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QUAECO-921; No. of Pages 9
ARTICLE IN PRESS
The Quarterly Review of Economics and Finance xxx (2016) xxx–xxx
Contents lists available at ScienceDirect
The Quarterly Review of Economics and Finance
journal homepage: www.elsevier.com/locate/qref

Firm efficiency, advertising and profitability: Theory and evidence

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ARTICLE INFO

Article history:
Received 15 September 2014
Received in revised form 9 February 2016
Accepted 10 April 2016
Available online xxx

JEL classification:
D21
D22
M37

Keywords:
Advertising
Market structure
Performance
Hotelling

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.

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.”[2] Incidentally, Gannett Co. Inc. recently experienced a 12% decline in earnings attributable to lower advertising expenditure.[3] Presumably, firms advertise to increase profitability, as indicated by a number of supporting studies (see, for example, Comanor & Wilson, 1974; Erickson, 1992; Lambin, 1976; Porter, 1974). 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 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.[4] One strand

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[2] *Source*: “Mattress Firm profit rises 46% as ads boost sales” by Tess Stynes, December 4, 2013, *Wall Street Journal* (http://www.marketwatch.com/story/mattress-firm-profit-rises-46-as-ads-boost-sales-2013-12-04).
[3] *Source*: “Gannett Q4 profit down 12% on lower ad spending” by Kerry Feltner, *Rochester Business Journal*, February 5, 2014 (http://www.rbj.net/article.asp?aID=205400).
[4] Bagwell (2007) provides an excellent review on the economics of advertising. Our simple model is also related to other studies on network externalities, including

http://dx.doi.org/10.1016/j.qref.2016.04.004
1062-9769/

Please cite this article in press as: Chen, J., & Waters, G. Firm efficiency, advertising and profitability: Theory and evidence. *The Quarterly Review of Economics and Finance* (2016), http://dx.doi.org/10.1016/j.qref.2016.04.004

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 (Comanor & Wilson, 1967, 1974; Nelson, 1974; Porter, 1974; Telser, 1964) and more recently firm- or brand-level data become prevalent (Thomas, 1989 on cigarettes and software drinks; Kwoka, 1993 on auto; Thomas, 1989 and Nevo, 2001 on ready-to-eat cereals; Tremblay & 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 1951; Comanor & Wilson, 1967). 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 to 1982. Further extending the approach, Iwasaki, Seldon, and Tremblay (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 γ 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 $\widehat{\omega}$, where $U_x(\widehat{\omega}) = U_y(\widehat{\omega})$. Computation gives an expression for $\widehat{\omega}$.

$$\widehat{\omega} = \frac{\gamma(a_x - a_y) - (p_x - p_y)}{2d} \quad (1)$$

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

$$\pi_x = (p_x - c_x)(\widehat{\omega} + 1) - C(a_x),$$
$$\pi_y = (p_y - c_y)(1 - \widehat{\omega}) - C(a_y).$$

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

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

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

Firms face increasing marginal costs of advertising. The cost function take the functional form $C(a) = \frac{\delta}{2}a^2$, so the parameter

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.

δ 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 γ and inversely related to the cost, represented by δ. 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 $[\cdot]>0$ is positive, firms with higher advertising have higher profits. It is possible for $[\cdot]$ to be negative for a very large parameter δ, 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 Eqs. (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 δ 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.[5] 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,[6] 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 5638 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

$$\ln\pi_{it} = \beta_{0t} + \beta_1 * \ln\pi_{i,t-1} + \beta_2 * \ln a_{it} + \beta_3 * MKT_{jt} + u_j + v_t + \varepsilon_{it}. \tag{3}$$

where the dependent variable, π_{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). π_{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 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.

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.[7] Our econometric strategy is to test the result in the previous section, or the sign of β_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.[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 $0.10 \leqslant HHI_{jt} < 0.15$, moderately concentrated or $MCON_{jt}$ if $0.15 \geqslant HHI_{jt} < 0.25$, and highly concentrated or $HCON_{jt}$ if $HHI_{jt} \geqslant 0.25$. 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.

After removing missing observations, the final sample consists of 5638 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

[5] Compustat provides the detailed information on balance sheet, income statement, and other financial data at the company level.

