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Price Competition in U.S. Brewing

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Does the King Use Its Power? Price Competition in U.S. Brewing

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Abstract

Pricing behavior of firms in differentiated product markets has been studied intensely in recent empirical work. Despite several accounts in various industries, price leadership has remained mostly unassessed. This study analyzes price competition in the U.S. brewing industry with a focus on price leadership by the largest U.S. beer producer Anheuser-Busch and its heavily marketed "King of Beers" brand Budweiser. This paper employs a unique nationwide data set on brand-level sales collected before and after a 100% increase in the federal excise tax on beer. Brand-level demand estimates are combined with several supply models, including several price leadership scenarios, to simulate prices that would have prevailed under each model after the tax increase. These "predicted" prices are then compared to "actual" prices after the tax increase to determine the fit of the different supply models. While Bertrand-Nash behavior appears to be a more suitable model of price competition, it tends to under-predict price increases of more price-elastic brands and to over-predict price increases of less price-elastic brands. In particular, the predicted price of Budweiser is much larger than its actual value. An interpretation of this result is that Anheuser-Busch could exert more market power through its flagship brand than it actually does. Overall, actual price movements as a result of the tax increase tend to be more similar across brands than predicted by any of the models considered. While this pattern is not inconsistent with leadership behavior, leadership models considered in this paper do not conform with this pattern.

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"A price increase is needed, but it will take Anheuser-Busch to do it"

-Robert Uihlein, Chairman of the Schlitz Brewery, Fortune (November, 1975: 92).

"I think the industry is stupid...If they only had price leadership...which they don't have...that isn't violative of anything"

-Allan T. Demaree, legal counsel for the Plumbing Fixture Manufacturers Association, after learning that members had been illegally colluding. Fortune (December, 1969: 97-98).

1 Introduction

In real life, markets with differentiated products are the rule rather than the exception. A large part of the empirical work on these markets has focused on the pricing behavior of firms. While this element of differentiated product markets is an important input for addressing issues such as merger simulation, market power and new product introductions, for the most part these studies have focused on static Bertrand-Nash and collusive models of pricing behavior.

Historical accounts of the existence of a leading brand or firm whose pricing decisions are closely followed by competitors have been reported in well scrutinized industries: the cigarette industry in the 1920's and 1930's, the U.S. automobile industry in the 1950's, the breakfast cereals industry between the 1960's and 1970's, and the U.S. brewing industry since the 1970's[1]. However, formal empirical assessments of this behavior in differentiated products have been limited.[2] Furthermore, the importance of price leadership goes beyond these frequent informal encounters. Price leadership not only allows firms to earn larger profits than competitive pricing, but, as shown by Rotemberg and Saloner, it may also be used as a collusive device ("collusive price leadership") that could cause higher welfare losses than overt collusion. Despite its potential anti-competitive features, price leadership is not clearly addressed by antitrust law (Scherer and Ross: 248).

Anheuser-Busch, the U.S. leading beer producer has a 50% market share and has been identified as a price leader especially through its heavily marketed "King of Beers" brand Budweiser (Greer; Tremblay and Tremblay; and references therein). For example, in 1954, after an increase in costs due to a new union wage agreement,

[1] See Scherer and Ross for accounts in the first three industries and Tremblay and Tremblay for accounts in the U.S. brewing industry

[2] Two exceptions are Kadiyali, Vilcassim and Chintagunta, and Gasmi, Laffont and Vuong. These studies, however, have been limited to a small number of differentiated products (4 and 2, respectively).

Anheuser-Busch raised the price of Budweiser. After some regional brewers in St. Louis did not follow suit, Anheuser-Busch decided to aggressively reduce the price of Budweiser in this region, which elevated its market share from 12.5% to 39.3%. A few months later, Anheuser-Busch increased the price of Budweiser and this time the regional brewers learned their costly lesson and followed. Some evidence supports the fact that by the 1990's Anheuser-Busch, assisted by this successful punishing strategy, had become the clear price leader (Tremblay and Tremblay: 171; Greer: 49-51).

This paper makes use of a unique scanner data set to empirically assess different models of price competition in the U.S. brewing industry. Two types of leadership models are considered. The first is a "collusive price leadership" model in which followers match Budweiser's price changes. The second is a Stackelberg model. In one variant of the Stackelberg model Budweiser acts as the price leader while in the other Anheuser-Busch leads with all its brands. These leadership models are compared to alternative hypothesis of Bertrand-Nash and collusion.

Frequently, the task of assessing different models of firm behavior involves constructing often complex non-nested econometric tests of the competing hypotheses. Alternatively, an exogenous variation in the data or "natural experiment" can be exploited to evaluate various models of pricing behavior; this paper utilizes the 1991 100% increase of the federal excise tax on beer.[3] This change in policy caused all beer producers and importers to simultaneously adjust their prices to the new per unit tax. The dataset is comprised of brand-level prices and quantities collected by scanning devices in the main U.S. metropolitan areas over a period of 20 quarters that span before and after the tax introduction (1988-1992). After controlling for other factors, model assessment is carried out by comparing how well the alternative models of firm behavior predict observed prices after the tax change.

To perform the assessment of pricing behavior, a structural demand system for 64 brands of beer in 58 major metropolitan areas of the United States is first estimated. Unlike most previous work on demand for differentiated products, the demand model is based on the neoclassical "representative consumer" approach rather than on a "discrete choice" approach. While for some products such as automobiles the discrete choice assumption maybe plausible, for others it appears less likely. The major challenge of estimating numerous substitution coefficients is dealt with the Distance Metric (DM) method devised by Pinkse, Slade and Brett. This study adds to previous applications of the DM method (Pinkse and Slade; Slade 2004) by applying a demand system that is more flexible and by estimating advertising substitution patterns.

In a second stage, the estimated demand parameters are used to compute the implied marginal costs for the different models of pricing behavior. Then, the exogenous increase in the federal excise tax from $9 to $18 per barrel levied on all brewers, together with the estimated marginal costs, are used to compute price increases for all brands that would have prevailed under each model of pricing behavior. These

[3]Hausman and Leonard use a similar strategy in which the introduction of a new brand is exploited to evaluate different models of competition.

predicted price changes are compared to direct estimates of the actual price changes to assess the predictive power of each model.

2 The Industry and the Excise Tax Increase

Commercial brewing began during the American colonial period. By 1810 there were 132 breweries producing 185,000 barrels of mainly English-type (ale, porter and stout) malt beverages. Lager beer was introduced in the mid nineteenth century and today it accounts for over 90 percent of the U.S. brewing industry's output.[4] Overall, total demand for beer in the U.S. has been constantly increasing since the mid twentieth century. While strong consumption growth patterns were registered between 1960 and 1980, for the last three decades total demand for beer has remained rather steady (between 180 and 210 million barrels per year). Per capita consumption has had more of a fluctuating pattern but has stagnated as well at approximately at 22 gallons.

Many features of the U.S. brewing industry have interested researchers for decades. Arguably, the dramatic change of the industry from a fragmented structure to a concentrated oligopoly has drawn most attention. The number of mass-producing brewers has declined from 350 in 1950 to 24 in 2000 with a corresponding increase in the Herfindahl index from 204 to 3612 (Tremblay and Tremblay: 187), making this industry one of the most concentrated in U.S. manufacturing.[5] In 2003, nearly 80% of beer consumption in the U.S. was served by the "big three": Anheuser-Busch (49.8%), SABMiller (17.8%) (formerly Miller and owned by Philip Morris) and Coors (10.7%).

Anheuser-Busch has been the largest beer producer after 1955, with an ever increasing market share (Table 1). Budweiser and Bud Light, Anheuser-Busch's two leading brands, currently capture approximately one third of beer sales nationwide.[6] Overall, Anheuser-Busch has consolidated as the leader in this industry through constant expansion and active advertising strategies (Elzinga, Tremblay and Tremblay). While imports and specialty beers have increased their combined market share from less than 1% in the 1970's to approximately 12% and 3%, respectively, their impact in the industry as a whole remains limited. The reason is that imports and specialty beers tend to compete less directly with traditional mass-producers since they target different types of consumers.

[4] A commonly used classification for beers sorts them into lagers and ales. Lagers are brewed with yeasts that ferment at the bottom of the fermenting tank. Ales, on the other hand, are brewed with yeasts fermenting at high temperatures and at the top of the fermenting tank. Porter and stout are malt beverages as well, although darker and sweeter than ale, with minimal market share in the United States.

[5] The Herfindahl indices for cigarettes, breakfast cereals and automobiles are 3100, 2446 and 2506 respectively; for all manufacturing industries the index is 91 (U.S. Census Bureau, 1997 concentration ratios).

[6] Based on 2001 production estimates (Tremblay and Tremblay: 13)

Table 1: Market Shares,Two and Four-Firm Concentration Ratios in the Beer Industry, Selected Years, 1950-2003

	1950	1955	1960	1965	1970	1975	1980	1985	1990	1996	2003
A-B	5.8	6.5	9.6	11.6	17.8	23.4	28.4	38.1	43.4	45.4	49.8
Miller	2.5	2.6	2.7	3.6	4.1	8.5	21.1	20.8	21.8	21.8	17.8
Coors	0.8	1.2	2.2	3.5	5.8	7.9	7.8	8.3	9.7	10.0	10.7
Stroh/Schlitz	6.7	9.2	8.8	10.8	14.8	18.9	11.9	12.9	8.1	8.3	4.2[7]
C2	11.9	13.3	16.0	20.1	29.9	38.8	49.5	58.9	65.2	67.2	67.6
C4	22.0	22.1	27.0	34.4	44.2	57.7	66.4	80.8	83.0	85.5	83.0

Source: Greer (1998), Beer Marketer's Insights, Anheuser-Busch's 2004 Annual Report

The U.S. brewing industry is characterized by numerous product introductions and, consequently, a large number of brands. However, beers from mass-producing brewers do not differ substantially in taste or quality. Instead, consumers "subjectively" differentiate brands by relying on cues such as price premiums and advertising (Tremblay and Tremblay, ch. 7). An interesting fact about brand differentiation is the increasing popularity of light beer. Since the successful introduction of Miller Lite in the 1970's, light beers have become the most popular beer type and now account for almost half the sales of beer in the U.S.

Advertising has played a central role in the industry. Currently, the advertising-to-sales ratio for beer is 8.7 percent compared to 2.9 percent for cigarettes, and 7.1 percent for other beverages.[8] National brewers have taken advantage of the more cost-effective marketing channel: national TV. Regional producers and other small brewers have lost market share to the rising national producers, or have dissapeared altogether, partly because of this marketing disadvantage but also because of technological changes that required larger brewing plants to achieve a minimum efficient scale (MES). In addition to the features briefly presented here, the potential negative externalities of alcohol consumption expand the scope of this industry to additional policy and social arenas.

The Federal Excise Tax Increase

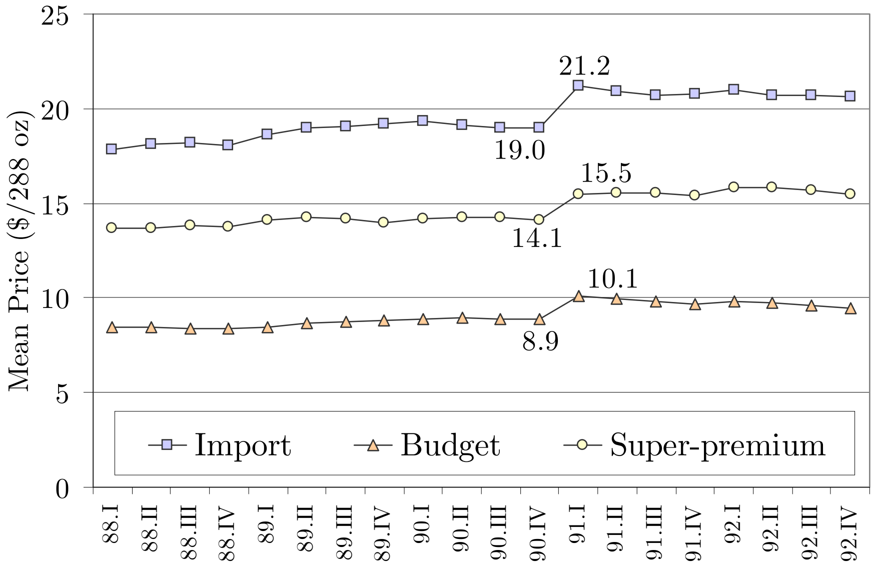
In 1990, U.S. Congress approved an increase in the federal excise tax on beer from \$9 to \$18 per barrel. All brewers and importers were required to pay this tax on all produced units as of January of 1991. This increase, which was equivalent to an additional 65.3 cents in federal taxes per 24-pack (288 ounces), represented the largest federal tax hike for beer in U.S. history.

Figure 1 shows mean quarterly prices (over all cities) for three beer segments from the dataset utilized in this paper. There is a clear shift in the mean price of all three

[7] Stroh exited the market in 1999. This number corresponds to Pabst's market share (the acquirer of some of Stroh's brands).

[8] Source: Advertising Age, 2000, cited in Tremblay and Tremblay.

