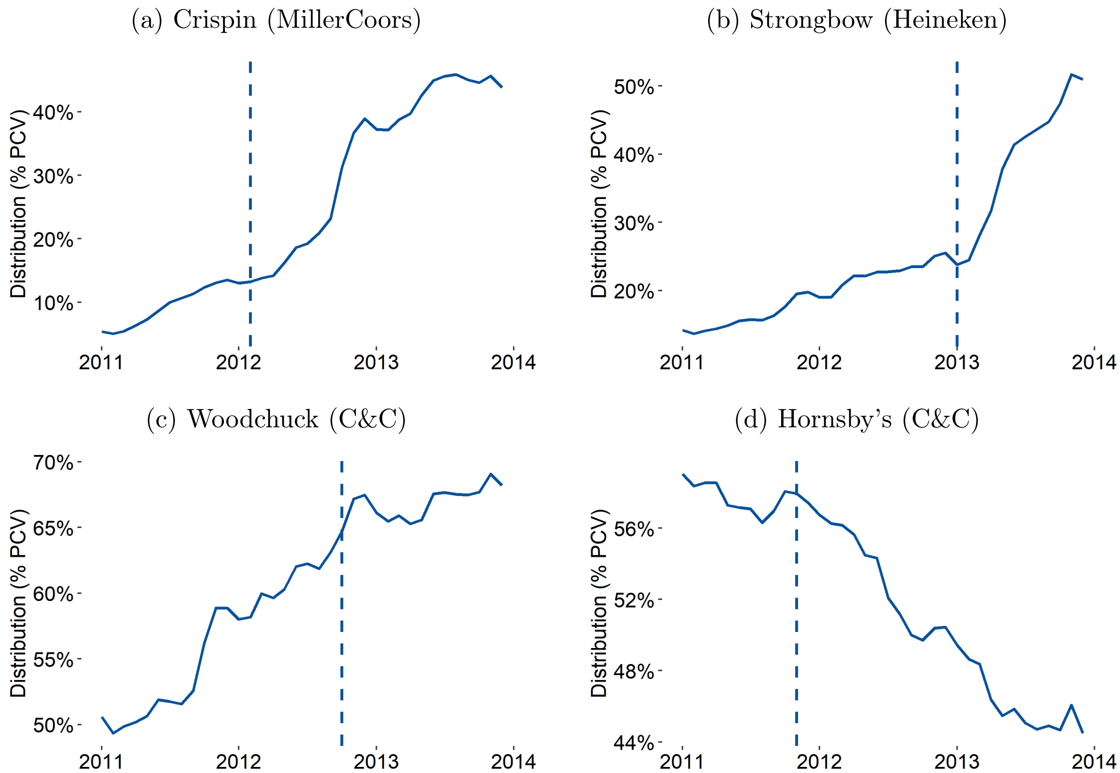
Note: Based on the new brands introduced by major brewers from 2012 to 2014.

As Figure 8 shows, product-*chain*-week fixed effects explain more variation in product carrying than product-*county*-week fixed effects, yet the latter do better in explaining sales and prices. For distribution, product-*chain*-week fixed effects account for 43% of the variation beyond that explained by product-week fixed effects, much more than the 20% by product-*county*-week fixed effects. For sales (and prices), product-*chain*-week fixed effects account for 24% (44%) of the difference, smaller than the 36% (57%) by product-*county*-week fixed effects. In short, the distribution is more retailer-specific than location-specific, while sales and prices are more local.

The results have three implications. First, new cider carrying decisions are likely to be made at the chain level or at least the chain-region level, instead of the store level, which would have reflected the local sales. This implies the decisions made by retailers can have a large influence on the distribution of new cider. Second, the assortment decisions are not entirely driven by product demand, so manufacturer-retailer relationships could have a role. Third, prices are less uniform than assortment within a chain, which could be explained by the differences in the excise tax and wholesale pricing regulations across states.

A.2 Distribution of Incumbent Brands around Ownership Change

Figure 9: Incumbent Brands



Notes: Crispin (a) and Strongbow (b) saw a jump in distribution after ownership was changed to brewers. Woodchuck (c) and Hornsby's (d) did not see a jump after being acquired by Irish cider company C&C.

