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Top-Down Versus Bottom-Up Demand Forecasts: The Value of Shared Point-of-Sale Data in the Retail Supply Chain

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Accurate demand forecasts are critical to maintaining customer service levels and minimizing total costs, yet increasingly difficult to achieve. Using weekly point-of-sale (POS) and order data for 10 ready-to-eat cereal stock-keeping units from 18 regional U.S. grocery distribution centers, this research empirically investigates two demand forecasting issues: (1) the accuracy of top-down versus bottom-up demand forecasts; and (2) whether shared POS data improve demand forecast accuracy. The results reveal a previously unexplored relationship between demand forecast methodology and the use of shared POS data. We find that the superiority of the top-down or bottom-up forecasting as the more accurate demand forecast method depends on whether shared POS data are used.

Keywords: bottom-up; demand; forecasting; point-of-sale; top-down

INTRODUCTION

Competitive retail environments exert tremendous pressure on suppliers to meet high customer service levels while minimizing costs; that is, suppliers must carefully balance their demand and supply processes. Effective demand planning facilitates this balance (Moon et al. 2000). However, even as retail environments have evolved in recent years and made demand forecasting an ever more critical element of effective demand management, forecast accuracy has declined over the past decade; this decline is attributed, in part, to the increased lack of familiarity with forecasting techniques and increased complexity due to product proliferation (McCarthy et al. 2006).

Recent literature suggests that suppliers use shared point-of-sale (POS) data to reduce demand forecast error and subsequently improve demand management processes (Kiely 1999; Lapide 1999, 2005; Romanow et al. 2004). Other literature suggests demand forecast accuracy may be improved through the use of either a top-down or bottom-up forecasting approach (Dunn et al. 1971; Dangerfield and Morris 1988, 1992; Gordon et al. 1997). In this study, we jointly analyze both issues within the context of a retail supply chain and suggest that the choice of method—whether to use top-down or bottom-up forecasting—depends on the availability of shared POS data.

Discussions of information sharing have proliferated in recent literature (Closs et al. 1998; Stank et al. 1999; Hoyt and Huq 2000; Sanders and Premus 2002, 2005; Xu and Dong 2004; Kaipia and Hartiala 2006). Thus, the conventional wisdom holds that suppliers can "take advantage of retailers' market-specific private information so as to improve forecasting performance and the efficiency of supply chain planning" (Xu and Dong 2004, 123), which should mitigate the impact of the bullwhip effect on forecast accuracy. In a recent study, Williams and Waller (2010) empirically investigated the benefit of POS for retail order forecast accuracy and find that in most cases, order forecasts based on POS data exhibit lower forecast errors than those based on order data.

Yet, even as the discussion of shared POS data has increased, the implementation of information sharing programs has not expanded at a similar rate. This phenomenon may be a result of two factors. First, though some high-profile retailers, such as Walmart, readily share POS data with suppliers, many retailers still do not provide this information or offer it to only a select group of suppliers. Second, little empirical evidence supports the decline in demand forecast error due to the incorporation of POS data into the demand forecasting process. Thus, though perhaps with reservations, many suppliers continue to rely on order data to forecast demand, even as they acknowledge that order data may provide less accurate forecasts because of their additional variability (i.e., the bullwhip effect).

Suppliers also must forecast demand at various organizational levels and may take different approaches depending on those levels. Using demand forecasts, suppliers make both supply-side and demand-side decisions. For example, suppliers use demand forecasts to position inventory across the distribution network, plan and procure transportation capacity, and adjust production schedules. In the longer term, suppliers determine projected inventory requirements, create production schedules, determine capacity requirements, and procure raw materials. On the demand side, demand forecasts also enable suppliers to develop sales and marketing plans to maintain and grow their retail sales.

Consider a ready-to-eat (RTE) breakfast cereal manufacturer that produces and sells a particular stock-keeping unit (SKU) to a large retailer and distributes this SKU from its manufacturing facility through its p distribution centers (DCs) to the retailer's network of k DCs, which services the retailer's n retail stores (Figure 1).

