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Strategic Pricing Behavior under Asset Value Maximization

By

Shinn-Shyr Wang, Kyle W. Stiegert & Tirtha P. Dhar

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Strategic Pricing Behavior under Asset Value Maximization

Shinn-Shyr Wang Kyle W. Stiegert Tirtha P. Dhar*

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Abstract

In this paper, we develop and estimate a model of strategic firm behavior under financial market uncertainty. The model employs an objective function derived from the capital asset pricing model (CAPM), which draws theoretical linkages between product market uncertainty and financial market returns. An interesting feature of the model is that profit maximization enters as a nested component of the general market value maximization (MVM) model. The model is tested using 4-week interval retail scanner data for margarine and butter from 1998-2002. The traditional profit maximization model is rejected in favor of the proposed MVM structure. Counterfactual simulations point toward significant biases in estimated Lerner indexes when capital market dimensions are ignored or if the wrong market structure is assumed.

Keywords: Market Value Maximization, AIDS, FIML, Model Selection.

JEL Codes: D43, G12, L13, L21.

* Wang: corresponding author, Associate Scientist, Food System Research Group, University of Wisconsin-Madison, 427 Lorch Street, Madison, WI 53706 (E-mail: swang17@wisc.edu); Stiegert: Associate Professor, University of Wisconsin-Madison; Dhar: Assistant Professor, Sauder School of Business, University of British Columbia. We would like to thank JP Chavas, Brian Gould, Tom Cox, and conference participants at the University of Toulouse and University of Wisconsin-Madison for many helpful comments and suggestions. Any errors or omissions are our responsibility.

1 Introduction

The vast majority of theoretical and empirical industrial organizational research is based on the premise that firms maximize profits. In practice, however, firm managers driven by concerns with job security and incentive packages instead may focus on equity valuation, which is only partially derived by profitability. Indeed, a summary of Compustat data indicates that salaries and wages of CEOs in the U.S. food industry since 2000 represent only 40% of total compensation. The remaining 60% is comprised of bonuses, stock offerings and stock options. While it might be difficult to tie bonuses to a single objective across all firms, managers with stock holdings and stock options have a clear personal incentive to raise the value of equity shares. Thus, instead of thinking in simplistic terms of profitability alone, managers may be interested in other objectives such as stability of profits and dividend flows, demonstratable growth in profits, and high anticipated earnings. As such, the firm manager may see a trade-off between short-term profit-maximizing decisions and attempting to endogenously control or minimize risk. This is not a new concept. Brealey and Myers (2000) make the point that stockholding by employees generates a conflict of interest with shareholders. Because shareholders can diversify their portfolios, they care only about market risk. Managers may be unable to diversify base salary, stocks, bonuses, and out-of-the-money options. As a result, managers may be justified in controlling for both diversifiable and market risk.

This paper provides a comprehensive assessment of a firm's strategic behavior under financial market uncertainty for a mature industry. The theoretical structure flows from Wang and Stiegert's (2005) market value maximization (MVM) model. The model employs an objective function derived from the traditional capital asset pricing model (CAPM), independently developed by Sharpe (1964), Lintner (1965), and Mossin (1966). In rapidly advancing industries, opportunities for large profit payoffs have much to do with patent/R&D races, product innovation, and/or accumulating other future growth options. As Fama and French (2004) point out, the CAPM has had limited success in modeling equity values in these industries.[1] Managers in mature industries tend to observe stock cycles between underpricing (low book value to market value) and correct values when hard times come and pass. For these industries, profit levels are an important but limited objective. Thus, managers seeking to enhance the value of firm equity may look to consistent and stable growth, and to creating perceptions about stable management governance structures and other factors that increase the actual/anticipated earnings of a firm while decreasing the actual/anticipated variance of earnings.

In this proposed model financial market uncertainty enters through a standard CAPM framework. As pointed out in Frankfurter (1995), the CAPM remains an acceptable approach for evaluating and pricing financial assets when compared with all other methodologies.[2] The CAPM's basic ideology is widely taught as part of core graduate and executive business curriculums. Therefore it is plausible that firm managers may consider financial market risk in product market decisions. Empirically, the effects of financial market risk enter very simply into our demand system. An interesting feature of the model is that profit maximization is a nested component of the general MVM model, which allows for an easy and direct test of financial market influence on product markets.

Based on the reasonable premise that managers in typical publicly owned firms

[1]See also Fama and French (1992), Black (1993a, 1993b), and Kothari, Shanken and Sloan (1995) for additional details.

[2]One alternative to CAPM is the arbitrage pricing model due to Ross (1976). In this framework, if risk can be fully or near fully arbitrated, then firms would care little about risk and could simply follow profit objectives. No anecdotal or empirical evidence suggest that risk transfer markets can now or will ever fully achieve such a theoretical objective.

care about market and diversifiable risk, their objectives will be to mirror the objectives of investors looking to build an efficient portfolio of assets under the CAPM. If the manager can limit risk through *intrafirm* behavior while maintaining profit levels and subsequent stock values appreciate, he may be rewarded through stock holdings or options and job-security increases. Furthermore, lower CAPM beta values convert to greater access to capital at lower costs, thus creating a form of scale economies which can act to drive out smaller firms (see Sherer and Ross, 1990, page 129 for a discussion and listed citations), leading to increasing concentration, increased current and future period profits, and ever-increasing equity values. As a result, managers of all firms in an industry face additional penalties for "rocking the boat" which implies that, to manage risk, firm pricing can be more collusive than standard industrial organization models (Wang and Stiegert, 2005).

