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Abstract

We used scanner data to test whether two competitive commodities respond symmetrically by volume to price changes. Our results indicate that consumers of the most expensive good (Coca-Cola) respond quite symmetrically when prices go either up or down. In contrast, consumers of the less expensive good (Pepsi-Cola) respond quite asymmetrically. We also introduce the substitution effect in ARDL asymmetric modelling as scanner data permits, showing that most previous asymmetric models using this technique experience omitted variables since this parameter is excluded.

JEL Classification: C22, C23 and D12

Key words: Scanner data, Asymmetric consumer demand, Autoregressive distributed lag model, Price change

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1. Introduction

The study of price movements and their effect on demand occupies a central role in modern economic research. In terms of microeconomic behaviour, understanding the symmetry of demand response to price changes is important for both the economic agents who set prices and the governmental institutions which regulate the markets.

From the theoretical viewpoint, the price and/or output setting plays a fundamental role in neo-classical economic theory, since this theory predicts that resource allocation and output production by economic agents are driven by prices. In this sense, the theory does not recognise the existence of either asymmetric price transmission or asymmetric demand response. Nevertheless, growing evidence from empirical studies shows that asymmetric price transmission (APT) and asymmetric demand response (ADR) arise frequently.[2]

To date, asymmetric models in econometrics have mostly been used to study the asymmetric price transmission of oil prices.[3] The asymmetric demand response to price change models has mostly been used in the context of the stock market.[4]

Scanner data provide a unique source from which to estimate asymmetries in demand response to price changes. These data can be obtained for a large variety of goods in almost any frequency; for example, daily, weekly, monthly or quarterly. The data can be obtained across time series as well as by cross section, since supermarkets store the data on a daily basis and cross section data can be

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[2] For APT between oil and petrol prices, see for example Bacon (1991), Borenstein et al. (1997), and regarding ADR, see for example Bentzen and Engsted (2001) regarding energy demand and Bidwell et al. (1995) regarding telephone calls demand.
[3] See for example Bacon (1991), Borenstein (1997), Brown and Yucel (2000), Bachmeier and Griffin (2003) and Manera and Grasso (2005).
[4] See for example: Moosa et al. (2003) and Gerlach et al. (2006).

collected by using stores or chains in different locations. Unlike previous studies on asymmetry, the use of scanner data allows us to control for cross demand response, which is a possible source of omitted variables bias.

In our research, we focus on the study of the demand response to price change of two well known competitive goods, namely, Coca-Cola and Pepsi-Cola. The appeal of these two goods is that in this sample, Coca-Cola is clearly the market leader and always has a higher price in our sample; therefore, it could be labelled the more expensive good as opposed to Pepsi-Cola, the less expensive good. These systematic differences in prices allow us to test the following questions: Do consumers of the more expensive good behave differently to consumers of the less expensive good when the price changes? Do consumers behave differently across stores? Finally, this rich data source allows us to test whether or not the introduction of competitive goods in econometric asymmetric models reduces omitted variables bias.

2. Asymmetric econometric models (literature review)

Asymmetric econometric studies have generally focused on the transmission mechanism between cost and retail prices on gasoline and on the stock market to evaluate the hypothesis that investors respond asymmetrically to exogenous shocks. Supermarket scanner data has been used to study the hypothesis that the transmission mechanisms between cost and retail prices move asymmetrically,[5] although the possibility that consumers respond asymmetrically when prices change using this data source have not been unexplored.

One of the first investigations to model asymmetric price behaviour was carried out by Bacon (1991). The motivation of this paper is the public concern in

[5] see for example Peltzman (2000) or Muller and Ray (2007)

the UK that ‘oil companies use the market power to set prices unjustifiably high relative to cost’ (Bacon, 1991, p. 211). In this study, Bacon used several econometric specifications of an error correction model (ECM) using UK fortnightly data from 1982 to 1989.

Moosa, Silvapulle and Silvapulle (2003) estimated the asymmetry in the price-volume relationship of the crude oil futures market using a thresholds autoregressive model (TAR). This study used daily data from 2 February 1985 to 23 October 1996 (excluding some periods of turbulence) of West Texas intermediate crude oil prices and volume.