B More Details of Cider Regulations

States usually have separate rules for beer, wine, and distilled spirits. Hard cider as a new category does not have its own group, and its classification as beer or wine varies across states and regulations. Many states (e.g., Washington) classify alcoholic beverages based on how they are made, in which case cider is considered a wine because it is obtained from the fermentation of fruit juice. Some states classify drinks based on alcohol content (e.g., Iowa), and cider with the usual amount of alcohol (5% ABV) is classified as a beer. Even within a state, the exact classification can vary depending on the purpose of the policy despite its general classification. For example, in Florida, cider producers need to obtain a wine manufacturing license to make cider. But they pay a much lower excise tax ($0.89 per gallon) than wine producers ($2.25 per gallon), which is closer to beer excise tax ($0.48 per gallon). For this paper, I collect information on the specific regulations cider manufacturers and retailers follow in each state, based on its classification.

The 16 Post & Hold states are Connecticut, Delaware, Georgia, Idaho, Indiana, Kansas, Massachusetts, Maine, Michigan, New Hampshire, New Jersey, Oregon, South Dakota, Tennessee, Vermont, and Wyoming. The 14 states that ban volume discounts are Connecticut, Delaware, Idaho, Kansas, Louisiana, Maine, Michigan, North Carolina, Ohio, Oklahoma, Oregon, Tennessee, Vermont, and Wyoming. Washington was a control state before Dec 8, 2011, and satisfied both. The laws discussed in this paper have no changes over the sample period, except for the privatization in Washington state on Dec 8, 2011.

C Robustness Checks

C.1 Relationship of Cider Availability and Manufacturer Past Beer Share by Retailer Size and Retailer Type

Table 11: New Product Availability and Past Beer Share by Retailer Size

	Coefficient (SE)
Mfr. Past Beer Share by Retailer	
Top 20 Chain	0.48*** (0.17)
Below 20 Chain	0.50*** (0.14)
Umbrella Brand Share by Retailer	
Top 20 Chain	6.40*** (1.27)
Below 20 Chain	3.83*** (0.89)
Brand-County-Week FE	Y
Store-Week FE	Y
Observations	10,499,897
R^2	0.70

Notes: Retailer ranking is based on the total dollar sales of cider, 2006-2016. Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

Table 12: New Product Availability and Past Beer Share by Retailer Type

	Coefficient (SE)
Mfr. Past Beer Share by Retailer	
Convenience Stores	0.31* (0.16)
Drug Stores	0.59*** (0.15)
Grocery Stores	0.44** (0.21)
Liquor Stores	0.46 (0.35)
Mass Merchandisers	0.47** (0.23)
Umbrella Brand Share by Retailer	
Convenience Stores	4.91** (2.37)
Drug Stores	5.17*** (1.47)
Grocery Stores	5.17*** (1.09)
Liquor Stores	−1.65 (1.74)
Mass Merchandisers	8.94*** (1.36)
Brand-County-Week FE	Y
Store-Week FE	Y
Observations	10,499,897
R^2	0.71

Notes: Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

C.2 Relationships by the Retailer's Share of Stores in Regulated States

Table 13: Relationships by the Retailer's Share of Stores in Regulated States

	carry	log(#UPC)
	(1)	(2)
Mfr. Past Beer Share by Retailer	0.45***	1.43***
	(0.15)	(0.49)
× Share of Stores in Regulated States	0.08	0.28
	(0.23)	(1.01)
Umbrella Control?	Y	Y
Brand-County-Week FE	Y	Y
Store-Week FE	Y	Y
Observations	10,499,897	3,325,976
R^2	0.70	0.88

Notes: Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

C.3 Relationships in States with Strict Beer Wholesale Pricing Rules

Table 14: States with Strict Beer Wholesale Pricing Rules

	carry	log(#UPC)
	(1)	(2)
Mfr. Past Beer Share by Retailer	0.47***	0.99**
	(0.14)	(0.40)
× **1**{Beer P&H or Ban Q.D.}	0.01	1.03*
	(0.14)	(0.61)
Umbrella Control?	Y	Y
Brand-County-Week FE	Y	Y
Store-Week FE	Y	Y
Observations	10,499,897	3,325,976
R^2	0.70	0.88

