Forecasting category sales and market share for wireless telephone subscribers: a combined approach

V. Kumar\textsuperscript{a,\ast}, Anish Nagpal\textsuperscript{b}, Rajkumar Venkatesan\textsuperscript{c}

\textsuperscript{a}ING Center for Financial Services, School of Business, Department of Marketing, University of Connecticut, Storrs, CT 06269-1041, USA
\textsuperscript{b}Bauer College of Business, Department of Marketing, University of Houston, Houston, TX 77204, USA
\textsuperscript{c}Department of Marketing, University of Connecticut, Storrs, CT 06269-1041, USA

Abstract

The ability to forecast market share remains a challenge for many managers especially in dynamic markets, such as the telecommunications sector. In order to accommodate the unique dynamic characteristics of the telecommunications market, we use a multi-component model, called MSHARE. Our method involves a two-phase process. The first phase consists of three components: a projection method, a ring down survey methodology and a purchase intentions survey. The predictions from these components are combined to forecast category sales for the wireless subscribers market. In the second phase, market shares for the various brands are generated using the forecast of the number of subscribers that are obtained in Phase 1 and the share predictions from the ring down methodology. The proposed methodology produces the minimum Relative Absolute Error for each market as compared to the forecasts from each individual component in the first phase. The value of the proposed model is illustrated by its application to a real world scenario. The managerial implications of the proposed model are also discussed.

\textsuperscript{\ast}Corresponding author. Tel.: +1-860-486-1086; fax: +1-860-486-8396. Analysts at AT&T forecasted a total of one million users today . . . and, paging is now celebrating the fifteenth year of its forecasted demise.’’

Jim Page, Vice President for Business Development FLEX™

1. Introduction

Analysts at AT&T forecasted a total of one million cellular subscribers in service by the year 2000. By 1993, the end of the first decade
of availability of cellular telephones, there were 16 million cellular telephones in use, with an additional 14,000 new users coming on line each day (Edwards & Dye, 1996). Table 1 compares the number of subscribers as forecasted by different agencies in 1995 to the actual number of subscribers by the end of 2000. As it can be seen in Table 1, different agencies underpredicted the number of cellular subscribers in Europe by the year 2000 to be between 11 million and 20 million. These validate long-held practitioner beliefs as evident in the above quote.

The telecommunications industry is facing continuous technological and regulatory changes. Jurisdictional differences are being removed and leading US carriers are forming joint ventures with foreign companies to enter new markets. As the industry becomes more competitive, consumers have benefited through lower prices, which have stimulated telecommunications demand to unprecedented levels. Techniques for forecasting the demands for product offerings over a planning horizon of several years are highly complex. Quantitative forecasting methods such as time series and econometric modeling have become less accurate because the industry no longer has the stable historical relationships that these models rely upon. The forecaster therefore needs to incorporate perceived future industry dynamics into the model (Ozturkmen, 2000).

There are several reasons why prediction in the telecommunications industry is a very difficult task. A representative issue is that the boundaries between television, computers and telecommunication products are being progressively eroded through the growth of the Internet and its service providers. Although data and message traffic is growing to enormous levels, this demand is being counterbalanced by substitution of technology (for example, email substitutes telephonic conversation) (Fildes, 2002). The introduction of new information technology significantly affects the demand for telecommunication services (Cristiano, 1993).

A person with forecasting responsibilities has three options. As the first option, he or she can use an intuitive approach—preparing forecasts based on his or her best judgment. The second option for the analyst would be to use a quantitative approach—preparing forecasts using statistical techniques such as regression and time series analysis. Finally, a combination of quantitative and intuitive approaches can be used. Specifically, a quantitative approach is used to arrive at a baseline forecast, and then the baseline prediction is adjusted by overlaying judgment to arrive at a prediction interval (Armstrong & Collopy, 1998).

Table 1
Comparison of forecast to the actual number of cellular subscribers

<table>
<thead>
<tr>
<th>Forecast horizon</th>
<th>Prediction in 1995</th>
<th>Actual outcome in 2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cellular subscribers in Europe by 2000</td>
<td>11.5 million (EMCI)</td>
<td>243 million in year 2000</td>
</tr>
<tr>
<td></td>
<td>16 million (ETCO)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>20 million (PA Consulting)</td>
<td></td>
</tr>
<tr>
<td>Cellular subscribers worldwide by 2000</td>
<td>100 million (Motorola)</td>
<td>689 million in year 2000</td>
</tr>
</tbody>
</table>

*Source: ITU, adapted from OECD (1995) “Mobile and PSTN communication services: Competition or complementarity?” and Micrologic Research.*
Instead of relying on intuition or using judgment, one could take the average of the independent forecasts to arrive at a more reliable forecast. This is the essence of the combination technique. The data can be from different sources or the methods used to forecast can be different, or both (Armstrong, 2001). The literature suggests that including forecasts from different statistical methods generally improves accuracy when significant trends are involved (Armstrong & Collopy, 1998). Using several sources of forecasts can add useful information and may adjust for biases. Instead of trying to choose the single best method, one should combine the results from different methods, which would help in reducing errors arising from faulty assumptions, biases, or mistakes in the data (Armstrong, 2001). For example, Fildes (1991) used three sources: a panel of experts, a naïve extrapolation and an econometric model for forecasting construction output. An equally weighted combined forecast from the three methods reduced the Mean Absolute Error (between predicted construction output and observed output) by 8%.

It is difficult to classify the wireless telephone industry as product-based or service-based. Wireless telephones can be categorized as a service with relatively slow replacement rates since the primary utility is enhanced communication facilities. However, they can also be categorized as a product, since the younger generation, in addition to the service features, derives utility from wireless telephones as a fashion accessory. The latter case leads to progressively accelerating replacement rates and low loyalty. The mobile telecommunication churn rate hovers around 30% (the reported values are based on a press release from Telebright Corporation and can be obtained from http://www.telebright.com/PressRelease0530.asp). This churn rate has a direct effect on the market share of each firm. The above mentioned issues make it necessary not only to capture the growth in the product category, but also to capture the shift in sales across firms and technologies (in other words, brand switching).

