Industrial Marketing Management 39 (2010) 298–307

Contents lists available at ScienceDirect

Industrial Marketing Management

# Forecasting organizational adoption of high-technology product innovations separated by impact: Are traditional macro-level diffusion models appropriate?[☆]

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ARTICLE INFO

*Article history:*
Received 8 February 2008
Received in revised form 12 September 2008
Accepted 1 November 2008
Available online 6 January 2009

*Keywords:*
Diffusion models
High-tech products
Organizational adopters
Forecasting

ABSTRACT

This study examines *forecasting accuracy* when applying *macro-level diffusion models* to *high-tech* product innovations among *organizational adopters*. In addition, it explores whether the accuracy of macro-level diffusion models differs according to the *impact* of the new product. As a benchmark for comparison, three types of basic diffusion models are compared to three simple trend extrapolation models. The role of innovation impact in explaining forecasting accuracy is also considered. These issues are addressed by empirically testing organizational adoption data for 39 new high-tech products. Results indicate that for radical innovations the Bass model is best while for incremental innovations an external influence model is best. However, simple trend extrapolation models produced the most accurate overall forecasts. The purpose of the study is to reintroduce an important topic and give practitioners better insight into forecasting the organizational adoption of high-tech products once initial sales data becomes available.


## 1. Introduction

Perhaps the most critical use of diffusion models is to forecast first-purchase sales volume. The value of predicting sales or adoptions cannot be overemphasized. For example, errors in sales projections can trigger a series of adverse reactions affecting budget forecasts, operating expenses, cash flows, inventory levels, pricing, advertising outlays, and so on. This is critical when new products are launched because typically there is little relevant information to rely upon. As important as forecasting is however, most executives will tell you that any given new product forecast of sales or adoptions will be wrong (Kahn, 2002).

For new products the likelihood of large forecasting errors is typical and there are several factors that increase both the probability and the scale of error. One factor is the forecasting of high-tech products. With high-tech products change is frequently rapid and the rate of new product introduction is fast therefore data series are often short or non-existent. Also, high-tech innovations are often more radically new, making their adoption more important. Therefore a different set of new product forecasting models may be more appropriate than when forecasting sales of low-tech products (Lynn, Schnaars, & Skov, 1999).

But what classifies a product as high-tech? Shaklin and Ryans (1984) suggest the following criteria for high-tech products: a strong scientific basis, new technologies that can quickly make existing technologies obsolete and new technologies whose application create new markets and demand. Based on these dimensions, products with no technical basis (e.g., food), products where improvements are gradual and non-threatening to the core technology (e.g., washers/dryers), and products whose market is primarily replacement sales (e.g., televisions) can be eliminated. Further research characterizes high-tech products along two additional dimensions: uncertainty and switching costs. High-tech products are characterized by higher levels of uncertainty as a result of both the rapid rate of technological change (Norton & Bass, 1987; Heide & Weiss, 1995) and the lack of relevant prior experience by adopters (von Hippel, 1986, 1988). Switching costs may prohibit potential adopters from purchasing a high-tech product due to earlier commitments to existing high-tech products (Moriarty & Kosnik, 1989; Heide & Weiss, 1995). A more straightforward way of classifying high-tech products that is consistent with previous research (Lynn et al., 1999) is to use SIC codes to select a high-tech industry.

A second factor that increases both the probability and the scale of error is forecasting organizational adoption. Traditional models of organizational buying behavior include individual characteristics, interpersonal factors and organizational factors as important variables affecting the organizational buying process. Marketing variables such as mass media promotions and word-of-mouth may impact diffusion at both the consumer and organizational levels but organizational diffusion literature suggests additional key variables that may require separate models (Fern & Brown, 1984). Specifically, Framback

☆ Data for this study was generously provided by Techtel Corporation of Emeryville, California (www.techtel.com).

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doi:10.1016/j.indmarman.2008.11.002

and Schillewaert (2002) identified adaptor characteristics such as firm size, structure and organization innovativeness or strategic posture as factors that influence the acceptance of new products by organizations.

An additional consideration in organizational diffusion is that while consumer diffusion research assumes there is only one purchase of an adopting unit, organizations rarely buy a single unit since purchases are usually for a group of users. As such, a single "adoption" of a new product by an organizational buyer may include thousands of units and have a great effect on its ultimate diffusion. Lastly, while most consumer diffusion research assumes an innovation is adopted by all potential users, organizational diffusion research suggests that investment costs, network externalities, and competitive pressure can all trigger the rejection of an innovation even if the adopters' preferences are favorable (McDade et al., 2002). In summary, high-tech products may not always diffuse among a population of organizations according to theories developed in the marketing literature based on consumer durables.

Over the years, modeling research has raised questions about the forecasting accuracy of macro-level diffusion models (Bernhardt & MacKensie, 1972; Collopy, Adya, & Armstrong, 1994; Heeler & Hustad 1980; Meade & Islam 2001; Lynn et al., 1999; Rao 1985). For example, Mahajan, Muller, and Bass (1990) point out that more empirical work is needed to identify conditions under which macro-level diffusion models work or do not work. Likewise, Collopy et al (1994) suggest that despite the large research base on macro-level diffusion models, only a handful of studies has empirically examined the conditions under which they are most appropriate (Meade, 1984; Rao, 1985).

