

An exploratory Investigation of new product forecasting practices

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Abstract

To guide new product forecasting efforts, the following study offers preliminary data on new product forecasting practices during the commercialization stage (prelaunch and launch stage). Data on department responsibility for and involvement in the new product forecasting process, technique usage, forecast accuracy, and forecast time horizon across different types of new products are reported. Comparisons of new product forecasting practices for consumer firms versus industrial firms are also reported.

Overall, study results show that the marketing department is predominantly responsible for the new product forecasting effort, there is a preference to employ judgmental forecasting techniques, forecast accuracy is 58% on average across the different types of new products, and two to four forecasting techniques are typically employed during the new product forecasting effort. Compared to consumer firms, industrial firms appear to have longer forecast time horizons and rely more on the sales force for new product forecasting. Additional analyses show that there does not appear to be a general relationship between a particular department's involvement and higher forecast accuracy or greater satisfaction, nor does it appear that use of a particular technique relates to higher forecast accuracy and greater satisfaction. Countering previous research findings, the number of forecasting techniques employed also does not appear to correlate to higher forecasting accuracy or greater satisfaction. Managerial and research implications are discussed. © 2002 PDMA. All rights reserved.

1. Introduction

Most executives would agree that any given new product forecast will be wrong. In fact, many executives characterize new product forecasting as an inaccurate endeavor. Some would even say that it is a frustrating, perhaps futile, effort because of minimal data, limited analysis time, and a general uncertainty surrounding a new product and the marketplace.

Nevertheless, companies cannot eliminate the need for a new product forecast nor disregard developing a new product forecast. This is especially true during the commercialization stage (prelaunch preparation and launch) where new product forecasts drive a variety of multifunctional decisions. These would include manufacturing decisions on raw materials procurement, manufacturing schedules, and finished goods inventory levels; logistics decisions on physical distribution planning and transportation schedules; marketing decisions on marketing budgets and promotion schedules; sales decisions on support materials and salespeople

training; and finance decisions on corporate budgets and financial expectations for the new product. Given this breadth of decisions, any forecast error at the commercialization stage has definite company-wide ramifications that can translate into significant bottom line consequences. Company management is therefore very interested in finding ways to improve the new product forecasting effort, and thereby minimize forecast error.

Unfortunately, most new product forecasting literature presents sophisticated statistical techniques without discussing the situations when and when NOT to employ the technique [11]. This has misled new product professionals into misapplying techniques, and subsequently, deriving erroneous forecasts [24]. For example, one product manager was found using diffusion models to forecast product improvements at the product item level. Diffusion models are best used at the aggregate level—not the individual product item level, and are intended to model emerging technologies/new-to-the-world products, not product improvements. Such evidence of misuse suggests a lack of knowledge surrounding new product forecasting, and correspondingly, indicates a need for guidelines on when to use particular new product forecasting techniques. There is also a need for general knowledge regarding the management of the new

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product forecasting process, which literature has not yet detailed.

To address these considerations, an exploratory study was undertaken to describe the new product forecasting endeavor. Sponsored by the Product Development & Management Association (PDMA) through its sponsored research program, this study sought to identify current industry practices and attempt to identify preferable, if not better, practices related to new product forecasting from the standpoint of a broad-based, cross-industry perspective. Such practices included department involvement in the new product forecasting effort, technique usage, and new product forecast accuracy. The present paper reports on the study's findings, indicating current practice and those practices that might relate to higher forecast accuracy and greater satisfaction with the new product forecasting effort. The paper concludes with a set of preliminary guidelines for new product forecasting management and a suggested agenda to spur continued research on this topic.

2. A literature review of new product forecasting practices

As previously mentioned, many articles on the subject of new product forecasting have been illustrations of specific forecasting techniques, often representing sophisticated statistical methodologies [for example, 7,8,20,21,22]. A significant number of the remaining articles have been normative in nature, prescribing the need for continued study on the topic of new product forecasting for sake of improving prediction capabilities [for example, 1,12]. Only a handful of articles have empirically examined managerial practices related to new product forecasting management and thereby provided industry benchmark data.

Much of these articles have focused intently on the issue of new product forecast accuracy. For example, Tull [25] studied 53 products from 16 firms and found that the mean forecast error was 53%. Beardsley and Mansfield [2] studied the accuracy of forecasting profit, and found that it took 4 to 5 years after new product launch for a company to estimate discounted profits reasonably well. And Shelley and Wheeler [24], who investigated market forecasts for the high technology products of personal computer, artificial intelligence, and fiber-optics, found that the average ratio between actual sales and forecasted sales was 0.79 in the first year, 0.60 in the second year, 0.51 in the third year, 0.46 in the fourth year, and 0.41 in the fifth year.