The brand switching behavior can be captured by implementing a brand level diffusion model. In order to implement such a model, one needs brand level data from the introduction of the product in the market. However, consider the following situation: category level sales data is available from introduction (1983/84) until the current time period (1992). Managers need category level subscriber forecasts and brand level market share estimates for the next two years. Given that data on the number of subscribers at the brand level is not available for the past, it is necessary to improvise to be able to address the needs of the manager in generating forecasts. In this study, we propose the use of multiple forecasting techniques to make accurate forecasts of future category sales of a new product and market shares of brands in that product category.

In line with the genuine concerns mentioned above, we use a multi-component model, called MSHARE, which involves a two-phase process. In the first phase, a ring down survey methodology, a purchase intentions survey, and a projection method are used to forecast category sales for the wireless subscribers market. In the second phase, estimates of market shares for various brands in the market are generated. The ring down method involves calling up a sample of telephone numbers for each firm in each market to estimate the number of wireless subscribers by brand in each market. In the projection method the total number of subscribers at the national level is estimated from historical secondary data on category sales, and these estimates are then scaled to the market level. The purchase intentions method involves conducting a survey and asking respondents about their likelihood of subscribing to a wire-
less service in the near future. We propose a methodology to combine the forecasts from these three different techniques that updates weights used in the combination of forecasts in a dynamic fashion.

The next section describes the literature on various market share forecasting models. Section 3 discusses our proposed framework, MSHARE. In Section 4 we provide an empirical illustration using data on subscribers for wireless service in three markets in the United States and discuss the results from our framework. We conclude the paper with discussions and implications of our proposed framework.

2. Forecasting category sales and market share

2.1. Market share

Many firms gear their company’s strategy to maximize their market share. There are various market share forecasting models: time series models, multiple linear regression models, logit models, and conjoint analysis models (Geurts & Whitlark, 1992–1993). In order to predict market share with univariate time series models, past market share values are used as input data to spot trends and patterns in the data. These methods are good when the relative prices and advertising expenditures remain constant over time. However, these methods do not capture the influence of marketing mix variables on market share.

Multiple linear regression models, also known as market response models, predict the influence of marketing variables on the market share. The regression coefficients thus obtained, allow inferences regarding elasticity of market share with respect to marketing mix elements. The input data for these models are the past market shares and the corresponding marketing mix variables. The use of market share models for forecasting was challenged when a study showed that a naive time series model, based on the previous market share, attains better forecasts (Brodie & De Kluyver, 1987; Alsem, Leefflang, & Reuyl, 1989). However, many recent studies (Kumar & Heath, 1990; Kumar, 1994; Brodie & Bonfrer, 1994) have shown that market share models in fact fare better than the naive time series models, thus assuring the forecasting utility of market share models. The validity and the generalizability of the out of sample performance of naive models have been questioned. Bass (1987) argued that market share models are typically misspecified as they exclude sales promotions. Also, Wittink (1987) argues that aggregate data used in market share models may not exhibit enough variability to render valid results. Kumar and Heath (1990) compared the OLS and the GLS estimates of the full and reduced market share models using disaggregate (weekly) data. In their study, the econometric models performed better than the naive models and they hypothesize that the reason for this is because of the use of disaggregate data and the inclusion of promotion variables. They also reason that naive models perform better than econometric models only when the econometric models are misspecified.

Logit models differ from the multiple regression models in the form of the dependent variable. An attraction model is represented as

\[ S_i = \frac{A_i}{\sum_j A_j} \]

where

\[ A_i = \exp \left( a_i + \sum_{k=1}^{K} b_k X_{ik} + e_i \right) \]

\[ S_i = \text{market share of brand } i; \ A_i = \text{attraction of brand } i; \ a_i = \text{constant influence of brand } i; \ e_i = \]
error term: \( X_k = k_{ih} \) marketing instrument such as advertising, promotions, etc.; \( b_k \) estimated coefficient for the \( k_{ih} \) marketing instrument.

One advantage of this model over the multiple regression models is that the forecasted market share is constrained between 0 and 1, which is not always the case with multiple regression models, wherein the forecasted market share can be greater than 1 or less than 0. There are many logit models that have been used to forecast market share (Jones & Zufryden, 1980). The “independence of irrelevant attributes” problem (Guadagni & Little, 1983) in logit models leads to misleading inferences regarding the influence of changes in values of independent variables (such as price) on market shares of all the brands in a market. Nested logit models are recommended in scenarios where such biases may be evident. In addition to the above problem, the issue of incorporating unobserved heterogeneity and endogeneity issues into a logit model makes the model framework intractable while leading to complex estimation algorithms.

In order to forecast the market share of new products, analysts typically use conjoint analysis (Cattin & Wittink, 1982). This is a survey-based technique wherein the respondent states his/her preference (0–100 points) for each product. A regression is run for each individual and the partworth utility for each product characteristic is obtained. The next step involves forecasting the market share by aggregating the partworths across individuals.

Diffusion models for predicting the market share are uncommon, as these models of market potential are used at the category level. However, Krishnan, Bass, and Kumar (2000) introduce a brand level diffusion model to predict the impact of a late entrant on the diffusion of various other brands of wireless phones in a given market. Specifically, the impact of a new entrant on the sales growth of the product category and the competitive effects on existing brands are measured. However, the brand level diffusion model may not be useful when the products are in the growth phase of their product life cycle due to estimation issues involved with Non-Linear Least Squares (NLS). In order to forecast brand level sales before the peak period, the use of Genetic algorithms is recommended (Venkatesan & Kumar, 2002). While the category sales can be forecasted using the discrete form of the Bass model, the brand level forecasts need the Bass model to be combined with multiple longitudinal surveys. Also, repeated surveys can examine the stability of the estimates. When combined with the observed and the estimated diffusion paths, it can provide for the convergence on the actual market potential (Fildes, 2002).

