ESTIMATING DYNAMIC PRICING DECISIONS IN OLIGOPOLISTIC MARKETS:

AN EMPIRICAL APPROACH USING MICRO- AND MACRO-LEVEL DATA

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ABSTRACT

It is well documented in the marketing literature that households' brand choices within categories of inexpensive, frequently consumed packaged goods - such as soft drinks and coffee – are characterized by *state dependence* effects, i.e., a household's brand choice in the current period depends on the household's previous brand choices. Such effects arise out of households' tendencies to repeat-purchase brands out of habit ("inertia") or switch brands in a desire for variety ("variety-seeking"). When such state dependence effects are present, market shares of brands will tend to be correlated over time, i.e. the share of a brand in the current period will be a function of not just the current marketing activities of firms, but also lagged shares of the brand in previous periods. To the extent that state dependence effects characterize the evolution of brands' market shares over time, firms must dynamically compete in prices over time taking into account inter-temporal linkages in demand for their brands. In this study, we model and estimate such dynamic pricing policies of firms.

First, we use micro-level scanner panel data on a product category to estimate a household-level brand choice model with state dependence. We then use the estimates of this brand choice model, along with observed inter-purchase times in the product category, to construct a predictive model for market-level brand sales. This brand-sales model serves as an input into a dynamic pricing model of firms, which is based on the idea that firms compete on prices in an infinite-period, repeated dynamic game with discounting. We estimate the supply-side parameters – specifically, brand-specific marginal costs – using macro-level store scanner data on brands' market shares and prices, adopting a recently proposed estimation technique (Berry and Pakes 2000). We benchmark these estimates against the supply-side estimates obtained under the assumption that firms are not forward-looking and maximize the profit for the current period only ("myopic" model), and those obtained under the (traditional) assumption that firms assume that there is no state dependence in demand ("static" model). Comparing these three sets of estimates to marginal costs in the relevant industry allows us to understand whether price-competition is dynamic, myopic or static in the industry under study. Using scanner panel data and store scanner data on two product categories – cola and coffee - we find that households are strongly inertial in their brand choices. Estimating the proposed dynamic pricing model after taking into account the effects of such inertia generate intuitively reasonable estimates of costs, and hence profit margins, of brands in the product category. Our study is the first in the marketing literature to estimate a fully structural, dynamic pricing model on actual data, and is useful to understand both demand dynamics and the cost structure of competing firms in an oligopoly.

Key-words: Dynamic Pricing , State Dependence, Dynamic Controls, Dynamic Optimization.

1. INTRODUCTION

The importance of pricing within a firm's marketing mix cannot be underemphasized (for a detailed review of pricing models in marketing, see Rao 1993). While pricing its product, a firm must take into account the effects of competition from other firms within the product category (Moorthy 1985). A large number of oligopolistic models of pricing have been accordingly developed in normative and empirical domains over the past few decades (see Vives 2001). In addition to incorporating the effects of competitive prices, a firm must also account for the effects of *demand dynamics*. For example, firms such as Coke, Folgers etc. manage brands in inexpensive, frequently purchased categories of packaged goods that are routinely characterized by *state dependence* effects (Seetharaman, Ainslie and Chintagunta 1999). In other words, which brand of cola a given household is likely to buy on a visit to the store is partly a function of which brand the household bought on its previous purchase in the cola category. For example, one household may buy Coke on consecutive purchase occasions "out of habit" (even if Pepsi were on sale at the second purchase occasion), while another household may switch from Coke to Dr. Pepper (even if Coke were on sale at the second purchase occasion) just to "try something different." Both households do not simply respond to marketing activities (such as price) in making their brand choices. While the first household exhibits positive state dependence ("inertia") in their brand choices, the second household exhibits negative state dependence ("variety-seeking"). When such state dependence effects characterize household-level brand choices, it is likely that such state dependence will characterize market-level brand shares as well. For example, if Coke experiences an increase in its market share on a given week, the effects of such increased share are likely to persist in the future if households are predominantly inertial in the cola category. Conversely, Pepsi's future market share is likely to benefit from the current increased share of Coke if households are predominantly variety-seeking in the category. Given such inter-temporal dependencies in brands' market shares, manufacturers must account for their effects while determining optimal pricing policies for their brands. For example, in the presence of inertia, manufacturers must recognize the long-term benefits of a price promotion, since households that buy their brand on promotion in the current period are likely to "stick around" with the same brand in the future. Conversely, in the presence of variety-seeking, manufacturers must recognize the long-term pitfalls of promoting their brands, since households that buy their brand on promotion in the current period are likely to defect to competing brands in the future. If there is a heterogeneous mix of households, some of whom are inertial and others are variety-seeking, the pricing implications for manufacturers may be even more complicated. In short, it is important for manufacturers to recognize and respond to the effects of demand dynamics, such as due to state dependence, while making pricing decisions for their brands. In this paper, we estimate an oligopolistic pricing model using empirical data from two product categories that are characterized by significant demand dynamics.

The existing literature on oligopolistic pricing of brands in packaged goods categories shows a surprising dearth of papers that incorporate the effects of demand dynamics, although there is an extensive empirical literature that documents the effects of state dependence in households' brand choices using scanner panel data (for a recent paper, see Seetharaman, Ainslie and Chintagunta 1999)[2]. This paper addresses this gap in the pricing literature. Chintagunta and Rao (1996) develop the normative pricing implications of estimated state dependence in a duopoly. Freimer and Horsky (2001) develop an analytical model of duopolistic pricing to demonstrate that if each manufacturer responds to demand dynamics by alternating their brand's prices over time, they will reap greater profits than if they adopted a constant price over time. These two *analytical* efforts motivate our *empirical* effort to understand whether observed prices in oligopolistic markets are indeed consistent with dynamic pricing practices of firms. Unlike previous work, we do not limit our attention to a duopoly and/or steady-state behavior. More importantly, we explicitly *estimate* a dynamic, structural model of pricing using the first-order conditions of the dynamic pricing game on scanner data.

Our proposed dynamic pricing model is based on the idea that firms compete on prices in an infinite-horizon, dynamic, Bertrand-Nash game with discounting. Therefore, firms are forward-looking while determining current optimal prices for their brands. The dynamics in the pricing game arise on account of state dependence effects in each firm's demand function, i.e. a firm's demand in a given period is a function of lagged demand of all firms in the product category, taking into account pair-wise inter-product similarities between brands (as in Seetharaman, Feinberg and Chintagunta 2002). The parameters of these demand functions are calibrated using *micro-level* scanner panel data on households' inter-purchase times and conditional brand choices. The calibrated demand equation serves as an input for the dynamic pricing model, whose parameters – specifically, marginal costs of firms - are then estimated using *macro-level* scanner data on brand sales and prices, using a recently proposed estimation technique (Berry and Pakes 2001). Our study is unique in combining micro- and macro-level data to empirically calibrate the parameters of the pricing model.