Figure 1: Quarterly Mean Prices, Various Segments (1988-1992)



Source: IRI Database, University of Connecticut

categories. While the mean price increase in imports is larger than the other two series, all mean increases are higher than the actual tax hike of 65.3 cents per 288 ounces: $2.2 for imports, $1.4 for super-premium beers and $1.2 for budget beers. These increases were, on average, 237%, 114%, and 84%, respectively, larger than the tax increase of 65.3 cents per case. As shown by Anderson, de Palma and Kreider, in oligopolies with differentiated products an excise tax can be passed on to consumers by more than 100%.

3 The Empirical Model

The approach taken in this paper involves the comparison of different models of firm pricing behavior by exploiting the exogenous variation of an increase in the federal excise tax. Since all models depend on demand parameters, the first step is to estimate brand-level demand. With these estimates, marginal costs of each brand are recovered for all models in each quarter that preceded the tax increase. Using each brand's median marginal cost (over the pre-tax period), the demand estimates and the pre-tax values of the remaining variables, a search for the prices that would prevail under each model after the excise tax increase is conducted. The price increases resulting from this exercise are then compared to direct estimates of the actual price increases. This section describes the demand and supply models utilized as well as some details on recovering marginal costs.

3.1 Demand

The functional form is based on the representative consumer approach of neoclassical demand models. In this paper, a linear approximation to the Almost Ideal Demand System (LALIDS) developed by Deaton and Muellbauer is used because of its desirable aggregation properties. Using a LALIDS model also allows a specification that is linear in the parameters to be estimated.

Formally, let $\Psi = \{1, ..., J\}$ be the product set, $t = \{1, ..., T\}$ the set of markets (in this study a market is defined as a city-quarter pair), $q_t = (q_{1t}, ..., q_{Jt})$ the vector of quantities demanded, $p_t = (p_{1t}, ..., p_{Jt})$ the corresponding price vector and $x_t^* = \sum_j p_{jt} q_{jt}$ total expenditures. The ALIDS is given by the following formula:

$$w_{jt} = a_{jt}^* + \textstyle\sum_k b_{jk} \log p_{kt} + d_j \log(x_t^*/P_t) \tag{1}$$

where $w_{jt} = \frac{p_{jt} q_{jt}}{x_t^*}$ is brand j's sales share and $\log P_t$ is a price index approximated the loglinear analogue of the Laspeyeres index:[9]

$$\log P_t \approx \textstyle\sum_j w_j^o \log(p_{jt}) \tag{2}$$

where w_j^o is brand j's 'base' share, defined as $w_j^o \equiv T^{-1} \sum_t w_{jt}$. An advantage of this price index is that it does not contain w_{jt} directly, but rather a 'fixed' base, w_j^o, thereby moderating the problem of having an additional endogenous variable on the right hand side of (1).

Following Sutton (45-46) advertising is assumed to be persuasive rather than informative. The focus is on traditional advertising (e.g. television, radio and press), rather than on local promotional activity (e.g. local paper, in-store promotions, and end-of-aisle product location), as the key advertising variable because it has played a crucial role in the development and research of the industry. Also, traditional advertising is more apt to be independent of the pricing strategy, since, in general, mass media advertising by brewers seldom informs consumers about price. Further, only the flow effects of advertising are considered with all lagged own- and cross-advertising terms being omitted for the demand equation.[10]

Advertising is incorporated into equation (1) through the intercept term a_{jt}^*, which is modified to equal:

$$a_{jt}^* = a_{jt} + \textstyle\sum_k c_{jk} A_{kt}^{\gamma} \tag{3}$$

where A_k represents advertising expenditures of brand k. The parameter γ is included to account for decreasing returns to advertising. Following Gasmi, Laffont and Voung, γ is set equal to 0.5. Substituting equation (3) into equation (1) gives:

[9] Moschini explains how this price index can have superior approximating properties than the Stone price index of Deaton and Muellbauer.

[10] The existence of possible stock effects was investigated but the estimated coefficients on lagged advertising expenditures were found not to be statistically different than zero.

$$w_{jt} = a_{jt} + \sum_k c_{jk} A_{kt}^{\gamma} + \sum_k b_{jk} \log p_{kt} + d_j \log(x_t^* / P_t) + e_{jt} \tag{4}$$

Equation (4) can now be interpreted as a first-order approximation in prices and advertising to the demand function that allows for unrestricted price and advertising parameters. However, estimation becomes problematic given the large number of coefficients.

To solve this dimensionality problem, the Distance Metric (DM) method of Pinkse, Slade and Brett is employed. This method simplifies the computation of cross-coefficients (b_{jk} and c_{jk}) by specifying them as a function of the distance between brands j and k in product space. This distance is, in turn, determined by brands' observed product characteristics (i.e. their location in product space).

Distance measures may be either continuous or discrete. For example, the alcohol content of a brand is an example of a variable that can be used to construct a continuous distance measure. Dichotomous variables that identify brands by product segment, such as light beer or premium beer, can be used to construct a discrete distance measure. The continuous distance measures use an inverse measure of distance, or closeness, in product space between brands j and k. The discrete distance measures take the value of 1 if j and k belong to the same grouping and zero otherwise.

Specifically, b_{jk} and c_{jk} are specified as a linear combination of distance measures:

$$b_{jk} = \sum_{r=1}^{R} \lambda_r \delta_{jk}^r \tag{5}$$

$$c_{jk} = \sum_{s=1}^{S} \tau_s \mu_{jk}^s \tag{6}$$

where $\delta_{jk} = \{\delta_{jk}^1, ..., \delta_{jk}^R\}$ is the set of distance measures used for cross-prices and $\mu_{jk} = \{\mu_{jk}^1, ..., \mu_{jk}^S\}$ the set of measures used for cross-advertising, while λ and τ are the coefficients to be estimated. Replacing (5) and (6) into (4) and regrouping terms gives the following empirical model:

$$w_{jt} = a_{jt} + b_{jj} \log p_{jt} + c_{jj} A_{jt}^{\gamma} + \sum_{r=1}^{R} \left(\lambda_r \sum_k \delta_{jk}^r \log p_{kt} \right) + \tag{7}$$

$$+ \sum_{s=1}^{S} \left(\tau_s \sum_k \mu_{jk}^s A_k^{\gamma} \right) + d_j \log(x_t^* / P_t) + e_{jt} \tag{8}$$

Because the distance measures are symmetric by definition, symmetry may be imposed by setting λ and τ to be equal across equations. This implies that $b_{jk} = b_{kj}$ and $c_{jk} = c_{kj}$. In principle, $(J-1)$ seemingly unrelated equations can be estimated. However, if J is very large, as is the case in this paper with 64 brands, then it may become impractical to estimate such a large system of equations. One method to reduce the dimensionality of the estimation procedure is to assume that the own-price and own-advertising coefficients (b_{jj} and c_{jj}), as well as the price index coefficient (d_j), are constant across equations thereby reducing estimation to a single equation. Since this is too restrictive of an assumption, following Pinkse and Slade the coefficients b_{jj}, c_{jj}, and d_j are specified as linear functions of brand j's characteristics.[11] The estimated coefficients in (7), λ_l and τ_m, together with the distance measures between brands (δ_{jk} and μ_{jk}) are then used to recover cross-terms (b_{jk} and c_{jk}) and cross-elasticities.[12]

3.2 Supply

Formally, let $\Lambda = \{1, ..., N\}$ denote the set of firms and F_n the set of brands produced by firm $n \in \Lambda$. Assuming constant marginal costs and linear additivity of advertising, the profit of firm n in each market can be expressed as:

$$\pi_n = \sum_{j \in F_n} (p_j - c_j) q_j(p, A) - \sum_{j \in F_n} A_j, \tag{9}$$

where c_j denotes brand j's marginal cost, p_j its price and A_j firm n's advertising expenditures on brand j. From (9), firm $n's$ first order conditions can be expressed as:

$$\begin{aligned} q_j(p, A) + \sum_{k \in F_n} (p_k - c_k) \left[\frac{\partial q_k}{\partial p_j} + \sum_{m \notin F_n} \frac{\partial q_k}{\partial p_m} \underbrace{\frac{dp_m}{dp_j}} \right] &= 0, \text{ with respect to } p_j \quad (10) \\ \sum_{k \in F_n} (p_k - c_k) \frac{\partial q_k}{\partial A_j} - 1 &= 0, \text{ with respect to } A_j \quad (11) \end{aligned}$$

While derivatives are obtained directly from demand estimates, the term with a horizontal brace in (10) takes different values depending on the model of interest. In principle, different games in advertising may also be modeled by setting $\frac{\partial q_k}{\partial A_j}$ to an expression similar to the one in brackets in equation (10). However, given the small magnitude of advertising coefficients obtained from demand estimation, advertising games (collusion, Bertrand-Nash and Stackelberg) produced equilibrium conditions that were essentially indistinguishable from each other. As a consequence, price is treated as the main strategic variable of interest while it is assumed that firms compete in a Bertrand-Nash fashion in advertising.

For Bertrand-Nash competition in prices, the term $\frac{dp_m}{dp_j}$ in (10) takes a value of zero, leaving only the partial derivative term $\frac{\partial q_k}{\partial p_j}$ multiplying price-cost margin $(p_k - c_k)$.

Stackelberg Leadership

[11] Specifying a coefficient as a linear function of product or market characteristics amounts to interacting the variable to which the coefficient corresponds with these characteristics.

[12] See Rojas and Peterson for further details on demand estimation.

For the Stackelberg leadership game, the term $\frac{dp_m}{dp_j}$ takes a value of zero if j is a follower brand. If j is a leading brand the term $\frac{dp_m}{dp_j}$ is computed from the first order conditions of followers by applying the implicit function theorem.[13] More specifically, define a partition of the product set as $\Psi = (\Psi_f, \Psi_l)$, where Ψ_f is the set of follower brands and Ψ_l is the set of leading brands. The first order condition of all follower brands with respect to price (10) is totally differentiated with respect to all followers' prices (p_f, for all $f \in \Psi_f$) and one of the leaders' prices, p_l ($l \in \Psi_l$):[14]

$$\sum_{f\in\Psi_f} \underbrace{\left[\frac{\partial q_j}{\partial p_f} + \sum_{k\in\Psi_f}\left(\Delta^*_{kj}(p_k - c_k)\frac{\partial^2 q_k}{\partial p_j \partial p_f}\right) + \Delta^*_{fj}\frac{\partial q_f}{\partial p_j}\right]}_{g(j,m)} dp_f + \\ + \underbrace{\left[\frac{\partial q_j}{\partial p_l} + \sum_{k\in\Psi_f}\left(\Delta^*_{kj}(p_k - c_k)\frac{\partial^2 q_k}{\partial p_j \partial p_l}\right)\right]}_{h(j,l)} dp_l = 0; \quad j,k,f \in \Psi_f \tag{12}$$

where Δ^*_{jk} takes the value of one if brands j and k are produced by the same firm and zero otherwise. For a given p_l, there are J^F (where J^F is the number of followers) expressions like (12). Let G be the $(J^F \times J^F)$ matrix that contains all g elements above and define the $(J^F \times 1)$ vectors D_s and H_l as:

$$D_s = \begin{bmatrix} dp_1 \\ . \\ . \\ . \\ dp_{J^F} \end{bmatrix}; \qquad H_l = \begin{bmatrix} -h(1,l) \\ . \\ . \\ . \\ -h(J^F,l) \end{bmatrix}$$

For a given p_l, and using the above definitions, (12) can be written in matrix notation as:

$$GD_s - H_l dp_l = 0$$

where dp_l is treated as a scalar (for matrix operations). The J^F derivatives of the followers' prices with respect to a given p_l can then be computed as:

[13] Villas-Boas uses a similar strategy and notation in her study of models of vertical competition.

[14] It is assumed that the advertising (11) does not play a role in deriving $\frac{dp_m}{dp_j}$. Without this assumption, inversion of matrix G below is not possible since it is not a square matrix. Results are unlikely to be sensitive to this assumption given the small impact advertising has on demand.

$$\frac{D_s}{dp_l} = G^{-1}H_l \tag{13}$$

Concatenating the $(J - J^F)$ vectors of dimension $(J^F \times 1)$ given in (13) (i.e. one vector for each p_l) gives $D = G^{-1}H$. The $(J^F)\times(J - J^F)$ matrix D has all the derivatives of the followers' prices with respect to all of the leaders' prices. Specifically, D has typical element $\frac{dp_f}{dp_l}$, for $f \in \Psi_f$ and $l \in \Psi_l$.

Collusive Price Leadership

Based on accounts reported in the industry, it may be assumed that followers exactly match Budweiser's price changes. In this case, called "collusive price leadership" (see Scherer and Ross: 248), only the first order conditions of the firm producing the leading brand (i.e. Anheuser-Busch) are relevant, since followers do not price via profit-maximization but rather by imitating the leader. The term $\frac{dp_m}{dp_l}$ in (10) is set to 1 in Budweiser's first order condition and to zero for Anheuser-Busch's remaining first order conditions.

