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Market Power and Price Competition in U.S. Brewing

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Market Power and Price Competition in U.S. Brewing

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Abstract

This paper analyzes the degree of market power in the U.S. brewing industry as measured by the closeness between the observed pricing behavior of firms and the equilibrium prices predicted by various pricing models: Bertrand-Nash, leadership, and collusion. Price leadership focuses on the largest U.S. beer producer Anheuser-Busch and its heavily marketed brand Budweiser whereas collusion focuses on the three largest brewers. Results indicate that Bertrand-Nash predicts the pricing behavior of firms more closely than other models. Concerns about non-competitive pricing of the forms studied here should hence be low in this industry. Despite its closeness to the observed pricing behavior, Bertrand-Nash under-predicts prices of more price-elastic brands and over-predicts prices of less price-elastic brands.

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"*With so few mass producers, there is continued concern about cooperative behavior among the leading brewers. Further research is needed to monitor the degree of market power in the industry*"

-Victor and Carol Tremblay in *The U.S. Brewing Industry: Data and Economic Analysis,* MIT Press (2005: 283).

"*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).

1 Introduction

A distinctive feature of U.S. brewing has been its dramatic change from a fragmented industry to a highly concentrated oligopoly. The number of mass-producing brewers has declined from 350 in 1950 to 24 in 2000 with a corresponding increase in the Herfindahl-Hirschman index from 204 to 3612 (Tremblay and Tremblay, 2005: 187), making this industry one of the most concentrated in the U.S.[1]

This rising concentration has often raised concerns about deviations from competitive pricing. The concern for increased market power and cooperative behavior among the few large producers is noted in the statement by Tremblay and Tremblay at the beginning of this paper. In addition, another deviation from competitive pricing has been noted in this market. Greer (1998) and Tremblay and Tremblay (2005, and references therein) identify Anheuser-Busch as a price leader especially through its heavily marketed brand Budweiser.[2] For example, in 1954, after a cost increase due to a new union wage agreement, Anheuser-Busch raised the price of Budweiser. Some regional brewers in St. Louis did not follow suit. After this, Anheuser-Busch decided to aggressively reduce Budweiser's price in St. Louis, which elevated its market share in the region 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. Evidence supports the fact that by the 1990's Anheuser-Busch, assisted by this punishing strategy, had become the clear price leader (Tremblay and Tremblay, 2005: 171; Greer: 49-51).

[1]For comparison with other highly concentrated industries, the HHI's for cigarettes, breakfast cereals and automobiles are 3100, 2446 and 2506, respectively. The average index for all manufacturing industries is 91 (U.S. Census Bureau, 1997 concentration ratios).

[2]Price leadership has also been noted elsewhere: the cigarette industry in the 1920's and 1930's, the U.S. automobile industry in the 1950's and the breakfast cereals industry between the 1960's and 1970's. See Scherer and Ross (1990).

Earlier studies (Tremblay and Tremblay; 1995 and 2005) have found that the degree of market power in U.S. brewing is low; however, their analysis is limited to firm-level data. This limitation is particularly relevant in the U.S. brewing market where product differentiation is important and can give rise to prices above marginal costs even under healthy competition.

The sources of market power in differentiated products are usually attributed to either unilateral effects (i.e. a firm's ability to raise price above marginal cost through product differentiation) or coordinated effects (i.e. collusion). In this paper, the analysis of market power focuses in a broader definition of the latter source in which collusion and several price leadership models pricing are considered possible sources of market power (we call these "non-unilateral" effects). Therefore, a number of pricing models that range from Bertrand-Nash competition (the benchmark) to collusion are analyzed.

The brand level data and econometric approach used in this paper allow to model the U.S. brewing market from a differentiated products perspective. Also, the methods employed allow for the identification of the two sources of market power previously described. Focus is then placed on the non-unilateral source. The general strategy is to compare the observed pricing behavior of firms with the equilibrium prices predicted by various models of competition and then choose the best fit.

While brand-level studies in other industries (e.g. Nevo, 2001; Slade 2004) have considered Bertrand-Nash and collusion as the alternative modes of competition, this paper entertains two types of leadership models in addition to Bertrand-Nash and collusion.[3] Both leadership models are intended to reflect and formally test the forms of leadership noted earlier in the introduction. The first model is called "collusive price leadership" in which followers match Budweiser's price changes. The second model is Stackelberg with two variants. In one variant, Budweiser acts as the price leader while in the other variant Anheuser-Busch leads other brands with its entire product line.

The data set is comprised of brand-level prices and quantities collected by scanning devices in 58 major metropolitan areas of the United States over a period of 20 quarters (1988-1992). The general strategy consists of two stages. First, a structural demand system for 64 brands of beer is 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 the discrete choice assumption seems appropriate for products like automobiles, it appears less natural for beer. The major challenge of estimating numerous substitution coefficients is dealt with the Distance Metric (DM) method devised by Pinkse, Slade and Brett (2002). This paper extends previous applications of the DM method (Pinkse and Slade, 2004; Slade) by employing a more flexible demand system

[3] Two exceptions are Kadiyali, Vilcassim and Chintagunta, and Gasmi, Laffont and Vuong who consider price leadership as an alternative mode of competition. These applications are limited to the Stackelberg model and a small number of products (4 and 2, respectively).

and also by estimating advertising substitution patterns.

Incorporating advertising into the demand system helps improve the validity of the price instruments. Following the previous work of Hausman, Leonard and Zona (1994), this paper employs the assumption that demand shocks are independent across regions so that prices in other regions can be used as price instruments. Unlike previous applications that employ this assumption, controlling for advertising reduces the likelihood of common demand shocks across regions thereby making our instruments more apt to be uncorrelated with the error term.

Model assessment makes use of a unique natural experiment in the data: the 1991 100% increase of the federal excise tax on beer.[4] In a second stage, the estimated demand parameters are used to compute the implied marginal costs for the different models during the pre-tax-increase period. Then, the increase in the federal excise tax is combined with the estimated pre-tax-increase marginal costs to compute equilibrium prices that would have prevailed under each model during the post-tax-increase period. Model comparisons are based on metrics that quantify the closeness of each model's equilibrium prices to the "observed" prices in the post-increase period.

Results indicate that Bertrand-Nash predicts the pricing behavior of firms more closely than other models, although Stackelberg leadership does not predict prices that are substantially different from Bertrand-Nash. Concerns about deviations from competitive pricing of the forms studied in this paper should hence be low in this industry. Despite its closeness to the observed pricing behavior, Bertrand-Nash under-predicts prices of more price-elastic brands and over-predicts prices of less price-elastic brands. A discussion of the implications of this finding and its relation to previous work is presented in the conclusion.

2 The Industry and the Tax Increase

Commercial brewing began during the 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.[5] 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). On a per capita basis, consumption has fluctuated but has stabilized at approximately 22 gallons.

[4] Hausman and Leonard (2002) use a similar strategy to evaluate different models of competition. The variation in their data is given by the introduction of a new brand.

[5] 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 are brewed with yeasts fermenting at high temperatures and at the top of the fermenting tank. Porter and stout are darker and sweeter than ale, with minimal market share in the United States today.

Advertising has also played a central role in this 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 (Advertising Age, 2000; cited in Tremblay and Tremblay, 2005.) National brewers have taken advantage of the more cost-effective marketing channel: national TV. Larger national producers have driven many regional producers out of business partly because of this marketing disadvantage but also because of technological changes that required larger plants to achieve a minimum efficient scale (MES).

In 2003, nearly 80% of beer sales in the U.S. was concentrated among three firms: 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 1960, with an ever increasing market share (Figure 1). Budweiser and Bud Light, Anheuser-Busch's two leading brands, currently capture approximately one third of beer sales nationwide.

<Figure 1 about here>

The industry is characterized by numerous product introductions and, consequently, a large number of brands. 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.

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.

U.S. brewing remains as one of the most interesting industries because of its ramifications to other important issues such as health, taxation and regulation. Tremblay and Tremblay (2005) present the most comprehensive economic analysis of this industry to date.

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 64 cents in federal taxes per 288 ounces (a 24-pack), represented the largest federal tax hike for beer in U.S. history.

<Figure 2 about here>

Figure 2 shows mean quarterly prices (over all cities) for three beer segments using the data set available for this paper. There is a clear shift in the mean price of all three categories in the first quarter of 1991. All mean increases are higher than the actual tax hike of 64 cents per 288 ounces: \$2.2 for imports, \$1.4 for super-premium beers and \$1.2 for budget beers. These mean increases were 237%, 114%, and 84%, respectively, larger than the tax increase of 64 cents per case. This is consistent with the theoretical findings of Anderson, de Palma and Kreider (2001) who show that in oligopolies with differentiated products an excise tax can be passed on to consumers by more than 100%.

3 The Empirical Model

In this paper, comparison of different pricing models is carried out 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, the implied marginal costs of all brands are computed for each of the models. This computation is carried out in each quarter that preceded the tax increase. After combining each brand's median marginal cost (over the pre-tax-increase period) with the demand estimates and the pre-tax-increase values of the remaining variables, a search is conducted for the equilibrium prices that would have prevailed under each model in the post-tax-increase period. Price increases resulting from this exercise are then compared to the actual price increases. This section provides details on demand, supply and the computation of marginal costs. Sections 5.2 and 5.3 present details on the computation of equilibrium prices and actual prices increases.

