AN EXAMINATION OF NEW PRODUCT DIFFUSION

IN JAPAN AND TAIWAN

A Thesis presented in partial fulfillment
of the requirements of the degree of
Master of Business Studies (Hons) at Massey University

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1999

This thesis is delicated to my dear ah'-po
-Mrs Chiu Chang Yu Mei

For a lady who could not afford the luxury of formal education, she had great faith and unshakable belief in the power of knowledge.

She taught me how to treasure the privilege of education, something that women were not entitled to in her time, and many generations before her.

ACKNOWLEDGMENTS

I am indebted to the guidance and patience provided by my supervisor, Tony Lewis. This task would not have been possible without your encouragement and support.

My regards and appreciation go to my co-supervisor, Malcolm Wright, for his incisive guidance, sharp-witted comments, and support all through the writing of this thesis.

I would also like to express my deepest appreciation to my mentor, Don Esslemont, for his valuable guidance, insightful thoughts, philosophical stimulation and continual encouragement throughout my years at Massey University, whose inspiration, kindness, and unfailing support will always be remembered with gratitude.

I am indebted to those who kindly assisted me in collecting the data - Junko, Mr. Tetsuyuki, Ms Young, Mr. Fong, and Wayne. Your generosity and months of work have made this thesis possible.

To my dearest friends, Grant, Emma, Hara, Helen, Junko, Shirley, and Wendy. Your friendship is the fondest memory of my university life. While the institution taught me knowledge, you enlightened me on so many other equally important things in life.

My heartfelt thankfulness to my parents for their support and giving me the opportunity to study abroad.

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1 SUMMARY

The main objectives of this thesis here is to examine the applicability of the Bass model in Japan and Taiwan and to explore the diffusion characteristics of the adoption of new products in these two countries. The model was applied to thirteen consumer durables, of which five were common in both Japan and Taiwan. The time series data used in this study was obtained from relevant government publications in each country.

The performance of the Bass model was assessed in three broad ways: its ability to reproduce the diffusion process by using the full set of time-series data (descriptive ability); its adequacy in predicting future sales at any stage of a product's life (predictive ability); and the stability of the model when estimated on data at quarterly, semi-annual, and annual levels of aggregation (model stability). The nonlinear least squares (NLS) estimation procedure recommended by Srinivasan and Mason (1986) was used to estimate the diffusion parameters and consequently the diffusion curves for each of the products. Measures of performance used in this thesis include the plausibility of the estimated diffusion parameters, the adjusted R^2 between estimated and actual sales, and the accuracy of estimated and actual timing and magnitude of peak sales.

With respects to the tests of descriptive ability, the obtained results provided empirical support for the model's ability to produce the new product diffusion processes in both Japan and Taiwan. Based on the entire annual data set, the Bass model produced plausible diffusion parameters and described the diffusion curves more than adequately in most cases. The reported adjusted R^2 values were above 0.8 for fourteen of the eighteen products (nine products in each country) and the graphic presentations of the estimated versus actual diffusion curves indicated that the model provided adequate approximation of the diffusion cycle in the remaining cases.

The timing of peak sales were adequately estimated in both countries. However, while the model's estimates of peak magnitude were acceptable for the Japanese products, the level of peak sales was grossly underestimated in nearly half of the Taiwanese models. In most cases, this under-prediction was a consequence of the model not capturing drastic sales increases in the peak

time period. Future research is required to incorporate other exogenous variables into the original Bass model to produce better depictions of this unique diffusion event in Taiwan.

Overall, the model's ability in describing the diffusion processes in Japan and Taiwan provides support for using it to understand the diffusion phenomenon in these two countries and to further compare their diffusion patterns with those in the literature.

The forecasting performance of the Bass model in regard to predicting the diffusion parameters, peak timing and magnitude, and next period sales was somewhat disappointing. In about two-thirds of the cases, the model did not estimate the diffusion parameters accurately until one period after peak sales. The same observation was also found in the estimation of the timing and level of peak sales. Accurate estimates of peak timing and magnitude were only obtained after the inclusion of the peak time period. In terms of next period sales, the model produced inaccurate predictions in most cases and the results did not seem to improve as the number of data points increased. Overall, the results indicate that the validity of using the Bass model as a forecasting tool in Japan and Taiwan is questionable.

When applied to quarterly, half-yearly, and yearly data, the Bass model to produce stable estimates across the aggregation levels. In both Japan and Taiwan, the model was robust in producing plausible diffusion parameters, satisfactory model fits, comparable parameter estimates, and similar annual sales estimates across all aggregation levels. Although the fit of the model was affected by the amount of seasonality in the data, it did not translate into differences in the parameter estimates or annual sales predictions.

As the majority of international diffusion studies were based on annual data, this confirmation of the effectiveness of the Bass model at lower data aggregation levels adds significant value to the existing body of knowledge on new product diffusion in international markets. Moreover, as lower aggregation levels offer benefits of shorter waiting periods for each data point, it implies that marketing practitioners and academics can gain some insight on the diffusion process within three years of the product launch.

Since the generalisability of the Bass model was validated in Japan and Taiwan, the obtained diffusion parameters for air conditioners, personal computers, facsimiles, video cassette recorders, and microwave ovens were further compared between these two countries and with results reported from other studies.

The cross-national analysis indicated that while the coefficient of external influence p was significantly higher in Japan than Taiwan for air conditioners, video cassette recorders, and microwave ovens the coefficient of internal influence q was higher in Taiwan than in Japan in all cases. Also, when applying the learning model to all five products, the learning effect coefficient was only substantial for the two business-oriented products, i.e. personal computers and facsimiles. For the other three consumer durables, the faster rate of adoption in Taiwan was not the result of learning from Japanese consumers. In terms of future research, other relevant variables could be incorporated into the original Bass model to explore the underlying factors that govern the faster diffusion process in Taiwan.

Finally, a cross-study comparison was conducted with the purpose of finding out how the new product diffusion patterns in Japan and Taiwan differ from those reported in the literature. While the Japanese diffusion parameters were more closely aligned with European estimates, Taiwan was found to have a comparably lower external coefficient, p, and much higher internal coefficient, q, than Europe. In contrast to Takada and Jain (1991)'s findings where faster rate of adoption (as reflected in high q values) was observed in Japan and Taiwan than in the US, this study found that the Japanese diffusion patterns are more comparable with other industrialised European economies than with Taiwan. While the level of interpersonal influence has remained high in Taiwan, it seems to have decreased in Japan over the years. This observation appears to suggest that new product diffusion is not necessarily a constant phenomenon over time, with factors such as economical development and product characteristics impacting on diffusion patterns.

The scope of any study is finite with the main consequence being limits on the generalisability of the findings. Future research should focus on expanding the range of countries and common product categories studied across them. In particular, the inclusion of fast moving consumer goods, a dynamic and innovative area in these countries, would be of much interest. Furthermore, it would be interesting to fit the model to brand level data in the same way as the study by Healey (1996).

The tests of predictive ability were only conducted at the annual level of aggregation and therefore, generalising to half-yearly, quarterly, or other levels of aggregation is not possible. This is of particular importance as diffusion effects such as seasonality would vary at these different aggregation levels. In practice, the model would be used for forecasting using shorter time periods.

The models estimated in this study were (with the exception of the learning model) all based on the original Bass (1969) model. Extensions of the model to include marketing mix variables, repeat purchases, and multiple product generations, and other external factors may help to better depict the Taiwanese diffusion curves, in terms of capturing the drastic increase of sales prior to and during peak sales, improve the forecasting performance of the model, and to provide useful insights into the diffusion characteristics in these countries.

2 INTRODUCTION

The diffusion of new products and services is an important marketing issue given the vast number of new products, brands, and brand extensions being developed and launched every year. Shorter product life cycles mean companies have less time to recoup development costs and optimise elements of the marketing mix. Accordingly, any prior information about the particular innovation or market is essential in aiding decision making.

As important is the development of models that can forecast sales and diffusion patterns prior to product launch and during the early stage of the product's life. Furthermore, understanding the diffusion dynamics of different geographic regions is a prerequisite for success in an increasingly global environment that retains many cultural nuances. All of these issues are addressed to some extent in this thesis, but it is the last of these which is the main focus.

The Bass diffusion model of new product growth (Bass, 1969) is a mathematical model which focuses on the process by which an innovation is adopted within a social system over time. The original model has three parameters: external influence, p, which represents the impact of factors external to the adopting population such as mass media and advertising; internal influence, q, which includes both verbal and nonverbal interpersonal effects within the adopting population; and the expected total number of adopters or market potential, m. Being inherently non-linear, the model is able to duplicate the s-shaped cumulative adoption curve regularly observed for new products (Dodds, 1973; Sharif and Ramanathan, 1981; Mahajan, Muller and Bass, 1995).

Since its introduction, the Bass model has become one of the most empirically researched subjects in marketing and the consequential body of knowledge consists of several dozen articles, books, and other assorted publications. Research has shown the model is adept at capturing and describing the diffusion process of a wide variety of products such as consumer durable goods, industrial technology, retail services, educational, agricultural, and pharmaceutical products (Mahajan, Muller, and Bass 1990).

By fitting the model to historical time series data, it can be used to explain diffusion patterns and test diffusion-related hypotheses, thus providing insight into the product life cycles of new products (Mahajan, Muller and Bass, 1990). For example, Rao and Yamada (1988) showed that the diffusion process of an innovation is affected by potential adopters' perceptions of the product.

The Bass model has been shown to have some value in predicting the timing and level of peak sales and the number of first purchase adopters in each time period (Dodds, 1973; Lawton and Lawton, 1979). These forecasting applications are of particular interests to marketing managers as they can be used to support decisions with regard to resource allocation (especially the marketing mix) and production.

A fruitful area of research has focused on extensions to the original Bass (1969) model. These accommodate marketing mix and other theoretically important variables, and generally involve relaxing the main assumptions underlying the model. For example, models incorporating non-constant market potential (Mahajan and Peterson, 1978), non-constant p, q, and m (Easingwood, Mahajan and Muller, 1983), repeat purchase (Lilien, Rao, and Kalish, 1981), product extensions (Norton and Bass, 1987), and marketing mix variables (Horsky and Simon, 1983; Kalish and Lilien, 1986; Bass, Krishnan and Jain, 1994) have been developed.

Apart from improved performance in terms of describing and predicting the new product diffusion process, these model extensions can be used for normative purposes. This involves the development of general decision rules regarding marketing mix and other variables over the product's planning horizon in order to maximise profits (Mahajan, Muller, and Bass, 1990, p16).

In international marketing, the normative value of Bass model extensions lies in guiding marketing mix decisions in different contextual situations (Mahajan, Muller, and Bass, 1990). For example, the learning effect model (Ganesh and Kumar, 1996; Ganesh, Kumar, and Subramaniam, 1997) assumes that the diffusion process in the lag country is affected by the rate of adoption in the lead country. If there are strong learning effects within a region, it may be profitable to concentrate marketing resources on the lead country, based on the expectation that this will have a flow-on effect to other countries (i.e. a waterfall strategy). If the learning effects are minimal, then it could be more profitable to spread resources across the countries on the basis of market potential (i.e. a sprinkler strategy).

Diffusion researchers have also endeavoured to derive the most appropriate estimator of the Bass model's parameters in cases where historical data exists. In terms of fit, unbiasedness, and accuracy of standard errors, estimators have improved considerably since the first method of ordinary least squares (OLS) proposed by Bass (1969). The main procedure now used is non-linear least squares (NLS) estimation though maximum likelihood (ML) estimation has also been used on occasions. Methods for estimating the Bass model when little or no data is available have also been developed and tested with some promising results reported (Mahajan and Sharma, 1986; Gatignon, Eliashberg, and Robertson, 1989; Sultan, Farley, and Lehmann, 1990).

Unfortunately, to the detriment of the generalisability of the results in the marketing literature, most reported empirical applications of the Bass model have been in the U.S. and to a lesser extent Europe. As these nations are more economically developed and culturally different than other markets in the world, the obtained results might not be universally generalisable. The increasingly influential and developing Asian region is one example where previous Bass model findings may not apply. Only the study by Takada and Jain (1991) has attempted to understand the diffusion patterns of countries in this region. However, this study considered only older type consumer durable products such as televisions and air conditioners where peak sales were achieved more than two decades ago and whose relevance today is questionable.

The overall goal of this study is to continue adding to the already sizeable body of knowledge on the Bass model by extending the generalisability of the model to more recent product innovations in Japan and Taiwan. This will involve examining the Bass model's capacity to capture the diffusion process in Japan and Taiwan when calibrated on all available data, assessing the forecasting ability of the model in the two countries, and deciding if the model's estimates are stable and comparable across different levels of data aggregation.

Subsequently, the model will be used in an explanatory mode to test hypotheses related to innovation diffusion across the two countries. The learning model will be estimated with Japan and Taiwan the lead and lag countries respectively. Finally, the diffusion patterns for Taiwan and Japan will be compared with results reported in the literature.

3 LITERATURE REVIEW

- diffusion theory and the proposed new product diffusion models
- the Bass diffusion model of new product growth
- the application of the Bass model in domestic/ single market settings
- theory and the application of the Bass model in international settings
- objectives of this study

Given the vast number of diffusion based studies in marketing, this literature review focuses on areas of particular relevance to this study. First, a general review of diffusion theory will be undertaken. Following this review, the most widely researched model, devised by Bass (1969), will be examined with specific attention to its underlying behavioural and mathematical assumptions. Past empirical applications of the model in domestic/single markets (i.e. where the model was fitted to sales data of different products in the same country) will then be reviewed before studies that have an international focus. Finally, the objectives of this study will be established on the basis of the preceding review.

3.1 DIFFUSION THEORY AND FIRST PURCHASE DIFFUSION MODELS

Diffusion theory is one of the most well-developed and widely used theories of communication. It describes the process of transmitting information about an innovation through a population. The core of diffusion theory is about the process by which knowledge about a new idea, practice, product, or service is "communicated through certain channels over time among the members of a social system"(Rogers, 1983, p 5) and is particularly relevant to new product strategy in marketing.

The theoretical origins of diffusion theory can be found in the early fifties, encompassing a number of disciplines such as cultural anthropology (Barnett, 1953), medical sociology (Coleman, Kakz, and Menzel, 1957), and industrial economics (Mansfield, 1961). In subsequent decades, extensive research on the diffusion process has resulted in a substantial body of knowledge. Literature in this area has been of value in explaining the flow of information both within and across different cultures, markets, and geographic regions (Gatignon and Robertson, 1985).

Since the diffusion perspective was introduced to marketing in the mid 1960s, it has sparked considerable academic and practitioner attention, particularly in consumer behaviour, marketing management, and marketing science. The intensive study on this subject was mainly motivated by the perceived high failure rate of new products and the consequent need for appropriate marketing decisions regarding new product launch and the control of production and sales levels over the new product's life (Wright and Charlett, 1995, p32).

As a theory of communication, the distinct focus of diffusion has been on interpersonal and mass-media communication channels. Interpersonal communication includes both verbal and non-verbal messages, while information conveyed via mass-media communication is primarily through television, radio, or other large-scale dissemination mechanisms. It is further assumed that potential adopters of an innovation are influenced exclusively by these two means of communication and have different propensities for relying on these channels when seeking information about an innovation (Mahajan, Muller, and Bass, 1990).

Moreover, while other factors such as product characteristics, marketing activities, economic conditions, and market competitiveness are suggested to have effect on the diffusion pattern of an innovation (Gatignon and Robertson, 1985), the effect of interpersonal influences is seen to mediate mass-media effects and is the key factor that determines the speed and shape of the diffusion curve (Gatignon and Robertson, 1985; Mahajan, Muller, and Bass, 1990; Rogers, 1983).

Another important facet of diffusion theory is time. Individuals who primarily rely on interpersonal communication, or internal influence, for their buying decisions are defined as imitators. The timing of adoption for this group is largely influenced by the increasing pressure from previous adopters over time. Conversely, innovators are those who make their adoption decisions mainly base on mass-media communication, or external influence, and their decisions to adopt are normally independent of other adopters. In other words, for innovators the adoption pressure does not increase with growth of the adoption process and therefore timing has no effect.

So far, one can see that this type of communication process, in accumulation, creates an adoption curve over time, which is capable of being modelled mathematically. Moreover, it should be noted that the diffusion curve of an innovation is represented by the number of first purchases made by the population. In other words, in a market of a given size, once all potential buyers have bought the product, there are no more sales. Consequently, the expected first purchase volume in each time period should rise at the beginning of the adoption curve and then decline until no potential buyers are left (Lilien, Kotler, and Moorthy, 1992).

As the first purchase diffusion process of an innovation can be depicted by mathematical models, it has significant implications for sales forecasting and strategic application in marketing. For decades, academics strove not only to produce valid mathematical models of the diffusion process but also to identify some criteria by which those models could be evaluated for their theoretical validity and practical usefulness.

The traditional purpose for innovation diffusion models was in the context of sales forecasting.

As Mahajan and Muller suggested in their 1979 study, a good diffusion model is one that can "depict the successive increase in the number of adopters and predict the continued development of a diffusion process already in progress." (p55). However, Mahajan and Wind (1986) and Kalish and Lilien (1986), also pointed out that except for being a forecasting tool, diffusion models could be utilised to generate descriptive and normative knowledge.

More precisely, as diffusion models are designed to describe the spread of diffusion for an innovation, they can also be used in an explanatory mode for testing specific diffusion-based hypotheses (Mahajan, Muller, and Bass, 1990). For instance, Srivastava, Rajendra, Mahaja, Ramaswami, and Cherian (1986) and Rao and Yamada (1988) both reported the diffusion process of an innovation is affected by potential adopters' perceptions of the product. Furthermore, because diffusion models are created to estimate or reproduce the product life cycle of a new product, they can be used for normative (i.e. decision guiding) purposes, as the basis of how a product should be marketed (Mahajan, Muller, and Bass, 1990). In the relevant literature, normative studies on diffusion models are often concerned with how a company can incorporate appropriate marketing mix variables into the models in order to maximise the profits over the planning period (for a detailed summary see Mahajan, Muller, and Bass, 1990, p16).

As a result of the above discussion, it can be concluded that the validity and usefulness of a diffusion model can be evaluated in three main ways: first, its reliability as a forecasting tool in terms of predicting first purchase sales at any stage of a product's life; second, its descriptive/explanatory power in relation to various hypotheses concerned with the nature of the diffusion process; and finally, whether the model can satisfy its normative objectives by aiding decision makers in strategic planning or in developing optimal marketing mix strategies.

The initial form of diffusion modelling was based on the earlier, well-developed theory of contagious diseases or the spread of epidemics (Lilien, Kotler, and Moorthy, 1992). Subsequently, the principles of the theory were then used to investigate the nature of information transmission within a human society. In marketing, diffusion models assume that the development of first-time purchases of an innovation, made by a population, is distributed in some fashion over time. These models are expressed in a general category of models of diffusion rate at time t

(Sultan, Farley, and Lehmann, 1990), that is:

$$dN(t) / dt = g(t)[N^{*} - N(t)] \qquad \textbf{[3.0]}$$

where

$dN(t)/dt$ is the rate of diffusion at time t;

$N(t)$ is the cumulative number of adopters at time t;

N^{*} is the total number of potential adopters in the population, and;

$g(t)$ is the probability of adoption for individuals who have not yet adopted.

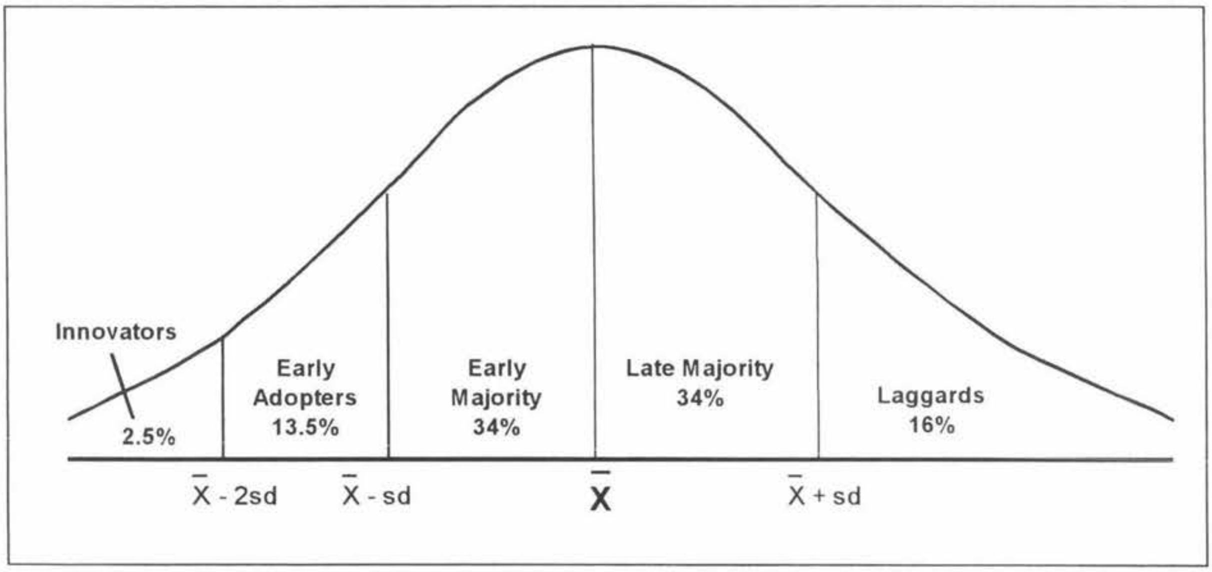
Different specifications of g(t) lead to models that imply different diffusion processes (Sultan, Farley, and Lehmann, 1990). Prior to Bass (1969), most diffusion models could be classified as pure external influence or pure internal influence. A pure external influence model assumes that the diffusion process is driven exclusively by factors external to the adopting population such as advertising. As demonstrated by Fourt and Woodlock (1960), this proposition can be incorporated into the diffusion formula as $g(t)= p$, where p is the coefficient of external (mass media) influence. By contrast, a pure internal influence model, as proposed by Mansfield (1961), suggests that the diffusion process is influenced solely by internal factors, ie. interpersonal communication. This process can be mathematically described as $g(t)= q$, where q is the coefficient of internal (or interpersonal) influence. As in most practical situations, where a mixed effect of these two factors can be expected to be present, such models are of limited use.

With the aim of circumventing the weaknesses of these models, Rogers (1962) developed a diffusion theory which incorporates both external and internal factors into the model. Rogers' (1962) asserted that the diffusion of an innovation is a "bell-shaped" normal distribution curve, represented by the number of adopters over time. Furthermore, when the accumulated number of adopters is plotted, it yields an S-shaped curve.

Rogers (1962) claims that the normal distributed diffusion curve is prompted by the learning effect, due to personal interaction, within a social system. More precisely, as the number of adopters increases, the level of interpersonal influence also grows within people who have not yet adopted. Consequently, this type of effect results in a binomial expansion, that is, "a mathematical function that follows a normal curve when plotted over a series of successive periods." (Wright and Charlett, 1995, p33).

Rogers (1983) further classified adopters of an innovation into five categories based on the criteria of innovativeness. He defines innovativeness as "the degree to which an individual is relatively earlier in adopting new ideas than other members of a social system" (p245). As can be seen in Figure 3.1, these adoption categories are mathematically defined "in terms of the number of standard deviations from the mean time of adoption for the population" (Wright and Charlett, 1995, p33) , and they are titled as: innovators (the first 2.5% of adopters), early adopters (the following 13.5%), early majority (the following 34%), late majority (the following 34%), and laggards (the final 16%).

Figure 3.1 Rogers' Adopter Classification



With the attempt to specify the "ideal types" for each of the adopter categories, Rogers (1983) developed detailed adopter profiles by matching various demographic, socioeconomic, and personality characteristics with time of adoption. For example, one of Rogers' (1983) thirty-one generalisations of adopter characteristics claims that early adopters generally have a higher education level than later adopters. In marketing, these generalisations on adopter characteristics have been viewed as having strategic importance for speeding up the diffusion process. More precisely, these generalisations can be used as guidelines for tailoring differential communication programs to reach potential adopters in each category more efficiently (Gatignon and Robertson, 1985). As described by Hawkins, Best, and Coney (1989), this technique is known as the moving target approach.

According to this approach, companies should identify and target the innovators and early adopters at the initial stage of a product's life, because their innovativeness presents the highest purchase probability among all adopters. As the product gains acceptance, the word-of-mouth effect in combination with progressively tailored mass media programs will then assure the early and later majority adopters to be more inclined to adopt the innovation. Consequently, this will speed up the diffusion process, resulting in increased first purchase sales volume, and thus, profitability (Wright and Charlett, 1995).

Despite the acceptance of the Rogers' model in marketing, several problems with the model have provoked academics to challenge its theoretical and practical validity. While Rogers model has intuitive appeal, a lack of consistent empirical findings have failed to provide support for its practical usefulness, which has resulted in the model being described as "largely literary" (Nevers, 1972, p78).

The first problem with Rogers' model is the underlying assumption that the non-cumulative adoption distribution of an innovation is a bell-shaped curve (i.e. normally distributed). This was questioned by Mahajan, Muller, and Srivastava (1990), citing Peterson (1973) who argued that new product diffusion patterns are more likely to exhibit non-normal adopter distributions in most marketing situations. Moreover, based on Mahajan and Peterson's (1985) research of relevant studies, several different innovation diffusion patterns were documented.

Second, since the adopter classification is based on the mean adoption time, the calculation of the model's parameters (i.e. standard deviation and mean) and, thus, the identification of adopter categories can not be undertaken until the diffusion process is complete. In other words, while the diffusion is in process, the model is unable to predict the level of adoption at any particular point of time. As being a reliable forecasting tool is one of the important functions of a useful diffusion model, the inability of the Rogers' model to meet this criteria leads it to criticism. It is viewed by some as "only valid as a tautological system of post hoc classification" (Wright and Charlett, 1995). Indeed, in most practical situations, successful adopter classifications made by the end of a diffusion process are unlikely to be of much use to marketers.

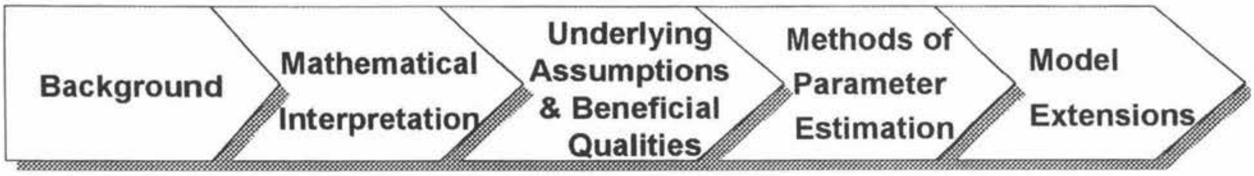
Third, the model's normative ability in assisting decision making has also been brought into question. As discussed previously, the moving target approach indicates that the adopter profile is the most important key for speeding up the diffusion process and maximising the adoption level for an innovation. However, based on research results, there is no consistent link between the trait of innovativeness and other personal, demographic, and socioeconomic characteristics. As pointed out by Kotler (1991), one's innovativeness tends to vary with the type of product. Consequently, there is no empirical evidence to support any concrete descriptions of the adopter profiles.

Although Rogers (1983) acknowledged that adopter profiles are product-specific, no method was given for predicting how these profiles will vary across industries. Thus, it seems that individuals are classified as innovators purely because they are among the first 2.5% to adopt rather than any internal level of innovativeness or their adoption behaviour in other circumstances. Therefore the inconsistent nature of adopter profiles prevents the identification and targeting of innovators and early adopters.

Another problem with the moving target approach is the assumption that successfully targeting innovators will speed up the diffusion process through word-of-mouth effects on potential adopters. However, the magnitude of interpersonal communication in some industries is minimal and this process will therefore not proceed as hypothesised. Moreover, even when interpersonal influence is puissant, given various logical and practical problems associated with market segmentation, there is no definite evidence that targeting specific segments would produce a better result than mass marketing (see Hoek, Gendall, and Esslemont, 1993; Wright and Esslemont, 1994).

In conclusion, as Rogers' model suffers from practical difficulties it can not be used as an effective forecasting tool. Furthermore, the theoretical problems associated with the differences between the proposed diffusion shape and adoption categories have limited the model's post hoc value. In the following section, an alternative diffusion model of new product growth proposed by Bass (1969) will be discussed. The Bass model takes a different approach to describe the diffusion process of an innovation which overcomes the theoretical and practical problems found in Rogers' model.

3.2 THE BASS DIFFUSION MODEL OF NEW PRODUCT GROWTH



- general background information

- detailed descriptions of the model's mathematical interpretation

- underlying assumptions of the Bass model and its beneficial qualities

- Ordinary Least Squares (OLS)
- Maximum Likelihood (ML)
- Nonlinear Least Square (NLS)
- practical implications of using different estimators

- non-constant market potential
- non-constant imitation and innovation
- marketing mix variables
- other Bass model extensions

3.2.1 Background

Bass (1969)'s model generalised the models of Fourt and Woodlock (1960) and Mansfield (1961) by including both internal and external influences in its specification. It represents "the main impetus underlying diffusion research in marketing" (Mahajan, Muller, and Bass, 1990). The mathematical theory underlying this mixed influence model originated from the simple stochastic models used to examine the spread of an epidemic through a population (Bartlett, 1960). The assumption of symmetrical exponential growth and decay about the peak sales level results in a S-shaped generalised logistic cumulative adoption curve. Of course, this shape is advantageous given the apparent empirical regularity of S-shaped cumulative adoption (Dodds, 1973; Sharif and Ramanathan, 1981; Mahajan, Muller and Bass, 1995) for products with a low incidence of repeat purchase (such as consumer durables).

However, it is important to note that the Bass model (and subsequent extensions) is not a 'naive' S-shaped model. Fitting one of a number of common S-shaped functions (such as the logistic, normal, lognormal, or Gompertz) to cumulative sales data with no regard for the behavioural process generating the S-shape creates these naive models. In contrast, the Bass model is a causal model that estimates the impact of internal and external influences on adoption. This specification leads to the S-shaped temporal diffusion pattern, not vice versa. The Fourt and Woodlock (1960) and Mansfield (1961) models are also causal in nature but are special cases of the Bass model.

3.2.2 Mathematical Interpretation of the Bass Model

The mathematics underlying the Bass model are simple yet the result is an elegant model which accommodates a diverse range of adoption processes. Assume the function F(t) is the cumulative probability that an individual will adopt an innovation at time t. F(t) is a non-decreasing and continuous function and which approaches unity as t tends to infinite. It follows that the rate of adoption at time t, f(t), is found by differentiating F(t) over the limit 0 to infinite.

The conditional likelihood that an individual will adopt at exactly time t given they have not yet adopted, L(t), equals:

$$L(t) = f(t) / [1 - F(t)] \qquad \textbf{[3.1]}$$

For the Bass model:

$$L(t) = p + q/m\,[N(t)] \qquad \textbf{[3.2]}$$

where

p is the coefficient of external influence (innovation)
q is the coefficient of internal influence (imitation)
m represents the market potential

N(t) is the cumulative number of adopters at time t.

The two components of this conditional likelihood function are p which is independent of other factors and q/m [N(t)] which is a linear function of the number of previous adopters. This second term increases over time because N(t) increases over time. However, the rate of change of n(t) only increases until such time as the potential number of non-adopters is greater than the number of adopters. From this point on (the sales peak), n(t) decreases.

The formula for the rate of adoption, f(t), can be found through simple manipulation after letting [3.1] equal [3.2]:

$$f(t) / [1 - F(t)] = p + q/m\,[N(t)]$$

$$f(t) = [p + q/m\, N(t)][1 - F(t)] \qquad \textbf{[3.3]}$$

Finding the number of adopters at time t, n(t), is also uncomplicated. The cumulative number of adopters at time t, N(t), is equal to the market potential multiplied by cumulative adoption at time t, i.e.:

$$N(t) = mF(t), \qquad \textbf{[3.4]}$$

where

$$F(t) = [1 - e^{-(p+q)t}] / [1 + (q/p)\, e^{-(p+q)t}] \qquad \textbf{[3.5]}$$

As n(t) equals mf(t), the market potential multiplied by the rate of adoption at time t, it follows that n(t) equals:

$$n(t) = g(t)\,(m - [N(t)]) \qquad \textbf{[3.6]}$$

$$= (p + q\,[N(t)])\,(m - [N(t)]) \qquad \textbf{[3.7]}$$

$$= pm + (q - p)\,[N(t)] - q/m\,[N(t)]^2 \qquad \textbf{[3.8]}$$

where

g(t) = the adoption rate.

Bass (1969) gave an algebraic equivalent of [3.8] where time is the only variable:

$$n(t) = [m(p+q)^2 / p] * [e^{-(p+q)t}] / [1 + (q/p)\, e^{-(p+q)t}]^2 \qquad \textbf{[3.9]}$$

This equation is used most often to forecast future sales and is preferable for a number of reasons. First, [3.9] only requires the time period for which the prediction is to be made to yield an estimate of sales. For example, if you have estimated the model on the first 55 years of data and want to predict sales for year 57, you would substitute 57 for t in [3.9] to get an estimate of sales in that year. However, the one-step-ahead method (which uses [3.8]) first requires you to estimate sales for year 56 as this estimate is needed to calculate sales in year 57. In this regard, equation [3.8] is more sensitive to outliers than [3.9].

A common interpretation of the Bass model involves both innovators and imitators purchasing the product. Innovators are not influenced by the number of previous adopters but can be converted by marketing activities. The number of innovators decreases monotonically over time. In contrast, the number of previous adopters primarily influences imitators. Not surprisingly, the proportion of imitators relative to innovators increases over time.

The analytical structure of the Bass model is best demonstrated in figure 3.2.1. The greatest proportion of adoptions due to external influence (innovators) occur in the time periods immediately following product release. In contrast to this, the highest number of imitators occurs about the peak sales period. The adoption density function is symmetrical about the peak sales period. If $q > p$, then imitation is dominant and the diffusion curve (rate of adoption over time) resembles the curve in figure 3.2.2a. If $q < p$, then innovation is dominant and the curve appears like figure 3.2.2b.

Figure 3.2.1 Analytical Structure of the Bass Model

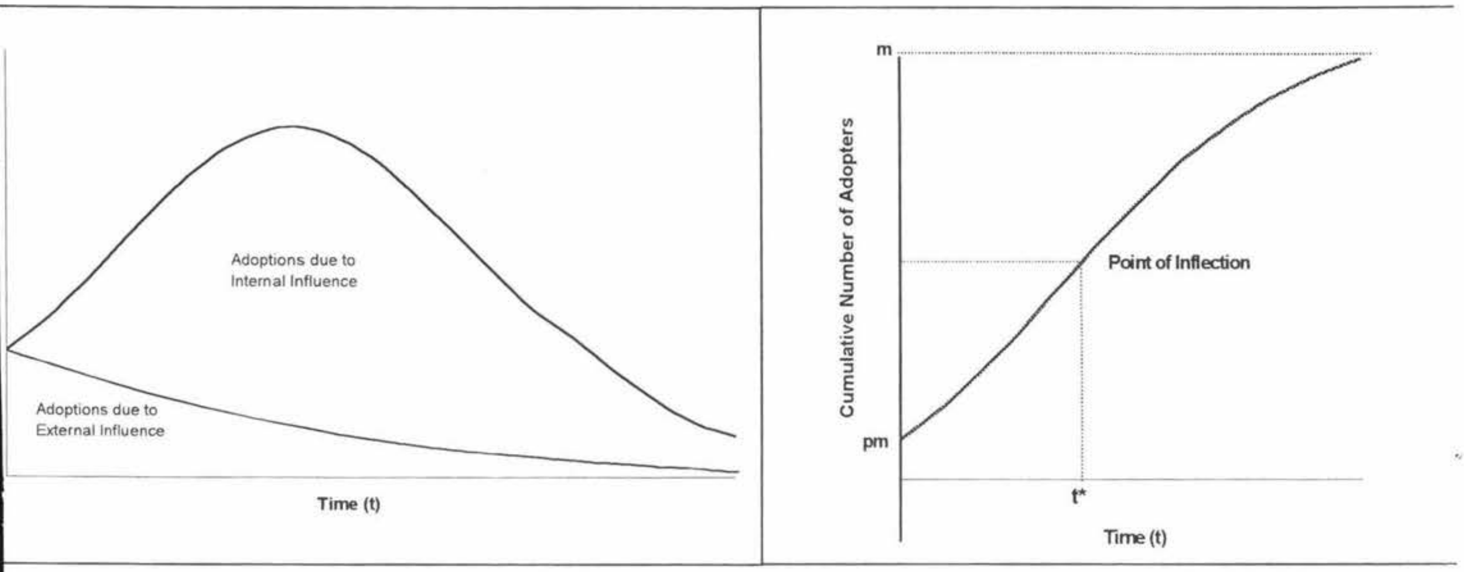
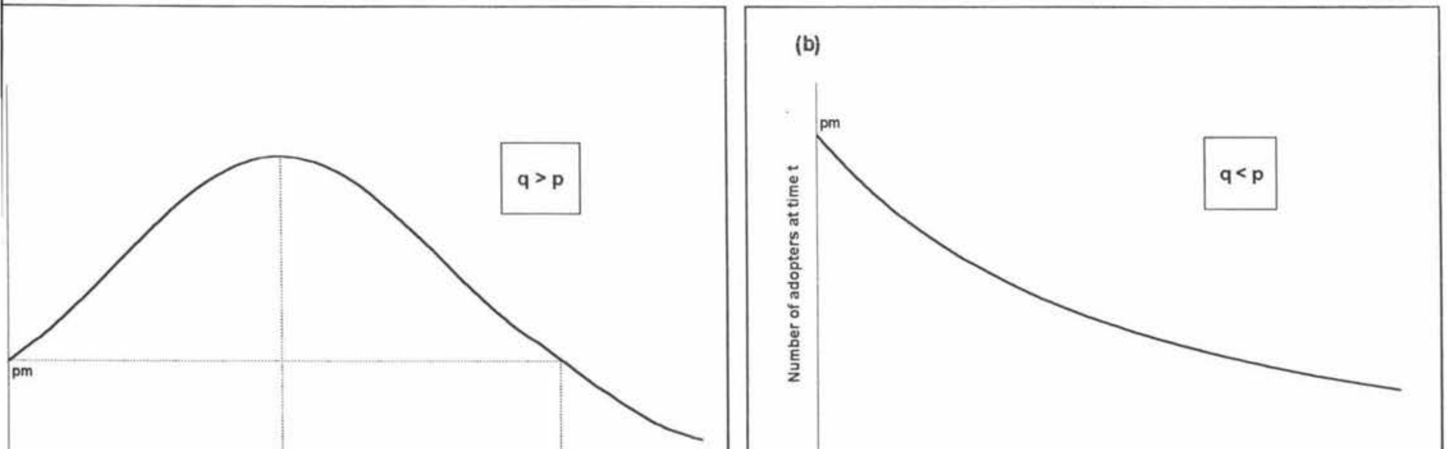


Figure 3.2.2 Rate of Adoption (Density Function) in the Bass Model



3.2.3 Underlying Assumptions and Beneficial Qualities

This parsimonious mathematical structure is an outcome of four simplifying assumptions that may or may not be strictly true in practice:

- Market potential (m) is fixed over time;
- Coefficient of external influence (innovation), p, is fixed over time;
- Coefficient of internal influence (imitation), q, is fixed over time, and;
- Population of individuals are equally prone to adoption (i.e. homogenous adopter population).

An expanded discussion of violations of these assumptions and possible remedies is contained in the section discussing Bass model extensions. Nevertheless, it would seem in practice that the Bass model is robust in conditions where these assumptions could be breached. This is one of the reasons for the popularity of the model in academic circles though other reasons are more compelling.

First, the model's parameters are derived from clear and explicit behavioural assumptions. This is in contrast to the Rogers' (1962) model where the parameters are tautological in nature. In his framework, by definition innovators are the first 2.5% of adopters. There is unfortunately no behavioural reason for the first 2.5% of adopters being innovators as opposed to the first 10% or 25%. An innovator is purely someone who happens to be one of the first 2.5% of adopters regardless of any factors exogenous to the model. In the Bass model however, innovators are those adopters whose probability of adoption is conditional on external factors rather than the number of previous adopters. The number or proportion of innovators in the Bass model framework can vary depending on the extent to which external influence is effective in the market.

Second, the Bass model also predicts sales declines in periods where sales are still increasing (Nevers, 1972; Lawton and Lawton, 1979). In contrast, naive models continue to predict sales growth until after peak sales have been achieved (Dodds, 1973). Nevertheless, this apparent advantage of the Bass model is only useful if the model can accurately predict the sales peak and subsequent decline. If the model incorrectly predicts peak sales, then there is potential for the predictions it makes leading to a self-fulfilling prophecy (in terms of management making decisions that lead to the decline rather than in response to the decline). Obviously, managerial judgement plays an important role here.

Third, the Bass model and particularly its extensions can be used to test different marketing mix scenarios and their consequent effects on adoption (Bass, 1980; Kalish, 1985; Norton and Bass, 1987). The models of Robinson and Lakhani (1970), Bass (1980), Horsky (1990) are examples where the Bass model can be used to develop strategy.

However, finally and most importantly, the Bass model is behaviourally and empirically sound but flexible enough to be accommodate a variety of regularly occurring phenomena. The number of extensions of the Bass model is proof of this flexibility. These extended models provide a richer behavioural insight into the processes driving diffusion and contribute to the body of knowledge in marketing by allowing evaluation of the relative impact of different variables. In this way, the conditions under which, for example, price impacts on the diffusion process can be determined and compared with advertising. Or as in this case, the impact of the diffusion rate in one country on the rate of diffusion in another country can be determined (i.e. the learning effect) and possibly the reasons for this influence investigated.

3.2.4 Estimation of the Bass Model's Parameters

Diffusion researchers have also explored the derivation of the most appropriate estimator of the Bass model's parameters in cases where historical data exists. In terms of fit, unbiasedness, and accuracy of standard errors, estimators have improved considerably since the first method of ordinary least squares (OLS) proposed by Bass (1969). The main procedure now used is non-linear least squares (NLS) estimation though maximum likelihood (ML) estimation has also been used on occasions.

For the practical purpose of making forecasts prior to or in the early stages of a product launch, estimates are required that can make use of either managerial judgment (Mahajan and Sharma, 1986), historical comparisons with similar products/countries (Gatignon, Eliashberg, and Robertson, 1989; Sultan, Farley, and Lehmann, 1990; Montgomery and Srinivasan, 1989; Mahajan, Muller, and Bass, 1990) or Bayesian or feedback filter approaches (Bretschneider and Mahajan, 1980; Lilien, Rao, and Kalish, 1981; Sultan, Farley, and Lehmann, 1990).

Methods for estimating the Bass model's parameters when little or no data are available are not discussed in this thesis as they are largely unconnected with the objectives and methodology. However, the main estimators (OLS, ML, and NLS) when calibration data is available are closely associated and are now discussed in detail.

3.2.4.1 Ordinary Least Squares (OLS)

The ordinary least squares (OLS) estimator was the first used to derive the Bass model parameters from time series data by Bass (1969). He suggested a discrete regression analogue of [3.8] that could be used to obtain the estimates of p, q, and m:

$$x(t) = pm + (q - p)\,N(t-1) - (q/m)\,N(t-1)^2 + \varepsilon(i) \quad \textbf{[3.10]}$$

$$= a + bN(t-1) + c\,(N(t-1)^2) + \varepsilon(i) \quad \textbf{[3.11]}$$

where x(t) = sales at time t, N(t-1) is cumulative sales at time t-1, $N(t-1)^2$ is squared cumulative sales at time t-1, a = pm, b = $(q - p)$, c = - (q/m), and the ε (i) are independently and identically distributed with $E[\varepsilon(i)] = 0$ and $var[\varepsilon(i)] = \sigma^2$.

Therefore, using S(t) as the dependent variable and N(t-1) and $N(t-1)^2$ as the independent variables, ordinary least squares regression can be undertaken to yield estimates of a, b, and c. These estimates can then be used in conjunction with the following relations to obtain the OLS estimates of *p*, *q*, and *m*:

$$m = \{[-b - (b2 - 4ac)] / 2c\}^{1/2} \quad \textbf{[3.12]}$$

$$p = a / m \quad \textbf{[3.13]}$$

$$q = - mc \quad \textbf{[3.14]}$$

The OLS method is not without defects. It produces unstable estimates and/or parameters with wrong signs when few data points exist or in the presence of multicollinearity between N(t-1) and N(t-1)2 (Bass, 1969; Schmittlein and Mahajan, 1982; Srinivasan and Mason, 1986). Also, OLS does not produce standard errors for the Bass model parameters *p*, *q*, and *m* as these are related in a nonlinear manner to the estimates of a, b, and c derived from the regression analogue (Srinivasan and Mason, 1986; Mahajan and Sharma, 1986).

More importantly, the estimates of *p*, *q*, and *m* contain a bias that results from incorrect aggregation across the time intervals (Srinivasan and Mason, 1986). This problem is a consequence of the use of discrete time series data to estimate the continuous Bass model (Mahajan and Sharma, 1986). The expected number of adopters (E[n (t)]) in a time period should be equivalent to the derivative of N(t) (i.e. dN(t) / dt). However, OLS instead uses x(t), sales at time t (which in effect is the difference between sales at time t and t-1), which is not equivalent to the rate of change in N(t) at time t. The practical consequence of this is that the rate of adoption is underestimated for time intervals prior to the sales peak and overestimated after this point.

It should be recognised that OLS estimation was a compromise in a time where non-linear estimation was not a feasible option. It is rarely used now as most standard spreadsheet and statistical packages have non-linear optimisation algorithms that can be used to estimate any specified function.

3.2.4.2 Maximum Likelihood (ML)

Schmittlein and Mahajan (1982) were the first to propose estimating the Bass model using a maximum likelihood approach. OLS is inferior to ML in terms of predictive validity because OLS estimates are derived from fitting a continuous model to discrete data and are consequently biased (as discussed above). ML estimates are not biased in this way as the continuous model is correctly aggregated over the time intervals represented by the data (Schmittlein and Mahajan, 1982; Srinivasen and Mason, 1986). Therefore, under general conditions, maximum likelihood estimates are asymptotically normal, asymptotically efficient, and consistent.

The likelihood function derived by Schmittlein and Mahajan (1986, p 62) equals:

$$L\,(a, b, c, x_i) = [1 - F(t-1)]^{xT} \prod_{i=1}^{T-1} [F(t-1) - F(t-1)]x_i \qquad [3.15]$$

Taking the log of this likelihood function yields the log likelihood function (see Schmittlein and Mahajan (1986, p 62)). A solution is obtained by selecting values of a, b, and c which maximise the log likelihood function. The parameters p, q, and m are then obtained by substituting a, b, and c into the following formulas:

$$p = b/(a+1) \qquad \mathbf{[3.16]}$$

$$q = ab\,/\,(a+1) \qquad \mathbf{[3.17]}$$

$$m = cM \qquad \mathbf{[3.18]}$$

where

p, q, and m are the parameters of the Bass model;

a, b, and c are obtained by maximising the log likelihood function, and;

M is the sample size.

Additionally, estimates of the standards errors of the parameters can be obtained which enables hypothesis testing and confidence intervals for p, q, and m. However, these standard errors only capture sampling errors and fail to account for non-sampling errors caused such as mis-specification of the model (e.g. omitting relevant variables) and therefore can underestimate the standard errors (Srinivasen and Mason, 1986).

Another problem (which also pertains to NLS) is the search algorithms used to estimate p, q, and m are sensitive to the starting values selected, may be slow to converge and in some cases may not provide a global optimum (Mahajan and Sharma, 1986). For an explanation of these problems in a geometry context, see Kendall and Stuart (1977).

3.2.4.3 Nonlinear Least Squares (NLS)

Nonlinear least squares represents an improvement over both OLS and ML even though it is relatively minor for the later. The NLS approach involves minimising the sum of squared errors between the actual rate of adoption and that estimated by the following equation (Srinivasen and Mason, 1986):

$$\tilde{n}(t) = [m - X(t-1)][(F(t) - F(t-1))/(1 - F(t-1))] \quad \textbf{[3.19]}$$

where

X(t-1)	=	actual cumulative adoption at time t-1
m	=	market potential
F(t)	=	cumulative proportion of adopters as defined in [3.5].

This equation [3.19] is the estimator of [3.9]. The time-interval bias present in OLS estimates is also not present in NLS estimates.

The main reason NLS is superior to ML is that the standard errors reflect both sampling and non-sampling errors. Johnston (1984) suggests that ML standard errors are likely to be more optimistic than those yielded by NLS. In their study, Srinivasen and Mason (1986) compare their NLS standard errors with those estimated using ML. They found for a sample of 50 million US households, the ML approach underestimates the standard errors significantly but for a sample of 200 hospitals, the difference was insignificant.

In fact, a number of comparative measures were used by Srinivasen and Mason (1986) to test the relative performance of OLS, ML, and NLS. In most cases they found ML and NLS outperformed OLS but that the difference in performance between NLS and ML was negligible. A sensitivity analysis also indicated that NLS estimates were not sensitive to the chosen starting values.

3.2.4.4 Practical Implications of Using Different Estimators

The meta-analysis of Sultan, Farley, and Lehmann (1990) studied the impact of OLS, MLE, NLS, and numerical solution techniques such as those outlined by Mahajan and Sharma (1986) on the estimates of p (coefficient of innovation) and q (coefficient of imitation) obtained from 15 published articles. They found that the estimates of p and q were different across the estimators. OLS tended to produce higher estimates of p and q whereas ML and NLS produced lower estimates.

Obviously, more empirical research needs to be undertaken to understand the reasons for these differences. Nevertheless, given the problems with OLS, and the fact that ML and NLS perform similarly in terms of predictive ability and model fit (Srinivasen and Mason, 1986), it is unlikely that OLS would be selected ahead of the other methods. Overall, NLS is preferable because of its superior estimates of standard errors and the consequences for hypothesis testing.

3.2.5 Bass Model Extensions

Underlying the Bass model are a series of assumptions, some of which may or may not hold depending on the adoption process being modelled. The most serious of these are connected to the parameters p, q, and m and the assumption that they are constant over time. In situations where there is clear behavioural justification that one or more of these assumptions is violated, a number of more flexible Bass models can be used. These models not only relax the assumptions about p, q, and m, but also endeavor to model changes in p, q, and m as a function of other variables (such as marketing mix variables). Other Bass model extensions incorporate diffusion across multiple adopter populations, diffusion simultaneously in time and space, repeat purchase, product extensions (successive generations), and multiple diffusion stages.

Obviously, these extended models will produce a superior fit to sales data, but parsimony and practical considerations need to be considered before a more complex model is applied. In fact, in many cases, the simple Bass model will take account of the additional explanatory variables. Bass, Krishnan, and Jain (1994) demonstrate that if the x(T) (i.e. variables that impact the diffusion process such as marketing variables) in the Generalised Bass Model are constant (or if percentage changes in x(T) between time periods are approximately constant), then the Bass model will provide approximately the same fit as the full Generalised Bass Model.

Further difficulties are introduced when additional variables are incorporated into the Bass model. First, it may be difficult to collect the information. For example, collecting sales data over the lifetime of a product is complicated as many countries do not collate this information, but in some cases gaining reliable estimates of other variables (such as advertising or promotional data) may be impossible. Second, some additional variables make the task of forecasting difficult because reliable estimates of the future values of these variables are also needed to obtain predictions. For a monopolistic supplier, estimates of future price, advertising and promotion may be relatively straightforward to obtain. But in competitive markets and for variables such as population growth, estimates would require more effort. These two issues illustrate that in each diffusion situation fitting the best theoretical model may not represent the best practical option.

3.2.5.1 Non-constant market potential

One of the more tenuous assumptions underlying the Bass model is that the number of potential adopters (m) is constant over time. A number of reasons have been forwarded to support the view that a constant m may not be justified (Mahajan and Peterson, 1978; Sharif and Ramanathan, 1981):

- Improvements in cost and performance over time increase the range of practical application of the innovation. The number of potential adopters can therefore increase over time.
- Changes in socio-economic conditions such as population and GDP are likely to increase or decrease the size of the potential market.
- Proximity and access to the market and/or infrastructure restrict the number of adopters. For example, consumers in some geographic locations may initially be unable to purchase digital mobile telephones as they do not have access to a comprehensive digital network. However as the network expands, the number of potential adopters increases.
- The demand for process innovations depends largely on the demand for the output produced by the innovation. Therefore, unless output demand is constant over time, the assumption of constant m for the process innovation may be unrealistic.

Some authors adamantly deny the validity of this assumption:

> "Such an assumption is obviously inconsistent both with regard to theory and practice. There is no theoretical rationale for a static potential adopter population in a social system. Indeed, the opposite - a potential adopter population continuously in flux - is to be expected." (Mahajan and Peterson, 1978, p 1590)

Consequently, Mahajan and Peterson (1978) developed a model with a dynamic potential adopter population. In their model, m is not fixed over time and is a function of any variables considered to be impacting on market potential:

$$m(t) = f[s(t)], \qquad \textbf{[3.20]}$$

where

$m(t)$ = market potential at time t

$s(t)$ = the vector of explanatory variables that explain the variation in $m(t)$.

As can be seen, if the explanatory variables are approximately constant over time or if the change in their value is constant, then they will add little predictive power to the simple Bass model.

Mahajan and Peterson (1978) test their model by fitting it to UN membership data and sales of washing machines in the U.S. For the UN membership model, $s(t)$ is the number of countries in the world while for washing machines, $s(t)$ is the number of houses that have started to be built. In both cases, the model fits the data well (OLS is used to estimate the regression analogue) though unfortunately the models are not compared to the simple Bass model with constant m.

Sharif and Ramanathan (1981) develop four "intuitively appealing" diffusion models that allow market potential to be non-constant. In these models, $m(t)$ is represented by a standard monotonic function that is deemed to capture temporal population changes. For example, if a researcher suspects that market potential steadily increases over time, but does not have data on this population or variables related to it, then they can assume that it increases according to some known function, the parameters of which can be estimated in addition to the standard diffusion parameters.

The authors show how the generalised diffusion model (from which the Bass model can be derived) can be rewritten to incorporate a dynamic potential adopter population. Unfortunately, only the pattern $m(t) = N0eg(t)$ has an exact solution flexible enough to be estimated using regression. Sharif and Ramanathan (1981) show these models have superior forecasting capabilities. Unfortunately, questions about parsimony and a comparison with the Bass model are left unresolved.

Another stream of research has models that take into account the effect of price on market potential. The argument here is that a fall in price increases the size of the potential number of adopters and vice versa. In a section below, we discuss model extensions that assume price and other marketing mix variables impact on the diffusion parameters p and q. Additionally, some model extensions such as Bass (1980) consider price to impact on both the market potential and the diffusion rate. Robinson and Lakhani (1975) were the first to explicitly develop a dynamic pricing model. The main motivation for this was that most pricing strategy was grounded in short-term profit terms rather than over the life cycle of the product. They specifically related market potential, m(t), to price m(p) and provided an illustrative example of how this specification could be used to aid pricing decisions.

Kalish (1985) viewed market potential as a function of price and the reduction in uncertainty about product performance as the number of adopters increases. The process of adoption requires two steps: (1) awareness which involves being informed about the important search attributes and (2) adoption within the potential adopter population. The first stage is affected by word of mouth and advertising while the size of the adopter population in the second is dependent upon awareness, price, and uncertainty.

The first stage (awareness) is specified as follows:

$$z(t) = [1 - Z(t)]\,[a_1(A(t)) + b_1(Z(t) - X(t)/Q_0) + b_2(X(t)/Q_0)], \qquad \textbf{[3.21]}$$

where

$z(t)$	=	rate of awareness at time t
$Z(t)$	=	cumulative proportion of potential adopters aware at time t
Q_0	=	size of potential population
$a(t)$	=	rate of advertising spend at time t
a_1	=	coefficient of the effect of advertising on unaware population
b_1	=	coefficient of the effect of aware non-adopters on unaware population
b_2	=	coefficient of the effect of adopters on the unaware population
$X(t)$	=	the cumulative number of adopters at time t.

Clearly, awareness is a function of three main effects: the effect of advertising on those unaware of the product (a_1), the effect of the aware non-adopters on the unaware (b_1), and the effect of adopters on the unaware (b_2).

Two assumptions are made about the potential adopter population:

- Individuals will only purchase the product once its price is less than the value of that product to him/her (for example, the value in terms of possible time savings), and;

- Individuals are risk averse with their probability of adoption increasing as more members of the market become familiar with and use the product (i.e. uncertainty decreases as market experience increases).

These assumptions impact on market potential with:

$$m(t) = Q(t)\,[\,p(t) / u\,(\,X(t) / Q_0) \qquad \textbf{[3.22]}$$

where

m(t)	=	market potential at time t
Q(t)	=	size of potential population at time t
X(t)	=	number of adopters at time t
p(t)	=	price at time t
u	=	the ratio of the value of the uncertain product to value under certainty or the discount due to product uncertainty

Adoption is assumed to follow the pattern established by the Bass model but with non-constant market potential.

Other authors have also looked to relax the assumptions about market potential. Horsky (1990)'s study generalised the Bass model to include income distribution, price, and population size. Lackman (1978) proposed a model where market potential was a function of product profitability. Jones and Ritz (1987) related market potential to distribution effects (namely the number of retail outlets stocking the product). Jain and Rao (1990) specified market potential to be a function of price and found price to be a significant influence. As mentioned previously, Bass (1980) explored the impact of price on both market potential and the adoption parameters p and q. The market potential for compact discs was viewed by Bayus (1987) as a function of the number of adopters of compact disk players.

3.2.5.2 Non-Constant Imitation and Innovation

The Bass model assumes p and q are constant over time. These assumptions lead to a model whose density function is symmetrical about peak sales. Furthermore, the maximum rate of adoption must occur after 50% of the market has been penetrated (Easingwood, , Mahajan, and Muller, 1983). However, Easingwood, Mahajan, and Muller (1983) view the assumption of a constant word of mouth effect over time as the most likely assumption to be violated. However, little behavioural research has investigated the likely change in word of mouth effects over time. Kotler (1971) suggests that q would decrease over time because the latter adopters are likely to be less responsive to communication related to the product though this type of claim has not been investigated in a systematic manner.

Additionally, research by Chow (1967) and Dixon (1980) suggests that growth rates are initially higher and lower at the end of the diffusion curve. Bewley and Fiebig (1988) suggest that "the appropriate function should be consistent with a skewed growth curve" (p 178).

The nonuniform influence model (NUI) developed by Easingwood, Mahajan, and Muller (1983) extends the Bass model to allow for a non-symmetrical diffusion curve and non-constant word of mouth effects (of course, assumptions about constant p and q can also be relaxed by representing them as a function of marketing mix or other variables as discussed in the ensuing section). The model is specified:

$$n(t) = [p + q\,(N(t)/m)^{d}]\,[m - N(t)] \qquad \textbf{[3.23]}$$

where

d = the nonuniform influence coefficient.

The value of d determines the shape of the density function by allowing imitation to be non-constant and also permits asymmetry. The Bass model is a special case of NUI where d = 1.

Despite this model's flexibility in capturing these effects, its main limitation is the lack of a behavioural theory underlying the estimate of the nonuniform influence coefficient. If this variable was related to some factor such as advertising or price, then more robust explanations of the behavioural process could be made. Nevertheless, one could easily incorporate such effects by setting d to be a function of relevant variables (i.e. d = p(t) where p(t) equals price at time t). But as Easingwood, Mahajan, and Muller (1983) note, "many new product diffusions are characterised by the simultaneous interplay of several factors. It would, in such cases, be difficult, if not impossible, to statistically estimate these causal relationships, especially as there are usually few data points available for diffusion modelling" (p277).

Another limitation of the NUI approach is that the coefficient of imitation is constrained to be asymptotic and consequently cannot vary up and down from time period to time period. However, a more relaxed specification of d could permit this variation if d were a function of some known variable such as advertising or price.

In a later paper, Easingwood (1987) proposes nine unique diffusion patterns whose characteristics are dependent upon the values of the imitation and nonuniform influence coefficients. He fits the NUI model to 26 new products and demonstrates that nonuniform influence varies among these products. The fact that nonuniform influence does differ from product to product provides support for modelling this effect. It may be possible to derive the behavioural by classifying products in the way Easingwood (1987) suggests and looking for common factors within the groups and factors differing across them but this type of research is in its infancy.

3.2.5.3 Marketing Mix Variables

A growing stream of diffusion research has focussed on modelling the effects of marketing mix variables. Marketing mix variables have been incorporated into the Bass model in two ways. First, as previously discussed, market potential (*m*) has been modelled as a function of price and advertising (e.g. Robinson and Lakhani, 1975; Kalish, 1985). Other models have viewed marketing mix variables as impacting on the diffusion parameters p and q (e.g. Horsky and Simon, 1983) and this type of model will be discussed here.

However, theoretical rather than empirical analysis (modelling) has been the norm. In a theoretic framework, price or advertising are assumed to influence the rate of diffusion in an explicit way and normative conclusions are inferred (Simon and Sebastian, 1987). Unfortunately, the conclusions reached are generally an obvious consequence of the assumptions made rather than empirically measured behaviour. This type of research is definitely a solid foundation on which to build empirical knowledge, but in itself is less than useful in answering questions of validity. Empirical research and general models incorporating marketing mix effects are now discussed.

Horsky and Simon (1983) assume advertising impacts on the coefficient of external influence (innovation). Advertising is postulated to have decreasing influence over time through being specified as a logarithmic function. They specify the relationship between p and advertising as:

$$p = a_1 + a_2 [\ln A(t)] \qquad \textbf{[3.24]}$$

where

$A(t)$ = cumulative advertising at time t

a_1 = coefficient of innovation independent of advertising

a_2 = coefficient reflecting the impact of advertising on innovators.

They attempted to empirically validate the model by testing it on the diffusion of telephone banking in five different banks in the United States. The model was fitted using OLS regression and in three of the five cases, a_2 was found to be significant.

Simon and Sebastian (1987)'s study into the impact of advertising on diffusion is the most comprehensive. They test a variety of hypotheses about the effect of advertising on p and q for the diffusion of new telephones in the former West Germany. They confirmed the belief that "an advertising dependent imitation coefficient" is the most valid method of representing the impact of advertising on the diffusion process. They also found that a Nerlove-Arrow model was best for explaining the advertising lag structure. However, they warn that the results are not strictly generalisable beyond the study.

The Generalised Bass model (GBM) was developed by Bass, Krishnan, and Jain (1994) to incorporate the effects of marketing mix variables on the rate of diffusion. In fact, the authors use the GBM to illustrate the conditions under which the Bass model will fit sales data without marketing mix variables. The model assumes that marketing effort can be used to increases the rate of adoption and takes the following form:

$$f(t) \quad = \quad [\, p + (q/m)\, N(t)\,]\, [\, 1 - F(t)]\, x(t) \qquad \textbf{[3.25]}$$

where

$x(t)$ = function of marketing mix variables at time t.

The GBM reduces to the Bass model when x(t) equals unity or when it is constant over time. The model is extremely flexible in accommodating marketing mix variables and allows for evaluation of the impact of these variables on all three generic parameters p, q, and m. The authors then estimate a number of different models using the GBM demonstrating its flexibility and the improvement in fit over the Bass model.

Other authors have also investigated the impact of product quality (Srivastava, Mahajan, Ramaswami, and Cherian, 1985; Kalish and Lilien, 1986) on the diffusion process with favourable results. Overall, the problem with incorporating marketing mix variables is that it is relatively simple to specify a model with marketing mix effects but difficult to collect the required data in practice. This is probably one of the main reasons most studies lack empirical validation (Mahajan and Wind, 1986; Simon and Sebastian, 1987).

A further problem is deciding which variables impact on the different diffusion parameters. It is econometrically difficult to estimate models which have marketing mix variables impacting on both innovation and imitation (a consequence of multicollinearity) (Simon and Sebastian, 1987). Therefore, decisions have to be made about the relationships (ideally) prior to estimating the model or after fitting the model to the data. In some cases, the marketing mix variable will have a significant effect on p or q, but when both are included, the model provides unstable or illogical results. This could lead to omitting relevant variables and biased estimates of the coefficients. In fact, in many cases we would expect interactions between the variables to also be significant contributors to the diffusion process i.e. advertising may be more effective when prices are lower. The failure to include these variables may lead to false conclusions about Bass model parameters. In any case, managerial judgement and prior experiential knowledge is an important ingredient in constructing a model that accurately depicts reality.

3.2.5.4 Other Bass Model Extensions

A number of other refinements and extensions to the basic Bass model have occurred. These include:

- Product extensions and innovation (Bayus, 1987; Norton and Bass, 1987) where successive generations of products create demand for themselves and cannibalise preceding generations or where the market potential for products such as CD's depends on the number of CD players sold.
- Repeat purchase (Lilien, Rao and Kalish, 1981; Mahajan, Wind and Sharma, 1983; Olson and Choi, 1985; Norton and Bass, 1987; Kamakura and Balasubramanian, 1987) where assumptions are made about the rate of repurchase or replacement purchase and are incorporated into the model.
- Multiple diffusion stages (Dodson and Muller, 1978; Sharif and Ramanathan, 1981; Kalish, 1985) where consumers move from unawareness to awareness to adoption.
- Disaggregate models (Lattin and Roberts, 1989; Chatterjee and Eliashberg, 1990) where individual or segment level models are aggregated to yield population estimates.
- Diffusion over geographic boundaries (Mahajan and Peterson, 1979) where diffusion effects among near neighbours is explicitly accounted for.

3.3 THE APPLICATION OF THE BASS DIFFUSION MODEL IN DOMESTIC/SINGLE MARKET SETTINGS

One important aspect of a good theory is that it can withstand rigorous testing. In his book Modern Marketing Theory, Hunt (1991) defined theory testing as "...comparing the actual phenomena with the phenomena that the theory predicted would occur." (p79).

Since the publication of the Bass model, extensive research has been undertaken to test the model's applicability to assorted products and services in a variety circumstances. As a result, promising outcomes have been reported from studies on retail service, industrial technology, agricultural, educational, pharmaceutical, and consumer durable markets (Mahajan, Muller, and Bass, 1990). Apart from academic research, representative companies such as Eastman Kodak, IBM, AT&T, RCA, and Sears also used the Bass model in their real-life practice (Mahajan, Muller, and Bass, 1990).

The majority of articles reviewed in this section relate to the application of the original Bass model in domestic/single markets. An in-depth examination of the performance of Bass model extensions is not undertaken given the lack of replication and diversity in published studies. Furthermore, the additional variables included in these extended models will result in distinctly different and possibly biased estimates of p, q, and m. These models will also provide a better fit to the data as they have more variables. Nevertheless, the original Bass model is more relevant to this study as the main focus is on extending the original model's applicability to new geographic markets and in this respect, the studies using this model provide a better benchmark against which the performance can be gauged.

3.3.1 Empirical Tests of the Original Bass Diffusion Model

The performance of the original Bass model will be evaluated in terms of its descriptive and predictive abilities. Descriptive ability relates to the ability of the Bass model to reproduce the diffusion curve based on input from the entire data set whereas predictive ability relies on none or only a proportion of the available data to predict the values of future data points.

It should be noted that the fit of the model solution was generally evaluated by the variance explained i.e. R-squared or the adjusted R-squared, although other means of statistical measurements were occasionally used by some authors. Moreover, the level of aggregation in the majority of published studies was annual.

3.3.1.1 The Descriptive Ability of the Bass Diffusion Model

The model's descriptive ability can be evaluated, first, by examining the fit of the estimated diffusion curve to the actual time series data and second, by comparing the predicted versus actual timing and magnitude of peak sales.

The estimated versus actual number of adopters in each time period

In the original study of the Bass diffusion model, Bass (1969) tested the model's ability to reproduce the diffusion curve by using the annual time series data of eleven consumer durables, such as air conditioners, clothes dryers, and refrigerators, in the U.S. market. By using OLS regression, the model achieved an average R^2 of 0.86 for the regression analogue and an R^2 of 0.81 for the fit of the descriptive model solution to the actual time series data. These promising results indicated that the Bass model was viable in terms of producing a good fit to a complete set of historical data.

In another similar yet more comprehensive study, Jeuland (1994) examined the Bass model's performance in describing the diffusion process across thirty-two different data-sets. This included the same set of eleven consumer durables used by Bass (1969), seventeen VCR markets in U.S. and four surveys of hospitals and schools. The time periods covered by the historical data ranged from five to fifteen years. As the results indicated, the Bass model achieved a very good fit across the data-sets, with R^2 values around 0.9.

Inspired by Bass (1969)'s successful application of the model on the sales of colour televisions in the U.S., Dodds (1973) tested the model on another closely related product - cable television. When including ten years of data points, Dodds found that the Bass model provided "a very good description of the adoption pattern for cable TV." (p310). However, no statistical measurements were used to support this finding.

Other successful applications of the original Bass diffusion model on innovations in the U.S. include Kalish and Lilien's (1986) study on the adoption of photovolitaic home energy systems in the south-western United States over a ten year period. They found a high R^2 of 0.89 for the Bass model solution against the actual time series data. Moreover, Lawton and Lawton (1979) also reported an impressive R^2 of 0.98 when fitting the Bass model to eleven years of diffusion data relating to the adoption of educational innovations. In both cases, the NLS estimation procedure was used to estimate the diffusion parameters.

Another study on the diffusion of service-related products was conducted by Srivastava, Mahajan, Ramaswami, and Cherian (1985). The authors examined the diffusion process of fourteen investment alternatives in the U.S.. The results suggested the Bass model solution, generated by the maximum likelihood estimation procedure, described the diffusion of the fourteen investment products very well. The reported R^2 ranges from 0.90 to 0.99 and with a high average R^2 of 0.96.

Predicted versus actual timing and magnitude of peak sales

By using time as the variable of interest, the Bass model can estimate the timing and level of peak sales in addition to the diffusion curve. These estimates can be attained by utilising the diffusion parameters obtained from fitting the model to the entire data set. A comparison between the predicted versus actual timing and magnitude of peak sales is another useful measurement of the model's descriptive ability.

By including all data points, Bass (1969) achieved fairly accurate estimation of the timing and magnitude of the peak sales for ten consumer durables, with R^2 of 0.89 and 0.99 respectively. Lawton and Lawton (1979) reported a very accurate model estimation of the timing of peak adoption for six educational innovations, with the R^2 of 0.98.

With the attempt to extend the Bass model's generalisability to other markets, Never (1972) tested its applicability on four economic sectors in the U.S.- the retail service, industrial technology and agricultural, and consumer durable markets. The model's estimations of the timing and magnitude of peak sales proved to be successful in all sectors, as the R^2's were reported to be 0.94 and 0.99 respectively.

Although the above empirical evidence provides strong support for the Bass model's structural soundness, these results provide very limited usefulness in real life situations where estimates are required well before saturation has been achieved. Testing of this kind offers valuable information for ex post comparison of the model estimates and actual data, and is therefore more valid and effective when used for the purpose of theory-testing. As the future is of more interest to marketing managers, the long-range forecasting effectiveness of the Bass model based on limited or no prior data is another criterion used to evaluate the model's performance.

3.3.1.2 The Predictive Ability of the Bass Diffusion Model

In this section, two major areas of predictive testing will be discussed: 1) the ability to forecast the long-term pattern of diffusion of an innovation, and 2) the ability to predict the timing and magnitude of peak sales. In both cases, predictive ability relates to the Bass models effectiveness in forecasting the sales curve using limited data points.

The ability of the model to predict the long-term pattern of diffusion of an innovation

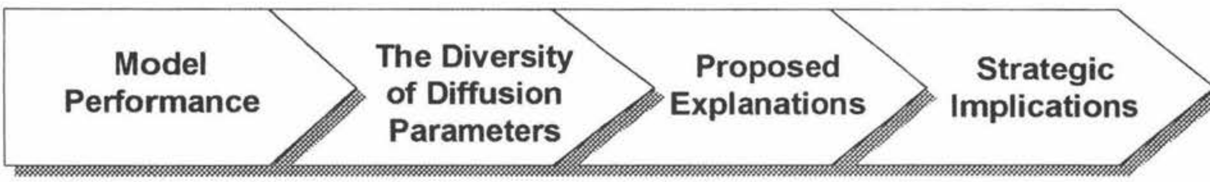
Srivastava, Mahajan, Ramaswami, and Cherian (1985) adopted a different approach to estimate the long-term diffusion pattern for the 14 investment alternatives in the U.S.. They used the average values of parameters p and q obtained across 14 products to project the diffusion pattern for each investment alternative. The performance of the model was assessed by the mean absolute deviations (MAD) and mean squared deviations (MSD) between the predicted and actual data points. The weighted average value for each statistical measurement was 0.0193 and 0.001072 respectively. These results indicate the Bass model predicted each investment alternative reasonably well. Moreover, it implies the fourteen investment products share a similar diffusion pattern. As the required average p and q values were obtained from all known data sets of all products, this forecasting method provides little forecasting insight for the diffusion of the products included. However, the practical usefulness of this method will be using the known average parameter values to project the diffusion curve of a new investment alternative when no prior data is available.

The ability of the model to forecast the timing and number of adoptions at peak

By using the first three known data points, Dodds (1973) predicted the diffusion of cable TV in the U.S. market. When comparing the estimated versus actual peak of adoption, the author commented "a forecast based on early data would have provided a reasonably good forecast of peak sales before the event" (p310). No actual figures or statistical measurements were reported.

Lawton and Lawton (1979) tested the Bass model's predictive validity by using limited data points to project the timing and level of peak adoption of a semester system among Ontario high schools in the U.S.. As a result, a forecast made based on the 1968 to 1973 data indicated the peak adoption would occur in 1976 with maximum of 228 schools, while the actual peak took place in 1976 with 257 school adopting.

3.4 THEORY AND APPLICATION OF THE BASS DIFFUSION MODEL IN INTERNATIONAL SETTINGS



- the descriptive and predictive ability of the Bass model

- the diversity of the diffusion parameters across countries

- the effect of country characteristics and the lead-lag time effect
- the learning effect

- foreign market selection and timing and order of entry
- country segmentation

Despite extensive examination in a variety of domestic/single market situations and successful results in terms of model fit, the Bass model has been sparingly applied in international settings. The view expressed by Barnhadt and Mackenzie (1972) seems pertinent:

> "the success of diffusion model forecasts has been due to the judicious choice of situation, population, innovation, and time frame for evaluating the data".

This shortcoming is reflected in the current diffusion literature which consists of less than a dozen published articles on the topic of new product diffusion in a non-US context. A few authors identified the difficulties associated with the availability of reliable and sufficiently long time series sales data across multiple countries as the major research hurdle (Heeler and Hustad, 1980; Douglas and Craig, 1983).

This section is structured in four parts, both with the overriding goal of examining the applicability of the Bass model in international markets. The first will summarise the model's performance in both describing and predicting the multinational diffusion process of various consumer durables. The second will detail the parameters estimated in the various studies and the patterns found across countries. Next, the proposed factors modifying the multinational diffusion patterns will be outlined along with the model extensions used to capture some of the more common effects. The final section will justify the importance of the Bass model in international markets by demonstrating its value as an input to strategic planning.

While the previous section (3.3) was devoted to the Bass model in domestic settings, the international studies discussed here (with the exception of Akinola, 1984) examine the diffusion of the same products across multiple countries. Thus, in addition to the standard model evaluations, they also provide useful insights into the different diffusion processes between countries. Multinational diffusion analysis allows for more robust conclusions to be made about the model's cross-national generalisability because the fit of the model can be more directly related to product or country specific factors.

3.4.1 The Performance of the Original Bass Diffusion Model in International Settings

As detailed in the previous section (3.3), evidence of the Bass model's success in fitting historical sales data in a variety of U.S. markets has lent credibility to the model's basic structural soundness and its ability as a forecasting device for marketers of new products (Heeler and Hustad, 1980). However, as market dynamics vary between countries, these results provide little support for the generalisability of the model to other economies. The scarcity of data in this particular area somewhat limits the practical value of the Bass model in international settings.

Among published international studies, equal attention has not been paid to markets in different regions. Most research has focussed on European countries which have predominantly developed economies. This trend is most likely an outcome of easier access to reliable multinational data and closer geographic proximity. Ganesh, Kumar, and Subramaniam (1997) recognised that these European studies have similar limitations to the U.S. research because findings might not be applicable to other developing or less developed economies.

Inspired by this background, Takada and Jain (1991) conducted research that systematically examined differences in diffusion patterns across several Asian countries. Thus far, it would appear to be the only article of this nature reported in the marketing or diffusion literature.

In order to be consistent with the previous domestic section (3.3.1), the descriptive and predictive performance of the Bass model was evaluated. The appraisal criterion are also the same as those reported in the domestic section to permit a fair and understandable comparison. In fact, throughout this section (3.4), the structure of the discussion is identical to that in the domestic review (3.3) except where not practicable.