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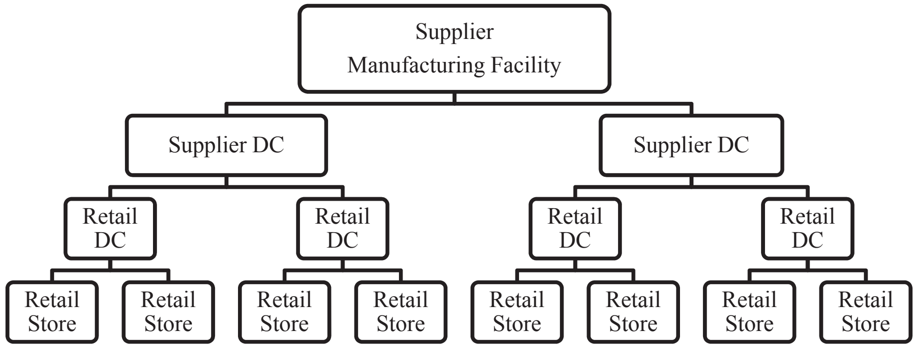
Figure 1: Supplier–retailer distribution network.



Note: DC, distribution center.

For purposes such as transportation planning, the supplier may forecast demand for each of its ship-to locations (i.e., each retailer-owned DC), which we refer to as "ship-to demand forecasts." By contrast, forecasts designed for broader decisions tend to be developed at a higher level of aggregation (Mentzer and Schroeter 1994). Because a few large retailers may account for a large portion of total retail market share and require different management techniques, suppliers probably create "account-level demand forecasts," which may improve longer-term, supply-side decision making and enhance marketing and sales planning for individual accounts (Lapide 2005). At the account level, a demand forecast represents the total expected demand across all the specific retail customer's ship-to locations.

Because suppliers must effectively position inventory throughout their distribution network and make customer-specific marketing and sales plans, suppliers probably forecast at both ship-to and account levels, and they may take multiple approaches for doing so. The supplier could take a more or less aggregate approach to creating demand forecasts, adopting "top-down" or "bottom-up" approaches to its ship-to and account-level demand forecasting, respectively. With a top-down approach, the supplier creates a single forecast for the customer's total demand (e.g., all DCs) and disaggregates that forecast into individual forecasts for each ship-to location. By contrast, the bottom-up approach dictates that the supplier creates demand forecasts for each ship-to location and then sums those forecasts to form an account-level forecast (Lapide 1998).

Top-down and bottom-up approaches have distinct benefits. Top-down forecasts should offer greater accuracy for account-level forecasts (Kahn 1998), such that if a company uses these demand forecasts for purposes such as account planning, the top-down approach may be preferable (Kahn 1997). Conversely, if demand forecasts serve to determine production and distribution schedules, bottom-up forecasting may be preferable (Kahn 1997). The choice of approach therefore should depend on the forecast objective, though most suppliers must accomplish both types of objectives. Thus, the supplier must determine whether to take a top-down or bottom-up approach to its demand forecasting and does so without much empirical evidence from existing literature to support its decision.

Suppliers need to reach another conclusion, namely, how incorporating shared POS data into their demand forecasting process might affect their top-down versus bottom-up decision. For example, the top-down approach can overcome some variability in DC order data because it aggregates those data and thus may improve account-level forecast accuracy. Yet, the trade-off is potentially lower ship-to demand forecast accuracy. Prior literature suggests that shared POS data can reduce the variability introduced into the demand forecast process, which would create advantages similar to those from the top-down approach. In this situation, any normative statement about top-down versus bottom-up forecasts must be contingent on whether the supplier integrates shared POS data into its demand forecasting process.

We begin this study by empirically testing previous claims about top-down versus bottom-up forecasting, at both the ship-to and account levels, in a fast-moving consumer goods (FMCG) context. We then investigate whether a given supplier's demand forecast, when based on shared POS data, might be more accurate than those forecasts based on order data, as well as the potential impact of using shared POS data on a supplier's forecast policy decision (i.e., top-down or bottom-up). Our empirical analysis, based on data from the RTE cereal category, offers some conclusions regarding demand forecasts in FMCG categories; we discuss how these results may generalize to other categories as well.

