

# Economic Foundations of Retailer Price Promotion: It's All Incremental

Kurt A. Jetta<sup>1</sup>, Erick W. Rengifo<sup>2\*</sup>, Dominick Salvatore<sup>3</sup>

<sup>1</sup>TABS Analytics, United States

<sup>2&3</sup>Fordham University, United States

kurtjetta@tabsanalytics.com<sup>1</sup>

rengifomina@fordham.edu<sup>2</sup>

salvatore@fordham.edu<sup>3</sup>

\*Corresponding author

**Abstract:** *This paper states that under several conditions that completely apply to CPGs, incremental retail sales generated by promotional price discounts are entirely incremental to the promoting manufacturer, the promoting retailer and the category, overall. In general, and as observed examining traditional retail point-of-sale data, this implies that there is no post-period reduction in sales (dip) either in the short or long-term, nor is there a reduction of sales for competing brands, nor is there a reduction of sales for the promoted item in competing retailers. It is a Complete Category Expansion Effect (CCEE). The paper discusses the underlying theories of consumer demand that support the CCEE and the lack of economic rationale offered by prior literature. A calibration-simulation example is offered to support the CCEE.*

**JEL Classification codes:** M30, M31, C01, C11

**Keywords:** Microeconomics; Consumer Demand Theory; Price Promotions; Marketing; Consumer Packaged Goods; Sales Dips.

## 1. INTRODUCTION

Up until 2007-08, few topics in the Marketing academic literature were, as analyzed, controversial and misunderstood as the effects of retail price promotions. These effects can occur on the promoting brand, competitive brands or promoting retailer. We refer to this research as Sales Decomposition Research (SDR) for Promotions. While interest from academia has declined significantly in recent years to move on to other more “interesting” topics such as digital marketing, the fundamental issues surrounding the sales decomposition issue have yet to be resolved. Also, this is a major oversight by researchers in that trade promotion still accounts for the largest portion of the typical Consumer Package Goods (CPG) brand marketing budget in the U.S. Gartner Research (2013) estimates this spending now exceeds 20% of revenue and is growing its share of marketing spending every year.

A retail price promotion is defined as a temporary price reduction (TPR) to consumers offered by retailers. There is no controversy in the literature that the vast majority of these events create a short-term spike in the sales of the promoting brand at the promoting retailer (Van Heerde, Leeflang, Wittink (2000) [17] Blattberg et al (1995)). Also, the work of Pauwels et al (2002)[12] and DelVecchio et al (2006)[3] have established a consensus that there are no

long-term effects on the promoting brand – positive or negative – from price promotions. What is still unanswered is where from the sales spike is sourcing its incremental sales in the short-term and intermediate term. That is, *who* does the incremental sales source from (own brand, competitive brand or some other source)? *When* do the adjustment effects of the substitution occur (short, intermediate or long term)? Finally, *where* does the adjustment occur (promoting retailer or competing retailer)?

An answer to this question is even more important today than it was 10-15 years ago when most of this type of research was conducted, given the higher share of spending being allocated to trade promotions (Kantar retail (2012)). Indeed, it is a recurring theme in the CPG (or fast Moving Consumer Goods (FMCG))<sup>1</sup> industry that trade promotion is a necessary evil or an addiction that must be cured. In this sense, in August 2014 the CEOs of two public companies, Kraft Foods (Anthony Vernon) and Campbell Soup (Denise Morrison), cited lower response from trade promotions as a significant cause of their weak

<sup>1</sup> CPGs or FMCG are products with relative low price and high turnover. CPG/FMCG products include soft drinks, toiletries, OTC drugs, processed food, etc. They are typically sold in mass market retailers such as Grocery Stores, Super Centers, Hypermarkets, Drug-Pharmacy Stores, Mass Merchandisers, Value-Dollar Stores, or Club Stores.

sales. To understand the importance of measuring the degree to which promotional sales are incremental, one needs to look no further than the disastrous results of department store retailer J.C. Penney when they completely eliminated promotions in 2012.<sup>2</sup>

Up to these days, the majority of the SDR literature on retailer price promotions deals with the “*who does the incremental sales source from (own brand, competitive brand or some other source)?*” aspect. Gupta (1988)[5], using household panel data of coffee purchasing, estimated that 84% of the sales increase source from brand switching and 16% from own Brand. Bell et al (1999) claimed to have replicated these results using a much broader database of 13 categories and 174 brands. Their study, however, yielded significantly different results in the coffee category, where Bell et al (1999) found 48% of the promoted sales where sourced from own brand vs. the 16% found by Gupta (1988).

Van Heerde et al (2003) offered a new measure for calculating sales decomposition that considers the critically important potential for *category expansion*. Previous studies had only looked at market share changes, which, by definition, leave no possibility of demand expansion. Just by redefining the sales elasticity from trade promotion to a unit-basis vs. share-basis, they found that only 33% of sales were sourced from brand switching, 33% from own brand and 33% came from category expansion. Around that same time Pauwels et al (2002) used a VAR modelling technique and a different data set to calculate a much higher category expansion (62% on average) with the remainder sourcing from brand switching (25%) and own brand cannibalization (13%).

As noted earlier, there is a consensus in the literature that there are no-long term effects from price promotion, nor is there controversy that the immediate effects are significant and positive on the promoting brand. This helps us to isolate most of the discussion of “*When do the adjustment effects of substitution occur?*” We define the short-term as the week of the promotion (week 0), and we will follow the definition for intermediate term offered by Pauwels et al (2002) to weeks 1 through 8. The interest lies in the potential for negative sales (i.e. sales dip) in that intermediate period. The negative sales can come from either pantry loading (taking a consumer out of the market for a repurchase during that time) or purchase acceleration (a consumer that purchased in the promotion week instead of their usual pattern that may have been a few weeks later).