Because of such relatively low accuracy associated with new product forecasting, Gartner and Thomas [5] conducted a study to examine and identify underlying factors contributing to such forecast error within the context of new computer software firms. Their results suggest that industry marketing experience, more attention and resources directed towards new product forecasting, the use of personal data sources, and the use of more techniques all correspond to

improved forecast accuracy. While not controllable per se, less market turbulence also was found to correspond to improved forecast accuracy. Based on these results, the following guidelines for generating more accurate forecasts were given:

- (1) recognize the importance of the new product forecasting task and develop a commitment (which includes financial resources) commensurate with the importance of the task to improve forecasts;
- (2) select new product forecasting data sources that bring the forecaster closer to the consumer (e.g., personal interviews, product demonstrations, focus groups);
- (3) use more than one method in combination throughout the product development process to develop forecasts; and
- (5) anticipate the volatility of the market to be entered and the behaviors of buyers within it as input to the new product forecasts." [5: page 48]

Recently, Lynn, Schnaars, and Skov [11] conducted a study comparing the use of new product forecasting techniques by industrial high technology businesses versus industrial low technology businesses. Their analysis of 76 industrial new product projects found that successful high-tech industrial projects tended to rely more on the internal qualitative forecasting techniques of internal expert judgment and internal brainstorming, versus unsuccessful high-tech industrial projects. Successful low-tech industrial projects tended to rely more on the traditional market research methods of one-on-one interviews with salespeople, surveys of buyers intentions, and formal surveys of customers. Results further suggested that successful firms, whether high-tech or low-tech, employed more new product forecasting techniques than unsuccessful firms. This latter finding corresponds to Gartner and Thomas's [5] finding that use of more techniques corresponds to greater forecast accuracy.

Another set of new product forecasting literature has promoted diffusion models and their applicability to new product forecasting [for example, 13,14,18,19,26]. Unfortunately, empirical research has suggested that there is very limited use of diffusion models in industrial/business settings [6,13]. One reason for this may be that diffusion models are sophisticated statistical models, which require expertise that most new product practitioners do not have. Another reason is the poor track record of diffusion models in actually predicting sales more accurately than other methods [6].

But is new product forecasting simply an application of forecasting technique(s)? The work of Mentzer, Bienstock, and Kahn [17] would suggest no. They contend that sales forecasting should be viewed as a process, encompassing such issues as accuracy measurement, forecasting technique application, and department participation, for example, department responsibilities and department involvement in the forecasting process. Given this, the present study sought to investigate the following two questions: [1] Which department is responsible for the new product forecasting process?

[2] Which departments are involved in the new product forecasting process? The present study also investigated how accuracy, forecast time horizon, and forecasting technique usage might differ across different types of new products, that is, cost improvements, product improvements, line extensions, market extensions, new category entries, and new-to-the-world products? Additional analyses were undertaken to investigate possible differences between consumer and industrial firms to reveal any striking differences. To the author's knowledge, the question of department responsibility and involvement and the latter question regarding a segmentation of accuracy, time horizon, and technique usage by type of new product have not been addressed by forecasting or product development literature.

3. Methodology

A survey methodology was employed to explore current new product forecasting practices during the commercialization/launch stage. Survey questions asked respondents to indicate the department responsible for the new product forecasting function, departments' involvement in new product forecasting, new product forecast accuracy per each type of new product launched, average time horizon for new product forecasts per each type of new product launched, the new product forecasting techniques typically used for each type of new product, and degree of satisfaction with the new product forecasting process.

Similar to the methodology of Griffin et al. [4], multiple sources were surveyed, helping to diversify and increase the sampling base. Each mailing list was reviewed to ensure no repetition of names across the three lists. The first source was a random sample of 500 PDMA practitioner members, provided by the association's headquarters. A proofing of this list was conducted to remove consulting agencies who would not normally be involved in new product forecasting of their own products – 90 such agencies were removed. After two mailings, 36 surveys were returned completed; 37 surveys were returned as undeliverable; 16 surveys were returned uncompleted because the respondent was not involved in new product forecasting; 11 surveys were returned uncompleted because new product forecasting was not an activity of the company (e.g., consulting agency); and 6 surveys were returned because the respondent did not have the time or and/or felt the information to be provided was too sensitive. The effective return rate of the PDMA sample was 36 out of 340 or 11%. A follow-up interview with five nonrespondents indicated similar reasons akin to surveys being returned uncompleted – the majority of which was that new product forecasting was not part of the respondent's job. This suggests that new product forecasting is a specialized function, and one which is not necessarily assigned to product development practitioners.

The second source was sample of marketing managers,

Table 1
Where the new product forecasting function resides

Department	Primarily responsible for new product forecasting (% of respondents) (n = 144)	Average level of involvement* (n = 144)
Marketing	62%	4.29 (s = 1.10)
Sales	13	3.61 (s = 1.31)
Sales forecasting	10	3.50 (s = 1.50)
Finance	6	2.22 (s = 1.26)
Market research	3	3.34 (s = 1.46)
R&D	3	2.92 (s = 1.46)
Manufacturing	2	2.34 (s = 1.36)
Logistics/distribution	1	2.04 (s = 1.28)

Involvement was assessed using a 1–5 scale, where 1 = “Does Not Participate” to 5 = “Highly Involved.”

n = sample size.

s = standard deviation.

product managers, and sales forecasting managers associated with Georgia Tech's Marketing Analysis Laboratory. Of the 150 managers in this sample, 30 responded for an effective response rate of 20%. Follow-up with several nonrespondents indicated time to complete the survey was a major factor inhibiting participation in the study.

