

An Investigation of Causality between Advertising and Operating Activity: Macro and Micro Evidence from Japan

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Abstract: The relationship between advertising and operating activity is one of the topical issues in marketing and economic research. However, micro data have not been analyzed. In this paper, causality between them is empirically examined by using macro and micro data and applying four models-conventional Vector Autoregressive (VAR) model, vector error correction model, homogeneous parameter panel VAR model and heterogeneous parameter panel VAR model. Granger causality tests are applied to Japanese advertising and operating activity data. Empirical results indicate that operating activity causes advertising and not vice versa.

Keywords: Advertising, Granger Causality, Operating Activity, Panel VAR

Introduction

Since the seminal work by Wagner (1941), the causality relationship between advertising and sales has been one of the topical issues in marketing and economic research. Wagner (1941) measured the annual volume of advertising in magazines and found that changes in advertising lagged behind changes in industrial activity. In addition, Blank (1962) found that, in national advertising, peaks follow the business cycle while troughs precede the troughs in the business cycle. Since then, a large number of empirical studies have investigated the causality relationship.

Since the present paper considers only statistical papers using the Granger (1969) causality test, the following papers should be reviewed. Ashley *et al.* (1980) first found that fluctuations in consumption cause fluctuations in advertising and not the other way around. Furthermore, empirical results obtained by Hsu *et al.* (2002) suggest the presence of a causality running from aggregate sales to advertising. Empirical studies on reverse causality are scarce. One exception is the work by Fridriksson and Zoega (2012) who provided empirical evidence that changes in the volume of advertisements precede changes in investment. Dual causality is empirically confirmed by Jung and Seldon (1995) for advertising and consumption. Finally, no causality relationship is presented by Chowdhury (1994).

One of the reasons for mixed empirical results is the existence of two driving forces in the causality relationship between advertising and sales. The first force is that advertising stimulates sales, which is advocated by Galbraith (1967). As discussed by Hsu *et al.* (2002), the Galbraith hypothesis implies that higher personal

income from economic development causes more advertising, which in turn leads to increased sales. On the other hand, the second driving force can work so that sales stimulate advertising. The advertising budgeting process can be described as decision making under uncertainty (Farris and Buzzell, 1979). This process indicates that sales cause advertising. Which force is strongest can be determined not theoretically but empirically.

However, the fundamental drawback of previous studies is that they have not conducted micro data analysis. This study aims to examine the causality between advertising and operating activity using macro and micro data in Japan. To the best of my knowledge, this study is the first to do so. The reason of using not sales data but profit data is that macro and micro analyses are made consistent (Empirical results obtained by using operating profit data are substantially the same as those obtained by using sales data. Empirical results are available upon request). Regarding macro data, the Ministry of Economy, Trade and Industry (METI) has been publishing monthly data on all industrial activities including advertising since 1998 (<http://www.meti.go.jp/english/statistics/tyo/zenkatu/index.html>). Using the above macro data, causality among industrial production, advertising activity and tertiary activities (excluding advertising) is analyzed.

Further, micro data analysis is performed. Unlike macro data, real output data are unavailable for each firm. Based on financial reports, however, micro data on advertising expenditure and operating activity can be easily obtained. Several kinds of operating activity data can be adopted. In this paper, operating profit is used as a variable representing operating activity. This is because sales consist of several costs and is less sensitive to

business cycles than operating profit. Furthermore, similar to industrial production, operating profit is one of the business cycle indicators in Japan. Therefore, causality between advertising expenditure and operating activity is empirically examined.

This paper considers macro and micro data analyses simultaneously, as each type of analysis has certain shortcomings. Macro data analysis involves the aggregation problem. Stoker (1993) notes that.

The aggregation problem is simply stated. Any incomplete summary of heterogeneous behavioral reactions, such as a relationship among aggregates, will fail in systematic ways to take account of behavioral reactions.

To control such heterogeneity, the individual effect model is applied for panel data analysis. However, such a micro data analysis involves other serious problems. For example, Fernandez-Villaverde and Krueger (2007) used aggregate data instead of micro data for the US Consumer Expenditure Survey and applied the observed group means as a panel for estimation purposes. They noted that a pseudopanel reduces the attrition problem, approximately averages out expectational errors and eliminates the need to control for individual effects, because it aggregates across agents. Hence, both macro and micro data analyses have their own limitations. A comprehensive analysis using both macro and micro data could be useful.

The outline of the present paper is illustrated in Fig. 1. At the micro level, managers in each firm consider whether advertising leads to operating activity; if so, they can determine a suitable level of advertising

expenditure in order to increase operating profits. If there is an adverse relationship, managers should decide the advertising expenditure in accordance with the level of operating profits. At the macro level, real output fluctuates in accordance with the fluctuations in operating profits. In Japan, industrial production and operating profit are both included in the 11 business cycle indicators. Hence, the relationship between advertising and operating activity can be examined at both macro and micro levels.