3.4.1.1 The Descriptive Ability of the Bass Diffusion Model

The Bass model's descriptive ability can be evaluated, first, by examining the fit of the estimated diffusion curve to the actual time series data and second, by comparing the predicted versus actual timing and magnitude of peak sales. As was previously clarified, descriptive ability relates to the Bass model reproducing the diffusion curve based on input from the entire data set whereas predictive ability relies on none or only a proportion of the available data to predict the values of future data points.

In the literature, diffusion parameter estimates are computed by using either the ordinary least squares (OLS) procedure proposed by Bass (1969) or the nonlinear least square (NLS) estimator suggested by Srinivasan and Mason (1986). The fit of the estimated model solution to the actual data is mostly expressed by the variance explained i.e. R^2 or the adjusted R^2. It should be noted that the level of aggregation in the majority of published studies is annual.

The estimated versus actual number of adopters in each time period

The study conducted by Heeler and Hustad (1980) was among the first to focus on the performance of the Bass model in international settings. After applying the Bass model to fifteen consumer durables in a number of non U.S. countries, the authors concluded that "the fit of the model to the data was found sufficiently poor in about a third of the cases"(p 1011). However, measures of fit such as R^2 or mean absolute error (MAE) were not reported to support this finding. The emphasis of this study was mainly the comparison of estimated and actual timing and magnitude of peak sales (see below)). While these are important performance metrics, ideally the authors should also consider measures that gauge the performance of the model over all time periods.

In addressing the poor model fit reported by Heeler and Hustad (1990), Helsen, Jedidi, and DeSarbo (1993) claimed that the inappropriate type of data used in the study was one important cause of the model's failure: "we should add that the data sets they used were production, not sales data"(p 63). Product figures are unsuitable in consumer-based diffusion models because they reflect managers expectations of future sales rather than the actual purchases made by consumers.

In another study, Gatignon, Eliashberg, and Robertson (1989) examined the diffusion of six consumer durables (dishwashers, deep freezers, lawnmowers, pocket calculators, car radios, and colour television) in fourteen European countries and a similar result was found. The OLS procedure yielded inappropriate coefficient signs which prevented the estimated model from reproducing the diffusion curve in nearly one third of the cases (i.e. 24 out of the entire 84 cases). However, the fit of the estimated model was extremely high with R^2s ranging from 0.966 to 0.999. The authors claimed the inability of the model to estimate correct diffusion parameters is, in some cases, due to the insufficient time series data which did not contain the inflection point.

However, more encouraging results were reported by Ganesh, Kumar, and Subramaniam (1997) when fitting the Bass model to four new generation product innovations (microwave oven, VCR, home computer, and cellular phone) in sixteen European countries. The nonlinear least squares procedure recommended by Srinivasan and Mason (1986) was used to estimate the diffusion curve for each of the innovations in individual countries. The results suggested that, overall, the Bass diffusion model captured the diffusion patterns adequately. A high proportion of variance was explained across all product categories with R^2s ranging from 0.80 to 0.90.

While consumer durables were the focus of most researches, Ganesh and Kumar (1996) examined the adoption of new retail point-of-sale (POS) scanner technology in European Union countries, the United States, and Japan. Both ordinary least squares (OLS) and nonlinear least squares (NLS) procedures were used to estimate the diffusion parameters p, q, and m but only the NLS results were reported as this model produced better statistical fits, with the adjusted R^2 values ranging from 0.90 to 0.99.

With a different geographic focus, Takada and Jain (1991) investigated the applicability of the Bass model in Pacific Rim countries, including Japan, South Korea, Taiwan, and the US. The authors concluded that the results, generated by the NLS procedure, showed the original Bass model fitted "the data remarkably well in all of the countries" (p.51). However, no statistical measurements were reported to support this assertion which hinders further comparison of their results with other European and US studies. Consequently, the generalisability of the Bass model in Asian markets needs further confirmation.

Among the relevant international studies, Akinola (1986) was the only research based on a single country and the reported results were also encouraging. In an investigation of the adoption of cocoa-spraying chemicals among Nigerian cocoa farmers from 1955 to 1980, the author found the Bass model solution (using the NLS estimator) produced a high R^2 of 0.96 against the actual time-series data.

In conclusion, the above findings provide empirical support for the Bass model's ability in fitting full-set sales data in a variety of foreign markets.

Estimated versus actual timing and magnitude of peak sales

The second test of the Bass model's descriptive ability involves scrutinising the accuracy of the estimated timing and peak sales. Due to the poor fit of the model, Heeler and Hustad (1980) found the peak sales estimations were inconceivable in about one third of the international applications and most of the estimated models produced inaccurate timing predictions. The authors speculated that insufficient time-series data and cultural and environmental differences were the likely causes of the models failure.

In contrast, Akinola (1986) reported some more promising results. In the case of the adoption of chemical spraying equipment among Nigerian farmers, the author found the Bass model predicted the magnitude of peak adoption reasonably well, with the estimated peak level of adoption within 4.5 percentage points of actual values.

These contradicting findings require further research to draw a more definitive conclusion on the models ability to efficiently capture the timing and level of peak sales in international markets. At this stage, the weight of results would suggest the Bass model does not produce precise estimates of these figures.

3.4.1.2 The Predictive Ability of the Bass Diffusion Model

Predictive ability can be assessed by using subsets of data to predict future sales values. However, in the international marketing literature, an alternative method exists for assessing predictive ability. This alternative forecasting method involves estimating the entire diffusion curve even before the product was introduced to the country of interest. For this kind of 'no-prior-data' estimation, the average estimated parameter values from the other sample countries, normally countries where the product was launched before the holdout country, are used to predict the diffusion curve for the holdout country.

As pointed out by Ganesh and Kumar (1996), such a technique could be of great value to international marketers as it would: a) provide managers with an idea of potential adopters' possible reactions to new products even before their introduction to foreign markets, and b) assist in making market selection or entry decisions by allowing market planning to take place in advance of launch in the given country.

Here, a wide variety of statistical measurements were used to evaluate the models predictive validity in multinational settings. The degree of fit between the forecasting results and the actual data was gauged by mean absolute deviation (MAD), mean squared error (MSE), mean squared deviation (MSD), and mean absolute percentage error (MAPE). And the models ability in terms of predicting the peak sales before its occurrence was appraised by simply comparing the predicted versus actual timing and magnitude of peak sales.

The ability of the model to predict the long-term diffusion curve

Following a method proposed by Bass (1969) and Mahajan and Peterson (1978), Akinola (1984) divided the known diffusion data into two sets and used the early subset to predict the rest of the diffusion curve for the adoption of Cocoa-spraying chemicals in Nigeria. Their predictive model solution achieved an R^2 of 0.95 against the actual data over a four year period.

By using the no-prior-data forecasting method, Ganesh, Kumar, and Subramaniam (1997) tried to predict the diffusion of four major consumer durable products (home computers, microwave ovens, cellular phones, and VCRs) in several holdout European countries.

To forecast each products' adoption rate in each sales period, the parameters p, q, and m had to be estimated first for each lag country. The estimated external and internal coefficients in the lag country, p and q, were obtained by taking the average of parameter values in the lead countries. For example, to estimate the p and q values for microwave ovens in the lag country Portugal, the average values of p and q from United Kingdom, the Netherlands, Belgium, Frances, Austria, Denmark, Italy, and Spain where microwave ovens were introduced prior to Portugal were used.

Next, the market potential, m, for each of the lag countries was estimated through multiplying the population of the lag country by the average population penetration rate (market potential divided by population) obtained from the lead countries. After all three parameters p, q, and m are calculated, the diffusion curve for each consumer durable can then be estimated in each of the lag countries.

The mean absolute deviation (MAD) and mean square error (MSE) were computed to measure the fit of the Bass model predictions to the actual data for each of the product categories, for all of the countries. The forecasting results were acceptable, with the MADs ranging from 0.002 to 0.0363 and the average MAD value of 0.025.

With respect to the MSE, a similar successful result was found. In more than 90 percent of the cases, the MSE values ranged from 0.0002 to 0.0018, with the average MSE value equal to 0.0007. The only instance where the MSE value fell outside this range, 0.0059, was for microwave ovens in Finland. It should be noted however that as the relative sales units were not reported in the study, a more precise interpretation of the magnitude of the MAD and MSE values could not be made.

A similar methodology was adopted by Ganesh and Kumar (1996) for forecasting the diffusion of point-of-sale (POS) scanners in three holdout countries, i.e. Sweden, Austria, and Finland. The procedure for estimating the lag/holdout country's external and internal influence coefficients p and q was exactly the same as in the Ganesh, Kumar, and Subramaniam (1997) study. The average of the lead countries' p and q values for the scanners were used to estimate the lag country's p and q parameters.

Since the product investigated in this study is mainly used by retailers, the market potential m for scanners was estimated based on the number of potential retail outlets in the country rather than individual consumers. The exact procedure for estimating the value of the parameter m for each of the lag countries was, first, to compute the average percentage of retail outlets using the POS scanner system from all of the lead countries. Then, the market potential m was calculated by multiplying this average adoption percentage by the total number of retail outlets in the respective countries.

Apart from using the above estimated parameters to predict the diffusion curves for the POS scanners in each of the three countries, the authors also produced another set of predictions by utilising the average p and q values for technological products reported in Sultan, Farley, and Lehmann (1990)'s meta-analysis study. Subsequently, the forecasting performance of both models was evaluated by computing the mean absolute percentage errors (MAPE's), as recommended by Parker (1994). The reported results are summarise in table 3.4.1.

Table 3.4.1 Comparison of Forecasting Performance of the Bass Model by using different parameter estimates

Country	Average lead countries estimates	Meta-analysis estimates
Sweden	44.10%	364.84%
Austria	59.91%	251.23%
Finland	52.71%	313.12%

Note: this table is an extract from Ganesh and Kumar (1996, p 355)

As indicated in the above table, the original Bass model did not produce satisfactory predictions in either of the cases. The authors explanation for these disappointing results was that the diffusion of industrial technological innovations could be driven by factors other than internal and external influences. To test this hypothesis, Ganesh and Kumar (1996) added another variable to the original Bass model (i.e. the learning effect). The test results of this extended model will be discussed in the following "Bass model extension" section.

The ability of the model to predict the timing and level of peak sales with limited data points

As stressed in the early section of this literature review, one of the major advantages of the Bass model over naïve diffusion models is its ability to predict peak sales before they occur, even in conditions of where sales are growing. Unfortunately, this important aspect of the model's utility was neglected in most studies. Heeler and Hustad (1980) are the only published authors in the international marketing who have systematically investigated this issue and to some extent the disappointing results may have deterred other authors from following their lead.

In the forecast test, Heeler and Hustad (1980) used different amounts of time series data to estimate the timing and magnitude of the first purchase peak for nineteen products in U.S. and a variety of countries. The time periods included in the forecasting model were the first four, six, eight, ten, and twelve years of sales data. The accuracy of the predictions were examined by comparing the predicted versus actual timing and level of peak sales for each product in each of the countries.

On short runs of the U.S. data for consumer durables, the model appeared to be precarious. The authors reported that "stable and reasonably accurate predictions of the peak year of sales only occurred with at least ten years of input data, generally after the peak has already occurred" (p 1013). As for the magnitude of peak sales, the model produced usable forecasts with eight years of input data which is slightly shorter compared with the required input for the peak time estimation. Interestingly, peak forecasts for two non-consumer durables, weed spray and new drugs, appeared to be far superior than other cases. Predictions were consistently good even when only using four years of data inputs. The authors speculated the very early peak experienced by those products might be the reason for the pleasing forecast results.

For the international data, the level of peak sales is only adequately predicted in ten, out of the entire sixty-seven, instances. However, the shortest years of input, six years, were employed to produce these predictions. In some of the other cases, even ten years of data input generated vastly inaccurate forecast results. With these findings, Heeler and Hustad (1980) concluded that regardless of the original Bass model's structural validity, the model is too unstable to be utilised as a forecasting tool in international markets.

The following table is a summary of all applications of the original Bass diffusion model in multinational settings and their results:

Table 3.4.2 A Summary of International Studies on the Bass Diffusion Model

Study	Findings
Heeler & Hustad (1980)	The fit of the Bass model to the international time series data was found to be poor in about one third of cases. The level of peak sales was only adequately predicted in about one in seven cases.
Akinola (1984)	The Bass model produced an excellent fit to the time series data, with an R2 of 0.96. By using early subset data, the predictive model solution achieved an R2 of 0.95.
Gatignon, Elishberg, & Robertson (1989)	Inappropriate coefficient signs prevented the model from reproducing the diffusion curve in about one third of cases. However, the fit of the estimated model was extremely high with R2's ranging from 0.80 to 0.90.
Takada & Jain (1991)	The Bass model fitted remarkably well for selected products in US, Japan, Taiwan, and Korea. No statistical measurements were reported.
Ganesh, Kumar, & Subramaniam (1997)	A good fit of the Bass model to the data was found with R2 ranging from 0.80 to 0.90. When using the average parameter values of the lead countries to predict the diffusion processes for the lag countries, the model produced good sales predictions.
Ganesh & Kumar (1996)	The Bass model yielded an excellent fit with the adjusted R2's ranging from 0.90 to 0.99. When using the average parameter values of the lead countries to predict the diffusion processes for the lag countries, the model did not produce satisfactory predictions for the adoption of point-of-sales scanners in those countries.

In conclusion, the fit of the Bass model to international data was successful in most cases. It was especially noticeable that for studies using NLS estimation (Akinola, 1984; Takada and Jain, 1991; Ganesh and Kumar, 1996; Ganesh, Kumar, and Subramaniam, 1997) the performance of the model was significantly improved. In terms of predictability, mixed results were produced. The poor performance reported by Heeler and Hustad (1980) may have been due to the OLS estimation procedure or the fact that they used production rather than sales data. Nevertheless, their study did suggest that the Bass model performs best only when the data used to estimate the model includes the peak sales period.

3.4.2 The Diversity of Bass Model Parameters Across Countries

The main focus of this section is the diverse array of diffusion parameters found across the countries reported in the literature. A number of factors with explicit behavioural assumptions have been proposed to capture these differences. These factors and the attempts at modelling them will be discussed here.

After investigating the generalisability of the original Bass model in a multinational setting, Heeler and Hustad (1980) observed that the pattern of new product adoption in various countries contrasted with those seen in the U.S. Unfortunately, no specific diffusion parameter comparisons were made to address this issue. The authors speculated that the causes of the observed differences were the alternate communication patterns and economic constraints that exist. Heeler and Hustad (1980)'s study activated other academics to further investigate the potential underlying factors causing the diffusion diversity .

In Sultan, Farley, and Lehman (1990)'s meta-analysis study, two interesting diffusion phenomenon in the international marketing literature were summarised. First, the lead-lag time effect was detected as data from European countries produced higher coefficients of innovation (external influence) p, than U.S. data. It was reasoned that as most of the products were introduced and sold to the U.S. market first, consumers in the lag European markets perceived the risk associated with adopting this particular product as lower, the result being a higher level of innovativeness. In contrast, no significant difference was detected in the level of imitation coefficient (internal influence) q, across countries.

Second, it was observed that industrial and medical innovations have higher q values than consumer durables and other innovations. Due to the high cost and risk associated with these two particular products, interpersonal factors seem to have substantially more influence on buying decisions.

Contradicting Sultan, Farley, and Lehman (1990)'s finding on the internal coefficient q, Takada and Jain (1991) reported that this parameter appeared to be higher in the lag Asian countries, Japan, Taiwan, and South Korea, than the lead country, United States (i.e. the mean values of q for all products were 0.290, 0.431, 0.582, and 0.533 for the U.S., Japan, South Korea, and Taiwan respectively).

The least-significant-difference t-test was then carried out to investigate whether the observed parameter difference was statistically significant. The results confirm that the difference in the mean value of q between Taiwan and the U.S. and between South Korea and the U.S. is statistically significant at 5% level. As for Japan and the U.S. the difference between the mean value of q is statistically significant at the 10% level.

The different cultures, communication systems and the lead-lag time effect were proposed as contributing factors to the varying diffusion patterns across these countries. It was asserted that innovations generally diffuse faster in high-context cultures such as Taiwan, Japan, and South Korea where word-of-mouth effects are more prominent as interpersonal communication is encouraged by the relatively homogeneous cultural and socioeconomic background. On the other hand, the rate of adoption is lower in low-context cultures, such as the U.S., because the heterophilous communication system (derived from their relatively heterogeneous cultural and socioeconomic background) manifests low interpersonal influence (Hall, 1976, 1987, and Rogers, 1983).

Takada and Jain (1990) also suggested the higher rate of adoption in lag countries was a result of a better product knowledge and buying position possessed by the potential adopters. The time gap that exists between the lead and lag countries was suggested to give consumers in the later market benefits in observing and understanding the relative advantage of the product more thoroughly and possibly enjoying lower prices due to lower manufacturing costs.

It should be noted that only the q parameters were examined in this study. The authors asserted that since interpersonal influence q, is the factor that determines the speed and shape of the diffusion process, it will represent differences across countries more clearly and distinctly than the coefficient of external influence p.

Takada and Jain (1990)'s findings on the behaviours of the internal coefficient q, was supported by Ganesh, Kumar, and Subramaniam (1997). They studied the diffusion of home computers, microwave ovens, cellular phones, and VCRs in a variety of European countries, and found q increased over time. For example, in the case of VCRs, the values of q ranged from 0.36 for the lead country, Germany (where the product was introduced in 1970), to 0.62 for the lag country, Portugal (where the product was introduced in 1982). The same pattern was also found in the other three product categories.

Furthermore, in examining the timing of peak sales for the adoption of a new industrial technology, point-of-sale scanners, Ganesh and Kumar (1996) found the sales peaked progressively earlier for countries in which the technology was introduced later. For example, it took 17 years for the adoption of scanners to peak in the lead country, the U.S., 9 years in Germany and Belgium where the technology was introduced in 1980, and 4 years in Denmark and Spain where the technology was introduced in 1986. The authors conclude that this trend indicates that the diffusion process accelerates in lag markets.

In all of the studies above, evidence indicates that the diffusion of innovation is a phenomenon that varies between countries. However, the suggested underlying factors for the diversified diffusion patterns were only supported by the interpretations of parameter values or the time of peak sales. No systematic measurements were conducted to capture the effect of those possible factors on the multinational diffusion process.

3.4.3 Explaining the Varying Diffusion Patterns Across Countries: Bass Model Extensions

With the attempt to explain the diversified diffusion patterns across countries, several Bass model extensions were constructed to systematically capture and empirically verify the effect of some underlying factors, other than the external and internal influences, on the diffusion of innovations in international settings. This sections looks specifically at those Bass model extensions aimed at capturing the diffusion patterns across countries.

3.4.3.1 Models that include Country Characteristics and Lead-Lag Time Effect

Based on the assumption that the diffusion of a new product or technology is influenced by country-specific factors, Gatignon, Eliashberg, and Robertson (1989) proposed an econometric version of the Bass (1969) model. The objective was to explain the fluctuating diffusion parameters across countries by including three social system characteristics (cosmopolitanism, mobility, and the role of women) in the model.

The proposed model extended the original single time-series based diffusion model to a multiple time-series one, with a simultaneous generalised least squares approach to estimate the effect of country characteristics on the diffusion parameters across time periods and countries. Moreover, the authors claimed a major methodological advantage offered by the simultaneous generalised estimation procedure is it can estimate diffusion parameters even in cases where no prior data is available.

Three main hypotheses drawn by the authors based on the included social characteristics were: (1) countries with a higher degree of cosmopolitanism should have greater propensity to innovate, p; and a smaller propensity to imitate, q; (2) mobility would be positively associated with propensity to imitate, q as it increases the opportunity for social interaction within the country, and; (3) the percentage of women in the labour force is negatively related to the propensity to innovate, p for time-consuming innovations and positively related to the propensity to imitate, q when the work context provides a level of heterophilous influence (derived from heterogeneous cultural and socioeconomic influences).

The results indicated that cosmopolitanism had a positive effect on the propensity to innovate, however, a mixed effect was found for the propensity to imitate. The final overall joint test result supported the negative effect of cosmopolitanism on imitation (with a χ^2=55.27, d.f.=12). Nevertheless, product characteristics were surmised to have some influence on the role of cosmopolitanism in the case of imitation.

The effect of mobility on the propensity to imitate showed a mixed pattern although the overall joint test supported a positive effect (χ^2=56.35, d.f.=12). The importance of women in the labour force was statistically significant in all cases but the sign of effect depended on the innovation, for deep freezer as an example, the propensity to innovate was positively related to the number of women in the labour force.

In addition to these reported findings, it should be noted that although the authors claim that the included country characteristics (cosmopolitanism, mobility, and the role of women in the society) can explain the underlying nature of the diffusion process in multinational settings, the results also indicate that, in all cases, product characteristics also play an important role on deciding the magnitude of the country effect on the diffusion patterns.

Unlike most of the other relevant studies, Helsen, Jedidi, and DeSarbo (1993) employed a segmentation method to investigated the diversity in international new product diffusions. Instead of striving to find common spheres for countries with similar diffusion patterns, the authors examined whether countries that are grouped based on a variety of macroeconomic variables share similar/different diffusion patterns within/across segments.

By using a country-based segmentation method, the included 12 countries (U.S., Japan, and 10 other European countries) were grouped into three clusters based on five country characteristic variables (mobility, health, trade, lifestyle, and cosmopolitanism). Another three diffusion-based segments were also produced according to each country's diffusion parameter values for each of the selected consumer durables (colour TV set, VCR player, and CD player). Subsequently, a comparison between these two segments was conducted to detect if any consistent correspondence existed between these two segments.

If comparable diffusion patterns were found for countries in the same segment, then country characteristics would be proven to have impacted on the diffusion processes across countries. Nevertheless, the results showed a lack of congruence between the two segmentation schemes.

In addition to the five country variables, Helsen, Jedidi, and DeSarbo (1993) also tested the validity of using the high-low context culture concept as an explanatory factor for the diversified diffusion patterns in international markets (Hall, 1976; Takada and Jain, 1991). The results indicated that, across the three products, countries in the same diffusion-based segment did not necessarily have the same type of cultural context. In other words, these results show little evidence of linkage between the high-low culture theory and the new product diffusion process.

Since the country-based segments provide very little information on diffusion similarities, another method was adopted to explore the explanatory strength of the five country factors. The authors ran an OLS regression analysis for the pairwise differences in the values of estimated external and internal coefficients, derived from the latent structure procedure, for all three durables. The time effect variable, proposed by Takada and Jain (1990), was also added to the analysis to test its impact on the diffusion process.

The results indicated that the directional impact of the five factors was generally unsystematic across the products. For example, only lifestyle, health status, and the lead-lag time effect were found to be statistically significant and systematically correlated to the external influence parameter p.

As for the internal influence parameter q, countries rated high on cosmopolitanism appeared to have a stronger tendency to imitate which is contrary to Gatignon, Eliashberg, and Robertson

(1989)'s finding. Additionally, a negative relationship between the time effect and the imitation variable was reported which indicates the diffusion process decelerates in the lag country. This result, again, contradicts the finding reported by Takada and Jain (1991) and later by Kumar and Subramaniam (1997). Apart from cosmopolitanism and the time effect, a high level of economic development was coupled with a lower propensity to imitate while high spending on leisure activities appeared to be associated with a higher level of imitation.

In their conclusion, Helsen, Jedidi, and DeSarbo (1993) addressed the possibility of the product characteristic effect on the underlying pattern of the diffusion process: "there are certain constructs that may relate to new product diffusion patterns. However, it is not always clear when such variables will have an impact and in which direction, especially among different product classes" (p 68-69). More research would appear to be the only solution to this problem.

3.4.3.2 The Learning Effect Model

In their study on the diffusion of an industrial technological innovation, point-of-sale scanners, Ganesh and Kumar (1996) give a refined explanation for the influence of time (i.e. lead-lag effect) on the rate of innovation diffusion in multinational countries. The authors claimed that the acceleration of the diffusion process in the lag country is not purely a phenomenon caused by the time lag. Consistent with Gatignon, Elishberg, and Robertson (1989) and Takada and Jain (1990)'s, they viewed the learning of product characteristics/benefits from adopters in the lead countries as decreasing the perceived risk in lag country consumers and thus, creating a faster diffusion process.

In order to systematically capture the existence of this learning effect in the international diffusion process, a variation of the original Bass model proposed by Peterson and Mahajan (1978) was used. This extended model, named the learning model, allowed for one-way interaction between any pair of countries. It captured the influence of the diffusion of one innovation in a lead country on the diffusion of the same innovation in a lag country (this effect is represented by the learning parameter c). Another difference between the learning model and the original Bass model is that the market potential parameter m is provided exogenously.

The learning effect model is represented by the following formula:

$$dF_2(t) / dt = [p + q^*F_1(t) + c^*F_2(t)] * [1 - F_1(t)] \quad \textbf{[3.26]}$$

where

$F_1(t)$	=	cumulative penetration ratio till time t for the lag country ($N1(t)/m_1$)
$F_2(t)$	=	cumulative penetration ratio till time t for the lead country ($N2(t)/m_2$)
p	=	coefficient of innovation for the lag country
q	=	coefficient of imitation for the lag country
c	=	learning coefficient for the lag country

As industrial technological innovations are generally more complex and expensive than consumer durables, the risk associated with their adoption is greater. In order to control this uncertainty, some method of communicating the benefits and features of the innovation is required. In other words, the decision of adoption in the lag market relies heavily on the feedback and opinion about the technology provided by previous adopters in the lead market. In this case, a second model, named the pure learning model is relevant. This assumes that the diffusion process of an industrial technological innovation in the lag country is purely driven by the learning effect and this theory was also tested.

A nonlinear least squares (NLS) procedure was used to estimate the coefficients of both learning and pure learning models. For the purpose of detecting learning and time effects, the U.S. was regarded as the lead market for POS scanner technology with the remaining nine countries (Japan and other European countries) ordered by the year of introduction.

The results indicated a good fit for both models, with adjusted R2's ranging from 0.89 to 0.99. Although there was little difference between the learning model and the pure learning model with respect to variance explained, the pure learning model generated better estimates for parameters q and c (the learning coefficient). Both coefficients were positive, plausible, and were statistically significant at the 0.05 level across all countries.

As the learning coefficient c obtained from the pure learning model was statistically significant, it provides empirical support for the existence of the learning effect for industrial technological innovations between lead and lag countries. Also, the fact that the learning effect is captured foremost by the pure learning model indicates the diffusion of industrial technological innovation is mainly driven by the learning effect and internal influence which is different from consumer durables.

Moreover, the coefficients of external influence (p) in the learning model were negative in most cases and these estimates were not statistically significant in all cases. The authors claimed that this finding supported their argument that the influence of external influence is nonexistent in the case of industrial technological innovation. In summary, these results seem to support Robertson and Gatignon (1986) and Gatignon and Robertson (1989)'s argument that the nature of the diffusion process for industrial innovations is different from that of consumer durable goods.

In the case of time lag, the correlation between the size of the learning coefficient and the year of introduction was reported to be 0.89. This result indicates that a longer time lag seems to result in a greater learning effect in the lag country. However, it should be noted that it is merely a correlation relationship and it does not mean that a longer time lag is the causal factor for stronger learning effect. Also, as the magnitude of the learning coefficient c appears to differ between lag countries, it suggests that the degree of learning might depend on other factors.

After achieving a successful fit to the historical data, the forecasting ability of both the learning model and the pure learning model was tested. The average values of p, q, and c obtained from the European countries where POS scanner was introduced prior to Sweden, Austria, and Finland were used to forecast the diffusion process for these three holdout countries. The following table shows the mean absolute percentage errors (MAPEs) between actual and forecasted adoption for the three holdout countries produced by the learning and the pure learning model:

Table 3.4.3 Comparison of Forecasting Performance Across Models (MAPE's)

Country	Learning Model	Pure Learning Model
Sweden	12.75	5.68
Austria	12.52	8.95
Finland	16.50	9.35

Note: this table is extracted from Ganesh and Kumar (1996, p 355)

As the table indicates, the pure learning model consistently performed better than the learning model in all three cases. Moreover, when further comparison is made with the results from the original Bass model forecasts based on the same data the pure learning model's predictions appear to be superior as its MAPEs consistently lower than the MAPEs for the original Bass model estimates (range from 44.10 to 52.71).

After successful results were reported from the above study, Ganesh, Kumar, and Subramaniam (1997) replicated the learning effect study consumer durable goods and further investigated the potential factors which influence the degree of learning effect among lag countries. The authors believed that the learning effect was an outcome of multiple factors. Based on past research on multinational diffusion and international marketing, the proposed factors were classified into three major categories: 1) country-specific factors; 2) the lag time effect, and; 3) product/innovation-specific factors. The country-specific factors include geographical proximity, cultural similarity, economic similarity, and product/innovation-specific factors include type of innovation and technical standard. Consequently, the total of six factors were proposed as the underlying elements influencing the learning process between lead and lag countries.

The diffusion patterns of four consumer durable goods, VCRs, microwave ovens, home computers, and cellular phones, were analysed for 11 to 16 European countries. As in the Ganesh and Kumar (1996), the learning effect between lead and lag countries was capturing by using the learning model. The difference in the learning effect parameter c across lag countries was then explained by the six factors. The learning model parameters were estimated by the nonlinear least squares (NLS) procedure for all countries and product categories. The simultaneous generalised least squares estimation, as recommended by Gatignon, Eliashberg, and Robertson (1989), was then used for identifying the factors influencing the learning process for all products.

The variance explained by the learning model, represented by the R2, ranged from 0.80 to 0.99. The model coefficients were found to be statistically significant at the 0.01 percent level of confidence in all cases. The values of the learning coefficient *c* were 0.09, 0.27, 0.30, and 0.36 for VCRs, cellular phones, microwave ovens, and home computers respectively. As the existence of the learning effect was detected, the learning model (including the three categories of factors) was re-estimated simultaneously by using generalised least squares estimation for all product categories.

The re-estimated learning model reported a good fit to the data for the four product categories, with adjusted R^2s ranging from 0.87 to 0.97, with all coefficient estimates statistically significant at the 0.01 level. The values of external and internal influence p and q were positive, plausible, and within the typical range of values as reported in the literature (Sultan, Farley, and Lehmann, 1990).

Two main findings result from this study. First, in line with Ganesh and Kumar (1996)'s study, the results indicate that the learning effect exists systematically across all product categories. This signifies that the learning effect phenomenon does not only exist in industrial technological innovations but also across consumer durable products between the lead and lag countries. Moreover, five of the six factors examined in the study, cultural similarity, economic similarity, time lag, type of innovation, and existence of technical standards, were discovered to be significantly related to the learning process. This finding extended the existing knowledge by using country-specific, time lag, and product/innovation-specific factors to explain the variation in the learning effect between lag markets.

To evaluate the forecasting ability of the learning model, several countries were used as a holdout sample for each product category. The forecasting performance of the learning model was then compared with the original Bass model. The mean absolute deviation (MAD) and the mean squared error (MSE) were computed to assess the relative ability of the two models.

The MADs for the learning model ranged from 0.003 to 0.0234 in comparison to the original Bass model in which the MADs range from 0.002 to 0.0363, while the average MAD for each model is 0.015 and 0.025 respectively. A similar MSE trend was found between the two models. In general, the forecasting performance of the learning model was better than the original Bass model in 12 of the 17 cases. However, the Bass model is still superior to the learning model in terms of parsimony and was hardly inferior given the fact that the learning model contains substantially more parameters.

3.4.4 Strategic Applications of the Bass Diffusion Model in International Marketing

This section discusses some of the major strategic issues facing international marketers and demonstrates how the Bass new product diffusion model can be used as a tool to aid decision making.

3.4.4.1 Foreign market selection, timing and order of entry

For the past two decades, the world economy has been characterised by rapid business internationalisation and accelerating globalisation. This phenomenon is reflected in the increasing number of industries that have extended their markets to a global scope. As logistical barriers, especially in convenience and economic terms, continue to diminish and telecommunication networks develop, globalisation is expected at the least to continue.

The impact of the integrating international markets has enlightened marketing researchers to focus on strategic formulations for major international market entry issues. Ayal and Zif (1979) identified two major international market entry decisions faced by modern marketing managers: 1) potential foreign markets selection; and 2) the timing and order of entry.

In the literature, the traditional solution for the first issue is to make the selection decision based on an analysis of macro-level country-market characteristics such as foreign market size, growth rate, and attractiveness based on perceived risks. For timing and order of entry decisions, Ohmae (1985, 1987, 1989) suggests a firm can either employ a sequential waterfall approach or a sprinkler strategy. The former involves the company introducing the product to other countries after a successful launch in the domestic market, while for the latter the firm enters multiple foreign markets at the same time. However, these approaches lack the support of empirical evidence, especially regarding the circumstances upon which a firm should choose a particular strategy.

As a firm's success in a given foreign country is dependent on how consumers perceive its product and more importantly, how they react to it (Ganesh and Kumar, 1996), it is vital for managers to procure some knowledge on the new product diffusion patterns in potential foreign markets. As demonstrated in the previous section, the Bass new product diffusion model is a useful tool in these situations as it provides descriptive insights on how, why, and to what extent the diffusion processes for different products or innovations vary between countries or cultures. Alternatively, the model can also be used to predict the possible diffusion pattern for the innovation in potential foreign markets based on the diffusion parameters obtained from lead countries or similar products. This information helps managers to foresee product performance in each potential market and consequently, to select the alternative that best matches the firm.

For the timing and order of entry decisions, Kalish, Mahajan, and Muller (1995) conducted a study using the Bass model to examine the optimal conditions for implementing waterfall or sprinkler strategies. Their findings suggest that "a firm is shown to prefer a waterfall strategy if 1) the product has a very long life cycle, 2) the foreign market, as compared to the home market, is small, 3) the foreign market is characterised by a slow growth rate, 4) the foreign market is not innovative, 5) there are weak competitors in the foreign market, 6) competitors engage in collusive behaviour, and 6) the firm enjoys a monopoly position in the foreign market." (p 115).

In contrast, a sprinkler strategy was suggested to be adopted in opposite circumstances to those above.

Due to the dynamic nature of a market, it was stressed that these conditions are affected by other internal and external factors such as product characteristics, market, cost conditions, and the level of competition. The results of this study give managers some empirical guidelines on how to incorporate these market variables into decisions regarding timing and order of entry.

3.4.4.2 Country Segmentation

In the international marketing literature, country segmentation has been recognised as a critical tool in assisting strategic marketing decisions. Sethi (1971) summed up the importance of country segmentation by stating that "developing a successful strategy for global marketing depends to a large extent upon a firm's ability to segment its world markets so that uniform sets of marketing decisions can be applied to a group of countries." (p 348). Jain (1993) also argued that cross country segmentation is more realistic than the standard domestic approach as each country is viewed as a single unit. Thus, the implementation of target marketing will be more efficient as the boundary of each cluster is more distinct and 'spillover' (Wright and Esslemont, 1994) across the segments (i.e. countries) is less likely to occur.

Traditionally, international segmentation schemes either classify countries based on one single factor such as GNP per capita or on a set of socioeconomic, political, and cultural criteria. As one can see, none of the stated criteria represent any behavioural propensity on the part of consumers towards the potential or relevant products. In their examination on the merits of traditional cross-country segmentation methods, Helsen, Jedidi, and DeSarbo (1993) found country segments derived on the basis of the macro-level socioeconomic, political, and cultural criteria "provide little guidance as to the success of specific new product introductions". Alternatively, the authors suggested to segment the international markets on the basis of actual purchase behaviour represented by aggregate new product diffusion patterns.

Their results show that as the country segments formed on the basis of diffusion patterns tend to differ by product, the same country may exhibit a substantially different diffusion process for products that possess different characteristics. In order to validate the diffusion-based segmentation method, the authors called for further research on more product categories and preferably products with varied characteristics.

In conclusion, this section has demonstrated how the Bass diffusion model can be used as a strategic tool in international marketing. The model's descriptive ability provides insights on the varying nature of the multinational diffusion process across countries and its predictability allows marketing managers to foresee possible performance of their products in new foreign markets.

3.5 OBJECTIVES OF THE PRESENT STUDY

As demonstrated in the literature review, research on the original Bass model and its extensions have resulted in a well-documented theory of new product diffusion. While the majority of research provided empirical support for the models theoretical soundness and practical efficiency, there remain several research issues which must be addressed to improve its usefulness as a reliable forecasting tool. The impact of marketing mix variables on the diffusion process, the effectiveness of various parameter estimators, and the accuracy of the models behavioural assumptions in different product, market, and multinational situations are examples where further research and refinement is needed.

In respect to international marketing, the applicability of the model needs to be examined in more varied and diversified market situations to extend its generalisability to a global level. In the world of integrated economies, knowledge of the diffusion process and the ability to foresee potential sales in different countries are of significant importance to marketers as modern firms often operate in multinational markets. However, although this need for reliable forecasting methods for predicting diffusion rates across countries has long been identified as a top research priority by marketing academics (Nehrt, Truitt, and Wright, 1970; Douglas and Craig, 1992; Wight and Ricks, 1994), difficulties involved in obtaining reliable and sufficiently long times-series data have restrained the amount of studies that explicitly address these issues.

As discussed in the previous section, the focus of current diffusion studies has been mainly on industrialised markets such as the US and European countries. Inspired by the lack of diffusion studies in the Asian region and its increasingly important role in the global economy (notwithstanding the recent economic crisis), this study investigates the validity of the Bass model when applied to a number of innovations in Japan and Taiwan. The main determining factor for this country selection was accessibility to quality data on domestic sales units. Data from other countries was sought but was either unavailable (e.g. China and Singapore) or responses were not forthcoming (e.g. South Korea).

The overall goal of this study is to continue adding to the already sizeable body of knowledge on the Bass model. However, extending the generalisability of the model to Japanese and Taiwanese environments and consequently enriching the existing body of knowledge encompassing multinational diffusion theories is the central purpose.

In order to achieve the intended ends, the objectives were classified into two major categories with six sub-objectives:

3.5.1 TO EXTEND THE GENERALISABILITY OF THE BASS DIFFUSION MODEL TO THE JAPANESE AND TAIWANESE MARKETS

1. to assess the descriptive ability of the original Bass model when applied to data on a number of consumer durable goods;

2. to examine the model's predictive validity by using only a few initial data points;

3. to scrutinize the stability of the model under different levels of data aggregation.

This first group of objectives are aimed at determining if the Bass model is generalisable to Japan and Taiwan. Objective one examines the Bass model's capacity to capture the diffusion process in Japan and Taiwan when calibrated on all available data. A good fit means the model can be used to describe the diffusion of innovations in the two countries, as a function of the external and internal parameters. Subsequently, the model may be used in an explanatory mode to test hypotheses related to innovation diffusion across countries, as stated in the second part of the objectives.

Of more importance to marketing managers is the second objective which looks at the ability of the model to make accurate forecasts of future sales. If it can be established that the Bass model is a precise tool for determining future sales, then it would become an important aid to decision making when manufacturing in or exporting products to these countries, and especially with regard to resource allocation and the marketing mix.

The third objective is more concerned with the mechanics of the model, but again this has definite implications for all potential users of the model. The focus is deciding if the model's descriptive ability is affected by the confounding factors that occur at different levels of aggregation. For example, seasonal effects are much greater in monthly data than annual data. It is postulated that a stable model should be expected to produce similar diffusion estimates in these different conditions. This would be the first test in determining if marketers can use models estimated at lower levels of aggregation. However, it should be noted that a test of the predictive validity of the Bass model at different levels of aggregation is not undertaken here and warrants a separate investigation for definitive conclusions to be reached.

3.5.2 A CROSS-NATIONAL ANALYSIS OF THE DIFFUSION OF NEW PRODUCTS IN JAPAN AND TAIWAN

4. to compare the diffusion pattern for the same product categories across the two countries;
5. to determine if a significant learning effect exists between the two countries;
6. to compare the diffusion patterns for Taiwan and Japan with the results for other countries reported in the literature;

The second group of objectives aims to identify any distinct characteristics regarding the diffusion of new products in Japan and Taiwan. They also aim to determine if a learning effect exists between these two countries. In order to conduct these cross-country comparisons and hypothesis tests in a robust manner, the Bass model must satisfy the descriptive tests outlined in objective one.

The fourth objective compares the diffusion processes of the same five consumer durables in

Japan (lead country) and Taiwan (lag country). If the diffusion patterns are proven to be significantly different, the next objective is to determine if the observed diffusion differences can be explained by the learning effect. The assumption underlying learning model is that the diffusion of innovations accelerates in the lag country (Taiwan) because consumers have an opportunity to learn about the product from the lead country (Japan). If the learning model does describe the diffusion process better than the original Bass model, then it provides evidence for the impact of the learning effect on the rate of adoption in the lag market. This finding can further be used for normative purposes, such as aiding marketing managers in tailoring their strategies to the specific diffusion characteristics in that country, and more accurately forecasting sales in the lag country based on sales in the lead.

The final objective involves comparisons of the diffusion parameters found in this study for Japan and Taiwan with those reported in the literature. The purpose of this cross-study comparison is to obtain insight into the specific diffusion differences that exist between Japan and Taiwan and countries with Western origins. The expectation is that any differences/similarities observed in the diffusion patterns may broaden marketing managers' knowledge of the diffusion characteristics of each country and tailor their marketing strategies accordingly.

4 METHODOLOGY

4.1 DATA PROFILE

Sales data is required to estimate the Bass model and in this thesis the models were calibrated on 'domestic sales units'. Originally, data was sought from a number of Asian countries including Singapore, China, South Korea, Japan, and Taiwan. However, only two of these countries, Japan and Taiwan, possessed the data necessary to produce meaningful and reliable diffusion models. This could explain the relative shortage of Bass model studies in Asia (Takada and Jain, 1991) compared to the more developed economies in the United States and Europe.

Data was eventually collected for thirteen different consumer durable goods in Japan and Taiwan. All products examined in this study were selected from statistical records published by the governments of each country. Data on monthly production, export, and import units for each country was obtained from the following sources:

1. "Industrial Production Statistics Monthly, Taiwan Area, The Republic of China", Department of Statistics, Ministry of Economic Affairs, Taiwan, ROC.
2. "Monthly Statistics of Imports/Exports, Taiwan District, The Republic of China", Directorate General of Customs, Ministry of Finance, Taiwan, ROC.
3. "Industrial Statistics Monthly", Research and Statistics department, Minister's Secretary, Ministry of International Trade and Industry, Japan.
4. "Japan Export and Import Commodity by Country", Japan Tariff Association.

These sources differed from those used by Takada and Jain (1991). Initially, the same publications as these authors were sought but officials in the respective countries were not aware of their existence. One possible reason for this could have been the translation of the publication names into English.

Of the product data collected, five were common to both countries, namely air conditioners, personal computers, facsimiles, VCRs, and microwave ovens. Figure 4.1 details the products for which data was collected

Figure 4.1 List of Consumer Durables Studied

Taiwan	1. Air conditioners.	6. Induction cookers.
	2. Personal computers.	7. TV games (Nintendo, etc).
	3. Facsimiles.	8. Floppy disks.
	4. VCRs.	9. Clothes dryers.
	5. Microwave ovens.	
Japan	1. Air conditioners.	6. Video disk players.
	2. Personal computers.	7. Video cameras.
	3. Facsimiles.	8. Digital audio disk players.
	4. VCRs.	9. Vacuum cleaners.
	5. Microwave ovens.	

Clearly, the products numbered six through nine were not comparable across the countries. Nevertheless, their inclusion adds significant value in terms of broadening the generalisability of the Bass model to both countries. In cases one though five, care was taken to ensure that the product definitions were equivalent between the countries.

As domestic sales units were not directly available from both countries, the data was derived by subtracting the export unit sales from and adding the import unit sales to the total unit production (i.e. domestic sales units = total production - exports + imports). This formula was recommended by Takada and Jain (1991) as the authors assert it ensures the data correctly reflects the diffusion process within the respective markets. They also stress that this procedure is particularly important for Japan and Taiwan because their economies rely heavily on exporting to other countries.

Most published Bass model studies use annual data to calibrate the model, but in this thesis monthly data was collected. One major advantage of using data collected in monthly intervals is it enables models to be estimated at different levels of aggregation, i.e. quarterly, semi-annual, and annual intervals. Examining the performance of the Bass model in conditions where other effects such as seasonal patterns are present gives insight into the stability of the model and its parameters. From a theory-building perspective, this adds significant value to the generalisability of the Bass model as the performance of the model had not yet been tested at different data aggregation levels in a cross-national setting.

In order to make the research findings comparable with those found in the literature, the descriptive and predictive ability of the Bass model was first examined using annual time-series data. The robustness and applicability of the model to other levels of data aggregation (i.e. monthly, quarterly, and semi-annual) was then determined in a subsequent analysis.

The time period covered by the entire data set was from January 1961 to August 1997. For each product, the included time-series data varies as it comprises data from when the product first appeared on the records to August 1997. Also, when there was clear evidence of repeat purchase occurring (Bass suggested that the level of sales plateaus after the peak, rather than mirroring the before peak diffusion pattern, as a consequence of repeat purchase) before August 1997, the sales plateau period was excluded from the calibration data set. The Bass model was not designed to capture such distinct patterns of repeat purchase.

On first plotting the data, it was clear that there was discernable qualitative differences in the data between the two countries. The Taiwanese data tended to conform with the diffusion pattern expected for consumer durables as established in the marketing literature: sales increased to a peak then declined to a level where repeat purchase could conceivably be taking place. In contrast, the Japanese data steadily increased over time with little sign of declining. The recent recession experienced by Japan may go some way to remedy this. In either case, this unusual sales pattern in Japan could be a consequence of incorrect measurement of sales or a high level of repeat purchase.

The Japanese data yielded another interesting practical problem with implementing Takada and Jain (1991)'s formula for calculating domestic unit sales. Using their formula, negative monthly sales figures were obtained for a few products. Two potential causes of this were identified. First, import and export records usually start before production, which tends to become available only after production levels are of significant value in the economy. As a result, the absence of early production figures creates negative sales values at the beginning of a product's life. Second, the published production data was obtained through surveys of major manufacturers whereas export and import figures were based on records from the relevant Customs Department. This difference occasionally results in production figures that are less than the number of exports, thus, leading to negative sales figures.

Subsequently, one can see the recommended calculation of domestic sales units in this manner introduces three potential sources of error and in this regard, the figures may be less reliable. Unfortunately, this issue is difficult to resolve and as the majority of the data points are valid, it is best to assume that data collected accurately reflects the respective factors.

The data collected here is superior to that used by Takada and Jain (1991) in a few respects. First, the time gap between lead and lag countries is much smaller and therefore there is less contrast in the development and accessibility of the communication infrastructure in each countries, a situation that is more realistic in the prevailing global business environment.

For example, in the Takada and Jain (1991) study, the Bass model was estimated for washing machines in the United States for the years 1927-54 and Taiwan for the years 1968-82. While the authors claim the lead-lag effect caused the diffusion process to be faster in Taiwan than in US, the forty-year time gap also allows for more intervening factors to explain this difference. With the aid of more advanced communication systems (for example in terms of broadcasting and telecommunication) it is not surprising that the diffusion process is comparatively faster in Taiwan. It would be easier for Taiwanese consumers to learn about the new product through mass media channels or to communicate their opinions to other members of the population than those in US. Consequently, in order to rule out other factors, it is important to ensure that no great disparity exists in the relevant external factors.

The second advantage of this data over Takada and Jain (1991)'s research is that the type of innovations used are more current. As a result, findings obtained from these new product categories can offer better understanding of how consumers react to new products in modern markets.

4.2 PROCEDURE

The first group of objectives required the application of the 'original' Bass diffusion model (Bass, 1969) to examine the diffusion process for the selected consumer durable goods in Japan and Taiwan. Later in the second section, an extension of the Bass model, the learning model (Ganesh and Kumar, 1996; Ganesh, Kumar and Subramaniam, 1997), was fitted to investigate the existence of the learning effect between Japan and Taiwan. All models were estimated using the nonlinear least squares (NLS) estimation procedure recommended by Srinivasan and Mason (1986). The Bass model and the corresponding NLS procedure were entered as a set of calculations into Microsoft Excel version 7.0 for Windows (see section 9.1 in the Appendices for details). The output and measures generated are also detailed in section 9.1, as is the estimation of the learning model.

Descriptive ability in this study was defined as the ability of the Bass model to accurately capture the diffusion curve when fitted to all available data. This involves examining the plausibility of the model's parameters and the model fit. The key requirements for parameter plausibility included:

- the parameters p, q, and m should all be greater than zero;
- q should be greater than p;
- the estimated market potential m should be within plausible bounds for the social system and approximately equal to the actual total cumulative sales, M, at the completion of the diffusion process, and;
- pm should be approximately equal to sales in the first time period.

There are a number of methods available for determining the fit of a model to a given set of data. In the case of the Bass model, many measures have been used by a variety of authors to demonstrate its superior or inferior fit. These include mean square error (MSE) (Tigert and Farivar, 1981), mean absolute deviation (MAD) (Simon and Sebastian, 1987; Ganesh, Kumar, and Subramaniam, 1997), mean absolute percentage error (MAPE) (Ganesh and Kumar, 1996), R-Squared and Adjusted R-Squared (Bass, 1969; Mahajan and Peters, 1978; Gatignon, Eliashberg and Robertson, 1989; Ganesh, Kumar, and Subramaniam, 1997), predicted versus actual timing of peak sales, and the difference between estimated and predicted peak sales (Heeler and Hustad , 1980). The emergence of these benchmarks has occurred because all have their respective disadvantages when used to ascertain the adequacy of fit.

In this thesis, all of the above measures were calculated during the process of fitting the models. However, only the later four are used to assess model fit (for completeness, the values of MSE, MAD, and MAPE are reported in the appendix 9.2). The other measures are not used to determine model fit for a number of reasons. First, the size of MSE and MAD is directly related to the sales units of the product. Therefore, a product with higher sales will generally have higher values for MSE and MAD. Furthermore, deciding upon the level of MSE or MAD that indicates lack of fit for a particular model is speculative because there is no statistical theory which can be used to test the significance or otherwise of these measures.

However, a more fundamental flaw with MAPE is the fact that the contribution of each data point to the statistic is not scaled according to the relative size of the data point. For example, a 200% error about an actual sales level of 10 (i.e. an error of 20 units) is given the same weight as a 20% error about an actual sales level of 200 (i.e. an error of 40 units). From a practical point of view, the second error is of far more significance than the first and should be scaled accordingly when calculating a fit statistic. This does not happen with MAPE which based on these two values would report a misleading value of 110%.

The predictive ability of the Bass model is gauged by examining the accuracy of forecasted parameters p, q, and m, next period sales, and the timing and magnitude of peak sales compared to the true values. These forecasts are obtained when the Bass model is calibrated on subsets of the full data set. Of course, the true parameters can never be known so the assumption is made that the best estimate of the true parameters is the estimates obtained from the full data set. It should be noted that only models at the annual level of aggregation are considered here.

Although a number of authors have examined the predictive validity of the Bass model, few if any have conducted the systematic examination of the model's forecasting performance when fitted to n = 3 to n = total data points undertaken in this study. This enables an analysis of the predictive validity of the model but also the small sample properties of the NLS estimator. In statistics, asymptotic theory relates to the long term behaviour of an estimator as $n \to \infty$. In most practical applications of the Bass model, it is unlikely that n would approach thirty, aside from ∞, except in instances where data at lower levels of time aggregation are used. In this study, only Japan Vacuum Cleaner exceeds this value. Therefore, the small sample behaviour of the NLS estimator would seem an important area of investigation.

The main expectation with regard to the estimates produced by the model as n increases is that they will tend towards some limit. However, given the importance of the peak in determining the shape of the diffusion curve, this behaviour might not occur until after peak sales. If the model estimates do not display some degree of convergence as n increases, then the predictive validity of the model and the adequacy of the NLS estimator for small samples may be brought into question.

Thus far, models fitted at different levels of data aggregation have been rarely examined in multinational diffusion studies, the exception being Wright, Upritchard, and Lewis (1997). The main reason for the scarcity of research in this area is the difficulties associated with obtaining reliable multinational sales data at any level other than annual. The objectives related to model stability are addressed by investigating the Bass model's estimates under different levels of data aggregation . The Bass model is fitted to data at different levels of aggregation, in particular yearly, half-yearly, and quarterly. Model stability is determined by examining the plausibility of the estimated parameters, the fit of the model, the parameters p, q, and m, the timing and magnitude of peak sales, and annual sales predictions across the aggregation levels.

Plausibility is defined in the same manner as for the descriptive ability and the same measures are used to gauge model fit. The model parameters would be expected to differ across the aggregation levels. We would expect, all things being equal, the rate of change in the number of adopters, the number of innovators, and the number of imitators in a year to be greater than in a half-year or quarter (i.e. both p and q will be progressively larger as the level of aggregation increases). A more precise approximation would be, p and q from the yearly models being twice the size of the estimates from the half-yearly models and four times the size of the estimates from the quarterly models assuming that the model is capturing the same diffusion process across the aggregation levels.

To fulfil the second group of objectives, a cross-national analysis was carried out for the five products where data existed for both Japan and Taiwan, i.e. air conditioner, personal computer, facsimiles, VCR, and microwave oven. The estimated coefficients of internal and external influence were compared across these two countries. This procedure was only undertaken for annual data for the reason of further cross-study comparisons. Consequently, standard errors for these p's and q's were estimated through simulation (using the method advocated by Srinivasan and Mason, 1986) and used to determine if the parameter values were significantly different across the countries.

The learning model (Ganesh and Kumar, 1996) was fitted to the data using NLS estimation to determine if the learning effect, coefficient c, was significant. This analysis was only for those five products where data from both countries was available at the annual level of aggregation. The findings were then compared to the relevant results reported by Ganesh, Kumar, and Subramaniam (1997).

4.2.1 Simulation of Standard Errors

Simulated standard errors were used instead of asymptotic approximations because as Srinivasen and Mason (1986) suggest, "given the small number of time periods for which data are usually available, one may wonder about the validity of the asymptotic approximations" (p 174). Srinivasen and Mason (1986)'s method involves a number of steps. First, the Bass model is estimated and the values of p, q, and m derived are assumed to be true. Also, the variance of the error term, var(e), is assumed to be true. Then in conjunction with these true values, normally distributed errors with mean zero and variance var(e) are generated and used to produce simulated sales for each time period. Times are considered to be 0, 1, 2, 3,..., T. The Bass model is then fitted to these simulated sales to generate estimates p_i, q_i, and m_i.

After repeating the steps above R times (R equals the number of replications), separate averages and standard deviations (i.e. standard errors) of p_i, q_i, and m_i were calculated and used to test diffusion hypotheses about p and q. More precisely, the average of the R parameter estimates is the mean of the sampling distribution of the estimate and the standard deviation of these R estimates is the standard error of the sampling distribution. In this study, the number of replications, R, equaled 50. This was larger than the 30 used by Srinivasen and Mason (1986) and is considered large enough to accurately estimate the standard errors.

4.2.2 Data Issues - Repeat Purchases and Product Extensions

For a number of products, repeat purchases are likely to be occurring in the calibration data. This is undesirable given the underlying assumptions of the Bass model which make it only applicable to first time purchases. The main implication is that the observed diffusion parameters would be confounded with the repeat purchase effect. Any observed differences between Japan and Taiwan in terms of p and q may be a consequence of different rates of repeat purchase in the two countries.

In Takada and Jain (1990)'s study, repeat purchase is obviously a factor given the sizeable forecasting periods (e.g. for Japan electric washing machines, the calibration data covered the period 1953-75). These authors make no reference to this or offer solutions. The same also applies to the study by Ganesh, Kumar, and Subramanium (1997), especially with regard to personal computers and microwave ovens.

In this study, a reasonable assumption is made with respect to repeat purchase across the two countries. If the repeat purchase rate is constant and equal across the countries, then comparing the Bass model parameters across the countries is possible. The product where this assumption is most likely to apply is personal computer.

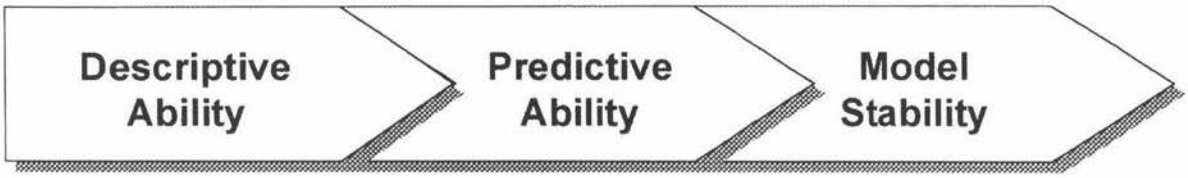
In particular, for clothes dryers (Taiwan) and vacuum cleaners (Japan) this will be a sizeable component given the large time period covered by the data. The parameter estimates for these two products are lower than for the others, but an examination of figures 6.6 and 6.7 shows that they are not unreasonably small. Therefore, they are included because cross-country comparisons are not made for these products and for completeness. Despite the incorrect application of the Bass model in these cases, they do reveal the behaviour of the model under these circumstances. For example, their inclusion in the predictive validity section guides users of the model as to the reliability of the predictions in these circumstances.

Models for repeat purchase have been developed by Lilien, Rao and Kalish (1981), Mahajan, Wind and Sharma (1983), Olson and Choi (1985), Norton and Bass (1987), and Kamakura and Balasubramanian (1987). These models make assumptions about the rate of repurchase or replacement purchase but are beyond the scope of this study.

Apart from repeat purchase, product extensions are likely to have an impact on the observed diffusion pattern (esp. for products such as personal computers and TV games). However, the various product extensions would have been accessible to both Taiwan and Japan at the same point in time, and therefore any impact could be expected to be the same. Therefore, the cross country comparison of p and q for personal computers should not be effected. For those products where extensions were a factor, the parameters were examined to determine if they were unreasonably large or small and in all cases, they were within acceptable limits (i.e. could not be classed as outliers).

As mentioned previously, models for product extensions have been developed by Bayus (1987) and Norton and Bass (1987). These models have data requirements which are not met in this study and hence were not estimated. In other international diffusion studies such as Takada and Jain (1990) and Ganesh , Kumar and Subramaniam (1997) where extensions would have been present in their data, the issue of product extensions were not acknowledged by the authors.

5 GENERALISABILITY OF THE BASS MODEL TO JAPANESE AND TAIWANESE MARKETS



- parameter plausibility
- model fit

- using limited early data points to predict the rest of the diffusion curve
- using limited early data points to predict n time periods ahead

- the stability of the Bass model at quarterly, half-yearly, and yearly data aggregation level

In order to fulfill the first objective of this thesis, this chapter examines the applicability of the Bass diffusion model to Japanese and Taiwanese markets. As relevant Asian studies on diffusion theory were scarce in the literature, research of this nature can add much value to existing theory and extend the model's generalisability to new markets. Additionally, the obtained results can enable comparisons of the similarities and differences found in the diffusion patterns of markets from Western and Eastern origins. Knowledge on this particular aspect is vital to modern marketers as increasing numbers of companies operate in a multinational environment which requires tailored marketing strategies to different cultures.

As shown in the diagram above, the performance and generalisability of the Bass model was assessed in three ways. The initial test relates to the model's descriptive ability, in terms of generating plausible diffusion parameter estimates and providing valid model solutions using all available data as input (section 5.1). The second part of the evaluation involves the model's ability to predict the sales volume in the next time period or the rest of the diffusion curve based on only a portion of the early data points (section 5.2). For the purpose of cross-study comparison, only yearly data was used for the first two sections.

The final section of this chapter (5.3) is concerned with model stability under different levels of data aggregation. The estimated model solutions based on quarterly, half-yearly, and yearly data were summarised and compared.

5.1 DESCRIPTIVE ABILITY

Parameter Plausibility

- p, q, and m greater than zero
- q greater than p
- m within plausible social bounds
- estimated versus actual total sales
- estimated versus actual first period sales, pm

Model Fit

- comparative fit of the estimated model to the actual data (adjusted R^2)
- plot of estimated versus actual diffusion curve
- estimated versus actual timing and magnitude of peak sales

Summary

- evaluation of the overall descriptive ability of each estimated Bass model solutions in Japan and Taiwan.

Descriptive ability in this context is the extent to which the Bass model accurately captures the diffusion process, in terms of the rate of adoption over time, when fitted to all available data. Assessing the Bass model's descriptive ability involves examining the plausibility of the parameters and the fit of the model. The model needs to produce both plausible parameters and accurate estimates of sales over time to have descriptive ability. Implausible parameters could be caused by one of two factors: confounding factors and/or noise; and the models underlying assumptions not adequately capturing the diffusion process. If the model is accurate but the parameters are not plausible (e.g. negative), then our confidence in the predictive and comparative uses of the model is reduced. Conversely, plausible parameters with inaccurate sales estimates means the model is not capturing important effects impacting on the diffusion process.

In section 5.1.1, the plausibility of the Bass model parameters for the diffusion of products in Japan and Taiwan is investigated. In section 5.1.2, the fit of the model using a number of common measures is examined. The final section (5.1.3) will summarise the overall descriptive ability of the Bass model in the two countries. For the purpose of cross-study comparisons, only models fitted to annual data are examined in this section. Plausibility and fit issues for models fitted to half-year and quarterly data (i.e. different levels of aggregation) are discussed in section 5.3.

5.1.1 Parameter Plausibility

Parameter plausibility has been stressed since the first Bass model study (Bass, 1969). This issue is particularly important when the more unstable OLS estimator is used to calibrate the model (as mentioned previously, multicollinearity, instability when few data points exist, and time interval bias all impact detrimentally on the parameter estimates). Today, NLS estimation is more robust to the extent where constraints can be placed on the sign of the estimated coefficients (i.e. p, q, and m can be restricted to being positive numbers). However, these constraints were not enforced in this study as a true test of the model's ability.

In this context, plausibility will be examined in respect to four key expectations:

- the parameters p, q, and m should all be greater than zero;
- q should be greater than p;
- the estimated market potential m should be within plausible bounds for the social system and approximately equal to the actual total cumulative sales, M, at the completion of the diffusion process, and;
- pm should be approximately equal to sales in the first time period.

5.1.1.1 Plausibility of Japanese Parameters

As shown in Table 5.1, all estimated Japanese diffusion parameters, are positive and each internal coefficient, q, is greater than the external coefficient, p. Except for satisfying the requirements for sensible model estimates, these results also indicate that both internal and external influences exist (the significance of these estimates are discussed in section 6.1 based on the simulated standard errors) and the effect of interpersonal influence is dominant in the diffusion process. Therefore, the rate of adoption will resemble the classic diffusion curve in section 3.

Except for personal computers, the estimated market potential, m, appears to be plausible (i.e. within reasonable bounds for the social system) when compared to the population. Based on the available yearly data, the Bass model's estimate for the potential market size for personal computers is approxmately 4.7 billion units, which amounts to nearly 40 times the population of Japan. Due to the rapid adoption of computers for industrial, commercial, academic and personal applications during the past decade, it is difficult to judge whether this figure is plausible. Repeat purchases and multiple product generations are also likely to be causing this inflated estimate.

Table 5.1 Diffusion Parameter Estimates Based on Yearly Japanese Data

Product	p	q	m	Total Sales Est.	Total Sales Actual M	Total Sales differences	First Period Sale Est. pm	First Period Sale Actual	First Period Sale differences
Japan									
Air Conditioner	0.038	0.22	880	880	766	14.9%	33.3	40.5	-18%
Personal Computer *	0.0001	0.18	474548	3444	3549	-3.0%	68.9	132.3	-48%
Facsimile *	0.0006	0.20	29152	1582	1646	-3.9%	16.8	14.6	15%
VCR	0.039	0.38	5418	5418	5199	4.2%	208.8	245.6	-15%
Microwave Oven *	0.008	0.19	5418	2821	2870	-1.7%	44.8	112.1	-60%
Video Disk Player *	0.035	0.26	888	701	705	-0.5%	30.9	40.3	-23%
Video Camera *	0.032	0.46	7588	5794	5815	-0.4%	242.9	325.4	-25%
Digital Audio Disk Player *	0.017	0.26	19579	13631	13534	0.7%	341.3	75.5	352%
Vacuum Cleaner *	0.0039	0.07	44181	15450	15409	0.3%	171.8	147.0	17%

* diffusion curvenot yet completed

** m measured in ten of thousands (0,000's)

The second requirement for a plausible m is its value should be approximately equal to the actual total sales at the end of the diffusion process. However, as the diffusion process for most of the Japanese products has not yet completed, such a comparison could only be carried out reliably for air conditioners and video cassette recorders. The results indicated the deviation between estimated m and actual total sales was within an acceptable range in both cases, with the percentage difference of 14.9% and 4.2% respectively.

For those products with an incomplete diffusion curve, an alternative method was adopted by comparing actual cumulative sales, over the time period where data was collected, with estimated cumulative sales over the same period. The fit between the two measures was excellent in most cases, with a 5% difference between actual and predicted. However, it should be noted that such a comparison is less desirable in determining the plausibility of m.

This is because the results apply only to a limited portion of the total diffusion process.

The difference between first period sales and *pm* is another measure suggested by Bass (1969) for evaluating parameter plausibility. Clearly, three of the models performed poorly: digital audio disk players, personal computers, and microwave ovens. In the case of digital audio disk players, the model overestimated the level of first period sales by just over 350%. Two potential explanations exist for the lower than expected actual first period sales. Either consumers were not aware of or did not value the benefits offered by this product and consequently, the adoption risk was too high, or the distribution and/or range of audio compact disks was lacking in the initial stages of product launch.

The first period sales of personal computers and microwave ovens was 48% and 60% higher than that predicted by the model. Clearly, the initial popularity of these products was not sustained in the short term as indicated by high first period sales followed by lower or negative growth in the ensuing time periods (see figures 5.3 and 5.6 for actual and estimated diffusion curves).

Despite this, for most products the difference between actual first period sales and *pm* ranged from 15% to 25%. Given the relative size of initial sales compared to total sales, the magnitude of these differences is within acceptable bounds.

5.1.1.2 Plausibility of Taiwanese Parameters

In the case of Taiwanese products, all parameters are positive (Table 5.2) and all q values are greater than their respective p values with the p values generally being very small. It is also important to note the high q values for personal computer, facsimile, and video cassette recorder (i.e. higher than 1). As more of the products have completed the diffusion process (four out of nine), the plausibility of m can be better gauged than for Japan. As indicated by table 5.2, the difference between estimated and actual m is good (all estimated values within 10% of the actual value).

Table 5.2 Plausibility of Taiwanese Model Parameters

Product	p	q	m	Market Potential Est.	Actual M	differences	First Period Sale Est. pm	Actual	differences
Taiwan									
Air Conditioner	0.00009	0.40	4309	4309	3923	9.8%	0.38	0.09	300%
Personal Computer *	0.00007	0.36	6597	3991	4021	-0.7%	0.43	0.24	80%
Facsimile	0.0015	1.03	358	358	349	2.7%	0.53	1.41	-62%
VCR	0.0000005	1.09	702	702	646	8.7%	0.0004	0.04	-99%
Microwave Oven	0.0012	1.75	146	146	152	-4.1%	0.17	0.48	-65%
Induction Cooker *	0.022	0.35	390	304	305	-0.2%	8.58	11.92	-28%
TV Game *	0.013	0.29	1477	1158	1182	-2.1%	19.51	29.53	-34%
Floppy Disk *	0.032	0.38	128	85	85	0.5%	4.08	3.74	9%
Clothes Dryer *	0.0018	0.26	203	174	167	4.2%	0.36	0.12	192%

* diffusion curve not yet completed.

* m measured in 0,000's of units

However, the fit between estimated and actual first period sales was poor in most cases. Large differences were found for six of the products. Given the relatively small size of first period sales compared to total sales, this is not seen as a major weakness.

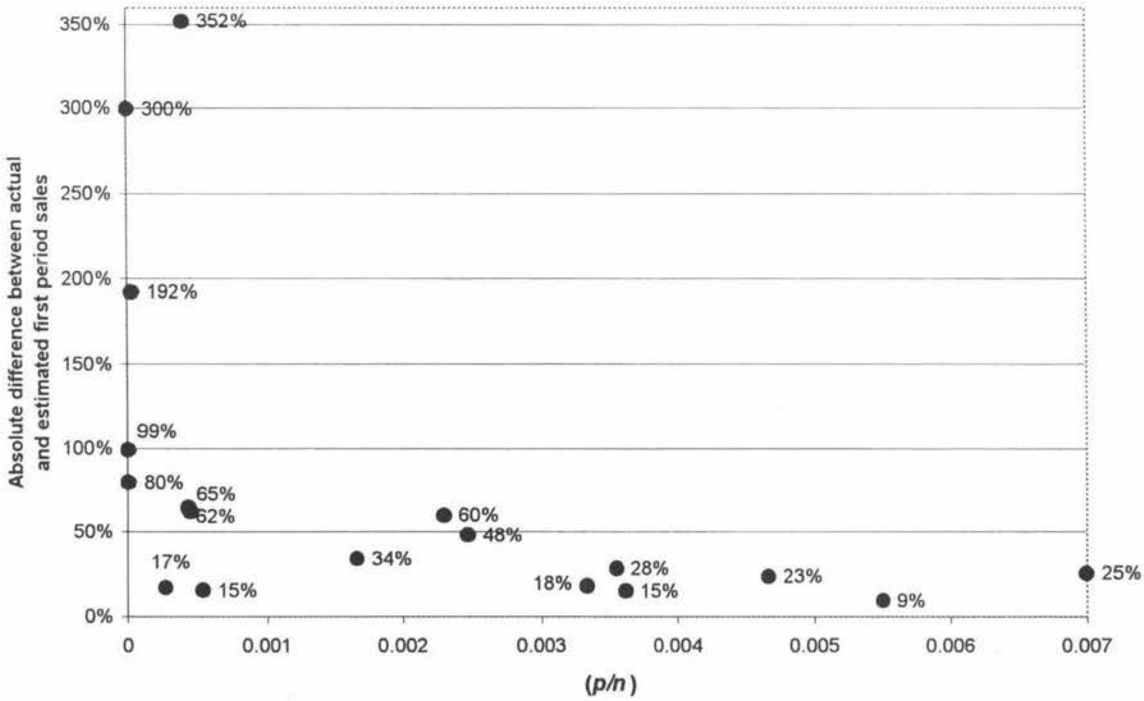
A further analysis was undertaken to resolve some issues related to the difference between *pm* and actual first period sales. It is hypothesised that the size of the percentage error is largely related to two factors, the size of *pm* relative to *m* (i.e. $pm/m = p$), and the number of time periods (n). This is based on two expectations. The first is related to the NLS estimation procedure and its objective of minimising the sums of squares of errors. This procedure gives more weight to reducing the error in data points with higher sales levels. Therefore, a first period sales level that is higher as a proportion of overall sales will be better predicted than one which is smaller. For example, 10% error on a sales level of 100 makes a contribution to sums of squares of 10^2 while 10% error on a sales level of 10 is 1^2. It is obvious that the NLS procedure would more effectively reduce overall sums of squares for error by more accurately predicting the value of the data point with larger sales.

Second, as n (the number of data points) tends to infinite the fit of the model will decline. In other words, the Bass model will fit four data points better than ten. As the number of data points increases, the estimate of the diffusion parameter q becomes relatively more important than p. This is because q determines the shape of the diffusion curve and as the number of data points increases, it is the shape of the diffusion curve that most reduces the error in the model. The precision of the estimate of p (and the estimate of first period sales, pm) therefore declines.

Figure 5.1 shows absolute percentage difference between pm and actual first period sales plotted against p/n. The later value will increase as p increases and n decreases and vice versa and therefore captures the two expectations in a simple yet sufficient manner. Clearly, the hypotheses are corroborated because values with smaller p/n have higher percentage errors and as p/n grows, the percentage error decreases. Microwave ovens (60%) in Japan appears to be the only product whose value does not fit the general pattern.

This analysis has served to illustrate that making simple judgements about the difference between pm and actual first period sales (i.e. parameter plausibility) should not be made without taking into account the size of pm relative to m (i.e. $pm/m = p$), and the number of time periods (n). This is nevertheless a preliminary study of these hypotheses and to ensure that the results are not a consequence of variation in p alone, further research is required.

Figure 5.1 Relationship between *pm*, actual first period sales, and *p/n*



5.1.2 Model Fit

There are a number of methods available for determining the fit of a model to a given set of data. In the case of the Bass model, many measures have been used by a variety of authors to demonstrate its superior or inferior fit. These include mean square error (MSE) (Tigert and Farivar, 1981), mean absolute deviation (MAD) (Simon and Sebastian, 1987; Ganesh, Kumar, and Subramanium, 1997), mean absolute percentage error (MAPE) (Ganesh and Kumar, 1996), R-Squared and Adjusted R-Squared (Bass, 1969; Mahajan and Peters, 1978; Gatignon, Eliashberg and Robertson, 1989; Ganesh, Kumar, and Subramanium, 1997), predicted versus actual timing of peak sales, and the difference between estimated and predicted peak sales (Heeler and Hustad , 1980). The emergence of these benchmarks has occurred because all have their respective disadvantages when used to ascertain the adequacy of fit.

In this thesis, all of the above measures were calculated during the process of fitting the models. However, only the later four are discussed below. The other measures are not used to determine model fit for a number of reasons detailed in the methodology.

Ultimately, the best measures of fit are Adjusted R-Squared, variance between predicted peak time period and actual, and difference between predicted magnitude of peak sales and actual peak sales. Nevertheless, arguably the best method for gauging fit in this context is a plot of actual versus predicted sales. A plot for each product is presented in the following sections in addition to the fit statistics mentioned. For completeness, the values of MSE, MAD, and MAPE are reported in the appendix 9.2.

5.1.2.1 Fit of Japanese Models

In general, the Bass model captures the diffusion pattern of Japanese products more than adequately. For six of the products, Adjusted R-Squared ranges from 80% to 93%. In the case of air conditioners and personal computers, a reasonable fit is achieved of 68% and 77% respectively. However, for video disk players the model produced a poor fit to the data with an Adjusted R-Squared of only 40%. This was due to fluctuating sales throughout the diffusion process which made it difficult for the Bass model to produce a good fit (i.e. these large period to period fluctuations are not captured by the Bass model though a post hoc variable representing these changes could be included in the model's specification).

Table 5.3 Fit of Japanese Models

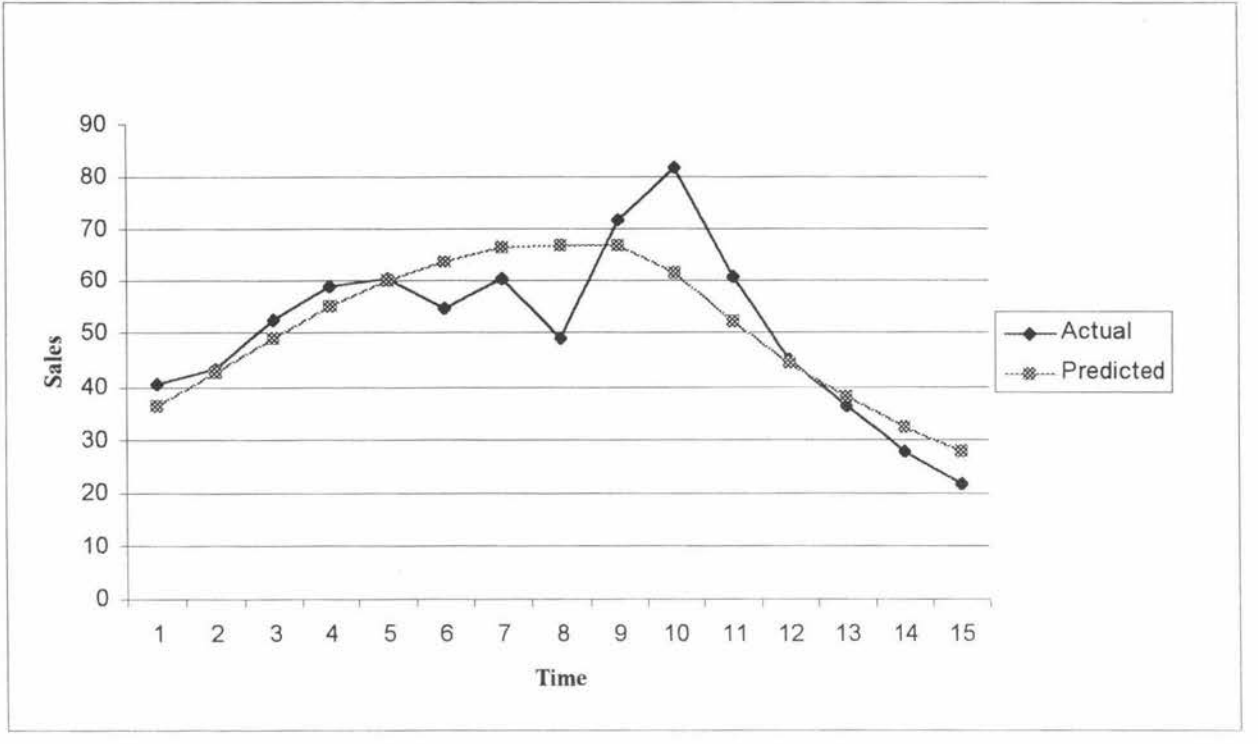
Product	Adjusted R^2	Peak Timing		Peak Magnitude		
		Estimated	Actual	Estimated	Actual	differences
Japan						
Air Conditioner	68.3%	9	10	67	82	-18.3%
Personal Computer	76.6%	13	13	615	687	-10.4%
Facsimile	82.8%	15	15	293	345	-15.0%
VCR	84.9%	6	6	637	675	-5.6%
Microwave Oven	80.4%	17	13	270	305	-11.4%
Video Disk Player	40.4%	7	10	74	100	-25.7%
Video Camera	88.4%	6	6	1013	1174	-13.7%
Digital Audio Disk Player	86.0%	11	12	1454	1622	-10.3%
Vacuum Cleaner	93.3%	34	33	765	850	-10.0%

* Estimated and actual peak magnitude are measured in tens of thousands (i.e. 0,000's)

Except for two products, personal computers and facsimiles which have not reached peak sales, the model produced fairly precise estimates of the timing of peak sales. An average timing error of 1.43 periods was achieved for the Japanese models. Microwave ovens and video disk players had the greatest disparity between estimated and actual timing of peak sales with errors of 4 and 3 time periods respectively. The timing error for the remaining five products was minimal with only 1 period difference in three cases and two accurate predictions.