3.1 Demand

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 linear approximation to the Almost Ideal Demand System (LALIDS) of Deaton and Muellbauer is used due its desirable theoretical properties:

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

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:[6]

$$\log P_t \approx \sum_j w^o_j \log(p_{jt}) \tag{2}$$

where w^o_j is brand j's 'base' share, defined as $w^o_j \equiv T^{-1} \sum_t w_{jt}$.[7]

Traditional advertising (e.g. television, radio and press) is considered the key advertising variable because of its crucial role in the development of the industry.

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

[7]The 'fixed' base w^o_j moderates the problem of having an additional endogenous variable on the right hand side of (1).

Traditional advertising is assumed to be persuasive rather than informative since mass media beer advertising 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.[8]

Advertising for brand k (A_k) is incorporated into equation (1) by defining the intercept term as $a^*_{jt} = a_{jt} + \sum_k c_{jk} A^{\gamma}_{kt}$. 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 the redefined intercept into equation (1) and including an econometric error term gives:

$$w_{jt} = a_{jt} + \sum_k c_{jk} A^{\gamma}_{kt} + \sum_k b_{jk} \log p_{kt} + d_j \log(x_t/P_t) + e_{jt} \tag{3}$$

Equation (3) is as a first-order approximation in prices and advertising to a demand function that allows unrestricted price and advertising parameters. The Distance Metric (DM) method of Pinkse, Slade and Brett is employed in the estimation by specifying each cross-coefficient (b_{jk} and c_{jk}) as a function of the distance between brands j and k in product space.

Distance measures may be either continuous or discrete. For example, alcohol content can be used to construct a continuous distance measure. Dichotomous variables that group brands in segments are used to construct discrete distance measures. Continuous distance measures use an inverse measure of distance (closeness) between brands.[9] Discrete distance measures take the value of 1 if j and k belong to the same grouping and zero otherwise.

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

$$b_{jk} = \sum_{r=1}^{R} \lambda_r \delta^r_{jk} \tag{4}$$

$$c_{jk} = \sum_{s=1}^{S} \tau_s \mu^s_{jk} \tag{5}$$

where $\delta_{jk} = \{\delta^1_{jk}, ..., \delta^R_{jk}\}$ is the set of distance measures for cross-prices and $\mu_{jk} = \{\mu^1_{jk}, ..., \mu^S_{jk}\}$ the set of measures for cross-advertising; λ and τ are the coefficients to be estimated.[10] After replacing (4) and (5) into (3) and regrouping terms gives the empirical demand equation:

[8] 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.

[9] The distance measure is an inverse expression of the distance between brands j and k: $1/[1 + 2 \times (\textit{Euclidean distance between } j \textit{ and } k)]$

[10] Various specifications of the semi-parametric estimator proposed by Pinkse, Slade and Brett were implemented to check that the parametric specification of h and g in (4) and (5) is not a restrictive functional form. These results are available upon request.

$$
\begin{aligned}
w_{jt} \quad = \quad & a_{jt} + b_{jj} \log p_{jt} + c_{jj} A_{jt}^{\gamma} + \sum_{r=1}^{R} \left(\lambda_r \sum_k \delta_{jk}^{r} \log p_{kt} \right) + \\
& + \sum_{s=1}^{S} \left(\tau_s \sum_k \mu_{jk}^{s} A_k^{\gamma} \right) + d_j \log(x_t^*/P_t) + e_{jt} \qquad (6)
\end{aligned}
$$

Cross-terms (b_{jk} and c_{jk}) and cross-elasticities are computed using the estimated coefficients λ_l and τ_m and the distance measures between brands (δ_{jk} and μ_{jk}). The distance measures are symmetric by definition. Thus, symmetry (i.e. $b_{jk} = b_{kj}$ and $c_{jk} = c_{kj}$) may be imposed by setting λ and τ to be equal across equations. In principle, $(J-1)$ seemingly unrelated equations can be estimated. However, since J is very large it becomes impractical to estimate such a large system. Alternatively, it is assumed that the own-price and own-advertising coefficients (b_{jj} and c_{jj}), and the price index coefficient (d_j), are equal across equations thereby reducing estimation to one equation. Since this is too strong of an assumption, and following Pinkse and Slade, the coefficients b_{jj}, c_{jj}, and d_j are specified as linear functions of brand j's characteristics.

In the analysis that follows, each cross-price and cross-advertising distance measure in a given market is depicted as a $(J \times J)$ "weighing" matrix with element (j,k) equal to the distance between brands j and k when $j \neq k$, and zero otherwise. Thus, when the $(J \times J)$ weighing matrix is multiplied by the $(J \times 1)$ vector of prices or advertising, the appropriate sum over k in the share equation is obtained.

Continuous Distance Measures

The characteristics utilized are alcohol content (ALC), product coverage (COV), and container size ($SIZE$). Product coverage measures the fraction of the city that is covered by a brand and is defined as the all commodity value (ACV) of stores carrying the product divided by the ACV of all stores in that city. Beers with low coverage may be interpreted as specialty brands that are targeted to a particular segment of the population. Beer is sold in a variety of sizes (e.g., six and twelve packs), and the variable $SIZE$ measures the average package "size" of a brand. Higher volume brands (e.g., typical sales of twelve packs and cases) may compete less strongly with brands that are sold in smaller packages (e.g., six packs).

The distance measures are computed in one-and two-dimensional Euclidean space and stored in "weighing" matrices, W, where the j,k entry in each matrix corresponds to the distance measure between brands j and k. The one-dimensional matrices are denoted $WALC$, $WCOV$, and $WSIZE$ and the two-dimensional matrices are denoted WAC, WAS, and WCS, where A, C, and S stand for alcohol content, product coverage and container size, respectively.

Discrete Distance Measures

Three different types of discrete distance measures are utilized. The first type focuses on various product groupings including product segment, brewer identity, and national brand identity. With no clear consensus on product segment classifications, five different classifications are considered: (1) budget, light, premium, super-premium, and imports, (2) light and regular, (3) budget, light, and premium, (4) domestic and import, and (5) budget, premium, super-premium, and imports. The weighing matrices for the product segment classifications, denoted $WPROD1$ through $WPROD5$, are constructed such that element (j, k) is equal to one if brands j and k belong to the same product segment and zero otherwise. The weighting matrix $WBREW$ has element (j, k) is equal to one if brands j and k are produced by the same brewer and zero otherwise. The weighting matrix $WREG$ takes a value of one if brands j and k are either both regional or both national, and zero otherwise. This measure is used to test whether brands that are national (regional) compete more strongly with each other. 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.

Following PSB, 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 both brands and prefer these two brands over any other brand in product space. The nearest neighbor (NN) and common boundary (CB) measures are computed for all pairs brands based on their location in alcohol content and coverage space (weighing matrices $WNNAC$ and $WCBAC$) and coverage and container size space (weighing matrices $WNNCS$ and $WCBCS$). A j, k entry of a common boundary matrix is equal to one if brands j and k share a common boundary and zero otherwise, while a j, k entry of a nearest neighbor matrix is equal to one if brands j and k are nearest neighbors (mutual or not) and zero otherwise.[11]

A second set of nearest neighbor and common boundary measures are computed using product characteristics and price thereby allowing consumers' brand choices to be influenced not only by distance in characteristics space but also by price. For this case nearest neighbors and common boundaries are defined based on the square of the Euclidean distance between brands plus a price differential between brands. 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, increasing computational time and complexity.

Own-Price and Own-Advertising Interactions

Two product characteristics are interacted with own-price and own-advertising in

[11] 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 weighing matrices. 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. Restricting the product space in this manner eases the calculation of common boundaries. Without this restriction, common boundaries of brands located on the periphery of the product space are difficult to define.

the model: the inverse of product coverage ($1/COV$) and the number of common boundary neighbors (NCB). The number of common boundary neighbors is a measure of local competition that determines the number of competitors that are closely located to a brand in product space. NCB is computed in product coverage-container size space and alcohol content-coverage space.

3.2 Supply

Let F_n be the set of brands produced by firm n. Assuming constant marginal costs and linear additivity of advertising, the profit of firm n in a given market is expressed as:

$$\pi_n = \sum_{j \in F_n} (p_j - c_j) q_j(p, A) - \sum_{j \in F_n} A_j, \tag{7}$$

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

$$\begin{aligned} q_j(p, A) + \sum_{k \in F_n} (p_k - c_k) \overline{\frac{\partial q_k}{\partial p_j}} &= 0, \text{ with respect to } p_j & (8) \\ \sum_{k \in F_n} (p_k - c_k) \frac{\partial q_k}{\partial A_j} - 1 &= 0, \text{ with respect to } A_j & (9) \end{aligned}$$

where, $\overline{\frac{\partial q_k}{\partial p_j}} = \frac{\partial q_k}{\partial p_j} + \sum\limits_{m \notin F_n} \frac{\partial q_k}{\partial p_m} \frac{dp_m}{dp_j}$. Partial derivatives in (8) and (9) can be obtained from demand estimates for equation 6. The term $\frac{dp_m}{dp_j}$ in $\overline{\frac{\partial q_k}{\partial p_j}}$, however, takes different values depending on the model of interest; this term is the "conjecture" of firm n about how the price of product m will react to a change in the price of product j.

