Firm Efficiency, Advertising and Profitability:

Theory and Evidence

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Abstract

This paper presents a linear-city model where firms compete on price and levels of advertising, which affects the perceived utility of products. More cost efficient firms extend their advantage with more advertising, which leads to higher profits, if advertising is sufficiently effective. We test this relationship using a unique S&P sample. Our empirical results indicate a positive relationship between profits and levels of advertising for all model specifications.

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1 Introduction

In the third quarter of 2013, Mattress Firm Holding Corp. reported a 46% increase in profit, thanks to increased advertising that “helped drive customer traffic and sales growth.”\(^1\) Incidentally, Gannett Co. Inc. recently experienced a 12% decline in earnings attributable to lower advertising expenditure.\(^2\) Presumably, firms advertise to increase profitability, as indicated by a number of supporting studies (see, for example, Comanor and Wilson, 1974; Porter, 1974; Lambin, 1976; Erickson, 1992). However, identifying the reasons why one firm might advertise more than another is not a simple task. For example, a highly productive firm may be able to extend its market share with advertising. Alternatively, an inefficient firm may use advertising to compensate for its high cost of production. Explaining the relationship between firm efficiency, profits and advertising is the goal of the present work.

We first develop a linear city model where two firms decide on advertising expenditures then choose prices. Advertising is costly and has a status effect on the good perceived by consumers. The primary finding is that firms with an advantage in productive efficiency, advertise more and have higher profits if advertising is sufficiently cost effective. The stylized model provides testable theoretical predictions for a subsequent empirical study. The estimation results using Compustat data across several industries show support for the latter interpretation where advertising expenditures and profits are directly related. The results are consistent for OLS regression on differenced data and dynamic panel (the two-step Arellano-Bond generalized method of moments, or GMM) estimation on

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levels. Moreover, we show that industry concentration is not a significant variable in the estimations in contrast to the results in Bain (1951).

As a robustness test to mitigate problems of aggregation, we conduct similar estimations on firms within individual industries. Furthermore, to guard against endogeneity issues, estimations of a system of equations for data from manufacturing industries are included as well. The qualitative results are unchanged in both cases.

This paper belongs to the vast theoretical literature on market structure, conduct, and performance, or SCP.\footnote{Bagwell (2007) provides an excellent review on the economics of advertising. Our simple model is also related to other studies on network externalities, including Chwe (2001), Pastine and Pastine (2002), and Clark and Horstmann (2005). Hamilton (2009) examines the efficiency of informative advertising in a differentiated-good market in a linear city model.} One strand studies informative advertising in the framework of spatial models. Grossman and Shapiro (1984) study a circular Hotelling model where firms independently and simultaneously make pricing and advertising decisions. They conclude that product differentiation increases advertising. However, in contrast to the conclusions of most empirical studies, they argue that advertising does not boost profit due to enhanced price competition.

Early empirical studies on the relation between advertising and profitability mostly analyze inter-industry data (Telser, 1964; Nelson, 1974; Comanor and Wilson, 1967, 1974; Porter, 1974) and more recently firm- or brand-level data become prevalent (Thomas, 1989 on cigarettes and software drinks; Kwoka, 1993 on auto; Thomas, 1999 and Nevo, 2001 on ready-to-eat cereals; Tremblay and Tremblay, 2005 on beer). In an important study, Comanor and Wilson (1974) find that advertising has a significant and positive effect on profitability based on consumer-good industry-level data spanning three consecutive years. Using two industry-level samples, Sherman and Tollison (1971) show that the inclusion of cost variability, as opposed to advertising, better explains the profitability
in consumer-good and other industries. More recent studies generally provide supportive evidence for the latter conclusion. For example, Notta and Oustapassidis (2001) compare the effectiveness of media advertising using firm-level Greek data and argue that television advertising significantly affects profitability. More recently, Vardanyan and Tremblay (2006) show the importance of market efficiency to business success, both theoretically and empirically, in the brewing industry. These studies focuses on advertising effectiveness across different media (e.g., television, printing, and radio), while we evaluate the efficiency of marketing media at the aggregated level.