In the studies in the existing literature which use scanner data, the main focus is mainly on the asymmetric transmission mechanism between the changes in the cost and retail price of retail goods. These studies are generally motivated by the menu cost theory, which states that prices do not adjust immediately to clear markets if adjusting prices is costly, given that firms may need to modify price lists, send new catalogues, etc., when prices change. Consequently, asymmetric prices may arise with inflation, because retailers tend to make more substantial price increases to avoid changing prices frequently.

One of the first researchers to study this effect using scanner data was Peltzman (2000), who used US supermarket scanner data from the Bureau of Labor Statistics. The research mainly used producer and consumer price samples (of the same products) to investigate whether prices rise faster than they fall. The main finding of this study is that the prices of some goods react faster to an increase in the price of an important output than they do to a decrease.

Muller and Ray (2007) complemented Peltzman’s studies by using more disaggregated wholesale and retail price scanner data to study the asymmetric price adjustment between cost and retail price. The supermarket scanner data was acquired from the same data source as Peltzman (2000), although more disaggregated data was used in this study with the purpose of uncovering asymmetries that could be missed at an aggregated level. The econometric methodology used in the paper is also an autoregressive distributed lag model (ARDL) and the specifications are similar to Peltzman (2000). This study found that asymmetric adjustments are used by retailers; however, there is no evidence of a pervasive chain asymmetric price strategy.

A common shortcoming of all previous econometric models which estimate asymmetries in response to price changes is that the nature of the data obtained for these studies does not allow any control for the substitution effect, which may lead to bias.

3. Asymmetric definition

The behaviour of Coca-Cola and Pepsi-Cola consumers in relation to demand response to price changes can be evaluated in terms of symmetry. Following Moosa, Silvapulle and Silvapulle (2003), we begin by defining symmetry based on the contemporaneous relationship between price change and volume sold (contemporaneous symmetry). If p_{it} is the price change and v_{it} is the volume of a brand of soft drink at time t for store i, the relationship is symmetric if:

$$\left|(v_{it} \middle| p_{it}^{+})\right| = \left|(v_{it} \middle| p_{it}^{-})\right| \qquad (1)$$

Therefore asymmetry implies that:

$$\left|(v_{it} \middle| p_{it}^{+})\right| \neq \left|(v_{it} \middle| p_{it}^{-})\right| \qquad (2)$$

Where: $p_{it}^{+} = p_{it} - p_{i,t-1} > 0$ and $p_{it}^{-} = p_{it} - p_{i,t-1} < 0$

Equation (1) implies that the absolute average volume sold of a given soft drink brand associated with an increase in its price is equal to the absolute average volume sold associated with the same absolute decrease in its price. By contrast, equation (2), implies that the absolute average volume sold of a given soft drink brand associated with an increase in price is not equal to the absolute average volume sold associated with the same absolute decrease in price.

Following Manera and Grasso (2005), the asymmetric relationship can be tested econometrically using an ARDL, as follows:

In an ARDL model, a variable $y_t, t = 1,...,n$ depends on its lags and on a vector of variable X , both contemporaneous and lagged.

$$y_t = \sum_{h=1}^{r} \beta_h y_{t-h} + \sum_{i=0}^{s} \alpha_i x_{t-i} + \xi_t \tag{3}$$

To test for asymmetry, equation 3 can be adapted as:

$$y_t = \sum_{h=1}^{r} \beta_h y_{t-h} + \sum_{i=0}^{s} \alpha_i x^{+}_{t-i} + \sum_{i=0}^{q} \alpha_j x^{-}_{t-j} + \xi_t \tag{4}$$

where asymmetry can be tested by assuming that x has a different impact on y , according to whether its sign is positive (+) or negative (-).