[2] There is an extensive body of work in marketing on dynamic pricing in *monopolistic* markets (for a recent example, see Krishnan, Bass and Jain 2000).

We benchmark our cost estimates both against those obtained under the assumption that firms are not forward-looking and maximize profits for the current period only ("myopic" pricing model), and against those obtained under the (traditional) assumption that firms ignore state dependence in demand ("static" pricing model). Comparing these three sets of estimates to actual marginal costs in the relevant industry allows us to understand whether observed prices in the industry are consistent with dynamic-, myopic- or static- price competition. Another study that investigates dynamic pricing policies of firms in the presence of state dependence effects is one by Che, Seetharaman and Sudhir (2002). However, we propose a *structural* model of pricing that is based on an infinite-period, dynamic game played between firms, while their study takes a *reduced-form* approach by looking at two-period and three-period pricing models only[3].

Our dynamic pricing model is in the same spirit as the dynamic choice models of Pakes (1986), Rust (1987), Keane and Wolpin (1994) and Erdem and Keane (1996), in that it requires the solution of a discrete-time, stochastic dynamic optimization problem from the agent's standpoint, except that our agent is the firm instead of the consumer. However, our model is more complicated then these dynamic choice models in the following sense: 1. It has *continuous controls*, i.e. prices can take values from a continuum (instead of *discrete controls*, i.e. consumers choosing between a discrete number of actions in the dynamic choice models), which greatly increases the dimensionality of the agent's decision problem, and 2. It has *multiple agents simultaneously making decisions*, i.e. multiple firms solving not only their own dynamic optimization problems but also their best responses to each other's dynamic optimization problems! In terms of these two features, our model is directly in line with the recent work of Pakes (1994), Pakes and McGuire (1994), and Pakes and McGuire (2001). The estimation procedure that we employ, recently developed by Berry and Pakes (2000), imaginatively circumvents having to analytically or numerically solve for the equilibrium of the dynamic pricing game using the *rational expectations* assumption (as will be explained later). We believe that our work is the first in the marketing literature to propose an empirically estimable dynamic pricing model for an oligopoly[4]. Also, the fact that we use both micro- and macro-level data in the empirical estimation is a unique aspect of our work.

The remainder of the paper is organized as follows. In section 2, we develop a firm's dynamic pricing problem as a discrete time, stochastic dynamic optimization problem. Section 3 presents the brand sales model,

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[3] Their study models the strategic behavior of the retailer while ours does not.

[4] Berry and Pakes (2000) demonstrate the viability of their estimation approach using simulated data. Ours is the first empirical validation of their approach using real-world data.

while section 4 presents the brand choice model. In section 5 we discuss the estimation procedure for the brand choice model using micro-level data. In section 6, we develop the estimation procedure for the dynamic pricing model using macro-level data. Section 7 presents the empirical results from two different product categories. In section 8, we conclude with a brief summary and directions for future research.

2. MANUFACTURER PRICING MODEL

Our pricing model is based on the assumption that brands' prices are the outcome of a Nash-Bertrand dynamic pricing game between manufacturers, i.e. we ignore the strategic role of the retailer in determining the price of a brand, as in Chintagunta and Rao (1996) and Freimer and Horsky (2001)[5]. Manufacturers are assumed to choose a pricing policy for their brand in order to maximize the net present value of the expected lifetime profits for their brand (also called the *optimal return* function), as shown below.

$$V_j(\Sigma_t) = \sup_{\{p_{jt}\}} E\left[\sum_{s=t}^{\infty} g^{s-t} \mathbf{p}_{js} \mid \Sigma_t\right], \tag{1}$$

where $V_j(.)$ stands for the net present value of the expected lifetime profits of brand j[6], g is a discount factor, $\Sigma_t = (Z_{t-1} Z_{t-2} \ldots Z_{t-U})$ is the information set available to the manufacturer of brand j at time t, $Z_{t-u} = (Z_{1t-u} Z_{2t-u} \ldots Z_{Jt-u})'$ is a J-dimensional vector of observed sales of the J brands at time $t-u$, and $\mathbf{p}_{js}$ is a single-period profit function (also called *single-period return* function) given by

$$\mathbf{p}_{js} = (p_{js} - c_j) Z_{js}, \tag{2}$$

where p_{js} is the price of brand j at time s, c_j is the (constant and time-invariant) marginal cost associated with brand j, and Z_{js} stands for the sales of brand j at time s. The objective of the manufacturer, as embodied in equation (1), is to find the optimal pricing policy that has value equal to the optimal return function. $\Sigma_t = (Z_{t-1} Z_{t-2} \ldots Z_{t-U})$ defines the continuous *state space* of the firm's discrete-time, dynamic optimization problem. What renders this dynamic optimization problem *stochastic* is the fact that the state

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[5] We can also handle retail competition based on the assumption that each retailer maximizes category profits. We ignore this in this study and instead (tacitly) assume that retailers fully cooperate with each manufacturer in their pricing decisions in order to maximize the total channel profit from each brand.

[6] In the case of manufacturers with multiple brands, our assumption will be that profits are maximized over the product line.

variable $Z_t = (Z_{1t}Z_{2t}...Z_{Jt})'$ evolves from one period to the next in a probabilistic manner, given the continuous decision variable $p_t = (p_{1t}p_{2t}...p_{Jt})'$, according to a *transition law*. We describe this next.

3. BRAND SALES MODEL

Since firms typically deal with aggregate sales (or market shares) of their brands and their competitors' brands, and not individual households' brand choices, they require a predictive model for brand sales in order to make their optimal pricing decisions. Brand *j*'s sales in period t are assumed to obey the following equation.

$$Z_{jt} = q_{jt} * m_t + h_{jt}, \tag{3}$$

where Z_{jt} stands for the sales of brand *j* at time t, q_{jt} stands for the market share of brand *j* at time t, m_t stands for product category sales at time *t* (assumed to be exogenously specified), and $h_{jt} \sim iid\,\mathrm{N}(0, s_j^2)$.

We assume that all households purchase the product at least once in *N* weeks, and on average a fraction of households, f_u (*u=1*, …, *N)*, buys the product once in every *u* weeks, where *N* and f_u are estimated using micro-level scanner panel data on households' inter-purchase times in the product category. We also assume that f_u is independent of households' brand choices and marketing variables[7]. Given the estimated f_u (*u=1*, …, *N)*, a predictive model for a brand's market share can be written as shown below.

$$q_{jt} = \sum_{u=1}^{U} f_u * \left\{ \sum_{k=1}^{J} \left(q_{kt-u} * \sum_{r=1}^{R} p_r * P_{r(k \to j)t} \right) \right\}, \tag{4}$$

where q_{jt} stands for the (predicted) market share of brand *j* at time *t*, q_{kt-u} stands for the (observed) market share of brand *k* at time *t-u*, p_r stands for the prior probability of a household belonging to segment *r* (i.e. support *r* of the unobserved discrete heterogeneity distribution), and $P_{r(k \to j)t}$ stands for the transition probability characterizing a household's transition from brand *k* to brand *j* at time *t* given that the household belongs to segment *r*.

