The challenges of pre-launch forecasting of adoption time series for new durable products

Paul Goodwin*

Sheik Meeran

Karima Dyussekeneva

School of Management
University of Bath
Bath
BA2 7AY
United Kingdom

Email: mnspg@bath.ac.uk

Tel: 44 (0)1225-383594
Fax: 44 (0)1225-386473

***Corresponding author**

31 May 2014

The challenges of pre-launch forecasting of adoption time series for new durable products

ABSTRACT

The successful introduction of new durable products is important in helping companies to stay ahead of their competitors. Decisions relating to these products can be improved by the availability of reliable pre-launch forecasts of their adoption time series. However, producing such forecasts is a difficult, complex and challenging task mainly because of non-availability of past time series data relating to the product and the multiple factors that can affect adoptions such as customer heterogeneity, macro-economic conditions following the product launch and technological developments which may lead to the product's premature obsolescence. This paper critically reviews the literature to examine what it can tell us about the relative effectiveness of three fundamental approaches to filling the data void : i) management judgment, ii) analysis of judgments by potential customers and iii) formal models of the diffusion process. It then shows that the task of producing pre-launch time-series forecasts of adoption levels involves a set of sub-tasks, which involve either quantitative estimation or choice, and argues that the different nature of these tasks means that forecasts are unlikely to be accurate if a single method is employed. Nevertheless, formal models, rather than unstructured judgment should be at the core of the forecasting process. Gaps in the literature are identified and the paper concludes by suggesting a research agenda to indicate where future research efforts might be most profitably employed.

Key words

new product forecasting; judgment; diffusion models; choice models

1. Introduction

The introduction of new products is crucial to the success and survival of many companies. However, forecasting whether new products will be successful is one of the most difficult tasks faced by managers (Wind, Mahajan, & Cardozo, 1981) and huge costs can be associated with failed products. New product forecasting is therefore a critical activity and, not surprisingly, a large number of methods have been developed to produce these forecasts. Indeed by the mid 1980s Assmus (1984) found the number of methods too numerous to include in his review paper and many new techniques have been developed in the intervening years. The forecasts produced by these methods can be used to guide decisions made during the product development stages and go-no-go decisions on whether to launch a developed product. They can also assist capacity planning for production of the product and decisions relating to its distribution to consumers.

Forecasts can be made either for adoption level or sales. Adoption levels refer to the number of customers who have purchased one or more units of a product. Sales levels refer to the actual number of units purchased and will include not only the initial purchase but also multiple and repeat purchases and purchases made to replace units bought in earlier periods. Sometimes forecasts are made for the total adoption or sales level that a product will achieve over a given time duration of ‘n’ periods or within its entire lifetime. Also forecasts can be made prior to the launch of a product or after the first few sales or adoption levels have been observed.

This paper focuses on one particular forecast task –the production of pre-launch forecasts of the *adoption* time series for new durable products (i.e. the period-by-period adoption of a new product over n future periods)[1]. For durable products the difference between sales and adoptions is likely to be less important than for non-durables, particularly in the crucial early years of a product's life. To keep the review tractable we do not consider in depth the literature on multiple generations of products where the 'new' product is an enhanced version of a previous offering

The paper asks what the extant literature can tell us about how such forecasts should be made and identifies future directions for research in this area. Forecasts of adoption time series can be important where new products are concerned. Investment appraisal techniques that might be applied to new products, such as net present value (NPV) or the internal rate of return (IRR), depend on period-by-period estimates of future cash flows. Capacity planning decisions require estimates of the size of future peaks in adoption and when these are likely to occur. The identification of the period when adoption levels are starting to decline may signal that a new generation of the product should be available by this time. Similarly, low adoption levels in the early periods of a product's life may be tolerated when forecasts for later periods show that a take off in adoption levels can be expected (Golder & Tellis, 2004).

Despite the large number of methods referred to by Assmus (1984) most new product time series forecasting methods for the adoption of durable products usually fall into at least one of three general categories: i) management judgment, ii) analysis of judgments made by potential customers and iii) formal models –these may involve fitting mathematical models to

[1] By time series forecasts we refer to the forecasting of the future period-by-period sequence of a new product's adoption. This can be carried out in a variety of ways, including both management judgment and statistical methods. This is to be distinguished from the term 'time series forecasting methods' which refers exclusively to a range of statistical methods, such as Box-Jenkins and exponential smoothing.

time series of analogous products launched in earlier periods or may employ methods such as system dynamics (Peres, Muller, & Mahajan, 2010). (Other methods like test marketing tend to be more suitable for non-durables.) We argue that each of these approaches is likely to be inadequate on its own and that an approach employing multiple methods is necessary.

The paper is structured as follows. We first examine the new product time-series forecasting task and then the methods that are commonly considered to be good candidates to carry out the task. Then we decompose the task into a series of sub-tasks and assess how useful each method is in the context of that sub-task, according to research and what the strength of the evidence is to support these assessments. Finally, we suggest possible future areas where research might lead to improved forecasting.

2. The time series forecasting task

New product forecasting involves substantial risk so ideally the task will involve identifying a probability distribution (or density forecast) for adoption levels at each of the relevant points in time in the future. However, this is rarely, if ever, done. Indeed even forecasts in the form of prediction intervals rarely appear in the literature (Meade & Islam, 2001) and the focus is almost exclusively on point forecasting. Thus much of this review focuses on the point forecasting task, but later on we will consider approaches that could be used to incorporate uncertainty into the forecasts.

When making point forecasts the primary task of forecasting adoption time-series for new products will involve the need to estimate either the number of adoptions per period for multiple periods in the future or the cumulative number of adoptions from the launch date to each period. The primary task can also be decomposed into a series of sub-tasks which will collectively determine the time series forecasts. These sub-tasks can be divided into those requiring direct quantitative estimates and those involving a choice between available options. Where management judgment is used the distinction can be important as there is evidence that judgment and choice may invoke different cognitive processes. For example, the literature suggests that choice tends to involve the use of fewer items of information or cues (Tversky, Sattath, & Slovic, 1988) so the choice may be made superficially.

Sub-tasks involving quantitative estimates can relate to direct estimates of adoption levels at different points in time, or estimates of a product's market saturation level and when it will occur, the market shares of an individual brand, the future values of independent variables (e.g. those relating to future economic conditions or possible competing products) and the size of adjustments that should be applied to statistical forecasts to take into account information not included in the statistical model.

Sub-tasks involving choice can include the identification of products launched in earlier periods that are analogous to the new product (Goodwin, Dyussekeneva, & Meeran, 2013), the choice of which diffusion model and fitting method to use and whether to assume that the saturation level of a product is static or dynamic.

3. Overview of forecasting methods

We next give an overview of three main methods that are associated with forecasting for new durable products in the literature: i) management judgment ii) methods based on judgments by potential customers, and iii) formal models.

3.1 Management Judgment

Management judgment was the most common method used to forecast new product sales in surveys by Gartner & Thomas (1993) and Kahn (2002). In another study, Lynn, Schnaars, and Skov (1999) found that management judgment was more predominant when sales of hi-tech products were being forecast and where the novelty of the product was associated with greater uncertainty in relation to sales. In Kahn's study the forecast lead times were typically no longer than 36 months. However, it is unclear whether the forecasts he reported were single forecasts for a particular lead time or time-series forecasts, made before the product's launch, for each intervening period up to and including the stated lead time.

Judgmental forecasts by managers may be made either by individuals or by groups. In the latter case (Ozer, 1999) the group may bring a range of different perspectives and information sources to the forecasting process. These benefits may be reduced when managers' judgments are not made independently (Surowiecki, 2005), where particular managers dominate the process or there are social pressures to conform which might be the case, for example, in a meeting called to agree on the forecasts. A balance needs to be struck between the value of obtaining judgments which are free from social pressures and the advantages of individuals being able to freely exchange information and views before they make their forecasts. The Delphi method attempts to achieve this by allowing managers to make their forecasts anonymously and privately, while also allowing them to revise their forecasts when unattributed arguments and statistical summaries of the group's current view are fed back to them (Rowe & Wright, 1999). The survey by Kahn (2002) found that the Delphi method was used in 8% of new product forecasts.

Prediction markets, offer an alternative way of aggregating the judgmental forecasts of a group of managers (Wolfers & Zitzewitz, 2004). In prediction markets individuals buy and sell contracts that will have a final value which is dependent on whether or not a particular event occurs. The current market price of the contract can be used to determine the current overall opinion of the group. Wolfers and Zitzewitz illustrate how different contracts can be designed to reveal various types of forecasts such as the probability of sales exceeding a prescribed value or the market share of the product. In the latter case a typical contract might pay out $1 for every percentage point in market share that a product achieves by the end of its first year after launch. If certain assumptions apply then the current price can be interpreted as the group's forecasts of the market share. Examples of the successful application of prediction markets in sales forecasting have been widely reported (Chen & Plott, 2002; Karniouchina, 2011) though these did not involve pre-launch times series forecasts for multiple periods.

3.2 Judgments by potential customers

These judgments are generally used to obtain estimates of the probability that a given product or brand will be purchased. Adoption forecasts can then be obtained by multiplying 'aggregate' probabilities by the size of the market. Customer intentions surveys usually involve asking potential customers directly about their likelihood of purchasing the new product, though many other related questions may also be included in the survey (Bass, Gordon, Ferguson, & Githens, 2001). The customer's stated likelihood of purchase can be measured on a variety of scales, including binary, five-point or eleven point scales, and the survey result can be summarised using the mean or median response or the percentage selecting the response indicating the greatest level of likelihood (Morwitz, Steckel, & Gupta, 2007).

An alternative approach is to build models based on potential customers' expression of their preferences for different products. Conjoint analysis involves eliciting potential consumers' preferences for products with different combinations of attributes, usually in a market research survey, and modelling how these preferences are related to the attributes. An alternative technique, discrete choice modelling, assumes that the decision maker faces a single choice from a finite set of alternatives and is based on observations of which alternatives are selected. Each alternative is assumed to yield a utility to the decision maker, based on its attributes, and the model determines the probability that the utility of a given alternative will exceed that of the others. A range of choice models have been proposed including the multinomial logit model (McFadden, 1974) and the nested logit model (McFadden, 1978) which allows for correlations between the utilities of similar products. More recently mixed logit models have gained in popularity. These allow for flexibility in the use of different probability distributions to represent the random, and hence unexplained, behaviour of consumers (e.g. see Train, 2003). In some models the probability of the consumer refraining from purchasing any of the products can also be estimated (Farias, Jagabathula, & Shah, 2013).When the size of the potential market is known probabilities obtained from these models can be converted to a forecast of market shares.

There may be potential for involving potential customers in prediction markets for new products, rather than managers, but we are unaware of any studies in the literature documenting such applications. Christiansen (2007) demonstrated a successful application of prediction markets, using the general public as traders, to forecast the winners of rowing races. However, Graefe and Armstrong (2011) conducted an experiment involving students, and reported that the participants found their involvement in prediction markets to be relatively difficult when compared to participation in other group forecasting processes.

