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Finding the True Voice of the Customer in CPG Supply Chains: Shopper-Centric Supply Chain Management

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Demand and supply integration is the subject of increasing scholarly attention. The theoretical emphasis on combining market and supply chain data as the basis for strategic and operational decision making is particularly relevant in the context of Consumer Packaged Goods (CPG) supply chains, and offers the basis for advancing our understanding and knowledge in this field. Point-of-sale (POS) data are commonly used as the demand signal in CPG supply chains. Using empirical data, this research demonstrates that POS data can be influenced by nondemand factors. We present a number of issues raised by this finding.

Keywords: demand and supply integration; point-of-sale data; supply chain risk; voice of the customer

CONCEPTUAL AND THEORETICAL FRAMEWORK

Mainly because of space restrictions, grocery retailers limit the number of brands and product varieties available for sale on their store shelves. Category management is the strategic merchandising tool, which retailers use to make assortment decisions for each product category (Barrenstein and Tweraser 2004). In-store execution, or shelf restocking, is the operational process used to move inventory from the stockroom ("back-of-the-store") to the shelves, making items available for purchase by shoppers. Previous research (e.g., Murry and Heide 1998; Raman et al. 2001; Immink et al. 2004; Fisher et al. 2006) shows the importance of effective and efficient in-store execution for achieving desired levels of On-Shelf-Availability (OSA) of products. As Trautrims et al. (2009) argue, high OSA is a necessary condition for retail sales performance.

Consumer packaged goods (CPG) are low-involvement items for shoppers (Zaichkowsky 1985). Therefore, purchase decisions can be easily influenced by marketing stimuli in the store (e.g., sales displays, etc.), the ease with which shoppers can locate items, and ultimately, the availability of product on the shelf (Broderick and Mueller 1999; Sorensen 2009). Thus, OSA is a critical variable that must be effectively managed, to satisfy shoppers' *primary or first choice demand*, that is, those items shoppers are looking to purchase when they enter the store and expect to be part of the store's regular assortment (Trautrims et al. 2009; Vulcano et al. 2012).

Traditionally, in CPG supply chains, point-of sale (POS) or checkout scanner data provide the basis for replenishment decision making (Grewal et al. 2009; Cooke 2013). Based on these historic sales data, firms develop demand forecasts on which production and inventory management planning are based. In effect, by using past sales as a predictor for future demand this approach "pushes" inventory to market (Sandelands 1994) in order to have products available when shoppers arrive in the store.

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Williams and Waller (2010, 2011) find that using POS data as the basis for replenishment planning reduced forecast errors compared to using warehouse depletion data. However, retail POS data, theoretically, could only provide a completely accurate representation of first choice demand when a retailer's product assortment includes every variation of every CPG brand available and when in-store execution consistently achieves 100% OSA. Only under these optimal conditions would a shopper be guaranteed to find whatever they were looking for during every store visit. Therefore, given the category management-driven assortment decisions and in-store execution issues affecting OSA, shoppers' actual purchases could be an incomplete depiction of first choice demand, reflecting instead items shoppers purchased based on what was available to them during a specific shopping trip (Campo et al. 2003; Campo and Gijsbrechts 2005). Based on this observation, Vulcano et al. (2012) developed a method to approximate first choice demand based on the estimated market share, product availability, and sales data from a particular retail location.

The challenge of efficiently and effectively (i.e., profitably) meeting customer demand is the impetus for recent research advancing the concept of demand and supply integration (DSI) (Juttner et al. 2007; Esper et al. 2010; Stank et al. 2012). The main characteristic of DSI is the strategic collaboration between the customer-facing and supply chain-facing functions of firms in a supply chain. DSI suggests that a collaborative approach to acquiring and sharing market intelligence and supply chain operational data within and among firms will improve the performance of both marketing and supply chain processes (Esper et al. 2010), providing a competitive advantage over other less collaborative supply chains.