In this study, the causality between advertising and operating activity is examined using macro and micro data. Furthermore, four kinds of econometric models are considered-the vector error correction model, conventional VAR model, homogeneous parameter panel VAR model and heterogeneous parameter panel VAR model. The empirical results show that operating activity causes advertising and not vice versa and can provide useful information to managers and policymakers. These empirical results can provide implications for media firms and policymakers. First, media firms should understand that firm managers passively decide on advertising expenditure in accordance with the level of operating profits. Next, policymakers should understand that advertising is not a leading indicator of business activities and that they cannot obtain useful information regarding whether economic recession or expansion is starting.

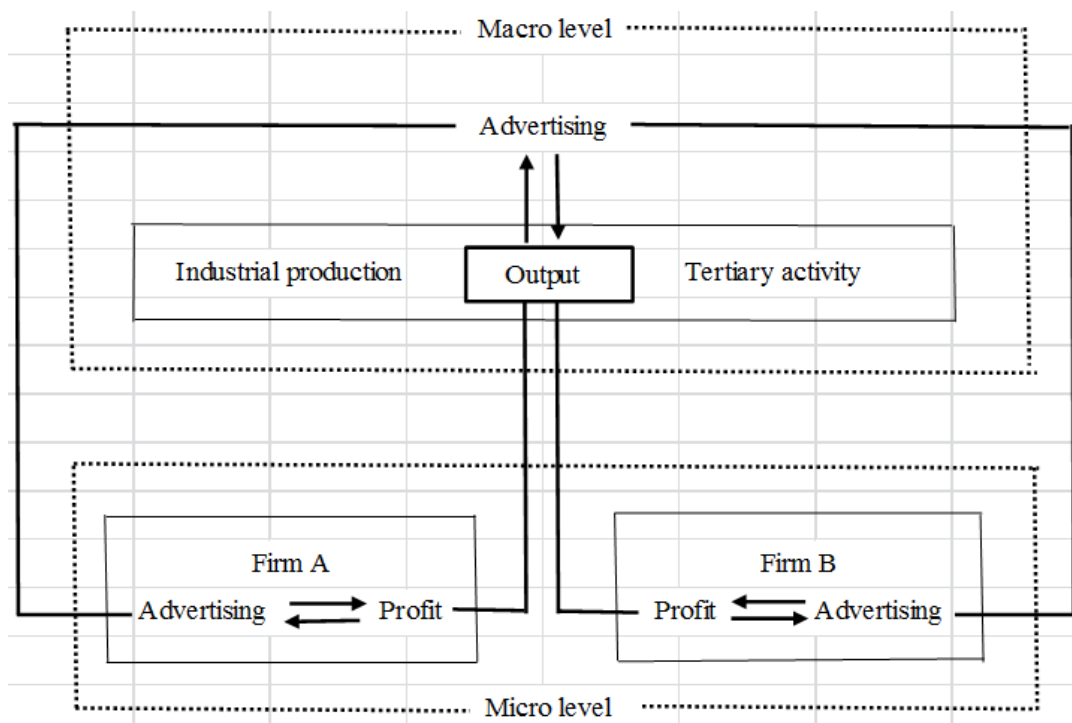


Fig. 1. An illustration of macro and micro link in advertising and firm performance

The rest of the paper is organized as follows. The second section discusses the research methods. The third and fourth sections, respectively, present the macro and micro data analyses. The fifth section provides implications for media firms and policymakers. Concluding remarks are presented in the last section.

Method

Although causality is one of the most important concepts in the sciences, it is treated differently in each discipline (see Pearl (2000) for a comprehensive survey on statistical treatments). In a dynamic relationship such as that between advertising and operating activity, the Granger (1969) causality test is the most popular concept in empirical scientific research.

If a researcher considers K -variate variables for N firms and T periods, denoted by $Y_{nt} = (y_{1nt} \dots y_{Knt})'$ ($n = 1, \dots, N; t = 1, \dots, T$), he or she will conventionally present the following panel Vector Autoregressive (VAR) model, first developed by Holtz-Eakin *et al.* (1988):

$$Y_{nt} = \lambda_n + \varphi(L)Y_{nt} + V_{nt},$$

$$\varphi(L) = 1 - \varphi_1 L - \dots - \varphi_l L^l,$$

where, $\varphi_i (i = 1, \dots, l)$ are $K \times K$ coefficient matrices with

$$\varphi_i = \begin{pmatrix} \varphi_{i11} & \dots & \varphi_{i1K} \\ \vdots & \dots & \vdots \\ \varphi_{iK1} & \dots & \varphi_{iKK} \end{pmatrix}, \lambda_n \text{ is a } K \times 1 \text{ vector of individual effects,}$$