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[7] Using this assumption we ignore the problem of households stocking up product inventory on deals.

Therefore, the temporal evolution in brand sales (Z_{jt}) is a function of the temporal evolution in brand market shares (q_{jt}), which in turn is a function of the temporal evolution in a household's brand choice probabilities, captured by the transition probabilities $P_{r(k\rightarrow j)t}$. We specify these transition probabilities next.

4. BRAND CHOICE MODEL

The Seetharaman, Feinberg and Chintagunta (2002; henceforth SFC) model, an extension of the model of Lattin and McAlister (1985), is a first-order Markov model of brand choice which rests on the following premise: households switching among products in response to their variety-seeking needs are, on a given purchase occasion, more likely to buy a product that is dissimilar to the one purchased on the most recent purchase occasion; households switching among products in response to inertial tendencies are, on a given purchase occasion, more likely to buy a product that is similar to the one purchased on the most recent purchase occasion. The SFC model presumes that, in the absence of state dependence, an individual household goes about its purchases in multinomial logit fashion, with an *unconditional* probability of purchasing brand *i* given by $P_{rit} = \exp\left(X_{it} b_r\right) / \sum_{k=1}^{k=K} \exp\left(X_{kt} b_r\right)$, where $\mathbf{X_{it}}$ is the vector of marketing variables characterizing product *i* at time *t*, and $b_{\mathbf{r}}$ is the corresponding vector of response parameters for households belonging to segment *r* (assumed to be common across products). However, for a household exhibiting state dependence, products similar to that just purchased are less or more attractive depending on whether the household seeks variety or inertia respectively. This is modeled as

$$P_{r(j\rightarrow i)t} = \frac{P_{rit} - V_r S_{rjit}}{1 - V_r \sum_{k=1}^{K} S_{rjkt}} , \tag{5}$$

where $P_{r(j\rightarrow i)t}$ stands for the household's probability of switching from product *j* to product *i* at time *t* (i.e., the household's *conditional* probability of buying product *i* given that product *j* was purchased at the previous purchase occasion), V_r *Î [-¥, 1]* denotes the household's state dependence parameter, with positive values representing variety-seeking and negative values representing inertia, and S_{rjit} measures the degree of similarity between products *j* and *i*, as perceived by a consumer in segment *r*, and is given by

$$S_{rjit} = c_{ji} \min(P_{rjt}, P_{rit}) \tag{6}$$

where $c_{ji} \in [0,1]$, $c_{ij} = c_{ji}$, and $c_{ii} = 1$.

As per equation (5), the more positive the value of V_r, the greater the degree to which a household seeks variety, with $V_r = 1$ corresponding to maximal variety-seeking (achieved, for example, by switching back and forth between a pair of dissimilar products). Similarly, the more negative the value of V_r, the greater the degree to which a household exhibits inertia, with $V_r = -\infty$ corresponding to maximal inertia (achieved, for example, by switching back and forth between a pair of similar products). $V_r = 0$ indicates an absence of state dependence in the household's brand choices and implies that $P_{r(j \to i)t} = P_{rit}$, corresponding to a zero-order multinomial logit model. The parameter c_{ji} is a measure of inter-product similarity between products j and i, so that $c_{ji} = 0$ indicates a lack of similarity (that is, no shared features), and $c_{ji} = 1$ corresponds to complete similarity (only shared features, in that the smaller-share brand of the pair offers no unique features beyond its larger-share competitor). The appealing feature of the SFC model is that it not only models the effects of inertia and variety-seeking on household choice behavior (through the parameter V_r), but also allows such effects to depend on inter-product similarities in a parsimonious manner (through the parameters c_{ji}).

5. ESTIMATION OF BRAND CHOICE MODEL USING MICRO-LEVEL DATA

The SFC brand choice model is estimated by maximizing the following sample likelihood function.

$$L = \prod_{h=1}^{H} \left[\sum_{r=1}^{R} p_r \prod_{t=1}^{T_h} \prod_{i=1}^{J} \left(\frac{P_{rit} - V_r S_{rj_{h(t-1)}i}}{1 - V_r \sum_{k=1}^{K} S_{rj_{h(t-1)}k}} \right)^{d_{hit}} \right], \tag{7}$$

where δ_{hit} is an indicator variable that takes the value 1 if product i is purchased by household h at time t, $j_{h(t-1)}$ is the product purchased by household h on the previous purchase occasion, H is the number of households, T_h is the number of purchases made by household h, and all other variables are as defined previously (see equation 3). We address the *initial conditions* problem by assigning the MNL choice probability P_{ri0} for each household's first purchase (at time $t = 0$).

We calibrate the parameters f_u ($u=1, \ldots, N$) using the empirical distribution of inter-purchase times in the product category. Using the estimated $P_{r(k \to j)t}$, p_r and f_u in equation (4), one can predict the temporal evolution of brands' market shares q_t. It is important to note that f_u and p_r cannot be separately identified using macro-level data. This is the main reason for our using micro-level scanner panel data to estimate the parameters of the demand equations.

6. ESTIMATION OF PRICING MODEL USING MACRO-LEVEL DATA

Given that a brand's expected demand in a given period is a function of its own lagged demand and the lagged demand of its competitors' brands (as shown in equation 4), the price chosen by a brand in the current period will affect not only its own current demand and the current demand of its competing brands, but also its own future demand and the future demand of competing brands. Therefore, manufacturers' pricing policies have to take the future into account. This is the intuition for our dynamic pricing model, also called a *stochastic accumulation model* (Leonard and Long 1992).

