IMPROVING ORDER FORECAST ACCURACY: A VECTOR ERROR CORRECTION APPROACH

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ABSTRACT

In this study, we use an econometric model--the vector error correction model (VECM)--which has been heavily used in other disciplines, to improve retail order forecast accuracy by leveraging the long-run equilibrium of point-of-sale (POS) and order history. Deviations from this long-run equilibrium relationship, which we describe as deviations from the retailer's inventory target, are leveraged by the VECM to improve the supplier's retail DC order forecast. We test the performance of the VECM in the ready-to-eat (RTE) cereal, canned soup and yogurt categories, using 104 weeks of data supplied by a global consumer packaged goods (CPG) company. From the results, we find significant improvement in the order forecasting accuracy of the VECM relative to other commonly used time series methodologies, which likely leads to improvement of key supplier metrics such as inventory turnover, gross margin return on inventory investment, in-stock levels, and ultimately profitability.

Keywords: Orders, Point-of-Sale Data, Retail, DC orders, Forecasting, Vector Error Correction Model

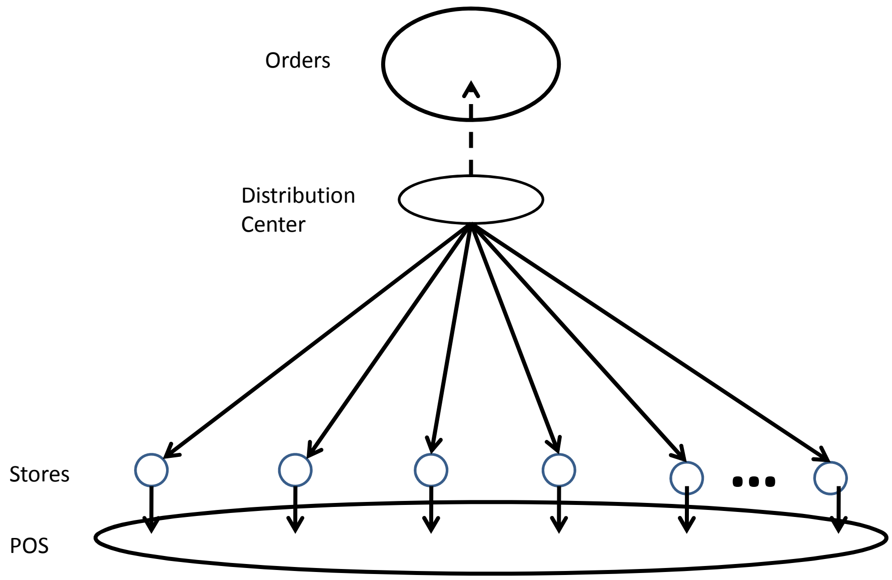
INTRODUCTION

In the retail and consumer packaged goods (CPG) industry, there exist many challenges associated with achieving competitive levels of product availability at the retail shelf. One major obstacle to meeting this challenge is the supplier's inability to accurately forecast orders placed by downstream retail partners. As a result, each supply chain partner suffers severe consequences. In a Grocery Manufacturers of America (GMA) study, 50% of retail out-of-stocks in the consumer goods industry are linked to poor ordering, replenishment and forecasting processes (Gruen, Corsten and Bharadwaj 2002).

One might expect that predicting retail order quantities might be as simple as summing the previous consumer sales at the retail outlet(s) since the last replenishment. However, there are processes such as store replenishment and execution processes as well as retailer-owned distribution center replenishment processes, and distribution center operating procedures that introduce complexity into the ordering process of the retailer. These complexities create variability that is layered onto the uncertainty of consumer demand. This complexity, variability and uncertainty make forecasting orders difficult. Because the ability to forecast orders is such an integral aspect of achieving supply chain efficiencies, it is obvious that improved order forecasting is of great strategic importance to both the CPG supplier and retailer partnering to deliver product to the consumer.

Recently, there has been a great deal of interest in the literature and among practitioners regarding the benefit of sharing retail point-of-sale (POS) data to upstream supply chain members (Croson and Donohue 2003, Kiely 1999, Lapide 2005, Lee et al. 1997, Lee et al. 2000, Raghunathan 2001, Steckel et al. 2004). One area where manufacturers and retailers may benefit from shared POS information is improved accuracy of order forecasts. Currently, many CPG suppliers use order history as a means to forecast future orders by using traditional time series forecasting methods, such as moving averages and exponential smoothing. However, due to recent developments in the ability of retailers to share POS history with upstream supply chain partners, there is a great deal of interest in determining whether using POS history can improve the ability of a supplier to predict future retailer orders. In Figure 1, we visually describe a general retail echelon and manner in which orders are placed to a supplier by a retail distribution center (DC).

FIGURE 1: RETAIL ECHELON



Williams and Waller (forthcoming) compared the forecast accuracy of order forecasts based on POS history with those based on order history. The study found that POS history based forecasts generally outperform those based on order history in approximately 65% of the sample. However, the authors do point out that order history did outperform POS history in 35% of the sample and when order history was the better predictor, the average improvement over POS history was significant. Therefore, there is evidence that both POS and order history may each have pertinent information that may aid the accuracy of order forecasts.

The majority of sales forecasting research tends to focus on univariate techniques; however, Hanssens (1998) took a multivariate approach to order forecasting. By employing an error correction model which utilizes both POS and order history, Hanssens was able to substantially improve the accuracy of order forecasts. We extend the application of the error correction model to order forecasting by showing that multivariate models, which utilize both POS and order history can improve order forecast accuracy beyond the cases where POS is non-stationary.

In the remainder of this section, we review literature relevant to the study of order forecasts, shared demand information, and the econometric modeling of sales and orders. We then develop the theoretical rationale of the endogeneity of POS and order history as well as a long-run equilibrium relationship between POS and order history. Next, we examine the long-run statistical properties of POS and order history. We find that the conventional, necessary statistical conditions for using an error correction model are not apparent in all cases. We subsequently appeal to the theoretical properties of POS and orders and apply the error correction model to our sample of POS and order history and evaluate its effectiveness in terms of order forecast accuracy. Finally, we discuss our results and provide managerial implications to both suppliers and retailers in the retail supply chain.

BACKGROUND

The understanding of the need for short-term order forecasts was clearly shown in the *Journal of Marketing* by Parkany (1961), who underscores the importance of short-term order forecasts to production economies. Parkany explains that orders placed by an immediate downstream partner will reflect the “rhythm” of the ordering entity rather than the “rhythm” of consumer demand. While the “rhythm” of the ordering entity is affected by consumer demand, other factors, such as inventory changes, also affect ordering patterns. Parkany further explains that an upstream firm (manufacturer) must take into account downstream firm's (retailer) inventory changes and sales to the consumer. Thus, we find early in the literature the recognition of the importance of order forecasting as well the recognition that sales and order history are important to producing short-term order forecasts.

While Parkany's recognition of the importance of order history, changes in inventory, and consumer sales was insightful, the inability to share information throughout the supply chain was prohibitive. As the ability to share consumer demand information with supply chain partners increased, the literature began to focus on the characteristics of order history and sales information and benefit associated with sharing consumer demand information.