3.3 Mathematical models of the diffusion process

Unlike methods based on potential customers' judgments, growth curves or diffusion models are designed to directly produce time-series forecasts. When no demand history is available it may be possible to obtain data on previously-launched products that are similar to the new product. Models can be fitted to this data and used to produce forecasts for the new product on the assumption that its adoption will follow a similar time-series pattern (Bayus, 1993). This process has been referred to as guessing-by-analogy (Bass, et al., 2001) or forecasting-by-analogy (FBA). Alternatively, 'off–model' estimates may be made of values such as the timing of inflection points and market saturation levels. Models can then be obtained which conform to these values.

The most well known basic model used in new product forecasting is the Bass model (Bass, 1969) which is represented by the following differential equation.

$$\frac{dY_t}{dt} = p(m - Y_t) + q\frac{Y_t}{m}\left(m - Y_t\right) \qquad (1)$$

where: m = the market saturation level.

Y_t = the cumulative number of adopters at time t

p = the coefficient of innovation

q = the coefficient of imitation

This equation models the adoption process in continuous time. Usually, the process is observed at discrete points in time. In this case, Bass suggests the following model.

$$Y_t = Y_{t-1} + p(m - Y_{t-1}) + q\frac{Y_{t-1}}{m}\left(m - Y_{t-1}\right) \qquad (2)$$

This basic model assumes that potential adopters are either innovators or imitators. Innovators are willing to adopt a product on the basis of external information, like media reports or advertising. Imitators are motivated to adopt on the basis of 'word of mouth' recommendations by existing adopters. As such they may be conceived as being more risk averse than innovators as they are only willing to purchase a new product when it has been well tested by other consumers. Peres, Muller and Majajan (2010) have suggested extending the notion of word of mouth influences in diffusion to include 'social interdependence of all kinds'. This includes network externalities, where the utility of a product increases when there are more adopters of the product (e.g. telephones) and social signals where people 'follow the consumption behavior of people in their aspiration groups' Several extensions of the basic Bass model have been suggested (see Peres, Muller and Majajan, 2010). These include models that can take into account marketing mix variables, like advertising expenditure or price (Simon & Sebastian, 1987), wage levels, size of the population and income (Horsky, 1990) replacement purchases (Islam & Meade, 2000) (though this usually relates to sales, rather than adoption forecasting) and non-uniform interpersonal influences (Easingwood, Mahajan, & Muller, 1983). Steffens (2003) used the Bass model as a basis for modelling multiple unit adoption. Many other curves also can be used to model patterns of growth in new product adoption levels, including the Gompertz curve, the logistic curve, the non symmetric responding logistic model and the Weibull model (Young, 1993).

Sood, James and Tellis (2009) have proposed an alternative approach to new product forecasting using functional regression. This involves decomposing the smoothed market penetration curves of analogous products into principal components and regressing the variable to be predicted (e.g. penetration level ten years after launch) onto the component scores. Other independent variables such as country or product type can also be included in the model. The method was demonstrated on products where the first few years of sales were already available. The authors state that their method could be used to make forecast for new products where there is, as yet, no sales data available by using the principal components scores of similar products. However, as far as we know, the method has not yet been tested in pre-launch forecasting.

The models discussed in this section so far can be referred to as data-driven in contrast to theory-driven models which may use psychological, economic or marketing theories to explain diffusion. For example, theories can be used to explain how customers trade off the advantages of early purchase of a product with the benefits of delayed purchase when they anticipate falling prices and improvements in technology. Models based on such theories can then be fitted to available data (e.g. Song and Chintagunta, 2003, Decker and Gnibba-Yukawa, 2010). However, the necessary data for a specific product will not be available before its launch which limits the usefulness of these types of models in this situation unless models fitted to analogous products launched in earlier periods are valid. We know of no research which has tested the value of analogies in this context. Other formal models of the diffusion process have been far less widely used in new product forecasting research so data on their effectiveness is sparse. These include systems dynamics models (Kreng & Wang, 2013) and agent-based modelling (Mueller & de Haan, 2009).

4. Making direct estimates of adoption levels at different points in time

4.1 Challenges of the task.

In many markets potential adopters will be heterogeneous in their preferences, their perceptions of products, their choice processes and their propensity to take risks. This heterogeneity may be observed at the level of the individual consumer or between different segments of the market and it may be particularly prevalent in emerging markets (Qian and Soopramanien, in press). Heterogeneity may, in part, be explained by the different social, economic and demographic characteristics of individuals. In some cases it may reflect the existence of different markets. For example, Vakratsas and Kolsarici (2008) identified a dual market in the demand for a new drug. Patients with severe health problems, for whom demand had built up before the drug's launch, formed an 'early' market. In contrast, a 'late' market consisted of patients with mild symptoms - their demand for was possibly generated by the drug's launch.

Failure to take heterogeneity into account can lead to biased forecasts. For example, the choice processes of consumers may differ so using a single model to represent these processes is likely to be inappropriate. Heterogeneity can also lead to biases in the estimation of the parameters of diffusion models, like the Bass model (Bemmaor & Lee, 2002).

In addition, in some cases, an S-shaped curve of the cumulative number of adopters will not be observed and diffusion patterns may be more complex (Parker, 1994). After the launch of a product, there can be a very long 'incubation' period before adoption levels take off. This can be an average of ten years for 'really new' consumer durables (Foster, Golder, & Tellis, 2004; Golder & Tellis, 1997, 2004; Kohli, Lehmann, & Pae, 1999) and it may reflect the time taken for percieved quality improvements to be made to initially 'primitive' innovations as new firms enter the market (Agarwal and Bayus, 2002). Even after the incubation period many other factors are likely to affect adoption rates and may lead to departures from an S-shaped curve. Studies by Goldenberg, Libai, and Muller (2002) and Chandrasekaran and Tellis (2011) found that the adoption levels of many products experienced a significant drop after a period of rapid growth followed by a recovery to the former peak. Chandrasekaran and Tellis (2011) suggested that these 'saddles' or 'chasms', which tend to last for several years, appeared to result from discontinuities in the transition between early and late markets (i.e. from customer heterogeneity), from economic slumps and from consumers' reluctance to purchase because they expected technologically superior products to be available in the near future. Other variables, which can also significantly affect the shape of the diffusion curve include (i) competition (Islam & Meade, 2012), ii) the effectiveness of advertising (part of which may be hidden - the so called slope-endogeneity problem (Luan & Sudhir, 2010)), (iii) the effects of consumer generated media, such as on-line product reviews or blogs (Niederhoffer, Mooth, Wiesenfeld, & Gordon, 2007), and (iv) consumers' propensities to switch from old to new generations of a product (Jun, Kim, Park, Park, & Wilson, 2002; Kim & Srinivasan, 2009; Kontzalis, 1992; Orbach & Fruchter, 2011; Sohn & Ahn, 2003). For some types of products special influences may also apply. For example, for pharmaceutical products two parties (doctors and patients) may be involved in adoption decisions (Ding & Eliashberg, 2008) and also there may be a pent up demand that exists before a drug is launched from patients with particular conditions (Vakratsas & Kolsarici, 2008).

Finally, when forecasts are to be made for periods of less than a year seasonal patterns may need to be incorporated into the forecasts. Large seasonal fluctuations are likely to have important implications for capacity planning and inventory management decisions.

4.2. A comparison of how well alternative methods meet these challenges

To what extent are the three fundamental methods, outlined above, likely to meet these challenges to produce reliable pre-launch forecasts of new product adoption time-series? Hyndman and Athanasopoulos (2013) argue that: "Judgmental forecasting is usually the only available method for new product forecasting as historical data are unavailable". We argue below that unaided judgment is unlikely to tackle adequately the primary task of producing pre-launch time series forecasts of adoption for multiple periods, and that formal quantitative models, albeit informed by judgement, should be at the core of the forecasting process.

4.2.1. Management judgment.

We know of no research which has looked specifically at the role of management judgment, obtained from either individuals or groups, in directly producing *time-series* forecasts for new products, as opposed to estimating first year adoption levels or total adoption levels over the product's lifetime. Research into judgmental time series forecasting has focused on people's ability to extrapolate existing time series patterns (Lawrence, Goodwin, O'Connor, & Onkal, 2006), rather than their ability to forecast new patterns. This is perhaps surprising given the widespread belief we referred to above. Despite the lack of research we will attempt to draw inferences from these time-series-history based studies.

If *unaided* judgment is used directly to produce new product time series forecasts then it seems likely that the resulting forecasts would be unreliable. The simple heuristics that people employ to make time-series forecasts mean that they have difficulties in accurately extrapolating even straight-forward linear trends (Bolger & Harvey, 1993) from existing data. Judgmentally estimating the more complex non-linear patterns associated with new products' life cycles, when no earlier data is present, would, we expect, be much less amenable to these heuristics. For example, there is evidence that people are unable to produce accurate forecasts of series exhibiting exponential growth (Timmers & Wagenaar, 1977), seasonal patterns or longer term cycles (Lawrence, et al., 2006). It seems likely that customer heterogeneity would only add to the complexity of the judgmental task with further detrimental effects on forecast accuracy. Whether judgment would be effective if a structured process was available to support it (e.g. decomposition or the provision of a gallery of time series profiles for analogous products) is not clear given the absence of research on this topic.

Unaided judgment is likely to fare no better if it is used to forecast the combined effect of the many factors (or cues) that will affect future adoptions, such as advertising, network effects and competition (Brehmer & Brehmer, 1988). Cognitive limitations mean that the reliability of judgment is likely to decline as the task complexity increases and people have to process more information (Karelaia & Hogarth, 2008). In particular, negative linear relationships between each cue and the variable-to-be-forecast, and U and inverted-U relationships, pose progressively greater problems for judges (Sniezek & Naylor, 1978). People also have difficulty in making accurate predictions when there is inter-cue redundancy (this is presumably because they add-in the effect of the redundant cues so that a given effect is counted multiple times). Again, it is possible that the use of support systems or the replacement of managers' 'raw' judgments by a psychological bootstrap model of their judgments (Dawes, 1979) could improve the judgmental time-series forecasts, but this also remains not researched in this context.

We know of no research where the Delphi method has been used to produce forecast of *time-series* for new products, but it would still be limited by the inability of individual panellists to extrapolate complex patterns or to integrate cues. Moreover, obtaining multi period time-series forecasts through Delphi would be time consuming and might lead to the loss of panellists over the rounds. In research in other contexts which has evaluated the effectiveness of using Delphi for forecasts of time series, albeit where panellists have had access to past time-series data, either a single forecast for each series was required (Sniezek, 1990) or panellists had the opportunity to adjust statistical forecasts if they wished, rather than being required to make forecasts for many periods based entirely on their judgment (Song, Gao, & Lin, 2013). Prediction markets would also be appear to be unsuitable for period-by-period time series forecasts as they would require the issuing of multiple contracts -one for each period - and, when forecasts are made for several years into the future, traders will have long waits before they receive their potential reward.