The technique to solve for the optimal pricing policy that yields the firm its optimal return function, as given in equation (1), is to take derivatives of the firm's value function and set them to zero. Since this is difficult to do, we can use *Blackwell's Condition* and recast this problem using a contraction mapping, whose fixed point is the solution to the Bellman equation, as shown below.

$$V_j(\Sigma_t) = \sup_{\{p_{jt}\}} \left\{ Ep_{jt}(p_{jt}, \Sigma_t) + g \int V_j(\Sigma') dF(\Sigma' | \Sigma_t, p_{jt}) \right\} \qquad (8)$$

where *F(.|.,p)* is the Markov transition kernel for $\{\Sigma_t\}$ conditional on the action *p*. It is well known that looking at the fixed point of this functional equation (8) is a lot easier than taking derivatives of equation (1). However, this is still difficult to do using conventional dynamic optimization techniques. Specifically, for a given set of parameters, one has to compute the solution to the Bellman equation for each firm and then compute the pricing equilibrium across firms (assuming that it is unique). This procedure needs to be repeated until one can locate an optimal set of parameters that "explains" the observed data well. This is very difficult to implement even by existing computational standards (Pakes 1994, Pakes and McGuire 1994, Pakes and McGuire 2001). Further, there may exist a multitude of equilibria in the Nash-Bertrand dynamic pricing game, in which case figuring out which of these equilibria will indeed be observed becomes an additional source of difficulty. In order to get around these problems, we adopt a recently proposed estimation technique that is based on the optimality conditions for dynamic controls (Berry and Pakes 2000). This technique relies on two assumptions:

1. *Rational Expectations*, i.e. $\sum_{s=t}^{\infty} g^{s-t} p_{js} = V_j(\Sigma_t) + e_{jt}$, and $E(e_{jt} \mid (\Sigma_t)) = 0$. In other words, the actual lifetime profits can be written as a sum of expected lifetime profits plus a random error whose mean is zero conditional on the information set.

2. *Smoothness*, i.e. $F(\Sigma' \mid \Sigma_t, p)$ has support independent of *p*. Its density function *f(.|.,p)* is differentiable in p for all Σ_t.

From equation (7) the first-order conditions for each j and t can be written as follows.

$$\begin{aligned} 0 &= \frac{\partial E p_{jt}(\Sigma_t, p_{jt})}{\partial p_{jt}} + g \cdot \int V_j(\Sigma_{t+1}) \frac{\partial f(\Sigma_{t+1} \mid \Sigma_t, p_{jt})}{\partial p_{jt}} d\Sigma_{t+1} \\ &= \frac{\partial E p_{jt}(\Sigma_t, p_{jt})}{\partial p_{jt}} + g \cdot E[V_j(\Sigma_{t+1}) \frac{\partial \ln f(\Sigma_{t+1} \mid \Sigma_t, p_{jt})}{\partial p_{jt}} \mid \Sigma_t] \end{aligned} \tag{9}$$

Using assumption 1 (i.e. rational expectations), this can be rewritten as follows.

$$\begin{aligned} 0 &= \frac{\partial E p_{jt}(\Sigma_t, p_{jt})}{\partial p_{jt}} + \sum_{s=t+1}^{\infty} g^{s-t} \cdot p_{js} \cdot \frac{\partial \ln f(\Sigma_{t+1} \mid \Sigma_t, p_{jt})}{\partial p_{jt}} + x_{jt} \\ &= (p_{jt} - c_j) \cdot \frac{\partial q_{jt}(\Sigma_t, p_{jt})}{\partial p_{jt}} \cdot m_t + q_{jt}(\Sigma_t, p_{jt}) \cdot m_t + \sum_{s=t+1}^{\infty} g^{s-t} \cdot p_{js} \cdot \frac{\partial \ln f(\Sigma_{t+1} \mid \Sigma_t, p_{jt})}{\partial p_{jt}} + x_{jt} \end{aligned} \tag{10}$$

where $q_{jt}(\Sigma_t, p_{jt})$ is defined in equation (5),

$$x_{jt} = g \cdot E[V_j(\Sigma_{t+1}) \frac{\partial \ln f(\Sigma_{t+1} \mid \Sigma_t, p_{jt})}{\partial p_{jt}} \mid \Sigma_t] - \sum_{s=t+1}^{\infty} g^{s-t} \cdot p_{js} \cdot \frac{\partial \ln f(\Sigma_{t+1} \mid \Sigma_t, p_{jt})}{\partial p_{jt}} \tag{11}$$

and $E[\xi_{jt} \mid \Sigma_t] = 0$. Indexing all functions in (9) with the parameter vector of interest β, and using x_{jt} to denote the observed data at period t for j, we have

$$E[x(x_{jt}, b) \mid \Sigma_t] = E[\frac{\partial E p_{jt}(\Sigma_t, p_{jt}; b)}{\partial p_{jt}} + \sum_{s=t+1}^{\infty} g^{s-t} \cdot p_{js}(b) \cdot \frac{\partial \ln f(\Sigma_{t+1} \mid \Sigma_t, p_{jt}; b)}{\partial p_{jt}} \mid \Sigma_t] = 0$$

(12)

This equation underlies the estimation of β. It implies that we can use the market shares of all brands in previous periods as well as current marketing variables as our instruments in model estimation. In this sense, as in Hansen and Singleton (1982), our instruments are derived from the information structure of the model and not arbitrarily assumed.

Let h(Σt;β) denote a rich function of (Σ_t;β), and T denote the total number of observations. We can form moment conditions based on (11) as follows.

$$G_T(b) = \frac{1}{T}\sum_{j,t} m(x_{jt}, b) \equiv \frac{1}{T}\sum_{j,t} x(x_{jt}, b)h(\Sigma_t, b) \quad (13)$$

An estimator of β can be obtained by minimizing a norm of $G_T(\beta)$. This estimator will be consistent and asymptotically normal.

The key simplification of this estimation technique comes from the *rational expectations* assumption, which says that future prices and shares can be assumed to be generated by a process that is consistent with the firm's beliefs at the time that they are making their pricing decision. The researcher is agnostic about what equilibrium the firm is in, and only relies on the assumption that the firm knows which equilibrium the firm is in! In equation (7), the firm's competitors' equilibrium actions are all incorporated in $V_j\left(\Sigma'\right)$ and $F(\Sigma' \mid \Sigma_t, p_{jt})$. This technique avoids the "curse of dimensionality" problem associated with conventional solution techniques for the dynamic pricing game. The computational advantages of this technique are three-fold: first, there is no need to search for a fixed-point for $V(\Sigma_t)$ as required in conventional dynamic optimization algorithms; second, we do not need to numerically compute the equilibrium in the Nash-Bertrand pricing game; third, when multiple equilibria exist, we need to neither subjectively pick an equilibrium nor assign probabilities for each possible equilibrium. Instead, we just let the data tell us which equilibrium is obtained and, by assumption, first-order conditions have to be satisfied for each observation.

We estimate the pricing model using weekly data on prices and market shares of brands at the store-level over a period of 104 weeks, from a set of seven stores in the same metropolitan market in which the IRI scanner panel data was collected. The estimates of the demand function obtained using our micro-level (i.e. household-level) dataset will be appropriate to predict market shares in our macro-level dataset since both datasets pertain to the same geographic market ("single-source data"). We pool the weekly observations across stores to obtain 728 usable observations, from which we use the first 511 observations for model estimation and the final 217 observations as the "truncation sample" since we need to observe future data for all periods in the estimation sample, including the last period. This is not unlike having an "initialization" sample for distributed lag models, where one needs to observe past data for all periods in the estimation sample, including the first period (Seetharaman 2002).