4. Data and variables selection

To investigate the relationship between the volume sold and the retail price of soft drinks, we employ weekly scanner data from February 2007 to April 2008 (64 weeks) from the Australian Bureau of Statistics (ABS). The regression analysis is carried out using the weekly balanced panel data of a two litre bottle of Coca-Cola and a two litre bottle of Pepsi-Cola across 78 stores of a supermarket chain in an unidentified location in Queensland.

The dependent variables volume vc_{it} and vp_{it} are the volumes sold in each store on a weekly basis of Coca-Cola and Pepsi-Cola respectively. The independent variables lag volume $vc_{i,t-j}$ or $vp_{i,t-j}$ is constructed using past periods of the dependent variable, where j is the lag value selected by the Bayesian information criterion (BIC). The independent variable price is the sale price (after tax) reported by each store during the given period. We also include the sale price of the substitutive brand in the model as an independent variable. In other words, we include the sale price of Coca-Cola as an independent variable when the dependent variable is the volume sold of Pepsi-Cola, and we include the sale price of Pepsi-Cola as an independent variable when the dependent variable in the regression is the volume sold of Coca-Cola.

In this sample, the average price of Coca-Cola is approximately 11% higher than the price of Pepsi-Cola and the standard deviation for Pepsi-Cola is slightly larger than the standard deviation for Coca-Cola.

The average volume sold of Coca-Cola is 706 units per week. Pepsi-Cola's average volume sold is approximately 100 units per week. The standard deviation and the distance between the minimum values with respect to the maximum value are high in both series, reflecting the difference in size of the stores.

5. Stationary and unit root test

As a first step in time series (or panel data) analysis, all variables are tested for unit root process. Formally, the Newey-West Bandwidth set of tests for unit root in panel data is used, assuming a common unit root process (e.g., Levin, Lin & Chu and Breitung tests) and assuming an individual unit root (e.g., Im, Pesaran & Shin, ADF-Fisher Chi-square and PP-Fisher Chi-square tests). Our results show that the null hypothesis of unit root presence is rejected at 1% level in all valid tests for the prices and volumes of both Coca-Cola and Pepsi-Cola, confirming the visual inspection that these series are stationary.

Since all valid tests to detect the presence of unit root lead to overwhelming results of stationary series in all four variables of interest (price and volume of Coca-Cola and Pepsi-Cola sold for all stores), the ARDL can be used.

6. Specification problems in previous modelling

Asymmetric models in econometrics that examine asymmetric price transmission or asymmetric price response to price changes using either ARDL or ECM have generally used only the lagged value of the independent variable, the price of the good or service in question and its lagged values and, when applicable, the time trend and/or seasonal dummy variable as an independent variable. Nevertheless, the issue of possible omitted variable bias arising from the substitution effect is still unaddressed.

A typical case is found in the study of asymmetric responses in the stock market. Although it is relatively easy to obtain data for stock volumes and prices, specifying substitutive stocks turns out to be a very difficult task, as stocks sometimes move in the same direction and sometimes they do not.

Our models consequently present a good opportunity to test whether controlling for a substitute good can change the sign, the statistical significance or the magnitude of the relevant coefficients, since there is no doubt that Coca-Cola and Pepsi-Cola products of the same size compete in the soft drink market.

7. Model specification

The ARDL model has largely been used to test for asymmetric price effect.[6] The frequency of the data used in previous studies is typically weekly or monthly, with daily data used only in stock market studies.

The main advantages of using an ARDL model for this purpose are, firstly, that the autoregressive part of the model can control for the possible correlation between the autocorrelation of the dependent variable with the contemporaneity and lags of the independent variables. Secondly, the ARDL has a very flexible functional form which allows testing for a long autoregressive structure in both dependent and independent variables, as well as testing for asymmetry in each lag of this structure.

Models 1 to 4 are estimated using ARDL to investigate the symmetry of the volume response to price changes (variables are described in Appendix 1). In Model 1, the variable volume of Coca-Cola sold is used as the dependent variable, the independent variables being the lag of the dependent variable, the increases and decreases of the price of the same good, and seasonal and time trend variables. In Model 2, only the price of the substitute good is added to Model 1, the objective being to analyse whether the price of the competitive good impacts our previous estimation.