This sales dip has been a great puzzle for numerous researchers such as Gupta (1988), Bell et al (1999), Pauwels et al (2002), Van Heerde et al (2003), Hendel and Nevo (2003). All of them expressed surprise that evidence of this sales dip did not exist when examining traditional retail point-of-sale data. Curiously though, several articles managed to use more exotic models and data sources to

identify that the dip did, in fact, exist despite the lack of evidence in syndicated sales data, which is considered to be the standard of reality for measuring sales performance (Dekimpe, Hanssens, Nijs and Steenkamp (2005)).

The issue of “*where does the adjustment occur (promoting retailer or competing retailer)?*” is the least researched element of SDR, and the few results available are inconclusive. Walters (1991) found some weak evidence for cross channel effects or channel shifting. Dawes (2004) concluded that the source of the sales spike was from competing retailers for competing brands in future weeks, a rather dubious conclusion that begs the question of why there were no obvious immediate effects on competing brands in the promoting retailer.

While there are highly variable conclusions emanating from this stream of literature, one thing in common with all of them is the minimal effort of offering a theoretical basis for evaluating the validity of results and conclusions. We would suggest that this lack of theoretical foundation is the primary reason for the continued controversy on this topic. Marketing literature, in general, has been content to rely on empirical generalization for the organization of knowledge (Bell, Chiang and Padmanabhan (1999), Hanssens (2010)) rather than on constructing or using a theoretical framework for the discipline. In particular, there are few mentions of the theories or laws of economics. Jetta (2008) notes that in Neslin’s book, *Trade Promotion (2002)* – which was a broad-reaching audit of extent literature on the topic, only 5% of the citations are from economics journals.

This paper shows that a logical progression of three well-known economic theories support the Complete Category Expansion Effect (CCEE). Slutsky (1915) established the need for an empirically derived Substitution Effect in the Law of Demand; Hicks (1946) proved that substitution effect can be considered in the context of one product substituting with all discretionary income rather than just a specific product or category, and Cournot (1838) who showed that when substitution is considered in the context of all discretionary income the substitution effect for a low-priced product on any other specific product is immaterial. We join this background together with two well-known utility functions to finally show that CCEE is completely feasible in real life. We support our findings with robust mathematical tools, economic theory and by a calibration-simulation data analysis.

The remaining of the paper is organized as follows. Section 2 presents a brief description of the economic foundations of the paper, describes the utility function and the data used to verify that CCEE is technically feasible and that does not contradict any economic theory or law. Section 3 develops a calibration example and, Section 4 concludes and presents future venues of research.

## 2. ECONOMIC FOUNDATIONS

We now look to the field of microeconomics to identify the source of the incremental sales. There is one law,

<sup>2</sup>[http://www.nytimes.com/2012/01/26/business/jc-penneys-chief-ron-johnson-announces-plans-to-revamp-stores.html?\\_r=0](http://www.nytimes.com/2012/01/26/business/jc-penneys-chief-ron-johnson-announces-plans-to-revamp-stores.html?_r=0)

Slutsky's (1915) Fundamental Value Theory or Slutsky equation, and two theorems, Hicks' (1946) Composite Goods Theorem and Cournot's (1846) Aggregation Condition of Demand. The rationale described in this paper is built by taking them in sequence. After we

introduce these law and theorems, we present two utility functions that will help us to better understand these three theoretical components and to implement a calibration exercise to support our theoretical development.

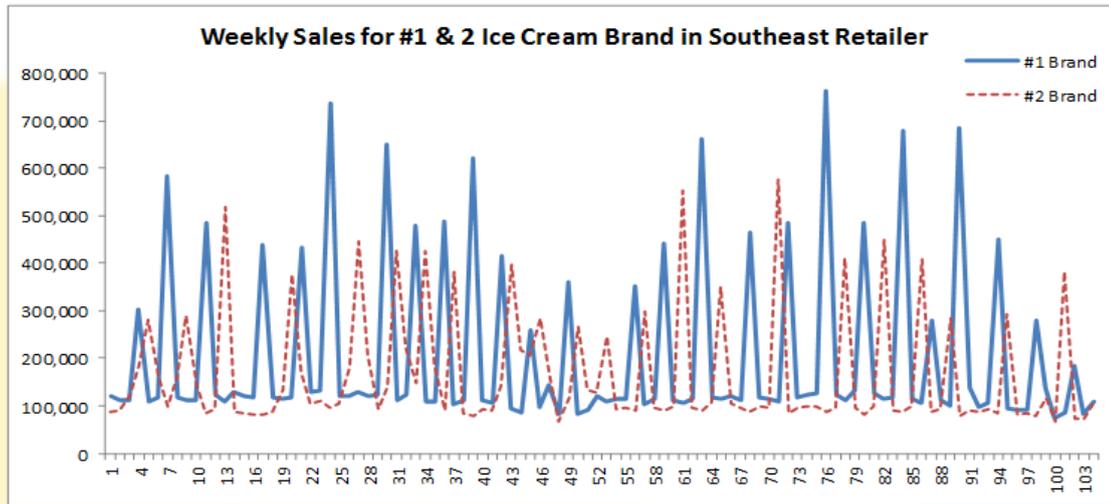


Exhibit 1 presents examples of the types of retail sales data that puzzled so many researchers.