### 2.2. Category sales

Among the models used to forecast category sales of new products, the Bass (1969) diffusion model has been found to be very robust and accurate (Mahajan, Muller, & Bass, 1990). In established markets, competing brands maintain a rough state of equilibrium, and small changes in competitive activity may lead to very minor shifts in market share. Hence, a simple extrapolation model can provide sufficiently accurate forecasts. However, for large changes in competitive activity and where the market is dynamic (say, the telecommunications industry) multivariate forecasting techniques need to be used. Research about market share forecasting has been based largely on analyzing data about established markets for frequently purchased branded supermarket items. There is very little known about the accuracy of forecasting with respect to durables and services (Armstrong, 2001). This diffusion model, combined with the market share forecasts can help identify whether the shifts in the market shares are due to the increase in the category sales or otherwise.
2.3. Combining forecasts

There are three reasons why a combination of forecasts is recommended for forecasting market share of wireless subscribers. First, combining forecasts usually improves accuracy and decreases the variance of forecasting errors. Second, combination of forecasts provides a simple tool that even managers with relatively little experience can use. Finally, combining can be done with little or no increase in cost given the component forecasts (Mahmoud, 1989). In a survey of sales forecasting practices in the US, Dalrymple (1987) reports that on average, respondents used 2.7 forecasting methods on a regular basis. Approximately 40% of the firms combined forecasts. Most forecasts are a combination of a judgmental forecast and a quantitative forecast. In a study that combined four intentions-based methods to forecast the sales for existing consumer products and services, an equally weighted combination of forecasts reduced the Relative Absolute Error (RAE) from a typical intention method by 5.5% and by about one-third in comparison with a simple extrapolation of past sales (Armstrong, Morwitz, & Kumar, 2000). However, one word of caution is that managers must consider the costs that are involved in combining forecasts. The trade-off between higher cost (for generating the component forecasts) and improved accuracy needs to be evaluated. An analysis of costs can include the cost of forecasting error and the costs of implementing multiple forecasting procedures.

The naïve approach, or the benchmark, or the sales extrapolation method utilizes last period's sales to forecast the sales in the current period. More specifically, the current sales are equal to last period's sales plus a drift (Armstrong et al., 2000). The drift is calculated by estimating the annual percentage change rate by using a regression across time and then setting the drift at one-half of this rate. This method is adopted in line with the evidence on damping forecasts (Gardener & McKenzie, 1985).

In the next section, we describe the three forecasting methods that are used in our study.

3. MSHARE—An alternative framework

3.1. Methodology

The purpose of using MSHARE (see Fig. 1) is to capture different facets of forecasting. This methodology incorporates the dynamic nature of the forecasting environment, the preferences of the people, and the valuable information present in secondary data. Specifically:

1. The projection method utilizes macro level trend information from secondary data sources to obtain a market category forecast at the national level.
2. The ring down surveys capture dynamic shifts in consumer choice.
3. The purchase intention surveys capture expectations of consumers to purchase in the future, which are influenced by consumer expectations of future economic conditions.

3.1.1. Phase I—estimation of the number of wireless subscribers

In Phase I, we utilize three methods in order to forecast the overall category sales for a major wireless service provider and its competitors. The three individual components are briefly described below. Before we explain each method, let us review the forecasting scenario. A firm that deals in wireless products wishes to forecast its market share over a two-year horizon while constantly updating its expectations/forecasts at the end of each quarter. The implementation of MSHARE began in the year 1993. During that time, there were two firms operating in the markets that we are concerned
with. These two firms are referred to as Firm 1 and Firm 2 in the rest of the paper. In about 1995, other firms started entering the market and by about 1998, there were six firms operating in each of these markets.

**Projection method.** The projection method involves forecasting the total number of subscribers, using a Bass diffusion model, at the national level, and then scaling down these estimates to a market level. Let us assume the

---

**Fig. 1. MSHARE framework.**
current time period is January 1, 1998. Consider forecasting the number of subscribers as of December 31, 1998.

**Step 1.** From published sources, obtain the total number of subscribers nationwide (on an annual basis) until December 31, 1997.

**Step 2.** Use the above data to fit the diffusion model in order to arrive at a forecast for the number of subscribers in the year 1998, at a national level.

**Step 3.** Interpolate the estimate of the number of subscribers obtained for 1998 to a quarterly level, that is, interpolate to arrive at an estimate of the number of subscribers for each quarter in the year 1998, at a national level.

**Step 4.** Project these findings to a market level, that is, project the quarterly estimate of the number of wireless phone subscribers obtained nationwide to each market in the following manner:

- **Step 4a.** Define the target population (say for example, 18–64 year olds and annual income greater than $30,000) and obtain the number of households in the target population, nationwide.
- **Step 4b.** Obtain the number of households in the target population for each market.
- **Step 4c.** Compute the percentage of the number of households in the target population in a given market (say Market 1) relative to that of the target population nationwide (say $x_1\%$ of the target population resides in Market 1).
- **Step 4d.** Estimate the number of wireless phone subscribers in each market (say Market 1) by multiplying the total number of wireless phone subscribers (forecasted for the year 1998 and interpolated for each quarter) nationwide by the $x_1\%$ computed above. Thus, the number of wireless phone subscribers is estimated at a quarterly level, for each market.

Thus, the overall estimate ($E_p$) of the total number of subscribers in each market is obtained using the projection method.

**Ring down method.** The ring-down method involves telephoning a sample of numbers to estimate the number of subscribers of the brands in the market. In the ring down methodology, a sample of telephone numbers is dialed and, depending on the response, we assess if a particular number is active or not. If the phone is answered by a person or we hear an answering message, we label the number as being active. If we hear an automated response that indicates that the number that we have dialed does not exist, we label the number as being inactive. The advantage of using this method for the wireless subscriber market is that even when a customer does not answer the phone, the message by the service provider (or the customer) would allow one to learn whether the particular number is used by a customer or not. In order to sample customers, we use a systematic random digit dialing procedure. The Systematic Random Digit Dialing sampling procedure is a common technique for selecting respondents. This procedure has been commonly used to decide which numbers to call in order to conduct telephonic interviews (for example, see Fornell, 1992; Krieger & Green, 1996; Ganesh, Arnold, & Reynolds, 2000). The advantage of this technique over calling numbers listed in a directory is that the random digit dialing technique includes the possibility of dialing numbers that are unlisted, a possibility that cannot be entertained by using a telephone directory.