Next, we compare the proposed dynamic pricing model, given in equation (10), with two other pricing models, that will serve as benchmark models. One model, which we call the *static model*, ignores state dependence in the demand function, assumes market shares of brands to take the multinomial logit functional form, and therefore assumes one-period profit maximization for manufacturers. In other words, manufacturer j's pricing problem is now given by.

$$\max_{\{p_{jt}\}} E[\boldsymbol{p}_{jt} \mid \Sigma_t] \tag{14}$$

From (13) we can derive the first-order condition as follows.

$$\begin{aligned} 0 &= \frac{\partial E\boldsymbol{p}_{jt}(\Sigma_t, p_{jt})}{\partial p_{jt}} + \boldsymbol{x}_{jt} \\ &= (p_{jt} - c_j) \cdot \frac{\partial \boldsymbol{q}_{jt}(\Sigma_t, p_{jt})}{\partial p_{jt}} \cdot m_t + \boldsymbol{q}_{jt}(\Sigma_t, p_{jt}) \cdot m_t + \boldsymbol{x}_{jt} \end{aligned} \tag{15}$$

where $\theta_{jt}(.)$ is the expected market share of brand *j* at time *t* and given by the (heterogeneous) MNL brand choice probability.

Another pricing model, which we may call the *myopic model*, does not ignore state dependence in the demand function, but assumes that manufacturers maximize current-period profits only. The objective function and first-order condition for this model are still given by equations (14) and (15) respectively, except that $\boldsymbol{q}_{jt}(\Sigma_t, p_{jt})$ now accounts for state dependence, and looks as in equation (4).

Assuming that all other parameters in the demand function remain the same, the absolute magnitude of $\frac{\partial \boldsymbol{q}_{jt}(\Sigma_t, p_{jt})}{\partial p_{jt}}$ will decrease in the presence of inertia and increase in the presence of variety-seeking. This implies that optimal prices under the myopic pricing model, compared to those under the static pricing model, will be higher in the presence of inertia and lower in the presence of variety-seeking. The intuition for this result is that if households are inertial (variety-seeking), they will be less (more) price responsive which makes it more profitable for firms to charge a higher (lower) price.

Compared to equation (15), there is an additional term given by $-\sum_{s=t+1}^{\infty} g^{s-t} \cdot p_{js} \cdot \frac{\partial \ln f(\Sigma_{t+1} \mid \Sigma_t, p_{jt})}{\partial p_{jt}}$, in equation (10), i.e. the proposed dynamic model of pricing. This term represents the effects of current prices on future market shares, and hence future profits. If firms take the effects of current prices on future profits into account, they will tend to charge lower prices, which will decrease their price-cost margins. This tendency is more significant in the presence of inertia because the effects of current prices on future profits will be much stronger than in the case of variety-seeking. This implies that optimal prices under the proposed dynamic pricing model, compared to those under the myopic pricing model, will be lower in the presence of inertia and higher in the presence of variety-seeking.

7. EMPIRICAL RESULTS

We employ IRI's scanner panel database on household purchases in a metropolitan market in a large US city. For our analysis, we pick two product categories: cola and coffee. The datasets cover a period of two years from June 1991 to June 1993 and contain shopping visit information on 494 panelists across four different stores in an urban market. Choosing households that bought at least twice in the product category (since we need to exclude the first purchase of each household while estimating the brand choice model, in order to compute households' transition probabilities starting from their second purchase) yields 484 households for cola and 491 households for coffee. For each product category, the dataset contains information on marketing variables – price, in-store displays, and newspaper feature advertisements – at the SKU-level for each store/week. The cola category contains four brands: Coke, Pepsi, Royal Crown and Private Label. The coffee category contains five brands: Hills Brothers, Maxwell House, Folgers, Eight O Clock and Other (an aggregation of all other brands in the product category). Descriptive statistics pertaining to both categories, based on the micro-level scanner panel data, are given in Table 1.

(Insert Table 1)

In the cola category, Coke is the most expensive brand (77 cents per unit), while the Private Label is the least expensive brand (54 cents per unit). Pepsi enjoys much higher display activity (32%) and feature activity (40%) than the other brands, and also has the highest share in the category (47.9%) over the period of study. In the coffee category, Other is the most expensive brand ($5.81 per regular purchase size), while Eight

O Clock is the least expensive brand ($2.14 per regular purchase size). Hills Brothers enjoys higher display activity (18%) and feature activity (20%) than the other brands, and also has the highest share in the category (28.1%). Descriptive statistics pertaining to both categories, based on the macro-level store scanner data, are given in Table 2.

(Insert Table 2)

There is good agreement between Tables 1 and 2, especially in terms of brands' market shares, which is satisfactory from the standpoint of using the micro-level parameter estimates with the macro-level data in the estimation of the supply-side pricing model. The estimated model parameters, along with their standard errors, are given in Tables 3-5.

(Insert Tables 3-5)

In terms of intrinsic brand preferences, the Private Label is the least preferred in the cola category, while Eight O Clock is the least preferred brand in the coffee category, which is consistent with the observed market shares in Tables 1 and 2. The magnitude of the estimated price parameters are larger under the MNL model than under the SFC model, which suggests that households' responsiveness to prices will be overstated if one does not model the effects of state dependence. The opposite is true of the estimated display and feature parameters, i.e. the magnitudes of the estimated display and feature parameters are smaller under the MNL model than under the SFC model, which suggests that households' responsiveness to displays and features will be understated if one does not model the effects of state dependence. There is a significant degree of inertia uncovered in both product categories, with the estimated state dependence coefficients (V) being -4 and -4.07 for the two supports in the cola category, and -39.48 and -1.73 for the two supports in the coffee category. In terms of the estimated similarity parameters, Coke and Pepsi are perceived to be much more similar, along unobserved product attributes, than other pairs of cola brands (with a similarity coefficient of 0.6282). In the coffee category, Eight O Clock is perceived to highly dissimilar to the other four brands of coffee in terms of unobserved product attributes. In terms of model fit (using the Schwarz Bayesian Criterion, i.e. SBC), the proposed state dependence model of Seetharaman, Feinberg and Chintagunta (SFC) is observed to clearly outperform the Multinomial Logit (MNL) model, which indicates that state dependence effects are significant in both product categories under study. These results are consistent with previous studies that have documented strong effects of inertia in consumer choices among packaged goods (see, for example, Erdem

1996, Seetharaman, Ainslie and Chintagunta 1999). Next, we present the results of estimating the supply-side pricing model in Tables 6 – 9.

