New Product Sales Forecasting in the Mobile Phone Industry: an evaluation of current methods

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Abstract
Today's technological development and global competition in markets, requires suppliers of products and services to introduce new products or to improve their current products in order to survive. Fast technological development in the high tech sector also makes this global competition even harder for firms in today's market place, because technology advances have shortened the life cycle for many products. Demand forecasting is crucial for firms operating in this environment who need to make decisions relating to future production capacity, marketing budgets, human resource planning, and research and development. This is especially true of pre-launch forecasts of demand time series where products have a short life cycle. However, producing such forecasts is a difficult, complex and challenging task mainly because of the unavailability of past data and short life cycles of earlier products. This paper assesses the pros and cons of a range of new product forecasting methods where products have short life cycles. The potential effectiveness of methods such as individual and group management judgments, prediction and preference markets, intention surveys, diffusion models, conjoint analysis, market testing and agent based modelling, are evaluated in the context of the UK mobile phone industry. Areas where there is a need for future research are identified.

Key words: New product forecasting, forecasting methods, products with short life cycles, Telecommunications, Mobile phones, pre-launch sales forecasting

1. Introduction

Today's technological development and global competition in markets, requires suppliers of products and services to introduce new products or to improve their current products in order to survive (Bose, 2002). Fast technological development in the high tech sector also makes this global competition even harder for firms in today's market place, because technology advances have shortened the life cycle for many products in this sector (Reiner et al., 2009).

Demand forecasting is crucial for firms operating in this environment who need to make decisions relating to future production capacity, marketing budgets, human resource planning, and research and development. In particular, forecasts of sales time series will be required to estimate the discounted future returns on the investment to assess its likely return and viability (Goodwin, Dyussekeneva and Meeran, 2012). More accurate forecasts can give companies better insights during the product development stages, inform go-no-go decisions on whether to launch a developed product and also support decisions on whether a recently launched product should be withdrawn or not due to poor early stage sale (Dyussekeneva et al, forthcoming).

However, this is also an environment that creates problems for forecasters. By definition no past time series will exist for products that have yet to be launched, but time series relating to similar products that have already been launched will be short. Rapid technological development and competition also mean that these series may carry little information that is relevant for the estimation of the demand patterns of future products. Yet forecast errors can be costly. For instance a PC division of one major manufacturer reportedly lost $1 billion for the year because of demand underestimation in Christmas sale season (Weng, 1999).

As a result, suppliers and retailers who have the aim of decreasing the risk of product unavailability, due to the risk of losing sales to their competitors, rely on large inventory holdings. This large inventory holding strategy is very costly, especially in the case of high tech sector products because such products lose value every day due to relatively high speed of development and innovation in this sector. This means that the stored products must be deeply discounted or sold through alternative channels. In extreme cases, the annual costs of holding inventory for such products could reach up to 50% of their costs (Reiner et al., 2009), which can be decreased by more accurate forecasting. According to Hofmann and Reiner (2006), mobile phones are categorised as high technology products with a short life cycle, which lose their value over time. In the mobile phone industry, the obsolescence costs are 5–15 times higher than the average of 1% of revenue for products that do not have a short life cycle (Hofmann and Reiner, 2006). Although a number of methods have been developed, despite the critical roles of new products sales forecasting, the topic has received relatively little attention in the literature (Kahn, 2006 cited by Goodwin et al, 2012). This lack of attention is also the case for mobile phones in the telecommunication industry that have a short life cycle.

This paper reviews the literature to assess the likely effectiveness of a range of new product sales forecasting methods in the mobile phone industry. These methods includes management judgment, prediction and preference markets, intention surveys, diffusion models, conjoint analysis, market testing and agent based modelling. It then suggests areas where future research is likely to be most fruitful.

The paper starts by reviewing the literatures on product life cycles and the challenges this poses for sales forecasters. This is followed by a review of the literature on the telecommunication sector, with special reference to the mobile phone industry in the UK which is representative of a saturated market with short life cycle products. Afterwards, the paper introduces various methods of new product forecasting, followed by critical discussion of pros and cons of different methods. Finally, possibility of future research will be concluded.

