Causality among sales, advertising and prices: new evidence from a multivariate cointegrated system

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Abstract

The main purpose of this paper is to discern the dynamic causal relationships (in the Granger (temporal) sense) among sales, advertising and prices in the context of the Portuguese car market. The present research (based on multiple cointegration tests preceded by various unit root or non-stationarity tests) is one of the first attempts at putting the sales-marketing mix analysis within a multivariate cointegrated system. The results, based on a three-step procedure (cointegration, VECM and VDCs) confirm that a strong one-way relationship $(A \rightarrow S,\ \mathrm{A} \rightarrow \mathrm{P})$ between advertising and sales (prices) is complemented by a feedback relationship $(S \leftrightarrow P)$ between sales and prices.

Keywords: Car market; Cointegration analysis; Granger-causality; Marketing-mix; Sales; Variance decompositions; Vector error-correction model

1. Introduction

Basically, two approaches have been used in the past to estimate the relationship among sales (demand) and marketing-mix variables at various levels of aggregation. Most commonly, a regression model is estimated which includes e.g., advertising expenditure (or a proxy) among its explanatory variables and appropriate dynamics. The list of such studies is rather long; only Clarke (1976) reviews 69 of them. The second, and more recent, approach is to estimate a Box-Jenkins time series model as was done by Helmer and Johansson (1977), Hanssens (1980), Bhattacharyya (1982), and Heyse and Wei (1985).

The direction of causality is usually assumed to run from advertising to sales whereas the possibility of an effect of sales on advertising, whereby advertising budgets are set as a percentage of sales, although recognized (Schmalensee, 1972), it has received much less attention. Ashley et al. (1980) and Heyse and Wei (1985) present evidence supporting causality from consumption (sales) to advertising rather than the reverse.

The causal chain (among sales and other marketing activity such as advertising, price, and promotions) implied by the existing marketing paradigms still remains ambiguous. The issue, therefore, as to the dynamic causal relationships (even in the Granger temporal sense rather than in the structural sense) remains unresolved and is an empirical one [1].

In order to empirically resolve the issue of the direction of causation in a bivariate context, a lot of causality tests have been applied based mainly on the standard Granger (1969), Sims (1972), and the modified Sims suggested by Geweke et al. (1983). But the studies applying these tests suffered from the following methodological deficiencies:

(*i*) These standard tests did not examine the basic time series properties of the variables. If the variables are cointegrated, then these tests incorporating differenced variables will be misspecified unless the lagged error-correction term is included (Granger 1988).

(*ii*) These tests turn the series stationary mechanically by differencing the variables and consequently eliminated the long-run information embodied in the original level form of the variables. The error-correction model (ECM) derived from the cointegrating equations, by including the lagged error-correction term reintroduces, in a statistically acceptable way, the long-run information lost through differencing. The error-correction term (ECTs) stands for the short-run adjustment to long-term equilibrium trends. This term also opens up an additional channel of Granger causality so far ignored by the standard causality tests.

(*iii*) Moreover, although recently, there has been a beginning of the application of ECM in causality testing in the bivariate context, such as Baghestani (1991), Chowdhury (1994), Dekimpe and Hanssens (1995), Jung and Seldon (1995), Lee, Shin and Chung (1996), and Zanias

[1] Causality is a subject of great controversy among economists. see, e. g., Zellner (1988). Interested readers could refer to a sumplementary issue of the *Journal of Econometrics,* September-October, 1988 that includes studies discussing this issue. Without going into the debate, I would like to state that the concept used here is in the stochastic or "probabilistic" sense rather than in the philosophical or "deterministic" sense. Also the concept used here is in the Granger "temporal" sense rather than in the "structural" sense.

(1994), there has been very little attempt at testing the Granger causality channel in a dynamic multivariate Marketing context through vector error-correction modelling (VECM), variance decompositions (VDC) and impulse response functions (IRF).