L is a lag operator and V_{nt} is a $K \times 1$ vector of random disturbances. In the case of $N = 1$ the conventional VAR model, which was first introduced by Sims (1980) in economics, can be estimated for macro data. Similar to the conventional VAR model, the panel VAR model can be estimated from one equation to another, but the Ordinary Least Squares (OLS) method cannot be applied because the individual effect term λ_n is included. The Generalized Method of Moments (GMM), first advocated by Arellano and Bond (1991), is applied in the present paper. After the estimation of the model, the Granger causality test can be performed. For example, if the null hypothesis of $\varphi_{jk} = 0 (j = 1, \dots, l)$ were rejected, the k -th variable Granger would cause the j -th variable.

This paper applies the system GMM estimation (Arellano and Bover, 1995; Blundell and Bond, 1998) (The `xtabond2` (Roodman, 2009a) command is applied. This consists of several inputs. Four predetermined variable names are listed in the "GMM" option and time dummies are listed in the "iv" option. The "robust" option is needed for a robust covariance matrix estimation and the "small" option for a small sample correction. Finally, a one-step method is applied because it is set as the default and the two-step method does not necessarily provide correct

results (Roodman, 2009a). A system GMM user has two checkpoints where satisfactory results can be obtained. First, as pointed out by Roodman (2009b), too many instruments can provide misleading results based on Hansen's statistics (Because of its robustness, Hansen's test is applied in this paper, instead of the non-robust Sargan's test, to test the correctness of over-identifying restrictions. However, Hansen's test can be weakened with the use of too many instruments). To overcome this problem, the "collapse" option is used and the number of instruments is gradually increased by extending the lag length. Second, since the GMM system estimator is not consistent when residuals are serially correlated, the AR (2) statistics developed by Arellano and Bond (1991) should be checked. If this statistic is significant at the 5% level, the lag length for the panel VAR is increased.

Another drawback in the above model is the assumption that the coefficient matrix ϕ_i is the same across different firms. This assumption seems too restrictive to verify the feasibility of the model. Very recently, Dumitrescu and Hurlin (2012) developed new Granger causality tests in which the coefficient matrix ϕ_i differs across different firms. However, their model can be applied only to bivariate systems.

Finally, the above panel VAR model can be applied to stationary data. If the null hypothesis of unit root cannot be rejected using the panel unit-root test, the panel cointegration test should be performed. If the null hypothesis of no cointegration cannot be rejected, the differenced series, rather than level, should be applied to the VAR model. The panel vector error correction model can be estimated if the null hypothesis is rejected. However, Dumitrescu and Hurlin's (2012) method cannot be applied to the panel vector error correction model, because this model has the error-correction term.

Macro Analysis

Data

All of the macro data sets for Japan can be obtained at the METI website. The production index includes the following industries, with the production share of the industries in 2005 mentioned in brackets: (1) agriculture, forestry and fisheries production [1.4%]; (2) construction industry activities [5.7%]; (3) industrial production [18.3%]; (4) tertiary industry activities [63.2%]; and (5) public administration-related activities [11.4%]. This paper considers the industries in (3) and (4) only, because the production share of the industries in (1) and (2) is very small in the macro-economy and the activity of the industry in (5) is policy-oriented. As shown in Table 1, the weight of advertising in the Index of Tertiary Activity (ITA) is about 1% (<http://www.meti.go.jp/english/statistics/tyo/sanzi/index.html>). Further, this paper considers the Index of Industrial Production (IIP) as it is one of the 11 business cycle indicators. I believe that the trivariate VAR model describes the business cycle fluctuations in the Japanese economy.

Table 1. Components of tertiary industry

Industry name	Weight
Tertiary Industry	10000.0
Electricity, Gas, Heat supply and Water	372.9
Information and Communications	951.2
Transport and Postal Activities	2641.2
Wholesale and Retail Trade	889.3
Finance and Insurance	971.1
Real Estate and Goods Rental and Leasing	903.4
Scientific Research, Professional and Technical Services	551.3
Scientific and Development Research Institutes	9.4
Professional Services	180.2
Advertising	105.6
Technical Services	256.1
Accommodations, Eating and Drinking Services	496.0
Living-Related and Personal Services and Amusement Services	552.7
Learning Support	116.9
Medical, Health Care and Welfare	921.1
Compound Services	6.2
Miscellaneous Services (Except Government Services etc.)	626.7

Table 2. Unit root tests

	IAA	IIP	ITAA
ADF	-2.074	-2.952	-1.354
PP	-3.102*	-2.446	-1.730
GLS	-2.225	-2.953**	-1.319

Note: IAA = Index of Advertising Activity, IIP = Index of Industrial Production

ITAA = Index of Tertiary Industry Activity Excluding Advertising

ADF = Augmented Dickey-Fuller PP = Phillips and Perron

GLS = ADF using generalized least squares. *p<0.1. **p<0.05
 The lag length is 2 for all cases