2. Mobile Phone Industry in the UK

Business executives began to use mobile communication devices such as wireless cell phones in 1970's and 80s and these evolved into an essential daily communication device for every level of end users from children to older people to business people on the go (Sek et al, 2010). Since that time, due to rapid speed of development and innovation, the industry has been under a high level of uncertainty. Frequent changes of product design, competition and the willingness of customers to substitute new products for their existing ones have all contributed to uncertainty in the target markets. The high number of competitors in the mobile industry changed the nature of competition from that of product or service performance to the effective use of complementary assets such as marketing, distribution, competitive manufacturing (e.g. process innovation), and after-sales support (Funk, 2004). As result, accurate forecasts of sales of new products play a significant role in winning customers from competitors in this industry.

The UK market, which we focus on here, is representative of a saturated market (level have reached 134% saturation, Forbes, 2013) of high technology products with short life cycles in a developed country with intensive levels of competition.

The comedian, Ernie Wise made the UK's inaugural mobile phone call on 1 January 1985. Coverage was restricted to London and costs were prohibitive, but Britain's mobile culture had arrived. Britain's mobile phone users were either very rich or used a mobile in their jobs. When digital technology arrived in 1992 and two new networks, One2One and Orange, launched their first products a year later, the market opened up to consumers for the first time" (Mobile Phone History Website, 2012). The UK mobile phones market had total revenues of $3.1 billion in 2010, representing a compound annual growth rate (CAGR) of 4.5% between 2006 and 2010; the UK mobile market has more than 83 million subscribers.

In the late nineties, the mobile phone industry witnessed a large increase in the capacity of production in order to fulfil the requirements of a fast growing market, which caused the market saturation due to overcapacity among suppliers and shifted the power balance towards the mobile phone service providers. Market saturation increases pressure on suppliers' competition and costs which resulted in the bankruptcy of BENQ Siemens in 2006 (Reiner et al., 2009). The market saturation increases the level of competition in this industry and raised the necessity of providing good service levels with reasonable prices in order to improve customer satisfaction, which is only possible when supplier knows what the accurate demand is in the market.

Nowadays, the UK mobile market is mainly served by five main network providers i.e. O2, Orange, Vodafone, Three and T-mobile (Orange and T-mobile have recently merged as Everything Everywhere), which provide both network service and handsets from different handset manufacturing suppliers (e.g. Apple, Nokia, HTC) (Telecom Market Research Website, 2011). These service providers supply customers in both contract and pre-pay (Pay as you go) categories through their own retail outlets. There are other insignificant players such as Virgin, Asda, Tesco, Vectone, Lyca and Lebara that mostly provide a pre-pay service through unspecialised retailers in different sectors from that of mobile phone such as off-licence supermarkets, supermarkets and grocery stores. Above named insignificant players in mobile industry in the UK provide their network through the network infrastructures of five main providers by using a virtual network on their own name; for example Tesco mobile uses O2 network infrastructure; however by using a virtual network customer can see their reception from Tesco itself (Research and Market website, 2011).

The manufacturers of handsets (original suppliers) divide the handsets market into various classes so that each class has various models with similar technological features i.e. smart phones, comfort phones, low end phones and outdoor phones. In this industry, specific models within a class and contract type usually see a pattern of declining prices over time, so providers practice a markdown strategy such that the price at each stage of the life cycle is perceived as ‘fair’ relative to its technological features (Reiner et al., 2009). Mobile providers, who follow this reference/fair price, cannot encourage demand through a pricing strategy and therefore the actual sale price has to be lower than this reference price in order to stimulate sales significantly. In contrast a price higher than the fair price leads to a sales decrease (Winer, 1986). The mobile phone selling price is normally below its constant purchasing price (seller price) after a certain period (or even right away after the product has been launched to the market). According to Reiner et al. (2009), the pricing of a mobile subscription service with a handset by a service provider depends on various interdependent criteria such as service level, customer satisfaction, handset price, sales forecasting accuracy and stock inventory.