4.2.2 Judgments by potential customers

Intentions surveys are likely to be needed if the heterogeneity of potential customers is to be observed, measured and taken into account by the forecasts. However, there remains the problem of translating the results of intentions surveys into time series forecasts. Some intentions surveys include a time horizon in their questions (e.g. do you intend to buy the product within the next 12 months?). Clearly, these cannot be used directly to produce time-series forecasts of adoption for intervening or later periods. To use these surveys to produce time series forecasts for intervening periods strong assumptions are needed (e.g. that the probability of adoption increases linearly over time between zero and the stated probability).

Obviously, such simplifications would be unable to directly represent seasonal patterns in demand. A study by Van Ittersum and Feinberg (2010) suggested that it is possible to obtain accurate time series forecasts directly from intentions surveys of the percentage of potential customers who will adopt a product by asking them to assess the likelihood that they will have purchased a product at several points in the future (e.g. within one month, six months or twelve months from now). This form of question was found to lead to more accurate forecasts than the alternative of asking people how many months from now will elapse before they intend to adopt the product. A high level of accuracy was achieved by 'processing' the 'raw' intentions expressed by respondents in a hierarchical Bayes model. This smoothed out the possible noise in the responses and stabilised the model's forecasts by drawing on the full set of respondents.

Much more research in needed in this area. For example, the Van Ittersum and Feinberg (2010) forecasting study was confined to a single product and single set of potential customers - it investigated the purchase intentions relating to cell phones with GPS technology of students at a university. Also, only 8 (non-independent) data points were used in the accuracy evaluation. However, even if the model's accuracy is validated on a larger data set it is only able to supply forecasts of the *percentage* of people who will have adopted a product at different points in time, rather than the actual number of adopters (hence the sub-task of estimating the size of the market still needs to be completed). Moreover, the reported model only made forecasts until the adoption percentage reached a maximum of 50%. Thus the forecast lead times were relatively short (up to 24 months) and it seems unlikely that people will be able to make reliable predictions of their purchase intentions for longer periods ahead, such as 2 to 5 years (Morwitz, Steckel & Gupta, 2007). This may be less important given that many product life-cycles are shortening (Agarwal, Shankar, & Tiwari, 2007). Nevertheless, on its own, and based on our current knowledge, this approach would be unlikely to be adequate for time series forecasts of adoptions, in general.

Besides the usual errors associated with surveys such as sampling error and non-response biases, there are a number of additional potential sources of forecast errors associated with intentions survey when they are being used in this context (Morwitz, et al., 2007). First, because the product is new, and yet to be launched, it will be unfamiliar to respondents and their knowledge of what the product has to offer is likely to be limited. Also, many people are imitators and hence they will only make a purchase decision after hearing about other consumers' experiences of the product (Ho & Chen, 2007). This source of error is likely to be more significant the greater the 'newness' of the product (Ozer, 2011). Customers are likely to have better knowledge of their future purchasing decision in the near future and as time passes new information on the new product will accrue which may cause a change in the original decision. Finally, the act of eliciting intentions can itself change purchaser's behaviour - when respondents have predicted their own behaviour they are more likely to act in a way that is consistent with this (Morwitz, 2001). Hence those who participate in an intentions survey may behave differently from other members of the target population. Other biases can emanate from a tendency to overstate one's intention to purchase socially desirable products (e.g. an exercise machine) and understate intentions to purchase a product that may be deemed to be undesirable (e.g. a gas-guzzling vehicle).

The literature suggests a number of ways in which the correlation between a person's stated purchase intentions and their subsequent purchases can be improved. Van Ittersum and Feinberg (2010) argue that the very act of requiring respondents to indicate their purchase intentions at different points in time increases reliability because it requires respondents to use greater cognitive effort in their responses. Ozer (2011) found, in a study of purchase intentions relating to two new products (a camera phone and a new type of organic frozen yoghurt), that surveying both people who were knowledgeable about the products and those who believed that they were knowledgeable improved accuracy. In the latter case this was believed to be because those who considered themselves to be knowledgeable were motivated to seek new information when this was needed in order to maintain their self-image as an expert. Morwitz, et al. (2007) found that stated intentions were more reliable when they related to specific brands, rather than the entire product category and when respondents were asked to compare their purchase intentions between product variants, rather than indicating their intentions relating to a single product variant in isolation. There is also some evidence that reliability of responses is improved by asking respondents to reflect on their own individual characteristics when indicating their intention (Morwitz, 2001). As indicated earlier, a problem of intentions surveys is that potential customers may have limited knowledge about the new product. Urban, Weinberg, and Hauser (1996) experimented with a multi-media method that places potential consumers in a virtual buying environment that simulates the information that would be available to the consumer in the real market. This also allows probabilities to be estimated for customers moving through the different stages of a purchase decision (Urban, Hulland, & Weinberg, 1993).

Once the raw results of an intentions study are obtained they might be improved by adjusting for possible biases (Morwitz, 2001). For example, biases may be estimated from historical data which compares stated intentions with purchase decisions for similar products (Bass, et al., 2001). Alternatively, adjustments can be made by applying different weights for people indicating each level of likelihood (e.g. 0.96 to the most likely, 0.36 to the second level of likelihood, and so on). These weights can be based on observations of how the different responses translated into adoption levels for analogous products that were launched in earlier periods (Morwitz, 2001).

4.2.3 Formal quantitative models

These are usually mathematical diffusion models which can be used to create forecasts of future time-series patterns, but for pre-launch products the absence of past data means that they are unable to complete the primary task without inputs from some of the sub-tasks. For example, they may require estimates of market saturation levels, or of the timing of inflection points or the identification of analogous products launched in earlier periods. Systems dynamics and agent-based models offer an alternative formal quantitative approach to forecasting the time series patterns but they have not been widely tested in research studies.

When applied to the entire market, diffusion models at best only provide a coarse representation of customer heterogeneity (i.e. they may distinguish between innovators and imitators). If heterogeneity is not modelled it implies that individuals who have yet to adopt all have the same probability of adopting in a given period of time. Any differences in individual times to adoption are assumed to be random (Chatterjee and Eliashberg, 1990).

The modelling of heterogeneity can be enhanced by having separate diffusion models for different market segments (e.g. Vakratsas and Kolsarici, 2008, Qian and Soopramanien, in press). Other approaches have attempted to forecast adoption time series by modelling individual consumer choices. For example, Chatterjee and Eliashberg (1990) developed an elegant decision analytic model for each participant in a survey of potential adopters and then aggregated the resulting predicted adoption behaviour. However, the models made restrictive assumptions about the potential adopters that are inconsistent with findings in behavioural decision making. For example, they assumed that the potential adopters updated their (probabilistic) perceptions of the product's performance according to Bayes theorem when new information was received (e.g. see Goodwin (forthcoming) for a discussion of contrary evidence) and that their decisions would be consistent with an exponential utility function (see Kahneman and Tversky, 1979).

A second problem is that most diffusion curves have a single point of inflection and hence cannot be used to model, the variation in diffusion in the incubation period and any subsequent chasms and saddles in addition to long term growth patterns. Because of this, Bass suggested that his model should not be applied until adoptions reach 1-3% of the peak adoption levels. This would suggest the possibility of using separate models for the different stages of a product's life but research is needed to address this problem, and in particular how to model the adoption in the early stages. Proportional hazards models have been used to model the time it takes before the demand for products takes off (Agarwal & Bayus, 2002) but in new product forecasting their use would require data on analogous products and forecasts of the values of independent variables, such as the number of new firms entering the market. Of course, for some products, data on advance orders may be available prior to launch and it may be possible to exploit this to produce early adoption forecasts (Moe & Fader, 2002).

Nevertheless, for the periods that follow the early stages of a product's life these types of formal models are more likely than the previous two approaches to be able to represent the complex, non-linear time-series patterns associated with diffusion (Chandrasekaran & Tellis, 2011; Goldenberg, et al., 2002; Golder & Tellis, 2004; Kohli, et al., 1999) . In the case of the different forms of the Bass model, they are also based on a firm theoretical rationale. Given the likely inadequacies of management judgment in estimating these patterns and the limitations of timed-intentions surveys, together with the lack of research into their effectiveness, it appears that these formal quantitative models should be at the heart of the new product time-series forecasting process.

There has been relatively little work on incorporating seasonality into formal models for new product forecasting. Analogies are likely to be particularly informative when it comes to estimating seasonal patterns as similar products are likely to have demand with similar seasonal characteristics. A key issue is whether seasonality should be assumed to be independent of the diffusion process. Radas and Shugan (1998) handled seasonality when modelling diffusion in the movie industry by transforming time so that they regarded it as speeding up in peak periods and slowing down in quiet periods. This allowed the product to 'age' more quickly during peaks and more slowly in low seasons. An advantage is that the seasonality is not regarded as being independent of the underlying diffusion process. For example a high number of adopters at a peak in a given year may lead to more imitators in a later period. More recently, Peers, Fok and Franses (2012) demonstrated a method that allows seasonality to be estimated consistently with the underlying S-shaped pattern of diffusion curves. The method assumes that extra sales at seasonal peaks are drawn from earlier or later periods. This does imply that the underlying diffusion pattern is not influenced by the seasonal pattern. If this assumption is correct, an advantage of the method is that it allows unbiased estimates of diffusion parameters to be obtained from data recorded at weekly, monthly or quarterly intervals (rather than annually) and these estimates are still unbiased even when data on the entire diffusion process is unavailable. This is potentially useful when unbiased estimates of parameters for analogous products are needed in order to produce forecasts for new products.

5. Tackling the sub-tasks involving quantitative estimation

5.1 Estimating the market saturation level or market potential

A decision has to be made on whether the market saturation level can be assumed to be constant or whether it can vary over time as a result of factors such as a changing unit price, economic conditions and competition (Islam & Meade, 2012). Meade and Islam (2001) suggest that forecast accuracy does not benefit by modelling the saturation level as a function of its influencing variables because separate forecasts have also to be made for the future values of these variables, before the saturation level, itself can be forecast. This leaves open the question of how varying saturation levels can be forecast. Another question is whether it is better to estimate the market saturation levels for a product, as opposed to specific brands of that product.., There is shortage of empirical evidence to resolve both of these issues.