Similarly, in Models 3 and 4 we construct the same models for Pepsi-Cola. The variable volume sold of Pepsi-Cola is used as the dependent variable, with independent variables being the lag of the dependent variable, the increases and decreases in prices of the same good, and seasonal and time trend variables.

[6] See for example Frey and Manera (2005) or Moosa, Silvapulle and Silvapulle (2003).

The Ordinary Least Square (OLS) robust standard error is estimated to correct for any heteroskedasticity that may arise. To test for autocorrelation, the Wooldridge test for autocorrelation in panel data (Wooldridge 2002, p. 282) is carried out for the four OLS regressions. The null hypothesis (no first autocorrelation) is rejected at 5% level for all models. To correct for autocorrelation, the Prais-Winsten correction regression is estimated.

For lag selection, we favour a methodology in this study that selects shorter models, since a number of lags for both the volume sold and price changes must be specified. Consequently, the Bayesian Information Criterion (BIC) is used, by which method eleven lags are selected for three out of four models for volume sold, and no lags for either positive or negative price changes, or for the price of the competitive good.

Dependent variable: Volume of Coca-Cola sold

Model 1

$$vc_{it} = \beta_0 + \sum_{j=1}^{n} \beta_1 vc_{i,t-j} + \gamma^+ pc_{it}^{\;+} + \gamma^- pc_{it}^{\;-} + \sum_{j=1}^{3} \lambda sd_{it} + \sum_{j=1}^{64} \delta w_{it} + \varepsilon_{it} \quad (5)$$

Model 2

$$vc_{it} = \beta_0 + \sum_{j=1}^{n} \beta_1 vc_{i,t-j} + \gamma^+ pc_{it}^{\;+} + \gamma^- pc_{it}^{\;-} + \sum_{j=1}^{3} \lambda sd_{it} + \psi pp_{it} + \sum_{j=1}^{64} \delta w_{it} + \varepsilon_{it} \quad (6)$$

Model 3

$$vp_{it} = \beta_0 + \sum_{j=1}^{n} \beta_1 vp_{i,t-j} + \gamma^+ pp_{it}{}^+ + \gamma^- pp_{it}{}^-$$

$$+ \sum_{j=1}^{3} \lambda sd_{it} + \sum_{j=1}^{64} \delta w_{it} + \varepsilon_{it} \quad (7)$$

Model 4

$$vp_{it} = \beta_0 + \sum_{j=1}^{n} \beta_1 vp_{i,t-j} + \gamma^+ pp_{it}{}^+ + \gamma^- pp_{it}{}^-$$

$$+ \sum_{j=1}^{3} \lambda sd_{it} + \psi pc_{it} + \sum_{j=1}^{64} \delta w_{it} + \varepsilon_{it} \quad (8)$$

Where: $\beta_0, \beta_1, \gamma^+, \gamma^-, \lambda, \psi$ and δ are parameters to be estimated and ε_{it} is the error term.

8. Econometric results

<Insert Figure 1>

9. Regression results

Figure 1 shows the results of the OLS Prais-Winsten regressions: in all models, the coefficients γ^+ and γ^- are statistically significant at 1% level. In Model 1, it is observed that the impact of price changes of Coca-Cola on the volume sold on the same good is around 3% higher in absolute value when the price decreases than when the price increases. In Model 2, the price of Pepsi-Cola is included; this coefficient is statistically significant at 1% level, suggesting that a 10 cent increase in the price of Pepsi-Cola leads to an increase in consumption of Coca-Cola of 19 bottles for the average store (around 2.7% increase of the average volume sold).

In Models 3 and 4, the volume of Pepsi-Cola sold is used as a dependent variable and the OLS regression in Model 3 shows that when the price of Pepsi-

Cola increases by 10 cents, the demand for this good decreases by 3.97 units in the average store. Nonetheless, when the price decreases by 10 cents, the volume sold increases by 5.99 units, implying that the volume sold in response to the price change is around 34% higher in absolute value when the price decreases than when the price increases. The intuition behind these results is that consumers of the less expensive good stock up when prices go down.