Table 3. Unrestricted cointegration rank test

Rank	No. of Parameters	Log likelihood	Trace statistic	0.05 critical value
0	30	-904.2	33.19	29.68
1	35	-892.8	10.49	15.41
2	38	-889.0	2.78	3.76

The three variables are Index of Advertising Activity (IAA), IIP and ITAA (tertiary activity excluding advertising activity). All the variables are seasonally adjusted, indexed as 2005 = 100 and obtained for January 1998 to December 2012. Furthermore, they are log transformed and multiplied by 100. The sample size is 180.

Unit-Root Test

Table 2 shows the results of the unit-root tests. In this study, three kinds of unit-root tests are applied: Augmented Dickey-Fuller (ADF) (1979) test, Phillips-Perron (1988) test and ADF test using Generalized Least Squares (GLS) (Elliott *et al.*, 1996). For brevity, the lag length is 2 for all cases, while the test results are invariable in the case of other lag lengths (All test results are available upon request). It can be clearly concluded that the ITAA has a unit root. The test results are mixed

for the other two variables. Based on the PP test, the null hypothesis of a unit root was rejected at the 10% level for the IAA. Based on the GLS test, the null hypothesis of a unit root was rejected at the 5% level for the IIP.

Hence, I adopted the following two strategies. First, under the assumption that all three variables have a unit root, I estimated the vector error correction model after the Johansen (1991) cointegration test. Second, I estimated the conventional VAR model for the cyclical components of the three variables obtained by applying the Hodrick and Prescott (1997) filter. Based on a rigorous econometric theory, a researcher should adopt the first strategy if all variables are integrated of order one. In this study, however, this assumption does not necessarily hold. In other words, it seems that the integration order of the three variables is inconsistent. In this case, the second strategy could be useful, even though it seems slightly ad hoc. Many influential studies have adopted the second strategy (For a recent example, see Koellinger and Thurik (2012)).

Vector Error Correction Model

First, several conventional VAR models were estimated by changing the lag length under the condition that the maximum lag length is 12. Based on the AIC, the lag length was determined to be 4. Table 3 presents the results of the unrestricted cointegration rank tests. This table clearly shows that the cointegration rank is one. Next, the vector error correction model with one cointegrating vector was estimated, as shown in Table 4. Figure 2 depicts the causality relationship among the three variables, using Granger causality tests. This figure clearly shows that advertising activity causes neither industrial production nor other tertiary activities but that both IIP and ITAA cause advertising activity.

