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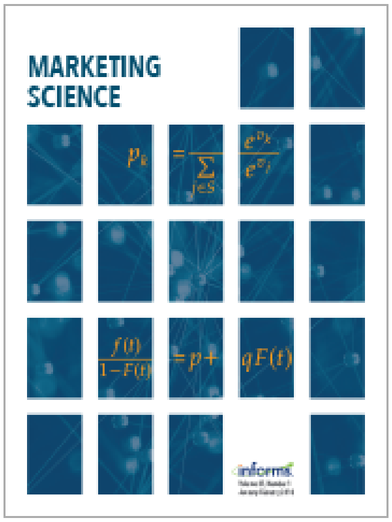

Marketing Science

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Practice Prize Article—CHAN4CAST: A Multichannel, Multiregion Sales Forecasting Model and Decision Support System for Consumer Packaged Goods

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To cite this article:
Suresh Divakar, Brian T. Ratchford, Venkatesh Shankar, (2005) Practice Prize Article—CHAN4CAST: A Multichannel, Multiregion Sales Forecasting Model and Decision Support System for Consumer Packaged Goods. Marketing Science 24(3):334-350.
https://doi.org/10.1287/mksc.1050.0135

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MARKETING SCIENCE
Vol. 24, No. 3, Summer 2005, pp. 334–350
ISSN 0732-2399 | EISSN 1526-548X | 05 | 2403 | 0334

DOI 10.1287/mksc.1050.0135
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Practice Prize Article

CHAN4CAST: A Multichannel, Multiregion Sales Forecasting Model and Decision Support System for Consumer Packaged Goods

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We discuss the development and implementation of *CHAN4CAST*, a sales forecasting model, by pack size, category, channel, region, customer account and a Web-based decision support system (DSS) for consumer packaged goods. In addition to capturing the effects of such variables as past sales, trend, own and competitor prices and promotional variables, and seasonality, the model accounts for the effects of temperature, significant holidays, new product introductions, trading day corrections, and adjustments to the wholesale level. In general, the model forecasts sales volume satisfactorily for a leading consumer packaged goods company. The DSS enables top- and mid-level executives in sales, marketing, strategic planning, and finance to develop accurate forecasts of sales volume, plan prices, and promotional activities over a long time horizon; to track sales response to marketing actions over time; and to simulate forecast scenarios based on possible marketing decisions and other variables. *CHAN4CAST* is being rolled out for more users and more divisions in the company. The key take-aways are that successful development and implementation of a rigorous marketing science model require a strong internal champion, a careful balance between modeling sophistication and practical relevance, good diagnostic features, regular validations, and greater attention to the development of a fast and responsive DSS.

Key words: forecasting; econometric models; channels; decision support system; marketing mix; pricing; promotions; strategic planning
History: This paper was received July 21, 2004, and was with the authors 4 months for 2 revisions; processed by Gary Lilien.

"The ability to reconcile (sales) forecasts with performance is (critical). It is very important we have a format that allows the field managers (to) access the model and change inputs as needed during the month."

Senior Marketing Executive

"Predicting the future is hard, especially for those who create it."

Anatole France

Editor Note: This article was formally reviewed by *Marketing Science*. As is the case with all *Marketing Science* articles, although *Marketing Science* is unable to guarantee the claims made in our articles, our review process employs high standards usually involving the input of multiple reviewers and multiple editors who are considered experts in their fields.

1. Introduction

Forecasting sales volume or demand is a complex and difficult process that is of paramount importance to consumer packaged goods companies like PepsiCo and Kraft Foods. Consumer packaged goods are increasingly sold through multiple channels such as grocery (e.g., Kroger), drug (e.g., CVS), mass merchandise (e.g., Wal-Mart), and convenience and gas (C&G, e.g., 7-Eleven) stores in multiple geographic regions such as the East Coast and the Midwest. Other channels, such as food service, restaurants, vending machines, and movie theaters also constitute a sizable proportion of sales. Since consumer patronage and sales of consumer packaged goods at different channels are driven by different factors (Inman et al. 2002, 2004), it is important to develop separate sales forecasts by channel. Accurate sales forecasting in each channel is also critical to managing both the business and the expectations of investors and Wall Street analysts, especially because the markets for most consumer packaged goods are mature. For example, a 0.1% deviation of actual sales from forecast sales in just one channel could result in an annual revenue difference of \$20 million for a packaged goods company.

In addition to a good sales forecasting model by channel and region, managers also need a knowledge-based information or decision support system (DSS) to help them make sound marketing decisions. When there is a gap between the actual volume and forecast volume, they need diagnostic information on the drivers of the gap. In many cases, these diagnostics are possible only if forecasts are available by product category, channel, region, and major customer chain or account within each channel, so that managers can drill down and analyze the diagnostic issues in depth.

In this paper, we discuss the development and implementation of *CHAN4CAST*, a sales forecasting model, and a DSS for carbonated and noncarbonated soft drinks (CSD and NCSD) for a leading marketer of beverages and other food products ("the company"). The model is used to develop quarterly and annual revenue and earnings forecasts for investors. Furthermore, the model and the DSS are used by the company's sales organization in developing forecasts for specific channels and regions and for planning marketing activities. The project began in 2001 at the behest of the company's senior executive responsible for forecasting, who was dissatisfied with the company's forecasts. Given the available data and a tight timeline, we developed a forecasting model using the best available econometric procedures. We validated this model against alternative models, using holdout samples. The model forecasts sales volume well. Our approach has been used to develop four major annual forecasts and has undergone several improvements. Although our forecasting procedure is established in the company, it is still undergoing refinement and modification.

We believe that this paper contributes to marketing science in three major ways. First, we offer insights into the application of marketing science models to practice. We outline the modeling approaches that appear to be the most useful in practice, those that may be hard to apply to real data, and the areas where further study might be fruitful. In particular, we not only extend the literature on forecasting and marketing mix effects for the grocery channel but also show why other channels are quantitatively as important as the grocery channel to overall forecast accuracy. Despite the fact that these other channels do not have the same quality of data as the grocery channel, we were able to develop robust models for these channels. Second, we provide insights into the trade-offs between relevance and sophistication that researchers are faced with when applying marketing science models. Third, we offer key take-aways on the development of a DSS involving a marketing science model. Our approach is generalizable because the challenges involved in forecasting soft drink sales are similar to those faced in forecasting the sales of other packaged goods.

2. Forecasting Needs and Challenges at the Company

The company is one of the largest consumer packaged goods companies in the world with 2004 revenues of about \$29 billion and over 153,000 employees. It has beverage, snacks, sports drinks, juice, and breakfast foods divisions. Its brands are available in about 200 countries. It is the largest supplier to grocery retailers in the United States. Its beverage division, for which the forecasting system was developed, is the second largest division of the company.

The key objectives of the forecasting model were to develop accurate forecasts for CSD and NCSD categories by channel, region, and major customer account (such as the top national grocery accounts, major regional grocery accounts, and the three top mass merchandiser accounts) and to get managerial diagnostics for price and promotional planning. The company needed the forecasting process to be automated, amenable to "what-if" scenarios, and built into a user-friendly DSS.

Sales forecasting at the company is challenging for several reasons. First, the previous forecasting approaches within the company did not meet senior management expectations because: (a) multiple forecasts were generated by different users such as finance, sales, brand management, and strategic planning based on different methods that lacked rigor and transparency; (b) they were often inaccurate; (c) they changed frequently without explicit rationale; and (d) there were no diagnostics and accountability for the personnel when actual sales deviated from forecast sales. A new forecasting approach also needed a

Table 1 Data Challenges by Channel

Channel	Challenges
Grocery and drug	Definition of regions are different for the company and the various grocery/drug accounts
Mass merchandiser	Wal-Mart's Retail Link data do not include any information on the competing brands or promotional activity
Convenience and gas	Only quad-weekly data available
IBS, restaurant, entertainment, other food service, club, military	Only wholesale revenue and shipment data available for one major wholesaler. Price = revenues/shipments. No competitive data. Need to scale wholesaler data to national level.

strong champion for buy-in and implementation by multiple users within the company.

Second, several data challenges had to be addressed, as summarized in Table 1. These challenges varied by channel but can be classified into four categories: (1) mismatch between company-defined vs. retailer-defined regions; (2) incomplete data for some channels (no competitive data available for Wal-Mart); (3) availability of data only at a higher level of aggregation (quad-weekly, instead of weekly, for the C&G channel); and (4) nonavailability of retail data (only wholesale shipment data available for the Independent Business Store (IBS) channel).

Third, in addition to capturing the effects of such variables as past sales, trend, own and competitor prices and promotional variables, and seasonality, the model had to account for the effects of temperature, significant holidays, and new product introductions. Moreover, we had to develop trading day corrections to convert weekly forecasts to monthly estimates. We also had to adjust forecasts developed on retail data to the wholesale level, which is the level of the company's forecasts.

