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Structural Change and Market Power in the U.S. Food Manufacturing Sector

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ABSTRACT

This study develops an intertemporally linked market model to explore the relationships between price-cost margins, market concentration, and advertising outlay. The study used data from 48 four-digit SIC (standardized industrial classification) codes for the Food and Tobacco Processing Industries during the 1970s, 1980s, and 1990s. The authors' findings provide evidence that both high and low levels of performance provide signals to industries to consolidate, but for obvious and different reasons. Further, increased consolidation leads to increased entry barriers (advertising) and higher profits to the industry. Our findings are supportive of both Chicago and Traditionalist Schools of thought about antitrust enforcement: Neither emerges in a dominant position. Endogeneity issues and findings within the intertemporal structure cast considerable doubt about overly simplistic structure–performance paradigms of firm behavior. [JEL Code: L11, L40, L66]. © 2009 Wiley Periodicals, Inc.

1. INTRODUCTION

Over 60 years ago, the paradigm known as Structure–Conduct–Performance (SCP) was forwarded by Bain (1951) as a formal model to explain the behavior of firms in an industry. Associated with the Harvard Tradition, this new approach came to replace the old case-study approach. The primary distinction of SCP from case studies was in the way researchers looked at data. The SCP approach relied on cross-sections of industry data, insisting that industries are shaped by some basic conditions: demand elasticities, product durability, and technology, which determine the market *structure*: number and size of firms, entry conditions, product differentiation, and vertical integration, which lead to *conduct*: pricing, advertising and R&D strategies, which, in turn, determine market *performance*: efficiency, equity, and technological change.

High rank correlations across industries in different developed countries suggested that tastes and technology, which are likely to be constant across regions, determine the equilibrium structure. Researchers in the 1950s through the 1970s produced numerous marquee articles that regressed price-cost margins (PCMs) with variables such as industry concentration, minimum efficient scale (MES), capital intensity, R&D, and quadratic- (inverted U-) shaped effects from advertising to sales ratios (see Collins & Preston, 1969 and Kwoka, 1979 for excellent reviews of the literature and relevant findings). Market concentration was generally found positively related to higher PCMs, which confirmed the emerging conventional wisdom portended by Bain. Support for the inverted U-shaped role of advertising was also found, which suggested waning competition from new entry and even for incumbent market share once an industry was sufficiently concentrated. Armed with convincing evidence of concerns about concentration, U.S. antitrust authorities took an aggressive stance during the 1960s and 1970s on mergers, predatory pricing, and resale price maintenance, while ushering in premerger notification laws and stepped up information reporting.

According to Reder (1982), the opposing Chicago School view, which emerged in the 1970s, laid its initial foundations shortly after World War II. Reder points to the arguments of Pareto efficiency, articulate lay communications by Chicago scholars, and the vacuum of free-market thought in the wake of the U.S. depression as major contributing forces that gave the Chicago School momentum for its rise. The Chicago technical critique of the SCP approach is derived from its efficiency undergirdings and lies primarily in the SCP treatment of concentration as a purely exogenous variable. When this does not hold, the error term in the SCP regression is correlated with concentration and the ordinary least squares (OLS) properties of the model are lost (biased parameters, asymptotically biased parameters, efficiency, asymptotic efficiency, consistency). Indeed, it could be that industry structure, prices, and profits are simultaneously determined. The Chicago School provided a related critique. If several firms in an industry are very efficient, they may earn large rents on their efficiency and also grow their market shares. Industries with a few such efficient firms will be concentrated and this concentration is derived not by high prices but low average costs for some firms. Demsetz (1973, 1974) and others estimated versions of the following equation using firm-level data:

$$P_{if} = b_0 + b_1 C_i + b_2 s_{if} + \mathbf{b}\mathbf{Z} + \varepsilon_{if}, \tag{1}$$

where P is the performance (profit or PCM) of firm f in industry i, C is concentration, s is market share, and $\mathbf{Z}$ is a vector of other relevant exogenous variables. Although they usually found that the parameter on concentration was almost never significant and positive, the coefficient on market share was significant, which lent considerable support to the Chicago critique. Antitrust authorities in the 1980s and 1990s shifted attention toward the economic benefits of lower costs (i.e., efficiency) and looked harder for ways in which concentrated industries could be forced to price competitively. Theories arriving from a plethora of game theory contexts broadened our understanding of the firm behavior and the new empirical industrial organization emerged to provide a framework for the testing of structural based market power for specific industries.

In this article, we conducted research on the premise that both the Traditionalist School (TS) and Chicago School (CS) have redeeming merits. Our methods flow from work by Kambhampati (1996, pp. 133–148) and also from Delorme, Klein, Kamerschen, and Voeks (2002) [hereafter DKKV]. Both studies use a system of simultaneous equations similar to Strickland and Weiss (1976) and extend beyond Martin's (1979) early use of intertemporal relations between structure, conduct and performance. Even after Martin's pathbreaking work, numerous TS studies bypassed the known intertemporal relationships with simple contemporaneous systems, for examples, Gupta (1983), Schmalensee (1989), and Weiss (1991).