In order to aid better understanding, we briefly describe how the phone system works in the US. Each phone number (a ten-digit number, e.g. 860-487-1234) consists of three parts: The first three digits represent the area code (e.g.
numbers beginning with 860 belong to the Connecticut area). The next three digits form the ‘Prefix’ of the telephone number. For a given area code, there can be a number of prefixes (e.g., 487 in the above mentioned number is a prefix which belongs to an area in Connecticut). For a given prefix, there can be a maximum of 10,000 numbers (0000 to 9999), which form the last four digits. In the cellular phone market each service provider is allotted prefixes within which they can provide customers’ telephone numbers. Every quarter the new prefixes allocated to each brand are obtained from each service provider. Finding the prefix allocated to each service provider significantly reduces the number of telephone numbers that need to be sampled in order to estimate the number of subscribers. Once the prefixes are found, the next task is to estimate the number of customers that have subscribed to the particular service provider with each prefix. The steps we adopt to estimate this are outlined below:

Again, consider estimating the number of active wireless phone subscribers, say as of December 31, 1998.

**Step 1.** We obtain the area codes and prefixes that belong to the corresponding firms from the respective service providers.

**Step 2.** For each firm, we implement the Systematic Random Digit Dialing (SRDD) process. We call 400 \((n)\) numbers for a given area code and prefix. Once we fix an area code and a prefix, we dial 400 numbers out of a possible 10,000 \((k)\). The first step in the SRDD process is to compute the sampling interval \((L)\), which is calculated by the formula, \(L = k/n\). In our case, the sampling interval is 25. We then choose a random telephone number, in the interval 0000–9999. Once a number is chosen (say, 860-487-1025), then, to generate additional numbers, the value of \(L\) (25) is added to each of the previously selected numbers (Kumar, Aaker, & Day, 2002).

**Step 3.** A call log, in which the response for each call is recorded, is maintained in order to estimate the number of active/inactive numbers in each prefix. The call log would allow us to estimate the number of active customers for a service provider within each prefix.

**Step 4.** To validate, we repeat the entire process (by choosing a different starting value) to check for the convergence of the estimates.

One thing to be noted here is that we call a sample of 400 numbers (just 4%) in a given area code to estimate the number of subscribers, from a population of 10,000 numbers. (There are a total of 10,000 numbers in a given area code, from 0000 to 9999.) If the number of active numbers estimated above by the sampling procedure is 200 out of the 400 numbers dialed, it would mean that 50% of the numbers are active. This percentage is then extrapolated to arrive at the number of 5000 active numbers out of a possible 10,000, in a particular area code and prefix. We repeat this process for all the prefixes in each market.

The level of accuracy of the estimates is not reliable because we sample only 4% of the population. The lower sample size necessitates the importance for using the combination method. Since we had the entire population data for one of the firms (Firm 1), we used the above method only to project the number of active numbers of the competitors. However, in order to test the validity of this method, the results obtained by this method were first compared to the actual population data of Firm 1. The number of subscribers estimated by this method is comparable with the actual population data of Firm 1. The direction and the magnitude of the bias that existed in the ring down estimates for Firm 1 is noted in terms of percentage and
adding the other firm’s estimates. Finally, the 
estimates of the number of subscribers for each firm are added up to arrive at an overall 
estimate ($E_n$) of the total number of subscribers 
for each firm in each market.

Purchase intentions method. Purchase intentions are 
often used to forecast sales of existing consumer durables and 
new consumer products (Morrison, 1979; Lehmann, 1989). In 
many instances, the purchase intention measure is 
easy to acquire and is inexpensive, which 
accounts for its use by many managers. There is 
well-documented evidence that purchase intentions 
are positively correlated to behavior (Morwitz & 
Schmittlein, 1992; Morwitz, Steckel, & 
Gupta, 1996), and that the purchase intention 
measure can improve forecasting over a simple 
extrapolation of sales trends (Armstrong, 
Morwitz & Kumar, 2000). Intention surveys that 
were used to predict the effects of a possible 
entrant on the Dutch advertising-media market 
for branded goods and services obtained more 
accurate forecasts than those based on expert 
opinions (Alsem & Leeflang, 1994). Thus, 
intentions data have proven to be a valuable 
input to sales forecasts.

Also, the purchase intentions of the respondents may 
change over time because of exogenous 
events. It is also possible that the average 
stated purchase intentions score might be a 
biased estimate of the proportion that actually 
buy the product because of systematic error, for 
example, response style biases (Morrison, 
1979). Since we had the actual sales data and 
the purchase intentions data, we used Mor- 
rison’s framework to formulate a predictive 
model:

\[
\text{Percent of buyers (t)} = \frac{\text{mean intent (t)}}{\text{bias (t - 1)}}
\]

The mean intent is computed as a number 
between 0 and 1, using the current year’s 
intentions data. The bias is estimated by taking 
the difference between the mean intentions and 
the percent that purchased during the previous 
year (Armstrong, Morwitz & Kumar, 2000).

In our study, the purchase intention measure 
was collected through primary research 
spurred by a commercial firm. Consider forecasting 
the number of subscribers as of December 
31, 1998, and the information is available until 
December 31, 1997. Four hundred telephone 
surveys were completed every quarter to assess 
the propensity to subscribe to wireless service 
within the next 2, 3, 6 and 12 months in each 
market. The survey was restricted to a target 
population between the age group 18–64 with 
an annual income of $30,000 or greater. This 
survey is repeated at the beginning of each 
subsequent quarter, which gives us an estimate 
of the number of subscribers for the end of 
every quarter. Respondents who met the target 
market criteria were asked about their purchase 
expectations for wireless telephone service. The 
purchase intention question was, “How likely are you to subscribe to wireless service in the 
next $X$ months?” The value of $X$ was varied as 
2, 3, 6 and 12 months. The choices for the 
response were Definitely, Probably, Might, 
Probably Not, and Definitely Not. After each 
quarter, the respondents are contacted again and 
asked if they had subscribed to a wireless 
service. This helped us calculate the bias (see 
Eq. (1) above). From this value of the mean 
intent (see Eq. (1) above), we subtract the bias 
calculated in the previous time period. Once the 
measure at time period $t$ is obtained, this bias is 
updated. We also collected demographic data in 
order to profile the prospects. Once the percentage 
of buyers forecasted to purchase a 
wireless phone is calculated by using the above 
mentioned formula, it is used to calculate the 
number of people (say, $X_t$) for the “twelve 
months’ question) who might buy in the target 
population. $X_t$ is then added to the cumulative 
umber of subscribers prior to conducting the 
survey to arrive at a forecast of the number of 
subscribers in the next year. 

An estimate ($E_n$) of the total number of
subscribers in each market is obtained using the purchase intentions method.