Fourth, the forecasting DSS should: (1) use field sales inputs, (2) unify and integrate the various forecasting systems in the company, and (3) simulate "what-if" scenarios for decision-making. It also had to capture the forecasts sent by the field supervisors and category managers to the headquarters and allow senior managers to make decisions on marketing variables based on their understanding of the forecasting model and the forecasts.

Finally, in the development and application of a marketing science model like a forecasting model by channel and region, several trade-offs needed to be appropriately addressed. These trade-offs included one between the use of aggregate versus disaggregate data, the trade-off between model relevance and sophistication, one between model simplicity and completeness (e.g., Little 1970, 2004; van Heerde et al. 2002), and one between model development and DSS development. With regard to data aggregation, although less aggregated data would likely yield more accurate results, aggregate data are far less expensive. Regarding model sophistication, efforts to build sophisticated models have to be balanced against practical considerations such as timely completion of the forecasts and automation of the analysis. As far as model completeness goes, the complexity and comprehensiveness of a model have to be viewed against the need to communicate results and diagnostics to managers in a simple manner. Both model development and DSS development are time intensive with different emphases. While accurate forecasts or predictions of sales volume are critical for an effective forecasting model, a user-friendly and fast tool with a good drill-down of causal factors driving demand is important for the DSS.

These needs and challenges are not unique to the company but are common to most consumer packaged goods companies. Therefore, the development of a multichannel, multiregion forecasting model and DSS should be generalizable to any consumer packaged goods organization.

3. Related Literature

Related prior forecasting models have focused on either new product forecasts at the aggregate manufacturer level or promotional effects at the retailer level. Models for forecasting the sales of new consumer packaged goods such as ASSESSOR and BASES (e.g., Fader and Hardie 2001, Silk and Urban 1978), spatial new product tracking models (e.g., Bronnenberg and Mela 2004), dynamic new product models (e.g., Fader et al. 2004), and prelaunch diffusion models (e.g., Roberts et al. 2005) are available. However, the purpose of these prior models is not to forecast sales of existing products by channels.

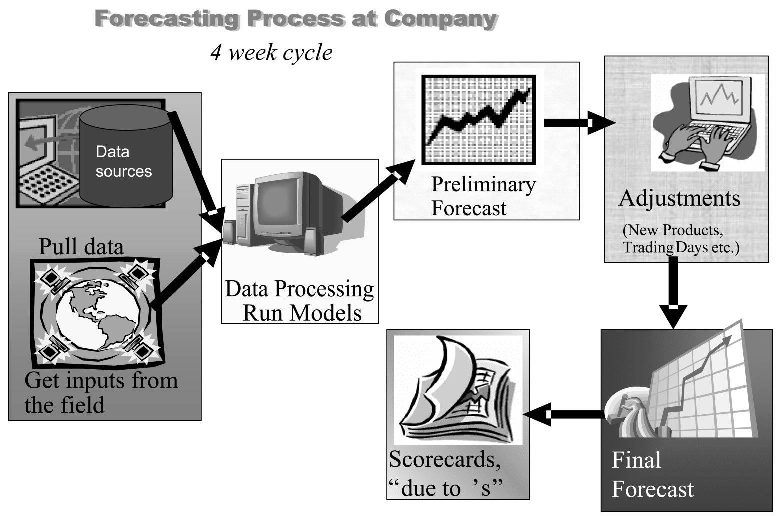
One of the most extensive literatures in marketing is devoted to measuring the effects of marketing mix variables, particularly promotions, on packaged goods. Some models capture the effects of price and promotion on brand choice using panel data (e.g., Guadagni and Little 1983). Other models estimate the effects of price and promotion using store level data (e.g., Abraham and Lodish 1987, 1993; Allenby et al. 2004; Blattberg and Levin 1987; Blattberg and Wisniewski 1989; Naik et al. 2005; Wittink et al. 1988) and highlight methodological issues related to the use of scanner data obtained from stores (e.g., Besanko et al. 1998, Christen et al. 1997).[1] There are also studies that use store-level data in drawing substantive conclusions about consumer price sensitivity and retailer pricing behavior (e.g., Bolton and Shankar 2003, Hoch et al. 1995, Shankar and Bolton 2004). These analyses of scanner data, however, are not directly designed for forecasting and generally consider only the grocery channel.

A few studies address the soft drink market. Dube (2004) analyzed choice of soft drinks using a combination of household and store level scanner data. Soft drinks were also included as one of the focal categories in Bell et al. (1999), Hoch et al. (1995), and van Heerde et al. (2003). These studies, however, focus on developing the appropriate models for capturing consumer choice and promotional effects, not on forecasting soft drink sales by channels or regions.

DSSs have been developed for different marketing applications and are useful for widespread adop-

[1] Researchers van Heerde et al. (2002) provide an interesting discussion of the development of the SCAN*PRO model for evaluating promotions.

Figure 1 The Forecasting Process at the Company



tion of marketing models in practice (e.g., Abraham and Lodish 1987, 1993; Alavi and Joachimsthaler 1992; van Bruggen et al. 1998; Wierenga and van Bruggen 1997, 2000; Wierenga et al. 1999). We extend this literature by describing the development of a Web-based forecasting DSS that enables top- and mid-level executives in sales and marketing to: (1) develop good forecasts of sales volume, (2) plan prices and promotional activities over a long time horizon, (3) track sales response to marketing actions over time, and (4) simulate new forecast scenarios based on possible marketing decisions and other variables. The distinctive features of the tool include easy data inputs; sales decomposition or drill-down graphs by channel, region, and account; "what-if" scenario graphical plots; and completely menu-driven commands.

In sum, related literature has focused on either aggregate forecasts for new products or marketing mix effects for packaged goods in the grocery channel and not on forecasting across multiple channels. In addition, the literature has focused mainly on developing methodologies and substantive results. In contrast, our focus is primarily on forecasting sales volume by channel and region by applying established methods to solve managerial problems in a leading packaged goods company. A major component of the forecasting solution is a Web-based DSS for managers to use.

4. Data and Model Development

Given our objectives, we developed forecasts of sales volume for CSD, water, and noncarbonated (NCSD) nonwater drinks at monthly intervals for a time horizon of one year for each of the following channels: grocery, drug, mass merchandise (Wal-Mart, Target, Kmart) convenience and gas, IBS, restaurants, business, industry and education, entertainment, other food service, clubs (e.g., BJ, Costco, Sam's), and the military. We chose the aggregate volume measure, cases, measured as the equivalent of 24 eight-oz. units (192 oz.) because they were most relevant to management decisions. We developed forecasts at pack-size level, not at brand level, mainly because the impetus for the modeling came from the sales organization, not the marketing organization.

In addition to the forecasts by channel, we developed separate forecasting models for each of the major grocery chains and the major mass merchandisers. These models are used in planning by the sales organization and are important inputs into the DSS. For CSD, we developed separate forecasts for several pack sizes, including 6-pack, 12-pack, 24-pack, and 2-liter sizes. Forecasts for water and NCSD other then water, which are smaller categories, are at the aggregate level.

An overview of the forecasting procedure at the company is presented in Figure 1. Data are collected from different sources, stored in a central data warehouse, and processed in a central server. Using our models, preliminary sales volume forecasts are developed for the relevant level of aggregation. Adjustments for effects such as trading days and new product introductions are made to each level of forecast, and final forecasts are produced. Several outputs are generated, including forecast scorecards and drill-down analysis of forecast volume and gaps between forecast and actual volume. We will discuss each of these steps in greater detail.

4.1. Data

Table 2 presents a summary of data for each channel, along with each channel's share of volume.[2] We used four major available data sources, *IRI Infoscan* data, the company's wholesaler shipment data, *ACNielsen's*

[2] Data in this table and subsequent tables and analyses are disguised to protect company confidentiality.

Table 2 Share of Volume by Channel

Channel	Data source	Data interval	Market level and price data	Competitive and promotion data	Share of volume* (%) CSD	NCSD
Grocery	IRI Infoscan	Weekly	Retail	Yes	35	30
Drug	IRI Infoscan	Weekly	Retail	Yes	2	2
Mass	IRI/Wal-Mart Retail Link	Weekly	Retail	Some**	13	7
Convenience and gas	Nielsen Scantrack	Quad-week	Retail	Yes***	14	23
IBS	Major wholesaler	Weekly	Wholesale	No	7	6
Restaurants	Major wholesaler	Weekly	Wholesale	No	12	15
BI&E	Major wholesaler	Weekly	Wholesale	No	6	8
Entertainment	Major wholesaler	Weekly	Wholesale	No	6	5
Other food service	Major wholesaler	Weekly	Wholesale	No	2	2
Club	Major wholesaler****	Weekly	Wholesale	No	2	1
Military	Major wholesaler	Weekly	Wholesale	No	1	1

*CSD accounts for approximately 88% of total volume.
**Available for Kmart and Target, not Wal-Mart.
***Only data on display.
****Except for Sam's Club, data for which is available from Wal-Mart Retail Link.