The MVM model is tested using 4-week interval scanner data from 1998 to 2002 for the U.S. margarine and butter retail market. Demand is modeled using a nonlinear Almost Ideal Demand System (AIDS) under the assumption of expenditure endogeneity.[3] Full information maximum likelihood (FIML) is used to estimate AIDS along with the derived first order conditions to evaluate model fit, optimal pricing strategies, and investigate the degree of market power in this industry. We use both the Wald and the likelihood ratio tests, to test for the appropriateness of standard profit maximization against our proposed MVM model with risk considerations. In terms of pricing games between firms, Vuong and Wald type tests are used to select

[3] A common alternative is the random coefficients discrete choice model. Although this model can reduce the number of parameters to be estimated, it often imposes restrictions that may not be implied by the general utility theory. See Bajari and Benkard (2003) for a discussion of this point. Choice of demand system is also motivated by the fact that in the butter and margarine market, brands can either be complements or substitutes due to household purchasing behavior. Our extensive and detailed discussions with store and brand managers have led us to believe that households tend to buy assortment of butter and butter blends to meet various household demand. Due to the strong assumption of unit purchase in discrete choice models, this kind of complex complementary and substitutable brand relationship is difficult to capture (Dubé, 2004).

from a menu of benchmark equilibrium outcomes (i.e. Bertrand, Stackelberg, etc.) or a conjectural variations model. Our exhaustive battery of tests rejects the standard profit maximization in favor of MVM pricing behavior. Two counterfactual experiments assuming Bertrand pricing and profit maximization indicate that significant errors are associated with ignoring MVM or assuming the wrong market structure.

The remainder of this paper is organized as follows. In the next section, the MVM model is presented followed by discussions of the empirical model and data used in this paper. Next, all estimation procedures and empirical results are discussed and reported. Finally, we provide our concluding remarks and suggestions for further research.

2 Conceptual Model

A model built on the concept of asset value maximization necessarily involves a framework for dealing with uncertainty. To model MVM, it is assumed that capital value is priced according to the capital asset pricing model (CAPM) posited by Sharpe (1964), Lintner (1965) and Mossin (1966). By CAPM,

$$E(\tilde{r}_i) = r + \beta_i \left[E(\tilde{r}_m) - r \right], \tag{1}$$

where r is the risk-free interest rate, $E(\tilde{r}_i)$ and $E(\tilde{r}_m)$ are expected rates of return of asset i and market portfolio, respectively, while β_i is systematic risk defined by $Cov(\tilde{r}_i, \tilde{r}_m)/Var(\tilde{r}_m)$. The firm i's market value can be obtained by $V_i = \widetilde{\pi}_i/(1+\tilde{r}_i)$, where $\widetilde{\pi}_i$ is the stochastic perpetual flow of net earnings. Because $\widetilde{\pi}_i = (1+\tilde{r}_i)V_i$,

$$\begin{aligned} \frac{E(\widetilde{\pi}_i)}{V_i} &= 1 + E(\tilde{r}_i) = 1 + r + \frac{Cov(\tilde{r}_i, \tilde{r}_m)}{Var(\tilde{r}_m)} \left[E(\tilde{r}_m) - r \right] \\ &= 1 + r + \left[\frac{E(\tilde{r}_m) - r}{Var(\tilde{r}_m)} \right] \frac{Cov(\widetilde{\pi}_i, \tilde{r}_m)}{V_i}. \end{aligned} \tag{2}$$

We may rearrange (2) to get firm's market value. Thus, the MVM firm i maximizes

$$V_i = \frac{1}{1+r}\left[E(\widetilde{\pi}_i) - \lambda Cov(\widetilde{\pi}_i, \widetilde{r}_m)\right], \tag{3}$$

where λ is the equilibrium shadow price of market risk reduction, defined by $\lambda = [E(\widetilde{r}_m) - r]/\sigma_m^2$ and $\sigma_m^2 = Var(\tilde{r}_m)$.

Assuming that managers of each firm know both the pricing strategies of other firms (i.e., market structure is known) and the prices of raw materials, uncertainty can enter the model in form of unanticipated demand.[4] Thus, we assume that anticipated market demand is accurate up to a normally distributed error term and uncertainty is additively linear, i.e., firm i's demand is defined by $\tilde{X}_i = X_i + \widetilde{e}_i$, where random variable $\widetilde{e}_i$ is firm i's idiosyncratic shock and normally distributed, with a mean of zero and a variance of σ_e^2.[5] As a result, firm i's net earnings are given by

$$\widetilde{\pi}_i = (p_i - c_i)(X_i + \widetilde{e}_i) - U_i, \tag{4}$$

where p_i is price of goods X_i, c_i is a constant marginal cost, and U_i is firm i's fixed cost. Firm i faces demand function $\tilde{X}_i = X_i(p_i, p_{-i}) + \widetilde{e}_i$ and p_{-i} is the pricing strategy of all rivals of firm i. In equation (4), the assumption of constant marginal cost simplifies the supply of raw material and promotion expenditure used to determine marginal costs and subsequently the output-market's structural characteristics.

Therefore, from equations (3) and (4) the first-order conditions in price of MVM are given by

$$X_i - \lambda Cov(\widetilde{e}_i, \widetilde{r}_m) = -(p_i - c_i)\sum_{j=1}^{n}\frac{\partial X_i}{\partial p_j}\frac{\partial p_j}{\partial p_i}, \ \forall i. \tag{5}$$

[4] Obviously, the covariance of firm profits to market returns are complicated and involve perhaps multiproduct strategies, research and development outlays, mergers, spinoffs or other fixed costs facing the firm. Our analysis is constrained to consider only the linkage between uncertainty that product managers might face in pricing a good and their ability to reduce the covariance of that uncertainty to the market returns.

[5] See section 3.2 for specific details of $\widetilde{e}_i$.

The conjectural variation parameter of pricing $\tau_{ji} = \partial p_j / \partial p_i$ is given by firm i's conjecture of firm j's price response. Note that $\tau_{ji} = 0,\ \forall j \neq i$ under the Bertrand competition in price. Under the set-up of additively linear uncertainty, the difference between MVM and profit maximization is the second term on the left side of the equation. Next, we introduce an additional parameter θ to construct a general MVM presentation of first-order conditions.

$$X_i - \theta\lambda Cov(\widetilde{e}_i, \widetilde{r}_m) = -(p_i - c_i) \sum_{j=1}^{n} \frac{\partial X_i}{\partial p_j} \frac{\partial p_j}{\partial p_i},\ \forall i, \tag{6}$$

where θ measures the financial component's impact on the product market. A positive θ implies that the decision maker considers financial market risk when making product market decisions. Equation (6) turns out to nest two benchmark objectives that firms could pursue. If $\theta = 1$, the market outcome is consistent with a full incorporation of the CAPM styled financial objectives. If $\theta = 0$, the market data reveals behavior consistent with pure profit maximization. By restricting $\theta = 0$, we can derive a straightforward likelihood ratio test of whether or not profit maximization is a valid assumption.