(Insert Tables 6 -9)

Upon inspecting the supply-side estimates from the heterogeneous model in either product category (see Tables 8 and 9), we find the estimated costs, and therefore margins, to be plausible. For example, in the cola category, the national brands – Pepsi, Coke and Royal Crown – have higher estimated costs[8] (~ 45 to 55 cents) than the private label (~ 38 cents). Further, the private label passes through a more-than-commensurate amount of the cost-savings in the form of a reduced price to the marketplace that renders its margins lower (~ 14%) than the national brands' (~ 20 – 25%). However, since the estimated margins are for the entire channel (i.e. manufacturer plus retailer), it is not clear if the *retailer's margin* is lower for the private label compared to the national brand. If the private label were a store brand, for example, it is possible that the retailer's margin on the brand is actually *higher* than that on the national brands. In the coffee category, Maxwell House has the highest estimated cost ($3.14) and the lowest estimated margin (13.2%). This appears curious since Maxwell House is well known to have strong brand equity in this category, which should give it greater pricing leverage, and therefore higher margins. We hypothesize that the retailer may be steeply discounting Maxwell House in order to draw customers to the store (since coffee is known to be one of the widely used *loss-leader* categories in grocery retailing). Folgers extracts the highest margin (25.5%) in the category despite its high cost ($2.76). All of these findings appear believable and give some face validity to the proposed estimation procedure.

Compared to the estimated costs in the dynamic pricing model, the estimated costs from the myopic model and from the static model are severely understated for all brands. In other words, the margins are severely overstated. For example, in the cola category, the estimated price-cost margin for the private label is only 13.9 % under the dynamic model, but 88.4 % under the myopic model, and 99.6 % under the static model! In the coffee category, the estimated costs for all brands are zero under the myopic model [9]! Given the

[8] Note that costs refer not only to manufacturing costs but also include advertising, sales promotions, distribution and all relevant economic costs incurred in the supply chain.

[9] The reason for this finding is that the estimated price elasticity in the coffee category is greater than –1, indicating a price-inelastic market, which means that observed prices are forced to be as higher than possible than the costs (which are restricted to be non-negative) under the myopic model.

popular wisdom in the grocery industry, it appears that the cost estimates from the dynamic pricing model are more believable than those from the myopic and static models.

The intuition for lower estimated costs under the static model is as follows: if firms are not forward-looking and respond to zero-order market shares of brands, optimal prices will be higher than those in the presence of inertia (because in the latter case, firms have an incentive to lower price in order to benefit from the effects of inertia in the future). Since the observed prices used in the estimation are the same under both the dynamic and static specifications, the empirical consequence of the higher optimal price under the static model is a lower estimated cost. This is what is observed in Tables 8 and 9. Comparing Tables 6 and 8, we find that the supply-side estimates for cola under the dynamic pricing model are quite robust to whether or not we incorporate unobserved heterogeneity in the parameters of the demand-side model. Comparing Tables 7 and 9, however, we find that the estimated cost for 8 O Clock coffee is overstated ($3 instead of $2.34) from ignoring unobserved heterogeneity. This leads to the estimated margin for 8 O Clock, using the (mis-specified) homogeneous demand model, being insignificantly different from zero!

The estimated price elasticities in the coffee category are smaller than 1 in magnitude, which suggests that coffee demand is inelastic to price. This is in conflict with the static profit maximization prescription that (given market power) manufacturers will price their products in the elastic part of the demand curve. Therefore, the finding of price inelasticity of demand may lead researchers using static or myopic pricing models to falsely surmise that coffee is a "loss-leader" category for the retailer. Our dynamic pricing model offers an alternative explanation: The presence of inertia in households' brand choices induces manufacturers to price low in the current period in the hope of reaping dividends in the future.

8. CONCLUSIONS

In this paper, we propose and estimate a dynamic pricing model in which manufacturers' current prices have an impact not only on their current demand, but also on the future demand for all brands. Such temporal dynamics arise on account of state dependence in households' brand choices in the product category. We estimate a dynamic brand choice model, recently proposed by Seetharaman, Feinberg and Chintagunta (2001), using micro-level scanner panel data, and then use the estimated parameters of this model to build a predictive model of aggregate demand for brands, and finally estimate the parameters of a dynamic pricing model using macro-level store scanner data from stores in the same geographic market. Demand-side estimation proceeds using likelihood-based techniques. The state dependence model is observed to fit observed brand choices better than the multinomial logit model. Supply-side estimation entails the solution of dynamic optimization problems of firms, as well as the solution of equilibrium pricing strategies between firms. We use an estimation technique, recently proposed by Berry and Pakes (2000), to handle the computational difficulties associated with the estimation of the supply-side equation. We find that the observed data are consistent with the proposed dynamic pricing model in terms of the reasonableness of the estimated cost parameters. The cost parameters recovered under alternative (myopic and static) pricing models look unrealistically low. The proposed technique will be of value not only to firms hoping to understand marginal costs of competitors in their industry, but also to regulators who want to characterize the cost-structure in industries involving frequently purchased products.

There are some interesting areas for future research. First, we assume that the micro-level scanner panel data contain a representative sample of the households that together constitute the macro-level store data. The predictive demand model used in our supply-side analysis is predicated on this assumption. Explicitly investigating whether panel data provide representative inferences about store-level effects will be an interesting area of future research (see Gupta, Chintagunta, Kaul and Wittink 1996). Second, we pool aggregate shares and prices across the seven stores in our dataset to estimate the supply-side pricing equations. Explicitly investigating differences across stores and/or retail competition would be an interesting area of future research, although this would require sufficiently long time series of observations for each store in the market to enable the identification of store-specific parameters (for an structural model of store competition, see Villas-Boas 2001). Third, we use a probabilistic model of brand choices in our study. Testing whether our inferences are robust to a random utility model of brand choices would be an interesting avenue for future research Given that a recent paper by Seetharaman (2003) documents that probabilistic and random utility models of state dependence yield very similar inferences about the estimated price elasticities and steady-state market shares of brands, we believe that an alternative model of brand choices, based on random utility, would yield insights pretty similar to those obtained in this study. Since this paper introduces an empirical methodology to estimate dynamic pricing games using store-level data to the marketing literature, future research can investigate substantive issues from the *New Empirical Industrial Organization* (NEIO) literature within our dynamic pricing framework (for a review of this literature, see Kadiyali, Sudhir and Rao 2001).