Assuming that these decisions have been made the next issue is how to estimate the saturation level or levels. Most researchers recommend the use of consumer intentions surveys, demographic data (Chun & Hahn, 2008) or management judgment (Bass, et al., 2001; Tigert & Farivar, 1981). Meade and Islam (2001) suggest that judgment should not be used, but they supply only limited empirical evidence for this. There are, however, good reasons why *unstructured* judgment may lead to inaccurate estimates, as a result of motivational and cognitive biases. When there is competition for resources to support the development and commercialization of a new product, managers may consciously over estimate the prospects for their product. This has been referred to as advocacy bias (Tyebjee, 1987). Involvement in the development of a new product can also lead to wishful thinking and the selective processing of information to confirm that the product will be a success so that the resulting estimates suffer from optimism bias. For example, studies of supply-chain forecasting for established products have found consistent evidence of optimism bias when managers involved with products use their judgment to adjust statistical forecasts (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009; Franses & Legerstee, 2009). Unlike advocacy bias this tendency may be unconscious (Tyebjee, 1987).

In addition, psychology research suggests that a host of other cognitive biases may come into play –though research is needed to establish that these biases apply in the new product forecasting. Availability bias may occur when forecasts are over influenced by recent experiences with other products or recent news about the product's market. There may also be a tendency to anchor on adoption levels achieved by other analogous products so that there is too little adjustment from these figures to take into account the specific conditions that relate to the new product (Kahneman, 2011).

Structuring the judgmental estimation processes (e.g. by decomposing the task) *may* lead to improved accuracy because they reduce the cognitive burden on forecasters, thereby reducing reliance on over-simplified heuristics. Also, by making the estimation process explicit, biases may be open to challenge. Alternatively, judgment can be combined with other approaches. For example, Thomas (1987) proposed a method which starts with a clear definition of market potential in terms of attributes such as the relevant customer group, geographical area, time period and marketing program. It then proceeds to combine expert judgment with estimates based on intentions surveys and other methods. Thomas suggests that the separate estimates can be simply averaged using either equal weights or judgmental weights.

Evidence from other fields suggests that judgment of saturation levels from groups may be more reliable than those from individuals if appropriate procedures, such as Delphi, are used (Rowe & Wright, 1999). Prediction markets are likely to be less useful in predicting saturation levels. The final value of the contracts will need to be associated with a particular date, but the date when market saturation levels or peak adoption levels will be reached will not be known. It is also essential that it is clear whether or not an event has occurred by the contract payment date, but reported market penetration levels, for example, may be based on estimates, which may be subject to change. Also, when a product's life-cycle is likely to be long, forecasts of the market penetration many periods into the future will mean that traders will have to wait, possibly for years, before they receive their possible payoff (Green, Armstrong, & Graefe, 2007).

The key problem is that there is an absence of adequate empirical testing of these different methods. One difficulty is that establishing exactly what the market potential has turned out to be is not an exact calculation. In addition, many studies report forecasts for many years into the future for single series so it will be a long time before we can even try assessing the accuracy of their estimates (Kaynak & Rojas-Mendez, 2009, Qian and Soopramanien, in press). In other cases authors seem to prefer to provide 'illustrations' of their proposed methods on very limited out-of-sample data as opposed to robust testing on large data sets. For example, Kreng and Wang (2013) developed an elaborate 'systems dynamics' model to allow them forecast the dynamic market potential for a brand of golf club. Although they claimed that their method led to better forecasts, they tested it only *three* out-of-sample data points and apparently no benchmark method was used as a basis for comparisons so it is unclear what 'better forecasts' means.

5.2. Estimating the market share of an individual brand over time

Conjoint analysis and choice models can be particularly useful in estimating market share when the new product represents an improvement on existing products (Kontzalis,1992, Jun, et al., 2002; Kim & Srinivasan, 2009, Orbach and Fruchter,2011) Once again customer heterogeneity may need to be taken into account but modern software (embodying methods like hierarchical Bayesian estimation) now allows choice models to be obtained for individual consumers or market segments.

While choice models may yield estimates of market share at particular points in time, forecasting changes to market share over time may be difficult, especially if it is partly dependent on the actions of competitors. Such forecasts are themselves likely to require forecasts of future values of the independent variables in the choice models such as prices (Qian and Soopramanien, in press) or socio-economic variables. Moreover, the resulting so-called dynamic choice models usually assume that the relative importance (or weights) of the independent variables remain constant. We know little about the extent to which the weights associated with a product's attributes are likely changeable for individual consumers over time or the circumstances where such changes might be expected. Forecasting such changes would require individual choice data over multiple periods so that any trends could be explained, estimated and extrapolated.

Despite these challenges a number of researchers have produced time series forecasts of market share, for example by asking potential customers when they intend to make their next purchase or switch between products (Eggers & Eggers, 2011). Lee, Cho, Lee, and Lee (2006) used conjoint analysis to produce time-series forecasts of adoptions of LCD TVs in Korea. This involved forecasting future prices of the product, based on an analogy and then using choice-based conjoint models for each individual consumer, with price as one of the attributes, to predict the probability that they would choose a given product, rather than competing products, at time t. The diffusion of all large screen TVs was forecast using a Bass model (the model was estimated from 22 quarters of sales data for all large screen TVs that had been launched before LCD TVs). Forecasts for adoptions of LCD TVs, specifically, were obtained by multiplying the average of the consumers' choice probabilities for these TVs by the Bass forecast of total large screen TV adoptions. More recently, Qian and Soopramanien, (in press) made forecasts of the demand for green cars in China up the year 2030 by segmenting the market between current car owners and non-car owners and estimating choice models for each segment (rather than for individual consumers).

Probability flow models (e.g. Roberts, Nelson & Morrison, 2005) provide a more detailed explanation of consumers' choices at different stages of the buying process. For example, they may include probabilities of a potential customer being aware of the product, of recognising a need for the product given that they are aware and of choosing the product given awareness and need recognition (Ozan, Sireli, & Kauffmann, 2007). By linking these probabilities to a distribution of the time it will take before an individual customer moves from one state to another (e.g. a negative exponential distribution) time-series forecasts of adoption levels can be obtained. Market research surveys and/or conjoint analysis can be used to determine the transition probabilities. There is evidence that models can be improved by allowing for heterogeneity in consumer behaviour by specifying mixes of the distributions (Fader, Hardie, & Zeithammer, 2003).

None of the above choice modelling studies involved extensive testing of forecast accuracy for the periods following a product's launch. For example. Ozan, et al. (2007) provided a simulated model demonstration, while other studies tested accuracy over only a few periods or did not test accuracy at all. Choice models would therefore benefit from more empirical studies, particularly as they may suffer from a number of limitations in some circumstances.

For example, Fildes and Kumar (2002) point out that choice experiments are limited because they only model current attitudes. In fast developing industries, like telecoms, the novelty of the proposed new product may change these attitudes, especially where imitator's attitudes depend on their observations of others' experiences of the product. It may also be difficult for a conjoint study to replicate consumers' buying behaviour in the marketplace. For example, the analysis assumes that choices are compensatory (weak performance on one attribute is compensated by good performance on others) while actual decisions may be non-compensatory (Wittink & Bergestuen, 2001). In addition, some models also assume that a new product will take customers from existing products in the generic domain in proportion to their current share of the market. In reality, new products tend to gain share from products that are similar to them (e.g. a new sports car will attract customers who are currently sports car owners, rather than customers who currently own saloon cars). Tsafarakis, Grigoroudis, and Matsatsinis (2011) suggest how these last two problems can be overcome.

Methods based on game theory or systems dynamics (Kreng & Wang, 2013) or approaches such as agent-based modelling may offer a way forward. For example systems dynamic could allow forecasters to examine the effect on market share of particular policies that are within a company's control, such as the marketing mix, or allow the effect of alternative assumptions to be modelled. In agent-based modelling computer software is used to simulate the actions and interactions of consumers according to pre-defined behavioural rules. The models allow a rich mixture of factors to be taken into account, such as consumer traits (e.g. social connectedness, imitativeness) and environmental characteristics (e.g. geographical variables, shopping location). These models are potentially useful because they can be used to represent heterogeneity in consumers' behaviour (Peres, et al., 2010). However, many problems remain to be solved (Zenobla, Weber, & Daim, 2009). Consumer behaviour rules need to be realistic, but not overly complex (Shafiei, et al. (2012) used a choice model to establish these rules). Issues on how to calibrate and validate a model, in the absence of adoption level data remain unresolved and the sensitivity of models to initial conditions means that point forecasts are impractical. Although, Mueller and de Haan (2009) used agent based micro-simulation to simulate and forecast consumer choices of new cars the technique was not used to produce time series forecasts. Given the current status of research in this area it currently seems premature to expect agent-based models to produce accurate time series forecasts of new product market shares. If the problems with the technique can be resolved it may offer potential benefits to new product forecasters in the future.

5.3 Other sub-tasks involving quantitative estimation

These tasks include forecasting future values of independent variables, such as those relating to future economic conditions, and the size of judgmental adjustments that should be applied to statistical forecasts to take into account information not included in the statistical model. The quality of the forecasts of the future values of independent variables can be a crucial factor in determining the accuracy of forecasts for a new product (Meade & Islam, 2001) but sometimes these have been based on simple univariate methods. Judgmental adjustment to model-based forecasts has been studied extensively (Fildes, et al., 2009). This body of research suggests that adjustments should be carried out sparingly, should only address the effect of unmodelled factors, should have a rationale that is recorded and documented and should ideally be supported by a formal process of decomposition (Lawrence, et al., 2006).

6. Tackling the sub-tasks involving choice

6.1. Identification of products launched in earlier periods that are analogous to the new product

The task of identifying analogies requires answers to a number of questions: i) What characterises a suitable analogy? ii) Should more than one analogy be selected? iii) What process should be used to select analogies (e.g. judgmental or statistical)? iv) Given that the analogy is unlikely to have a perfect resemblance to the new product, how can the analogy's model be adapted to take into account the differences between the analogy and the new product?

What characterises a suitable analogy? Analogies are unlikely to provide reliable estimates of the market saturation level as the size of markets is likely to change over time. This means that the suitability of an analogy should be based on its probability of yielding a similar adoption levels pattern to the new product, irrespective of the scale of these adoption levels. For radical or discontinuous innovations this probability may be so low that forecasting by analogy is inadvisable.

Lawrence and Lawton (1981) suggest that similar adoption patterns are to be found amongst industrial and consumer products, respectively. However, Thomas (1985) suggests that more product-specific factors should be used to identify suitable analogies and lists 25 of these factors, such as those relating to the environment within which the product will be launched, the behaviour of buyers, the marketing strategy that will apply to the product and the nature of the innovation. Thomas suggests that a similarity score for each potential analogy can be calculated based on these factors. However, many of these factors are only vaguely defined and it is unclear how well such a detailed specification would work in practice. Goodwin, et al. (2013) used 13 factors to assess the similarity of previously launched electronics products to new products. These included whether or not the product was portable, whether it would be useful to a typical small business, the product's launch date and the mean number of days that an average consumer would have to work to buy the product. However, when the Bass model was used to produce forecasts, there was only weak evidence that using analogies based on these factors yielded more accurate forecasts than randomly selected analogies. Ilonen, Kamarainen, Puumalainen, Sundqvist, and Kalvianen (2006) used multiple factors to select analogous national markets for internet usage and cell phone subscriptions, while Lee, Boatwright, and Kamakura (2003) used characteristics of music albums to predict sales of other albums. However, neither study produced 'true' forecasts -the dates of the analogous time-series coincided with the dates of the series being forecast so information was used to produce the forecasts of values that could not have been known in advance.