3 Empirical Model Specification and Data Description

To build an empirical model capable of testing MVM, we begin by first specifying a demand framework. In the New Empirical Industrial Organization (NEIO) literature, strategic behavior of firms is typically modeled by estimating demand and subsequently, the departure of demand from marginal costs. In many cases, researchers simplify the structural model by specifying ad-hoc or approximated demand specifications, and utilize reduced form conditions because of the prohibitive complexity of flexible demand and cost functions. However, ad-hoc demand specifications fail to satisfy all the requirements of consumer theory. Pioneered by Deaton and Muellbauer (1980a, b), the AIDS approach has been extensively used in the economics, marketing and agricultural economics literature.[6] Recently, Dhar, Chavas, and Gould (2003) estimated a NEIO pricing system for the U.S. carbonated soft drink industry and rejected the commonly applied assumption of expenditure exogeneity. We begin with the AIDS structure, which provides a fully flexible functional form for the purpose of demand estimations, and then incorporate risk concerns into the demand system. We also estimate expenditures as endogenous to the system.

Following the traditional Barten-Gorman AIDS model,[7] the modified AIDS model can be specified as:

$$\begin{aligned} w_{ilt} &= \alpha_{0i} + \sum_{k=1}^{K} \lambda_{ik} Z_{klt} + \sum_{j=1}^{n} \gamma_{ij} \ln(p_{jlt}) + \left[\eta_i \ln(M_{lt}) - \eta_i \ln(P_{lt})\right], \\ & i = 1, \ldots, n; l = 1, \ldots, L; t = 1, \ldots, T; \end{aligned} \tag{7}$$

where $w_{ilt} = p_{ilt} X_{ilt} / M_{lt}$ is the market share for the product of firm i consumed in city l at time t, X is consumer goods, p is goods price for X, and M is total expenditure on n goods. Z_{klt} is the k^{th} socio-demographic variable, and γ_{ij} is a cross-effect of firm j's price on the market share of firm i. η_i can be interpreted as the slope of demand function, while P is a price index defined by

$$\begin{aligned} \ln(P_{lt}) &= \delta + \sum_{m=1}^{n} \alpha_m \ln(p_{mlt}) + \sum_{m=1}^{n} \sum_{k=1}^{K} \lambda_{mk} Z_{klt} \ln(p_{mlt}) \\ & + \frac{1}{2} \sum_{m=1}^{n} \sum_{j=1}^{n} \gamma_{mj} \ln(p_{mlt}) \ln(p_{jlt}). \end{aligned} \tag{8}$$

The theoretical structure implies symmetry restrictions (Equation (9a)) and ho-

[6] For example, Blanciforti and Green (1983), Alessie and Kapteyn (1991), Taube and MacDonald (1991), Browning (1991), Hunt-McCool, Kiker, and Ng (1994), and Cotterill, Putsis, and Dhar (2000).

[7] More discussions on the Barten-Gorman AIDS model can be found in Perali (2003).

mogeneity restrictions (Equation (9b)):

$$\gamma_{ij} = \gamma_{ji}, \forall i \neq j. \tag{9a}$$

$$\sum_{i=1}^{n} \alpha_{0i} = 1; \;\; \sum_{i=1}^{n} \lambda_{ik} = 0, \forall k; \;\; \sum_{i=1}^{n} \gamma_{ij} = 0; \;\; \sum_{i=1}^{n} \eta_i = 0. \tag{9b}$$

To maintain theoretical consistency with the AIDS model, additional restrictions are applied to the demographic translating parameters

$$\alpha_{0i} = \sum_{r=1}^{9} \nu_{ir} D_r, \;\; \sum_{r=1}^{9} d_{ir} = 1, \;\; i = 1, \ldots, n, \tag{9c}$$

where ν_{ir} is the parameter for firm i associated with the regional dummy variable D_r for region r. As a result, the demand equations have no intercept terms. The parameter δ may be difficult to estimate and is often set to some predetermined value. We follow the approach suggested by Moschini, Moro, and Green (1994) and set $\delta = 0$.

3.1 Marginal Cost and Expenditure Endogeneity

Estimating the nonlinear AIDS specification presents serious computational challenges. Because uncertainty enters the model on the demand side, it become practical to specify costs linearly. Furthermore, the assumption of constant marginal costs is common and has performed well in past structural market analysis (see for example Vilcassim, Kadiyali, and Chintagunta, 1999). Marginal cost c_i is assumed observable and is specified as

$$c_i = \mu_0 + \mu_1 UPV_i + \sum_{j=1}^{2} \mu_{2j} MCH_{ij}, \tag{10}$$

where UPV_i is the unit per volume and represents the average size of the purchase, and MCH_{ij} is in-store marketing, including price reductions and all other merchandising components (display and feature). This setting differs from that in the model with no cost information, for example, Nevo (2001). Nevo (2001) presumes Bertrand competition and uses demand side parameters to recover marginal costs. Our approach allows for evaluation and selection of the correct market structure using the menu approach developed by Gasmi, Laffont and Vuong (1992).

Although demand systems are regularly estimated assuming that expenditures are exogenous, recent finding by Blundell and Robin (2000) and Dhar, Chavas, and Gould (2003) have shown this may not hold. To control for expenditure endogeneity, the reduced form expenditure equation is specified as

$$\begin{aligned} M_{lt} &= f(\text{time trend, income}) \\ &= \xi Trend_t + \sum_{r=1}^{9} \zeta_r D_r + \psi_1 INC_{it} + \psi_2 INC_{it}^2,\ t = 1, \ldots, T, \end{aligned} \tag{11}$$

where $Trend_t$ is a linear time trend, capturing any time-specific unobservable effect on consumers' expenditures. The variable INC_{it} is median household income in city l at time t, and is used to capture the effect of income differences on purchases.