LITERATURE REVIEW

Extant literature recognizes the critical nature of demand forecasting for all aspects of firm success, as well as the importance of the proper management of the forecast process (Mentzer et al. 1999). In the past two decades, the tools available for demand forecasting have improved substantially, though improvements in demand forecast accuracy have not followed suit (McCarthy et al. 2006). McCarthy et al. (2006) find that, compared with previous levels (Mentzer and Cox 1984; Sanders and Manrodt 1994; Mentzer and Kahn 1995), recent demand forecast accuracy has actually declined. They speculate that the decline may be due to a lack of focus on demand forecasting management. Mentzer and Bienstock (1998) provide a four-dimensional model of the demand forecasting process: management, systems, techniques, and performance measurement. McCarthy and Golicic (2002) note that a firm must emphasize each dimension to engage successfully in collaborative forecasting through collaborative planning, forecasting, and replenishment (CPFR).

In addition, prior literature acknowledges information sharing among supply chain partners and information sharing technology as means to integrate supply and demand processes (Closs et al. 1998; Stank et al. 1999; Hoyt and Huq 2000; Sanders and Premus 2002, 2005; Angulo et al. 2004; Xu and Dong 2004; Kaipia and Hartiala 2006). Shared POS data can facilitate the effective integration of supply and demand by improving demand forecast accuracy. Williams and Waller (2010) empirically investigated the effect of shared POS data on a supplier order forecasting process, which requires the supplier to forecast the orders of its customers. Yet, no research empirically investigates the influence of shared POS data on the demand forecast process, which may increase forecast accuracy by mitigating the bullwhip effect (Bourland et al. 1996; Lee et al. 1997, 2000; Gavirneni et al. 1999; Cachon and Fisher 2000).

A particular aspect of the demand forecasting process that has not been explored thoroughly, despite widespread practitioner debate (Gordon et al. 1997), is the relative effectiveness of top-down versus bottom-up demand forecasting. A few empirical studies address the topic (Dunn et al. 1971; Dangerfield and Morris 1988, 1992), yet none is recent enough to consider top-down and bottom-up demand forecasting in conjunction with the benefits of shared POS data. We proceed by formulating both top-down and bottom-up demand forecasting approaches and hypothesizing the relevant effects on the ship-to and account-level demand forecast error.

HYPOTHESIS DEVELOPMENT

As mentioned previously, suppliers forecast demand for each ship-to location and may adopt either a bottom-up or top-down approach. When adopting a bottom-up approach, they forecast demand for each ship-to location as an individual time series, generally based on the DC's order data instead of POS data, because few suppliers receive POS data from their retail partners (Lapide 2005). Therefore, at n-steps ahead, the bottom-up, ship-to forecasts $\hat{B}_{i,t+n}$ can be formulated as:

$$\hat{B}_{i,t+n} = f(o_{i,t}, o_{i,t-1}, \ldots, o_{i,t-m}),$$

where $o_{i,t}$ denotes the order placed by DC_i in period t, and f probably refers to a commonly used time-series forecast methodology (e.g., moving average, weighted moving average, smoothing technique).

By contrast, suppliers may adopt a top-down approach, in which they develop a single, aggregate demand forecast, then decompose it into i ship-to forecasts. Thus, at n-steps ahead, the top-down forecast $(\hat{T}_{t+n})$ can be formulated as:

$$\hat{T}_{t+n} = f(O_t, O_{t-1}, \ldots, O_{t-m}),$$

where O_t denotes the retailer's orders (i.e., cumulative across all retail DCs) in period t. The aggregate forecast gets disaggregated into demand forecasts for each ship-to location through a decomposition that entails some allocation method. Therefore, the n-steps ahead top-down forecasts $(\widehat{\mathrm{TD}}_{i,t+n})$ must be generated for each DC, formulated as $\widehat{\mathrm{TD}}_{i,t+n} = g(\hat{T}_{t+n})$, where g denotes the chosen allocation method. The allocation methods vary; the supplier might use equal shares across all components or component shares based on either historical demand or forecasted demand from each component, for example (Lapide 1998).

Although the top-down approach may be easier to manage and less computationally intensive, it potentially introduces error, because the supplier must choose some allocation technique to disaggregate the single demand forecast into multiple ship-to demand forecasts (Gordon et al. 1997), which induces method-related error. Therefore, we expect that the bottom-up approach to ship-to demand forecasting is preferable to the top-down approach and results in significantly lower ship-to demand forecast error.