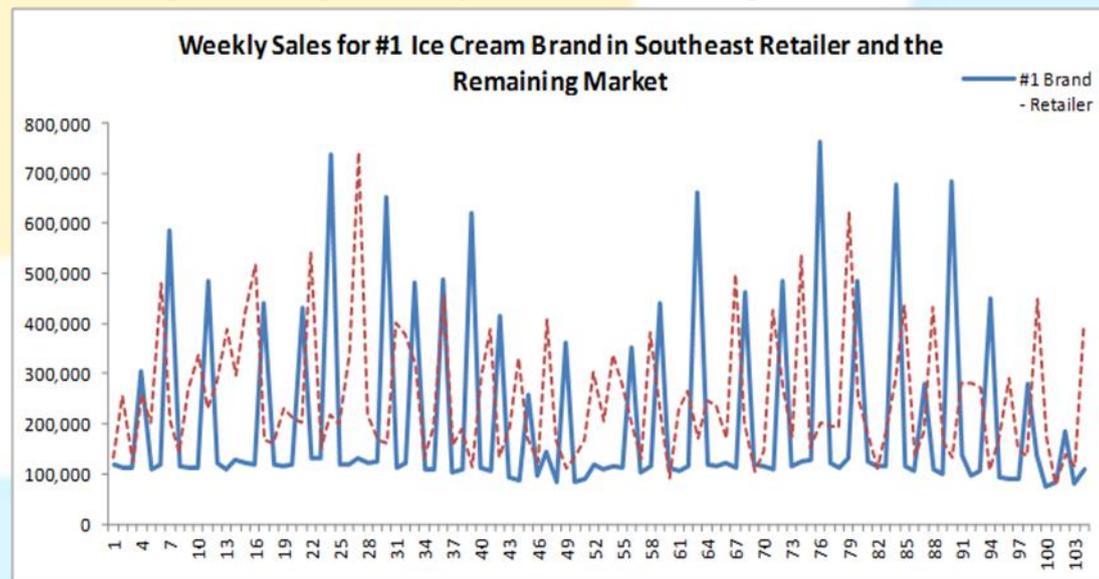


Exhibit 1: upper panel shows the lack of evidence of brand switching and the lower panel presents lack of evidence of channel shifting. The figures present weekly sales for #1 ice Cream brand sold by a southeast retailer.

## 2.1 Slutsky's Fundamental Value Theory (1915)

The Slutsky equation was expanded upon by Hicks and Allen (1936) to become the Law of Demand. The Law of Demand states that the quantity demanded for a good,  $Q^D$ , is a function of its price at a fixed point in time ( $t$ ), subject to certain assumptions such as static tastes and preferences, static income, static information and static prices of competitive and substitute products.  $Q^D$  always has a negative slope as it responds inversely to price changes: quantity demanded increases with a price reduction and it decreases with a price increase.

The change in demand is a function of two effects: the *Substitution Effect* and the *Income Effect*. The intuition of the Substitution Effect is that when price is reduced (similar to what we see for retailer price promotions) a consumer will substitute their purchases of other goods (that in *relative terms* are more expensive) in order to purchase more of the promoted good (that in relative terms is cheaper). The intuition of the income effect is that for a sufficiently large reduction in price, the consumer can have an increase in *real purchasing power*, which accentuates the increase in  $Q^D$  even more.

Hicks (1946) stated in his discussion about the Income Effect that "It is therefore a consideration of great

importance that this unreliable income effect will be of relatively little importance in all those cases where the commodity in question plays a fairly small part in the consumer's budget." This statement is of great importance in the discussion that follows in the next sections. Also, without the Income Effect we are left purely with the Substitution Effect for an understanding of the Complete Category Expansion Effect.

Past literature (Van Heerde et al (2002), Hendel and Nevo (2003)) presupposed that this substitution effect came from either brand switching or lower demand of the product ( $Q^D$ ) in weeks  $t+1, t+2...t+8$ . These authors, despite their acknowledgement that this substitution effect was not observable in scanning data, did not search for any explanation outside of the category construct used or with what Lancaster defined as "intrinsically similar goods". Henderson and Quandt (1980) make it clear that the substitution effect cannot be assumed, it must be empirically derived. Up to this point and even accepting the 33% category expansion estimate by Van Heerde et al (2003) or the 62% by Pauwels et al (2002), we are still left with the question: *where does the substitution effect come from?* Hicks (1946) provides a logical and appropriate explanation with his Composite Goods Theorem.

### 2.2 Hicks Composite Goods Theorem (1946)

Hicks posited that the collection of remaining goods can be treated as a single unit so long as their prices remain constant. "A collection of physical things can always be treated as if they were divisible into units of a single commodity so long as their relative prices can be assumed to be unchanged...So long as the prices of other consumptions goods are assumed to be given, they can be lumped together into one commodity 'money' or 'purchasing power in general.'"

The Composite Goods Theorem is the reason why the Complete Category Expansion Effect (CCEE) can exist. The sales promotion spike would not only source from competitive items in the same category, but from *all* items for which the consumer can spend money: entertainment, clothes, fuel, home improvements, etc. Given that competitive, non-promoted products are part of the remaining discretionary income, we would still expect there to be some volume sourcing from these products, as well.

The only remaining issue, then, is why we have never been able to measure this effect. The Cournot Aggregation Condition provides the explanation.

### 2.3 Cournot's Aggregation Condition (1838)

The Cournot's Aggregation equation shows the relationship between own and cross-price effects. It is obtained by differentiating the individual's budget constraint with respect to the price of a given good  $x$ . Recall that the simplest budget constraint for 2 bundles of goods,  $x$  and  $y$ , is given by:

$$p_x x + p_y y = I \quad (1)$$

Where,  $p_x$  and  $p_y$  represent the prices of bundles  $x$  and  $y$ , respectively.  $I$  represent the individual's income.