3. Product Life Cycle

In 1950, the Product Life Cycle (PLC) concept was introduced by Dean as “The evolution of product attributes and market characteristics through time.... [the PLC concept can be]....used prescriptively in selection of marketing actions and planning” (Rink and Swan, 1979). Kotler, Wong, Saunders and Armstrong (2005) define product life cycle as the course of a product’s sales and profits over its lifetime. Although over the life a product, a company does not know how the sales will change in the future from one period to the next, the sales of any one product to some extent will normally follow the PLC curve from initial stage to the termination of product life through several distinct phases as it is greatly studied and discussed in literature (Cox, 1967; Rink and Swan, 1979; Day, 1981; Gardner, 1987).

A product’s life cycle includes four distinct stages such as Introduction, Growth, Majority and Decline; however some authors add an initial stage of development and other add final phase of cancellation (Tibben-Lembke, 2002) to these four stages (Kotler et al, 2005), as follows:

1. *Product Development:* developing the concept of a product into physical product with the aim of ensuring that the product idea can be turned into a workable product, at this stage there are no sales at all.
2. *Introduction:* once the product is launched into market, there is period of slow sales growth as the product is being introduced.
3. *Growth:* in this period, the product is accepted in the market and sales grow rapidly.

4. *Maturity:* as the product has achieved acceptance by most potential buyers at this stage, the sales growth slows down.
5. *Decline:* it is a period when sales fall off and profits stop.
6. *Cancellation:* it is a time for termination of production of a specific product.

According to Everett (1962) (cited by Rink and Swan (1979)), the theoretical rationale behind the PLC concept derives from the *adoption and diffusion theory of innovations.* In the introduction stage, there are low sales as few consumers are aware of the new product or service. More consumer awareness and acceptance of the product or service raises the amount of sales, thereby signalling the beginning of the growth stage. However, the growth rate shrinks as more competitors enter the industry and the market becomes smaller. In the maturity stage, sales become more stable as most of the mass market has already purchased the item. This is followed by decline stage as most consumers look for newer counterparts.

Golder and Tellis (2004) believe that the forecasting of PLC is an essential activity in marketing for at least three reasons. First of all, there are various dramatic pressures on managers before and after the turning point in the life cycle. In the introduction stage prior to start of growth stage, pessimism abounds and managers are under escalating pressure to pull the plug on new products. In the growth stage prior to slowdown optimism abounds and managers are eager to meet the apparently greedy demand with fresh capacity and more marketing activities. Forecasting the turning points of take-off and slowdown are vital to avoid premature withdrawal or excessive investments. Second, the level and increase of sales is considerably different across stages of the life cycle. Managers need to have accurate forecast of sales and the PLC in order to appropriately plan the corresponding levels of production, inventory, sales staff, distribution, marketing, and advertising. Third, expenses and prices decrease significantly over the PLC, especially during the early stages, because consumers become more sensitive to price through various stages of the PLC. Managers need to have great understanding of sales patterns and changes their pricing strategy accordingly. As a result, having an accurate forecast of sales is a necessity (Parker, 1994) and errors in sales projections can trigger serious consequences.

Although a product may go through all of the mention stages, not all of the products follow the product life cycle; some products never reach their intended customers and fail to reach growth phase (Tibben-Lembke, 2002) for example according to Gallo (1992) the failure rate of new product is approximately 85 to 90 percent in the grocery industry and here products do not follow the usual shape of the PLC curve. In the grocery industry, steep growth is followed by stable maturity and sharp decline (Jensen, 1982). There are other products that die quickly, soon after their introduction and hence they do not have all the distinct stages such as fashion apparel, PCs, mobile phones. These are called Products with Short Life Cycle. The PLC can be as short as a few months (a season) in fashion apparel (Kurawarwala and Matsuo, 1998) and PCs (Angelus and Porteus, 2002).

4. Challenges of Sales Forecasting for Product with Short Life Cycle

The fast pace of new product introduction has led to shortened life cycles for products in many industries, especially products in high-tech sector. According to Decker and Gnibba-Yukawa (2010), the term high-tech market refers to newly established, rapidly growing markets, which are mainly driven by technological innovations. Traditional demand forecasting methods are not oriented toward forecasting of short life cycle products. Retailers or providers, who market products with a short selling season and/or a short life cycle, find the task of forecasting sales challenging due to high levels of uncertainty in the demand for these products, especially in absence of a long sales history (Subrahmanyan, 2000).