3.3 Price-Cost Margins and Marginal Costs

Adding up (10) and (11) in a given market obtains:

$$q_j(p, A) - 1 + \sum_{k \in F_n} (p_k - c_k) \left[\frac{\partial q_k}{\partial p_j} + \sum_{m \notin F_n} \frac{\partial q_k}{\partial p_m} \frac{dp_m}{dp_j} + \frac{\partial q_k}{\partial A_j} \right] = 0, \tag{14}$$

In vector notation, (14) can be expressed as:

$$Q^o - \Delta(p - c) = 0, \tag{15}$$

Q^o and $(p - c)$ are $J \times 1$ vectors with elements $(q_j(p, A) - 1)$ and $(p_j - c_j)$, respectively; Δ is a $J \times J$ matrix with typical element $\Delta_{jk} = -\Delta^*_{jk} \left[\frac{\partial q_k}{\partial p_j} + \sum_{m \notin F_n} \frac{\partial q_k}{\partial p_m} \frac{dp_m}{dp_j} + \frac{\partial q_k}{\partial A_j} \right]$, where Δ^*_{jk} takes a value of 1 if brands j and k are produced by same firm and zero otherwise. Applying simple inversion to Δ in (15) gives the implied marginal costs:

$$c = p - \Delta^{-1} Q^o \tag{16}$$

Using the demand estimates, (16) is computed in all markets. For the Bertrand-Nash model, this is done in a straightforward fashion. For Stackelberg, collusion, and collusive price leadership models some details and considerations are presented next.

Stackelberg Model

Operationally, marginal costs are also obtained by applying (16). However, the derivative $\frac{dp_m}{dp_j}$ is computed via (13). Several technical difficulties arise in this model.

First, there is an immense number of possible Stackelberg scenarios. Given the motivation in this paper, only the case in which Anheuser-Busch acts as a leader, both with all its brands as well as with Budweiser only, are considered.

Second, since the term $\frac{dp_m}{dp_j}$ in the leaders' first order conditions is a function of followers' marginal costs (see equation (13)), these need to be computed first. When Anheuser-Busch acts as a leader with all its brands, followers' marginal costs can be obtained by inversion of a smaller system of dimension J^F in (16). These marginal costs are used to compute $\frac{dp_m}{dp_j}$ and then to estimate the marginal costs of the leading brands. When Budweiser is a sole brand leader, it is assumed that it only leads brands produced by rival firms (i.e. not by Anheuser-Busch) to reduce computation to a manageable level. Hence, except for Budweiser, the term $\frac{dp_m}{dp_j}$ is set to zero if m is produced by Anheuser-Busch.

Collusive Price Leadership Model

In this case, only Anheuser-Busch's marginal costs can be derived since first order conditions of other firms are not relevant (see section 3.2). These marginal costs are also recovered by applying (16) to a system of dimension J^L (where J^L is the number of brands produced by Anheuser-Busch) and by setting $\frac{dp_m}{dp_j}$ to 1 in Budweiser's first order condition and zero in the remaining first order conditions.

Collusive Model

Any collusive possibilities (e.g. between specific products or firms) can be investigated by appropriately modifying the ownership elements Δ^*_{jk}. For example, full collusion, or joint profit maximization, can be represented by setting $\Delta^*_{jk} = 1$ for all j, k in the product set.

4 Data

Table (2) provides a description and summary statistics for all variables used in this study. The main data source is the Information Resources Inc. (IRI) Infoscan Database.[15] The IRI data includes prices and total sales for several hundred brands for up to 58 cities over 20 quarters (1988-1992). Volume sales (Quantity) in each city are reported as the number of 288-ounce units sold each quarter by all supermarkets in that city and price is an average price for a volume of 288 oz. for each brand. To maintain focus on brands with significant market share, all brands with a local market share of less than 3% are excluded from the sample. Using this selection criterion, 64 different brands produced by 13 different brewers are included in the sample. On average there are 37 brands sold in each city market with a minimum of 24 brands and a maximum of 48 brands. Appendix A contains a table of all the brands chosen as well as other details of the database and the data selection procedure.

[15]IRI and LNA data was kindly provided by Ronald Cotterill, Director of the Food Marketing Policy Center at the University of Connecticut.

In addition to price and sales data, the IRI database contains information on several additional brand specific and market variables. Because beer is sold in a variety of sizes (e.g., six and twelve packs), the variable $UNITS$ provides the number of units, regardless of size, sold each quarter. These data are used to create an average size distance measure defined as $SIZE = Quantity/UNITS$. The variable COV (Coverage) measures fraction of market coverage for each brand and is defined as the sum of all commodity value (ACV) sold by stores carrying the product divided by the ACV of all stores in the city. Beers with low coverage may be interpreted as specialty brands that are targeted to a limited fraction of the population. Lastly, the variable $OVER50K$, which is the fraction of households that have an income above \$50,000 in each city-quarter pair, was also included in the estimation.

Advertising data (A) was obtained from the Leading National Advertising annual publication. These are quarterly data by brand comprising total national advertising expenditures for 10 media types. Alcohol content (ALC) was collected from various specialized sources. With no clear consensus on brand product classifications, five different classifications are considered to construct discrete distance measures. These classifications are (a) budget, light, premium, super-premium, and imports, (b) light and regular, (c) budget, light, and premium, (d) domestic and import, and (e) budget, premium, super-premium, and imports (Greer).

Because not all brands are sold in all city markets, a binary variable (R) takes a value of one if brand j is a regional brand and zero if it is a national brand. This variable is used to construct a distance measure to test whether brands that national (regional) compete more strongly with each other (see next section).

Data for demand side instruments were collected from several additional sources. A proxy for supermarkets labor cost ($WAGES$) is constructed from data from the Bureau of Labor Statistics CPS monthly earning files. City density estimates (DEN), collected from Demographia and the Bureau of Labor Statistics, were included to proxy for cost of shelf space. For expenditures, median income ($INCOME$) from the IRI database was used.

5 Estimation

5.1 Distance Measures

Continuous Distance Measures

The characteristics utilized are alcohol content (ALC), product coverage (COV), and container size ($SIZE$). The one-dimensional measures ALC^*, COV^* and $SIZE^*$ between brands j and k are defined as $1/(1+2\,|z_j - z_k|)$, where z is the characteristic used. The two-dimensional space measures are computed with a similar expression with the denominator equal to $(1 + 2 \times \textit{Euclidean Distance})$ and are denoted AC, AS, and CS. A, C, and S depict the characteristic used (alcohol, coverage and size)

Table 2: Data Description and Summary Statistics

Variable	Description	Units	Mean	St D	Min	Max
Price	Average Price per brand	\$/288oz	12.1	3.9	0.82	28.96
Quantity	Volume Sold	288 oz.	23.5	63.6	0.001	2652
SIZE	Quantity/Units	N/A	0.38	0.117	0.08	1.30
	Units=# of units sold, all sizes					
Coverage (COV)	Sum of all commodity value (ACV) sold by stores with the product / ACV of all stores in the city	%	74	28.61	0.26	100
OVER50K	% households with income>\$50k/year	%	23.3	6.1	10.3	44.8
A	National advertising expenditures per quarter	Mill \$	3.54	6.3	0	40.28
ALC	Alcohol Content	%/vol	4.48	0.94	0.4	5.25
R	1 if brand is regional, 0 otherwise	0/1	0.15	-	-	-
WAGES	Average worker wage in retail sector	\$/hour	7.3	1.17	3.58	12.3
DEN	Population per square mile	(000)	4.73	4.13	0.73	23.7
INCOME	Median Income	(000) \$	31.99	6.9	18.1	53.4

in the two-dimensional space in which the Euclidean distance is calculated.[16] Note that two products at the same location in product space have a closeness measure of one.

Discrete Distance Measures

Three different types of discrete distance measures are utilized. The first type focuses on different product groupings including product segment, brewer identity, and national brand identity. The five different product segment classifications defined in the previous section are considered. Each measure is denoted $PROD1$ through $PROD5$ and is equal to one if brands j and k belong to the same product segment and zero otherwise. A discrete distance measure, $BREW$, is equal to one if brands j and k are produced by the same brewer and zero otherwise. Utilizing this distance measure will allow the model to determine if consumers are more apt to substitute between brands of the same firm when there are price changes, and if there are rival, or spillover, effects in advertising among beers produced by the same brewer. The distance measure REG distinguishes between regional and national brewers and it takes a value of one if either brands j and k are regional ($R_j = R_k = 1$) or national ($R_j = R_k = 0$). This distance measure is used to test whether brands that are

[16]Because the continuous product characteristics alcohol content (ALC), product coverage (COV), and container size ($SIZE$) have different units of measurement, their values are rescaled before computing the distance measures. To restrict the product space for each of these characteristics to values between 0 and 1, each continuous product characteristic is divided by its maximum value. This facilitated the definition of common boundaries (see below) for brands located in the periphery of the product space.

national (regional) compete more strongly with each other.[17]

Following Pinkse and Slade, two other types of discrete measures are constructed based on the nearest neighbor concept and if products share a common boundary in product space. Brands j and k share a common boundary if there is a set of consumers that would be indifferent between either brand and prefers these two brands over any other brand in product space. A common boundary measure is equal to one if brands j and k share a common boundary and zero otherwise while a nearest neighbor measure is equal to one if brands j and k are nearest neighbors (mutual or not) and zero otherwise. The nearest neighbor (NN) and common boundary (CB) measures are computed for all brands based on their location in alcohol content-coverage space ($NNAC$ and $CBAC$) and coverage-container size space ($NNCS$ and $CBCS$).

Each of the nearest neighbor and common boundary measures has an exogenous version and an endogenous version. For the computation of exogenous measures the criterion used is the Euclidean distance. Endogenous measures are constructed in a similar fashion, except that product k's distance from j is equal to the square of the Euclidean distance between them plus k's price (i.e. k's 'delivered price' at j's location).[18] Including price in the nearest neighbor and common boundary measures allows consumers' brand choices to be influenced by both the distance in characteristics and in price (an endogenous variable).

To measure how crowded is the product space around a specific brand, the number of common boundaries shared by a brand in ($\#CB$) is computed. This variable is included in the constant and also interacted with own-price and own-advertising.

5.2 Demand and Instruments

Given the strategic nature of price and advertising, all terms containing these two variables may be correlated with the error term and are hence treated as endogenous. To avoid simultaneity bias, an instrumental variables approach is used to consistently estimate θ.

Let n_z be the number of instruments, Z the $(T \times J) \times n_z$ matrix of instruments, S the collection of right hand side variables in equation (7), θ the vector of parameters to be estimated and $\underline{w}$ sales shares in vector form. The generalized method of moments (GMM) estimator $\hat{\theta}_{GMM} = (S'P_zS)^{-1}S'P_z\underline{w}$ is employed. The consistent estimator for its asymptotic variance is defined as $Avar(\hat{\theta}_{GMM}) = (S'P_zS)^{-1}$, where $P_z = Z(Z'\hat{\Omega}Z')^{-1}Z$ and $\hat{\Omega}$ is a diagonal matrix with diagonal element equal to the squared residual obtained from a 'first step' 2SLS regression.

Endogeneity issues follow the approach suggested by Nevo (2001). The identifi-

[17] These discrete measures are normalized so that weighted prices and advertising expenditures of rival brands that are in the same grouping are equal to their average.

[18] The square of the Euclidean distance is employed because a common boundary is defined by a non-linear equation when price is added to Euclidean distance, thereby increasing computational time and complexity.

cation assumption is that, after controlling for brand, city and time specific effects, demand shocks are independent across cities. Because beer is produced in large-scale plants and then distributed to various states, the prices of a brand across different markets share a common marginal cost component, implying that prices of a given brand are correlated across markets. If the identifying assumption is true, prices will not be correlated with demand shocks in other markets and can hence be used as instruments for other markets. In particular, the average price of a brand in other cities is used as its instrument.[19]

The data employed in this study are based on broadly defined city-regional markets. These broad market definitions, which are similar to those used by the Bureau of Labor Statistics, reduce the possibility of potential correlation between the unobserved shocks across markets. Furthermore, demand shocks that may be correlated across markets because of broad advertising strategies are controlled for by including national advertising expenditures in the demand equation. In general, any unobserved regional or national shock, like an interest rate shock will affect demand in various markets and will violate the independence assumption. To further control for such unobserved national shocks, time dummies are included in the specification.

Although a similar instrument could be constructed for advertising, brand-level advertising expenditures are only observed at the national level in each quarter and are thus invariant across markets. Alternatively, lagged advertising expenditures are used as instruments for advertising. This can be done if the identifying assumption is extended to independence of demand shocks over time, in addition to across cities, and there is correlation of advertising expenditures over time. Since expenditures, (x_t^*), are constructed with price and quantity variables, this term is also treated as an endogenous variable and is intsrumented with median income. A final identification assumption, which is common practice in the literature, is that product characteristics are assumed to be mean independent of the error term.

Whereas the identifying assumption of independence of demand shocks across markets may be problematic and difficult to assess, it has been widely used in the literature.[20] Despite its wide acceptance, however, the validity of the proposed instruments is assessed by conducting a formal test. Following Nevo (2001), additional instruments for price are created from city-specific marginal costs (i.e. proxies for shelf space and transportation costs) and instrument validity is checked with an overidentifying restrictions test.