3.2 Simulation of Uncertainty Term

The uncertainty term, $\widetilde{e}_i$ is central to our efforts and requires a detailed explanation. The firms we study in this paper produce multiple products, including those other than margarine and butter. Therefore, it is almost impossible to compute specific β's for the margarine and butter sector only. As such, we simulate the uncertainty term and use the simulation results in subsequent calculations. Because we adopted a scaling technique on all relevant variables throughout the empirical implementations, we define $\Psi = \lambda Cov(\widetilde{e}_i, \widetilde{r}_m)$ and a normalized random variable $\widetilde{\phi}_i = [\widetilde{e}_i - E(\widetilde{e}_i)]/\sigma_e$. By the scaling technique, we define scaled Ψ_s as $\Psi/E(\Psi)$. It turns out that

$$\Psi_s = \frac{\lambda Cov(\widetilde{e}_i, \widetilde{r}_m)}{E\left[\lambda Cov(\widetilde{e}_i, \widetilde{r}_m)\right]} = \frac{\lambda \sigma_e Cov(\widetilde{\phi}_i, \widetilde{r}_m)}{\lambda \sigma_e E\left[Cov(\widetilde{\phi}_i, \widetilde{r}_m)\right]} = \frac{Cov(\widetilde{\phi}_i, \widetilde{r}_m)}{E\left[Cov(\widetilde{\phi}_i, \widetilde{r}_m)\right]}.$$

Thus, the assumption that $\tilde{e}$ is a normally distributed random variable allows us to present uncertainty using $\widetilde{\phi}_i$, which is randomly drawn from a standard normal distribution $N(0,1)$.[8] The normalized samples $\widetilde{\phi}_i$ are used for all calculations. As a result, the covariance term $Cov(\widetilde{\phi}_i, \widetilde{r}_m)$ used in the estimation can be computed from $\widetilde{\phi}_i$ and $\widetilde{r}_m$.

It is worthwhile to recall that $\widetilde{e}_i$ is an idiosyncratic demand shock facing each firm i. The covariance term $Cov(\widetilde{e}_i, \widetilde{r}_m)$ or its counterpart $Cov(\widetilde{\phi}_i, \widetilde{r}_m)$ is not specified to be within any certain range, but determined by the random drawing and the rate of return of the market portfolio. To be robust, we estimate each model 30 times with different draws of $\widetilde{\phi}_i$ and assume this approach is sufficient to eliminate any noticeable error.

3.3 Data

The data sets for this study are from Information Resources, Inc. (IRI), Current Population Survey (CPS), and Center for Research in Security Prices (CRSP). Table 1 contains appropriate descriptive statistics for all the data used in this study.

The data set from IRI includes different measures of sales and prices, and in-store marketing activities. The information contains all UPC-coded products in the margarine and butter category from retail store scanners for 28 cities/markets[9] across

[8] The moment matching technique is usually used to adjust the samples so that the adjusted samples have a correct mean of zero and a correct standard deviation of 1. However, the technique is not needed here. The reason is simple. To match the first and second moments let us define the mean of samples, m_ϕ, and the standard error of the samples, s_ϕ. The adjusted samples $\widetilde{\phi'}_i$ can be obtained by $(\widetilde{\phi}_i - m_\phi)/s_\phi$, $i = 1, 2, \ldots N$, where N is the sample size. Equation (12) shows why $\Psi'_s = \Psi_s$.

$$\Psi'_s = \frac{Cov(\widetilde{\phi'}_i, \widetilde{r}_m)}{E\left[Cov(\widetilde{\phi'}_i, \widetilde{r}_m)\right]} = \frac{Cov((\widetilde{\phi}_i - m_\phi)/s_\phi, \widetilde{r}_m)}{E\left[Cov((\widetilde{\phi}_i - m_\phi)/s_\phi, \widetilde{r}_m)\right]} = \frac{Cov(\widetilde{\phi}_i, \widetilde{r}_m)}{E\left[Cov(\widetilde{\phi}_i, \widetilde{r}_m)\right]} = \Psi_s. \tag{12}$$

[9] They are Atlanta, Baltimore/Washington, Boston, Buffalo/Rochester, Chicago, Columbus, Dallas/Ft Worth, Denver, Des Moines, Detroit, Indianapolis, Jacksonville, Kansas City, Little Rock, Memphis, Milwaukee, New Orleans/Mobile, New York City, Oklahoma City, Philadelphia, Portland (OR), Raleigh/Greensboro, Richmond/Norfolk, Salt Lake City, San Diego, San Francisco/Oakland, Seattle/Tacoma, and Tampa/St. Petersburg.

the United States. It measures 58 periods based on 4-week intervals from January 25, 1998[10] to June 9, 2002. As a result, there are 13 periods in 1998-2001 and 6 periods in 2002.

In IRI's main dataset, market shares of top three firms are 37.5%, 15.66%, and 9.6% while the remaining is 13.29% with which the market share is less than 3% for the fourth ranking firm producing branded products. Therefore, the estimation involved the top three firms, an aggregate "all others" group, and private labels. Both private labels and all others are treated as two individual firms. That is, firms of private labels and all others are assumed to behave in coordination, with the same pricing and marketing strategies within their own categories. This assumption was made for the following reasons. First, our IRI database only provides aggregated private label data and the "all others" category is created to control for the large number of residual brands in the market place with small market share for each brand. Given non-trivial computational demand of our proposed model, it was not feasible to incorporate each of these residual brands in the present model. Second, our preliminary exploratory data analysis of the market share also implied stable market shares in most weeks for all aggregate firms and private labels. The market appears quite mature in its overall structure. Twelve dummy variables ($Season$) were added to adjust for seasonality across the 13 4-week intervals. Firm 3 charges relatively high prices because its major product is pure butter. We add a dummy variable ($Butter$) to control for this quality difference.

We estimate our model using data from 28 major cities with 58 weekly observations for each city, each firm has 1624 (=58×28) complete data observations. The variables used in the analysis include price, volume sales, dollar sales, unit sales, volume per unit, in-store marketing variables such as price reduction, and all other merchandising

[10] The first period runs from December 29, 1997 to January 25, 1998.

components (feature and display).[11]

For the demographic data, we use the following three sources: (1) 9 division binaries are from Census Bureau Geography,[12] (2) variable POPU (overall population) is from IRI, and (3) 6 other demographic variables are from the Current Population Survey – Annual Demographic Survey (March CPS Supplement)[13] for 1998-2002, which include PERLT10K (percentage of households earning less than $10,000), PERGT50K (percentage of households earning more than $50,000), HUNDER15 (average number of people under age 15), H_NUMBER (average household size), A_AGE (median household age), and FSPANISH (percentage of Hispanics).