The third source was a sample of forecasting, marketing, and product management executives attending the Institute of Business Forecasting (IBF) June 1999 Tutorial Conference. A total of 102 out of 300 attending executives completed the survey, giving an effective response rate of 34%.

The combined data set comprising a total of 168 respondents from a cross-section of industries including automotive products, medical products, health and beauty products, construction equipment, electronics – to name a few. A little more than half of the companies were strictly consumer market-focused (54%), while roughly a third (34%) of responding companies were strictly focused on the business-to-business market. The remaining companies characterized themselves as an equal mix of consumer and business-to-business products/services.

4. Results

4.1. Sales forecasting practices across all firms

Almost two-thirds (62%) of respondents indicated that the marketing department is primarily responsible for the new product forecasting function (see Table 1). This shows that the marketing department is the predominant department responsible for the new product forecasting function. Only two other departments reflected greater than 10% of respondents: the sales department was responsible for new product forecasting in 13% of the cases, and the sales forecasting department was responsible for new product forecasting in 10% of the cases.

As expected, the level of participation by these three departments is high. Marketing is very much involved in the new product forecasting process, and is the most involved department. Sales and sales forecasting departments are also more involved in the new product forecasting process than other departments besides marketing. Market research is more involved in the new product forecasting process as well. This indicates that market research plays an important role in new product forecasting, but that it is not typically responsible for the new product forecasting function.

Survey recipients were asked to indicate technique usage across six types of new products, corresponding to Crawford's list of new product types [3]. These included cost improvements (reduced cost or price versions of the product for the existing market); product improvements (new, improved versions of existing products/services, targeted to the current market); line extensions (incremental innovations added to existing product lines and targeted to the current market); market extensions (taking existing products/services to new markets); new category entries (new-to-the-company product and new-to-the-company market, but not new to the general market); and new-to-the-world (radically-different products/services vs. current offerings and markets served). To guide survey recipients, a list of twenty common sales forecasting techniques compiled from a variety of sales forecasting and technological forecasting sources [for example, 15,16] was provided. Those completing the survey also were given the option of an "other" category, which allowed the writing in of forecasting techniques not listed (refer to the Appendix for a list and description of the given techniques).

As shown in Table 2, the more popular new product forecasting techniques (those techniques receiving greater than 10% average usage across the six types of new products) were customer/market research, jury of executive opinion, sales force composite method, looks-like analysis, trend line analysis, moving average, and scenario analysis. These results correspond to Lynn et al. [11], which had suggested that managers prefer to rely on judgment and market research techniques, versus traditional sales forecasting techniques like time-series analysis and regression. Such correspondence is interesting in light of the fact that there are a number of quantitative techniques, which literature espouses. Forecasting executives nonetheless show a strong preference towards less sophisticated, qualitative forecasting techniques like jury of executive opinion, sales force composite method, and looks-like analysis, along with a preference towards customer/market research, which may be quantitative or qualitative in nature. It is also interesting to observe that these techniques appear to be somewhat equally applied across the different types of new products, which suggests that new product forecasters commonly employ qualitative forecasting techniques along with market research, regardless of the type of new product. Results further show that on average, companies use about three techniques when forecasting each of the six types of new

products. This latter finding supports research, which indicates new product forecasting to be a process that comprises more than one technique (refer to Table 2).

Table 3 shows the mean values of achieved new product forecasting accuracy across the six types of new products (accuracy data were collected by asking respondents to indicate the average forecast accuracy achieved and the typical forecast time horizons across the six types of new products). A total of 49 companies provided data on their new product forecast accuracies. The overall average accuracy across the six types of new products was 58%, with cost improvements generally 72% accurate; product improvement forecasts 65% accurate; line extension forecasts 63% accurate; market extension forecasts 54% accurate; new category entry (new-to-the-company) forecasts 47%; and new-to-the-world products 40% accurate (refer to Table 3).

The nature of these accuracies suggests that newer markets are more troublesome to forecast (i.e., market extensions, new category entries, and new-to-the-world products), than those situations where a current market is being served (i.e., cost improvements, product improvements, line extensions). While it may seem intuitive, these results suggest that it is not the product/technology, but rather the market/customer-base that impacts new product forecast accuracy.

The overall average forecast time horizon for these forecasts is approximately 26 months. As shown in Table 3, the average time horizons for cost improvements, product improvements, line extensions, and market extensions were below this average (21 months, 20 months, 21 months, and 24 months respectively), while the average time horizons for new category entries and new-to-the-world products were above this average (35 months and 36 months, respectively). These results suggest that forecasts for new category entries and new-to-the-world products are characteristically longer-term in nature, and correspondingly, more strategic in nature than forecasts for the other types of new products.