Many of the basic ideas founded by the TS are not in conflict with CS. For example, both schools of thought have long recognized that basic market characteristics such as minimum efficient scale help to determine market structure. The key difference, as alluded to above, is that CS thought hinges more closely on the role that firm level performance may have on structure while the TS focus is on the role that structure has on performance. The history of TS thought before Martin (1979) was principally that performance had no feedback role on changing the structure. In our setup, we are able to evaluate the simultaneous role that industry performance has on structure and vice versa.

The research was conducted on the 48 Food and Kindred Product and Tobacco (FKPT) industries defined by the U.S. Census Bureau's 4-digit SIC (standard industrial classification) codes during the 1970s, 1980s, and 1990s. Average market concentration in the FKPT industries increased significantly over the past 50 years. As a result, about 40% of the FKPT industries are commonly considered to be highly concentrated, as defined by four firms controlling 60% or more of sales (Mueller & Rogers, 1980, 1984; Rogers & Tokle, 1995). To date, a number of studies have examined market structure–performance relationships in the FKPT industries (see Rogers, 2001, and citations therein). These studies have used various measures of profits and/or industry PCMs to measure profit performance, and most were conducted using data for years before 1980. Critically, these studies are purely in the TS format: Performance is restricted from having a role in determining structure. In the present article, we investigated the simultaneous, intertemporally linked relationships among performance (PCMs), structure (market concentration), and conduct (advertising outlays). To date, no cross-sectional study of the U.S. FKPT industries have considered the potential for intertemporal relations in a simultaneously determined system.

Kambhampati (1996) and DKKV assert that each variable in the SCP model influences the other variables in a time-dependent manner. Kambhampati (1996) argues that (a) structure is affected by lagged conduct and both lagged and current performance, (b) past conduct represents a potential barrier to entry, (c) improving past and current performance leads to more concentrated structures, (d) previous year's performance influences the current conduct, and (e) performance determinants remain contemporaneous as the profits are computed in the current period. In this study, we explore the intertemporal interrelations suggested by Kambhampati (1996) and DKKV. Although our modeling framework follows closely to that of DKKV, at least four major differences are noteworthy:

1. Study focus: The present study focuses on partitioning the FKPT industries into low and high advertising categories. DKKV considered a broader set of industries and they used firm data available in the Compustat database (Standard & Poor's, McGraw-Hill, New York, NY). The problem with using Compustat data lies in that potential biases might arise when considering only publicly traded firms.
2. Lagged terms: Our data set spans five census years (1972, 1977, 1982, 1987, and 1992) and lagged variables are contained in the census years.[1] The DKKV study used data in 1982, 1987, and 1992, but adopted lagged variables from just the previous year.

[1]See section 5 for discussions on issues of more recent data.

3. Concentration on advertising: Following Greer (1971), Cable (1972), and Strickland and Weiss (1976), we examine whether the effect of concentration on advertising takes an inverted-U shape. DKKV restricted their model to consider only a linear relationship.
4. Minimum efficient scale (MES): We incorporate MES to model the effect of scale of economies in the analysis (Connor et al., 1985; Sutton, 1991). The DKKV study lacked the data to include MES in the analysis.

To evaluate the relationship among PCMs, market concentration, and advertising properly, a simultaneous-equation model is needed to obtain consistent and unbiased estimates. For this study, we estimated the simultaneous-equation system using two-stage least squares (2SLS). The rest of this article is organized as follows. The simultaneous-equation framework is presented and discussed in Section 2. The empirical setup and data used in this study are discussed in Section 3. Section 4 contains the result from three regressions. Finally, Section 5 provides concluding remarks and suggestions for further research.

2. THE MODEL

Following Kambhampati (1996) and DKKV, the intertemporal system of equations presumes three endogenous variables: industry concentration ($CR4$), advertising (AD), and industry price-cost margins (PCM). Each of the system's equations are developed and discussed below.

Beginning first with industry structure, we are interested in evaluating the role of current and past performance and potential barriers to entry in shaping the industry level concentration. The equation is written:

$$CR4_t = \alpha_0 + \alpha_1 AD_{t-1} + \alpha_2 KO_{t-1} + \alpha_3 PCM_{t-1} + \alpha_4 PCM_t + \alpha_5 MES_{t-1} + \alpha_6 MES_t + \eta_{1t}, \tag{2}$$

where $CR4$ is the four-firm concentration ratio, AD is advertising intensity calculated by the ratio of advertising expenditure to value of shipments, KO (capital-output ratio) is gross fixed assets relative to value of shipments, PCM is the price-cost margin, and MES is the minimum efficient scale. The subscripts t and $t-1$ represent current and lagged one period, respectively. All of the coefficients are expected to be positive.

An important determinant of concentration may indeed be the MES defined as smallest optimum firm size divided by a measure of market size. Three different approaches are used for estimating the MES numerator: (a) economic-engineering studies, (b) midpoint plant size as a proxy, and (c) plant size with the lowest labor costs as a proxy. Using 13 four-digit SIC industries in the U.S. food and drink sector, Connor et al. (1985) report that median plant estimates based on the 1972 Census of Manufactures and engineering estimates over 1970–1980 are highly correlated ($\rho = 0.83$; pp. 93–95). Therefore, we used the size of the industry's median plant divided by industry sales to be a proxy of MES. The median plant size is defined as the size of the plant that is at the midpoint of the industry shipments size distribution (Connor et al., 1985; Strickland & Weiss, 1976). Because MES represents the set-up costs of installing a new plant, the impacts are likely to take time to impact industry concentration; thus, we expect $\alpha_5 \geq \alpha_6$.