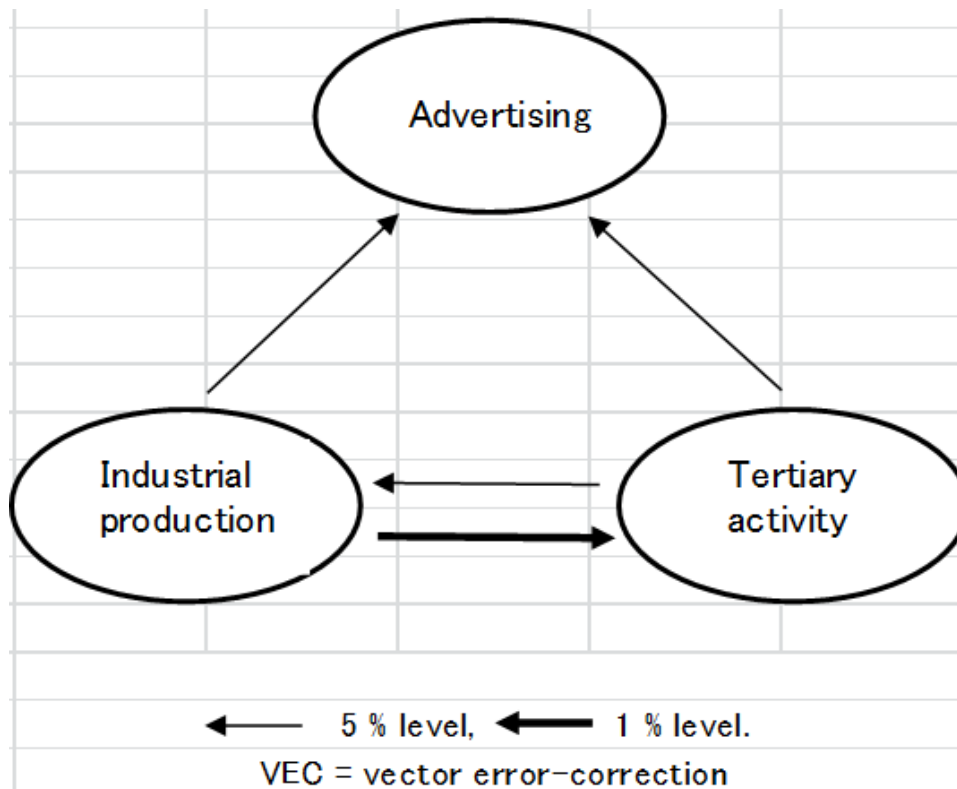


Fig. 2. Granger causality based on VEC model

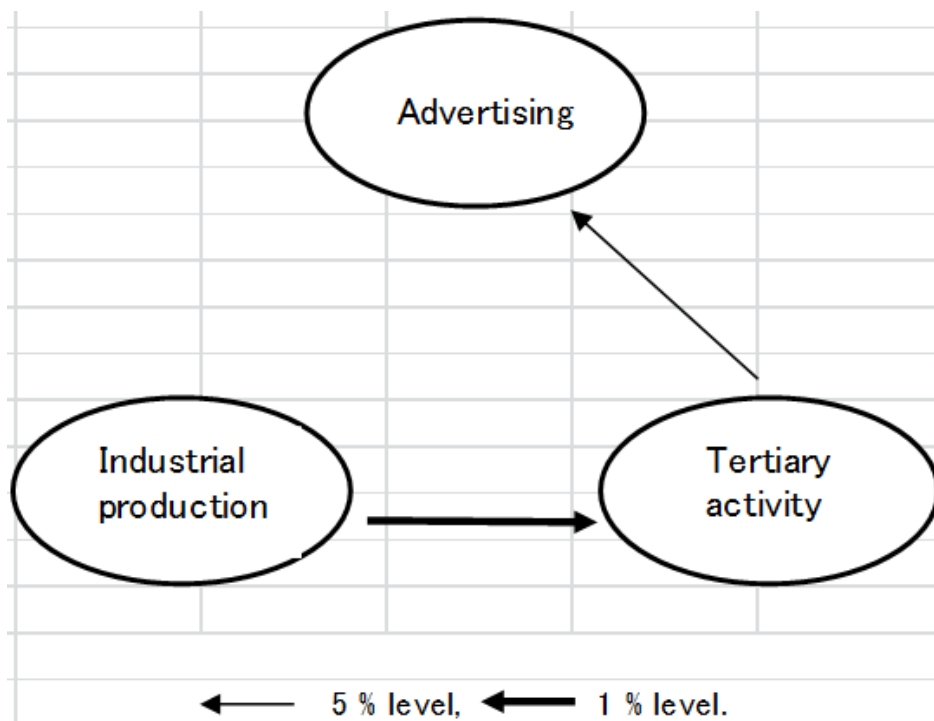


Fig. 3. Granger causality based on VAR model

Table 4. Vector error-correction estimation

	Δ (Advertising)	Δ (Indust. Prod.)	Δ (Tertiary act.)
Error correction term	-0.157** (0.048)	0.074 (0.051)	-0.018 (0.015)
Δ (Advertising(-1))	-0.420** (0.082)	-0.010 (0.088)	0.040 (0.026)
Δ (Advertising(-2))	-0.373** (0.084)	0.063 (0.090)	0.034 (0.027)
Δ (Advertising(-3))	-0.107 (0.079)	0.112 (0.084)	0.043 (0.025)
Δ (Industrial production(-1))	0.051 (0.092)	0.348** (0.098)	0.102** (0.029)
Δ (Industrial production(-2))	0.037 (0.096)	0.296** (0.103)	0.087** (0.031)
Δ (Industrial production(-3))	-0.263** (0.096)	-0.023 (0.102)	-0.025 (0.030)
Δ (Tertiary activity(-1))	0.362 (0.310)	-0.837* (0.332)	-0.698** (0.099)
Δ (Tertiary activity(-2))	0.457 (0.346)	-0.943* (0.370)	-0.482 ** (0.110)
Δ (Tertiary activity(-3))	0.947** (0.312)	-0.359 (0.334)	-0.059 (0.099)
Constant	-0.001 (0.170)	0.024 (0.182)	0.107* (0.054)
R-squared	0.298	0.128	0.271
χ -squared	69.9**	24.3*	61.4**