Differentiating the individual's budget with respect to  $p_x$  and making this equal to zero to keep the individual's income unchanged and by some algebraic manipulations, we have:

$$p_x \frac{\partial x}{\partial p_x} \frac{p_x x}{I x} + x \frac{p_x x}{I x} + p_y \frac{\partial y}{\partial p_x} \frac{p_x y}{I y} = 0 \rightarrow$$

$$\frac{p_x x}{I} \frac{\partial x}{\partial p_x} \frac{p_x}{x} + \frac{p_y y}{I} \frac{\partial y}{\partial p_x} \frac{p_x}{y} = -\frac{p_x x}{I} \rightarrow S_x \varepsilon_{x,p_x} +$$

$$S_y \varepsilon_{y,p_x} = -S_x \quad (2)$$

Where  $s_x$  and  $s_y$  represent the percentages of the individual's income spent on bundle  $x$  and  $y$ , respectively. The variable  $\varepsilon_{x,p_x}$  and  $\varepsilon_{y,p_x}$  represent the price elasticity of  $x$  and the cross price elasticity of  $y$  with respect to the price of  $x$ . Using Equation (2), Cournot (1838) showed that when substitution is considered in the context of *all discretionary income*, the substitution effect for a *low-priced* product on any other specific product is *immaterial*. To see this, note that if  $s_x$  (the percentage of the individual's income spent on bundle  $x$ ) is small, a change on bundle  $x$ 's price ( $p_x$ ) has an insignificant effect on the quantity spent in bundle  $y$ . With this result at hand together with the Hicks Composite Goods, we can construct a two dimensional space made of two bundles (say the CPGs bundle ( $x$ ) and the all-the-other bundle ( $y$ )) and calculate the expected change in sales of both bundles given a percentage decrease in the price of one of them (in our case a change in the price of bundle  $x$ ,  $p_x$ ).

Before moving to the calibration example we briefly introduce the concept of utility functions. Utility is understood as the perceived ability of a good to satisfy needs of the individuals. As soon as the utility that a good provides to individuals are not directly observed, economists have created mathematical ways of representing and measuring utility in terms of economic choices that can be measured (Samuelson (1938)). In this sense, economists consider utility to be revealed in people's willingness to pay different amounts for different goods. Under this understanding, utility functions are simply mathematical functions that rank alternatives according to the perceived utility they provide to an individual.

In the next section we present one of the most used utility functions.<sup>3</sup> We introduce the Constant Elasticity of Substitution (CES) utility function that provides us with more flexibility to model what could be happening in real markets. The following Sections present the main mathematical results. We refer the reader to any microeconomics book for a detailed explanation of this utility function.

### 2.4 The Constant Elasticity of Substitution (CES)

The mathematical representation of the CES utility function is given by:

$$U(x, y) = (\alpha x^\rho + (1 - \alpha)y^\rho)^{\frac{1}{\rho}} \quad (3)$$

<sup>3</sup> We have also results for the Cobb-Douglas utility function. Results are available upon request.

The parameters  $\alpha$  and  $\beta$  are the share parameters and  $\rho$  the parameter that controls for the elasticity of substitution. The variables  $x$  and  $y$  represent bundles of goods.<sup>4</sup> A few statistics can help us to understand how this function works. The Marginal Rate of Substitution ( $MRS_{y,x}$ ) measures the amount of  $y$  a consumer needs to get in order to give up a little of good  $x$ , keeping the same level of utility.<sup>5</sup> Mathematically:

$$MRS_{y,x} = \left(\frac{\alpha}{1-\alpha}\right) \left(\frac{y}{x}\right)^{1-\rho} \quad (4)$$

The *elasticity of substitution* measures the curvature of the indifference curve estimating the degree to which the consumer's valuation of good  $x$  depends on his holdings of  $x$ . Recall that utility functions are in general increasing at a decreasing rate. This means that utility provided by an extra unit of a good depends on how much someone already has of it. If some HH has very few of the good, having an additional one significantly increases the utility of that good. In the other hand, if some HH already has plenty of a good, the marginal utility of this additional units will not be as high as the previous case; thus his or her utility, even though increases, it does at a lower rate. This is the information that we get from the elasticity of substitution. The elasticity of substitution is measured as:

$$\varepsilon = \frac{1}{(1-\rho)} \quad (5)$$

Note that the parameter  $\alpha$  controls the  $MRS_{y,x}$  and that  $\rho$  influences the elasticity of substitution that determines the slope of the demand curve. Using the CES utility function in order to determine the demand functions of bundles  $x$  and  $y$ , subject to a budget constraint, allows us to get the main intuition about why it is perfectly feasible to have a Complete Category Expansion Effect (CCEE). In this case, the maximization problem is presented below:

$$\max_{x \geq 0, y \geq 0} (\alpha x^\rho + (1-\alpha)y^\rho)^{\frac{1}{\rho}} \quad (6)$$

*s. t.*  $p_x x + p_y y = I$

The quantity of bundle  $x$  demanded is given by:

$$x = \frac{I}{p_x + p_y \left(\frac{1-\alpha}{\alpha} \frac{p_x}{p_y}\right)^\varepsilon} \quad (7)$$

Using some algebraic manipulations, we get:

$$x = \frac{(p_x/\alpha)^{-\varepsilon}}{\alpha^\varepsilon p_x^{1-\varepsilon} + (1-\alpha)^\varepsilon p_y^{1-\varepsilon}} I \quad \text{and};$$

$$y = \frac{(p_y/(1-\alpha))^{-\varepsilon}}{\alpha^\varepsilon p_x^{1-\varepsilon} + (1-\alpha)^\varepsilon p_y^{1-\varepsilon}} I \quad (8)$$

We use this model to obtain estimates that we compare with the benchmark provided by the Cobb-Douglas utility function.

### 3. A SIMPLE EXAMPLE

In this section we use US economic and demographic data to show that the Complete Category Expansion Effect (CCEE) is indeed feasible in the CPGs environment. As

<sup>4</sup> In our case  $x$  will represent the CPGs category and  $y$  will represent all the other goods in the consumer's basket.

<sup>5</sup> Recall that if a consumer has a lot of  $x$  relative to  $y$ , then  $x$  is much less valuable than  $y$ , then  $MRS$  will be low.

soon as data directly related to CPGs supply and demand are not completely known, we are going to base our analysis on a category that is highly tracked: food. Specifically, we use income and expenditure related data for the U.S. We describe the data in the following section.