Respondents also were asked about their satisfaction with their company's new product forecasting process using a five point Likert scale. Of the 150 who responded to the question, 8% were "very dissatisfied" with their new product forecasting process, 45% were "dissatisfied," 27% were neutral, 19% were "satisfied," and only 1% of respondents were "very satisfied" with their new product forecasting process. Because more than half of companies surveyed were dissatisfied with their new product forecasting process, it appears that new product forecasting is an area in need of improvement, and consequently, deserving of continued study.

A possible relationship between accuracy and satisfaction was examined due to the premise that companies achieving better new product forecast accuracy would likely be more satisfied with the new product forecasting process [9]. Analysis revealed statistically significant ($p < .05$) correlational relationships between satisfaction and

Table 2
Use of new product forecasting techniques by all responding firms

Forecasting technique	Average use across all types of new products	CI (<i>n</i> = 45)	PI (<i>n</i> = 117)	LE (<i>n</i> = 12)	ME (<i>n</i> = 108)	NCE (<i>n</i> = 58)	NTW (<i>n</i> = 103)
Customer/market research	57%	42%	54%	54%	57%	71%	62%
Jury of executive opinion	44	49	38	40	45	53	48
Sales force composite	39	38	38	46	41	40	29
Looks-like analysis	30	22	26	32	32	36	29
Trend line analysis	19	29	25	18	18	14	14
Moving average	15	24	17	17	14	10	11
Scenario analysis	14	7	14	11	15	19	18
Exponential smoothing techniques	10	7	13	15	11	3	7
Experience curves	10	18	11	10	8	7	8
Market analysis model (including the ATAR model)	10	4	9	8	9	17	12
Delphi method	8	9	8	8	6	10	9
Linear regression	7	9	9	9	6	0	5
Decision trees	7	13	4	3	6	9	10
Simulation	5	0	6	4	6	5	8
Expert systems	4	4	6	4	4	0	3
Other	3	2	2	4	2	5	3
Nonlinear regression	2	2	1	2	3	2	1
Diffusion models	2	0	0	1	2	3	3
Pre-cursor curves (correlation method)	1	0	1	1	0	0	0
Box-Jenkins techniques (ARMA/ARIMA)	1	2	2	2	2	0	0
Neural networks	0	0	0	0	0	0	0
Average number of techniques employed		2.80 (<i>s</i> = 1.56)	2.83 (<i>s</i> = 1.84)	2.83 (<i>s</i> = 1.93)	2.84 (<i>s</i> = 1.95)	3.00 (<i>s</i> = 1.71)	2.75 (<i>s</i> = 1.96)

CI = Cost Improvements: reduced cost or price versions of the product for the existing market;

PI = Product Improvements: new, improved versions of existing products/services, targeted to the current market;

LE = Line Extensions: incremental innovations added to existing product lines and targeted to the current market;

ME = Market Extensions: taking existing products/services to new markets;

NCE = New Category Entries: new-to-the-company product and new-to-the-company market, but not new to the general market;

NTW = New-to-the-World Products: radically-different products/services versus current offerings and markets served.

Average Use = a weighted average across the six types of new products.

n = sample size.

s = standard deviation.

Note that multiple responses were allowed.

achieved forecast accuracy across four of the six types of new products, and between satisfaction and overall forecast accuracy ($p < .01$). Such results support the premise of an accuracy-satisfaction relationship (see Table 4), but because the magnitudes of each correlation are below 0.50, it appears that accuracy explains less than 25% of satisfaction's variance, and vice versa. Thus, forecast accuracy may be driver of satisfaction, but it is not the only driver; conversely, satisfaction may be considered a corresponding measure of forecast accuracy, but it should not be considered an equivalent measure.

Further analysis investigated how different departments' involvement, use of various techniques, and the number of techniques used might correlate to higher forecast accuracy and/or greater satisfaction with the new product forecasting process. Due to the finding of a significant correlation be-

tween accuracy and satisfaction, partial correlations were employed to examine each respective variable's relationship with accuracy, while controlling for satisfaction, and satisfaction, while controlling for accuracy (a partial correlation is an index of the proportional increase in explained variance between two variables, holding all remaining variables constant [10]).

Overall, results failed to show a general linkage relating involvement of any particular department, use of any particular technique, and/or the number of techniques used with accuracy or satisfaction across the six types of new products. Although various statistically significant individual findings were identified, the large number of nonsignificant findings suggests that these variables alone are not drivers of new product forecast accuracy or satisfaction (see Tables 5 and 6). This counters previous research, which has

Table 3
Forecast accuracy and forecast horizon for new product forecasts

Type of new product	Average % accuracy achieved (standard deviation, sample size)	Forecast horizon in months (standard deviation, sample size)
Cost improvements	71.62 (s = 22.46, n = 29)	21.15 (s = 21.15, n = 40)
Product improvements	64.88 (s = 23.63, n = 45)	19.96 (s = 18.20, n = 102)
Line extensions	62.76 (s = 22.25, n = 45)	20.84 (s = 18.58, n = 97)
Market extensions	54.33 (s = 24.02, n = 42)	23.58 (s = 21.26, n = 93)
New category entries (new-to-the-company)	46.83 (s = 24.31, n = 30)	34.56 (s = 35.21, n = 45)
New-to-the-world	40.36 (s = 24.72, n = 39)	36.08 (s = 35.96, n = 93)

n = sample size.

s = standard deviation.

suggested that the greater the number of techniques used will lead to higher forecast accuracy [5]. Based on the results of the present study, it appears that simply increasing various departments' involvement, focusing on a particular technique, and/or increasing the number of techniques used will not likely translate into a more accurate or a more satisfying new product forecasting effort.