One of the major empirical challenges in studying SCP involves the endogeneity concern about advertising and market concentration, for which the literature proposes several approaches. Early studies usually estimate single equation models (Bain, 1956; Comanor and Wilson, 1979). Later studies often adopt a system of simultaneous equation models, which account for the interconnections among key elements of SCP in an industry. For example, Lambin (1976) estimates simultaneous equations using European brand-level data in the 1960s, but finds little evidence that advertising affects sales, especially in saturated industries. Pagoulatos and Sorensen (1981) estimate three equations of profitability, advertising, and concentration simultaneously and conclude that advertising affects profitability, which in turn affects both advertising and concentration. In addition to proposing a simultaneous equation model, their empirical contribution is to take into consideration several key control variables (i.e., international trade and interindustry differentials in price elasticities of demand) that had been missing in the previous studies. Using the Greek data, Vlachvei and Oustapassidis (1998) use 3SLS method to estimate a system of profitability, concentration and advertising model, and find supportive evidence of Pagoulatos and Sorensen’s (1981) main finding.
In a seminar work, Martin (1979) proposes a system of profit, concentration, and advertising equations which reflects long-run dynamic adjustments of industry concentration. More recently, Jeong and Masson (2003) establish a non-monotone relationship between steady-state profits and concentration dynamics, using a panel of Korean manufacturing data from 1978-1982. Further extending the approach, Iwasaki et al. (2008) apply a system of dynamic models to the U.S. brewing industry, taking into consideration the war of attrition, and argue that both advertising and economies of scale attribute to rising concentration level in the industry.

While previous studies use either cross-sectional or time-series data, our analysis contributes to the literature by applying the dynamic panel estimation method to a wide range of industries, as the Arellano-Bond GMM estimation offers a rigorous treatment for the potential simultaneity/endogeneity issues (Tregenna, 2009). Our paper also adds to the literature on the SCP paradigm by providing more recent evidence of the relationship between advertising and profitability.

The remainder of the paper is organized as follows. In Section 2, we develop a stylized model which results in several testable implications. In Section 3, we collect a unique data set from Standard & Pool’s Compustat to test the theoretical predictions derived in Section 2. Incorporating additional data from the Census Bureau, we also estimate a system of advertising, concentration, and profitability as a robustness test in Section 3. Finally, Section 4 offers several concluding remarks.

2 A Simple Model

To motivate the empirical analysis, this section describes a linear city model where advertising impacts consumer utility but is also an extra cost to the firms. Production costs
vary across firms. Consumers are distributed uniformly along the interval \([-1, 1]\), firm \(x\) is located at the left endpoint, and firm \(y\) is located at the right. The advertising by firms \(x\) and \(y\) are denoted \(a_x\) and \(a_y\) respectively and the prices they charge are \(p_x\) and \(p_y\). The utility to a consumer located at \(\omega \in [-1, 1]\) buying a good at firm \(i\) is \(U_i(\omega)\). The per unit cost of travel is \(d\), the intrinsic value of the good is \(f\), and the parameter \(\gamma\) measures the effect of advertising on the utility of the consumers of the goods of each firm, so the utility for the consumer using each firm is

\[
U_x(\omega) = f + \gamma a_x - p_x - d(1 + \omega),
\]

\[
U_y(\omega) = f + \gamma a_y - p_y - d(1 - \omega).
\]

Since the model includes heterogeneous marginal cost of production, one can assume without loss of generality that the intrinsic utility of the good \(f\) is the same for both firms. The effect of advertising on utility could be due to consumer perception, or status conferred on the seller, or both.

The consumer who is indifferent between the goods of the two firms is located at \(\tilde{\omega}\), where \(U_x(\tilde{\omega}) = U_y(\tilde{\omega})\). Computation gives an expression for \(\tilde{\omega}\).

\[
\tilde{\omega} = \frac{\gamma (a_x - a_y) - (p_x - p_y)}{2d}
\]

Firms must choose the level of advertising \(a\), for which they pay a cost \(C(a)\), then set prices. Assuming the market is covered, each consumer buys one good from the firm that gives higher utility. The cost of production is linear and heterogeneous with marginal
costs \(c_x, c_y\) for each firm. Hence, profits for firm \(x\) and firm \(y\) are

\[
\pi_x = (p_x - c_x) (\tilde{\omega} + 1) - C (a_x),
\]

\[
\pi_y = (p_y - c_y) (1 - \tilde{\omega}) - C (a_y).
\]

For given levels of advertising \(a_x\) and \(a_y\), the prices satisfying the Nash equilibrium are as follows.

\[
p_x = \frac{1}{3} \left[ \gamma (a_x - a_y) + 2c_x + c_y + 2d \right]
\]

\[
p_y = \frac{1}{3} \left[ \gamma (a_y - a_x) + 2c_y + c_x + 2d \right]
\]

Firms face increasing marginal costs of advertising. The cost function take the functional form \(C(a) = \frac{\delta}{2} a^2\), so the parameter \(\delta\) indicates the relative cost of advertising. Increased advertising allows firms to charge a higher price and gain market share.