TABLE 1: Descriptive Statistics from Micro-Level Scanner Panel Data

A. Cola

Number of households = 484
Number of purchases = 8454

Brand	Price ($/unit)	Display	Feature	Share
Private Label	0.5397	0.10	0.09	10.5 %
Pepsi	0.6899	0.32	0.40	47.9 %
Coke	0.7660	0.18	0.26	26.1 %
Royal Crown	0.7309	0.13	0.14	15.5 %

B. Coffee

Number of households = 491
Number of purchases = 4701

Brand	Price ($/unit)	Display	Feature	Share
Hills Bros.	2.4000	0.18	0.20	28.1 %
Maxwell House	3.5110	0.08	0.08	19.9 %
Folgers	3.7995	0.07	0.08	18.0 %
Eight O Clock	2.1467	0.08	0.05	8.1 %
Other	5.8070	0.03	0.05	25.9 %

TABLE 2: Descriptive Statistics from Macro-Level Data

A. Cola

Number of stores = 7
Number of weeks = 104

Brand	Price ($/unit)	Display	Feature	Share
Private Label	0.4329	0.19	0.12	4.5 %
Pepsi	0.7482	0.36	0.27	55.0 %
Coke	0.7130	0.39	0.32	26.2 %
Royal Crown	0.6147	0.32	0.34	14.4 %

B. Coffee

Number of stores = 7
Number of weeks = 104

Brand	Price ($/unit)	Display	Feature	Share
Hills Bros.	2.5727	0.20	0.26	25.0 %
Maxwell House	3.6372	0.14	0.14	18.6 %
Folgers	3.8808	0.07	0.08	16.4 %
Eight O Clock	3.0569	0.05	0.14	4.7 %
Other	5.0079	0.06	0.09	35.3 %

TABLE 3: Parameter estimates of Homogeneous Brand Choice Models (Standard Errors in Parentheses)

MNL: Multinomial Logit, SFC: Seetharaman, Feinberg and Chintagunta (2001)

Parameter	MNL (Cola)	SFC (Cola)	MNL (Coffee)	SFC (Coffee)
α_1	-1.00 (0.05)	-0.67 (0.06)	-1.10 (0.05)	-1.13 (0.07)
α_2	1.01 (0.04)	0.87 (0.06)	-0.87 (0.05)	-0.86 (0.07)
α_3	0.63 (0.04)	0.50 (0.06)	-0.86 (0.06)	-0.91 (0.08)
α_4	0	0	-2.24 (0.07)	-1.83 (0.10)
α_5	na	na	0	0
Price	-4.04 (0.12)	-3.96 (0.16)	-0.36 (0.01)	-0.32 (0.02)
Display	0.86 (0.05)	1.17 (0.07)	1.33 (0.08)	1.42 (0.10)
Feature	0.56 (0.05)	0.68 (0.06)	1.40 (0.07)	1.84 (0.10)
V	na	-5.19	na	-4.76
C_{12}	na	0.0545	na	0.2903
C_{13}	na	0.0147	na	0.3328
C_{14}	na	0.0102	na	0.0494
C_{15}	na	na	na	0.3276
C_{23}	na	0.2736	na	0.1724
C_{24}	na	0.1633	na	0.0010
C_{25}	na	na	na	0.2618
C_{34}	na	0.0997	na	0.0042
C_{35}	na	na	na	0.3282
C_{45}	na	na	na	0.0056
Log-Lik.	-8216	-6628	-4714	-4115
SBC	16486	13373	9487	8382

TABLE 4: Parameter estimates of Heterogeneous Brand Choice Models (Cola) (Standard Errors in Parentheses)

Parameter	MNL - Support 1	MNL - Support 2	SFC - Support 1	SFC - Support 2
α_1 (Pvt. Label)	-2.83 (0.12)	0.63 (0.13)	-2.60 (0.14)	0.40 (0.11)
α_2 (Pepsi)	1.16 (0.04)	0.64 (0.12)	1.03 (0.07)	0.30 (0.12)
α_3 (Coke)	-0.08 (0.06)	1.86 (0.13)	-0.55 (0.10)	1.46 (0.11)
α_4 (R. Crown)	0	0	0	0
Price	-4.48 (0.19)	-3.93 (0.24)	-4.20 (0.24)	-4.11 (0.28)
Display	0.99 (0.08)	0.74 (0.09)	1.42 (0.10)	1.09 (0.11)
Feature	0.30 (0.07)	0.95 (0.09)	0.46 (0.09)	1.03 (0.11)
V	Na	Na	-4.00	-4.07
C_{12}	Na	Na	0.3328	Same
C_{13}	Na	Na	0.0027	Same
C_{14}	Na	Na	0.0847	Same
C_{23}	Na	Na	0.6282	Same
C_{24}	Na	Na	0.1187	Same
C_{34}	Na	Na	0.1958	same
Support prob.	0.60	0.40	0.55	0.45
Log-Lik.	-7205		-6152	
SBC	14527		12493	

TABLE 5: Parameter estimates of Heterogeneous Brand Choice Models (Coffee) (Standard Errors in Parentheses)

Parameter	MNL - Support 1	MNL - Support 2	SFC - Support 1	SFC - Support 2
a_1 (Hills)	-1.54 (0.09)	0.58 (0.15)	-3.89 (0.10)	-0.37 (0.09)
a_2 (M. House)	-1.18 (0.07)	0.31 (0.15)	-1.04 (0.14)	-0.78 (0.12)
a_3 (Folgers)	-0.89 (0.07)	-0.59 (0.18)	-0.98 (0.14)	-0.77 (0.10)
a_4 (8O Clock)	-2.78 (0.11)	-1.35 (0.19)	-2.97 (0.33)	-1.32 (0.11)
a_5 (Pvt. Label)	0	0	0	0
Price	-0.27 (0.02)	-2.37 (0.35)	-0.43 (0.03)	-0.31 (0.02)
Display	1.29 (0.11)	1.09 (0.19)	1.39 (0.52)	1.33 (0.10)
Feature	1.30 (0.10)	0.99 (0.19)	1.64 (0.53)	1.70 (0.10)
V	Na	Na	-39.48	-1.73
C_{12}	Na	Na	0.5756	Same
C_{13}	Na	Na	0.5315	Same
C_{14}	Na	Na	0.0111	Same
C_{15}	Na	Na	0.5478	Same
C_{23}	Na	Na	0.2012	Same
C_{24}	Na	Na	0.0008	Same
C_{25}	Na	Na	0.2683	Same
C_{34}	Na	Na	0.0029	Same
C_{35}	Na	Na	0.4240	Same
C_{45}	Na	Na	0.0059	Same
Support prob.	0.72	0.28	0.31	0.69
Log-Lik.	-4304		-3954	
SBC	8734		8136	

TABLE 6: Supply-Side Cost Estimates (Based on the Homogeneous Demand Model)

COLA

A. Dynamic Model (i.e. State Dependent Demand Model, Forward-Looking Pricing Model)

Brand	Estimated Cost (c_j) & Std. Error	Price (P_j)	Margin
Private Label	$ 0.3723 ($ 0.0137)	$ 0.4361	14.6 %
Pepsi	$ 0.5420 ($ 0.0038)	$ 0.7263	25.4 %
Coke	$ 0.5503 ($ 0.0051)	$ 0.6906	23.1 %
Royal Crown	$ 0.4723 ($ 0.0055)	$ 0.6115	22.8 %