H_1: Bottom-up demand forecasts, based on order data, have significantly lower ship-to forecast error than do top-down demand forecasts, based on order data.

However, the bottom-up approach is susceptible to the bullwhip effect (Kaipia and Hartiala 2006; Waller et al. 2006, 2008), because of the limited information available to most demand planning organizations (Sari 2007; Vigtil 2007; Yao and Dresner 2008). Few retailers share demand information with their supply chain partners, which means most demand planning organizations must rely on customer order data (a supplier's most immediate demand signal) to create both order and demand forecasts. Order data may contain relevant information for predicting future customer orders, but they probably do not result in the most effective demand forecasts, which would reflect future consumer demand, not customer orders. Therefore, the additional variance (i.e., bullwhip effect) in order data induces randomness and probably increases demand forecast error. In turn, suppliers may use shared retail demand information (i.e., POS data) to mitigate the impact of the bullwhip effect. The sum of demand from the stores served by the DC (the ship-to level) likely has less variance than the orders from the DC, as a result of the bullwhip effect.

H_2: Bottom-up demand forecasts, based on POS data, have significantly lower ship-to forecast errors than do bottom-up demand forecasts, based on order data.

Suppliers also must use demand forecasts to make decisions about, for example, sales and marketing plans. To do so, many suppliers rely on account-level demand forecasts rather than ship-to demand forecasts. Account-level demand forecasts probably exist for each SKU and each key customer (Lapide 2005); they can be particularly effective for creating demand plans for key customers and assessing the effectiveness of marketing activities with greater accuracy (Lapide 2005).

As with ship-to forecasting, suppliers may take one of two approaches to create account-level demand forecasts: top-down or bottom-up. The top-down demand forecast ($\hat{T}_{t+n}$) is an n-steps ahead forecast based on data aggregated to the account level. By contrast, the bottom-up approach creates an account-level forecast by adding all the ship-to forecasts. That is, the n-steps ahead ship-to forecasts ($\hat{B}_{i,t+n}$) for each DC are summed to the account-level to reach a bottom-up, account-level demand forecast ($\widehat{\mathrm{BU}}_{t+n}$), which we formulate as:

$$\widehat{\mathrm{BU}}_{t+n} = \sum_{i=1}^{k} \hat{B}_{t+n}.$$

In this context, risk pooling has the potential to make the top-down approach preferable to the bottom-up approach for account-level forecasting. Risk pooling underlies several major economic activities (Gerchak and He 2003) and has long been a part of logistics and supply chain management literature, because it underlies the portfolio effect (Zinn et al. 1989; Ronen 1990; Mahmoud 1992; Evers and Beier 1993, 1998; Tallon 1993; Evers 1995, 1996, 1997; Das and Tyagi 1999; Ballou 2005). The portfolio effect occurs when the consolidation of inventory holding locations reduces the aggregate safety stock required. Similarly, risk pooling underlies the aggregate approach to demand forecasting, in that the variance of aggregate demand is less than the sum of the variances of the individual entities, because individual random errors have a canceling effect when aggregated. Therefore, we expect that the top-down forecasting approach will be superior to the bottom-up approach for account-level forecasting, as we formalize in $\mathbf{H_3}$:

$\mathbf{H_3}$: Top-down demand forecasts, based on order data, have significantly lower account-level forecast error than do bottom-up demand forecasts, based on order data.

Because many suppliers continue to lack access to POS data, account-level demand forecasts likely are based on customers' order data. Although aggregating the data through the top-down approach may counteract some of the variance in the order data, the integration of POS data into account-level demand forecasting could further reduce the forecast error, due to the lower variances associated with POS data. Therefore, we hypothesize that top-down, account-level demand forecast error may be significantly reduced through the integration of POS data.

$\mathbf{H_4}$: Top-down demand forecasts, based on POS data, have significantly lower account-level error than do top-down demand forecasts, based on order data.