Firm decisions on levels of advertising rely on backwards induction. Given the equilibrium prices (2), firms maximize profits across their own level of advertising to derive a best-reply function. The resulting Nash equilibrium advertising levels are as follows.

\[
a_x = \frac{\gamma}{3\delta} \left[ 2 + \frac{2}{3d} \left( c_y - c_x + \frac{4d\gamma^2}{3d\delta} \right) \right]
\]

\[
a_y = \frac{\gamma}{3\delta} \left[ 2 + \frac{2}{3d} \left( c_x - c_y + \frac{4d\gamma^2}{3d\delta} \right) \right]
\]

As one would expect, the level of advertising \(a_x\) is directly related to its effectiveness \(\gamma\) and inversely related to the cost, represented by \(\delta\). To derive intuition from the
equilibrium results, we compute the differences in advertising and profits.

\[ a_x - a_y = \frac{4\gamma}{9d\delta} (c_y - c_x) \]

The more efficient firm, meaning the marginal cost of production is lower, advertises more. Advertising serves to extend the advantage of a more efficient firms rather than compensating for poor productive ability.

The difference in profits depends solely on the difference in advertising.

\[ \pi_x - \pi_y = (a_x - a_y) \left[ \frac{2\gamma}{9} + \frac{3d\delta}{\gamma} - \frac{8\gamma^3}{27d\delta} \right] \]

As long as the term \([:\] > 0 is positive, firms with higher advertising have higher profits. It is possible for \([:\] to be negative for a very large parameter \(\delta\), meaning the cost of advertising is very high and there would be relatively little advertising. So in an industry with advertising, one would expect a direct relationship between production efficiency, advertising and profits. The primary goal of the empirical work is to test the predicted relationship between the latter two.

The above discussion is summarized in the following proposition.

**Proposition 1** For the model of two firms \(x\) and \(y\) given by equation (1) and (2), if firm \(x\) has lower marginal cost \(c_x < c_y\),

- then firm \(x\) advertises more \(a_x > a_y\)
- and firm \(x\) has greater profit \(\pi_x > \pi_y\) for \(\delta\) sufficiently small.
3 An Empirical Test

To test the theoretical implications shown in the previous section, we have collected a data set from S&P’s Compustat, which consists of more than 600 companies spanning between 1993 and 2012. As indicated in Appendix A, our sample includes seven industries (consumer discretionary, consumer staples, health care, financials, industrials, information technology, and telecommunication services). It should be noted that a dozen companies changed their report dates from one month to another, which sometimes resulting in two entries for the same company during a given year. To construct a valid panel data for analysis, we redefine the timing dimension, \(t\), of the second report and those from the subsequent years to be \(t + 1\) to avoid the repeated time series within a panel problem. After removing missing observations (particularly with advertising information), the final sample consists of a total of 5,638 company-year observations.

3.1 Estimation Strategy

Given the dynamic nature of the panel data, we are interested in modeling how advertising expenditures affect company profitability or

\[
\ln \pi_{it} = \beta_0 + \beta_1 \ln \pi_{i,t-1} + \beta_2 \ln a_{it} + \beta_3 \times MKT_{jt} + u_j + v_t + \varepsilon_{it}.
\]  

(3)

where the dependent variable, \(\pi_{it}\) refers to gross profit for company \(i\) in year \(t\), and \(\pi_{i,t-1}\) is the lagged dependent variable to capture the “goodwill” effects (Bagwell, 2007). \(\pi_{it}\) is obtained from converting gross profit margin, or \(\frac{Sale_{it} - Cogs_{it}}{Sale_{it}} \times 100\), to gross profit by multiplying \(Sale_{it}\) and then dividing by 100, where \(Sale_{it}\) represents company \(i\)’s gross

\footnote{Compustat provides the detailed information on balance sheet, income statement, and other financial data at the company level.}