Another issue relates to the length of time that should elapse between the launch of an analogy and the launch of the new product. In order to estimate parameter values reliably for the analogous product a sufficiently long data series must be available (Hyman, 1988). For example, for the Bass model insufficient data (or right hand truncation) can lead to under-estimates of p and overestimation of q when a non-linear least squares method is used to fit the model (Bemmaor & Lee, 2002; Van den Bulte & Lilien, 1997). When products have long life cycles this implies that only analogies launched many years earlier will provide useful estimates of p and q. However, the market into which older analogies were launched may be very different from current market conditions. In many markets life cycles are shortening (Wu, et al., 2010) and the speed of diffusion is increasing (Van den Bulte, 2000). For example, both Decker & Gnibba-Yukawa (2010) and Goodwin, et al. (2013) found evidence that the value of q (see equation 1) is increasing over time for consumer electronics products. Thus a trade-off will need to be made between the benefits of using a recently launched analogy and the possible biases associated with the estimation of its parameters. Of course, there is also the danger of a survivor bias when selecting analogies in that only products that have been successful will have a sales history that is sufficiently long to permit reliable estimation of parameters.

Should more than one analogy be selected? Bass, et al. (2001) used a single analogy to forecast subscriptions for satellite TV from 1994 to 1999. Managers judged whether the pattern of subscriptions would be most similar to that of either Color TV sales in the 1960s or Cable TV subscriptions in the 1980s. However, selecting a single analogy that appears to be most similar to the target product carries the risk that its estimated parameters will be unusual because special circumstances applied to it that will not apply to the new product. In contrast, basing parameter estimates on multiple analogies (e.g. by taking their means) will mean that less similar analogies are included in the estimation. On balance, the evidence favours the use of multiple analogies. In the study by Goodwin, et al. (2013) increasing the number of analogies from one to 23 improved the forecasting accuracy of a Bass model when the means of parameter values for individual analogies were used in the model. However, little was to be gained by using more than five analogies. When analogies were weighted depending on their similarity to the new product using five analogies also led to more accurate forecasts than using one.

Another possibility is to use all available analogies (e.g. sales histories for all spare parts produced by a company). Using the mean of the parameter values of all analogies to forecast the sales for the new product implies that they all share common parameter values and that any variation between their estimated values is due to sampling error. When this assumption is judged to be unreasonable two methods can be used - regression analysis (Gatignon, Eliashberg, & Robertson, 1989; Goodwin, et al., 2013; Srivastava, Mahajan, Ramaswami, & Cherian, 1985), and hierarchical Bayes procedures (Lenk & Rao, 1990; Neelamegham & Chintagunta, 1999; Talukdar, Sudhir, & Ainslie, 2002; Van Ittersum & Feinberg, 2010; Yelland, 2010). In regression analysis observed parameter values for the analogies are regressed on to the attributes of the analogies to obtain a model which explains variation in parameter values across analogies. The model can then be used to predict parameter values for a new product based on its specific characteristics. Typically, this approach gives equal weight to each analogy's estimated parameter values, irrespective of the sampling error that might be associated with the estimates (Goodwin, et al., 2013). Hierarchical Bayes procedures take into account *both* the variation between analogies' parameter values and the precision with which these parameters have been estimated for each individual product. This leads to an estimate of the parameter values that will apply to the new product. The accuracy of the resulting forecasts is likely to be higher when the estimate is based on a relatively homogeneous set of analogies (Lenk & Rao, 1990).

What process should be used to select analogies? When only a few analogies are to be selected as a basis for the new product's forecasts either judgmental or statistical methods can be employed. Judgmental selection of analogies may suffer from a number of biases. As indicated earlier there is evidence that in choice tasks people tend to use less information than they use in estimation tasks. Hence managers choosing analogous products from the past as the basis for their forecasts may focus on only a few attributes of those products. Analogies may be selected because they are recent or easily recalled (Lee, Goodwin, Fildes, Nikolopoulos, & Lawrence, 2007) or when their similarity with the target is superficial (Holyoak & Thagard, 1995). Potential analogies that are identified early in the process may continue to dominate judgment even when superior analogies are subsequently presented.

This problem may persist even where debiasing techniques are employed (Bolton, 2003). Improved selection may result from structuring the process (Green, et al., 2007; Thomas, 1985) though there is a dearth of evidence for this in the context of new product adoption levels forecasting. Statistical methods, such as cluster analysis or nearest neighbour analysis will avoid some of these biases, but judgment will still be needed to identify the relevant characteristics on which these analyses will be based (Goodwin, et al., 2013). For example, similar adoption level patterns may result from characteristics that are deeper than immediately apparent attributes, such as similarity of use or market segment.

Adapting analogies? Using parameters obtained for an analogy may produce innaccurate new product forecasts when the two products differ on some key dimensions, despite being otherwise similar. Earlier we reported evidence that the parameter, q, in the Bass model is increasing. This suggests that estimating, and taking into account, the rate of change of q over time might allow older analogies to be used to produce forecasts for the latest products, though we know of no research that has investigated this. Differences between analogies and new products may also be evident when a product's adoption levels in one country are used forecast its adoption levels following a subsequent launch in another country (Yalcinkaya, 2008). For example, Gatignon, et al. (1989) found evidence that the values of p and q in a country depend on the role of women in that country and the extent to which its population is cosmopolitan and mobile while Tellefsen and Takada (1999) found that the levels of mass media in countries influence p and q. Similarly, Talukdar, et al. (2002) found that developing countries have lower penetration levels and take longer to reach peak sales. Their penetration levels were influenced by levels of international trade and urbanization. When data is available on a sufficient number of countries and products, regression analysis may be useful in predicting the necessary adjustment in parameters to take into account these factors.

6.2 Choice of diffusion model

Ideally, the models that are fitted to the diffusion of analogous products will provide a good representation of the underlying patterns of adoption, excluding the noise. The basic Bass model assumes an S-shaped pattern, which as indicated earlier, may not be applicable. Extensions to the Bass model, like those referred to earlier, might overcome some of these problems but they will also increase complexity (Bottomley & Fildes, 1998; Fader, et al., 2003; Motes & Woodside, 2001). In particular, values of independent variables added to the model, such as prices or macro-economic variables will be known for the analogy but are unlikely to be known for the new product. Two possibilities suggest themselves here, though to our knowledge neither has been explored in research. First, the inclusion of additional variables could be used to estimate the effects of factors like prices or advertising, on the analogy's adoption levels. Once estimated these effects can be 'cleansed' from the analogy's data so that effects that were specific to the analogy do not influence forecasts for the new product. For example, some analogies may have unusually high initial adoption levels because they have been heavily promoted during their launch. If the effects of the promotion can be estimated these could be subtracted from the analogy's time series. The 'cleansed' series might then be more appropriate for forecasting the new product's adoption levels if it is not likely to see heavy early promotion. Second, if some of the additional independent variables for the new product can be forecasted with reasonable confidence (e.g. the future marketing mix) then analogies can be chosen partly on their similarity with respect to these variables and parsimonious models fitted to represent the shape of the analogies' diffusion or sales pattern. Parker (1994) has suggested parsimonious models that appear to represent long-run diffusion well. Research that has examined the role of analogies in new product forecasting has focused on the Bass model and we are unaware of any studies which have considered the use of other growth curves such as the logistic or Gompertz curves in forecasting-by-analogy or indeed the use of other forecasting methods that *might* apply in some circumstances such as those based on exponential smoothing.

6.3 Choice of model-fitting method

Models can be fitted to the series using ordinary least squares (OLS), maximum likelihood estimation (MLE) (Schmittlein & Mahajan, 1982) or non-linear least squares (NLLS) (Srinivasan & Mason, 1986). No single method is clearly superior to the others. For example, MLE seriously underestimated the standard errors of p, q, and m in a study by Srinivasan and Mason (1986). NLLS is sensitive to the initial estimate of parameter values that it requires and there is a risk that it will converge on local, rather than a global, optima. However, in a study by Schmittlein and Mahajan (1982) models obtained through MLE and NLLS were found to give a better fit to data than OLS. When only truncated data series are available Venkatesan and Kumar (2002) suggested that genetic algorithms produce parameter estimates that yield more accurate forecasts, though Wang and Chang (2009) argue that these algorithms are slow. They recommend a hybrid procedure where NLLS is used to produce initial estimates that are subsequently optimised using genetic algorithms.

Choice models can be estimated using MLE or hierarchical Bayes (HB). The latter has a number of advantages (Chen, Wassenaar & Hoyle, 2013) offers a more computationally efficient estimation of random parameters if the prior distribution of coefficients (or weights) in the choice model is assumed to be a multivariate normal distribution, Also, HB allows for retrieval of the coefficients for individual potential adopters while the MLE method only provides point estimates of their mean values.

7. Future Research

To date the world of new product forecasting research has been characterised by a wealth of proposed methods, but inadequate empirical testing of these proposals, a focus on explaining past diffusion, rather than forecasting, a huge emphasis on the Bass model and its variants, and a general failure to provide estimates of the risk and uncertainty associated with future adoption levels. Also, much of the work that has been carried out in forecasting has often assumed that early time series data is available and so is not relevant to pre-launch forecasting.

Please insert figure 1 about here

Nevertheless the area has strong theoretical foundations and, interestingly, perhaps more than any other area of forecasting, it appears to lend itself to the application of multiple complementary methods (see figure 1). The latest papers are acknowledging the advantages of combining many methods. For example, Tseng, Lin, and Yang (2012) combined conjoint analysis, scenario analysis, the Delphi method and a diffusion model to produce forecasts of Taiwan's TV market over a ten year period. However, no formal evaluation of how multiple methods should be applied to the task in different contexts has been carried out. Most researchers simply present one combination of methods and extol its merits, usually in relation to the forecasts of a single product. Nevertheless, we believe that formal models, such as diffusion models should be at the heart of any forecasting procedure given that managers using unaided judgment are unlikely to forecast the complex patterns in adoptions over time. Judgment should be confined to the sub-tasks where it is most effective or to providing inputs to the formal model, rather than providing the time series forecast themselves. The use of methods and support systems for aiding judgment in new product forecasting, where its use is appropriate, is likely to be an area worth exploring in future research.