Reconciling $E_g$, $E_p$, and $E_s$. The multi-component model, MSHARE, is unique as it uses secondary data (from secondary sources) as well as primary data (from the ring down methodology and purchase intentions surveys) in order to forecast the category sales and market share for wireless service providers through a diffusion model framework. In the first period, we give equal weights to the three methods in order to estimate the total number of wireless subscribers. At the beginning of the second period, once the actual number of subscribers for the previous period is known (available through trade publications), the combination weights are adjusted in order to minimize the error. The adjusting of weights involves a trial and error procedure. The combination of weights that gives the minimum difference between the actual sales and forecasted sales is chosen. In the second period, we use these adjusted weights to estimate the number of subscribers. Again, at the beginning of the third period, the estimate is compared to the actual number of subscribers in the second period, and the weights are recalibrated. This process continues till the weights stabilize. The integration of the three methods is shown in Fig. 1.

Our multi-component framework—MSHARE—(of combining the three methods) is similar to the ASSESSOR (Silk & Urban, 1978; Urban & Katz, 1983) model, wherein the task of predicting the brand's market share and sales volume is approached through the trial/repeat and attitude models. Convergent results from the two models strengthen the confidence in the results while divergent results indicate the need for further analyses. MSHARE and ASSESSOR are similar in the sense that both the models use a combination of forecasting techniques. However, they are different in terms of the inputs to the model. First, the ASSESSOR model is used before the product is launched to assess if it is worthwhile to launch the new product, whereas MSHARE is a post product launch forecasting tool. Second, the ASSESSOR model uses the trial/repeat measures (laboratory experiment) and attitude measures to forecast the market share, whereas MSHARE uses an intentions measure, a ring down technique and a projection technique (using secondary data and diffusion model) to forecast category sales and market share. Also, while the ASSESSOR technique is primarily laboratory based, MSHARE uses secondary data and primary data to arrive at the forecasts of market share ultimately.

Algorithm for combining forecasts. Assume that the current time period is the first quarter of 1998 and that we are trying to estimate the number of subscribers as of December 31, 1998. The triangulation of methods begins in the first quarter of 1998.

- A market survey is conducted in each market in order to assess the propensity to subscribe to a wireless service within the next 2, 3, 6 and 12 months. The expected numbers of new subscribers are added to the total number of subscribers up until the previous period to get an estimate of $E_s$ for each market, for the first quarter of 1998, as described previously.
- A diffusion model is run on national level data using the data available up until the previous year, in order to assess the market behavior for wireless services. These forecasts, which are at the national level, are then projected to the regional (market) level. This gives us an estimate of $E_p$ for each market, for the first quarter of 1998.
- The ring down methodology is conducted in each market for each firm in that quarter. This gives us an estimate of $E_r$ for each market, for the first quarter of 1998.
- The estimates from the three methods are weighted equally to arrive at an estimate of the number of subscribers as of the first quarter in 1998 in each market.
- This new data point is then added to the
previous data points of the total number of subscribers in each market. A diffusion model is run on this data (with the new data point) to forecast the number of subscribers in 1998 and 1999. (The reason the brand level diffusion procedure suggested by Krishnan et al. (2000) is not possible is due to the lack of brand level information prior to 1993 in all the markets.)

- This forecast is then interpolated to arrive at an estimate of the number of subscribers in each market in each quarter. The above mentioned process is repeated every quarter to obtain forecasts for the next two years (i.e. next 8 quarters).

- The equally weighted forecast is then compared to the actual number of subscribers (which is typically available at the beginning of the next quarter). These weights are adjusted so as to minimize the difference between the actual number and the forecast from MSHARE. At the end of the second quarter (in June 1998), when the estimates from the three methods are combined, these adjusted weights are used to arrive at a forecast of the number of subscribers. This new data point is then added to the previous data points and a diffusion model is run to arrive at an updated forecast for the number of subscribers by the end of the year 1998. This adjusting procedure continues until the weights stabilize.

3.1.2. Phase II—Estimation of the market share of each firm in each market

The computation of the market share for each firm is explained below. We assume that two firms, Firm 1 and Firm 2, represent the entire market, that is, Firm 1 and Firm 2 together constitute 100 percent of the market.

Suppose MSHARE forecasts the number of subscribers at the end of March 1998 to be \( N \) in Market 1. Also, the ring down methodology carried out at the end of the quarter estimates the number of subscribers at the end of the quarter in Market 1 to be \( n_1 \) and \( n_2 \), for Firm 1 and Firm 2 respectively. In the ideal case, the sum of \( n_1 \) and \( n_2 \) should be equal to \( N \). Then, the market share of Firm 1 (\( MS_1 \)) is \( n_1/N \) and the market share of Firm 2 (\( MS_2 \)) is \( n_2/N \). However, this is seldom the case. Invariably, the sum total \((n_1 + n_2)\) will be greater than or less than \( N \). For example, if \( N \), the MSHARE forecast, is greater than the sum of \( n_1 \) and \( n_2 \) by 10%, the ring down estimates for Firm 1 and Firm 2 respectively are increased by 10%. To reconcile this difference, we add 10% to the ring down estimates, \( n_1 \) and \( n_2 \). Thus, \( n_1' = 1.1*n_1 \) and \( n_2' = 1.1*n_2 \). Then, the market shares of the two firms, \( MS_1 \) and \( MS_2 \), are calculated as, \( MS_1 = n_1'/N \) and \( MS_2 = n_2'/N \), for Firm 1 and Firm 2 respectively, in Market 1. This can be extended to more than two firms.

4. Analysis and results

4.1. Phase I—Estimation of the number of wireless subscribers

**Projection method.**

**Step 1.** From published sources, we obtain the total number of subscribers nationwide (on an annual basis) up until December 31, 1997. The total number of subscribers nationwide ranges from 36,000 in 1983 to about 50 million in 1997 (see Fig. 2).