Additional barriers to entry can be observed when firms gain significant brand image from advertising or when firms operate in industries with high fixed costs. Therefore, lagged advertising and lagged capital investment are included in the model, and the associated coefficients are expected to be positive. The final two determinants of concentration include current and lagged *PCMs*. Inclusion of *PCMs* is suggestive of the meritorious incentives that profits might create in encouraging successful firms to grow and ineffective ones to shrink and/or exit.

The advertising intensity equation (second in our system) is given by:

$$AD_t = \beta_0 + \beta_1 PCM_{t-1} + \beta_2 GR_t + \beta_3 CR4_t + \beta_4 CR4_t^2 + \eta_{2t}, \quad (3)$$

where *GR* is the growth in industrial production calculated as the ratio of current year shipments to those in the previous period. Inclusion of the lagged *PCM* variable follows from Sutton's two-stage approach (1991, pp. 27–81), Kambhampati (1996), and DKKV. Previous year's profits are expected to have impacts on current advertising expenditure; i.e., the more past profits, the more current advertising outlays. In Greer (1971), Cable (1972), Comanor and Wilson (1974), and DKKV, the growth of sales is incorporated to control for successful new product development, positive demand shocks and/or greater levels of advertising induced product differentiation. The coefficients β_1 and β_2, are expected to be positive.

As investigated in Greer (1971), Cable (1972), and Strickland and Weiss (1976), the effect of concentration on advertising takes an inverted U shape. Advertising is expected to be increasing in concentration when concentration ratio is low (Dorfman & Steiner, 1954), but decreasing at very high levels of concentration when it becomes easier for firms to collude to avoid mutually offsetting advertising. Therefore, in the advertising equation we add a quadratic term ($CR4^2$) to capture this type of nonlinear relationship. An inverted U-shaped relationship requires that the coefficient on *CR*4 be positive and that of $CR4^2$ to be negative.

The equation for *PCMs* is essentially a performance measure that proxies industry profits. Many empirical studies explain PCMs with variables for concentration, advertising, and other cost related variables (see, for example, Collins & Preston, 1966, 1969; Kwoka, 1979; Liebowitz, 1982; Ornstein, 1975; Rhoades & Cleaver, 1973; Weiss, 1991). The quality of Census PCMs as a proxy for profits depends on whether appropriate adjustments can be made to reflect critical elements of cost not included in the Census PCMs of particular industries. In the food manufacturing industries, the two most important costs associated with Census-derived PCMs are the cost of advertising and promotion and the cost of capital. We address these concerns by adding advertising intensity *AD* and capital intensity *KO* to the equation. Although *AD* serves as a proxy for the production differentiation barrier, *MES* represents the scale barrier. In addition, unanticipated increases in demand or unanticipated decrease in costs might result in high margins. Output growth *GR* is incorporated to reflect the effects.

The census concentration ratios do not characterize market concentration correctly where markets are local or regional in nature because the ratios generally refer to national industries. Following Rogers (2001), we add a dummy (*NL*) for a local or regional industry, for example, milk or bread, to correct possible biases.

Therefore, the PCM equation is given by

$$PCM_t = \gamma_0 + \gamma_1 GR_t + \gamma_2 KO_t + \gamma_3 CR4_t + \gamma_4 AD_t + \gamma_5 MES_t + \gamma_6 NL + \eta_{3t}. \quad (4)$$

As a final note, to account for other possible unobservable factors such as aggregate demand shifts or technological change, we included a time trend variable in each equation.

3. EMPIRICAL ANALYSIS AND DISCUSSION OF THE DATA

We used two-stage least squares (2SLS) to estimate the proposed simultaneous-equation system. In the first stage, each endogenous variable (concentration, advertising, and price-cost margin) is regressed on all exogenous variables, including MES, lagged MES, capital-output ratio (KO), lagged KO, lagged AD, lagged PCM, lagged GR, nonnational market dummy, and time trend. In the second stage, the fitted values of endogenous variables from the first stage are used as instruments to estimate the three structural equations. Throughout this article, the critical level for determining strong statistical significance in a two-tailed test was established at the 5% level. We signified moderate statistical support with the significance level at 10%.

Except for advertising intensity and the local/regional dummy variables, all of the variables used to estimate Equations 2–4 are derived from the 1972, 1977, 1982, 1987, and 1992 Census of Manufactures. The Census variables are for 48 four-digit SIC FKPT Industries for each Census year. Thus, the data set contains 240 observations. Table 1 shows 48 four-digit SIC industries examined in this study. The four-firm concentration ratios for three selected census years (1972, 1982, and 1992) are also presented. Though the concentration ratio may increase or decrease for each individual industry across different Census years, the average $CR4$ increased from 44.10% in 1972 to 46.21% in 1982, and finally to 53.90% in 1992. Simple calculations of $CR4$ changes show the average concentration ratios increase moderately over these periods. We will discuss more details on the trend of $CR4$ in the estimation of simultaneous-equation system below.