In Model 4, the price of Coca-Cola is introduced to Model 3, this coefficient being statistically significant at 1% level, suggesting that a 10 cent increase in the price of Coca-Cola leads to an increase in the volume of Pepsi-Cola sold of around 8.6 bottles for the average store (around 8.6%). Also, it is observed that the inclusion of this variable slightly decreases the magnitude of the asymmetric effect from 34% to 33%.

With regard to seasonal effect, the difference in the volume sold from the base period 'winter' seems to be almost always statistically significant for summer and spring. The Coca-Cola volume sold in summer in relation to winter increases by approximately 80 units for the average store, which sells approximately 706 units per week (around 11% increase) and by approximately 145 units in spring (around 20% increase in relation to winter). The volume of Pepsi-Cola sold in summer in relation to winter increases by approximately 25 units for the average store (around 25%); however, in spring the winter-related increase is only around 12%.

9.1. Wald test

The symmetry between the absolute value of the coefficients γ^+ and γ^- can be tested more formally using the Wald test from our results in the previous econometric estimations.[7] That is, we test the null hypothesis:

$$H_0 : \gamma^+ = \gamma^- \quad (9)$$

$$H_1 : \gamma^+ \neq \gamma^- \quad (10)$$

The results of these tests are presented in Figure 2, revealing that there is no asymmetric price effect in response to the Coca-Cola volume sold to price changes in either Model 1 or Model 2 (for all econometric techniques used). This means that for the market leader (Coca-Cola), the volume sold does not respond asymmetrically when prices go up or down. This table also shows that the null hypothesis of symmetry can be rejected at the conventional level for Models 3 and 4, confirming the asymmetry in the volume sold response to price changes for Pepsi-Cola.

<Insert Figure 2>

10. Adding the price of the substitute good in the model

The inclusion of the price of the substitute good is shown to be statistically significant at 1% level (in all models), explaining the variation of the volume sold of the original good. Additionally, the adjusted R^2 is estimated for both sets of regressions, showing that it is higher when the price of the substitute good is included, confirming that this variable has some explanatory power.

[7] Note that for this purpose, all econometric models/techniques were re-estimated using the absolute values for negative and positive prices. We multiplied pc_{it}^- in Models 1 and 2, and pp_{it}^- in Models 3 and 4 by -1 to obtain the absolute values of price changes; thereafter, the Wald test was applied.

For the model of the volume of Coca-Cola sold, we use the F-statistic to test the robustness of the results, using the restrictive R^2 (R^2 in Model 1) and the unrestricted R^2 (R^2 in Model 2). The F-statistic for this test is 45.87 which rejects the null hypothesis that the price of Pepsi-Cola does not explain the volume variation of Coca-Cola sold at 1% level.

Similarly, for Models 3 and 4 (restrictive and unrestrictive R^2 respectively) the estimated F-statistic is 144.93, rejecting the null hypothesis that the price of Coca-Cola does not explain the volume variation of Pepsi-Cola sold at 1% level.

This finding may have important implications for past and future models in asymmetric demand response. In our results, the inclusion of the substitutive price seems to consistently reduce the asymmetry estimated in the demand response for Pepsi-Cola. However, this reduction does not alter the fact that this response is still asymmetric, although it can be argued that the inclusion of the price of all other substitute goods could significantly change the econometric estimations in this field. The opposite occurs with Coca-Cola, because the inclusion of the substitute price seems to consistently increase the asymmetry estimated in the demand response for Coca-Cola.