[6] Usually the reporting dates were changed to either mid-year (i.e., Jun) or end-year (i.e., Dec).

[7] *Source*: Compustat North America Data and Reference, 2013.

[8] Refer to Appendix A for a list of GICS industries included in the sample.

Table 1
Summary statistics for the full sample (unit: millions of dollars).

Variable	Obs	Mean	Std. Dev.	Min	Max
a	5638	250.0219	757.6943	0.001	8162.093
π	5638	2,255,631.000	17,000,000.000	−246,862.100	525,000,000.000
ln(a)	5638	2.600	2.932	−6.908	9.007
lnπ	5512	7.375	5.162	−17.728	20.079
UNCON	5638	0.585	0.493	0	1
MCON	5638	0.204	0.403	0.000	1
HCON	5638	0.212	0.409	0	1
HHI	5638	0.181	0.144	0.067	1

Table 2
Summary statistics for the subsample.

Variable	Obs	Mean	Std. Dev.	Min	Max
as	3593	0.052	0.261	0	10
hhi	3593	0.187	0.146	0.067	1
hhi2	3593	0.056	0.096	0.004	1
profm	3593	0.361	0.593	−32.000	0.983
gr	3593	0.027	3.241	−80	166.667
ks	3593	0.071	0.204	0	10.667
durable	3593	0.066	0.248	0	1
region	3593	0.342	0.475	0	1
pces	1685	0.015	0.442	0	16.499
imps	889	0.103	0.380	0	7.897
cdr	3593	0.075	0.061	0	0.304
mess	3593	0.246	0.186	0.085	1

correlation (Drukker, 2003).[9] A simple way to deal with autocorrelation is to difference the data, or

$$\Delta \ln \pi_{it} = \Delta \beta_{0t} + \beta_2 * \Delta \ln a_{it}.$$

We report the simple correlation between the first-differenced lnπ 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 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 Eq. (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 Eq. (3) to remove the two panel-level fixed effects (i.e., industry and year fixed effects), or

$$\begin{aligned}\Delta \ln \pi_{it} &= \Delta \beta_{0t} + \beta_1 * \Delta \ln \pi_{i,t-1} + \beta_2 * \Delta \ln a_{it} \\ &\quad + \beta_3 * \Delta MKT_{jt} + \Delta \varepsilon_{it}. \qquad (4)\end{aligned}$$

The pooled OLS (POLS) estimators from Eq. (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 Eq. (4), accounting for the possibility that $\Delta \ln a_{it}$ and ΔMKT_{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]

3.2. Results

Table 3 presents the results of the two-step Arellano-Bond GMM estimation. For comparison, we estimate Eq. (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

[9] The F-value for the autocorrelation test is 146.006 (Prob > F = 0.0000).

[10] See Greene (2002) and Wooldridge (2010) for detailed discussions on the Arellano-Bond GMM estimation.

Table 3
Regression results.

Dependent variable	(1) Δ Ln(π) Pooled OLS	(2) Ln(π) Pooled IV	(3) Ln(π) Pooled IV	(4) Ln(π) Arellano-Bond	(5) Ln(π) Arellano-Bond
Lagged Ln(π)		0.913*** (0.014)	0.913*** (0.014)	0.66*** (0.002)	0.67*** (0.005)
Δ Ln(a)	1.370*** (0.014)				
Ln(a)		0.117*** (0.021)	0.117*** (0.021)	0.23*** (0.001)	0.23*** (0.005)
MCON		0.004 (0.046)		-0.02*** (0.002)	
HCON		0.116 (0.099)		0.01** (0.004)	
HHI			0.976* (0.529)		0.01 (0.121)
Constant	0.021 (0.019)	0.742*** (0.082)	0.634*** (0.099)	1.91*** (0.017)	1.82*** (0.042)
GICS industry dummies		Y	Y	N	N
Year dummies		Y	Y	Y	Y
Arellano-Bond test for autocorrelation[a] (p-value)				0.1339	0.0925
Sargan test of overidentification[b] (p-value)				0.9989	0.9810
Observations	5419	4771	4771	4148	4148
R-squared	0.6541	0.9861	0.9861		
Number of id				528	528

Note: Standard errors in parentheses. The Pooled IV standard errors are robust to heteroscedasticity and serial correlation, and the estimates were obtained using ivreg2 in Stata 14. The GMM standard errors are obtained from an optimal weighting matrix, and the estimates were from using xtabond in Stata 14.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

[a] The null hypothesis is that there is no autocorrelation in first-differenced errors.