In principle, several games in advertising can also be considered. However, simulations of collusion, Bertrand-Nash and Stackelberg games in advertising produced equilibrium conditions that were essentially indistinguishable from each other; the reason is the small magnitude of advertising coefficients obtained from demand estimation. Consequently, price is treated as the main strategic variable of interest and it is assumed that firms compete in a Bertrand-Nash fashion in advertising.

Bertrand-Nash and Collusion

For Bertrand-Nash competition in prices, the conjecture takes a value of zero. The conjecture is also zero in the case of collusion but the ownership sets (F_n) of the colluding firms are modified to reflect the joint profit-maximizing first order conditions.

Stackelberg Leadership

Two cases are considered, one in which Budweiser leads brands produced by firms other than Anheuser-Busch and the other in which Anheuser-Busch leads with its entire product line. For this game, the conjecture term $\left(\frac{dp_m}{dp_j}\right)$ takes a value of zero if j is a follower brand. If j is a leading brand, the conjecture term is computed from the first order conditions of followers by applying the implicit function theorem. Appendix A contains details of this procedure.

Collusive Price Leadership

In this case followers exactly match Budweiser's price changes. In this "collusive price leadership" scenario 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 by imitating the leader. The term $\frac{dp_m}{dp_l}$ in (8) is set to 1 in Budweiser's first order condition and to zero in Anheuser-Busch's remaining first order conditions.[12]

3.3 Marginal Costs

In each market, there are two equations for each unknown marginal costs (c_k). After adding up (8) and (9) for each brand j, a solution for c_k is obtained in this new system.[13] The system in vector notation is:

$$Q^o - \Delta(p - c) = 0, \tag{10}$$

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 $\Delta_{jk} = -\Delta^*_{jk}\left(\frac{\partial q_k}{\partial p_j} + \frac{\partial q_k}{\partial A_j}\right)$, 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 (10) gives the implied marginal costs:

$$c = p - \Delta^{-1}Q^o \tag{11}$$

Marginal costs in each market are computed using the demand estimates and the appropriate values of the conjectures $\left(\frac{dp_m}{dp_j}\right)$ for each of the models. Collusive possibilities (e.g. between specific products or firms) are investigated by modifying the elements Δ^*_{jk} (which determine the ownership sets F_n). For example, full collusion, or joint profit maximization, is equivalent to setting all Δ^*_{jk} elements to equal one. Appendix A provides details on the computation of marginal costs for the leadership models.

[12] Appendix A contains details of computational problems (and the solutions adopted) that arise in both types of leaderhsip models (Stackelberg and Collusive).

[13] Since this is a linear problem, the solution is unique. Moreover, if c_k is the same in both (8) and (9) (which it is by assumption) the solution will solve (8) and (9) individually. If, on the other hand, two different c_k's solve (8) and (9), the solution of the added system will be a linear combination of the two c_k's.

4 Data

Table (1) provides a description and summary statistics of the variable used. The main source is the Information Resources Inc. (IRI) Infoscan Database. The IRI data includes prices and total sales for several hundred brands for up to 58 cities over 20 quarters (1988-1992).[14] 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. This selection criterion provides a sample of 64 brands produced by 13 different brewers. Appendix B contains a table of all the brands chosen as well as other details of the database and the data selection procedure.

In addition to price and sales data, IRI has information on other 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. An average size variable is created: $SIZE =$*Quantity*$/UNITS$. The variable COV measures the degree of city coverage for each brand. 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.

Data for demand side instruments were collected from 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. $INCOME$ from the IRI database was used to instrument for expenditures (x_t).

<Table 1 about here>

5 Estimation

5.1 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.

[14]The actual market definitions of these cities are broader than a single city and are usually referred to as "metropolitan areas". The term city here is used for simplicity. In general, the definition of these metropolitan areas is broader than the BLS definitons.

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 (6), 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.[15]

As in previous work, the instruments employed in this paper rely on the identification assumption that, after controlling for brand, city, and time specific effects, demand shocks are independent across cities. Because beer is produced in large plants and distributed to various states, the prices of a brand across different cities 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.

The data employed in this study are based on broadly defined 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. To further control of other potential unobserved national shocks, time dummies are included in the estimation.

Because advertising expenditures are only observed at the national level each quarter, lagged advertising expenditures are used as its instrument. Expenditures (x_t), which is constructed with price and quantity variables, is also treated as endogenous 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. The validity of the proposed instruments is assessed by conducting a formal test. Additional instruments for price are created from city-specific marginal costs (i.e. proxies for shelf space and transportation costs, see Nevo) and an overidentifying restrictions test is used to check the validity of instruments.

As observed by Berry (1994), an additional source of endogeneity may be present in differentiated products industries. Unobserved product characteristics (included in the error term), which can be interpreted as product quality, style, durability, status,

[15] Attempts to correct for spatial autocorrelation by assigning 'closeness' values to off-diagonal elements of the GMM weighing matrix were unsuccessful as a computational limitation was encountered when the number of non-zero elements of the already large $(T \times J) \times (T \times J)$ matrix $\hat{\Omega}$ increases.

or brand valuation, may be correlated with price and advertising and produce biases in the estimated coefficients. Following Nevo, this source of endogeneity is controlled for 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.

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 (Nevo). 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.

5.2 Predicted Prices with Higher Excise Taxes

Marginal costs (11) for the pre-tax-increase period are used to compute each model's predicted equilibrium prices after the tax change (i.e. the first quarter of 1991). Since excise taxes were increased for all beers at a uniform rate of E per unit, predicted prices in each city for quarter $y+1$ are computed by solving for p_j^{y+1} $(j = 1, \ldots J)$ in the following system of non-linear equations:

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

where the superscript y denotes the quarter prior to the tax increase: fourth quarter of 1990.[16] Because q_j and all derivatives are functions of price (p_j^{y+1}), the search includes these non-linear terms. Other variables (i.e. advertising, distance measures, product characteristics and total expenditures x_t) are held constant at time y values, while demand parameters are those obtained from estimation. The predicted prices are computed for every brand in each of the 46 cities for which data are available.[17]

Results are invariable to whether pre- or post-tax-increase advertising is used in the search. 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 for the subset of brands that were present in both quarters. The potential bias of this simplification is likely to be small as the ignored brands tend to be marginal in terms of sales.

[16] 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. Results, however, are qualitatively the same if only marginal costs for the fourth quarter of 1990 are used.

[17] 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, leadership models require several hours of computing power.

5.3 Estimates of actual Price Increases

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

$$p_{yz} = \theta_y + \eta' I + \xi_{yz} \quad (12)$$

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. If the dummy on the fourth quarter of 1990 is omitted (i.e. this is the reference quarter), the coefficient on the dummy for the first quarter of 1991 can be interpreted as the absolute mean price increase for that brand due to the tax increase. This coefficient, however, captures the mean effect on price of all city-invariant factors present in the first quarter of 1991 (i.e. other national shocks besides the tax increase). A dummy variable that takes a value of 1 in the first quarter of each year was included in (12) to control for a possible seasonality effect.

6 Results

6.1 Demand

Estimation is based on equation (6) and details presented in section 5.1. 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. Estimates are therefore robust to these two sample sizes. Demand estimates reported in this section were computed with the full sample.

The regressions below contain variables that consistently had the greatest explanatory power in different specifications. Table (2) reports the GMM regression results for two different models. The difference between models 1 and 2 is the inclusion of brand dummies. The two models contain time and city binary variables (coefficients not reported). The coefficients for alcohol content, brewer dummies and product segment variables can not be directly identified when brand dummies are included and are thus recovered using a minimum distance (MD) procedure.

<Table 2 about here>

The estimated coefficients from the MD procedure for model 2 are reported in the first set of variables of table 2. 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 ($NCBAC$). The negative coefficient on $NCBAC$ shows that brands that share a common boundary with more neighbors in alcohol content-coverage space have a lower sales share.

The estimated coefficients for own-price, own-advertising, and their interactions with product characteristics are reported in the second group of variables in table 2. 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.

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 approximately 80 percent in model 2. The better goodness-of-fit of 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.

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, belong to the same product segment, or have similar geographic coverage, 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 the existence of cooperative effects across brands that are more closely located in product space and with the same geographic coverage. However, the negative coefficient for product segment indicates that there are predatory advertising effects for brands in the same product segment, thereby potentially offsetting some of the cooperative effects.

The estimated coefficient on real expenditures, $\log(x_t/P_t^L)$, is not statistically different from zero. Several attempts to interact product or market characteristics with real expenditures yielded statistically significant coefficients. This result implies that the brand-level income elasticities are not statistically different from one.

Elasticities

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. In general, median own-price elasticities are slightly smaller 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. Estimated confidence intervals (not shown) indicate that all price elasticities are significantly different than zero at the 5% level.[18]

While most of the cross-advertising elasticities are positive, there are several negative cross-advertising elasticities. However, not all of the advertising elasticity estimates are statistically different than zero. Approximately 85% of negative advertising elasticities and 86% of positive elasticities are significant at the 5% level. A sample of median price and advertising elasticities and a further discussion are provided in Rojas and Peterson (2005).