The primary purpose of this research is to conduct empirical tests to discern the dynamic causal relationships (in the Granger (temporal) sense rather than in the structural sense) among sales and other marketing-mix variables such as total advertising expenditures, and price in the context of the Portuguese car market.

As mentioned before, at the moment a very few works (only about three or four) exist on the application of ECM in testing Granger causality. But even these few works are set in a bivariate context, and also do not apply the techniques of variance decompositions and impulse response functions to Granger causality. This study will make an attempt to improve and extend the existing few ECM-based works on Granger causality in the following ways:

(a) It will try to discern Granger causality in a car market in a multivariate framework and within the environment of vector error-correction modelling. This analysis will also make use of the techniques - variance decompositions, and impulse response functions - to unveil Granger causality in marketing activity in a dynamic context [2].

(b) The error-correction terms derived from the cointegrating vectors are arrived through Johansen's multivariate cointegrating testing procedure (in contrast to much of the pre-existing literature) which are then used as additional channels in order to identify Granger causation. Since this procedure identifies multiple cointegrating relationships and hence error-correction terms, this is an issue of crucial importance in Granger causality testing in a dynamic multivariate context.

2. Econometric methodology

The following sequential procedures will be adopted:

Step 1: Cointegration and Causality

The cointegration technique pioneered by Engle and Granger (1987), Hendry (1986) and Granger (1986) made a significant contribution towards testing Granger causality. According to this technique, if two variables are cointegrated (i.e., share a common trend), the finding of no-causality in either direction - one of the possibilities with the standard Granger and Sims tests - is ruled out. So long as the two variables have a common trend, causality (in the Granger sense, not in the structural sense), must exist in at least one direction (Granger 1988; Miller and Russek 1990). And this Granger (or temporal) causality can be detected through the vector error-correction model derived from the long-run cointegrating vectors [3].

[2] In an effort to examine the relationship between sales and advertising, or sales and price, some recent works such as Baghestani (1991), Dekimpe and Hanssens (1995), and Zanias (1994) have used multivariate causality tests and VARs including VDC and IRF. However, unlike mine, these causality tests were not conducted within the framework of Johansen's cointegrating tests and VECM. Zanias (1994) applied VECM in multivariate causality tests but did not apply Johansen's tests, VDC and IRF.

[3] The VAR, being a system of unrestricted reduced form equations, have been criticized by Cooley and Le Roy (1985). Runkle (1987) is a good example of the controversy surrounding this methodology. It is debatable whether the method of identification employed by the simultaneous equation structural

Step 2: Vector Error-Correction Modelling (VECM) and Exogeneity

Engle and Granger (1987) demonstrated that once a number of variables (say x and y) are found to be cointegrated, there always exists a corresponding error-correction representation which implies that changes in the dependent variable are a function of the level of disequilibrium in the cointegrating relationship (captured by the error-correction term) as well as changes in other explanatory variable(s). A consequence of ECM is that either Δx_t or Δy_t or both must be caused by ε_{t-1} which is itself a function of x_{t-1}, y_{t-1}. Intuitively, if y and x have a common trend, then the current change in x (say, the dependent variable) is partly the result of x moving into alignment with the trend value of y (say, the independent variable). Through the error-correction term, the ECM opens up an additional channel for Granger causality (ignored by the standard Granger and Sims tests) to emerge. The F-test applied to the joint significance of the sum of the lags of each explanatory variable and the t-test of the lagged error-correction term (or asymptotic χ^2-tests applied to the ECT coefficients jointly) will imply statistically the Granger exogeneity or endogeneity of the dependent variable. Here, one should acknowledge the concepts of weak and strict exogeneity within a cointegrated system, where weak exogeneity refers to ECM-dependence (i.e., dependence upon stochastic trends) and strict exogeneity to dependence on the sum of joint lagged differenced variables. F-tests or asymptotic χ^2-tests may be interpreted as within-sample causality tests but provide little evidence on the dynamic properties of the system which is given by the variance decompositions and impulse response functions which may be termed as out-of-sample causality tests (Bessler and Kling 1985) [4].