Note: * $p < 0.05$, ** $p < 0.01$. Standard error in parentheses

Table 5. VAR estimation

	Advertising	Indust. prod.	Tertiary act.
Advertising(-1)	0.329** (0.080)	-0.002 (0.086)	0.026 (0.025)
Advertising(-2)	-0.031 (0.084)	0.035 (0.090)	0.004 (0.026)
Advertising(-3)	0.168* (0.080)	-0.031 (0.085)	0.112 (0.025)
Industrial production(-1)	0.125 (0.089)	1.228** (0.095)	0.117** (0.028)
Industrial production(-2)	-0.002 (0.128)	-0.060 (0.137)	-0.015 (0.040)
Industrial production(-3)	-0.070 (0.090)	-0.224 (0.096)	-0.067* (0.028)
Tertiary activity(-1)	0.381 (0.303)	-0.701* (0.323)	0.215* (0.095)
Tertiary activity(-2)	0.210 (0.319)	-0.049 (0.341)	0.165 (0.100)
Tertiary activity(-3)	0.320 (0.301)	0.542 (0.321)	0.344** (0.094)
Constant	-0.001 (0.154)	0.005 (0.165)	0.012 (0.048)
R-squared	0.652	0.880	0.784
χ -squared	331.0**	1294.2**	643.6**

Note: * $p < 0.05$, ** $p < 0.01$. Standard error in parentheses

Conventional VAR Model

Next, the conventional VAR model is applied for the cyclical components of the three variables. Following Ravn and Uhlig (2002), the smoothing parameter value of the HP filter is set as 129600. Several conventional VAR models were estimated by changing the lag length under the condition that the maximum lag length is 12. Based on the AIC, the lag length was determined to be 3, as shown in Table 5. Figure 3 depicts the causality relationship among the three variables, using Granger causality tests. This figure clearly shows that advertising activity causes neither industrial production nor other tertiary activities but that tertiary activity causes advertising activity.

Summary

The VAR model requires the integration order to be identical among all component variables. As discussed in the previous section, the unit root test results cannot strongly indicate that all variables are integrated of order zero. In other words, it seems that some are stationary while others are non-stationary. Two kinds of VAR models were considered and estimated and both models

indicate that advertising activity causes neither industrial production nor tertiary activities but that tertiary activity causes advertising activity.

Micro Analysis

Data

All firm data were obtained from the Nikkei NEEDS Financial Quest (NNFQ) database, provided by Nikkei Media Marketing. The sample includes all companies, except for financial and insurance companies, listed on five Japanese stock exchanges (Tokyo, Osaka, Nagoya, Fukuoka and Sapporo) and other venture markets for 12-month fiscal years ending on March 31, between 1964 and 2012.

In this database, advertising data are incomplete as there are numerous missing observations. For example, as shown in Table 6, advertising data for 148 firms can be obtained for 1964-1983 but that for only 18 firms can be obtained for 1964-1993. Thus, I used data for 1998-2012 so that (1) the number of firm-year observations can be maximized in this period and (2) this period is identical to that considered in the previous section.

Table 6. Number of observations obtained for individual periods in Japanese advertising database

Starting year	65	67	69	71	73	75	77	79	81	83	85	87	89	91	93	95	97	99	1	3	5	7	9	11
1964	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
1965	3	3	3	3	3	3	3	3	3	3	3	3	2	1	1	1	1	0	0	0	0	0	0	0
1966	4	4	4	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1	0	0	0	0	0	0
1967	4	4	4	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1	0	0	0	0	0	0
1968	4	4	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1	0	0	0	0	0	0
1969	4	3	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1	0	0	0	0	0	0
1970	4	4	3	3	3	3	3	3	3	3	3	3	3	1	1	1	1	1	0	0	0	0	0	0
1971	4	4	4	4	4	4	4	4	4	4	4	4	2	1	1	1	1	1	0	0	0	0	0	0
1972	4	4	4	4	4	4	4	4	4	4	4	4	2	2	1	1	1	1	0	0	0	0	0	0
1973	5	5	5	4	4	4	4	4	4	4	4	4	2	2	1	1	1	1	0	0	0	0	0	0
1974	5	5	4	4	4	4	4	4	4	4	4	4	2	2	2	1	1	1	0	0	0	0	0	0
1975	5	5	5	4	4	4	4	4	4	4	4	4	2	2	2	2	1	1	0	0	0	0	0	0
1976	5	5	5	5	5	5	5	5	5	5	5	5	2	2	2	2	1	1	0	0	0	0	0	0
1977	5	5	5	5	5	5	5	5	5	5	5	5	2	2	2	2	1	1	0	0	0	0	0	0
1978	5	5	5	5	5	5	5	5	5	5	5	5	3	2	2	2	2	2	1	1	1	1	1	1
1979	6	5	5	5	5	5	5	5	5	5	5	5	3	2	2	2	2	2	1	1	1	1	1	1
1980	6	5	5	5	5	5	5	5	5	5	5	5	3	2	2	2	2	2	1	1	1	1	1	1
1981	6	6	3	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	0	0	0	0	0	0
1982	6	3	3	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	0	0	0	0	0	0
1983	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	0	0	0	0	0	0
1984	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	0	0	0	0	0	0
1985	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	0	0	0	0	0	0
1986	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	0	0	0	0	0	0
1987	3	3	3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	0	0	0	0	0	0
1988	4	3	3	3	3	3	3	3	3	3	3	3	3	2	1	1	1	1	0	0	0	0	0	0
1989	4	4	4	4	3	2	2	2	2	2	2	2	2	2	2	2	2	2	0	0	0	0	0	0
1990	5	5	4	4	3	2	2	2	2	2	2	2	2	2	2	2	2	2	0	0	0	0	0	0
1991	5	5	5	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	0	0	0	0	0	0
1992	6	5	4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	0	0	0	0	0	0
1993	6	4	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
1994	4	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
1995	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
1996	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
1997	5	4	4	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1
1998	12	10	7	6	6	6	5	5	5	3	2	2	2	2	2	2	2	2	6	6	6	5	4	4
1999	11	7	7	6	6	5	5	3	1	2	2	2	2	2	2	2	2	2	8	7	7	6	6	3
2000	8	8	7	7	6	6	3	3	3	2	2	2	2	2	2	2	2	2	12	12	11	10	9	5
2001	12	12	11	10	10	9	5	4	4	4	4	4	4	4	4	4	4	4	12	12	11	11	10	6
2002	12	12	11	11	10	6	4	4	4	4	4	4	4	4	4	4	4	4	12	12	11	10	6	5
2003	12	12	11	10	6	5	4	4	4	4	4	4	4	4	4	4	4	4	12	12	11	10	6	5
2004	12	12	11	6	5	5	4	4	4	4	4	4	4	4	4	4	4	4	12	12	11	6	5	5
2005	12	12	6	5	5	5	4	4	4	4	4	4	4	4	4	4	4	4	12	12	6	5	5	5
2006	12	7	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	12	7	5	5	5	5
2007	7	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	7	5	5	5	5	5
2008	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
2009	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
2010	6	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	6	5	5	5	5	5
2011	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6