As observed by Berry, an additional source of endogeneity may be present in differentiated products industries. Unobserved product characteristics, which can be interpreted as product quality, style, durability, status, or brand valuation, may be

[19] Alternatively, as in Nevo (2001), the average of regional prices can be used. However, in this application some brands appear in 1 or 2 cities, making this approach unfeasible.

[20] Hausman, Leonard and Zona, Slade (1995), Hausman, Nevo (2000b, 2001), Pinkse and Slade, and Slade (2004) use this assumption. Nevo assumes independence of the demand shock over markets and over time, as it is done here.

correlated with the error term and can lead to a bias in the estimated price coefficient. Following Nevo (2001), this source of endogeneity is controlled for by exploiting the panel structure of the data with the inclusion of brand-specific fixed effects. These fixed effects control for the unobserved product characteristics that are invariant across markets, reducing the bias and improving the fit of the model. While brand fixed effects do not control for the unobserved product characteristics that are market (city) specific, the instruments discussed at the beginning of this section are intended to address this issue.

One final detail on demand estimation is that the inclusion of brand fixed effects captures market-invariant product characteristics and hence their coefficients can not be identified directly. These coefficients are recovered using a minimum distance procedure, as suggested by Nevo (2000a). The estimated coefficients on the brand dummies from the demand equation (in which the invariant characteristics and the constant are omitted) are used as the dependent variable in a GLS regression, while the invariant product characteristics and a constant are used as the explanatory variables.

5.3 Predicted Prices by Models with Higher Excise Taxes

Marginal costs (16) are used to compute each model's predicted equilibrium prices after the tax change. Since excise taxes were increased for all beers at a uniform rate of E per unit, predicted prices in quarter $y+1$ can be computed in each city by solving for p_j^{y+1} $(j = 1, ...J)$ in the following system of non-linear equations:

$$q_j(p^{y+1}, A) - 1 + \sum_{k \in F_f} (p_k^{y+1} - c_k^y - E) \left[\frac{\partial q_k}{\partial p_j} + \sum_{m \notin F_n} \frac{\partial q_k}{\partial p_m} \frac{dp_m}{dp_j} + \frac{\partial q_k}{\partial A_j} \right] = 0, \text{ for } j = 1, .., J$$

where the superscript y denotes the quarter prior to the tax increase (fourth quarter of 1990).[21] Both q_j and the derivatives in brackets are also functions of price (p_j^{y+1}) so the non-linear search includes these terms as well. Other variables (i.e. advertising, distance measures, product characteristics and total expenditures x_t^*) are held constant at time y values and parameters are those obtained from demand estimation.[22] In some cities, a few brands (1 or 2) exited or entered the market between the fourth quarter of 1990 and the first quarter of 1991. In these cities, the search was performed with the subset of brands that were present in both quarters. While this simplification may be problematic since price movements due to changes

[21] To avoid sensitivity to potential outliers in quarter y, the median city-specific marginal cost of brand k over the period 1988-1990 is used for c_k^y.

[22] Because advertising expenditures play a small role in demand and do not change significantly after the tax increase, results are invariable to whether pre- or post-increase advertising is used in the simulation.

in the product set are ignored, the potential bias is likely to be small as these are marginal brands in terms of sales.

The predicted prices are computed in every city and for each brand. This system is solved by using the iterative Newton algorithm for large-scale problems provided by *Matlab*. While convergence is quickly achieved for the Bertrand-Nash and collusive models, it takes several hours for a computer to solve the system in all cities for the leadership cases.

5.4 Estimates of Actual Price Increases

Following Hausman and Leonard, for each brand a separate regression of the following form carried out:

$$p_{yz} = \theta_y + \eta' I + \xi_{yz}$$

where p_{yz} is price in quarter y and city z (i.e. each city-quarter pair y, z corresponds to a market t), θ_z are city fixed effects, I is a vector quarter dummy variables and η its corresponding vector of coefficients. The coefficient on the dummy for the first quarter of 1991 is interpreted as the absolute mean price increase for that brand due to the tax increase. One caveat with this interpretation is that this coefficient captures the mean effect on price of all city-invariant factors in the first quarter of 1991 (i.e. other national shocks besides the tax increase). Two factors that could have also shifted prices were inspected, namely input price changes and seasonality effects, but these were found to be statistically insignificant in this quarter.

6 Results

6.1 Demand

Estimation is based on equation (7) and details presented in section 5.2. Demand estimates presented below were obtained using data for the whole sample period 1988-1992. Because the functional form of demand constitutes only a local approximation to any unknown demand function, demand parameters can potentially differ between the two regimes (pre- and post-tax increase). However, aside from slightly larger standard errors, demand estimates with pre-increase data produced results that were essentially the same as those obtained with the full sample. Demand estimates, therefore, are robust to these two sample sizes.

The regressions below contain variables that consistently had the greatest explanatory power in different specifications. Table (3) presents the estimation results of two models. The difference between models 1 and 2 is the inclusion of brand fixed effects. City and time binary variables are included in both models (coefficients not reported). Coefficients are presented in six groups, one for each term in equation (7).

The first group contains the estimated coefficients of variables in the constant a_{jt}. Because alcohol content, brewer dummies and product segment variables for each brand are constant across time and cities, their coefficients can not be directly identified when brand dummies are included in model 2. A minimum distance (MD) procedure is utilized to recover these coefficients (see section 5.2). A second-stage regression is performed with the estimated coefficients on brand dummies as the dependent variable and alcohol content (ALC), product segments (budget, light, premium, super-premium and import), brewer dummies, and a constant as explanatory variables. While the market-invariant product characteristics in the MD procedure explained only 12% of the variation in the coefficients of the brand dummies, all coefficients recovered from the MD procedure except for the constant are significantly different from zero at the 1% significance level. The positive coefficients on the product segment binary variables indicate that these product segments have larger budget shares than the light (or base) product segment. An increase in alcohol content is associated with a reduction in the budget share.

The only product-specific variable that does vary by market is the number of common boundaries in alcohol content-product coverage space ($\#CBAC$). The negative coefficient on $\#CBAC$ shows that brands that share a common boundary with more neighbors in alcohol-coverage space have lower sales (budget) share than those with fewer common boundaries. Thus, the higher number of close neighbors, the greater the competition between brands. Conversely, the demographic variable $OVER50K$ has a negative sign which implies that sales shares tend to be smaller in cities where the fraction of high income families is larger. This finding is consistent with the fact that more that half of beer is consumed by households with an annual income of $45,000 or less (Beer Institute).

The estimated coefficients for own-price, own-advertising, and their interactions with product characteristics are reported in the next two groups in table 3. Because price and advertising are highly correlated with their corresponding interactions with product coverage, the inverse of this latter variable ($1/COV$) is used to avoid collinearity.

The own-price and own-advertising coefficients are significantly different from zero at the 1% level and have the expected negative and positive signs. The negative coefficients on the interaction of price and advertising with the inverse of product coverage indicates that as the coverage of a brand increases, the own-price effect for that brand decreases (becomes less negative) while the own-advertising effect increases (becomes more positive). Thus, the sales of brands that are widely sold within a city are less sensitive to a change in price than are brands that are less widely available. Also, advertising is more effective for brands that are more widely sold. Finally, as the number of common boundaries increases the own-price effect increases (becomes more negative) and the own-advertising effect decreases. This shows that higher brand competition is associated with more price responsive demand and less effective advertising.

Table 3: Demand Estimation Results with Instrumental Variables (GMM)

Dependent Variable: Sales Share (w_{jt}), equation (7)

Variable[±]	Coefficient Model 1	Coefficient Model 2
Brand Dummies	✓	×
a		
Constant[§]	-	-15.51 (-0.96)
ALC[§]	-	5.95 (3.24)
Popular[§]	-	49.98 (14.84)
Premium[§]	-	63.52 (13.95)
Super-premium[§]	-	131.81 (23.85)
Import[§]	-	211.18 (22.55)
#CBAC	-1.15 (-0.85)	-3.91 (-3.66)
OVER50K	-94.84 (-0.57)	-240.0 (-1.90)
Own-Price (b)		
$\log p$	-122.4 (-9.82)	-252.9 (-5.71)
$\log p \times (1/\text{COV})$	-0.56 (-2.38)	-1.09 (-3.46)
$\log p \times$#CBCSN	-4.82 (-7.28)	-7.14 (-11.35)
Own-Advertising (c)		
A^{γ}	8.48 (31.15)	1.32 (4.39)
$A^{\gamma} \times (1/\text{COV})$	-0.68 (-5.58)	-0.19 (-3.47)
$A^{\gamma} \times$#CBCS	-1.65 (-3.57)	-0.16 (-4.53)

Variable[±]	Coefficient Model 1	Coefficient Model 2
Brand Dummies	✓	×
Weighted Cross-Prices λ_l, $[\delta^l]^{\pm}$		
$[AC]$	2.10 (13.66)	5.32 (11.00)
$[NNAC]$	-0.21 (-0.30)	8.87 (15.62)
$[BREW]$	-12.18 (-5.38)	17.30 (5.31)
$[PROD2]$	52.39 (6.62)	93.56 (3.99)
$[REG]$	40.83 (5.85)	49.61 (5.39)
Weighted Cross-Adv τ_m, $[\mu^m]^{\pm}$		
$[SIZE^*]$	0.17 (7.83)	0.16 (8.64)
$[CBCSN]$	0.85 (15.50)	0.71 (15.23)
$[NNCS]$	0.61 (14.70)	0.40 (12.24)
$[PROD3]$	-2.78 (-14.58)	-3.22 (-9.10)
$[REG]$	-3.02 (-21.79)	5.30 (2.65)
Price Index (d)		
$\log(x_t/P_t)$	28.15 (1.08)	27.35 (1.38)

Overidentification J-Statistic (p-value): Model 1: (0.90); Model 2: (0.50)

R^2 from MD regression: 0.12

Based on 33,392 observations. Coefficients in table are original coefficients x 10^4. All specifications include time, city and brand dummies (not reported). Asymptotic t-statistics in parenthesis.

[§]Estimates for minimum distance (MD) procedure; it also includes brewer dummies (not shown)

[±]Description of variables and distance measures, $[\delta^l]$ and $[\mu^m]$, is presented in table 4 below

Table 4: Description of Variables and Distance Measures used in Demand Estimation

#CBAC	# of Common boundary neighbors in Alcohol-Coverage Space
#CBCS	# of Common boundary neighbors in Coverage-Size Space
#CBCSN	# of Common boundary neighbors in endogenous Coverage-Size Space
AC	1/[1+2×(Euclidean distance in Alcohol-Coverage space)]
NNAC	1 if j and k are nearest neighbors (mutual or not) in Alcohol-Coverage space, 0 otherwise
BREW	1 if j and k produced by same brewer, 0 otherwise
PROD2	1 if j and k in same segment: light or regular
REG	1 if j and k are regional or j and k are national, 0 otherwise
SIZE*	$1/(1+2\lvert \mathrm{SIZE}_j\text{-}\mathrm{SIZE}_k \rvert)$
CBCSN	1 if j and k share common boundary in endog. Coverage-Size space, 0 otherwise
NNCSN	1 if j and k nearest neighbors (mutual or not) in Coverage-Size space, 0 otherwise
PROD3	1 if j and k in same segment: budget, light or premium

Comparing models 1 and 2, the estimated own-price coefficient is nearly twice as large in absolute terms when brand dummies are included. Conversely, the own-advertising coefficient decreased by approximating 80 percent in model 2 compared to model 1. The better goodness-of-fit measures for model 2 and the magnitude of change on both price and advertising coefficients highlight the importance of accounting for endogeneity (resulting from unobserved product characteristics) with the inclusion of brand dummies. Furthermore, the overidentification test in model 2 (p-value=0.50) suggests that the choice of instruments is valid. Discussion of results is henceforth based on model 2.

The next two groups in table 3 contain the weighted cross-price and weighted cross-advertising terms. For each term, the weighing distance measure is in brackets. Several specifications were tried to determine the product spaces that were most relevant for weighing cross-prices and cross-advertising. Alcohol-Coverage appeared to be the most important continuous product space for price and Coverage-Size for advertising. Therefore, nearest neighbor and common boundary measures were computed in Alcohol-Coverage space for price and in Coverage-Size space for advertising. However, when using AC to weigh cross-price terms and CS to weigh cross-advertising terms in the same regression created collinearities. Replacing CS by the distance measure $SIZE^*$ reduced the collinearity problem while not affecting the other parameter estimates.

In model 2, the estimated coefficients on the weighted cross-price terms are all positive. Thus, brands that are closer in the alcohol content-product coverage space (both in terms of Euclidean distance and nearest neighbor), produced by the same brewer, have similar geographic coverage, or belong to the same product segment are stronger substitutes than other brands. Intuitively, consumers will more likely switch to a brand located nearby in product space and/or produced by the same brewer than to more distant brands. Based on the magnitude of the estimated coefficients, the strongest substitution effects are for brands in the same product segment and with similar geographic coverage.