Toda and Phillips (TP) (1993) provide evidence that the Granger causality tests in ECM's still contain the possibility of incorrect inference; they also suffer

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model which often relies on many simplifying assumptions and arbitrary exclusion restrictions together with the related exogenous-endogenous variables-classification (which are often untested), is superior to the identification procedure used in the VAR model. There is also a controversy within the VAR modelling as to whether unrestricted VAR or the Bayesian (restricted) VAR is superior to each other. Although in the context of exogeneity, the Bayesian VAR (which is restricted by priors), may beg the question of exogeneity, I applied Bayesian VAR (variance decompositions and Impulse response functions) and found the Granger-causal chain remaining mostly unchanged.

[4] The results based on VARs, VDCs, and IRFs are generally found to be sensitive to the lag length used and the ordering of the variables. A considerable time has been spent in selecting the lag structure through FPE criterion. FPE method is based on an explicit optimality criterion of minimizinf the mean squared prediction error. The criterion tries to balance the risk due to bias when a low order is selected, and the risk due to increase in the variance when a higher order is selected. By construction, the errors in any equation in a VAR are usually serially uncorrelated. However, there could be contemporaneous correlations across errors of different equations. These errors were orthogonalized through Choleski decomposition. In order to orthogonalize the innovations, a pre-determined triangular ordering of the three variables had to be made. In a small system like mine, one would expect the sales variable to respond more quickly to prices than to advertising. The innovations were orthogonalized in the following order: sales (S), advertising (A), and prices (P). The residual variance-covariance matrix being near diagonal, the results were not sensitive to alternative ordering of the variables based on alternative marketing paradigms.

from nuisance parameter dependency asymptotically in some cases (see TP for details). All of these indicate that there may be no satisfactory statistical basis for using Granger causality tests in levels or in difference VAR models or even in ECM. The sequential Wald tests of TP (1993) are designed to avoid these problems. Asymptotic theory indicates that their limiting distributions are standard and free of nuisance problems.

Step 3: Variance decompositions (VDC) and Relative Exogeneity

The VECM, F-and t-tests may be interpreted as within-sample causality tests. They can indicate only the Granger causality of the dependent variable within the sample period. They do not provide an indication of the dynamic properties of the system, nor do they allow me to gauge the relative strength of the Granger-causal chain or degree of exogeneity among the variables. VDCs which may be termed as out-of-sample causality tests, by partitioning the variance of the forecast error of a certain variable into proportions attributable to innovations (or shocks) in each variable in the system, including its own, can provide an indication of these relativities. A variable that is optimally forecasts from its own lagged values will have all its forecast error variance accounted for by its own disturbances (Sims 1982).

3. Empirical results

3.1 Data

The data base used for this study is a monthly time series sample of sales (S), and two marketing-mix variables, for the period 1988:1-1996:6 in the Portuguese car market. The decision variables included retail prices (P) and total advertising expenditures (A) for the leader brand (RENAULT) in the car market. The Portuguese market consists of twenty-five imported car brands, but the top seven account on average for 80.4% of the total market, with a standard deviation of 5.48%. The leader is a general brand, presented in all segments and represents an average market share of 15.9%, with a standard deviation of 4.95%. The sources of all these data are, respectively, the *Portuguese General Directorate of Transports*, the *Guia do Automóvel* and the *Sabatina* for the sales (in volume), retail prices, and total advertising expenditures series. The price and advertising variables are expressed in constant Portuguese escudos.

3.2 Integration and cointegration properties

The usual asymptotic properties cannot be expected to apply if any of the variables in a regression model is generated by a non-stationary process. Using unit root tests, I explore the properties of the S, A, and the P series. If a series contains a stochastic trend, it is said to be integrated of order *d*, *I(d)*. Differencing *d* times then yields a stationary series.