The media advertising data are from Competitive Media Reporting (CMR; Taylor Nelson Sofres plc, London, UK). We match advertising data to corresponding industries to create advertising-to-sales ratios in each Census year. The local/regional dummy is assigned on the basis of judgment, including industries of ice cream and ice (2024), fluid milk (2026), prepared feeds (2048), bread, cake, & related products (2051), bottled and canned soft drinks (2086), and manufactured ice (2097).

To explore the differences between high and low advertising intensive industries, we segmented the full sample (240 observations) into two groups by using advertising-to-sales (A/S) ratio and conducted the above-mentioned analysis on each subgroup. Group 1 was high advertising industries, in which their A/S ratios were greater than 0.25% for all Census years. Group 1 included 140 observations. The rest of the observations were classified as low advertising.[2] Table 2 gives the means for key variables based on full sample and both groups. The mean $CR4$ is quite a bit higher in the high advertising group compared to the low advertising group. This is consistent with Sutton's (1991) theory that advertising is a viable

[2]Our examination on the robustness showed that there is no change in the subsamples used for high and low advertisers as long as the critical level of A/S ratio is less than 0.35%.

TABLE 1. Concentration in Food and Tobacco Processing Industries, 1972–1992

SIC	Name	CR4 1972	CR4 1982	CR4 1992	Change 1972–82	Change 1982–92
2011	Meat packing plant products	26	27	50	1	23
2013	Sausages & prepared meats	16	15	25	−1	10
2021	Butter	37	29	49	−8	20
2022	Cheese, natural and processed	40	35	42	−5	7
2023	Condensed and evaporated milk	34	33	43	−1	10
2024	Ice cream and ices	27	22	24	−5	2
2026	Fluid milk	17	15	22	−2	7
2032	Canned specialties	62	59	69	−3	10
2033	Canned fruits and vegetables	18	20	27	2	7
2034	Dehydrated fruits, vegetables, soups	31	41	39	10	−2
2035	Pickles, sauces, salad dressings	30	40	41	10	1
2037	Frozen fruits and vegetables	28	28	28	0	0
2038	Frozen specialties	36	31	40	−5	9
2041	Flour & other grain mill products	32	40	56	8	16
2043	Cereal breakfast foods	84	86	85	2	−1
2044	Milled rice and byproducts	42	44	50	2	6
2045	Prep. flour mixes & refrigerated doughs	62	62	39	0	−23
2046	Wet corn milling	63	73	73	10	0
2047	Dog, cat, and other pet food	50	50	58	0	8
2048	Prepared feeds, n.e.c.	22	19	23	−3	4
2051	Bread, cake, & related products	27	32	34	5	2
2052	Cookies and crackers	58	59	56	1	−3
2061	Sugar cane mill products	43	41	52	−2	11
2062	Refined cane sugar	58	65	85	7	20
2063	Refined beet sugar	66	67	71	1	4
2066	Chocolate and cocoa products	72	69	75	−3	6
2067	Chewing gum[a]	84	87	96	3	9
2074	Cottonseed oil mill products	42	50	62	8	12
2075	Soybean oil mill products	52	56	71	4	15
2076	Vegetable oil mill products, n.e.c.	45	49	89	4	40
2077	Animal and marine fats and oils	17	24	37	7	13
2079	Shortening and cooking oils	40	40	35	0	−5
2082	Malt beverages	52	78	90	26	12
2083	Malt and malt byproducts	49	61	65	12	4
2084	Wines, brandy, and brandy spirits	52	52	54	0	2
2085	Distilled liquor, except brandy	50	46	62	−4	16
2086	Bottled and canned soft drinks	14	15	37	1	22
2087	Flavoring extracts & syrups n.e.c.	62	61	69	−1	8
2091	Canned & cured seafood inc soup	38	44	29	6	−15
2092	Fresh or frozen packaged fish	21	13	19	−8	6
2095	Roasted coffee	64	66	66	2	0
2097	Manufactured ice	29	17	24	−12	7
2098	Macaroni and spaghetti	34	37	78	3	41
2099	Food preparations, n.e.c.	26	29	22	3	−7
2111	Cigarettes	84	90	93	6	3
2121	Cigars	55	58	74	3	16

TABLE 1. Continued

SIC	Name	CR4 1972	CR4 1982	CR4 1992	Change 1972–82	Change 1982–92
2131	Chewing, smoking tobacco, snuff	60	75	87	15	12
2141	Tobacco stemming and redrying	66	68	72	2	4
	means for SIC 20-21	44.10	46.21	53.90	2.10	7.69

Note: The data source was the Census of Manufactures. CR4 = industry concentration; SIC = standard industrial classification; n.e.c. = not elsewhere classified.
[a]The 1992 CR4 for SIC 2067 is estimated by the authors.