**Step 2.** We use the above data to fit the diffusion model in order to arrive at a forecast for the number of subscribers in year 1998, at the national level. This estimate is approximately 56 million (see Fig. 2) subscribers. The diffusion models result in an innovation coefficient \((p)\) of 0.002 and an imitation coefficient \((q)\) of 0.587. The estimates indicate that word of mouth communication dominates the wireless telecommunications market.
Step 3. We interpolate the estimate of the number of subscribers obtained for the year 1998 (56 million as mentioned above) to a quarterly level. This interpolation results in a forecast of approximately 47 million subscribers at the end of the first quarter in 1998, approximately 49 million subscribers at the end of the second quarter in 1998, approximately 51 million subscribers at the end of the third quarter in 1998, and approximately 56 million subscribers at the end of the fourth quarter in 1998.

Step 4. We then project these findings to the market level. First, we compute the percentage of the number of households in the target population in a given market (say Market 1) relative to that of the target population nationwide. Approximately 2% of the target population nationwide resides in Market 1. We then estimate the number of wireless phone subscribers in each market (say Market 1) by multiplying the total number of wireless phone subscribers (forecasted for year 1998 and interpolated for each quarter) nationwide by 2%. Thus, the number of wireless phone subscribers, estimated at a quarterly level, for Market 1 is approximately 940,000 at the end of the first quarter in 1998, approximately 970,000 at the end of the second quarter in 1998, approximately 1 million at the end of the third quarter in 1998, and approximately 1.12 million at the end of the fourth quarter in 1998. The number of wireless subscribers for each quarter in 1998 was computed for Markets 2, 3 and 4 in a similar fashion. Thus, \( E_p \) is estimated in this manner.

Ring down methodology. Table 2 provides a sample of the results of the ring down methodology for Firm 1 in Market 1 conducted at the end of the first quarter (March 1998). As mentioned earlier, a SRDD process is implemented wherein we fix an area code and a prefix, and then dial 400 numbers out of a possible 10,000. In order to implement this process, we first obtain the prefixes from the respective firms. The total number of area code and prefixes serviced by Firm 1 in Market 1 is 100. Similarly, the total number of area code and prefixes serviced by Firm 2, 3, 4, 5 and 6 are 96, 16, 10, 11 and 10 respectively. As it can be seen from the first row of Table 2, out of the 400 numbers dialed for area code XYZ1 and
Table 2
A sample of the ring down methodology. (Firm 1 in Market 1)

<table>
<thead>
<tr>
<th>Area code*</th>
<th>Prefix*</th>
<th>Range</th>
<th>Active numbers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>XYZ1</td>
<td>ABC1</td>
<td>0000–9999</td>
<td>5050</td>
</tr>
<tr>
<td>XYZ2</td>
<td>ABC2</td>
<td>0000–9999</td>
<td>125</td>
</tr>
<tr>
<td>XYZ3</td>
<td>ABC3</td>
<td>0000–9999</td>
<td>1550</td>
</tr>
<tr>
<td>XYZ4</td>
<td>ABC4</td>
<td>0000–9999</td>
<td>800</td>
</tr>
<tr>
<td>XYZ5</td>
<td>ABC5</td>
<td>0000–9999</td>
<td>100</td>
</tr>
<tr>
<td>XYZ6</td>
<td>ABC6</td>
<td>0000–9999</td>
<td>4850</td>
</tr>
<tr>
<td>XYZ7</td>
<td>ABC7</td>
<td>0000–9999</td>
<td>4825</td>
</tr>
<tr>
<td>XYZ8</td>
<td>ABC8</td>
<td>0000–9999</td>
<td>600</td>
</tr>
<tr>
<td>XYZ9</td>
<td>ABC9</td>
<td>0000–9999</td>
<td>4700</td>
</tr>
<tr>
<td>XYZ10</td>
<td>ABC10</td>
<td>0000–9999</td>
<td>3900</td>
</tr>
<tr>
<td>XYZ11</td>
<td>ABC11</td>
<td>0000–9999</td>
<td>5000</td>
</tr>
<tr>
<td>TOTAL</td>
<td></td>
<td></td>
<td>405,025</td>
</tr>
</tbody>
</table>

* The area code and the prefix are not mentioned for confidential reasons.

prefix ABC1, approximately 50.5% of the numbers were active. This percentage was then extrapolated to arrive at the number of 5050 active numbers out of a possible 10,000, in a particular area code and prefix. We repeat this process for all the prefixes in each market. For example, there are 100 prefixes in Market 1. In each of those 100 prefixes, we called up 400 numbers to arrive at the estimate of the number of active wireless subscribers. According to the ring down estimate, the total number of wireless subscribers of Firm 1 (as of March 31, 1998) is determined to be 405,025, 13,800, 401,835 and 236,575 in Markets 1, 2, 3 and 4 respectively. Similarly, for Firm 2, the total number of wireless subscribers, as of March 31, 1998, is determined to be 390,000, 12,875, 326,462 and 100,023 in Markets 1, 2, 3 and 4 respectively. The number of subscribers for the Firms 3, 4, 5 and 6 are computed in a similar fashion. Thus, $E_R$ is estimated by adding the number of subscribers for Firms 1, 2, 3, 4, 5 and 6 in each market. This results in an $E_R$ value of 900,000 (405,025 + 390,000 + ⋯) subscribers for Market 1 at the end of the first quarter 1998.

Purchase intentions method. Four hundred telephone surveys were completed at the beginning of the first quarter of 1998 to assess the propensity to subscribe to a wireless service within the next 2, 3, 6 and 12 months. Respondents who met the target market criteria were asked about their purchase expectations for wireless telephone service. From this survey, the mean intent was converted to a number between 0 and 1. The bias was then subtracted from the mean intent measure. About 19% of prospects are expected to subscribe to the wireless service within the next 3 months. This projection is based on the assumption of current market conditions prevailing over the next 12 months. The total number of subscribers at the end of the first quarter of 1998 is forecasted to be approximately 1.08 million in Market 1. Thus, $E_S$ is estimated in this manner.

Reconciling $E_R$, $E_P$ and $E_S$.