Table I reports the results of the Dickey-Fuller tests (DF) (Dickey and Fuller, 1979), Augmented Dickey-Fuller tests (ADF), and Phillips-Perron tests (PP) (Phillips and Perron, 1988) that the S, A, and P series might have up two unit roots. In no case is there significant evidence against the single unit root hypothesis. Thus the null hypothesis that both series are non-stationary in levels cannot be rejected. All test statistics for a second unit root, that is, a unit root in the first differences of the series, are highly significant. I therefore adopt the alternative hypothesis that the series are stationary in first differences [5].

Since the series contain a stochastic trend, I proceed with investigating whether they share a common stochastic trend. This refers to testing for cointegration which is a way of testing for a long-run equilibrium relationship among S, A, and P. Two variables are said to be cointegrated of order one, *CI(1,1)*, if they are individually *I(1)* and yet some linear combination of the two is *I(0)* (Engle and Granger, 1987). Under the assumption that a first-order model is correct, I test whether the estimated residual of the cointegrating regression is stationary. Specifically, I perform ADF tests in order to test the null hypothesis that the residual series of the cointegrating regression is non-stationary. Reporting a value of -3.70 an ADF test with one lag and with S as the independent variable rejects the null of no cointegration at the 2.5% level [6]. Since the cointegrating vector establishes an equilibrium relationship, the ADF test should not lead to a different conclusion if the cointegrating equation is estimated with A as the independent variable. With a value of -3.76 the result confirms this requirement.

Given the low power of standard unit root tests against fractional alternatives (Diebold and Rudebush, 1991) I apply the semi-nonparametric procedure suggested by Geweke ans Porter-Hudak (GPG, 1983) to the S, A, and P series. The GPH test avoids the knife-edged *I(1)* and *I(0)* distinction in the PP test by allowing the integration order to take on any real value (fractional integration). Table II reports the empirical estimates for the fractional differencing parameter. I find no evidence in support of the fractional alternative for any of my sample series. I therefore conclude that all series are integrated processes of order one and subsequently apply my analysis to the S, A, and P changes. This is a necessary step in order to test the cointegration of the variables. The results based on Johansen's (1988) and Johansen and Juselius's (1990) multivariate cointegration tests (Table III) tend to suggest that these three variables are cointegrated , i.e. have common trends. In other words, these three variables are bound together by long-run equilibrium relationships (either one or two as indicated by the test of null or alternative hypotheses through the maximum eigenvalue and trace statistics).

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[5] Critical values at the 1% and 5% significance level, respectively, are -3.44 and -2.87.

[6] Critical values for the ADF test are -3.59 and -3.34 at the 2.5% and 5% significance levels, respectively. These values differ from those used above as the asymptotic distributions of residual based cointegration test statistics are not the same as those of ordinary unit root test statistics (see Davidson and MacKinnon, 1993, p. 720).

Table I. Tests for integration

	Single unit root			Second unit root		
Series	DF	ADF	PP	DF	ADF	PP
S	-1.25	-1.41	-1.26	-	-13.5[b]	-
				17.5[b]		17.5[b]
A	-1.84	-1.78	-1.81	-	-14.2[b]	-
				17.7[b]		17.7[b]
P	-1.39	-1.52	-1.31	-	-15.8[b]	-
				18.4[b]		17.9[b]

Notes: [b] Statistically significantly different from zero at the 0.01 significance level. The optimal lag used for conducting the ADF test statistic was selected based on an optimal criterion (Akaike's FPE), using a range of lags. The truncation lag parameter *l* used for PP tests was selected using a window choice of $w(s,l) = 1 - \frac{s}{(l+1)}$ where the order is the highest significant lag from either the autocorrelation or partial autocorrelation function of the first differenced series (see Newey and West, 1987).