We merged the CPS data with IRI data by using the GMMSA variable (Geography - MSA or PMSA FIPS Code) in the CPS database. The areas covered by CPS and IRI are approximately the same. Furthermore, because the March CPS Supplement database is annual, linear projection is used to obtain the 4-week interval data.

For the financial components of the model, several data sources were used. The annual rate of return of the market portfolio ($\widetilde{r}_m$) and the annual risk-free rate (r) were available from the Center for Research in Security Prices (CRSP). The annual rate of return of the market portfolio is computed from CRSP Indices on the S&P 500. The annual risk-free rate is based on actual 90 Day Bill Returns reported by the U.S. Treasury.

4 Procedures and Results

The estimating model included four sets of equations: AIDS demand (7), expenditure (11), MVM first order condition (6), and marginal cost (10). Table 2 contains details

[11] In-store marketing is measured in dollars-per-pound.

[12] See Reference Resources for Understanding Census Bureau Geography available at: http://www.census.gov/geo/www/reference.html.

[13] See http://www.nber.org/data/cps_basic.html.

about each set of equations estimated and a description of the parameters. The system was estimated in GAUSS (version 6.0) using the full information maximum likelihood module. The structural model essentially measures the wedge between price and marginal costs while simultaneously accounting for revenue uncertainty through the CAPM structure. As described earlier, the estimation is run for 3 firms, an aggregate category for all other firms, and a final category for private label firms, in which firms 1 and 2 produce margarine and firm 3 produces butter only, while All Others and Private Labels produce both butter and margarine.

Note that, by definition, $\sum_{i=1}^{5} w_i = 1$, where w_i is the expenditure share of good i. Thus, the dependent variables are linearly dependent, implying the singularity of the variance of the error terms. This singularity problem can be handled by dropping one equation, thus estimating the remaining four demand equations. The parameters from the equation dropped can be recovered from the homogeneity restrictions. As a result, the FIML estimation in this study consists of 10 equations in the system, including 4 demand equations, 5 first-order conditions, and 1 equation for expenditure endogeneity.[14]

With regard to the number of parameters in the estimation, there are 91 demand-related parameters from equation (7), 12 expenditure endogeneity parameters from equation (11), and 20 marginal cost parameters from equation (10). For equation (6) the parameters include one parameter capturing financial market impact and the conjectural variation of price parameters (CV) whose numbers depend on the market structure specified in each competing model. Table 2 provides description of estimated parameters.

The issue of parameter identification in non-linear structural model using FIML is rather complex. As a first cut, we checked the order condition for identification that

[14]Note that marginal cost, equation (10), is part of the first order conditions.

would apply to a linearized version of the demand equations and then derived first order conditions and found it to be satisfied. Finally, we did not uncover numerical difficulties in implementing the FIML estimation and our estimated results are robust to iterative process of estimation. As pointed out by Mittelhammer, Judge and Miller (2000, pages 474-475) in nonlinear full information maximum likelihood estimation, we interpret this as evidence that structural model is identified.

4.1 Model Selection I: MVM vs. Profit Maximization

Our first goal was to evaluate the general MVM model versus a restricted version that assumes profit maximization. The general MVM presentation in equation (6) nests pure MVM ($\theta = 1$) and profit maximization ($\theta = 0$). We use both likelihood ratio[15] and Wald tests to demonstrate the robustness of the model selection results. At this stage, because the correct market structure had not been identified, the LR and Wald tests were performed across the entire menu of structures (see below for details). Although not reported, the MVM-profit test did not depend on any specific market structure. That is, by hypothesizing different market structures from the menu, the MVM-profit tests lead to the same qualitative conclusions.

Results of the LR and Wald tests from the best-fitted model (see below for details on best-fitted model) are presented in Table 3. The range of estimated θ was from 0.3252 to 0.3751, while the mean was estimated at 0.3456. The Wald statistics are more than 1000 and the LR statistics are more than 250 in all draws, which demonstrates the statistical significance of the financial component. Thus, a significant

[15] The likelihood ratio statistic for model selection is given by $LR = -2\left[\ln L(\mathbf{b}^{*}) - \ln L(\mathbf{b})\right]$, where $\mathbf{b}^{*}$ is the vector of parameter estimates from the restricted version of the MVM that presumes profit maximization; $\mathbf{b}$ is the vector of parameter estimates of the general model; and $\ln L(\cdot)$ is the log value of the likelihood function. LR has an asymptotic $\chi^2(q)$ distribution, where q is the number of restrictions imposed. That is, the degrees of freedom equal to the difference between the number of parameters in the general model and the restricted model (pure MVM or profit maximization). For the current work, $q = 1$.

finding is that financial market risk (as perceived through the CAPM) has an important role in shaping the strategic interaction among firms in the margarine and butter market. This is a crucial finding because we reject traditional profit maximization models in favor of the unrestricted MVM model.

The mean of estimated θ, 0.3456, is also statistically different from the "pure" CAPM result of $\theta = 1$. Several plausible reasons exist for this outcome. First, the firm may be able to internally manage risk using a portfolio of products or owning assets in other industries. As a result, managing product-derived diversifiable risk through product pricing alone is not the way multiproduct firms operate. Second, equity valuation is an inexact science based primarily on expected outcomes for profit and risk. It is reasonable to assume that not all managers can effectively forecast equity market behavior and translate that to product market pricing. Third and perhaps most obvious, there will likely be periods in which demand and supply conditions supersede a goal of an industry-level equity value maximization. Pure strategies in pricing or quantity games are rarely observed over long periods of time, thus it would seem equally unlikely that other more complex benchmark outcomes would be observable empirically.