Scantrack data, and *Wal-Mart's Retail Link* database for generating the forecasts. *IRI Infoscan* provides scanner data obtained from stores on grocery, drug, and mass merchandisers (excluding Wal-Mart) by company-defined region and retailer marketing area (RMA). The wholesaler shipment data include data about on-premise consumption and sales to IBS and military and warehouse clubs, broken down by the wholesaler's regions. The *ACNielsen Scantrack* data cover data on C&G channel by company-defined region. From *IRI Infoscan*, we also obtained data on specific chains, including the top nine grocery chains and the top regional grocery accounts, broken down by retailer RMA.

As Table 2 indicates, among the channels, while grocery has the highest share, it accounts for only about one-third of volume, with C&G, mass merchandise, and restaurant channels accounting for a significant share of volume. Among the major product categories, while CSD accounts for 88% of volume, its revenue share is lower since CSD prices tend to be lower than NCSD prices. Moreover, the NCSD category is growing faster than the CSD category. Table 2 also indicates that promotion data cover only about half of the volume, the only half that is extensively promoted to consumers. About two-thirds of the volume is covered by retail price and sales data, and the other third by wholesale data.

4.2. Development of Baseline Sales Forecasts

We first developed a baseline forecasting model for each channel. We needed to develop a pilot version of a model for one channel to establish the accuracy of our forecasting model. We chose the grocery channel for the pilot version because data on multiple potential driver variables were available for this channel.

In principle, data from IRI for the grocery, drug, and mass channels can be analyzed at the store level using a panel of stores and then aggregated up. Such an analysis might lead to better parameter estimates and forecasts than regional-level analyses (Christen et al. 1997, Fockens et al. 1994). However, since IRI maintains control of the store-level data, analyses on IRI store level data were prohibitively expensive. Furthermore, data for channels other than grocery, drug, and mass are available only at the regional level of aggregation. For these reasons, we used regional and RMA level data. For the most part, these data have provided satisfactory results.

For channels/retailers for which we had IRI data, we considered the following IRI-measured independent variables in a category: average price per volume, % all commodity volume (ACV) on display only, % ACV on feature only, % ACV on both feature and display, and % ACV on price reduction only.[3] Because cold drinks become more attractive as the weather gets warmer, we also included average temperature in a region as an independent variable. Because there are often large increases in demand at holiday periods, it is important to account for holiday effects. We considered the following holidays: New Year's Day, Super Bowl Sunday, Valentine's Day, Easter, Memorial Day, Independence Day, Labor Day, Halloween, Thanksgiving, and Christmas. Because many of these holidays fall on a Monday and IRI weeks end on Sunday, we used a dummy variable for the week prior to the holiday, as well as for the holiday week itself. To capture troughs in sales after holidays, we also tested dummy variables for the week following each

[3] The various measures are ACV-weighted averages across stores in a particular region. While we also had data on items per store and ACV-weighted distribution, these variables had little variance, and therefore were not used. We did not use IRI base price or base volume due to concerns about the interpretation of these measures at the level of aggregation of our data.

holiday. Finally, we included seasonal effects for winter, spring, summer, fall, weekly trend, and lagged volume as predictors.[4]

For non-IRI channels other than C&G, we considered the same variables, except for the promotional and competitive measures. We computed price as weekly revenues/weekly volume. For the C&G channel, we considered own and competitive price and display measures, temperature, seasonal effects, trend, and lagged sales. Since data for the C&G channel are available only quad-weekly, we could not consider holidays for this channel.

Given time constraints and the need to explain our procedures to managers, we tried to develop models that were as simple as possible. Because we had a large number of variables to consider, and our model development time was limited, we needed an automated procedure to help us in model selection. We chose stepwise regression as a device to come up with preliminary models. These preliminary models were examined for correct signs and reasonableness and modified as needed. While the drawbacks of stepwise regression are well known (e.g., propensity to capitalize on variables that correlate highly by chance), in practice, it is unlikely that this would lead us to miss important predictor variables, given that we examined several models. In addition to variable selection, we generally compared linear functions with double log functions (having both sales and prices expressed in log form) and functions comprising differing degrees of aggregation across regions, pooled regressions, and models with coefficients varying randomly across regions. We based these comparisons on specification tests and predictive performance on holdout samples. For cases in which independent variables had to be forecasted, we also developed equations for predicting these variables as a function of exogenous variables. While space does not permit a detailed presentation of our results for each channel/category combination, we will provide two examples of our model development, one for sales of a product category in the grocery channel and another for a channel that had only wholesale data (IBS). Following that, we will provide comparisons with some benchmark models.

4.2.1. Model Development: Grocery and IBS Channels. We will present examples of models developed on the data for four company-defined regions for the grocery category and seven wholesaler regions for the IBS channel.[5] The examples presented here are based on a dataset spanning 149 weeks. We use the first 104 weeks of data as an analysis sample and the remaining 45 weeks of data as a holdout sample. Using 45 weeks of data as a holdout sample allows us to assess the accuracy of forecasts for most seasons and holidays. We employed stepwise selection as a preliminary step and further refined the preliminary models. In the final model, we retained only the statistically significant variables. Further, in general, it was not possible to include all promotion variables because of collinearity. We retained measures of feature and display, since these are the most managerially relevant.

We compared linear and log-linear versions of separate regression models by region and linear and log-linear versions of a model that allowed for random variation in parameters across regions. The random coefficient model, which was estimated using the PROC MIXED procedure in SAS, can be written as:

$$V_{it} = \mathbf{X}'(\boldsymbol{\beta} + \boldsymbol{\gamma}_i) + \varepsilon_{it}, \tag{1}$$

where V is sales volume in equivalent unit sales, $\mathbf{X}$ is a matrix of independent variables, t is time, $\boldsymbol{\beta}$ is a vector of fixed effect parameters, and $\boldsymbol{\gamma}_i$ are random effects associated with region/channel i assumed to be multivariate normally distributed with a 0 mean vector and variance-covariance matrix $\mathbf{G}$. The matrix $\mathbf{G}$ is assumed to be uncorrelated with ε_{it}, the random error associated with each observation. We also assume that $\mathbf{G}$ is independently and identically distributed across regions and time periods and also set covariances in $\mathbf{G}$ to 0. Given estimates of $\mathbf{G}$ and the other parameters of the model, estimates of the effects $\boldsymbol{\gamma}_i$ for each region can be obtained. Because preliminary tests indicated that the other variables did not have significant random effects, we estimated the random effects model for groceries with only the intercept, prices, and temperature having random variation across regions. For a similar reason, we estimated the random effects model for IBS with only the intercept, temperature, and the spring seasonal dummy varying across regions.

Results for linear and log-linear models were qualitatively very similar. Because they are probably easier to interpret (price effects measure elasticities), we present pooled regressions in logs of volume and prices in Table 3. The R^2 for each channel regression model is above 0.9. The results for neither regres-

[4] We did not include advertising in the first two forecasts. Although we are under pressure to demonstrate advertising effects, we are having difficulty getting significant effects for advertising variables in the current forecasting effort. This could be due to differences in the levels of aggregation of the sales and advertising data. Consequently, we do not include advertising in the model examples presented in this paper.

[5] For ease of exposition, we refer to the company's brand as "Pepsi" and the competing brand as "Coke." However, these are not necessarily the two brands that are actually used in the example. Although accurate in all essentials, the results for our example are disguised whenever they might reveal the category employed in the example. However, all reported elasticities and forecasting results are the actual ones.

Table 3 Example of Results from Forecasting Models: Log (Volume)-Dependent Variable

Grocery channel			IBS channel		
Variable	Parameter estimate	t value	Variable	Parameter estimate	t value
Intercept	17.6449	95.92	Intercept	14.4078	130.62
Log (Pepsi's price)	−2.3424	−23.88	Log (Pepsi's price)	−1.7509	−24.32
Log (Coke's price)	0.5835	5.88	Fall	−0.0257	−2.68
Pepsi's display	0.0028	3.15	Spring	0.0729	7.38
Pepsi's feature	0.0020	3.46	Temperature	0.0070	24.80
Coke's display	−0.0023	−2.48	Week after Easter	−0.0672	−2.36
Temperature	0.0018	6.64	Week prior July 4	0.1378	4.92
Week prior July 4	0.1105	4.08	Week prior Meml Day	0.1130	4.00
Week prior Meml Day	0.1914	7.13	Week prior Thanks	0.1286	4.55
Week prior Xmas	0.1187	4.29	Week prior Labor Day	0.1719	6.12
Week prior Thanks	0.0834	3.11	Mid-Atlantic region	0.7178	51.09
Week prior Labor Day	0.1223	4.43	Northeast region	0.2629	18.68
Easter	0.1978	7.64	Pacnorth region	0.3217	22.47
July 4	0.2564	8.97	S. California region	−0.3066	−19.90
Super Bowl	0.1127	4.34	Southeast region	0.4072	53.84
East region	−0.3023	−23.27	Great West region	0.7212	51.11
South region	−0.2613	−13.30			
West region	−0.3132	−20.98			
R-squared	0.9004			0.9270	
Sample	416			728	

sion showed evidence of serial correlation possibly because sales tend not to follow a neat pattern over time. For the grocery channel, the estimated price elasticity of −2.34 is in line with that in other studies (e.g., Dube 2004, Hoch et al. 1995). The coefficient of Coke price implies a cross-elasticity of 0.58. Because display and feature are measured in percentages, their impact is calculated by multiplying by 100 and taking the exponential of the result. For example the display effect is $\exp(0.0028 * 199) = 1.32$, e.g., display increases volume by 32%. Similarly, feature is estimated to increase volume by 22%, and Coke's display to decrease the company's sales volume by 25%, but Coke's feature was not significant. These estimates, which pertain to aggregates of brands and pack sizes, are somewhat below those reported by Dube (2004) for specific brand/pack sizes. We will subsequently discuss this difference.