#### 3.1 Food Consumption Expenditure in the US

Figure 1 shows information from the Consumer Expenditure Survey of 2013 on In-Home Food spending by income quintile, from the US Bureau of Labor Statistics (BLS).

In Exhibit 2 we can see that spending on food increases measurably in the absolute for the higher income quintiles, from a low of \$3,655 to the lowest income quintile (Q1) to \$11,184 for the highest income quintile (Q5). More importantly, we see the proportion of Total Income spent on Food falls dramatically from Q1 (36.2%) to Q5 (only



6.9%). This information will be used to estimate utility functions for each quintile under promotional conditions.

#### Exhibit 2: Food Consumption Expenditures in the US

A more complete dataset of quintile income and Food expenditures is provided in Table 1.<sup>6</sup> In this paper we use the expenditures in food as proxy for the expenditures in CPGs. From Table 1 we can see that total Food expenditures are roughly \$829B. According to Nielsen, CPGs food sales tracked through scanners were \$390B in 2013. Projecting out another 20% for channels not tracked (e.g. Costco, Natural Food, Value Food, Convenience Stores, Specialty) brings the total CPG universe for Food to roughly \$488B, or about 59% of total food. Based on these numbers, we expect the CPG category to have a smaller impact on households' income than the one observed in food. In this sense our results should be considered conservative. Finally, we note the wide disparity in average income between Q1 and Q5, with Q5 average income 16 times higher than Q1.

This table presents data on food expenditures in the US, per average income quintile for 2013 as reported by US Bureau of Labor Statistics. The per-capita mean dollar spent on food equals the average income per quintile, times food expenditures as share of income. The aggregate mean dollar spent on food per quintile equals per-capita mean dollar spent on food times the number of HH in each income quintile.

<sup>6</sup> These numbers come from the Bureau of Labor Statistics. <http://www.bls.gov/cex/2013/combined/quintile.pdf>.

**Table 1: Food Expenditures in the US per Quintile**

Income Quintile	Number of HH (in thousands)	Population quintile distribution (%)	Food expenditures as share of income (%)	Average income per quintile (\$)	Per-capita mean dollar spent on food per quintile (\$)	Aggregated mean dollar spent on food per quintile (\$)
lowest	25,090	20.0%	36.2%	10,092	3,655.00	91,703,950
second	25,219	20.1%	18.2%	26,275	4,781.00	120,572,039
middle	25,082	20.0%	12.5%	45,826	5,728.00	143,669,696
fourth	25,178	20.0%	10.3%	74,546	7,655.00	192,737,590
highest	25,101	20.0%	6.9%	162,720	11,184.00	280,729,584
<b>total</b>	<b>125,670</b>	<b>100%</b>				<b>829,412,859</b>

**Table 2: Probabilities of Buying on Promotions**

Quintile	Number of HH (in thousands)	Food expenditures as share of income (%)	Probabilities of response to a promotion
lowest	25,090	36.2%	100.0%
second	25,219	18.2%	50.2%
middle	25,082	12.5%	34.5%
fourth	25,178	10.3%	28.4%
highest	25,101	6.9%	19.0%

### 3.2 Probability of Buying on Promotions

We now make use of the food expenditure share of income by proposing that the likelihood of buying food on promotion is directly proportional to the share of income spent on food. The rationale for the construct is that the higher the percentage of food expenditures with respect to the average income, the higher the likelihood of buying on promotions.<sup>7</sup> We standardize all the shares of food expenditure relative to Q1 and obtain an estimate of the likelihood of buying on promotion for the other quintiles. This means that the likelihood of Q2 buying on promotion is 50.2% that of Q1 (18.2%/36.2%), and so on. The results of applying this metric are presented in Table 2.<sup>8</sup>

This table presents the construct to explain the probabilities that a given HH has depending on its income quintile.

The basic idea underlying this construction is that the larger the expenditure to income ratio a quintile has, the more care and attention HH pays to ways of optimizing its consumption. Looking for promotions is a natural way of doing that, since this allows to buy the same quantity for less money, buy more for the same expenditure as before

or buy even more sacrificing the consumption of the other categories and products in their basket.

An additional mathematical fact that helps us support this probability construct is given by noting that HHs' percentage change in their utilities, change accordingly not only to price changes but also by the actual share of income of a given category (food in our case). This can be clearly seen in Equation (13) that shows that the percentage change in the HH's utility depends on the ratio of actual prices ( $P_x$ ) to discounted prices ( $P_{x1}$ ) and more importantly, depends on the share of income that product  $x$  has ( $\alpha$ ). As soon as  $\alpha$  is defined in  $[0, 1]$ , the larger  $\alpha$  the larger the percentage change in utility. In terms of the column "Food expenditures as share of income" in Table 2, HHs in the lowest income quintile are the ones that experience the highest changes in utility even though their actual increases in units consumed is low with respect to the ones observed in the higher quintiles HHs. This, mathematical fact together with the economic intuition that HHs maximize utility functions, can be interpreted as HHs in the lowest quintiles being those more prone to look and to actually buy on promotions. With this last piece of information, we are able to present several numerical simulations and calibrations that help us prove that indeed a Complete Category Expansion Effect (CCEE) is feasible.<sup>9</sup>

<sup>7</sup> We are not arguing anything about what literature already discussed in terms of promotion effectiveness and related issues. We simply propose a logic idea that the higher the expenditure ratio with respect to income, assuming that the needs of the HH of the lower quintile are at least similar to the ones in higher quintiles, the higher the likelihood of actively looking for promotions and actually buying on promotions.

<sup>8</sup> We also used to set the lowest quintile to be a number in between 80% to 100% and, adjusted the other probabilities accordingly. Directionally the findings remain the same. Results are available upon request.

<sup>9</sup> It is important to note that in the following example we assume a 20% aggregate price discount on food prices assumed to be proxies for CGPs. In real life the aggregate food price discounts are of the order of 2-3%. Also in this sense, our results allow us to present more conservative results that the actual ones that could be observed in reality.