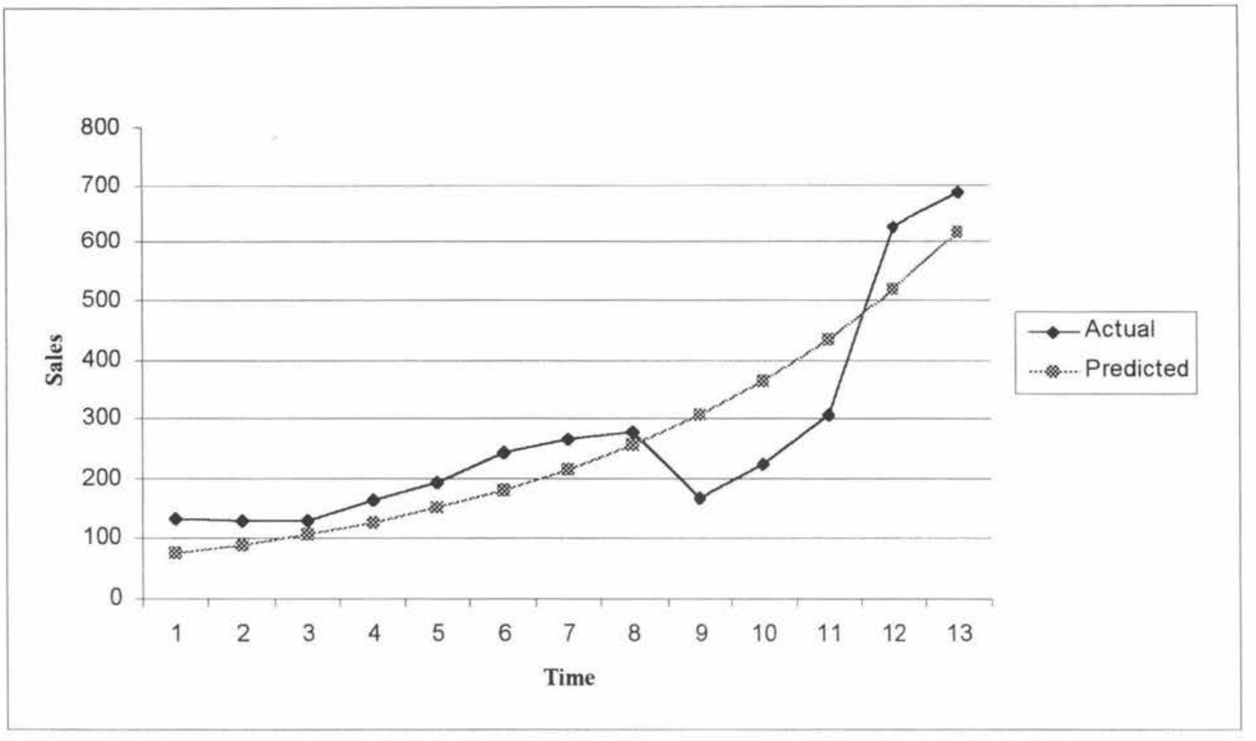
In terms of predicting the magnitude of peak sales, the model produced acceptable estimates in eight of the nine cases with percentage errors ranging from -6% to –18%. Video disk players had the worst result with the model under-predicting peak sales by 26% as a result of large fluctuations in period-to-period sales (see figure 5.7). Despite this, from a managerial viewpoint, under-prediction is preferable to over-prediction in terms of resource allocation and profitability, a result delivered by the Bass model. An examination of each product's diffusion curve in graphical form and in terms of other fit measures is now undertaken.

Figure 5.2 Air Conditioner Diffusion Curve- Japan



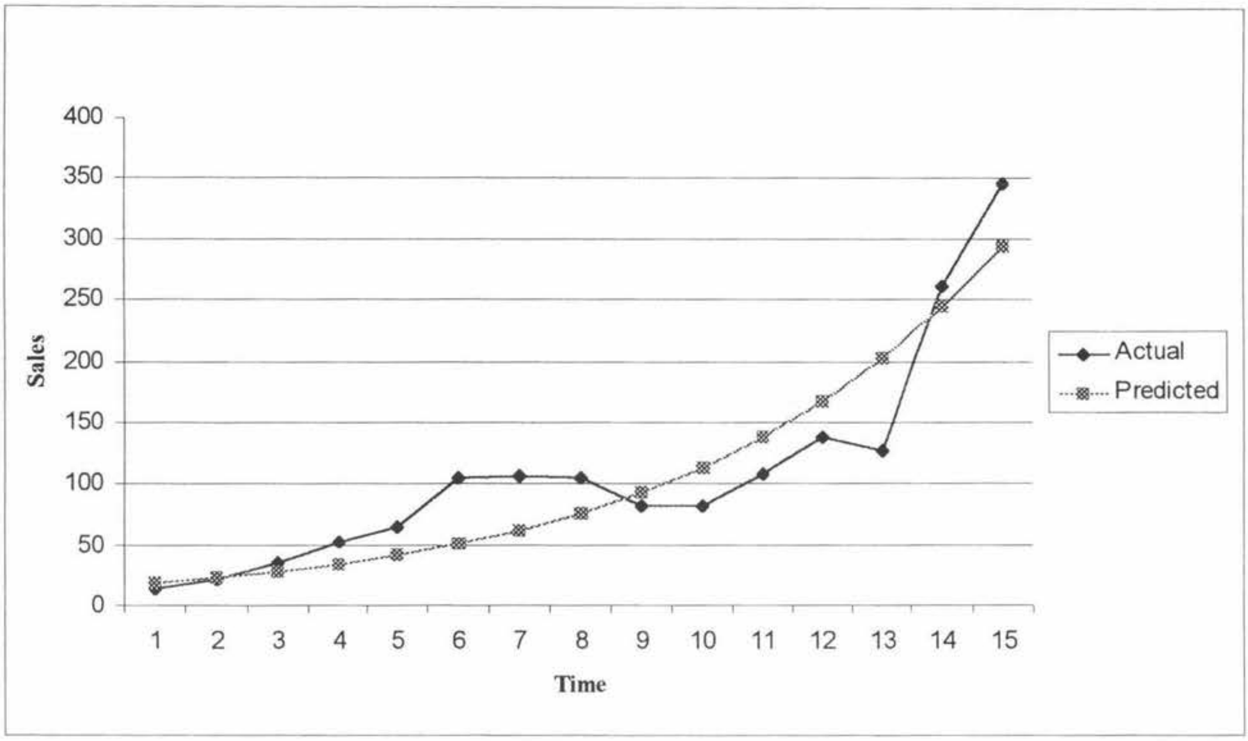
- **Air Conditioner, 1970-1984** (Figure 5.2): The diffusion curve exhibits some variability before peak sales due to some possibly non-diffusion related factors not captured by the basic Bass model. This impacts on the estimation of peak sales which is underestimated by 18%. Timing of peak sales is one period later than predicted. Overall, the Adjusted R-Squared of 68% indicates the model is more than adequate at capturing most of the variation in the diffusion process which is a fair reflection of the graphical depiction.

Figure 5.3 Personal Computer Diffusion Curve- Japan



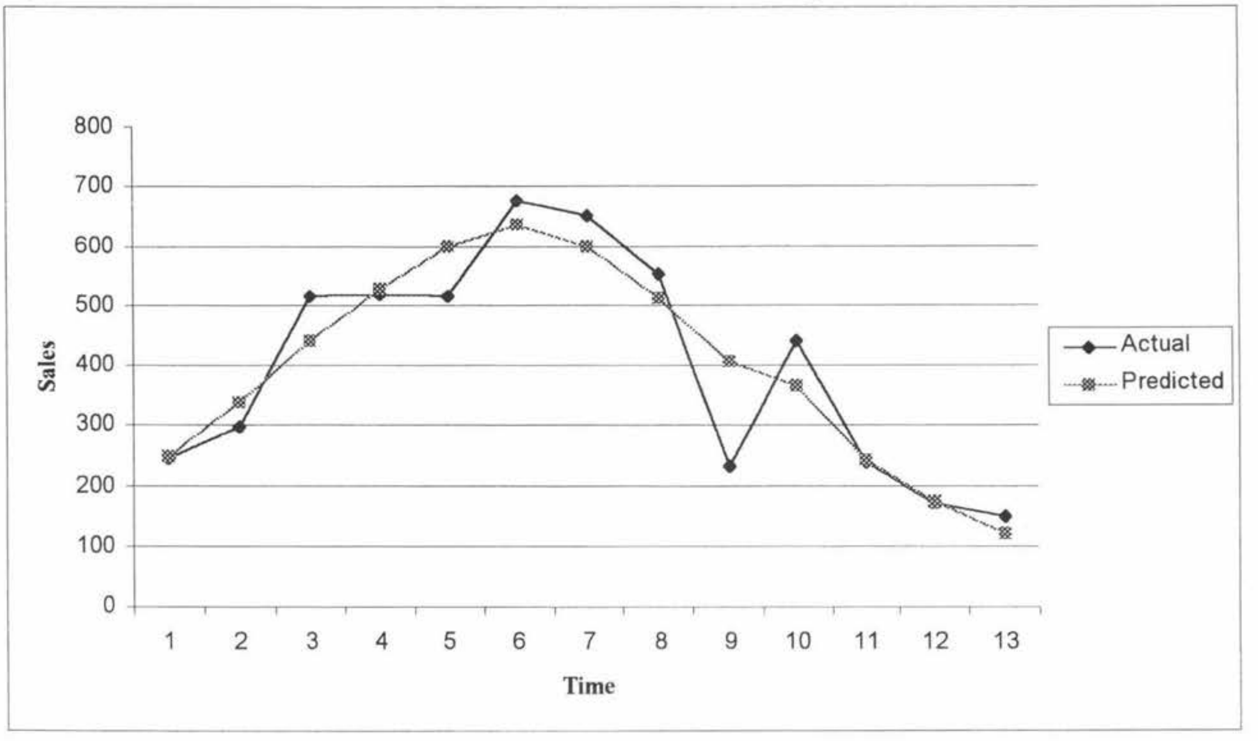
- **Personal Computer, 1984-1996** (figure 5.3): Again, there is some variability prior to peak sales which impacts on the fit of the model. There is some evidence of a second generation product beginning in 1992. Despite the Bass model capturing the diffusion process well (Adjusted R-Squared of 77%), the model under-predicts final period sales by 10%. Not surprisingly, sales of this product are yet to peak. Replacement sales are no doubt a factor here and may be a reason for the growth in sales after period nine (see methodology for a discussion of the implications of repeat sales on results).

Figure 5.4 Facsimile Diffusion Curve- Japan



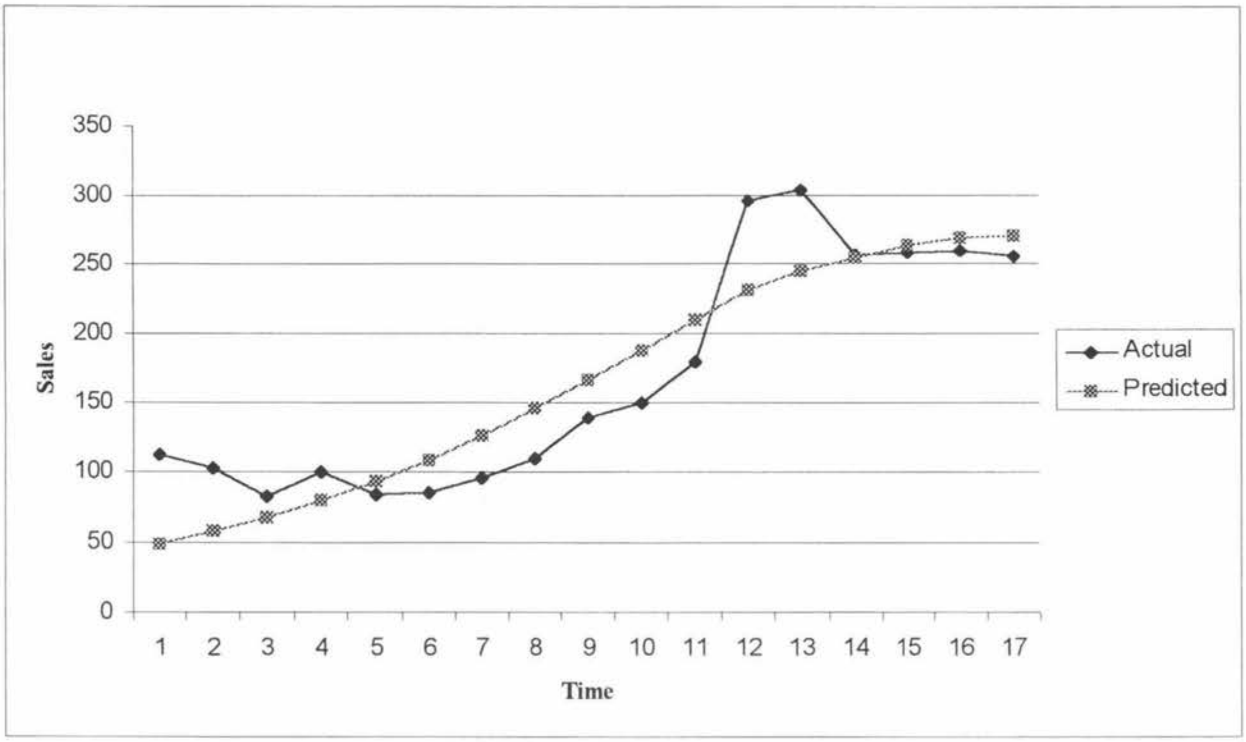
- **Facsimile, 1982-1996** (figure 5.4): Sales have been increasing rapidly in the last two years and the model tends to approximate this pick up reasonably well. Nevertheless, final period sales are under-predicted by 15%. Thus far, the model is depicting the diffusion process very well (Adjusted R-Square of 83%).

Figure 5.5 Video Cassette Recorder Diffusion Curve- Japan



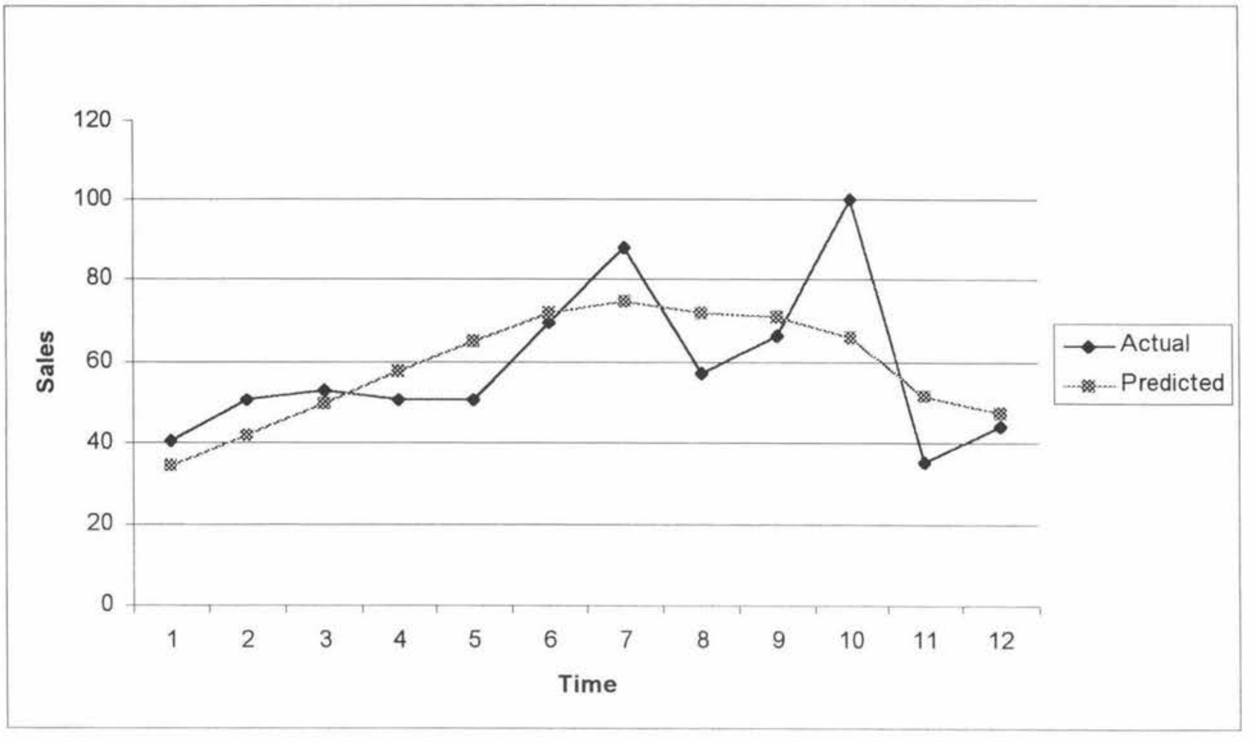
- **Video Cassette Recorder, 1982-1994** (figure 5.5): A classical diffusion curve with some variability especially after peak sales. Timing of peak sales is accurate and the magnitude of peak sales is relatively precise (under-predicted by 6%). With an Adjusted R-Square of 85%, the Bass model fits very well.

Figure 5.6 Microwave Oven Diffusion Curve- Japan



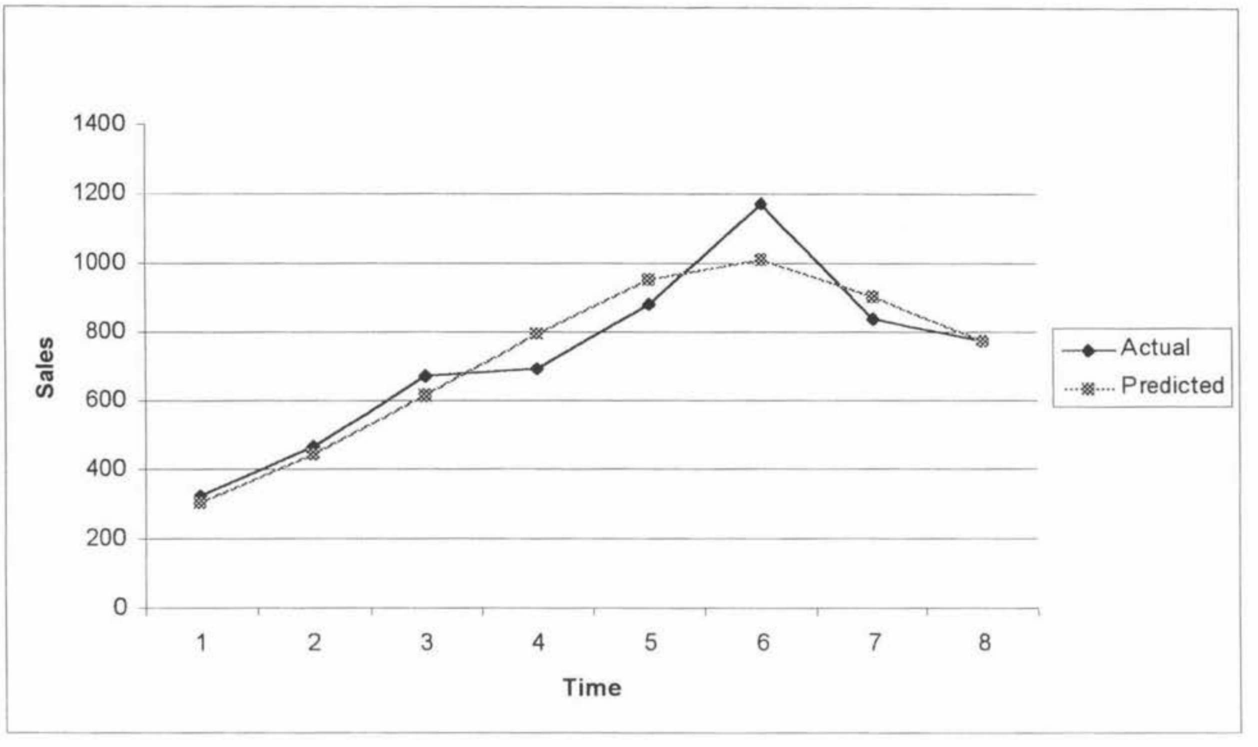
- **Microwave Oven, 1976-1992** (figure 5.6): There are two periods of variability in the sales data. Initial sales are high then decline slightly for a time before rising again. The model does not accurately depict sales in this initial period. Also, sales in 1986/87 are substantially higher than predicted by the model which may be indicative of a non-diffusion based influence. Peak sales are underestimated by 11% and timing is also inaccurate. The model fits reasonably well (Adjusted R-Squared of 80%). There is some evidence of repeat purchase after period fourteen with the sales level appearing to plateau. However, given this plateau's proximity to peak sales, it was decided to include these sales periods.

Figure 5.7 Video Disk Player Diffusion Curve- Japan



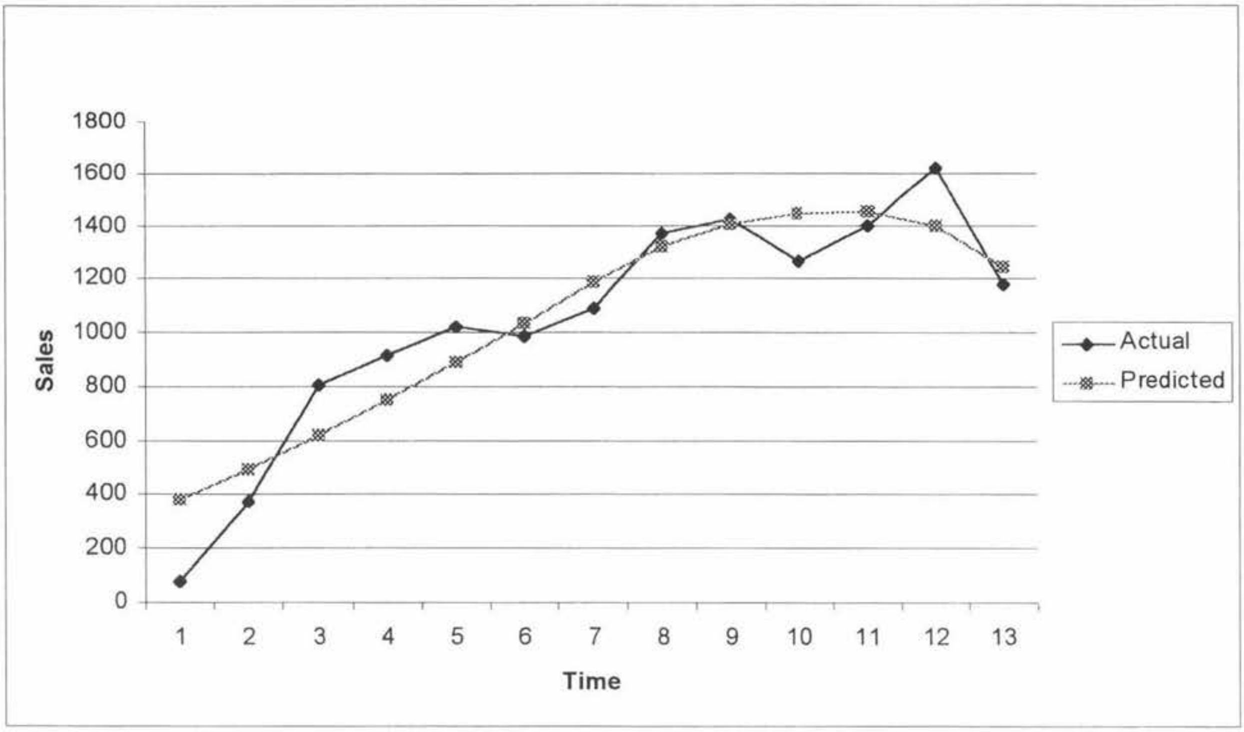
- **Video Disk Player, 1984-1995** (figure 5.7): By far the worst fitting model with an Adjusted R-Squared of 40%, the diffusion pattern is not clear due to large period-to-period fluctuations (especially between 1988 and 1994). Timing and magnitude of peak sales are inaccurate (3 years early and 26% underestimated). Despite this, the model provides a reasonable approximation of the diffusion process.

Figure 5.8 Video Camera Diffusion Curve- Japan



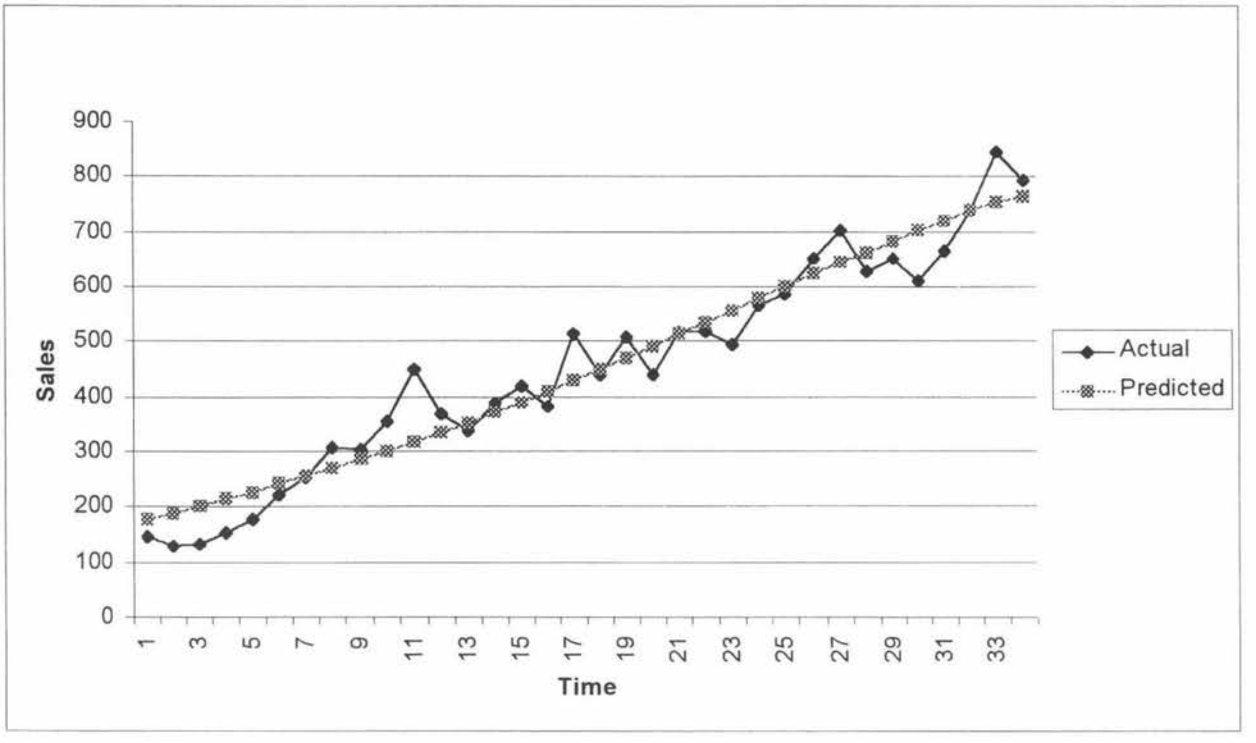
- **Video Camera, 1986-1993** (figure 5.8): Video camera sales are generally well behaved though peak sales are underestimated by 14%. Consequently, the model fits well in terms of Adjusted R-Square (88%).

Figure 5.9 Digital Audio Disk Player- Japan



- **Digital Audio Disk Player, 1984-1996** (figure 5.9): Initial sales are lower than expected but sales are generally well behaved and a good fit results (86%). Timing of peak sales are predicted one year early and magnitude is underestimated by 10%.

Figure 5.10 Vacuum Cleaner Diffusion Curve- Japan



- **Vacuum Cleaner, 1963-1996** (figure 5.10): Sales of vacuum cleaners have not peaked but this is more than likely due to repeat sales and multiple product variants over time. Variability about the estimated diffusion curve is minimal and consequently, an extremely good fit is achieved (93%).

5.1.2.2 Fit of Taiwanese Models

In terms of overall fit, the Bass model achieved good results for eight of the nine products, with Adjusted R-Squared values higher than 80% in all cases and an average value of 87% (see table 5.4). Excellent fits were found for facsimiles and induction cookers (94% for both products) while microwave ovens had an Adjusted R-Squared score of 90%. TV games had the worst fit between actual and predicted sales with 49% of the variance explained by the model.

Table 5.4 Fit of Taiwanese Models

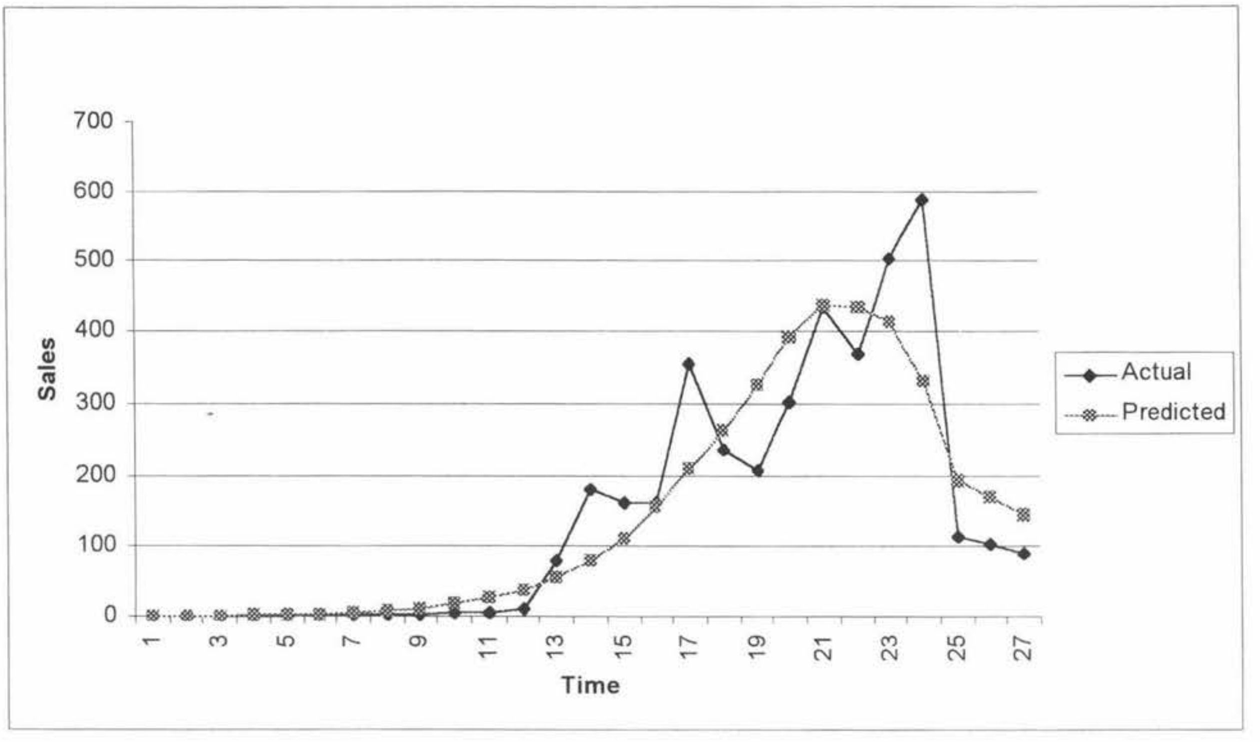
Product	Adjusted R^2	Peak Timing		Peak Magnitude		
		Estimated	Actual	Estimated	Actual	differences
Taiwan						
Air Conditioner	80.3%	21	24	438	589	-25.7%
Personal Computer	87.2%	24	24	621	930	-33.2%
Facsimile	94.3%	6	6	87	82	6.2%
VCR	79.8%	14	14	56	344	-83.7%
Microwave Oven	89.7%	5	4	56	55	1.8%
Induction Cooker	94.1%	8	6	38	39	-2.8%
TV Game	48.5%	11	13	116	191	-39%
Floppy Disk	86.0%	7	5	14	15	-4.3%
Clothes Dryer	85.4%	19	23	13.9	14.4	-3.6%

The model also produced acceptable estimates for the timing of peak sales with an average timing error of 1.56 periods. Accurate timing estimates were reported for personal computer, facsimile, and video cassette recorder. For microwave oven, induction cooker, TV game and floppy disk, the timing error was between 1 and 2 periods. The estimates of peak timing were poor in the cases of air conditioner and clothes dryer where the timing error was 3 and 4 periods respectively.

In nearly half the cases, the level of peak sales was seriously underestimated with mean percentage errors ranging from –26% to –39%. In most cases, this under-prediction was a consequence of the model not capturing drastic sales increases in the peak time period. However, for the other five cases, the models peak estimates were very accurate with percentage errors ranging from –4.3% to 6.2%.

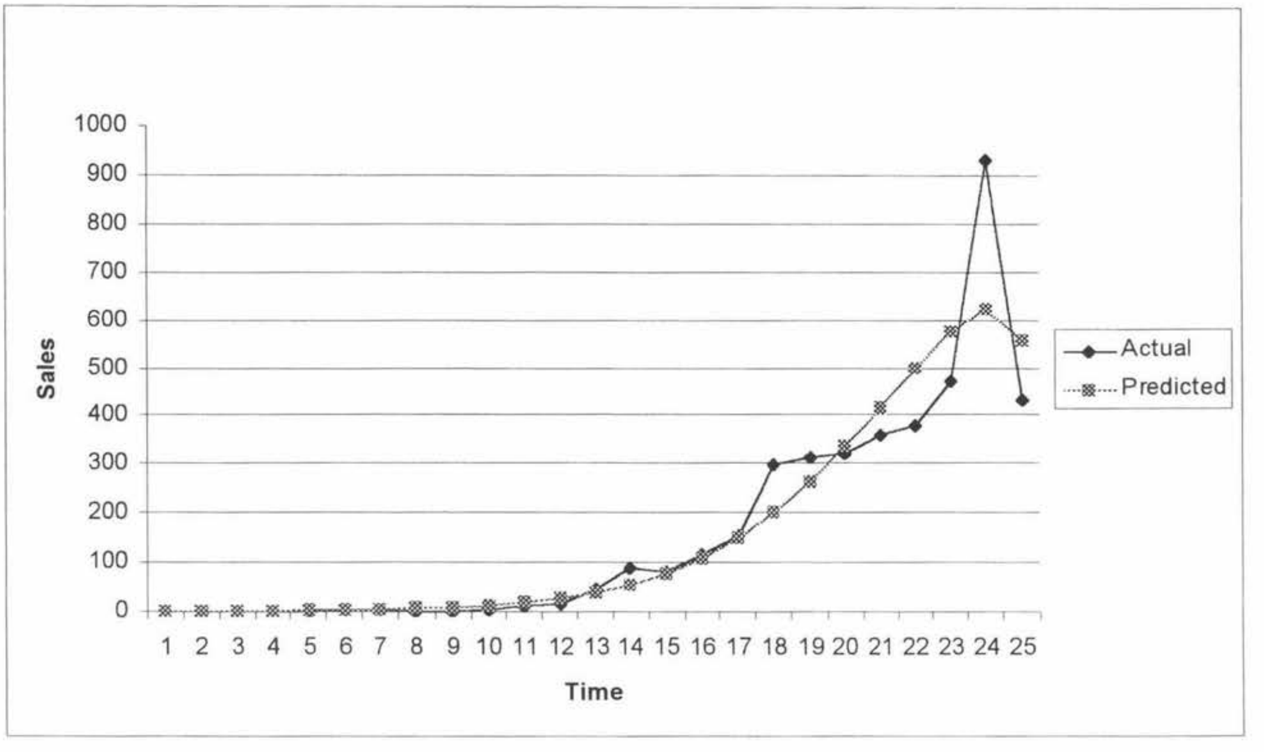
An examination of each product's diffusion curve in graphical form and in terms of fit other measures is now undertaken.

Figure 5.11 Air Conditioner Diffusion Curve- Taiwan



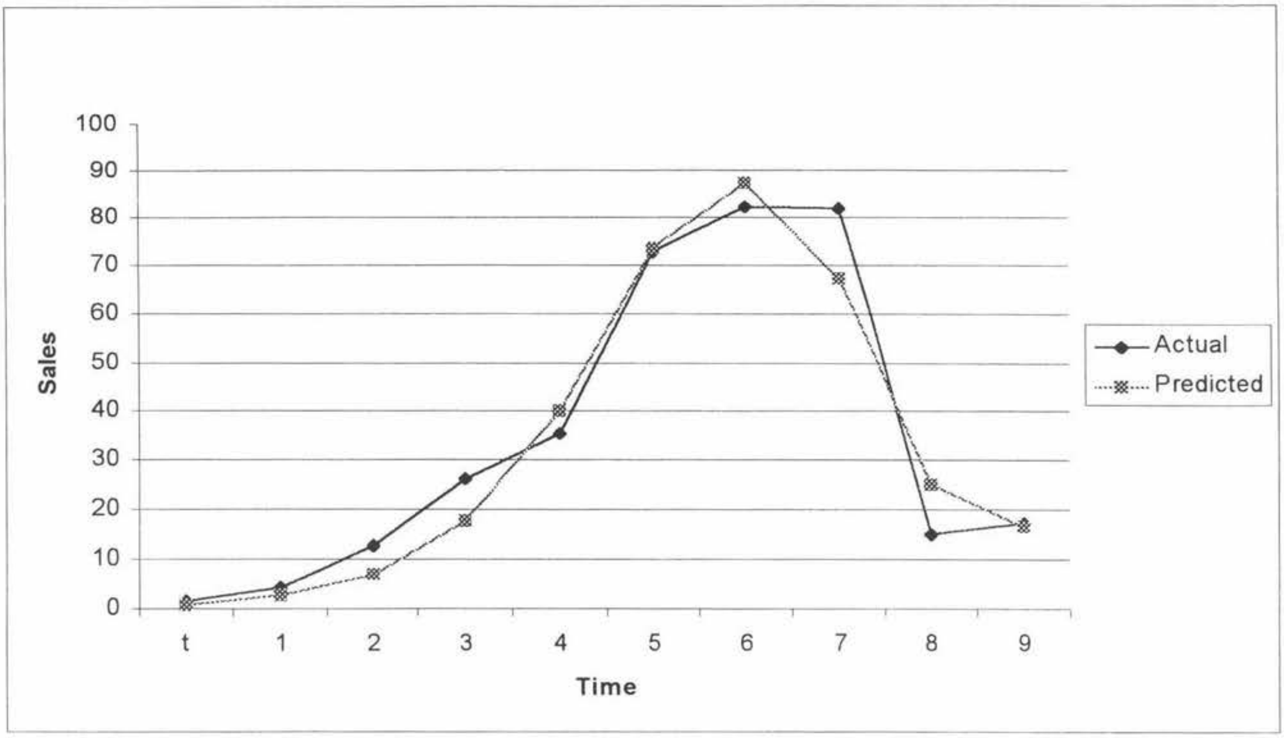
- **Air Conditioner, 1965-1991** (figure 5.11): Air conditioner sales do not 'take-off' for almost a decade but once they do there is a large amount of variability in period-to-period sales. The most dramatic change occurs after the peak when sales plummet. However, the Bass model captures this overall variability relatively well as indicated by the Adjusted R-Squared of 80%. Peak sales are predicted to occur three years earlier than they do and the magnitude of peak sales is underestimated by 26%.

Figure 5.12 Personal Computer Diffusion Curve- Taiwan



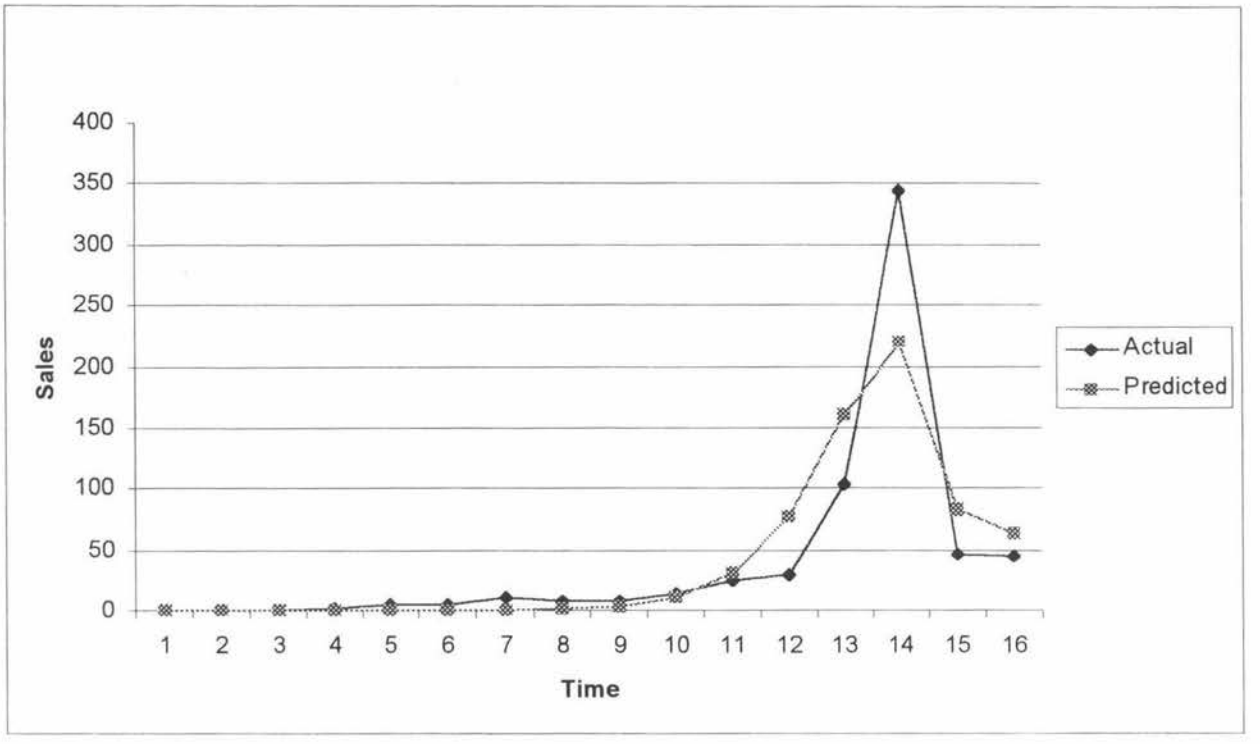
- **Personal Computer, 1972-1996** (figure 5.12): Sales of personal computers are relatively orderly though the peak sales period is unusually higher than predicted by the Bass model. Peak sales are consequently under-predicted by 33%. With the exception of this one data point, the fit of 87% is more than adequate and the timing of peak sales is accurately predicted. Repeat purchase is likely to be a factor here (see methodology).

Figure 5.13 Facsimile Diffusion Curve- Taiwan



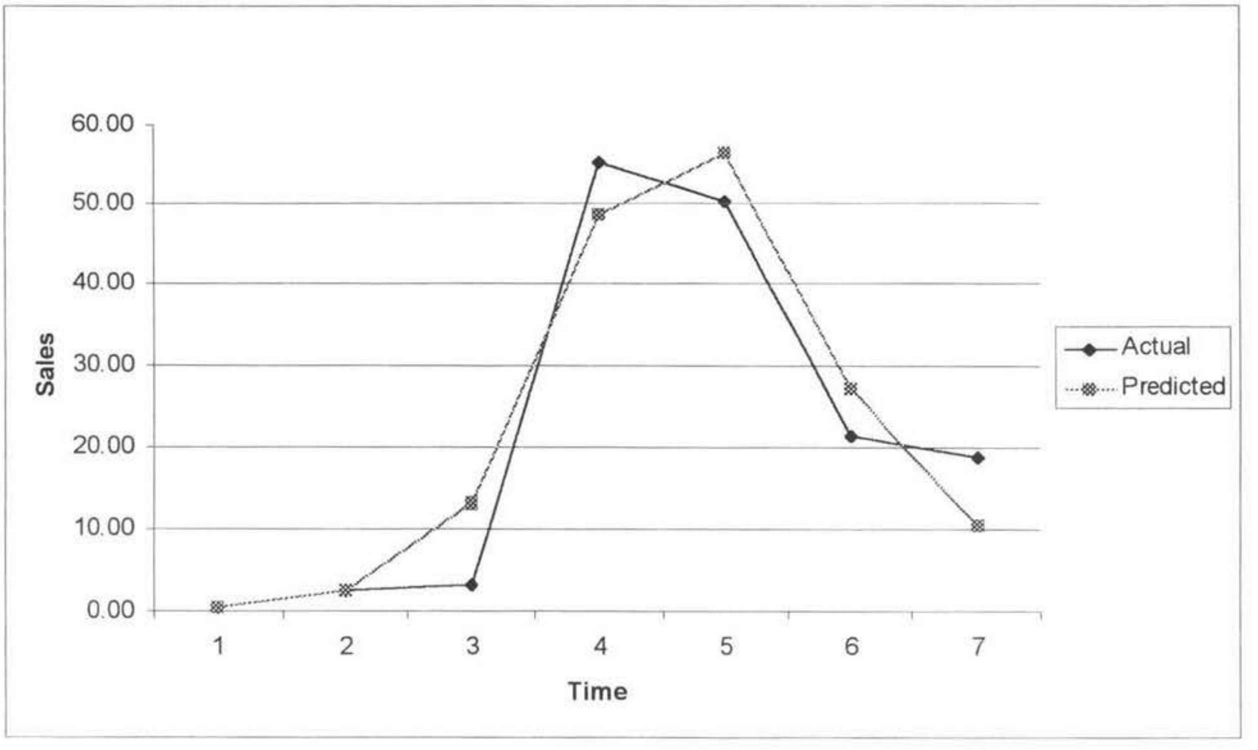
- **Facsimile, 1983-1992** (figure 5.13): A classical diffusion curve with little variation leads to a model with an Adjusted R-Squared of 94%. Peak sales are over-predicted by only 6% though the peak timing is correct.

Figure 5.14 Video Cassette Recorder



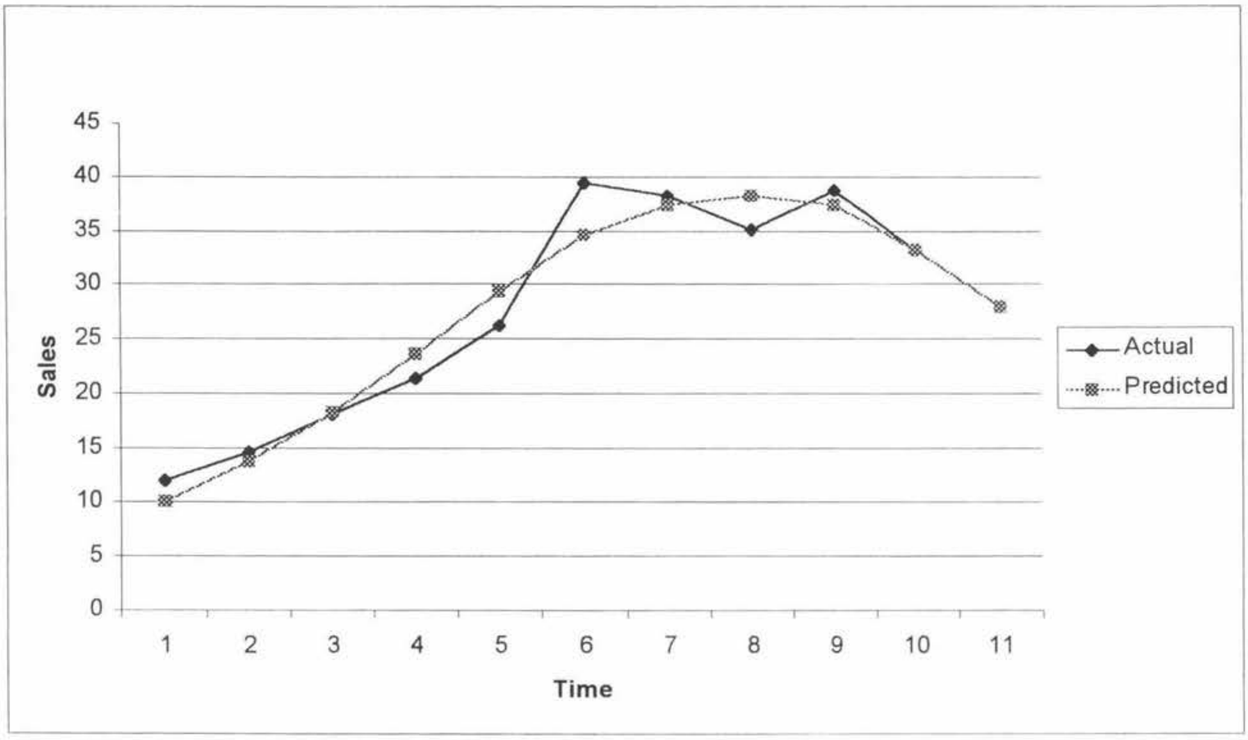
- **Video Cassette Recorder, 1975-1990** (figure 5.14): VCR sales are relatively steady except for two years where sales increase dramatically. This sudden increase and subsequent decline is not very well captured by the model though the fit is reasonable (80%). Despite the timing being correctly predicted, the magnitude of this peak is underestimated by a sizeable 36%.

Figure 5.15 Microwave Oven Diffusion Curve- Taiwan



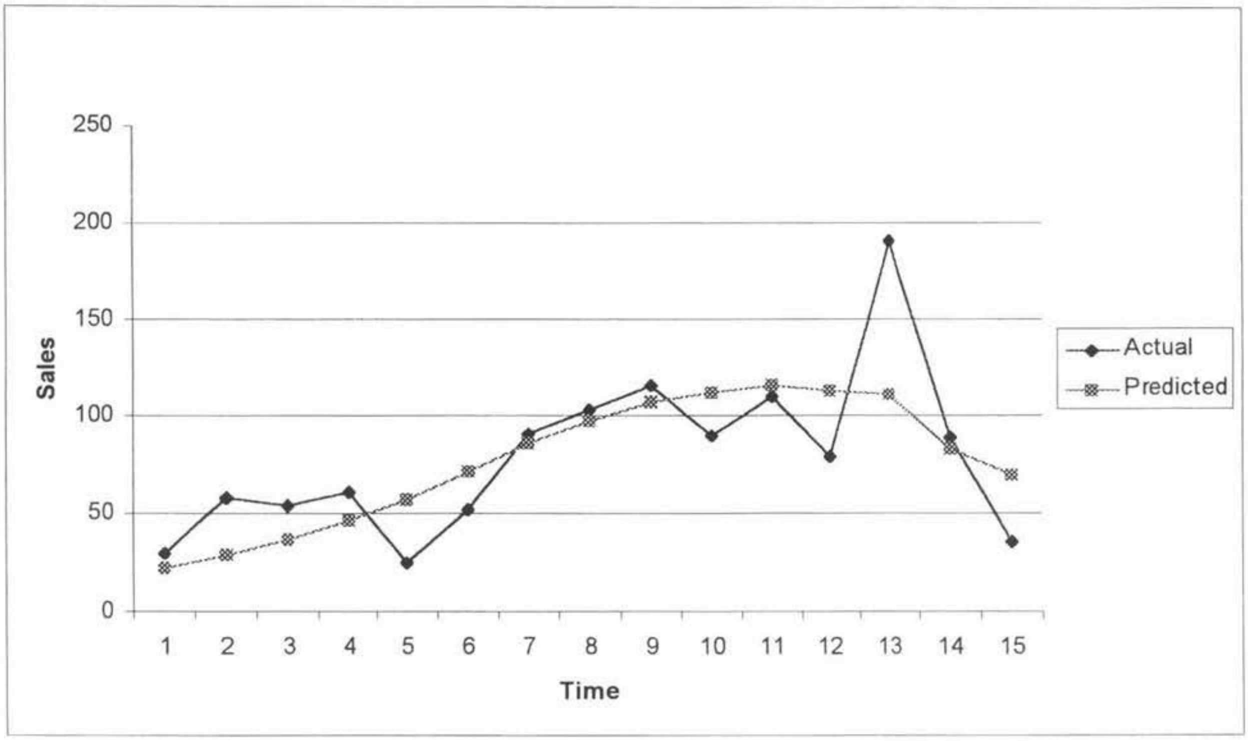
- **Microwave Ovens, 1986-1992** (figure 5.15): A classical diffusion curve with relatively little period-to-period variation leads to a very good fit (90%). Although peak sales are predicted one year late, the magnitude of the sales peak is only overestimated by 2%.

Figure 5.16 Induction Cooker Diffusion Curve- Taiwan



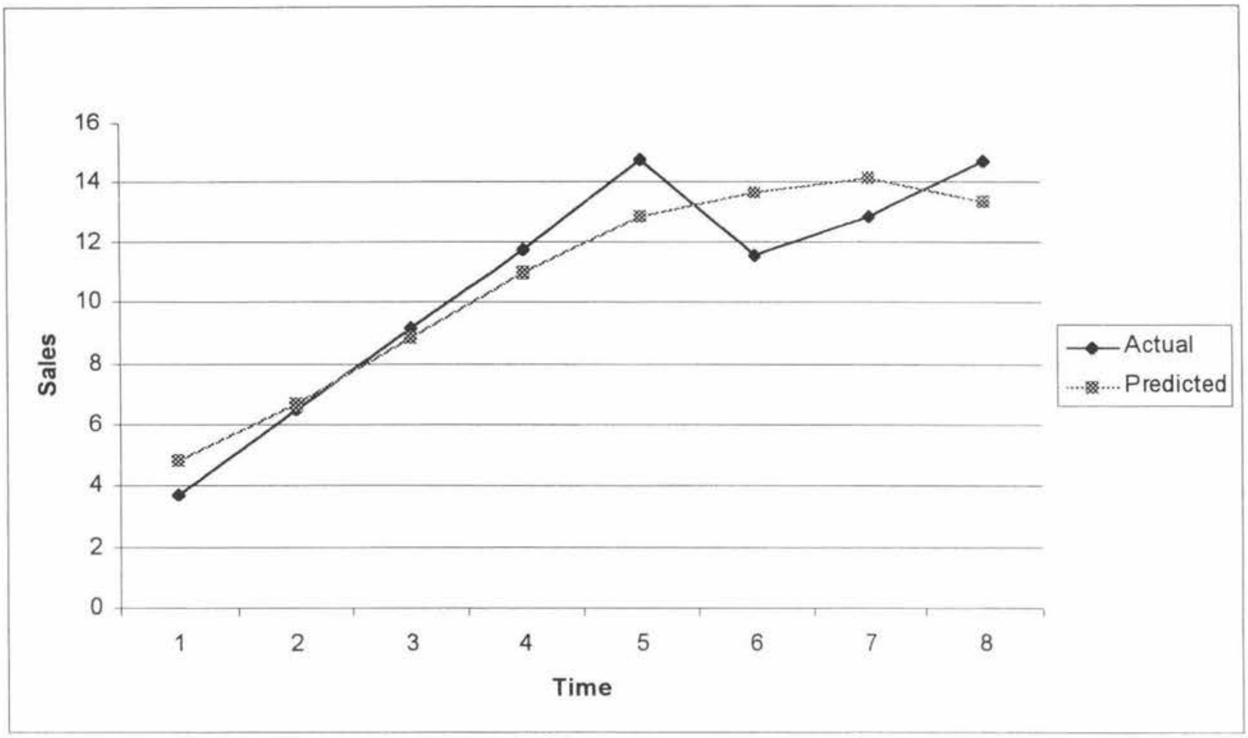
- **Induction Cooker, 1986-1996** (figure 5.16): Another classical diffusion curve with some variation about peak sales but an excellent fit (94%). The estimated timing of peak sales is two years late and under-predicted by 3%.

Figure 5.17 TV Game Diffusion Curve- Taiwan



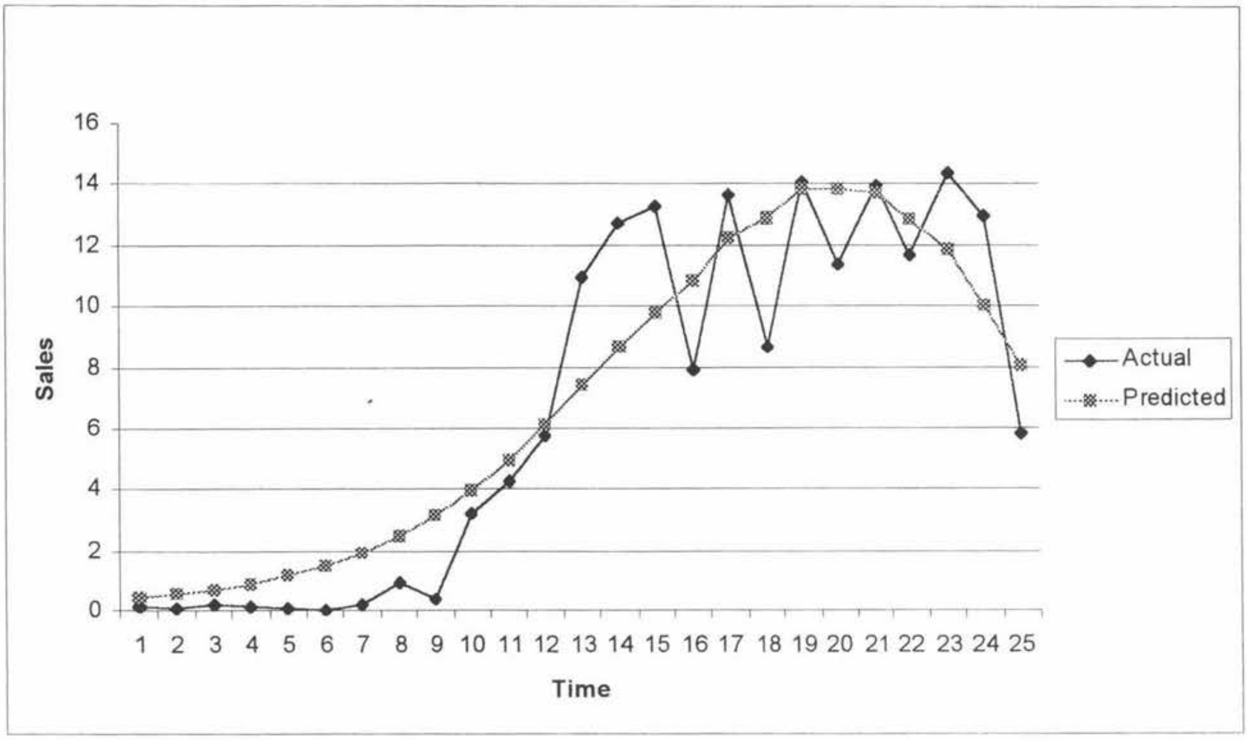
- **TV Game, 1982-1996** (figure 5.17): Sales of TV Games are characterised by large fluctuations possibly as a consequence of second- and third-generation products and increasing competition. Despite the poor Adjusted R-Squared value of 49%, the Bass model produces a reasonable approximation to the actual sales pattern. Peak sales are estimated two years early by the model and greatly underestimated by 39%.

Figure 5.18 Floppy Disk Diffusion Curve- Taiwan



- **Floppy Disk, 1989-1996** (figure 5.18): A gradual linear increase in sales followed by downward and upward movement in sales results in a fit of only 86%. The timing of peak sales occurs two years after the predicted peak and the magnitude is underestimated by 4%. Overall, the Bass model provides a very good estimate of the actual sales curve for this product.

Figure 5.19 Clothes Dryer Diffusion Curve- Taiwan



- **Clothes Dryer, 1972-1996** (figure 5.19): Except for the large period-to-period variation in sales for the nine years leading to the peak, the pattern of sales is consistent with the classical diffusion model. The reason for the variation is not clear but the model still manages to fit actual sales well with an Adjusted R-Squared of 85%. Peak sales are predicted to occur four years early but the magnitude of the sales peak is only underestimated by 4%.

5.1.3 Summary of the Descriptive Ability of the Japanese and Taiwanese Models

As a whole, the Bass model more than adequately depicts the pattern of sales of consumer durables in Japan and Taiwan. In the majority of cases the model provides a fit of at least 80% with all parameters being plausible and defendable. The exceptions in terms of fit are TV Games in Taiwan, and Air Conditioners, Personal Computers, and Video Disk Players in Japan. Nevertheless, the poor fit in these cases is due to large period-to-period variations in sales which can not be captured by the Bass model without the addition of other variables in the models specification. The reasons for these fluctuations is not clear in these cases but could be due to economic, marketing, or other social factors which are not modelled in the basic Bass diffusion model.

Despite the poor fit for some models, it is reassuring to know that the Bass model provides a more than adequate approximation of the diffusion process for these cases. The model also seems to be robust against period-to-period variation: plausible parameters are produced and the estimated sales bisect the points of variation It is interesting to note that the model captures the diffusion process for diffusion curves with and without the classical shape frequently found in the marketing literature.

Also, the diffusion patterns of products where information was collected on both Japan and Taiwan (i.e. air conditioner, personal computer, facsimile, video cassette recorder, and microwave oven) is more than adequate to make robust conclusions about differences between the two countries. In all cases, the fit of the estimated model is more than 68% and for most products, the estimated and actual timing and magnitude of peak sales is relatively precise (the exceptions being air conditioner and personal computer in Taiwan where dramatic changes immediately before and after peak sales are seen).

5.2 PREDICTIVE VALIDITY

- ability of the model to accurately predict the diffusion parameters *p*, *q*, and m before and after peak sales
- small sample behaviour of the estimates of *p*, *q*, and *m*

- ability of the model to accurately predict next period sales
- forecast ability around the peak sales period
- small sample behaviour of the estimates of next period sales

- ability of the model to accurately predict the peak timing and magnitude before and after the peak sales period
- small sample behaviour of the estimates of peak timing and magnitude

In the previous section (5.1), the Bass model was found to more than adequately describe the pattern of sales of consumer durables in Japan and Taiwan (except for the cases where large period-to-period fluctuations occurred as a consequence of non-diffusion based factors). This section goes further by examining the practical usefulness of the Bass model in terms of its ability to accurately estimate the parameters *p*, *q*, and *m*, and forecasts of next period sales. Of course, the true parameters can never be known so the assumption is made that the best estimate of the true parameters is the estimates obtained from the full data set. It should be noted that only models at the annual level of aggregation are considered here.

Also, as discussed earlier, one of the advantages of the Bass model is its ability to forecast a sales decline in the future even when current sales are increasing. Of course, this is only an advantage if the model can do this with a degree of precision. Heeler and Hustad (1980) conducted one the most comprehensive studies on the ability of the Bass model to accurately predict the timing and level of peak sales. They found the model generally did not accurately predict the timing and magnitude of peak sales until after the peak had been reached. Therefore, this hypothesis is tested here.

Although a number of studies have examined the predictive validity of the Bass model, few if any have conducted a systematic examination of the performance of the model from $n = 3$ to n = total data points. This would not only enable an analysis of the predictive validity of the model but also the small sample properties of the NLS estimator. In statistics, asymptotic theory relates to the long term behaviour of an estimator as $n \to \infty$. In most practical applications of the Bass model, it is unlikely that n would approach thirty, aside from ∞, except in instances where data at lower levels of time aggregation are used. In this study, only Japan Vacuum Cleaner exceeds this value. Therefore, the small sample behaviour of the NLS estimator would seem an important area of investigation.

The main expectation with regard to the estimates produced by the model as n increases is that they will tend towards some limit. However, given the importance of the peak in determining the shape of the diffusion curve, this behaviour might not occur until after peak sales. If the model estimates do not display some degree of convergence as n increases, then the predictive validity of the model and the adequacy of the NLS estimator for small samples may be brought into question.

The section is structured into the three separate areas where predictive performance and small sample behaviour is important:

- model parameters;
- next period sales, and;
- peak timing and magnitude.

It should be noted that Japan Personal Computer and Japan Facsimile are not examined in this section as they have not yet peaked. As will be seen in the subsequent analysis, behaviour of the estimates before the peak is different to after the peak and therefore the two products mentioned add little to this discussion. The charts related to these products are however contained in the appendices.

5.2.1 Predictive Validity – Model Parameters *p*, *q*, and *m*

Published marketing studies are making increasing use of the parameters produced by the Bass model (and its various extensions) to make statements about the diffusion processes in different countries. It is therefore surprising that seemingly no research has investigated the predictive accuracy of the Bass model in relation to these parameters and their stability and general behaviour as the number of data points increases. The main expectation is that as n increases (and especially after peak sales), the estimates of the parameters should converge towards some "true value".

Parameter accuracy in this context is determined by examining if the estimate from the model fitted to incomplete data is within the 95% confidence interval of the estimate from the full data set. The simulated standard errors are used in the calculation of the confidence interval ("Full Data Set Estimate" ± 1.96 * Standard Error). Appendix 9.3 presents graphs of the estimated parameters (p, q, and m) from n = 3 to n = total number of data points for each product with error bars.

Table 5.5 below details the results with regard to predictive accuracy. An examination of the graphs in the appendices reveals that the main factor impacting on the accuracy of the estimates is not the number of data points but the location of peak sales.

For both Japan and Taiwan, the estimates are generally accurate after the peak has occurred. However, a reasonable proportion of estimates of p (38%), q (50%), and m (31%) were accurately determined prior to the peak. The fact that q is the most stable parameter is not surprising given its importance in setting the shape of the Bass diffusion curve and neither is m being the worst as it can only ever be accurately established after peak sales have started to decline or when the decline has been clearly telegraphed before the peak.

Table 5.5 Predictive Accuracy of *p*, *q*, and *m*

Country/Product	*p*	*q*	*m*
Japan			
Air Conditioner	One period after peak sales	Always within 95% confidence interval	One period after peak sales
VCR	Peak sales period	Eight period after peak sales	Two periods after peak sales
Microwave Oven	Three periods after peak sales	One period before peak sales	Three periods after peak sales
Video Disk Player	One period after peak sales	One period after peak sales	One period after peak sales
Video Camera	One period after peak sales	One period after peak sales	One period after peak sales
Digital Audio Disk Player	Three periods prior to peak sales	Three periods before peak sales	One period before peak sales
Vacuum Cleaner	One period before peak sales	Six periods before peak sales	Nine periods before peak sales
Taiwan			
Air Conditioner	One period after peak sales	One period after peak sales	One period after peak sales
Personal Computer	One period after peak sales	Seven periods before peak	Two periods before peak sales
Facsimile	Three periods after peak sales	One period after peak sales	One period after peak sales
VCR	Four periods before peak sales	Four periods before peak	Four periods before peak sales
Microwave Oven	Always within 95% confidence interval	One period after peak sales	One period after peak sales
Induction Cooker	Two periods after peak sales	One period after peak sales	One period after peak sales
TV Game	Two periods before peak sales	Six periods before peak sales	One period after peak sales
Floppy Disk	One period before peak sales	One period after peak sales	Always within 95% confidence interval
Clothes Dryer	15 periods before peak sales	One period before peak sales	One period before peak sales

Table 5.6 Convergent Behaviour of p, q, and m

Country/Product	p	q	m
Japan			
Air Conditioner	Definite evidence of convergence after peak sales	Evidence of convergence after peak sales	Some evidence of convergence after peak sales
VCR	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Evidence of convergence before peak sales
Microwave Oven	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Unclear convergent behaviour
Video Disk Player	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Some evidence of convergence before peak sales
Video Camera	Some evidence of convergence before peak sales	Evidence of convergence before peak sales	Some evidence of convergence before peak sales
Digital Audio Disk Player	Evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales
Vacuum Cleaner	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales
Taiwan			
Air Conditioner	Evidence of convergence close to peak sales	Evidence of convergence before peak sales	Definite evidence of convergence before peak sales
Personal Computer	Unclear convergent behaviour	Evidence of convergence before peak sales	Definite evidence of convergence before peak sales
Facsimile	Evidence of convergence before peak sales	Evidence of convergence before peak sales	Evidence of convergence after peak sales
VCR	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Evidence of convergence before peak sales
Microwave Oven	Evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales
Induction Cooker	Evidence of convergence after peak sales	Definite evidence of convergence before peak sales	Evidence of convergence after peak sales
TV Game	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Evidence of convergence before peak sales
Floppy Disk	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Some evidence of convergence before peak sales
Clothes Dryer	Evidence of convergence before peak sales	Definite evidence of convergence before peak sales	Definite evidence of convergence before peak sales

Table 5.6 details the findings related to the convergent behaviour of the estimates. Ideally, we would hope that the estimates of p, q, and m would converge prior to peak sales rather than after. The results suggest that the majority of estimates show evidence of convergent behaviour prior to peak sales but these estimates are generally not accurate until after the peak sales period.

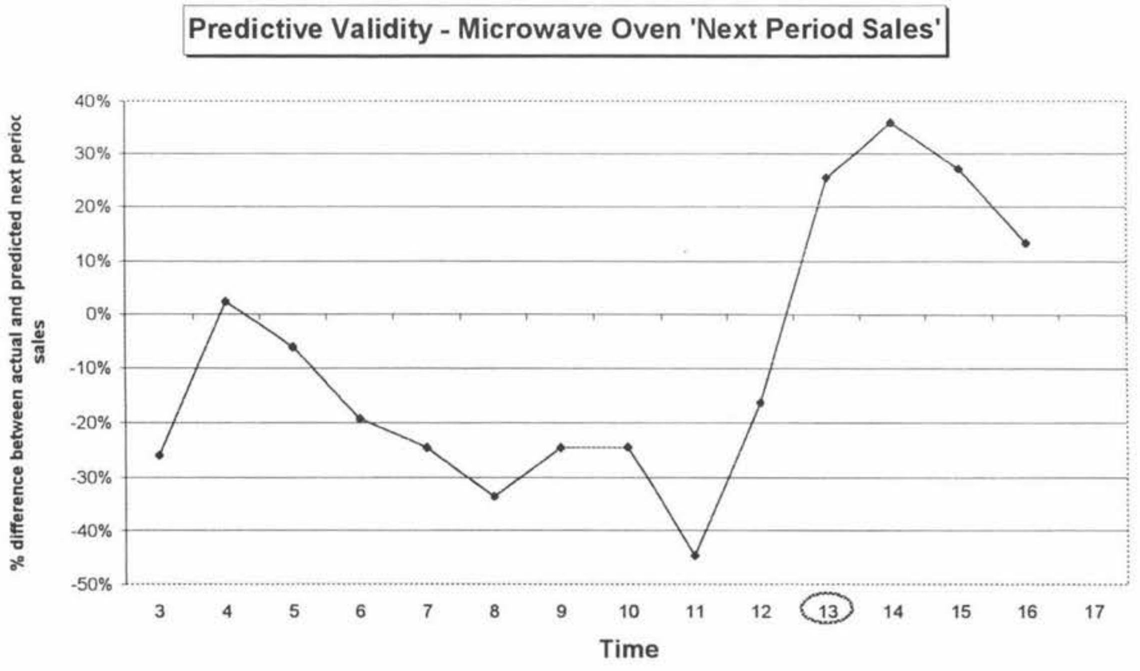
Therefore, parameter estimates do tend to converge to their "true value" as n increases. This convergent behaviour is particularly noticeable after peak sales. More importantly, estimates of the diffusion parameters are generally accurate one period after peak sales. Therefore, for marketing academics making diffusion claims, the most robust estimates of the Bass model parameters are from data that includes the peak sales period.

5.2.2 Predictive Validity – Next Period Sales

In practical applications of the Bass model, being able to predict next periods sales is vitally important. This section examines the performance of the Bass model from $n = 3$ to $n =$ total available data points in predicting next period sales. The graphs for each product are shown in the appendices (section 9.3).

The results are far from impressive. In the majority of cases, the model's predictions of next period sales are inaccurate to a large extent. Of particular importance is the fact that in a number of cases, the peak sales period was the most erroneous. Unfortunately, there is no pattern of convergence over time or any change in error from before and after the peak sales period. This may be a consequence of serial correlation with error from earlier data points impacting on predictions made later in the diffusion process. A typical example is shown in figure 5.20 below for microwave ovens in Japan. Only two of the fifteen predicted points are within ten percent of the actual sales value.

Figure 5.20 Prediction of Next Period Sales – Japan Microwave Oven



A number of factors could improve the predictive accuracy of the model in practice. First, managers would be privy to information not included in the specification of the model that could allow them to adjust next period estimates. For example, forecasts of measures of consumer confidence and economic activity may indicate an upcoming "soft" sales period. Second, the value of m (market potential) was allowed to vary in this instance. However, in practice the market potential may be fixed to some value estimated by management. This may improve the ability of the model to predict next period sales. Finally, new generations of products may be impacting on the sales patterns and could be incorporated in the model. It should be recognised that these are just a few of the possible methods available for adjusting the predictions made by the Bass model.

5.2.3 Predictive Validity – Peak Timing and Magnitude

As mentioned previously, the Bass model can be of great strategic value as it can predict the timing and magnitude of peak sales. Nevertheless, this is only an advantage if the model's predictions are accurate. In this section, the ability of the model in predicting peak sales is examined. In terms of accuracy, we do not have confidence intervals to aid evaluation of the difference between actual and predicted timing and magnitude. Therefore, the decision of when the predictions are accurate is more subjective than in the first section. Again, the graphs accompanying this analysis are in Appendix 9.3.

The expectation is that peak timing and magnitude will not be accurate until the peak sales period is included in the data the model is fitted to. Of course, from a practical point of view, the ideal result would be if peak timing and magnitude could be successfully estimated well in advance of peak sales occurring .

Table 5.7 details the results in regard to the accuracy of peak timing and magnitude predictions. The results show that accurate estimates of peak timing and magnitude do not occur until after peak sales. The exceptions are Taiwanese Clothes Dryers (magnitude), Taiwanese VCRs (timing) and Japanese Vacuum Cleaners (timing). This result is disappointing but to a large extent consistent with the findings of Heeler and Hustad (1980).

In terms of convergent behaviour, the graphs in Appendix 9.3 indicate strong convergence for peak magnitude, in most cases before peak sales. Therefore, as *n* increases, the predictions of peak magnitude tend towards their "true" value. This is also the same for peak timing with evidence of convergence, though more notably after the peak had occurred.

Table 5.7 Predictive Accuracy of Peak Timing and Magnitude

Country/Product	Timing	Magnitude
Japan		
Air Conditioner	Two periods after peak sales	Peak sales period
VCR	Two periods after peak sales	Peak sales period
Microwave Oven	Never accurate	Three periods after peak sales
Video Disk Player	Never accurate	Never accurate
Video Camera	One period after peak sales	One period after peak sales
Digital Audio Disk Player	Peak sales period	Peak sales period
Vacuum Cleaner	One period before peak sales	Peak sales period
Taiwan		
Air Conditioner	Never accurate	Never accurate
Personal Computer	One period after peak sales	Never accurate
Facsimile	One period after peak sales	One period after peak sales
VCR	Seven periods before peak sales	Never accurate
Microwave Oven	Peak sales period	One period after peak sales
Induction Cooker	Never consistently accurate	One period after peak sales
TV Game	Never consistently accurate	Never accurate
Floppy Disk	Never consistently accurate	Peak sales period
Clothes Dryer	Never consistently accurate	9 periods before peak sales

* Accuracy here is not an objective statistical measure as in the preceding sections but a subjective assessment based on the relative size of the error.

5.2.4 Conclusion

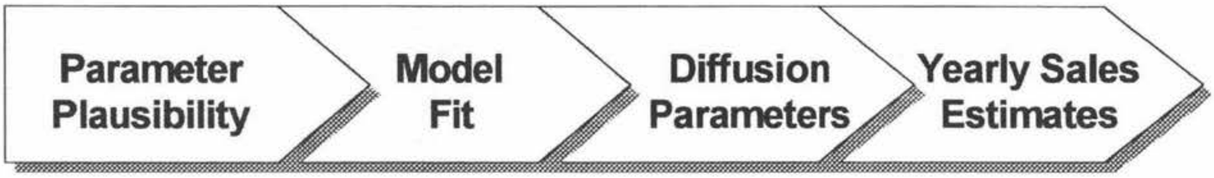
The analysis of predictive validity suggests the parameter estimates made by the Bass model may only be valid after peak sales has been included in the calibration data. However, in about one-third of cases, the parameter estimates are accurately predicted prior to peak sales but clear determinants of this were not apparent. Estimates of next period sales were disappointingly inaccurate. This may be a problem specific to Japan and Taiwan though it must be suggested that the diffusion curves of the two countries are hardly abnormal relative to those in other published studies.