11. Fixed effect dummy variable regression with interaction terms

So far, our results have implications for the ‘average store’ since panel data across 78 stores is used. In order to observe for the number of stores for which our results hold true, the following model is proposed and estimated:

Model 5

$$vc_{it} = \beta_0 + \sum_{j=1}^{n} \beta_1 vc_{i,t-j} + \gamma^+ pc_{it}{}^+ + \gamma^- pc_{i,t-j}{}^-$$
$$+ \sum_{i=1, i\neq 14}^{78} \tau st_{it} + \sum_{i=1, i\neq 14}^{78} \kappa^+ st_{it} * pc_{it}^+ + \sum_{i=1, i\neq 14}^{78} \kappa^- st_{it} * pc_{it}^- +$$
$$\sum_{j=1}^{3} \lambda sd_{it} + \psi pp_{it} + \sum_{j=1}^{64} \delta w_{it} + \varepsilon_{it} \quad (11)$$

Model 6

$$vp_{it} = \beta_0 + \sum_{j=1}^{n} \beta_1 vp_{i,t-j} + \gamma^+ pp_{it}{}^+ + \gamma^- pp_{i,t-j}{}^-$$
$$+ \sum_{i=1, i\neq 14}^{78} \tau st_{it} + \sum_{i=1, i\neq 14}^{78} \kappa^+ st_{it} * pp_{it}^+ + \sum_{i=1, i\neq 14}^{78} \kappa^- st_{it} * pp_{it}^- + \quad (12)$$
$$\sum_{j=1}^{3} \lambda sd_{it} + \psi pc_{it} + \sum_{j=1}^{64} \delta w_{it} + \varepsilon_{it}$$

The additional variables with respect to our previous models are described in Appendix 1, Figure 3. As can be seen in equations 11 and 12, we included three sets of variables to Models 2 and 4, commencing with a set of dummy variables for every store except store 14. This is because store 14 sold the most units of both products across these 64 weeks and also had the greatest number of transactions, consequently making it a good candidate for comparison purposes. These store-dummy variables are multiplied by either the price increase or price decrease in both equations to obtain an estimation of symmetry for each store.

12. Econometric results (fixed effect dummy variable)

<Insert Figure 3>

Figure 3 summarizes the results of Models 5 and 6 of the core variables previously reported. The results in Figure 3 ratify the previous finding, in particular for Coca-Cola (Model 5) in which the coefficient γ^- is around 25 percent larger than γ^+ ,both coefficients being statistically significant at 1%; against these results, the null hypothesis of symmetry (described in Model 6) cannot be rejected at 10%. In line also with previous results, the coefficient γ^- for Pepsi-Cola is almost 4 times larger than γ^+, both coefficients being statistically significant at 1%. In addition, the null hypothesis of symmetry can be rejected at 1% level.

To conserve space, the new sets of coefficients are not reported, However, results show that in most stores, the volume of Pepsi-Cola sold responds asymmetrically to price changes, while the volume of Coca-Cola sold responds more symmetrically to price changes. In line with our previous models, we use the Wald test to check whether or not each store's consumers respond asymmetrically to price changes (equations 13 and 14)

$$H_0 : \kappa_s^+ = \kappa_s^- \qquad (13)$$

$$H_1 : \kappa_s^+ \neq \kappa_s^- \qquad (14)$$

Using coefficients from Model 5, it is observed that consumers in 13 out of 78 stores respond to price changes asymmetrically in terms of the volume sold with respect to Coca-Cola. Using coefficients from Model 6, it is observed that consumers of 72 out of 78 stores respond asymmetrically to Pepsi-Cola price changes in terms of the volume sold.

Finally the F-statistic is reported in the last row of Figure 3 to test the joint hypothesis that store and/or interaction coefficients added in Models 5 and 6 have any explanatory power, these coefficients being statistically significant at the 1%

level which suggests that both sets of coefficients should be included in both models.

13. Conclusions

In this paper, we used ARDL models to test whether or not the volume sold of two popular soft drinks responds symmetrically to price changes. Apart from the rich and new results obtained in our estimations, this study is also novel insofar as we introduce the use of supermarket scanner data to measure the asymmetric demand response to price changes. This data seems to be quite adequate for this purpose, because scanner data provides very accurate information regarding volume sold and price changes in almost any frequency (e.g., daily, weekly or monthly), as well as information regarding substitutive and complementary goods, which is a crucial theoretical element for any model concerning demand.