6.2 Implied Price-Cost Margins

For each model, implied marginal costs in the pre-tax-increase period are calculated according to details in section 3.3. Summary statistics of marginal costs can be informative about differences in the equilibrium predictions of the models; however, price-cost margins are more readily interpretable. Pre-tax-increase summary statistics of price-cost margins (PCM) as a percentage of price ($100 \times [p - c]/p$) are presented in table 3. 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 the leading regular brand produced by each of the three largest firms (Budweiser, Coors and Miller Genuine Draft). The full collusion case produced unlikely price-cost margins (over 100%); therefore the other two plausible collusive scenarios described were explored.

<Table 3 about here>

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

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

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

One way to measure market power is to compare implied PCMs with observed PCMs. However, observed PCMs are unavailable. A raw measure of PCM is the gross margin (total shipments minus labor and materials) calculated from the Annual Survey of Manufacturers (as in Nevo). The average gross margin for the U.S. brewing industry in the pre-tax increase period (1988-1990) is 44.53% (27.5% for all food industries), which is close to all models except collusive leadership. The next section provides brand-level closeness measures between the observed prices and the prices predicted by the different models during the post-tax-increase period.

6.3 Predicted vs. actual Price Increases

Theoretically, pass-through rates with excise taxes are unrelated to pre-tax-increase prices. Thus, absolute price increases $(p_j^{y+1} - p_j^y)$ are compared to estimates of observed or "actual" price increases (see sections 5.2 and 5.3).

Figures 3 to 9 plot the means (across cities) of the predicted and actual price increases for each brand. For predicted price increases, the mean is calculated using each brand's predicted price increases over 46 cities. Mean actual price increases are computed according to details in section 5.3. 95% confidence intervals are displayed for the mean of actual price increases.[19]

While the Bertrand-Nash model (figure 3) appears to be a reasonable predictor of actual firm behavior, there are several patterns in the data that merit discussion. Bertrand-Nash behavior tends to under-predict price increases: 41 out of 63 are "under-predicted" brands. Also, over-predicted brands appear to be more frequent among the two largest beer producers: Anheuser-Busch (8 out of 10) and Miller (4 out of 7). Since more inelastic brands are associated with higher tax pass-through rates, the two largest mean predicted increases correspond to the first and third

[19] 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.

most inelastic brands in the sample: Budweiser (predicted: \$4.94, actual \$1.63) and Bud Light (predicted: \$3.24, actual \$1.59). 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 brewers that tend to produce nationally: Anheuser-Busch, Coors, Pabst, Miller and Stroh.

The Stackelberg model in which Anheuser-Busch acts as the price leader with all its brands (figure 4) has a pattern that is similar to Bertrand-Nash. Although it can not be discerned from the figure, in this model predicted increases are higher than in Bertrand-Nash for all but one brand. For Anheuser-Busch's brands, especially Budweiser, Bud Light and Natural Light, this difference is larger and hence discernible from the figures.

Aside from a larger over-prediction for Budweiser (60 ¢), the Budweiser Stackelberg model (figure 5), yields predicted mean price increases that are essentially the same to the Bertrand-Nash case. The reason for the small difference between Bertrand-Nash and Stackelberg models is that reaction functions of followers depend heavily on very small cross-price coefficients. Thus the term $\frac{dp_m}{dp_j}$ in (8) takes small positive values making the first order conditions of the leader not substantially different from those in Bertrand-Nash.

Collusive price leadership by Budweiser (figure 6) predicts unlikely price increases that are, on average, almost 7 times larger than actual mean price increases, with some of Anheuser-Busch's brands in the vicinity of \$15-\$16. This extreme case can therefore be rejected.

The 3-firm collusion scenario (figure 7) 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. The 3-brand collusion scenario (figure 9) differs less strikingly with Bertrand-Nash: there is a higher over-prediction for Budweiser and, less noticeably, for the other two colluding brands: Coors and Miller Genuine Draft.

<Figures 3 through 8 about here>

The left part of table 4 presents summary statistics of price increases (i.e. the absolute difference in prices between the two quarters). The mean of predicted increases between Bertrand-Nash, the two Stackelberg models and collusion among three brands are similar and also close to the mean of actual increases, suggesting that these are superior models. Although the Anheuser-Busch Stackelberg model predicts the mean of actual increases more accurately than Bertrand-Nash, closer inspection of graph 4 indicates that this is due to larger over-predictions for Anheuser-Busch's brands, and not by smaller under-predictions of other brands. A similar argument can be made for the model of collusion among three brands.

Medians and standard deviations indicate that price increases are more heterogeneous in the models than suggested by actual increases. While the median of actual increases is similar to its mean, means of predicted increases are higher than their respective medians (except in collusive price leadership) as a consequence of the outliers of highly over-predicted brands (e.g. Budweiser, Bud Light). Larger standard deviations of predicted increases with respect to standard deviations of actual price increases corroborates this heterogeneity.

One metric of assessing the different models is the number of brands whose predicted mean price increases fall within the confidence intervals of actual mean price increases shown in the graphs. The right part of table 4 presents this number (# Non-Rejections) for the models considered. According to this metric, collusion among 3 firms explains firm behavior better than the other models.

Two more rigorous metrics are considered. The first weighs price increases by each brand's market share. With this metric, accuracy in prediction is more important for more widely sold brands. Using this criterion, the Bertrand-Nash outperforms the other models, though it is more than twice the value of weighted actual price increases (3.13 vs. 1.33). The second metric is the sum of squared deviations, where a deviation is defined as the difference between the predicted increase and the actual increase.[20] This criterion confirms the superiority of Bertrand-Nash.

<Table 4 about here>

The large difference between the weighted mean of predicted increases and actual increases is due to the over-prediction of more popular brands: the combined share of Budweiser (19%), Bud Light (6%), Coors Light (7%) and Miller Lite (9%) is 41%. In all models, there is an over-prediction for these brands, the largest of which is for Budweiser. The similarity between the weighted actual increases and its non-weighted counterpart indicates that actual price increases tend to be homogeneous across brands.

7 Conclusion

This paper analyzes market power and price competition in the U.S. brewing industry where there are some concerns about non-competitive behavior by the largest firms. Bertrand-Nash, leadership and collusive models are considered as possible candidates of pricing behavior. Leadership focuses on the largest firm Anheuser-Busch and its leading brand Budweiser. Collusive scenarios consider both the three largest firms as well as the three leading regular brands of beer. To choose the model that is best supported by the data, the 100% increase in the federal excise tax in January of 1991 is used to compare observed price increases as a result of the tax hike with price increases predicted by the different models considered.

Several metrics of closeness between predicted price increases and observed price increases revealed that, overall, Bertrand-Nash appears to predict more closely the actual behavior of firms, although Stackelberg predicts similar price increases to Bertrand-Nash competition. The reason for the closeness between these two models

[20] The same conclusion is reached if each deviation is weighted.

is the small magnitude of cross-price coefficients (common in markets with many differentiated products) which ultimately define the closeness between Stackelberg and Bertrand-Nash.

One policy implication of the results in this paper is that antitrust concern towards the leading beer producers should be low in terms of the non-competitive pricing forms considered in this paper. Although price-cost margins are relatively large in this industry as indicated in section 6.2, results indicate that their source is not non-competitive pricing. This result is consistent with recent brand-level research in other industries. In a study of market power in the ready-to-eat breakfast cereals, Nevo suggests that the main source of market power is the result of product differentiation and the portfolio effect of firms carrying more than one brand (the unilateral effects) rather than actual collusive behavior (the coordinated effects). Slade can not reject the null hypothesis of Bertrand-Nash competition in UK brewing and concurs with Nevo's conclusion.

There are some systematic discrepancies at the brand level between Bertrand-Nash prices and observed prices, however. Observed price increases do not conform well with the inverse relationship between own-price elasticity and excise tax pass-through rates predicted by all models. As a consequence, Bertrand-Nash tends to over-predict tax pass-through rates of more price-inelastic brands, especially Budweiser, and to under-predict price increases of more price-elastic brands. Overall, observed price increases tend to be more similar across brands than any of the models predict. An interpretation of this evidence is that, in a static oligopoly setting, Anheuser-Busch could exert more market power even under Bertrand-Nash competition.

The large heterogeneity in prices predicted by Bertrand-Nash is a special characteristic of the present study. As opposed to the ready-to-eat breakfast cereal industry where the largest brand Corn Flakes captures less than 6% of the market[21], the two largest brands in this study (Budweiser with 19% and Miller Lite with 9%) capture more than one quarter of all beer sales. Thus, price sensitivity in beer is heavily driven by quantity sold and significant brand loyalty. In breakfast cereals, in contrast, brand concentration is more moderate and hence elasticities (and predicted prices) are more homogeneous across brands.

The models considered here, as most models of pricing behavior, are built upon the assumption of profit maximization. The unexplained homogeneity in price increases reported in 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

[21]Based on IRI data used by Nevo (2001).

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 of larger brewers. While this conjecture is consistent with the informal observations in the industry, the leadership models considered do not conform with this pattern.[22] 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 coordination existed in the brewing industry as a consequence of the tax increase it appears that it benefited smaller brewers rather than large firms.