Note: Each figure is obtained as $[\times/100]$, where \times is original value (= number of observation). $[y]$ is indicator function such as that $[y] = n$ when y is equal to and larger than $100n$ and smaller than $200n$

Table 7. Descriptive statistics for 2012

Variable	Sample	Number of Firms	Mean	Standard deviation	Minimum	Maximum
Advertising	Full sample	613	6012	25046	1	357106
Cost	My sample	116	4970	10637	5	82209
Operating	Full sample	2146	11986	52194	3	1222966
Profit	My sample	116	16876	32168	21	147465

Table 8. Panel unit root tests

Lag	Advertising	Profit
1	-1.133 (0.129)	-4.346 (0.000)
2	-1.13.7 (0.000)	-1.042 (0.149)
3	1.020 (0.846)	-0.623 (0.267)
4	-1.383 (0.083)	-0.143 (0.443)

Note: p-value in parentheses
 Time trend is included in regression

Table 9. Panel cointegration test

	Statistic	p-value
Panel v-statistic	-0.056	0.522
Panel rho-statistic	-0.211	0.412
Group rho-statistic	3.417	0.999

Note: Pedroni (2004)

Several variables can represent operating activity. This study considers operating profit because, in previous section, the relationship between advertising activity, industrial production and tertiary activities is analyzed from the macroeconomic perspective. Similar to industrial production, operating profit is one of the business cycle indicators in Japan (The other variables are producers' shipments, large industrial power consumption, shipments of consumer durable goods, non-scheduled worked hours, shipments of investment goods, retail sales value, wholesale sales value, shipments in small and medium-sized firms and effective job offer rate).

Table 10. Estimation results for panel VAR model

Independent variables	Lag	Dependent variables	
		Advertising	Profit
Advertising	1	-1.0091** (0.0274)	0.0257 (0.0224)
	2	-0.9756** (0.0173)	0.0191 (0.0205)
F-value			0.97 [0.381]
Profit	1	0.0445 (0.0448)	-0.1917** (0.0547)
	2	0.0352 (0.0524)	-0.1188 ** (0.0390)
F-value		0.50 [0.606]	
Year dummy		Yes	Yes
Number of observations		1392	1392
Number of instruments		17	17
Collapse option		Yes	Yes
Lag length for instrument		(12)	(23)
F-value		543.3** [0.000]	4.58** [0.000]
AR(2) statistics		-0.38 [0.706]	0.82 [0.410]
Hansen statistics		0.70 [0.705]	1.98 [0.371]

Note: Estimation is implemented via xtabond2 in Stata 10

See Roodman (2009) for details. **p<0.01, *p<0.05

The Figures in parentheses and in brackets indicates standard error and p-value, respectively. Lag length for instrument (= i) shows that $t-2, \Delta(t-1), \dots, t-i, \Delta(t-i)$ are adopted as instruments

Table 11. Causality test

Causality	Statistic	P-value
Advertising to profit	1.68	0.092
Profit to advertising	9.54	0.000

Table 7 shows the advertising expenditure of 613 firms in 2012. However, only 116 firms are considered in the study for the following reasons: (1) only the firms with advertising expenditure for 15 consecutive years are considered; (2) the firms with minus operating profits are beyond the scope of the study, because log transformation is applied to ease firm heterogeneity.