Our results indicate that consumers of the most expensive good (Coca-Cola) respond quite symmetrically when prices go either up or down. In contrast, consumers of the less expensive good (Pepsi-Cola) respond quite asymmetrically. Consumers of Pepsi-Cola increase their purchase of this good in larger proportion when prices go down than they decrease their purchase – hence, volume sold – of this good when prices go up in the same proportion. These results suggest that consumers of the less expensive good (Pepsi-Cola) stock up when prices go down, whereas consumers of Coca-Cola do not stock up (at least not in the same magnitude). The intuition behind this result is that consumers of the less expensive good may be more careful with money when it comes to making a purchase. Consequently, a reduction in price of an item that they frequently consume seems to provide a good opportunity to stock up and reduce the cost of future purchases.

The use of this data also allows us to dispute some of the previous models which study asymmetric demand response to price changes. In particular, our models are the first to account for the substitution effect. We find that the asymmetric demand response to price change is underestimated in the case of Coca-Cola using the ARDL model if we do not include the price of Pepsi-Cola in the model. However, the asymmetric demand response to price changes is overestimated in the case of Pepsi-Cola using the ARDL model if we do not include the price of Coca-Cola in the model. In short, the absence of a substitute good could lead to either underestimation or overestimation of the asymmetric effect in previous models.

Appendix 1. Variable descriptions

<Insert figure 4>

<Insert figure 5>

Reference

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Figure 1. Prais-Winsten Regression (autocorrelation correction)

Coefficient	**Model 1**	**Model 2**	**Model 3**	**Model 4**
β_0	21.247	-344.089***	7.114	-184.253***
$\beta_{(t-1)}$	0.327***	0.318***	0.023***	0.225***
$\beta_{(t-2)}$	-0.085***	-0.077***	-0.113***	-0.081
$\beta_{(t-3)}$	0.090***	0.091***	0.022	0.009
$\beta_{(t-4)}$	0.041**	0.046**	0.045***	0.054
$\beta_{(t-5)}$	0.124***	0.125***	0.126***	0.108**
$\beta_{(t-6)}$	0.073***	0.073***	0.040**	0.042
$\beta_{(t-7)}$	0.078***	0.081***	0.042***	0.044
$\beta_{(t-8)}$	0.052**	0.056**	0.118***	0.124**
$\beta_{(t-9)}$	0.045**	0.048***	0.082***	0.083
$\beta_{(t-10)}$	0.068***	0.067***	0.099***	0.101*
$\beta_{(t-11)}$	0.080***	0.071***	0.162***	0.179***
γ^{+}	-216.121***	-204.222***	-39.706***	-36.102***
γ^{-}	222.220***	216.884***	59.920***	53.817***
ψ	-	190.892***	-	85.914***
λ_{summer}	82.337***	79.293***	28.319***	22.807
λ_{spring}	147.067	144.167***	12.795**	11.981
λ_{autum}	-16.076	-15.250	-33.290***	-28.206
δ	0.970***	0.747	0.522***	0.587
Obs	4134	4134	4134	4134
R2	0.54	0.55	0.41	0.43

*,**,***Indicates coefficient is significantly different from zero at the 10%,5% and 1% level respectively.

Figure 2. Wald Test, Null Hypothesis: $H_0 : \gamma^+ = \gamma^-$

Model	Coefficients
1	0.02
2	0.08
3	2.52*
4	2.04*

*,**,***Indicates coefficient is significantly different from zero at the 10%,5% and 1% level respectively.