4.2. Examining differences between consumer and industrial firms

Additional analyses segmented study data to compare practices of strictly consumer versus strictly industrial (business-to-business) firms. Several statistically significant differences were found, but the most striking difference was that industrial firms have longer time horizons for new product forecasts than consumer firms. On average, industrial firms have a 34 month forecast horizon versus 18 months in the case of consumer firms. It may be that the contractual nature of industrial relationships and capacity issues surrounding the larger volumes associated with in-

Table 4
Examining the forecast accuracy—satisfaction relationship

	Pearson correlation between accuracy and satisfaction
Cost improvements (n = 29)	.419**
Product improvements (n = 45)	.230
Line extensions (n = 45)	.302**
Market extensions (n = 42)	.346**
New category entries (new-to-the-company) (n = 30)	.367**
New-to-the-world (n = 39)	.257
Overall average accuracy (n = 49)	.391***

** $p < .05$; *** $p < .01$.

n = sample size.

dustrial markets orient, if not mandates, an industrial firm to pursue longer-range forecasting.

Another striking difference is a preference by industrial firms to use the sales force composite method for forecasting product improvements, line extensions, and market extensions. This corresponds to research that shows the popularity of sales-based forecasts in the case of industrial firms [16]. It therefore would appear that industrial firms rely more on their sales forces than consumer firms to derive forecasts, regardless of whether such forecasts concern existing and/or new products. Refer to Table 7.

5. Conclusions

As previously discussed, most literature on new product forecasting focuses on forecasting techniques, and not on management issues such as department responsibility for the new product forecasting process and department involvement in this process. Literature also has not presented data on new product forecast accuracy that one might expect and the nature of forecasting techniques usage across different types of new products. The present study has sought to explore these issues and thereby serves as a starting point for understanding how to better manage the new product forecasting process.

Although the results of the present study should be considered preliminary, these results offer the following in sights into practices related to the new product forecasting effort:

- Almost two-thirds of companies have the marketing department responsible for the new product forecasting effort; even if not responsible, the marketing department is heavily involved in the new product forecasting effort.
- Sales, sales forecasting, and market research are other departments that appear to have an appreciable level of involvement in the new product forecasting effort.
- There is a preference towards qualitative forecasting techniques and market research (which may be qualitative or quantitative) when forecasting new products. In fact, a majority of companies indicated using customer/market research techniques to forecast new products.
- Companies appear to apply techniques equally across the different types of new products.
- Companies typically use more than one new product forecasting technique – on average, 2–4 forecasting techniques. However, results suggest that the greater the number of techniques used does not simply lead to higher new product forecast accuracy or greater satisfaction with the new product forecasting process.
- One should expect higher forecast accuracy with cost improvements and product improvements than new-

Table 5
Partial correlations between department involvement, accuracy, and satisfaction

Department	CI (n = 25)		PI (n = 40)		LE (n = 40)		ME (n = 37)		NCE (n = 26)		NTW (n = 34)	
	Acc	Sat	Acc	Sat	Acc	Sat	Acc	Sat	Acc	Sat	Acc	Sat
	Finance	-.05	.21	-.05	.13	.14	.08	-.01	.08	.06	.06	.02
Logistics/distribution	-.12	.01	-.05	.02	.02	.01	-.04	.02	-.11	-.08	.04	.02
Manufacturing	.06	.19	.21	.12	.24	.09	.18	.08	-.12	.20	-.01	.25
Market research	-.07	.13	-.11	.28	.05	.24	.10	.15	.12	.12	.22	.17
Marketing	.30	.26	.06	.17	.11	.15	.10	.10	.13	.15	.09	.14
R&D	.20	-.09	.21	.03	.23	.00	.19	.02	.21	-.02	.03	.03
Sales	-.10	.22	-.25	.21	-.13	.19	-.11	.14	.05	.07	.11	.07
Sales forecasting	-.14	.27	-.17	.23	-.04	.20	-.05	.20	-.16	.22	.10	.11

Acc = Partial correlation with Accuracy, controlling for Satisfaction.

Sat = Partial correlation with Satisfaction, controlling for Accuracy.

CI = Cost Improvements: reduced cost or price versions of the product for the existing market;

PI = Product Improvements: new, improved versions of existing products/services, targeted to the current market;

LE = Line Extensions: incremental innovations added to existing product lines and targeted to the current market;

ME = Market Extensions: taking existing products/services to new markets;

NCE = New Category Entries: new-to-the-company product and new-to-the-company market, but not new to the general market;

NTW = New-to-the-World Products: radically-different products/services versus current offerings and markets served.