Another explanation for the unexplained homogeneity of prices is firms' potential unwillingness to match competitors' price increases (Sweezy, 1939). This price stickiness in price increases has been documented in several industries (Bhaskar et al., 1991; Domberger and Fiebig, 1993). If Anheuser-Busch believes that followers are only going to match price increases up to a "reasonable" level, hiking prices above this threshold might not be profitable for Anheuser-Busch. Prices above the threshold might cause the demand for Anheuser-Busch's brands to become too elastic as Anheuser-Busch's consumers switch to competitors' cheaper brands. This is consistent with demand estimates not being sensitive over the studied period (pre-tax-increase vs. post-tax-increase).

The availability of more detailed data would allow to capture aspects not addressed here. Dynamic models can be better assessed with less aggregated data on the time dimension. A dynamic setting is particularly important when future profits are not independent of the current state thereby making the static solution suboptimal. Also, detailed cost data at the manufacturer and retailer level can allow to extend the analysis to vertical aspects and also more rigorous econometric tests of the competing pricing models considered here.

[22] The collusive leadership model considered yielded homogeneity in price increases that would match this observation. However, the magnitude of price increases is unlikely.

A Supply Details

A.1 Derivation of $\frac{dp_m}{dp_j}$

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, with J^F and J^L number of elements respectively. For each leader, a system of equations is constructed. Each l^{th} system of equations is used to compute the vector of all $\frac{dp_m}{dp_l}$ terms for leader l. An equation in system l is obtained by totally differentiating the price first order condition of all follower brands (8)[23] with respect to all followers' prices (p_f, for all $f \in \Psi_f$) and the price of the l^{th} leader, p_l ($l \in \Psi_l$):

$$\sum_{f\in\Psi_f} \underbrace{\left[\frac{\partial q_j}{\partial p_f} + \sum_{k\in\Psi_f}\left(\Delta^*_{kj}(p_k - c_k)\frac{\partial^2 q_k}{\partial p_j \partial p_f}\right) + \Delta^*_{fj}\frac{\partial q_f}{\partial p_j}\right]}_{g(j,m)} dp_f + \\ + \underbrace{\left[\frac{\partial q_j}{\partial p_l} + \sum_{k\in\Psi_f}\left(\Delta^*_{kj}(p_k - c_k)\frac{\partial^2 q_k}{\partial p_j \partial p_l}\right)\right]}_{h(j,l)} dp_l = 0; \quad j,k,f \in \Psi_f \tag{13}$$

where Δ^*_{jk} takes the value of one if brands j and k are produced by the same firm and zero otherwise. Therefore, for a given leader l there are J^F equations like (13). 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, (13) is 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 are computed as:

[23] It is assumed that the first order condition with respect to advertising (9) 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 estimated small impact advertising has on demand.

$$\frac{D_s}{dp_l} = G^{-1}H_l \tag{14}$$

Concatenating the $(J - J^F)$ vectors of dimension $(J^F \times 1)$ given in (14) (one vector for each p_l) gives $D = G^{-1}H$. The $J^F \times J^L$ matrix D has a typical element $\frac{dp_f}{dp_l}$, for $f \in \Psi_f$ and $l \in \Psi_l$.

A.2 Marginal Costs in Leadership Models

Stackelberg Model

While marginal costs are obtained by applying (11), the derivative $\frac{dp_m}{dp_j}$ needs to be computed first via equation (14). 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, 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 (14)), these marginal costs are 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 (11). These marginal costs are used to compute $\frac{dp_m}{dp_j}$, which is afterwards used to calculate the marginal costs of the leading brands.

When Budweiser is a sole brand leader, the term $\frac{dp_m}{dp_j}$ is set to zero if m is produced by Anheuser-Busch, except for the brand Budweiser. Also, it is assumed that Budweiser only leads brands produced by rival firms (i.e. not 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 (11) to a system of dimension J^L (where J^L is the number of brands sold 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.

B Data Details

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. On average there are 37 brands sold in each city market with a minimum of 24 brands and a maximum of 48 brands. Table 5 contains a list of the brands used with information on country of origin and the corresponding brewers.

The original data set 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. Brands are identified as regional or national as follows. First the percentage of cities in which each brand was present was averaged over time. Brands with an average percentage close to 100 are denoted national and brands with a percentage of (roughly) 50% or less are denoted regional. 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.

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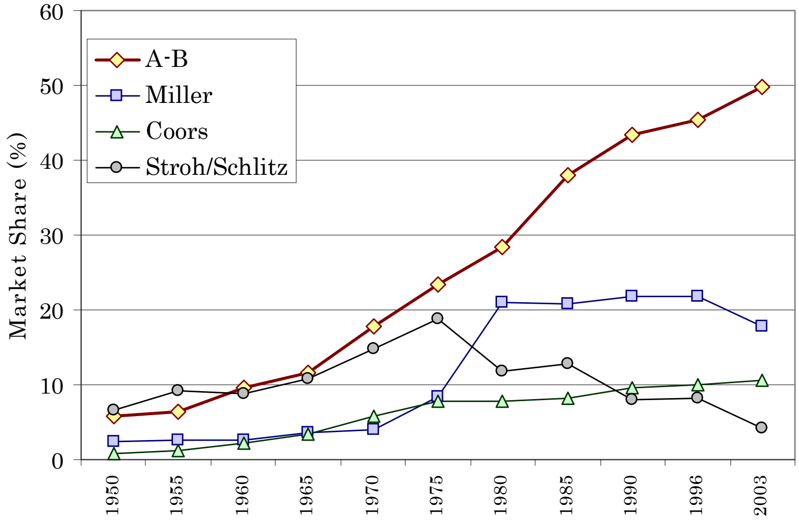
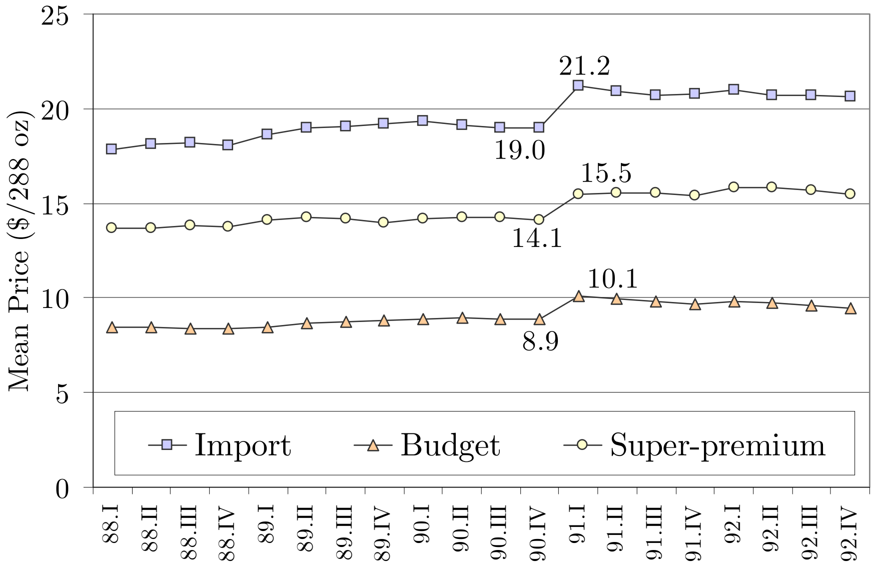
Figure 1: Market Shares of Largest Brewers



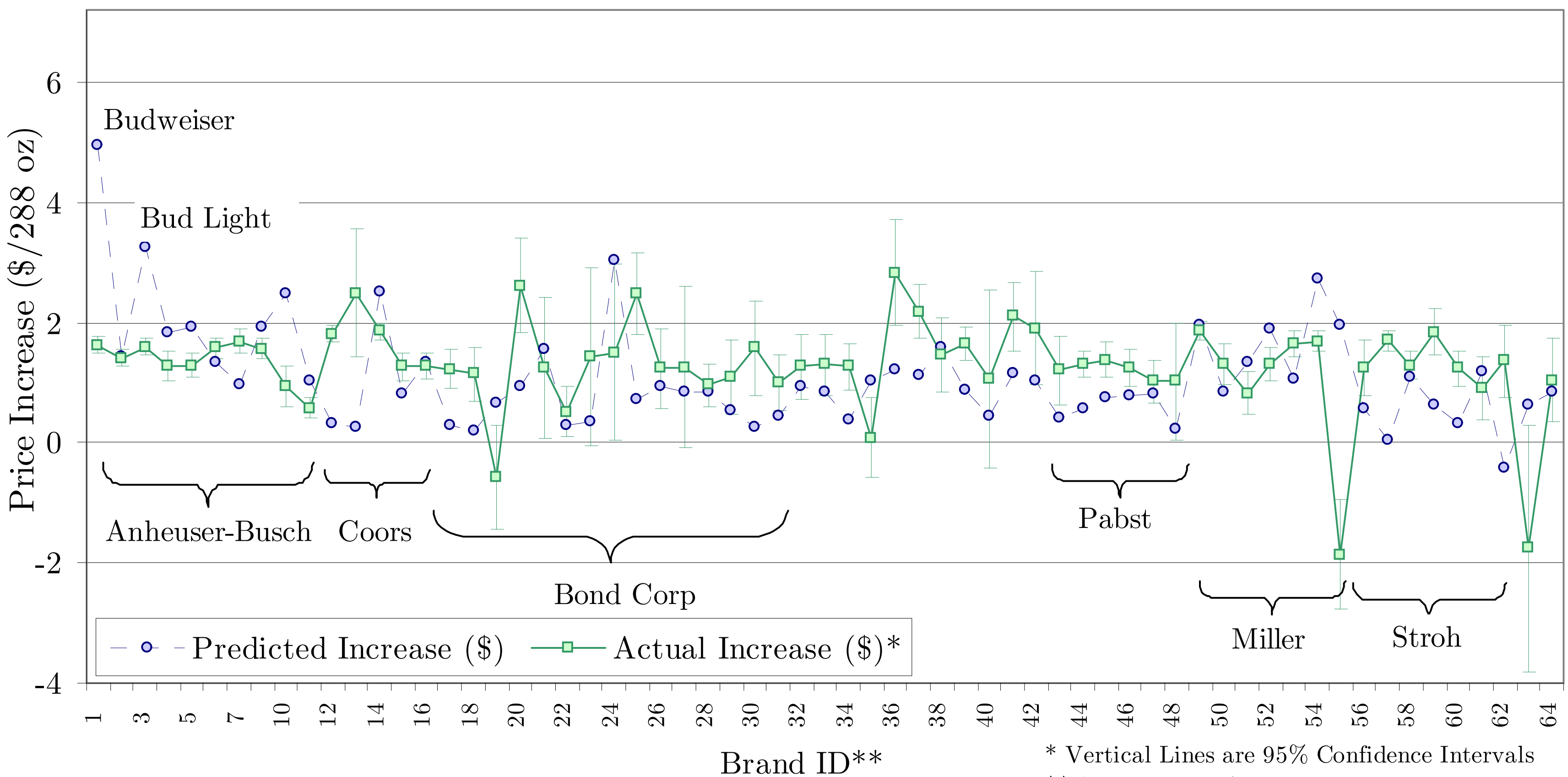
Source: Greer (1998), Beer Marketer's Insights, Anheuser-Busch's 2004 Annual Report
Note: Stroh exited the market in 1999. The 2003 number corresponds to Pabst's market share (the acquirer of some of Stroh's brands).