### 3.3 Aggregate Demand

To show that a Complete Category Expansion Effect (CCEE) is feasible, we need to have an aggregate demand function to understand the dynamics that could be observed during promotion and non-promotion periods. The log demand equations:

$$\ln(x) = \ln(\alpha) + \ln(I) - \ln(p_x) \quad (9a)$$

$$\ln(y) = \ln(\beta) + \ln(I) - \ln(p_y) \quad (9b)$$

These equations represent the individual demands for bundles x (CPGs in our case) and y (the other categories and products). If we know the individual demand functions of each HH, we can aggregate all the consumers (households in our case) to obtain the market demand function. We assume that in average the HHs measure their utilities based on the Cobb-Douglas (later on the more general CES utility function). This aggregated demand function is simply achieved summing up equations (9a) and (9b). However, we know that these HH demand functions are heavily affected by the income level that determines the proportion of income assigned to each bundle, i.e. different shares ( $\alpha$  and  $\beta$  coefficients). Thus, the aggregation should happen first at the quintile level and after at the market level, i.e.

$$\ln(X_1) = \sum_{i=1}^{n_1} [\ln(\alpha_1) + \ln(I_1) - \ln(p_x)] = n_1(\ln(x_1)) \quad (10)$$

$$\ln(X_5) = \sum_{i=1}^{n_5} [\ln(\alpha_5) + \ln(I_5) - \ln(p_x)] = n_5(\ln(x_5))$$

Where  $\ln(X_q)$  is the aggregated demand for HHs in the income quintile q for q=1, ..., 5;  $\alpha_q$  the share coefficient of bundle x corresponding to HHs in income quintile q. Finally,  $n_q$  represents the number of HHs in income quintile q. Finally, summing up each of the quintile demands, we obtain the market log-demand,

$$\ln(X) = \sum_{q=1}^5 \ln(X_q) \quad (11)$$

The last issue regarding the demand aggregation is to find a way to separate the aggregate market demand into promotional and non-promotional periods. For this, we assume that households decide, care about or are aware of promotions, based on the proportion of their expenditure to income ratio that the bundle x represents. We use the probabilities construct presented in Table 3 and proceed as before to find the aggregated market demand for x. Let's define the demand of bundle x during promotional and non-promotional periods as:

$$\ln(x^{prom}) = \ln(\alpha) + \ln(I) - \ln(p_x^{prom}) \quad (12)$$

$$\ln(x^{non-prom}) = \ln(\alpha) + \ln(I) - \ln(p_x^{non-prom})$$

We define the demand per HH belonging to a given quintile and, based on promotional or non-promotional periods as:

$$\ln(x_1) = \pi_1[\ln(x^{prom})] + (1 - \pi_1)[\ln(x^{non-prom})] \quad (13)$$

$$\dots$$

$$\ln(x_5) = \pi_5[\ln(x^{prom})] + (1 - \pi_5)[\ln(x^{non-prom})]$$

Where,  $\pi_q$  represents the probability that a HH in income quintile q (for q=1, ..., 5) buys the bundle x on promotion. The specific values of this probabilities are the ones presented in Table 3. Next, aggregating at the income quintile level:

$$\ln(X_1) = \pi_1[n_1\{\ln(\alpha_1) + \ln(I_1) - \ln(p_x^{prom})\}] + (1 - \pi_1)[n_1\{\ln(\alpha_1) + \ln(I_1) - \ln(p_x^{non-prom})\}] \quad (14)$$

$$\dots$$

$$\ln(X_5) = \pi_5[n_5\{\ln(\alpha_5) + \ln(I_5) - \ln(p_x^{prom})\}] + (1 - \pi_5)[n_5\{\ln(\alpha_5) + \ln(I_5) - \ln(p_x^{non-prom})\}]$$

Finally, the market log-demand is given by:

$$\ln(X) = \sum_{q=1}^5 \ln(X_q) \quad (15)$$

Note that Equation (14) is an interesting one since it shows the impact of a promotion in the overall market demand. Given the way the probabilities have been set, where households in the lowest quintile react more to promotions than households in the highest income quintile, not all sales are done during promotional events. The demand in periods of non-promotional activity allows for consumer loyalty or simply for households buying different products within a category not motivated by pricing.<sup>10</sup>

### 3.4 Calibration and Simulation Exercise

In what follows we make the following assumptions: x refers to CPGs bundle; y refers to all the other products and categories that are consumed or bought by the HHs. We assume that food is a category that can be used as a proxy to determine the behavior of CPGs. Note however, that apparently CPGs constitute only a third of the food market in terms of dollars spent. However, we believe that using food is the most conservative approximation we can choose. We assume an average price for CPG products of \$2 and average price for all the other product of \$10.<sup>11</sup> In this section we present the results of using the CES utility function described in Section 2.4. Other results are available upon request. In this case the demand of a given bundle depends also on the price of the other bundle, making the exercise a more realistic one. In this section we only present the results using a single combination of the CES parameters ( $\alpha$  and  $\rho$ ) for all income quintiles. We assume that households across income quintiles have the same elasticity of substitution that equals 1.25 (1/(1-0.2)). This implies that both bundles are assumed to be slightly substitutes, in the sense that households will be willing to marginally sacrifice consumption in one bundle when the price of the other one decreases.<sup>12</sup> The CES parameter values, that make the ratio of expenditure to income close to the ones observed in the economic data, is presented in

[Table 3.](#)

<sup>10</sup> There are other non-price related activities geared to increase demand. In this paper we just concentrate in the aggregate view in order to show that a complete category expansion is completely feasible and left these additional aspects for future research.

<sup>11</sup> We have run many different simulations with different price ranges and the results appear to be robust. At this point we are mostly interested in working with 2 significantly different prices. Results available upon request.

<sup>12</sup> We have changed this assumption from 1.10 to 1.50 to see the sensitivity of the model to these changes. Qualitatively the results stayed the same. These results are available upon request.