\footnote{Usually the reporting dates were changed to either mid-year (i.e., Jun) or end-year (i.e., Dec).}
sales (the amount of actual billings to customers for regular sales completed during the period) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers (in millions of dollars) in year $t$ and $Cogs_{it}$ represents all costs directly allocated by company $i$ to production, such as material, labor and overhead (in millions of dollars) in year $t$.\textsuperscript{6}

The variable $\ln a_{it}$ denotes the logarithm of company $i$’s cost of advertising media (i.e., radio, television, and periodicals) and promotional expenses (measured in millions of dollars) in year $t$.\textsuperscript{7} Our econometric strategy is to test the result in the previous section, or the sign of $\beta_2$. If the conclusion in Proposition 1 holds, we would expect a positive relationship between gross profit and advertising expenses, or $\beta_2 > 0$. $MKT_{jt}$ denotes industry concentration within each Global Industry Classification Standard (or GICS) $j$ in year $t$ and is represented by two sets of variables to measure firm concentration in the subsequent analysis: $HHI_{jt}$ and the level of concentration. Based on the companies’ $Sale_{it}$ that are reported to S&P, $HHI_{jt}$ is the Herfindahl–Hirschman Index for industry $j$ in year $t$.\textsuperscript{8} We also run regressions with an alternative specification of concentration that separates firms into three categories defined as follows: unconcentrated or $UNCON_{jt}$ if $0.10 \leq HHI_{jt} < 0.15$, moderately concentrated or $MCON_{jt}$ if $0.15 \geq HHI_{jt} < 0.25$, and highly concentrated or $HCON_{jt}$ if $HHI_{jt} \geq 0.25$. Caution may be used to interpret the measure of market shares that is obtained from this calculation, as S&P’s Compustat only collects information from publicly-traded companies, but not private-owned entities. Thus, the market share used for this analysis may represent the upper bound of the actual number. Finally, $u_j$ and $v_t$ refer to GICS industry and year dummy variables, respectively.

\textsuperscript{6}Source: Compustat North America Data and Reference, 2013.
\textsuperscript{7}Source: Ibid.
\textsuperscript{8}Refer to Appendix A for a list of GICS industries included in the sample.
After removing missing observations, the final sample consists of 5,638 company-year level observations. Table 1 reports the summary statistics of these variables. Advertising expenses vary significantly across companies and so do gross profit margins. Regarding market concentration, the average $HHI$ in the sample is 0.181. Specifically, the majority (about 59\%) of the sampled industries are unconcentrated (i.e., $UNCON = 1$), about 20\% are moderately concentrated (i.e., $MCON = 1$) and the rest are highly concentrated (i.e., $HCON = 1$).

A major concern is potential serial correlation in the data. Indeed, the significant test statistic indicates the presence of serial correlation (Drukker, 2003).\(^9\) A simple way to deal with autocorrelation is to difference the data, or

$$\Delta \ln \pi_{it} = \Delta \beta_{it} + \beta_2 * \Delta \ln a_{it}.$$ 

We report the simple correlation between the first-differenced $\ln \pi$ and the first-differenced $\ln a$ in column (1), which indicates a statistically significant positive relationship between the two. This is consistent with the prediction arising from our stylized model in the previous section. Next, we turn to a more sophisticated estimation approach.

First, the endogeneity concern regarding advertising and profitability is well documented in the literature (Bagwell, 2007). For one, both profits and advertising expenditures are measured simultaneously, and thus the direction of causation is difficult to determine in a single period model. For another, advertising costs may be correlated with unobserved factors that might affect a firm’s profitability, such as launching a new product line or a new leadership. Similarly, the direction of causation between profits and concentration is another important empirical question in the literature. The GMM

\(^9\)The F-value for the autocorrelation test is 146.006 (Prob > F = 0.0000).
method provides an efficient tool to deal with possible endogeneity of both advertising and concentration in our analysis, using lagged levels of the dependent variable and the predetermined and endogenous variables as well as differences of the exogenous variables (Tregenna, 2009). Finally, along with the fact that the lagged dependent variable appears on the right-hand-side of equation (3), our sample has a short time dimension (19 years) but a large cross-section dimension (528 companies), making it suitable for employing the Arellano-Bond linear dynamic panel-data estimation method. Following the Arellano-Bond procedure, we take first-difference of equation (3) to remove the two panel-level fixed effects (i.e., industry and year fixed effects), or

\[ \Delta \ln \pi_{it} = \Delta \beta_0 + \beta_1 \Delta \ln \pi_{i,t-1} \beta_2 * \Delta \ln a_{it} + \beta_3 * \Delta MKT_{jt} + \Delta \varepsilon_{it}. \]  \hspace{1cm} (4)

The pooled OLS (POLS) estimators from equation (3) are inconsistent given that \( \Delta \ln \pi_{i,t-1} \) might be correlated with \( \Delta \varepsilon_{it} \), as well as the serial correlation between the differenced error terms, \( \Delta \varepsilon_{it} \) and \( \Delta \varepsilon_{i,t-1} \). Arellano and Bond (1991) propose a full GMM estimation, which uses the lagged endogenous and exogenous variables as instruments to form moment conditions.