- As mentioned above, we have the estimate of the number of wireless subscribers from the three methods in Market 1 at the end of the first quarter in 1998 (in March 1998). Specifically, for Market 1, $E_P = 940,000$, $E_S = 1,080,000$ and $E_R = 900,000$.
- The estimates from the three methods are weighted equally to arrive at an estimate of the number of subscribers as of March 1998 in each market. This results in approximately 963,000 (0.33*940000 + 0.33*1080000 + 0.33*900000) subscribers at the end of the first quarter 1998 in Market 1.
- The secondary dataset is augmented using the forecasted category sales. A diffusion model is run on the augmented data to forecast the number of subscribers by the end of the year 1998 in Market 1. This results in an updated forecast.
- This forecast is then interpolated to arrive at an estimate of the number of subscribers in
each market in each quarter. Thus, the number of wireless phone subscribers, after the reconciliation of the estimates from the projection method, purchase intention survey method and the ring down method, is estimated to be approximately 963,000 at the end of the first quarter in 1998, approximately 1.01 million at the end of the second quarter in 1998, approximately 1.07 million at the end of the third quarter in 1998, and approximately 1.15 million at the end of the fourth quarter in 1998.

- The equally weighted forecast is then compared to the actual number of subscribers (which is now available at the end of the first quarter). These weights are adjusted so as to minimize the difference between the actual number and the forecast from MSHARE. At the end of the second quarter (in June 1998), when the estimates from the three methods are combined, these adjusted weights are used to arrive at a forecast of the number of subscribers. This new data point is then added to the previous data points and a diffusion model is run to arrive at an updated forecast for the number of subscribers by the end of the year 1998. This adjusting procedure continues until the weights stabilize.

For the first period forecasts, we use equally weighting for the three methods. As can be seen in Table 3, in the first period, we give an equal weighting of 0.33 for the ring down estimate ($E_R$), the projection method estimate ($E_P$), and the purchase intentions method ($E_I$). For the second period, we give a weight of 0.40 to ring down method, 0.30 to the projection method, and 0.30 to the purchase intentions method. The entire process of readjusting the weights is repeated until the weights stabilize. In our study, the stabilized weights for ring down, projection, and survey are 0.60, 0.20 and 0.20 respectively. The combination weights are robust to different starting values and under repeated analyses, converged quickly to the same values.

### 4.2. Phase II—Estimation of the market share of each firm in each market

The computation of the market share is the same as described earlier. The data is available from 1993 to 1997. MSHARE forecasts the number of subscribers at the end of March, 1998 to be 963,000 ($N$). Also, the ring down methodology carried out at the end of the quarter estimates the number of subscribers at the end of the quarter to be 405,025 ($n_1$) and 390,000 ($n_2$), for Firm 1 and Firm 2 respectively, in Market 1 (the two major firms in that market). Ideally, the sum of the number of subscribers for each firm ($n_1$ through $n_k$) should be equal to $N$. In this case, $N$, the MSHARE forecast, is greater than $n_1 + n_2 + n_3 + n_4 + n_5 + n_6$, the ring down estimates for Firms 1, 2, 3, 4, 5 and 6 by approximately 7%. To reconcile this difference, we add 7% to the ring down estimates of all the firms ($n_1$ through $n_k$). Thus, for example, $n'_1 = 433,376$ approximately and $n'_2 = 417,300$ approximately. The market share for each firm is calculated as $n_i/N$. For example, the market shares for Firm 1 and Firm 2 are calculated as, $MS_1 = 45\%$ ($n'_1/N$) and $MS_2 = 43\%$ ($n'_2/N$) respectively, in Market 1 (see Fig.

<table>
<thead>
<tr>
<th>Period</th>
<th>Ring down method</th>
<th>Projection method</th>
<th>Primary research method (Intentions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.33</td>
<td>0.33</td>
<td>0.33</td>
</tr>
<tr>
<td>2</td>
<td>0.40</td>
<td>0.30</td>
<td>0.30</td>
</tr>
<tr>
<td>3</td>
<td>0.52</td>
<td>0.26</td>
<td>0.22</td>
</tr>
<tr>
<td>4</td>
<td>0.60</td>
<td>0.22</td>
<td>0.18</td>
</tr>
<tr>
<td>5</td>
<td>0.60</td>
<td>0.21</td>
<td>0.19</td>
</tr>
<tr>
<td>6</td>
<td>0.60</td>
<td>0.20</td>
<td>0.20</td>
</tr>
</tbody>
</table>
projection, and purchase intention) with the MSHARE method.

Our proposed methodology, MSHARE, produces the minimum RAE for each market. The RAE in MSHARE for Markets 1, 2, 3 and 4 are 0.58, 0.61, 0.62 and 0.57 respectively as compared to the RAES from each individual component—ring down method (RAE ranging from 0.71 to 0.74), projection method (RAE ranging from 0.74 to 0.79), and primary research method (RAE ranging from 0.76 to 0.80). In Market 1, as we can see from the figures, the ring down methodology leads to a 28% reduction in error compared to the naïve sales extrapolation method. Similarly, the projection method and the primary survey methods lead to a reduction in error by 22% and 24% respectively. However, the MSHARE methodology leads to a reduction of 42% in error compared to the naïve sales extrapolation approach in Market 1, lending evidence to the superior performance of this approach.

5. Discussion and implications

The literature on combining forecasts is unequivocal. For example, Meade and Islam (1998) undertook the examination of extrapolation models for telecommunications forecasting. Using seven forecasting methods and 47 data sets, they found that for 77% of the forecasts, the combined forecast was more accurate than the respective individual forecasts. Previous research has relied on either combining forecasts from two or more surveys (Baker, West, Moss, & Weyant, 1980), or combining the judgment of more than one professional (Batchelor & Dua, 1995), or using judgmental and extrapolation methods (Lobo & Nair, 1990), or combining judgmental and econometric modeling forecasts (Weinberg, 1986). The multi-component model, MSHARE, is unique as it uses secondary data (from secondary sources) as well
as primary data (from the ring down methodology and purchase intentions surveys) in order to forecast the category sales and market share for wireless service providers through a diffusion model framework.

Given the following factors—lower prices, more wireless features, intense competition, higher awareness, and multiple phone households among others—the estimate for market potential should increase. Necessitated by the dynamic nature of the industry, better and more reliable forecasting tools are important for any firm and hence the updating of forecasts to reflect current market conditions. The MSHARE methodology updates the forecasts of the number of wireless subscribers on a quarterly basis.
Fig. 5. Trend plot of market share in Market 1 for Firms 3, 4, 5 and 6 (number of wireless phones). Please note that the above plot of market shares for Firms 3, 4, 5 and 6 are the forecasted values only. These values were close to the actual values.