Lee et al. (1997) highlighted the now, well-known bullwhip effect. The bullwhip effect is the phenomenon where the variance in consumer demand is amplified as orders travel up the supply chain toward the manufacturer and tremendous inefficiencies such as inflated levels of inventory are a result. As a means to mitigate the bullwhip effect, the authors suggest that consumer level data, such as point-of-sale (POS), be shared with upstream members of the supply chain, so that forecasts can be updated using consumption data, rather than "distorted" demand data. As a result, the literature thoroughly explores the benefit of information sharing to the supply chain from both practical and theoretical perspectives.

From a theoretical perspective, Lee et al. (2000) examines the issue by quantifying the benefit of information sharing to the supply chain, where demand is autocorrelated rather than independent and identically distributed (iid). The authors examine a two-stage supply chain which consists of a retailer and manufacturer. The assumption of autocorrelated demand is a key distinction between Lee et al. (2000) and previous articles (Bourland, Powell, and Pyke 1996;

Cachon and Fisher 2000; Gavirneni, Kapuscinski, and Tayur 1999) that have explored the benefit of information sharing in the supply chain. The fact that demand is autocorrelated should allow the manufacturer in this two-stage supply chain to more effectively forecast future retailer orders. Further, the authors show that under their assumptions information sharing benefits the manufacturer through inventory reduction and expected cost reduction. Particularly, they find that the manufacturer obtains higher benefit when the autocorrelation coefficient of demand is high, the variance of demand is high, or lead time is long. Raghunathan extends the work of LST (2000) by considering a supply chain that consists of one manufacturer and N-retailers. He finds that the value of information sharing is highly dependent on the degree of correlation amongst the information shared by the retailers, specifically as the degree of correlation increases, the value of shared information with additional retailers decreases. Therefore, the number of retail partners with which to enter shared information partnerships decreases as the correlation of the shared information increases.

Additionally, the literature explores the joint relationship between orders and consumer sales. Granger and Lee (1989) implies a long-run relationship between sales and orders at a macroeconomic level, indicating that the two will evolve similarly in a dynamic economy. Hanssens (1998) examines the joint relationship between orders and sales at a microeconomic level. The author finds that in a high-tech setting that orders and sales are co-integrated variables, which statistically implies a long-run relationship. Additionally, co-integration requires that each variable is non-stationary (not mean or trend reverting). Many recent studies have focused on using econometric methods to determine whether marketing variables are stationary or non-stationary (evolving). The focus of these studies is whether marketing events can have both a short and long-term impact on the sales of a particular SKU, brand, or category.

Dekimpe and Hanssens (1995b), in a meta-analysis, established a generalization regarding the long-run behavior of sales and market shares of consumer goods. In the meta-analysis, the authors examined 44 prior studies that included 180 sales series. They showed that market share was generally stationary (not evolving) while sales generally were evolving, in fact 68% of the products included in the meta-analysis were non-stationary time series, and they statistically define this evolution found in marketing data.

The fact that, in general, market share is stationary while sales are non-stationary was further explained by Srinivasan and Bass (2000). They noted that this seemingly confusing notion is possible if SKU or brand sales and category sales are cointegrated, meaning that the SKU or brand and the category are evolving similarly. Thus, the portion of the category sales (market share) attributed to the particular SKU or brand remains constant. This work was preceded by Dekimpe and Hanssens (1995a) which developed the idea of persistence modeling, where persistence is defined to be a measure of the impact of current changes in marketing variables on future changes in the variable. In 1999, Dekimpe, Hanssens, and Silva-Risso, used "unit root techniques to address market response in evolving markets" (p.269) and found category and brand sales to be generally not evolving.

Beyond the implication that the variables are non-stationary, cointegration further implies an error correction representation, which was popularized by Engle and Granger (1987). The key principle of the error correction representation of the variables is that any disequilibrium from the long-run relationship will be corrected by one or more of the cointegrated variables. Other studies have addressed the fact that error correction models can be effectively used to forecast the cointegrated variables. LeSage (1989) finds that inclusion of an error correction component improves forecast accuracy and Zhong et al. (2005) improve forecast accuracy when using a vector error correction model to forecast non-stationary variables. Zanias (1994) finds the error correction to be most efficient when forecasting using advertising and sales variables. Jiang et al. (2004) utilize an error correction model to capture the cointegrated relationship between sales and price, and Hanssens (1998) employs an error correction model to forecast orders in the high-tech sector

This line of research was extended by Hanssens (1998) to examine the issue of forecasting orders placed by retailers to manufacturers in light of the fact that retail demand data is often available to the manufacturer. In particular, Hanssens was interested in understanding whether forecasts of orders to manufacturers could be adjusted through error correction models to better capture the future impact of marketing activity. Hanssens used monthly sales and order data from a high-tech consumer durable product to show that the use of error correction models improves prediction of non-stationary marketing variables.

From a practical perspective, the supply chain literature also acknowledges the importance of information sharing between supply chain partners to improve the effective flow of product to the consumer through the improved matching of supply and demand processes. To better serve the consumer, buyers and sellers have begun to transition to alliances and partnerships aimed at satisfying consumer demand while minimizing supply chain costs. The literature has identified information sharing as a necessary condition to the success of these alliances, which tend to reflect the performance of organizations. Bowersox et al. (1989) states that “leading performers” seek out alliances with other “leading edge performers” to create competitive advantage. Whipple et al. (2002) empirically tests the proposed relationship between information sharing and alliance satisfaction which allows for the long-term success of the alliance and finds that “several elements of information exchange clearly have a significant impact on alliance satisfaction". In order to facilitate the effectiveness of information sharing, only "relevant and meaningful information" (Kaipia and Hartiala 2006) must be shared with supply chain partners. Further, we find the collaboration due to the information sharing is "facilitated by the existence of an efficient and effective information technology (IT) system" (Sanders and Premus 2005).

Further, the literature discusses several industry initiatives, which are founded on the principle of information sharing. Daugherty et al. (1999) notes that a fundamental component of popular automatic replenishment programs such as continuous replenishment planning (CRP) and vendor-managed inventory (VMI) (Cachon and Fisher 2000; Waller, Johnson, and Davis 1999; Pohlen and Goldsby 2003; Angulo, Nachtmann, and Waller 2004) as well as industry specific automatic replenishment programs such as efficient consumer response (ECR) (Whipple, Frankel, and Anselmi 1999; Stank, Crum and Arango 1999; Frankel, Goldsby, and Whipple 2002) and quick response (QR) is information sharing.

Since accurate order forecasts are a key piece of a CPG supplier's demand management process, where "demand management is the supply chain management process that balances the customers' requirements with the capabilities of the supply chain" (Lambert, 2006). Order forecasts are known to impact the supplier's ability to meet retailer customer service requirements while managing inventory holding costs. Mentzer and Cox (1984) notes the necessity of accurate short-term forecasts to facilitate logistics and supply chain activities, particularly inventory control. Further, much of the literature on collaborative forecasting identifies the consequences that forecast inaccuracy has on the supply chain in terms of increasing total supply chain costs and identifies the scope of the improvement opportunities (Aviv 2007, Kahn 2003, Raghunathan 1999, Sadarangani and Gallucci 2004).