In many of traditional forecasting methods, the long-term (long-term trend, cyclical component) and the short-term (seasonality, short-term trend) patterns are considered distinct and treated separately according to Kurawarwala and Matuso (1998). Some of the challenges of sale forecasting for product with short life cycles with some of traditional forecasting methods are:

1. *Decomposition Methods and Box-Jenkins models:* they are designed to identify and separate the time series into its various components. However, they require many data points for proper identification and parameter estimation. A sufficiently long time series is not available for short life cycle products until the end of their life cycles; therefore applications of these methods are not feasible and useful.
2. *Smoothing Methods:* methods such as moving averages, simple and linear exponential smoothing, perform well only when there is steady trend over the short term. A change in trend usually leads to a systematic lag or lead effect. As a result, undergo rapid growth, maturity, and decline along with seasonal variations in sales forecasting of product with short life cycle, made simple smoothing methods for these product inappropriate.
3. *Analogy methods:* Some researcher believe that they can use the available data on prior similar products; although these data may yield valuable information that can be

used to forecast future products, it has its own problem and downsides (the advantages and disadvantages of analogies will be discussed in more detail later on in this paper).

These traditional forecasting methods are not designed for application in new product forecasting (except when the analogy method is applied), especially for products with short life cycles. In the next section, we will discuss the specific methods that have been used for new product sales forecasting.

5. New Product Forecasting Methods and Dimensions

Wind (1981) refers to two general types of sales forecasting models that may be useful in new product forecasting. These are:

- *Diffusion models*, which are usually based on time series data from previously launch similar products and assume a sigmoid-shaped curve representing product penetration over time (Bass, 1969; Mahajan, et al, 2000; Mead and Islam, 2006).
- *Choice models*, which are based on individual level data to investigate the consumer preferences for different characteristics of products and how this will affect the choice of different opinions presented to the consumers (Greene, 2009).

In the absence of a sales history, the forecasters, who wants to apply the above models either use the similar product sales history (Analogy method) or employ conjoint analysis based on hypothetical scenarios to collect individuals' potential behaviours and preferences towards the new product before applying the choice model (Green et al, 2001; Gustafsson, et al, 2007). Some studies recently have been combined diffusion models and choice models to forecast new product demand (Jun and Park, 1999; Kumar et al, 2002; Lee et al, 2007; Lee and Cho, 2009; Lee, et al 2006). However, none of them have studied new product sales forecasting for products with short life cycles.

Apart from the aforementioned models, there are other methods that are not based on models; however they are frequently used by forecasters in order to forecast new product sales. These are:

- *Individual management judgment*, which is the most common method in new product sales forecasting, especially in the high-tech industry due to high level of uncertainty (Lynn et al, 1999; Kahn, 2002).
- *Judgments by group of managers* can be also used to obtain different opinions and perspectives with aim of having more accurate forecasting (Dyussekeneva et al,

forthcoming). Methods such as the Delphi method, prediction markets and preference markets can offer a structured process of eliciting judgments from groups of managers.

- *Customer intention surveys method*, which involve asking potential customers about their likelihood of purchasing the new product (Bass et al, 2001).
- *Market testing* and *agent base-modelling*. In former, a firm assesses the acceptance level and success of a new product in a sub-set market before launching into complete market. In latter approach, computer software models simulate the action and intention of customers by taking into account pre-defined behavioural rules (Dyussekeneva et al, forthcoming).