With the exception of product segment, the estimated coefficients on weighted cross-advertising terms are positive. This suggests that there are spillover effects in advertising across brands that are located more closely in the product space and with the same geographic coverage. However, the negative coefficient for product segment indicates that there are rival cross-advertising effects for brands in the same product segment, thereby potentially offsetting some of the spillover effects. In general, positive and negative cross-advertising effects have the same order of magnitude. However, as shown in table 6, there are more positive cross-advertising elasticities than negative cross-advertising elasticities, indicating that spill-over effects dominate rival effects.

The estimated coefficient on real expenditures, $\log(x_t/P_t)$, is not statistically different from zero. Various specifications were tried that interacted product or market characteristics with real expenditures, but none of these specifications yields statistically significant coefficients. This result implies that the brand-level income elasticities are all equal to one.

Elasticities were computed in each city-quarter pair with coefficients from model 2. The median own-price elasticity across all brands is -3.34 while the median own-advertising elasticity is 0.024. All own-price elasticities are negative while approximately 85% of own-advertising elasticities are positive. All cross-price elasticities are positive and have a median value of 0.0593 whereas 88% of cross-advertising elasticities are positive and have a median of 0.021.[23]

A sample of median price and advertising elasticities is presented in tables 5 and 6. To facilitate comparison of the cross-price and cross-advertising patterns, these tables also contain information on the distance measures used to compute the elasticities. Table 5 divides brands into light and regular. Brands that are located closer in product space have, in general, higher cross-elasticities. For example, Budweiser, Michelob, Coors, Miller Genuine Draft, and Miller High Life are located close to one another in the product space. The cross-price elasticities between these brands are generally larger than the cross-price elasticities with Keystone, Old Style, Olympia, Pabst, and all light beers. Estimated confidence intervals (not shown) indicate that all price elasticities are significantly different than zero at the 5% level.[24]

As shown in table 6, the median advertising elasticities vary considerably across brands. While all of the own-advertising elasticities in the table and most of the cross-advertising elasticities are positive, there are several negative cross-advertising

[23] In general, median own-price elasticities are similar to those reported in Hausman, Leonard and Zona (-4.98), and Slade (-4.1). Cross-price elasticities are similar to those in Slade but an order of magnitude smaller than those reported by Hausman, Leonard and Zona.

[24] The 95% confidence intervals were computed using 5,000 draws from the asymptotic distribution of the estimated coefficients.

elasticities. These negative cross-advertising elasticities occur between brands in the same product segment. This is due to the negative coefficient on the cross-advertising term that is weighted by the product grouping measure $PROD3$ (table 3). In these cases, the rival cross-advertising effects for brands in the same product segment outweigh the positive advertising spillover effects from closely located brands. Not all of the advertising elasticity estimates, however, are statistically different than zero. Approximately 85% of negative advertising elasticities and 86% of positive elasticities are significant at the 5% level.

6.2 Implied Price-Cost Margins

According to details in section 3.3, implied marginal costs in the pre-increase period are calculated for each model using the estimated demand parameters. Comparing these marginal costs across models is informative about differences in the equilibrium predictions of the models. Because price-cost margins as a fraction of price ($[p-c]/p$) are more readily interpretable than marginal costs, pre-increase summary statistics of this measure (in percentage format) are presented in table 7. Six different models are considered: Bertrand-Nash; two Stackelberg scenarios: firm leadership by Anheuser-Busch and brand leadership by Budweiser; collusive leadership by Budweiser; and two collusive scenarios: collusion of the three leading firms (Anheuser-Busch, Coors and Miller) and collusion of three brands, Budweiser, Coors and Miller High Life (the main regular brands of leading firms).[25]

[25] The full collusion case produced unlikely price-cost margins (over 100%). Hence, these two plausible collusive scenarios were explored.

Table 5: Sample of Median Own- and Cross-Price Elasticities

	Bud	Michb	Coors	Kstone	Old Style	Olymp	Pabst	MGD	High Life	Bud Light	Busch Light	Michb Light	Coors Light	Kstone Light	Old St Light	MGD Light	Miller Lite
Alcohol	4.9	5	5	4.8	5	4.8	5	5	5	4.2	4.2	4.3	4.2	4.1	4.1	4.5	4.5
Coverage	0.96	0.94	0.93	0.72	0.54	0.59	0.72	0.95	0.95	0.95	0.82	0.92	0.95	0.76	0.52	0.87	0.95
AB BUD	-1.152	0.006	0.005	0.005	0.004	0.005	0.005	0.005	0.005	0.004	0.004	0.004	0.003	0.003	0.002	0.003	0.003
AB MICHELOB	0.060	-2.500	0.069	0.047	0.032	0.044	0.051	0.081	0.088	0.040	0.042	0.041	0.026	0.028	0.015	0.035	0.029
AC COORS	0.040	0.054	-2.263	0.070	0.036	0.036	0.042	0.063	0.068	0.023	0.031	0.023	0.050	0.053	0.017	0.035	0.026
AC KEYSTONE	0.160	0.148	0.237	-6.072	0.125	0.186	0.149	0.147	0.149	0.095	0.097	0.099	0.183	0.181	0.065	0.107	0.108
B OLD STYLE	0.275	0.288	0.277	0.336	-15.15	0.318	0.320	0.297	0.291	0.146	0.176	0.153	0.136	0.164	0.377	0.162	0.166
P OLYMPIA	0.104	0.098	0.096	0.139	0.103	-4.924	0.185	0.097	0.098	0.066	0.068	0.069	0.064	0.065	0.064	0.064	0.073
P PABST	0.083	0.097	0.100	0.078	0.037	0.155	-3.886	0.100	0.111	0.049	0.048	0.051	0.050	0.048	0.016	0.047	0.054
PM MGD	0.026	0.034	0.037	0.023	0.019	0.020	0.028	-1.818	0.059	0.014	0.015	0.015	0.014	0.014	0.009	0.024	0.028
PM HIGH LIFE	0.026	0.039	0.043	0.025	0.017	0.023	0.028	0.065	-1.831	0.015	0.015	0.015	0.015	0.015	0.007	0.032	0.030
AB BUD LT	0.010	0.010	0.006	0.006	0.003	0.006	0.006	0.006	0.006	-1.347	0.028	0.031	0.039	0.028	0.017	0.021	0.027
AB BUSCH LT	0.031	0.030	0.021	0.023	0.010	0.020	0.021	0.021	0.021	0.105	-2.226	0.090	0.107	0.103	0.053	0.068	0.077
AB MICHB LT	0.047	0.046	0.031	0.032	0.016	0.039	0.029	0.030	0.030	0.177	0.125	-2.622	0.165	0.125	0.096	0.137	0.132
AC COORS LT	0.007	0.007	0.014	0.012	0.005	0.006	0.007	0.007	0.007	0.040	0.030	0.031	-1.363	0.035	0.031	0.024	0.028
AC KEYST LT	0.056	0.054	0.109	0.113	0.031	0.053	0.053	0.054	0.054	0.236	0.246	0.211	0.334	-4.112	0.137	0.167	0.198
B OLD STYLE L	0.169	0.162	0.162	0.197	0.933	0.192	0.161	0.162	0.162	0.915	0.869	0.917	0.926	1.128	-16.966	0.576	0.886
PM MGD LT	0.021	0.020	0.020	0.022	0.013	0.021	0.020	0.035	0.035	0.064	0.068	0.065	0.064	0.064	0.054	-2.045	0.106
PM MILLER L	0.006	0.005	0.005	0.006	0.003	0.005	0.005	0.010	0.010	0.019	0.017	0.020	0.019	0.018	0.012	0.030	-1.266

Each entry i, j represents the median i, j price elasticity over all markets (i.e. all city-quarter pairs)

Table 6: Sample of Median Own- and Cross-Advertising Elasticities

	Bud	Bud Light	Busch Light	Michb	Michb Light	Coors	Coors Light	Kstone	Kstone Light	Old Style	Old St Light	Olymp	Pabst	MGD	MGD Light	High Life	Miller Lite
Coverage	0.96	0.95	0.82	0.94	0.92	0.93	0.95	0.72	0.76	0.54	0.52	0.59	0.72	0.95	0.87	0.95	0.95
SIZE	0.41	0.42	0.47	0.29	0.29	0.40	0.42	0.44	0.45	0.41	0.48	0.46	0.43	0.36	0.36	0.39	0.43
AB BUD	0.0177	0.0138	0.0007	0.0006	0.0022	0.0013	0.0141	0.0053	0.0050	-0.0003	0.0006	0.0002	0.0023	0.0012	0.0082	0.0018	0.0166
AB BUD LT	0.0424	0.0326	-0.0002	0.0067	-0.0015	0.0112	-0.0046	0.0119	-0.002	0.0009	-0.0018	0.0003	0.0051	0.0102	-0.0018	0.0165	-0.0034
AB BUSCH LT	0.1115	-0.0124	0.0037	0.0136	-0.0032	0.0211	-0.0131	0.0415	-0.0040	0.0032	-0.0044	0.0008	0.0178	0.0412	-0.0066	0.0414	-0.0140
AB MICHELOB	0.0267	0.1027	0.0068	0.0521	0.0399	0.0087	0.1075	0.0521	0.0473	-0.0028	0.0049	0.0016	0.0218	0.0161	0.0992	0.0140	0.1267
AB MICHB LT	0.1461	-0.0418	-0.0019	0.0642	0.0316	0.0469	-0.0444	0.0580	-0.0131	0.0035	-0.0111	0.0019	0.0207	0.0543	-0.0128	0.0800	-0.0477
AC COORS	0.0334	0.0963	0.0070	0.0054	0.0157	0.0266	0.1216	0.0499	0.0404	-0.0027	0.0055	0.0012	0.0158	0.0096	0.0815	0.0138	0.1239
AC COORS LT	0.0386	-0.0048	-0.0002	0.0070	-0.0014	0.0128	0.0356	0.0122	-0.0021	0.0012	-0.0031	0.0004	0.0051	0.0099	-0.0021	0.0157	-0.0056
AC KEYSTONE	0.4538	0.3569	0.0248	0.0629	0.0510	0.1047	0.4052	0.1026	0.2052	0.0192	0.0218	0.0007	0.0087	0.1767	0.2552	0.1774	0.4526
AC KEYST LT	0.2709	-0.0330	-0.0012	0.0371	-0.0068	0.0540	-0.0380	0.1408	0.0515	0.0092	-0.0142	0.0025	0.0392	0.1060	-0.0148	0.0981	-0.0426
B OLD STYLE	-0.3792	0.4093	0.0396	-0.0964	0.0830	-0.1047	0.4136	0.2923	0.2645	0.0041	0.1451	0.0075	0.0579	-0.0908	0.2122	-0.1790	0.4387
B OLD STYLE L	0.5477	-0.9079	-0.0417	0.1573	-0.1773	0.1716	-0.8905	0.2678	-0.2785	0.2674	0.0109	0.0116	0.0778	0.1431	-0.3332	0.2451	-1.0173
P OLYMPIA	0.3203	0.2663	0.0184	0.0697	0.0421	0.0947	0.2776	0.0333	0.1247	0.0147	0.0331	0.0011	0.0157	0.1026	0.1523	0.1508	0.3258
P PABST	0.2501	0.2065	0.0136	0.0635	0.0380	0.0766	0.2300	0.0103	0.0765	0.0047	0.0053	0.0007	0.0163	0.0813	0.1128	0.1207	0.2594
PM MGD	0.0189	0.0605	0.0030	0.0044	0.0119	0.0050	0.0653	0.0253	0.0230	-0.0015	0.0026	0.0007	0.0104	0.0230	0.0392	0.0094	0.0746
PM MGD LT	0.0933	-0.0103	-0.0005	0.0143	-0.0016	0.0133	-0.0111	0.0335	-0.0043	0.0034	-0.0048	0.0006	0.0171	0.0566	0.0407	0.0377	-0.0130
PM HIGH LIFE	0.0208	0.0687	0.0036	0.0037	0.0119	0.0062	0.0697	0.0286	0.0257	-0.0013	0.0027	0.0009	0.0120	0.0059	0.0554	0.0403	0.0877
PM MILLER L	0.0283	-0.0038	-0.0002	0.0057	-0.0012	0.0082	-0.0041	0.0092	-0.0015	0.0006	-0.0013	0.0003	0.0040	0.0081	-0.0017	0.0131	0.0291

Each entry i, j represents the median i, j advertising elasticity over all markets (i.e. all city-quarter pairs)

Table 7: Summary Statistics of Price Cost Margins for Different Scenarios, (1988-1990)*

	Mean	Median	St. Dev
Bertrand-Nash	39.50	36.68	25.96
Anheuser-Busch Stackelberg Leadership	40.08	37.58	26.25
Budweiser Stackelberg Leadership	39.52	36.68	26.00
Collusive Leadership (Budweiser)**	70.51	60.88	45.09
Collusion 3 firms§	46.02	46.95	29.14
Collusion 3 brands±	40.20	37.17	26.50

* Margins are defined as $(p - c)/p$ (in percentage). Presented are the summary statistics of the 18,369 (brand-city-quarter) observations in the pre-increase period (1988-1990).