**Table 3: Coefficients used for the CES Utility Function with Same Elasticity of Substitution**

Coefficients	Lowest	Second	Middle	Fourth	Highest
$\alpha$	0.315	0.179	0.133	0.113	0.083
$\rho$	0.200	0.200	0.200	0.200	0.200
Average Income (I)	10,092	26,275	45,826	74,546	162,720
% Income allocated according to data	36.22%	18.20%	12.50%	10.27%	6.87%

**Table 4: Results Obtained from the CES Utility Function with Same Elasticity of Substitution**

	Lowest		Second		Middle		Fourth		Highest	
	Quant / Expend	% of total								
x (units) (Eq. (8))	1,827	74	2,391	53	2,864	42	3,828	36	5,588	27
y (units) (Eq. (8))	644	26	2,149	47	4,010	58	6,689	64	15,154	73
Spent on x (\$)	3,653	36	4,782	18	5,728	13	7,656	10	11,177	7
Spent on y (\$)	6,439	64	21,493	82	40,098	87	66,890	90	151,543	93
Utility0 (Eq. (6))	916		2,191		3,840		6,298		14,056	
<b>Consumption and expenditure after Promotion</b>										
x_promo (units)	2,365	79	3,128	60	3,759	49	5,030	43	7,357	33
y (units)	631	21	2,127	40	3,981	51	6,650	57	15,095	67
Spent on x_promo (\$)	3,784	38	5,004	19	6,014	13	8,047	11	11,771	7
Spent on y (\$)	6,308	63	21,271	81	39,812	87	66,499	89	150,949	93
Utility1 (Eq. (6))	995		2,284		3,951		6,447		14,278	
Increase quant sales	539		737		894		1,202		1,769	
% increase utility	8.57		4.24		2.90		2.38		1.59	

**Table 5: Complete Category Expansion Effect with CES Utility Function with Same Elasticity of Substitution**

Income Quintile	Number of HH (in thousands)	Modeled food per-capita consumption at regular price (units)	Modeled food per-capita consumption after price discount (units)	Modeled market consumption non promo (units)	Modeled market consumption after price discount (units)	Modeled market consumption non promo (\$)	Modeled market consumption after promotion (\$)
Lowest	25,090	1,827	2,365	45,831,364	59,343,473	91,662,729	94,949,557
Second	25,219	2,391	3,128	60,300,109	78,875,903	120,600,217	126,201,444
Middle	25,082	2,864	3,759	71,839,379	94,275,021	143,678,758	150,840,033
Fourth	25,178	3,828	5,030	96,377,074	126,636,809	192,754,148	202,618,894
Highest	25,101	5,588	7,357	140,270,853	184,670,254	280,541,706	295,472,407
Total	125,670			414,618,779	543,801,459	829,237,557	870,082,334

**Table 6: Complete Category Expansion Effect with CES Utility Function with Same Elasticity of Substitution, Adjusted for Probability of Promotional Participation**

Quintile	Number of HH (in thousands)	Prob. of response to a promotion	Modeled purchases during non-promotions (units)	Modeled purchases during promotions (units)	Modeled market consumption non promo (\$)	Modeled market consumption on promotion (\$)	Modeled total spent (\$)
Lowest	25,090	100%	0	59,343,473	-	94,949,557	94,949,557

<b>Second</b>	25,219	50%	30,004,201	39,628,736	60,008,401	63,405,978	123,414,379
<b>Middle</b>	25,082	35%	47,045,556	32,537,004	94,091,113	52,059,206	146,150,318
<b>Fourth</b>	25,178	28%	69,050,546	35,906,301	138,101,093	57,450,082	195,551,174
<b>Highest</b>	25,101	19%	113,650,518	35,046,369	227,301,036	56,074,191	283,375,226
<b>Total</b>	125,670		<b>259,750,821</b>	<b>202,461,883</b>	<b>519,501,642</b>	<b>323,939,012</b>	<b>843,440,655</b>

Table 3 presents the coefficients used for the CES utility function with same elasticity of substitution, the average income per quintile and the percentage allocated to buy the category according to the information presented in Table 2. Based on this parameter values and the assumptions stated before, the next table presents the main results obtained by the optimization described in Section 2.4. We first estimate bundle x demand growth (proxy for CPGs) assuming full response to price promotions.

Table 4 presents the demand results resulting from the assumptions for individual HHs shown in Table 3, in each of the income quintiles considered.

The first thing to note here is that a 20% price discount on bundle x, now has an impact on the sales of bundle y. The magnitude of this impact is governed by the elasticity of substitution (1.25 in our case). As soon as we have assumed same elasticity of substitution for all the households disregarded their income quintile, a 20% discount of the price of bundle x makes HHs to buy more of this good and slightly sacrifice consumption of the y bundle. For example, observe the income spent on y decreases from 64% to 63% for the lowest quintile. The same variation is observed across the board. Table 5 shows the growth in demand of bundle x based on the CES assumption.

Table 5 presents the growth in aggregated demand of bundle x (proxy for CPGs) assuming full response to price promotions and, that household utility functions are all based on the CES Utility Function with Same Elasticity of Substitution (see Table 3).

Now we can appreciate that indeed bundle x expansion appears not only in the quantity demanded but also in the amount spent on it (Complete Category Expansion Effect (CCEE)). Given a bundle x's 20% price discount, unit sales of this bundle increases by 31.16% and the amount spent increases by 4.93%.<sup>13</sup> Table 6 presents the dynamics under different probabilities of buying on promotion. With this last table we show that even though not everyone buys on promotion, Complete Category Expansion still is feasible. Not only total unit sales increases (462.2 versus 414.6 million) but also the total amount spent in bundle x, increases by 1.7% (843,440,655/829,237,557).