Figure 2: Quarterly Mean Prices, Various Segments (1988-1992)



Source: IRI Database, University of Connecticut

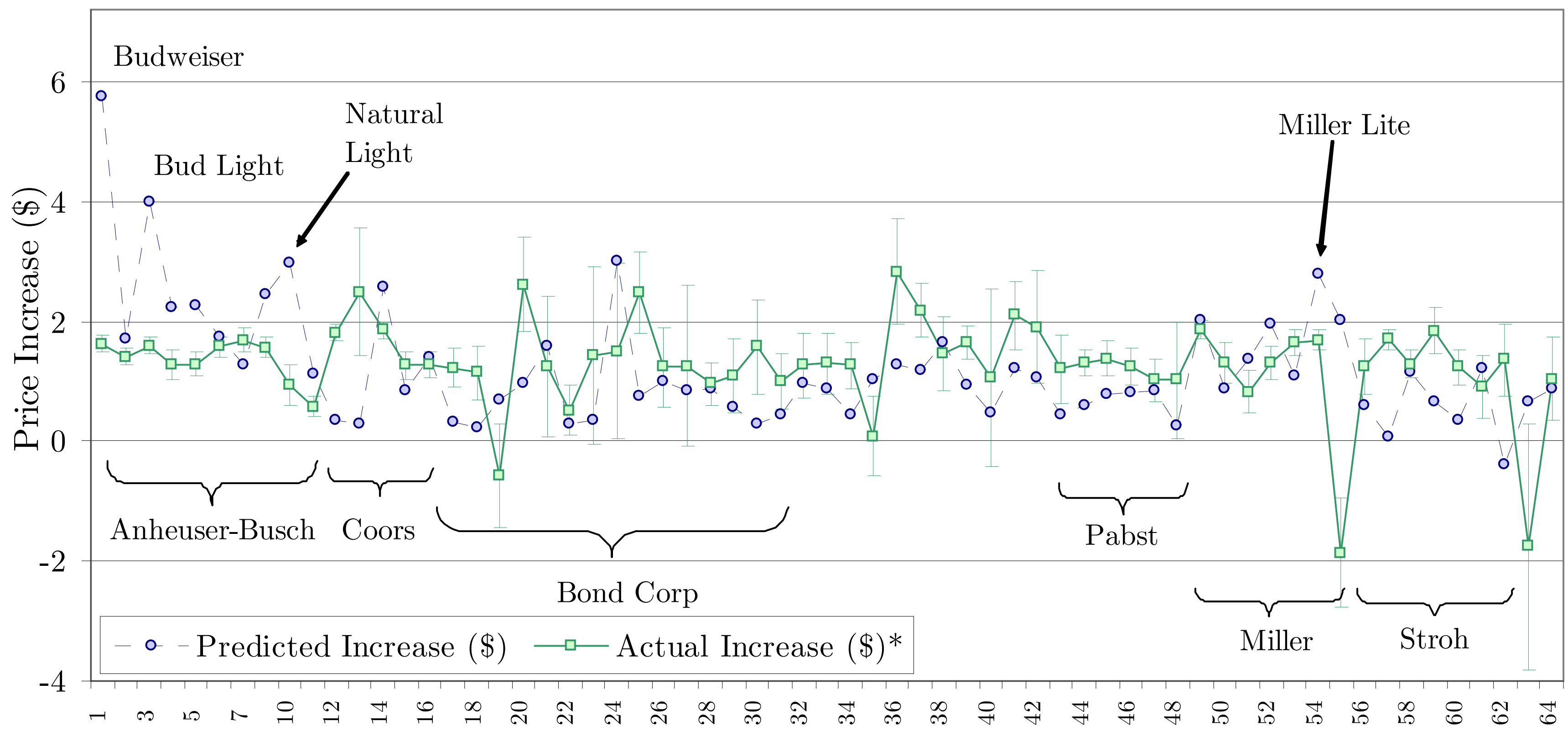
Figure 3: Predicted Price Increases by Bertrand-Nash behavior vs. Actual Price Increases per brand after 100% Hike in the Federal Excise Tax (Mean over 46 cities)



* Vertical Lines are 95% Confidence Intervals

** See appendix A for Brand ID's

Figure 4: 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 5: 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)

