



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Modeling Seasonal Unit Roots as a Simple Empirical Method to Handle Autocorrelation in Demand Systems: Evidence from UK Expenditure Data

Andres Silva*
Senarath Dharmasena**

*UR 1303 Food and Social Science (ALISS)
The French National Institute for Agricultural Research (INRA)
94205 Ivry sur Seine
France
Email: andres.silva@ivry.inra.fr
Phone: +33(0)1 49 59 69 00

**Agribusiness, Food and Consumer Economics Research Center (AFCERC)
Department of Agricultural Economics
Texas A&M University
College Station
TX 77843-2124
USA
Email: sdharmasena@tamu.edu
Phone: +1 (979) 862-2894

***Selected Paper prepared for presentation at the American Agricultural Economics Association
Annual Meeting, Washington DC, August 4-6, 2013***

Copyright 2013 by Andres Silva and Senarath Dharmasena. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Modeling Seasonal Unit Roots as a Simple Empirical Method to Handle Autocorrelation in Demand Systems: Evidence from UK Expenditure Data

Abstract

Economic data with substantial seasonality are likely to have unit roots in more than one frequency. Using non-alcoholic beverage expenditure data from the United Kingdom, we empirically show that the absence of unit roots in one frequency (e.g. monthly) does not imply the absence of unit roots in some other frequencies (e.g. quarterly, bi-annually, and annually). Given the evidence of seasonal unit roots, we estimated one static and three dynamic quadratic almost ideal demand system (QUAIDS) specifications. We found that the seasonal-habit QUAIDS outperforms the static, myopic-habit and rational-habit specifications. Additionally, we show that taking into account seasonal habits helps correct autocorrelation in residuals. Simply put, given the presence of seasonal unit roots, lagged seasonal terms can be a useful simple tool for practitioners modeling expenditure data using demand systems.

Keywords: seasonal unit roots, autocorrelation, demand systems

JEL Classification: D04, D10, D12

Modeling Seasonal Unit Roots as a Simple Empirical Method to Handle Autocorrelation in Demand Systems: Evidence from UK Expenditure Data

1. Introduction

Demand systems are cornerstone of applied demand analysis. Stone (1954) was the first to derive and estimate linear expenditure system (LES) for British consumer goods data for the period 1920-1938. Stone (1954) used Klein-Rubin constant utility index of the cost of living (Klein and Rubin, 1947) in deriving the LES. Since then, demand systems have primarily evolved from three different directions. They are demand derived from (a) pre-specified utility functions, such as LES, constant elasticity of substitution (CES); (b) specified indirect utility or expenditure functions, such as almost ideal demand system (AIDS) (Deaton and Muellbauer, 1980), quadratic almost ideal demand system (QUAIDS) (Banks *et al*, 1997); (c) differential approximation to Marshallian demand such as Rotterdam (1964, Theil, 1965), NBR (Neves, 1994), CBS (Keller and Van Driel, 1985), Barten's synthetic model (Barten, 1993). When aforementioned demand systems are used to estimate demand for aggregated set of goods at the market level for a representative consumer, time-series data (monthly, quarterly, annually) are used. In that event, almost every empirical demand system study suffers from "a severe econometric flaw" namely failure to deal with nonstationarity property of prices and expenditures (Lewbel and Ng, 2005). In other words, the presence of unit roots in prices and expenditures are ignored, although seasonality is traditionally captured through introduction of seasonal dummy variables. Furthermore, since demand system that is consistent with utility maximization must be nonlinear in relative prices, usual techniques for handling regressors with unit roots, such as cointegration or linear error correction models cannot be applied (Lewbel and

Ng, 2005). Also, according to Lewbel and Ng, (2005), this problem is further exacerbated by cross-equation restrictions inherent in demand systems as well as degrees of freedom problems at the estimation stage of such systems (large number of parameters relative to the number of available time periods). As a consequence of such problems, existing demand system studies ignore the unit root problem of price and expenditures entirely or use linear model cointegration methods to deal with them. These latter models may still not be appropriate because errors in demand systems, especially those with aggregate data, tend to be autocorrelated (Berndt and Savin, 1975, Lewbel, 1996, Lewbel, 1991, Lewbel and Ng, 2005, Pollak and Wales, 1992). Furthermore, this presence of unit roots in residuals (hence autocorrelation) would result in spurious regressions and inconsistent parameter estimates (Lewbel and Ng, 2005).

Therefore, in our study, we estimate a demand system for selected beverage purchases in the United Kingdom (UK), identifying and modeling the presence of unit roots in price and expenditure variables. This modeling exercise will then be used as a path to mitigate autocorrelation patterns inherent in modeling demand systems using time-series data.

The specific objectives of this study are to (i) empirically show that the absence (or presence) of unit roots in one frequency (say monthly) does not imply the absence (or presence) of unit roots in some other frequencies (say quarterly, bi-annually, annually); and (ii) propose a way that is data-driven to model seasonal unit roots in a demand system, which in turn help correct autocorrelation of residuals.

In order to achieve these objectives, first we test for presence seasonal unit roots in price and expenditure variables. Second, we compare four demand system specifications, namely static, and three systems incorporating dynamics (myopic, rational and seasonal). Finally, we run autocorrelation and normality tests for residuals from all four models to help select the most

appropriate empirical specification. Our findings provide empirical support for the relevance of taking seasonal unit roots into account. In addition, we show that modeling seasonal unit roots in a demand system corrects for autocorrelation in the residuals.

The remainder of this article is organized as follows: section 2 discusses extant literature on correction for autocorrelation in demand systems, lagged dependent variables and role of lagged dependent variables in modeling unit roots as well as habits, section 3 describes analytical framework; section 4 explains the data used in this study; section 5 presents the empirical results, and finally, section 6 summarizes the findings and relevance of this article.

2. Literature Review

In the past, researchers have used three ways to take care of autocorrelation of residuals. First, Berndt and Savin (1975) imposed three alternative restrictions on the first order autocorrelation matrix, which is composed of first-order autoregressive errors. Three sets of restrictions were used. They are zero matrix, diagonal matrix and full matrix. Zero matrix ensures that all of the elements are restricted to zero, also known as ‘no autocorrelation’. Diagonal matrix means that the diagonal elements are restricted to be unity, and the off diagonal elements are zero while the full matrix means that all the elements are non-zero. The work undertaken by Piggott *et al.* (1996) and Piggott and Marsh (2004) follow this approach and they present their results for each one of the autocorrelation matrix restrictions. Chern, *et al.* (1995) used a diagonal autocorrelation matrix to deal with autocorrelation of residuals.

Second, Zheng and Kaiser (2008) and Dharmasena and Capps (2012) included autoregressive terms in the demand system. The autoregressive terms they employed correspond to lagged error terms. These first two approaches are valid alternative ways to take

autocorrelation into account. However, in contrast to the following, they do not identify the actual cause of the autocorrelation in the error terms.

Third, Blanciforti and Green (1983) proposed that the lagged dependent variables be used as an explanatory variable as a means of taking care of autocorrelation problem. By doing this, the authors recognized that past consumption helps explain current consumption. This specification has numerous applications, such as in the work by Chen and Veeman (1991), Holt and Goodwin (1997) and Larivière, Larue and Chalfant (2000). Not only the inclusion of lagged dependent variables can be used as a measure to correct for unit roots (nonstationarity) property of price and expenditures, also as a way to model habit formation (habit is an inertia preventing abrupt changes in desired consumption).

In formal way, Dynan (2000) defined habits as the utility depending on the current expenditure, as well as on a “stock” formed by lagged expenditure. In other words, the utility derived from current consumption is conditioned by lagged consumption patterns. Habit formation implies the non-separability of intertemporal consumption, which has been tested numerous times, such as by Ferson and Constantinides (1991), Naik and Moore (1996) and Zhen, *et al.* (2011).