LONG RUN EQUILIBRIUM DEVELOPMENT AND HYPOTHESES

Theoretical Development

While POS and order history are not expected to be exactly equal in any particular time period, we do expect the time series to be independent over time. We do not expect that POS and order history are exogenous. That is, the time series of one variable may affect the time series of the other variable and the variables are causally linked in some manner. The causal relationship of POS on DC orders is intuitive. From the literature, we find that retailers partially base orders placed to suppliers upon the expectation of future consumer sales (Lee, So and Tang 2000; Gilbert 2005). Thus, it is clear that a shift in POS (consumer sales) will most likely cause a shift in DC order patterns. The causal relationship of DC orders on POS is less intuitive. However, a shift in DC orders may affect POS, primarily due to increased inventory in the retail echelon. DC orders may increase due to a quantity discount given to the retailer by the supplier. The retailer may push the additional inventory to the retail stores that the DC serves. Since retail stores generally have limited backroom storage space, the additional inventory must be placed in the store. If demand is inventory dependent, this is particularly true for impulse items.

Beyond a bi-directional causal relationship, we expect that POS and DC orders have a long-run equilibrium relationship, which are the result of retailer inventory policies. Retailers have policies in place that force long-run equilibrium between POS and DC orders. Inventory targets are in place for each item, which sets the desired amount of inventory to be held. For example when a firm uses a periodic review (R,T) model (Hadley and Whitin 1963, Silver et al. 1998, Axsäter 2000, Zipkin 2000, Chopra and Meindl 2004) to manage inventory, orders are placed to set the inventory position to an order-up-to level (R) at each review interval (T). In this widely used model, R is the firm's inventory target at each review interval.

If during any review period POS unexpectedly increase or decrease, POS and DC orders are in a temporary disequilibrium and the inventory position at the end of the review period is either less than or greater than the expected level (safety stock). If POS exceed orders in a period, then the retailer's inventory position decreased in that period. Conversely if orders exceed POS in a period, then the retailer's inventory position increased in that period. In either case, the retailer must adjust its order in a future period to maintain its inventory target.

Consider a retail system, consisting of a distribution center and its accompanying retail outlets, each being inventory holding nodes. We know that product is leaving the retail inventory system when consumers purchase the product at the retail outlets and product is entering the retail system when a supplier ships that product to the retail DC. We know that the difference between the product entering the retail system, DC orders, and the product leaving the system, POS, must keep the retailer's inventory position within some bounds, otherwise it would be possible to have an infinite amount of inventory or an infinite amount of backorders. Therefore, we know POS and DC orders have a long-run equilibrium.

Engle and Granger (1987) address the issue of long-run equilibrium from a macroeconomic perspective and states that an equilibrium relationship is "a stationary point characterized by forces which tend to push the economy back toward equilibrium whenever it moves away" (p. 251). While we are examining POS and DC orders at the firm level, the principle of a long-run equilibrium still applies.

If a retailer's inventory system was in steady state and POS is stationary, then orders should also be stationary, and thus the system would have a steady state equilibrium level of inventory. Any short-term deviations from the equilibrium will be corrected in future periods, and the system will tend back to its stationary long-run equilibrium. If POS is non-stationary and does not fluctuate around a stable mean throughout time, then we assume that orders must also follow the same stochastic process for the retail system to maintain its inventory position within some reasonable bounds. Therefore even in the case of non-stationary POS, we expect a long-run equilibrium between POS and orders to exist, even if we cannot statistically detect non-stationarity in orders. The key point is that, in order for a target amount of inventory to be in the system, whether that amount is static or dynamic, there must be equilibrium between POS and DC orders.

Modeling a system of variables using the vector autoregressive model (VAR) is appropriate when the variables are not known to be exogenous and are stationary (i.e. do not contain a unit root). The VAR allows contemporaneous and lagged effects of each variable on the other and is modeled as follows,

$$\begin{aligned} S_t &= a_{10} + a_{1,1,1}S_{t-1} + \ldots + a_{1,1,l}S_{t-l} + a_{1,2,1}O_{t-1} + \ldots + a_{1,2,l}O_{t-l} + e_{1t} \\ O_t &= a_{20} + a_{2,1,1}S_{t-1} + \ldots + a_{2,1,l}S_{t-l} + a_{2,2,1}O_{t-1} + \ldots + a_{2,2,l}O_{t-l} + e_{2t} \end{aligned}.$$

Under the conditions mentioned above, we know that POS and DC orders are in long-run equilibrium due to the fact that both variables are stationary. Next, we used the VAR, specified above, to forecast DC orders and found that the results did not significantly improve DC order forecast accuracy relative to the exponential smoothing methodology based on either POS or DC orders.

However, we find in the literature that sales or POS is generally not stationary (i.e. contains a unit root) (Dekimpe, Hanssens and Silva-Risso1999). Engle and Granger (1987) formalize the concept of a long-run equilibrium between non-stationary variables as cointegration. When two or more time series are non-stationary (stochastic trend) and have common underlying stochastic processes, then the time series are said to be cointegrated. Srinivasan and Bass (2000) describe the concept of cointegration as a powerful one; they state that it “describes the existence of an equilibrium or stationary relationship among two or more time series, each of which is individually non-stationary” (p. 166). Therefore, we know that if we observe deviations from the long-run equilibrium of the cointegrated time series, then in the future one or both of the series will adjust back toward the long-run equilibrium. This leads us to believe that by observing deviations from the long-run equilibrium, we can better predict future changes in one or more of the cointegrated time series.

For a formal representation of the idea of cointegration, we refer to Enders (2004) where two time series, such as orders $\{O_t\}$ and POS $\{S_t\}$ are each modeled according to a random walk,

$$O_t = \mu_{ot} + \varepsilon_{ot}$$

$$S_t = \mu_{st} + \varepsilon_{st} \ ,$$

where μ_{it} are non-stationary components and ε_{it} are the stationary error components. If there exists a linear combination of the two non-stationary series that is stationary, then $\{O_t\}$ and $\{S_t\}$ are cointegrated. Now consider if some non-zero vector, (β_1, β_2) that when multiplied with the vector that contains $\{O_t\}$ and $\{S_t\}$, produces a stationary process as follows:

$$\beta_1 O_t + \beta_2 S_t = \beta_1 (\mu_{ot} + \varepsilon_{ot}) + \beta_2 (\mu_{st} + \varepsilon_{st})$$

$$\beta_1 O_t + \beta_2 S_t = (\beta_1 \mu_{ot} + \beta_2 \mu_{st}) + (\beta_1 \varepsilon_{ot} + \beta_2 \varepsilon_{st})$$

Since $\beta_1 \mu_{ot} + \beta_2 \mu_{st}$ is the non-stationary portion of the linear combination of $\{O_t\}$ and $\{S_t\}$, (β_1, β_2) can be defined such that $\beta_1 \mu_{ot} + \beta_2 \mu_{st} = 0$ and thus $\beta_1 \varepsilon_{ot} + \beta_2 \varepsilon_{st}$ remains, which we know is stationary due to the fact that both ε_{ot} and ε_{st} are stationary.