Panel Unit Root Test and Cointegration Test

Although several panel unit root tests exist, the most popular one-the Im-Pesaran-Shin (IPS) test developed by Im *et al.* (2003) is applied in this study. In each regression, the time trend and the constant term are included. Furthermore, lag length is changed from 1 through 4. As shown in Table 8, both advertising expenditure and operating profit seem to be non-stationary, while the test results change depending on the lag length. Next, the panel cointegration test, developed by Pedroni (2004), is performed. As shown in Table 9, there seems to be no cointegration between advertising expenditure and operating profit (Pedroni (2004) developed seven statistics, but four statistics (panel PP, panel ADF, group PP and group ADF) can be considerably over-sized in the case of short panel data. Hence, three other statistics are adopted in the present study). Hence, the first difference, rather than level, of each variable is adopted in the subsequent analysis.

Panel Granger Causality Tests

Two kinds of panel VAR models, as discussed in the previous section, were estimated. Table 10 shows the estimation results of the panel VAR model using the system GMM method. The VAR (2) model was applied using year dummies. The AR (2) statistics and Hansen's statistics indicate that both estimation results are permissible. The null hypothesis (profit does not cause advertising) cannot be rejected with an F-value of 0.50. Further, the null hypothesis for adverse causality cannot be rejected with an F-value of 0.97.

Next, Dumitrescu and Hurlin's (2012) test was implemented. The selected lag length is 2. As shown in Table 11, the null hypothesis (profit does not cause advertising) can be rejected with a p-value of 0.000. On the other hand, the null hypothesis for adverse causality cannot be rejected with a p-value of 0.092. Hence, both models provide empirical evidence that advertising does not cause operating profit.

Implications for Media Firms and Policymakers

The causality between advertising and operating activity is a very important matter for media firms and policymakers. If advertising causes operating activity, a firm manager can progressively determine a suitable level of advertising expenditure in order to increase operating profits. If there is an adverse relationship between the two, he or she should passively decide on advertising expenditure in accordance with the level of operating profits. These decisions can be made based on the results of the empirical micro data analysis.

Accordingly, media firms should understand this mechanism. If advertising causes operating profits, they can induce firm managers to increase advertising expenditure. If not, they cannot influence firm managers positively. The present paper provides the suggestion that media firms should understand that firm managers not actively but passively decide on advertising expenditure considering the obtained level of operating profits.

On the other hand, empirical results of macro data analysis can provide useful information to policymakers. They should consider the empirical results regarding whether advertising is a leading indicator of business cycles. If so, they can obtain useful information regarding whether economic recession or expansion is starting and can adopt a suitable macroeconomic policy accordingly. The present paper provides the suggestion that policymakers should understand that advertising is not a leading indicator of business activities and that they cannot obtain useful information regarding the timing of economic recession or expansion. Hence, they should adopt other leading indicators, such as stock prices and business sentiment, to predict business activities.

Conclusion

There can be two different mechanisms in the advertising-sales nexus. Based on the Galbraith hypothesis, higher personal income from economic development causes more advertising, which in turn leads to increased sales. On the other hand, the advertising budgeting process can be described as decision making under uncertainty. This process indicates that sales cause advertising. Thus, the causality relationship between advertising and operating activity has been empirically analyzed with inconclusive results. One of the major drawbacks in previous studies is no use of micro data.

In this study, the causality between advertising and operating activity was examined using macro and micro data. Four kinds of econometric models were considered: The vector error correction model, conventional VAR model, homogeneous parameter panel VAR model and heterogeneous parameter panel VAR model. Empirical results obtained by all four models indicate that operating activity causes advertising and not vice versa. These empirical results can provide implications for media firms and policymakers. First, media firms should understand that firm managers passively decide on advertising expenditure in accordance with the level of operating profits. Next, policymakers should understand that advertising is not a leading indicator of business activities and that they cannot obtain useful information regarding whether economic recession or expansion is starting.

In general, owing to the aggregation problem, the empirical results obtained using macro data are different from those obtained using micro data. In this paper, the data source for macro data is different from that for micro data and four kinds of econometric model were applied to these data sets. Empirical results were almost the same across the different cases. Hence, the obtained results seem robust despite the change in data source and models. The above empirical evidence is expected to provide useful information to Japanese managers and policymakers.

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All authors equally contributed in this work.

Ethics

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