Previous research, for the most part, recognizes two types of habit formation patterns (Alessie and Teppa, 2010): Rational habits, occur when current consumption depends upon past and expected consumption (Spinnewyn, (1981). Myopic habits are formed when current consumption depends only on past consumption, a type initially introduced by Stone (1954).

Richards and Patterson (2006) explained that alcohol, cigarettes and caffeine consumption have been historically characterized as rational habits. Policy interventions that increase expected future price would be effective to deter consumption. Conversely, food

consumption is characterized by myopic habits, in which the pre-existing condition, such as genetic predisposition, plays a significant role, and policy interventions that increase future prices would be less effective unless specifically targeting so-called unhealthy foods. In some cases, empirical evidence does not support the statements by Richards and Patterson (2006). Zhen, *et al.* (2011) found that it was ambiguous whether a myopic or a rational habit formation was the most appropriate specification.

Besides habit formation, seasonality is another dynamic element that characterizes food expenditure. Seasonality is often linked with supply-related events, such as produce availability, weather conditions and holidays (Heien, 2001). Heien and Durham (1991) suggested that the use of the lagged dependent variable as a proxy of habit formation can overstate the true effect because lag structure may depend on the season. Heien (2001) provides evidence that much of what has traditionally been identified as habitual behavior is, in fact, attributable to seasonal effects.

The confounding of habitual and seasonal effects can be associated with an empirical misspecification. As a common practice, depending on data frequency, empirical models include a set of consecutive dummy variables. This procedure can only incompletely capture seasonal patterns (Osborn, 1988). Therefore, a better understanding and modeling of seasonal effects would improve dynamic specification, and thus, it may mitigate autocorrelation. As a result, a desirable demand specification would include separate elements to control for habit formation and seasonality.

Consequently, since autocorrelation is a common problem when using time series data, previous research on demand systems has tried different approaches to control for

autocorrelation, such as, impose an *ex-ante* error term structure, add autoregressive terms, or include habit formation variables.

We build upon the work done by Heien (2001) in distinguishing seasonality from habits, and Gil and Molina (2009) in the habit augmentation of a quadratic demand system. In this way, we expect to make a contribution to the debate on demand system modeling, first by showing the relevance of testing for unit roots in alternative frequencies, and second by providing empirical evidence as to how correction for seasonal unit roots can possibly take care of autocorrelation problem.

3. Analytical Framework

Augmented Dickey-Fuller test (Dickey and Fuller, 1979) is performed to identify the presence of unit roots in price and expenditure data.

$$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \sum_{i=1}^k \beta_i \Delta X_{t-i} \quad [1]$$

$$\text{where } \Delta X_t = X_t - X_{t-1}$$

The null hypothesis is that the series is non-stationary or have a unit root, i.e $H_0: \alpha_1 = 0$. When the ordinary least squares estimate of the α_1 in equation (1) is significantly negative, we reject the null of series non-stationary (this means series is stationary in levels or no unit root in levels).

The t -statistic is the test statistic used in the Augmented Dickey-Fuller test. The approximate 5% critical value estimated using Monte Carlo simulation is -2.89.

We test for unit roots at different data frequencies. We convert the data to quarterly frequency and use the procedure developed by Hylleberg, *et al.* (1990) for testing seasonal unit roots at quarter, bi-annual and annual frequencies in addition to monthly frequency. According to

Hylleberg, *et al.* (1990), a stationary seasonal process can potentially be generated by $\varphi(B)$, where,

$$\varphi(B)x_t = \varepsilon_t, \text{ where } \varepsilon_t \sim n(iid) \quad [2]$$

with all of the roots of $\varphi(B) = 0$ lying outside the unit circle, however some are complex pairs with seasonal periodicities. An autoregressive model with unit root can be expressed as follows,

$$x_t = \beta x_{t-s} + \varepsilon_t \quad [3]$$

where, if $\beta = 1$, then there is a unit root at the s th seasonal frequency. For quarterly data, $s = 4$ and the appropriate filter for quarterly data with unit root is to fourth difference the series x_t (i.e. $\Delta_4 x_t$). Equation (4) shows the quarterly seasonally integrated process with a unit root.

$$\Delta_4 x_t = (x_t - x_{t-4}) = \varepsilon_t \quad [4]$$

If B is the standard lag operator such that $B^k x_t = x_t - x_{t-k}$, the unit roots at the quarterly frequency can be factored as follows (Hylleberg, *et al.* 1990).

$$(1 - B^4)x_t = (1 - B)(1 + B + B^2 + B^3)x_t \quad [5]$$

For quarterly data, equation (5) can be further expressed as;

$$(1 - B^4)x_t = (1 - B)(1 + B)(1 - iB)(1 + iB)x_t \quad [6]$$

where the unit roots are 1, -1, i , and $-i$, which corresponds to zero frequency, half-cycle per quarter or two cycles per year, and quarter cycle per quarter or one cycle per year. The last root, $-i$ is indistinguishable from the one at i with quarterly data and is therefore also interpreted as the annual cycle (Hylleberg, *et al.* 1990). Factorization depicted in equation (6) was used by Hylleberg, *et al.* (1990) to develop a test regression of the following form;

$$\Delta_4 x_t = \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-2} + \pi_4 y_{3,t-1} + \varepsilon_t \quad [7]$$

where,

$$y_{1,t} = (1 + B + B^2 + B^3)x_t \quad [8]$$

$$y_{2,t} = -(1 - B + B^2 - B^3)x_t$$

$$y_{3,t} = (1 + B^2)x_t$$

$$y_{4,t} = (1 - B^4)x_t$$

The coefficients for seasonal unit roots are shown in π_i . When $\pi_1 = 0$, the series contains a long-run unit root; when $\pi_2 = 0$, the series under consideration contains a biannual unit root; and when $\pi_3 = \pi_4 = 0$, the series contains an annual unit root. The asymptotic distribution of the t -statistics from ordinary least squares regression of equation (7) was analyzed by Chan and Wei (Chan and Wei, 1988). They found that the asymptotic distribution theory for these tests can be extracted from that of Dickey and Fuller (1979) and Fuller (1976) for π_1 and π_2 , and from Dickey, Hasza and Fuller (1984) for π_3 and π_4 . Later on, we interpret each one of them to establish the nature of the seasonality. The intuition behind this is to decompose the four-differences of the series in seasonal elements to characterize its seasonality. The seasonal unit root test provides evidence of the series patterns to augment the demand system equations.

Finally, after testing for seasonal unit roots, we estimate a QUAIDS, which was developed by Banks *et al.*, (1997). The budget shares for group i , w_i , are defined by $w_i = p_i q_i / m$. The QUAIDS specification is shown in equation (9) below.

$$w_i = \alpha_i + \sum_{j=1}^n \gamma_{ij} \ln p_j + \beta_i \ln \left[\frac{m}{a(p)} \right] + \frac{\lambda_i}{b(p)} \left\{ \ln \left[\frac{m}{a(p)} \right] \right\}^2 + v_i \quad [9]$$

where,

$$\ln a(p) = \alpha_0 + \sum_{i=1}^n \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \gamma_{ij} \ln p_i \ln p_j \quad [10]$$

$$\ln b(p) = \prod_{i=1}^n p_i^{\beta_i} \quad [11]$$

and α, β, γ and λ are parameters to be estimated, $\ln p_j$ is the natural logarithmic of the price index for group j , m is the total expenditure of the beverage subgroup and v_i is the residual term.