Esper et al. (2010) contend that supply chain managers should collect demand data to use as the *voice of the customer* (VOC) and operational data showing the capability of the firm's supply chain, called the *voice of the supply chain* (VOSC). Replenishment is managed based on integrating VOC *and* VOSC data (Esper et al. 2010). To apply DSI in a CPG supply chain, the customer-centricity fundamental to value marketing (Ballantyne and Varey 2008) must be extended across all echelons of the supply chain, effectively replacing traditional manufacturer-driven push replenishment with customer-centric pull replenishment (O'Marah 2005; Cooke 2013).

Replenishment models in retail and supply chain management literatures use retail *out-of-stock* (OOS) as the replenishment signal. However, as a measure for retail performance, it has been convincingly argued that it is more relevant to focus on product availability to shoppers, that is, OSA as we define it for this study (Fernie and Grant 2008; Trautrims et al. 2009). OSA and OOS are counterparts, although low OOS does not automatically lead to high OSA, unless merchandise moves reliably and efficiently from the back-of-the-store stockroom to the correct retail shelf. With some distinct exceptions (e.g., Fernie and Grant 2008; Grant and Fernie 2008; Trautrims et al. 2009) these "last 50 yards" of the CPG supply chain have received little scholarly attention, with in-store execution described as a "black box" (Ailawadi et al. 2009; Aastrup and Kotzab 2010). OSA is measured at the point in time and place (the store aisle) where the demand and supply sides of the CPG retail chain meet (Aastrup and Kotzab 2010). Therefore, in an organization emphasizing DSI, OSA would be superior to OOS as a service-level measure of product availability.

PROPOSITION

DSI research has not yet extensively investigated the optimal characteristics of VOC and VOSC data. Thus, the question remains, to support efforts to synchronize supply chain replenishment with market intelligence, what do marketing and supply chain managers use as VOC? Recent supply chain research suggests that the data stream used as the VOC should represent shopper/consumer first choice demand and that the VOC should not be influenced by nondemand factors (Askegar 2004; Helo and Luomala 2011; Trautrims et al. 2011). It is also contended that improving a retail supply chain's ability to adapt and respond by capturing shoppers' true demand is essential (Cecere et al. 2004; Helo and Luomala 2011). Further, Barrett (2007) finds that to effectively apply a customer-centric pull approach to supply chain replenishment, it is critical that managers base replenishment decisions on *true* demand. This research explores whether POS data are affected by nondemand factors.

Research Proposition: POS data are affected by nondemand factors.

For example, the limitations on product assortment imposed by category management strategies or low OSA due to deficient in-store execution are factors that could result in actual sales, as reflected in POS data, deviating from shoppers/consumers true demand.

METHOD

To test our proposition, it was necessary to capture empirical evidence that POS data are in fact susceptible to the influence of forces not related to the demand for items sold. Therefore, this research examines store-level activities of CPG manufacturer representatives (CMRs) and their interactions with store personnel to investigate whether the actions of CMRs influenced sales represented by POS data. The CMRs we studied constituted a "nontraditional" sales force, specifically instructed to, in addition to their other activities, monitor OSA and re-stock shelf locations they found empty.

Sample composition

To investigate the effect of the CMRs' efforts on OSA, we compared stores that were and were not visited by CMRs. The sample consisted of stores located in the United States, owned and operated by a large, global retail firm. In the United States, this retailer operates four store banners. Each store studied had a consistent assortment of food and nonfood items. Table 1 shows, for the retailer's U.S. locations, the number of each store type and average outlet size: stores included in the research sample were all *Market* or *Large Market* locations. Table 1 also shows that these store types are consistently sized, given the value of one standard deviation (SD) of store size. Layout, atmosphere and product assortment are largely standardized across all stores, particularly in the departments where the stock keeping units (SKUs) included in the investigation are sold. Therefore, we consider the store sample to be homogeneous.

Table 2 shows the number of stores investigated fluctuated by month over the analysis period. However, the research uses only data from continuously operated stores: to avoid biasing OSA data, we excluded data from stores undergoing remodeling or relocation. The final sample of stores mimics the mix of *Market* and *Large Market* stores within this retailer's entire set of U.S. locations. Those stores CMRs visit are labeled *test stores:* CMRs did not visit *control stores*.