TABLE 2. Means for Selected Variables in Food and Tobacco Industries, 1972–1992

Variable	Full sample	Group 1: High advertising[a]	Group 2: Low advertising
Sample size	240	140	100
CR4 (%)	48.00	52.27	42.03
	(21.14)	(20.72)	(20.36)
A/S (%)	1.94	3.19	0.19
	(2.84)	(3.16)	(0.30)
PCM (%)	33.09	40.81	22.28
	(14.45)	(12.14)	(9.29)
Value of shipments ($B)[b]	7.89	8.01	7.73
	(1.19)	(1.06)	(1.34)
MES (%)	3.82	4.34	3.09
	(4.88)	(5.57)	(3.61)
KO (%)	31.63	27.93	36.81
	(20.42)	(9.83)	(28.71)

Note: CR4 = industry concentration; A/S = advertising-to-sales ratio; PCM = price-cost margin; $B = billions of dollars; MES = minimum efficient scale; KO = capital-output ratio.
[a]A/S ratios were greater than 0.25% for all (5) census years. Standard deviations are in parentheses.
[b]All corresponding group means are different at the 5% level except those of Value of shipments.

barrier to entry. Simple *t*-ratios indicate that *CR4*, *PCM*, *MES*, and *KO* have statistically different means in the two samples. The mean *PCM* in the high advertising group is almost twice the mean from the low advertising group.

4. RESULTS

Three pretests revealed important findings and led to modifications in the estimation procedures for the system defined in Equations 2 to 4. Autocorrelation was detected using a modified Durbin-Watson test useful for panel data (Bhargava, Franzini, & Narendranathan, 1982). The Breusch-Pagan test detected cross-sectional heteroscedasticity. Following the procedures in Beck and Katz (1995), we first correct for autocorrelation assuming a first-order autoregressive process for each industry and then adjust the error terms for cross-section heteroscedasticity to attain panel corrected standard errors (PCSE). The heteroscedasticity adjustments are similar to

White's robust standard errors, but consider the time-series cross-sectional arrangement of the data as well. For the third pretest, pairwise correlation analysis revealed that *PCM* and lagged *PCM* were highly collinear. Thus, it seems that almost all of the variability in profitability occurred cross-sectionally. Initial estimates of the base model indicated this collinearity may not allow for a fair hypothesis test critical to this analysis: that increased lagged and/or current profitability lead to higher levels of concentration. Dropping one of the variables in this case represents a viable option, but theory cannot say which one should remain. Though not reported in a table, the coefficients on both variables yield the same statistical results and nearly the same parameter values when the opposing variable is dropped. Given the agnostic stance of either variable to the overall model result, we chose to use $\overline{PCM}$, obtained from $(PCM_t + PCM_{t-1})/2$, in the $CR4$ equation for all the models estimated.

4.1. Base Model

Table 3 contains the estimation results using the entire dataset. For concentration (Equation 2), we found that lagged advertising is responsible for increasing industry concentration, supporting the widely held TS belief that firms will build entry barriers when they can. Although the $\overline{PCM}$ variable was not significant, very interesting findings emerge about this variable in the subsequent regressions that use partitioned data. We found that increases in lagged *MES* and current *MES* were statistically significant and positive. These findings support the TS views that structure is influenced by technical scale economies in the production process. The time trend in the $CR4$ equation is positive and significant. This finding is consistent

TABLE 3. Two-stage Least Squares Estimates of Simultaneous Equations With PCSE

Dependent variable	CR4		AD		PCM	
	Estimate	*t*-value	Estimate	*t*-value	Estimate	*t*-value
Constant	24.7792	6.1930**	−0.4880	−0.1139	−1.1721	−3.7817**
CR4			0.0616	1.9605*	0.0193	6.0014**
$CR4^2$			0.0002	1.1352		
AD_{-1}	1.6169	2.0303**				
AD					−0.0053	−0.9037
PCM_{-1}			6.9903	3.5398**		
$\overline{PCM}$	2.2755	0.1318				
MES_{-1}	1.4413	4.6605**				
MES	1.3269	4.1965**			−0.0434	−7.5831**
KO_{-1}	0.1685	1.5415				
KO					−0.0036	−3.6152**
GR			−2.6322	−0.6458	0.8004	2.3219**
NL					0.4151	6.0471**
Year	2.7744	7.7752**	−0.4764	−3.7999**	−0.0261	−2.5550**

Note: Subscript−1 = lagged one period. CR4 = industry concentration; AD = advertising; PCM = price-cost margin; MES = minimum efficient scale; KO = capital-output ratio; GR = output growth; NL = dummy for a local or regional industry.

*Denotes significance at 10% level.

**Denotes significance at 5% level.

with the notion that all increases to the average concentration ratio cannot be explained by the structural variables introduced in our model.[3]

For the advertising (Equation 3), we found that the industry conduct (advertising) is affected positively and linearly by industry structure (concentration): The coefficient on $CR4^2$ is not statistically significant. Thus, our findings support the linear specification used by Kambhampati (1996) and DKKV and we reject the hypothesis of an inverted U shape effect suggested by Greer (1971), Cable (1972), and Strickland and Weiss (1976). Advertising is also found to be explained by past price-cost margins. This finding serves to suggest that advertising, financed or motivated by profits, may be used to create future barriers to entry. Interestingly, the industry growth does not affect advertising. The result seems to suggest a life-cycle effect on advertising, that is, fluctuations in sales do not change the advertising decisions. Instead, the advertising expenditure appears to be planned according to market shares and past profits.