The results of the examination of the small sample properties of the NLS estimator were more encouraging. In general, the estimates of the parameters and peak timing and magnitude indicate a strong pattern of convergence as n increases. However, this pattern of convergence was particularly strong after peak sales. With the exception of next period sales, the pattern of estimates as n increased was consistent with expectations.

Based on these results, the simple Bass model should not be used as a forecasting tool in Japan and Taiwan for the type of product examined here. A more complex Bass model (including other variables known to impact on the diffusion process) could be developed to overcome this problem. In terms of the variables to be included, this study can offer no guidance. In fact, these errors may be entirely random which means additional factors will not improve the models forecasting ability. It would be easy to suggest that additional analysis is required but due to the lack of data on the key diffusion factors, this is unlikely to be achieved or generalisable.

However, the results do suggest that the model can be used to make parameter comparisons between countries. The parameters are especially robust after the peak sales period has been included in the calibration data.

5.3 MODEL STABILITY ACROSS LEVELS OF AGGREGATION



Parameter Plausibility

- p, q, and m greater than zero
- q greater than p
- m within plausible social bounds
- estimated versus actual total sales
- estimated versus actual first period sales

Model Fit

- comparative fit of the estimated model to the actual data (adjusted R^2)
- plot of estimated versus actual diffusion curve
- estimated versus actual timing and magnitude of peak sales

Diffusion Parameters

- p stable across the aggregation levels
- q stable across the aggregation levels
- m equal across the aggregation level

Yearly Sales Estimates

- comparative yearly sales estimates from yearly, half-yearly, and quarterly models
- comparative fit of actual and estimated yearly sales from yearly, half-yearly, and quarterly models

5.3.1 Background

In modelling, it is vital for the manager to use the data aggregation level that yields reliable information for future predictions, and at the same time has practical time advantages. In this context, annual data has the highest level of reliability as common sources of non-diffusion based variation, such as seasonal effects, are eliminated in this longer time interval. However, one major shortcoming of annual data is the long time period required for each data point. Of course, a minimum of three data points are needed to fit the simple Bass model which translates to three years when using annual data. This waiting time is becoming unacceptable as products now reach peak in a shorter time period than two or three decades ago.

Monthly or weekly data is at the other end of the scale. This aggregation level has an obvious time advantage, however it is weak in terms of reliability. A diffusion curve that is plotted based on monthly data is highly variable to the extent that the diffusion pattern over time can be masked. In these conditions, the Bass model may have difficulty establishing the true diffusion pattern (or more precisely, as we do not know the true diffusion pattern, a diffusion pattern that is similar across the aggregation levels). But as Wright, Upritchard and Lewis (1997) suggest, the best level of aggregation "will be the one which produces a smooth and regular diffusion pattern, without reducing the degrees of freedom too far" (p 11).

So far, although encouraging results have been reported in previous Bass model studies, the fact that annual level data was used in most cases discounts the practical value of the model. Heeler and Hustad (1980) and Tigert and Farivar (1981) recognised this problem and suggested that quarterly time series data should be preferred as seasonal effects are reduced and the shorter time interval provides more data points than yearly data. However, there is a lack of empirical evidence to support this supposition.

Another equally important reason for examining the stability of the Bass model at different levels of aggregation relates to the robustness of the model and its underlying assumptions. The Bass model assumes a certain pattern of sales based on behavioural assumptions regarding the diffusion process. These assumptions should be robust against systematic sources of disturbance such as seasonality. In this context, we expect a robust model to produce relatively similar predictions of *annual sales* and *diffusion parameters* from yearly, half-yearly, and quarterly data. If this does not occur, then the Bass model is modelling seasonality and other random error rather than the actual assumed behaviour underlying the diffusion process. By exposing the model to the increased levels of random and systematic error that come with half-yearly and quarterly data, we are providing a rigorous test of the models stability.

The objective of this section is to investigate the Bass model's stability under different levels of data aggregation and to test the feasibility of using shorter time intervals, as suggested by Heeler and Hustad (1980) and Tigert and Farivar (1981), in practical situations. This will involve examining the plausibility of the estimated parameters, the fit of the model, the parameters p and q, and the extent to which the annual sales predictions from the yearly, half-yearly and quarterly models equate. Ultimately, it is the final two performance diagnostics which will determine the stability of the model.

5.3.2 Parameter Plausibility at Different Aggregation Levels

For the Bass model to be useful and robust at different levels of aggregation, its parameters must be at the very least plausible. The idea of parameter plausibility is the same here as discussed in section 5.1.1.

5.3.2.1 Parameter Plausibility at Different Levels of Aggregation - Japan

Data aggregation does not have a sizeable impact on the plausibility of the Japanese Bass model parameters. In all cases (see table 5.8), the estimated diffusion parameters are positive and q is greater than p. Also, with the exception of facsimile and personal computer, the estimated market potential, m, is similar across the three aggregation levels for all products. This contrasts with the results of Wright, Upritchard, and Lewis (1997) who found differences in plausibility, though they used data at lower levels of aggregation (e.g. weekly, fortnightly).

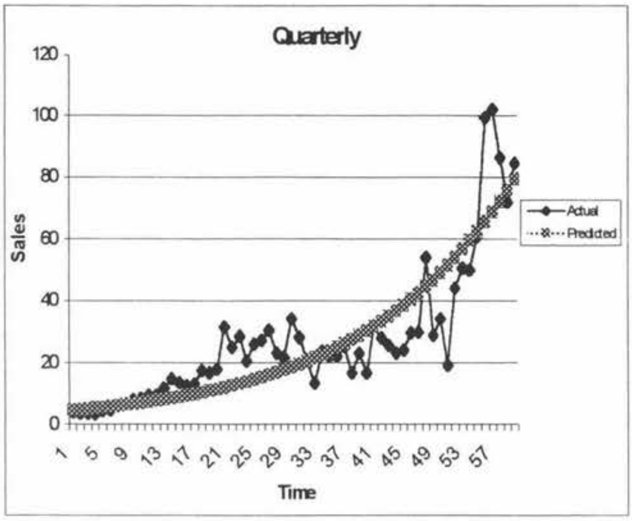
These initial results demonstrate that the Bass model is generally stable under different data aggregation levels. Additionally, they provide proves for the model's ability to capture the underlying external and internal factors that contribute to the diffusion of new products.

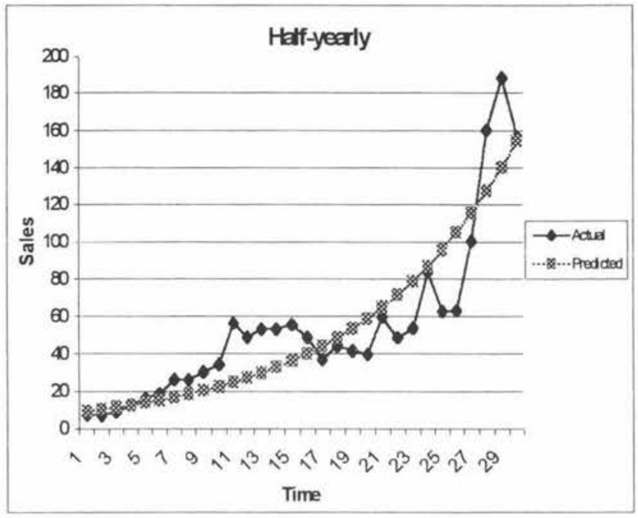
Table 5.8 Parameter Plausibility at Different Data Aggregation Level- Japan

Product	Aggregation Level	p	q	m	M= Total Sales (% difference)	PM= First Period (% difference)
Air Conditioner	Quarterly	-	-	-	-	-
	Half-yearly	0.0188	0.12	858	11.95%	-20%
	Yearly	0.0378	0.22	880	14.86%	-18%
Personal Computer *	Quarterly	0.0007	0.04	32065	-0.74%	-37%
	Half-yearly	0.000003	0.08	12467944	-2.34%	-47%
	Yearly	0.0001	0.18	474548	-2.95%	-48%
Facsimile *	Quarterly	0.000001	0.05	5011296	-3.63%	11%
	Half-yearly	0.000005	0.10	1823847	-3.51%	20%
	Yearly	0.0006	0.20	29152	-3.89%	15%
VCR	Quarterly	0.0095	0.10	5394	3.74%	-47%
	Half-yearly	0.0188	0.20	5348	4.75%	-47%
	Yearly	0.0385	0.38	5418	4.20%	-15%
Microwave Oven *	Quarterly	0.0021	0.05	5423	-1.80%	-70%
	Half-yearly	0.0038	0.08	6408	-1.36%	-66%
	Yearly	0.0083	0.19	5418	-1.69%	-60%
Video Disk Player *	Quarterly	0.0082	0.05	1004	-0.27%	-18%
	Half-yearly	0.0169	0.13	894	-0.60%	-25%
	Yearly	0.0348	0.26	888	-0.50%	-23%
Video Camera *	Quarterly	0.0079	0.11	7726	-0.37%	-21%
	Half-yearly	0.0157	0.24	7284	-0.65%	-26%
	Yearly	0.0320	0.46	7588	-0.35%	-25%
Digital Audio Disk Player	Quarterly	0.0043	0.06	20035	0.76%	393%
	Half-yearly	0.0086	0.13	19902	0.76%	389%
	Yearly	0.0174	0.26	19579	0.71%	352%
Vacuum Cleaner *	Quarterly	0.0009	0.02	46104	0.28%	23%
	Half-yearly	0.0019	0.03	45372	0.28%	17%
	Yearly	0.0039	0.07	44181	0.27%	17%

Clearly in the case of facsimile, the estimated m for the quarterly and half-yearly data is extremely large and implausible. The estimated market potential of 50 and 18 billion units respectively is at variance with the actual population size of approximately to 100 million. The reason for this is clear. As shown in figure 5.21, the Bass model does not capture the post-peak sales decline in both cases and assumes sales are still increasing, thus leading to an inflated estimate of m.

Figure 5.21 Quarterly and Half-yearly Facsimile Diffusion Curves- Japan



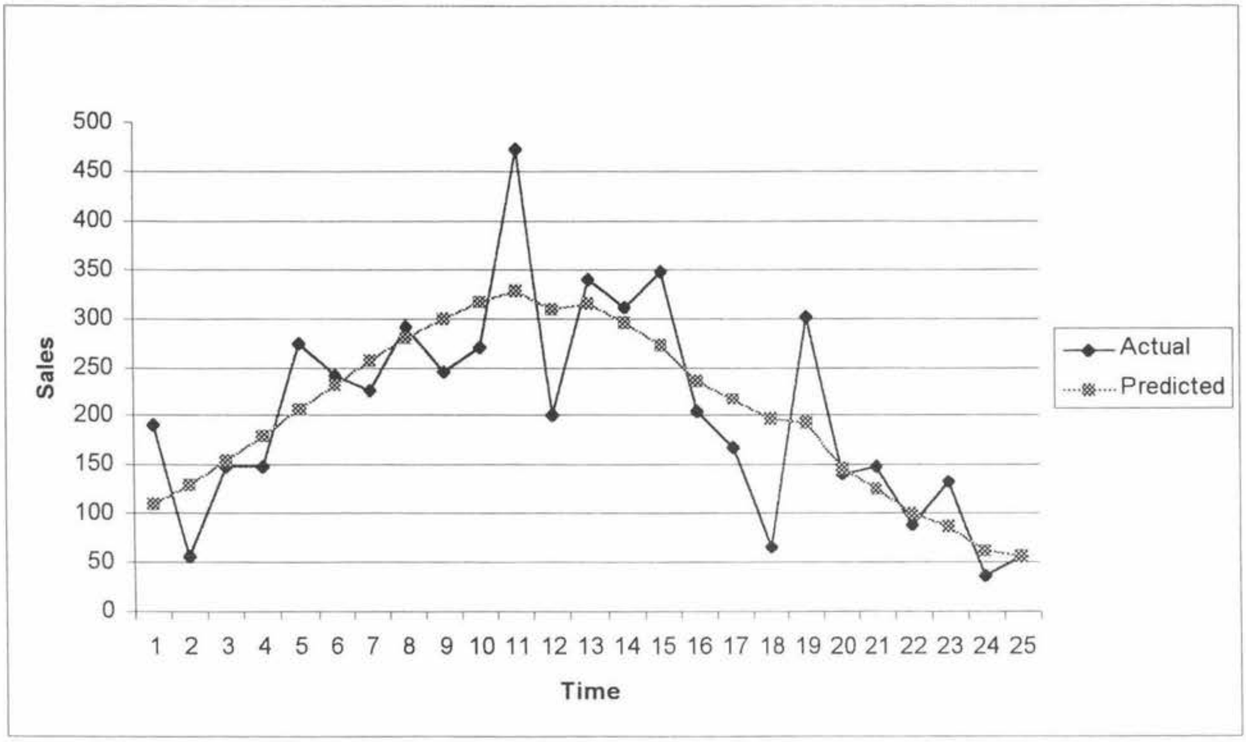


The Bass model for personal computer produces three substantially different estimates of *m*. The estimated *m* from the half-yearly model was not plausible (i.e. 12 billion units). As discussed previously, market potential was estimated to be 4 billion units based on the annual data, which was about 40 times the population. It is difficult to judge whether this figure is plausible considering the increasing use of computers for both organisational and personal applications. Nevertheless, there can be little doubt that repeat purchase and multiple product generations are contributing factors. The estimated *m* based on quarterly data was 320 million units, an average of 3 units per person, which is more realistic and points to seasonality adversely impacting on the estimates of market potential at the more granular levels of aggregation.

Another measure, the percentage difference between estimated and actual total sales, *M*, was generally small across all products. Nevertheless, as previously mentioned in section 5.1.1.1, the incomplete diffusion process for the majority of Japanese products (7 out of 9) resulted in comparisons being made between estimated and actual total sales over the available time period. This alternative does not provide the same level of generalisability and practical value as a comparison based on the entire diffusion curve. It is meant to act as a general gauge for ensuring the model's ability to produce reasonable sales estimates based on the available data points.

An analysis of the estimated and actual first period sales, *pm*, reveals little differences across the data levels. The only case of note is the video cassette recorder, where quarterly and half yearly data produced much larger differences between the actual and estimated *pm* than the annual data. As shown in figure 5.22, this occurrence was explained by the high sales level in the first half of the year after the product was introduced to the market, possibly as a consequence of new product advertising or promotion.

Figure 5.22 Half-yearly Video Cassette Recorder Diffusion- Japan



In conclusion, the overall results obtained suggest that the parameter estimates are stable at different levels of data aggregation across the Japanese products analysed.

5.3.2.2 Parameter Plausibility at Different Levels of Aggregation - Taiwan

For Taiwan, the estimated Bass models produced positive parameter estimates for each product across all three aggregation levels. As expected, q was greater than p in all cases. The estimated market potentials were all within a plausible range and were fairly constant across the three levels for all products.

Table 5.9 Parameter Plausibility at Different Data Aggregation Level- Taiwan

Product	Aggregation Level	p	q	m	M= Total Sales (% difference)	PM= First Period (% difference)
Air Conditioner	Quarterly	0.000007	0.11	4300	9.62%	549%
	Half-yearly	0.00004	0.20	4310	9.87%	880%
	Yearly	0.00009	0.40	4309	9.84%	300%
Personal Computer *	Quarterly	0.00002	0.09	6419	-0.72%	404%
	Half-yearly	0.00004	0.17	6918	-0.16%	286%
	Yearly	0.00007	0.36	6597	-0.74%	80%
Facsimile	Quarterly	0.001	0.27	355	2.10%	-73%
	Half-yearly	0.0011	0.52	360	0.70%	-75%
	Yearly	0.0015	1.03	358	2.67%	-62%
VCR	Quarterly	9.2084E-12	0.46	649	0.42%	-100%
	Half-yearly	0.0000002	0.55	715	10.64%	-99%
	Yearly	0.0000005	1.09	702	8.73%	-99%
Microwave Oven	Quarterly	0.002	0.35	150	-1.28%	11%
	Half-yearly	0.003	0.73	149	-1.77%	-4%
	Yearly	0.0012	1.75	146	-4.10%	-65%
Induction Cooker *	Quarterly	0.006	0.08	407	-0.08%	-29%
	Half-yearly	0.011	0.16	414	-0.02%	-26%
	Yearly	0.022	0.35	390	-0.22%	-28%
TV Game *	Quarterly	0.003	0.08	1408	-2.33%	-31%
	Half-yearly	0.006	0.15	1402	-2.45%	-35%
	Yearly	0.013	0.29	1477	-2.06%	-34%
Floppy Disk *	Quarterly	0.008	0.09	133	0.66%	83%
	Half-yearly	0.015	0.19	130	0.56%	52%
	Yearly	0.032	0.38	128	0.55%	9%
Clothes Dryer *	Quarterly	0.0024	0.06	204	1.85%	671%
	Half-yearly	0.0045	0.12	205	2.07%	1393%
	Yearly	0.0018	0.26	203	4.16%	192%

In general, the percentage difference between the estimated *m* and actual total sales was fairly small and consistent across the aggregation levels. The only stand-out was the quarterly VCR model where the percentage difference was substantially lower (0.4%) compared to the half-yearly and yearly models (11% and 9% respectively).

In terms of the accuracy of the first period sales estimates, the percentage error increased as the aggregation level decreased for the air conditioner, personal computer, floppy disk, and clothes dryer models. These errors are largely due to instability caused by seasonal variation, unaccounted for marketing mix variables, and as Bass (1969) indicated variation due to the new nature of the product and the uncertainty that accompanies this in the initial stages of product launch.

However, the opposite trend was observed for microwave oven. Unlike the previous products, the percentage error was smaller for the two lower aggregation levels than the yearly data, i.e. 11%, -4%, and 65% for the quarterly, half-yearly, and yearly data respectively. Nevertheless the percentage errors should be evaluated relative to the size of the total market to determine the seriousness of the difference in the practical terms. For this product, the size of first period sales relative to total sales is very small. Furthermore, since the overall fit of the yearly model was later found to achieve the highest adjusted R^2 of 80%, it would be unwise to reject the overall model solution based on the high difference between the estimated and actual first period sales.

Based on the above findings, one can conclude that the Bass model generated plausible and stable diffusion parameters at all data aggregation levels for each of the products in the Taiwanese market. The performance of the Bass models in terms of the fit of estimated models to the actual times series data is investigated in the next section.

5.3.3 Fit of the Model at Different Aggregation Levels

Measures of model fit as defined in section 5.1.2 are used here to gauge the relative abilities of the models estimated on different data aggregation levels. However, we have a different expectation with regard to the adjusted R^2 value at different levels of aggregation. This value should decrease as the level of aggregation decreases because of the greater number of data points and also seasonal variation. The mere fact that there is more data points gives greater opportunity for non-diffusion factors to cause variation in sales. Consequently, yearly models should produce a better fit to the data than half-yearly and quarterly models, with the proviso that aggregation has not reduced the degrees of freedom too far (Wright, Upritchard and Lewis, 1997). Therefore, this measure is only a preliminary gauge of model instability at different aggregation levels.

5.3.3.1 Model Fit at Different Data Aggregation Levels - Japan

As expected, adjusted R^2 decreases as the level of data aggregation increases. Noticeably, for the products facsimile, video camera, digital audio disk player, and vacuum cleaner, the fit of the half-yearly and quarterly models was comparatively good, with adjusted R^2 values higher than 75%. These products are obviously less prone to seasonal and other period-to-period sales fluctuations.

As can be seen in table 5.10, a quarterly model was not fitted for air conditioner. This was due to the existence of some negative figures in the quarterly data (the cause of this particular shortcoming of quarterly data was discussed in section 4.1 data profile). Additionally, when comparing the adjusted R^2 between the estimated models, it was clear that the fit of the half-yearly model was poor (adjusted R^2 of 22%) mostly due to seasonality. Based on the nature of the product, it is not surprising that the sales volume differs between the first half and second half of the year.

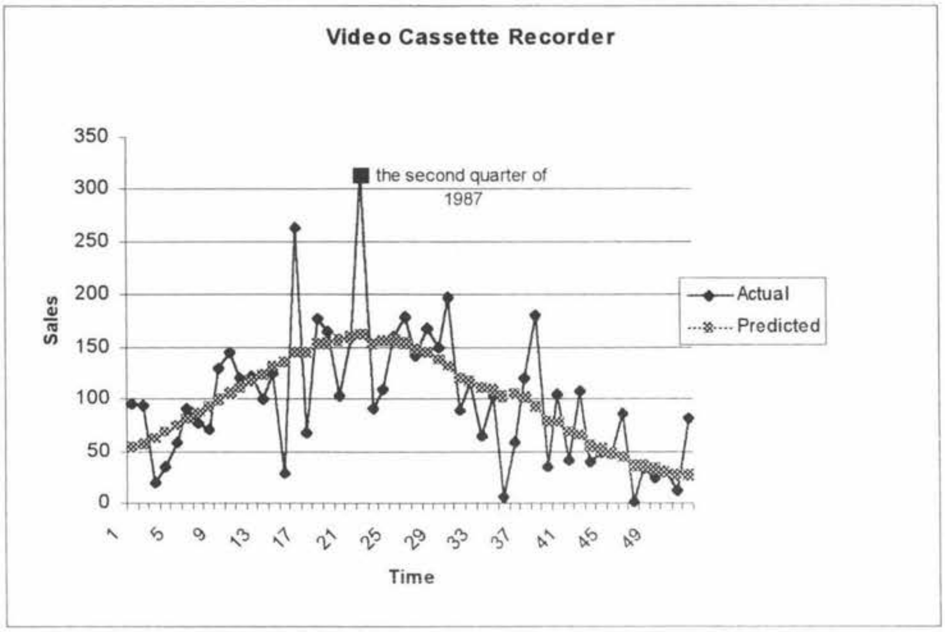
Table 5.10 Model Fit at Different Levels of Data Aggregation- Japan

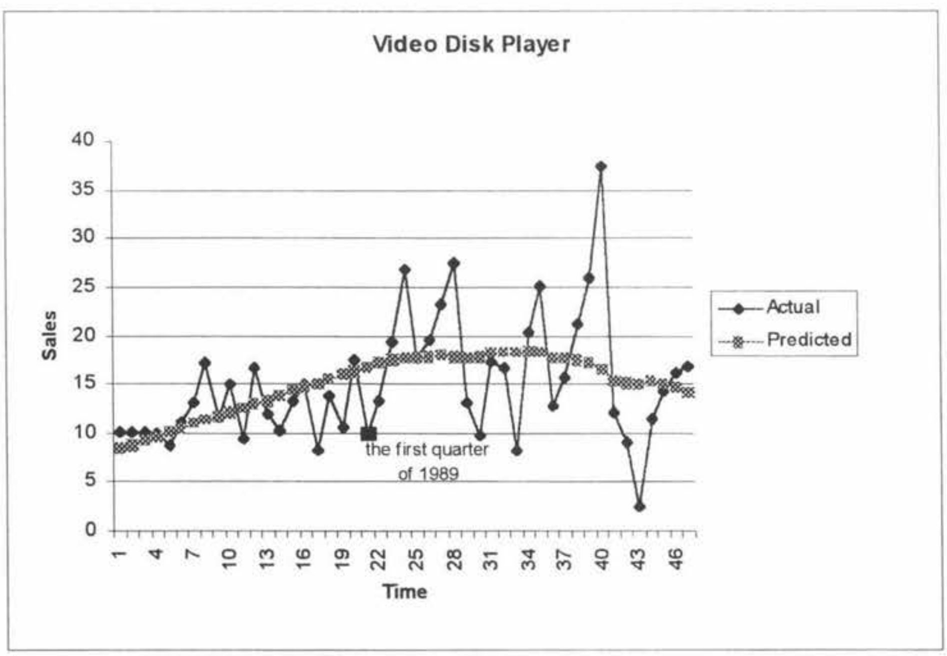
Product	Aggregation Level	Adjusted R^2	Peak Timing		Peak Magnitude		
			Est.	Actual	Est.	Actual	difference
Air Conditioner	Quarterly	-	-	-	-	-	-
	Half-yearly	22%	26	25	36	67	-47.2%
	Yearly	68%	9	10	67	82	-18.3%
Personal Computer	Quarterly	50%	54	50	140	225	-37.9%
	Half-yearly	66%	26	25	313	438	-28.4%
	Yearly	77%	13	13	615	687	-10.4%
Facsimile	Quarterly	76%	60	57	80	102	-22.0%
	Half-yearly	80%	30	29	155	188	-18.0%
	Yearly	83%	15	15	293	345	-15.0%
VCR	Quarterly	44%	22	22	162	315	-48.5%
	Half-yearly	63%	11	11	327	438	-25.2%
	Yearly	85%	6	6	637	675	-5.6%
Microwave Oven	Quarterly	69%	64	48	68	98	-31.0%
	Half-yearly	78%	34	25	145	165	-12.3%
	Yearly	80%	17	13	270	305	-11.4%
Video Disk Player	Quarterly	19%	34	40	18	37	-50.8%
	Half-yearly	28%	14	20	37	63	-41.4%
	Yearly	40%	7	10	74	100	-25.7%
Video Camera	Quarterly	78%	22	24	251	336	-25.2%
	Half-yearly	82%	11	12	506	646	-21.7%
	Yearly	88%	6	6	1013	1174	-13.7%
Digital Audio Disk Player	Quarterly	75%	42	47	370	475	-22.2%
	Half-yearly	79%	22	24	735	880	-16.5%
	Yearly	86%	11	12	1454	1622	-10.3%
Vacuum Cleaner	Quarterly	87%	136	132	194	243	-20.3%
	Half-yearly	92%	68	66	385	435	-11.4%
	Yearly	93%	34	33	765	850	-10.0%

The video cassette recorder and video disk player models are two cases where the adjusted R^2 experiences sizeable decreases as the level of aggregation decreases. For the VCR, the adjusted R^2 is substantially lower for the quarterly model when compared to the yearly model (44% and 85% respectively). For the video disk player, these values were 19% for the quarterly and 40% for the yearly model.

Interestingly, an examination of the diffusion curves (figure 5.24) for these two products reveals that they are qualitatively similar in terms of large period-to-period sales fluctuations. As they share similar functional characteristics the similarity between their diffusion patterns is less than surprising. Furthermore, there is some evidence to suggest that the sales levels of the two products are interacting. For example, sales of the video disk player do not increase rapidly (from approximately 1989 to the peak in 1993) until after the video cassette recorder sales have peaked in 1987.

Figure 5.24 Comparison of Diffusion Curves between Quarterly Video Cassette Recorder and Video Disk Player Models- Japan





The accuracy of the predictions of peak timing and magnitude also serve as a measure of model fit. As summarised in Table 5.11, the MAD across the aggregation levels are similar with the yearly model producing the best estimate. These findings were expected as the longer yearly time interval in most cases reduces the amount of period-to-period variation, therefore enabling a better prediction of peak sales. In general, the Bass model produced fairly good estimates of the timing of peak sales for the Japanese products.

The magnitude of peak sales was underestimated in all cases. Additionally, the pattern in the errors was the same as for the peak timing estimates - the mean percentage error (MPE) decreases as the aggregation level increases, i.e. 32%, 25%, and 13% for the quarterly data, half-yearly data, and yearly data respectively.

These findings suggest that the loss of precision in estimating the sales peak through the use of quarterly and half-yearly data is outweighed by the advantages of the shorter time intervals.

Table 5.11 Summary of MAD and MAPE for Peak Sales Estimates- Japan

Aggregation Level	Peak Timing (MAD)	Peak Magnitude (MAPE)
Quarterly	5	32.3%
Half-Yearly	5.2	24.7%
Yearly	4.4	13.4%

* The MAD for peak timing is measured on a quarterly basis to aid comparison.

5.3.3.2 Model Fit at Different Aggregation Levels – Taiwan

When the overall fit results are compared with those obtained for Japan, the Taiwanese models are more stable at different levels of aggregation (table 5.12). This may be due to the type of products included in the data from Taiwan rather than any inherent variability caused by Taiwanese market conditions. A close inspection of the five products common to both countries shows the Taiwanese models are better fitting in all cases ruling this out to some extent.

The estimates of peak magnitude are not as stable as those in Japan. It is hypothesised that this is due to the peak sales occurring at the top of a sharp sales increase whereas in Japan the peak follows from a sustained sales rise over a number of time periods.

Table 5.12 Model Fits at Different Levels of Data Aggregation- Taiwan

Product	Aggregation Level	Adjusted R^2	Peak Timing		Peak Magnitude		
			Est.	Actual	Est.	Actual	difference
Air Conditioner	Quarterly	66%	89	94	119	213	-44.1%
	Half-yearly	75%	42	47	224	340	-34.0%
	Yearly	80%	21	24	438	589	-25.7%
Personal Computer	Quarterly	84%	93	96	150	249	-39.9%
	Half-yearly	86%	47	48	309	471	-34.4%
	Yearly	87%	24	24	621	930	-33.2%
Facsimile	Quarterly	84%	22	19	23	29	-19.9%
	Half-yearly	90%	13	11	45	47	-4.4%
	Yearly	94%	6	6	87	82	6.2%
VCR	Quarterly	75%	54	54	77	130	-41.2%
	Half-yearly	69%	27	27	117	222	-47.1%
	Yearly	80%	14	14	219	344	-36.3%
Microwave Oven	Quarterly	71%	15	14	13	18	-24.1%
	Half-yearly	80%	8	6	27	28	-0.9%
	Yearly	90%	5	4	56	55	1.8%
Induction Cooker	Quarterly	31%	32	36	10	118	-91.6%
	Half-yearly	73%	16	18	19	25	-22.2%
	Yearly	94%	8	6	38	39	-2.8%
TV Game	Quarterly	31%	41	51	29	55	-47.4%
	Half-yearly	35%	21	25	58	96	-39.4%
	Yearly	49%	11	13	116	191	-39.0%
Floppy Disk	Quarterly	46%	28	19	4	8	-52.6%
	Half-yearly	62%	13	10	7	11	-33.0%
	Yearly	86%	7	5	14	15	-4.3%
Clothes Dryer	Quarterly	37%	55	56	4	7	-50.5%
	Half-yearly	64%	28	28	7	9	-23.7%
	Yearly	85%	19	23	14	14	-3.6%

The most noticeable variations in fit across the aggregation levels occurs for the products induction cooker, clothes dryer, and floppy disk. The poor performance of the first two products' models at the half-yearly and quarterly levels of aggregation can be explained by seasonality. However, other factors such as multiple product generations are accounting for the non-diffusion based variation in floppy disk sales. These types of variants are also much more difficult to model without additional data compared to seasonal effects.

The personal computer and facsimile models have an excellent fit at all levels of aggregation (i.e. adjusted R^2 greater than 80%) while the VCR and microwave oven models produce admirable results (greater than 70% adjusted R^2). The air conditioner model (adjusted R^2 greater than 65%) is acceptable.

As shown in table 5.13, the estimated timing of peak sales were generally similar as the reported MADs suggest. Surprisingly, the yearly model had the largest deviation. Again, this may be due to the peak sales occurring at the top of a sharp sales increase with the half-yearly and quarterly models better equipped to capture the sudden sales increases.

Except in the cases of yearly microwave and facsimile models, the magnitude of peak sales was under-estimated in all cases. Although the same decreasing error with the increasing aggregation level trend was observed in the Taiwanese models, the MAPE of the estimated peak magnitude was higher at each data aggregation level when compared to the results for the Japanese data.

Table 5.13 Summary of MAD and MAPE for Peak Sales Estimates- Taiwan

Aggregation Level	Peak Timing (MAD)	Peak Magnitude (MAPE)
Quarterly	4	45.7%
Half-Yearly	4.2	26.6%
Yearly	6.4	17.0%

* The MAD for peak timing is measured on a quarterly basis to aid comparison.

5.3.4 Behaviour of diffusion parameters across different levels of aggregation

In section 5.3.2, parameter plausibility was examined across the aggregation levels. This section goes one step further by specifically comparing the estimates of p, q, and m for each product across the aggregation levels. As discussed in section 3.2, the p's and q's are respectively the coefficients of innovation and imitation. They represent the rate of change in the number of innovators and imitators over time. The total market potential is represented by m and should be relatively constant across the aggregation levels if the Bass model is robust.

However, p and q should not be equal across the different aggregation levels. We would expect, all things being equal, the rate of change in the number of adopters, the number of innovators, and the number of imitators in a yearly period to be greater than in a half-year or quarter (i.e. both p and q will be progressively larger as the level of aggregation increases). A more precise approximation would be, p and q from the yearly models being twice the size of the estimates from the half-yearly models and four times the size of the estimates from the quarterly models assuming that the model is capturing the same diffusion process across the aggregation levels.

Therefore, if the Bass model is capturing the same diffusion pattern from the different data aggregation levels then (where i = the 18 products modelled here):

- $2p_{half\text{-}yearly,i} / p_{yearly,i} = 1$
- $4p_{quarterly,i} / p_{yearly,i} = 1$
- $2q_{half\text{-}yearly,i} / q_{yearly,i} = 1$
- $4q_{quarterly,i} / q_{yearly,i} = 1$
- $m_{half\text{-}yearly,i} / m_{yearly,i} = 1$
- $m_{quarterly,i} / m_{yearly,i} = 1$

The main reason for presenting this ratio rather than the actual values of p and q is for ease of comparability across aggregation levels. Table 5.14 below presents these ratios for p, q, and *m* respectively. We would hope that the estimates of market potential across the aggregation levels are similar or even better the ratio being equal to one. If they are not, then marketers could mistakenly over- or underestimate the size of the potential buyer population.

Table 5.14 Parameter Comparability across Different Aggregation Levels

Product	*p*		*q*		*m*	
	4Q/Y	2HY/Y	4Q/Y	2HY/Y	4Q/Y	2HY/Y
Japan						
Air Conditioner	-	0.99	-	1.09	-	0.97
Personal Computer	**19.87**	**0.04**	0.85	0.95	**0.07**	**26.27**
Facsimile	**0.01**	**0.02**	0.96	0.95	**171.90**	**62.56**
VCR	0.98	0.98	1.02	1.05	1.00	0.99
Microwave Oven	0.99	0.93	1.00	0.90	1.00	1.18
Video Disk Player	0.95	0.97	0.85	1.00	1.13	1.01
Video Camera	0.99	0.98	0.98	1.05	1.02	0.96
Digital Audio Disk Player	0.99	0.99	0.98	0.98	1.02	1.02
Vacuum Cleaner	0.96	0.98	0.99	1.00	1.04	1.03
Taiwan						
Air Conditioner	**0.32**	0.91	1.13	1.01	1.00	1.00
Personal Computer	1.05	1.21	1.00	0.96	0.97	1.05
Facsimile	**2.86**	1.50	1.04	1.01	0.99	1.00
VCR	**0.00**	0.83	1.69	1.02	0.92	1.02
Microwave Oven	**6.05**	**5.33**	0.81	0.84	1.03	1.02
Induction Cooker	1.00	1.02	0.94	0.91	1.04	1.06
TV Game	1.00	0.98	1.05	1.06	0.95	0.95
Floppy Disk	0.98	0.97	0.96	1.00	1.04	1.01
Clothes Dryer	**5.31**	**5.07**	0.95	0.94	1.00	1.01

These results point to some instability across the aggregation levels. The coefficient of innovation, *p*, is the most unstable, especially for the quarterly models. Specifically, there are substantial differences between the expected value of this ratio (i.e. one) and the actual values for *p* for the following products:

- Japan Personal Computer – quarterly and half-yearly
- Japan Facsimile – quarterly and half-yearly
- Taiwan Air Conditioner – quarterly
- Taiwan Facsimile – quarterly

- Taiwan Video Cassette Recorder – quarterly
- Taiwan Microwave Oven – quarterly and half-yearly
- Taiwan Clothes Dryer – quarterly and half-yearly

The coefficient of imitation, q, is surprisingly stable with only one notable discrepancy for the quarterly Taiwan Video Cassette Recorder model. The market potential is also reasonably static with the only products to note being:

- Japan Personal Computer – quarterly and half-yearly
- Japan Facsimile – quarterly and half-yearly.

It is possible to test specific hypotheses about the differences between the expected and estimated parameters by making use of the simulated standard errors from the yearly models. The yearly model estimates are used here as the benchmark against which models from other levels of aggregation can be tested. As the yearly models are less prone to non-diffusion based sources of variation, these models are seen as the best yardstick for testing the stability of the models' parameters across the aggregation levels. These tests are (where i = the separate 18 products from Japan and Taiwan):

- H_o: $2p_{half\text{-}yearly,i} = p_{yearly,i}$
- H_1: $2p_{half\text{-}yearly,i} \neq p_{yearly,i}$
- H_o: $2q_{half\text{-}yearly,i} = q_{yearly,i}$
- H_1: $2q_{half\text{-}yearly,i} \neq q_{yearly,I}$
- H_o: $2m_{half\text{-}yearly,i} = m_{yearly,i}$
- H_1: $2m_{half\text{-}yearly,i} \neq m_{yearly,I}$
- H_o: $4p_{quarterly,i} = p_{yearly,i}$
- H_1: $4p_{quarterly,i} \neq p_{yearly,i}$
- H_o: $4q_{quarterly,i} = q_{yearly,i}$
- H_1: $4q_{quarterly,i} \neq q_{yearly,i}$
- H_o: $m_{quarterly,i} = m_{yearly,i}$
- H_1: $m_{quarterly,i} \neq m_{yearly,i}$

The statistical test used to evaluate these hypotheses is (where i = the 18 products, and σ_i^2 is the simulated standard errors from the yearly models):

- $(2p_{\text{half-yearly},i} - p_{\text{yearly},i}) / \sqrt{(2\sigma_i^2)}$
- $(2q_{\text{half-yearly},i} - q_{\text{yearly},i}) / \sqrt{(2\sigma_i^2)}$
- $(4p_{\text{quarterly},i} - p_{\text{yearly},i}) / \sqrt{(2\sigma_i^2)}$
- $(4q_{\text{quarterly},i} - q_{\text{yearly},i}) / \sqrt{(2\sigma_i^2)}$
- $(4q_{\text{quarterly},i} - p_{\text{yearly},i}) / \sqrt{(2\sigma_i^2)}$
- $(4q_{\text{quarterly},i} - q_{\text{yearly},i}) / \sqrt{(2\sigma_i^2)}$
- $(m_{\text{half-yearly},i} - m_{\text{yearly},i}) / \sqrt{(2\sigma_i^2)}$
- $(m_{\text{quarterly},i} - m_{\text{yearly},i}) / \sqrt{(2\sigma_i^2)}$

It should be noted that these are not exact tests as the quarterly and half-yearly standard errors for the temporally standardised Bass model parameters are assumed to equal the yearly standard error:

- σ^2 of $2p_{\text{half-yearly},i} = \sigma^2$ of $p_{\text{yearly},i}$
- σ^2 of $2q_{\text{half-yearly},i} = \sigma^2$ of $p_{\text{yearly},i}$
- σ^2 of $m_{\text{half-yearly},i} = \sigma^2$ of $m_{\text{yearly},i}$
- σ^2 of $2p_{\text{quarterly},i} = \sigma^2$ of $p_{\text{yearly},i}$
- σ^2 of $2q_{\text{quarterly},i} = \sigma^2$ of $p_{\text{yearly},i}$
- σ^2 of $m_{\text{quarterly},i} = \sigma^2$ of $m_{\text{yearly},i}$.

We would expect the size of σ^2 for the half-yearly and quarterly models to be larger than the yearly models due to non-diffusion errors such as seasonality. In this case, the tests are likely to be biased in favour of rejecting H_1 rather than accepting it, not the ideal situation but an adequate preliminary measure of model robustness. The results of these tests are shown in Tables 5.15, 5.16, and 5.17 for p, q, and m respectively.

Table 5.15 Stability across aggregation levels - *p*

Product	Z Score		Significance	
	Quarterly	Half-Yearly	Quarterly	Half-Yearly
Japan - *p*				
Air Conditioner	-	0.019	NS	NS
Personal Computer	4.289	0.218	0.01	NS
Facsimile	0.331	0.327	NS	NS
VCR	0.086	0.118	NS	NS
Microwave Oven	0.028	0.255	NS	NS
Video Disk Player	0.164	0.088	NS	NS
Video Camera	0.052	0.082	NS	NS
Digital Audio Disk Player	0.050	0.055	NS	NS
Vacuum Cleaner	0.149	0.088	NS	NS
Taiwan - *p*				
Air Conditioner	0.438	0.057	NS	NS
Personal Computer	0.033	0.130	NS	NS
Facsimile	2.590	0.702	0.01	NS
VCR	0.716	0.125	NS	NS
Microwave Oven	2.353	2.015	0.05	0.05
Induction Cooker	0.029	0.185	NS	NS
TV Game	0.007	0.029	NS	NS
Floppy Disk	0.106	0.139	NS	NS
Clothes Dryer	8.432	7.963	0.001	0.001

Table 5.16 Stability across Aggregation Levels - *q*

Product	Z Score		Significance	
	Quarterly	Half-Yearly	Quarterly	Half-Yearly
Japan - *q*				
Air Conditioner	-	0.176	NS	NS
Personal Computer	0.541	0.186	NS	NS
Facsimile	0.113	0.132	NS	NS
VCR	0.140	0.279	NS	NS
Microwave Oven	0.001	0.367	NS	NS
Video Disk Player	0.385	0.007	NS	NS
Video Camera	0.107	0.244	NS	NS
Digital Audio Disk Player	0.121	0.081	NS	NS
Vacuum Cleaner	0.060	0.027	NS	NS
Taiwan - *q*				
Air Conditioner	0.636	0.052	NS	NS
Personal Computer	0.003	0.099	NS	NS
Facsimile	0.271	0.071	NS	NS
VCR	7.820	0.176	0.01	NS
Microwave Oven	0.955	0.813	NS	NS
Induction Cooker	0.563	0.866	NS	NS
TV Game	0.108	0.140	NS	NS
Floppy Disk	0.129	0.010	NS	NS
Clothes Dryer	0.323	0.397	NS	NS

Table 5.17 Stability across Aggregation Levels - *m*

Product	Z Score		Significance	
	Quarterly	Half-Yearly	Quarterly	Half-Yearly
Japan - *m*				
Air Conditioner	-	0.306	NS	NS
Personal Computer	1.377	37.318	NS	0.001
Facsimile	52.414	29.512	0.001	0.001
VCR	0.107	0.163	NS	NS
Microwave Oven	0.490	0.492	NS	NS
Video Disk Player	0.571	0.033	NS	NS
Video Camera	0.431	0.297	NS	NS
Digital Audio Disk Player	0.050	0.122	NS	NS
Vacuum Cleaner	0.036	0.058	NS	NS
Taiwan - *m*				
Air Conditioner	0.014	0.002	NS	NS
Personal Computer	0.085	0.152	NS	NS
Facsimile	0.145	0.049	NS	NS
VCR	0.377	0.070	NS	NS
Microwave Oven	0.024	0.115	NS	NS
Induction Cooker	0.235	0.817	NS	NS
TV Game	0.019	0.268	NS	NS
Floppy Disk	0.036	0.020	NS	NS
Clothes Dryer	0.051	0.077	NS	NS

The results for the coefficient of innovation, p, suggest that the instability across the aggregation levels may not be as serious as mentioned above. The only significant results now are:

- Japan Personal Computer – quarterly vs yearly ($\alpha = 0.01$)
- Taiwan Facsimile – quarterly vs yearly ($\alpha = 0.01$)
- Taiwan Microwave – quarterly vs yearly ($\alpha = 0.05$); half-yearly vs yearly ($\alpha = 0.05$).

The coefficient of imitation, q, is only significantly different for the Taiwan Video Cassette Recorder quarterly and yearly models ($\alpha = 0.01$). For the market potential estimate, m, the significant differences are:

- Japan PC – quarterly vs yearly ($\alpha = 0.001$); half-yearly vs yearly ($\alpha = 0.001$)
- Japan Facsimile – half-yearly vs yearly ($\alpha = 0.001$).

These results indicate that the parameters estimated by the Bass model are generally robust across yearly, half-yearly, and quarterly levels of aggregation. The coefficient of imitation, q, is particularly stable reflecting the importance of this parameter in determining the shape of the diffusion curve and the larger number of imitators in general. Market potential, m, is also robust.

The most unstable of the three parameters in the Bass model is p, the coefficient of innovation. Given the relative importance of this parameter and innovators in the diffusion of these products, it is far from surprising that this parameter is less reliable. Also, as Bass (1969) noted, early sales estimates are more prone to fluctuation as the product becomes established. Consequently, as most innovators adopt in the early stages of the products diffusion, the estimate of p is more likely to be effected by these early fluctuations, particularly at the quarterly and half-yearly levels of aggregation where other non-diffusion based error is introduced.

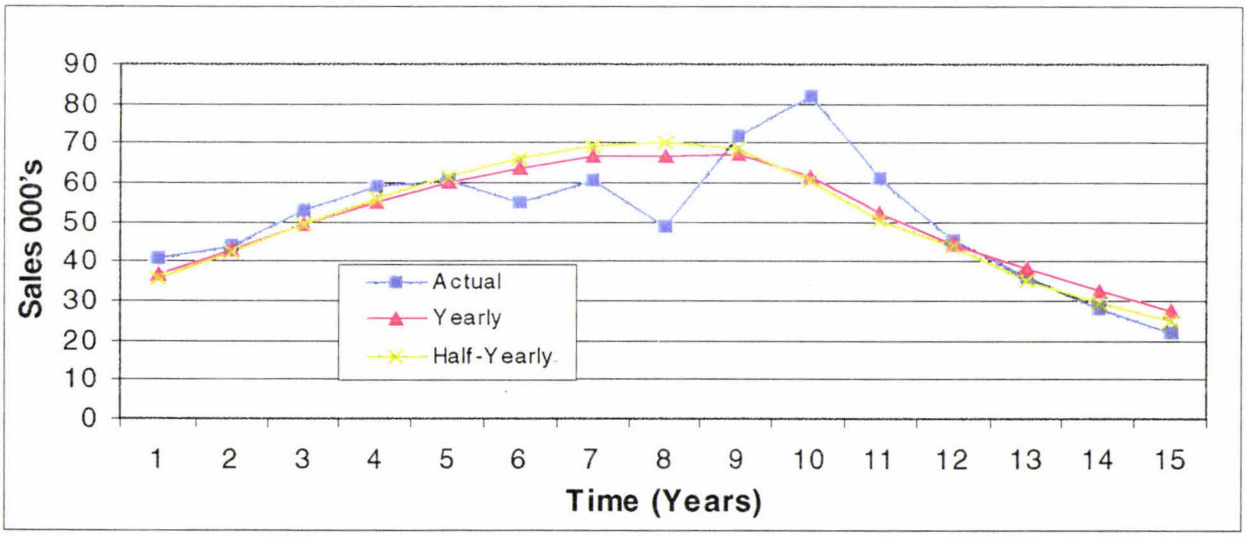
5.3.5 Annual Sales Estimates from Bass Models Calibrated at Different Levels of Aggregation

The preceding section indicated that the Bass model's parameters are generally robust across the aggregation levels. Given this finding, the sales estimates produced by these models should be comparable across the aggregation levels. In this section, we compare the actual annual sales (A_t) with the *annual* estimates produced by the quarterly (Q_t), half-yearly (HY_t) and yearly (Y_t) models to ensure that this is the case. Half-yearly and quarterly model sales estimates are aggregated to produce the annual sales estimates which represents a common standard against which the models can be evaluated.

5.3.5.1 Japan – Annual Sales Estimates Across Aggregation Levels

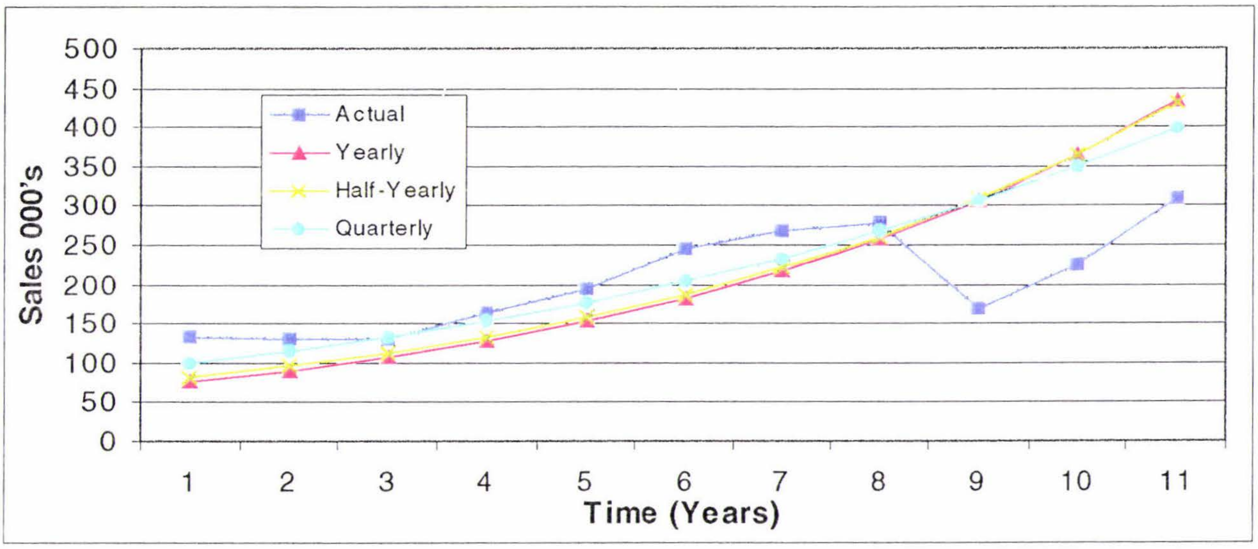
First, A_t is plotted against Q_t, HY_t, and Y_t to give a preliminary indication of the sales patterns produced by the different models.

Figure 5.25 Japan Air Conditioner – Annual Sales Predictions



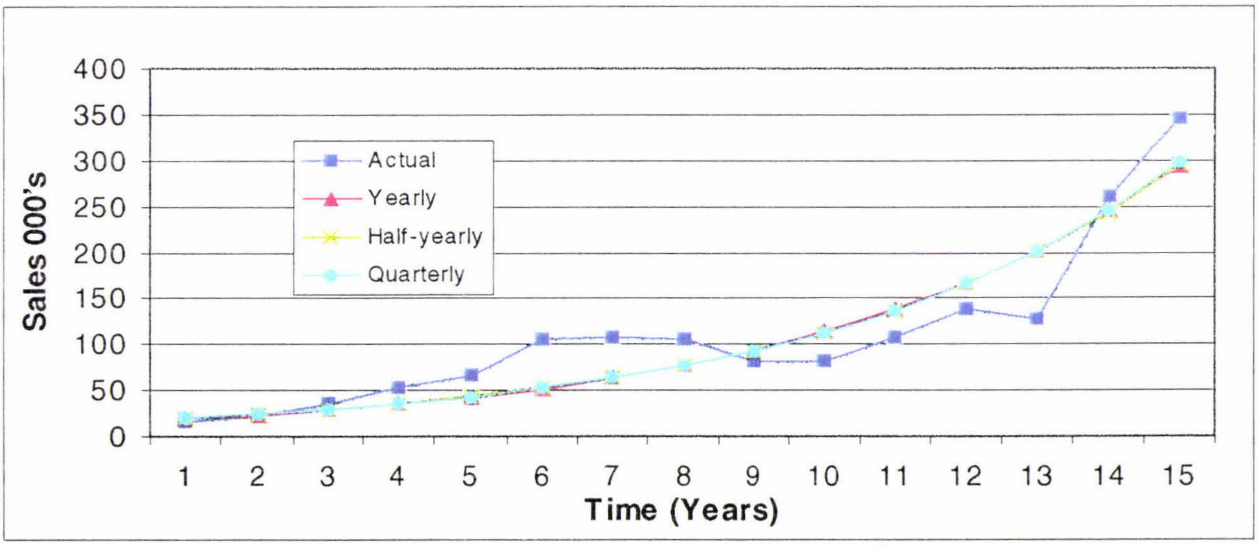
The half-yearly and yearly models produce comparable estimates of annual sales though the half-yearly model has a worse fit to the actual annual sales pattern.

Figure 5.26 Japan Personal Computer – Annual Sales Predictions



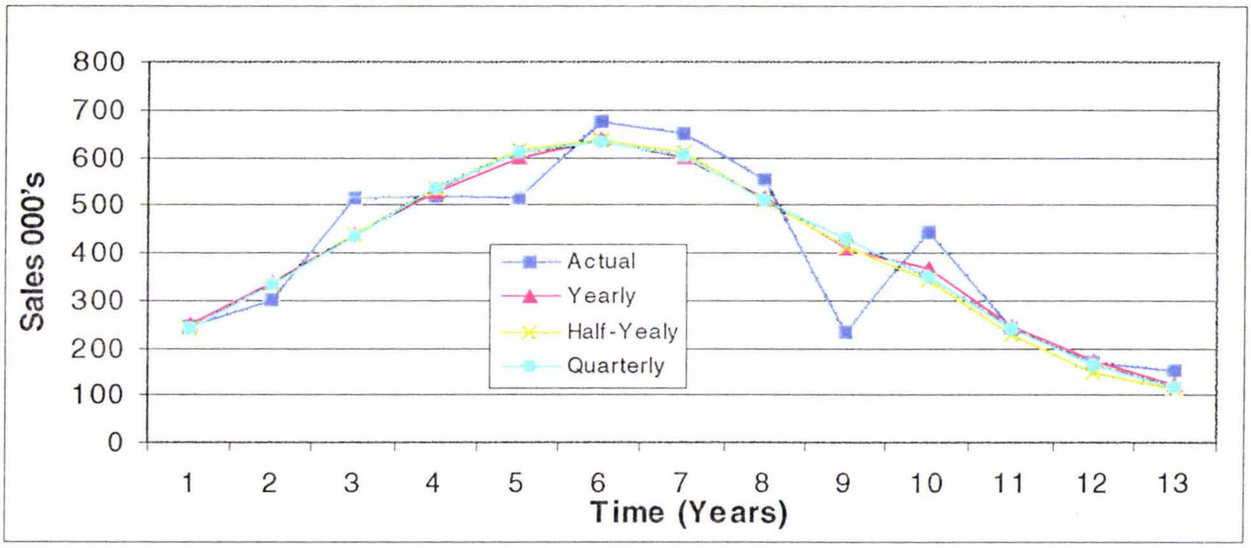
The yearly and half-yearly models produce equivalent estimates of annual sales. The quarterly model produces a slightly different diffusion pattern though it has the best fit overall.

Figure 5.27 Japan Facsimile – Annual Sales Predictions



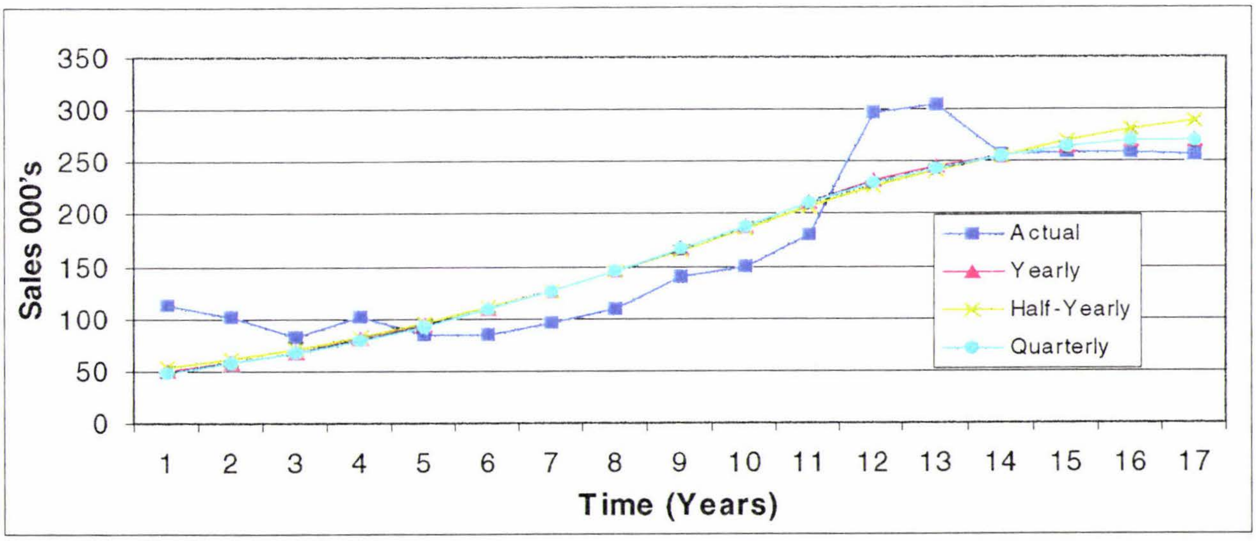
The yearly, half-yearly, and quarterly models produce almost identical estimates of annual sales and consequently very similar measures of fit.

Figure 5.28 Japan Video Cassette Recorder – Annual Sales Predictions



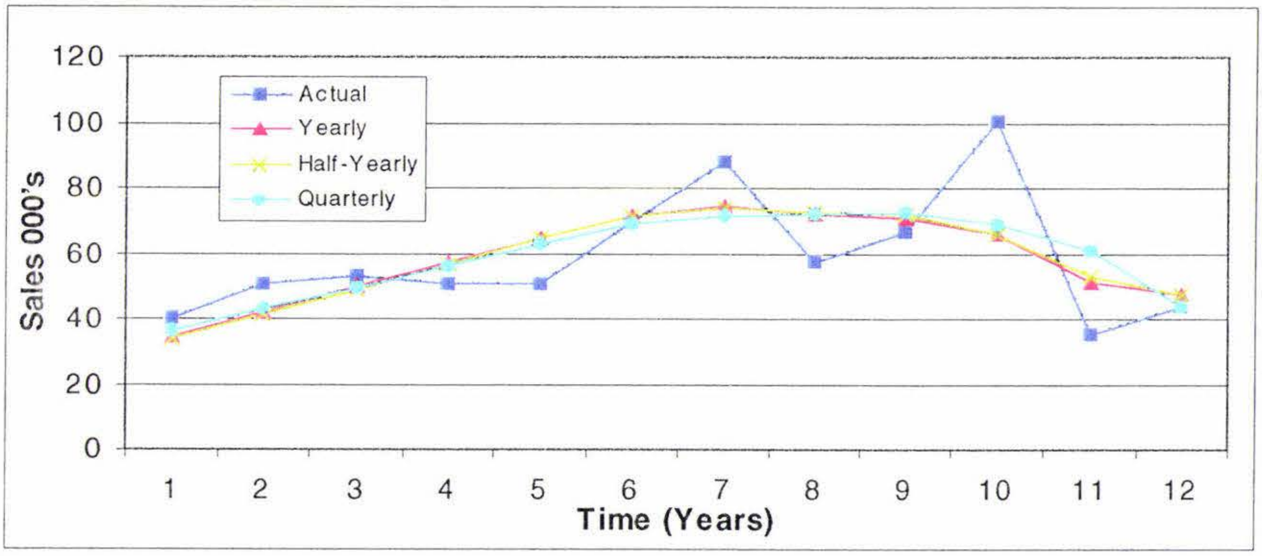
The yearly, half-yearly and quarterly models produce comparable diffusion curves though the yearly model has slightly the better adjusted R^2 overall.

Figure 5.29 Japan Microwave Oven – Annual Sales Predictions



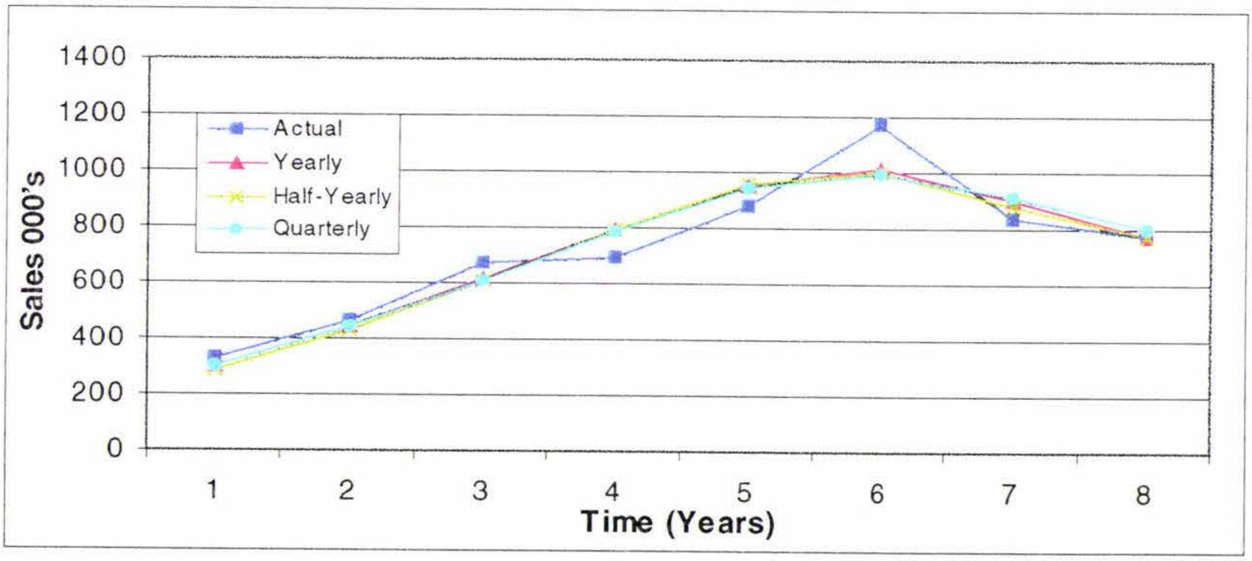
A stable annual sales pattern is produced across the aggregation levels for microwave oven.

Figure 5.30 Japan Video Disk Player – Annual Sales Predictions



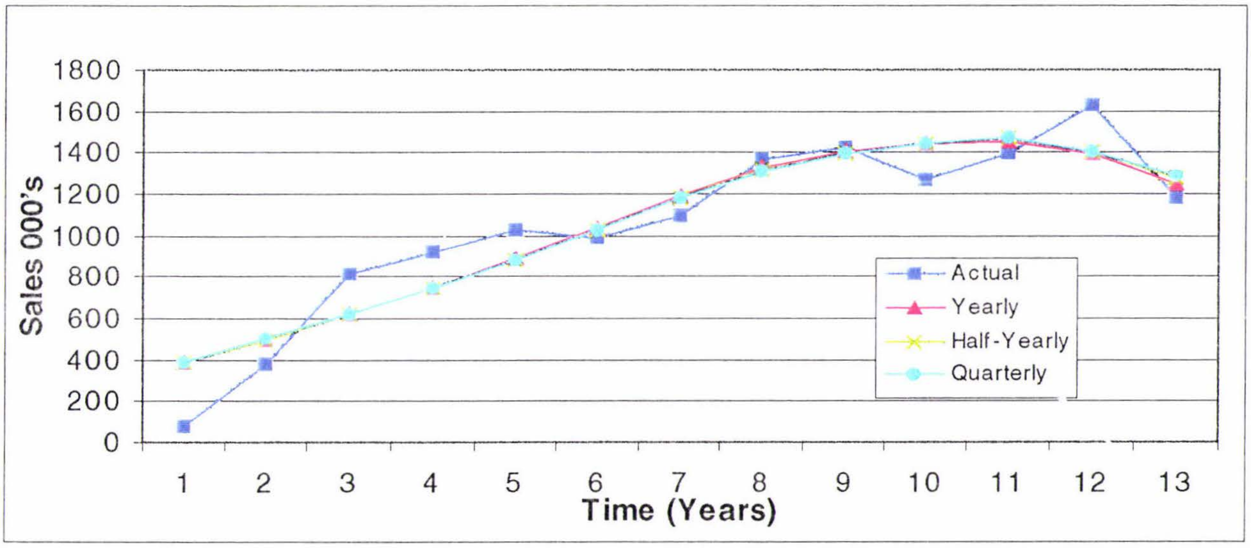
The yearly and half-yearly models have similar sales patterns but the quarterly model produces a different diffusion pattern and slightly worse fit.

Figure 5.31 Japan Video Camera – Annual Sales Predictions



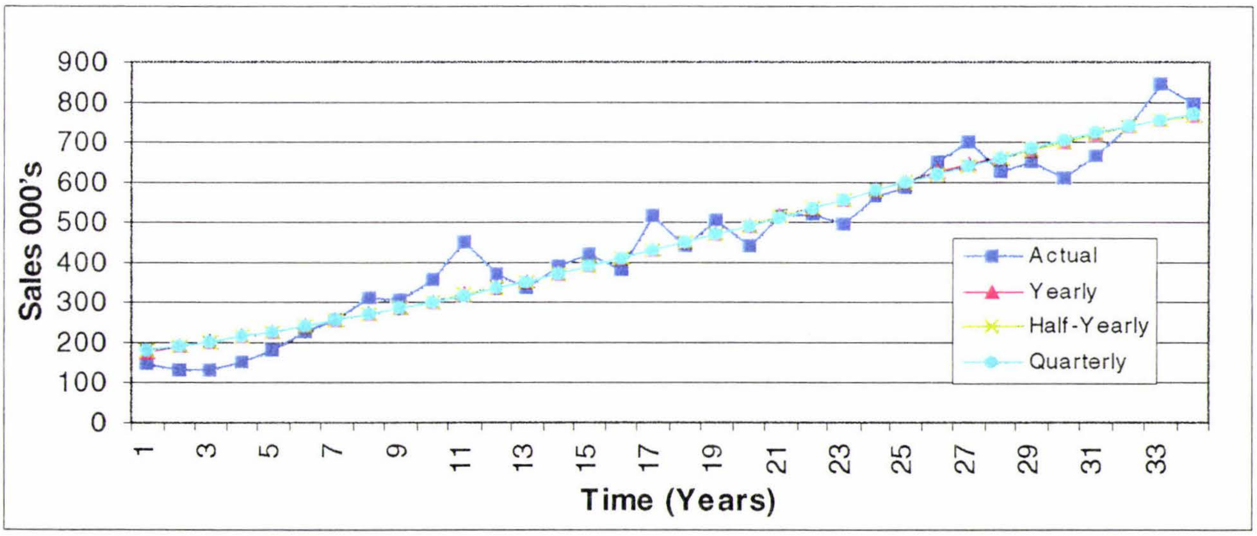
The different aggregation levels produce similar annual sales and measures of fit.

Figure 5.32 Japan Digital Audio Disk Player – Annual Sales Predictions



A stable annual sales pattern is produced across the aggregation levels for digital audio disk player.

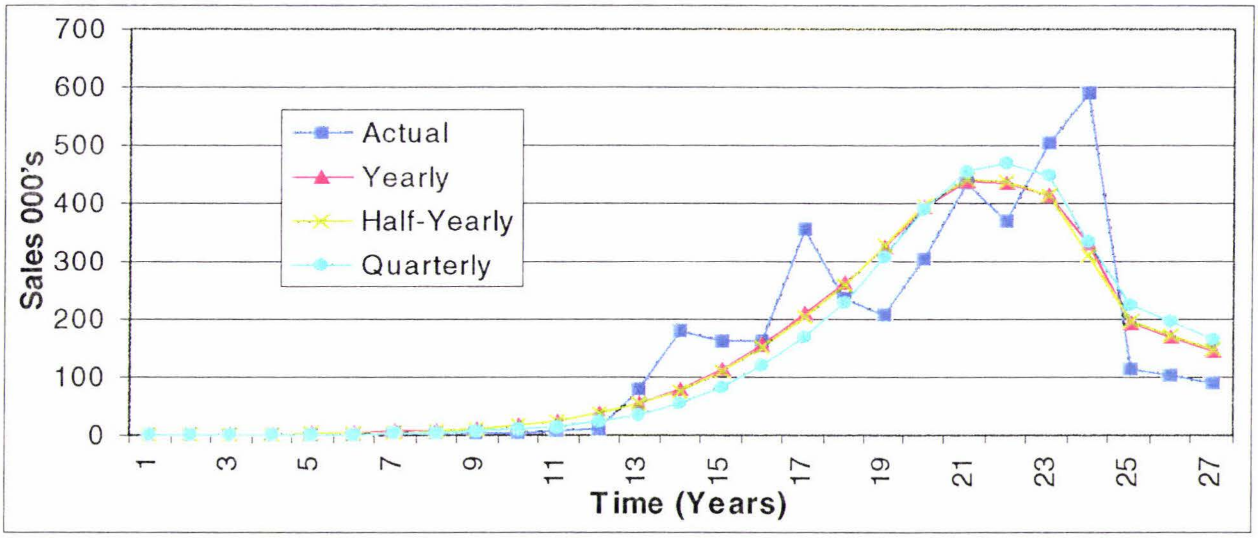
Figure 5.33 Japan Vacuum Cleaner – Annual Sales Predictions



The model produces very stable estimates of annual sales and adjusted R^2 across the levels of aggregation.

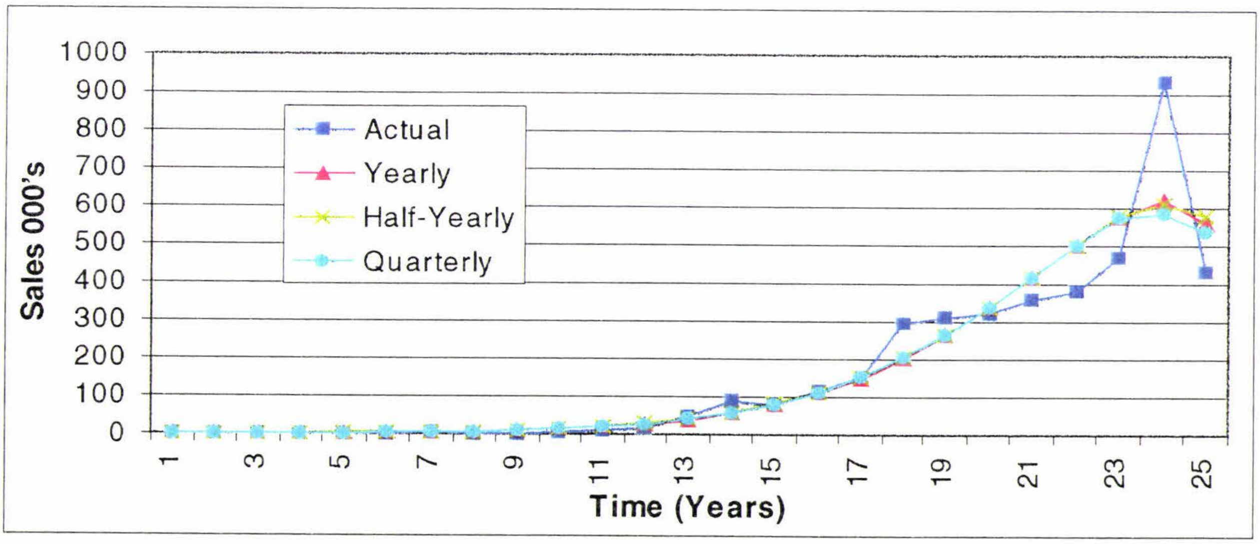
5.3.5.2 Taiwan – Annual Sales Estimates Across Aggregation Levels

Figure 5.34 Taiwan Air Conditioner – Annual Sales Predictions



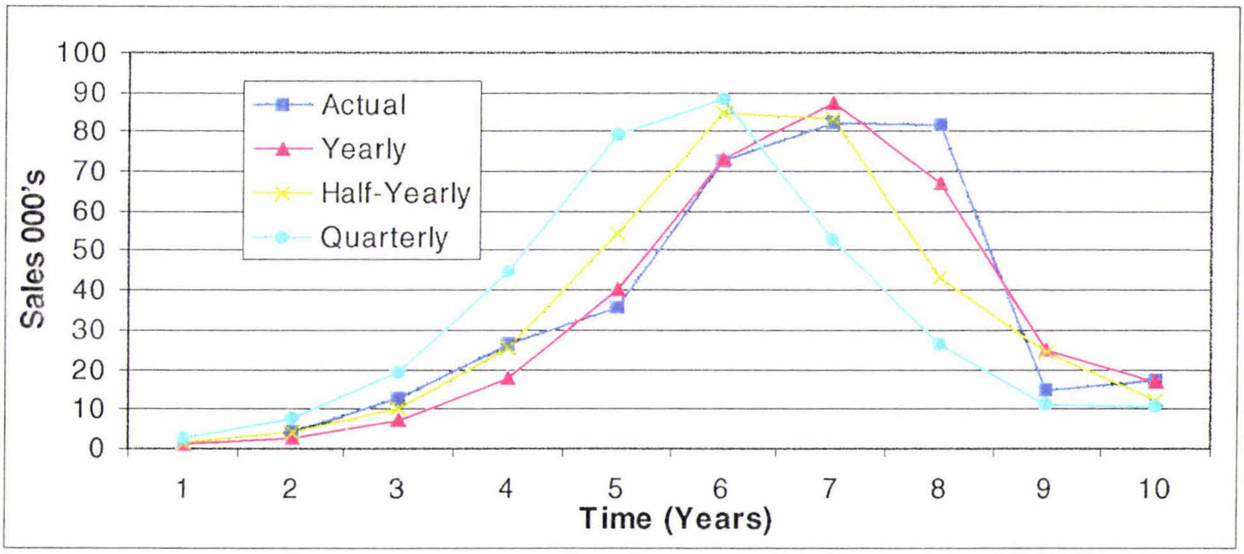
The quarterly model has a slightly different pattern of annual sales compared to the half-yearly and yearly models though the fit of the model is broadly similar.

Figure 5.35 Taiwan Personal Computer – Annual Sales Predictions



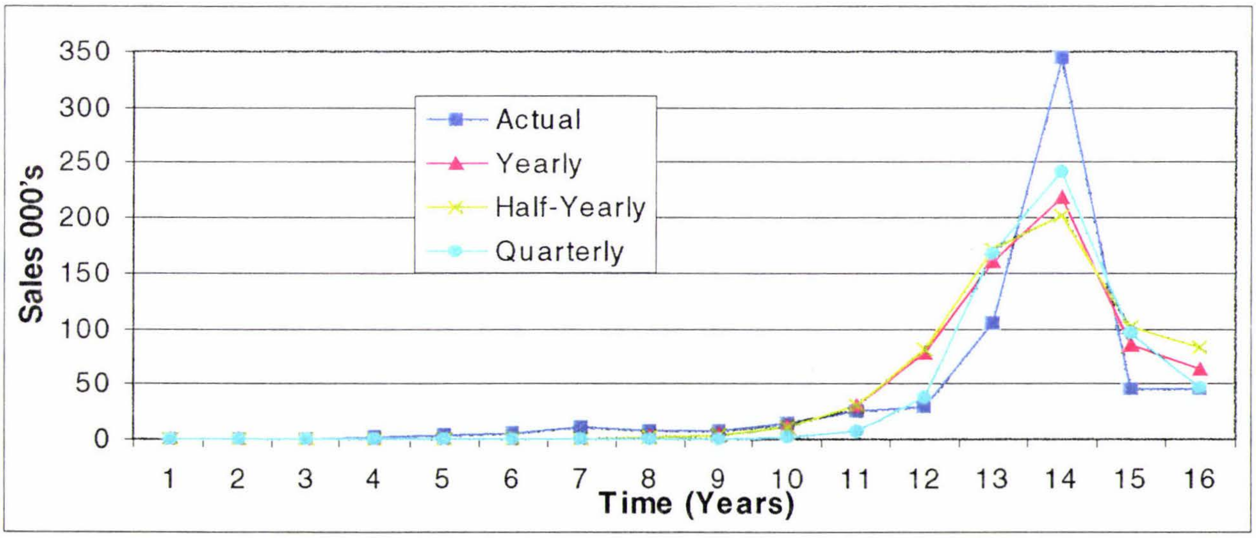
A similar diffusion pattern and fit is seen across the aggregation levels for personal computer in Taiwan.