Bolded items are statistically different at $p < .10$.

n = sample size.

Table 6
Partial correlations between use of a particular technique, number of techniques used, accuracy, and satisfaction

Forecasting technique (in order of most-used to least-used)	CI (n = 21)		PI (n = 38)		LE (n = 36)		ME (n = 33)		NCE (n = 23)		NTW (n = 31)	
	Acc	Sat	Acc	Sat	Acc	Sat	Acc	Sat	Acc	Sat	Acc	Sat
	Customer/market research	.51	.15	.07	.03	.26	-.23	.16	.17	.47	-.09	.26
Jury of executive opinion	-.01	-.11	.02	-.33	.01	-.28	-.06	-.27	.11	-.05	.30	-.20
Sales force composite	-.29	-.06	-.05	-.20	-.09	-.29	-.02	-.17	.01	-.16	-.14	-.14
Looks-like analysis	-.10	-.37	-.14	-.19	-.10	-.13	-.16	-.16	-.07	-.50	-.02	-.17
Trend line analysis	-.19	-.19	-.25	-.18	.04	-.25	-.12	-.20	.11	.09	.06	-.05
Moving average	-.20	.03	-.10	-.13	.01	-.14	.13	-.24	.34	-.32	.33	-.26
Scenario analysis	-.12	.13	-.13	-.05	-.16	.04	-.20	-.03	-.21	.02	-.33	-.01
Exponential smoothing techniques	-.26	-.13	-.15	.03	-.08	.04	.07	-.11	-.02	-.14	.03	-.12
Experience curves	.11	-.22	.09	.15	.06	.20	.04	.22	.22	.02	.09	.23
Market analysis model (incl. ATAR model)	n/a	n/a	.08	.07	.07	.21	.10	.22	.22	.06	-.03	-.08
Delphi method	-.13	-.17	-.16	-.12	-.02	-.13	-.12	.01	-.05	-.20	-.14	-.10
Linear Regression	.11	.09	-.15	.34	-.24	.22	.10	.22	n/a	n/a	-.20	-.06
Decision trees	.18	-.08	-.14	-.14	-.17	.14	.07	.03	.10	.07	-.10	.19
Simulation	n/a	n/a	-.25	.11	-.36	.18	-.14	.27	.18	.18	.22	.11
Expert systems	.04	.30	-.10	.14	.15	.04	.28	.15	n/a	n/a	-.20	-.06
Nonlinear regression	.04	.30	n/a	n/a	n/a	n/a	n/a	n/a	-.29	-.07	n/a	n/a
Diffusion models	n/a	n/a	n/a	n/a	-.06	-.09	.21	.03	.24	.21	.13	.11
Pre-cursor curves (correlation method)	n/a	n/a	.02	.22	-.01	.23	n/a	n/a	n/a	n/a	n/a	n/a
Box-Jenkins techniques (ARMA/ARIMA)	n/a	n/a	-.11	.08	.12	.02	-.06	.09	n/a	n/a	n/a	n/a
Neural networks	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Average number of techniques employed	-.06	-.19	-.26	-.16	-.07	-.20	-.00	-.08	.29	-.24	.09	-.17

Acc = Partial correlation with Accuracy, controlling for Satisfaction.

Sat = Partial correlation with Satisfaction, controlling for Accuracy.

CI = Cost Improvements: reduced cost or price versions of the product for the existing market;

PI = Product Improvements: new, improved versions of existing products/services, targeted to the current market;

LE = Line Extensions: incremental innovations added to existing product lines and targeted to the current market;

ME = Market Extensions: taking existing products/services to new markets;

NCE = New Category Entries: new-to-the-company product and new-to-the-company market, but not new to the general market;

NTW = New-to-the-World Products: radically-different products/services versus current offerings and markets served.

Bolded items are statistically different at $p < .10$.

n = sample size.

Table 7
Statistically significant differences between consumer and industrial firms