OSA measure: core SKU distribution

To measure OSA in test and control stores, we compiled a list of core SKUs from the manufacturer's products. For the manufacturer, core SKUs are items that, when available on the retail shelf, sell consistently over time in all retail locations. Based on the consistency of sales for core SKUs, the manufacturer infers that if a core SKU is not selling, it is because it is not available on the retail shelf. So, for a core SKU, whether that SKU sold (or not) during a specific time period becomes, for the manufacturer, a categorical measure of OSA: if a core SKU did not sell during a specific time period, the manufacturer concludes it was not physically available to shoppers during that time; if the core SKU did sell during a specific time period, the manufacturer concludes it was physically available to shoppers during that time. Inferring product availability from sales data, as done here, is a common practice in the retail industry (Rosenblum 2014),

Table 1: Focal retailer's store types operating in the United States

Store banner*	No. of stores	Avg. size (sq. ft.)	SD size (sq. ft.)
Compadre	29	25,716	7,956
Corner store	199	40,777	8,866
Market	626	100,278	4,664
Large Market	3,066	181,129	3,489

*Store names are pseudonyms.

Table 2: Sample composition by month

Month	Total sample	Market stores	MS%	Large market	LM%	Market test stores	MS test%	Large market test	LM test%	Total no. of test	Market control stores	MS control%	Large market control stores	LM control%	Total no. of control stores
01	1,493	213	14	1,280	86	103	13	717	87	820	110	16	563	84	673
02	1,442	201	14	1,241	86	94	12	705	88	799	107	17	536	83	643
03	1,432	202	14	1,230	86	93	12	691	88	784	109	17	540	83	649
04	1,433	202	14	1,231	86	93	12	784	89	877	110	17	539	83	649
05	1,376	175	13	1,201	87	94	12	692	88	786	81	14	509	86	590
06	1,397	197	14	1,200	86	105	13	674	84	798	92	15	526	85	618
07	1,459	210	14	1,249	86	117	14	724	86	841	93	15	525	85	618
08	1,504	219	15	1,285	85	119	14	742	86	861	100	16	543	84	643
09	1,598	254	16	1,344	84	119	13	766	87	885	135	19	578	81	713
10	1,778	278	16	1,500	84	142	14	907	86	1,049	136	19	593	81	729
11	3,817	777	20	3,040	80	639	21	2,539	82	3,088	138	19	591	81	729
12	1,813	293	16	1,520	84	150	14	912	86	1,062	143	19	608	81	751

and in research (Campo and Gijsbrechts 2005). For this research, we tracked the proportion of core SKUs that sold one or more units over a one-month period. This gives the manufacturer a categorical overview of the retailer's in-store execution and OSA. If the core SKU distribution is higher, the manufacturer concludes the retailer's in-store execution is effectively supporting adequate OSA. On the other hand, if the core SKU distribution is lower, the manufacturer concludes the retailer's in-store execution is deficient in achieving acceptable OSA.

This research included only those core SKUs the manufacturer and retailer agreed, prior to the start of the investigation, to have available across all test and control stores included in the sample. The list of core SKUs varied slightly from month-to-month to adjust for promotional events and seasonal influences and usually totaled between 30 and 40. All core SKUs for each month included in the analysis were market share leading products in their respective categories, promoted nationally by the manufacturer and regionally by the retailer. As previously noted, all core SKUs were products that sell consistently when physically available to shoppers. The CMRs were specifically charged to check, during their regular store visits, the availability of these core SKUs on the shelf and, when necessary, to assist store personnel in re-stocking the core SKUs.

Exploratory analysis of the monthly core SKU distribution revealed the data were strongly negatively skewed and leptokurtic. Since normalization did not improve normality of the data distribution, we used Welch's test (Welch 1938; Ruxton 2006) to compare differences in core SKU distribution between test and control stores. Table 3 shows the monthly comparison of mean percentage of core SKU distribution over the one-year analysis period. As *Large Market* stores comprise a greater proportion of the test group than the control group, we conducted a similar comparative analysis on the mean values of core SKU distribution for each store banner separately. Tables 4 and 5 contain the results of these analyses.