[b] The null hypothesis is that overidentifying restrictions are valid.

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 industrials, 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 Eq. (4) by each industry and report the results in Table 4.[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.[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 (Jeong & Masson, 2003; Martin (1979); Strickland and Weiss, 1976). 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.

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; Iwasaki et al., 2008; Jeong & Masson, 2003). 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.

[11] Note that market structure variables are not included for the industries with a single sub-industry. See Appendix A for more information.

[12] *Source*: *Advertising Age* is a leading magazine on marketing and media. For more information, visit http://www.adage.com/.

Table 4
Regression results: by industry group.

Dependent Var: Ln(π) Industry group	(1) Industrials	(2)	(3) Consumer staples	(4)	(5) Consumer discretionary	(6)	(7) Health care	(8)	(9) Financials	(10)	(11) IT	(12)	(13) Telecomm	(14)
Lagged Ln(π)	0.11	0.11	0.64***	0.66***	0.68***	0.70***	0.51***	0.51***	0.44***	0.56***	0.12	0.12	0.53***	0.53***
	(0.732)	(0.732)	(0.017)	(0.016)	(0.003)	(0.003)	(0.059)	(0.059)	(0.115)	(0.085)	(0.700)	(0.700)	(0.118)	(0.118)
Ln(a)	0.34	0.34	0.16***	0.17***	0.29***	0.30***	0.09**	0.09**	0.08	-0.00	-0.03	-0.03	0.41***	0.41***
	(0.741)	(0.741)	(0.008)	(0.014)	(0.004)	(0.004)	(0.039)	(0.039)	(0.164)	(0.159)	(0.525)	(0.525)	(0.044)	(0.044)
MCON			-0.06*		-0.05***				0.11					
			(0.031)		(0.005)				(0.114)					
HCON			-0.10**		-0.33***				0.09					
			(0.040)		(0.034)				(0.221)					
HHI				0.23		1.61***				1.49				
				(1.015)		(0.055)				(1.793)				
Constant	8.77	8.77	2.16***	1.86***	1.71***	1.11***	3.08***	3.08***	11.15	14.26	8.41	8.41	3.26***	3.26***
	(8.078)	(8.078)	(0.123)	(0.136)	(0.025)	(0.025)	(0.516)	(0.516)	(9.111)	(8.893)	(5.591)	(5.591)	(1.048)	(1.048)
Observations	158	158	1,010	1,010	1,993	1,993	285	285	241	241	142	142	318	318
Number of id	18	18	123	123	243	243	46	46	42	42	14	14	42	42

Note: Standard errors in parentheses.
All model specifications include a set of year dummies.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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 1685. 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) classification 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.[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

$$\begin{aligned} as_{it} &= \alpha_0 + \alpha_1 * durable_j + \alpha_2 * pces_k + \alpha_3 * imps_{jt} + \alpha_4 * gr_{i,t-3} \\ &\quad + \alpha_5 * profm_{it} + \alpha_5 * HHI_{jt} + \alpha_6 * HHI_{jt}^2 + \varepsilon_{ijt}^{as} \end{aligned} \tag{5}$$

$$\begin{aligned} HHI_{jt} &= \beta_0 + \beta_1 * region_j + \beta_2 * pces_k + \beta_3 * gr_{it} + \beta_4 * as_{it} \\ &\quad + \beta_5 * mess_{jt} + \beta_6 * cdr_{jt} + \beta_7 * profm_{i,t-1} \\ &\quad + \beta_8 * HHI_{j,t-1} + \varepsilon_{ijt}^{hhi} \end{aligned} \tag{6}$$

$$\begin{aligned} profm_{it} &= \gamma_0 + \gamma_1 * profm_{i,t-1} + \gamma_2 * region_j + \gamma_3 * pces_k \\ &\quad + \gamma_4 * imp_{kt} + \gamma_5 * gr_{i,t-3} + \gamma_6 * as_{it} + \gamma_7 * ks_{it} \\ &\quad + \gamma_8 * mess_{jt} + \gamma_9 * cdr_{jt} + \gamma_{10} * HHI_{jt} + \varepsilon_{ijt}^{prof} \end{aligned} \tag{7}$$

where the α's, β's, and γ's are parameters and the ε'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.[14]

Eq. (5) regresses the firm advertising-sales ratio (as_{it}) on the durable good industry dummy (dur_j), the ratio of industry personal consumption expenditures to sales ($pces_k$), 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

[13] Refer to Appendix B for a detailed explanation for data conversion.