Characteristic	Statistical differences ($p < .10$)		
Department responsibility	<ul style="list-style-type: none"> ✓ Finance is responsible for new product forecasting in 10% of Consumer Firms versus 0% of Industrial Firms [$p < .05$] ✓ R&D is responsible for new product forecasting in 0% of Consumer Firms versus 7% of Industrial Firms [$p < .05$] 		
Average level of involvement	<ul style="list-style-type: none"> ✓ R&D is more involved in new product forecasting in the case of Industrial Firms (mean = 3.58, sd = 1.23) versus Consumer Firms (mean = 2.41, sd = 1.46) [$p < .05$] 		
Technique usage	<ul style="list-style-type: none"> ✓ 32% of Industrial Firms use Experience Curves to forecast Cost Improvements versus 0% of Consumer Firms [$p < .05$] ✓ 19% of Industrial Firms use Experience Curves to forecast Product Improvements versus 6% of Consumer Firms [$p < .05$] ✓ 51% of Industrial Firms use the Sales Force Composite Method to forecast Product Improvements versus 28% of Consumer Firms [$p < .05$] ✓ 11% of Consumer Firms use Simulation to forecast Product Improvements versus 2% of Industrial Firms [$p < .10$] ✓ 10% of Industrial Firms use Expert Systems to forecast Line Extensions versus 0% of Consumer Firms [$p < .05$] ✓ 50% of Industrial Firms use Jury of Executive Opinion to forecast Line Extensions versus 29% of Consumer Firms [$p < .05$] ✓ 62% of Industrial Firms use the Sales Force Composite Method to forecast Line Extensions versus 29% of Consumer Firms [$p < .05$] ✓ 9% of Industrial Firms use Expert Systems to forecast Market Extensions versus 0% of Consumer Firms [$p < .05$] ✓ 53% of Industrial Firms use the Sales Force Composite Method to forecast Market Extensions versus 29% of Consumer Firms [$p < .05$] ✓ 12% of Industrial Firms use Experience Curves to forecast New-to-the-World Products versus 2% of Consumer Firms [$p < .10$] ✓ 19% of Consumer Firms use Trend Line Analysis to forecast New-to-the-World Products versus 5% of Industrial Firms [$p < .10$] 		
Forecast accuracy	No statistical differences revealed		
Time horizon	<ul style="list-style-type: none"> ✓ Industrial Firms have a longer forecast time horizon across all types of new products than Consumer Firms (all statistically significant at $p < .05$, except line extensions which is statistically significant at $p < .10$): 		
	Type of new product	Consumer firms	Industrial firms
	Cost improvement	13.09 months (s = 6.47, n = 11)	24.60 months (s = 16.62, n = 20)
	Product improvement	16.08 (s = 12.70, n = 49)	23.53 (s = 17.68, n = 32)
	Line extension	17.85 (s = 19.59, n = 47)	25.88 (s = 17.27, n = 32)
	Market extension	16.58 (s = 13.62, n = 44)	31.88 (s = 21.74, n = 32)
	New category entry	16.54 (s = 8.65, n = 13)	48.29 (s = 41.76, n = 21)
	New-to-the-world	24.51 (s = 26.81, n = 45)	51.15 (s = 44.03, n = 33)

n = sample size.

s = standard deviation.

Differences in %'s for the areas of Department Responsibility and Technique Usage were evaluated using z-tests.

Differences in numbers for the areas of Average Level of involvement, Forecast Accuracy, and Time Horizon were evaluated using t-tests.

to-the-world products. Overall, the average forecast accuracy across all types of new products is 58%.

- Compared to consumer firms, industrial firms have

longer forecast time horizons and rely more on the sales force for new product forecasting.

Naturally, the exploratory nature of this study warrants continued study to confirm the present study's results, and delineate ways to improve the new product forecasting effort. Such process improvement is certainly needed given that the overall accuracy of new product forecasts is 58%. Indeed, this level of achieved forecast accuracy suggests that companies are either making approximately twice as much inventory as they need, or companies are meeting only half of the actual demand for a new product. Hence, efforts to improve accuracy can serve to improve new product success and business performance, that is, inventory, customer service, which corresponds to a direct bottom line impact. Satisfaction also may have a relationship with new product success and business performance, but maybe not as clear a relationship as forecast accuracy. A pending research question is which one of these constructs is more important for new product success and business performance? Or can new product forecast accuracy and satisfaction with the new product forecasting process be considered equally important to forecasting success and business performance? Study of other effectiveness measures like customer service, on-time delivery, inventory turns, profitability –to name a few, is warranted as well due to the uniqueness of each of these constructs coupled with their importance to new product commercialization and launch.

Another research avenue concerns customer/market research. Results show customer/market research, which actually encompasses a variety of approaches, to be the most popular new product forecasting technique. One possible explanation for such "popularity" is a perception that this technique may be important to new product forecasting success (although the empirical results of the present study failed to show that use of customer/market research correlates to higher forecast accuracy or greater satisfaction). A pending research question therefore is which types of customer research should be prescribed for predicting sales at launch, that is, concept tests, product use tests, market tests, specific tests within each of these categories, and so forth? While the present study has concentrated on forecasting efforts at launch, analysis should investigate that impact of forecasting at other stages in the new product development (NPD) process, especially with regards to how performing market research at various points during the NPD process can lead to better forecasts in the launch stage?

Three other research avenues are offered. One, research might consider examining the effects of type of market served and type of industry on new product forecasting parameters. Two, research might consider an in-depth examination into the decision-making processes that companies go through to develop and agree upon a new product forecast. And three, research might consider examining the causes and effects of overforecasting versus underforecasting on the respective company.

If there is any particular insight to be stressed from the present study, it is that new product forecasting should be conceived as more than just applying a forecasting tech-

nique and measuring the accuracy of that technique. Indeed, new product forecasting should be viewed as a process comprising the use of multiple techniques and the involvement of multiple departments with the goal to derive a sales estimate of what is most likely to occur. Although more research is needed to delineate the most preferable or even "best" process for new product forecasting, it is hoped that the present exploratory study has provided a foundation on which to base such study and stimulate ongoing discussion of the new product forecasting topic.