For IBS, where sales and price data are at the wholesale level, we have data only on own-brand prices and none on promotions (the promotion in this channel is not extensive). The estimated price elasticity for IBS is −1.75. Both of the channels show significant effects of temperature, holidays, and region. In addition, IBS indicates a significant trough in the week after Easter and seasonal effects for fall and spring. Neither regression exhibited a significant effect of trend or lagged sales. In sum, the models in Table 3 fit the data well and generally provide reasonable coefficient estimates.

Table 4 presents a holdout sample comparison of the various models on the basis of mean percentage error (MPE) and mean absolute percentage error (MAPE). The MPE is a measure of bias (whether forecasts are persistently high or low) that is relevant to the company because persistent errors have a cumulative effect that can create problems for financial and other plans. We present these measures of predictive fit at three levels of aggregation: the week/region combination, weekly across regions, and quad-weekly, which is the most relevant measure for the company's purposes. At this level, the best model for groceries achieves a MAPE of 1.84%, while the best model for IBS is about 1% higher. From the company's standpoint, this performance is regarded as satisfactory.

While pooling tests rejected the null hypothesis of equal slopes at the 0.01 level for both functional forms for the grocery channel ($F = 3.05$ for log, $F = 7.75$ for linear, both with 42,356 d.f.), the log-pooled model gave the best results for this channel at the quad-weekly level, which may reflect efficiency gains from pooling the data. The results for the IBS channel for three versions of the log model had almost the same MAPE at the quad-week level, possibly because the hypothesis of equal slopes across regions could not be rejected at the 0.01 level for the log models ($F = 1.37$, d.f. 54,658), indicating that the three models are roughly equivalent. While the log models generally have a significantly lower MAPE at the region and time level, differences between log models and their linear counterpart are never significant at the 0.01 level. To summarize, the simple pooled models performed comparably to alternative models, and the log-linear models tended to perform slightly

Table 4 Holdout Sample Results for Alternative Functional Forms and Aggregation Levels

	Region and time		Aggregated across regions		Quad-week	
	MPE	MAPE	MPE	MAPE	MPE	MAPE
Grocery channel model						
Linear—by region	1.04	6.14	0.48	3.26	0.54	2.07
Linear—pooled	−0.88	5.95	−0.97	3.33	−0.82	2.12
Linear—random coefficient	1.02	6.15	0.44	3.21	0.56	2.03
Log—by region	0.87	5.55	0.37	3.14	0.33	2.03
Log—pooled	−0.17	4.81	−0.45	2.86	−0.45	1.84
Log—random coefficient	0.51	4.74	0.11	2.87	0.11	1.86
Number of observations	180		45		11	
IBS channel model						
Linear—by region	2.55	9.24	1.41	5.18	1.09	3.22
Linear—pooled	0.98	10.58	0.34	5.29	0.02	3.05
Linear—random coefficient	2.37	9.26	1.26	5.17	0.95	3.19
Log—by region	1.57	8.98	0.32	4.97	−0.05	2.80
Log—pooled	1.44	8.82	0.19	5.11	−0.21	2.83
Log—random coefficient	1.44	8.89	0.20	5.09	−0.19	2.86
Number of observations	315		45		11	

better than the linear models. However, the differences between forecasts are small. This finding that degree of aggregation and functional form did not affect overall results a great deal held up throughout the data analyses.

4.2.2. Prediction of Price and Promotional Variables. To use the regression models of sales volume on predictors for forecasting, estimates of future values of the price, promotion, and temperature variables are required. For temperature, we used forecasts of temperatures from Biz Weather, the supplier of our temperature data. While estimates of overall planned price increases are generally available, data on exactly how aggregate prices will vary through the year are generally unavailable at the channel level (at the retailer level these can be obtained from promotion calendars, although they have proven difficult to obtain in practice). Further, channel-level data on planned promotional activity by week are hard to obtain. Consequently, we needed a method of getting forecasts of the price and promotion variables in cases where external estimates of these variables were lacking. Given the large number of estimates required, such a method had to be easy to automate. Our solution was to develop forecasts of the promotion variables from a recursive model that includes separate equations for each promotion variable and an equation for sales. For the grocery data example, this would be the following six-equation system:

$$
\begin{aligned}
PP &= \mathbf{Z}'\boldsymbol{\beta}_1 + \varepsilon_1,\\
FP &= \mathbf{Z}'\boldsymbol{\beta}_2 + c_{12}PP + \varepsilon_2,\\
DP &= \mathbf{Z}'\boldsymbol{\beta}_3 + c_{13}PP + c_{23}FP + \varepsilon_3,\\
PC &= \mathbf{Z}'\boldsymbol{\beta}_4 + c_{14}PP + c_{24}FP + c_{34}DP + \varepsilon_4,\\
DC &= \mathbf{Z}'\boldsymbol{\beta}_5 + c_{15}PP + c_{25}FP + c_{35}DP + c_{45}PC + \varepsilon_5,\\
FC &= \mathbf{Z}'\boldsymbol{\beta}_6 + c_{16}PP + c_{26}FP + c_{36}DP\\
&\quad + c_{46}PC + c_{56}DC + \varepsilon_6,
\end{aligned}
\tag{2}
$$

where PP is Pepsi's price, FP is Pepsi's feature, DP is Pepsi's display, PC is Coke's price, DC is Coke's display, FC is Coke's feature, and $\mathbf{Z}$ is a matrix of independent variables (e.g., temperature, holiday effects). The system in Equation 2 can be estimated by OLS if the error terms in the six equations are uncorrelated (Greene 2003, p. 679).[6] Because the choice of feature and display would seem to be contingent on decisions relating to price, we estimate the price equation first. A key assumption is that price and promotions do not depend on sales, which can be justified by the fact that weekly promotional activities are planned well in advance of the realization of sales. This assumption will be addressed in the next section. After we estimated the system in Equation (2) by OLS, we used the predicted values of price and promotion in the sales forecasting equation to develop forecasts.

Estimates of the equations used in forecasting prices, feature, and display for the grocery data pooled across regions are presented in Table 5. Since the recursive model in Equation 2 requires the same $\mathbf{Z}$ matrix for all equations in the system, we retained some insignificant variables in the estimates presented in Table 5.[7] The estimates in Table 5 show that price and feature activity are largely predictable. Both competitors tend to lower prices around holidays,

[6] In model testing, this recursive procedure provided slightly better predictions than the alternative of dropping independent variables from some equations to provide identification and then employing conventional simultaneous equation techniques.

[7] We tested prices and other variables for trends but did not find any significant trends.

Table 5 Results of Regressions Used to Forecast Independent Variables for Grocery Channel

	Log (Pepsi's price)		Pepsi's feature		Pepsi's display		Log (Coke's price)		Coke's display	
Variable	Parameter estimate	*t* value	Parameter estimate	*t* value	Parameter estimate	*t* value	Parameter estimate	*t* value	Parameter estimate	*t* value
Intercept	1.3038	148.62	133.1427	12.20	91.4714	11.71	0.7194	8.94	63.6695	6.81
Temperature	0.0003	1.98	0.0052	0.22	0.0941	6.47	0.0000	−0.01	0.0003	0.02
Week prior July 4	−0.0829	−5.92	−0.9171	−0.38	−0.6505	−0.44	−0.0692	−5.23	2.0924	1.44
Week prior Meml Day	−0.0782	−5.68	0.1486	0.06	−1.4625	−1.00	−0.0767	−5.90	2.5910	1.80
Week prior Xmas	−0.0432	−3.10	−7.5087	−3.19	−0.8707	−0.60	−0.1008	−7.78	3.8893	2.64
Week prior Thanks	−0.0861	−6.23	−3.3411	−1.39	−2.6471	−1.79	−0.0659	−5.00	−0.0319	−0.02
Week prior Labor Day	−0.0995	−7.12	−2.2335	−0.90	2.3739	1.57	−0.0723	−5.36	1.3941	0.94
Easter	−0.0593	−4.31	−2.8516	−1.22	0.0147	0.01	−0.0577	−4.51	−0.7254	−0.52
July 4	−0.1308	−9.31	−1.8746	−0.73	−0.2965	−0.19	−0.0711	−5.07	0.1409	0.09
Super Bowl	−0.0616	−4.39	−3.3094	−1.38	0.6651	0.45	−0.0133	−1.02	−3.3981	−2.45
East region	−0.0400	−7.47	12.3997	13.02	−3.8495	−5.55	−0.0297	−4.63	−0.1382	−0.20
South region	−0.0194	−3.51	−25.9537	−27.81	−6.5328	−6.70	0.0580	6.34	5.5397	5.44
West region	0.0453	8.48	10.6670	11.04	−6.5114	−9.66	0.0232	3.49	−7.1750	−10.01
Log (Pepsi's price)			−53.4495	−6.44	−0.7777	−0.15	0.2875	6.07	−7.7534	−1.48
Pepsi's feature					−0.0999	−3.28	0.0021	7.46	0.0711	2.28
Pepsi's display							0.0013	2.95	0.1702	3.57
Log (Coke's price)									10.3694	1.96
R-squared	0.5716		0.8537		0.4065		0.6082		0.5808	

and there are regional differences. In addition, Coke's price tends to move with Pepsi's price. Pepsi's feature activity also tends to coincide with price cuts and to vary across regions. There are also regional differences in display activity. While a model of Pepsi's display has a lower R^2 than other models, this variable does not exhibit much variation over time in our regional data. Hence, errors in predicting display should not have a major impact on forecasts of sales volume.