Notes: This table shows that the main results hold for states with strict beer wholesale pricing rules. This rules out the explanation that brewers offer wholesale discounts for their beer to induce retailers to buy their cider. Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

C.4 Local Logistics Efficiency

Table 15: Brand-Store Pairs with Positive Manufacturer Past Beer Share at the Store

	carry	log(#UPC)
	(1)	(2)
Mfr. Past Beer Share by Retailer	0.39***	1.52***
	(0.15)	(0.57)
Umbrella Control?	Y	Y
Brand-County-Week FE	Y	Y
Store-Week FE	Y	Y
Observations	8,028,897	2,908,333
R^2	0.72	0.89

Notes: This table shows that the main results are robust when focusing on brand-store pairs that the store has already been buying beer from the brewer. This rules out the alternative explanation of last-mile shipping efficiency (i.e., stores are just buying cider from manufacturers that they have already been buying beer). Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

C.5 Do the Brewers Replace Beer with Cider on Shelf?

Table 16: Manufacturer Current Beer Share and the Number of Cider Products

	Mfr. Current Beer Share at Store
#UPC, Mfr. Cider at Store	0.00061*
	(0.00033)
Manufacturer-Store FE	Y
Manufacturer-Week FE	Y
Store-Week FE	Y
Observations	10,728,436
R^2	0.95386

Notes: This table shows that the manufacturer's current beer share does not decrease as the retailer carries its cider (increase in #UPC), suggesting the cider distribution pattern in Table 3 is not driven by direct replacement of the manufacturer's beer (either a product or a facing). The result also suggests there is no specific substitution between the cider and beer from a manufacturer. Regression at the manufacturer-store-week level. Sample includes periods before and after the cider launches. Standard errors are clustered at the manufacturer-chain level. *p<0.1; **p<0.05; ***p<0.01

C.6 Category Captaincy

Table 17: Regression without Each Retailer's Highest Share Manufacturer

	carry	log(#UPC)
	(1)	(2)
Mfr. Past Beer Share by Retailer	0.82*	3.33*
	(0.48)	(1.88)
Umbrella Control?	Y	Y
Brand-County-Week FE	Y	Y
Store-Week FE	Y	Y
Observations	5,067,116	2,049,570
R^2	0.83	0.93

Notes: This table shows that the main results are robust without each retailer's highest share manufacturer. Since almost half of the observations are removed, the results are not as statistically significant as the main ones. Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01

C.7 Relationships with Chains vs. with Stores

An alternative explanation for the results in Table 3 is the relationships between stores and wholesalers, which represent manufacturers' interests. That is, the relationships are between wholesalers (manufacturers) and stores built through daily transactions, rather than between manufacturers and retailers through strategic interdependence. To address this concern, I add the manufacturer's past beer share by store as an additional control, which proxies the relationship between the wholesaler and the store and captures the variation across stores for a given retailer. If the pattern is consistent across stores, then the relationships should be with chains and captured by the chain-level shares. If the relationships are with stores, then the store-level shares should pick up the effect.

Table 18 shows that the relationships are mainly with chains instead of with stores. The estimates of the chain-level coefficients are similar to the main results in Table 3, implying strong manufacturer-retailer level relationships that manufacturer-store level shares cannot explain away. The store-level beer share is insignificant in predicting whether the cider brand is carried (−0.06). It is statistically significant in predicting the number of products carried (0.24), but the size is much smaller than the chain level share. Thus, the relationships with retailers are the primary driver, and wholesalers serve as an extension of the brewers that takes care of the logistics.

Table 18: Relationships with Chains vs. with Stores

	carry	log(#UPC)
	(1)	(2)
Mfr. Past Beer Share by Retailer	0.50***	1.34***
	(0.14)	(0.50)
Mfr. Past Beer Share by Store	−0.06	0.24**
	(0.06)	(0.12)
Umbrella Control?	Y	Y
Brand-County-Week FE	Y	Y
Store-Week FE	Y	Y
Observations	10,499,897	3,325,976
R^2	0.70	0.88

Notes: Standard errors are clustered at the brand-chain level. *p<0.1; **p<0.05; ***p<0.01