We apply the two-step Arellano-Bond GMM estimation to equation (4), accounting for the possibility that \( \Delta \ln a_{it} \) and \( \Delta MKT_{jt} \) may be endogenous. In the first step, the identity matrix is used as the weighting matrix in the GMM objective function to obtain a consistent but inefficient estimator. In the second step, residuals from the first step are used to compute the optimal weighting matrix in the GMM objective function. The resulting estimator from this step is both consistent and efficient.\(^{10}\)

\(^{10}\)See Greene [2002] and Wooldridge [2010] for detailed discussions on the Arellano-Bond GMM estimation.
3.2 Results

Table 3 presents the results of the two-step Arellano-Bond GMM estimation. For comparison, we estimate equation (3) using OLS with standard errors calculated by using the Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance matrix. These results are reported in columns (2) and (3) of Table 3.

In Table 3, the estimated coefficients for \( \ln a \) are positive and statistically significant and provide supportive evidence for Proposition 1. The elasticity of gross profit with respect to advertising expenses is 0.117 in both columns (2) and (3), while the elasticity becomes 0.23 in the last two columns. Therefore, the results correspond to the situation where advertising is cost effective, the condition in Proposition 1 is satisfied, and efficient (in terms of production costs) firms advertise more.

There is also some evidence that as an industry becomes more concentrated, the gross profit rises, *ceteris paribus*. However, when breaking down by the level of industry concentration, there seems no statistical difference regarding profitability between more concentrated industries and less-concentrated ones. This observation indicates the absence of obvious tacit collusion in terms of advertising strategies among the sampled firms, even in relatively concentrated industries. Recall that our measure of market share might overestimate the actual value since only publicly traded companies are included in the calculation. As long as the omission of any private company in a given industry remains consistent during the sample period, it should not cause serious estimation bias.

The results of the Arellano-Bond test for serial correlation in the first-differenced errors and the Sargan test are also presented in Table 3. The tests of second-order autocorrelation and of overidentification are overall satisfactory.

The sample consists of companies from seven different industry groups, including in-
dustrials, consumer staples, consumer discretionary, health care, financials, information technology (IT), and telecommunication services. One would thus expect sufficient disparity in making advertising decisions from industry to industry. Moreover, the existing literature is concerned about pooling data across industries (Iwasaki et al., 2008). Taking into consideration industry heterogeneity, we estimate equation (4) by each industry and report the results in Table 4.\textsuperscript{11} Consistent with the findings in Table 3, the return of advertising is statistically significant and positive for firms in telecommunication services, consumer discretionary, consumer staples, and health care. Specifically, each additional 1\% in advertising expenditures leads to a 0.41\% increase in the gross profit margin on average in the telecommunication industry, compared to 0.30\% in consumer discretionary, 0.17\% in consumer staples, and 0.09\% in health care, respectively. These findings are consistent with anecdotal evidence that leading telecommunication companies such as AT&T and Verizon had been ranked top advertisers during the sample period, according to Advertising Age.\textsuperscript{12} In contrast, we do not find a significant effect of advertising on profits for the sampled firms in the industrials, financials, and IT industries.

In light of industry heterogeneity, in the next section, we re-examine the relationship between advertising and profitability, taking into consideration market concentration. The analysis focuses on the sampled manufacturing industries, following previous empirical studies on SCP (Strickland and Weiss, 1976; Martin, 1979; Jeong and Masson, 2003). Aside from using more recent data, our analysis also adds to the literature by relating advertising, concentration, and profitability using firm-level data, rather than the industry level.