The relative effectiveness of these methods is likely to depend on the nature of the forecasting task. Dyussekeneva et al, (forthcoming), defined seven dimensions of this task, of which six are applicable to the mobile phone industry. These are set out below:

1. *The product's 'newness'*. This has been defined differently by various scholars. One definition relates to the 'radicalness' of an innovation. This can be divided into three categories: "A. incremental: products whose innovations made a marginal improvement over existing technology, such as improvements of camera, display resolution, and the processor in iphone 5 comparing to that of a iphone 4 (apple UK website, 2012); B. semi-radical: those products whose innovation represented a significant improvement over existing technology such as a cordless phone; C. radical: those product innovations that represented a major or revolutionary technological advance, such as the concept of the smartphone by Ericsson for first time in 2000 (Teardown Report, 2001). The Ericsson R380 smartphone combined the functions of a mobile phone and a personal digital assistant (PDA). Other scholars consider the newness of the product through its influences on consumer behaviour: continuous innovations will not disrupt behavioural patterns, (e.g. an improved version of iphone), dynamically continuous innovation will lead to small changes in behaviour, (e.g. camera phone) whereas discontinuous innovation will lead to significant changes in consumer behaviour and substantial learning will be required on the part of consumers such as launching of ipad as new generation of PDA that generate new demands in market and taste of consumers about tablets performance by its radical innovation.

2. *The intrinsic nature of the product* determines the frequency and amount of spent each time to purchase a product, the essentiality of product and perceived associated risk of impulse purchasing; for instance, the product might be a consumer durable (e.g. smartphone),

a consumer packaged good (e.g. a new chocolate bar) or a service (e.g. internet mobile subscription).

3. *The type of purchasers*. different purchasers show various buying behaviour for same product; for instance, there are special subscriptions for business customers in terms of tariff and usages as business to business selling strategy differ in mobile phone industry from that of business to consumers.

4. *Product Life Cycle* is different among various products, which affects sales forecasting for a new product as we discuss it earlier in this paper mobile phones has short life cycle. Rapid growth and decline and also short maturity of mobile phones due to speed of innovation in this industry, makes the forecasting task much more complicated.

5. *Whether the aim of forecast is the size of the total market or the market share of a product*. Forecasts of market share require estimates of the probability of consumers choosing a particular product or brand (e.g. the probability of a consumer choosing an Apple iphone over the Samsung Galaxy). This requirement will be different when the total size of a market is required for a specific product in a period of time (e.g. total size of smart phone market in the UK in summer 2012).

6. *The extent to which forecasting is essential* for a company may differ in different industries. It is crucial to keep the right balance between level of complexity and accuracy in the adoption of a method.

We next consider the likely pros and cons of these methods when they are applied to new product sales forecasting in the mobile phone industry.

5.1. Management Judgments

Graefe and Armstrong (2011) suggest that human judgment can be used in new product sales forecasting where a lack of appropriate or available information precludes one from using quantitative methods. Human judgment or management judgement can be divided into two categories: individual manager judgment and judgments from groups of managers.

Judgments by individual managers was the most common method used to forecast new product sales, especially for forecasting sales of high-tech products in survey by Kahn (2002).

A number of issues are associated with the application of management judgment as a single method of forecasting. The main concern is that managers have difficulties in accurately extrapolating simple linear patterns; therefore, the more complex non-linear patterns associated with new products' life cycles would be much less amenable. Hence this method is likely to be less reliable as result of inconsistency and cognitive limitations (Dyussekeneva et al., forthcoming).

In addition, there are other elements that may influence managers' judgments, such as unrealistic views about the prospects for a specific product by some of the managers who are involved in developing the product, resources competition among managers to support the development and commercialization of a new product, peer pressure and motivational biases from independent forecasters who deliberately tell the managers the overestimated forecast which is what manager want to hear, and also wrong indicators from market may mislead the management judgment like any other human judgments as human judgment is quite subjective (Dyussekeneva et al., forthcoming).

While the use of judgment on its own may be problematical, it can be a valuable method in combination with other methods of forecasting[1]. For example, it can be used to estimate initial sales or to select appropriate analogies when applying diffusion models. Also judgmental adjustments of statistical forecasts can improve accuracy where a manager has information that is not taken into account by the statistical methods.

Judgment by groups of managers instead of individuals' judgment can be a way to decrease biases and improve the accuracy of judgment. Common approaches are: unstructured face to face meetings, nominal groups, the Delphi method and prediction and preference markets.