In developing predicted values of price, our procedure included subtracting trend (if present) and adjusting for planned price increases in the forecast year. For this example, we incorporated a 3% price increase for Pepsi and Coke. Using this adjustment and the other equations described in Table 4 to generate predictions on the pooled regression for groceries presented in Table 3, we obtained the following: region and time, MPE = 0.45, MAPE = 8.35; weekly aggregate, MPE = 0.01, MAPE = 5.11; quad-week, MPE = −0.28, MAPE = 2.83. Thus, MAPE increases by about 3.5 points at the region/time level when independent variables have to be predicted, about 2.25 points at the aggregate weekly level, and about one point at the quad-week level.[8] The errors due to missing timing of promotions tend to cancel out when moving to the quad-week or monthly levels, leading to satisfactorily results.

4.2.3. Model Validation/Benchmarking. We present a comparison of the forecasting accuracy for the grocery channel model with three competing models: a model that treats prices as endogenous, a model that uses Bayesian updating to incorporate prior information, and a model run on national aggregate data. For the comparisons, we use the pooled log-linear model, which had the best forecasting performance.

Typically, price and promotion variables are set well in advance, but some or all of these variables could be endogenous. While preliminary analysis showed that feature and display are exogenous, an endogeneity test (Greene 2003, p. 385; Wu 1973) indicated that Pepsi's and Coke's prices are endogenous ($F = 14.58$, with 2,398 d.f., significant at 0.01). Consequently, we estimated a regression model by two-stage least squares (2SLS), using the independent variables other than prices in Table 3, and logs of prices and volume lagged by one period as instruments. Since OLS may still be more efficient although coefficient estimates may be biased, we do not necessarily expect the 2SLS model to yield better forecasts.[9] The 2SLS estimates are presented in Table 6. The results show a numerically lower own price elasticity and a higher cross-price elasticity. The holdout sample results in Table 6 also indicate a higher MAPE for the 2SLS model than for OLS (quad-week MAPE = 4.24 versus 1.84 for OLS) and a tendency for the 2SLS model to consistently overpredict.

Since we have a large number of observations per region, there is no real advantage to using hierarchical Bayesian procedures with diffuse priors to

[8] A regression model of log (IBS price) on exogenous variables had an R^2 of 0.43. Using predictions from this model, the quad-week MPE is −0.34 and the quad-week MAPE is 3.84, about one point above that reported in Table 4.

[9] For example, Besanko et al. (1998) found that a SUR model that assumes exogenous prices provided forecasts that were comparable to a 3SLS model that allowed for endogenous prices.

Table 6 Results of Benchmark Models

	2SLS			Bayesian			Aggregate		
Variable	Parameter estimate	Standard error	*t* value	Sample mean	Sample Std. Dev.	Mean/SD	Parameter estimate	Standard error	*t* value
Intercept	16.1187	0.4606	34.99	17.5109	0.1919	91.26	19.0230	0.2956	64.35
Log (Pepsi's price)	−1.6758	0.5013	−3.34	−2.2278	0.1069	−20.85	−2.7121	0.1906	−14.23
Log (Coke's price)	1.1009	0.4228	2.60	0.4557	0.1079	4.22	0.6224	0.2117	2.94
Pepsi's display	0.0022	0.0011	2.01	0.0071	0.0007	9.93	0.0056	0.0019	2.88
Pepsi's feature	0.0024	0.0015	1.57	0.0048	0.0006	8.72	0.0003	0.0014	0.23
Coke's display	−0.0024	0.0012	−2.04	−0.0067	0.0007	−9.23	−0.0010	0.0021	−0.47
Temperature	0.0016	0.0003	4.88	0.0015	0.0003	5.04	0.0017	0.0004	4.61
Week prior July 4	0.2090	0.0369	5.67	0.1115	0.0302	3.69	0.0893	0.0346	2.58
Week prior Meml Day	0.2890	0.0371	7.80	0.1939	0.0299	6.48	0.1795	0.0349	5.14
Week prior Xmas	0.2139	0.0434	4.93	0.1349	0.0305	4.42	0.0997	0.0382	2.61
Week prior Thanks	0.1861	0.0374	4.98	0.0866	0.0299	2.90	0.0610	0.0336	1.81
Week prior Labor Day	0.2363	0.0395	5.98	0.1120	0.0305	3.67	0.0781	0.0356	2.20
Easter	0.2755	0.0334	8.24	0.1897	0.0289	6.56	0.1877	0.0322	5.83
July 4	0.3924	0.0458	8.57	0.2487	0.0317	7.83	0.2220	0.0373	5.95
Super Bowl	0.1696	0.0365	4.64	0.0993	0.0290	3.42	0.0893	0.0330	2.71
East region	−0.2748	0.0169	−16.28	−0.3183	0.0136	−23.36			
South region	−0.2388	0.0477	−5.00	−0.1581	0.0191	−8.27			
West region	−0.3741	0.0227	−16.50	−0.3391	0.0150	−22.54			
R-squared		0.8584			0.8879			0.9275	
Sample size		416			416			104	
Holdout sample results									
MAPE—Week		5.05			4.98			3.06	
MAPE—Quad-week		4.24			3.23			2.02	
MPE—Week		4.36			−0.06			−0.39	
MPE—Quad-week		4.24			−0.18			−0.39	

estimate random coefficient models.[10] However, as noted by Bucklin and Gupta (1999), if prior information is incorporated correctly using Bayesian procedures, better forecasts might result. However, since the literature addresses different levels of aggregation, product, and markets, it was difficult to determine what prior information implied for our model parameters. It appears that our price elasticity estimates are reasonable (Bucklin and Gupta 1999, p. 253). However, Dube (2004) reports that feature and display increase volume about two to three times, a somewhat stronger effect than what we found, which would imply a coefficient for these parameters of approximately 0.01 (since $\exp(0.01 * 100) = 2.72$, where 100 is the maximum value of feature and display). This is about 4 to 5 times the value of our estimates in Table 3.

To see whether incorporating a prior that coefficients of feature and display equal 0.01 would lead to improved forecasts, we estimated a Bayesian counterpart to the pooled fixed model in Table 3. We assumed that priors for all effects were independently, normally distributed. Diffuse priors were assumed for all coefficients except feature and display (precision = 0.00001, which implies a standard error of 316.23). For feature and display, we assumed priors with a mean of 0.01 and standard error of 0.001.[11] The results in Table 6 show that the coefficients of feature and display are about midway between the assumed priors and the OLS estimates in Table 3. Other coefficients are very similar to Table 3, except that coefficients of price are slightly closer to zero and the coefficient for the South region also moves closer to zero. The quad-weekly MAPE for the Bayesian model is 3.23, compared to 1.84 for OLS. Thus, the OLS model produces better forecasts than a model based on our assumptions about priors. Nevertheless, the Bayesian approach might be useful for incorporating information from multiple sources into the forecasting model, especially at the retailer level. We plan to pursue this issue in the future.

The final model presented in Table 6 is a regression on data provided by IRI that is aggregated across regions and pertains to the entire United States.

[10] With diffuse priors, MCMC methods are most useful for models that are difficult to compute using conventional methods, which was not the case for the models we employed. With diffuse priors, MCMC should give essentially the same results as those from conventional methods. Using WINBUGS, we verified that this is the case for the models presented in Table 3.

[11] We used 40,000 iterations for "burn in" and based our results on the next 40,000; the MC errors were all less than 0.006 of the corresponding standard deviation. We verified that a model with diffuse priors replicated our OLS estimates of the same model.