FINDINGS

In test stores, the consistently higher proportion of core SKUs that sold one or more units during the months covered by the investigation (see Table 3) shows that fielding a team of CMRs tasked to assist store personnel did significantly increase OSA. This finding shows that focusing on in-store processes can affect OSA. Therefore, in this case, maintaining OSA does not depend on shopper/consumer demand alone, but is also influenced by store-level management policies and operational decision making.

Our OSA metric depends on POS data to indicate whether a core SKU was physically available to shoppers. This establishes the link between OSA and POS data and demonstrates that POS volume tracks OSA: in other words, if OSA increases, so does the presence of the item in POS data. Therefore, we conclude our data support our research proposition.

IMPLICATIONS OF THIS RESEARCH

There are a number of strategic decisions retailers make that could frustrate shoppers' attempts to satisfy their first choice

Table 3: Month by month comparison of core stock keeping unit (SKU) distribution

Month	Control stores mean SKU distribution % (SD)	Test stores mean SKU distribution % (SD)	Welch's test statistic	Effect size (*d*)
January	84.89 (22.07)	94.46 (2.60)	$t_{(688.29)} = 11.04$***	.57
February	88.02 (20.39)	96.19 (2.50)	$t_{(657.59)} = 10.11$***	.54
March	85.74 (18.55)	94.70 (3.41)	$t_{(683.31)} = 12.13$***	.64
April	85.76 (18.54)	94.71 (3.41)	$t_{(684.32)} = 12.14$***	.64
May	90.22 (7.76)	92.53 (3.19)	$t_{(738.98)} = 6.80$***	.37
June	85.85 (8.50)	88.97 (3.25)	$t_{(788.63)} = 8.77$***	.47
July	85.81 (6.18)	88.47 (2.45)	$t_{(759.71)} = 10.11$***	.54
August	86.18 (10.30)	91.87 (3.77)	$t_{(771.59)} = 13.42$***	.70
September	89.04 (17.90)	96.59 (3.11)	$t_{(46.58)} = 11.12$***	.56
October	87.35 (19.80)	96.42 (2.75)	$t_{(747.53)} = 12.28$***	.59
November	87.93 (17.83)	95.49 (3.85)	$t_{(796.95)} = 11.42$***	.54
December	86.25 (19.10)	94.24 (3.37)	$t_{(783.10)} = 11.34$***	.54

***$p < .001$.

Table 4: Month-by-month comparison of mean percentage of core stock keeping unit (SKU) distribution for "market stores"

Month	Control stores *n*	Control stores SKU distribution % (SD)	Test stores *n*	Test stores SKU distribution % (SD)	Welch's test statistic
January	110	65.02 (32.67)	103	92.78 (3.55)	$t_{(111.75)} = 8.86$***
February	107	66.02 (33.52)	94	94.53 (3.57)	$t_{(108.73)} = 8.74$***
March	109	66.83 (29.28)	93	92.77 (4.52)	$t_{(114.01)} = 9.12$***
April	109	66.83 (29.28)	93	92.77 (4.52)	$t_{(114.01)} = 9.12$***
May	81	84.79 (9.88)	94	91.34 (3.29)	$t_{(95.23)} = 5.70$***
June	92	80.31 (11.05)	105	87.29 (3.10)	$t_{(103.54)} = 5.86$***
July	93	79.02 (11.39)	117	87.2 (2.76)	$t_{(100.61)} = 6.77$***
August	100	73.47 (17.04)	119	89.88 (4.49)	$t_{(110.58)} = 9.36$***
September	135	71.11 (28.84)	119	95.06 (3.39)	$t_{(138.19)} = 9.57$***
October	136	67.23 (30.83)	142	94.73 (3.16)	$t_{(137.73)} = 10.35$***
November	138	70.50 (27.69)	141	93.56 (3.71)	$t_{(141.81)} = 9.70$***
December	143	66.17 (29.63)	150	92.51 (4.01)	$t_{(111.11)} = 10.54$***

***$p < .001$.

demand. First, assortment decisions, most often made using category management techniques, determine the variety of products offered. So, category management decisions strategies can create the possibility that shoppers buy different items than they intended to buy when they enter a store. This could introduce variation between shoppers' first choice demand and POS data. Also, if such variation exists, it could influence the data used to make future category management decisions and reduce the degree to which the demand signal reflects shopper/consumer first choice demand.