Error Correction Process

When variables are co-integrated, Engle and Granger (1987) suggests that the variables follow an error correction process, where any short-term deviation from the long-run equilibrium of the variables is corrected by one or more of the co-integrated variables in the next period. The concept of an error correction process was seen early in the literature regarding the short-term relationship between consumers' expenditure and disposable income (Davidson, Hendry, Srba, Yeo 1978) and was later re-introduced by Granger (Granger 1986, 1987, 1989).

The error correction process of orders and POS is explicitly modeled by Hanssens (1998). In the following two-equation error correction system (vector error correction model), Hanssens models changes in POS and orders as a function of lagged values of changes in POS and orders as well as any short-term deviation from the long-run equilibrium of the two variables (e_t):

$$\Delta S_t = a_1 + b_1\left(L\right)\Delta S_{t-l} + c_1\Delta O_{t-l} + d_1 e_{t-1} + \mu_t$$

$$\Delta O_t = a_2 + b_2\left(L\right)\Delta O_{t-l} + c_2\Delta S_{t-l} + d_2 e_{t-1} + \nu_t$$

In an error correction process, such as the above specification, one or both of the variables will adjust the system back to long-run equilibrium when disequilibrium occurs. In this system, we expect retail orders to make the adjustment, due to the fact that the retailer has an inventory target in place that will force the adjustment.

Given our development of a theoretical long-run equilibrium relationship between POS and DC orders and our explanation of how the error correction model can be used to model this relationship under conditions of nonstationarity, we make the following hypotheses regarding the cointegrating nature of POS and DC orders as well as the improvement of the VECM in DC order forecast accuracy.

H1: When both POS and DC orders are nonstationary, the variables are cointegrated of order one, *CI*(*1*,*1*).

H2: When POS and DC orders are cointegrated, the VECM will improve short-term DC order forecast accuracy when compared to exponential smoothing forecasts based on POS.

DATA

For our empirical analysis, we obtained data from a major consumer packaged goods (CPG) manufacturer that competes in multiple grocery categories. The data spanned three categories: ready-to-eat (RTE) cereal, canned soup, and yogurt. Each category has differentiating characteristics. RTE cereal is a $6 billion category and one of the highest volume grocery categories in the supermarket. The category is dominated by three major CPG manufacturers: Kellogg's, General Mills, and Post, two of which (Kellogg's and General Mills) jointly account for approximately 70% of the market share; however according to Hitsch (2006), the category contains approximately 130 national brands, most of which have small market shares except for the major brands, such as Kellogg's Corn Flakes and General Mills' Cheerios. Further, Hitsch (2006) explains that the RTE cereal category experiences a high rate of product entry and exit.

Next, the canned soup category is similar to RTE cereal in that it is a highly shopped category and has experienced a high degree of product proliferation. Sinha et al. (2005) describes the category as competitive and highly fragmented due to the presence of multiple national brands as well as private labels. However, category sales have generally been flat over recent years. In particular, the demand for canned soup has declined over the past several years; however, category sales have remained healthy due to recent increase in demand for RTE soups.

A key distinguishing factor of the canned soup category, to this data set, is its seasonal nature. Also, the shelf-life of canned soup is long relative to the other included categories.

In addition to RTE cereal and canned soup, data was collected from the yogurt category. The yogurt category is distinct for three primary reasons. First, the yogurt category has experienced explosive growth in recent years. According to recent trade publications, annual category growth is approximately 7% to 9%, which is much higher than that of total grocery growth (Kissas, 2007). Second, yogurt is a fresh product meaning its shelf-life is short and subsequent flow through the distribution network is relatively fast. Finally, yogurt is a refrigerated product, whereas as RTE cereal and canned soup are dry grocery categories. In Table 1, we summarize the differentiating characteristics of the three categories included in the study.

TABLE 1: CATEGORY CHARACTERISTICS

Category	Life Cycle Stage	Shelf Life	Seasonal	Annual Sales
RTE Cereal	Mature	6-12 months	No	$6 billion
Canned Soup	Decline	12-18 months	Yes	$4 billion
Yogurt	Growth	7-14 days	No	$2.5 billion

STATISTICAL PROPERTIES OF POS AND DC ORDERS

From the data, we notice that in general the means of orders and POS are quite similar, which we expect due to the fact that a long-run equilibrium relationship between the variables exists, while the variability and range of orders are much greater than those of POS. In addition, we are particularly interested in the long-run properties of POS and orders. We examine each time series for non-stationarity. If the variables are stationary, then the time series has a stable mean in the long-run and thus fluctuations represent only short-term changes. If a variable has a stochastic trend (non-stationarity), then the variable does not revert to a stable mean over time, is evolving, and the conditional mean of the time series is not constant over time.

We rigorously test for non-stationarity in each item by testing for a unit root, which indicates that the time series of interest has a random walk component and does not revert to a stable mean over time. To test for the presence of a unit root, we use a common method, the Augmented Dickey Fuller (ADF) test. Under the assumption that the time series of interest is not a simple AR(1) process and has higher order correlated lags, the Augmented Dickey Fuller test equation is as follows,

$$\Delta O_t = \beta O_{t-1} + \sum_{j=1}^{m} \alpha_m \Delta O_{t-j} + \varepsilon_t$$

where O_t represents the order placed at time *t*. Also, the Augmented Dickey Fuller test equation is applied to POS although we do not explicitly formulate the ADF test in those terms. The ADF test then compares the t-statistic associated with β to the critical values in Dickey and Fuller (1979). If the t-statistic on β is less than the Dickey Fuller critical value, then the null hypothesis that the time series contains a unit root is then rejected.

In Tables A-1, A-2 and A-3 of the Appendix , we report the results of the augmented Dickey-Fuller tests for orders and POS, respectively, for each item in the RTE cereal, canned soup, and yogurt categories. Notice that we compared the t-statistic of β against the 5% ADF critical value to determine whether the time series exhibits a unit root (stochastic trend). We summarize the results in Table 2.

TABLE 2: SUMMARY OF AUGMENTED DICKEY FULLER TEST RESULTS

		Unit Root	
Category	N	Orders	POS
RTE Cereal	30	1	16
Canned Soup	36	24	34
Yogurt	20	5	17

Notice that of the items examined, we found a unit root in POS in the majority of the cases (78%), meaning generally that POS has an underlying stochastic process. This finding is consistent with the finding of Dekimpe and Hanssens (1995b), where the majority of sales data in the literature were found to be non-stationary. In fact, Dekimpe and Hanssens found that 68% of the sales time series analyzed were non-stationary. However, we only find a unit root in orders in approximately 35% of the SKUs examined. This is likely due to the additional variance in order history, which may mask the underlying stochastic nature of many of the time series.