Unstructured face to face meeting is the most common form of group decision making in organisations. While the approach may give participants the enjoyment and satisfaction of direct human interaction and working together, it also may be subject to many biases and drawbacks. For instance, a group requires time and effort to be maintained, and also peer pressure may influence members' decision. For example, the presence of people from different hierarchical levels within an organisation company the politics may mean that, not all members are willing to express their own ideas or decisions (Armstrong, 2006).

Van den Van and Delbecq (1974) tried to improve traditional unstructured face to face meeting drawbacks by giving structure it by proposing a method called the nominal group technique. This technique consists of three steps: first, group member work independently and produce their own decisions based on their individual estimations; second, the group enters an unstructured face to face meeting to discuss the issue with the aim of finding a solution; and finally, they work independently again and prepare their final individual decision. The group result is the aggregated outcome of these final individual estimates. The

[1] Other methods can be Diffusion model, statistical methods, to name but a few.

face to face interaction in the second phase of the nominal group technique helps group members to justify and clarify their point of view to achieve more informed decisions. On the other hand, the final phase of decision making which prevents direct interaction between group members, decrease the drawbacks associated with traditional face to face meetings.

The Delphi method was developed in 1950s by RAND corporation workers while they are involved in US Air force sponsored project. It involves an anonymous multiple-round survey about a problem. After each round summaries of the individual estimates are reported to all participants and then, by taking into account this information, participants start their new round of estimation. The result is the aggregate estimate of the final round outcome of all individuals. Clearly, this method avoids the drawbacks and biases that associated with direct interaction. "Delphi is not a procedure intended to challenge statistical or model-based procedures, against which human judgment is generally shown to be inferior: it is intended for use in judgment and forecasting situations in which pure model-based statistical methods are not practical or possible because of the of appropriate historical /economic/ technical data, and thus where some form of human judgmental input is necessary" (Rowe and Wright, 1999).

Prediction market and preference market can also be categorised as a group judgment approach (Graefe and Armstrong, 2011; Dyussekeneva et al., forthcoming); however this paper discuss these in the next section as they are based on significantly different approach, which this method has received more attention in recent years.

5.2. Prediction and Preference Market

Graefe and Armstrong (2011) found that prediction markets are gaining attention in various field of forecasting. The approach involves setting up a contract whose payoff depends on the result of an uncertain future situation. The participants of prediction markets can trade this contract, which can be interpreted as a bet on the outcome of the underlying future event. Participants are paid off in exchange for contracts they hold as soon as the outcome reveals. Participants can win money based on their individual performance in the same way as on the stock market. Ivanov (2009) believes that the prediction market is a useful tool of forecasting to harness collective wisdom. Unlike Delphi, it offers incentives for accurate forecasting and can instantly respond to new information. However, there are several serious issues associated with the method. First user friendly software has to be adopted and developed to support the method. Second, according to Graefe and Armstrong (2011) participants find it hard to understand and implement prediction markets, even after a proper training session.

Prediction markets also suffer from the long period between the forecast and potential payoff, though this would be less of a problem in the mobile phone industry given its short product life cycles. Preference markets offer an alternative method that addresses this issue by replacing the occurrence of the event as the basis for the payoff with the group's mutual expectation.

5.3. Intention Surveys

Asking potential customers about their likelihood of purchasing a new product in a questionnaire is called an "intentions survey". Clearly, by eliciting judgments directly from potential customers important information about the potential market can be obtained. However, according to Dyussekeneva et al (forthcoming), in addition to the usual errors associated with surveys, such as sampling error and non-response biases, there are numbers of other kind of error could potentially be associated with sales forecasts based on intentions surveys.

First, the unfamiliarity of participants with a product reduces the accuracy of their judgments about their probability of purchasing it. Clearly, most users will be familiar with mobile phones. However, the speed of innovation in this industry and the newness of products may still have a negative impact on accuracy. However, the method is known to be more reliable for durable products, like mobile phones rather than non-durable products, like packets of crisps. This is because buying decisions for durable products are less likely to be based on impulse and are more likely to be the results of thoughtful and planned buying. Second, the timing of intention surveys influences the accuracy of its responses; the closer the time of product launching, the more accurate the customer responses would be to the surveys. Third, one of the significant issue that associated with this method in the mobile industry research context, is "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; hence those who participate in an intention survey may behave differently from other member of target population. Finally, previous research has shown that intention surveys are more reliable when they are related to a specific brand rather than the entire product category (Morwitz, 2001 cited by Dyussekeneva et al, forthcoming).