The specification may include demographics and seasonal dummies as intercept shifters. Six beverage categories considered in the system are depicted, $i=1,2,3,4,5,6$. We impose theoretical restrictions on parameters¹.

The QUAIDS nests the popular AIDS of Deaton and Muellbauer (1980). While saving all flexible properties of the AIDS model, the QUAIDS model allows for nonlinearity of Engel curves which are not captured via AIDS specification (AIDS model assumes linear Engel curves). Few QUAIDS applications in the extant literature include habit formation variables. Gil and Molina (2009) augment a QUAIDS with elements from the Theory of Addictions. Even more, this study does not report residual test results, which implies that they assume, rather than test, that residuals are normally distributed, not autocorrelated or contemporaneously correlated.

4. Data

In this study, we use data from the Living Cost and Food Survey² in the UK, which is a continuous survey of household expenditures. This includes data for food and non-food items, income sources, and demographics. The survey is commissioned by the Social Survey Division of the Office for National Statistics and the UK Department for Environmental and Rural Affairs

¹¹ The adding-up restrictions are given by: $\sum_{i=1}^6 \alpha_i = 1, \sum_{i=1}^6 \beta_i = 0, \sum_{i=1}^6 \lambda_i = 0, \sum_{i=1}^6 \gamma_{ij} = 0$, where $j = 1, 2, \dots, 6$. The homogeneity restrictions are given by: $\sum_{j=1}^6 \gamma_{ij} = 0, i = 1, 2, \dots, 6$. The Slutsky symmetry conditions are satisfied via the restrictions:

$$\gamma_{ij} = \gamma_{ji}, i, j = 1, 2, \dots, 6.$$

² The Living Cost and Food Survey was originally collected as the British Family Expenditure Survey, which has been used in seminal articles in applied microeconomics. Some examples of well-known works: Banks, J., R. Blundell, and A. Lewbel. 1997. "Quadratic Engel Curves and Consumer Demand." *The Review of Economics and Statistics* 79:527-539. Blundell, R., P. Pashardes, and G. Weber. 1993. "What Do We Learn About Consumer Demand Patterns from Micro Data?" *The American Economic Review* 83:570-597. Atkinson, A.B., and N.H. Stern. 1980. "On the Switch from Direct to Indirect Taxation." *Journal of Public Economics* 14:195-224. and Wales Pollak, R.A., and T.J. Wales. 1978. "Estimation of Complete Demand Systems from Household Budget Data: The Linear and Quadratic Expenditure Systems." *The American Economic Review* 68:348-359. Consequently, we are working with a dataset with an established reputation.

(DEFRA). Annually, a stratified random sample of around six thousand households is selected across the UK. By regularly changing the surveyed households, information is obtained continuously throughout the year, except for a break at Christmas. Household-level data is reported on a weekly basis for a given month. We use per capita weekly expenditures per month for select non-alcoholic beverage categories from April 2001 through December 2010, a total of 117 months.

The survey collects food expenditure from food at home, as well as from food away from home sources. However, food at home items are registered in more detail (more than 250 food categories), and as a consequence, for the purposes of this analysis, we use at-home expenditure data from select non-alcoholic beverage categories.

The Living Cost and Food Survey contains twenty one non-alcoholic beverage categories. We aggregated them to represent six expenditure groups. They are fluid milk (group 1), dried milk (group 2), juice and water (group 3), coffee and tea (group 4), concentrated soft drinks (group 5) and non-concentrated soft drinks (group 6). Then, we created price indexes aggregating several products into a single group expenditure price index. Deaton and Muellbauer (1980) explained that the true-cost-of-living index is the ratio of minimum expenditures to reach a referential indifference curve given two sets of prices. Therefore, the cost-of-living index would indicate how price changes between two periods. The cost-of living price index would normally be approximated by the Laspeyres index (Deaton and Zaidi, 2002). Taking this into account, we used the Laspeyres index to aggregate similar non-alcoholic expenditure categories into a single price index. Table 1 shows the summary statistics of budget shares, price indexes and total expenditure.

Table 1: Summary Statistics

Variable	Month	Mean	Std. Dev.	Min	Max
<i>Expenditure Shares</i>					
w ₁ fluid milk	117	0.13	0.02	0.07	0.16
w ₂ dried milk	117	0.03	0.01	0.01	0.07
w ₃ juice & water	117	0.13	0.02	0.09	0.16
w ₄ coffee & tea	117	0.26	0.03	0.19	0.32
w ₅ concentrated soft drink	117	0.38	0.03	0.32	0.48
w ₆ non-concentrated soft drink	117	0.08	0.01	0.04	0.13
<i>Laspeyres Price Index</i>					
P ₁ fluid milk	117	0.99	0.05	0.87	1.12
P ₂ dried milk	117	1.02	0.09	0.75	1.34
P ₃ juice & water	117	0.99	0.06	0.85	1.22
P ₄ coffee & tea	117	1.04	0.05	0.91	1.16
P ₅ concentrated soft drink	117	1.01	0.05	0.86	1.13
P ₆ non-concentrated soft drink	117	0.98	0.09	0.76	1.20
total beverage expenditure* (£)	117	7.92	1.32	6.07	12.00

*weekly per capita non-alcoholic beverage expenditure in British pounds

5. Empirical Estimation and Results

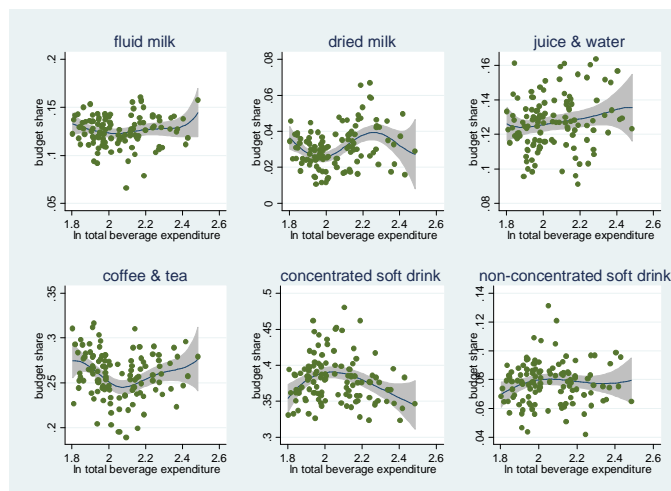
We estimate one static and three dynamic versions of QUAIDS³. Non-linear Seemingly Unrelated Regression (NLSUR) procedure in Stata statistical software package is used for the estimation of the demand system given that QUAIDS is a non-linear model and residuals are expected to be contemporaneously correlated. This last assumption will be empirically tested. The static QUAIDS model does not include dynamic elements, the myopic-habit QUAIDS model (assumes past expenditure matters) includes previous period expenditure share as an explanatory variable. The rational-habit QUAIDS model (assumes both past and future expenditure matters) includes past period ($t - 1$) and one period ahead ($t + 1$) expenditure

³ The potential endogeneity problem with respect to total expenditure variable is corrected using predicted total expenditures obtained using an auxiliary regression as suggested by Dharmasena and Capps (2011), page 667, footnote 5. Estimates of respective coefficients of this auxiliary regression are available from the authors upon request.

shares as explanatory variables, and the seasonal-habit QUAIDS model includes dependent variables with three (quarterly), six (bi-annual) and twelve (annual) lagged expenditure share variables. Then, for each of the four models, we test for properties of error terms such as, normality and autocorrelation or contemporaneous correlation. We hypothesize that the static QUAIDS specification would have stronger autocorrelation than the myopic and rational models, which would in turn have stronger autocorrelation than the seasonal QUAIDS specification. We use the residual tests to provide empirical support for the most appropriate empirical specification.