Now for the SKUs that exhibit a stochastic trend in both orders and POS, we determine if POS and orders are cointegrated. To test for the cointegration of two or more series, test the order of integration, *I(d)*, of the series using the Augmented Dickey-Fuller test. Upon completing the augmented Dickey-Fuller test for POS and orders, which we discussed above, we find that in the cases where POS and orders have unit roots, both are $I(1)$. After determining that the time series have a common stochastic process, we estimate the long-run equilibrium relationship of the processes for each SKU in which we found matching orders of integration among POS and orders. The general form of the equilibrium regression is

$$O_t = \beta_0 + \beta_1 S_t + \varepsilon_t .$$

We then check the residuals of the equilibrium regression for stationarity, which indicates the processes included in the equilibrium are cointegrated. For each of the cases where both orders and POS were found to be *I(1)*, we found the variables to be *CI(1,1)*, that is cointegrated of order 1. For detailed results, see Tables A-4, A-5 and A-6 in the Appendix. From these tables, we find strong support for H1. In each case where POS and DC orders are found to be nonstationary, POS and DC orders are found to be *CI*(*1,1*)

APPLYING THE ERROR CORRECTION MODEL

Conventionally, vector error correction models (VECM), which model the short-term and long-term effects of a system, have been used when a system of variables are found to be cointegrated. Jiang et al. (2004) clearly explains the accepted necessary conditions of cointegration, which requires non-stationarity of the variables, to using the VECM. The authors then use the VECM as one method to investigate brand-specific effects in category management. Zhong et al. (2005) incorporates the VECM into a category forecasting decision support system. Shoesmith (1992) investigates retail sales from a macroeconomic perspective and specifies both a vector autoregressive model and incorporates an error correction component when the variables of interest, retail sales and personal income, are found to be cointegrated. Hanssens (1998) examines sales and orders at the firm level and finds them to be cointegrated variables. The author then uses an error correction model to forecast orders placed by the manufacturing firm's retailers; the study finds that the error correction model outperforms the benchmark model in terms of forecast accuracy.

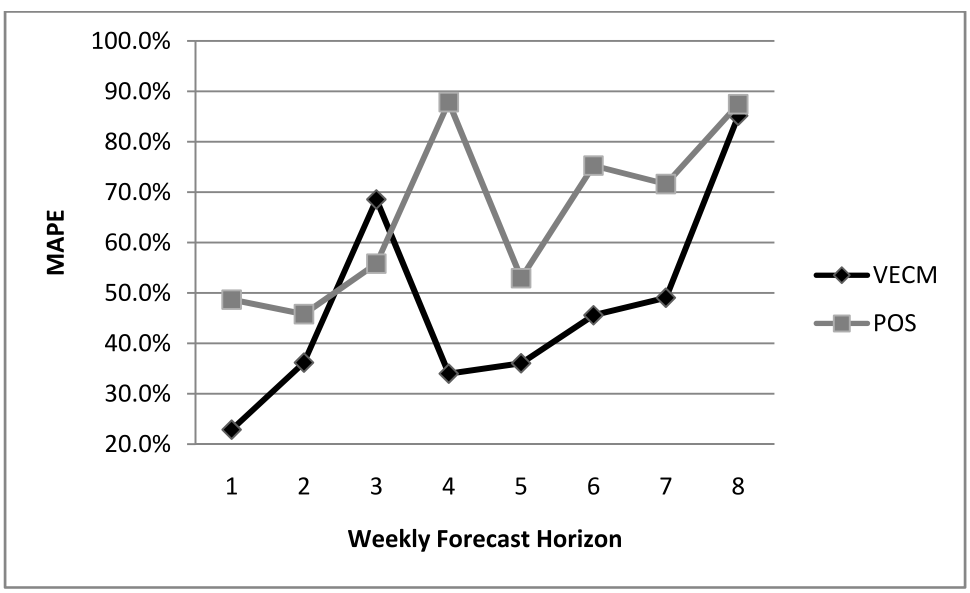
Forecast Comparisons where POS and DC orders are cointegrated

We now apply the VECM where POS and DC orders are known to be cointegrated. We compare the VECM out-of-sample forecast performance against the performance of the widely-used exponential smoothing methodologies: simple exponential smoothing and Holt-Winters exponential smoothing. The appropriate benchmark methodology is chosen at the category level depending upon the category's demand characteristics. For a detailed explanation of the exponential smoothing methodologies, we refer readers to Gardner (1985), which provides a thorough review of the methodologies. Further, we apply the appropriate exponential smoothing methodology to POS to test H2.

We begin our forecast comparison by examining the one-step ahead DC order forecast error of each methodology. We find the one-step ahead DC order forecast MAPE to be 22.9% and 48.7% for the VECM and exponential smoothing based on POS, respectively. Notice that we find the VECM to substantially outperform the benchmark models in terms of one-step ahead DC order forecast accuracy. To further our comparison of the forecasting performance of the VECM to the exponential smoothing methodologies, we examine the accuracy of multiple-step-ahead forecasts, in which we use dynamic forecasting to produce multiple-step-ahead VECM forecasts.

In Figure 2, we find the comparison of the MAPE of the VECM and the exponential smoothing model based on POS over an eight week out-of-sample forecast horizon.

FIGURE 2: VECM VERSUS POS - COINTEGRATED



From Figure 2, we find improvement in DC order MAPE by the VECM relative to the exponential smoothing methodology based on POS history, also up to seven weeks ahead except for the three week ahead forecast. In Table 3, we test whether the differences in the forecast error shown in Figure 2 are statistically significant.

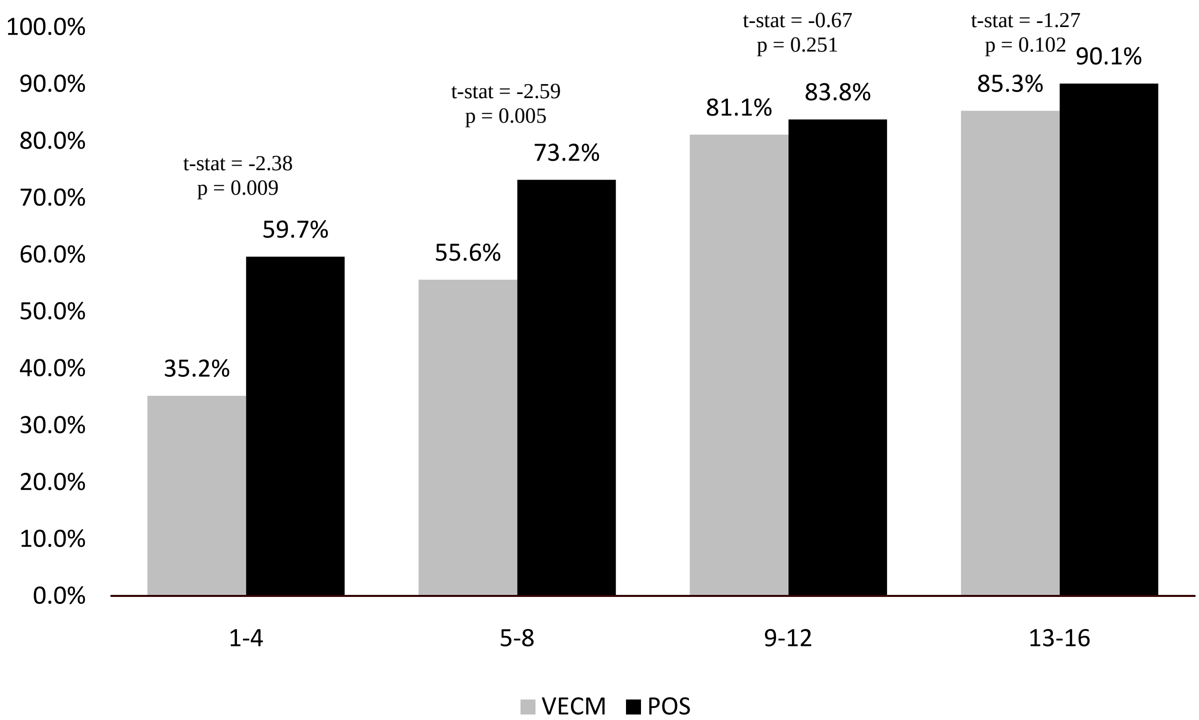
TABLE 3: VECM VERSUS POS MAPE T-TEST RESULTS