HYPOTHESIS TESTING AND RESULTS

To test our hypotheses, we create a ship-to and account-level demand forecast competition (DF-Competition). The ship-to DF-Competition compares bottom-up versus top-down weekly out-of-sample ship-to demand forecasts; the account-level DF-Competition compares the top-down versus bottom-up weekly out-of-sample account-level demand forecasts. To conduct the DF-Competitions, we obtain case-level data from a large consumer packaged goods supplier that competes in the RTE cereal category. As a \$6 billion category, RTE cereal is mature and represents one of the highest volume grocery categories in a typical supermarket. The sample includes weekly POS and order data for 10 RTE cereal SKUs at a large retail partner's 18 U.S. regional grocery DCs, which constitute a total of 180 distinct time series. The weekly data were collected over a period of two years (February 2004–February 2006).

Because the retailer's sales generally grew during the sample period, we find positive trends in the RTE cereal POS. Thus, the DF-Competitions utilize a well-known time-series methodology, Holt's exponential smoothing,[1] to forecast demand at the ship-to and account levels (Chopra and Meindl 2004). Holt's exponential smoothing is a trend-adjusted version of the exponential smoothing methodology. Exponential smoothing methodologies are among the most popular quantitative forecast methodologies for both ship-to and account-level forecasts (McCarthy et al. 2006). Weekly demand forecasts were created for a 13-week (one-quarter) out-of-sample period. To evaluate the out-of-sample forecast performance, we use mean absolute percentage error (MAPE) and mean square error (MSE). The most frequently used forecast error metric (Mentzer and Kahn 1995; McCarthy et al. 2006), MAPE, enables an easy comparison of SKU forecast error across multiple dimensions, such as sales volume, or across different locations (e.g., retail stores, DCs). Because MSE averages the squared values of the forecast errors, it penalizes large forecast errors and thus can complement MAPE. In Tables 1 and 2, we present the results from the ship-to and account-level DF-Competitions, respectively.

The ship-to results in Table 1 indicate a surprising result: At the ship-to level, top-down forecasts have significantly ($p < .05$) lower MAPE (t-stat $= -40.435$, $p = .000$) and MSE (t-stat $= -17.281$, $p = .000$) than do the bottom-up forecasts using order data.[2] That is, for order data, we must reject $\mathbf{H_1}$. However, if the supplier receives POS data from the retailer, it may benefit from avoiding a top-down approach; the bottom-up ship-to forecasts based on POS data have a significantly ($p < .05$) lower MAPE (t-stat $= 31.306$, $p = .000$) than do the top-down forecasts.

[1]We choose three values for each smoothing parameter ($\alpha = 0.02, 0.19, 0.51$; $\beta = 0.005, 0.053, 0.176$) on the basis of the range of reasonable values (Silver et al. 1998). As with the single exponential smoothing method, we must initialize the level component; we set this initialized value to equal the value of actual demand for the first period. The initialized value of the trend component also is required; we set this initialized value to 0 (Hanke and Wichern 2005).

[2]Because we expect large positive correlations between the samples, we test all hypotheses using a paired t-test (Montgomery and Runger 2003).

Table 1: Ship-to forecast comparisons

	MAPE		MSE	
Input	**Bottom-up**	**Top-down**	**Bottom-up**	**Top-down**
Orders	27.72%	20.41%	6,305.50	4,274.59
POS	16.20%	18.71%	3,616.35	3,449.10

Note: MAPE, mean absolute percentage error; MSE, mean square error; POS, point-of-sale.

Table 2: Account-level forecast comparisons

	MAPE		MSE	
Input	**Bottom-up**	**Top-down**	**Bottom-up**	**Top-down**
Orders	15.00%	14.51%	923,077	891,352
POS	14.05%	14.61%	900,870	933,199

Note: MAPE, mean absolute percentage error; MSE, mean square error; POS, point-of-sale.

The surprising finding with regard to ship-to demand forecasts based on order data may indicate the importance of the smoothing effect of the top-down approach when the supplier uses order data to forecast ship-to demand. However, the ship-to forecast MSE based on POS data is higher than that based on order data (t-stat = −3.333, p = .001).

Also from Table 1, we note that the MAPE and MSE decrease for both approaches when shared POS data provide the forecast input, instead of order data. The MAPE for the top-down approach based on order data is significantly (p < .05) higher than that for either the top-down approach based on POS (t-stat = 15.951, p = .000) or the bottom-up approach based on POS (t-stat = 37.745, p = .000). In support of our prediction in $\mathbf{H_2}$, using POS for ship-to forecasts, reduces forecast error. Whether a supplier is using a top-down or bottom-up approach, it can benefit from basing its ship-to demand forecasts on POS data rather than on order data.