\textsuperscript{11}Note that market structure variables are not included for the industries with a single sub-industry. See Appendix A for more information.
\textsuperscript{12}Source: Advertising Age is a leading magazine on marketing and media. For more information, visit http://www.adage.com/.
3.3 A robustness test

As a robustness test, we now estimate a simultaneous-equations system of advertising, concentration, and profitability in the manufacturing industries (e.g., Martin, 1979; Jeong and Masson, 2003; Iwasaki et al., 2008). The results from the system estimation are consistent with those in the previous section.

For the purpose of this task, we have gathered available data from S&P’s Compustat, the Census Bureau, and the Bureau of Labor Statistics (BLS) to construct additional variables. Table 2 reports the summary statistics of the variables used for this section. Appendix B presents detailed variable definitions, along with data source when applicable. Focusing on the key variables, the mean of the advertising-sales ratio \((as)\) is 0.052, and that of the profit-margin \((profm)\) is 0.361, while the average market concentration \((hhi)\) is 0.187, comparable to the mean of 0.181 in the full sample.

Several issues arise when assembling this subsample. First, not all 528 companies in the original sample reported the information on capital expenditures and 3-year sales growth during the entire sample period (1993-2012). In addition, due to recent mergers and acquisitions (such as in the airline industry), acquired companies no longer report their financial data to S&P as they did during our first data collection in 2012. Consequently, the sample size reduces to 3,801 observations. Second, the annual information on personal consumption expenditures is only available from 1997 from the BLS, which in effect further reduces the sample size to 1,685. Third, by incorporating the import data, we automatically exclude non-manufacturing industries (refer to Appendix A for a list of these industries) from the sample. As a result, the subsample for the system estimation includes 889 observations with a total of 96 companies across 9 GICS industries.

Note that the Census Bureau ceased using the Standard Industry Code (SIC) classifi-
cation system in 1997, and has since adopted the North American Industry Classification System (NAICS). A data conversion issue emerges to assemble a usable data set that effectively replicates the Martin (1979) analysis, which relies on the 1963 and 1967 Census data. Nevertheless, we have used multiple concordances to combine data from various sources with the full sample, although this process unavoidably contributes to the loss of observations.\textsuperscript{13} Related, the input-output data from the BLS are indexed under industry sector codes, a different classification system from what Compustat uses. Thus, these two sets of codes do not match perfectly. In many cases, two or more NAICS codes correspond to a single sector code, making personal consumption expenditure variable more aggregated than other variables (Strickland and Weiss, 1976) (hereafter SW). Similar aggregation issues arise when combining industry import data from with the sample, as multiple Harmonized System (HS) codes often correspond to a single SIC code.

In particular, the system of advertising, concentration, and profitability equations includes

\begin{equation}
as_{it} = \alpha_0 + \alpha_1 \times \text{durable}_j + \alpha_2 \times \text{pces}_k + \alpha_3 \times \text{imps}_{jt} + \alpha_4 \times \text{gr}_{i,t-3} + \alpha_5 \times \text{prof}_m_{it} \tag{5} + \alpha_5 \times \text{HHI}_{jt} + \alpha_6 \times \text{HHI}_{jt}^2 + \varepsilon_{as}^{as}
\end{equation}

\begin{equation}
\text{HHI}_{jt} = \beta_0 + \beta_1 \times \text{region}_j + \beta_2 \times \text{pces}_k + \beta_3 \times \text{gr}_{it} + \beta_4 \times \text{as}_{it} + \beta_5 \times \text{mess}_{jt} + \beta_6 \times \text{cdr}_{jt} + \beta_7 \times \text{prof}_m_{i,t-1} + \beta_8 \times \text{HHI}_{j,t-1} + \varepsilon_{ij}^{hhi} \tag{6}
\end{equation}

\begin{equation}
\text{prof}_m_{it} = \gamma_0 + \gamma_1 \times \text{prof}_m_{i,t-1} + \gamma_2 \times \text{region}_j + \gamma_3 \times \text{pces}_k + \gamma_4 \times \text{imp}_{kt} + \gamma_5 \times \text{gr}_{i,t-3} + \gamma_6 \times \text{as}_{it} + \gamma_7 \times k_{si} + \gamma_8 \times \text{mess}_{jt} + \gamma_9 \times \text{cdr}_{jt} + \gamma_10 \times \text{HHI}_{jt} + \varepsilon_{ij}^{prof} \tag{7}
\end{equation}

where the \(\alpha\)'s, \(\beta\)'s, and \(\gamma\)'s are parameters and the \(\varepsilon\)'s are error terms. In addition, the subscripts \(i, j, k, t\) denote company \(i\), GICS industry \(j\), SIC industry \(k\), and year \(t\), respectively.\textsuperscript{14}

\textsuperscript{13}Refer to Appendix B for a detailed explanation for data conversion.