B. Myopic Model (i.e. State Dependent Demand Model, Current-Period Pricing Model)

Brand	Estimated Cost (c_j) & Std. Error	Price (P_j)	Margin
Private Label	$ 0.0621 ($ 0.0152)	$ 0.4361	85.8 %
Pepsi	$ 0.2806 ($ 0.0231)	$ 0.7263	61.4 %
Coke	$ 0.5310 ($ 0.0262)	$ 0.6906	23.1 %
Royal Crown	$ 0.2927 ($ 0.0182)	$ 0.6115	52.1 %

C. Static Model (i.e. Multinomial Logit Demand Model, Current-Period Pricing Model)

Brand	Estimated Cost (c_j) & Std. Error	Price (P_j)	Margin
Private Label	$ 0.0000 ($ 0.0104)	$ 0.4353	100 %
Pepsi	$ 0.2505 ($ 0.0061)	$ 0.7229	65.4 %
Coke	$ 0.2893 ($ 0.0050)	$ 0.6916	58.2 %
Royal Crown	$ 0.1935 ($ 0.0055)	$ 0.6006	67.8 %

TABLE 7: Supply-Side Cost Estimates (Based on the Homogeneous Demand Model)

COFFEE

A. Dynamic Model (i.e. State Dependent Demand Model, Forward-Looking Pricing Model)

Brand	**Estimated Cost (c_j) & Std. Error**	**Price (P_j)**	**Margin**
Hills	$ 2.0908 ($ 0.0521)	$ 2.5645	18.5 %
Maxwell House	$ 3.0767 ($ 0.0448)	$ 3.6248	15.1 %
Folgers	$ 2.7705 ($ 0.0375)	$ 3.7092	25.3 %
8 O Clock	$ 3.0045 ($ 0.1180)	$ 2.9644	-1.4 %
Other	$ 4.7007 ($ 0.0439)	$ 5.3138	11.5 %

B. Myopic Model (i.e. State Dependent Demand Model, Current-Period Pricing Model)

Brand	**Estimated Cost (c_j) & Std. Error**	**Price (P_j)**	**Margin**
Hills	$ 0.0000 ($ 0.2965)	$ 2.5645	100 %
Maxwell House	$ 0.0000 ($ 0.2687)	$ 3.6248	100 %
Folgers	$ 0.2593 ($ 0.2711)	$ 3.7092	93.0 %
8 O Clock	$ 0.0000 ($ 0.2786)	$ 2.9644	100 %
Other	$ 1.1820 ($ 0.2244)	$ 5.3138	77.8 %

C. Static Model (i.e. Multinomial Logit Demand Model, Current-Period Pricing Model)

Brand	**Estimated Cost (c_j) & Std. Error**	**Price (P_j)**	**Margin**
Hills	$ 0.0000 ($ 0.1858)	$ 2.5607	100 %
Maxwell House	$ 0.0000 ($ 0.1583)	$ 3.6034	100 %
Folgers	$ 0.0000 ($ 0.1494)	$ 3.6986	100 %
8 O Clock	$ 0.0000 ($ 0.1333)	$ 2.9357	100 %
Other	$ 0.3944 ($ 0.0948)	$ 5.1948	92.4 %

TABLE 8: Supply-Side Cost Estimates (Based on the Heterogeneous Demand Model)

COLA

A. Dynamic Model (i.e. State Dependent Demand Model, Forward-Looking Pricing Model)

Brand	Estimated Cost (c_j) & Std. Error	Price (P_j)	Margin
Private Label	$ 0.3761 ($ 0.0146)	$ 0.4367	13.9 %
Pepsi	$ 0.5418 ($ 0.0041)	$ 0.7270	25.5 %
Coke	$ 0.5427 ($ 0.0037)	$ 0.6907	21.4 %
Royal Crown	$ 0.4686 ($ 0.0044)	$ 0.6111	23.3 %

B. Myopic Model (i.e. State Dependent Demand Model, Current-Period Pricing Model)

Brand	Estimated Cost (c_j) & Std. Error	Price (P_j)	Margin
Private Label	$ 0.0508 ($ 0.0133)	$ 0.4367	88.4 %
Pepsi	$ 0.2364 ($ 0.0191)	$ 0.7270	67.5 %
Coke	$ 0.4857 ($ 0.0238)	$ 0.6907	29.7 %
Royal Crown	$ 0.2767 ($ 0.0164)	$ 0.6111	54.7 %

C. Static Model (i.e. Multinomial Logit Demand Model, Current-Period Pricing Model)

Brand	Estimated Cost (c_j) & Std. Error	Price (P_j)	Margin
Private Label	$ 0.0016 ($ 0.0070)	$ 0.4356	99.6 %
Pepsi	$ 0.1823 ($ 0.0095)	$ 0.7229	74.8 %
Coke	$ 0.2292 ($ 0.0067)	$ 0.6924	66.9 %
Royal Crown	$ 0.1869 ($ 0.0071)	$ 0.6006	68.9 %

TABLE 9: Supply-Side Cost Estimates (Based on the Heterogeneous Demand Model)

COFFEE

A. Dynamic Model (i.e. State Dependent Demand Model, Forward-Looking Pricing Model)

Brand	**Estimated Cost (c_j) & Std. Error**	**Price (P_j)**	**Margin**
Hills	$ 2.1088 ($ 0.0426)	$ 2.5645	17.8 %
Maxwell House	$ 3.1476 ($ 0.0398)	$ 3.6248	13.2 %
Folgers	$ 2.7649 ($ 0.0392)	$ 3.7092	25.5 %
8 O Clock	$ 2.3472 ($ 0.1188)	$ 2.9644	20.8 %
Other	$ 4.9094 ($ 0.0756)	$ 5.3138	7.6 %

B. Myopic Model (i.e. State Dependent Demand Model, Current-Period Pricing Model)

Brand	**Estimated Cost (c_j) & Std. Error**	**Price (P_j)**	**Margin**
Hills	$ 0.0000 ($ 1.7135)	$ 2.5645	100 %
Maxwell House	$ 0.0000 ($ 1.4456)	$ 3.6248	100 %
Folgers	$ 0.0000 ($ 1.3692)	$ 3.7092	100 %
8 O Clock	$ 0.0000 ($ 0.5720)	$ 2.9644	100 %
Other	$ 0.0000 ($ 2.0913)	$ 5.3138	100 %

C. Static Model (i.e. Multinomial Logit Demand Model, Current-Period Pricing Model)

Brand	**Estimated Cost (c_j) & Std. Error**	**Price (P_j)**	**Margin**
Hills	$ 0.0741 ($ 0.1216)	$ 2.5607	97.1 %
Maxwell House	$ 0.3140 ($ 0.1008)	$ 3.6034	91.3 %
Folgers	$ 0.0000 ($ 0.1016)	$ 3.6986	100 %
8 O Clock	$ 0.8585 ($ 0.0814)	$ 2.9357	70.8 %
Other	$ 0.0000 ($ 0.0671)	$ 5.1948	100 %

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