This study looks to examine the forecasting accuracy when applying macro-level diffusion models to high-tech product innovations among organizational adopters. Additionally it explores whether the accuracy of macro-level diffusion models differs according to the impact of the new product. Exploration is done in two ways, first by validating six widely used forecasting models for 39 high-tech product time series over 3 ex ante forecasting periods, and second by comparing the accuracy of the forecasting models for high-tech product innovations of both incremental and radical impact. The purpose of the study is to assist forecasters in choosing appropriate models for predicting organizational adoption of high-tech products once the product is on the market and initial sales data becomes available. This forecasting situation is particularly relevant because research has found that relative to consumer firms, sales-based forecasting is widely used by industrial firms (Kahn, 2002).

## 2. Types of forecasting techniques

Basic macro-level diffusion models depict the diffusion process as purely innovative (Fourt & Woodlock, 1960), purely imitative (Fisher & Pry 1971), or as a combination of the two (Bass, 1969). A purely innovative model assumes only external factors (mass media communication, promotion, government incentives or tax breaks, etc.) influence the diffusion process. Conversely a purely imitative model assumes only internal factors (word of mouth, social pressure, etc.) influence the process (Mahajan et al., 1990). Bass (1969) integrated these two schools of thought in a landmark model that distinguishes between two homogenous groups: the innovators and the imitators. Each of these macro-level approaches to modeling the diffusion process has resulted in different diffusion curves that predict sales (adoptions) of a new product.

Purely innovative or external influence diffusion models imply adoption is driven by information external to the population. Mahajan and Peterson (1985) suggest the external influence diffusion model is appropriate when members of a social system do not interact, innovations are not complex and not subject to interpersonal communications (e.g. conspicuous products), and adequate information about the innovation is only available from a source external to the social system (e.g. advertisements). In general, these conditions hold for innovations that are not complex, readily available, and extremely familiar to adopters (Gatignon & Robertson, 1985). This type of model would be appropriate to apply to the organizational diffusion of high-tech product innovations because high-tech products are frequently incremental improvements that build on existing knowledge. Graphically speaking, the external influence model is depicted by a decaying or modified exponential diffusion curve that shows the cumulative number of adopters increasing over time but at a decreasing rate.

Purely imitative or internal influence diffusion models are based on the assumption that diffusion occurs exclusively through interpersonal contacts. The typical model assumes that everyone in the population is equally inclined to adopt and that the rate of adoption increases until 50% of the population has adopted. Then the rate of adoption declines and 100% adoption is approached asymptotically. The result is an S-shaped diffusion pattern. Mahajan and Peterson (1985) suggest the internal influence model is most appropriate when an innovation is complex, is socially visible, when not adopting it places the adopter at a disadvantage, when the social system is small and homogeneous, and when there is a need for legitimizing information prior to adoption. This type of model would apply to the organizational diffusion of high-tech product innovations when these innovations are radial new products that represent a significant change from the past (Gatignon & Robertson, 1985) and interpersonal communication is important due to the greater uncertainty involved in adoption. It also defines the so-called institutional bandwagon when non-adoption may put an organization at a disadvantage (Abrahamson & Rosenkopf, 1993).

The mixed diffusion model is also considered because it seems counterintuitive that the diffusion of radical high-tech products would be explained without any reference to external influence. As Mahajan and Peterson (1985, p. 21) correctly point out, "seldom can the assumptions of either the external influence or the internal influence diffusion model alone be met unequivocally when investigating a diffusion process." The most influential and recognized mixed influence diffusion model is the Bass (1969) model. This model distinguishes between two homogeneous groups: (1) the innovators, who are not influenced by pressure from social emulation but only by external influences; (2) the imitators, for whom the diffusion process is based on internal influences. According to the model, the product message is first picked up by a few innovators who then, through word-of-mouth, pass it on to other members of the social system. Bass's model gives rise to a positively skewed logistic curve similar to the internal influence model. But unlike the classic logistic curve, the Bass model assumes innovators are present at any stage of the diffusion process. Like the internal influence model, the Bass model appears more appropriate for radical high-tech new products than incremental ones.

For the past 35 years, marketing scholars have tried extending the Bass model through so-called "flexible" diffusion models which relax some of the assumptions of the Bass model; for example, the constant parameters. However, in a critical review of new product diffusion models, Mahajan et al. (1990) found most diffusion models still rely on the basic Bass formulation. For this reason, the original Bass model, or basic building block for other flexible diffusion models, was used for comparison.

The three basic types of diffusion models discussed, the internal influence, the external influence, and the mixed (Bass) model, concentrate solely on the time-dependent aspects of the diffusion process and assume their parameters implicitly reflect the effects of the many actionable variables on the phenomenon (Bass, 1969; Easingwood, Mahajan, & Muller, 1983; Mansfield, 1961). Eqs. (2.1)–(2.3) depict