Table 6 we present the dynamics using the probabilities of buying on promotion and, the aggregated market demand presented in Sections 3.2 and 3.3, respectively.

In our research we also considered the scenario in which we allow the elasticity of substitution to change according to what is expected from someone from a given income

quintile buying a given amount of bundle x. The results showed that even though not everyone buys on promotion, Complete Category Expansion still is feasible. The total unit sales increases (from 414.7 to 462.95 million) and the total amount spent in bundle x, increases by 1.8%. We have performed several other calibrations. The results are qualitatively similar and are available upon request.

#### 4. CONCLUSIONS

Applying some fundamental principles of Consumer Demand Theory, with supporting empirical evidence, we have proven that economic theory supports what is observed in real world. Using well known utility functions, largely used in economics, we have been able to proof that CPGs incremental sales from promotional spikes can create Complete Category Expansion Effects (CCEE) which sources from an extremely small marginal reduction on spending from every other good that would be considered for purchase in a consumer's discretionary income.

The ultimate validation comes with the ability of this framework to explain results in the real world. In the U.S. there have been four specific instances in the mass market which are explained by the Complete Category Expansion Effect, most notably the calamitous and immediate decline in sales and profitability of JC Penney when they eliminated price promotions in the first quarter of 2012. Other, less publicized, cases in the U.S. are Food Lion, Stop & Shop and Walgreens. In each of the four instances, major shifts in promotional strategy were cited by senior management as reasons for gains or declines in revenue, with the revenue changes moving in the same direction as changes in promotional depth and frequency. To a lesser extent, promotional activity has been identified as a likely cause of sluggish results in same-store sales for both Walmart and Target.

With this paper we intent to provide the economic basis for marketing researchers that can help them justify their results with well-established theoretical frameworks. Additionally, more care should be taken to ensure that results confirm to the laws and theories of microeconomics. In this sense, this paper is among the first ones in the Marketing literature to draw an explicit link between the empirical results and their consistency with microeconomic theory.

Obvious next steps for this research is to add more empirical evidence that tests the theory. A particular area of focus should be on intrinsically identical products as a source of the substitution effect. Specifically, there should be a broader based of products that are identical to the promoted product in every way except for package

<sup>13</sup> The difference in market consumption non-promo (in US\$) is due to rounding errors.

quantity (e.g. the effect on 6 pack Coca-Cola when 12 pack is promoted).

## 5. ACKNOWLEDGMENT

The authors would like to thank, Luc Bauwens, Andreas Heinen, Rossen Trendafilov, David Butcher, Bill Laros, for helpful suggestions. The usual disclaimers apply

## 6. REFERENCES

- [1] Cournot, A., (1838). "Recherches sur les Principes Mathématiques de la Théorie des Riches" ("Researches into the mathematical Principles of the Theory of Wealth").
- [2] Dekimpe Marnik, Dominique Hanssens, Vincent Nijs and Jan-Benedict Steenkamp (2005). "Measuring Short- and Long-Term Promotional Effectiveness on Scanner Data Using Persistence Modelling". *Applied Stochastic Models in Business and Industry*. 2005, vol 21, 409-416.
- [3] DelVecchio, Devon, David H. Henard, and Traci H. Freling (2006), "The effect of sales promotion on post-promotion brand preference: A meta-analysis," *Journal of Retailing*, Vol. 82 (3), 203
- [4] Gupta, Sachin, Pradeep K. Chintagunta, Anil Kaul, and Dick R. Wittink (1996), "Do Household Scanner Data Provide Representative Inferences from Brand Choices: A Comparison with Store Data," *Journal of Marketing Research*, 33 (November), 383-98.
- [5] Gupta, Sunil (1988), "Impact of Sales Promotion on When, What, and How Much to Buy," *Journal of Marketing Research*, 25 (November), 342-55.
- [6] Hendel, Igal and Aviv Nevo (2003). "The Post-Promotion Dip Puzzle: What do the Data Have to Say?" *Quantitative Marketing Economics*, 2003, vol 1, 409-424.
- [7] Hicks, J.R. and R.G.D. Allen (1934), "A Reconsideration of the Theory of Value. Part I. A Mathematical Theory of Individual Demand Functions," *Economica*, Vol. 1 (1), 52-76.
- [8] Hicks, J.R. (1946), *Value and Capital, Second Edition*. Oxford University Press, Oxford, UK.
- [9] Kantar Retail (2012): Trade Promotion Industry Benchmarking Study, 2012.
- [10] Leeflang, Peter S.H., Josefa Parreño Selva, Albert Van Dijk, Dick R. Wittink (2008). "Decomposing the sales promotion bump accounting for cross-category effects". *International Journal of Research in Marketing*, September 2008, Vol. 25, No. 3, 201-214.
- [11] Lancaster, Kelvin (1966), "A New Approach to Consumer Theory," *The Journal of Political Economy*, Vol. 74 (2), 132-157.
- [12] Pauwels, Koen, Dominique M. Hanssens, and S. Siddarth (2002), "The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice, and Purchase Quantity," *Journal of Marketing Research*, 39 (November), 421-39.
- [13] Samuelson, Paul (1938), "The Empirical Implications of Utility Analysis," *Econometrica*, Vol. 6 (4), 344-356.
- [14] Samuelson, Paul (1938). "A Note on the Pure Theory of Consumers' Behaviour". *Economica* 5 (17): 61-71.
- [15] Samuelson, Paul (1948), "Consumption Theory in Terms of Revealed Preference," *Economica*, Vol. 15 (60), 243-253.
- [16] Slutsky, Eugen (1915), "On the Theory of the Budget of the Consumer," *Giornale degli Economisti*, Vol. LI, 1-26
- [17] Van Heerde Harald, Peter Leeflang, Dick Wittink (2000). "The Estimation of Pre- and Post-Promotion Dips with Store-Level Scanner Data". *Journal of Marketing Research*, August 2000, Vol XXXVII, 383-395.