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Biographical Sketch

Kenneth B. Kahn, Ph.D. is an Assistant Professor of Marketing in the College of Business Administration at the University of Tennessee. His teaching and research interests concern product development, product management, sales forecasting, and interdepartmental integration. He has published in various journals, including *Journal of Product Innovation Management*, *Journal of Business Research*, *IEEE Transactions on Engineering Management*, *Marketing Management*, and *R&D Management*, and is the author of the book *Product Planning Essentials* (Sage Publications). Dr. Kahn is PDMA-certified as an NPD Professional.

Appendix

Description of forecasting techniques

Box-Jenkins Models: Box-Jenkins Techniques represent a set of advanced statistical approaches to forecasting, which incorporate key elements of both time series and regression model building. Three basic activities (or stages) are considered: (1) identifying the model, (2) determining the model's parameters, and (3) testing/applying the model. Critical in using any Box-Jenkins Technique is understanding the concepts of autocorrelation and differencing.

Customer/Market Research: Customer/Market Research represents typical market research activities. Customer feedback on current and/or new products would be collected to forecast customer demand patterns.

Decision Trees: Decision Trees are a probabilistic approach to forecasting. Various contingencies and their associated probability of occurring are determined. Conditional probabilities are then calculated, and the most probable events are identified.

Delphi Method: The Delphi forecasting method is based on subjective expert opinion gathered through several structured anonymous rounds of written interviews. Each successive round provides consolidated feedback to the respondents, and the forecast is further refined. The objective of the Delphi method is to capture the advantages of multiple

experts in a committee, while minimizing the effects of social pressure to agree with the majority, ego pressure to stick with your original forecast despite new information, the influence of a repetitive argument, and the influence of a dominant individual.

Diffusion Models: Diffusion models estimate the growth rate of product sales by considering various factors that influence consumers adopting a product. These models are typically employed for new product forecasting.

Experience Curves: Forecasting using experience curves is based on the assumption that as the cumulative production volume for a product rises, the cost of producing each unit falls according to a predictable curve. The slope of the line depends on the nature of the product and the manufacturing process.

Expert Systems: Expert Systems are typically computer-based heuristics or rules for forecasting. These rules are determined by interviewing forecasting experts and then constructing "if-then" statements. Forecasts are generated by going through various applicable "if-then" statements until all statements have been considered.

Exponential Smoothing Techniques: Exponential smoothing techniques develop forecasts by addressing the forecast components of level, trend, seasonality, and cycle. The weights or smoothing coefficients for each of these components are determined statistically and are applied to "smooth" previous period information.

Jury Of Executive Opinion: A forecast arrived at through the ad hoc combination of the opinions and predictions of informed executives and experts.

Linear Regression: Regression analysis is a statistical methodology that assesses the relation between one or more managerial variables and sales. As given in the name, linear regression assumes that those relationships are linear.

Looks-Like Analysis (Analogous Forecasting): Looks-Like Analysis attempts to map sales of other products onto the product being forecast. Typically, Looks-Like Analysis is employed for new product forecasting to determine what new product sales might be, given previous product introductions.

Market Analysis Models (Atar Model, Assumption-Based Models): Market analysis models attempt to model the behavior of the relevant market environment by breaking the market down into market drivers. Then by assuming values for these drivers, forecasts are generated.

Moving Average: A forecasting technique which averages only a specified number of previous sales periods.

Neural Networks: Neural Networks are advanced statistical models that attempt to decipher patterns in a particular sales time-series. In most cases, the models are proprietary.

Nonlinear Regression: Regression analysis is a statistical methodology that utilizes the relation between one or more managerial variables and sales. Nonlinear regression does not assume that those relationships are linear.

Pre-Cursor Method (Correlation Method): Pre-Cur-

Curve forecasting is a form of forecasting by analogy but a correlation is determined between the product to be forecast and other products. The product reflecting the highest correlation with the product to be forecast is selected as an analogous product. Once identified, forecasts are made by assuming that the product will follow the same pattern as the analogous product.

Sales Force Composite: Sales force composite method is a “bottoms-up” forecasting technique. Individuals (typically salespeople) provide their forecasts. These forecasts are then aggregated to calculate product line forecasts.

Scenario Analysis: This type of analysis involves the development of scenarios to predict what sales might be. Two types of scenario analysis include Normative and Ex-

ploratory approaches. The Normative approach leaps out to the future and works back to determine what should be done to achieve what is expected to occur. The Exploratory approach starts in the present and moves out to the future based on current trends.

Simulation: Simulation represents an approach to incorporate market forces into a decision model. “What-if” scenarios are then considered. Normally, simulation is computer-based. A typical simulation model is Monte Carlo simulation, which employs randomly generated events to drive the model and assess outcomes.

Trend Line Analysis: The objective of trend line analysis is to fit a line to a set of data. This can be done either graphically or mathematically.