There is also plenty of scope for improving individual methods. As product life cycles become shorter there may be greater scope for using analogies in forecasting because this will allow complete information on the analogies' life cycles to be used without the need to use old analogies which may have been launched in very different market conditions. The use of analogies in combination with models, other than the Bass model, such as other types of diffusion curve, functional regression, and theory-based models is also likely to be worth exploring. However, we need to know more about how analogies should be selected. For example are Delphi panels of experts or even preference markets likely to be effective methods for improving the judgmental selection of analogies? (Preference markets are similar to prediction markets but payoffs depend on the proportion of participants who choose the different options). Is it possible to use statistical methods to identify deeper attributes of analogies that will signal their appropriateness for a given forecasting task, given that surface similarities, such as the purpose of a product, have yielded disappointing results?

Intentions surveys and choice models suffer from the problem that it is difficult for potential consumers to envisage new products and how they may be useful. Virtual reality technologies have advanced significantly since Urban, et al. (1996) used multimedia methods to allow consumers to make choices in virtual markets and there may be great scope for exploiting these methods to obtain more accurate indications of consumers' intentions.

Prediction markets have the disadvantage that long waits may be needed before investors realise their potential payoffs. Imaginative alternatives may be worth exploring here. For example, two parallel independent prediction markets could base their payoff on what the other market had predicted after a relatively short period of time, rather than the actual outcome (Meeran, Dyussekeneva, & Goodwin, 2013). That way the power of the group judgment is harnessed, people have an incentive to think hard and honestly about their judgments and the time between investment and payoff would be short. The mean of the two group's estimates could be used as the forecast.

There is also likely to be scope in the future for exploiting data from social network sites and other internet data. For example, recently, Kulkarni, Kannan, and Moe (2012) used hierarchical Bayesian methods to obtain models that linked on-line search activity before a film was released and the film's characteristics to forecast box office sales. When applied to out-of-sample data the results showed that the use of search data improved forecast accuracy. However, there may be difficulties in obtaining longer-term time series forecasts from such data. Agent-based modelling offers further prospects for future researchers if the challenges its poses can be overcome.

Of course, the biggest challenge to new product forecasting researchers is that of taking into account the huge uncertainty associated with future adoption levels. As pointed out earlier, researchers have tended to restrict themselves to examining the accuracy of point forecasts, and hence this uncertainty has been ignored. Prediction intervals are one way of conveying this uncertainty, but there is conflicting evidence as to whether they aid decision making (Goodwin, Onkal, & Thomson, 2010, Ramos, van Andel & Pappenberger, 2013). For example, if standard coverage probabilities (such as 95% or 99%) are used their bounds are unlikely to coincide with critical levels such as production capacity or break-even points. Also, in new product forecasting they are likely to be extremely wide so they are unlikely to have credibility with managers (Du & Kamakura, 2011) who may regard them as being uninformative.

Nevertheless uncertainty does need to be addressed when rational decisions about new products are being made. Density forecasts may be seen as more informative by managers and more useful in their decision making –though this assertion needs to be tested. One method that provides such forecasts that has been under explored in new product forecasting is Monte-Carlo simulation (Sugiyama, 2007). In this approach probability distributions are estimated for each of the factors that it is thought will affect the adoption levels of a product and random numbers are used to simulate combinations of these factors and the resulting adoption levels. By repeating this process a large number of times a probability distribution for adoption levels can be obtained. The method has the advantage that it decomposes the forecasting task into a series of smaller, and hopefully easier, tasks and it is also transparent and easy to understand. In some cases the input distributions may be estimated empirically, thus avoiding potential judgmental biases. A number of commercial software products, such as @RISK, Oracle ® Crystal Ball and Risk Solver, are available to support this process. Other approaches to estimating uncertainty are also worth exploring further. For example, Gaur, Kesavan, Raman, and Fisher (2007) found that the dispersion of experts' forecasts is correlated with the level of uncertainty associated with the forecasts.

In situations of high uncertainty a commonly advocated approach is to use scenario planning as an alternative to conventional forecasting (Wright & Goodwin, 2009). In this approach attempts are made to write narratives that explain how alternative futures might unfold up to a horizon date. It is hoped that the set of scenarios generated will bound the possible futures allowing the robustness of alternative courses of action to be tested against this range of future events. While not strictly a forecasting process itself it is possible that scenario planning may have a useful role in the new product forecasting process. Immersion in the scenario planning process may challenge managers' views of the future and sensitise them to both the uncertainty they face and possible future events that may impact on adoption levels (Mackay & Metcalfe, 2002). Research on the use of scenario planning as a prelude to new product forecasting might therefore yield valuable results. As reported earlier it has already been applied as one of several combined methods to produce forecasts of sales of televisions in Taiwan (Tseng, et al., 2012).

Finally, managers are likely to have some influence on the future adoptions of their products through their actions and decisions relating to marketing mix variables, date of launch, initial production levels and so on. This suggests that, rather than producing a single forecast based on a fixed set of assumptions, forecasting models will have their greatest value if they can provide 'what-if' estimates of future adoptions enabling managers to estimate the effect of alternative strategies and hence make decisions which will maximise the chances of a product's success.

Acknowledgments

The authors would like to thank Robert Fildes, two anonymous reviewers and an Associate Editor for their detailed and insightful comments on earlier versions of this paper. Their suggestions have led to significant improvements in the paper.

References

Agarwal, A., Shankar, R., & Tiwari, M. K. (2007). Modeling agility of supply. *Industrial Marketing Management, 36*, 443-457.

Agarwal., & Bayus, B.L.(2002). The market evolution and sales takeoff of product innovations. *Management Science, 48,* 1024-1041.

Assmus, G. (1984). New Product Forecasting. *Journal of Forecasting, 3*, 121-138.

Bass, F. M. (1969). New product growth for model consumer durables. *Management Science Series a-Theory, 15*, 215-227.

Bass, F. M., Gordon, K., Ferguson, T. L., & Githens, M. L. (2001). DIRECTV: Forecasting diffusion of a new technology prior to product launch. *Interfaces, 31*, S82-S93.

Bayus, B. L. (1993). High-definition television - assessing demand forecasts for a next-generation consumer durable. *Management Science, 39*, 1319-1333.

Bemmaor, A. C., & Lee, J. (2002). Research note the impact of heterogeneity and ill-conditioning on diffusion model parameter estimates. *Marketing Science, 21*, 209-220.

Bolger, F., & Harvey, N. (1993). Context-sensitive heuristics in statistical reasoning. *Quarterly Journal of Experimental Psychology, 46A*, 779-811.

Bolton, L. E. (2003). Stickier priors: The effects of nonanalytic versus analytic thinking in new product forecasting. *Journal of Marketing Research, 40*, 65-79.

Bottomley, P. A., & Fildes, R. (1998). The role of prices in models of innovation diffusion. *Journal of Forecasting, 17*, 539-555.

Brehmer, A., & Brehmer, B. (1988). What have we learned about human judgment from thirty years of policy capturing? In B. Brehmer & C. R. B. Joyce (Eds.), *Human Judgment: The SJT view* (pp. 75 -114). Amsterdam: Elsevier Science Publishers BV.

Chandrasekaran, D., & Tellis, G. J. (2011). Getting a Grip on the Saddle: Chasms or Cycles? *Journal of Marketing, 75*, 21-34.

Chatterjee, R., & Eliashberg, J. (1990). The innovation diffusion process in a heterogenous population: a micromodeling approach. *Management Science, 36,* 1057-1079.

Chen, K.-Y., & Plott, C. (2002). Information Aggregation Mechanisms: Concept, Design and Implementation for a Sales Forecasting Problem. *CalTech Social Science Working Paper, 1131*.

Chen, W., Wassenaar, H.J. & Hoyle, C. (2013). *Decision-based design*. London: Springer-Verlag.

Christiansen, J. D. (2007). Prediction markets: practical experiments in small markets and behaviours observed. *Journal of Prediction Markets, 1*, 17-41.

Chun, S. Y., & Hahn, M. (2008). A diffusion model for products with indirect network externalities. *Journal of Forecasting, 27*, 357-370.

Dawes, R. M. (1979). Robust beauty of improper linear-models in decision-making. *American Psychologist, 34*, 571-582.

Decker, R., & Gnibba-Yukawa, K. (2010). Sales Forecasting in High-Technology Markets: A Utility-Based Approach. *Journal of Product Innovation Management, 27*, 115-129.

Ding, M., & Eliashberg, J. (2008). A dynamic competitive forecasting model incorporating dyadic decision making. *Management Science, 54*, 820-834.

Du, R. Y., & Kamakura, W. A. (2011). Measuring Contagion in the Diffusion of Consumer Packaged Goods. *Journal of Marketing Research, 48*, 28-47.

Easingwood, C. J., Mahajan, V., & Muller, E. (1983). A Nonuniform Influence Innovation Diffusion Model of New Product Acceptance. *Marketing Science, 2*, 273-295.

Eggers, F., & Eggers, F. (2011). Where have all the flowers gone? Forecasting green trends in the automobile industry with a choice-based conjoint adoption model. *Technological Forecasting and Social Change, 78*, 51-62.

Fader, P. S., Hardie, B. G. S., & Zeithammer, R. (2003). Forecasting new product trial in a controlled test market environment. *Journal of Forecasting, 22*, 391-410.

Farias, V. F., Jagabathula, S., & Shah, D. (2013). A Nonparametric Approach to Modeling Choice with Limited Data. *Management Science, 59*, 305-322.

Fildes, R., Goodwin, P., Lawrence, M., & Nikolopoulos, K. (2009). Effective forecasting and judgmental adjustments: an empirical evaluation and strategies for improvement in supply-chain planning. *International Journal of Forecasting, 25*, 3-23.

Fildes, R., & Kumar, V. (2002). Telecommunications demand forecasting - a review. *International Journal of Forecasting, 18*, 489-522.

Foster, J. A., Golder, P. N., & Tellis, G. J. (2004). Predicting sales takeoff for Whirlpool's new Personal Valet. *Marketing Science, 23*, 182-185.

Franses, P. H., & Legerstee, R. (2009). Properties of expert adjustments on model-based SKU-level forecasts. *International Journal of Forecasting, 25*, 35-47.

Gartner, W. B., & Thomas, R. J. (1993). Factors affecting new product forecasting accuracy in new firms. *Journal of Product Innovation Management, 10*, 35-52.

Gatignon, H., Eliashberg, J., & Robertson, T. S. (1989). Modeling multinational diffusion patterns - an efficient methodology. *Marketing Science, 8*, 231-247.

Gaur, V., Kesavan, S., Raman, A., & Fisher, M. L. (2007). Estimating demand uncertainty using judgmental forecasts. *Manufacturing & Service Operations Management, 9*, 480-491.

Goldenberg, J., Libai, B., & Muller, E. (2002). Riding the saddle: How cross-market communications can create a major slump in sales. *Journal of Marketing, 66*, 1-16.

Golder, P. N., & Tellis, G. J. (1997). Will it ever fly? Modeling the takeoff of really new consumer durables. *Marketing Science, 16*, 256-270.