Table II. Empirical estimates for the fractional-differencing parameter $\tilde{d}$

Series	$\tilde{d}(0.50)$	$\tilde{d}(0.55)$	$\tilde{d}(0.60)$
Sales (S)	0.086 (0.513)	-0.036 (-0.276)	-0.154 (-1.503)*
Advertising (A)	-0.031 (-0.179)	0.009 (0.058)	-0.165 (-1.313)*
Price (P)	0.037 (0.361)	0.072 (0.754)	-0.174 (-1.251)*

Notes: d is the fractional differencing parameter corresponding to the S, A, and P series whereas $\tilde{d}$ is the fractional differencing parameter corresponding to the S, A, and P change series (d = 1+$\tilde{d}$). $\tilde{d}(0.50)$, $\tilde{d}(0.55)$, and $\tilde{d}(0.60)$ give the $\tilde{d}$ estimates corresponding to the GPH spectral regression of sample size $v = T^{0.50}$, $v = T^{0.55}$, and $v = T^{0.60}$, respectively. The *t*-statistic are given in parentheses and are constructed imposing the known theoretical error variance of $\pi^2/6$. The superscripts ***, **, * indicate statistical significance for the null hypothesis $\tilde{d} = 0$ (d = 1) against the alternative $\tilde{d} \neq 0 (d \neq 1)$ at the 1, 5, and 10 per cent levels, respectively.

Table III. Johansen's test for multiple cointegrating vectors

Hypothesized cointegrating	number of relationships	Test statistics		Critical values (95 per cent)	
H_0	H_1	Max. eigenvalue	Trace	Max. eigenvalue	Trace
$r = 0$	$r > 0$	86.65*	79.32*	33.46	68.52
$r \leq 1$	$r > 1$	45.78*	51.34*	27.06	47.21
$r \leq 2$	$r = 3$	18.05	21.17	20.96	29.68

Notes: r indicates the number of cointegrating relationships. The optimal lag structure of the VAR was selected by minimizing the Akaike's FPE criteria. Critical values are taken from Johansen and Juselius (1990). * indicates rejection at the 95 per cent critical values

3.3 Vector error correction model and Granger causality test

The number of cointegrating relationships found in Table III will result in a corresponding number of residual series, and hence error correction terms (ECTs), to be used in the subsequent vector error correction model (VECM), results based on which appear in Table IV.

As stated earlier, cointegration cannot detect the direction of Granger causality, which will be done by an analysis of results based on estimating a VECM (Table IV). The relative contribution of the explanatory variables in explaining the variation in the dependent variable beyong the sample period will be done by variance decompositions (Table V).

Sales - Results based on the VECM (Table IV) indicates that in the short run, each explanatory variable (A and P) significantly Granger-cause sales (as reflected in the significance of the F-tests of the lags of the explanatory variables), but the proportion by which the sales (S) variable adjusted endogenously in the short run to its long-term equilibrium relationship with other cointegrating variables is nevertheless significant (as evidenced in the significance of the *t*-test of the lagged error correction term derived from the long-term cointegrating relationship). These findings are further supported by the post-sample VDCs (Table V). A substantial portion of the variance of S (65%) is explained by its own innovations (or shocks) in the short-run (say, at 3-month horizon) but only a small portion (31%) in the long run (say, 12-month horizon); shocks in other variables (A and P) explain about 40% and 28% of the shocks in the sales, respectively. One would expect that the impact of mix-variables will take some time to produce a cumulative effect on sales.

Advertising - Results based on the VECM (Table IV) indicate that advertising remains econometrically exogenous, i.e. unexplained by the explanatory variables incorporated (as evidenced in the non-significance of both the F-tests as well as the *t*-tests). The VDCs (Table V) also confirm that finding, since even after 12-month horizon about 69% of the shocks in advertising are explained by its own shocks. The frequently used rule of setting advertising as a percentage of sales does not apply for this particular brand.