\textsuperscript{14}Note that SIC and GICS codes do not match perfectly and sometimes multiple SIC codes correspond to a single GICS code. For this reason, we use both industry levels in the equations.
Equation (5) regresses the firm advertising-sales ratio \((as_{it})\) on the durable good industry dummy \((d_{urt})\), the ratio of industry personal consumption expenditures to sales \((pces_{kt})\), industry imports \((imp_{kt})\), growth rate of firm sales \((gr_{it})\), and firm profit margin \((profm_{it})\). In addition, the level of industry concentration \((HHI_{jt})\) and its square term \((HHI_{jt}^2)\) are also included to account for a nonlinear relationship between advertising and concentration (Martin, 1979; Iwasaki et al., 2008). Equation (6) represents the concentration model and includes the advertising-sales ratio \((as_{it})\), the lagged concentration level \((HHI_{jt,t-1})\) and the lagged profit margin \((profm_{it,t-1})\) as explanatory variables (Martin, 1979). In addition to \(pces_k\) and \(gr_{it}\), we also control for industry technical entry conditions (Caves et al., 1975), industry minimum efficient scale to sales ratio \((mess_{jt})\) and cost disadvantage ratio \((cdr_{jt})\), as well as the regional industry dummy \((region_j)\) that allows market concentration to vary in industries mainly serving regional or local markets (Martin, 1979). Equation (7) is the profitability equation and adds the lagged profit margin \((profm_{it,t-1})\) and the firm capital-sales ratio \((ks_{it})\), along with other explanatory variables. As in Section 3.1, \(profm_{it,t-1}\) is to control for the “goodwill” effects (Bagwell, 2007). Given the three endogenous variables and potential correlation across equations, we estimate the system using three-stage least squares (3SLS) (Zellner and Theil, 1962).

In Table 5, the first three columns represent a system of equations similar to that of SW, with advertising, concentration, and profitability equations in each column, respectively. The two-stage least squares (2SLS) estimates in the three equation are largely qualitatively the same as SW (1976, Table 2, p.1117). For example, concentration has a nonlinear and statistically significant effect on advertising in column (1), and the effect of advertising on profitability is positive and statistically significant in column (3). However, contrast to the result in SW, advertising appears to be inversely related to industry concentration in the subsample (column (2)).

Turning to our preferred model specifications, the last three columns of Table 5, we find that most 3SLS estimates are consistent with those in Martin (1979, Table 1, p.645). In particular, the effects of concentration and its quadratic term on advertising are statistically significant in column (4), and the estimates on \(profm_{it,t-1}\) and \(HHI_{jt,t-1}\) in
column (5) suggest the dynamic nature of industry concentration (Martin, 1979; Iwasaki et al., 2008). Most importantly, consistent with the findings in Section 3.2, advertising positively affects profit margin and the estimate is statistically significant in the sampled manufacturing industries (column (6)).

Furthermore, in all three equations, the estimates for $p_{ces_{kt}}$ are positive and statistically significant, while those for $im_{p_{s_{kt}}}$ are not. The mixed results on the demand-side variables are, to some extent, in line with those in Martin (1979) where consumer and producer good industries are estimated separately. As expected, technical entry conditions ($mess_{jt}$ and $cdr_{jt}$) are important explanatory variables in the concentration equation (column (5)). However, both become statistically insignificant in the profit equation.

4 Conclusion

In this paper, we study the relationship between advertising expenditures and production efficiency through a stylized Hotelling model and an empirical analysis. In the theoretical analysis firms strategically interact on both price and advertising expenditures, which affect consumer utility. The model demonstrates that advertising expenditures are directly related to profits for industries with significant advertising expenditures.

The empirical results based data across many industries should be comforting to advertisers. Firms who advertise have higher profits. The theoretical result thereby implies that firms with greater advertising do so to advance their existing advantages in production efficiency. On the methodology end, this paper adds to the vast literature on market structure, conduct, and performance through the use of the dynamic panel estimation method. Naturally, analysis using data aggregated across industries should be supplemented by more micro-oriented approaches using inter-industry data or case studies. Formal studies of the interaction between advertising and market structures such as oligopoly is another area for future work.
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