** Price-cost margins obtained for Anheuser-Busch brands only

§ Anheuser-Busch, Adolph Coors, Miller (Philip Morris)

± Budweiser, Coors, Miller Genuine Draft

The mean price-cost margin of Budweiser as a Stackelberg leader does not to differ substantially from that of Bertrand-Nash competition. Both Anheuser-Busch as a Stackelberg leader and collusion among three brands predict similar mean price-cost margins that are slightly higher than Bertrand-Nash. Collusion among the 3 largest firms predicts the largest mean price-cost margin. When analyzing the medians and standard deviations, however, values are similar across models, except for the 3-firm collusion and the collusive price leadership scenarios.

Since in the collusive price leadership scenario price-cost margins are only computed for Anheuser-Busch brands, summary statistics for this case are not directly comparable with those of other models. However, price-cost margins are unreasonably large for Budweiser (mean price-cost margin of 164% vs. 82% in Bertrand-Nash, not shown) and similar to Bertrand-Nash price-cost margins for other brands (mean price-cost margin 56% vs 54% in Bertrand-Nash, not shown). In all models, price-cost margins vary considerably across brands. When calculating each model's predicted prices, this heterogeneity plays an important role.

6.3 Predicted vs. Actual Price Increases

Following details in section 5.3, the estimated demand parameters of model 2 in table 3 together with the implied marginal costs are used to compute the predicted prices (p_j^{y+1}) that would have prevailed under each model after the tax increase. Estimates of actual mean price increases are, in turn, computed according to details presented in section 5.4. In this section, predicted price increases, $(p_j^{y+1} - p_j^y)$ are compared to estimates of actual price increases. The reason for using absolute price increases rather than a measure relative to the pre-increase price is that the excise tax is based on quantity sold and hence tax pass-through should be unrelated to the pre-tax price.

The next figures plot predicted and actual **mean** price increases for each brand. For predicted price increases, the mean is calculated using each brand's predicted price increases over 46 cities. For actual price increases, one regression per brand is estimated with the price of the brand as the dependent variable and time and city dummies as regressors. The coefficient on the first quarter of 1991 time dummy is interpreted as that brand's mean price increase. Each figure corresponds to one of the scenarios discussed in the previous section. 95% confidence intervals are displayed for actual mean price increases.[26] Table 8 displays summary statistics of the actual and predicted mean price increases.

Figure 2 corresponds to the Bertrand-Nash model. Except for a handful of brands (especially Budweiser and Bud Light), Bertrand-Nash behavior tends to underpredict price increases. This pattern is reflected in a median value of actual mean increases that is more than 100% greater than the median value of predicted mean price increases ($1.85 vs. $0.88, table 8). Absolute variability is similar between the two series (standard deviation of 0.93 for actual mean price increases and 0.88 for predicted mean price increases). However, relative to their mean, predicted mean price increases are more variable than actual mean price increases.

The predicted mean price increase for Budweiser is the largest ($4.95) and it is more than twice the value of the actual price increase ($1.91). In general, more inelastic brands are associated with higher the pass-through rates of a tax increase. To illustrate, the two largest predicted mean price increases are for Budweiser and Bud Light, the first and third most inelastic brands in the sample. Many brands have tight 95% confidence intervals around actual mean increases (around 15¢ and 20¢), indicating that price increases do not vary substantially across cities. This pattern can particularly be observed for Anheuser-Busch and Coors brands, and, to a lesser extent, for Pabst, Miller and Stroh brands (brewers that tend to produce nationally).

The Stackelberg scenario in which Anheuser-Busch acts as the price leader with all its brands (figure 3) has a pattern that is similar to the Bertrand-Nash case. Although it can not be discerned from the figure, in this model predicted increases are higher than in the Bertrand-Nash case for all but one brand. For Anheuser-Busch's brands, especially Budweiser, Bud Light and Natural Light, this difference is larger and hence discernable from the figures. Table 8 shows that the Anheuser-Busch Stackelberg model predicts larger mean price increases than Bertrand-Nash.

[26] The non-linear systems for predicted price increases require 12 hours of computing time. Calculating confidence intervals for predicted mean price increases with a bootstrapping technique are hence extremely costly even with a modest number of draws.

Figure 2: Predicted Price Increases by Bertrand-Nash behavior vs. Actual Price Increases per brand after 100% Hike in the Federal Excise Tax (Mean over 46 cities)

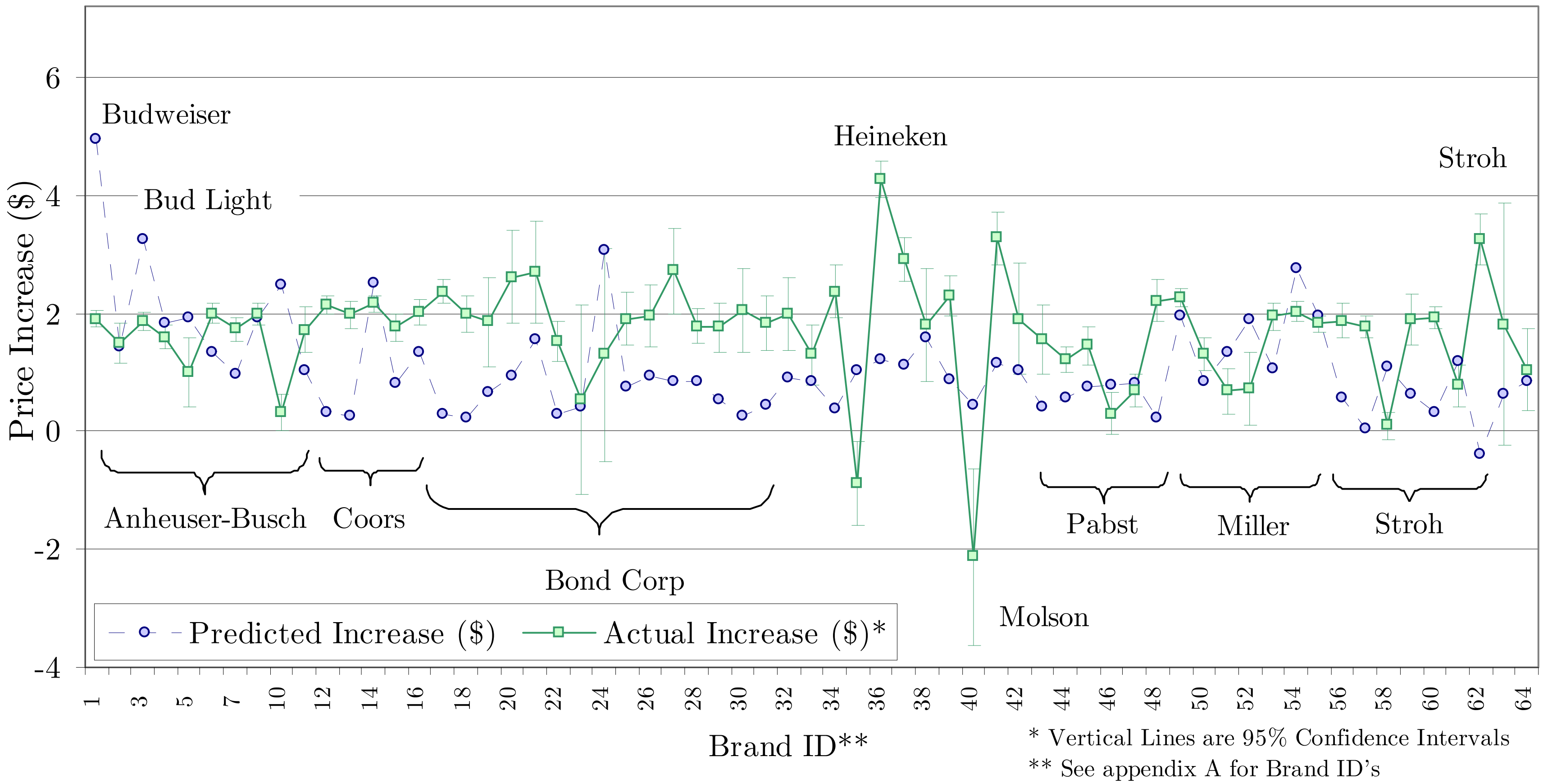
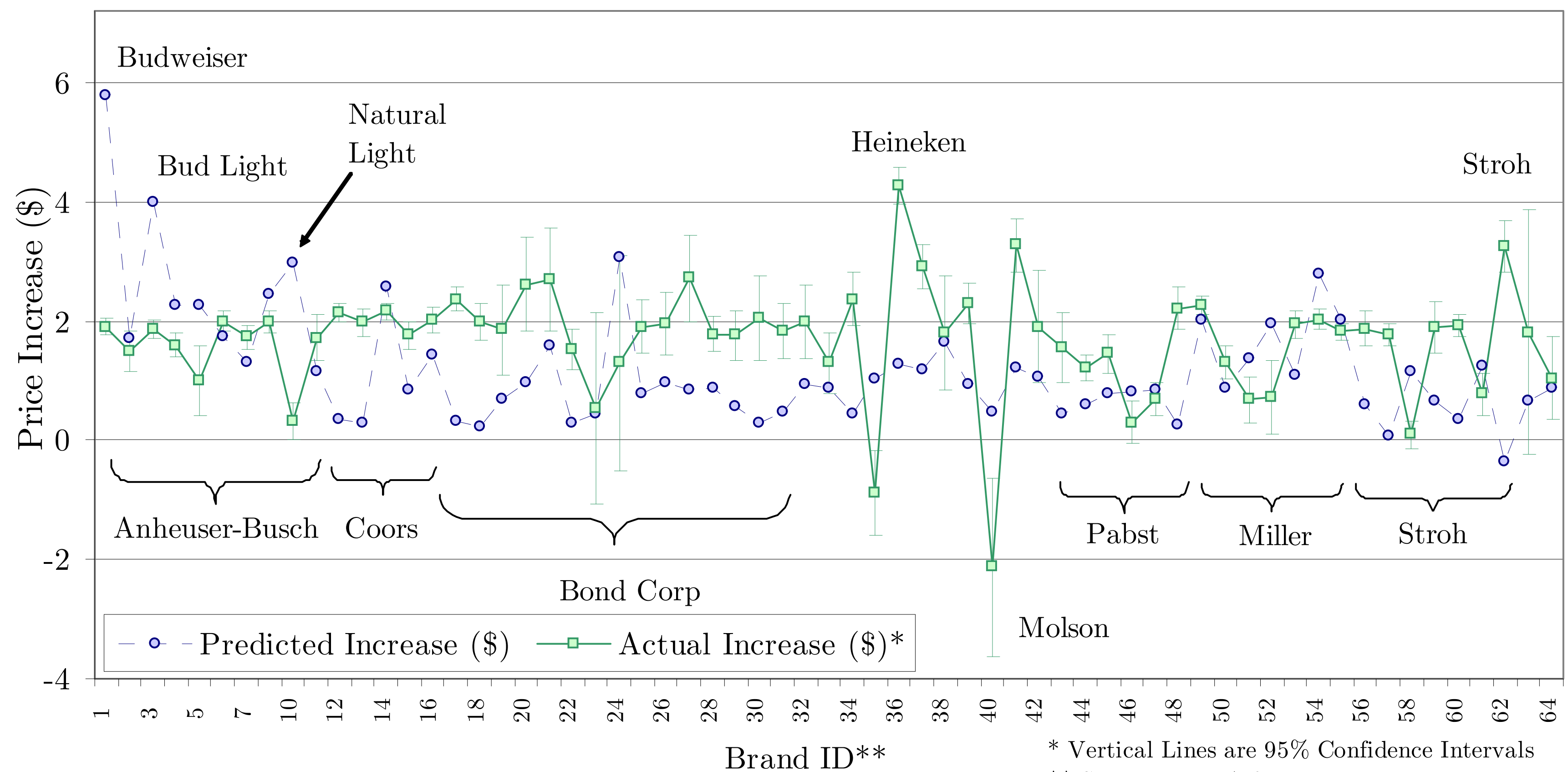


Figure 3: Predicted Price Increases by Leadership of Anheuser-Busch vs. Actual Price Increases per brand after 100% Hike in the Federal Excise Tax (Mean over 46 cities)



* Vertical Lines are 95% Confidence Intervals
** See appendix A for Brand ID's

Figure 4: Predicted Price Increases by Leadership of Budweiser vs. Actual Price Increases per brand after 100% Hike in the Federal Excise Tax (Mean over 46 cities)