4.2 Model Selection II: Market Structure

Our second goal is to statistically select the best-fitted model from four benchmark oligopoly outcomes (Stackelberg Leadership, Stackelberg followship, non-cooperative Nash-Bertrand, and collusion), or an unrestricted conjectural variations (CV) model. It turns out that there are 4^5 possible combinations of benchmark pricing strategies that could be investigated. The procedure for choosing the best-fitted model is greatly simplified by the fact that all of the pure strategy equilibriums except for collusion are nested in an unrestricted CV model. Thus, we first choose from the unrestricted CV models with five possible collusion schemes using the Vuong test (VT) and augmented with tests using Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC).[16]

The non-nested test results are presented in Table 4. Five possible market conditions were considered, including C0 (each firm operates non-collusively), C1 (firm 1+firm 2 collude), C2 (firm 1+firm 3 collude), C3 (firm 2+firm 3 collude), and C4 (firm 1+firm 2+firm 3 collude). We did incorporate All Others or Private Labels in the collusion schemes. Further, we assume that those firms outside the collusion play CV strategies since the CV model is unrestricted and convenient for nesting most pure strategy games. We should further note that in order to simplify the analysis we assume that only one collusion can exist. That is, we do not deal with cases where more than two coalitions exist in the market. Because the statistics all exceed 1.96, the Vuong test and its adjustments (AIC and SIC) indicate that model C0 is the best-fitted model, in which each firm operates non-collusively in price.

Having eliminated all collusive schemes that seemed reasonable, we now turn to the tests of pure strategy equilibriums nested in the general CV model. We tested for Bertrand pricing (B), Stackelberg leadership for the top three firms (S1, S2 and S3),

[16] For the Vuong test, let the likelihood ratio

$$LR_t(\widehat{\mathbf{b}}_i, \widehat{\mathbf{b}}_j) = \ln\left(\frac{f_i(y_t|\mathbf{x}_t)}{f_j(y_t|\mathbf{x}_t)}\right),$$

where $f_k(y_t|\mathbf{x}_t)$ is the probability that the random variable $\mathbf{Y}$ equals y_t when the assumed distribution is $f_k(y_t|\mathbf{x}_t)$, for $k = i, j$. Vuong's statistic for the non-nested hypothesis test of model F_i against model F_j is given by

$$V = \frac{\sqrt{n}\left[\frac{1}{n}\sum_{t=1}^{n} LR_t\right]}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(LR_t - \overline{LR}_t\right)^2}}.$$

Vuong (1989) shows that V is standard normal asymptotically. If $|V|$ is below the critical value, no conclusion can be drawn from the test; otherwise, model F_i is preferred by large V, while model F_j is preferred by small (negative) V. This implies that the Vuong statistic not only tells us whether the models are significantly different from each other but also that the sign of the test statistic indicates which model is appropriate.

the All Others (SAO), the Private Labels (SPL), and consistent conjectures (CS) in pricing strategies. Because B, S1-S3, SAO, SPL, and CS are nested in the CV model, we may use the Wald test to test different combinations of Bertrand, Stackelberg leader, Stackelberg follower, and consistent conjectures. To test the Stackelberg and consistent conjectures games, the slopes of reaction functions must be estimated before the Wald test can be implemented.

Table 5 shows that all the various combinations of Bertrand, Stackelberg leadership, and consistent conjectures for the pricing strategies are rejected. This result implies that the CV model for pricing strategies in model C0, where each firm operates non-collusively in price, is the final winner. After the best-fitted model is determined, we then work on the price and expenditure elasticities[17] derived from this model, as presented in Tables 6 and 7.

4.3 Elasticities

In Table 6, all own price elasticities are significantly negative. Since All Others and Private Labels are aggregated from many of differentiated niche-type products, it is not surprising that this group of products is relatively inelastic in price. Firm 1 is more inelastic than firms 2 and 3, which supports the notion that this dominant firm may have strong customer loyalty and strategies to differentiate these lines have been successful. Firms 2 and 3 are relatively more price sensitive than the other firms in the study. This may signal relatively lower firm loyalty, poor differentiation strategies, and/or other factors that limit these firms from improving their market position relative to firm 1 or private labels.

Moving to cross elasticities, firms 1 and 2 are found to be substitutes, which was

[17]The elasticity estimates can be derived from the AIDS model. They are all computed at the means of relevant variables and the associated standard errors are obtained by the delta method.

not surprising given that both are margarine product lines. Meanwhile, there exist no clear relationships between either firms 1 and 3 or firms 2 and 3. The negative cross elasticities of the rest of the products imply that they are roughly complements of each other. The result is consistent with Gould, Cox, and Perali (1991), where different food fats and oils, including butter, margarine, short, cooking, and lard are generally complements. Alternatively, the negative cross elasticities might emerge because retail firms control final prices and have no true complementary relationship. For example, when branded products are offered at lower prices, supermarkets can instantaneously react by lowering the price of their own private labels.

The expenditure elasticities are reported in Table 7. All are positive and statistically significant. Recall that firm 3, All Others, and Private Labels all have significant butter components aggregated within, while firms 1 and 2 are lower priced, margarine firms. Private Labels, All Others, and firm 3 are above unity, consistent with the finding that these items contain butter products and generally charge relatively higher prices.

4.4 Lerner Indexes

Table 8 provides a key set of results with respect to Lerner indexes. The Lerner indexes for the best-fitted model (MVM-conjectural variations) are presented in column 1. The Lerner indexes range from 0.0092 and no statistical significance (All Others) to 0.2821 (firm 3). The lowest Lerner index of All Others is consistent with the smaller market shares of these firms and possible fringe market positioning. The major firms (firms 1, 2, and 3) all operate with considerably higher margins indicating superior levels of market power. Private labels also have a high Lerner index and similar to the major firms. This is consistent with the growing concerns about market power of supermarkets.

To examine the importance of model specification, two added experiments are presented in terms of Lerner indexes. Because Bertrand pricing is oftentimes an operational assumption of retail market studies, Column 2 contains the MVM-Bertrand result and column 4 shows, in percentage terms, the difference between Lerner indexes between column 2 and column 1. Because Bertrand pricing is a stable benchmark that essentially drives a wedge between marginal cost and demand, the cost of imposing this restriction emerges in the form of higher Lerner indexes. In all cases except the All Others category, the error is around 35% and in a range of 25% to 45%. These results underscore the importance of getting the correct model assumptions in place and casts doubt on using a Bertrand-pricing assumption without a formal statistical test of its validity. What is particularly troubling is the estimated Lerner index for the All Others category. The Bertrand assumption leads to a result that the All Others category operates with a statistically significant Lerner index of 0.4, an egregious 99% error versus the correct model and generating a Type I error. In this case, the Bertrand assumption leads the researcher to believe this is the most troubling category when it is the least troubling.