Second, use of in-store marketing tactics, such as price promotions, may influence a shopper to select a different item than the one they came to the store intending to buy. Again, the change in purchase decision changes POS data in relation to first choice demand and reduces the degree to which POS data reflects first choice demand. Also, conventional wisdom, supported by extensive research, is that prominent product displays and other forms of trade promotions will, at least temporarily, increase sales of the items thusly promoted (Murray et al. 2010). Even such a temporary change in shopper behavior (Erdem and Sun 2002; Slotegraaf and Pauwels 2008) effectively changes POS data in relation to shoppers' first choice demand.

The use of category management strategies, price promotions, and trade promotions in general represent intentional strategic and tactical choices that marketing managers make to influence and manage the demand stream that their firms' supply chain must subsequently satisfy. However, the results of our research call attention to the fact that unintended factors, such as deficient in-store execution, may also be reducing the accuracy with which POS data represents the actual demand a supply chain should be satisfying.

Nachtmann et al. (2010) note that supply chain literature mentions demand error, that is, the discrepancy between recorded POS data and actual demand for a particular SKU, but that it is not widely researched. They developed a one-echelon retail supply model to simultaneously investigate the impact of simulated

Table 5: Month-by-month comparison of mean percentage of core stock keeping unit (SKU) distribution for "large market stores"

Month	Control stores *n*	Control stores SKU distribution % (SD)	Test stores *n*	Test stores SKU distribution % (SD)	Welch's test statistic
January	563	89.26 (15.60)	717	94.70 (2.34)	$t_{(581.82)}$ = 8.19***
February	536	92.41 (12.65)	705	96.42 (2.23)	$t_{(560.45)}$ = 7.25***
March	539	89.57 (12.43)	691	94.96 (3.15)	$t_{(592.17)}$ = 9.84***
April	540	89.58 (12.42)	691	94.97 (3.14)	$t_{(593.13)}$ = 9.85***
May	509	91.08 (7.00)	692	92.69 (3.14)	$t_{(659.33)}$ = 4.85***
June	526	87.42 (4.16)	674	89.24 (3.15)	$t_{(951.29)}$ = 8.36***
July	525	87.02 (3.55)	724	88.67 (2.33)	$t_{(843.42)}$ = 9.33***
August	543	88.49 (6.11)	742	92.19 (3.55)	$t_{(806.66)}$ = 12.64***
September	578	93.23 (10.47)	766	96.82 (2.99)	$t_{(648.53)}$ = 8.00***
October	593	91.96 (12.30)	907	96.68 (2.58)	$t_{(626.25)}$ = 9.21***
November	729	87.93 (17.74)	1,047	95.53 (3.80)	$t_{(774.78)}$ = 11.38***
December	608	90.97 (11.32)	912	94.52 (3.17)	$t_{(670.7)}$ = 7.55***

***$p < .001$.

inventory and demand errors for a single SKU. The simulation shows that demand error increases forecasting error, which leads to inaccurately set cycle and safety stocks (see also Williams and Waller 2011). Consequently, demand errors reduce the fill-rate less than inventory errors because safety stocks remain at higher levels. However, the one-echelon model does not account for any in-store process issues and their effect on recorded POS data, as we investigate in this research.

To illustrate the impact of in-store processes on demand error, Nachtmann et al. (2010) describe how the practice of a "zero-balance-walk" may well correct part of demand error. And it is known that the timing of such OSA audits and replenishment routines will affect a store's sales performance (Aastrup and Kotzab 2009). Thus, these supply chain and in-store process management procedures (not components of demand) influence the sales volumes compiled in POS data and contribute to demand error. Therefore, the widespread use of POS data as the demand signal presents academics and practitioners with a dilemma: current CPG inventory/replenishment management systems become self-fulfilling prophecies in that retailers will only sell what's available on the shelf and will only re-stock the items they sell, regardless of shoppers' first choice demand.