Golder, P. N., & Tellis, G. J. (2004). Growing, growing, gone: Cascades, diffusion, and turning points in the product life cycle. *Marketing Science, 23*, 207-218.

Goodwin, P (forthcoming) When simple alternatives to Bayes formula work well: Reducing the cognitive load when updating probability forecasts. *Journal of Business Research*

Goodwin, P., Dyussekeneva, K., & Meeran, S. (2013). The use of analogies in forecasting the annual sales of new electronics products. *IMA Journal of Management Mathematics, 24*, 407-422.

Goodwin, P., Onkal, D., & Thomson, M. (2010). Do forecasts expressed as prediction intervals improve production planning decisions? *European Journal of Operational Research, 205*, 195-201.

Graefe, A., & Armstrong, J. S. (2011). Comparing face-to-face meetings, nominal groups, Delphi and prediction markets on an estimation task. *International Journal of Forecasting, 27*, 183-195.

Green, K. C., Armstrong.J.S., & Graefe, A. (2007). Methods to elicit forecasts from groups. Delphi and prediction markets compared. *Foresight: the International Journal of Applied Forecasting, 8*, 17-20.

Ho, T. H., & Chen, K. Y. (2007). New product blockbusters: The magic and science of prediction markets. *California Management Review, 50*, 144-+.

Holyoak, K. J., & Thagard, P. (1995). *Mental Leaps: Analogy in Creative Thought.* . Cambridge, MA: MIT Press.

Horsky, D. (1990). A diffusion-model incorporating product benefits, price, income and information. *Marketing Science, 9*, 342-365.

Hyman, M. R. (1988). The timeliness problem in the application of bass-type new product-growth models to durable sales forecasting. *Journal of Business Research, 16*, 31-47.
Hyndman, R. J., & Athanasopoulos, G. (2013). Forecasting: principles and practice. In. https://www.otexts.org/fpp: O-texts.
Ilonen, J., Kamarainen, J. K., Puumalainen, K., Sundqvist, S., & Kalvianen, H. (2006). Toward automatic forecasts for diffusion of innovations. *Technological Forecasting and Social Change, 73*, 182-198.
Islam, T., & Meade, N. (2000). Modelling diffusion and replacement. *European Journal of Operational Research, 125*, 551-570.
Islam, T., & Meade, N. (2012). The impact of competition, and economic globalization on the multinational diffusion of 3G mobile phones. *Technological Forecasting and Social Change, 79*, 843-850.
Jun, D. B., Kim, S. K., Park, Y. S., Park, M. H., & Wilson, A. R. (2002). Forecasting telecommunication service subscribers in substitutive and competitive environments. *International Journal of Forecasting, 18*, 561-581.
Kahn, K. B. (2002). An exploratory Investigation of new product forecasting practices. *Journal of Product Innovation Management, 19*, 133-143.
Kahneman, D. (1979). Prospect theory: an analysis of decision making under risk. *Econometrica*, *47*, 263-292.
Kahneman, D. (2011). *Thinking fast and slow*. London: Penguin.
Karelaia, N., & Hogarth, R. M. (2008). Determinants of linear judgment: A meta-analysis of lens model studies. *Psychological Bulletin, 134*, 404-426.
Karniouchina, E. V. (2011). Are Virtual Markets Efficient Predictors of New Product Success? The Case of the Hollywood Stock Exchange. *Journal of Product Innovation Management, 28*, 470-484.
Kaynak, E., & Rojas-Mendez, J. I. (2009). Predicting Tourism Market Potential of Chile by Use of Qualitative Forecasting Technique. In E. Kaynak & T. D. Harcar (Eds.), *Management Challenges in an Environment of Increasing Regional and Global Concerns* (Vol. 18, pp. 127-135).
Kim, S. H., & Srinivasan, V. (2009). A Conjoint-Hazard Model of the Timing of Buyers' Upgrading to Improved Versions of High-Technology Products. *Journal of Product Innovation Management, 26*, 278-290.
Kohli, R., Lehmann, D. R., & Pae, J. (1999). Extent and impact of incubation time in new product diffusion. *Journal of Product Innovation Management, 16*, 134-144.
Kontzalis, P. (1992). Identification of key attributes, gap analysis and simulation techniques in forecasting market potential of ethical pharmaceutical products. *International Journal of Forecasting, 8*, 243-249.
Kreng, V. B., & Wang, B. J. (2013). An innovation diffusion of successive generations by system dynamics - An empirical study of Nike Golf Company. *Technological Forecasting and Social Change, 80*, 77-87.
Kulkarni, G., Kannan, P. K., & Moe, W. (2012). Using online search data to forecast new product sales. *Decision Support Systems, 52*, 604-611.
Lawrence, K. D., & Lawton, W. H. (1981). Applications of diffusion models: some empirical results. In Y. Wind, V. Mahajan & R. Cardoz (Eds.), *New Product Forecasting*. Lexington, MA.: Lexington Books.
Lawrence, M., Goodwin, P., O'Connor, M., & Onkal, D. (2006). Judgmental forecasting: A review of progress over the last 25 years. *International Journal of Forecasting, 22*, 493-518.
Lee, J., Boatwright, P., & Kamakura, W. A. (2003). A Bayesian model for prelaunch sales forecasting of recorded music. *Management Science, 49*, 179-196.

Lee, J., Cho, Y. S., Lee, J. D., & Lee, C. Y. (2006). Forecasting future demand for large-screen television sets using conjoint analysis with diffusion model. *Technological Forecasting and Social Change, 73*, 362-376.
Lee, W. Y., Goodwin, P., Fildes, R., Nikolopoulos, K., & Lawrence, M. (2007). Providing support for the use of analogies in demand forecasting tasks. *International Journal of Forecasting, 23*, 377-390.
Lenk, P. J., & Rao, A. G. (1990). New models from old - forecasting product adoption by hierarchical Bayes procedures. *Marketing Science, 9*, 42-53.
Luan, Y. J., & Sudhir, K. (2010). Forecasting Marketing-Mix Responsiveness for New Products. *Journal of Marketing Research, 47*, 444-457.
Lynn, G. S., Schnaars, S. P., & Skov, R. B. (1999). Survey of new product forecasting practices in industrial high technology and low technology businesses. *Industrial Marketing Management, 28*, 565-571.
Mackay, M. M., & Metcalfe, M. (2002). Multiple method forecasts for discontinuous innovations. *Technological Forecasting and Social Change, 69*, 221-232.
McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarmebka (Ed.), *Frontiers in Econometrics* (pp. 105-142). New York: Academic Press.
McFadden, D. (1978). Modeling the choice of residential location. In A. Karlquist, L. Lundqvist, F. Snickars & K. Weibull (Eds.), *Spatial Interaction Theory and Planning Models* (pp. 75-96). Amsterdam: North-Holland.
Meade, N., & Islam, T. (2001). Forecasting the Diffusion of Innovations: Implications for Time-Series Extrapolation. In J. S. Armstrong (Ed.), *Principles of Forecasting: A Handbook for Reseachers and Practitioners* (pp. 577-595). Boston: Kluwer Academic Publishers.
Meeran, S., Dyussekeneva, K., & Goodwin, P. Sales forecasting using a combination of diffusion model and forecast market: an adaptation of prediction/preference markets. In *IFAC* (Vol. 7, pp. 87-92). St. Petersburg.
Moe, W. W., & Fader, P. S. (2002). Using advance purchase orders to forecast new product sales. *Marketing Science, 21*, 347-364.
Morwitz, V. G. (2001). Methods for forecasting from intentions data. In J. S. Armstrong (Ed.), *Principles of Forecasting: A Handbook for Practitioners and Researchers* (pp. 33-56). Boston: Kluwer Academic Publishers.
Morwitz, V. G., Steckel, J. H., & Gupta, A. (2007). When do purchase intentions predict sales? *International Journal of Forecasting, 23*, 347-364.
Motes, W. H., & Woodside, A. G. (2001). Purchase experiments of extra-ordinary and regular influence strategies using artificial and real brands. *Journal of Business Research, 53*, 15-35.
Mueller, M. G., & de Haan, P. (2009). How much do incentives affect car purchase? Agent-based microsimulation of consumer choice of new cars-Part I: Model structure, simulation of bounded rationality, and model validation. *Energy Policy, 37*, 1072-1082.
Neelamegham, R., & Chintagunta, P. (1999). A Bayesian model to forecast new product performance in domestic and international markets. *Marketing Science, 18*, 115-136.
Niederhoffer, K., Mooth, R., Wiesenfeld, D., & Gordon, J. (2007). The origin and impact of CPG new-product buzz: Emerging trends and implications. *Journal of Advertising Research, 47*, 420-426.
Orbach, Y., & Fruchter, G. E. (2011). Forecasting sales and product evolution: The case of the hybrid/electric car. *Technological Forecasting and Social Change, 78*, 1210-1226.

Ozan, E., Sireli, Y., & Kauffmann, P. (2007). A new market adoption model for the information systems industry. *Emj-Engineering Management Journal, 19*, 13-21.
Ozer, M. (1999). The use of Internet-based groupware in new product forecasting. *Journal of the Market Research Society, 41*, 425-438.
Ozer, M. (2011). Understanding the impacts of product knowledge and product type on the accuracy of intentions-based new product predictions. *European Journal of Operational Research, 211*, 359-369.
Parker, P. M. (1994). Aggregate diffusion forecasting models in marketing - a critical review. *International Journal of Forecasting, 10*, 353-380.
Peers, Y., Fok, D., & Franses, P.H. (2012). Modeling seasonality in new product diffusion. *Marketing Science, 31,* 351-364.
Peres, R., Muller, E., & Mahajan, V. (2010). Innovation diffusion and new product growth models: A critical review and research directions. *International Journal of Research in Marketing, 27*, 91-106.
Qian. L., & Soopramanien, D. (in press). Incorporating heterogeneity to forecast the demand of new products in emerging markets: green cars in China. *Technological Forecasting and Social Change.*
Radas, S., & Shugan., S.M. (1998). Seasonal marketing and timing new product introduction. *Journal of Marketing Research, 35* 296-315.
Ramos, M.H., van Andel, S.J., & Pappenberger, F. (2013). Do probabilistic forecasts lead to better decisions? *Hydrology and Earth Systems Sciences*, *17*, 2219–2232.
Roberts, J. H., Nelson, C. J., & Morrison, P. D. (2005). A prelaunch diffusion model for evaluating market defense strategies. *Marketing Science, 24*, 150-164.
Rowe, G., & Wright, G. (1999). The Delphi technique as a forecasting tool: issues and analysis. *International Journal of Forecasting, 15*, 353-375.
Schmittlein, S. C., & Mahajan, V. (1982). Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance. *Marketing Science, 1*, 57-58.
Shafiei, E., Thorkelsson, H., Asgeirsson, E. I., Davidsdottir, B., Raberto, M., & Stefansson, H. (2012). An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. *Technological Forecasting and Social Change, 79*, 1638-1653.
Simon, H., & Sebastian, K. H. (1987). Diffusion and advertising - the German telephone campaign. *Management Science, 33*, 451-466.
Sniezek, J. A. (1990). A comparison of techniques for judgmental forecasting by groups with common information. *Group & Organization Studies, 15*, 5-19.
Sniezek, J. A., & Naylor, J. C. (1978). Cue measurement scale and functional hypothesis testing in cue probability-learning. *Organizational Behavior and Human Performance, 22*, 366-374.
Sohn, S. Y., & Ahn, B. J. (2003). Multigeneration diffusion model for economic assessment of new technology. *Technological Forecasting and Social Change, 70*, 251-264.
Song, H. Y., Gao, B. Z., & Lin, V. S. (2013). Combining statistical and judgmental forecasts via a web-based tourism demand forecasting system. *International Journal of Forecasting, 29*, 295-310.
Song, I., & Chintagunta, P.K. (2003). A micromodel of new product adoption with heterogenous and forward-looking consumers: application to the digital camera category. *Quantitative Marketing and Economics, 4,* 371-407.
Sood, A., James, G.M., & Tellis, G.J. (2009). Functional regression: a new model for predicting market penetration of new products. *Marketing Science, 28,* 36-51.
Srinivasan, V., & Mason, C. H. (1986). Technical Note: Nonlinear Least squares Estimation of New Product Diffusion Models. *Marketing Science, 5*, 169-178.