Figure 5.36 Taiwan Facsimile – Annual Sales Predictions



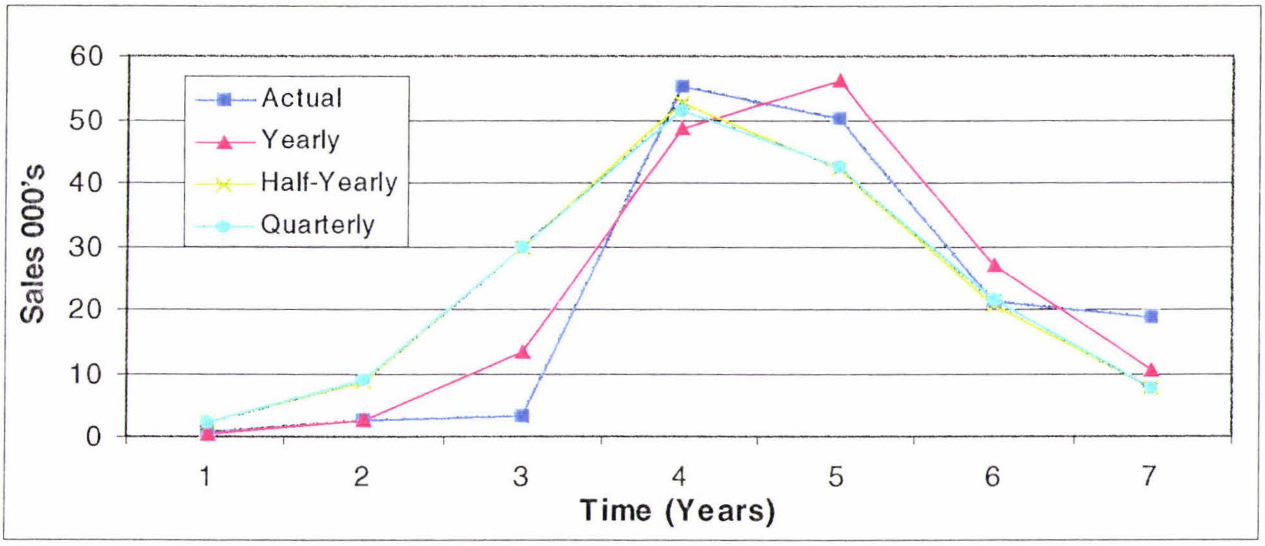
The yearly, half-yearly, and quarterly models for facsimile produce vastly different diffusion patterns and measures of fit compared to the actual annual sales. Of the three, the annual sales estimates are the closest to the actual pattern.

Figure 5.37 Taiwan Video Cassette Recorder – Annual Sales Predictions



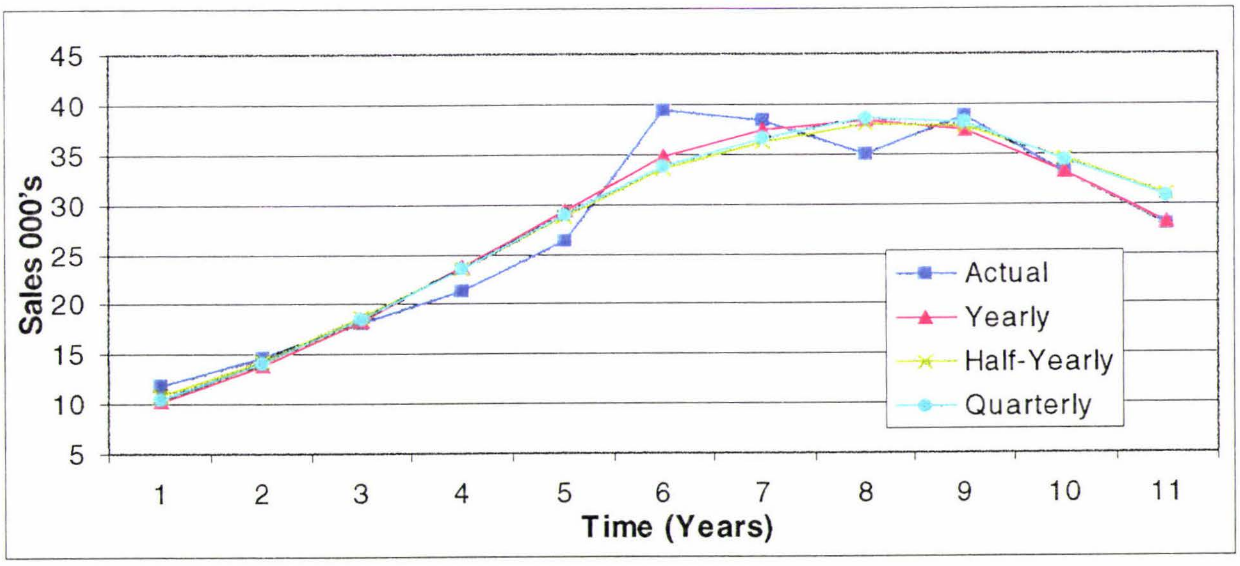
Different sales patterns are produced by the three models especially around peak sales. This divergence at the peak translates into the measures of fit with the quarterly model best capturing the dramatic increase in sales in the peak sales period and consequently having the highest adjusted R^2.

Figure 5.38 Taiwan Microwave Oven – Annual Sales Predictions



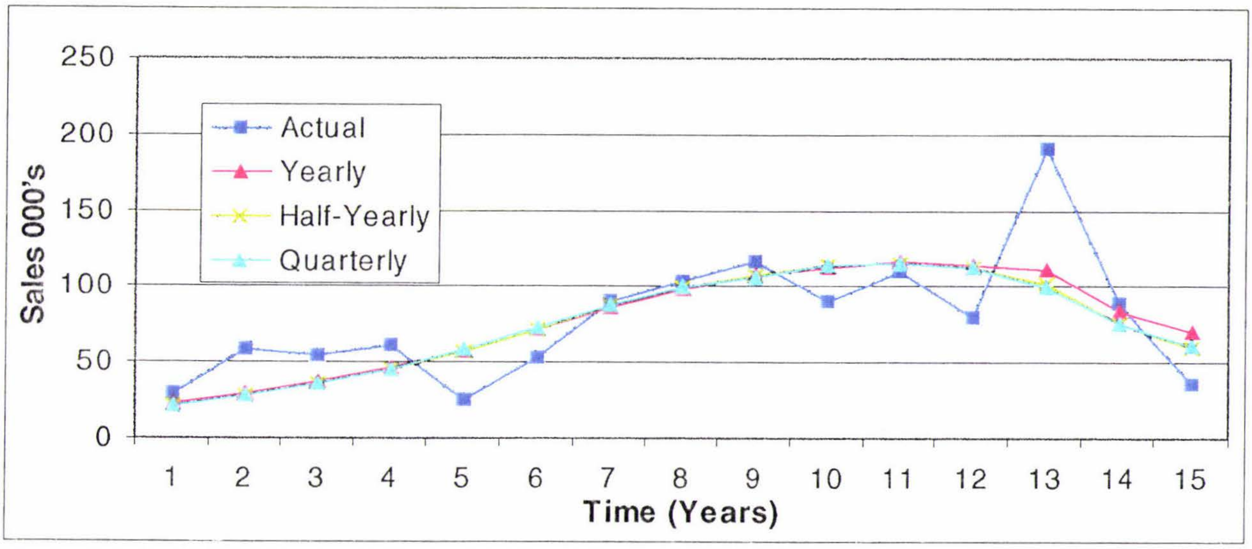
The quarterly and half-yearly models produce sales estimates that are substantially different from the yearly models. The yearly model has the best fit overall with seasonal variation impacting upon the quarterly and half-yearly model estimates.

Figure 5.39 Taiwan Induction Cooker – Annual Sales Predictions



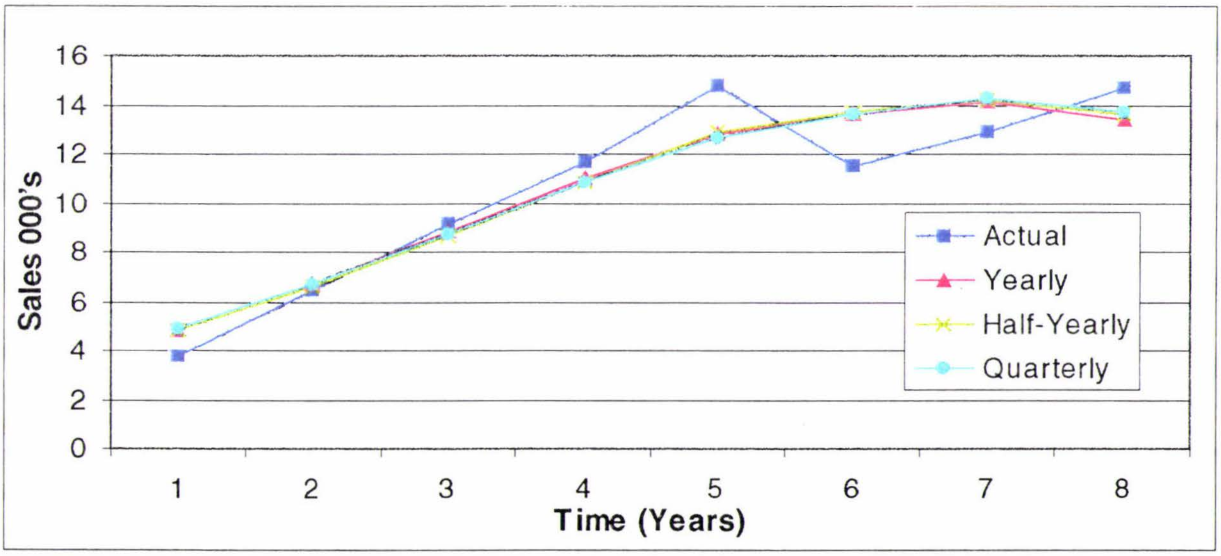
The diffusion curves and fit statistics are similar across the aggregation levels.

Figure 5.40 Taiwan TV Game – Annual Sales Predictions



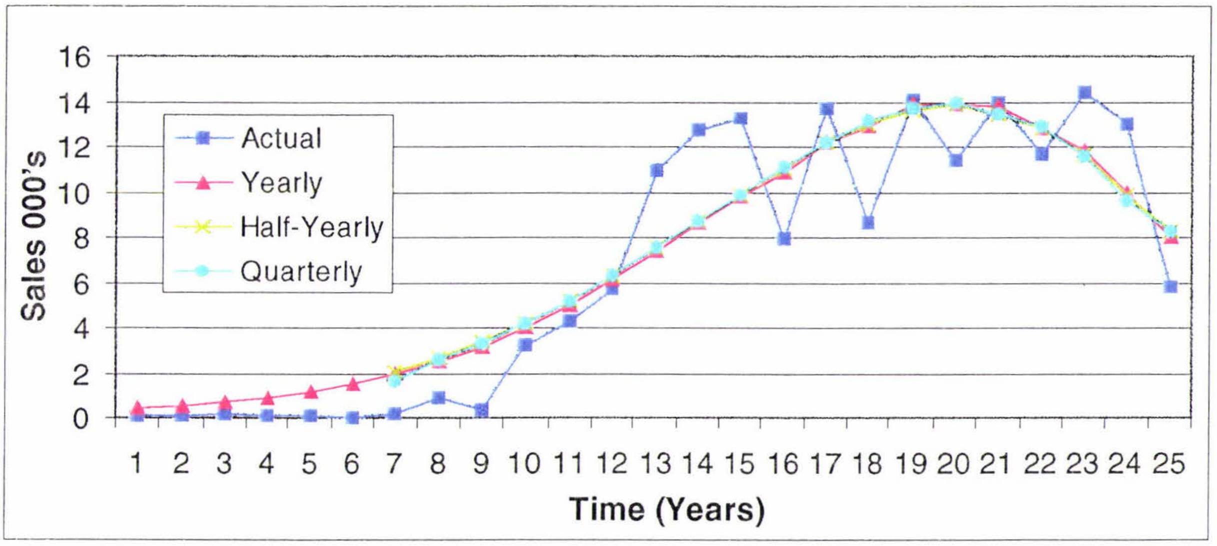
The different models produce similar sales patterns across the aggregation levels but peak sales is captured best by the yearly model which therefore has the best fit.

Figure 5.41 Taiwan Floppy Disk – Annual Sales Predictions



A similar diffusion pattern and fit is seen across the aggregation levels for floppy disk in Taiwan.

Figure 5.42 Taiwan Clothes Dryer – Annual Sales Predictions



The yearly, half-yearly and quarterly models produce similar diffusion patterns for clothes dryer in Taiwan.

In conclusion, in most cases (especially Japan) annual sales estimates across the aggregation levels are similar. However, for the products facsimile, VCR and microwave oven in Taiwan, different diffusion patterns are produced. An examination of the diffusion parameters of these products reveals that they are the only products with $q > 1$. Diffusion curves with $q > 1$ are steep about the peak sales level. For some reason, in these cases the estimate of peak sales differs across aggregation levels and this causes the different predicted sales patterns.

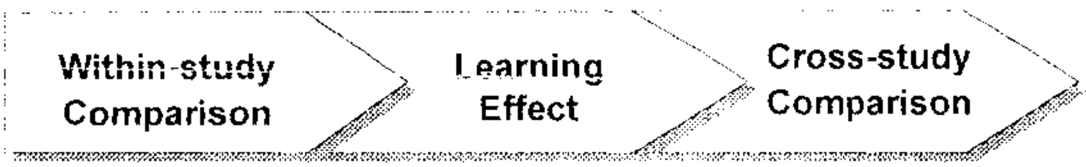
5.3.6 Conclusion – Stability Across Aggregation Levels

In general, the Bass model produces stable estimates across the aggregation levels. In particular, the model was robust across the aggregation levels in terms of:

- plausibility of parameters,
- model fit,
- parameter estimates, and
- annual sales estimates

Of note was the fact that the Taiwanese models were more unstable than the Japanese models in terms of model fit. However, these differences are hardly large enough to make a difference in practical applications. The coefficient of external influence p was relatively more unstable than q and m though this was not noticeably so. The annual sales estimates produced by the models were very similar except for the case where q [illegible] 1 in which case different diffusion patterns were predicted (for three Taiwanese products). Not surprisingly, R^2 was primarily affected by the amount of seasonality but this did not translate into differences in the parameter estimates or sales predictions.

6 CROSS-NATIONAL ANALYSIS OF DIFFUSION PATTERNS IN JAPAN AND TAIWAN



- significance test of diffusion parameters, p, q, and m, in both Japan and Taiwan
- compare diffusion parameters, p and q of same products between Japan and Taiwan

- detect the existence of learning effect between Japan and Taiwan

- compare diffusion parameters, p and q, obtained from this study with ones reported from other relevant studies

As the Bass model generated plausible diffusion parameters and sensible model solutions for Japanese and Taiwanese products, the focus of this study now shifts to a cross-national analysis of the diffusion of innovations in these two countries. The main objective of this analysis is to detect any significant differences in the new product diffusion process between the two countries and to determine whether the detected difference can be explained by the learning effect as proposed by *Ganesh and Kumar (1996)*.

Additionally, in order to expand the existing literature on international diffusion theory, the diffusion parameters of Japan and Taiwan were summarised and further compared with other relevant published research results. As annual data is the aggregation level that is most often used in multinational diffusion studies, only findings on yearly models were included in this chapter. In section 6.1, results on the significance of each diffusion parameter for all the products estimated in this study is reported. The learning model is then fitted to ascertain if a learning effect exists between Japan and Taiwan (6.2). Finally, a cross-study comparison of the diffusion parameters based on the five products common to both Taiwan and Japan was completed (6.3).

6.1 Within-Study Diffusion Comparison

As suggested in the relevant literature, the new product diffusion process is a phenomenon that varies between countries or different cultures. In an attempt to provide empirical evidence to support this assertion, the diffusion process of the five consumer durables with data from both countries were compared. The relevant statistical tests proceeded after the standard error of each diffusion parameter was obtained through simulation.

6.1.1 Significance of Diffusion Parameters in Japan and Taiwan

Before a comparison was made between the diffusion parameters in the two countries, the significance of the parameters was first gauged by testing if they were significantly different from zero. As shown in table 6.1, the estimated q (coefficient of internal influence) was found significant at the 99% confidence level in all cases. This indicates that interpersonal influence is a significant contributor to the diffusion of new products in both Japan and Taiwan. On the contrary, the external coefficient, p, was found not significantly different from zero in some cases, i.e. personal computer and facsimile in Japan, and air conditioner, personal computer, VCR, and microwave oven in Taiwan.

Except for the case of facsimile in Japan, the value of the market potential, m, was significant in all cases. The insignificance of the facsimile m was possibly the result of diffusion process not yet peaking. As the diffusion curve had a clear upward trend, it was difficult for the Bass model to provide an accurate estimate of the size of the potential market for this particular product. Consequently, the simulated standard error was large which caused the insignificance of the parameter value.

Table 6.1 Significance of diffusion parameters in Japan and Taiwan

Product	p	standard error	q	standard error	m	standard error
Japan						
Air Conditioner	0.038 **	0.0075	0.22 **	0.08	880 **	52
Personal Computer	0.0001	0.0005	0.18 **	0.03	474548 *	227252
Facsimile	0.001	0.0012	0.20 **	0.05	29152	43001
VCR	0.039 **	0.0054	0.38 **	0.05	5418 **	304
Microwave Oven	0.008 **	0.0016	0.19 **	0.04	5418 **	1423
Video Disk Player	0.035 **	0.0080	0.26 **	0.07	888 **	137
Video Camera	0.032 **	0.0047	0.46 **	0.07	7588 **	724
Digital Audio Disk Player	0.017 **	0.0024	0.26 **	0.04	19579 **	1878
Vacuum Cleaner	0.004 **	0.0007	0.07 **	0.01	44181 **	14469
Taiwan						
Air Conditioner	0.00009	0.0001	0.40 **	0.06	4309 **	443
Personal Computer	0.00007	0.0001	0.36 **	0.09	6597 **	1489
Facsimile	0.0015 *	0.0008	1.03 **	0.10	358 **	24
VCR	0.0000005	0.000001	1.09 **	0.07	702 **	124
Microwave Oven	0.0012	0.0018	1.75 **	0.25	146 **	22
Induction Cooker	0.022 **	0.0018	0.35 **	0.02	390 **	21
TV Game	0.013 *	0.0056	0.29 **	0.09	1477 **	197
Floppy Disk	0.032 **	0.0047	0.38 **	0.08	128 *	65
Clothes Dryer	0.0018 **	0.0006	0.26 **	0.03	203 **	20

** 99% confidence level   * 95% confidence level

The specific level of significance was determined by calculating confidence intervals around the parameter estimate:

$x \pm 1.645$ * simulated standard error. 90% level of confidence;

$x \pm 1.96$ * simulated standard error. 95% level of confidence;

$x \pm 2.575$ * simulated standard error. 99% level of confidence.

where

x = estimated diffusion parameter (p, q, and m).

If the interval did not include zero, then the parameter was deemed significantly different from zero at the specific level of confidence. These results also add insight to the validity of the Bass model. The overwhelming majority of parameters are significant, suggesting the Bass model is capturing some of the significant diffusion effects.

6.1.2 Difference between Diffusion Parameters in Japan and Taiwan

As the diffusion parameters reflect the underlying assumptions of the diffusion process, it is the difference in these behaviours between Japan and Taiwan that is of interest. In this section, the coefficients of external and interpersonal influence for the five common consumer durables were compared. The simulated standard errors for each diffusion parameter enabled the calculation of the level of significance for the difference between the two countries.

The following test was used to determine the z-value and consequently alpha for the products where data existed for both countries.

$$Z = (x_{Japan} - x_{Taiwan}) / SQRT(\sigma^2_{Japan} + \sigma^2_{Taiwan})$$

where

x = estimated diffusion parameter (p, q or m) for Japan and Taiwan

σ^2 = simulated standard error

Table 6.2 **Significance of the differences between Japanese and Taiwanese Parameters**

Product	*p* Japan	*p* Taiwan	z value	alpha	*q* Japan	*q* Taiwan	z value	alpha
Air Conditioner	0.032	0.00009	5.0262	0.0001 ***	0.22	0.40	-1.82	0.04 *
Personal Computer	[illegible]	0.00007	0.1739	0.43	0.18	0.36	-1.9	0.03 *
Facsimile	[illegible]	0.0015	-0.6282	0.268	0.20	1.03	-7.5	0.0001 ***
VCR	0.039	0.0000005	7.1962	0.00 ***	0.38	1.09	-8.61	0.0001 ***
Microwave Oven	0.008	0.0012	2.9520	0.0016 ***	0.19	1.75	-6.20	0.0001 ***

Note: *** at the 99% level of confidence
** at the 95% level of confidence
* at the 90% level of confidence

As shown in table 6.2, in the case of air conditioner, VCR, and microwave oven, the external coefficient p of Japan and Taiwan were significantly different from each other at the 99% level of confidence. Clearly, a relatively high level of innovativeness is present in the Japanese market.

However, this trend was not observed for personal computers and facsimiles. The statistical tests revealed that the difference between the external coefficient, p, was not significantly different between these two countries. This difference could be due to the fact that personal computers and facsimiles have more of a business orientation. Given competitive pressures and market forces, businesses in Japan and Taiwan would both have the same need to adopt these products. In contrast, air conditioners, VCRs, and microwave ovens, are more likely to be observed. It would seen that Japanese consumers are more innovative than their Taiwanese counterparts.

The discrepancy between Japanese and Taiwanese internal coefficient q was found significant in all cases, with a 95% confidence level for air conditioners and personal computers and a 99% confidence level for facsimiles, VCRs, and microwave ovens. The level of internal influence is about two times greater for air conditioners and personal computers, three times greater for VCRs, five times greater for facsimiles and nine times greater for microwaves in Taiwan compare to Japan. No systematic differences for these rates exist across products. Needless to say, these findings indicate that the rate of adoption is faster in Taiwan than in Japan (since internal influence, q, is the dominant factor in the new product diffusion process).

Contrary to the above findings, in another cross-national diffusion analysis conducted by Takada and Jain (1991), the authors found no significant difference in the value of q (interpersonal coefficient) between Japan and Taiwan. Instead, the difference was detected between US and the other three Asian countries, i.e. Japan, Taiwan, and South Korea. The authors proposed explanation for the similar diffusion patterns between those three Asian countries were based on the concept of cultural orientation (Hall, 1976, 1987) and the time effect.

According to the theory of cultural orientation, Japan, Taiwan, and South Korea are regarded as countries with high-context culture, where the transfer of an idea occurs most frequently due to the common, singular cultural background shared by individuals (Takada and Jain, 1991). Thus, this factor explains why a similar diffusion pattern was observed for those countries and the rate of adoption was faster in these countries than in the relatively more multicultural United States.

The time effect theory advocates that the later a product is introduced to a country, the faster the rate of adoption will be as potential consumers have more time to understand the relative advantage of the product. Consequently, the authors claim the average time gap of 20 years in the introduction of these products to the US compared to the selected Asian countries explains the higher rate of adoption. However, it is interesting to note that the average time lag of 10 years between Japan and Taiwan did not seem to have the same effect on the diffusion rates in the same study (Takada and Jain, 1991).

The contradictory results obtained in this study (in comparison to Takada and Jain) raises the interesting proposition of diffusion patterns in a specific country varying over time - an outcome possibly induced by changes in market characteristics and consumer behaviour. In contrast to the findings of Takada and Jain (1991), the level of interpersonal influence for all innovations tested was significantly larger in Taiwan than Japan.

In order to explore the possible reasons for the differences across the studies, the ranges of the internal coefficients, q_{Japan} and q_{Taiwan}, were examined. It was found that the internal parameter q in Japan was generally smaller for this study, ranging from 0.176 to 0.38, than for Takada and Jain (1991) which ranged from 0.19 to 0.76. In contrast, the level of internal influence remained high for Taiwan across the studies with a range of 0.36 to 0.75 for Takada and Jain (1991) compared to a range of 0.36 to 1.75 for this study.

In this case, the theory of communication cannot be used to explain the difference because the ethnic composition of each country has not changed for the past time been. Additionally, the difference in the level of internal influence is unlikely to be the result of any time effect. In reality, the time gap between the introduction of new products to Japan and Taiwan has shortened considerably for the products tested by Takada and Jain (1991) to those tested here.

Three plausible reasons for the inconsistency between the two studies can be forwarded. First, the types of products included in the two studies were different. The products examined by Takada and Jain (1991) were older generation home appliances such as Black and White Televisions and Refrigerators while this study examined newer technological innovations such as home entertainment products.

Second, the origin and sequence of product introduction is different across the studies. Takada and Jain (1991)'s study had products that largely originated from the United States or from European countries. In contrast, the new technologies (such as digital audio tape recorder and new generation VCRs) included in this study were initially introduced in Japan and then sold in other markets. This could explain the different diffusion patterns in Japan and Taiwan seen in this study.

Finally, and related to the previous point, the Japanese economy has experienced drastic post-war development and is the only officially developed country in Asia. Moreover, Japan's advancement in the invention and production of new generation electrical and communication appliances means their consumers are amongst the most well-informed groups in the world. This combination has more than likely created more sophisticated consumers who have comprehensive knowledge of recent innovations. Consequently, modern Japanese consumers might have become more innovative and now rely less on personal recommendation when compared to their Taiwanese counterparts. These results and the apparent differences with the study by Takada and Jain (1991) indicate the time lag effect may be becoming inconsequential as an explanation of the differences between diffusion parameters across countries. While it may have been a factor for traditional products in the 1970s and '80s, products [illegible] lead and lag countries with a much smaller time interval.

6.2 The Learning Model

The learning model was estimated for the five products where data existed for both Japan and Taiwan (i.e. air conditioner, personal computer, facsimile, VCR, and microwave oven). The assumption was made that any learning effect that existed would be from Taiwanese consumers being influenced by their Japanese counterparts. There are strong economic and behavioural factors to support this assumption. A detailed discussion of the learning model appears in the literature review.

First, the Japanese economy is much larger and consequently more likely to influence the Taiwanese economy than vice versa. Second, the Japanese economy is the major innovator and manufacturer of consumer goods in the region and for some products the world. Therefore, Taiwanese manufacturers follow the lead established in Japan. Thirdly, Taiwanese consumers value Japanese products highly and consequently the information that emanates from that country. If a product has proven to be reliable and successful in Japan, Taiwanese consumers are likely to know this.

The results from the learning model are presented below in table 6.3. As [illegible] standard errors were not [illegible] for the learning models, the values of p, q, and m from the original Bass model shown [illegible] are also presented below.

Table 6.3 Comparison of the Taiwanese Bass Model and Learning Model Parameters

Product	Original Bass Model				Learning Model			
	p	q	m	Adj. R^2	p	q	c	Adj. R^2
Air Conditioner	0.000	0.40	4309	80.3%	0.0001	0.39	0.02	80.6%
Personal Computer	0.0001	0.36	6597	87.2%	0.0001	0.30	1.75	89.0%
Facsimile	0.001	1.03	358	94.3%	0.0016	1.02	0.21	94.3%
VCR	0.0000005	1.09	702	79.8%	0.0000004	1.09	0.03	79.8%
Microwave Oven	0.001	1.75	146	89.7%	0.0013	1.71	0.03	91.7%

Clearly, for the products air conditioner, VCR, and microwave oven, the learning effect (c) is small and likely to be insignificant. The addition of this parameter adds little to the overall fit of the diffusion model as represented by the adjusted R^2. However, for the products personal computer and facsimile, the learning parameter is sizeable and likely to be significant (especially for personal computer). In the case of personal computer, the addition of the learning model makes a noticeable difference to the adjusted R^2. Again, personal computer and facsimile are products that have a strong business orientation. It seems that Taiwanese businesses are quick to follow the lead set by their Japanese counterparts but Taiwanese consumers are less affected.

More importantly, the additional parameter does not have a sizeable effect on the estimated values of p and q from the original Bass model. In all cases, the difference between the estimates is not significantly different at the 95% level of confidence (based on the simulated standard errors for the original Bass model presented previously). In fact, the differences between the learning model estimates of p and q for Taiwan and the Japanese estimates are still likely to be significantly different. Therefore the difference between the Japanese and Taiwanese parameters cannot be explained as a consequence of learning between the lead and lag countries. The lack of change in the values of the estimated parameters also adds to the validity of the Bass model and supports the underlying behavioural assumptions.

As well as comparing the parameters, the annual sales predictions produced by the Bass and learning models were compared. The following graphs (figures [illegible] to [illegible]) show few substantial differences between the predictions except for personal computer, where the learning model performs much better, and microwave oven, of which most [illegible] post-peak sales. Of course, an improvement in performance would be expected as the learning model contains an extra parameter.

In conclusion, the addition of a learning parameter to the original Bass model does not radically improve the fit of the models for Taiwan. The learning parameter is however substantial for the business-oriented products, facsimile and personal computer, adding explanatory power to the model and suggesting that a waterfall strategy (expending more resources in Japan relative to Taiwan) is warranted. Furthermore, the significant difference between the parameters for Japan and Taiwan cannot be explained by the learning effect as the estimates are still likely to be significantly different after adding the learning parameter.

Figure 6.1 Air Conditioner – Sales Estimates from Bass and Learning Models

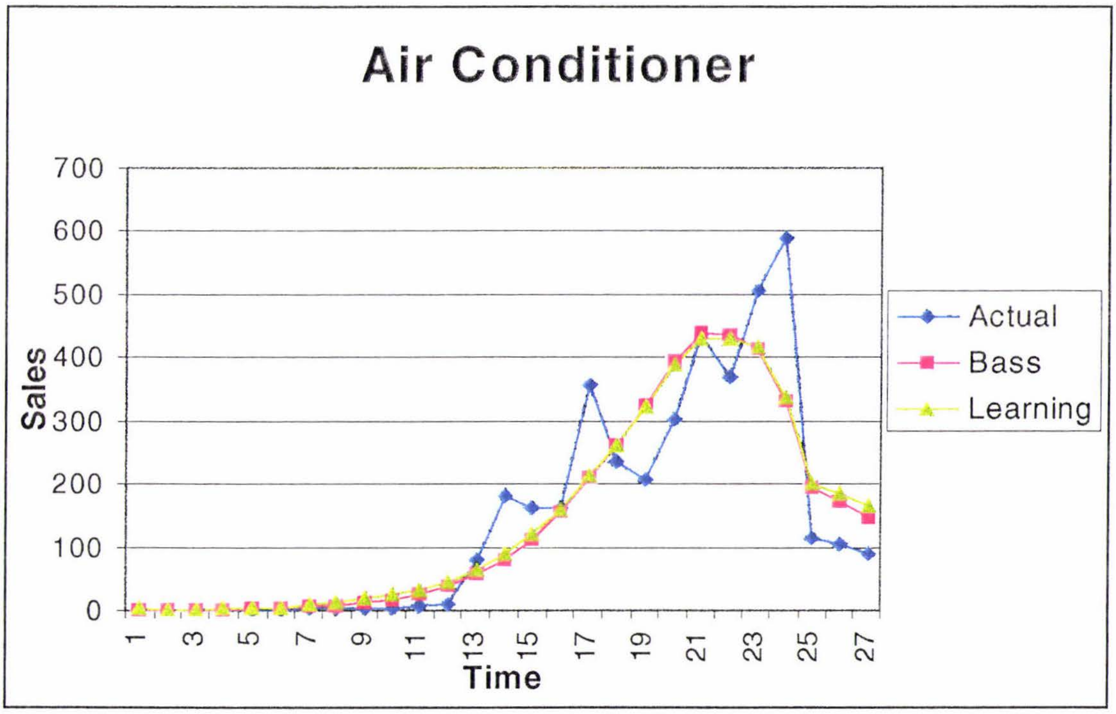


Figure 6.2 Personal Computer – Sales Estimates from Bass and Learning Models

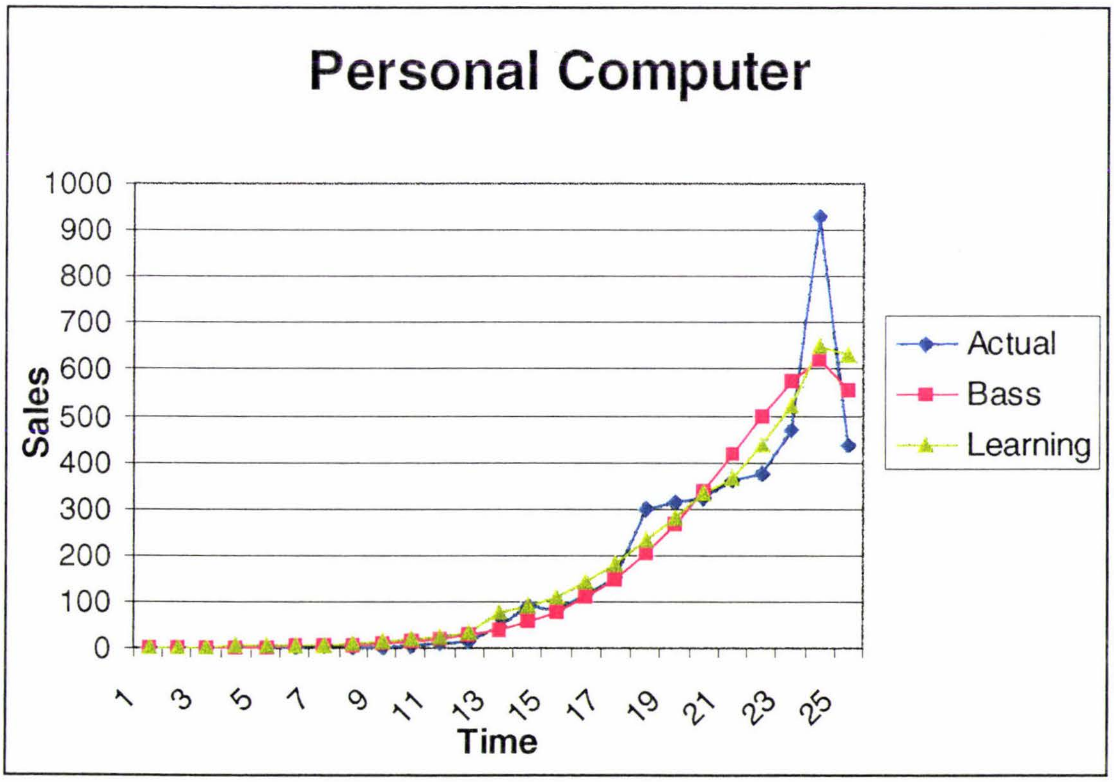


Figure 6.3 Facsimile – Sales Estimates from Bass and Learning Models

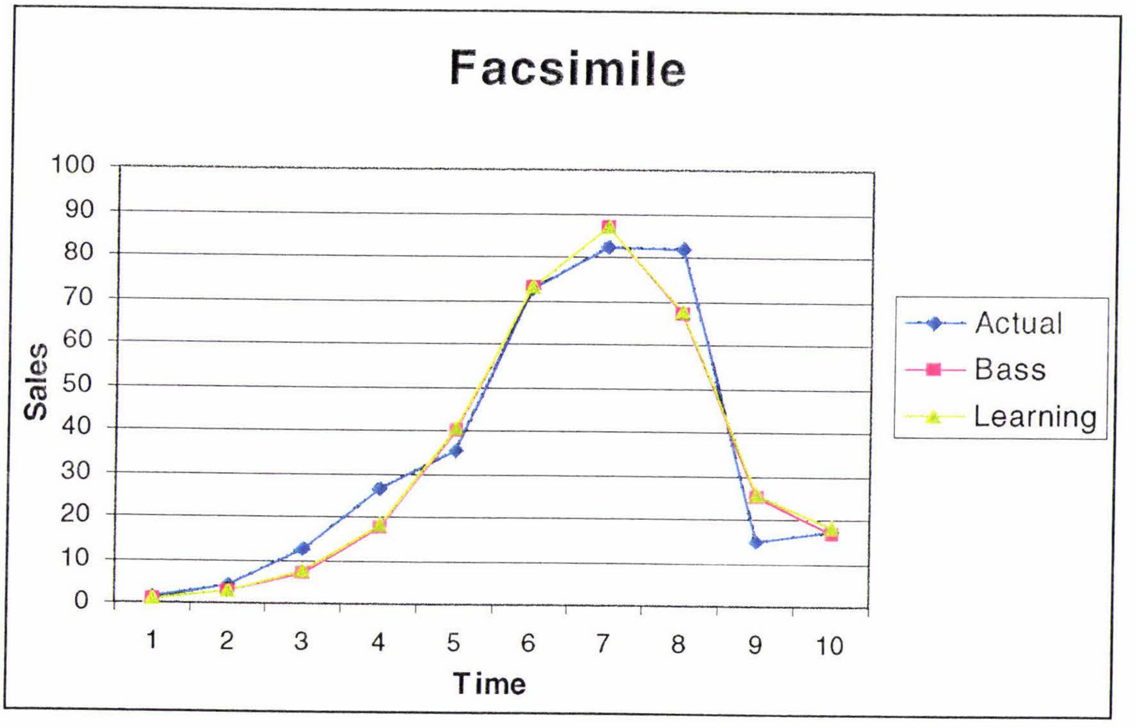


Figure 6.4 VCR – Sales Estimates from Bass and Learning Models

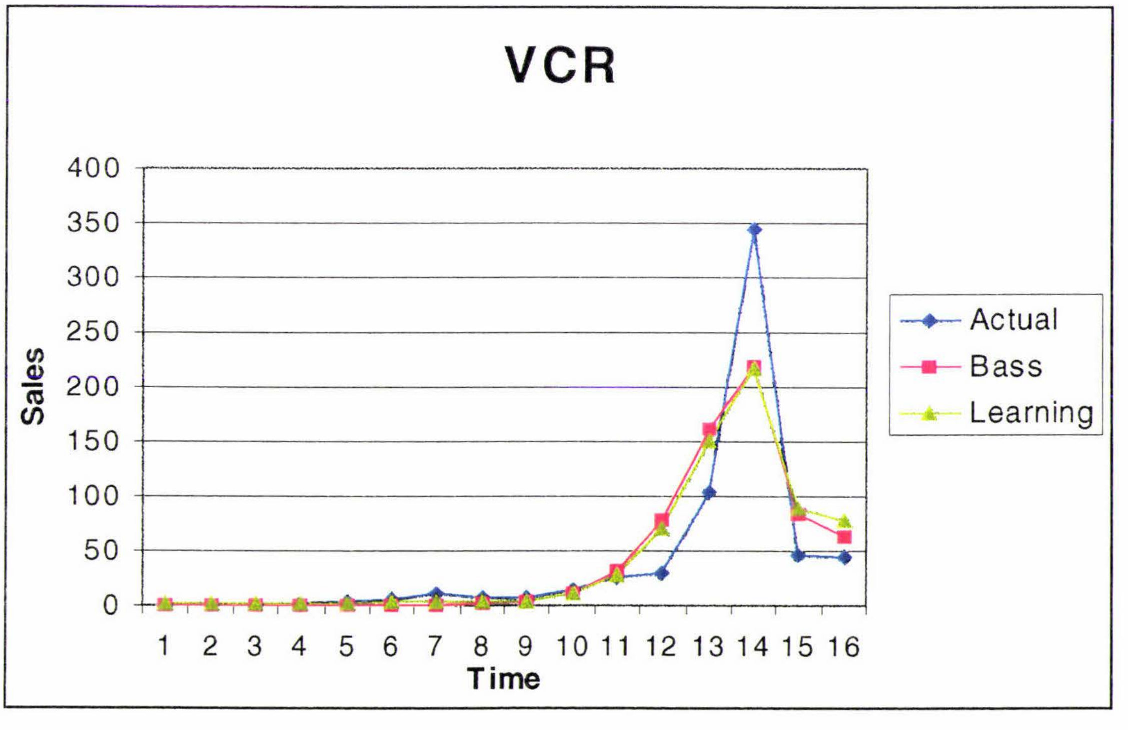
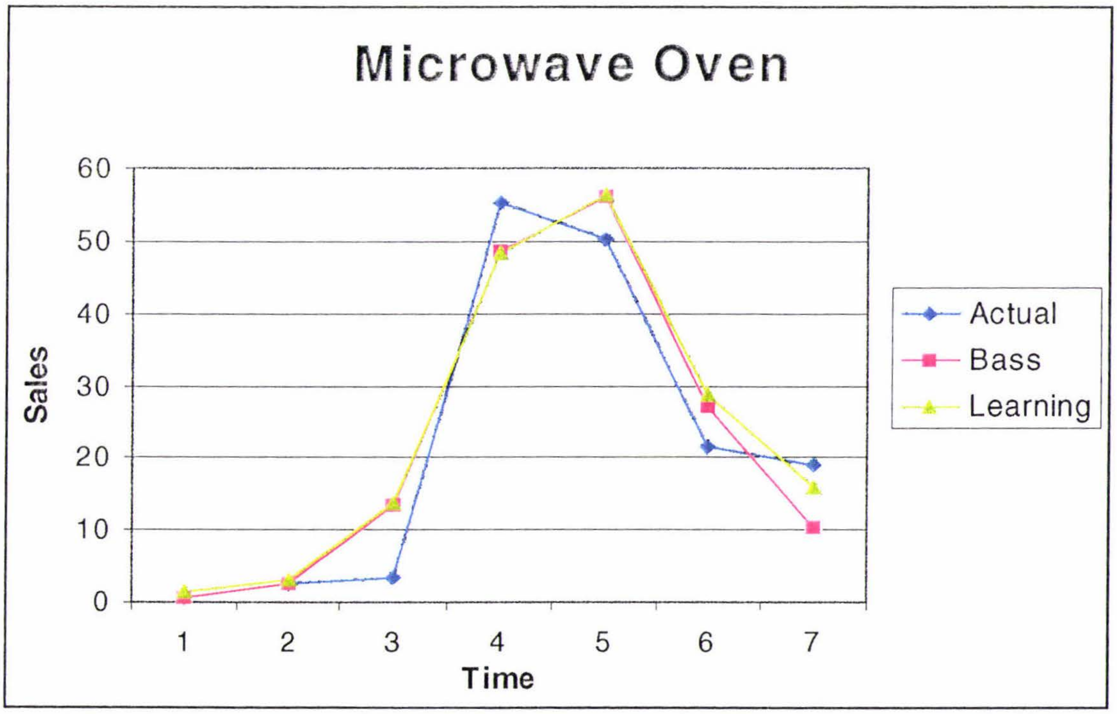


Figure 6.5 Microwave Oven – Sales Estimates from Bass and Learning Models



6.3 Cross-Study Diffusion Comparison

The focus of this section lies in comparing the Bass diffusion parameters for products in Japan and Taiwan with countries examined in other studies. As previously mentioned, one of the shortcomings of the existing international diffusion literature is the lack of research in regions other than the US or Europe. Takada and Jain (1991)'s study provided a preliminary insight into the diffusion of innovations in Japan, Taiwan, and South Korea. However, as products included in their research were mostly older-generation consumer durables, the results were unable to be compared with those more recent European studies.

In an attempt to broaden the knowledge on the diffusion of innovations in Asian markets and how it may differ from other regions, products included in this study were selected with the intention to enable a direct cross-national comparison. As a result, three out of four innovations used in the Ganesh, Kumar, and Subramanium (1997) were investigated in this study. The diffusion parameters of personal computer, VCR, and microwave oven in Japan and Taiwan are compared with those from numerous European countries.

Before comparing the diffusion parameters for specific products, the general trend of the parameter values in Japan and Taiwan are compared with those reported in the literature. Based on a meta-analysis conducted by Sultan, Farley, and Lehman (1990), the grand mean of the diffusion parameters p and q obtained by nonlinear estimation procedure were 0.040 and 0.302 respectively. As the diffusion of innovation varies between products, an average figure of this nature only provides a general indication of where typical diffusion parameters are located. It should not be used as the criteria for judging the magnitude of the diffusion parameters for specific products.

A preliminary comparison of the estimated diffusion parameter values (as listed in table 6.1) with the grand mean for p and q was undertaken. It would seem that the majority of Japanese external coefficients (p) were close to the average value reported in the meta-analysis while most of the Taiwanese parameter values were noticeably smaller than the grand mean. As for the internal coefficient q, with the exception of vacuum cleaner, the parameter values for all Japanese products were close to or within an acceptable range when compared with the grand mean. Again, more variations were observed among Taiwanese products. The q values for facsimile and VCR were nearly three times more than the mean value found by Sultan, Farley and Lehmann (1990) and more than five times larger for microwave oven.

Based on these results, it could be concluded that the majority of the diffusion parameter values were close to or within a plausible range to the meta-analysis grand mean, although some of the Taiwanese products demonstrated lower external and higher internal influences than the average diffusion parameter value found in the literature.

In order to gain more useful insight into the reasons for the diffusion parameters in Japan and Taiwan differing from those obtained for other countries, the estimated parameters from this thesis were compared to those reported by Ganesh, Kumar, and Subramaniam (1997). The diffusion of four new generation innovations in approximately a dozen European countries were investigated in their study (see figure 6.6). Based on Ganesh, Kumar, and Subramaniam (1997)'s findings, the value of the external coefficient, p, ranged from 0.0002 to 0.05, and the internal coefficient, q, extended from 0.23 to 0.91 (see figures 6.6 and 6.7 below).

Figure 6.6 Range of Reported *p*'s – Taiwan, Japan, and Europe

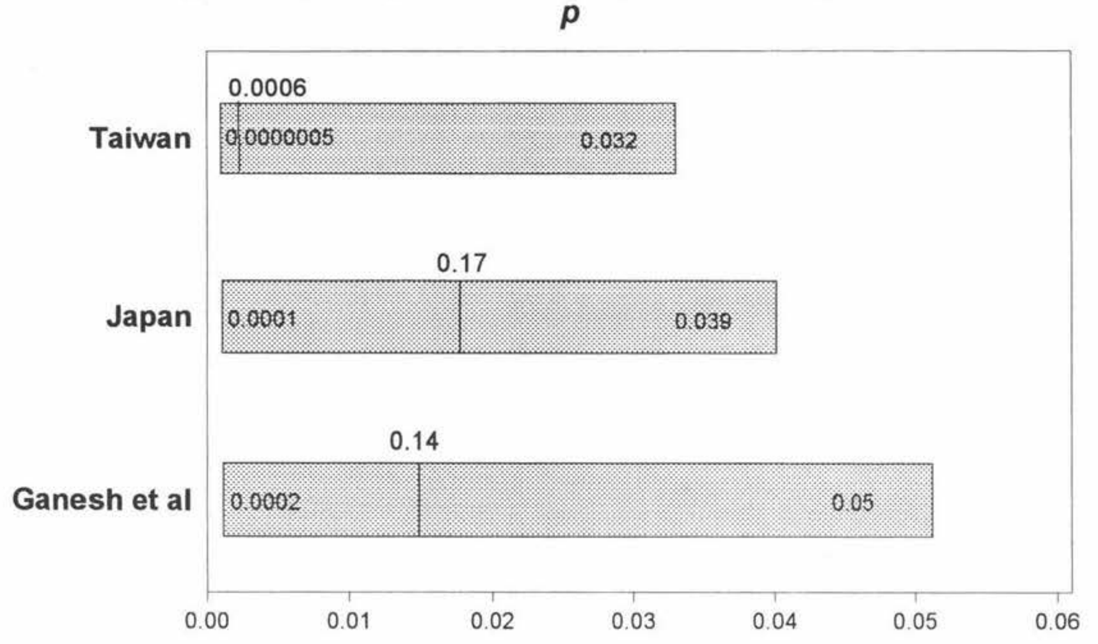
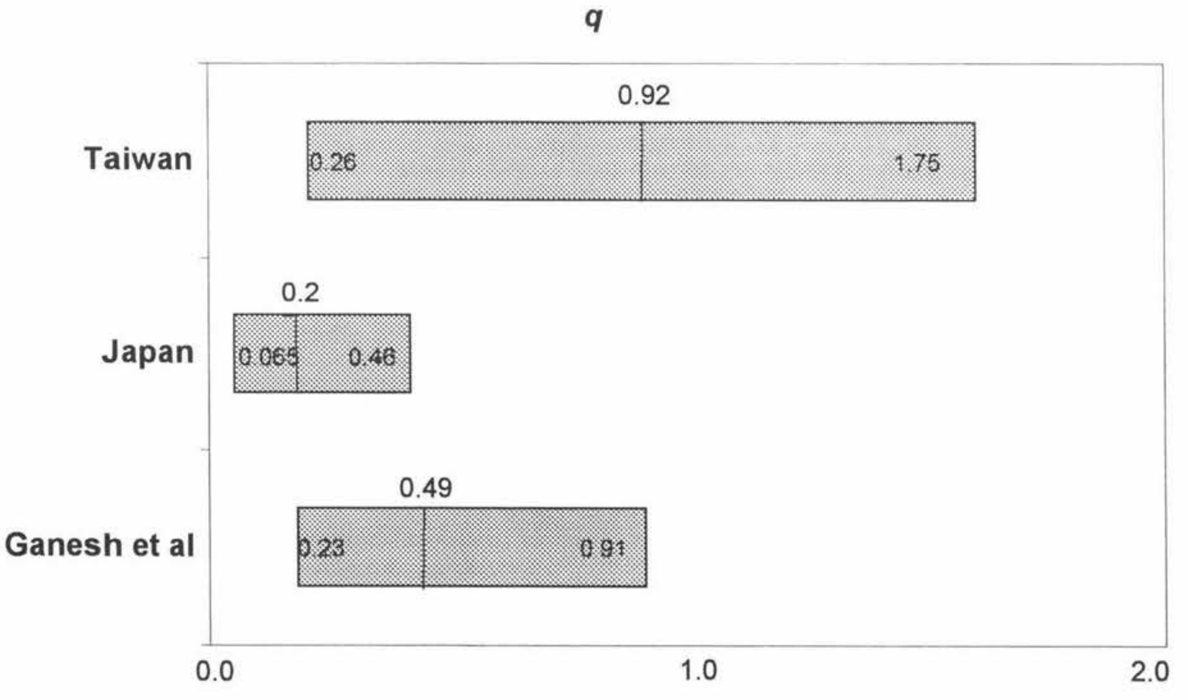


Figure 6.7 Range of Reported q's – Taiwan, Japan, and Europe



Using these values as a broad rule of thumb, it was found that, with the exception of personal computer where p equaled 0.0001, all Japanese external coefficients fell within the reported range. One prominent case was also observed for the internal coefficient q for vacuum cleaner (0.065) which was notably smaller than the lowest value reported by Ganesh, Kumar and Subramanium (1997). Although the q value of four other Japanese products, namely air conditioner, personal computer, facsimile, and microwave oven also fell out of this range, their coefficient values were in fact reasonably close to the lower limit of 0.23. In general, although the q tends to be comparably small in Japan, it can be concluded that the diffusion parameters of Japan are within a similar range as those for the European countries studied by Ganesh, Kumar and Subramanium (1997).

For Taiwan, three external coefficients were outside the 0.0002 to 0.05 interval being substantially smaller, i.e. 0.00009, 0.00007, and 0.0000005 for air conditioner, personal computer and VCR respectively. Interestingly, three products were also found to much have sizably different internal coefficients than those obtained for the European countries. In these cases however, the parameter values were larger than the upper limit, i.e. 1.03, 1.09, and 1.75 for facsimile, VCR, and microwave oven respectively.

These notably different cases indicate that the diffusion of new products in Taiwan is somehow different from those reported in European countries. This outcome was somewhat foreseen by Ganesh, Kumar, and Subramaniam (1997) who intimated that their "findings [could not] be generalised to other developing and less developed economies" (p 226). This was due to their models being based predominantly on data from developed European economies. This claim is consistent with the literature as it stresses the diffusion of innovation is a phenomenon affected by country-specific factors. Of course, it has yet to be determined conclusively what these factors are, the extent of there impact, and the direction of the effect.

After ensuring the results obtained in this study are generally comparable to those in the literature, some product-specific comparisons were carried out for the three products examined in both this study and that of Ganesh, Kumar, and Subramaniam (1997). The plots of the p and q estimates obtained from the respective studies and countries are shown in figures 6.6 through 6.8 on the following pages.

For personal computer, Taiwan and Japan have noticeably smaller external coefficients than other European countries. It is interesting to see that the European countries with the smallest values of p (i.e. Germany, Spain, France, and Italy) are relatively large in economic terms and developed economies. An explanation for this is not obvious. Japan as the economic powerhouse of Asia and Taiwan as the most successful "Asian Tiger" share similar characteristics with these countries. However, there are some factors unique to Taiwan and Japan that has inhibited the level of innovative behaviour with respect to personal computers.

Taiwan and Japan are closer to the European countries in respect of the coefficient of imitation (q). Nevertheless, Japan has the lowest internal coefficient of the countries examined although a reason for this is not readily available.

For VCR p, Japan is a definite outlier. Even the next highest country (United Kingdom) is more than four standard errors away from the Japan estimate. The most plausible explanation for this is the fact that the VCR was invented in Japan. This would have had a sizeable impact on the initial rate of adoption in Japan relative to the other countries.

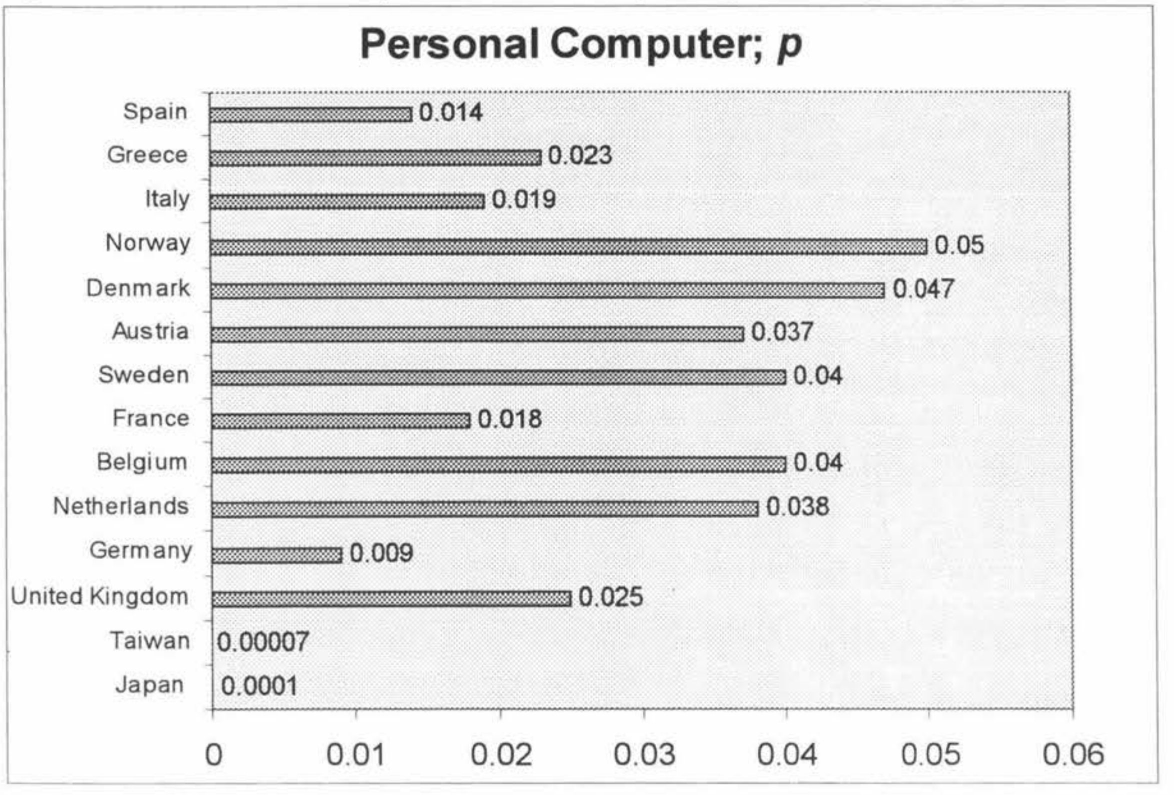
The main feature of the graph of the estimates of q for VCR is the significantly larger value for Taiwan. This value (1.09) is more than six standard errors larger than the q for Greece and Italy (0.65), the next highest countries. Obviously, word-of-mouth with respect to this product was strong.

For microwave oven, Japan has a significantly higher p coefficient and the smallest q value. Again, a reason for this is not readily apparent. However, the most striking feature for this product is the significantly high internal coefficient q for Taiwan. This is similar to VCR so the same explanation of word-of-mouth communication of the product benefits increasing the rate of adoption is applicable.

The main implication of this is that Japan, Taiwan, and possibly a number of other Asian countries have different innovation diffusion parameters to European nations. They tend to have smaller levels of external influence, p, especially Japan. For internal influence, Japan has comparatively lower q values while Taiwan has higher values than European nations. This difference suggests that treating Japan the same as Taiwan could be erroneous. The similarity between Japan and Europe could be due to the developed nature of the economies whereas Taiwan is still a developing nation.

Word of mouth is more important in Taiwan and less important in Japan in comparison to Europe. For marketers, it would be wise to be aware of these differences in order to construct differentiated plans for the respective countries. However, it should be noted that the differences that exist can be confounded by product specific characteristics. For example, the estimated q parameter for personal computers in Taiwan are similar to Europe, but for microwave ovens and VCR's they are greatly higher.

Figure 6.8 Personal Computer - Cross-Study Comparison of p and q



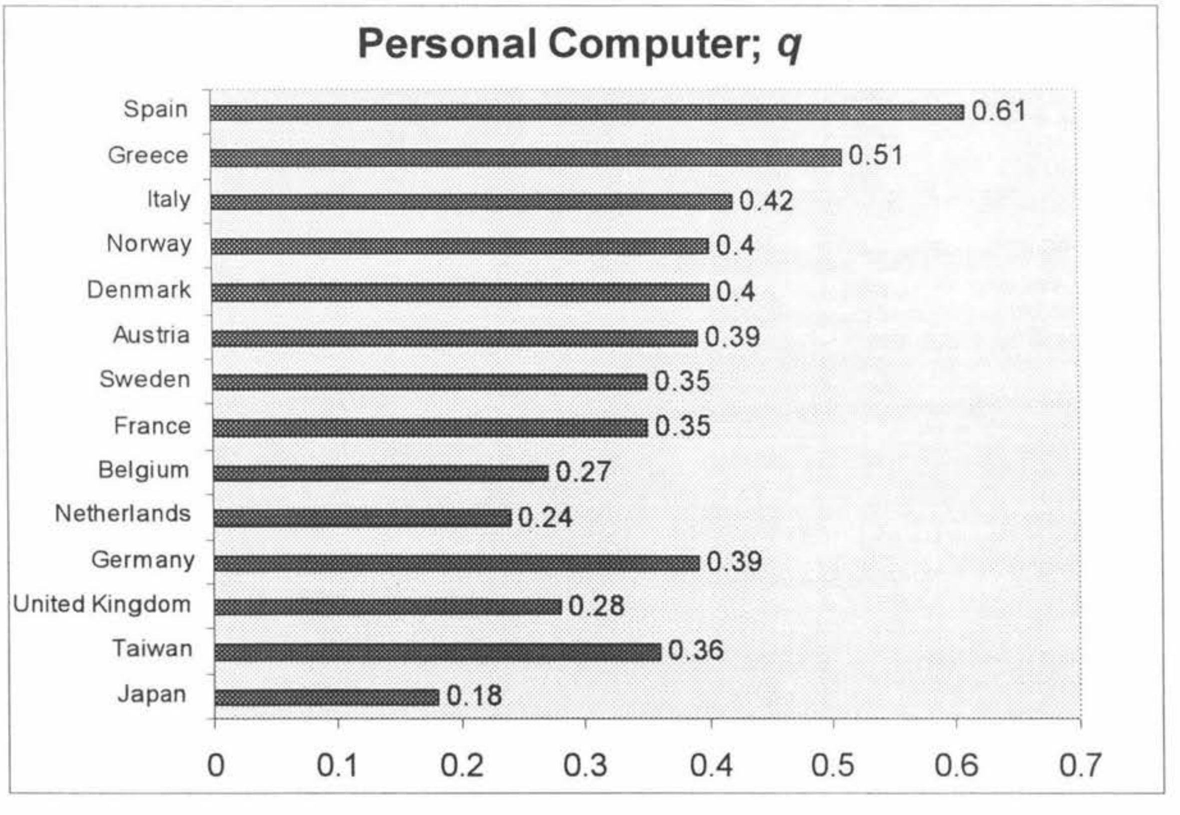
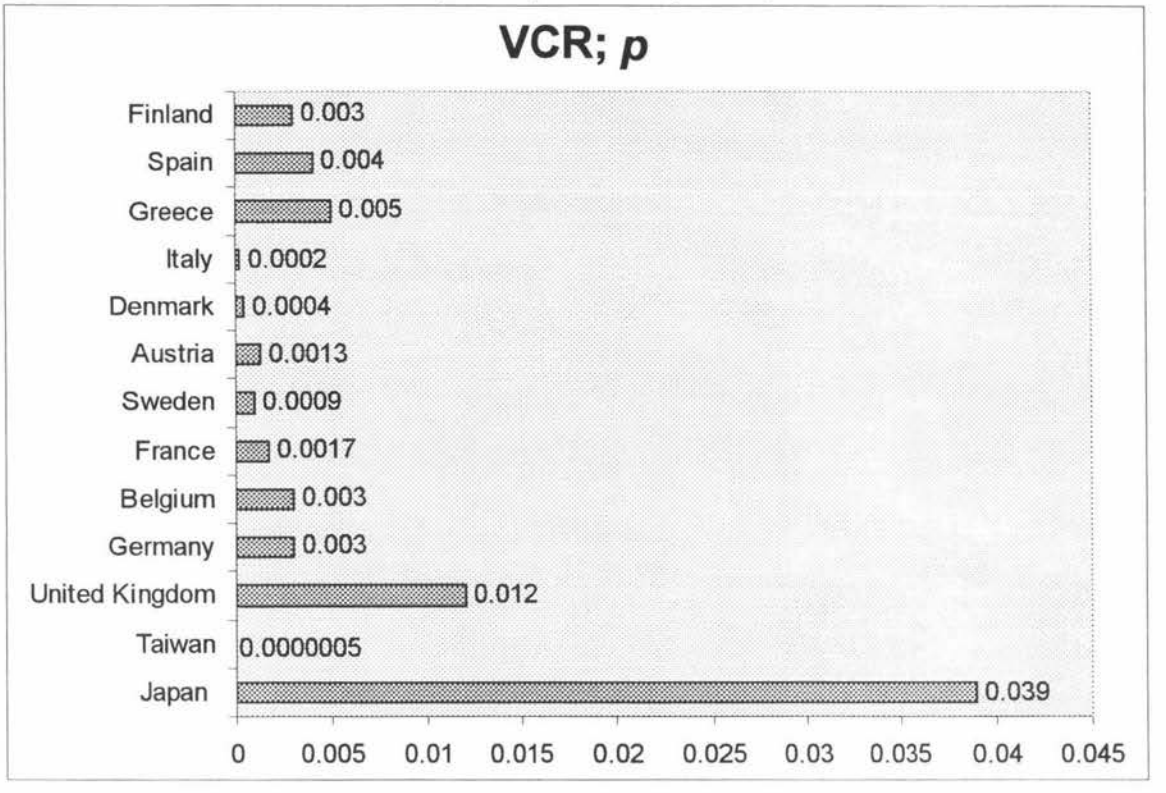


Figure 6.9 VCR - Cross-Study Comparison of p and q



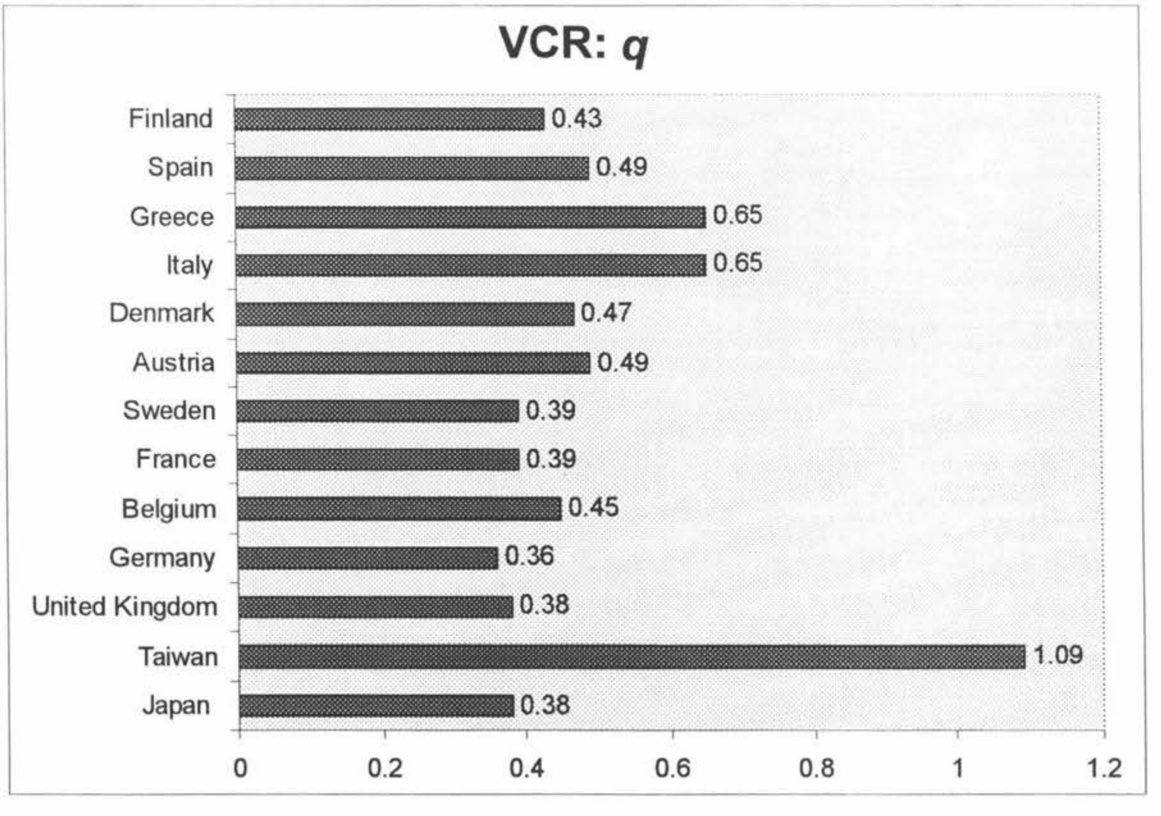
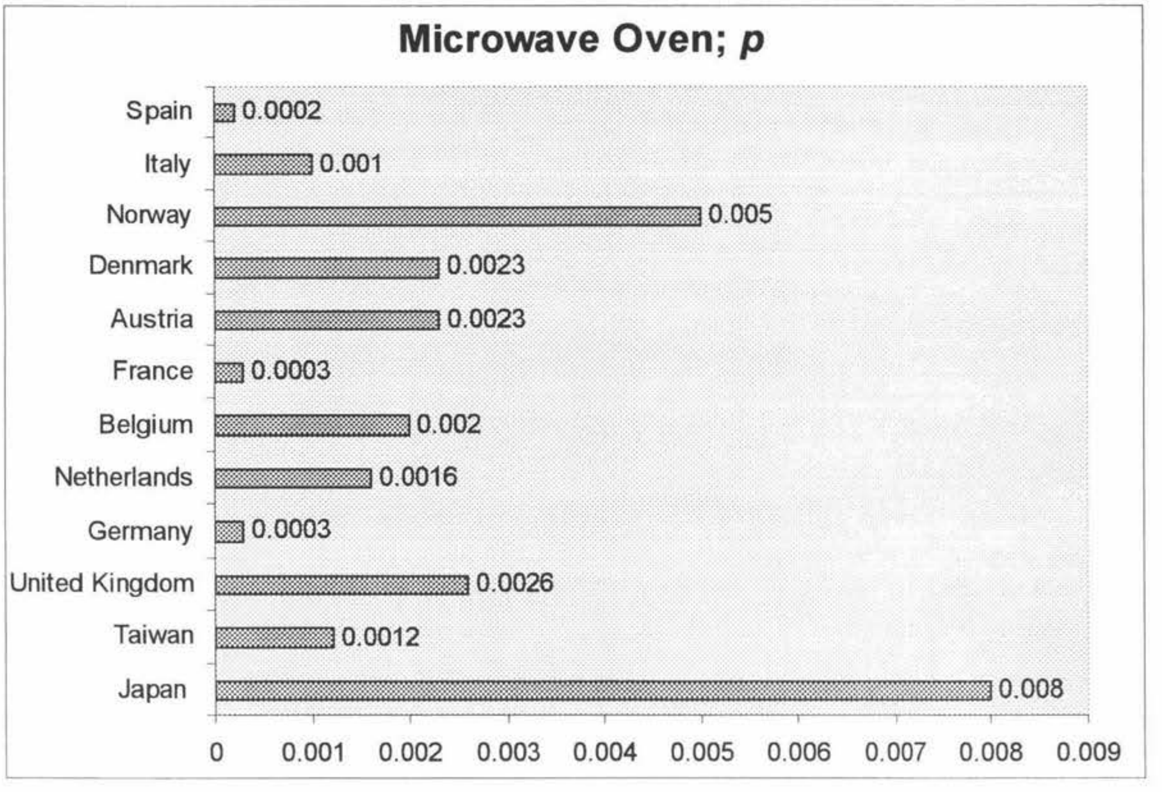
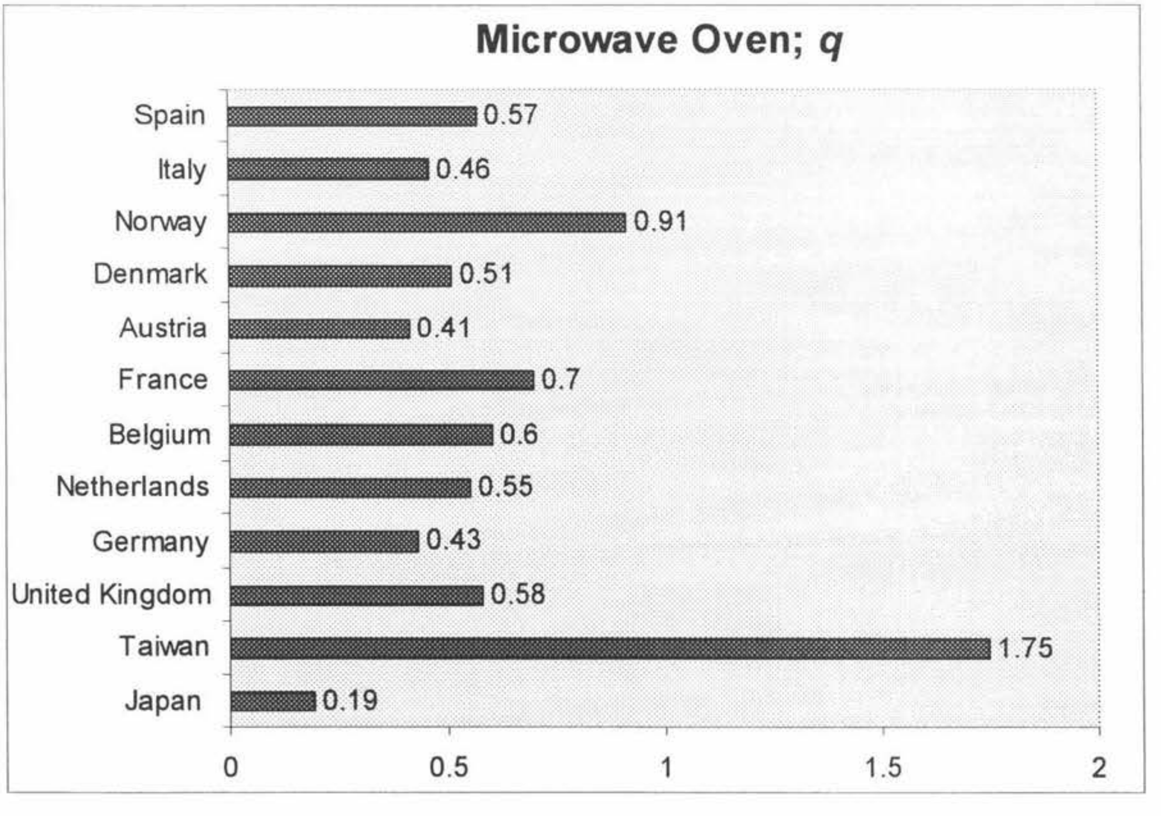


Figure 6.10 Microwave Oven - Cross-Study Comparison of *p* and *q*





7 CONCLUSION

The structure of the conclusion is consistent with the objectives of this study and the results and discussion section. Findings connected to the issue of the generalisability of the Bass model to Japan and Taiwan are discussed first, before the cross-national analysis. The managerial implications, research limitations, and directions for future research are then considered in light of these results.

7.1 Generalisability to Japan and Taiwan

A number of criteria were developed in order to gauge the generalisability of the Bass model to Japan and Taiwan. These included the ability of the model to accurately capture the diffusion curves in the two countries (descriptive ability), to be used as a forecasting tool (predictive ability), and to produce similar parameter and sales estimates at different levels of data aggregation (model stability). It was found that the model performed favourably in terms of descriptive ability and model stability for both countries but is deficient as a forecasting tool.

Descriptive ability was determined by calibrating the Bass model on all available data for each product in the separate countries and examining the model's performance in explaining the observed diffusion curve. For the Bass model to have adequate descriptive ability, it had to produce both plausible parameters and competently fit the actual time-series data.

The model was found to produce plausible parameters for both countries in almost all instances. The coefficients of external and internal influence, p and q, were all positive as were the estimates of market potential, m. In keeping with the classical s-shaped diffusion curve, all q's were greater than their respective p's. In most cases, estimates of market potential, m, were plausible. The exception was personal computers in Japan where multiple product generations and repeat purchases are believed to be inflating the estimate of market potential. Of note is the finding that for some Taiwanese products (personal computers, facsimiles, and video cassette recorders), q values were greater than one. These large coefficients of internal influence are indicative of sizeable interpersonal and word of mouth effects for these consumer durables and are rarely seen in the Bass model literature.

The measures of fit used to determine the capability of the Bass model in capturing the diffusion processes included adjusted R-squared and the difference between the estimated and actual first period sales, peak sales magnitude and peak sales timing.

In both countries, the Bass model performed very well with only two products producing unacceptable results. With the exception of video disk players, all Japanese models had a satisfactory fit with the majority having adjusted R-squared values of 0.8 and better. The estimates of magnitude and timing of peak sales were also adequate. Interestingly, all estimates of peak sales in Japan were underestimates with most erroneous by between -6 and -18 percent. On average, timing estimates were incorrect by 1.4 periods.

A good model fit was achieved for Taiwanese products although the estimates of peak sales magnitude were not as accurate as those in Japan. The obtained adjusted R-squared values were 0.8 or higher for all but one product (TV games). The average peak timing error was 1.5 periods but the peak magnitude was unacceptably underestimated by 25 to 85% in four cases, i.e. air conditioners, personal computers, video cassette recorders, and TV games. This was due to the model's failure to capture sudden large (and somewhat 'fad-like') increases in sales in the peak sales period. However, for the other five products the estimation of peak magnitude was fairly accurate, within $\pm$ 6 percent.

In respect to first period sales, *pm*, Bass model estimates were in most cases inaccurate with errors in the range of 20 to 350%, being relatively worse for Taiwan. Nevertheless, after examining the data, it was hypothesised that error in *pm* was largely a result of two factors: (1) the size of *pm* relative to *m* and (2) the number of time periods (*n*). This contention could not be disproved on the basis of available evidence, however, further research is warranted to be more conclusive.

The results prove the Bass model has descriptive ability in both Taiwan and Japan as it seemed to capture most variance in the diffusion patterns of the consumer durables tested. In cases where the model produced poor fit statistics, a visual examination of the observed and estimated diffusion curves showed the model to be a more than adequate approximation, with the main cause of the poor fit statistics being large period to period sales fluctuations which could not be captured by the original Bass model without additional explanatory variables. These large fluctuations may also be due to random effects.

The forecasting ability of the Bass model in Japan and Taiwan was examined in respect to the diffusion parameters, peak timing and magnitude, and next period sales. The model produced disappointing results in most cases and its use as a forecasting tool , especially of next period sales, should be undertaken with caution.

Testing the models predictive ability involved fitting the model to subsets of data from the first three time periods to the maximum number of time periods. Only annual level models were utilised for these tests. The pattern as the number of data points increased was examined and any convergence behaviour toward the true value observed. For the diffusion parameters, the parameter estimates from the full data set model were assumed to be the true values and simulated standard errors used to construct confidence intervals in order to have an objective measure of predictive accuracy. In about two-thirds of the cases, the diffusion parameters were not accurately estimated until one period after the diffusion peak had been included in the calibration data. For the other one-third, accurate estimates were made before the peak but no clear factor/s could explain why these products performed better than the others. There were no apparent differences in this result across the countries. Robust comparison of parameters can therefore be made after the sales peak is included in the model calibration data. The timing and magnitude of peak sales was also only accurately estimated after peak sales had been reached.

In terms of next period sales, the model's performance was well below expectations. In the majority of cases, predictions of next period sales were very inaccurate with little, if any, observable convergent behaviour as the number of time periods in the calibration data increased.

These results indicate that the validity of using the Bass model to predict next period sales in the two countries is questionable.

Observing the pattern of the estimates as the number of data points increased indicated that the small sample properties of the NLS estimator of the Bass model were more strongly related to the sales peak rather than the number of data points. Convergent behaviour, in particular, occurred more often than not after the sales peak rather than before. This is not to say that the number of data points has no effect, but this appears to interact with the location of the sales peak.

The issue of model stability across various levels of aggregation was tested using a number of performance metrics. Parameter plausibility was one issue tested as was the comparative diffusion parameter estimates produced across the aggregation levels. Of course, the parameter estimates for p and q will be different for yearly, half-yearly and quarterly models. However, a reasonable approximation would be to expect half-yearly and quarterly models to produce estimates half and one quarter the size of the yearly estimates respectively. Also, the annual sales estimates produced across the aggregation levels was compared.