5.4. Diffusion models

Diffusion models have been developed since the 1960s to model and forecast the diffusion of innovations (Mead and Islam, 2006). Wind et al (1981) believes that diffusion models can be adapted to model new product forecasting in the early stages. As we discussed earlier, new product sales forecasting is often necessary prior to the launch of a product and the unavailability of past data is therefore one of the main challenges to the application of diffusion models in this context. One solution is "to fit the model to the sales time series of similar products that have been launched in an earlier time period and to assume that the parameter values identified for the analogy are applicable to the new product" (Goodwin et al, 2012). This process called "forecasting by analogy".

Three well-known diffusion models are: Gompertz, logistic and Bass models. All three models represent cumulative diffusion as S-shaped curves, with a point of inflection and a 'flattening' of the curve as diffusion approaches the market ceiling. For example, Gregg et al, (1964) applied the Gompertz model to study the car market and ownership, where the aggregate car ownership level at time *t* is:

$$Nt=M.\exp(-\alpha.\exp(-\beta.t))$$

Nt: number of adaptors at time t

M: the market saturation level

α and β: define the shape of growth curve

In the above model the inflection point occurs before half of the market adopts the product implying a slow diffusion speed and longer diffusion duration (Mead and Islam, 1995). This is unlikely to be the case for mobile phone diffusion due to its short PLC and rapid speed of innovation. The logistic model is symmetrical about its inflection point, which means market growth slowdown after half of the market has adopted the product. It can be defined as follows:

$$Nt=M/1+\alpha.\exp(-\beta.t))$$

α and β: determine the initial level and growth speed

The Bass model (Bass, 1969) has been frequently used for purpose of forecasting by analogy. This model categorises adopters into two categories: innovators and imitators. The number of adaptors based on the Bass model at time t can be defined as follows:

$$Nt=M(1-\exp(-(p+q)t)/1+(q/p)\exp(-(p+q)t)$$

Nt: the cumulative number of adaptors at time t

M: the market saturation level

p: coefficient of innovators

q: coefficient of imitators

The Bass model has been extended to take into account various characteristic such as marketing mix variables, wage levels, size of the population and income, replacement purchases, non-uniform interpersonal influences, and also modelling of multiple unit adoption. However, there are some limitations associated with the method when it is applied to analogous products. The market may react very differently to similar products and the selection of appropriate analogues, which may be judgment based, is also potentially problematical.

Another issue that is specific to diffusion models is the complexity of adoption curves for high tech products. Sometimes after a surge at the beginning the adoption curve falls for a while on account of competition (Lee et al, 2006) or expectancy of higher technology or an upgrade in the near future (Kim and Srinivasan, 2009). Alternatively, slow growth of sales at the beginning of the product launch can turn into a boost of sales few weeks later. This can be the result of a wrong initial marketing strategy or an ethical scandal relating to a major competitor. For example, the Apple ethical scandal in China increased sales of the Samsung Galaxy (Routers, 2012).

Gupta et al (1999) believe that adoption of a product depends on large variety of factors, which directly or indirectly affect its diffusion patterns. For instance, an increase in the number of smartphone users directly influences the number of subscriptions to the mobile internet of a service provider in the UK. However, an increase in the number of smart phone application users *indirectly* affects the number of mobile internet subscribers.

All in all, the main concern about the accuracy of sales forecasts by using analogy in the mobile phone industry is the high speed of technological development and the large annual number of radical innovations in this sector, which may reduce the product similarity and hence the similarity of sales pattern over time in this industry.