Figure 1 shows the Engel curves, where the budget share of a beverage is plotted against the logarithm of total expenditure. According to Figure 1, we clearly see the non-linearity of Engel curves for consumption of different non-alcoholic beverage categories. Overall, there is a drop in expenditure shares of dried milk and concentrated soft drinks as total expenditure rises. On the other hand, there is a rise in consumption of fluid milk, juice and water, coffee and tea, and non-concentrated soft drinks with rising expenditures.

Figure 1: Engel Curves for selected non-alcoholic beverage categories



First, using monthly data, we test for unit roots using the Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979). Table 2 shows the Augmented Dickey Fuller statistics and their critical values.

Table 2: Augmented Dickey Fuller Statistics for monthly budget shares and price

Variable	Order	Stat	Critical Values	
			5%	10%
<u>Expenditure Shares</u>				
w ₁ fluid milk	I(0)	-8.82	-2.89	-2.58
w ₂ dried milk	I(0)	-10.10	-2.89	-2.58
w ₃ juice & water	I(0)	-9.06	-2.89	-2.58
w ₄ coffee & tea	I(0)	-6.88	-2.89	-2.58
w ₅ concentrated soft drink	I(0)	-6.86	-2.89	-2.58
w ₆ non-concentrated soft drink	I(0)	-7.22	-2.89	-2.58
<u>Laspeyres Price Index</u>				
P ₁ fluid milk	I(0)	-5.93	-2.89	-2.58
P ₂ dried milk	I(0)	-8.74	-2.89	-2.58
P ₃ juice & water	I(0)	-8.39	-2.89	-2.58
P ₄ coffee & tea	I(0)	-7.22	-2.89	-2.58
P ₅ concentrated soft drink	I(0)	-8.59	-2.89	-2.58
P ₆ non-concentrated soft drink	I(0)	-8.20	-2.89	-2.58

According to information provided in Table 2, expenditure shares and price index series are stationary at levels, meaning it rejects the presence of unit roots at levels in monthly data. Second, we test for seasonal unit roots. Table 3 corresponds to the seasonal unit root test by Hylleberg, *et al.* (1990), whose routine has been implemented in Stata statistical package by Depalo (2009). When the test statistic is not significantly different from zero, the presence of a unit root is indicated in that frequency.

Table 3: Seasonal Unit Root Test (HEGY Test)

frequency	budget shares						critical values
	W ₁	W ₂	W ₃	W ₄	W ₅	W ₆	5%
quarter	-2.06	-2.29	-2.88	-2.80	-3.71	-1.95	-3.71
bi-annual	-2.40	-0.94	-2.79	-2.17	-1.57	-1.72	-3.08
annual	5.64	3.66	8.62	4.22	0.53	5.09	6.55
joint	5.92	3.74	8.65	9.80	5.75	4.27	6.53

frequency	price index						critical values
	P ₁	P ₂	P ₃	P ₄	P ₅	P ₆	5%
quarter	-2.77	-1.23	-1.12	-0.35	-2.57	-2.16	-3.71
bi-annual	-1.14	-1.57	-1.16	-1.86	-1.98	-1.74	-3.08
annual	5.90	6.15	1.31	1.63	5.45	6.24	6.55
joint	4.78	4.19	1.22	1.74	5.41	5.09	6.53

Using the HEGY procedure, we are able to test for unit roots at quarterly, bi-annual and annual frequencies. At these three frequencies, each of the share and price series has evidence of unit roots, or seasonal unit roots. Quarterly seasonal unit roots are evident in five out of six budget share series. Likewise, all price index series show quarterly seasonal unit roots. At the bi-annual frequency, all budget shares and price indexes have seasonal unit roots. At the annual frequency, five out of the six series of budget shares show presence of seasonal unit roots. All price index series show evidence for presence of annual seasonal unit roots. Finally, we conduct the joint test of quarterly, bi-annual and annual frequencies. The results show that four out of the six series of budget shares and all price indexes have seasonal unit roots.

Therefore, even though the standard ADF tests reported in Table 2 suggest that there are no unit roots at the monthly frequency, in most of the cases the budget shares and price indexes display evidence for unit roots at quarterly, bi-annual and annual frequencies. Now, the challenge is how to take into account the “hidden” seasonal patterns in the analysis of demand systems. Our strategy is to allow the data to tell the story. We estimated one static and three dynamic versions of QUAIDS and then allowed tests of the residuals to inform the best specification.

Table 4 shows the results of each QUAIDS specification. Following Heien and Durham (1991), we include a set of dummy variables to control for seasonality in each empirical specification to avoid overstating the true habit effect. In this exercise, we find that quarterly dummy variables tend to be significantly different from zero.

Lagged budget shares tend to be significant in most of the expenditure share equations in the myopic-habit model and in some cases in the rational-habit model. In the seasonal-habit model, the sixth lagged budget share is significant in the two soft drink expenditure groups. Therefore, the seasonal-habit model is able to capture some of the high frequency patterns that were found in the HEGY test.

Table 4: QUAIDS Estimation

	<i>Static (model A)</i>		<i>Myopic-Habit (model B)</i>		<i>Rational-Habit (model C)</i>		<i>Seasonal-Habit (model D)</i>	
	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.
fluid milk								
Habits								
w_{-1t} (w_{-3t} in model D)			0.31	0.07	0.14	0.07	0.01	0.07
w_{+1t} (w_{+6t} in model D)					0.12	0.06	0.10	0.07
w_{-12t} in model D							-0.03	0.07
Ln price index								
fluid milk	0.06	0.05	0.01	0.02	0.05	0.05	0.07	0.06
dried milk	-0.003	0.02	-0.01	0.01	-0.01	0.02	-0.01	0.02
juice & water	-0.04	0.02	0.02	0.01	-0.04	0.02	-0.04	0.02
coffee & tea	-0.003	0.03	-0.08	0.02	0.01	0.03	0.01	0.03
concentrated soft drink	0.01	0.03	0.06	0.02	-0.002	0.03	0.02	0.04
non-concentrated soft drink	-0.02	0.07	0.01	0.02	-0.002	0.07	-0.06	0.10
total beverage expenditure	-0.04	0.06	-0.06	0.07	-0.02	0.06	-0.06	0.07
lambda	0.005	0.01	0.01	0.01	0.01	0.01	0.00	0.01
Seasonal dummies								
jan-mar	0.01	0.004	0.003	0.004	0.01	0.004	0.01	0.004
apr-jun	-0.01	0.004	-0.001	0.004	-0.004	0.004	-0.01	0.004
jul-sep	-0.005	0.004	0.003	0.004	-0.002	0.004	-0.01	0.004
Linear trend	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001
Constant	-0.03	0.16	0.12	0.09	-0.01	0.15	-0.08	0.17
dried milk								
Habits								
w_{-1t} (w_{-3t} in model D)			0.09	0.08	0.02	0.07	0.02	0.08
w_{+1t} (w_{+6t} in model D)					0.03	0.07	0.07	0.08
w_{-12t} in model D							0.02	0.08
Ln price index								
fluid milk	-0.003	0.02	-0.01	0.01	-0.01	0.02	-0.01	0.02
dried milk	-0.02	0.01	0.05	0.01	-0.02	0.01	-0.02	0.01
juice & water	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.004	0.01
coffee & tea	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
concentrated soft drink	0.03	0.02	0.02	0.02	0.03	0.02	0.04	0.02
non-concentrated soft drink	-0.01	0.02	-0.06	0.02	-0.01	0.02	-0.02	0.03
total beverage expenditure	0.02	0.03	0.08	0.09	0.02	0.03	0.004	0.03
lambda	-0.003	0.003	-0.02	0.02	-0.004	0.00	-0.01	0.00
Seasonal dummies								
jan-mar	0.001	0.003	0.01	0.002	0.001	0.003	-0.0003	0.003
apr-jun	-0.004	0.003	-0.0001	0.002	-0.004	0.003	-0.01	0.003
jul-sep	-0.003	0.003	0.002	0.002	-0.003	0.003	-0.004	0.003
Linear trend	0.00004	0.00005	0.0001	0.00005	0.00003	0.0001	0.00005	0.0001
Constant	0.11	0.08	-0.05	0.10	0.11	0.07	0.09	0.08
juice & water								
Habits								
w_{-1t} (w_{-3t} in model D)			0.13	0.07	0.07	0.06	-0.03	0.06
w_{+1t} (w_{+6t} in model D)					0.04	0.06	0.07	0.06
w_{-12t} in model D							0.11	0.06
Ln price index								
fluid milk	-0.04	0.02	0.02	0.01	-0.04	0.02	-0.04	0.02
dried milk	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.004	0.01
juice & water	0.02	0.02	0.05	0.01	0.02	0.02	0.03	0.02
coffee & tea	0.04	0.02	-0.06	0.02	0.03	0.02	0.03	0.02
concentrated soft drink	-0.04	0.02	0.00	0.02	-0.04	0.02	-0.02	0.03
non-concentrated soft drink	0.02	0.02	0.02	0.02	0.03	0.02	0.005	0.02
total beverage expenditure	0.01	0.03	-0.07	0.07	0.02	0.03	0.002	0.03
lambda	0.004	0.003	0.01	0.01	0.00	0.00	0.01	0.003
Seasonal dummies								
jan-mar	0.003	0.004	0.01	0.003	0.003	0.004	0.003	0.004
apr-jun	0.01	0.004	0.01	0.003	0.01	0.004	0.01	0.004
jul-sep	0.01	0.004	0.01	0.003	0.01	0.004	0.01	0.004
Linear trend	0.0002	0.0001	-0.00002	0.00005	0.0001	0.0001	0.0001	0.0001
Constant	0.11	0.09	0.16	0.08	0.12	0.08	0.05	0.09