The Bass model did, in most cases, produce comparable estimates across the aggregation levels. The coefficient of external influence, p, was slightly more unstable than the estimates of q and m. Of most note is the fact that annual sales estimates produced by models where q was greater than one were noticeably different. The fit of the models was primarily determined by the amount of seasonality in the data. However, this lack of fit at the half-yearly and quarterly levels caused by seasonality did not translate into differences in annual sales estimates or the comparative diffusion parameters produced by the models.

7.2 Cross-National Diffusion Patterns

Since the descriptive ability of the Bass model was validated in Japan and Taiwan, the subsequent analysis built on this finding by comparing the diffusion parameters between the two countries and with other countries reported in the literature. Additionally, the learning model was calibrated and the results compared with those achieved by the original Bass model. However, the first piece of analysis involved determining the significance of the diffusion parameters based on the estimated values and simulated standard errors.

Hypothesis tests were conducted to establish if the separate diffusion parameters for all the products in the two countries were significantly different from zero. In all cases, the coefficient of internal influence, q, was found to be significant at the 99% level of confidence. However, p was not significantly different from zero for personal computers and facsimiles in Japan and air conditioners, personal computers, VCRs, and microwave ovens in Taiwan. The estimates of market potential, m, were all statistically significant, with facsimiles in Japan the only exception.

For those five products where data from both Taiwan and Japan existed, significance tests were conducted to determine if the diffusion parameters p and q were different between the two countries. For air conditioners, video cassette recorders and microwave ovens, the coefficient of external influence, p, was significantly higher in Japan than Taiwan at the 99% level of confidence. There was no significant difference in the external coefficient, p, for the more business oriented products such as facsimile and personal computer.

In all cases, the coefficient of internal influence, q, was significantly higher in Taiwan than Japan which signifies that the rate of adoption is faster in Taiwan than in Japan. This finding is in contrast to Takada and Jain (1991)'s study where the authors found no difference between the q-values between Japan and Taiwan.

An extension of the Bass model, the learning model, was estimated for the five products where data from both Taiwan and Japan was available. The learning model assumes that buyers in the lag country are influenced by those in the lead country. In this case, based on sound behavioural factors, Japan was assumed to be the lead country and Taiwan the lag. The learning models produced a slightly better fit than the original Bass model, especially for personal computers and microwave ovens. The learning parameter was considerably high for personal computers and facsimiles. These products have a greater propensity for use in business rather than household applications, and indicates a greater willingness for Taiwanese businesses to adopt those products used by their Japanese counterparts.

As for the other products (air conditioners, video cassette recorders, and microwave oven), no substantial learning effect was detected. This finding failed to support the hypothesis that the faster rate of adoption in Taiwan is a result of consumers learning about the product from Japan.

The comparison of Japanese and Taiwanese parameters estimated in this study with those from other countries found in the literature produced some interesting results. While the Japanese diffusion parameters, p and q, were found to be comparable with the meta-analysis findings of Sultan, Farley, and Lehmann (1990), Taiwan has significantly smaller p and larger q than the respective grand mean. These parameter differences are particularly noticeable for facsimile, video cassette recorder, and microwave oven.

For specific products studied also by Ganesh, Kumar, and Subramaniam (1997) (personal computers, video cassette recorders, and microwave oven) differences in diffusion parameters were recognised. Taiwan and Japan had significantly smaller p-values than most European countries for personal computers. Furthermore, while the Japanese q appeared to be the smallest among the fourteen countries compared, the Taiwanese q was more closely aligned with the European estimates. For video cassette recorders, Japan clearly has a higher coefficient of external influence possibly because the VCR was invented in Japan. The coefficient of internal influence for Taiwan is also unmistakably higher than the European countries. This result is duplicated for microwave ovens.

These results establish that Asian countries have different diffusion parameters from those of other countries reported in the literature. Japan has a higher coefficient of external influence, p, and a slightly smaller coefficient of internal influence, q. In contrast, Taiwan has smaller p-values and much larger q-values than European countries. However, the results also strongly indicate that Asian countries should not be treated as one homogenous group because Taiwan is as different from Japan as it is from other European countries.

7.3 Managerial Implications

This research has revealed a number of potentially useful outcomes for business managers and provided direction for the use of the Bass model in Japan and Taiwan.

First, results from this study validated the use of the Bass model to describe diffusion patterns in Japan and Taiwan for a wide variety of recent consumer technological innovations. This extends the model's applicability beyond the countries used in previous studies. When calibrated on data from the completed diffusion process, the model's estimated diffusion curve closely matched the actual rate of sales in most cases. Where fit statistics were less than desired, the model still provided a reasonable approximation of the actual diffusion curves. Furthermore, the diffusion curves and parameter estimates produced by the model were comparable at different levels of data aggregation. Managers can therefore use the model's parameters (especially p and q) to compare and contrast diffusion patterns in these two countries with those from U.S. and Europe, safe in the knowledge that these parameters are a reliable measure of the actual diffusion process in the countries. In addition, the Bass model can also be used in an explanatory model to test diffusion-related hypothesis which helps marketing managers to gain more insight on the nature of new product diffusion in these two countries.

While the model's descriptive validity and stability across different levels of data aggregation have led some credibility to the model's structural soundness, care should be exercised when the Bass model is employed for sales forecasting purposes. This particularly applies to models calibrated on annual sales data. The results indicate the predictions are unreliable when used to forecast next period sales, and far worse when used to predict the remaining diffusion curve. Thus, recommended by Bass (1969), managerial judgements or other exogenous sources of information should be included to improve the model's performance.

An interesting discovery was that Japan had a higher coefficient of external influence, p, and lower coefficient of internal influence, q, than Taiwan. In some cases, Taiwan had an extremely fast rate of adoption with q-values greater than one. Word of mouth effects and personal interaction are seemingly more prominent in Taiwan than in Japan, possibly due to cultural reasons. If marketers wish to gain a first-mover advantage in Taiwan, then speed is of the essence – marketers need to move more quickly than in Japan if they want to enter the market before the peak sales period. This finding may also point to more fad-like behaviour in Taiwan compared to other more developed nations.

The finding that Taiwanese consumers 'learn' about business-oriented products from there Japanese counterparts is a beneficial result. For these types of products, marketers can use the waterfall strategy which recommends the allocation of relatively more resources to Japan on the understanding that there is some flow-on effect to the Taiwanese market. However, for the other household type products, the inconsequential learning effect suggests the markets should be treated as independent. In this case, the sprinkler strategy is preferred as simultaneous product launch offer competitive benefits such as first entry advantage and lower production and marketing costs.

Overall, Japan was closer to European countries in terms of the diffusion parameters than it was to Taiwan, but still distinct enough to be treated differently. Taiwan was significantly different from Europe and Japan. This could be due to factors such as economic development or even perhaps the more relaxed view of copyright in Taiwan which relieves their producers of the burden of research and development costs, and therefore allows the production of lower priced goods.

While Takada and Jain (1991) reported that Japan and Taiwan had comparable diffusion patterns to the US, the cross-study comparisons revealed that, for the more recent consumer durables, Japan is more comparable with the industrialised European countries than with Taiwan. This finding implies that diffusion of innovation is not a constant phenomenon over time and the level of economic development could have more effect on the new product diffusion process than geographic proximity or cultural similarities.

7.4 Research Limitations and Directions for Future Research

The scope of any study is finite with the main consequence being limits on the generalisability of the findings. Understanding these limitations is important in reducing inappropriate applications. In this case, although limitations exist, these have negligible impact on the within study findings.

As discussed in the methodology, the data collected would contain varying amounts of repeat purchases and multiple product generations across the products. However, for the products where this was perceived to be a problem (e.g. personal computers and vacuum cleaners), the parameters produced were not inconceivable and the observed patterns between the countries did not change. Nevertheless, these factors would detrimentally impact on the fit and generalisability of the model given that it does not explicitly account for them in its specification.

The limited number of countries studied is also a shortcoming, especially for generalising the results to other Asian countries. Taiwan and Japan are not likely to be representative of the region in terms of economic and cultural variables, one being a world economic power and the other the preeminent 'Asian Dragon'. Therefore, we could expect quite different results for other Asian countries.

Connected with above is the issue of the limited common product categories across the two countries. In this study, five products were common to both countries. Additional products would add considerable weight to the patterns discovered here.

The integrity of the data collected from government records in Taiwan and Japan is an area that needs further considerations. Underlying all analysis is the assumption that domestic sales, imports and exports are accurately measured and all units are accounted for. There is likely to be some error in the collection process which would reduce the fit of the Bass model. However, this error is likely to be small compared to the observed diffusion pattern and would have most impact in the initial periods of the diffusion process where sales levels are relatively small compared to the error. This would reduce the precision of the estimates of the coefficient of external influence, p.

Category definitions are also likely to differ across the countries. In this study, every effort was made to ensure that the definitions (especially of the common products) were comparable. This limited the range of products that could be examined as some definitions were quite different by including some product variants and omitting others.

Any future research would attempt to rectify the issues mentioned previously in this section. A broader range of countries and product categories would extend the generalisability of the model. In particular, the inclusion of fast moving consumer goods, a dynamic and innovative area in these countries, would be of much interest. Furthermore, it would be interesting to fit the model to brand level data in the same way as the study by Healey (1996).

The tests of predictive ability were only conducted at the annual level of aggregation and therefore, generalising to half-yearly, quarterly, or other levels of aggregation is not possible. This is of particular importance as diffusion effects such as seasonality would vary at these different aggregation levels. In practice, the model would be used for forecasting using shorter time periods. This limitation also applies to the small sample properties of the NLS estimator of the Bass model, which was only tested at the annual level of aggregation.

The models estimated in this study were (with the exception of the learning model) all based on the original Bass (1969) model. Extensions of the model to include marketing mix variables, repeat purchases, and multiple product generations, and other external factors may help to better depict the Taiwanese diffusion curves, in terms of capturing the drastic increase of sales prior to and during peak sales, improve the forecasting performance of the model, and to provide useful insights into the diffusion characteristics in these countries.

As mixed results regarding the existence of the learning effect between lead and lag countries were found in this study, more applications of the learning model in other Asian markets are required to be more conclusive.

8 REFERENCES

Akinola, A. A. (1984). An Application of the Bass Model in the Analysis of Diffusion of Coco-Spraying Chemicals Among Nigerian Cocoa Farmers. ***Journal of Agricultural Economics***, *37* (3), 395-404.

Ayal, I. & Zif, J. (1979). Market Expansion Strategies in Multinational Marketing. ***Journal of Marketing***, ***43*** (Spring), 84-94.

Barnett, H. G. (1953). ***Innovation: The Basis of Cultural Change***. New York: McGraw-Hill.

Bartlett, M. S. (1960). ***Stochastic Population Models in Ecology and Epidemiology***. London: Methuen.

Bass, F. M. (1969). A New Product Growth Model for Consumer Durables. ***Management Science***, ***15*** (5), 215-227.

Bass, F. M. (1980). The Relationship Between Diffusion Rates, experience Curve, and Demand Elasticities for Consumer Durable Technological Innovations. ***Journal of Business***, ***53***, 51-67.

Bass, F. M., Krishnan, T. V., & Jain, D. C. (1994). Why the Bass Model Fit Without Decision Variables. ***Marketing Science***, ***13*** (3), 203-223.

Bayus, B. L. (1987). Forecasting Sales of New Contingent Products: An Application to Compact Disk Market. ***Journal of Product Innovation Management***, ***4*** (December), 243-255.

Bernhardt, I. & Mackenzie, K. D. (1972). Some Problems in Using Diffusion Models for New Products. ***Management Science***, ***19*** (October), 187-200.

Bewley, R. & Fiebig, D. G. (1988). A Flexible Logistic Growth Model with Applications in Telecommunications. ***International Journal of Forecasting***, ***4*** (2), 177-192.

Bretschneider, S. I. & Mahajan, V. (1980). Adaptive Technological Substitution Models. ***Technological Forecasting and Social Change***, ***18*** (December), 129-139.

Chatterjee, R. & Eliashberg, J. (1990). The Innovation Diffusion Process in a Heterogeneous Population: A Micromodeling Approach. ***Management Science***, ***36***, 1057-1079.

Chow, G. C. (1967). Technological Change and the Demand for Computers. ***American Economics Review***, ***57*** (December), 1117-1130.

Coleman, J., Katz, E., and Menzel, H. (1957). The Diffusion of an Innovation Among Physicians. ***Sociometry***, ***December***.

Dixon, R. (1980). Hybrid Corn Revisited. *Econometrica*, *48* (September), 1441-1451.

Dodds, W. (1973). An Application of the Bass Model in Long Term New Product Forecasting. ***Journal of Marketing Research***, ***10*** (August), 308-311.

Dodson, J. A. & Muller, E. (1978). Models of New Product Diffusion Through Advertising and Word-of-Mouth. ***Management Science***, ***24*** (November), 1568-1578.

Douglas, S. P. & Craig, C. S. (1983). ***International Marketing Research***. Englewood Cliffs, New Jersey: Prentice-Hall.

Douglas, S. P. & Craig, C. S. (1992). Advances in International Marketing. ***International Journal of Research in Marketing***, ***9***, 291-318.

Easingwood, C. J. (1987). Early Product Life Cycle Forms of Infrequently Purchased Major

Products. ***International Journal of Research in Marketing***, ***4*** (1), 3-9.

Easingwood, C. J., Mahajan, V., & Muller, E. (1983). A Nonuniform Influence Innovation Diffusion Model of New Product Acceptance. ***Marketing Science***, ***2*** (3), 273-295.

Fourt, L. A. & Woodlock, J. W. (1960). Early Prediction of Market Success for New Grocery Products. ***Journal of Marketing***, ***25*** (October), 1568-1578.

Ganesh, J. & Kumar, V. (1996). Capturing the Cross-National Learning Effect: An Analysis of an Industrial Technology Diffusion. ***Journal of the Academy of Marketing Science***, ***24*** (4), 328-337.

Ganesh, J., Kumar, V., & Subramaniam, V. (1997). Learning Effect in Multinational Diffusion of Consumer Durables: An Exploratory Investigation. ***Journal of the Academy of Marketing Science***, ***25*** (3), 214-228.

Gatignon, H. & Robertson, T. S. (1985). A Propositional Inventory for New Diffusion Research. ***Journal of Consumer Research***, ***11*** (March), 849-867.

Gatignon, H. & Robertson, T. S. (1989). Technological Diffusion: An Empirical Test of Competitive Effects. ***Journal of Marketing***, ***53*** (January), 35-49.

Gatignon, H., Eliashberg, J., & Robertson, T. S. (1989). Modeling Multinational Diffusion Patterns: An Efficient Methodology. ***Marketing Science***, ***8*** (3), 231-247.

Hall, E. T. (1976). ***Beyond Culture***. New York: Doubleday.

Hall, E. T. (1987). ***Hidden Differences***. New York: Doubleday.

Heeler, R. M. & Hustad, T. P. (1980). Problems in Predicting New Product Growth for Consumer Durables. ***Management Science***, ***10*** (October), 1007-1020.

Helsen, K., Jedidi, K., & DeSarbo, W. S. (1993). A New Approach to Country Segmentation Utilizing Multinational Diffusion Patterns. ***Journal of Marketing***, ***57*** (October), 60-71.

Hawkins, D. I., Best, R. J., & Coney, K. A. (1989). ***Consumer Behaviour: Implication for Marketing Strategy***. Homewood, Boston: BPI/IRWIN.

Healey, B., Wright, M., & Gendall, P. (1996). *An Application of the Bass model of New Product Growth to Brand Level Data*. Proceedings of the New Zealand Marketing Educators' Conference, Auckland University, Auckland.

Hoek, J., Gendall, P., & Esslemont, D. (1993). Market Segmentation: A Search for the Holy Grail? ***Asia-Australia Marketing Journal***, ***1***, 41-46.

Horsky, D. (1990). A Diffusion Model Incorporating Product Benefits, Price, Income, and Information. ***Marketing Science***, ***9*** (4), 342-365.

Horsky, D. & Simon, L. S. (1983). Advertising and the Diffusion of New Products. ***Management Science***, ***1*** (Winter), 1-18.

Hunt, S. D. (1991). ***Modern Marketing Theory- Critical Issues in the Philosophy of Marketing Science***. Cincinnati, Ohio: South-Western Publishing Co.

Jain, D. & Rao, R. C. (1990). Effect of Price on the Demand for Durables: Modeling, Estimation and Findings. ***Journal of Business and Economic Statistics***, ***8*** (April), 163-170.

Jain, S. C. (1993). ***International Marketing Management***, 4^{th} ed. Boston: PWS-KENT Publishing Company.

Jeuland, A. (1994). ***Empirical Generalizations in Marketing***. Draft Proceedings, February 16-18, SET Center for Advanced Studies in Management. The Wharton School of the University of Pennsylvania. In Wright, M. & Charlett, D. (1995). New product Diffusion

Models in Marketing: An Assessment of Two Approaches. ***Marketing Bulletin*, *6*** (May). 32-41.

Johnston, J. (1984). ***Econometric Method***, 3rd ed. New York: McGraw Hill.

Jones, J. M. & Ritz, C. J. (1987). Incorporating Distribution into New Product Diffusion Models. ***International Journal of Research in Marketing***, ***8***, 91-112.

Kalish, S. (1985). A New Product Adoption Model with Pricing, Advertising and Uncertainty. ***Management Science***, ***31***, 1569-1585.

Kalish, S. & Lilien, G. L. (1986). A Market Entry Timing Model for New Technoloigies. ***Management Science***, ***32*** (February), 194-205.

Kalish, S., Mahajan, V., & Muller, E. (1995). Waterfall and Sprinkler New-Product Strategies in Competitive Global Markets. ***International Journal of Research in Marketing***, ***12***, 105-119.

Kamakura, W. A. & Balasubramanian, S. K. (1987). Long-Term Forecasting with Innovation Diffusion Models: The Impact of Replacement Purchase. ***Journal of Forecasting***, ***6*** (1), 1-19.

Kendall, M. G. & Stuart, A. (1977). ***The Advanced Theory of Statistics.*** Vol. 1, Griffin, London.

Kotler, P. (1971). ***Marketing Decision Making: A Model Building Approach***. New York: Holt, Rinehart and Winston.

Kotler, P. (1991). ***Marketing Management***, 7th ed. Englewood Cliffs, New Jersey: Prentice-Hall.

Lackman, C. L. (1978). Gompertz Curve Forecasting: A New Product Application. ***Journal of the Market Research Society***. ***20*** (January), 45-47.

Lattin, J. M. & Roberts, J. H. (1989). ***The Role of Individual-Level Risk-Adjusted Utility in the Diffusion of Innovation***. Working paper, Graduate School of Business, Stanford University.

Lawton, S. B. & Lawton, W. H. (1979). An Autocatalytic Model for the Diffusion of Educational Innovations. ***Educational Administration Quarterly***, ***15***, 19-53.

Lilien, G. L., Kotler, P., & Moorthy, K. S. (1992). ***Marketing models***. Englewood Cliffs, New Jersey: Prentice-Hall Inc.

Lilien, G. L., Rao, A. G., & Kalish, S. (1981). Bayesian Estimation and Control of Detailing Effort in a Repeat Purchase Diffusion Environment. ***Management Science***, ***27*** (May), 493-506.

Mahajan, V. & Muller, E. (1979). Innovation Diffusion and New Product Growth Models in Marketing. ***Journal of Marketing***, ***43*** (Fall), 55-68.

Mahajan, V., Muller, E., & Bass, F. M. (1990). New Product Diffusion Models in Marketing: A Review and Directions for Research. ***Journal of Marketing***, ***54*** (January), 1-26.

Mahajan, V., Muller, E., & Bass, F. M. (1995). Diffusion of New Products: Empirical Generalizations and Managerial Uses. ***Marketing Science***, ***14*** (3), 79-88.

Mahajan, V., Muller, E., & Srivastava, R. K. (1990). Determination of Adopter Categories by Using Innovation Diffusion Models. ***Journal of Marketing Research***, ***Vol.27*** (February), 37-50.

Mahajan, V. & Peterson, R. A. (1978). Innovation Diffusion in a Dynamic Potential Adopter Population. ***Management Science***, ***15*** (November), 1589-1597.

Mahajan, V. & Peterson, R. A. (1982). Erratum to: Innovation Diffusion in a Dynamic Adopter Population. ***Management Science*, *28*** (September), 1087.

Mahajan, V. & Peterson, R. A. (1985). ***Models for Innovation Diffusion***. Beverly Hills, CA: Sage Publications Inc.

Mahajan, V., Peterson, R. A., Jain, A. K., & Malhotra, N. (1979). A New Product Growth Model with a Dynamic Market Potential. ***Long Range Planning*, *12*** (4), 62-69.

Mahajan, V. & Sharma, S. (1986). Simple Algebraic Estimation Procedure for Innovation Diffusion Models of New Product Acceptance. ***Technological Forecasting and Social Change*, *30*** (December), 331-346.

Mahajan, V. & Wind, Y. (1986). ***Innovation Diffusion Models of New Product Acceptance***. Cambridge, MA: Ballinger Publishing Company.

Mahajan, V., Wind, Y., & Sharma, S. (1983). An Approach to Repeat Purchase Diffusion Models. ***AMA Proceedings***, 49, Patrick E. Murphy et al., eds. Chicago: American Marketing Association. 442-446.

Mansfield, E. (1961). Technical Change and the Rate of Imitation. ***Econometrica*, *29*** (October), 741-766.

Montgomery, D. B. & Srinivasan, V. (1989). ***An Improved Method for Meta-Analysis: with Application to New Product Diffusion Models***. Working paper, Graduate School of Business, Stanford University.

Nehrt, L. C., Truitt, J. F., & Wright, R. W. (1970). ***International Business Research: Past, Present and Future***. Bloomington, Ind.: Indiana University Bureau of Business Research.

Nevers, J. V. (1972). Extensions of a New Product Growth Model. ***Sloan Management Review***, ***13*** (Winter), 77-91.

Norton, J. A. & Bass, F. M. (1987). A diffusion Theory Model of Adoption and Substitution for Successive Generations on High Technology Products. ***Management Science***, ***33*** (September), 1069-1086.

Ohmae, K. (1985). The Triad World View. ***Journal of Business Strategy***, *7* (Spring), 8-19.

Ohmae, K. (1987). ***Triad Power***. New York: The Free Press.

Ohmae, K. (1989). Managing in a Borderless World. ***Harvard Business Review***, *67* (May-June), 152-161.

Olson, J. A. & Choi, S. (1985). A Product Diffusion Model Incorporating Repeat Purchases. ***Technological Forecasting and Social Change***, *27*, 385-397.

Peterson, R. A. (1973). A Note on Optimal Adopter Category Determination. ***Journal of Marketing Research***, ***10*** (August), 325-329.

Peterson, R. A. & Mahajan, V. (1978). Multi-product Growth models. in ***Research in Marketing***, Jagdish N. Sheth ed., Greenwich, CT: JAI Press, Inc., 201-231.

Rao, A. G. & Yamada, M. (1988). Forecasting with a Repeat Purchase Diffusion Model. ***Management Science***, ***34*** (June), 734-752.

Robertson, T. S. & Gatignon, H. (1986). Competitive Effects on Technology Diffusion. ***Journal of Marketing***, ***50*** (July), 1-12.

Robinson, V. & Lakhani, C. (1975). Dynamic Price Models for New Product Planning.

Management science*, *21 (June), 1113-1132.

Rogers, E. M. (1962). ***Diffusion of Innovation***, 1st ed. New York: The Free Press.

Rogers, E. M. (1983). ***Diffusion of Innovations***, 3rd ed. New York: The Free Press.

Schmittlein, D. C. & Mahajan, V. (1982). Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance. ***Marketing Science*, *1*** (Winter), 57-78.

Sharif, M. N. & Ramanathan, K. (1981). Binomial Innovation Diffusion Models with Dynamic Potential Adopter Population. ***Technological Forecasting and Social Change*, *20***, 63-87.

Sethi, S. P. (1971). Comparative Cluster Analysis for World Markets. ***Journal of Marketing Research*, *8*** (August), 348-354.

Simon, H. & Sebastian, K. H. (1987). Diffusion and Advertising: The German Telephone Company. ***Management Science*, *33*** (April), 451-466.

Srinivasan, V. & Mason, C. H. (1986). Nonlinear Least Squares Estimation of New Product Diffusion Models. ***Marketing Science*, *5*** (Spring), 169-178.

Srivastava, R. K., Mahajan, V., Ramaswami, S. N., & Cherian, J. (1985). A Multi-Attribute Diffusion Model for Forecasting the Adoption of Investment Alternatives for Consumers. ***Technological Forecasting and Social Change*, *28***, 325-333.

Sultan, F., Farley, J. U. & Lehmann, D. R. (1990). A Meta-Analysis of Diffusion Models. ***Journal of Marketing Research*, *Vol. 27*** (February), 70-76.

Takada, H. & Jain, D. (1991). Cross-National Analysis of Diffusion of Consumer Durable Goods in Pacific Rim Countries. ***Journal of Marketing*, *55*** (April), 48-54.

Wright, M. & Charlett, D. (1995). New Product Diffusion Models in Marketing: An Assessment of Two Approaches. ***Marketing Bulletin***, ***6*** (May), 32-41.

Wright, M. & Esslemeont, D. (1994). The Logical Limitation of Target Marketing. ***Marketing Bulletin***, ***5***, 13-20.

Wright, M., Upritchard, C., & Lewis, T. (1997). A Validation of the Bass new Product Diffusion Model in New Zealand. *Marketing Bulletin*, *8*, 15-29.

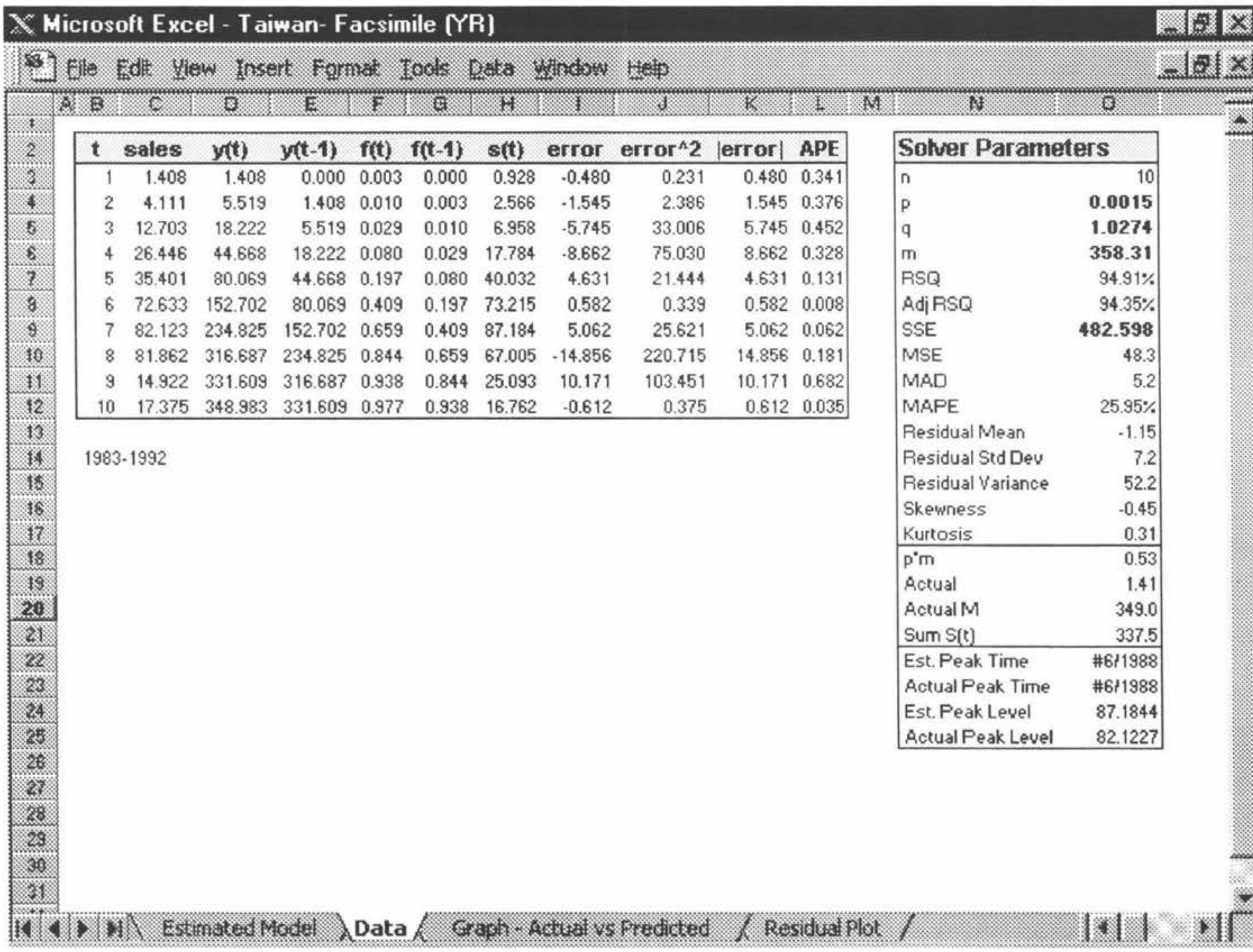
Wright, R. W. & Ricks, D. A. (1994). Trends in International Business Research: Twenty-Five Years Later. ***Journal of International Business Studies***, ***25*** (4), 687-701.

9 APPENDICES

9.1 Non-Linear Least Squares Estimation

The non-linear least squares (NLS) estimates of the Bass model parameters were calculated through the use of Microsoft Excel 97, in particular the Solver add-in function (solver.xla). A screen shot of the worksheet format is shown in figure 9.1 below with the yearly model for facsimile in Taiwan. Most of the cells are self-explanatory but detailed explanations are provided for completeness.

Figure 9.1 Example of Estimation Worksheet



Microsoft Excel - Taiwan- Facsimile (YR)

t	sales	y(t)	y(t-1)	f(t)	f(t-1)	s(t)	error	error^2	|error|	APE
1	1.408	1.408	0.000	0.003	0.000	0.928	-0.480	0.231	0.480	0.341
2	4.111	5.519	1.408	0.010	0.003	2.566	-1.545	2.386	1.545	0.376
3	12.703	18.222	5.519	0.029	0.010	6.958	-5.745	33.006	5.745	0.452
4	26.446	44.668	18.222	0.080	0.029	17.784	-8.662	75.030	8.662	0.328
5	35.401	80.069	44.668	0.197	0.080	40.032	4.631	21.444	4.631	0.131
6	72.633	152.702	80.069	0.409	0.197	73.215	0.582	0.339	0.582	0.008
7	82.123	234.825	152.702	0.659	0.409	87.184	5.062	25.621	5.062	0.062
8	81.862	316.687	234.825	0.844	0.659	67.005	-14.856	220.715	14.856	0.181
9	14.922	331.609	316.687	0.938	0.844	25.093	10.171	103.451	10.171	0.682
10	17.375	348.983	331.609	0.977	0.938	16.762	-0.612	0.375	0.612	0.035

1983-1992

Solver Parameters	
n	10
p	**0.0015**
q	**1.0274**
m	**358.31**
RSQ	94.91%
Adj RSQ	94.35%
SSE	**482.598**
MSE	48.3
MAD	5.2
MAPE	25.95%
Residual Mean	-1.15
Residual Std Dev	7.2
Residual Variance	52.2
Skewness	-0.45
Kurtosis	0.31
p*m	0.53
Actual	1.41
Actual M	349.0
Sum S(t)	337.5
Est. Peak Time	#6/1988
Actual Peak Time	#6/1988
Est. Peak Level	87.1844
Actual Peak Level	82.1227

Estimated Model | Data | Graph - Actual vs Predicted | Residual Plot

The eleven columns on the spreadsheet contain the following:

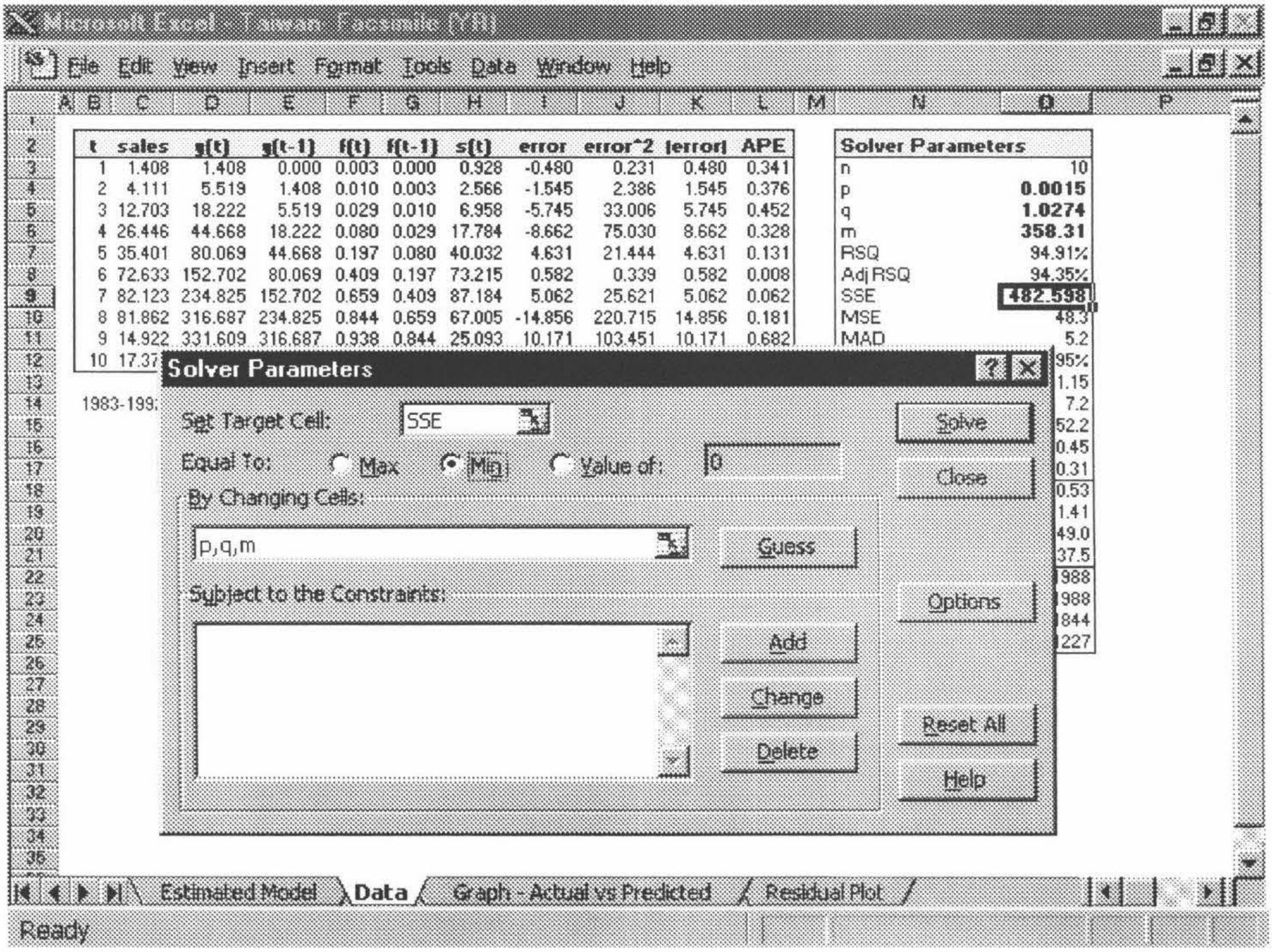
t	=	time period, being either yearly, half-yearly, and quarterly ;
sales	=	units sold in the specified time period ;
y(t)	=	cumulative sales to time t ;
y(t-1)	=	cumulative sales to time t-1 ;
f(t)	=	(1-EXP(-(p+q)*t))/(1+(q/p)*EXP(-(p+q)*t)) ;
f(t-1)	=	(1-EXP(-(p+q)*t-1))/(1+(q/p)*EXP(-(p+q)*t-1)) ;
s(t)	=	predicted sales in time p equals (m-y(t-1))*((f(t) –f(t-1))/(1-f(t-1)) ;
error	=	sales – s(t) ;
error^2	=	error squared ;
|error|	=	absolute value of (sales – s(t)) , and ;
APE	=	absolute percentage error.

In the 'Solver Parameters' box, the named cells are as follows:

n	=	number of time periods ;
p, q, and m	=	the Bass model parameters ;
RSQ	=	the Excel R-Squared function ;
Adj RSQ	=	1-(1-RSQ)*(n/(n-1)) , RSQ adjusted for the number of data points ;
SSE	=	sum of squared errors ;
MSE	=	mean of the squared errors ;
MAD	=	mean of the absolute deviations (i.e. mean of |error|) ;
MAPE	=	mean of the absolute percentage errors ;
Residual Mean	=	error mean (used in standard error simulation) ;
Residual Std Dev	=	error standard deviation (used in standard error simulation) ;
Residual Variance	=	error variance ;
Skewness	=	the Excel skewness function ;
Kurtosis	=	the Excel kurtosis function ;
p*m	=	model estimate of first period sales ;
Actual	=	actual first period sales ;
Actual m	=	cumulative sales over all time periods ;
Sum S(t)	=	sum of estimated sales ;
Est. Peak Time	=	estimated period where peak sales occurs ;
Actual Peak Time	=	actual period where peak sales occurs ;
Est. Peak Level	=	estimated magnitude of peak sales, and ;
Actual Peak Level	=	actual magnitude of peak sales.

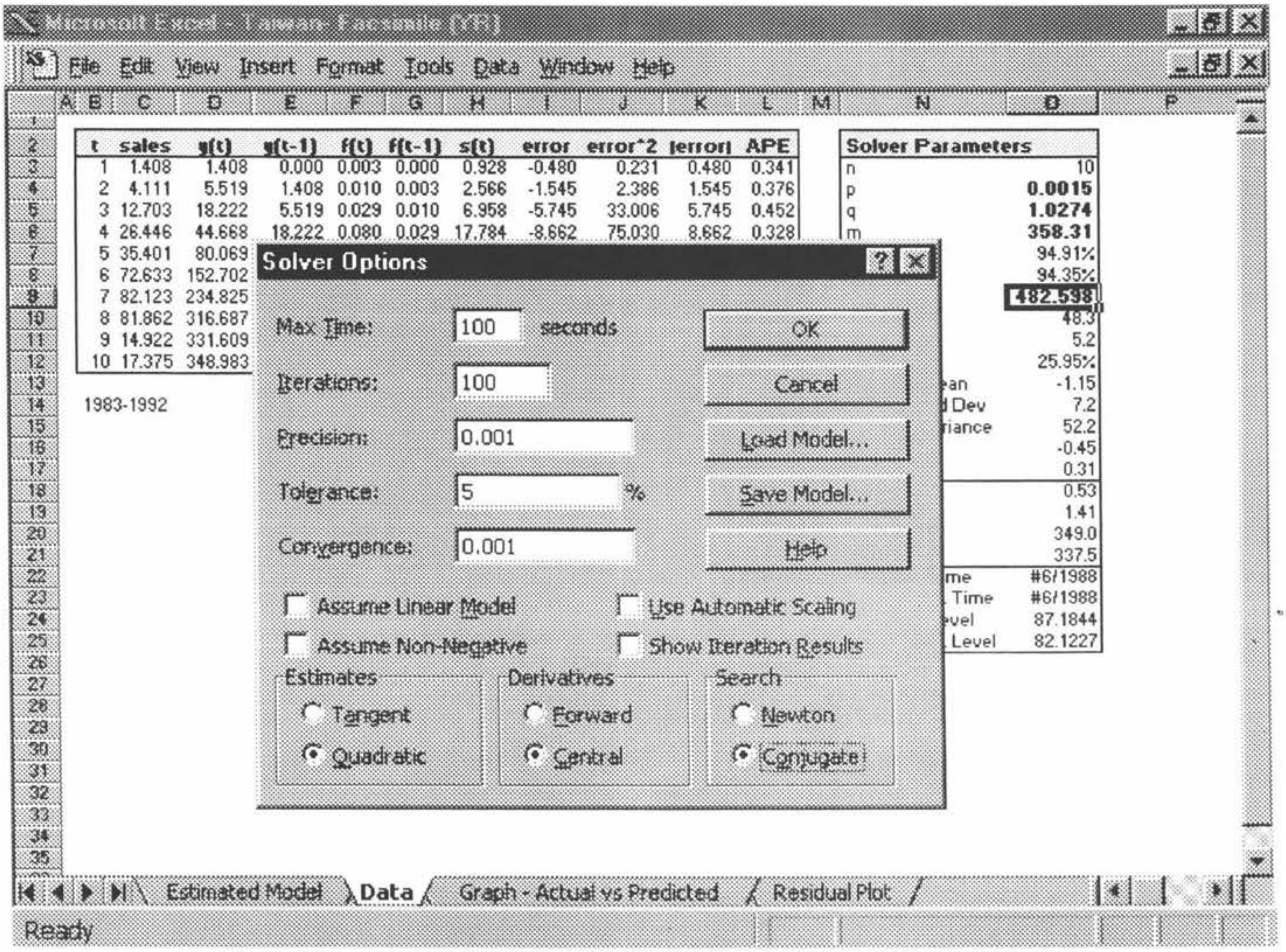
Once the worksheet had been constructed in the manner shown in figure 9.1, estimating the model simply involved using the Solver Excel add-in. The Solver menu is shown in figure 9.2. As can be seen, the goal of the Solver algorithm was to minimise the sum of squared errors (SSE) by changing the values of p, q, and m.

Figure 9.2 Excel Solver Menu Settings



Furthermore, the algorithm settings used by Solver had to be fixed. This algorithm uses interative search techniques to estimate the parameters based on the well known Newton-Rhapson method. In this case, the options shown in figure 9.3 below were selected given the non-linear nature of the Bass model, the simplicity of the modelling problem, and the lack of computing resource constraints.

Figure 9.3 Excel Solver Algorithm Settings



The learning model used almost exactly the same approach except the worksheet (figure 9.4) contained an extra column of data representing the cumulative penetration of the product in the lead country (P(t) in the example worksheet) and different formulas for f(t) as per equation [3.26] in the methodology. For the lead country, cumulative penetration was calculated by dividing estimated cumulative sales at time t by estimated market potential, *m*.

The solver goal was still to minimise the sum of squared errors, however, this was achieved by changing the values for p, q, and $c\_$, not the market potential m. The market potential for the lag country, m, is fixed to the value estimated in the Bass model. The same algorithm options were selected for the learning model as the Bass model.

Figure 9.4 Learning Model Example Worksheet

Microsoft Excel - LMod (J-T) Air Conditioner(YR)

File Edit View Insert Format Tools Data Window Help

t	sales	g(t)	g(t-1)	f(t)	f(t-1)	s(t)	P(t)	error	error^2	|error|	APE
1	0.1	0.1	0.00	0.00	0.000	4.710	0.046	4.6	21.3	4.615	48.731
2	0.1	0.2	0.09	0.00	0.001	0.790	0.046	0.7	0.4	0.652	4.711
3	0.2	0.4	0.23	0.00	0.001	1.170	0.046	1.0	1.0	0.977	5.039
4	0.5	1.0	0.43	0.00	0.002	1.733	0.046	1.2	1.4	1.187	2.174
5	0.9	1.8	0.97	0.00	0.002	2.565	0.046	1.7	2.9	1.692	1.937
6	1.5	3.4	1.85	0.00	0.003	3.795	0.046	2.3	5.2	2.281	1.506
7	1.9	5.3	3.36	0.01	0.003	10.112	0.096	8.2	67.6	8.220	4.345
8	3.5	8.7	5.25	0.01	0.006	13.750	0.155	10.3	105.9	10.291	2.975
9	3.3	12.0	8.71	0.01	0.009	18.400	0.223	15.1	226.9	15.064	4.515
10	4.6	16.6	12.05	0.02	0.013	24.390	0.291	19.8	391.8	19.794	4.307
11	5.6	22.2	16.64	0.03	0.019	32.380	0.353	26.8	718.9	26.812	4.815
12	10.7	32.9	22.21	0.04	0.026	45.485	0.422	34.8	1208.2	34.759	3.241
13	78.9	111.8	32.94	0.05	0.037	62.333	0.478	-16.6	274.6	16.572	0.210
14	179.9	291.8	111.84	0.07	0.051	89.169	0.559	-90.7	8234.2	90.743	0.504
15	162.4	454.1	291.75	0.10	0.071	121.127	0.652	-41.3	1702.1	41.257	0.254
16	162.7	616.8	454.14	0.14	0.099	160.434	0.722	-2.2	5.1	2.248	0.014
17	355.8	972.6	616.82	0.19	0.136	211.795	0.773	-144.0	20724.9	143.961	0.405
18	235.3	1207.9	972.58	0.25	0.186	260.514	0.814	25.2	635.6	25.212	0.107
19	207.6	1415.5	1207.88	0.33	0.249	321.797	0.846	114.2	13036.7	114.178	0.550
20	303.1	1718.6	1415.50	0.42	0.327	387.356	0.871	84.3	7101.5	84.270	0.278
21	435.0	2153.6	1718.58	0.51	0.417	430.461	0.871	-4.5	20.6	4.536	0.010
22	368.1	2521.7	2153.58	0.61	0.514	430.902	0.871	62.8	3946.7	62.822	0.171
23	504.6	3026.2	2521.66	0.70	0.611	415.481	0.871	-89.1	7934.8	89.077	0.177
24	589.2	3615.4	3026.22	0.78	0.702	336.901	0.871	-252.3	63638.5	252.267	0.428
25	113.7	3729.1	3615.39	0.84	0.780	201.507	0.871	87.8	7710.5	87.809	0.772
26	103.4	3832.5	3729.08	0.89	0.844	184.210	0.871	80.8	6526.8	80.788	0.781
27	90.4	3922.9	3832.50	0.93	0.894	165.466	0.871	75.0	5631.1	75.040	0.830

1965-1991

Solver Parameters	
n	27
p	0.0001
q	0.3927
m	4308.9
c_	0.021
RSQ	81.3%
Adj RSQ	80.6%
SSE	149875
MSE	5551
MAD	48.04
MAPE	347%
Residual Mean	0.59
Residual Std Dev	75.9
Residual Variance	5764.1
Skewness	-1.59
Kurtosis	3.95
p*m	0.435
Actual	0.095
Actual M	3922.93
Est. Peak Time	#21/1985
Actual Peak Time	#24/1988
Est. Peak Level	437.5729
Actual Peak Level	589.1678

Estimated Model | Data | Graph - Actual vs Predicted | Residual Plot

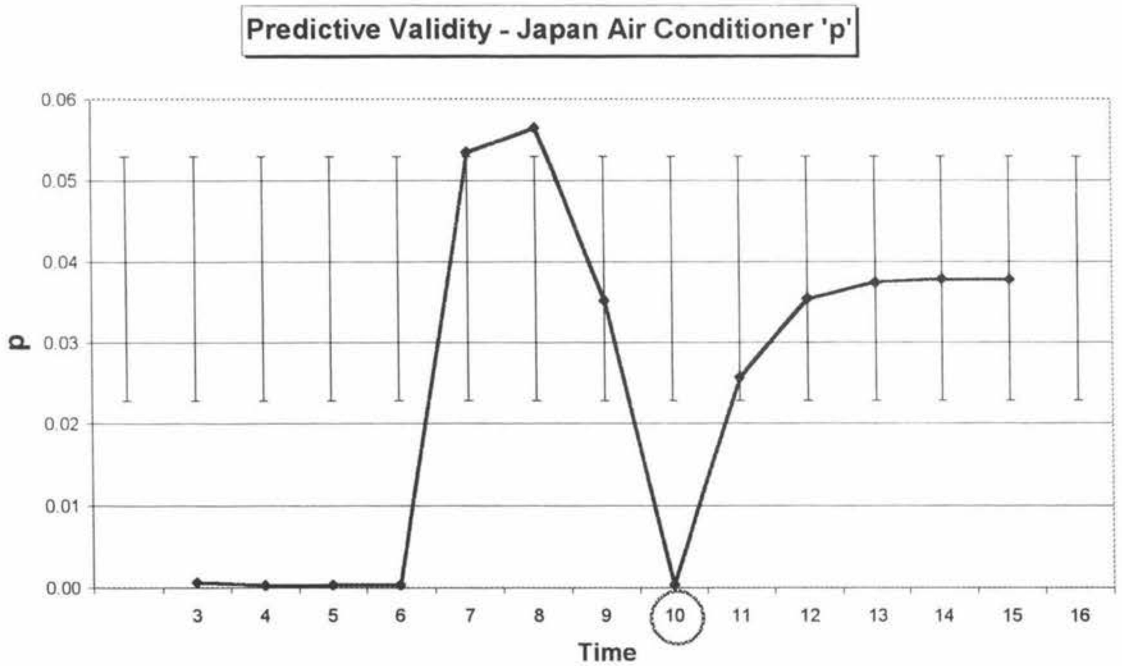
9.2 Measures of Model Fit – Complete List

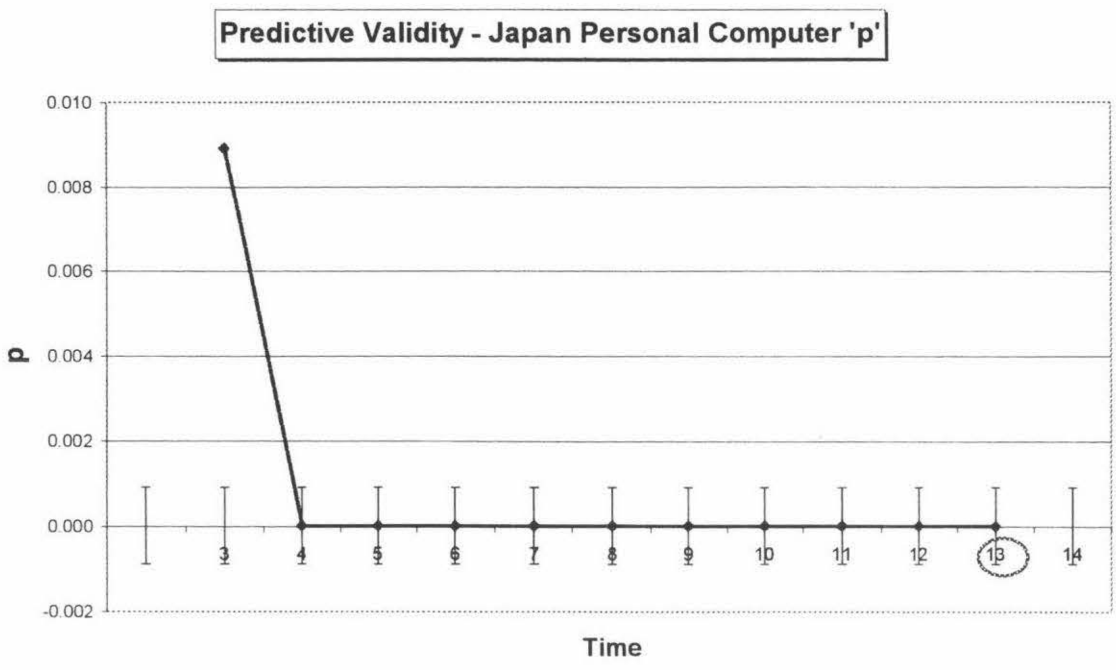
Product	Adjusted R^2	MAPE	MAD	MSE
Japan				
Air Conditioner	68.3%	12.3%	6.2	70
Personal Computer	76.6%	30.9%	70.5	6717
Facsimile	82.8%	28.4%	28.4	1206
VCR	84.9%	14%	48.0	4350
Microwave Oven	80.4%	21.2%	29.3	1236
Video Disk Player	40.4%	18.2%	10.6	188
Video Camera	88.4%	7.9%	61.2	6044
Digital Audio Disk Player	86.0%	42.5%	127.2	22699
Vacuum Cleaner	93.3%	12%	40.2	2466
Taiwan				
Air Conditioner	80.3%	136.9%	46.7	5613
Personal Computer	87.2%	235.8%	39.1	6101
Facsimile	94.3%	26%	5.2	48
VCR	79.8%	77.8%	20.6	1450
Microwave Oven	89.7%	57.3%	5.2	40
Induction Cooker	94.1%	6.6%	1.7	5
TV Game	48.5%	35.4%	21.3	809
Floppy Disk	86.0%	11.6%	1.1	2
Clothes Dryer	85.4%	6179%	1.8	5

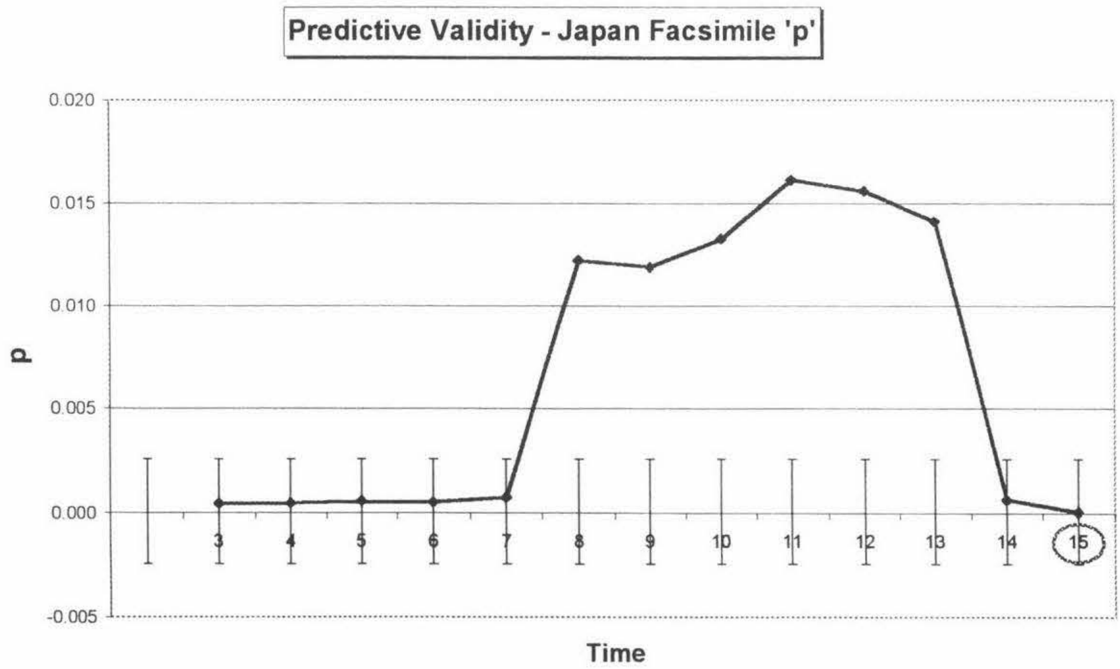
9.3 Predictive Validity/Small Sample Properties

The following series of charts are associated with section 5.2 which examined the predictive validity and small sample properties of the Bass model parameter estimates, next period sales, and timing and magnitude of peak sales. For the charts related to the parameters *p*, *q*, and *m*, the y-axis is the estimated parameter value, for next period sales and peak magnitude it is percentage error, and for peak timing it is the estimated timing of peak sales. In all cases, the x-axis is time with the total number of time periods represented by the last data point. Additionally, the peak sales period is circled on the x-axis.

9.3.1 Bass Model Parameters – Japan *p*




Predictive Validity - Japan Personal Computer 'p'
0.010
0.008
0.006
0.004
0.002
0.000
-0.002
p
3
4
5
6
7
8
9
10
11
12
13
14
Time


Predictive Validity - Japan Facsimile 'p'
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0.015
0.010
0.005
0.000
-0.005
p
3
4
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12
13
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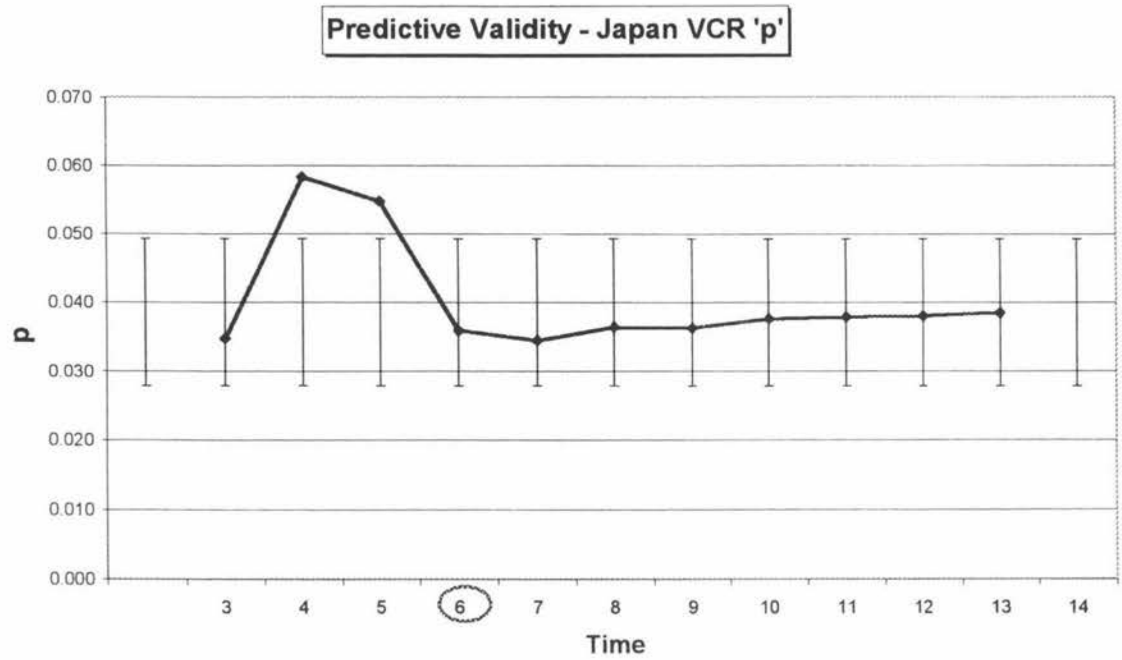
15
Time


Predictive Validity - Japan VCR 'p'
0.070
0.060
0.050
0.040
0.030
0.020
0.010
0.000
p
3
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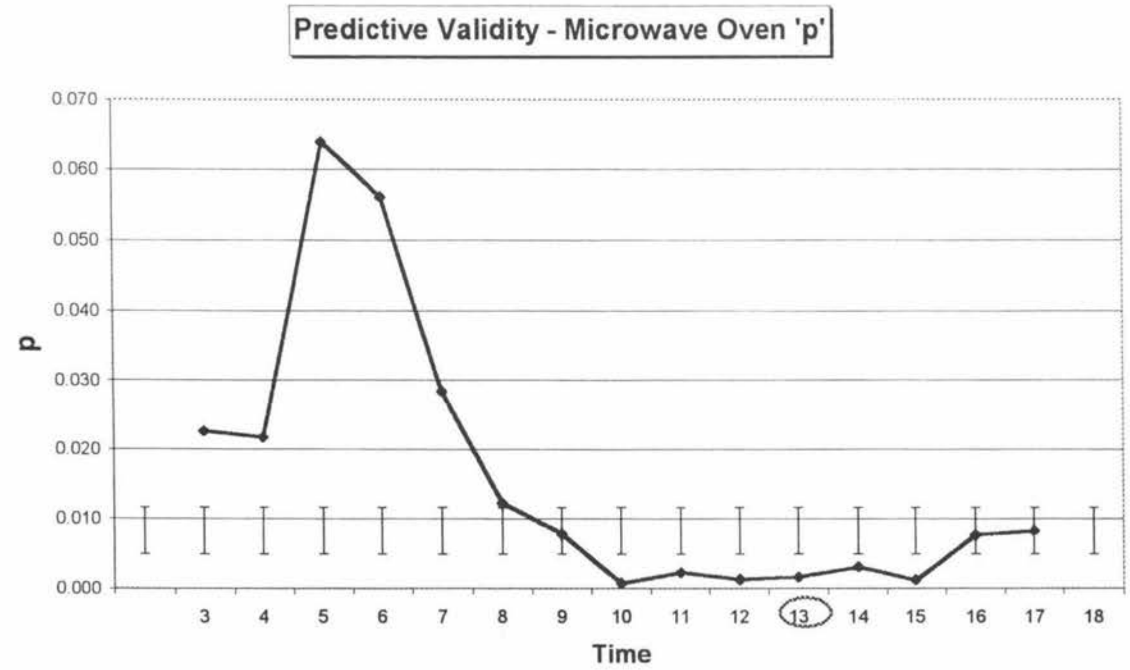
6
7
8
9
10
11
12
13
14
Time


Predictive Validity - Microwave Oven 'p'
0.070
0.060
0.050
0.040
0.030
0.020
0.010
0.000
p
3
4
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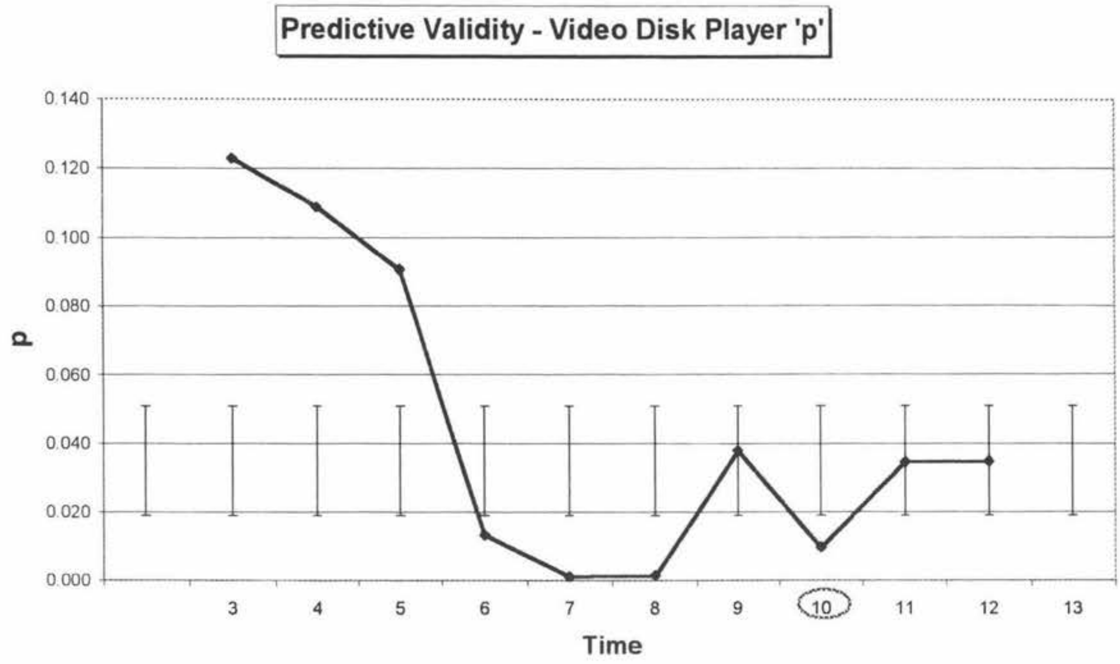
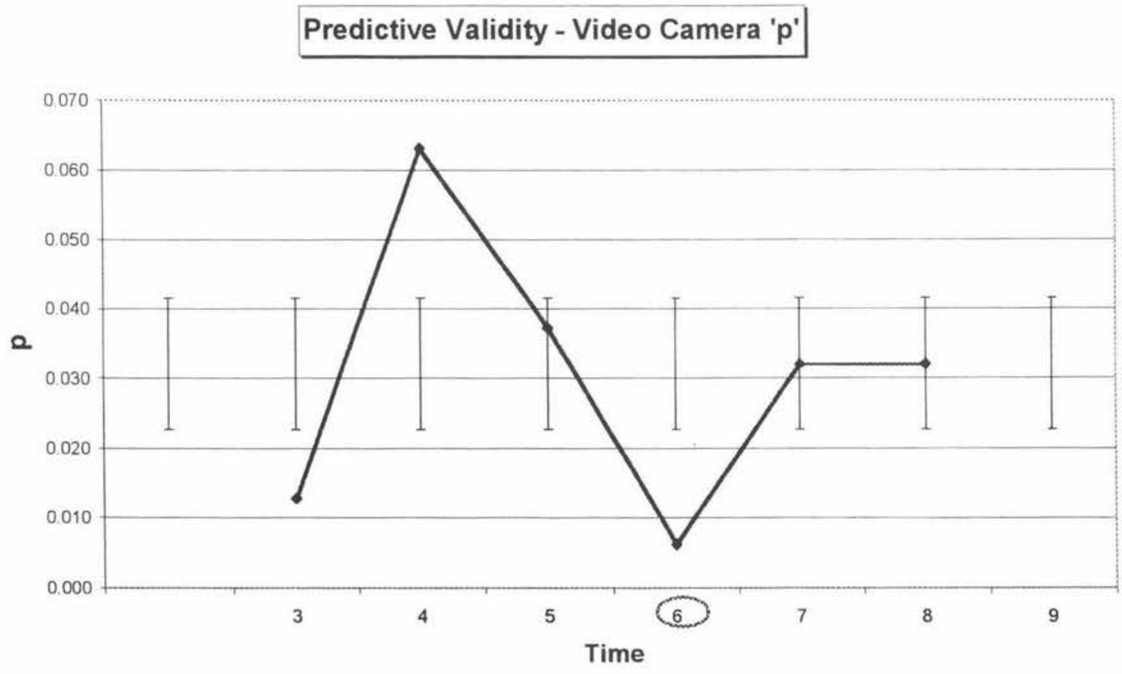
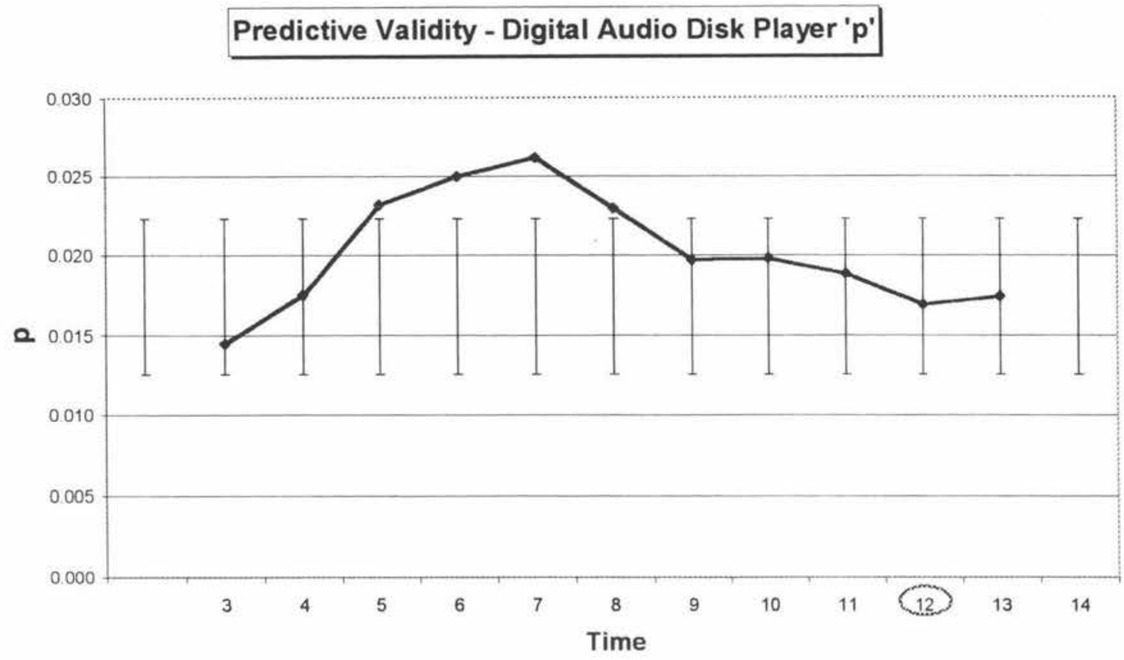
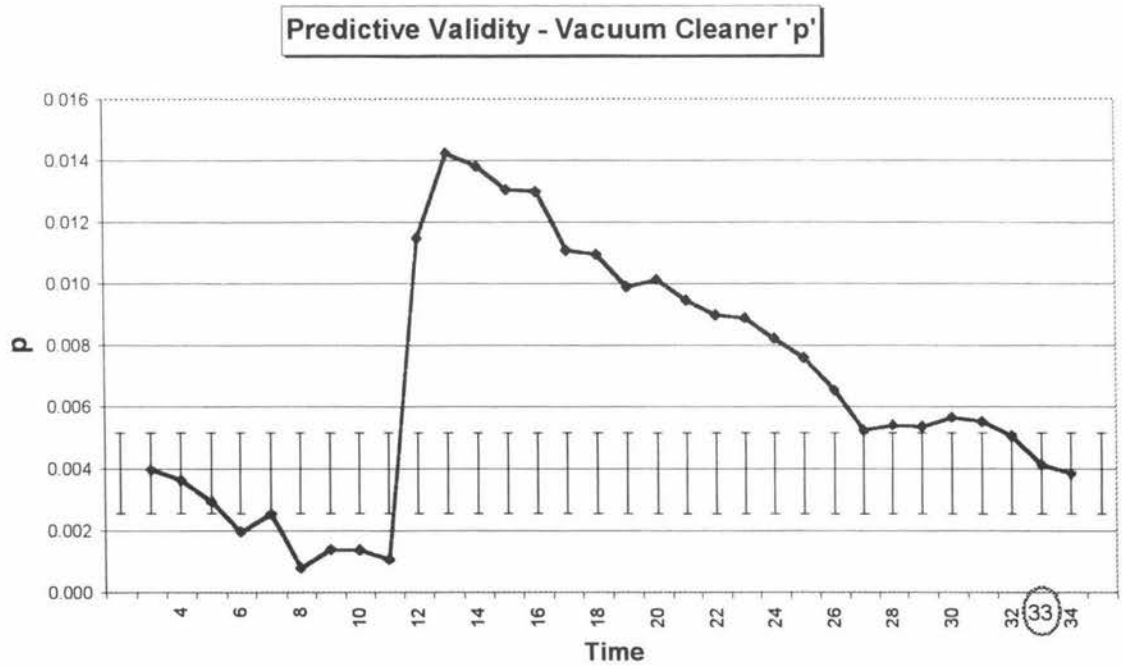
17
18
Time


Predictive Validity - Video Disk Player 'p'
0.140
0.120
0.100
0.080
0.060
0.040
0.020
0.000
p
3
4
5
6
7
8
9
10
11
12
13
Time


Predictive Validity - Video Camera 'p'
0.070
0.060
0.050
0.040
0.030
0.020
0.010
0.000
p
3
4
5
6
7
8
9
Time

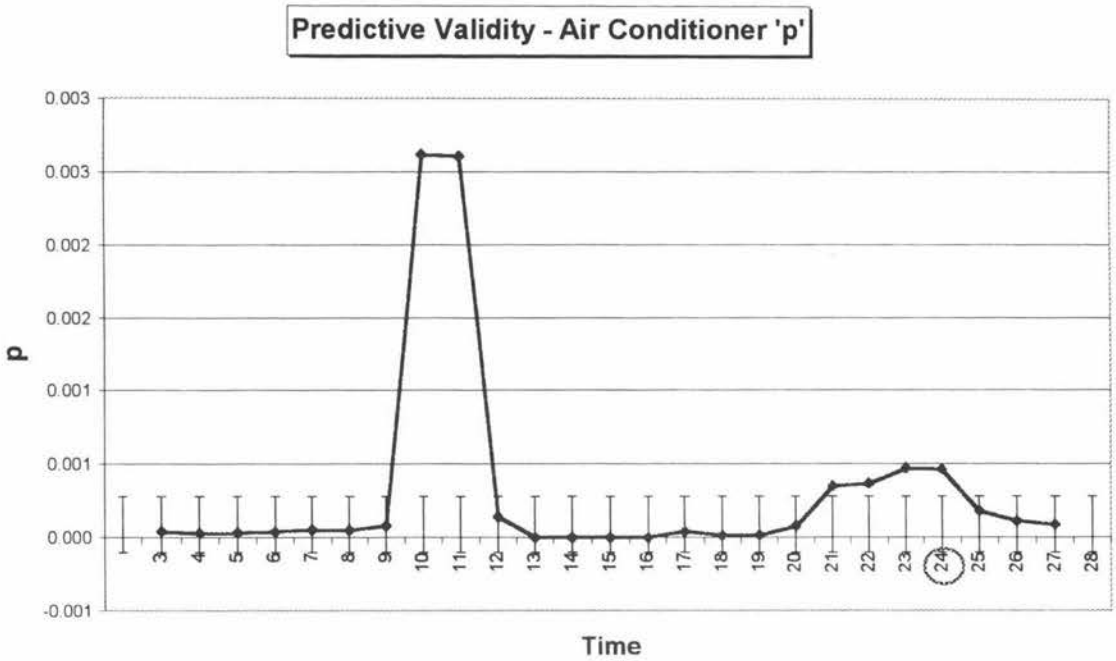


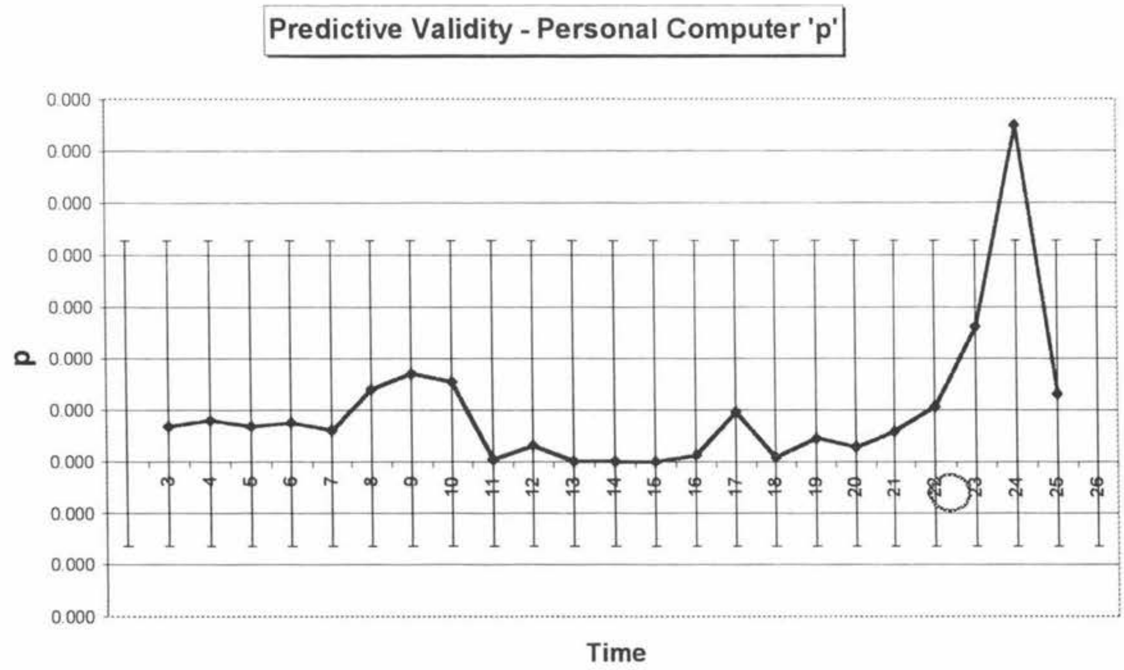
Predictive Validity - Digital Audio Disk Player 'p'
0.030
0.025
0.020
0.015
0.010
0.005
0.000
p
3
4
5
6
7
8
9
10
11
12
13
14
Time