Horizon	VECM	POS	t-stat(p-value)
1	22.9%	48.7%	-2.918(0.007)
2	36.2%	45.8%	-1.364(0.184)
3	68.6%	55.8%	0.635(0.531)
4	34.0%	87.9%	-4.468(0.000)
5	36.1%	52.9%	-2.263(0.032)
6	45.6%	75.3%	-3.118(0.004)
7	49.0%	71.6%	-4.115(0.000)
8	85.2%	87.4%	-0.623(0.539)

We conclude from Table 3 that the VECM produces more accurate DC order forecasts than does the exponential smoothing model based on POS in the short-term in the one, four, five, six and seven week ahead forecast horizons. We further note that the differences in forecast error in the two and three week ahead horizons are not statistically significant. From these results, we suggest that there is support for H2.

From these findings, we ascertained that the VECM performs more consistently in the soup category than in either the RTE cereal or yogurt categories. In Figure 3, we present the VECM comparison results in the soup category.

FIGURE 3: CANNED SOUP RESULTS



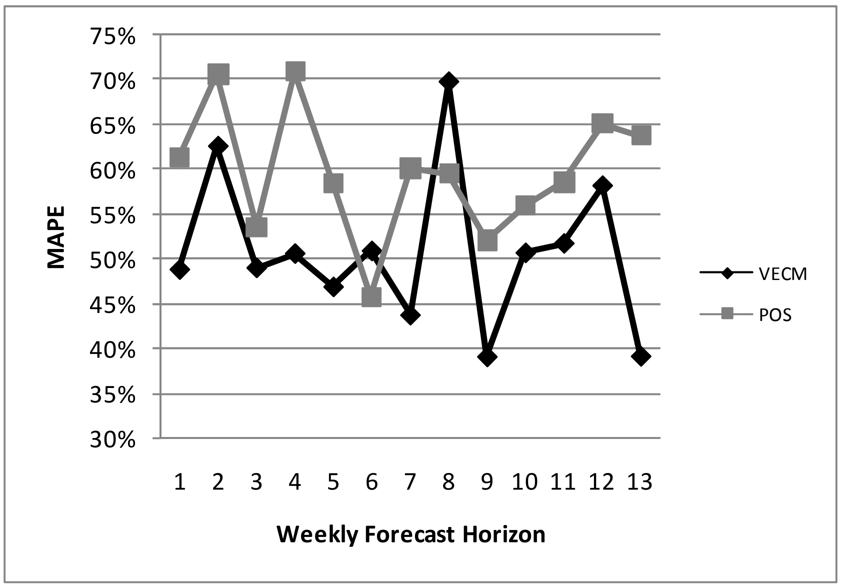
From Figure 3, we find that the VECM outperforms the benchmark model in the 1-4 and 5-8 week ahead horizons.

Forecast comparisons where only POS is nonstationary

We continue the investigation of using an error correction model to forecast retail orders; however at this point, we differ from the literature in that we appeal to the theoretical properties of sales (POS) and orders, discussed earlier, rather than the statistical properties (cointegration) to justify the use of the error correction model. While POS and orders were shown to be cointegrated in several cases within our sample, there were many additional cases where POS was shown to be non-stationary; however, orders for the same SKU were found to be stationary. In these cases, we appeal to our earlier discussion of theoretical properties of POS and orders, which dictate that a long-run equilibrium between the variables exists due to the fact that policies, used to manage inventory, require an inventory target, which forces the system to be in long-run equilibrium. We appeal to the fact that the variables must theoretically have a long-run equilibrium and follow an error correction process. Additionally, we know that the VECM incorporates changes in the retailer's inventory position into the DC order forecast.

In Figure 4, we find the comparison of the MAPE of the VECM and the exponential smoothing model based on POS over a thirteen week out-of-sample forecast horizon, where only POS is nonstationary.

FIGURE 4: VECM VERSUS POS – NOT COINTEGRATED



From Figure 4, we again find a substantial improvement in DC order MAPE by the VECM relative to the exponential smoothing methodology based on POS history, up to five weeks ahead. We conclude that the VECM produces more accurate DC order forecasts than does the exponential smoothing model based on POS in the short-term, although we do note the improvement of the VECM where POS and DC orders is less than under conditions of cointegration. Regardless, we do find significant improvement in order forecast accuracy by utilizing the VECM under both set of conditions.

SUMMARY AND CONCLUSIONS

In this study, we found strong support for our hypothesis that the VECM can improve short-term DC order forecast accuracy, relative to the standard methodologies currently, widely employed by suppliers in the retail supply chain. We began this study by establishing theoretical evidence that a long-run equilibrium relationship between POS and orders exists, which implies that the variables follow an error correction process. We then empirically examined the data for whether the conventional statistical conditions for using the VECM (i.e. cointegration) were apparent. We found several SKU/DC combinations where POS and DC orders were cointegrated. We used the VECM to forecast DC orders and found that the method reduced DC order forecast error, relative to the CPG industry's baseline methodologies.

Upon testing POS and DC orders for cointegration, we found that in a majority of the SKU/DC combinations that POS was non-stationary; however, orders appeared to be stationary. We then appealed to the theoretical relationship between variables to apply the VECM under this condition. From this exploratory analysis, we again found that the VECM improves short-term DC order forecast accuracy relative to the baseline methodologies. Thus from the analysis in this study, we find that the VECM can generally improve DC order forecast accuracy even when the traditionally held, statistical conditions for applying the model do not hold.

In practice, the forecasting models used by most commercial forecasting systems to predict retailer order quantities mostly utilize order history; however, some suppliers now have the sophistication to utilize shared demand information, such as POS, to forecast orders. In our analysis, we generally found time series models that use only POS to forecast orders outperform models that use order history. However based upon the findings in this study, we propose that suppliers utilize the VECM which utilizes both POS and order history to produce order forecasts due to the fact that both contain useful information for prediction and leverages the fact that a long-run equilibrium relationship between the variables exists.

MANAGERIAL IMPLICATIONS

As discussed throughout the paper, forecasting retail orders continues to be a popular topic among CPG suppliers. Many large CPG suppliers continually have on-going initiatives to improve order forecast performance. They spend a large amount of resources such as human resources, software packages and consulting fees on this issue. The reason for such emphasis on order forecasting is that the implications resonate throughout the entire organization and to the entire supply chain. Order forecast accuracy affects the entire retail supply chain from the suppliers of raw materials to the retailer and even to the consumer.