In Table 2, we consider the forecast error comparisons of the top-down and bottom-up approaches for account-level forecasting. The top-down approach has a significantly (p < .05) lower MAPE (t-stat = −4.059, p = .000) and MSE (t-stat = −2.261, p = .024) than does the bottom-up approach when order data provide the demand forecasting input. This finding probably reflects the risk pooling effect that is inherent in the top-down approach, in support of our prediction in $\mathbf{H_3}$. In addition, the top-down approach based on both order and POS data reveals no statistically significant (p < .05) difference in MAPE (t-stat = −0.392, p = .695) or MSE (t-stat = −1.073, p = .283), which leads us to reject $\mathbf{H_4}$. However, the bottom-up approach is best if POS data are available (t-stat = 3.735, p = .000).

These findings, taken together, suggest that if POS data are not available, suppliers should use a top-down approach for ship-to demand forecasts, as well as for account-level demand forecasting. If the POS data are available though, the supplier should adopt a bottom-up approach for ship-to and account-level demand forecasting.

EXPLORATORY ANALYSIS

The results of the hypothesis testing suggest several interesting findings with regard to potential moderating relationships, involving the bullwhip effect and the use of POS data, of the demand forecast error of top-down and bottom-up demand forecasts. Therefore, we develop and estimate three statistical models to explore these moderating relationships at the ship-to and account levels. To test for these moderating relationships, we use hierarchical ordinary least squares (OLS) regression, which enables us to assess the effects of the moderating relationships, beyond the combined effects of the control variables and direct effects. For each model, the dependent variable is the demand forecast MAPE, and variables representing each DC, SKU, forecast horizon, and the Holt smoothing parameters serve as the control variables in the first stage. The three models also feature three independent variables.

First, $\text{bullwhip}_{j,k}$ is a continuous variable that represents the degree of variance amplification of SKU_j at DC_k, calculated as the ratio of the coefficient of variation of orders (standard deviation divided by the mean) to the coefficient of variation of POS (Fransoo and Wouters 2000). Second, $\text{TDBU}_{j,k}$ is a binary variable that denotes whether the demand forecast for SKU_j at DC_k is a top-down (1) or a bottom-up (0) forecast. Third, $\text{POS}_{j,k}$ is another binary variable that denotes whether the demand forecast is based on POS (1) or order (0) data. Because the potential moderating relationships from the hypothesis development and testing are of interest for this exploratory analysis, we develop three statistical models to explore the moderating relationships separately. First, our findings suggest that the top-down approach is superior to the bottom-up approach when the supplier only uses order data. Second, we posit that as the bullwhip effect increases, the superiority of the top-down approach may increase when using order data. The high bullwhip situation should increase the forecast error for each ship-to demand forecast. The top-down approach would allow risk pooling to mitigate some of this variance, which may produce a more accurate forecast. Model 1 tests this potential moderating relationship. Third, our findings indicate that when suppliers use POS data to forecast demand, the superior approach (top-down or bottom-up) may change. Models 2 and 3 thus test the potential moderating relationship of the use of shared POS data on the relationship between the top-down and bottom-up approaches on demand forecast error at the ship-to and account levels, respectively. In Table 3, we present the independent variables and moderating relationship for each model. In Table 4, we present the hierarchical OLS regression results for Models 1, 2, and 3.

Notice that in Models 1 and 2, at the ship-to level, the F-values improve in Stage 2, the point at which the

Table 3: Statistical models

	Model 1	Model 2	Model 3
Level	Ship-to	Ship-to	Account
Independent	Bullwhip	POS	POS
	TDBU	TDBU	TDBU
Moderating	Bullwhip × TDBU	POS × TDBU	POS × TDBU

Note: POS, point-of-sale; TDBU, top-down bottom-up.