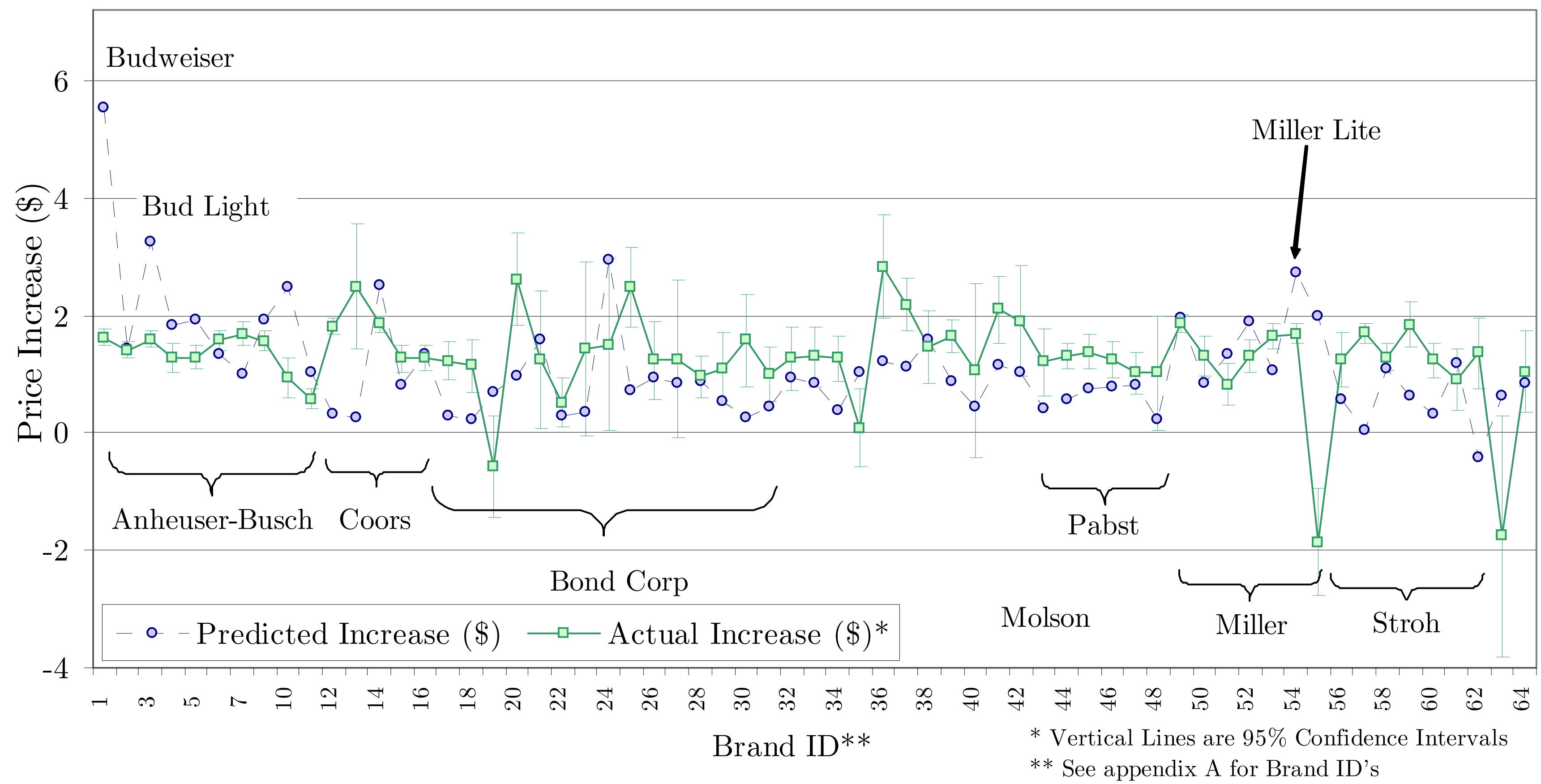
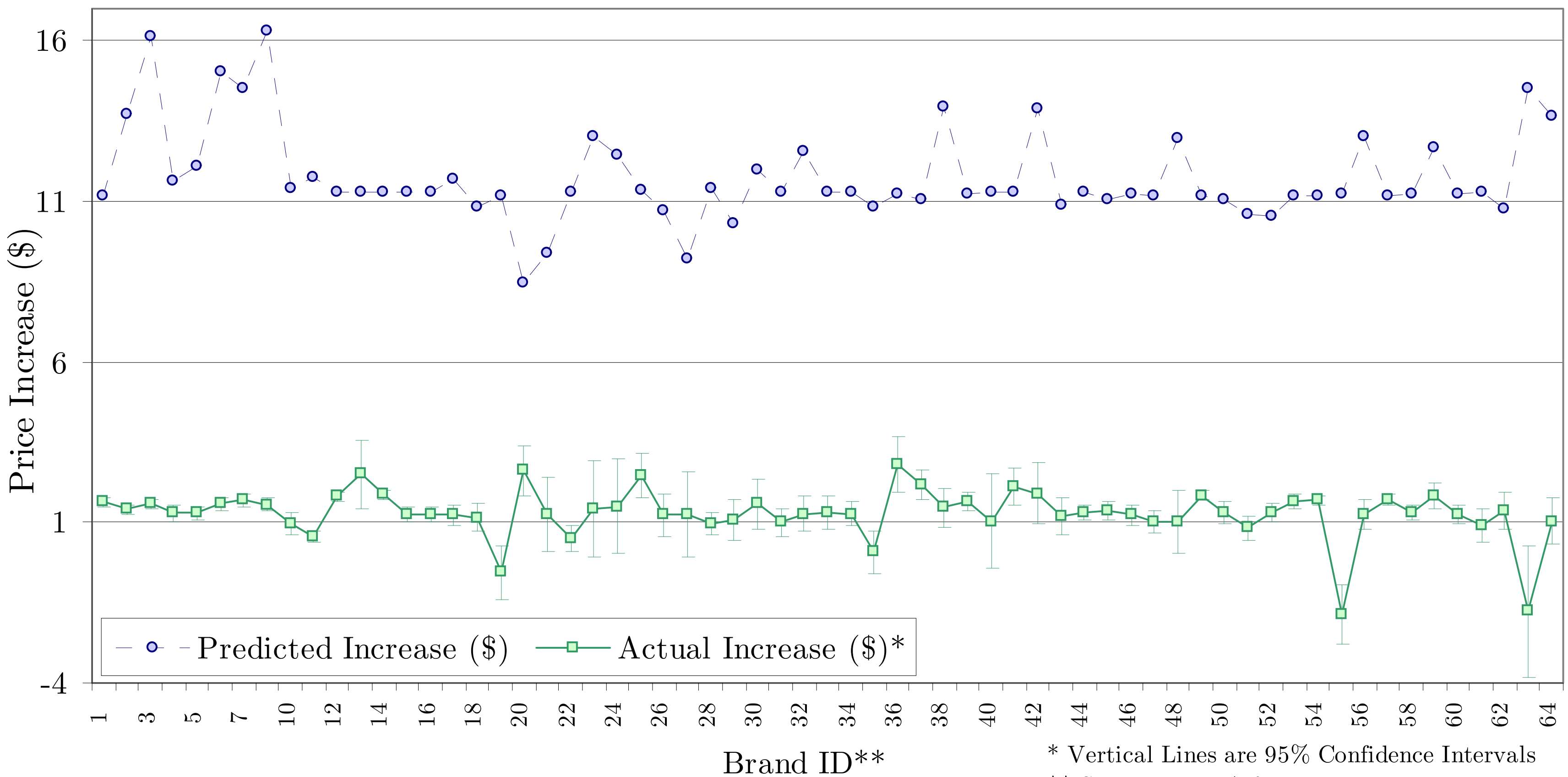


Figure 6: Predicted Price Increases of Collusive Price Leadership by Budweiser vs. Actual Price Increases per brand after 100% Hike in the Federal Excise Tax (Mean over 46 cities)



* Vertical Lines are 95% Confidence Intervals

** See appendix A for Brand ID's

Figure 7: 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)

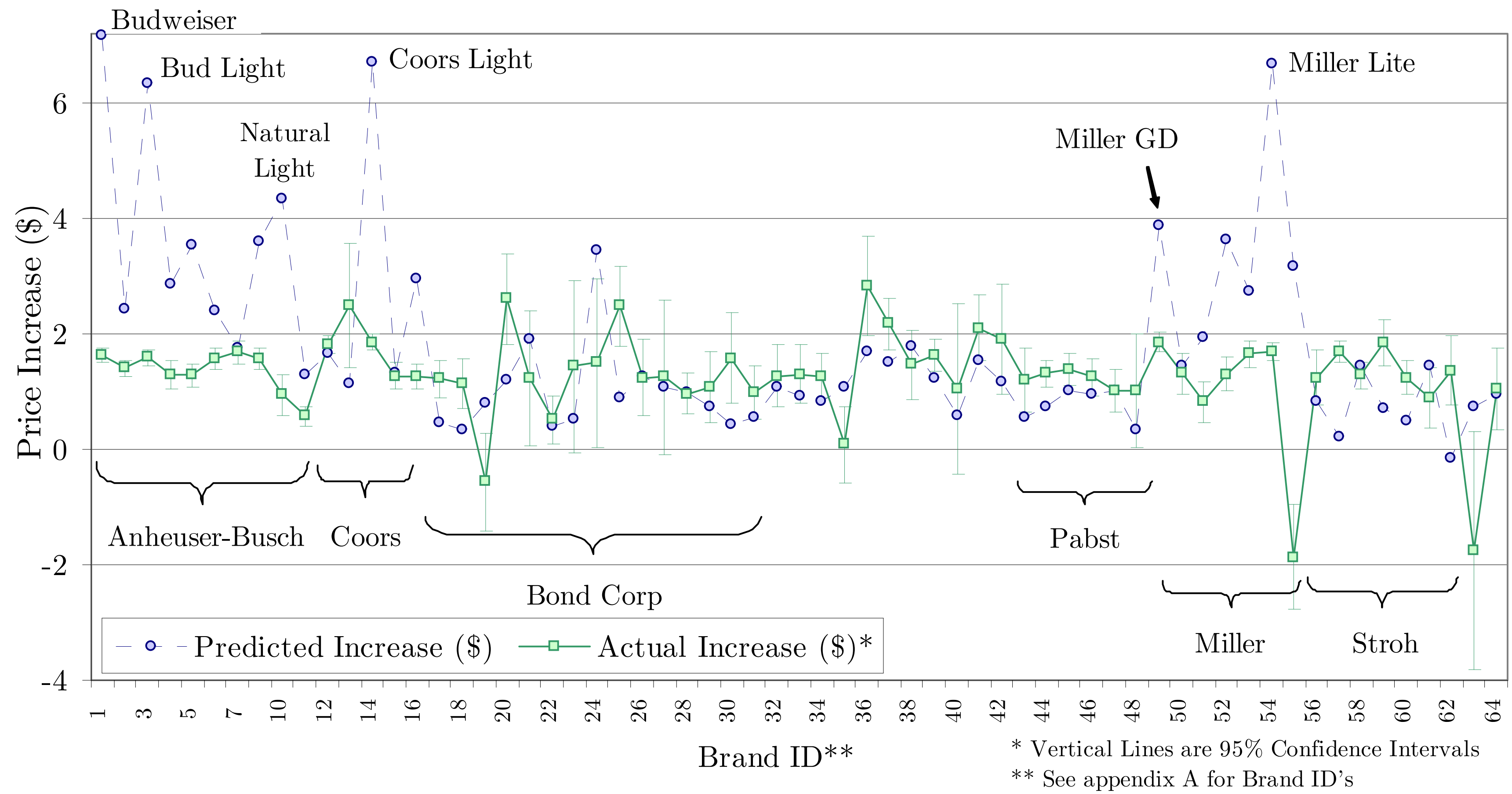


Figure 8: Predicted Price Increases by Collusive behavior between leading brands of 3 largest firms vs. Actual Price Increases per brand after 100% Hike in the Federal Excise Tax (Mean over 46 cities)