Suppliers not only need to forecast orders accurately to meet customer service objectives, such as target in-stock levels of the retailer, but they also must forecast accurately to effectively plan production, procure raw materials and transportation, as well as other planning activities. Effectively, the order forecast drives the planning process for all aspects of the CPG business. Production plans are built from order forecasts. Also, other resource planning activities such as transportation capacity planning are built from order forecasts. Further, order forecast accuracy has a direct impact on the amount of safety stock that the supplier must carry in the DCs. As we know, carrying additional inventory for any reason has negative consequences as does backorders and lost sales. Most obviously, additional inventory results in higher inventory holding costs to the supplier. More subtle is the fact that as the average inventory level increases so does the average age of the product being sold to the consumer. Additionally, the supplier will require fewer expedited shipments to its customers.

Therefore, we see that any improvement in order forecast accuracy can have large positive effects on key supplier metrics such as inventory turnover, gross margin return on inventory investment, in-stock levels, and ultimately profitability. Thus by incorporating the error correction model as a statistical option into order forecasting processes, suppliers can take advantage of its performance versus models currently employed by most of the commercial software packages, such as the exponential smoothing methodologies.

In addition to the benefits that suppliers experience due to improved order forecasting performance, the retail partners of the supplier also benefit. Due to the fact that increased forecast accuracy results in lower levels of variability in in-stock and lead-time performance, the retailer is also able to reduce its inventory levels by reducing the amount of safety stock that it must carry, thus resulting in lower cost delivery of products to the retail outlet and ultimately the consumer.

Fortunately, the model proposed is not complicated from a statistical perspective. Most commercial software packages can be customized to include the model as an option to suppliers. However, the most prohibitive factor to the use of the model is the fact that it requires both order history and POS data. While suppliers typically capture order history, POS data must be obtained from its retail partners. Many of the larger U.S. retailers either have or are in the process of making POS information available to upstream supply chain partners through information sharing systems. This study suggests that there is substantial benefit to incorporating POS information into an order forecast; therefore, the momentum of POS sharing should continue.

FUTURE RESEARCH

To further this research, the validity of applying the error correction model broadly must be further tested in additional categories. While each of the included categories have distinct characteristics, other less prominent food and general merchandise categories should be forecasted using the methodology, and its performance again compared against the traditional models currently used by suppliers.

In addition to validating the performance of the model in its current state, layers of complexity can be added to the model to increase its performance. While the model discussed in the paper adds to the literature by applying the error correction model more broadly and in a weekly forecasting process, other variables may also be included in the forecasting model. In particular, certain SKUs are known to influence the POS and orders of other SKUs. The phenomenon in which a SKU may influence the sales of another SKU is known as the substitution effect. Substitution occurs at the shelf when a SKU is out-of-stock on the retail shelf. When faced with an out-of-stock, the consumer must decide to either delay the purchase, purchase at another retail outlet, not purchase, or purchase another SKU. If the consumer decides to purchase another SKU, he or she may either substitute to a competitor's SKU or another SKU within the brand and thus demand is shifted from the out-of-stock SKU to the substituted SKU. Due to this phenomenon, previous POS of one SKU may influence the POS of another SKU. Additionally, we know that retailer's make joint ordering decisions for multiple SKUs. These joint ordering decisions affect the retailer's ordering patterns. Due to such effects, the effectiveness of order forecasting may be further improved by simultaneously modeling the orders and POS of multiple items that are substitutes or complements simultaneously.

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APPENDIX

TABLE A-1: RTE CEREAL UNIT ROOT RESULTS

	Ship Quantity				POS			
SKU #	**β**	**t**	**m**	**Unit Root**	**β**	**t**	**m**	**Unit Root**
1	-1.379	-7.494	2	N	-0.433	-5.298	0	N
2	-1.566	-6.799	3	N	-0.118	-1.955	8	Y
3	-1.224	-12.583	0	N	-0.223	-2.078	7	Y
4	-1.210	-12.439	0	N	-0.184	-1.911	7	Y
5	-0.581	-5.098	1	N	-0.164	-2.999	0	N
6	-1.261	-13.378	0	N	-0.343	-2.615	7	Y
7	-1.244	-7.287	1	N	-0.593	-6.406	0	N
8	-1.541	-9.872	1	N	-0.074	-1.279	4	Y
9	-1.257	-13.494	0	N	-0.037	-0.603	7	Y
10	-0.765	-3.678	3	N	-0.334	-2.675	5	Y
11	-1.058	-10.646	0	N	-0.593	-6.493	0	N
12	-1.748	-7.570	3	N	-0.198	-2.278	4	Y
13	-1.224	-12.561	0	N	-0.223	-2.248	3	Y
14	-1.470	-9.676	1	N	-0.264	-2.396	3	Y
15	-1.382	-9.031	1	N	-0.312	-2.750	3	Y
16	-1.181	-12.157	0	N	-0.394	-3.960	1	N
17	-0.819	-8.328	0	N	-0.347	-4.603	0	N
18	-0.784	-3.707	3	N	-0.450	-5.366	0	N
19	-1.456	-7.555	2	N	-0.474	-5.598	0	N
20	-1.046	-10.445	0	N	-0.140	-2.757	0	Y
21	-1.360	-14.759	0	N	-0.234	-2.218	4	Y
22	-0.987	-10.008	0	N	-0.442	-5.281	0	N
23	-0.935	-6.435	1	N	-0.365	-4.757	1	N
24	-1.327	-4.394	4	N	-0.166	-2.005	1	Y
25	-1.111	-8.132	1	N	-0.157	-2.373	1	Y
26	-0.955	-3.734	4	N	-0.462	-4.033	2	N
27	-0.917	-9.294	0	N	-0.406	-5.001	0	N
28	-0.543	-2.272	6	Y	-0.150	-2.199	2	Y
29	-1.347	-14.509	0	N	-0.302	-3.384	1	N
30	-1.495	-9.808	1	N	-0.283	-3.857	0	N

*t statistic compared against 5% ADF critical values

*Unit root lag length specification is based on minimizing the Akaike Information Criterion (AIC)