	<i>Static (model A)</i>		<i>Myopic-Habit (model B)</i>		<i>Rational-Habit (model C)</i>		<i>Seasonal-Habit (model D)</i>	
	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.	Parameter	St. Dev.
coffee & tea								
Habits								
w_{-1t} (w_{-3t} in model D)			0.0001	0.07	0.10	0.06	-0.02	0.06
w_{+1t} (w_{6t} in model D)					0.16	0.05	0.09	0.06
w_{-12t} in model D							0.06	0.06
Ln price index								
fluid milk	-0.003	0.03	-0.08	0.02	0.01	0.03	0.01	0.03
dried milk	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
juice & water	0.04	0.02	-0.06	0.02	0.03	0.02	0.03	0.02
coffee & tea	0.04	0.04	0.10	0.04	0.04	0.04	0.02	0.04
concentrated soft drink	-0.04	0.04	-0.02	0.04	-0.04	0.03	-0.03	0.04
non-concentrated soft drink	-0.05	0.03	0.06	0.04	-0.05	0.03	-0.05	0.04
total beverage expenditure	-0.07	0.04	0.02	0.11	-0.07	0.03	-0.07	0.04
lambda	-0.002	0.005	0.003	0.02	0.0004	0.005	-0.001	0.005
Seasonal dummies								
jan-mar	-0.004	0.01	-0.002	0.01	-0.001	0.01	-0.01	0.01
apr-jun	-0.03	0.01	-0.03	0.01	-0.02	0.01	-0.03	0.01
jul-sep	-0.03	0.01	-0.04	0.01	-0.03	0.01	-0.03	0.01
Linear trend	0.0001	0.0001	-0.0001	0.0001	0.0001	0.0001	0.0002	0.0001
Constant	0.08	0.12	0.25	0.14	-0.02	0.11	0.01	0.12
concentrated soft drink								
Habits								
w_{-1t} (w_{-3t} in model D)			0.21	0.06	0.14	0.05	-0.06	0.05
w_{+1t} (w_{6t} in model D)					0.03	0.05	0.19	0.06
w_{-12t} in model D							0.02	0.06
Ln price index								
fluid milk	0.01	0.03	0.06	0.02	-0.002	0.03	0.02	0.04
dried milk	0.03	0.02	0.02	0.02	0.03	0.02	0.04	0.02
juice & water	-0.04	0.02	-0.004	0.02	-0.04	0.02	-0.02	0.03
coffee & tea	-0.04	0.04	-0.02	0.04	-0.04	0.03	-0.03	0.04
concentrated soft drink	0.02	0.05	0.00	0.05	0.03	0.05	-0.02	0.05
non-concentrated soft drink	0.03	0.03	-0.05	0.04	0.03	0.03	0.01	0.04
total beverage expenditure	0.06	0.05	0.07	0.15	0.05	0.05	0.04	0.05
lambda	0.001	0.01	-0.01	0.03	0.00	0.01	0.002	0.01
Seasonal dummies								
jan-mar	-0.02	0.01	-0.02	0.01	-0.02	0.01	-0.02	0.01
apr-jun	0.01	0.01	0.01	0.01	0.02	0.01	0.02	0.01
jul-sep	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.01
Linear trend	-0.0003	0.0001	-0.0004	0.0001	-0.0003	0.0001	-0.0005	0.0001
Constant	0.56	0.16	0.23	0.18	0.46	0.15	0.45	0.16
non-concentrated soft drink								
Habits								
w_{-1t} (w_{-3t} in model D)			-0.74	0.20	-0.47	0.20	0.09	0.21
w_{+1t} (w_{6t} in model D)					-0.38	0.20	-0.53	0.22
w_{-12t} in model D							-0.19	0.22
Ln price index								
fluid milk	-0.02	0.07	0.01	0.02	0.00	0.07	-0.06	0.10
dried milk	-0.01	0.02	-0.06	0.02	-0.01	0.02	-0.02	0.03
juice & water	0.02	0.02	0.02	0.02	0.03	0.02	0.00	0.02
coffee & tea	-0.05	0.03	0.06	0.04	-0.05	0.03	-0.05	0.04
concentrated soft drink	0.03	0.03	-0.05	0.04	0.03	0.03	0.01	0.04
non-concentrated soft drink	0.02	0.05	0.03	0.07	0.01	0.06	0.05	0.09
total beverage expenditure	0.02	0.10	-0.04	0.19	0.00	0.10	0.08	0.12
lambda	-0.005	0.01	0.01	0.04	-0.01	0.01	0.00	0.01
Seasonal dummies								
jan-mar	0.01	0.003	0.005	0.004	0.01	0.003	0.01	0.004
apr-jun	0.02	0.003	0.01	0.004	0.01	0.004	0.02	0.004
jul-sep	0.02	0.003	0.02	0.005	0.01	0.003	0.01	0.004
Linear trend	0.00001	0.0001	0.0002	0.0001	-0.0001	0.0001	-0.0001	0.0001
Constant	0.18	0.24	0.30	0.23	0.34	0.24	0.47	0.29

Note: Bold numbers are significant at 5% significance level

Total beverage expenditure corresponds to the predicted values of an auxiliary regression.

Next, we conduct a set of residual tests to help select the most appropriate demand specification. We test for autocorrelation (see appendix A), normality (see appendix B) and contemporaneous correlation of the residuals (see appendix C). Table 5 provides a summary of the most relevant results, which show the normality test, the number of equations that have residuals with autocorrelation, and the total number of lags with autocorrelation. This last column provides an idea of the severity of the autocorrelation. We test for autocorrelation using twelve lags in each of the five residual series, which totals to sixty lags.