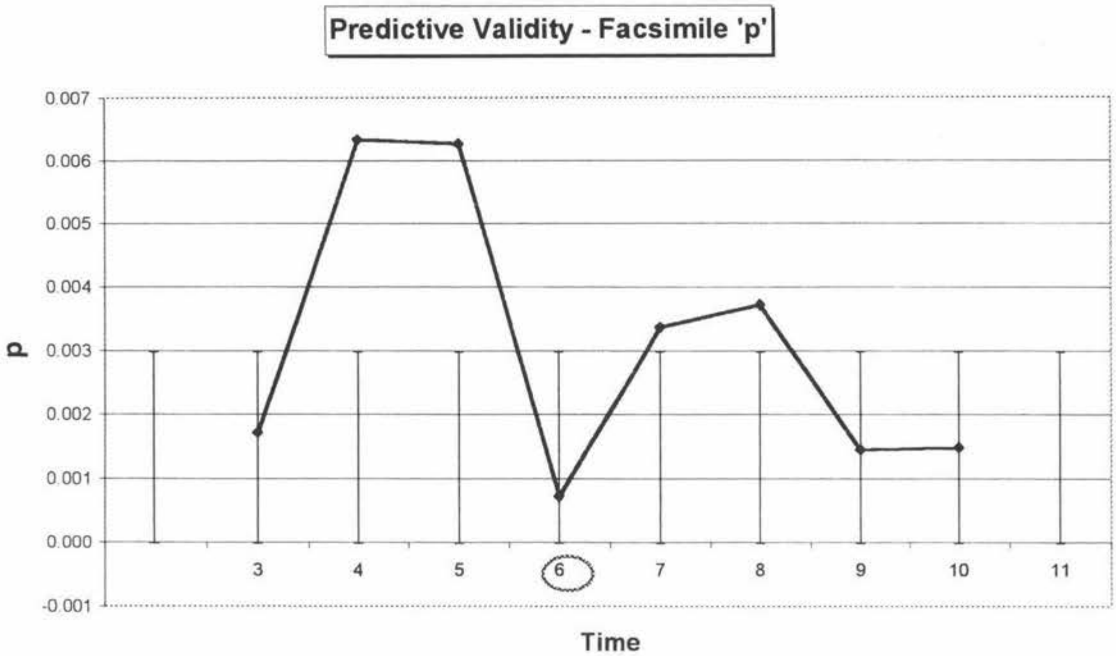


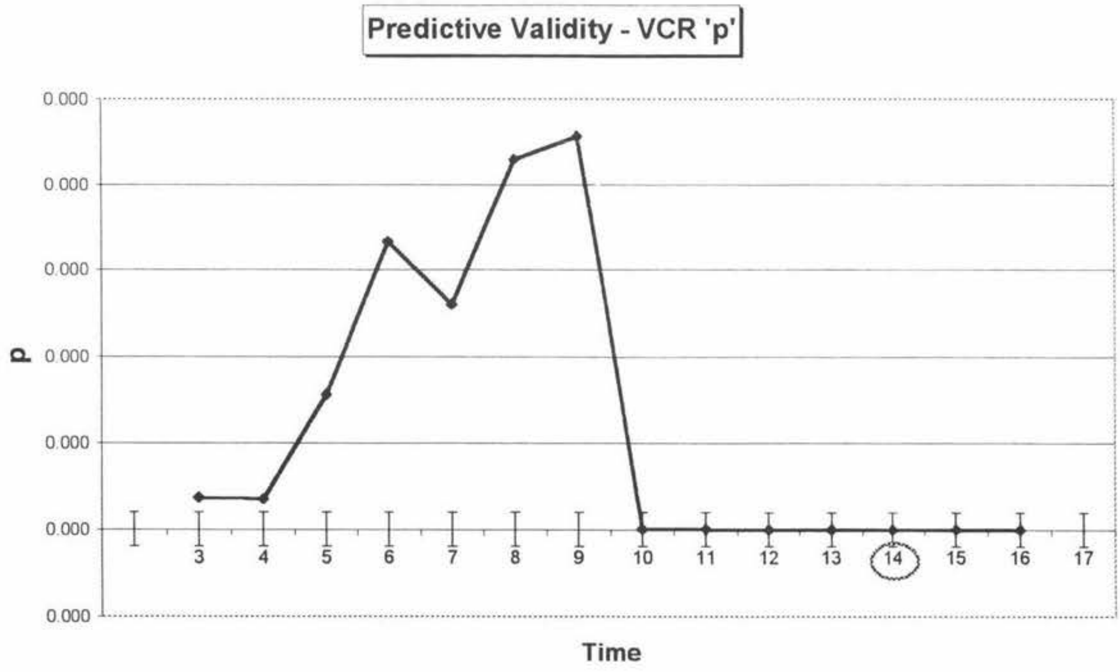
Predictive Validity - Vacuum Cleaner 'p'
0.016
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
p
4
6
8
10
12
14
16
18
20
22
24
26
28
30
32
33
34
Time

9.3.2 Bass Model Parameters – Taiwan *p*

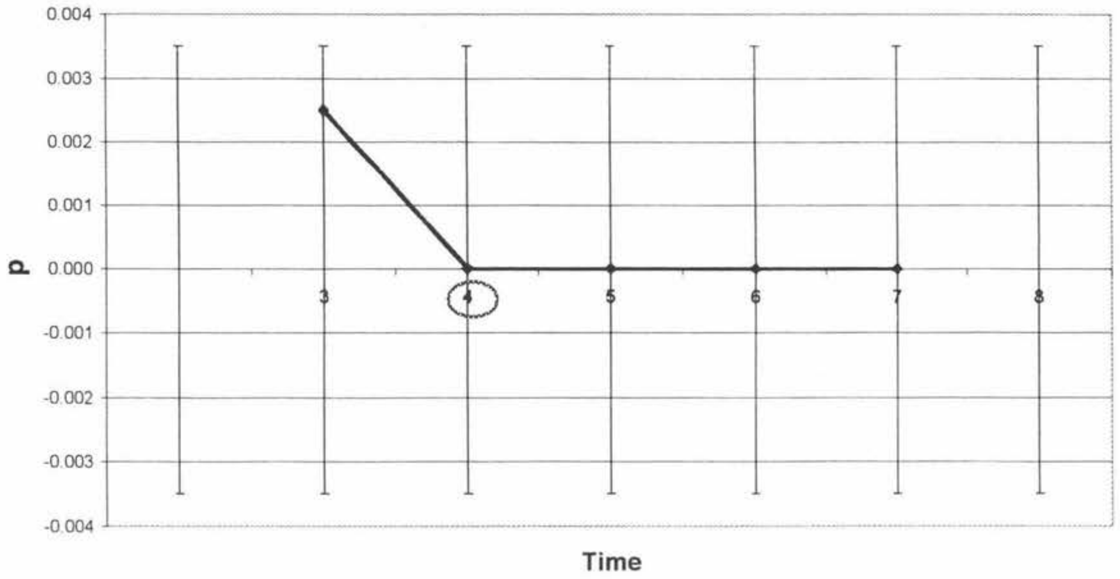




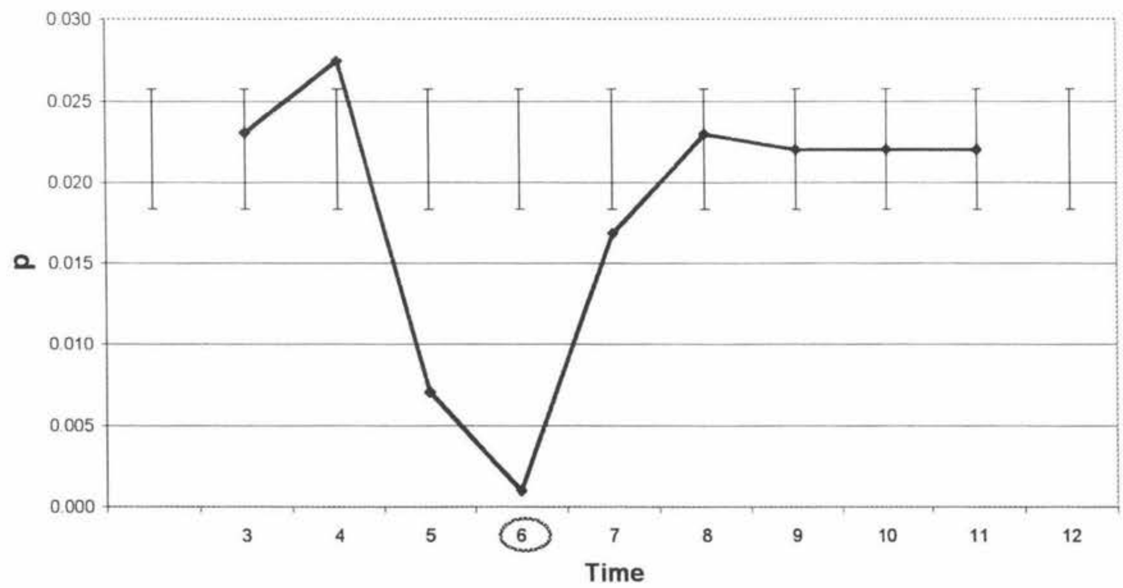

Predictive Validity - Facsimile 'p'
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000
-0.001
p
3
4
5
6
7
8
9
10
11
Time

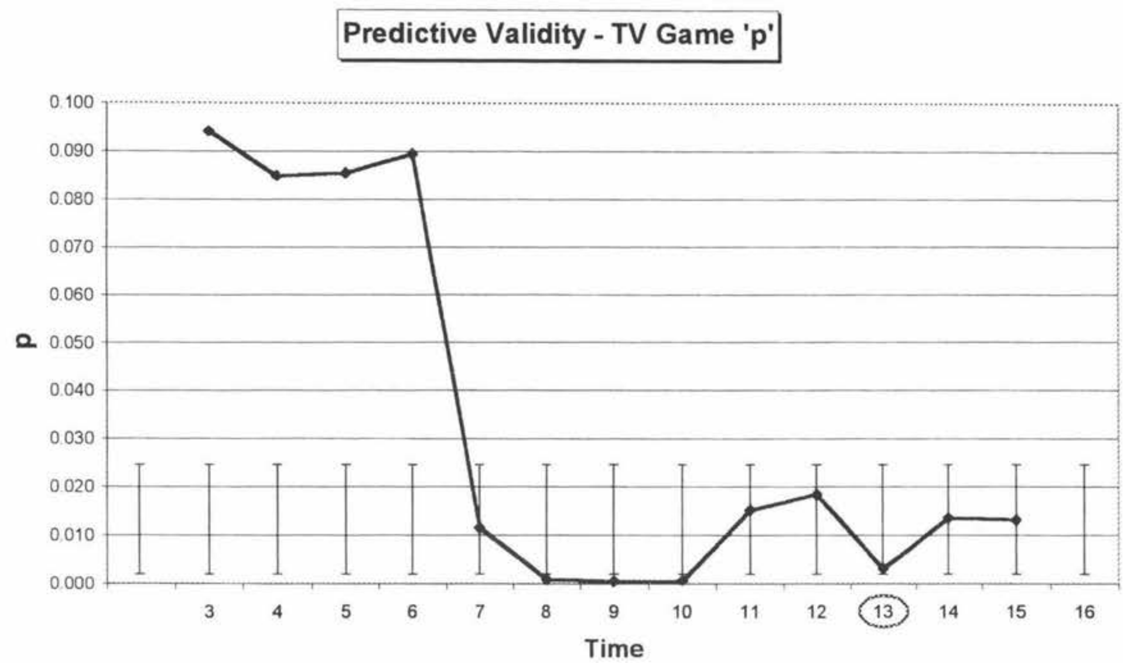

Predictive Validity - VCR 'p'
0.000
0.000
0.000
0.000
0.000
0.000
0.000
p
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
Time

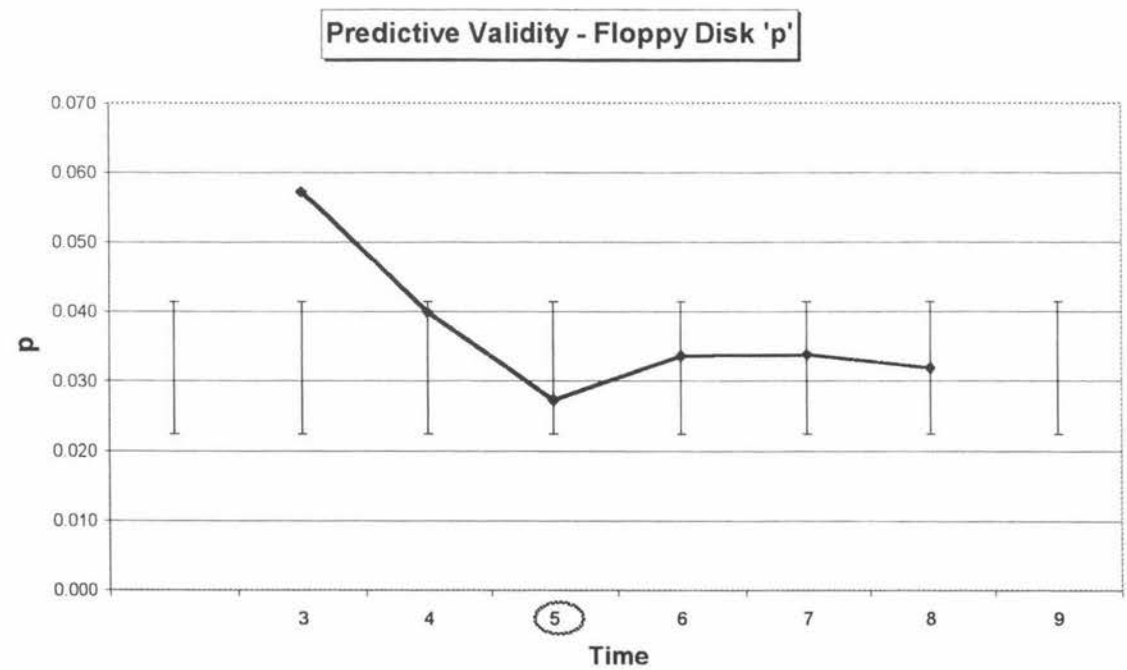
Predictive Validity - Microwave Oven 'p'

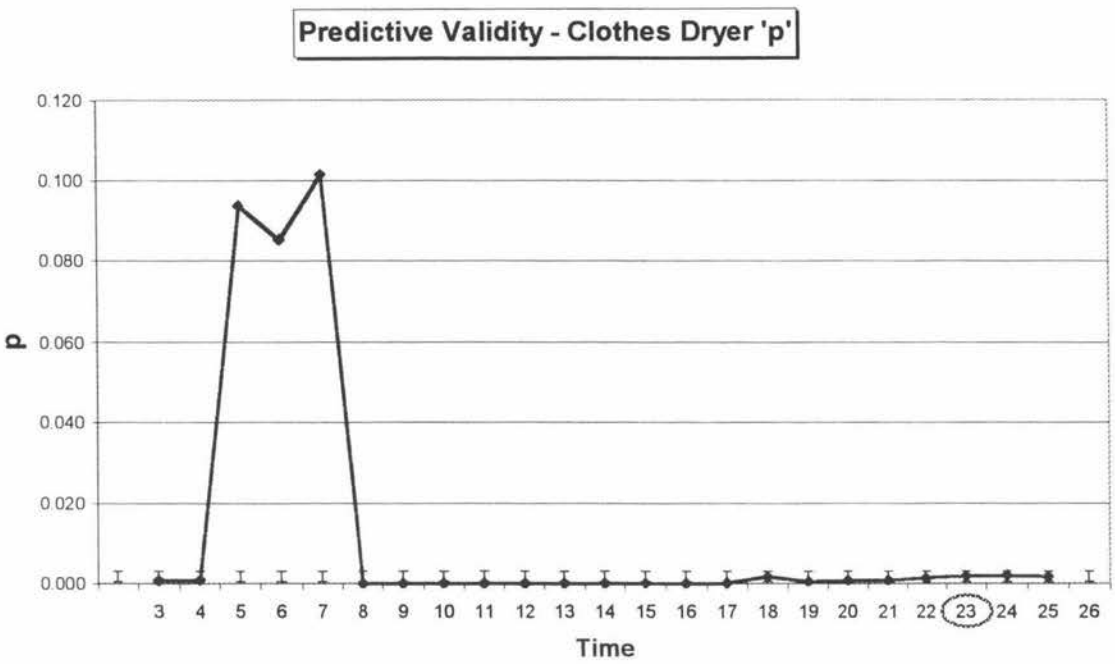


Predictive Validity - Induction Cooker 'p'

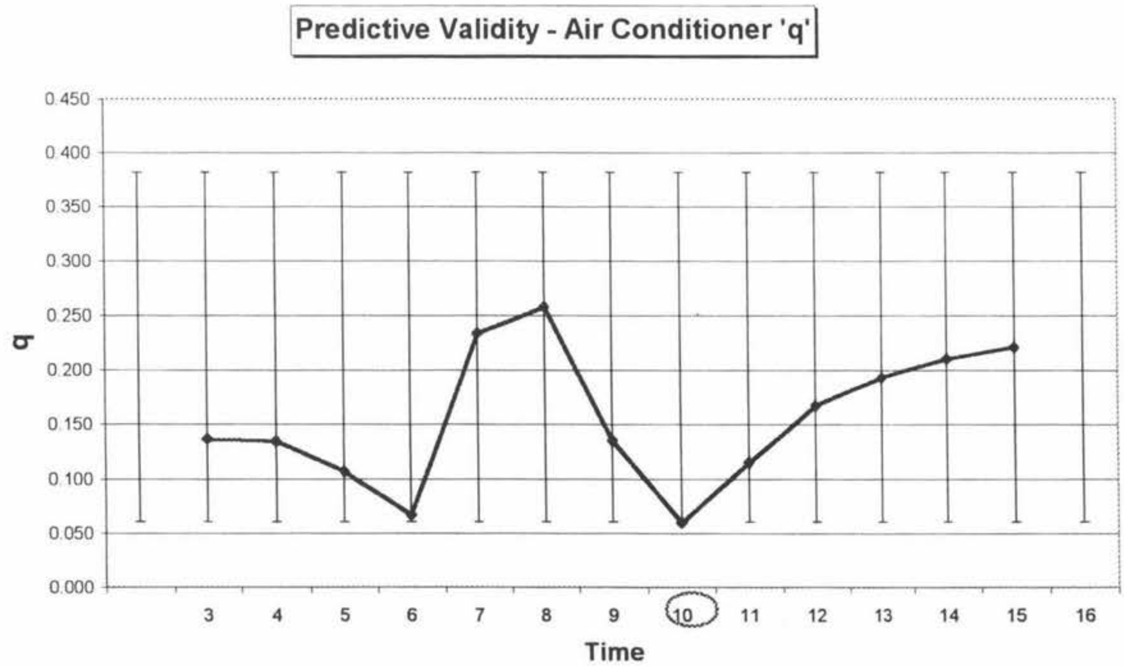


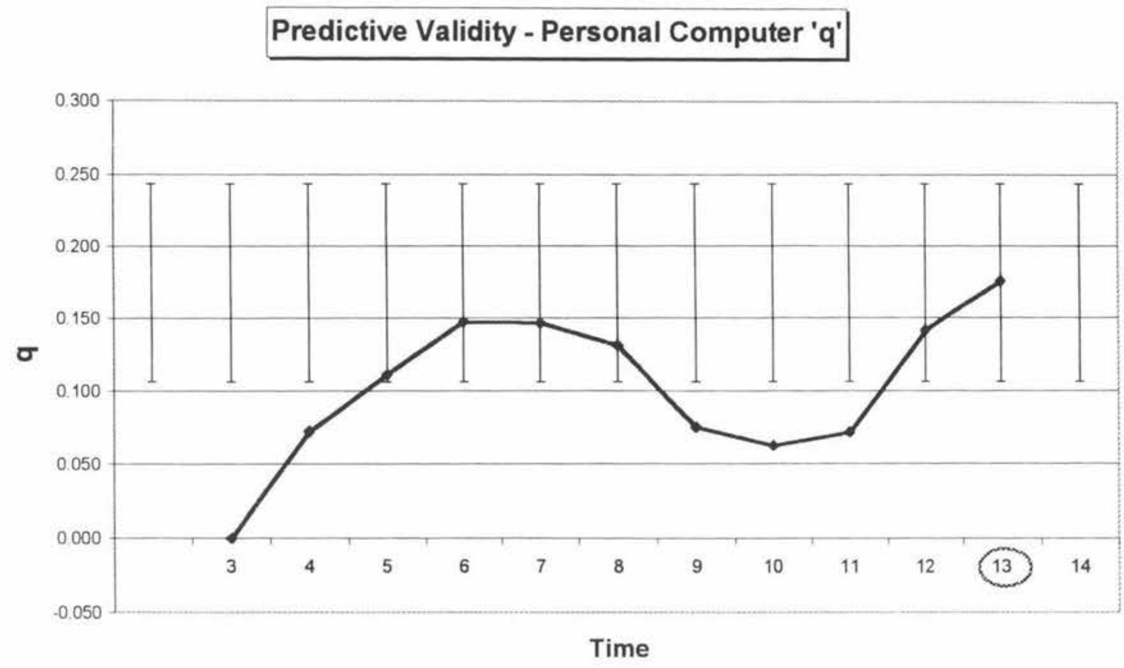

Predictive Validity - TV Game 'p'
0.100
0.090
0.080
0.070
0.060
p
0.050
0.040
0.030
0.020
0.010
0.000
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Time

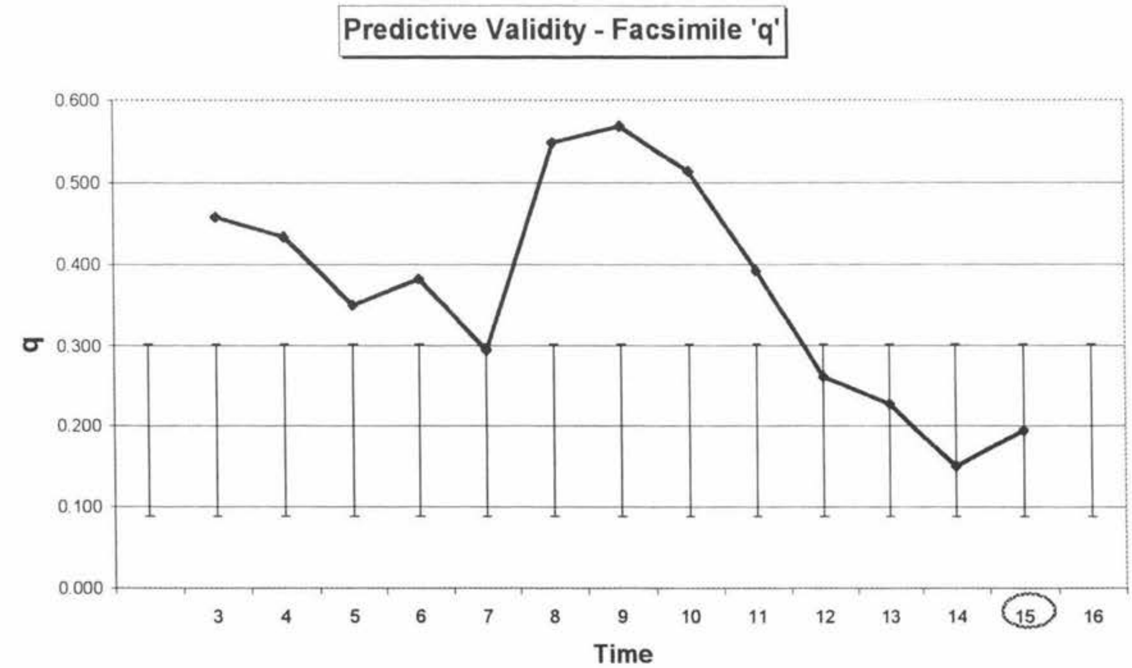

Predictive Validity - Floppy Disk 'p'
0.070
0.060
0.050
0.040
p
0.030
0.020
0.010
0.000
3
4
5
6
7
8
9
Time

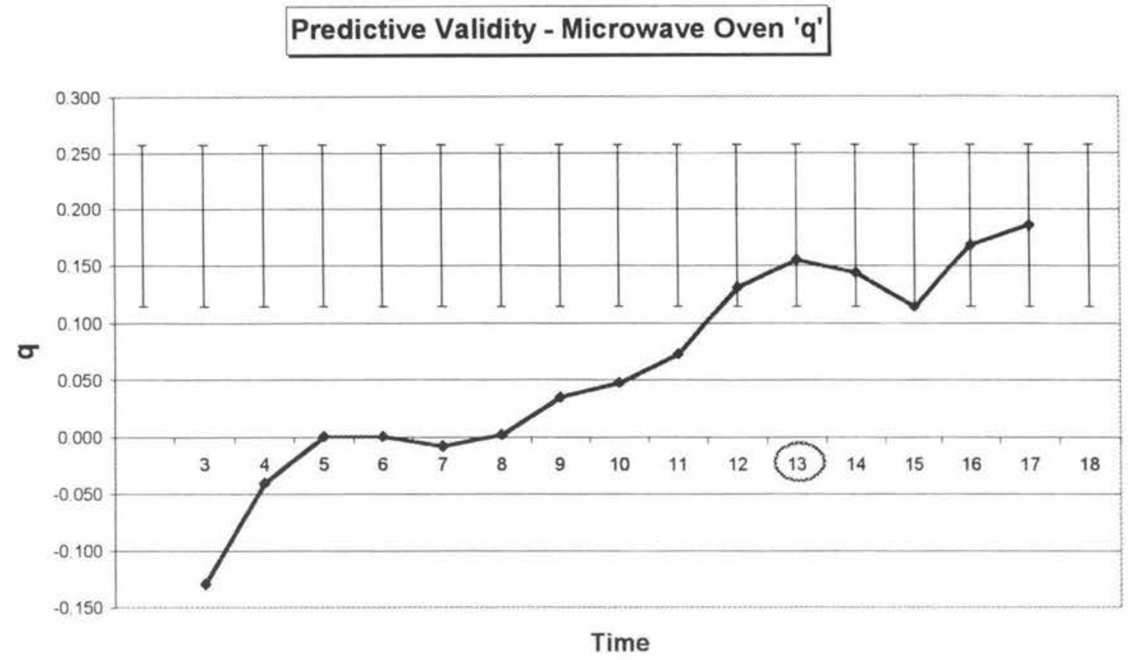


9.3.3 Bass Model Parameters – Japan *q*

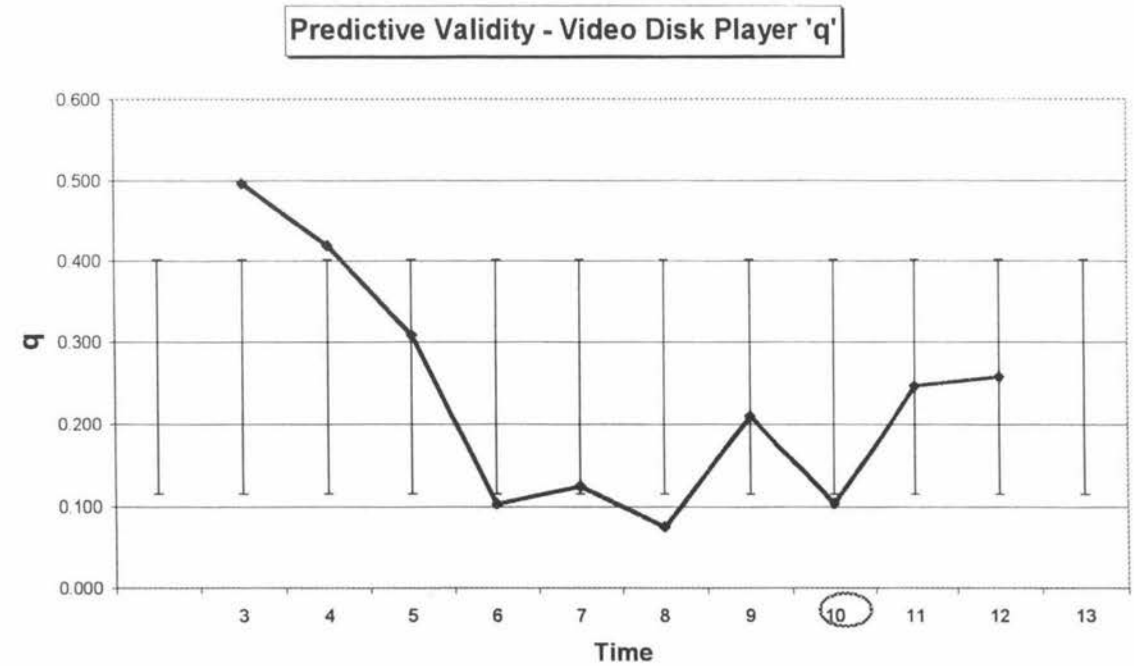



Predictive Validity - Personal Computer 'q'
0.300
0.250
0.200
0.150
0.100
0.050
0.000
-0.050
q
3
4
5
6
7
8
9
10
11
12
13
14
Time

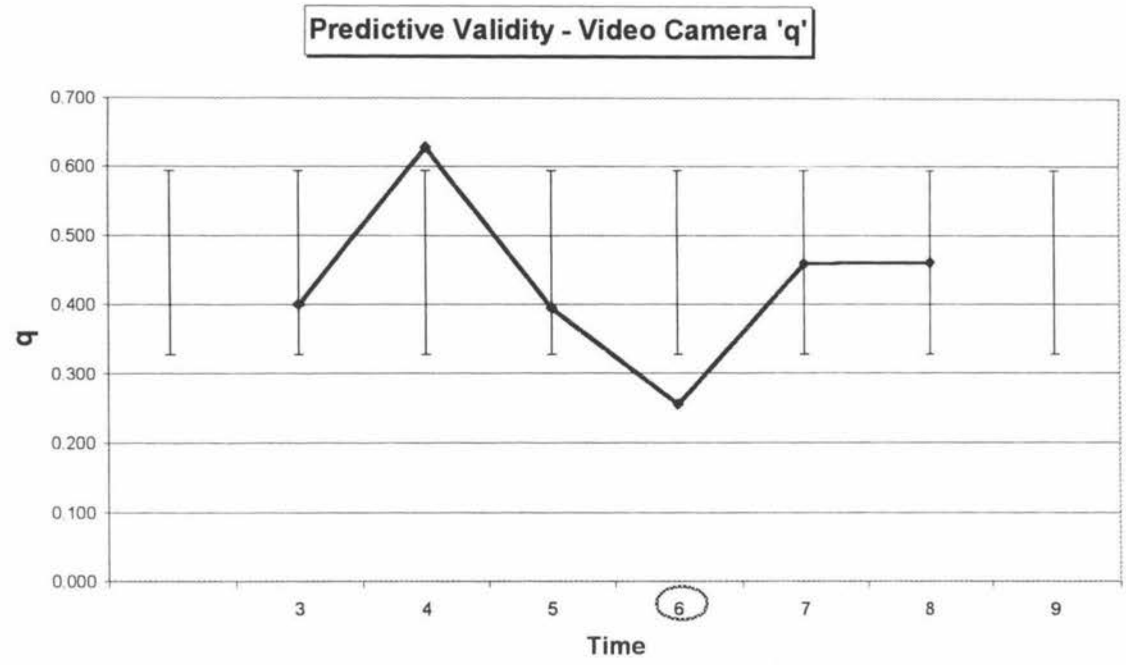

Predictive Validity - Facsimile 'q'
0.600
0.500
0.400
0.300
0.200
0.100
0.000
q
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Time

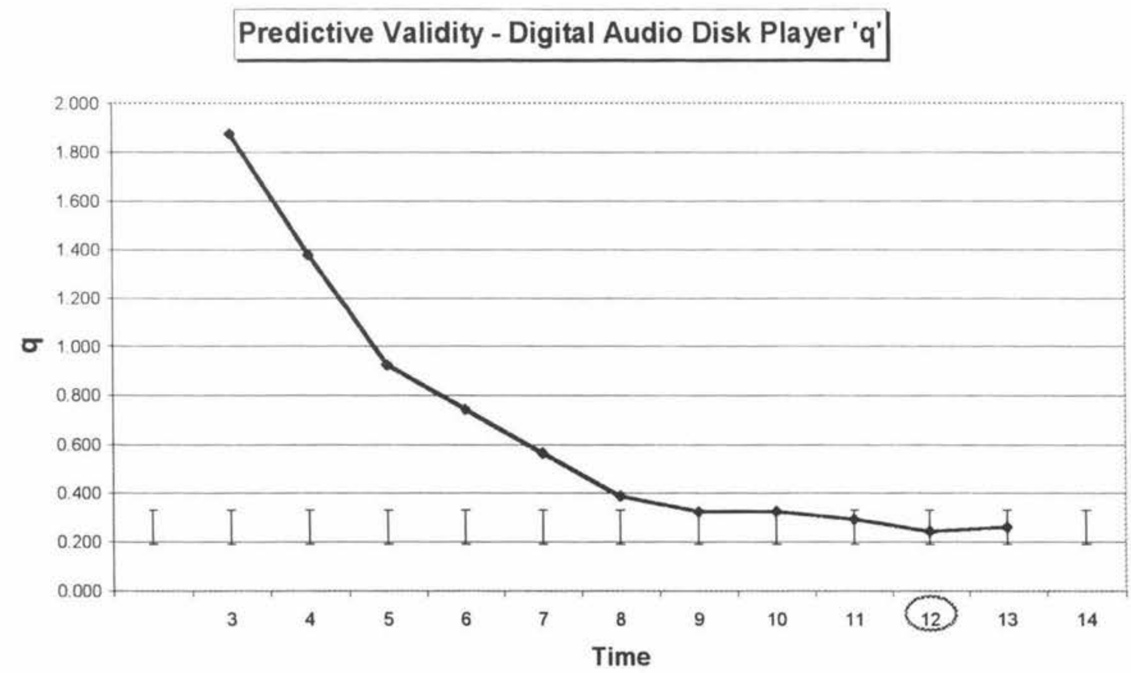


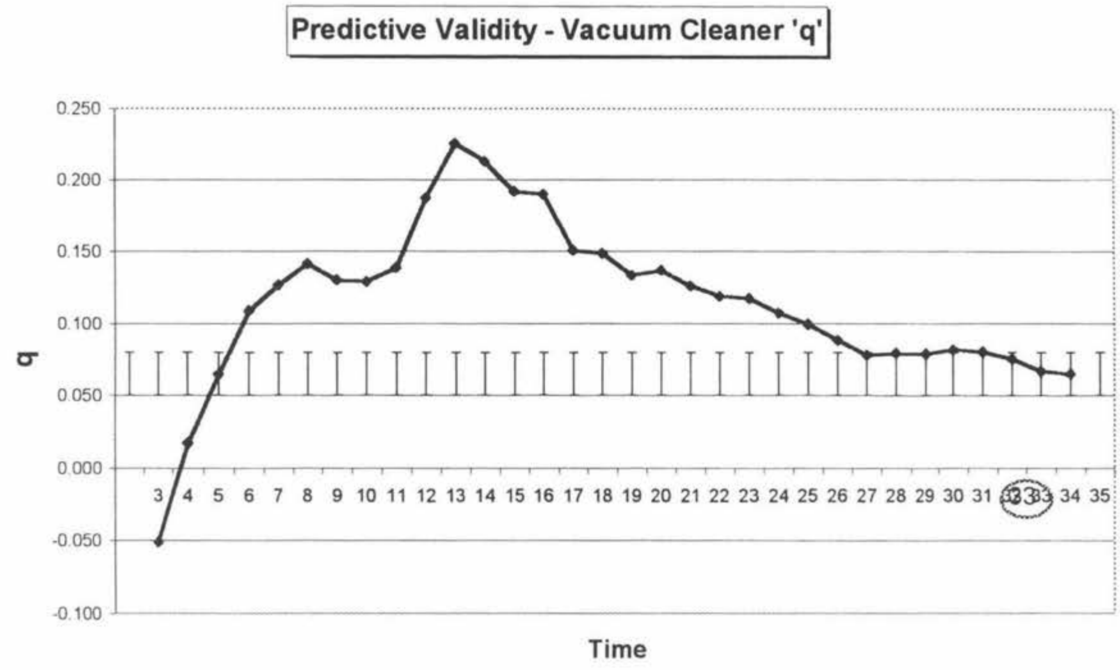
Predictive Validity - Microwave Oven 'q'
0.300
0.250
0.200
0.150
0.100
0.050
0.000
-0.050
-0.100
-0.150
q
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18
Time



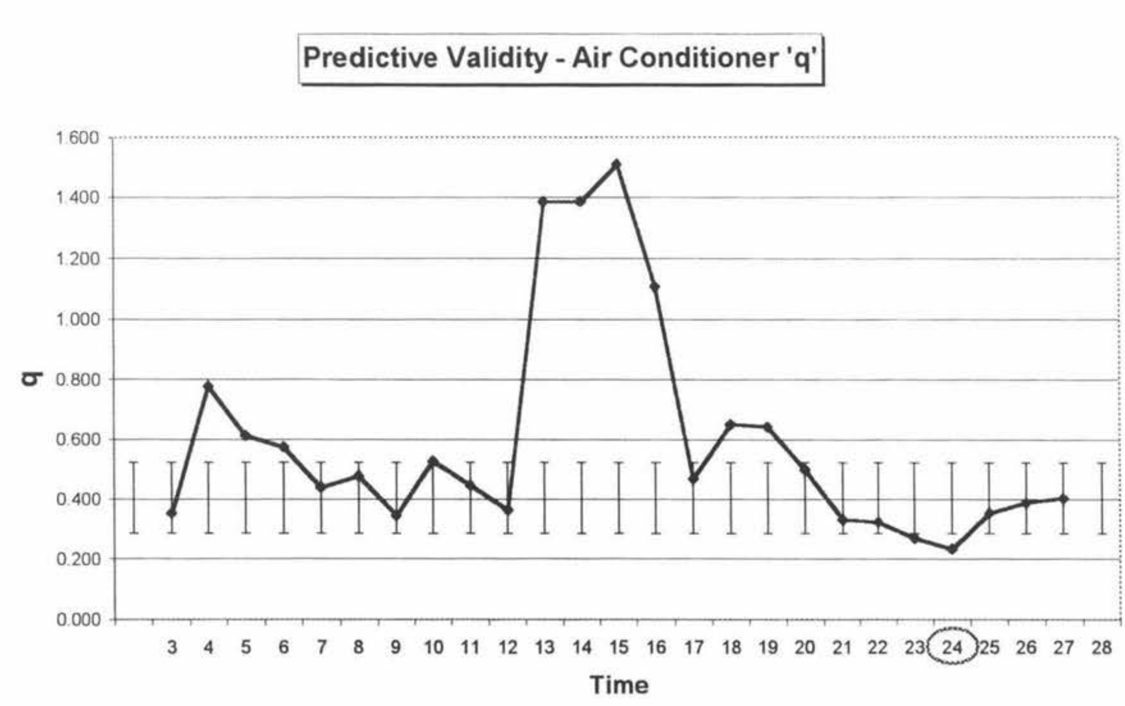
Predictive Validity - Video Disk Player 'q'
0.600
0.500
0.400
0.300
0.200
0.100
0.000
q
3 4 5 6 7 8 9 10 11 12 13
Time

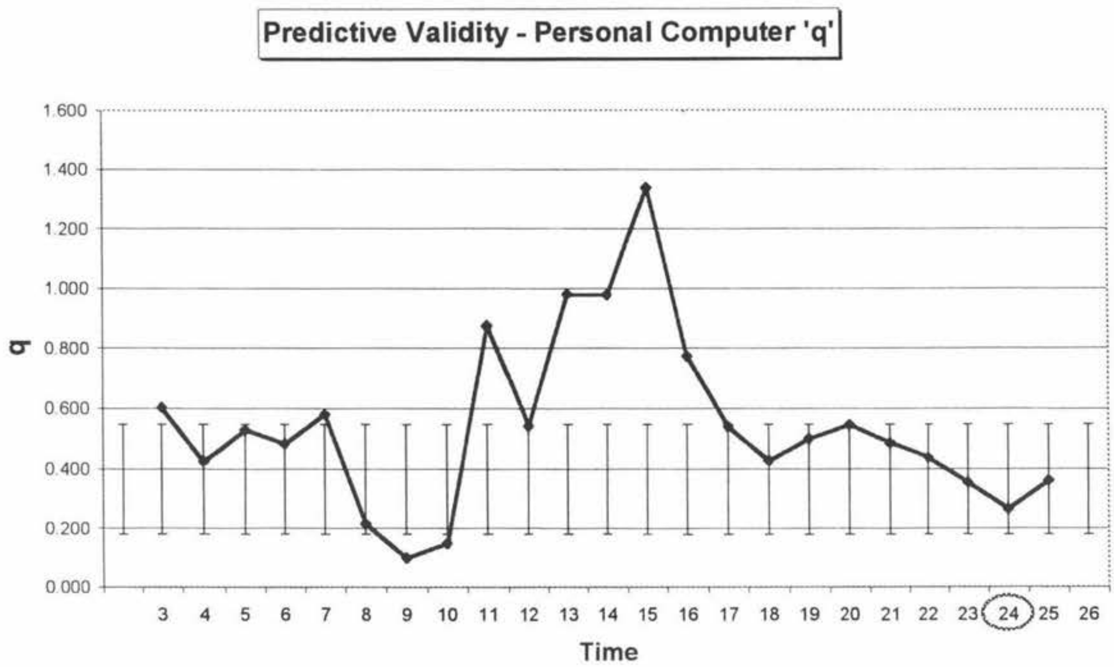

Predictive Validity - Video Camera 'q'
0.700
0.600
0.500
0.400
0.300
0.200
0.100
0.000
q
3
4
5
6
7
8
9
Time

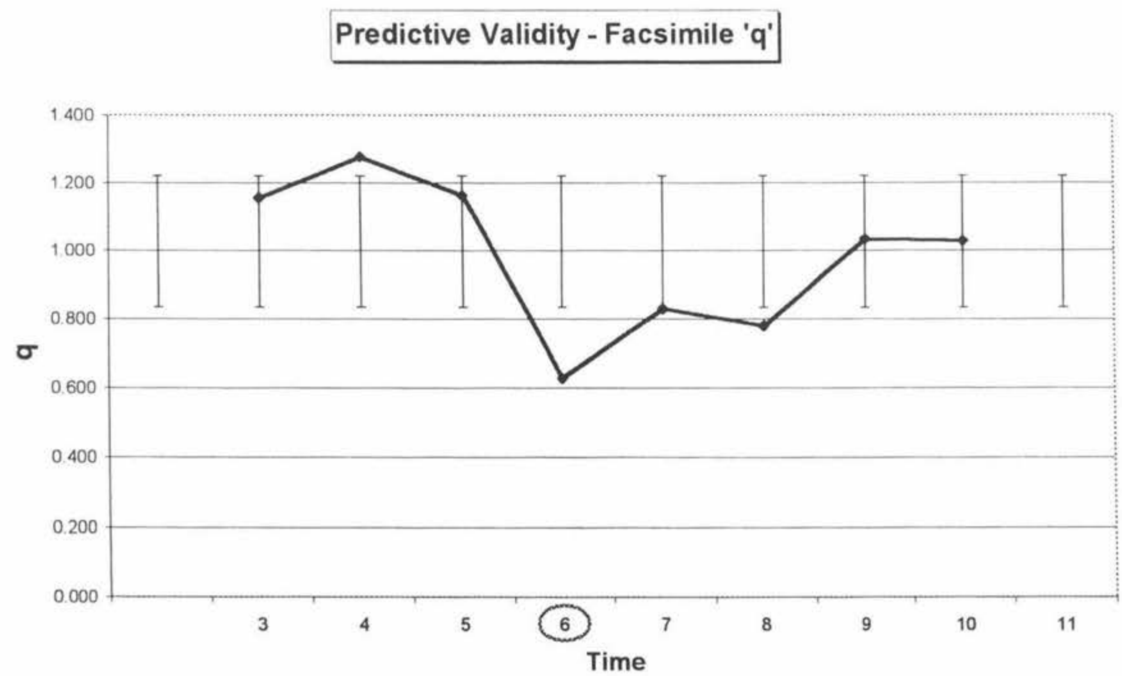

Predictive Validity - Digital Audio Disk Player 'q'
2.000
1.800
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
q
3
4
5
6
7
8
9
10
11
12
13
14
Time

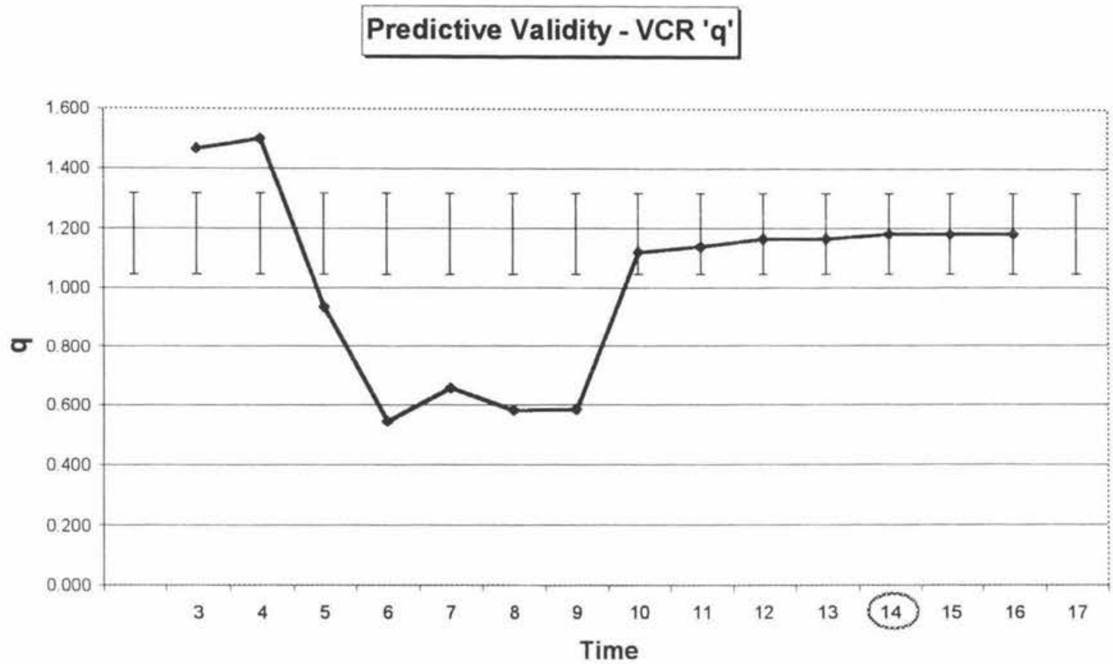


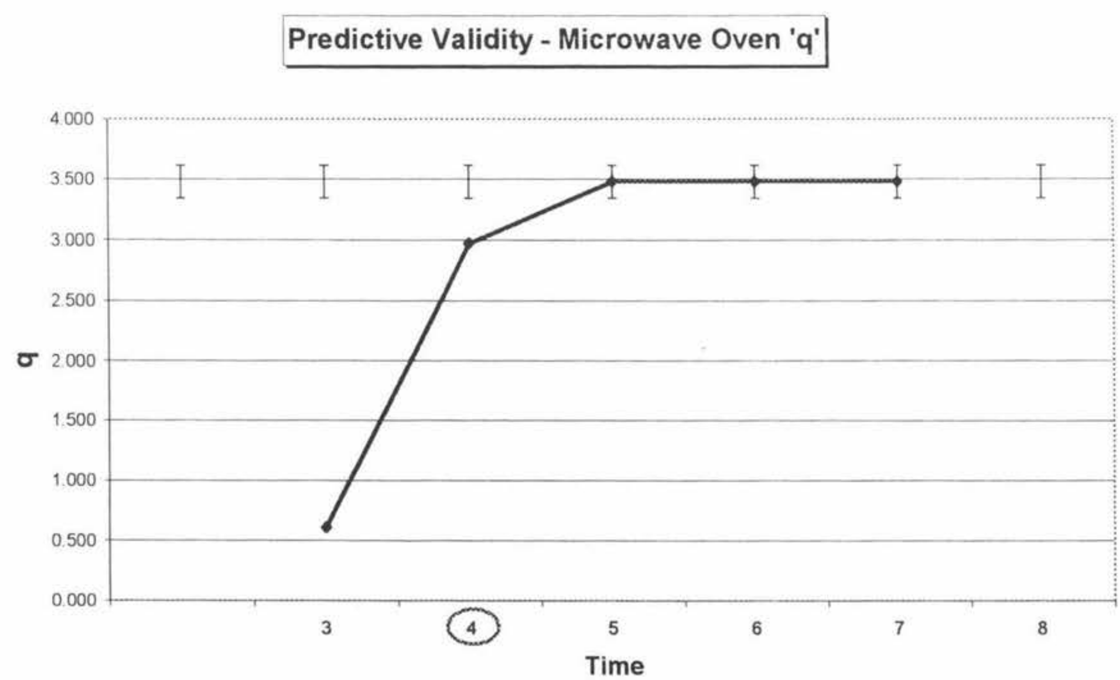
9.3.4 Bass Model Parameters – Taiwan *q*

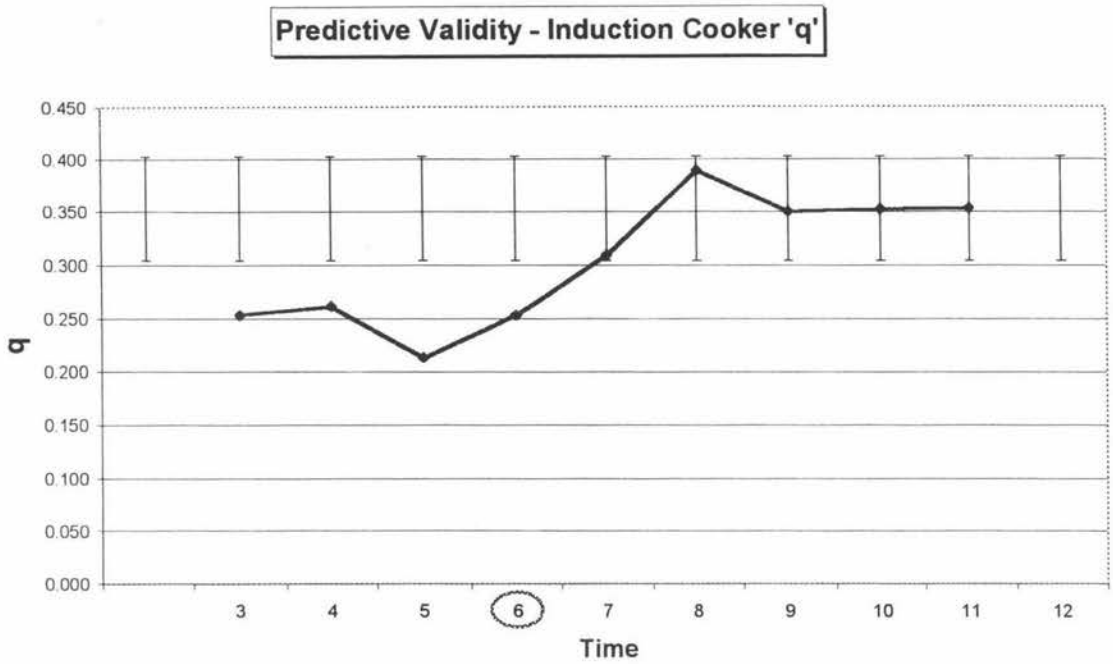


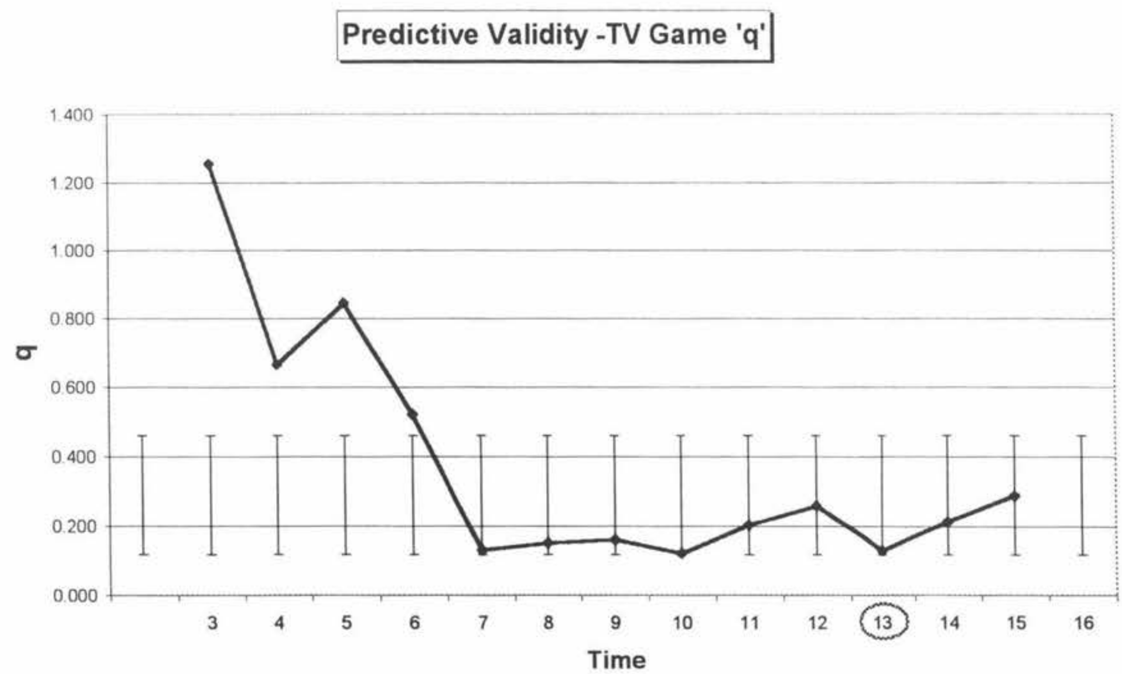

Predictive Validity - Personal Computer 'q'
q
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
Time

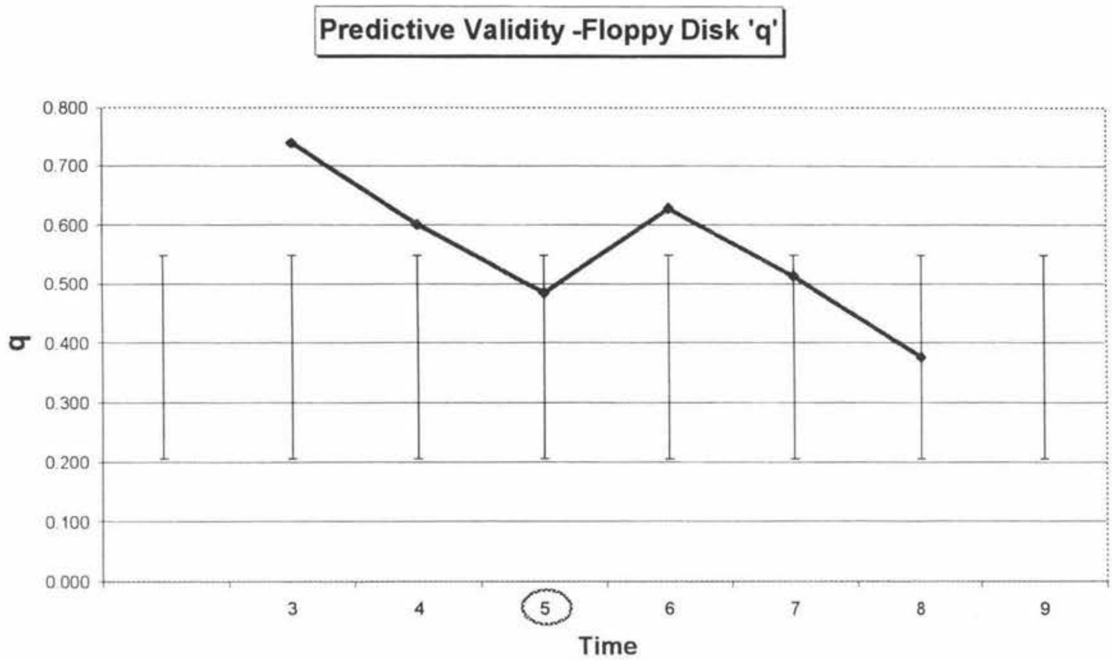

Predictive Validity - Facsimile 'q'
q
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
3 4 5 6 7 8 9 10 11
Time

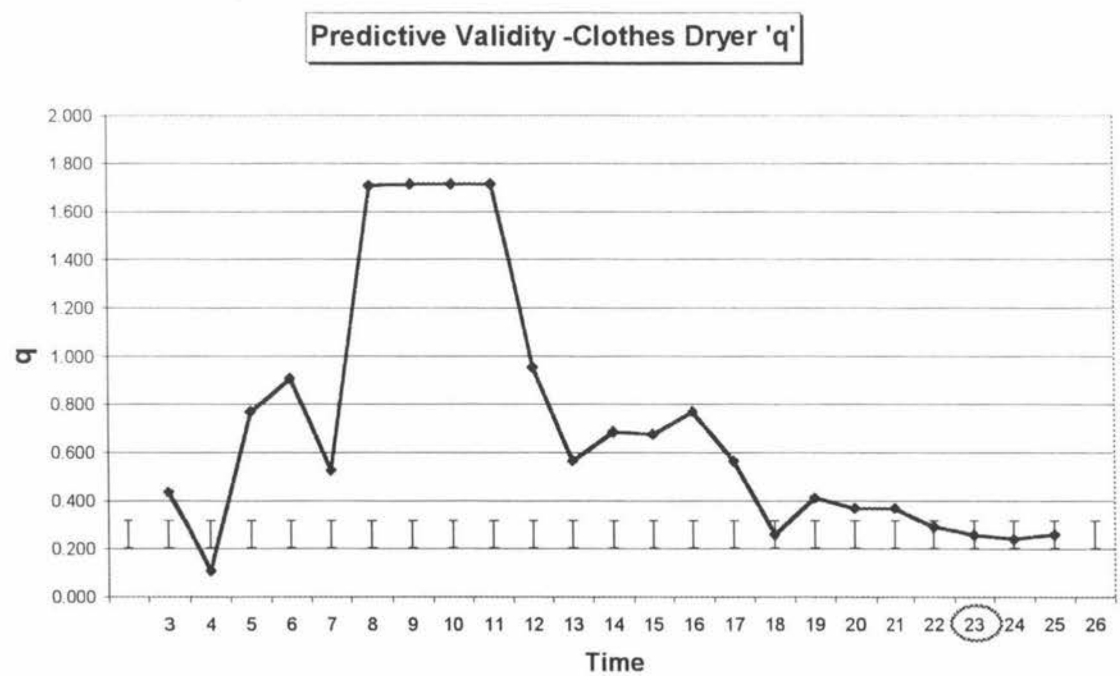

Predictive Validity - VCR 'q'
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
q
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
Time


Predictive Validity - Microwave Oven 'q'
4.000
3.500
3.000
2.500
2.000
1.500
1.000
0.500
0.000
q
3
4
5
6
7
8
Time

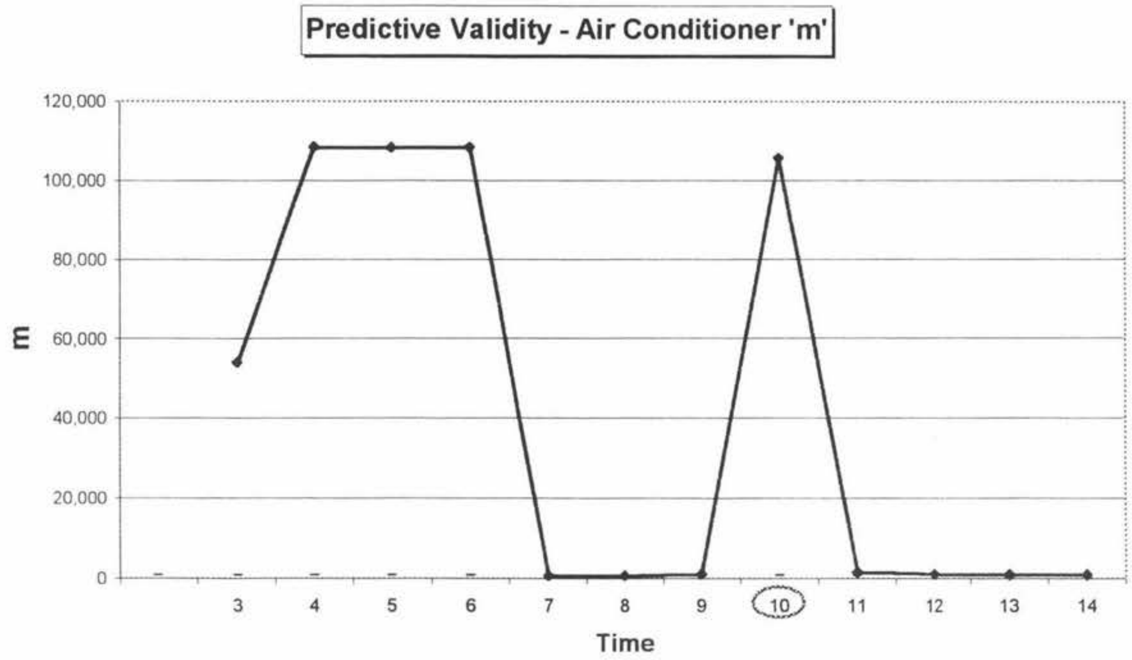

Predictive Validity - Induction Cooker 'q'
0.450
0.400
0.350
0.300
0.250
0.200
0.150
0.100
0.050
0.000
q
3
4
5
6
7
8
9
10
11
12
Time

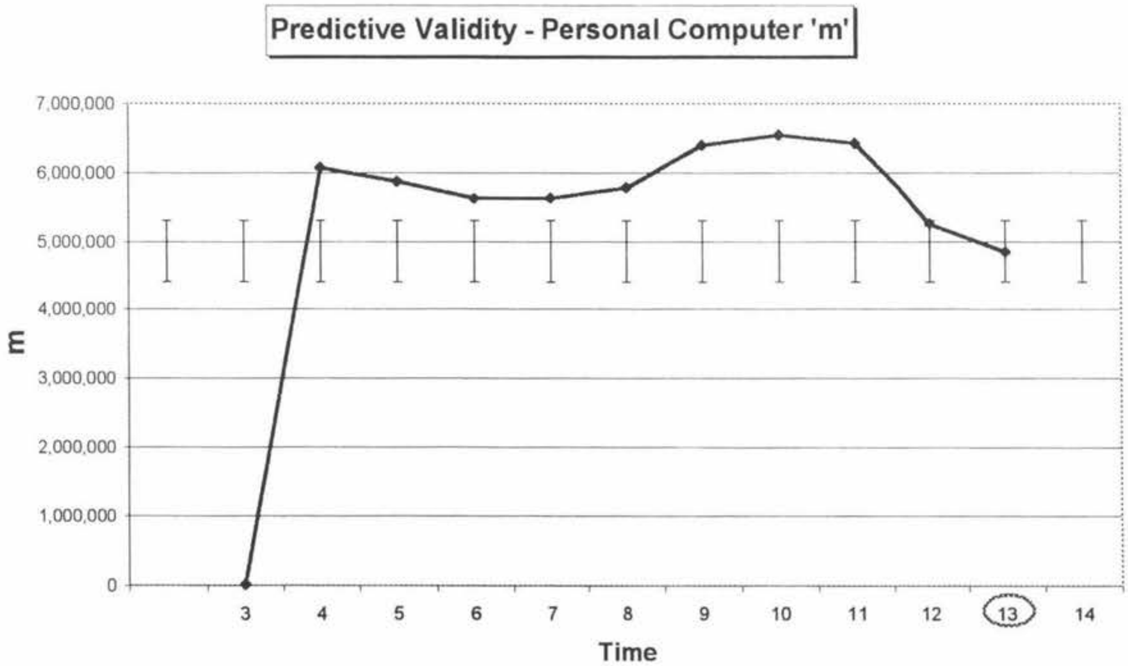

Predictive Validity -TV Game 'q'
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
q
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Time

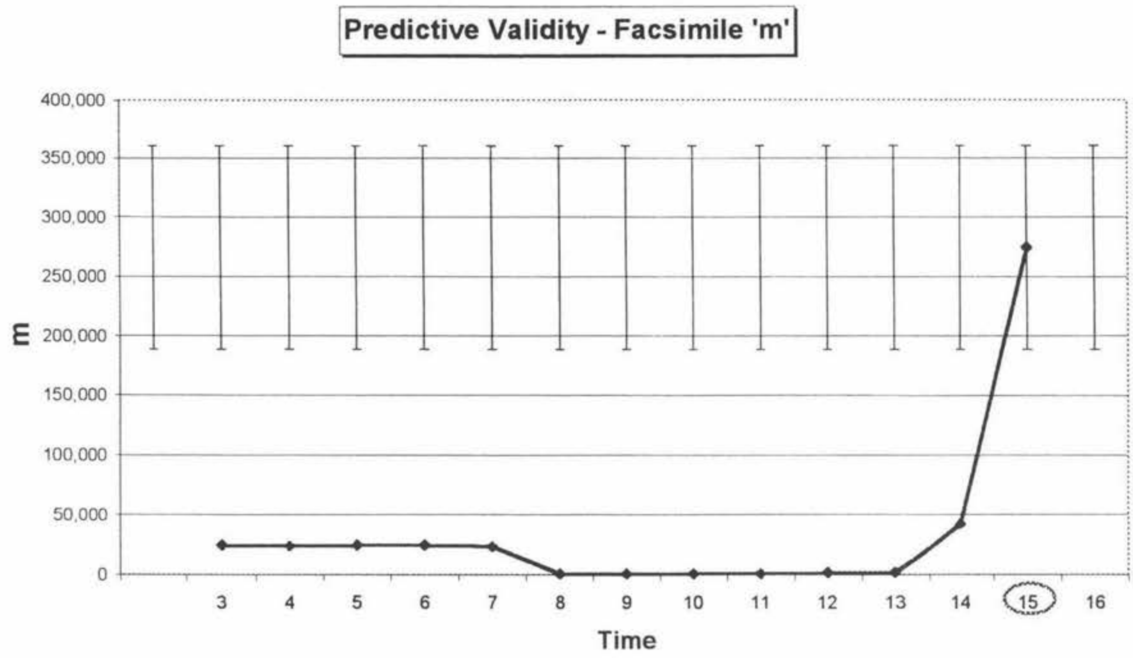

Predictive Validity -Floppy Disk 'q'
0.800
0.700
0.600
0.500
0.400
0.300
0.200
0.100
0.000
q
3
4
5
6
7
8
9
Time

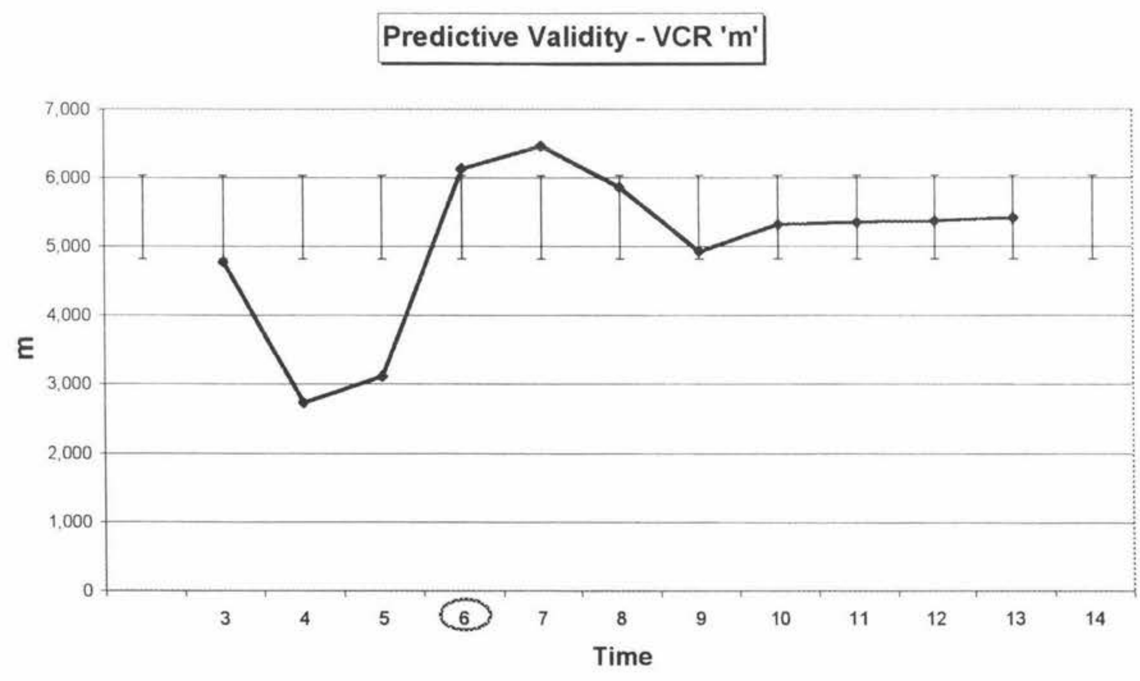

Predictive Validity -Clothes Dryer 'q'
2.000
1.800
1.600
1.400
1.200
1.000
0.800
0.600
0.400
0.200
0.000
q
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
Time

9.3.5 Bass Model Parameters – Japan *m*

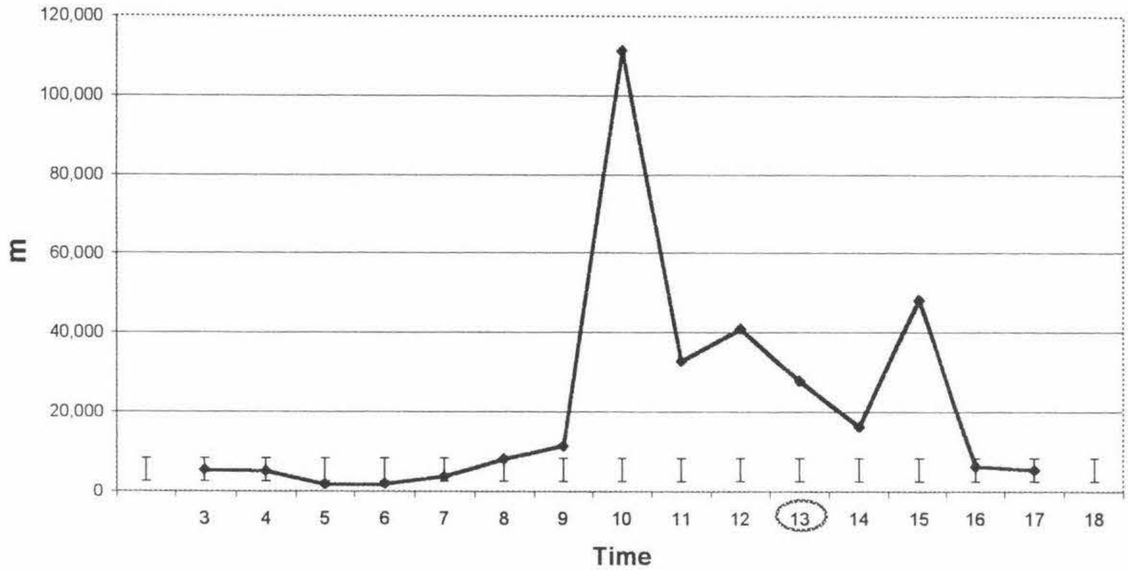




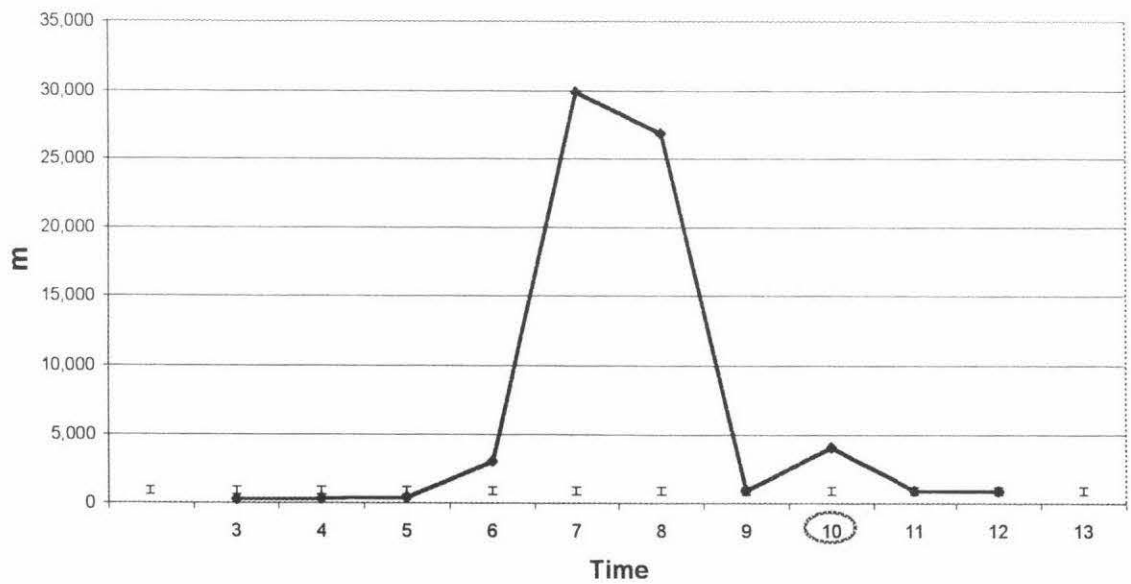

Predictive Validity - Facsimile 'm'
400,000
350,000
300,000
250,000
200,000
150,000
100,000
50,000
0
m
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Time

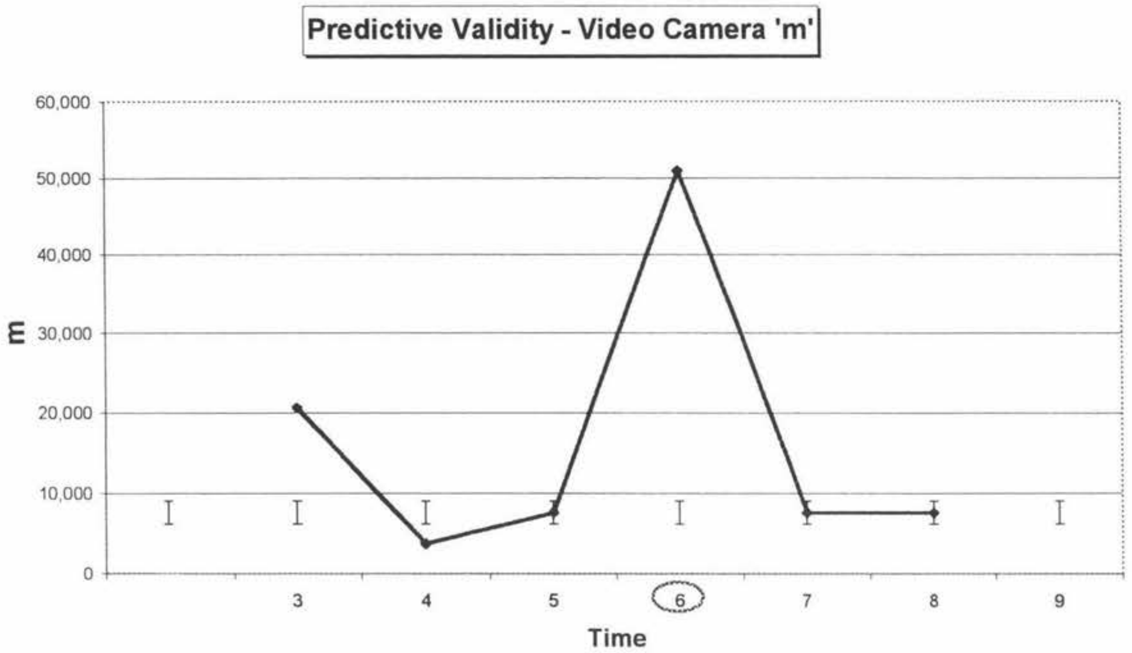

Predictive Validity - VCR 'm'
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
m
3
4
5
6
7
8
9
10
11
12
13
14
Time

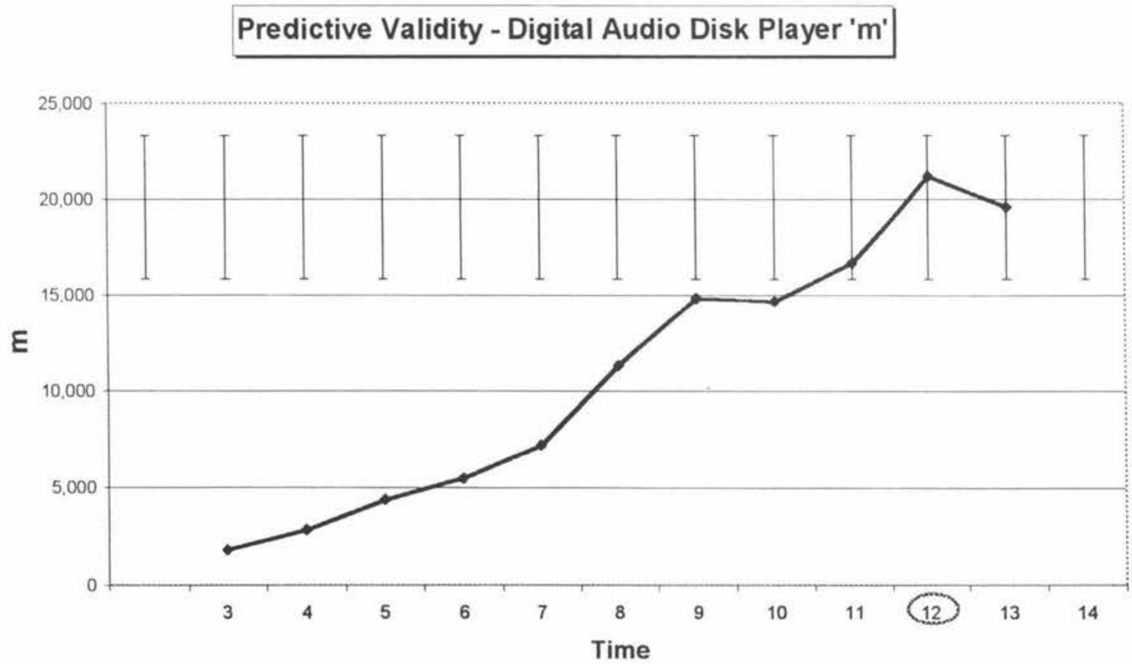
Predictive Validity - Microwave Oven 'm'