5.5. Conjoint analysis and Choice models

Green et al (2001) defined conjoint analysis as one of the most widely used marketing research methods for analysing consumers' trade-offs between two or more products with different profiles, and how consumers' product preferences are related to attributes of the product itself. Since the introduction of conjoint analysis in the early 1970s, it has been used not only to analyse consumer preferences or intentions to buy existing products, but also how consumers may react to potential changes in the existing product or to a new product being introduced to the market later (Qian, 2012).

The reason that researchers have chosen conjoint analysis over other methods is because it address key question: why do consumers' prefer one brand of a product over other? What attributes are they looking for and how do they make tradeoffs between these attributes?

According to Green et al (2001), it is a useful method for simulating how consumers might react to changes in current products or to new products introduced into an existing competitive array. For example, it is potentially useful if a marketer in the mobile phone industry wishes to examine the possibility of modifying its current line of services. One of the first steps in designing a conjoint study is to develop a set of attributes and corresponding attribute levels to characterize the competitive domain. This can be obtained via a qualitative method or through multiple methods such as a focus group, interview and observation and choice-based conjoint analysis can be employed by using data from a large scale survey.

Although choice models would benefit from further empirical studies to assess their effectiveness in different contexts, they may suffer from a number of limitations in some circumstances. For instance, choice experiments suffer from the defect of modelling current attitudes. In the mobile industry, a new product may change these attitudes, especially where imitator's attitudes depend on their observations of others' experiences of the product (Fildes and Kumar, 2002).

5.6. Market testing

Market testing is more common for forecasting sales of non-durable goods such as consumer packaged goods and grocery products. However, few researchers have been able to generate one or two years of accurate sales forecasting from almost market testing data which may cover periods shorter than six months (Fourt and Woodlock, 1960 and Baumen and Dennis, 1961 cited by Fader, 2003). Market testing is costly and it causes some delays in the launching of the product to the main market, the risk that competitors will imitate a product, especially in the mobile phone industry where novelty and innovation are likely to be its key competitive advantages.

5.7. Agent Based Modelling

In agent based modelling computer software models simulate the action and intentions of customers in accordance with pre-defined behavioural rules. This allows 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). Problems such as achieving a good balance between the realistic behaviour of consumers and the need for model simplicity, absence of historical data, the likely sensitivity of models to initial conditions, and model calibration and validation still need to be resolved. However, if these problems can be addressed in the future, this method has the potential to become a strong tool for new product sales forecasting (Dyussekeneva et al, forthcoming).

6. Future Research

Having reviewed the current status of methods that are used in new product sales forecasting, what further research and development is needed to meet the demands of the mobile phone industry with its fast moving markets and its short product life cycles?

A number of avenues seem worth pursuing. We need to establish whether new patterns of diffusion apply to such markets and whether analogies of the Bass model can be developed to account for such patterns. Clearly, such methods would only work if the patterns are stable across analogous products launched into different markets at different points in time, or if attributes of the market that are known at the time of the forecast can be used to determine the parameter values of the model. They will also require a solid theoretical base, on a par with Bass's model of the interaction of imitators and innovators. The signposts for such a theory may lie initially in qualitative research, such as that based on focus groups, where consumers' motivations and perceptions can be identified and explored.

Preference markets are an unexplored method in this context and their ability to provide rewards soon after the conclusion of the market means that they can potentially draw on the benefits of incentives, group judgments and information on consumer preferences all within the short time scales required by fast moving markets

Recent development of choice models in association with conjoint analysis could also prove to be productive. Currently, there is a dearth of empirical evidence on the out-of-sample accuracy of such methods. This is often because the methods have been used to forecast sales for many years ahead so that the accuracy of the forecast is still awaited. The mobile industry, with its short PLCs would seem to be ideal for obtaining this evidence at an early stage.

Research into individual management judgment in this context is also a neglected area. Most research has focussed on time series extrapolation or event forecasting. There is huge scope here for testing the effectiveness of techniques like providing feedback, decomposition, and judgmental bootstrapping,

Overall it seems most likely that a combination of complementary methods will lead to the greatest accuracy. This has proved to be the case in other areas of forecasting and it is important for future researchers to establish whether this is the case here and, if it is, how such combinations can be implemented in the most effective way.

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