Price - The within-sample VECM results (Table IV) indicate that price was Granger-caused by sales and advertising and by short-run adjustment to long-term equilibrium trend (as evidenced in the significance of the F-tests and *t*-tests). The post-sample VDCs (Table V) further confirms this finding but reinforce the role of sales and advertising in explaining a substantial portion of the variance of prices. About 62% of the shocks in prices (at the 12-month horizon) are accounted for by the shocks in S and A.

Table IV. Temporal causality results based on vector error correction model (VECM)

Dependent variable	ΔS	ΔA	ΔP	$\varepsilon_{1,t-1}$	$\varepsilon_{2,t-1}$
	Significant levels of *F*-statistics			*t*-statistics	
ΔS	-----	0.03^{**}	0.05^{**}	-4.56^{***}	-2.67^{**}
ΔA	0.27	-----	0.15	-1.39	-0.97
ΔP	0.01^{***}	0.05^{**}	-----	-2.48^{**}	-4.39^{***}

Notes: The ECTs were derived by normalizing the two cointegrating vectors on *S*, thereby resulting in two sets of residuals. The residuals were also checked for stationarity by way of unit root testing procedures applied earlier and inspection of their autocorrelation function respectively. The VECM was based on an optimally determined criteria (Akaike's FPE) lag structure and a constant. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table V. Variance decompositions (VDC´s)

Variable	Horizons	Sales (S)	Advertising (A)	Price (P)
Sales (S)	1	100.00	0.00	0.00
	3	65.25	24.75	10.00
	6	46.23	35.83	17.94
	12	31.42	40.31	28.27
Advertising (A)	1	0.00	85.84	14.16
	3	5.57	81.03	13.40
	6	9.68	72.38	17.94
	12	17.54	68.69	13.77
Price (P)	1	0.00	8.27	91.73
	3	4.45	12.03	83.52
	6	14.17	21.59	64.24
	12	32.86	29.61	37.53

Notes: Entries in each row are the percentages of the variance of the forecast error for each variable indicated in the rows that can be attributed to each of the variables indicated in the column headings. The decompositions are reported for one-, three-, six- and twelve-month horizons. Several alternative orderings of these variables were also tried, e.g., S - P - A and A - P - S. Such alterations, however, did not alter the results to any substantial degree. This is possibly due to the variance-covariance matrix of the residuals being near diagonal, arrived at through Choleski decomposition in order to orthogonalize the innovations across equations.

4.Conclusions

The main purpose of this paper is to discern the dynamic causal relationships (in the Granger (temporal) sense rather than in the structural sense) among sales (S) and two marketing-mix variables (advertising and price) at the firm level. The methodology employed uses various unit root tests, a semi-nonparametric procedure suggested by GPH, and Johansen's cointegration test followed by a vector error correction model and variance decompositions in order to capture both within-sample and out-of-sample Granger-causality among marketing activity.

The evidence of cointegration rules out the possibility of the estimated relationship being "spurious" and implies that Granger causality must exist among the variables in at least one direction, either unidirectional or bidirectional. The Granger causality may emerge either through the level of disequilibrium in the cointegrated relationships (captured by the ECTs) and/or the changes in the explanatory variables (as tested via the *F*-statistics for each). In other words, the VECM allow us to distinguish between "short-term" and "long-term" Granger causality (through the significance of the *F* and *t*-tests, respectively). In addition, the VDCs can discern the relative contribution of each variable in explaining the variation in a certain variable beyond the sample period.

Apart from pointing to the proper treatement of integrated series and from obtaining revised results for the sales-mix variables relationship at the firm level, the following important general conclusions are drawn. First, in the case of cointegrated variables, the error-correction term may prove of crucial importance in testing the direction of causality. Second, a strong one-way relationship b$A \to S$, $\mathrm{A} \to \mathrm{P}$g exists between advertising and sales (prices) is complemented by a strong feedback relationship $(S \leftrightarrow P)$ between sales and prices which are clearly shown for the RENAULT case.

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