Table 4
Relative Absolute Errors of the ring down method, projection method, and purchase intentions method compared with those produced by the combination of the three methods (MSHARE)

<table>
<thead>
<tr>
<th>Market</th>
<th>Ring down method</th>
<th>Projection method</th>
<th>Primary research method (Intentions)</th>
<th>MSHARE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market 1</td>
<td>0.72</td>
<td>0.78</td>
<td>0.76</td>
<td>0.58</td>
</tr>
<tr>
<td>Market 2</td>
<td>0.74</td>
<td>0.79</td>
<td>0.80</td>
<td>0.61</td>
</tr>
<tr>
<td>Market 3</td>
<td>0.71</td>
<td>0.74</td>
<td>0.77</td>
<td>0.62</td>
</tr>
<tr>
<td>Market 4</td>
<td>0.72</td>
<td>0.76</td>
<td>0.79</td>
<td>0.57</td>
</tr>
</tbody>
</table>

The values in the cells are the Relative Absolute Errors.
The benchmark method used is the Sales Extrapolation Method (Armstrong, Morwitz & Kumar, 2000).

In the first period of estimation, we give equal weights to the three methods. At the end of the period, the weights are adjusted in order to minimize the error. In the second period, we use the adjusted weights to forecast the number of subscribers. Again, at the end of the second period, the estimate is compared to the actual number of subscribers, and the weights are recalibrated. This process continues till the weights stabilize. The stabilized weights for ring down, projection, and survey methods are 0.60, 0.20, and 0.20 respectively. As can be noted, the ring down method gets the highest weight and the projection and the survey methods get equal weights. This suggests that the ring down methodology is the strongest predictor of the number of subscribers, but it is only when a combination is used, do you maximize the prediction accuracy.

The ring down methodology captures the dynamic shifts in the consumer’s choice. The purchase intention measure captures consumer expectations, which are determined partially by their expectations of future prices and supply conditions, and the projection method uses variation in the macro-level data in order to make long-term forecasts. MSHARE produces the minimum Relative Absolute Error as compared to using the three methods individually. An examination of the combination weights...
across the years reveals that while ring down methodology is able to provide more accurate forecasts during the maturity phase of the market, the purchase intentions measure contributes more during the initial phases of the product life cycle. This finding is congruent with Armstrong et al. (2000) and the basic assumptions of the ASSESSOR model.

Future studies can investigate the utility of MSHARE in other product markets in order to assess how the relative utility of various components varies across products and across markets. Also, we use a simple trial and error methodology to update the weights of the various components in our model; future studies can investigate whether a Bayesian updating procedure is able to produce more accurate weights and henceforth better forecasts. In our current study, we use the Bass model at the category level to forecast category sales. However, when enough data points at the brand level are obtained using the current methodology, a brand level diffusion model (Krishnan et al., 2000) can be used, in lieu of the ring down methodology to predict market shares. The brand level diffusion model requires more data points for estimation because it does not have a discrete form like the Bass model and therefore cannot be estimated using Ordinary Least Squares when there are a few data points. Another issue which can be raised is the non-availability of data points in the pre-take-off phase. However, when the data is censored (in this case, left-censored), it is reasonable to assume that the brands during the pre-take-off phase had equal market shares, given the marketing power of the two firms. Also, once the brand level diffusion model is implemented, the marketing mix variables can be added into the model to study their effect on product diffusion.

Managers need to realize the importance of combining forecasts (for market share and other economic predictors) so that the forecasting error is minimized and there is proper allocation of resources. One could argue that the combination of methods is an expensive option. To the extent that the advantage of reducing forecasting error is greater than the cost of developing each individual forecast, one should strive to combine forecasts. In the short run, the proposed method may be an expensive option. However, once set in place, the advantages are many. Further, as the market approaches maturity, the use of a category level and brand level diffusion model is sufficient. In summary, MSHARE appears to be a useful framework when brand level forecasts are needed in evolving markets, and when brand level sales information is unavailable.

Acknowledgements

The authors thank the editor-in-chief, the reviewers, Robert Fildes, Frank M. Bass, Trichy V. Krishnan and Jaishankar Ganesh for their helpful comments on earlier versions of this manuscript. Special thanks are owed to Renu for copy-editing this paper.

References


**Biographies:**

Anish NAGPAL is a doctoral student in marketing at the University of Houston. He has a Masters in Management Studies and Economics from the Birla Institute of Technology and Science, India. His research interests include influence of econometric models in managerial decision making and the effects of framing on the persuasiveness of messages.

V. KUMAR (VK) is the ING Chair Professor of Marketing, and Executive Director, ING Center for Financial Services in the School of Business, University of Connecticut. He has been recognized with many teaching and research excellence awards and has published numerous articles in many scholarly journals in marketing including the *Harvard Business Review, Journal of Marketing, Journal of Marketing Research, Marketing Science,* and *Operations Research*. He has co-authored multiple textbooks on *Marketing Research*. His interest in International and Forecasting area is very well reflected by his research publications in many major journals including the *International Journal of Forecasting, Journal of International Marketing, International Journal of Research in Marketing*, and the *Journal of World Business*. He has authored a book titled *International Marketing Research*, which is based on his marketing research experience across the globe. He is on the editorial review board on many scholarly journals and has lectured on marketing-related topics in various universities and organizations worldwide. His current research focuses on international diffusion models, customer relationship management, customer lifetime value analysis, sales and market share forecasting, international marketing research and strategy, coupon promotions, and market orientation. He served on the Academic Council of the AMA as a Senior V.P. for Conferences and Research and a Senior V.P. for International Activities. He was recently listed as one of the top fifteen scholars in marketing worldwide. He is a consultant for Fortune 500 firms and has also worked with these companies’ databases to identify profitable customers. He received his Ph.D. from the University of Texas at Austin.

Rajkumar VENKATESAN is Assistant Professor of Marketing at the University of Connecticut. He has a Bachelors degree in Computer Science and Engineering from University of Madras. Raj’s research interests include Customer Relationship Management, Customer equity vs. firm value, E-Business models, and new product innovations. He is the winner of the 2001 Alden G. Clayton Dissertation Proposal award from the Marketing Science Institute, the 2001 ISBM Doctoral Dissertation competition Outstanding Submission award and the Best Track Paper Award in the 1999 American Marketing Association Winter Marketing Educator’s Conference.