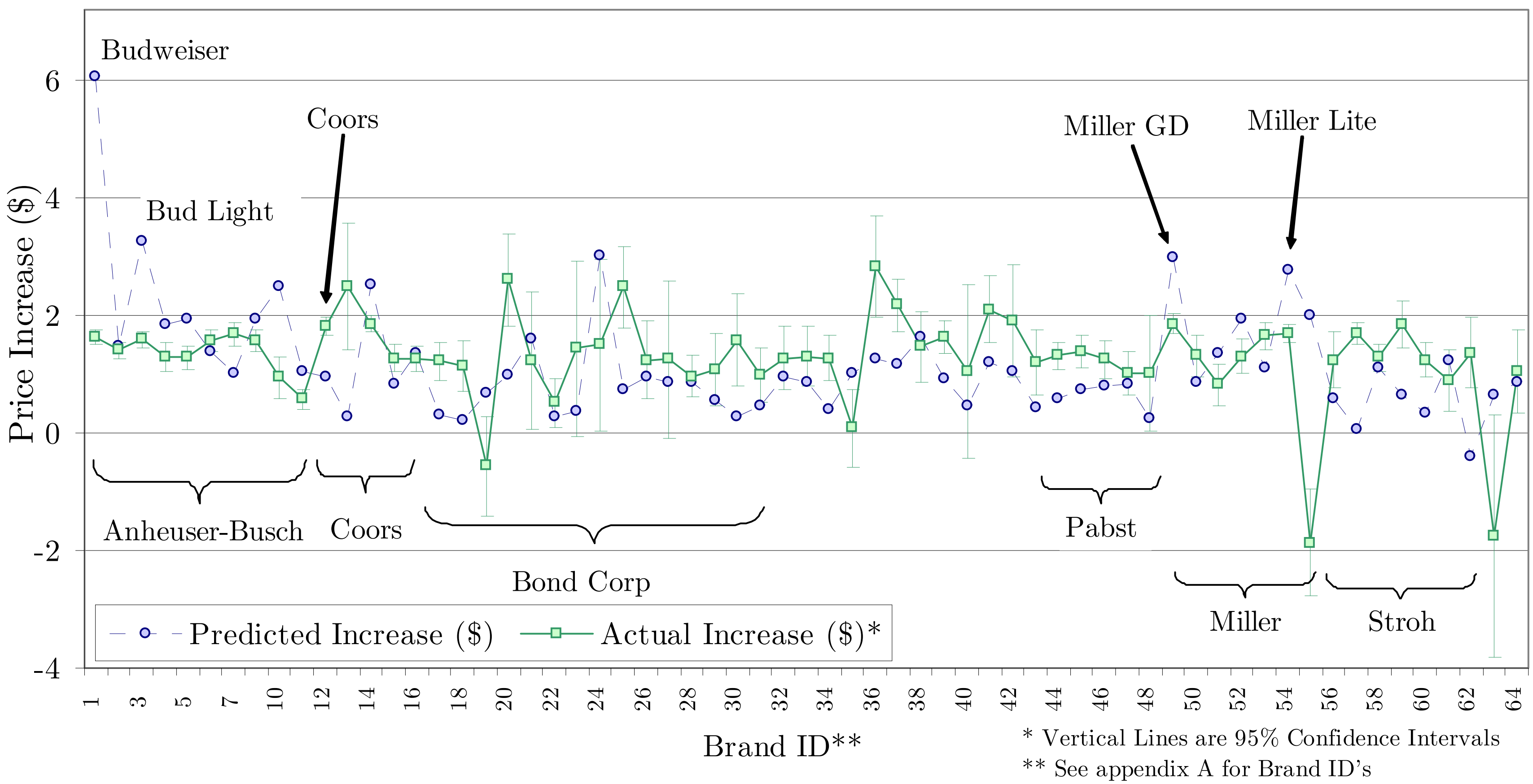


Figure 9:

Table 1: 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.(000)	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	Sum of all commodity value (ACV)	%	74	28.61	0.26	100
(COV)	sold by stores with the product /					
	ACV of all stores in the city					
OVER50K	% households with income>$50k/year	%	23.3	6.1	10.3	44.8
A	National advertising expenditures	$ (Mill)	3.54	6.3	0	40.28
	per quarter					
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

Table 2: Results of GMM Estimation of Demand Model

Dependent Variable: Sales Share $(w_{\mathbf{jt}})^a$	**Model 1**		**Model 2**	
Variable; Description	Coeff	(t-stat)[b]	Coeff	(t-stat)[b]
Constant, a_{jt}				
Brand Dummies	no	no	yes	yes
Constant[c]	-	-	-15.51	(-0.96)
ALC[c]	-	-	5.95	(3.24)
POPULAR[c]	-	-	49.98	(14.84)
PREMIUM[c]	-	-	63.52	(13.95)
SUPER-PREMIUM[c]	-	-	131.81	(23.85)
IMPORT[c]	-	-	211.18	(22.55)
NCBAC; # common boundary neighbors, Alcohol content-Coverage space	-1.15	(-0.85)	-3.91	(-3.66)
OVER50K	-94.84	(-0.57)	-240.0	(-1.90)
Own Price (b_{jj}) and Own-Advertising (c_{jj})				
$\log P$	-122.4	(-9.82)	-252.9	(-5.71)
$\log P \times (1/COV)$	-0.56	(-2.38)	-1.09	(-3.46)
$\log P \times NCBCSP$; NCBCSP= # of CB neighbors in CS - price space	-4.82	(-7.28)	-7.14	(-11.35)
A^γ	8.48	(31.15)	1.32	(4.39)
$A^\gamma \times (1/COV)$	-0.68	(-5.58)	-0.19	(-3.47)
$A^\gamma \times NCBCS$; NCBCS=# common boundary neighbors, CS space	-1.65	(-3.57)	-0.16	(-4.53)
Weighted Cross-Price and Cross-Advertising Terms (λ_l and τ_m)				
Distance Measures for Price (Weighing Matrix Acronym)				
Alcohol content-product coverage, two-dimensional product space, (WAC)	2.10	(13.66)	5.32	(11.0)
Nearest Neighbors in Alcohol Content-Product Coverage space (WNNAC)	-0.21	(-0.30)	8.87	(15.62)
Brewer Identity (WBREW)	-12.18	(-5.38)	17.30	(5.31)
Product Classification 2: Regular-Light (WPROD2)	52.39	(6.62)	93.56	(3.99)
National Identity (WREG)	40.83	(5.85)	49.61	(5.39)
Distance Measures for Advertising (Weighing Matrix Acronym)				
Container size, one-dimensional product space (WSIZE)	0.17	(7.83)	0.16	(8.64)
Common boundary in product coverage-cont. size-price space (WCBCSP)	0.85	(15.5)	0.71	(15.23)
Nearest neighbors in product coverage-container size space (WNNCS)	0.61	(14.7)	0.40	(12.24)
Product Classification 3: Budget, light, premium (WPROD3)	-2.78	(14.58)	-3.22	(-9.10)
National Identity (WREG)	-3.02	(-21.79)	5.30	(2.65)
Price Index (d_j)				
$\log(x_t/P_t^L)$	28.15	(1.08)	27.35	(1.38)
R^2 (Centered, uncentered)	0.40, 0.58		0.66, 0.76	
J-Statistic (p-value)	0.90		0.50	

[a]Based on 33,892 observations. Coefficients have been multiplied by 10,000 for readability. All specifications include time and city dummies (not reported) .[b]Asymptotic t-statistics in parenthesis.

[c] Estimates from minimum distance (MD) procedure. The MD regression includes brewer dummies (not reported).

Table 3: Summary Statistics of Price Cost Margins for Different Models, (1988-1990)*

Model	**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 $100 \times (p - c)/p$.

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 and Miller

± Budweiser, Coors, Miller Genuine Draft

Table 4: Summary Statistics of Actual and Predicted Price Increases and Performance Metrics of Models

	Summary Statistics[a]			Performance Metrics		
	Mean	Median	St. Dev	# No-Reject[b]	Weighted Mean[c]	SSD[d]
Actual Increases	1.38	1.37	0.65	N/A	1.33	N/A
Predicted Increases:						
Bertrand-Nash	1.24	0.97	1.41	20	3.13	3993
A-B Stackelberg Leader[e]	1.39	1.04	1.54	20	3.44	4663
Budweiser Stackelberg Leader	1.26	0.98	1.46	21	3.26	4232
Collusive Leadership (Bud)	11.83	11.03	2.93	0	11.44	20629
Collusion 3 firms[f]	2.21	1.50	2.40	22	5.20	11671
Collusion 3 brands[g]	1.34	1.03	1.52	19	3.52	4545

[a] Computed with absolute price increases for each brand: the absolute price difference between the first quarter of 1991 and the fourth quarter of 1990, over 46 cities (1748 observations)

[b] Number of brands for which mean of predicted increases falls within the confidence intervals of mean of actual increases (see graphs 3 to 9)

[c] Weighted average of absolute price increases (weight=volume of brand sold in city/ total volume of all brands in all cities in the first quarter of 1991)

[d] Sum of squared deviations over all brands and all cities; deviation=predicted-actual (1748 obs.)

[e] A-B = Anheuser-Busch. [f] Anheuser-Busch, Adolph Coors, Miller (Philip Morris).

[g] Budweiser, Coors, Miller Genuine Draft

Table 5: 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.]*:	(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

*These brands correspond to Hieleman Brewing, which was acquired in 1987 by Australian Bond Corp. Holdings; it is classified as a domestic brewer because this foreign ownership was temporary

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