The use of aggregated U.S. data is desirable since it would reduce the cost of developing forecasts, but the important question to the company managers is whether this level of aggregation would still yield accurate forecasts. Pepsi's feature and Coke's display are insignificant in this regression, possibly because regional variation in promotional activity is obscured in the aggregation. However, the effects of price and Pepsi's display are stronger than in the regional level OLS regression in Table 3. Despite the aggregation, this model forecasts almost as well as the region-level model, providing some evidence in favor of developing forecasts on data aggregated up to the level of the entire United States. In sum, the pooled log-linear model estimated by OLS produced better results in the holdout sample than alternative models.

4.3. Adjustments to Baseline Forecasts

In this section, we briefly describe adjustments required to provide monthly forecasts at the wholesale level. Because the IRI, Wal-Mart Retail Link, and Nielsen data are at the retail level, we had to convert the estimates into wholesale shipments. From an examination of cross-lagged correlations, ARMA models, and regression relationships between retail volume and current and lagged wholesale volume in the various regions, we concluded that the following relationship is approximately true. Wholesale volume at $t = 0.75 *$ (retail volume at t) $+ 0.25 *$ (retail volume at $[t+1]$). In other words, about 25% of the wholesale shipments at week t are used to support retail sales in the following week $(t+1)$. We used this relationship in converting forecasts of retail sales to forecasts of wholesale sales. We also had to scale up results obtained from the wholesaler data to the entire United States by dividing forecasted sales by the wholesaler's estimated share of U.S. sales.

Since management required monthly forecasts, it was necessary to convert weekly forecasts to monthly forecasts. Using data on wholesale shipments, we first estimated the share of wholesale shipments by day of week. We used these estimates of day of week share to allocate share among the months. In doing this, we had to account for the fact that the final day of the week differs in our data for grocery, drug, and mass merchandiser channels. As an example of our calculation, assume that the week ends on Saturday. Assume that Sunday–Wednesday is in Month 1 and Thursday–Saturday is in Month 2. If the average share of wholesale shipments on Sunday–Wednesday is 40% and the share on Thursday–Saturday is 60%, we allocate 40% of that week's wholesale volume (after the retail-wholesale adjustment noted above) to Month 1 and 60% to Month 2. Using our day-of-the-week share estimates, we created a table of between-month volume allocations for each year that we have forecasted. This table is used in an SAS program that performs the allocation procedure automatically. The monthly forecasts are adjusted judgmentally for new product introductions and other changes not accounted for in our regression analyses of historical data.

4.4. Forecasts for Other Channels

Since the procedures used were similar to those presented in the above example, we will only briefly discuss the differences in methods to develop forecasts for other channels. The purpose of forecasts for major accounts/chains is diagnostic—to provide input to the DSS that will allow study of the effectiveness of marketing strategy at the chain level. While weekly data are available for Wal-Mart, this chain does not provide a regional breakdown of its data and no longer shares competitive data with the manufacturers. The only marketing mix data available are data on average price. Accordingly, we estimated models of Wal-Mart sales volume as a function of price, national average temperature, and dummy variables for holidays and seasons. Data for the convenience channel are available from Nielsen for quad-weekly periods on own and competitive price and display. We developed separate forecasts for major product categories for both immediate and take-home sales. We did have a breakdown of sales by seven regions and estimated forecasts pooling across the regions (because we needed sufficient data as there are only 13 observations per year in the time series). We did have data on regional temperature but could not use holiday dummies, given the lack of weekly data. The earlier example of the IBS channel is representative of the analyses for the channels that use wholesaler data. In forecasting restaurant volume, however, we use data on restaurant traffic and sales in addition to other measures. Despite the lack of competitive data, we have generally been able to develop satisfactory forecasts for the other channels.

5. Overall Model Results and DSS

5.1. Overall Model Results

A summary of model fit and forecast accuracy by channel and region for the 2003 forecast appears in Table 7 for the four major company-defined regions. These results are representative of the results obtained in the different annual forecasts. The R^2 values are high and the magnitude of MPE for many channels and regions is below 1%. Figure 2 presents a summary of differences between actual and forecast sales volume for four channels: grocery, drug, C&G, and restaurant. We can see that the forecasts track the actual sales volume very well, with the magnitude of MPE ranging from -0.4% for grocery to 1.3% for drug. Even for the restaurant channel, for which we

Table 7 Model Fit and Forecast Accuracy by Channel/Region in 2003

	Region									
	Total		East		Central		South		West	
Channel	R^2 (%)	MPE (%)	R^2 (%)	MPE (%)	R^2 (%)	MPE (%)	R^2 (%)	MPE (%)	R^2 (%)	MPE (%)
Total	92.5	0.1	90.1	0.2	88.5	0.0	88.1	0.4	92.4	−0.2
Grocery	89.5	−0.4	91.4	−0.1	84.9	−0.7	83.0	−0.1	89.2	−0.9
C&G	91.4	0.1	83.4	0.4	88.2	0.0	89.8	0.0	82.0	0.1
Drug	78.3	0.5	65.0	1.4	80.9	−0.3	72.8	2.1	77.1	−2.8
Mass	94.5	−0.7	91.9	0.2	90.5	−1.0	94.9	−0.4	90.7	−1.6
IBS*	89.4	−1.4	84.9	−1.7	90.3	−1.3	90.3	−1.3	85.3	−1.2
Restaurants*	72.3	−1.0	80.2	−1.2	68.7	−0.8	68.7	−0.8	68.2	−1.0
BI&E*	79.3	0.8	74.6	0.7	75.3	1.0	75.3	1.0	83.4	0.4
Entertainment*	75.0	1.0	70.2	2.8	70.4	0.7	70.4	0.7	80.7	0.4
Other food service*	91.2	0.5	66.9	0.3	83.7	0.0	83.7	0.0	89.9	1.1
Club*	39.7	6.2	46.8	1.7	30.7	7.6	30.7	7.6	52.4	4.6
Military*	76.9	2.0	89.2	0.6	48.1	3.2	48.1	3.2	72.8	−0.6

*In these channels, there were virtually no measures available for model estimation (only historical wholesale volume shipments and revenue measures were used). Despite these limitations, the forecast accuracy is fairly good for all channels and regions, except for the club channel, where there are no data available on any variable that can explain the volume spikes.

do not have data on potential drivers of sales, the MPE is quite low (−1.0%). The forecast accuracy is similar at the region level. These forecasts are not shown to save space. The forecasts for seven of the nine major accounts were within 5% of actual sales volume during 2003. For three accounts, Albertsons, A&P, and Safeway, the forecast sales volumes were within 1% of the actual sales volume.

5.2. DSS

To ensure that our forecasting model was gainfully used by the right decision makers, it was important that we come up with a DSS that is fast in responsiveness and that improves over time. We developed a DSS that facilitates collection of input data on planned price and promotion levels, automatically generates benchmark forecasts using these data, presents the forecasts in tables and graphs, provides diagnostic information on the effects of plans and other variables on volume and enables a variety of drill-down capabilities and "what if" and "due-to" analyses by channel, category, geography, and pack size. The diagnostic ability of the DSS was as important as the accuracy of the forecasts.

A screen shot of the *CHAN4CAST* DSS, labeled *LIFT* (Liquid Refreshment Beverages [LRB] Interactive Forecasting Tool), appears in Figure 3.[12] The Tool provides a forecast grid that allows a manager to see the overall forecast volume, actual volume, and gap (difference between forecast and actual) by each month. From this screen, the manager can go to a screen that shows a breakdown of the forecast and actual volumes by channel and by region. If the manager wants to see how much of the gap is due to one particular variable (say, the weather or differences between the actual and forecast temperatures), she can look at a screen such as that shown in Figure 3. On the top of this screen, there is a series of "thumbnail" graphs that captures the volume gap by channel, region, category, and pack-size. The manager can drill down into all possible reasons for the gap in different channels and regions and accounts. She can also get a "dashboard" view of sales performance against forecasts through a scorecard.

Based on a good understanding of the drivers of the gap, managers can revise their plans on marketing variables such as price and promotion and come up with revised forecasts. To check the impact of a revised price and promotion plan, managers can do "what if analyses" and simulate possible forecasts through the tool. Analyses of marketing plans can be made by managers of each channel, account and region as appropriate and coordinated with the Vice President, Sales and Planning to arrive at final decisions and revised forecasts.

In developing the DSS tool, we proceeded as follows. First, we determined who the users would be and what forecasting information they needed to make decisions. For example, field sales people needed forecasts by the retailer and pack-size, whereas finance executives needed to know total volumes at regional and channel levels and corresponding prices. Second, we determined the desired contents and format of the outputs that each user wanted. We also ascertained the different types of information and drill-downs that each user sought.

[12] We show only one screen shot for illustrative purpose. A detailed set of screen shots of *CHAN4CAST* and *LIFT* is available at http://mktgsci.pubs.informs.org.