Table 4: Ordinary least squares regression results

	Model 1	Model 2	Model 3
Control			
F-value	761.028**	1,437.336**	298.696**
R^2	0.221	0.211	0.309
Stage 2			
Bullwhip	−0.004**		
TDBU	−0.114**	−0.048**	0.000
POS		−0.074**	0.000
F-value	835.035**	1,542.586**	261.366**
R^2	0.249	0.234	0.309
Stage 3			
Bullwhip	0.021**		
TDBU	0.140**	−0.114**	0.009*
POS		−0.140**	0.006
Bullwhip × TDBU	−0.035**		
POS × TDBU		0.132**	−0.018**
F-value	828.959**	1,607.177**	246.530**
R^2	0.253	0.247	0.310

Notes: TDBU, top-down bottom-up; POS, point-of-sale.
*$p < .10$, **$p < .05$.

independent variables enter the model. However, in Model 3, the control variables unequivocally explain the preponderance of the variance. That is, for account-level forecasts, forecast error results more from SKU-specific factors, the forecast horizon, and the choice of the smoothing coefficients than from whether the forecast is based on POS or order data. Suppliers generally cannot control SKU-specific factors or the forecast horizon, but the choice of forecast methodology and smoothing coefficients may fall more under their control. When it comes to account-level forecasts, suppliers should devote more effort to improving their forecast methods than to securing and using POS data. This finding provides further support for our conjecture, which we base on the hypothesis testing results, that the portfolio effect smoothes out variability and uncertainty to the point that POS data are significantly better than order data at the account level, and the negative impact of bullwhip can be counteracted through data aggregation.

In Table 4, we also consider each potential moderating relationship. They are all statistically significant, but the *F*-value only improves from Stage 2 to Stage 3 in Model 2. We graphically depict the moderating effect of POS on the relationship between ship-to MAPE and the top-down versus bottom-up decision in Figure 2. The exploratory analysis provides strong confirmation that ship-to forecast error can be significantly affected by the joint consideration of the forecasting approach and the availability and use of shared POS data.

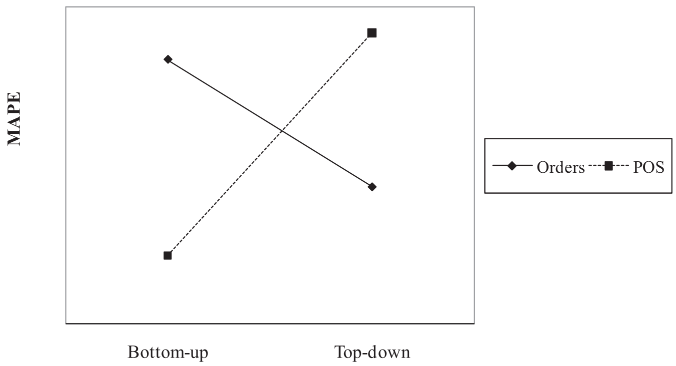
DISCUSSION AND MANAGERIAL IMPLICATIONS

Shared POS data between a retailer and supplier represent a form of supply chain integration, one of the cornerstones of supply chain management (Christopher 1997; Lambert et al. 1998; Frohlich and Westbrook 2001; Mentzer et al. 2001; Pagell 2004; Zailani and Rajagopal 2005). Fabbe-Costes and Jahre (2008) refer to this form as an *integration of flows* within the *limited dyadic upstream* scope, with a focus on the integration between a focal company and its suppliers. That is, sharing POS data offers a type of supply chain integration with limited scope. In their comprehensive review of logistics journals, Fabbe-Costes and Jahre (2008) find only one article focused exclusively on this limited dyadic upstream scope (Trent and Monczka 2003). Researchers also question the benefit of supply chain integration and recommend more research pertaining to the link between supply chain integration and performance (Christopher and Jüttner 2000; Bask and Juga 2001; Stank et al. 2001; Wisner 2003; Håkansson and Persson 2004; Rodrigues et al. 2004; Bagchi and Skjoett-Larsen 2005; Jahre and Fabbe-Costes 2005; Gripsrud et al. 2006; Fabbe-Costes and Jahre 2008). According to empirical evidence, supply chain integration affects financial performance by improving operational performance (Germain and Iyer 2006); we consider how one type of integration, namely, demand information sharing, may affect operational performance. Vickery et al. (2003) demonstrate that no statistically significant relationship exists between supply chain integration and financial performance and that the effect of supply chain integration on financial performance occurs through customer service. Demand forecast accuracy drives customer service performance.