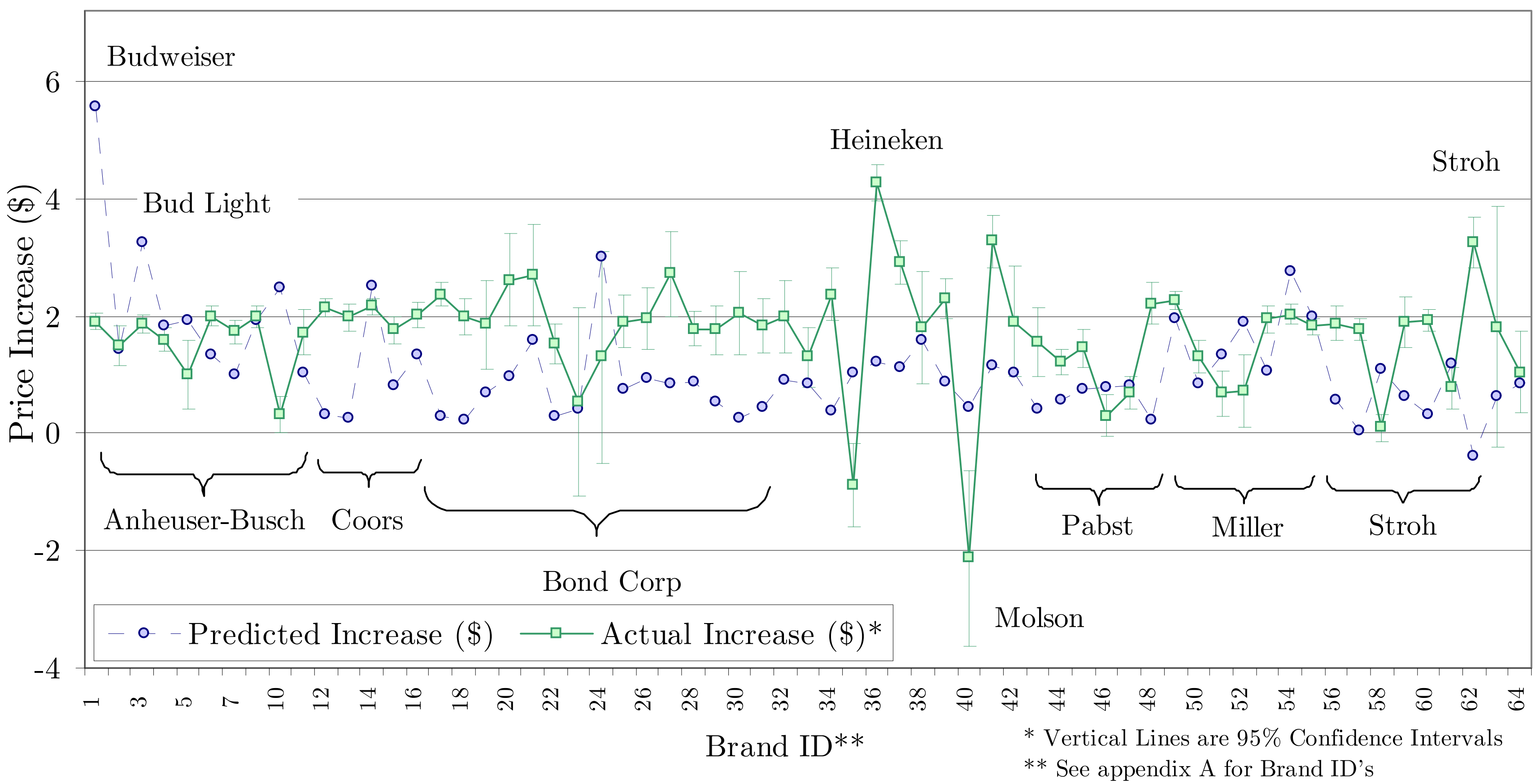
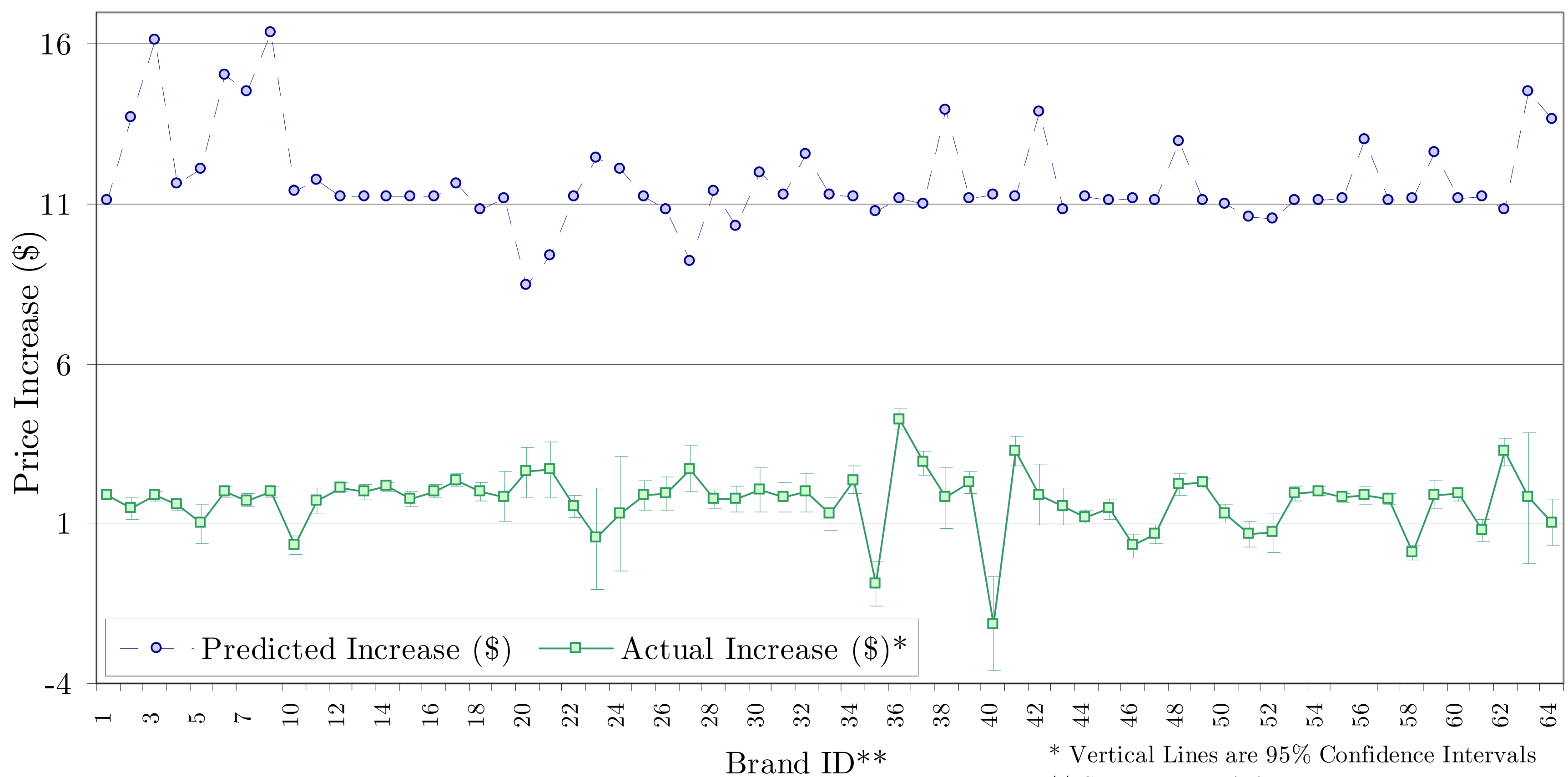


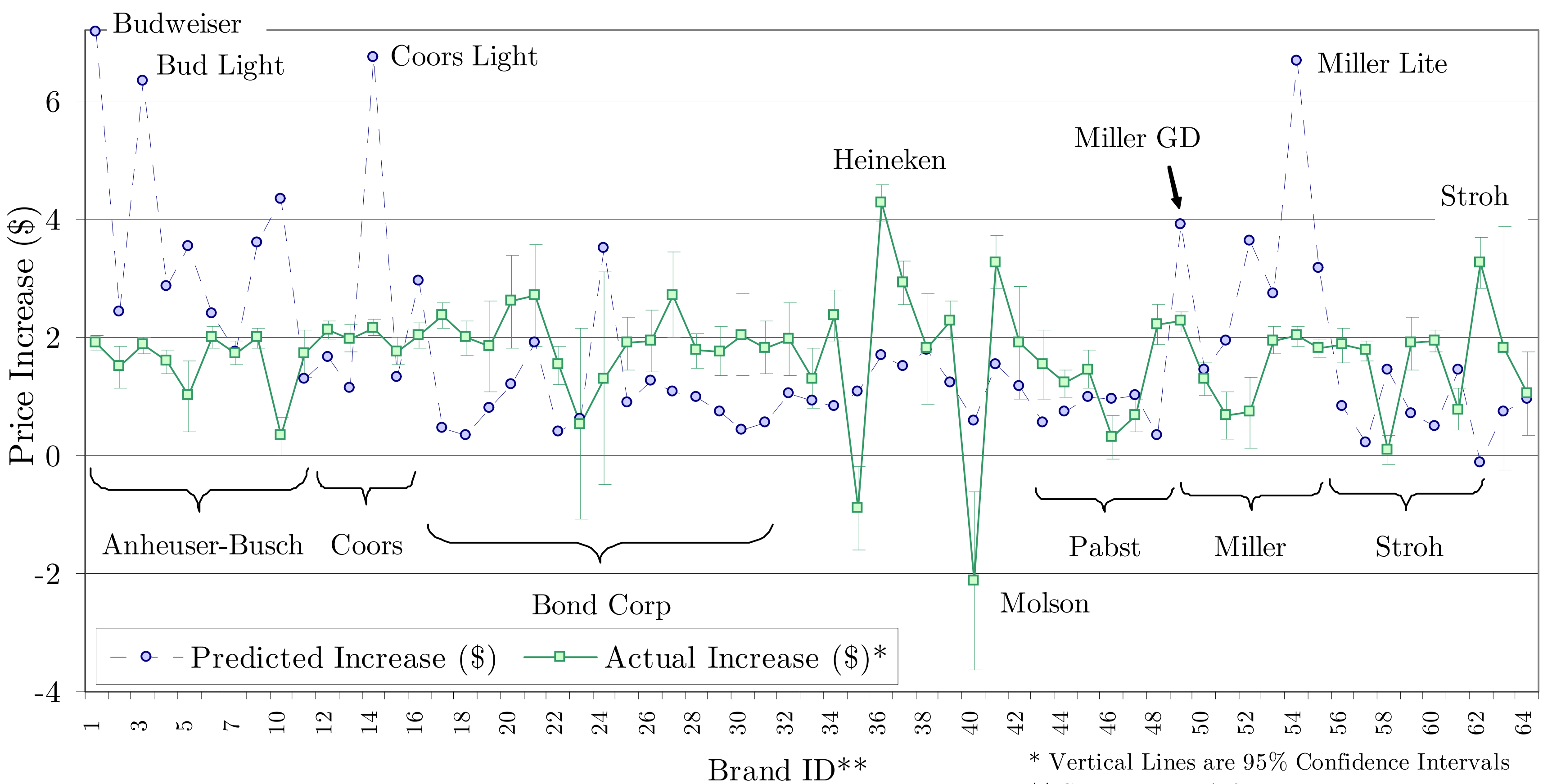
Figure 5: Predicted Price Increases of Collusive Price Leadership by Budweiser vs. Actual Price Increases per brand after 100% Hike in the Federal Excise Tax (Mean over 46 cities)



* Vertical Lines are 95% Confidence Intervals

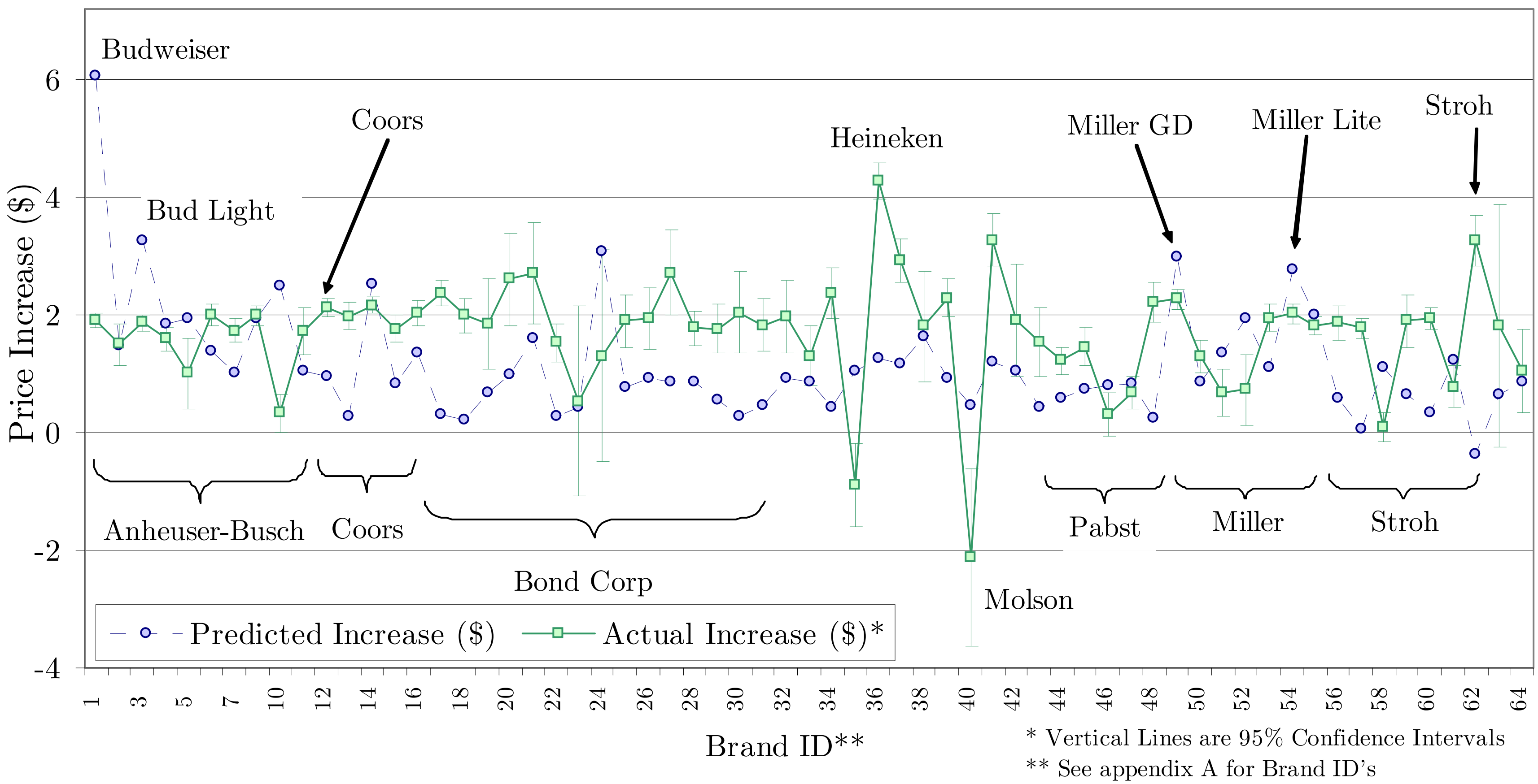
** See appendix A for Brand ID's

Figure 6: Predicted Price Increases by Collusive behavior between 3 largest firms vs. Actual Price Increases per brand after 100% Hike in the Federal Excise Tax (Mean over 46 cities)