Table 5: Summary of Residual Tests

	Normality	Autocorrelation	Total Lags
Static	Rejected*	3 out of 5 equations	14 out of 60 lags
Dynamic			
Myopic Habits	Fail to be rejected	3 out of 5 equations	16 out of 60 lags
Rational Habits	Fail to be rejected	3 out of 5 equations	9 out of 60 lags
Seasonal Habits	Fail to be rejected	None	None

(*) marginal rejection. Complete output in Appendix.

Table 5 shows that normality of static QUAIDS residuals are rejected and that three out of the five residual series have autocorrelation. Myopic- and rational-habit QUAIDS residuals may have a slight improvement over the static residuals. In contrast, seasonal-habit QUAIDS residuals show a substantial improvement over the static QUAIDS, myopic-habit QUAIDS and rational-habit QUAIDS residuals. Evidence suggest that seasonal-habit QUAIDS residuals are normally distributed and do not have any significant autocorrelation pattern.

Evidence from previous work by Zhen, *et al.* (2011) suggested that it was ambiguous whether a myopic or a rational habit formation was the most appropriate specification for consumption of selected non-alcoholic beverage categories. However, they did not provide residual tests. Our findings are consistent with Zhen, *et al.* (2011). We are still not clear whether

myopic-habit or rational-habit specification is the most appropriate model to explain non-alcoholic beverage expenditures. Nevertheless, according to our study, the proposed seasonal-habit model outperforms both myopic and rational habit models.

As expected, in all of the four models, most of the residuals are contemporaneously correlated, which provides support for our choice of NLSUR as the estimation method of the demand system.

Bottom line, as evidenced by residual tests, we have found empirical support for the use of seasonal-habit QUAIDS specification, which, in our case, is able to capture the dynamics of the beverage expenditures and solve the autocorrelation problem inherent in such data.

6. Concluding Remarks

According to Hylleberg, *et al.* (1990), economic series with substantial seasonality are likely to have unit roots in more than one frequency. Food expenditure tends to present significant seasonal patterns, so unit roots at multiple frequencies are expected. In our study, using a non-alcoholic beverage expenditure dataset from the UK, we empirically show that the absence of unit roots in one frequency (e.g. monthly) does not imply the absence of unit roots in some other frequencies (e.g. quarterly, bi-annually, and annually).

Moreover, given the evidence of seasonal unit roots, we estimate one static and three dynamic QUAIDS specifications. We found that the seasonal-habit QUAIDS outperforms the static, myopic-habit and rational-habit specifications. Additionally, we found that taking into account seasonal habits helps correct autocorrelation in residuals. Simply put, given the presence of seasonal unit roots, lagged seasonal terms can be a useful simple tool for practitioners modeling expenditure data using demand systems.

References

- Alessie, R., and F. Teppa. 2010. "Saving and Habit Formation: Evidence from Dutch Panel Data." *Empirical Economics* 38:385-407.
- Atkinson, A.B., and N.H. Stern. 1980. "On the Switch from Direct to Indirect Taxation." *Journal of Public Economics* 14:195-224.
- Banks, J., R. Blundell, and A. Lewbel. 1997. "Quadratic Engel Curves and Consumer Demand." *The Review of Economics and Statistics* 79:527-539.
- Barten, A.P. 1964. "Consumer Demand Functions under Conditions of Almost Additive Preferences." *Econometrica* 32:1-38.
- Berndt, E.R., and N.E. Savin. 1975. "Estimation and Hypothesis Testing in Singular Equation Systems with Autoregressive Disturbances." *Econometrica* 43:937-957.
- Blanciforti, L., and R. Green. 1983. "An Almost Ideal Demand System Incorporating Habits: An Analysis of Expenditures on Food and Aggregate Commodity Groups." *Review of Economics & Statistics* 65:511-515.
- Blundell, R., P. Pashardes, and G. Weber. 1993. "What Do We Learn About Consumer Demand Patterns from Micro Data?" *The American Economic Review* 83:570-597.
- Chan, N.H., and C.Z. Wei. 1988. "Limiting Distributions of Least Squares Estimates of Unstable Autoregressive Processes." *The Annals of Statistics* 16:367-401.
- Chen, P.Y., and M.M. Veeman. 1991. "An Almost Ideal Demand System Analysis for Meats with Habit Formation and Structural Change." *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 39:223-235.
- Chern, W.S., E.T. Loehman, and S.T. Yen. 1995. "Information, Health Risk Beliefs, and the Demand for Fats and Oils." *The Review of Economics and Statistics* 77:555-564.
- Deaton, A., and J. Muellbauer. 1980. *Economics and Consumer Behavior*. New York: Cambridge University Press.
- Deaton, A., and S. Zaidi. "Guidelines for Constructing Consumption Aggregates for Welfare Analysis." The World Bank.
- Depalo, D. 2009. "A Seasonal Unit-Root Test with Stata." *Stata Journal* 9:422-438.
- Dharmasena, S., and O.J. Capps. 2012. "Intended and Unintended Consequences of a Proposed National Tax on Sugar-Sweetened Beverages to Combat the U.S. Obesity Problem." *Health Economics* 21:669-694.
- Dickey, D.A., and W.A. Fuller. 1979. "Distribution of the Estimators for Autoregressive Time Series With a Unit Root." *Journal of the American Statistical Association* 74:427-431.
- Dickey, D.A., D.P. Hasza, and W.A. Fuller. 1984. "Testing for Unit Roots in Seasonal Time Series." *Journal of the American Statistical Association* 79:355-367.
- Dynan, K.E. 2000. "Habit Formation in Consumer Preferences: Evidence from Panel Data." *The American Economic Review* 90:391-406.
- Ferson, W.E., and G.M. Constantinides. 1991. "Habit Persistence and Durability in Aggregate Consumption: Empirical Tests." *Journal of Financial Economics* 29:199-240.
- Gil, A., and J. Molina. 2009. "Alcohol Demand Among Young People in Spain: An Addictive QUAIDS." *Empirical Economics* 36:515-530.
- Heien, D. 2001. "Habit, Seasonality, and Time Aggregation in Consumer Behaviour." *Applied Economics* 33:1649-1653.