The trend variable was negative and statistically significant. Inclusion of the trend variable does not carry a specific hypothesis test. The negative and significant sign is best interpreted as the model capturing a factor outside our theoretical setup. To speculate, at least two possible reasons exist that might explain this outcome. First, firms eager to increase their in-store brand strength may have opted for greater promotion efforts through displays and/or paying for premier shelf location. Because our data do not contain these sorts of advertising costs, a negative trend variable could be explaining why firms have simply shifted away from typical media advertising to a portfolio of promotional strategies. Second, with the strong theoretical links fully exposed between both concentration and lagged profits on advertising intensity, our negative trend variable may, in part, be picking up some of the mitigating effects that sustained profitability and market position may have in making the advertising decision. Simply put, firms in a strong position with erected entry barriers may back off their pursuit of even greater power.

Turning next to the estimation of price-cost margins (Equation 4), industry concentration is shown to have a positive impact on price-cost margins; i.e., industries with higher concentration ratios tend to be more profitable. This is a key result supporting the TS view that mergers leading to higher concentration should be taken seriously. Surprisingly, current period advertising was found to be insignificant in explaining current profitability, suggesting that firms see advertising in a longer-run capacity. This result is similar to Imel and Heimberger (1971), Nagle (1981), and DKKV, where no specific relationship can be inferred between advertising and price-cost margins.

[3]We also evaluated a regression model for the entire dataset that replaced the time trend variable with fixed effects for each of the census years. The signs on the regression parameters did not change and only small changes in the magnitudes of the parameter estimates were noted. However, the *MES* variable in the *CR4* equation and the *CR4* variable in the *AD* equation were no longer significant. Although no strong theoretical justification can support either approach, we believe that the use of a time trend variable represents a superior approach. The intent of the time trend variable was to capture trends such as technology, demand for healthier foods, etc., that are hard to quantify. It appears to that collinearity between these dummy variables and the *MES* term in the *CR4* equation and/or *CR4* variable in the *AD* equation causes a loss of power in explaining key relationships in the model. Thus, we opted not to pursue the fixed effects model as a base model or in specifying the models with low and high advertising.

Two variables, capital expenditure (*KO*) and minimum efficient scale (*MES*) inversely affected the price-cost margin, which is similar to the findings in DKKV, but not with others in the literature (see for example, Strickland & Weiss, 1976). Nevertheless, this result is consistent with the idea that time and monetary investments to adjust the firm size and its balance sheet may damage profitability at the margin. It is worth pointing out that full marginal impacts of MES include the feedback effects that MES has on concentration. Thus, $\frac{\mathrm{d}PCM}{\mathrm{d}MES} = \frac{\partial PCM}{\partial MES} + \frac{\partial PCM}{\partial CR4}\frac{\partial CR4}{\partial MES} = -0.0434 + 0.0193 \cdot 1.3269 \approx -0.0178$. The result remains statistically significant, but is only about 40% of the magnitude that the stand-alone MES parameter has on PCM.

The coefficient on the local/regional dummy variable (*NL*) was positive and significant. This implies those industries defined to sell in the local or regional market are more profitable than industries operating on a national or international scale. This is a key result because it insists that national concentration ratios are insufficient to describe how all markets are structured.

4.2. Partitioned Results

Table 4a and b contain the two-stage least squares results after partitioning the data in the manner discussed earlier and presented in Table 2. For the high advertising system of equations, unsurprising results emerge. Higher margins and lagged MES both led to higher levels of concentration. Thus, CS notions about performance (i.e., PCM) feedback effects on structure are supported. Lagged advertising was insignificant in explaining concentration, so we could not confirm if the feedback effects from conduct changed the industry structure. Increased concentration statistically explained higher levels of advertising within the high advertising group of industries, which implies that firms try to enhance entry barriers to preserve market power. Supporting the TS theory, the coefficient on concentration led to higher price-cost margins. In addition, parameters on minimum efficient scale and capital outlays were negative and significant. It appears that high advertising food industries were quick to respond to firm size and capitalization issues even though the marginal effects were negative. Finally, strong statistical support was found for the local/regional dummy variable indicating firms selling highly advertised goods in nonnational markets benefited from higher margins. Overall, these results are not much different from the results obtained by Kambhampati (1996) where both CS and TS effects were noted throughout the system. The results were also not very different from the results in Table 3 cover the entire range of industries.

The results for the low advertising industries were strikingly different. First, we found that lower price-cost margins led to higher concentration, a result that strongly supports a standard CS argument: The most profitable firms are likely to increase their market presence in industries where tight margins force inefficient firms to exit. The coefficients on the firm size (*MES* and lagged *MES*) and lagged capital outlays were all positive and significant. These results suggest a strong effect from increasing firm size and capitalization leading to greater concentration.

Only the coefficient on lagged profitability was significant in explaining advertising. In low advertising industries, concentration is highly insignificant and does not explain changes in advertising. Turning now to the performance equation, interesting and striking results emerged. Increased concentration led to lower

TABLE 4.