Columns 3 and 5 present a similar comparison as columns 2 and 4, but here, we impose the restriction that firms maximize profits. In all cases except the All Others category, the restriction of profit maximization causes Lerner Indexes to rise by about 4.74% with a range of 1.10%-7.39%. These results are consistent with the theoretical findings in Wang and Stiegert (2005) which suggest that Lerner indexes are overstated under profit maximization. For the All Others category, assuming profit maximization generates a very large error (51.09%) relative to MVM, but it was not statistically different from zero (thus, no Type I error). While the restriction of profit maximization generated some errors in precision relative to MVM, they are far less problematic than in the case of presuming the wrong market structure.

5 Concluding Remarks

Industrial organization research has a major focus of trying to determine how prices are formed when only a few competitors exist in defined markets. Usually, the operational assumption is that firms try to maximize profits. However, it is readily apparent that not all managers are compensated in ways consistent with simply increasing profits. In this paper, we investigate an objective function of (equity) market value maximization (MVM) in product market behavior for the U.S. margarine and butter retail market. We develop and implement a model of oligopoly pricing using a nonlinear Almost Ideal Demand Systems and structural first-order conditions derived from a CAPM based objective function. The data included retail scanner data from 1998-2002 over 28 demographic market areas in the U.S.

Two key objectives of the study were met. First and foremost, the model was constructed to incorporate a simple likelihood ratio or Wald test to determine if a restricted profit maximization version of the model was appropriate. The restricted model was soundly rejected and we concluded that financial market factors have an important role in determining the pricing behavior of firms in this industry. Second, a menu approach was used to search for the market structure that best describes the data. The MVM model using a general conjectural variations assumption was selected over several benchmark oligopoly structures such as Bertrand pricing, various Stackelberg leadership models, and various forms of collusion. This is not an overly surprising result. While static benchmark results are useful theoretical guides, they are hard to sustain over long periods of time and across different cities.

The best-fitted MVM model was also used to compare Lerner indexes when incorrect assumptions were used. In the case of assuming firms maximize profits, Lerner indexes were slightly higher for four of the firms with an average overstatement of about 4.74%. For the aggregated All Others category, the overstatement was much larger, but neither the MVM nor the profit maximization Lerner indexes were different from zero. Many retail oligopoly studies simply presume a Bertrand market structure. When the MVM model was restricted to Bertrand pricing, the results pointed to a much larger problem. In this case, the restriction generated 25% to 45% errors in the case of four firms and a 99% error for the All Others. Further, the MVM-Bertrand model generated a Type I error for the All Others in that it was found to be statistically different from zero. This result underscores the importance of statistically validating the market structure before moving forward with studies of imperfect competition.

The research in this study provides several important additions and extensions to the literature. We are not aware of any previous attempt to estimate a flexible demand system while introducing financial market risk into the market structure. The results offered here push the literature toward a richer model of firm behavior that links equity market objectives and product market behavior. Future research should attempt to consider similar linkages to the equity markets. For example, it is usually presumed that firms vertically integrate and/or vertically contract to gain efficiencies and improve profitability, but an additional factor may lie in managerial incentives to stabilize profit streams and increase the value of equity. The research also points to a reconsideration of how supra-normal profits are measured. While the discipline of finance has a long tradition in normalizing returns against risk exposure, the industrial organization field has struggled to define a clear or easy way to make this normalization process tractable for antitrust enforcement. Doing so would be a major advancement in merger analysis.

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Table 1 Descriptive Statistics

Firms	Price ($/lb)		Market Share (%)		Expenditure share (%)		Total Revenue ($M/city)	
F1 (M)	1.18	(0.17)	37.50	(6.85)	29.81	(6.26)	40.75	(29.64)
F2 (M)	1.05	(0.22)	15.66	(9.69)	13.66	(7.48)	15.06	(8.99)
F3 (B)	3.40	(0.62)	9.60	(4.46)	16.43	(7.62)	29.69	(37.94)
AO (M&B)	2.19	(0.51)	13.29	(8.80)	14.59	(10.59)	26.87	(42.01)
PL (M&B)	1.85	(0.52)	23.95	(6.64)	25.51	(7.38)	41.11	(37.14)

Firms	Unit Per Volume		All Merchandising (%)		Price Reduction (%)		All Others (%) [Display & Feature]	
F1 (M)	0.77	(0.07)	24.37	(9.03)	9.57	(6.90)	14.80	(8.32)
F2 (M)	0.91	(0.06)	31.21	(13.75)	12.56	(8.74)	18.65	(12.66)
F3 (B)	1.13	(0.06)	36.89	(23.42)	17.50	(16.04)	19.39	(20.49)
AO (M&B)	1.06	(0.08)	24.45	(15.42)	13.17	(9.84)	11.28	(12.60)
PL (M&B)	0.90	(0.09)	38.53	(21.41)	16.20	(13.97)	22.33	(17.73)

Mean Values of Other Explanatory Variables

Variables	Units	Mean		Variables	Units	Mean	
PERLT10K	%	8.64	(3.22)	Median Income	$	44317.32	(6484.37)
PERGT50K	%	44.03	(6.63)	Per Capita Expenditure	$	0.72	(0.19)
HUNDER15	#	0.58	(0.09)	r_m	%	7.35	(18.80)
H_NUMBER	#	2.57	(0.16)	r_f	%	5.23	(0.78)
A_AGE	Years	34.01	(2.42)				
FSPANISH	%	13.40	(10.74)				
POPU	#	3651213	(3361325)				

Note:

(1) Product produced: M=margarine; B=butter.

(2) Standard errors are in parentheses.

(3) F1~F3: Firm 1~Firm 3, AO: All Others, PL: Private Labels.