The timing of store replenishment and store auditing can influence OSA and POS volume. The effects on POS data, if any, of varying schedules of OSA auditing and physical replenishment of inventory (both in the stockroom and on the shelf) could not be tested. Nonetheless, the results of our research demonstrate that POS data can be influenced by the capability of in-store execution (not a direct component of shopper/consumer demand) to consistently maintain OSA. From this finding, a series of questions emerge:

- How significantly does in-store execution affect POS data?
- What other sources (either direct components of demand or not) of demand error exist?
- Is it feasible for customer-centric CPG supply chains to accurately estimate/understand first choice demand in a timely fashion?
- Can current market research techniques effectively estimate or predict first choice demand?
- To what extent can marketing and merchandising strategies and tactics fundamentally affect first choice demand?
- Does the effect of in-store execution (and other sources of demand error not investigated in this research) on POS data values vary across product categories and within categories; such as between brand and private-brand products?
- Is the influence of in-store execution on POS data consistent across different sales velocities? Since our OSA measure is based on fast-moving, consistently selling SKUs, this implies that in-store execution becomes even more important for slower-moving SKUs that sell intermittently and therefore face a greater risk of undetected low OSA.
- When using POS data as an indicator for OSA, how often should managers examine POS data to establish OSA? Our data are based on a monthly review, would a different review interval be beneficial for other product categories or different sales patterns?
- To support DSI in a customer-centric supply chain, to what extent should marketing and supply chain managers rely on POS data as the basis for replenishment decision making?
- Are there data streams, other than POS data, with less demand error, that could serve as the demand signal that drives replenishment decision making in CPG supply chains?
- Can supply chain managers detect the presence of demand error in their POS data and measure its magnitude to assess the validity of their POS data as a basis for replenishment decision making? In other words, by what magnitude does POS data differ from first choice demand?
- At what magnitude of demand error does it become advisable for supply chain managers to employ a demand signal other than POS data as the basis for replenishment decision making?
- Can retailers effectively and consistently perform in-store execution to minimize its effect on OSA? Or, should replenishment managers/planners learn to adjust supply chain operations to account for the effect of in-store execution on POS data?

Recent industry reports (Dickman et al. 2012; Cooke 2013) as well as academic research (Walsh and Bartunek 2011; Vulcano et al. 2012) suggest the development of more advanced analytic forecasting models that include some measure of first choice demand. Incorporating first choice demand into the VOC data stream requires new approaches to category management strategies that go beyond analysis of POS data. Further, the ability to introduce first choice demand factors into the VOC data stream will depend on market research activities designed to identify first choice demand by product category for each target shopper and consumer segments.

Category management strategies based on historical sales (i.e., POS data) but which exclude insights into shoppers' true wants and needs and purchase motivations under the influence of in-store marketing may well increase sales in the short run, but do not necessarily mean the retailer is optimizing its store's sales performance over the long run (Nijs et al. 2001; Slotegraaf and Pauwels 2008).

For a number of years, researchers have recognized the challenges managers face in assortment and stockout management decisions (Campo and Gijsbrechts 2005) and have been paying more attention to developing shopper-centric models that attempt to better link shopper demand with supply chain management and performance measurement (Helo and Luomala 2011). This linkage requires managers and academics to integrate shopper insights with supply chain management, effectively necessitating a DSI approach. The managerial implications of understanding and using first choice demand as the basis for replenishment requires marketing and supply chain managers to develop insights into shopper behavior (Frey et al. 2010).

Shopper marketing (Shankar et al. 2011) is aimed at using shopper insights to influence in-store purchasing decisions. The shopper is considered to be a common factor who should align all partners in the CPG retail channel (Stahlberg and Maila 2012). Shopper marketing's focus is on the "First Moment of Truth," when shoppers are in the aisle evaluating their purchase options (Inman et al. 2009), inherently requires high levels of OSA to capture value as revenue. Consequently, managers should consider the data used as the demand signal from a shopper marketing perspective. In other words, understanding the implications of first choice demand for replenishment decision making in a customer-centric CPG supply chain poses a concurrent shopper marketing as well as a supply chain management challenge.

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