Figure 2 Forecasts by Channel

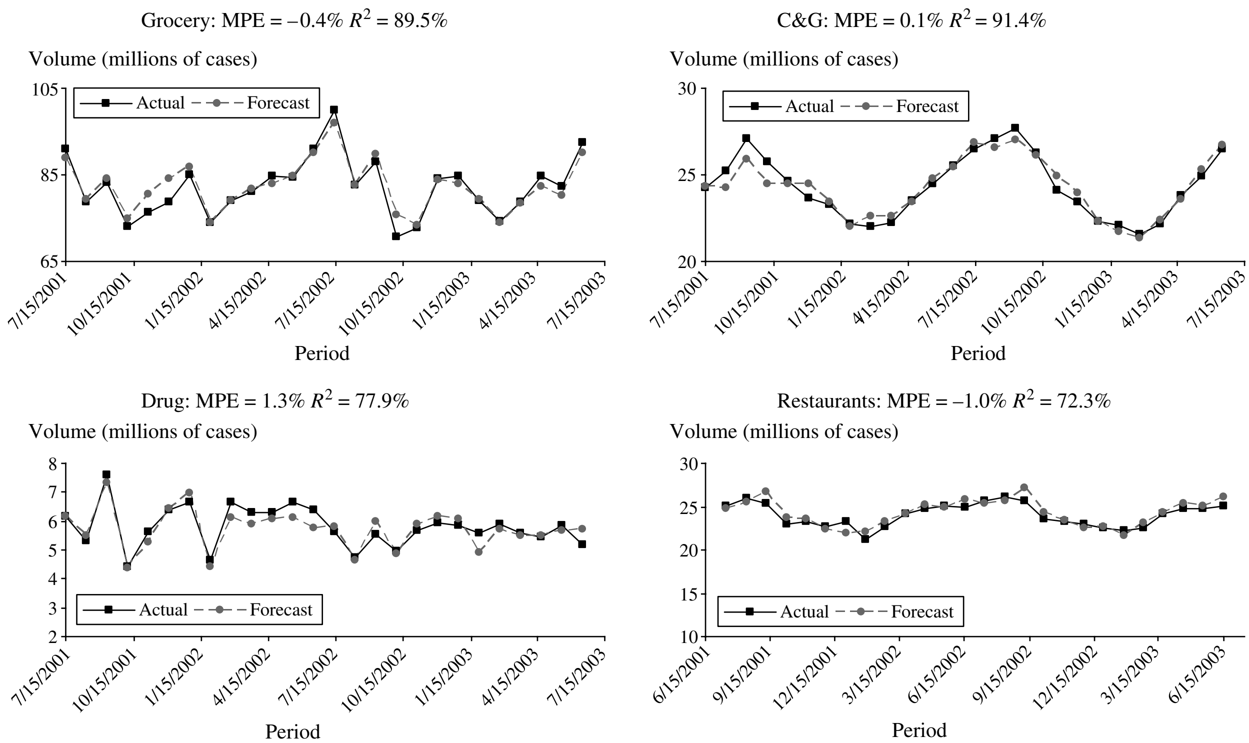
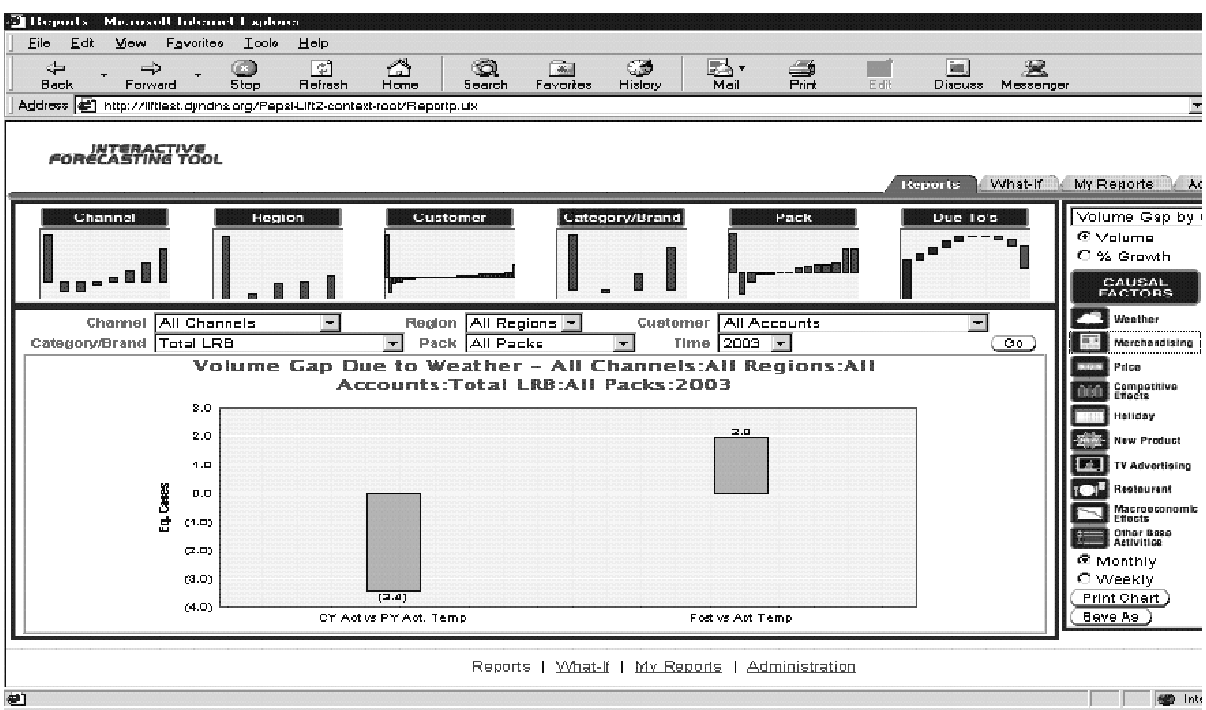


Figure 3 Screen Shot of a Driver of Sales Volume Gap (Weather) in *CHAN4CAST*



Note. The magnitude of MPE in each channel is low (less that 1.3%). It is low evern for the restaurant channel, which does not have data on causal variables. Importantly, the forecast volume tracks the actual volume very well over time in each channel. Microsoft product screen shot reprinted with permission from Microsoft Corporation.

Third, we worked with an information technology (IT) consultant to map the model forecast outputs to the desired outputs and the drill-downs of the users. Fourth, we developed specifications of the Web-based tool. Fifth, we developed a pilot DSS and tested it with different users. Finally, we improved the system based on feedback from the users during pilot testing and later. At each stage, we involved key users to ensure that the implementation was on track.

The company is using the DSS to forecast and track sales volume by channel using inputs from field sales personnel. There is full support from senior management and enthusiastic "buy-in" from field sales personnel in the implementation because this system (a) integrates all existing forecasting approaches into one system with field input, (b) has a scientific benchmark for coming up with the forecasts, (c) can offer diagnostics when the actual volumes deviate from the planned volumes, and (d) places accountability on the appropriate managers to meet sales targets. The company is in the process of extending *CHAN4CAST* to its other product categories and divisions.

It is expected that about 100–125 potential users from different areas, such as senior sales, field sales, category management, brand management, sales strategy, and finance will use the DSS in the beverage division. Currently, the DSS has about 30–40 users, mostly from senior sales, field sales, and category management. The sales people use it as often as every week. The category managers use the tool on a regular basis mainly for understanding the drivers of any gap between forecast and actual sales volume and performing "what if" scenarios analysis.

The DSS provides a benchmark that systematically uses and summarizes information in past data, helps to understand drivers of sales, allows for adjustments to this benchmark for new product introductions and other changes not reflected in historical data, and can be used to try out "what if scenarios" to make better decisions.

6. Impact

We believe our model and DSS have significant impact on the company along several dimensions: financial, methodological, knowledge management/transportability of solution, and cultural.

6.1. Financial Impact

The company believes that the impact of *CHAN4CAST* on the financial top line and bottom line is significant. The company estimates that the system has saved \$11 million for an investment cost of less than \$1 million. The return of \$11 million is from two components, mainly from productivity enhancement (estimated to be 0.05% on a sales revenue base of \$20 billion) and redeployment of personnel. The implementation cost, including modeling, consulting, and building of a Web-based client-server tool cost the company less than \$1 million. The estimated savings do not include the opportunity gains from better forecast accuracy and their impact on future profits. Thus, the estimated return is conservative, and the real return could be higher.

6.2. Methodological Impact: Use of Marketing Science Methodology

Our model and DSS represent a rigorous application of marketing science models to the company's forecasting problem and context, consistent with that of Leeflang and Wittink (2000) and Lilien and Rangaswamy (2002). Our approach involved choosing from a large number of modeling alternatives that fit the company's requirements with regard to data availability for the different channels and regions. For example, we had adequate data on the drivers of volume for the grocery channel, but less than adequate data for the on-premise channel (e.g., restaurants, vending machines). Subject to deadline constraints and the need to make results understandable to managers, we chose those functional forms, transformations, and the models that provided the best interpretability, fit, and diagnostics in each channel or major account. There are several important aspects of our model. First, our model captures the effects of nontraditional variables such as temperature and quality of day effects to improve forecasts. Second, our model incorporates several intricate "adjustments" to the forecasts. The adjustments include "day-of-week" lifts for the "cusp" weeks, "load-ins" that occur before special holidays (e.g., Fourth of July), as well as "trading-day adjustments" that account for differences in sales between weekdays and weekends in a month. These adjustments are critical to the accuracy of the forecasts and the success of a forecasting DSS and are not adequately emphasized in academic marketing science models. Third, because forecasts of wholesale shipments are key to the company, our model includes an appropriately derived quantitative relationship between weekly retail sales and wholesale shipments.