Dependent Variable	CR4 Estimate	CR4 t-value	AD Estimate	AD t-value	PCM Estimate	PCM t-value
(a) Two-stage Least Squares Estimates for High Advertising Group						
Constant	13.0340	1.4155	13.7604	0.9769	−0.6293	−3.1463**
CR4			0.1073	2.3675**	0.0169	10.5671**
$CR4^2$			0.0002	0.7169		
AD_{-1}	0.8159	1.4664				
AD					−0.0082	−2.0325**
PCM_{-1}			−1.7877	−0.4039		
$\overline{PCM}$	48.9709	1.7572*				
MES_{-1}	2.3088	4.2464**				
MES	0.0386	0.0695			−0.0313	−8.4350**
KO_{-1}	0.1767	0.8776				
KO					−0.0048	−6.6506**
GR			−14.3478	−1.1235	0.4065	2.3024**
NL					0.3404	8.2328**
Year	1.1699	1.5178	−0.5191	−2.3636**	−0.0115	−3.6985**
(b) Two-Stage Least Squares Estimates for Low Advertising Group						
Constant	35.8070	4.5578**	−0.8055	−0.9101	−0.4842	−6.4864**
CR4			−0.0037	−0.8995	−0.0082	−6.3504**
$CR4^2$			0.0000	0.6854		
AD_{-1}	6.7087	0.6362				
AD					0.1001	3.2718**
PCM_{-1}			1.1196	2.0887**		
$\overline{PCM}$	−62.8087	−1.7747*				
MES_{-1}	1.9798	2.5470**				
MES	1.6209	2.6913**			0.0202	5.3726
KO_{-1}	0.1684	1.6706*				
KO					0.0034	12.3877
GR			0.8273	1.0511	0.7933	8.4636
NL					−0.1079	−3.6455
Year	2.9772	2.6483**	−0.0340	−0.9633	0.0328	6.8125

Note: Subscript−1 = lagged one period. CR4 = industry concentration; AD = advertising; PCM = price-cost margin; MES = minimum efficient scale; KO = capital-output ratio; GR = output growth; NL = dummy for a local or regional industry.
*Denotes significance at 10% level.
**Denotes significance at 5% level.

industrial profits, not higher as suggested by TS theory. The results strongly suggest this group of industries is under significant competitive pressure, leading to consolidation and firm exit. Thus, despite the increased consolidation, firms were not able to use the improved structure to their benefit. Low advertising industries face the challenge of selling potentially close substitutes that do not benefit much from a brand identity. It appears that concentration levels are not sufficiently high enough to warrant concern about market power on prices during the years of this study.

TABLE 5.

	CR4	AD	PCM
(a) Elasticities in Two-Stage Least Squares Estimates for High Advertising Group			
CR4		2.1652**	2.1493**
AD_{-1}	0.0499		
AD			−0.0632**
PCM_{-1}		−0.2209	
$\overline{PCM}$	0.3759*		
MES_{-1}	0.1900**		
MES	0.0031		−0.3216**
KO_{-1}	0.0924		
KO			−0.3161**
GR		−4.6287	1.3081**
(b) Elasticities in Two-Stage Least Squares Estimates for Low Advertising Group			
CR4		−0.3940	−1.5417**
AD_{-1}	0.0299		
AD			0.0794**
PCM_{-1}		1.3572**	
$\overline{PCM}$	−0.3275*		
MES_{-1}	0.1512**		
MES	0.1080**		0.0993**
KO_{-1}	0.1427*		
KO			0.5288**
GR		4.7449	3.9856**

Note: $\varepsilon_{AD,CR4} = (\beta_3 + 2\beta_4 CR4_t)CR4_t/AD_t$. Its standard error is 0.4352 for (a) or 0.6179 for (b). $\varepsilon_{PCM,MES}$ includes an indirect effect through *CR4*. Its standard error is 0.0383 for (a) or 0.0340 for (b). $\varepsilon_{PCM,GR}$ includes an indirect effect through *AD*. Its standard error is 0.4110 for (a) or 0.3681 for (b). Subscript−1 = lagged one period. CR4 = industry concentration; AD = advertising; PCM = price-cost margin; MES = minimum efficient scale; KO = capital-output ratio; GR = output growth.
*Denotes significance at 10% level.
**Denotes significance at 5% level.

Table 5a and b contain elasticity information from the high and low advertising industries, respectively. It is interesting to compare the magnitude of change between each structure, conduct, and performance variable. For the high advertising industries a major finding is that the impact of increasing concentration on profit is over 5 times larger in magnitude than the impact of profit on concentration (2.1493/0.3759 = 5.72; *t*-ratio = 1.73). This finding is supported statistically and casts serious doubt on the belief that market structure is a benign feature in an efficient and competitive market process. Clearly, increased concentration has a significant economic effect on performance and this result supports the long-held traditional school of thought. Additionally, the elasticity of concentration on advertising was statistically significant, but the reverse relationship (i.e., lagged advertising on concentration) is not significant. This result suggests strongly that market structure (i.e., concentration) is a much more powerful driver in shaping industries than does market conduct.