[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.

Table 5
System estimates of advertising, concentration and profit equations.

Variables	(1) Advertising-sales ratio	(2) HHI	(3) Profit-cost margin	(4) Advertising-sales ratio	(5) HHI	(6) Profit-cost margin
	Two-stage Least Square (2SLS) estimates			Three-stage Least Square (3SLS) estimates		
region			0.0323***		-0.0207***	−0.0163
			(0.007)		(0.004)	(0.014)
durable	−0.0207***			−0.0261***		
	(0.004)			(0.006)		
pces	1.4127***	0.0370***		1.4085***	2.0165***	1.5955***
	(0.025)	(0.009)		(0.033)	(0.248)	(0.461)
imps				−0.0168		−0.0076
				(0.011)		(0.052)
gr	0.1679***		0.2790***	0.1636***	0.2728***	0.4716***
	(0.005)		(0.006)	(0.007)	(0.037)	(0.063)
as		−0.0588***	1.8072***		−1.1925***	0.6694**
		(0.015)	(0.046)		(0.127)	(0.271)
ks			0.1248***			0.0637
			(0.032)			(0.047)
mess		0.7780***	−0.6978***		0.4641***	−0.0053
		(0.003)	(0.141)		(0.031)	(0.243)
cdr					−0.1912***	−0.0432
					(0.031)	(0.050)
profm	0.0488***			0.1077***		
	(0.007)			(0.021)		
profm($t-1$)			0.8371***		0.1128***	0.8337***
			(0.015)		(0.029)	(0.033)
HHI	0.3817***		0.8377***	0.2803***		−0.0403
	(0.039)		(0.181)	(0.052)		(0.298)
HHI^2	−0.5217***			−0.3384***		
	(0.061)			(0.073)		
HHI($t-1$)					0.4270***	
					(0.030)	
Constant	−0.0202***	−0.0023***	−0.0212**	−0.0170**	0.0356***	0.0415**
	(0.004)	(0.001)	(0.009)	(0.008)	(0.012)	(0.018)
R-squared	0.9783	0.9717	0.7975	0.9899	0.7818	0.9597

Note: Standard errors in parentheses. * $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

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). Eq. (6) represents the concentration model and includes the advertising-sales ratio (as_{it}), the lagged concentration level ($HHI_{j,t-1}$) and the lagged profit margin ($profm_{i,t-1}$) as explanatory variables (Martin, 1979). In addition to $pces_k$ and gr_{it}, we also control for industry technical entry conditions (Caves, Khalilzadeh-Shirazi, & Porter, 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). Eq. (7) is the profitability equation and adds the lagged profit margin ($profm_{i,t-1}$) and the firm capital-sales ratio (ks_{it}), along with other explanatory variables. As in Section 3.1, $profm_{i,t-1}$ 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 & 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 adverting 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 $profm_{i,t-1}$ and $HHI_{j,t-1}$ 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 $pces_{kt}$ are positive and statistically significant, while those for $imps_{kt}$ 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 advertising0 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.

Acknowledgements

We are grateful to an anonymous reviewer for helpful comments and suggestions. We also thank Qinyang Sha, Jeff Barr, Yoonho Choi, Raina Kirchner, and Edna Mensah for their excellent research assistance. Finally, we acknowledge the generous assistance of the staff at Economic Indicators Division and Economy-Wide Statistics Division of the Census Bureau, and the Bureau of Labor Statistics.