6.3. Transportability of Solution

CHAN4CAST is generalizable and extendable to any other consumer packaged good. Most consumer packaged goods are sold through similar channels and are organized regionally. Some product categories are sold through direct store delivery (DSD) like beverages are, while other product categories may be sold through warehouse distribution channels. Regardless, the data sources and the marketing mix variables are similar. Any consumer packaged goods company can use the modeling approach underlying *CHAN4CAST* to build a good forecasting model and DSS.

CHAN4CAST is having a wide impact on the creation and dissemination of best practices in the organization. Although it is operational in one division, the model is widely transportable and is in the process of being rolled to the other divisions of the company. The company has the full backing of the senior management team, who are keen to leverage the best practice derived from *CHAN4CAST* across all the divisions.

6.4. Cultural Impact

Culturally, *CHAN4CAST* has changed (or modified) the way senior management looks at the forecasting process in four ways. First, prior to our work, forecasting had always been a "top-down" approach (e.g., "We need to achieve a 4% growth nationally ... let's see how we can allocate this growth to the various channels/regions"). Not much thought was given to whether this "forecast" was achievable or not—thus, it was more of a "plan" than a true forecast based on marketplace factors. Our forecasting approach is based on a scientific rationale that explicitly forecasts the business through drivers of volume of existing and new products. Second, we were able to convince the organization that, at a minimum, our forecasts provide a scientific validation or a reality check for the "top-down" approach. Third, our approach brings accountability to the sales organization, because it highlights the reasons for the gap, if any, between the forecasted and actual sales (e.g., the actual sales were below forecasts because we did not have the prices promised to account X in week Y). The model and DSS are similar in spirit to Albers' (1998) framework that decomposes profit contribution variance between actual and plan into partial variances associated with incorrect market response assumptions, deviations of actual marketing decisions from planned ones, and incorrect anticipation of competitor actions. Finally, we ensured "buy-in" from users within the organization through the easy-to-use, Web-based DSS.

7. Managerial Learning and Take-Aways

The development and implementation of *CHAN4CAST* offer several take-aways for managers who may want to apply this model to their products, services, and companies.

7.1. Seek a Strong Internal Champion

Having a strong internal champion for successful implementation of an ambitious project like *CHAN4CAST* is almost essential. A champion in a DSS project plays several roles, such as reference leader, change agent, and a top management representative (Curley and Gremillion 1983). *CHAN4CAST* had a strong champion, one at the highest level in the organization, namely, the President of Sales. It is difficult to predict the level of success of *CHAN4CAST* without the support of such an internal champion—at a minimum, the speed of adoption would have been slower.

7.2. Understand Data Challenges and Existing Ways of Forecasting

It is important to first understand the data challenges and the existing forecasting processes in the organization and explore whether those could be used to augment or supplement the new system. For example, in one of the company's other divisions, there was already a system that collects the field sales inputs to the forecasting process. In extending *CHAN4CAST* to this division, the DSS will be modified to directly take this input system. This calls for some extra effort but is useful in widening the adoption of our system.

7.3. Get Initial "Buy-Ins" from Key Stakeholders

It is critical to get initial buy-ins from the key stakeholders and users involved in forecasting. For example, the Finance Department may be involved in both short-term (to satisfy Wall Street) and long-term forecasting (for strategic planning). The sales managers may want forecasts by major account, and the brand managers may be generating brand-level forecasts. Thus, each group may be generating forecasts at different levels (brand versus account versus company) for different uses (sales quotas, new product forecasts, financial forecasts). Although a single forecasting model cannot address every issue of every stakeholder, it is important that in the initial phase, it attempts to determine and satisfy the *strategic* needs facing the *key* stakeholders for forecasting in the company.

7.4. Model Relevance Is Primary, Model Sophistication Is Secondary

Any forecasting application requires a large number of modeling choices and compromises for the context. When using *CHAN4CAST* in other situations, managers have to ensure that it fits company requirements (by region, by channel) and make the necessary adjustments, such as those for the day of month and new products. While sophisticated methods like Bayesian estimations can provide greater forecast accuracy in certain situations, their use will have to be balanced against the need for parsimony, communication, ease of automation, and decision making. There is a fine balance between model sophistication and relevance, and sophistication is only secondary to relevance.

7.5. Diagnostics Are at Least as Important as Forecast Accuracy

While a good sales forecasting model has to provide accurate forecasts, it should address the important managerial problem of determining why actual sales volume differs from forecast sales volume and deciding what managerial actions to undertake to realize the forecasts. A notable feature of *CHAN4CAST* is its diagnostic ability that allows a user to detect gaps between actual and forecast sales volume and drill down to determine the reasons for the gaps.

7.6. Validate the Model Through a Pilot Version for One Channel

After the forecasting model is developed, it is imperative to compare and validate its forecasts (monthly, quarterly, and yearly) with forecasts from existing approaches, as well as with the historical actual sales volumes through a pilot version of the model for one channel. Suitable model improvements should be made until the model outperforms the existing methods. The initial focus on one channel helps demonstrate the value of a forecasting model like *CHAN4CAST* to the key stakeholders and users and incorporate institutional nuances, which is necessary to provide a level of comfort to the existing stakeholders that the new forecasts would actually deliver greater accuracy and meet their needs.

7.7. DSS Needs More Time and Effort Than the Model

With many models to be estimated against a tight timeline, there is not enough time to make a detailed manual evaluation of each model. Automated decision rules for selecting variables and other model elements are necessary, as are automated procedures for making the adjustments needed to develop forecasts. Programming skill is just as critical as econometric skill. The need for having an easy-to-use front end to the DSS cannot be overemphasized. In a time-starved environment, there is often the need for some kind of "hand-holding" and training for the users. A user-friendly interface and tool that is visually pleasing and logical to use facilitates quick and widespread managerial adoption. The time and effort spent on building and implementing such a DSS should be as much or more than those spent on model development.

7.8. Speed of DSS Response Is Key to Successful Adoption

In addition to forecast accuracy, the speed of response from the tool (real-time performance) is also important, as it offers greater perceived control. Users download important information from the tool and use it for various reports and presentations. The usage of the DSS would be significantly enhanced if it allows users to easily import information. This is consistent with Morris and Marshall (2004), who found that timeframe, feedback signal, and feedback duration are important factors that represent a user's perception of control.

7.9. Be Responsive to User Needs and Continuously Improve

Being responsive to user needs and continuously improving the DSS tool helps to institutionalize the system. Although *CHAN4CAST* was widely perceived to be useful and easy to use, we also received valuable feedback from the various users in the company on the aspects needing improvement. These include such issues as speeding up input time, reducing the need to enter same information for multiple RMAs, accounting for forecasts of additional pack sizes, and breaking out forecasts of accounts at the RMA level. Inputs like these, if incorporated on a continuing basis, would lead to continuous improvement in the model and a more widespread and regular adoption of the system.

8. Limitations, Future Research, and Conclusions

The model and DSS we developed have a number of limitations that could serve as fruitful avenues for future research. First, because forecasting was the overall purpose, we did not focus on capturing accurately the effects of all of the possible variables affecting sales. If the managerial focus is on optimal marketing decisions, the model may have to be suitably modified. Second, the model does not include advertising and cross-category effects, since modeling these effects was beyond our scope given the focus on forecasting, not on understanding, these effects. Cross-category effects can be developed that are similar to Elrod et al. (2001) and Russell et al. (1999) to provide a valuable addition to our model. Third, the impact of new product introductions was included in our model based on past data on previous new product introductions by the company. Because the number of new products introduced in a year by a single company may be limited, a model of new product sales based on a larger database of new product introductions could be developed to get a more accurate estimation of the impact of the new product introductions on overall sales volume.

In conclusion, we developed a robust multichannel, multiregion forecasting model for packaged goods that is being successfully used by a leading consumer marketing company. An easy-to-use Web-based DSS tool with the forecasting model as the engine is enabling widespread use and continuous improvement within the company. Based on our experience in the project, we conclude that successful development and implementation of a rigorous forecasting or marketing science model requires a strong internal champion, a careful balance between modeling sophistication and practical relevance, good diagnostic features, regular validations, and greater attention to the development of a fast and responsive DSS.

Acknowledgments

The authors gratefully acknowledge the support provided for this project by Albert Carey, Ricardo Cuellar, and other members of PepsiCo; by Martin Lipman of IRI; and by Raj Ranganathan of Versaya, Inc. The authors also thank Steve Shugan, Gary Lilien, four anonymous reviewers, and the judges of the ISMS Practice Prize Competition for valuable comments and directions. The authors thank Surekha Shankar for copyediting assistance.

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