* Vertical Lines are 95% Confidence Intervals
** See appendix A for Brand ID's

Figure 7: Predicted Price Increases by Collusive behavior between leading brands of 3 largest firms vs. Actual Price Increases per brand after 100% Hike in the Federal Excise Tax (Mean over 46 cities)



Aside from a larger overprediction for Budweiser (50 cents), the Budweiser Stackelberg model depicted in figure 4, on the other hand, yields predicted mean price increases that are essentially the same to the Bertrand-Nash case (mean and median are almost equal to Bertrand-Nash, table 8). Overall, the two Stackelberg models considered do not differ substantially from Bertrand-Nash behavior. The reason for this is that because reaction functions of followers depend mainly on very small cross-price coefficients, the term $\frac{dp_m}{dp_j}$ in (14) takes small positive values making the first order conditions of the leader not substantially different from the Bertrand-Nash case (for which the term $\frac{dp_m}{dp_j}$ is equal to zero).

The third leadership model considered is collusive price leadership by Budweiser. Here, the term $\frac{dp_m}{dp_j}$ is set to equal 1 in Budweiser's first order condition. This scenario predicts unlikely predicted mean price increases that are on average almost 7 times larger than actual mean price increases, with some predicted prices in the vicinity of \$15-\$16 for some of Anheuser-Busch's brands. As a consequence, this extreme case can be rejected as a model of price competition.

The 3-firm collusion scenario depicted in figure 6 over-predicts the price increases of the best selling brands of the colluding firms (e.g. Budweiser, Bud Light, Coors Light, Miller Genuine Draft and Miller Lite) by a large amount. On average, this scenario predicts higher mean price increases than Bertrand-Nash behavior (table 8). The 3-brand collusion scenario differs less strikingly with Bertrand-Nash: it predicts slightly larger mean price increases than Bertrand-Nash (table 8). This shift is mainly the consequence of a higher over-prediction for Budweiser and, to a lesser extent, for the other two colluding brands: Coors and Miller Genuine Draft (figure 7).

One metric of the accuracy of different models in explaining observed firm behavior is the number of brands whose predicted mean price increases fall within the confidence intervals of actual mean price increases. Table 8 presents this number (# Non-Rejections) for the models considered. According to this metric, the Bertrand-Nash, 3-brand collusion and Budweiser leadership scenarios explain firm behavior better than the other models, though equally well among them.

To assess the adequacy of these models, another metric is considered. This metric weighs mean price increases by each brand's market share. Intuitively, the purpose of this metric is to penalize a model if it does not do a good job at predicting the mean price increases of the most important brands; after all, it would more critical to have greater accuracy for the brands that matter most. The last column in table 8 presents this weighted mean for the models considered. Under this metric, the Bertrand-Nash case performs best, though it takes a value of more than two times greater than the value for actual mean price increases (4.25 vs. 1.82).

The reason for the large difference in the weighted mean is that the over-prediction in all models is greater for more popular brands. The combined share of Budweiser (19%), Bud Light (6%), Coors Light (7%) and Miller Lite (9%) is 41%. In all models, these are brands for which there is an over-prediction, the largest of which is for Budweiser. The fact that the weighted mean for actual mean price increases is similar

Table 8: Summary Statistics of Actual and Predicted Brand Mean Price Increases*

	Mean	Median	St. Dev	# Non-Rejections**	Weighted Mean***
Actual Mean Increases	1.69	1.85	0.93	N/A	1.82
Predicted Mean Increases					
Bertrand-Nash	1.10	0.88	0.88	10	4.25
A-B Stackelberg Leader¥	1.20	0.94	1.01	9	4.77
Budweiser Stackelberg Leader	1.11	0.89	0.93	10	4.48
Collusive Leadership (Budweiser)	11.70	11.20	1.45	0	21.34
Collusion 3 firms§	1.79	1.19	1.64	9	7.76
Collusion 3 brands±	1.17	0.92	0.99	10	4.84

* Actual and predicted mean price increase for each brand are computed over 46 cities.

** Number of brands for which the predicted mean price increase falls within the confidence intervals of the actual mean price increase

*** Weighted average of mean price increases (weight=national market share in fourth quarter 1990)

¥ A-B = Anheuser-Busch

§ Anheuser-Busch, Adolph Coors, Miller (Philip Morris)

± Budweiser, Coors, Miller Genuine Draft

to the non-weighted mean (second column in table 8) indicates that there are no important differences in actual mean price increases across brands.

7 Conclusion

This paper analyzes pricing behavior in the U.S. brewing industry where there is some evidence of price leadership by Anheuser-Busch and its Budweiser brand. Bertrand-Nash, leadership and collusive models are considered as possible candidates of pricing behavior. To choose the model that is best supported by the data, an exogenous variation in the data, namely the 100% increase in the federal excise tax, is used to compare actual price increases with price increases predicted by the different models of pricing behavior.

Using several metrics of closeness between predicted price increases and actual price increases revealed that, from the models considered, Bertrand-Nash appears to be more consistent with the actual behavior of firms. However, the data fails to support the inverse relationship between own-price elasticity and excise tax pass-through rates predicted by all models. As a consequence, Bertrand-Nash and other models, tend to overpredict tax pass-through rates of more price-inelastic brands, especially Budweiser, and to under-predict price increases of more price-elastic brands. Overall, actual price increases tend to be more similar across brands than any of the models predict.

An interpretation of this evidence is that Anheuser-Busch could exert larger market power than it actually does even under competitive Bertrand-Nash behavior. One policy implication of this interpretation is that antitrust concern should be low in terms of anticompetitive pricing behavior by the leading beer producer. This result is consistent with the findings of Nevo (2001) in the ready-to-eat breakfast cereals who suggests that large price-cost margins can be the result of product differentiation and the portfolio effect of firms carrying more than one brand rather than actual non-competitive behavior.

The models considered here, as most models of pricing behavior, are built upon the assumption of profit maximization. The results of this paper may be consistent with simpler, yet plausible pricing strategies. For instance, the fact that actual price increases for large brewers' brands (Anheuser Busch, Coors, Miller) as a result of the tax increase have minimal variation across cities and are similar to actual price increases of smaller brewers' brands may be interpreted as leading brewers setting a common cost mark-up for all brands, regardless of where they are sold (and possibly of how elastic they are), and smaller brewers matching these mark-ups. This conjecture is strengthened by the fact that price increases for elastic brands, which are produced mainly by smaller brewers and are generally more limited in their ability to increase prices, appear much higher than what Bertrand-Nash and other models suggest, with values close to actual price increases of the more inelastic brands produced by larger brewers. While this conjecture is consistent with the informal observations in the industry, the models considered are not able to capture it. Moreover, there is no clear way to test it within the profit maximization framework used in this paper. This issue hence remains as a potential extension.

Scherer and Ross (p. 261-265) explain that a type of "rule-of-thumb" pricing of the sort suggested above is common in many industries and is used as a way to cope with "uncertainties in the estimation of demand function shapes and elasticities" (p. 262). Furthermore, this type of pricing behavior can be used as a coordinating device, especially when there are changes in costs and firms in the industry share similar production technologies. To the extent that this type of behavior is facilitating coordination in the brewing industry, it appears that, as a consequence of the tax increase, it benefited smaller brewers rather than large firms.

Given the available dataset, the contribution of this paper is to shed some light on one of the many interesting features of the U.S. brewing industry. Clearly, the availability of more detailed data would allow to capture aspects that are not addressed here. For example, dynamic models of price competition can be better assessed with less aggregated data on the time dimension. Cost data at the manufacturer and retailer level can permit analysis of manufacturer-retailer interaction in the industry and more rigorous econometric tests of the competing pricing models considered here.

A Data Description and Selection

IRI is a Chicago based marketing firm that collects scanner data from a large sample of supermarkets that is drawn from a universe of stores with annual sales of more than 2 million dollars. This universe accounts for 82% of all grocery sales in the U.S. In most cities, the sample of supermarkets covers more than 20% of the relevant population. In addition, IRI data correlates well with private sources in the Brewing Industry (the correlation coefficient of market shares for the top 10 brands between data from IRI and data from the Modern Brewery Age Blue Book is 0.95). Brands that had at least a 3% local market share in any given city were selected. After selecting brands according to this criterion, remaining observations are dropped if they had a local market share of less than 0.025%. Brands that appear in less than 10 quarters are also dropped. Also, if a brand appears only in one city in a given quarter, the observation for that quarter is not included either. This is done because some variables in other cities are used as instruments.

The original dataset contained observations in 63 cities; five cities were dropped because of minimal number of brands or quantities. Overall, the number of cities increases over time; however, some cities appear only in a few quarters in the middle of the period. The average number of cities per quarter is 47. The variable R was constructed as follows. First the percentage of cities in which each brand was present was averaged over time. A plot of these averages revealed two clusters of brands, one close to 100% (denoted national brands) and another (roughly) below 50% (denoted regional brands). The variable $WAGES$ was constructed by averaging the hourly wages of interviewed individuals from the Bureau of Labor Statistics CPS monthly earning files at the NBER. For a given city-quarter combination, individuals working in the retail sector were selected for that city over the corresponding three months. The average was then calculated over the number of individuals selected.

[27] These brands correspond to G. Hieleman Brewing Co., which was acquired in 1987 by Australian Bond Corporation Holdings; it is classified as a domestic brewer because this foreign ownership was temporary

Table 9: Selected Brands and their Brewers [acronym and country of origin] (Brand ID)

Brewer	Brand	Brewer	Brand
Anheuser-Busch:	(1) Budweiser	Grupo Modelo	(34) Corona
[AB, U.S.]	(2) Bud Dry	[GM, Mexico]:	
	(3) Bud Light	Goya [GO, U.S.]:	(35) Goya
	(4) Busch	Heineken	(36) Heineken
	(5) Busch Light	[H, Netherlands]:	
	(6) Michelob	Labatt [LB, Canada]:	(37) Labatt
	(7) Michelob Dry		(38) Labatt Blue
	(8) Michelob Golden Draft		(39) Rolling Rock
	(9) Michelob Light	Molson [M, Canada]:	(40) Molson
	(10) Natural Light		(41) Molson Golden
	(11) Odouls		(42) Old Vienna
Adolph Coors	(12) Coors	Pabst [P, U.S.]:	(43) Falstaff
[AC, US]:	(13) Coors Extra Gold		(44) Hamms
	(14) Coors Light		(45) Hamms Light
	(15) Keystone		(46) Olympia
	(16) Keystone Light		(47) Pabst Blue Ribbon
Bond Corp.	(17) Black Label		(48) Red White & Blue
[B, U.S.][27]:	(18) Blatz	Philip Morris/Miller:	(49) Genuine Draft
	(19) Heidelberg	[PM, U.S.]	(50) Meister Brau
	(20) Henry Weinhard Ale		(51) Meister Brau Light
	(21) Henry Weinhard P. R.		(52) MGD Light
	(22) Kingsbury		(53) Miller High Life
	(23) Lone Star		(54) Miller Lite
	(24) Lone Star Light		(55) Milwaukee's Best
	(25) Old Style	Stroh	(56) Goebel
	(26) Old Style Light	[S, U.S.]:	(57) Old Milwaukee
	(27) Rainier		(58) Old Milw. Light
	(28) Schmidts		(59) Piels
	(29) Sterling		(60) Schaefer
	(30) Weidemann		(61) Schlitz
	(31) White Stag		(62) Stroh
Genesee	(32) Genesee	FX Matts	(63) Matts
[GE, US]:	(33) Kochs	[W, U.S.]:	(64) Utica Club

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