TABLE A-2: CANNED SOUP UNIT ROOT RESULTS

	Orders				POS			
SKU #	**β**	**t**	**m**	**Unit Root**	**β**	**t**	**m**	**Unit Root**
1	-0.426	-2.295	9	Y	-0.121	-2.882	5	Y
2	-0.848	-9.726	0	N	-0.115	-2.669	2	Y
3	-0.700	-8.274	0	N	-0.078	-2.108	2	Y
4	-0.443	-2.511	4	Y	-0.105	-2.787	5	Y
5	-0.391	-2.427	4	Y	-0.097	-2.687	5	Y
6	-0.264	-2.106	4	Y	-0.093	-2.531	5	Y
7	-0.829	-9.523	0	N	-0.104	-2.620	0	Y
8	-0.347	-2.189	5	Y	-0.099	-2.606	5	Y
9	-0.548	-4.511	2	N	-0.077	-2.332	2	Y
10	-0.267	-2.302	3	Y	-0.094	-2.877	5	Y
11	-0.228	-2.172	3	Y	-0.086	-2.217	11	Y
12	-0.399	-2.475	9	Y	-0.090	-2.670	5	Y
13	-0.721	-8.498	0	N	-0.127	-2.920	0	N
14	-0.322	-1.859	6	Y	-0.110	-2.294	6	Y
15	-0.320	-2.261	7	Y	-0.089	-2.370	5	Y
16	-0.333	-2.292	4	Y	-0.086	-2.090	5	Y
17	-0.347	-2.509	4	Y	-0.085	-2.370	0	Y
18	-0.484	-3.894	2	N	-0.088	-2.212	7	Y
19	-0.831	-9.564	0	N	-0.130	-3.044	2	N
20	-0.677	-4.759	2	N	-0.107	-2.516	5	Y
21	-0.515	-5.149	1	N	-0.093	-2.323	5	Y
22	-0.368	-2.533	4	Y	-0.091	-2.467	5	Y
23	-0.375	-2.679	3	Y	-0.094	-2.598	5	Y
24	-0.409	-2.284	12	Y	-0.109	-2.841	5	Y
25	-0.705	-8.367	0	N	-0.092	-2.394	2	Y
26	-0.248	-2.115	4	Y	-0.079	-2.231	5	Y
27	-0.446	-3.890	2	N	-0.063	-2.009	2	Y
28	-0.240	-2.398	3	Y	-0.074	-2.429	5	Y
29	-0.208	-2.143	3	Y	-0.079	-2.494	5	Y
30	-0.237	-2.214	5	Y	-0.067	-2.526	5	Y
31	-0.844	-9.649	0	N	-0.123	-2.708	6	Y
32	-0.329	-2.282	4	Y	-0.088	-2.503	5	Y
33	-0.359	-2.328	7	Y	-0.075	-2.170	6	Y
34	-0.327	-2.676	5	Y	-0.089	-2.595	5	Y
35	-0.267	-2.398	3	Y	-0.078	-2.665	5	Y
36	-0.322	-2.447	4	Y	-0.093	-2.623	5	Y

*t statistic compared against 5% ADF critical values

*Unit root lag length specification is based on minimizing the Akaike Information Criterion (AIC)

TABLE A-3: YOGURT UNIT ROOT RESULTS

	Orders				POS			
SKU #	β	t	m	Unit Root	β	t	m	Unit Root
1	-1.187	-4.352	3	N	-0.074	-1.597	3	Y
2	-1.340	-14.265	0	N	-0.073	-1.650	3	Y
3	-1.197	-5.392	2	N	-0.049	-1.161	10	Y
4	-1.324	-13.988	0	N	-0.095	-1.838	9	Y
5	-0.827	-3.595	3	N	-0.111	-2.594	0	Y
6	-1.290	-13.521	0	N	-0.263	-3.991	0	N
7	-1.284	-13.358	0	N	-0.141	-2.273	8	Y
8	-1.342	-14.262	0	N	-0.142	-2.527	5	Y
9	-1.432	-15.950	0	N	-0.156	-2.040	7	Y
10	-1.220	-12.497	0	N	-0.122	-2.712	0	Y
11	-0.832	-3.124	6	N	-0.122	-2.673	0	Y
12	-0.964	-2.809	6	Y	-0.212	-2.685	4	Y
13	-0.304	-1.643	6	Y	-0.090	-1.338	10	Y
14	-0.394	-2.492	3	Y	-0.087	-1.661	5	Y
15	-0.390	-2.008	6	Y	-0.108	-1.812	11	Y
16	-1.537	-10.690	1	N	-0.210	-2.922	2	N
17	-1.084	-4.073	4	N	-0.251	-2.646	3	Y
18	-1.432	-15.913	0	N	-0.286	-4.178	0	N
19	-1.046	-6.723	1	N	-0.129	-1.830	3	Y
20	-0.590	-2.723	5	Y	-0.117	-2.756	0	Y

*t statistic compared against 5% ADF critical values

*Unit root lag length specification is based on minimizing the Akaike Information Criterion (AIC)

TABLE A-4: RTE CEREAL EQUILIBRIUM REGRESSION RESIDUAL UNIT ROOT RESULTS

SKU #	β	t	m	Unit Root
2	-1.944	-5.877	4	N
3	-1.582	-2.852	5	N
4	-1.260	-11.300	0	N
6	-1.748	-9.100	1	N
8	-2.061	-11.303	1	N
9	-1.302	-12.415	0	N
10	-1.991	-11.890	1	N
11	-1.629	-6.404	3	N
13	-1.268	-11.397	0	N
14	-1.213	-10.798	0	N
15	-1.737	-11.424	1	N
20	-1.571	-6.758	3	N
21	-1.245	-11.192	0	N
24	-1.871	-3.148	11	N
25	-1.206	-7.452	1	N
28	-1.218	-10.729	0	N

*t statistic compared against 5% ADF critical values

*Unit root lag length specification is based on minimizing the Akaike Information Criterion (AIC)

TABLE A-5: CANNED SOUP EQUILIBRIUM REGRESSION RESIDUALS UNIT ROOT RESULTS

SKU #	β	t	m	Unit Root
1	-1.715	-8.611	2	N
2	-0.894	-9.109	0	N
3	-0.774	-8.007	0	N
4	-1.929	-5.948	3	N
5	-2.422	-7.806	3	N
6	-1.293	-14.142	0	N
7	-0.920	-9.351	0	N
8	-1.551	-9.943	1	N
9	-0.484	-1.098	15	Y
10	-1.486	-9.937	1	N
11	-1.542	-9.730	1	N
12	-1.598	-9.811	1	N
14	-1.616	-10.151	1	N
15	-0.259	-0.702	15	Y
16	-1.700	-10.923	1	N
17	-0.664	-1.284	11	Y
18	-1.555	-10.928	1	N
20	-1.310	-14.005	0	N
21	-0.832	-8.537	0	N
22	-1.621	-10.053	1	N
23	-1.685	-10.300	1	N
24	-1.580	-9.842	1	N
25	-0.824	-8.489	0	N
26	-1.831	-5.554	4	N
28	-1.938	-8.441	2	N
29	-1.626	-9.762	1	N
30	-1.512	-9.628	1	N
31	-0.919	-9.313	0	N
32	-1.772	-8.239	2	N
33	-0.587	-1.768	13	Y
34	-1.651	-5.482	3	N
36	-1.569	-11.088	1	N

*t statistic compared against 5% ADF critical values

*Unit root lag length specification is based on minimizing the Akaike Information Criterion (AIC)

TABLE A-6: YOGURT EQUILIBRIUM REGRESSION RESIDUALS UNIT ROOT RESULTS

SKU #	β	t	m	Unit Root
1	-1.297	-11.551	0	N
2	-1.340	-12.154	0	N
3	-1.286	-4.722	2	N
4	-1.967	-7.169	2	N
5	-2.255	-11.438	1	N
7	-1.306	-11.785	0	N
8	-1.410	-13.352	0	N
9	-2.239	-7.288	2	N
10	-2.281	-7.131	3	N
11	-1.379	-12.779	0	N
12	-1.189	-10.445	0	N
13	-1.242	-10.983	0	N
14	-1.958	-7.299	2	N
15	-1.394	-10.886	0	N
17	-1.707	-3.180	7	N
19	-1.412	-13.481	0	N
20	-2.030	-5.622	3	N

*t statistic compared against 5% ADF critical values

*Unit root lag length specification is based on minimizing the Akaike Information Criterion (AIC)