- Heien, D., and C. Durham. 1991. "A Test of the Habit Formation Hypothesis Using Household Data." *The Review of Economics and Statistics* 73:189-199.
- Holt, M.T., and B.K. Goodwin. 1997. "Generalized Habit Formation in an Inverse Almost Ideal Demand System: An Application to Meat Expenditures in the U.S." *Empirical Economics* 22:293-320.
- Hylleberg, S., R.F. Engle, C.W.J. Granger, and B.S. Yoo. 1990. "Seasonal Integration and Cointegration." *Journal of Econometrics* 44:215-238.
- Keller, W.J., and J. Van Driel. 1985. "Differential Consumer Demand Systems." *European Economic Review* 27:375-390.
- Larivière, É., B. Larue, and J. Chalfant. 2000. "Modeling the Demand for Alcoholic Beverages and Advertising Specifications." *Agricultural Economics* 22:147-162.
- Lewbel, A. 1996. "Aggregation Without Separability: A Generalized Composite Commodity Theorem." *The American Economic Review* 86:524-543.
- . 1991. "The Rank of Demand Systems: Theory and Nonparametric Estimation." *Econometrica* 59:711-730.
- Lewbel, A., and S. Ng. 2005. "Demand Systems with Nonstationary Prices." *Review of Economics and Statistics* 87:479-494.
- Naik, N.Y., and M.J. Moore. 1996. "Habit Formation and Intertemporal Substitution in Individual Food Consumption." *The Review of Economics and Statistics* 78:321-328.
- Neves, P.D. 1994. "A Class of Differential Demand Systems." *Economics Letters* 44:83-86.
- Osborn, D.R. 1988. "Seasonality and Habit Persistence in a Life Cycle Model of Consumption." *Journal of Applied Econometrics* 3:255-266.
- Piggott, N.E., J.A. Chalfant, J.M. Alston, and G.R. Griffith. 1996. "Demand Response to Advertising in the Australian Meat Industry." *American Journal of Agricultural Economics* 78:268-279.
- Piggott, N.E., and T.L. Marsh. 2004. "Does Food Safety Information Impact U.S. Meat Demand?" *American Journal of Agricultural Economics* 86:154-174.
- Pollak, R.A., and T.J. Wales. 1992. *Demand System Specification and Estimation*. New York: Oxford University Press.
- . 1978. "Estimation of Complete Demand Systems from Household Budget Data: The Linear and Quadratic Expenditure Systems." *The American Economic Review* 68:348-359.
- Richards, T.J., and P.M. Patterson. 2006. "Native American Obesity: An Economic Model of the "Thrifty Gene" Theory." *American Journal of Agricultural Economics* 88:542-560.
- Spinnewyn, F. 1981. "Rational Habit Formation." *European Economic Review* 15:91-109.
- Stone, R. 1954. "Linear Expenditure Systems and Demand Analysis: An Application to the Pattern of British Demand." *The Economic Journal* 64:511-527.
- Theil, H. 1965. "The Information Approach to Demand Analysis." *Econometrica* 33:67-87.
- Zhen, C., M.K. Wohlgenant, S. Karns, and P. Kaufman. 2011. "Habit Formation and Demand for Sugar-Sweetened Beverages." *American Journal of Agricultural Economics* 93:175-193.
- Zheng, Y., and H.M. Kaiser. 2008. "Advertising and U.S. Nonalcoholic Beverage Demand." *Agricultural and Resource Economics Review* 37:147-159.

Appendix A: Autocorrelations, partial autocorrelations, and portmanteau (Q) statistics

Lag	Residual fluid milk eq.				Residual dried milk eq.				Residual juice & water Eq.				Residual coffee & tea eq.				Residual concentrated soft drink eq.			
	AC	PAC	Q	Prob>Q	AC	PAC	Q	Prob>Q	AC	PAC	Q	Prob>Q	AC	PAC	Q	Prob>Q	AC	PAC	Q	Prob>Q
1	-0.01	-0.01	0.02	0.89	-0.10	-0.10	1.10	0.29	0.09	0.09	0.92	0.34	0.10	0.10	1.13	0.29	0.20	0.20	4.62	0.03
2	0.02	0.02	0.05	0.97	0.13	0.12	3.05	0.22	0.14	0.13	3.17	0.21	0.06	0.05	1.58	0.45	0.09	0.05	5.54	0.06
3	-0.06	-0.06	0.49	0.92	0.21	0.25	8.67	0.03	0.15	0.13	5.77	0.12	0.06	0.05	2.05	0.56	0.15	0.14	8.40	0.04
4	-0.005	-0.01	0.49	0.97	0.02	0.05	8.74	0.07	0.01	-0.03	5.78	0.22	0.14	0.13	4.36	0.36	0.10	0.06	9.73	0.05
5	0.02	0.02	0.54	0.99	-0.02	-0.07	8.77	0.12	0.18	0.16	9.75	0.08	0.24	0.22	11.67	0.04	0.29	0.27	20.26	0.00
6	0.01	0.01	0.56	0.997	0.09	0.02	9.67	0.14	0.07	0.04	10.43	0.11	0.08	0.03	12.39	0.05	0.35	0.29	35.51	0.00
7	0.03	0.02	0.64	0.999	0.004	0.005	9.68	0.21	0.04	0.00	10.65	0.15	0.05	0.03	12.75	0.08	0.03	-0.09	35.64	0.00
8	0.04	0.04	0.82	0.999	-0.14	-0.16	12.30	0.14	-0.03	-0.09	10.75	0.22	0.05	0.01	13.02	0.11	0.05	-0.01	36.01	0.00
9	-0.04	-0.04	0.99	0.9995	0.12	0.09	14.18	0.12	-0.02	-0.03	10.82	0.29	0.14	0.08	15.64	0.07	0.19	0.13	40.46	0.00
10	0.08	0.09	1.83	0.998	0.04	0.11	14.37	0.16	0.06	0.06	11.29	0.34	0.12	0.05	17.67	0.06	0.17	0.08	44.29	0.00
11	0.10	0.12	3.22	0.99	-0.10	-0.05	15.65	0.15	-0.09	-0.12	12.30	0.34	0.18	0.16	21.98	0.02	0.24	0.09	51.83	0.00
12	0.04	0.04	3.46	0.99	-0.01	-0.10	15.67	0.21	0.08	0.10	13.24	0.35	0.15	0.12	24.84	0.02	0.26	0.19	60.70	0.00
1	-0.12	-0.12	1.63	0.20	-0.01	-0.01	0.01	0.92	-0.02	-0.02	0.07	0.79	0.09	0.09	0.86	0.35	-0.03	-0.03	0.11	0.74
2	-0.08	-0.10	2.40	0.30	-0.04	-0.04	0.20	0.91	0.03	0.03	0.15	0.93	0.04	0.03	1.01	0.60	-0.03	-0.03	0.23	0.89
3	0.33	0.34	15.47	0.00	-0.02	-0.02	0.24	0.97	0.19	0.19	4.33	0.23	0.02	0.02	1.06	0.79	0.11	0.11	1.76	0.62
4	0.02	0.09	15.52	0.00	0.03	0.03	0.33	0.99	-0.02	-0.01	4.36	0.36	0.22	0.23	6.75	0.15	0.04	0.05	1.97	0.74
5	-0.11	-0.05	17.00	0.00	0.04	0.04	0.49	0.99	0.08	0.07	5.11	0.40	0.23	0.22	13.06	0.02	0.22	0.24	7.94	0.16
6	0.12	0.01	18.87	0.00	0.02	0.02	0.53	0.998	0.08	0.05	5.93	0.43	0.03	0.00	13.14	0.04	0.24	0.27	15.17	0.02
7	0.25	0.29	26.93	0.00	0.18	0.21	4.82	0.68	-0.03	-0.03	6.03	0.54	0.03	0.02	13.23	0.07	-0.03	0.02	15.30	0.03
8	-0.12	-0.02	28.81	0.00	-0.14	-0.16	7.45	0.49	0.20	0.18	10.93	0.21	0.02	-0.04	13.30	0.10	-0.03	-0.06	15.39	0.05
9	0.07	0.06	29.36	0.00	0.07	0.12	8.16	0.52	0.05	0.04	11.24	0.26	0.04	-0.07	13.48	0.14	0.13	0.05	17.45	0.04
10	0.27	0.15	38.51	0.00	0.06	0.06	8.59	0.57	0.09	0.11	12.32	0.26	0.08	0.03	14.28	0.16	0.08	0.02	18.22	0.05
11	-0.05	0.09	38.80	0.00	0.002	-0.03	8.59	0.66	0.08	0.02	13.20	0.28	0.06	0.05	14.71	0.20	0.03	-0.06	18.34	0.07
12	-0.11	-0.13	40.41	0.00	-0.08	-0.10	9.48	0.66	-0.02	-0.03	13.27	0.35	0.07	0.07	15.30	0.23	0.19	0.16	23.00	0.03
1	-0.21	-0.21	5.14	0.02	-0.15	-0.15	2.68	0.10	-0.02	-0.02	0.05	0.83	-0.14	-0.14	2.21	0.14	0.05	0.05	0.26	0.61
2	0.02	-0.02	5.21	0.07	0.11	0.10	4.23	0.12	0.11	0.11	1.62	0.45	0.02	0.00	2.27	0.32	0.03	0.03	0.39	0.82
3	-0.07	-0.07	5.80	0.12	0.19	0.23	8.73	0.03	0.14	0.14	3.92	0.27	-0.01	0.00	2.27	0.52	0.13	0.13	2.30	0.51
4	-0.04	-0.07	5.95	0.20	0.01	0.06	8.74	0.07	-0.02	-0.03	3.95	0.41	0.12	0.12	4.08	0.40	0.04	0.03	2.51	0.64
5	0.01	-0.01	5.96	0.31	-0.02	-0.06	8.78	0.12	0.17	0.14	7.46	0.19	0.16	0.20	7.02	0.22	0.24	0.24	9.41	0.09
6	0.02	0.02	6.01	0.42	0.05	-0.01	9.12	0.17	0.05	0.04	7.75	0.26	0.06	0.11	7.43	0.28	0.34	0.34	23.79	0.00
7	0.02	0.03	6.07	0.53	-0.002	0.00	9.12	0.24	0.04	0.01	7.96	0.34	0.01	0.05	7.45	0.38	-0.03	-0.03	23.89	0.00
8	0.01	0.02	6.07	0.64	-0.15	-0.16	12.00	0.15	0.00	-0.06	7.96	0.44	0.03	0.02	7.57	0.48	0.003	-0.06	23.89	0.00
9	-0.05	-0.06	6.45	0.69	0.11	0.07	13.52	0.14	-0.02	-0.05	8.04	0.53	0.08	0.04	8.31	0.50	0.16	0.10	27.08	0.00
10	0.06	0.05	6.89	0.74	0.01	0.10	13.52	0.20	0.08	0.07	8.89	0.54	-0.01	-0.05	8.31	0.60	0.12	0.09	28.82	0.00
11	0.11	0.16	8.45	0.67	-0.09	-0.04	14.57	0.20	-0.10	-0.12	10.24	0.51	0.15	0.13	11.33	0.42	0.18	0.07	33.06	0.00
12	0.02	0.09	8.52	0.74	-0.02	-0.09	14.63	0.26	0.09	0.08	11.31	0.50	0.07	0.11	11.95	0.45	0.24	0.20	40.54	0.00
1	-0.05	-0.05	0.23	0.63	-0.07	-0.07	0.53	0.46	0.07	0.07	0.55	0.46	0.07	0.07	0.57	0.45	0.10	0.10	1.10	0.29
2	0.01	0.01	0.24	0.89	0.10	0.10	1.59	0.45	0.12	0.11	2.03	0.36	-0.05	-0.06	0.87	0.65	-0.05	-0.06	1.41	0.49
3	-0.08	-0.09	0.97	0.81	0.17	0.19	4.76	0.19	0.17	0.16	5.35	0.15	-0.06	-0.06	1.29	0.73	0.02	0.03	1.44	0.70
4	-0.03	-0.05	1.07	0.90	0.07	0.09	5.32	0.26	0.03	0.00	5.45	0.24	0.05	0.05	1.59	0.81	-0.003	-0.01	1.44	0.84
5	0.01	0.01	1.09	0.96	-0.03	-0.05	5.39	0.37	0.18	0.15	9.22	0.10	0.21	0.20	6.43	0.27	0.21	0.22	6.48	0.26
6	-0.08	-0.10	1.83	0.94	0.03	-0.03	5.50	0.48	0.04	-0.01	9.37	0.15	0.01	-0.01	6.44	0.38	0.11	0.08	7.83	0.25
7	0.01	-0.02	1.83	0.97	-0.05	-0.07	5.73	0.57	0.002	-0.04	9.37	0.23	-0.07	-0.05	6.98	0.43	-0.07	-0.06	8.37	0.30
8	-0.01	-0.01	1.83	0.99	-0.15	-0.17	8.29	0.41	-0.02	-0.08	9.40	0.31	-0.02	0.01	7.03	0.53	-0.09	-0.09	9.40	0.31
9	-0.06	-0.09	2.20	0.99	0.07	0.07	8.89	0.45	-0.03	-0.04	9.52	0.39	0.06	0.04	7.44	0.59	0.13	0.16	11.27	0.26
10	0.06	0.05	2.57	0.99	-0.01	0.08	8.90	0.54	0.07	0.07	10.11	0.43	0.03	-0.02	7.53	0.67	0.09	0.02	12.26	0.27
11	0.08	0.09	3.33	0.99	-0.10	-0.05	10.18	0.51	-0.13	-0.15	12.13	0.35	0.13	0.16	9.70	0.56	0.17	0.17	15.74	0.15
12	0.06	0.06	3.80	0.99	-0.08	-0.12	10.94	0.53	0.00	0.02	12.14	0.43	0.02	0.04	9.74	0.64	0.17	0.20	19.33	0.08