Figure 3. Fixed Effect Dummy Variable Regression with Interaction Terms

Model 5		Model 6	
β_0	254.815*	β_0	-47.099
$\beta_{(t-1)}$	0.388***	$\beta_{(t-1)}$	0.227***
$\beta_{(t-2)}$	-0.115***	$\beta_{(t-2)}$	-0.095***
$\beta_{(t-3)}$	0.019	$\beta_{(t-3)}$	-0.093***
$\beta_{(t-4)}$	0.016	$\beta_{(t-4)}$	-0.062***
$\beta_{(t-5)}$	0.072***	$\beta_{(t-5)}$	0.031**
$\beta_{(t-6)}$	-0.007	$\beta_{(t-6)}$	-0.027
$\beta_{(t-7)}$	0.039*	$\beta_{(t-7)}$	-0.063***
$\beta_{(t-8)}$	-0.019	$\beta_{(t-8)}$	0.028
$\beta_{(t-9)}$	-0.011	$\beta_{(t-9)}$	0.014
$\beta_{(t-10)}$	0.006	$\beta_{(t-10)}$	0.035
$\beta_{(t-11)}$	0.023	$\beta_{(t-11)}$	0.069***
γ^{+}	-356.786***	γ^{+}	-39.183***
γ^{-}	443.123***	γ^{-}	150.913***
ψ	185.903***	ψ	81.631
λ_{summer}	140.267***	λ_{summer}	-1.123
λ_{spring}	125.413***	λ_{spring}	-8.237*
λ_{autum}	72.495***	λ_{autum}	-9.567**
Obs	4134	Obs	4134
R^2	0.691	R2	0.576
F[1]	7.928***	F[1]	5.810***

*,**,***Indicates coefficient is significantly different from zero at the 10%,5% and 1% level respectively.

[1] F- statistics was carried out using the unrestricted R^2 from model 5 and 6 and the restricted R^2 are from model 2 and 4.

Figure 4 Models 1 to 4

vc_{it}	Volume of Coca-Cola sold.
$vc_{i,t-j}$	Lag volume of Coca-Cola sold.
pc_{it}^{+}	Increase of Coca-Cola price and it is constructed as: $pc_{i,t-j}^{+} = pc_{i,t-j} * D^{+}_{i,t-j}$ Where $D^{+}_{i,t-j}$ takes the value of 1 if the price of the contemporaneous period is higher than the price of the previous period and 0 otherwise.
pc_{it}^{-}	Decrease of Coca-Cola price and it is constructed as: $pc_{i,t-j}^{-} = pc_{i,t-j} * D^{-}_{i,t-j}$ Where $D^{-}_{i,t-j}$ takes the value of 1 if the price of the contemporaneous period is lower than the price of the previous period and 0 otherwise.
sd_{it}	Seasonal dummy variable having winter as base group and it is constructed as:` $Dsummer_{it}$ which takes the value of 1 if the weekly observation is in summer, and 0 otherwise, $Dspring_{it}$ which takes the value of 1 if the weekly observation is in spring, and 0 otherwise and $Dautumn_{it}$ which takes the value of 1 if the weekly observation is in autumn, and 0 otherwise.
vp_{it}	Volume of Pepsi-Cola sold.
$vp_{i,t-j}$	Lag of volume of Pepsi-Cola sold.
pp_{it}^{+}	Increase of Pepsi-Cola price and it is constructed as: $pp_{i,t-j}^{+} = pp_{i,t-j} * D^{+}_{i,t-j}$ Where $D^{+}_{i,t-j}$ takes the value of 1 if the price of the contemporaneous period is higher than the price of the previous period and 0 otherwise.
pp_{it}^{-}	Decrease of Pepsi-Cola price and it is constructed as: $pp_{i,t-j}^{-} = pp_{i,t-j} * D^{-}_{i,t-j}$ Where $D^{-}_{i,t-j}$ that takes the value of 1 if the price of the contemporaneous period is lower than the price of the previous period and 0 otherwise.
w_t	Week number (time trend)
i	Store subscript.
t	Time subscript.
n	Lag value selected by Bayesian information criterion (BIC).

Figure 5 Variables used in Models 5 and 6

st_{it}	Fixed effect dummy variable, that takes the value of 1 for the selected store (excluding store 14) and 0 otherwise .
$st_{it} * pp_{it}^{+}$	Interaction term, constructed by multiplying the fixed effect dummy variable by positive change in prices
$st_{it} * pp_{it}^{-}$	Interaction term, constructed by multiplying the fixed effect dummy variable by negative change in prices
s	Store subscript.

Note that all other variables included in either Model 5 and 6 are described in Figure 1.