Appendix A. List of sub-industries in the sample

Sub-industry code	Sub-industry	Industry group	Regional/local business	Manufacturing
20302010	Airlines	Industrials	N	N
25102010	Automobile manufacturers	Consumer discretionary	N	Y
25201010	Consumer electronics	Consumer discretionary	N	Y
25203020	Footwear	Consumer discretionary	N	Y
25301020	Hotels, resorts &cruise lines	Consumer discretionary	N	N
25301040	Restaurants	Consumer discretionary	Y	N
25401025	Cable &satellite	Consumer discretionary	N	N
25401030	Movies &entertainment	Consumer discretionary	N	Y
25502020	Internet retail	Consumer discretionary	N	N
25503010	Department stores	Consumer discretionary	Y	N
25503020	General merchandise stores	Consumer discretionary	Y	N
25504030	Home improvement retail	Consumer discretionary	Y	N
25504040	Specialty stores	Consumer discretionary	N	N
30101030	Food retail	Consumer staples	Y	N
30101040	Hypermarkets and super centers	Consumer staples	Y	N
30201010	Brewers	Consumer staples	N	Y
30202030	Package food &meats	Consumer staples	Y	Y
30302010	Personal products	Consumer staples	N	Y
35202010	Pharmaceuticals	Health care	N	Y
40101015	Regional banks	Financials	Y	N
40202010	Consumer finance	Financials	N	N
40203020	Investment banking &brokerage	Financials	N	N
40301040	Property &casualty insurance	Financials	N	N
40402070	Specialized real estate investment trusts	Financials	N	N
45202010	Computer hardware	Information technology	N	Y
50101020	Integrated telecommunication services	Telecommunication services	N	N

Source: Compustat North America Data and Reference, 2013.

Appendix B. Variable definitions

Variable name	Definition	Data source
as_{it}	Company *i*'s advertising-sales ratio in year *t*; a firm-level variable	Compustat
cdr_{jt}	Cost disadvantage ratio for sub-industry *j* in year *t*; a GICS-level variable	
ks_{it}	Company *i*'s capital-sales ratio in year *t*; a firm-level variable	Compustat
$durable_j$	The durable good industry dummy is defined as one if sub-industry *j* is classified as producing durable goods and zero otherwise; a GICS-level variable	
$profm_{it}$	Company *i*'s gross profit-cost margin in year *t*; a firm-level variable	Compustat
gr_{it}	Company *i*'s sales growth rate for the last three years; a firm-level variable	Compustat
HHI_{jt}	Hirfindahl-Hirschman Index for sub-industry *j* in year *t*; a GICS-level variable	
$imps_{kt}$	Import[a] (measured in dollars) to sales ratio for SIC industry *j* in year *t*; a SIC-level variable	Census Bureau
$mess_{jt}$	Minimum efficient scale to sales ratio for sub-industry *j* in year *t*; a GICS-level variable	
$pces_{kt}$	Personal consumption expenditures[b] (measured in dollars) to sales ratio for SIC industry *k* in year *t*; a SIC-level variable	Bureau of Labor Statistics
$region_j$	the regional industry dummy is defined as one if sub-industry *j* is identified as regional or local and zero otherwise; a GICS-level variable	

Note:
[a] Harmonized System (HS) District-level annual import data (1993–2012) were downloaded from USA Trade Online (https://usatrade.census.gov/), and then converted to match the SIC codes in the sample using the 1999 Export and Import HS-SIC Concordances, which were generously provided by the Census Bureau upon request.
[b] Annual personal consumption expenditure data (1997–2012) were extracted from Input–Output matrices (compressed in a zip file named "input-output.zip") assembled by the Bureau of Labor Statistics (http://www.bls.gov/emp/ep_data_input_output_matrix.htm). A total of 16 Excel files were downloaded for the nominal dollar input–output data from 1997 to 2012, where the first column denoted "(industry and commodity) sector numbers" and the second column "personal consumption expenditure ($)." Next, a series of conversions between classification systems were performed: (1) the input–output data were converted from sector numbers to three- to four-digit 2012 NAICS (using the file named "sect313.xlsx" in the same zip file); (2) three- to four-digit 2012 NAICS codes were then matched with six-digit 2012 NACIS; (3) these data were then converted to match the SIC codes in the sample using three sets of Concordances: 2012 NAICS to 2007 NAICS, 2007 NAICS to 2002 NAICS, and 2002 NAICS TO 1987 SIC, given the limited availability on the direct relationships between classification systems over time (https://www.census.gov/eos/www/naics/concordances/concordances.html).

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