For the low advertising industry elasticities (Table 5b), a similar dominance emerges in that structure has much larger impacts on conduct and performance than the reverse effects. However, neither concentration's effect on advertising nor lagged advertising's effect on concentration were statistically supported. This is not surprising given the lesser role of advertising in these industries. Additionally, concentration's effect on performance is not positively related. Thus, the most obvious conclusion is one consistent with CS underpinnings. In industries with tightening margins, performance informs market participants to restructure as perhaps an act of survival. For the years of this study, low advertising firms were simply unable to translate improved market structure into better margins.

The results from each of the three regressions informed us to consider a quadratic *PCM* term in the *CR*4 equation and to use the whole dataset. This allowed us to test the hypothesis that both very high and very low performance sends the strongest signal to restructure the industry toward higher concentration. We ran this regression and report only the relevant information on the quadratic terms with standard errors reported below each coefficient:[4]

$$CR4 = \ldots - \underset{(46.67)}{146.86\overline{PCM}} + \underset{(70.78)}{241.45\overline{PCM}^2} \ldots \tag{5}$$

Here, we find statistical support that both the most negative and positive *PCM*s sent the strongest signals for industry restructuring. Coincidentally, the minimum point of the U-shaped relationship (0.304) occurs close to the mean of PCM data (0.331), which certainly explains the opposing signs on the *PCM* coefficients from the partitioned regression. This result is suggestive that functional relationships spanning the cross section matter a great deal and that working with more homogeneous groups of industries is advisable.

5. CONCLUDING REMARKS

In this study, we explore the intertemporal and feedback interrelations among dependent variables of structure, conduct, and performance for 48 four-digit SIC food and tobacco processing industries during the 1970s, 1980s, and 1990s. Using an intertemporal simultaneous-equation framework provided a unique backdrop for comparisons between Chicago School and Traditionalist School views about industrial organization and antitrust enforcement. The model was estimated with entire dataset and with the data partitioned between high and low advertising industries. The models were coded in GAUSS and estimated using two-stage least squares with the structure (concentration) conduct (advertising) and performance (price-cost margins) assumed endogenous. All of the exogenous variables served as instruments in the first-stage estimations.

We can summarize our finding around five major points. First, clearly and convincingly, the CS point that performance informs the industry about how to

[4]The regression results for the advertising and *PCM* equations are identical to the results in Table 3. The unreported coefficients in the *CR4* equation are quite robust and maintain the same statistical significance found in the first column of Table 3.

structure was supported in both partitioned data estimations and in an auxiliary regression allowing for U-shaped performance effects on concentration. In the low advertising set of industries, as performance worsened, concentration pushed higher. This presumably suggests consolidation occurred to avoid economic losses. The explanation is also supported in the performance equation where increasing concentration was correlated with tighter PCMs. In high advertising industries, higher PCMs led to higher and statistically significant levels of concentration. The partitioned regressions and the auxiliary regression show that performance impacts on structure follow a U-shaped pattern: performance signals leading to restructuring are strongest in the highest and lowest performing industries.

Second, support for the TS point that exogenous forces shape both the structure and performance of the industry was evident in all the estimations. Minimum efficient scale, lagged minimum efficient scale, and lagged capital outlay were positive and mostly significant factors that led to higher industry concentration.

Third, the TS reference to structural linkages to performance was strongly supported in the all-industry regression, in the regression involving high advertising industries, and in the comparative elasticity analysis. Most revealing was the elasticity analysis, which showed that structure affects advertising levels and industry performance much more than the reverse effects. In particular, structural impacts on performance were over 5 times higher in magnitude than performance impacts had on structure.

Fourth, support was found in the full sample and in high advertising partition for the theory that local and regional firms enjoy higher levels of performance compared to national firms. Clearly, antitrust authorities should continue to pay close attention to relevant markets when evaluating acquisitions.

Fifth, and finally, in this article we took no parochial stand in placing favor with either the Chicago or the Traditionalist School of thought. Our results find elements of support in both viewpoints. In particular, the strong statistical support for performance informing structure was balanced with support for structure leading to increased performance. However, from an economic impact point of view, the magnitude of these effects is far more supportive of the traditionalist view when confronting the high advertising group of industries.

To conclude, cross-sectional industrial organization research such as this study provides useful policy-relevant results and paints a broad picture of the economic landscape. Our results point clearly to recommendations about mergers. Horizontal mergers should be carefully scrutinized and challenged when performance levels are high and/or products are branded through heavy advertising. Industries in decline or selling products in which firm prices are not protected by brands or other forms of differentiation may need a green light to restructure quickly. A more updated assessment of the U.S. food industry should include data from the more recent Census of Manufactures. However, changes in industry classification systems and availability of advertising data limited our scope to 1992 as the final year. The U.S. Standard Industrial Classification (SIC) system was changed in 1997 to the North American Industry Classification System (NAICS). The problem of matching data between these two classification systems is not difficult; however, it is not yet clear that the new classification system is a superior way to define the relevant industry boundaries. Additionally, organizing advertising data by industry remains an arduous and expensive task. Despite the hurdles, our research is suggestive that updated studies of this nature do a good job of informing policy makers and antitrust authorities about overall competitive condition in the U.S. food sector.

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