Table 2 Numbers of Parameters in FIML Estimation

Equation	Parameter	Number	Note
7	ν_r	36	division binary, $r = 1 \ldots 9$.
	λ_k	28	socio-demographic variable, $k = 1 \ldots 7$.
	η	4	income term in AIDS
	γ	10	cross price effect in AIDS
	$Season$	12	seasonality dummy
	$Butter$	1	butter dummy
11	ζ_r	9	regional dummy in income, $r = 1 \ldots 9$.
	ξ, ψ_1, ψ_2	3	time trend, median income and its square
10	μ_0	5	intercept term
	μ_1	5	unit per volume
	μ_{21}	5	all other merchandising
	μ_{22}	5	price reduction
6	τ	*	CV in price
	θ	1	finance component

* Numbers depend on the market structure. See column (4) in Table 4.

Table 3 Wald Test and Likelihood Ratio Test for Financial Component (MVM versus Profit Maximization in Pricing System)

Draw	Estimates	Standard Error	Wald statistic	LR statistic
1	0.3569	0.0098	1338.04	354.49
2	0.3527	0.0087	1630.99	365.42
3	0.3458	0.0075	2142.03	355.11
4	0.3330	0.0082	1654.55	381.26
5	0.3783	0.0063	3633.31	252.00
6	0.3690	0.0079	2178.67	289.22
7	0.3669	0.0103	1258.21	442.44
8	0.3208	0.0078	1698.22	395.88
9	0.3451	0.0083	1712.88	355.79
10	0.3301	0.0082	1611.63	367.73
11	0.3676	0.0095	1503.89	462.89
12	0.3346	0.0078	1820.77	392.40
13	0.3442	0.0076	2054.92	366.42
14	0.3467	0.0090	1468.48	432.95
15	0.3517	0.0074	2230.45	327.26
16	0.3336	0.0070	2245.63	382.20
17	0.3510	0.0096	1344.35	365.03
18	0.3751	0.0101	1387.73	287.55
19	0.3573	0.0073	2365.81	356.31
20	0.3480	0.0091	1468.77	429.54
21	0.3255	0.0083	1536.45	391.12
22	0.3458	0.0080	1863.96	383.16
23	0.3372	0.0077	1922.31	384.77
24	0.3322	0.0071	2187.97	369.22
25	0.3408	0.0083	1681.56	403.32
26	0.3252	0.0076	1807.23	379.63
27	0.3472	0.0081	1854.66	445.08
28	0.3348	0.0073	2102.72	385.18
29	0.3385	0.0106	1028.39	387.52
30	0.3331	0.0091	1339.98	361.41

Note: The critical values at the 5% level of significance are 3.84 for both the Wald test and the LR test.

Table 4 Vuong Test (Model C0 versus Others)

Model	(1) VT	(2) AIC	(3) SIC	(4) # of CV
C0	0.0000	0.0000	0.0000	20
C1	6.7337	6.7256	6.7038	18
C2	8.0815	8.0730	8.0501	18
C3	7.5138	7.5052	7.4822	18
C4	13.7437	13.7193	13.6537	14

Note:

(1) C0: each brand operates non-collusively
C1: Firm 1+Firm 2
C2: Firm 1+Firm 3
C3: Firm 2+Firm 3
C4: Firm 1+Firm 2+Firm 3

(2) The numbers in columns (1)-(3) indicate the Vuong statistics under the different criteria, which measure how mode1 C0 is superior to the others. For example, the three entries of model C1 indicate that model C0 is better than model C1 by those amounts. The critical values for the 5% level of significance are -1.96 and 1.96.

Table 5 Wald Test Statistic (Model C0)

Type of Game	Wald Statistic
B	19663.67
S1	45089.97
S2	59223.93
S3	15605.38
SAO	71549.50
SPL	23739.80
CS	151885.26

Note:

(1) The degree of freedom for all tests is 20 and the critical value is 31.41 at the 5% level of significance.

(2) **B** indicates Bertrand, **S*i*** signifies that brand *i* is a Stackelberg leader, and **CS** indicates consistent conjectures.

Table 6 Price Elasticity Matrix (MVM)

Firms	F1	F2	F3	AO	PL
F1	**-0.5561** (0.0096)	**0.1327** (0.0033)	**0.0425** (0.0027)	**-0.0348** (0.0036)	**-0.2733** (0.0097)
F2	**0.3329** (0.0081)	**-0.7873** (0.0055)	**0.1086** (0.0045)	**-0.1183** (0.0073)	**-0.0734** (0.0115)
F3	**-0.0714** (0.0030)	-0.0013 (0.0023)	**-0.8383** (0.0064)	**-0.0524** (0.0025)	**-0.1868** (0.0075)
AO	**-0.2514** (0.0063)	**-0.2169** (0.0059)	**-0.0800** (0.0032)	**-0.0925** (0.0242)	**-0.6212** (0.0250)
PL	**-0.5071** (0.0119)	**-0.1441** (0.0059)	**-0.1662** (0.0057)	**-0.3811** (0.0144)	**-0.1659** (0.0188)

Table 7 Expenditure Elasticity Matrix

Firms	Estimates
F1	**0.6872** (0.0105)
F2	**0.6315** (0.0162)
F3	**1.2220** (0.0057)
AO	**1.2711** (0.0170)
PL	**1.2648** (0.0160)

Note:
(1) Standard errors are in parentheses.
(2) Highlighted numbers are significant at the 5% level of significance.
(3) F1~F3: Firm 1~Firm 3, AO: All Others, PL: Private Labels.

Table 8 Estimated Lerner Index in Pricing System

Firms	(1) MVM	(2) MVM Bertrand	(3) Profit Maximization	(4) [(2)-(1)]/(1)*100%	(5) [(3)-(1)]/(1)*100%
F1	0.2694 (0.0165)	0.3492 (0.0140)	0.2893 (0.0129)	29.62	7.39
F2	0.2471 (0.0252)	0.3095 (0.0234)	0.2621 (0.0214)	25.25	6.07
F3	0.2821 (0.0088)	0.4084 (0.0097)	0.2852 (0.0077)	44.77	1.10
AO	0.0092 (0.0983)	0.4001 (0.0382)	0.0139 (0.1232)	4248.91	51.09
PL	0.2478 (0.0172)	0.3527 (0.0186)	0.2587 (0.0136)	42.33	4.40

Note:
(1) Standard errors are in parentheses.
(2) F1~F3: Firm 1~Firm 3, AO: All Others, PL: Private Labels.