In conjunction with research by Williams and Waller (2010), we show that if a supplier forecasts retailer orders or actual demand at the ship-to level, the use of POS data can reduce forecast error. However, the same effect may not hold if the supplier forecasts at the account level, in which case forecasts based on order data appear to be as accurate as those based on POS data. If demand forecasts pertain to broader decisions, such as production or capacity planning, our results call into question the overall value of POS data. Alternatively, for shorter-term decisions, such as inventory or transportation planning, POS data increase forecast accuracy and improve performance.

If a retailer has few DCs, sharing POS data may be more beneficial, because it cannot benefit from the risk pooling that occurs for a large number of DCs. At the extreme, if a retailer has only one DC, according to our analysis, the top-down and bottom-up approaches are the same, by definition. This point is not to suggest that risk pooling does not occur

Figure 2: Moderating effect of point-of-sale (POS) and top-down bottom-up on ship-to mean absolute percentage error (MAPE).



at the DC level; in comparing the sum of the variances of stores to the variance of demand at the DC echelon, as long as the correlation is less than unity, the sum of the variances will be higher, which implies risk pooling. However, we focus on the comparison of the DC echelon to the account echelon, in which context, we speculate that a supplier that uses a top-down approach based on order data can achieve more accurate demand forecasts for its large retailers than for its small ones, due to risk pooling. The paradox therefore becomes that it is more beneficial for a small retailer to share POS data than it is for a large retailer, but it remains more likely that large retailers share their POS data, because doing so requires a significant information technology investment.

In another paradox, a supplier is more likely to use POS data for demand planning for a large retailer than for a smaller one, because of the additional resources required. Yet, for regional and promotions planning, POS data are more valuable and require bottom-up forecasts. Promotions work only if the product is available to the consumer. In that regard, there are substantial benefits of using POS data in supplier demand planning processes. For smaller retailers that make the investment to provide POS data to their suppliers, this effect could be quite detrimental. Therefore, a possible solution for these retailers might be to provide not only POS data but also the forecast.

Finally, supply chain management research addresses both interfirm integration and cross-functional integration (Bagchi and Skjoett-Larsen 2003, 2005; van Hoek and Mitchell 2006; Chen et al. 2007). Significant research investigates the causes of a lack of cross-functional integration (Ellinger et al. 2006; van Hoek and Mitchell 2006), and within CPFR literature (Ackerman 2000; Ireland and Bruce 2000; Barratt and Oliveira 2001), calls for decisions based on a single forecast are frequent. The implication of these demands suggests that by using a single demand forecast, we can improve integration. Our findings support this normative recommendation. For example, if a firm has no access to POS data and needs an account-level demand forecast for longer-term planning purposes, as well as ship-to forecasts for shorter-term planning purposes, that supplier should use a top-down approach to create both types of demand forecasts. By contrast, if the supplier has access to POS data, a bottom-up demand forecast approach is more appropriate. Our research thus not only supports the call for a single demand forecast, but it also clarifies certain points in the supply chain at which a single approach is appropriate and reveals that this approach should depend on the availability of shared POS data. We summarize these results in Table 5.

Table 5: Summary of findings

	Is POS available?	
Forecast level	**Yes**	**No**
Account	Bottom-up	Top-down
Ship-to	Bottom-up	Top-down

Note: POS, point-of-sale.

LIMITATIONS AND FURTHER RESEARCH

Although the findings of our research study are robust, are based on recent data supplied by a large CPG manufacturer, and provide substantial insights into the use of shared POS data in both top-down and bottom-up demand forecast approaches, we note that some limiting factors exist. In particular, we conducted our DF-Competitions solely in the RTE cereal category at a single, large retailer. Further research should address our research questions in additional categories, especially those that sell at slower rates than does the RTE cereal category and with retailers that employ various formats (e.g., mass merchandizer, supermarket, warehouse club) and pricing strategies (e.g., everyday low price vs. Hi-Lo) (Waller et al. 2010).

Additional research also could examine demand forecast methods that use POS and order data simultaneously to improve demand forecast accuracy. Such methods may be particularly important in categories and for retailers for which practices such as forward buying are in wide use, because they could further improve performance through improved customer service and reductions of excess inventory.

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