Srivastava, R. K., Mahajan, V., Ramaswami, S. N., & Cherian, J. (1985). A multiattribute diffusion-model for forecasting the adoption of investment alternatives for consumers. *Technological Forecasting and Social Change, 28*, 325-333.
Steffens, P. R. (2003). A model of multiple-unit ownership as a diffusion process. *Technological Forecasting and Social Change, 70*, 901-917.
Sugiyama, S. (2007). Forecast Uncertainty and Monte Carlo Simulation. *Foresight: the International Journal of Applied Forecasting, 6*, 29-37.
Surowiecki, J. (2005). *The Wisdom of Crowds: Why the Many are Smarter than the Few* London: Abacus.
Talukdar, D., Sudhir, K., & Ainslie, A. (2002). Investigating new product diffusion across products and countries. *Marketing Science, 21*, 97-114.
Tellefsen, T., & Takada, H. (1999). The relationship between mass media availability and the multicountry diffusion of consumer products. *Journal of International Marketing, 7*, 77-96.
Thomas, R. J. (1985). Estimating market growth for new products - an analogical diffusion-model approach. *Journal of Product Innovation Management, 2*, 45-55.
Thomas, R. J. (1987). Forecasting new product market potential - combining multiple methods. *Journal of Product Innovation Management, 4*, 109-119.
Tigert, D., & Farivar, B. (1981). The Bass new product growth-model - a sensitivity analysis for a high technology product. *Journal of Marketing, 45*, 81-90.
Timmers, H., & Wagenaar, W. A. (1977). Inverse statistics and misperception of exponential growth. *Perception and Psychophysics, 21*, 6-558.
Train, K. E. (2003). *Discrete Choice Models with Simulation*. Cambridge MA: Cambridge University Press.
Tsafarakis, S., Grigoroudis, E., & Matsatsinis, N. (2011). Consumer choice behaviour and new product development: an integrated market simulation approach. *Journal of the Operational Research Society, 62*, 1253-1267.
Tseng, F. M., Lin, Y. T., & Yang, S. C. (2012). Combining conjoint analysis, scenario analysis, the Delphi method, and the innovation diffusion model to analyze the development of innovative products in Taiwan's TV market. *Technological Forecasting and Social Change, 79*, 1462-1473.
Tversky, A., Sattath, S., & Slovic, P. (1988). Contingent weighting in judgment and choice. *Psychological Review, 95*, 371-384.
Tyebjee, T. T. (1987). Behavioral biases in new product forecasting. *International Journal of Forecasting, 3*, 393-404.
Urban, G. L., Hulland, J. S., & Weinberg, B. D. (1993). Premarket forecasting for new consumer durable goods - modeling categorization, elimination, and consideration phenomena. *Journal of Marketing, 57*, 47-63.
Urban, G. L., Weinberg, B. D., & Hauser, J. R. (1996). Premarket forecasting really new products. *Journal of Marketing, 60*, 47-60.
Vakratsas, D., & Kolsarici, C. (2008). A dual-market diffusion model for a new prescription pharmaceutical. *International Journal of Research in Marketing, 25*, 282-293.
Van den Bulte, C. (2000). New product diffusion acceleration: Measurement and analysis. *Marketing Science, 19*, 366-380.
Van den Bulte, C., & Lilien, G. L. (1997). Bias and systematic change in the parameter estimates of macro-level diffusion models. *Marketing Science, 16*, 338-353.
Van Ittersum, K., & Feinberg, F. M. (2010). Cumulative Timed Intent: A New Predictive Tool for Technology Adoption. *Journal of Marketing Research, 47*, 808-822.
Venkatesan, R., & Kumar, V. (2002). A genetic algorithms approach to growth phase forecasting of wireless subscribers. *International Journal of Forecasting, 18*, 625-646.

Wang, F. K., & Chang, K. K. (2009). Modified diffusion model with multiple products using a hybrid GA approach. *Expert Systems with Applications, 36*, 12613-12620.

Wind, Y., Mahajan, V., & Cardozo, R. N. (1981). New Product Forecasting. In. Lexington, MA: Lexington Books

Wittink, D. R., & Bergestuen, T. (2001). Forecasting with Conjoint Analysis. In J. S. Armstrong (Ed.), *Principles of Forecasting: A Handbook for Researchers and Practitioners.* (pp. 147-167). Boston: Kluwer Academic Publishers.

Wolfers, J., & Zitzewitz, E. (2004). Prediction markets. *Journal of Economic Perspectives, 18*, 107-126.

Wright, G., & Goodwin, P. (2009). Decision making and planning under low levels of predictability: Enhancing the scenario method. *International Journal of Forecasting, 25*, 813-825.

Wu, S. D., Kempf, K. G., Atan, M. O., Aytac, B., Shirodkar, S. A., & Mishra, A. (2010). Improving New-Product Forecasting at Intel Corporation. *Interfaces, 40*, 385-396.

Yalcinkaya, G. (2008). A culture-based approach to understanding the adoption and diffusion of new products across countries. *International Marketing Review, 25*, 202-214.

Yelland, P. M. (2010). Bayesian forecasting of parts demand. *International Journal of Forecasting, 26*, 374-396.

Young, P. (1993). Technological growth-curves - a competition of forecasting models. *Technological Forecasting and Social Change, 44*, 375-389.

Zenobla, B., Weber, C., & Daim, T. (2009). Artificial markets: A review and assessment of a new venue for innovation research. *Technovation, 29*, 338-350.

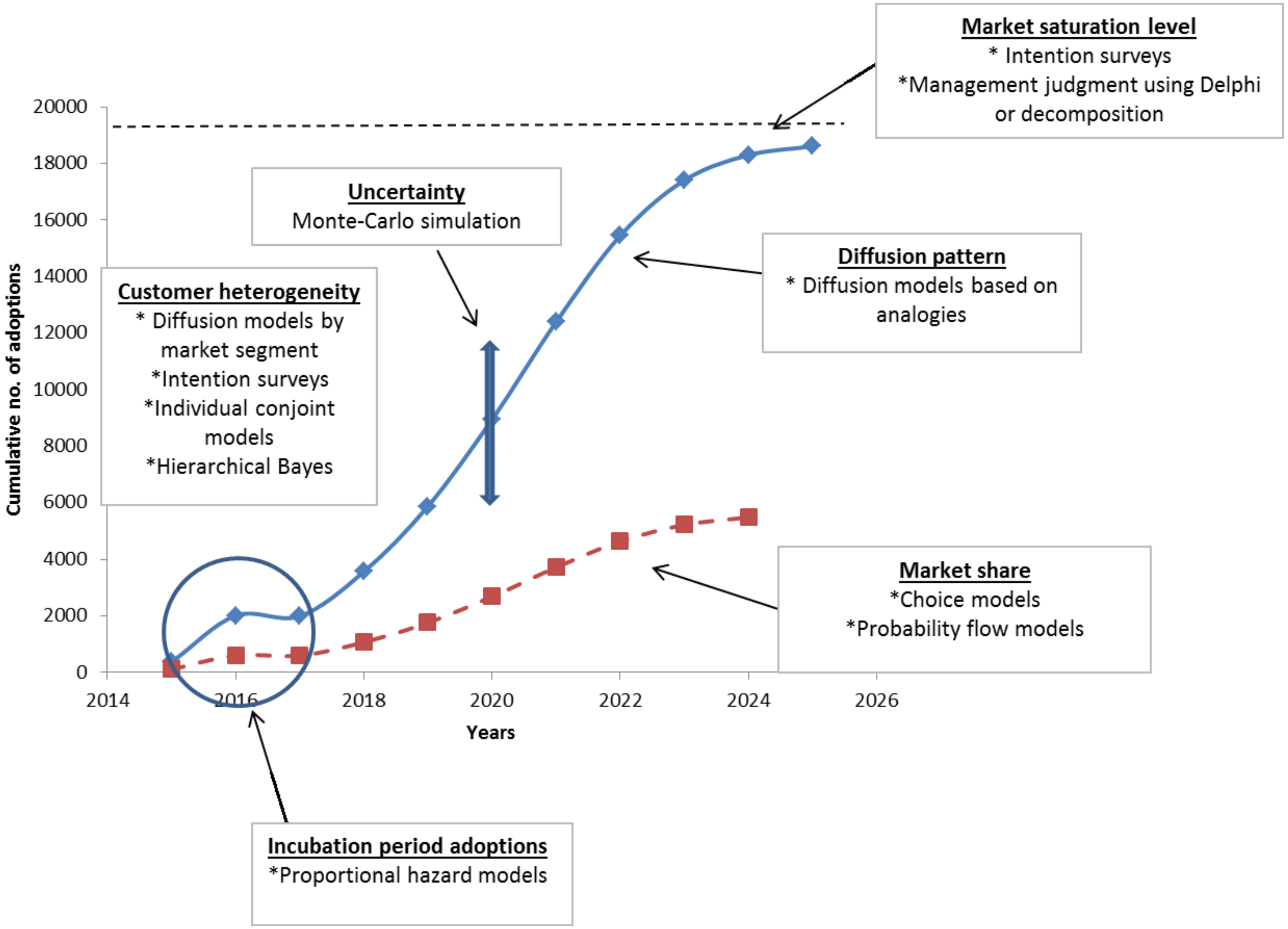

Figure 1. New product forecasting requires multiple diverse methods