Appendix B: Skewness/Kurtosis tests for Normality; Shapiro-Francia W' test for Normal Data

Residual	W'	V'	z	Prob>z
<i>Static</i>				
fluid milk	0.98	1.75	1.12	0.13
dried milk	0.98	2.38	1.73	0.04
juice & water	0.99	0.70	-0.70	0.76
coffee & tea	0.99	1.09	0.16	0.44
concentrated soft drink	0.99	1.33	0.57	0.29
<i>Myopic</i>				
fluid milk	0.99	0.90	-0.21	0.58
dried milk	0.99	0.63	-0.92	0.82
juice & water	0.98	1.64	0.98	0.16
coffee & tea	0.99	1.04	0.09	0.47
concentrated soft drink	0.99	1.13	0.25	0.40
<i>Rational</i>				
fluid milk	0.98	1.96	1.34	0.09
dried milk	0.98	2.12	1.50	0.07
juice & water	0.99	0.79	-0.48	0.68
coffee & tea	0.99	0.68	-0.77	0.78
concentrated soft drink	0.99	0.75	-0.58	0.72
<i>Seasonal</i>				
fluid milk	0.99	1.35	0.59	0.28
dried milk	0.98	1.92	1.29	0.10
juice & water	0.99	1.20	0.36	0.36
coffee & tea	0.99	0.87	-0.28	0.61
concentrated soft drink	0.99	0.58	-1.07	0.86

Note: Bold numbers are significant at 5% significance level

Null hypothesis is that residuals are normality distributed

Appendix C: Contemporaneous correlation test

Residual	fluid milk	dried milk	juice & water	coffee & tea
<i>Static</i>				
fluid milk	1			
dried milk	-0.08	1		
juice & water	-0.27	-0.01	1	
coffee & tea	0.34	-0.03	-0.38	1
concentrated soft drink	-0.51	-0.26	-0.18	-0.63
<i>Myopic</i>				
fluid milk	1.00			
dried milk	-0.01	1.00		
juice & water	-0.01	-0.19	1.00	
coffee & tea	-0.21	0.30	-0.25	1.00
concentrated soft drink	-0.29	-0.41	-0.16	-0.58
<i>Rational</i>				
fluid milk	1			
dried milk	-0.10	1		
juice & water	-0.30	-0.0002	1	
coffee & tea	0.30	-0.08	-0.38	1
concentrated soft drink	-0.46	-0.25	-0.18	-0.62
<i>Seasonal</i>				
fluid milk	1.00			
dried milk	-0.12	1.00		
juice & water	-0.28	0.00	1.00	
coffee & tea	0.35	-0.07	-0.40	1.00
concentrated soft drink	-0.50	-0.22	-0.18	-0.61

Note: Bold numbers are significant at 5% significance level