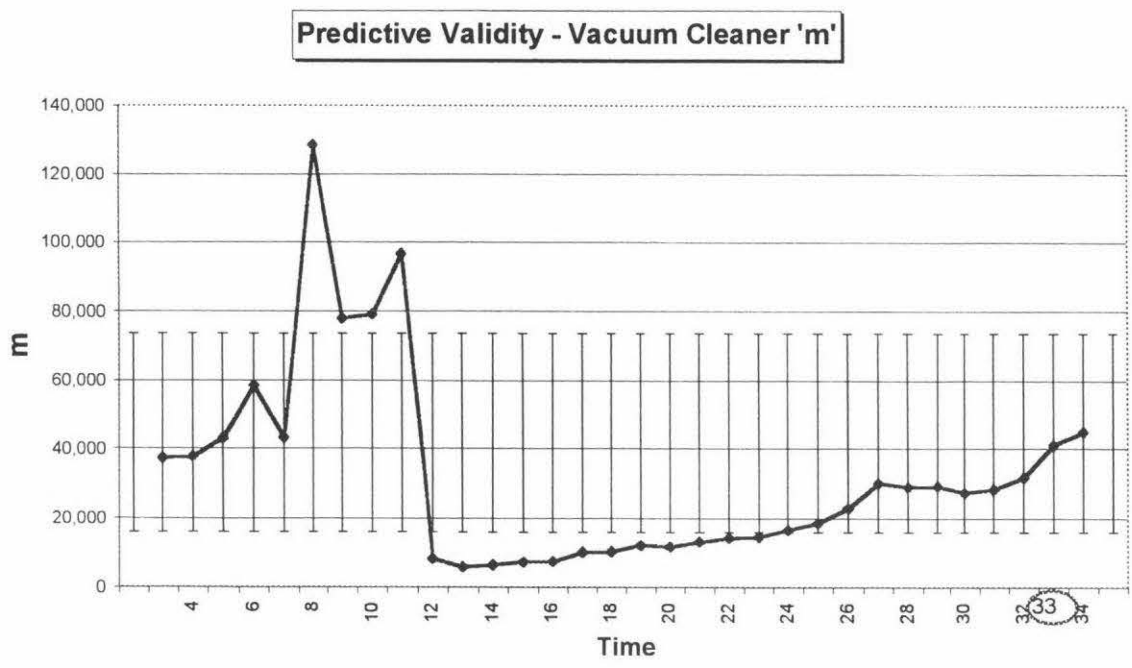


Predictive Validity - Video Disk Player 'm'

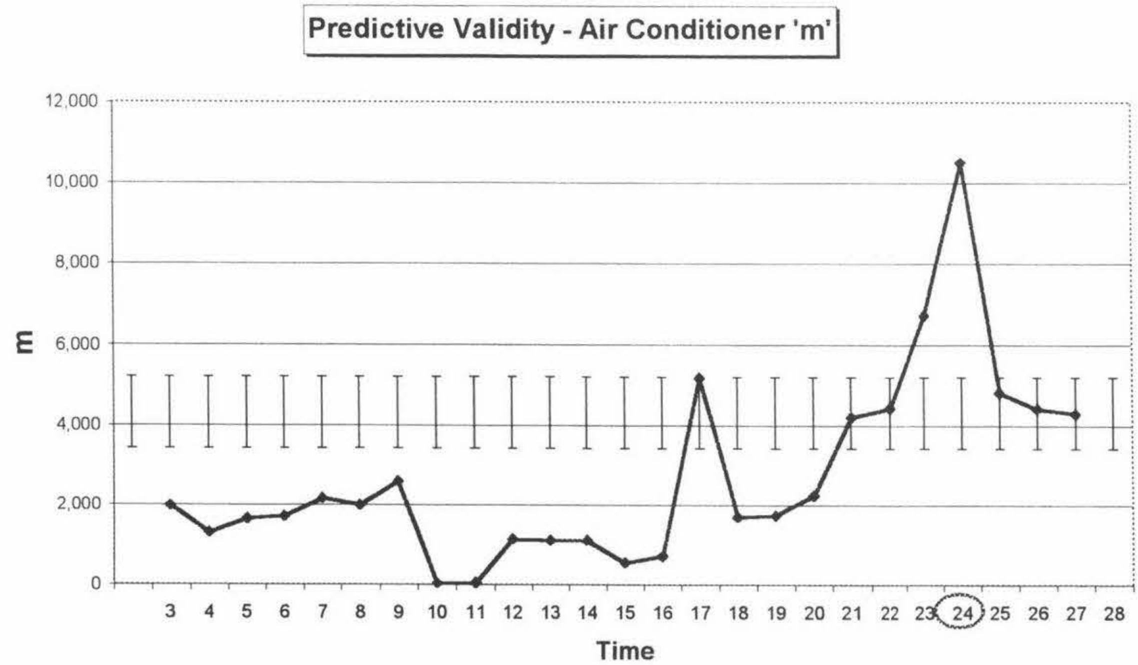


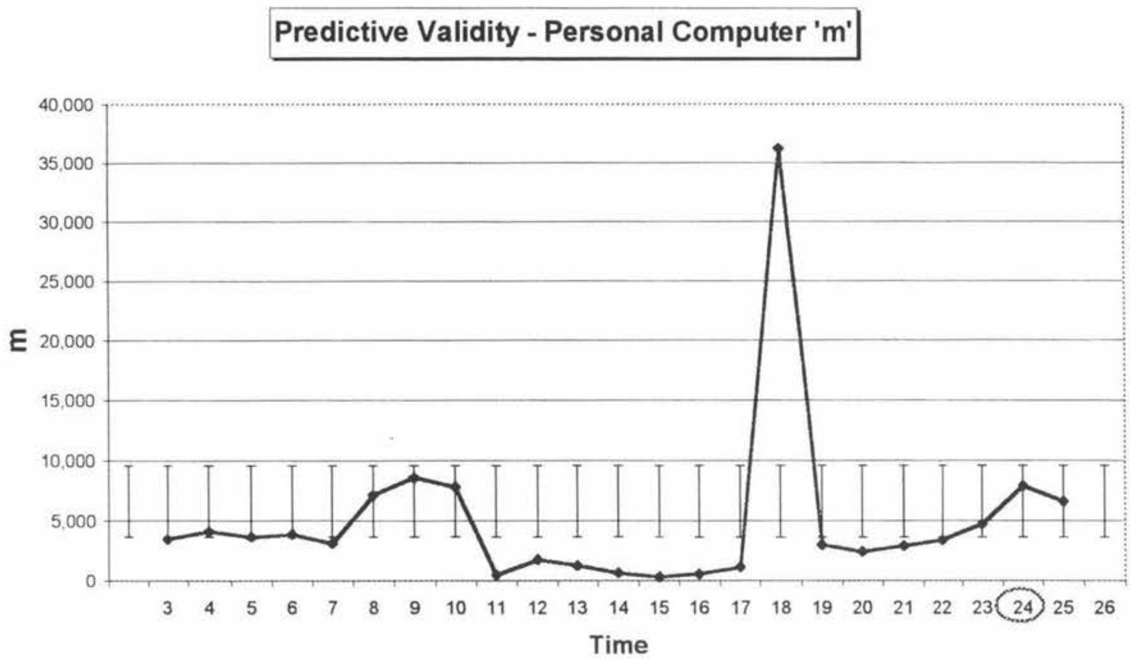

Predictive Validity - Video Camera 'm'
60,000
50,000
40,000
30,000
20,000
10,000
0
m
3
4
5
6
7
8
9
Time

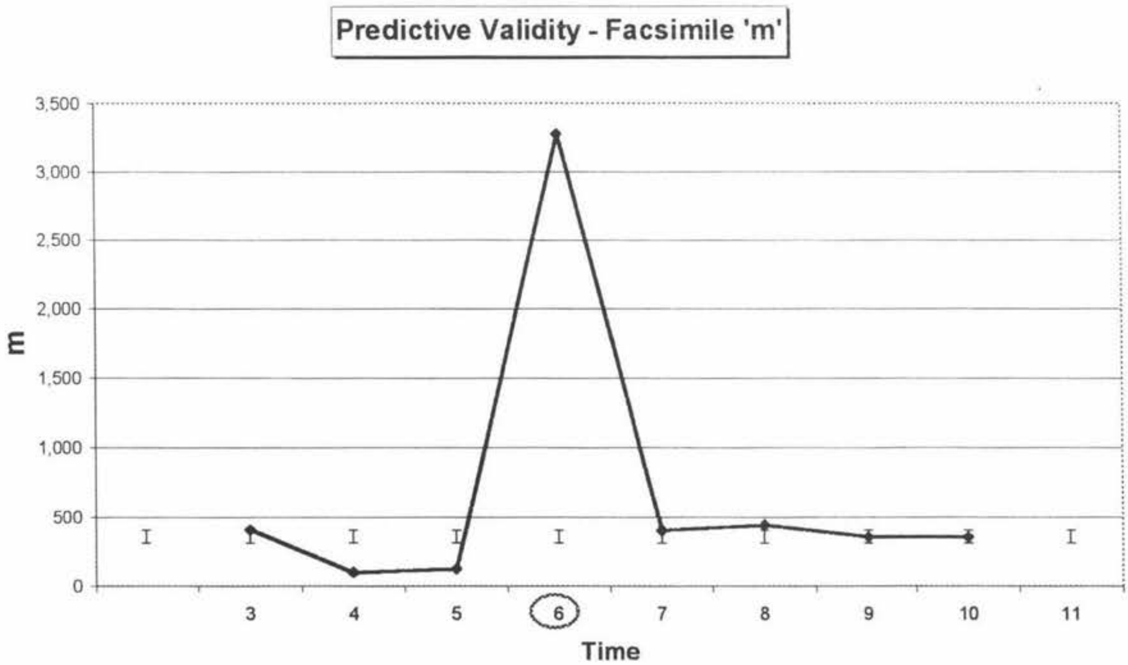

Predictive Validity - Digital Audio Disk Player 'm'
25,000
20,000
15,000
10,000
5,000
0
m
3
4
5
6
7
8
9
10
11
12
13
14
Time

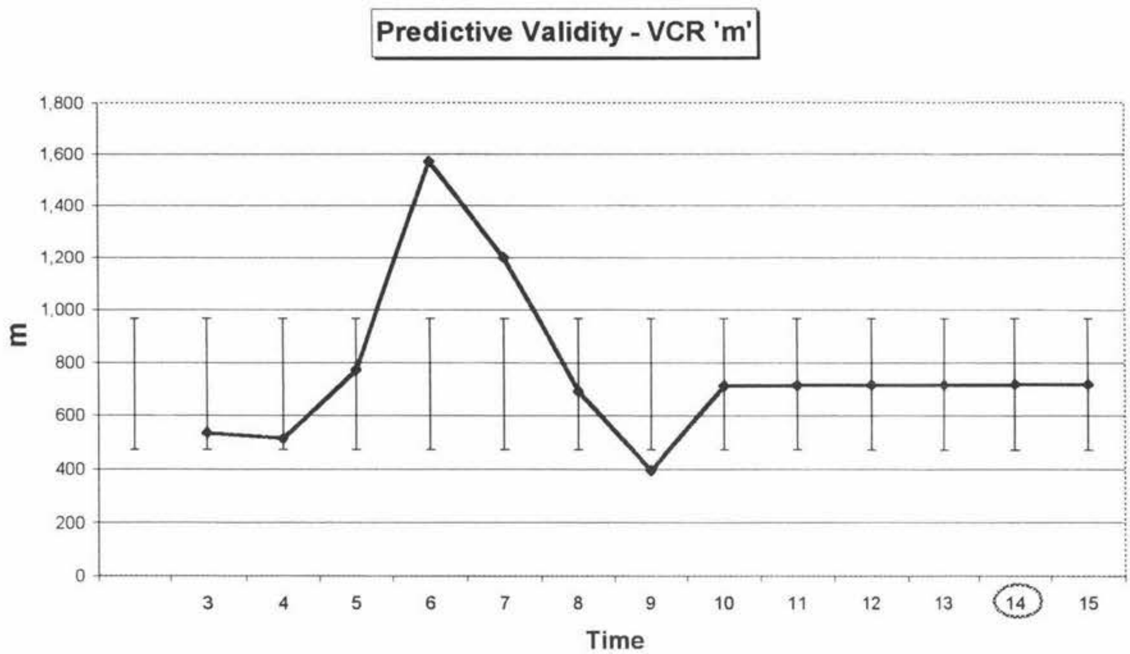


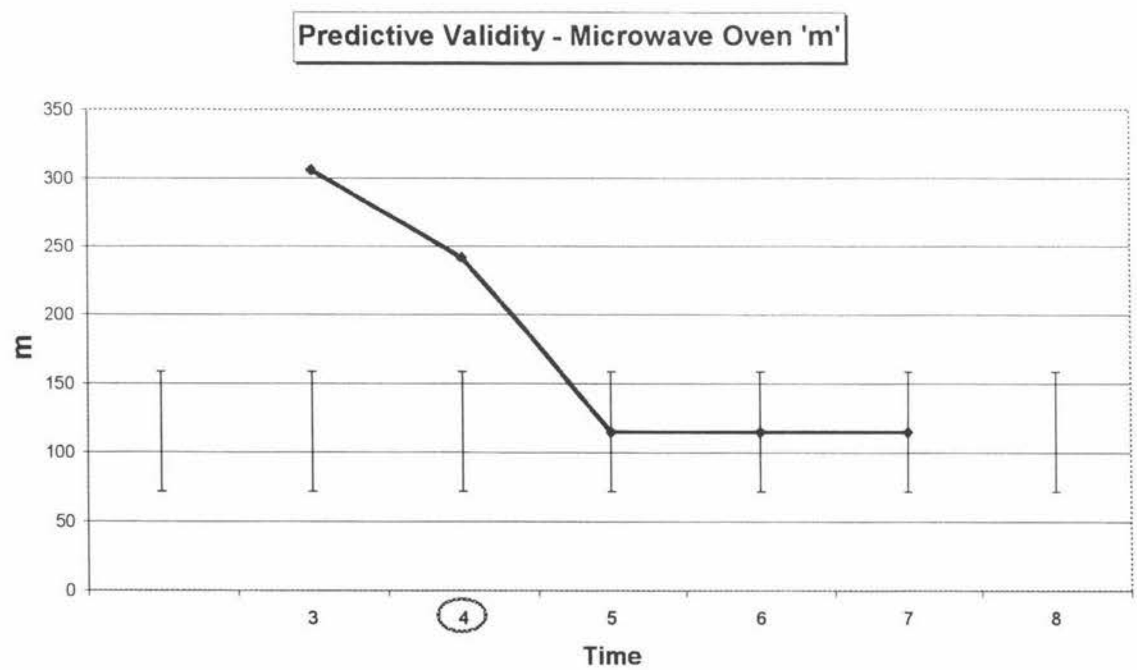
9.3.6 Bass Model Parameters – Taiwan *m*



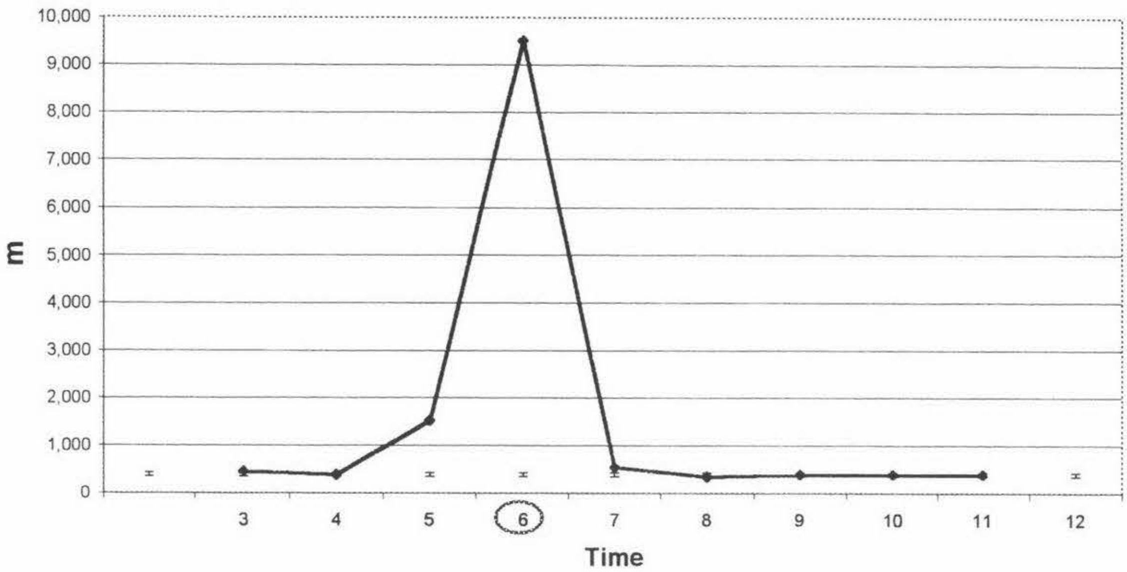

Predictive Validity - Personal Computer 'm'
40,000
35,000
30,000
25,000
20,000
15,000
10,000
5,000
0
m
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
Time


Predictive Validity - Facsimile 'm'
3,500
3,000
2,500
2,000
1,500
1,000
500
0
m
3 4 5 6 7 8 9 10 11
Time

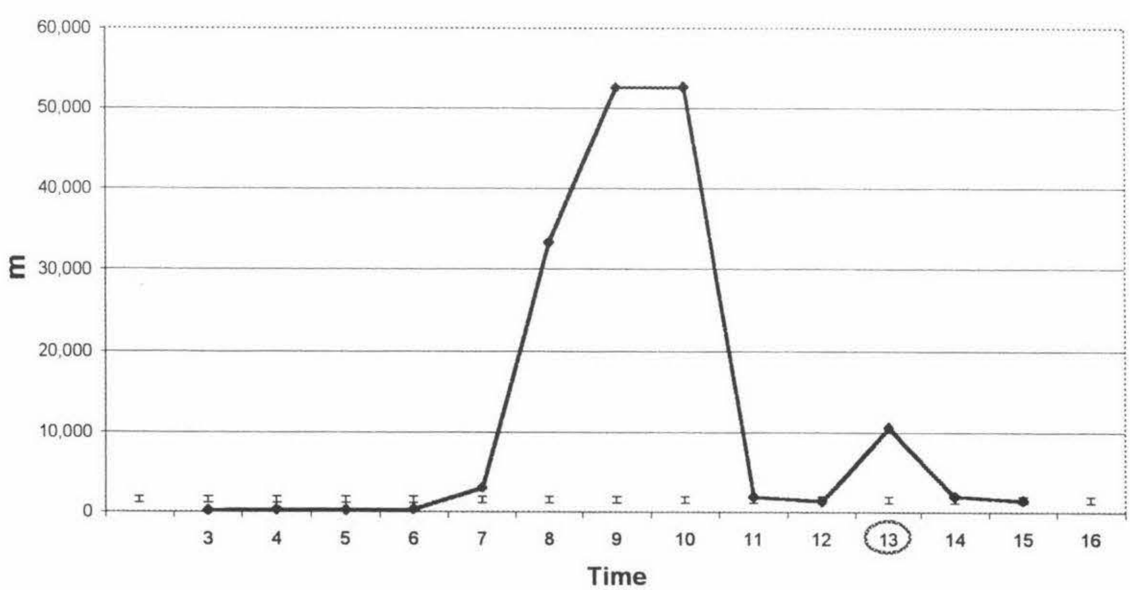

Predictive Validity - VCR 'm'
1,800
1,600
1,400
1,200
1,000
800
600
400
200
0
m
3
4
5
6
7
8
9
10
11
12
13
14
15
Time

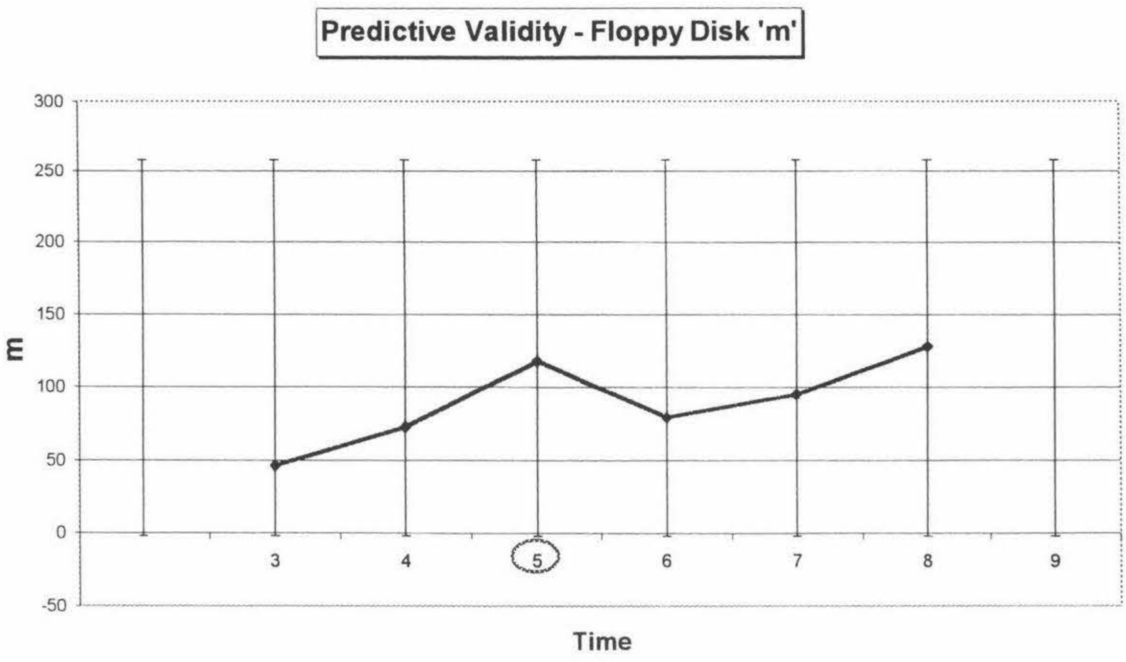

Predictive Validity - Microwave Oven 'm'
350
300
250
200
150
100
50
0
m
3
4
5
6
7
8
Time

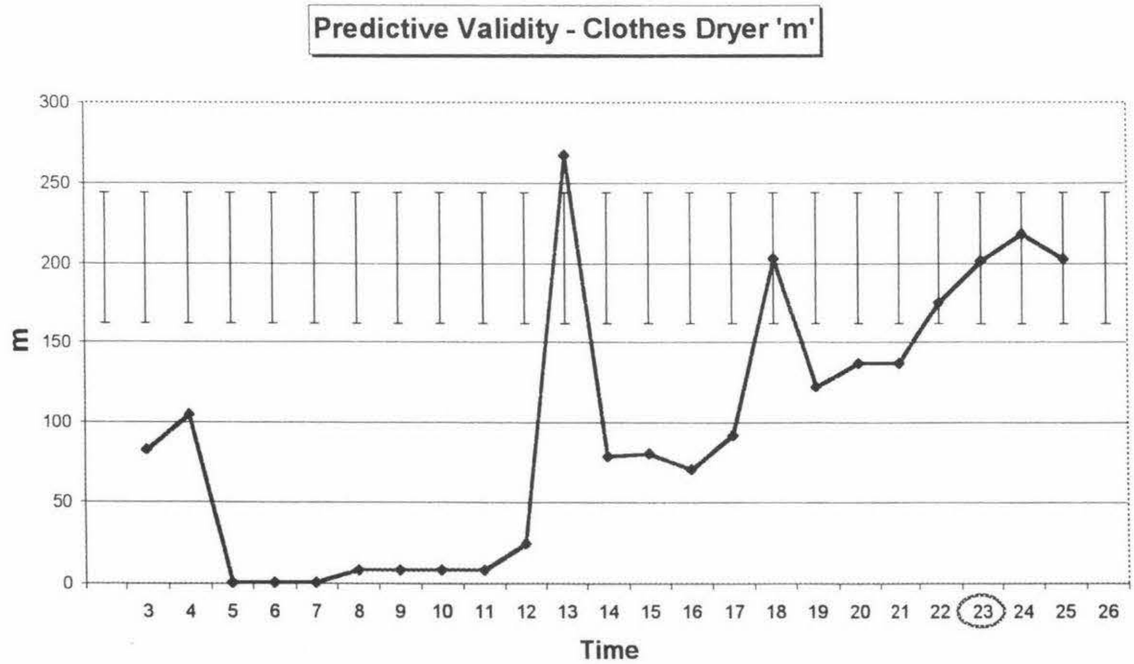
Predictive Validity - Induction Cooker 'm'



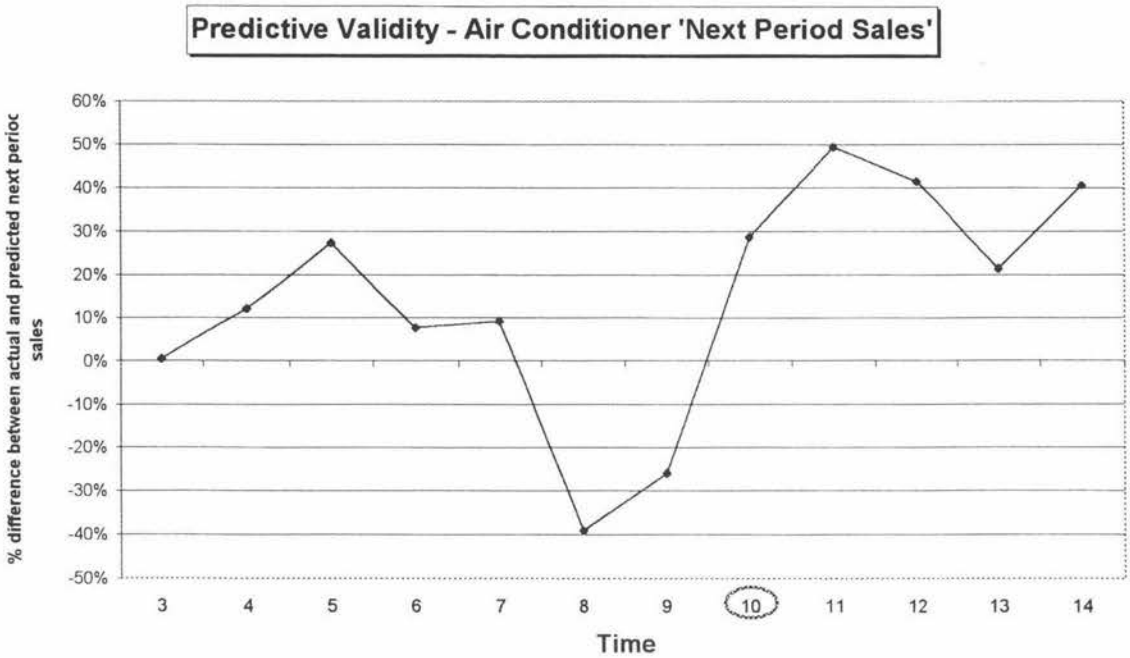
Predictive Validity - TV Game 'm'

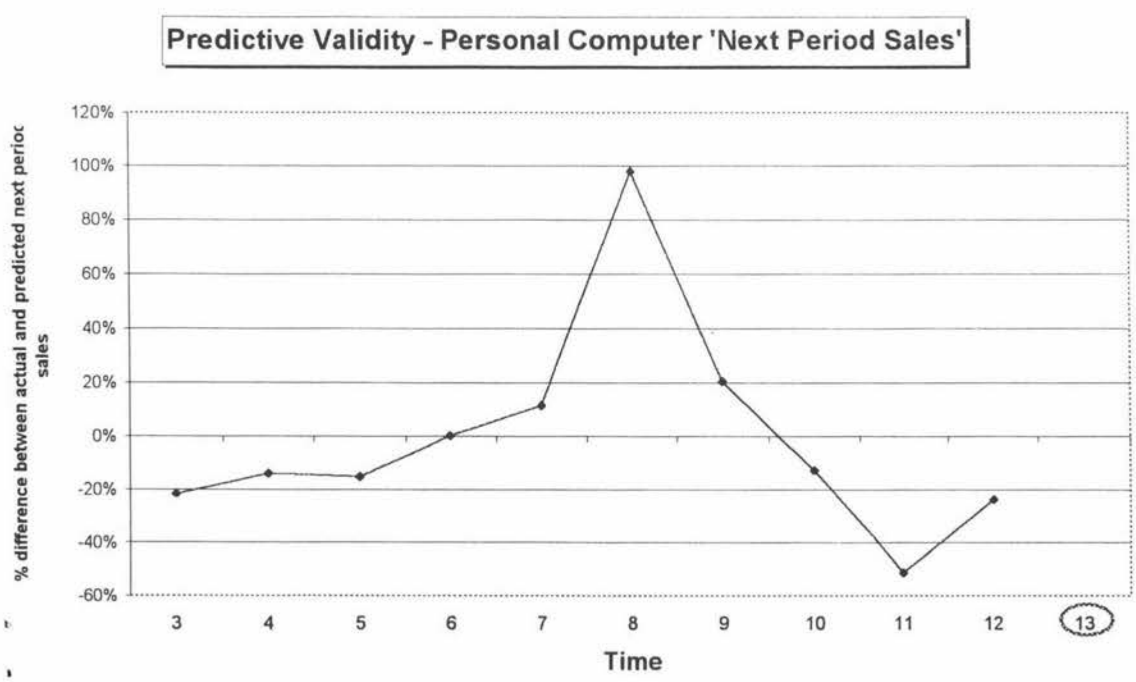



Predictive Validity - Floppy Disk 'm'
300
250
200
150
100
50
0
-50
m
3
4
5
6
7
8
9
Time

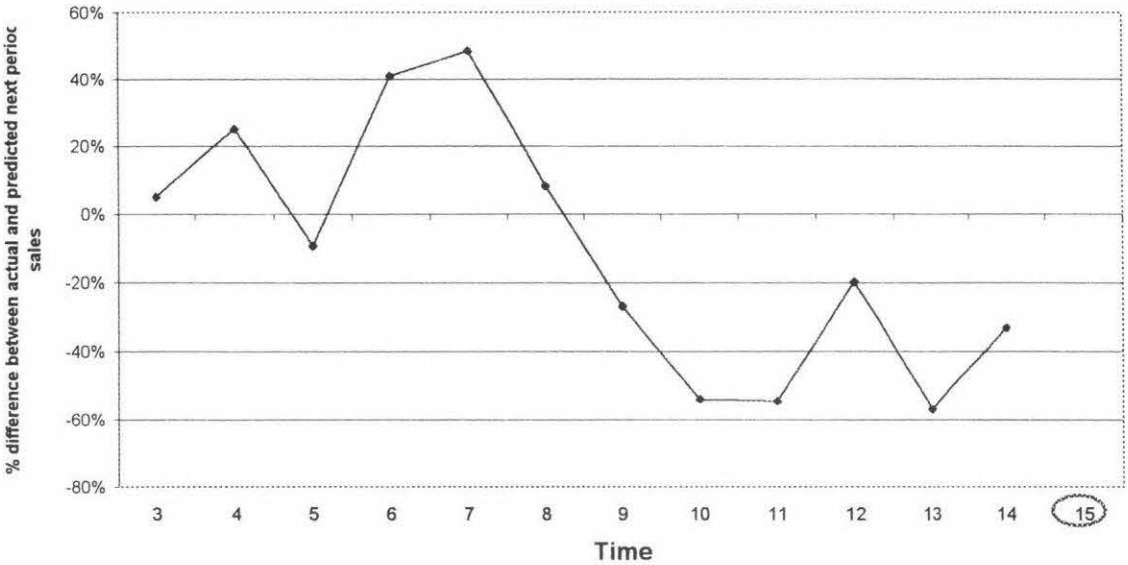

Predictive Validity - Clothes Dryer 'm'
300
250
200
150
100
50
0
m
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26
Time

9.3.7 Next Period Sales - Japan

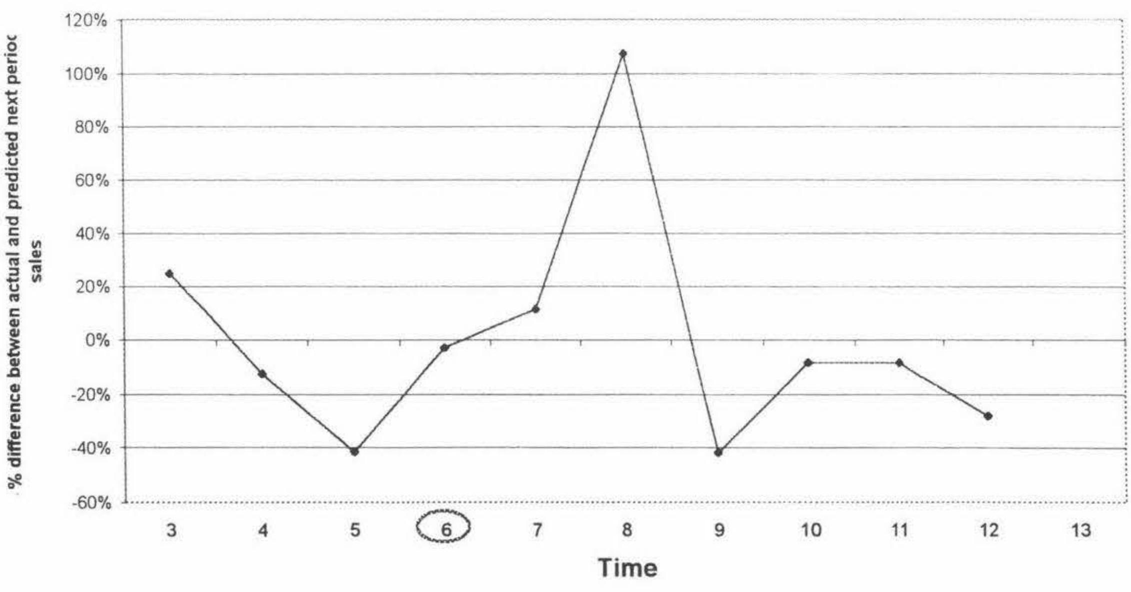


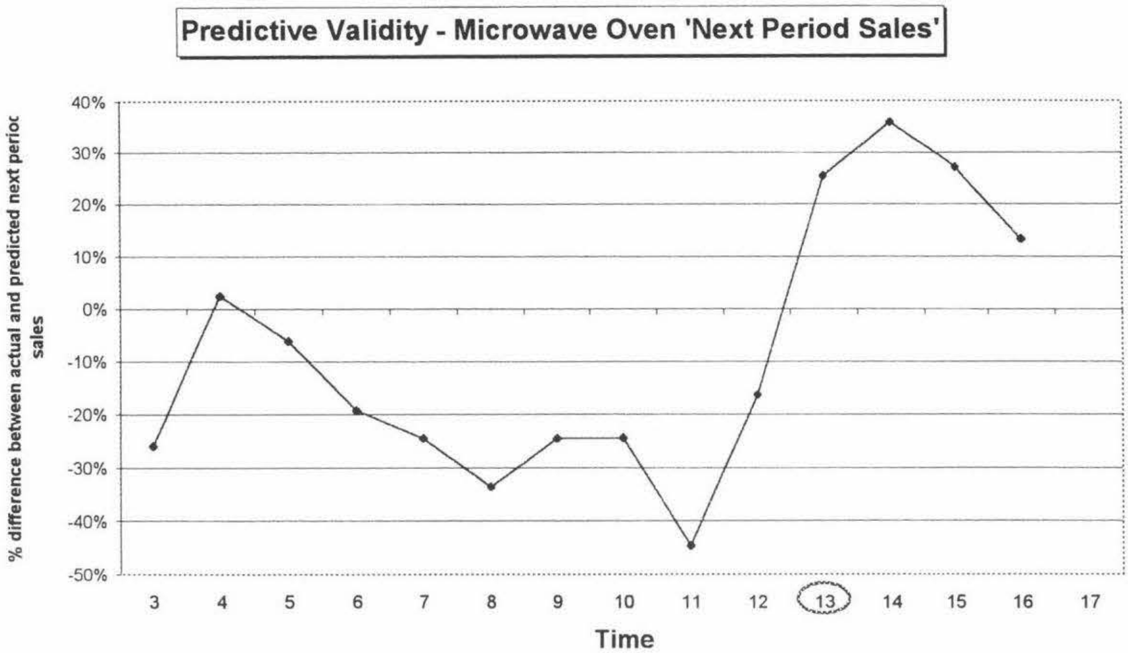


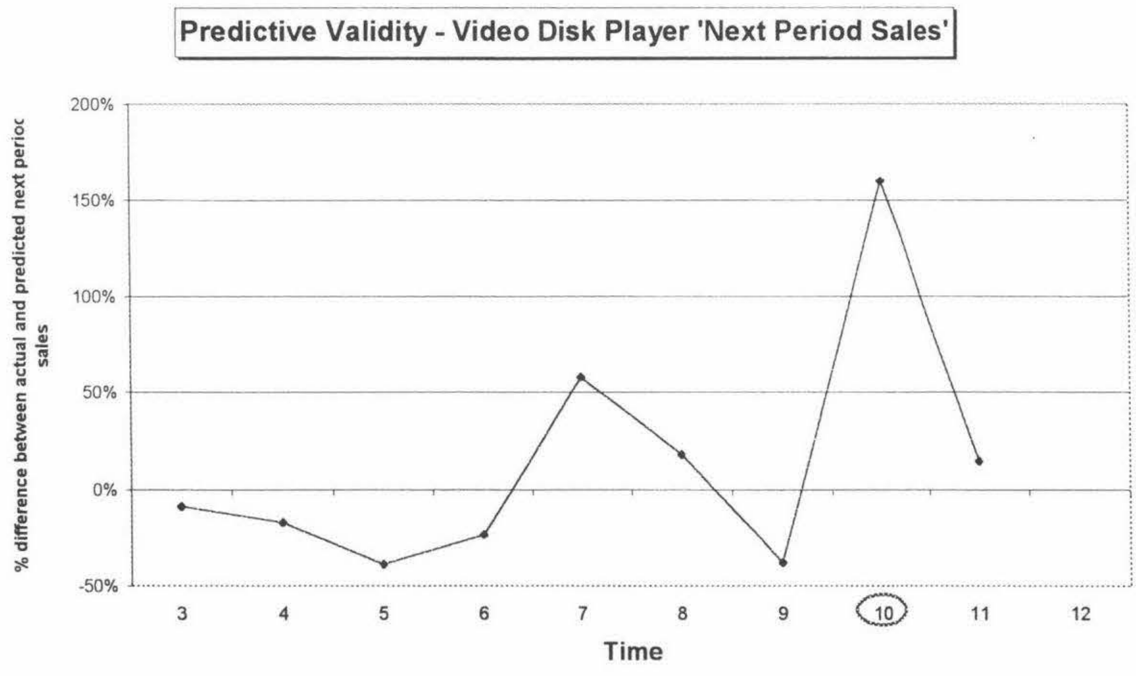
Predictive Validity - Facsimile 'Next Period Sales'

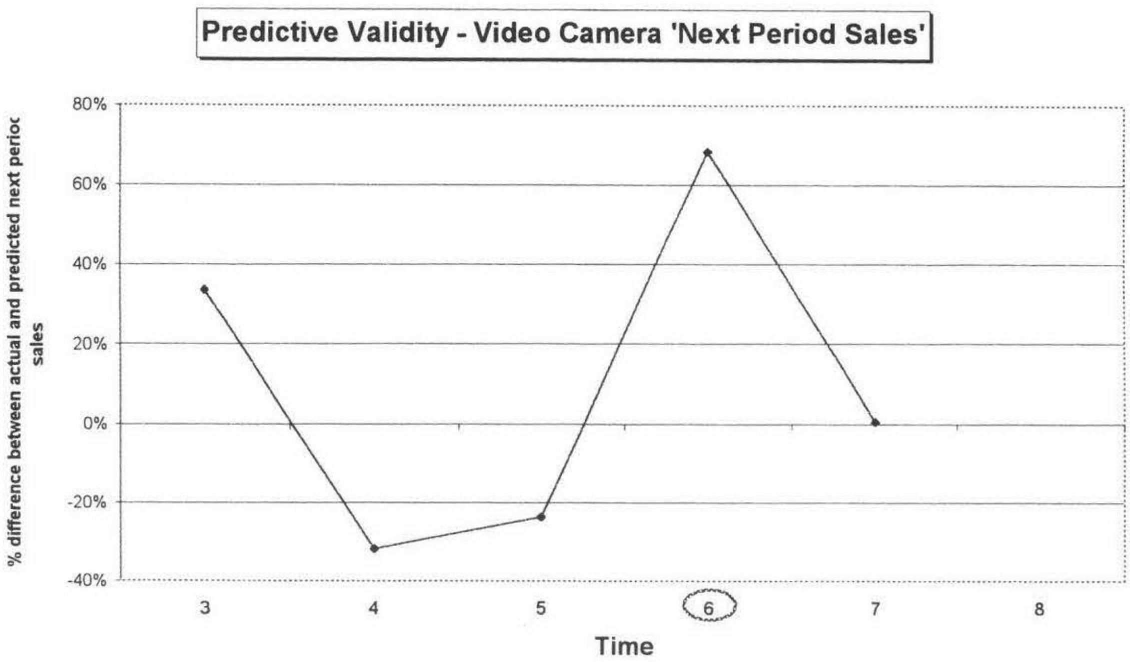


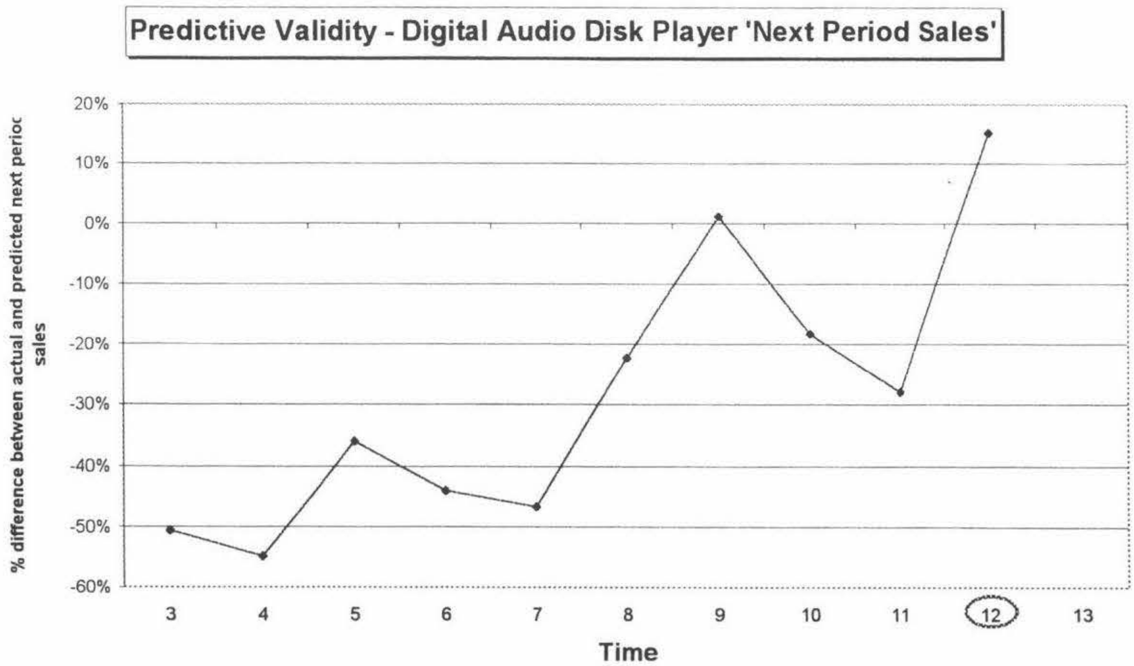
Predictive Validity - VCR 'Next Period Sales'

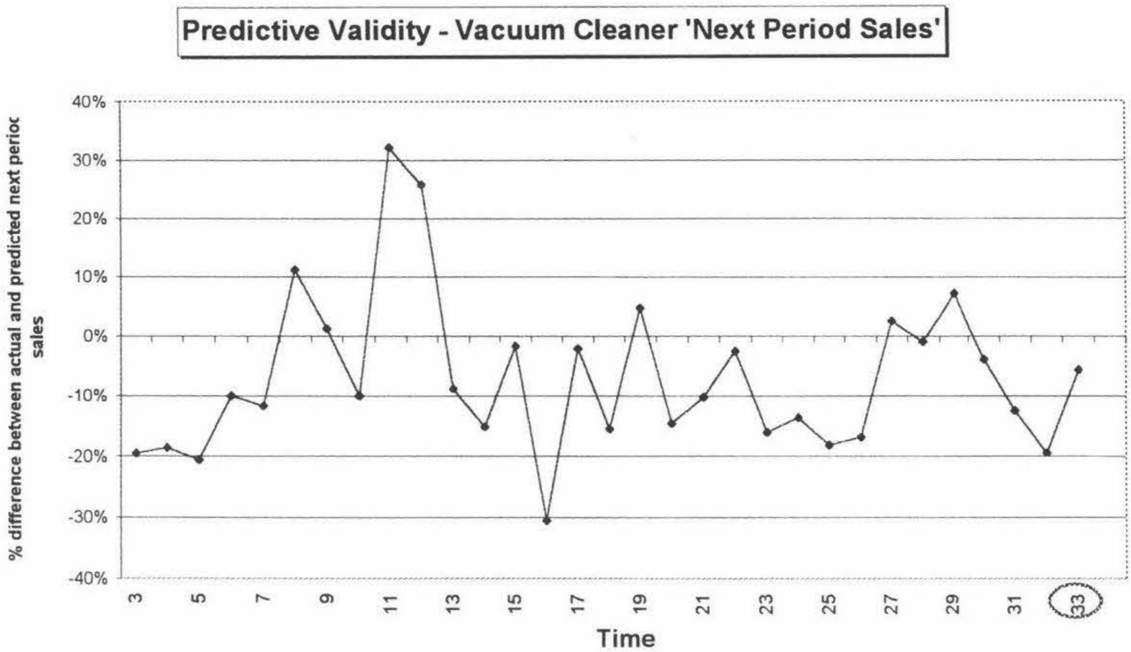



Predictive Validity - Microwave Oven 'Next Period Sales'
% difference between actual and predicted next perioc sales
40%
30%
20%
10%
0%
-10%
-20%
-30%
-40%
-50%
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
Time

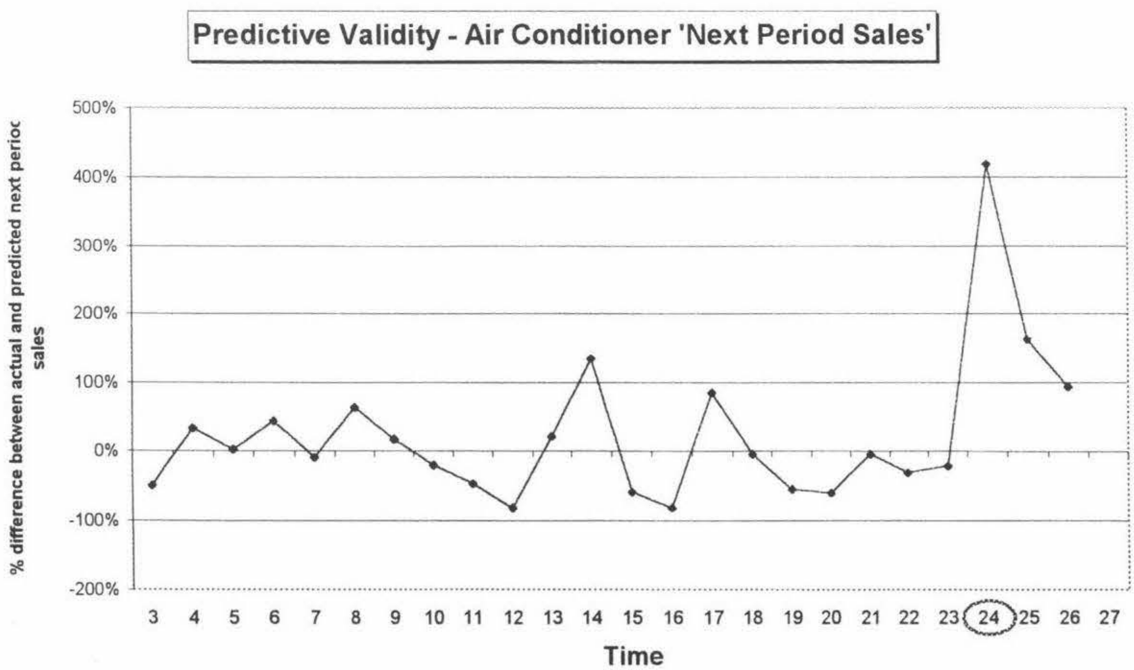

Predictive Validity - Video Disk Player 'Next Period Sales'
% difference between actual and predicted next perioc sales
200%
150%
100%
50%
0%
-50%
3
4
5
6
7
8
9
10
11
12
Time

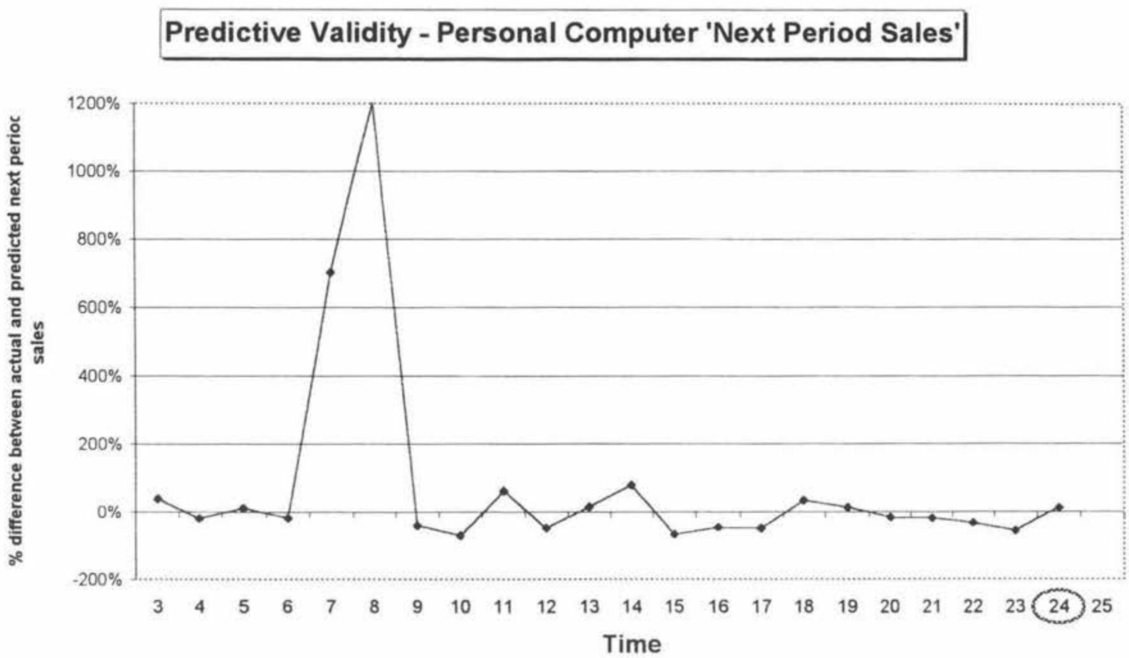

Predictive Validity - Video Camera 'Next Period Sales'
% difference between actual and predicted next perioc sales
80%
60%
40%
20%
0%
-20%
-40%
3
4
5
6
7
8
Time


Predictive Validity - Digital Audio Disk Player 'Next Period Sales'
% difference between actual and predicted next perioc sales
20%
10%
0%
-10%
-20%
-30%
-40%
-50%
-60%
3
4
5
6
7
8
9
10
11
12
13
Time

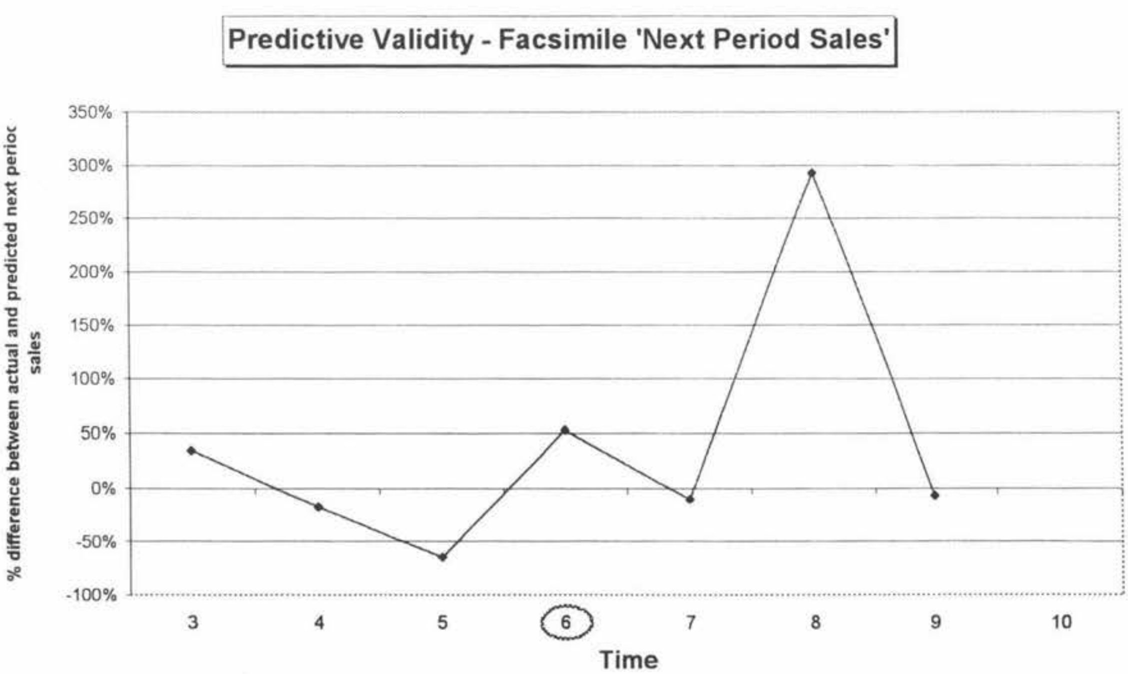


9.3.7 Next Period Sales – Taiwan

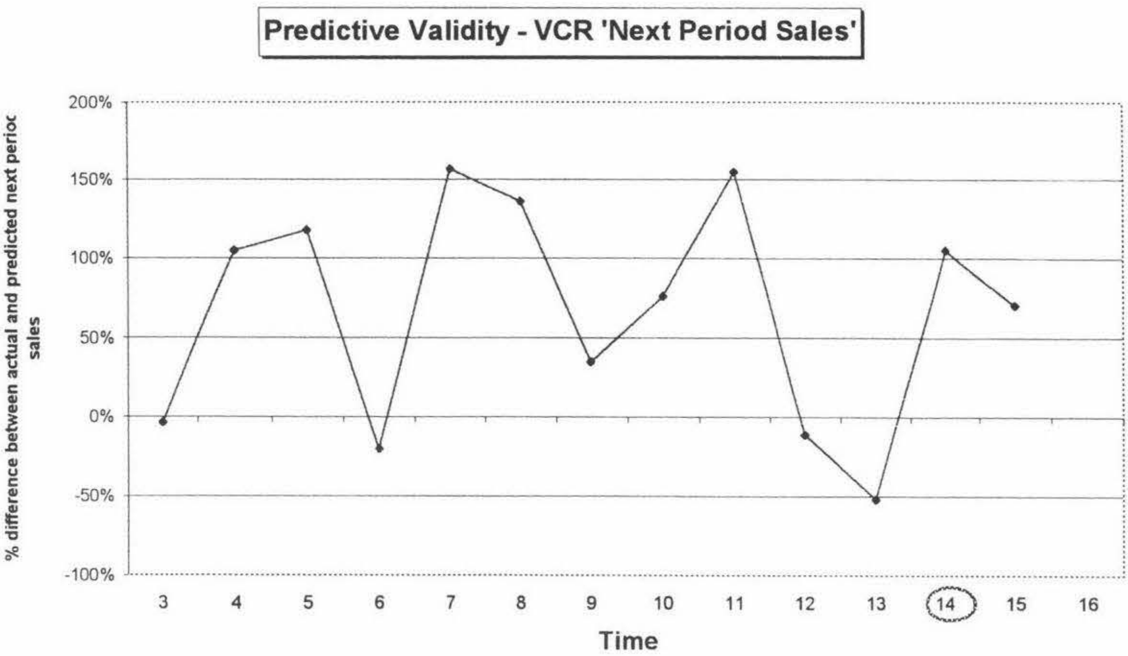


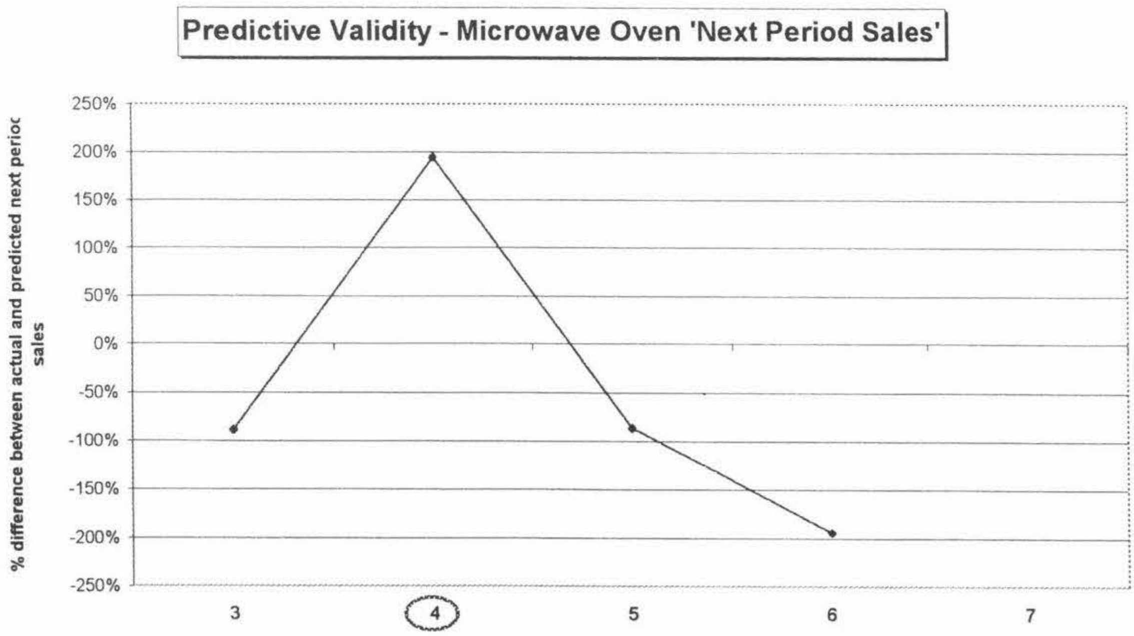


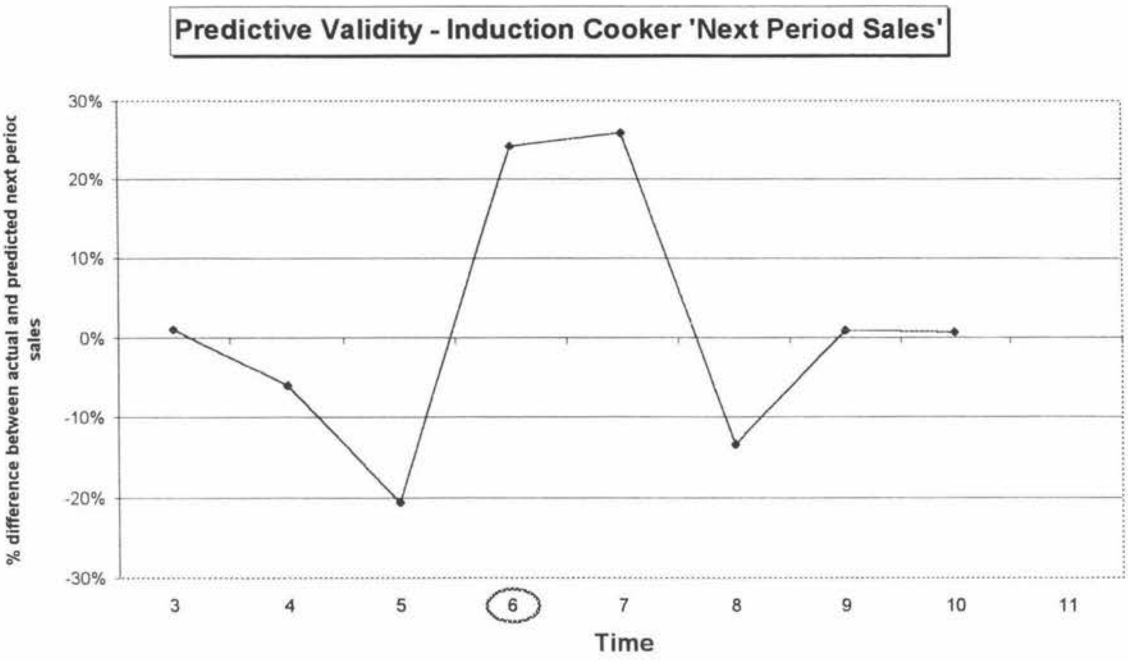
Predictive Validity - Personal Computer 'Next Period Sales'
% difference between actual and predicted next period sales
1200%
1000%
800%
600%
400%
200%
0%
-200%
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Time

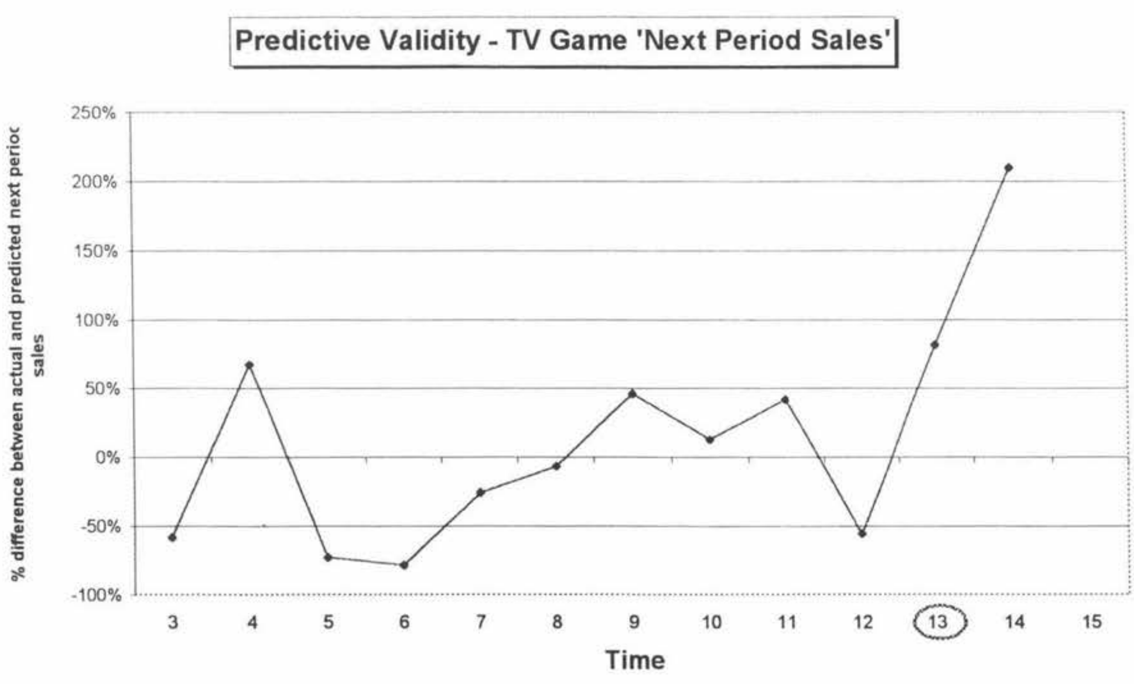


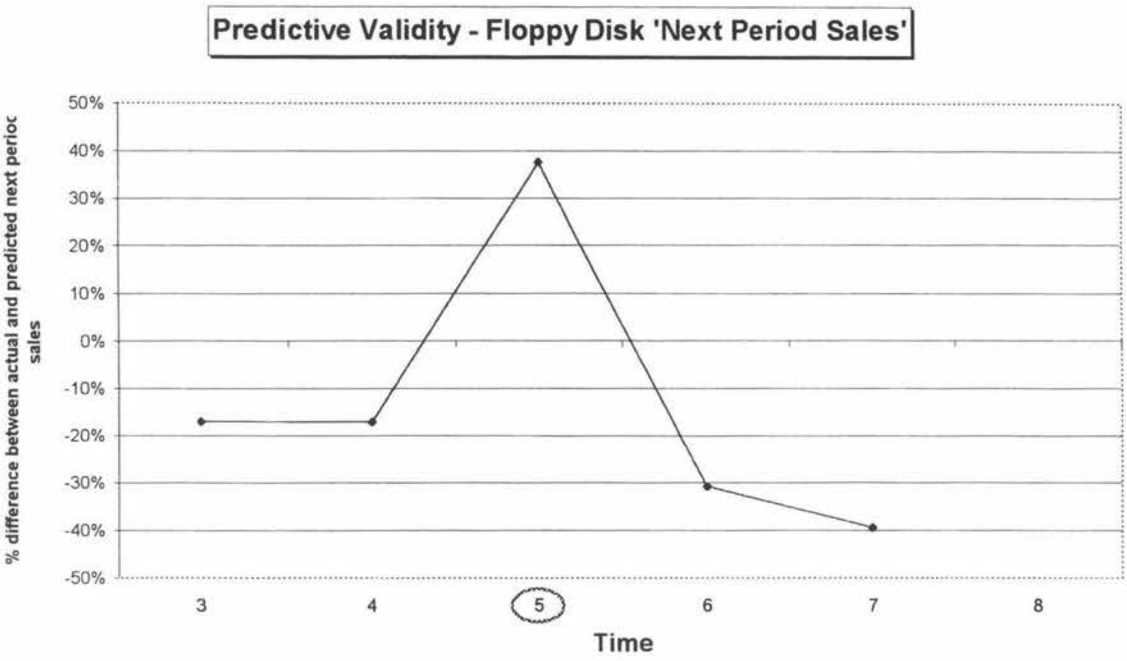
Predictive Validity - Facsimile 'Next Period Sales'
% difference between actual and predicted next period sales
350%
300%
250%
200%
150%
100%
50%
0%
-50%
-100%
3 4 5 6 7 8 9 10
Time

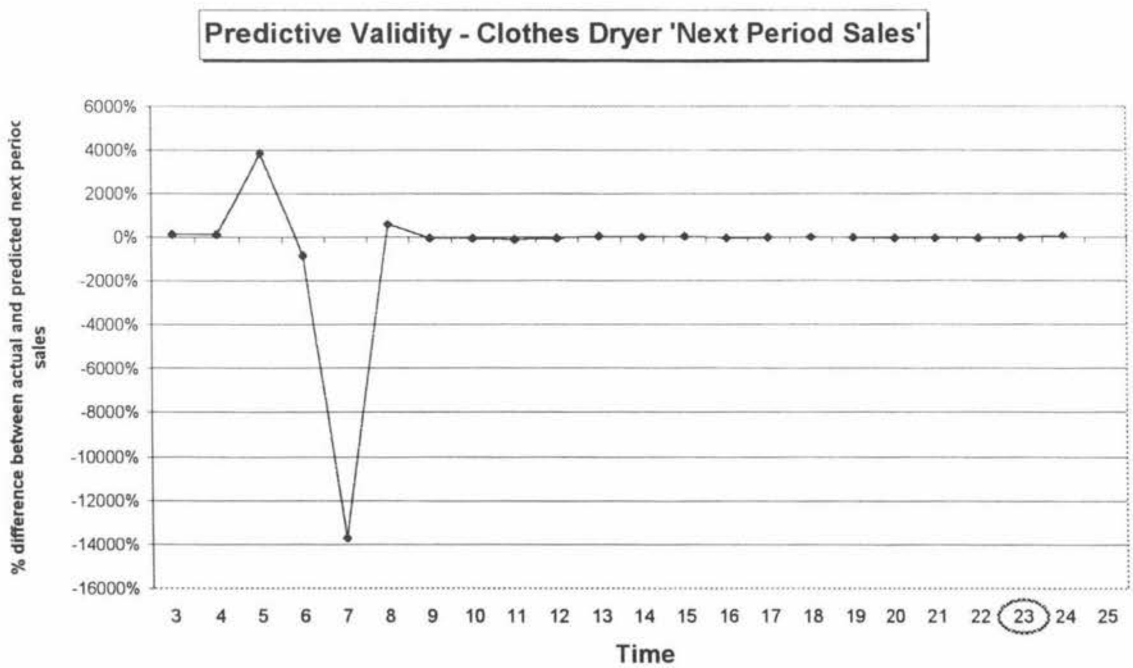

Predictive Validity - VCR 'Next Period Sales'
% difference between actual and predicted next perioc sales
200%
150%
100%
50%
0%
-50%
-100%
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Time

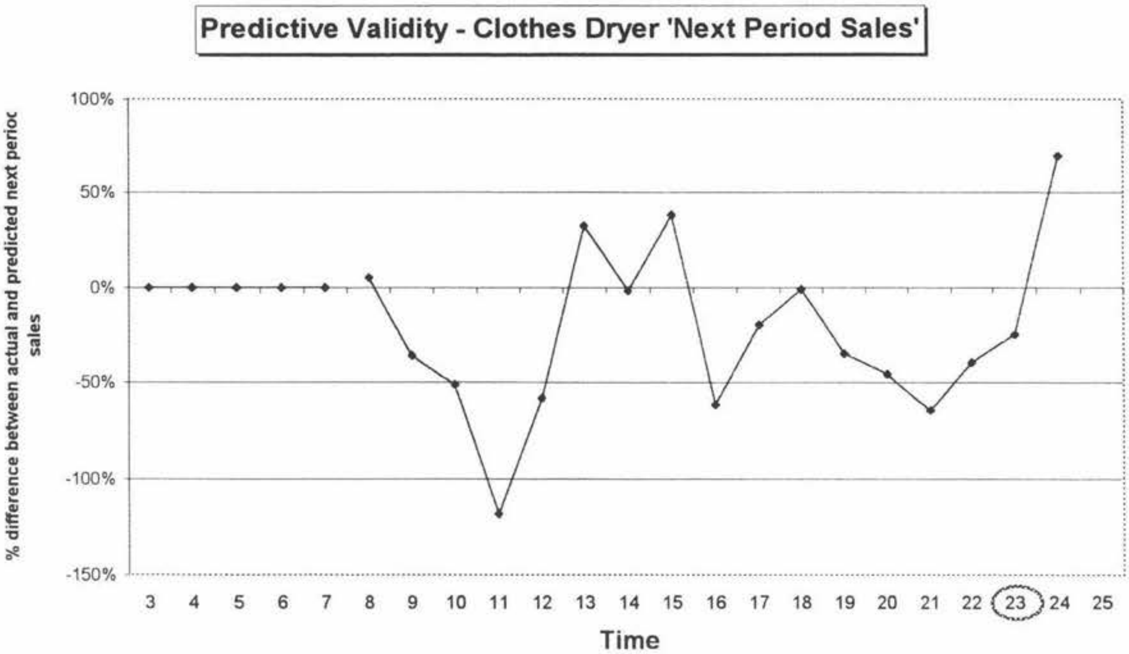

Predictive Validity - Microwave Oven 'Next Period Sales'
% difference between actual and predicted next perioc sales
250%
200%
150%
100%
50%
0%
-50%
-100%
-150%
-200%
-250%
3
4
5
6
7
Time


Predictive Validity - Induction Cooker 'Next Period Sales'
% difference between actual and predicted next perioc sales
30%
20%
10%
0%
-10%
-20%
-30%
3
4
5
6
7
8
9
10
11
Time

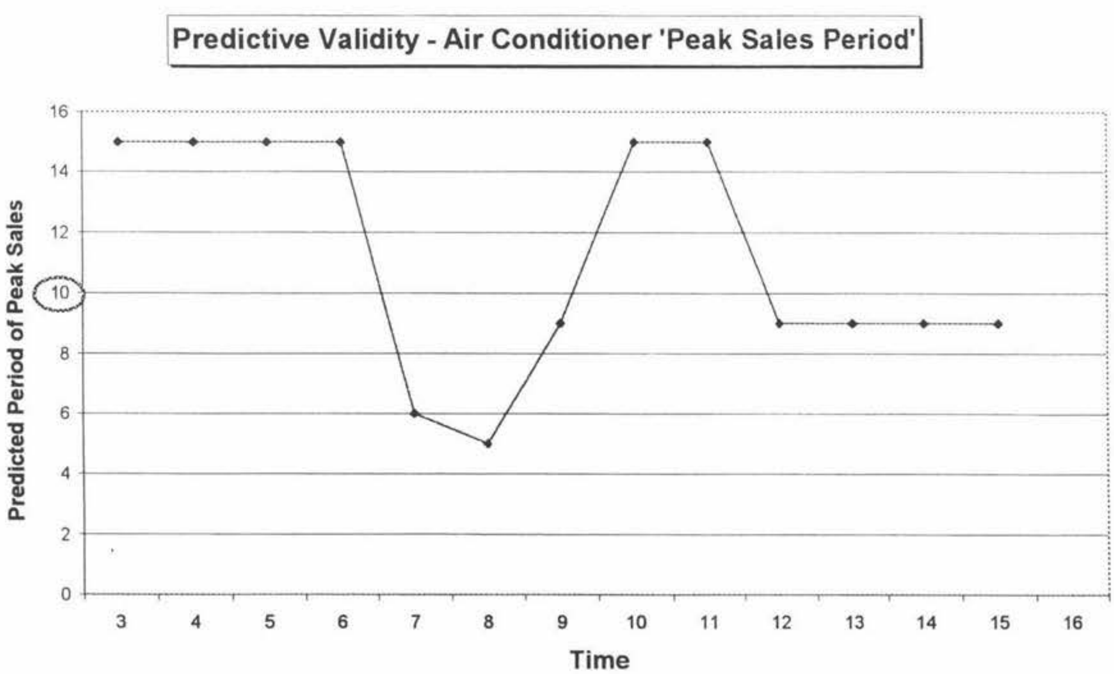

Predictive Validity - TV Game 'Next Period Sales'
% difference between actual and predicted next perioc sales
250%
200%
150%
100%
50%
0%
-50%
-100%
3
4
5
6
7
8
9
10
11
12
13
14
15
Time

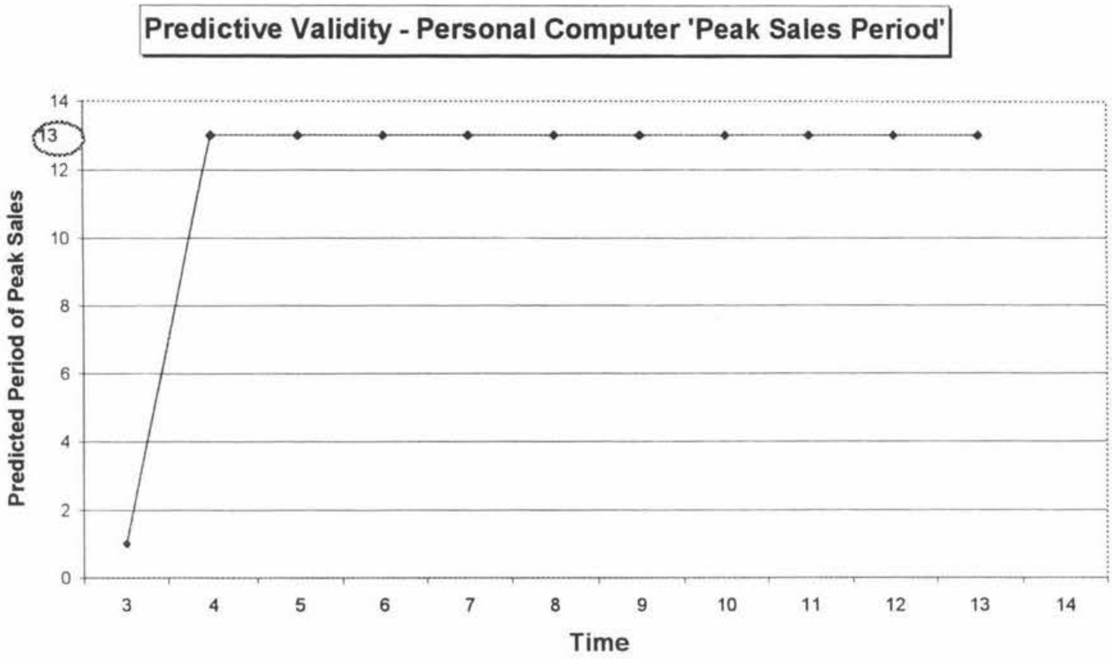

Predictive Validity - Floppy Disk 'Next Period Sales'
% difference between actual and predicted next perioc sales
50%
40%
30%
20%
10%
0%
-10%
-20%
-30%
-40%
-50%
3
4
5
6
7
8
Time

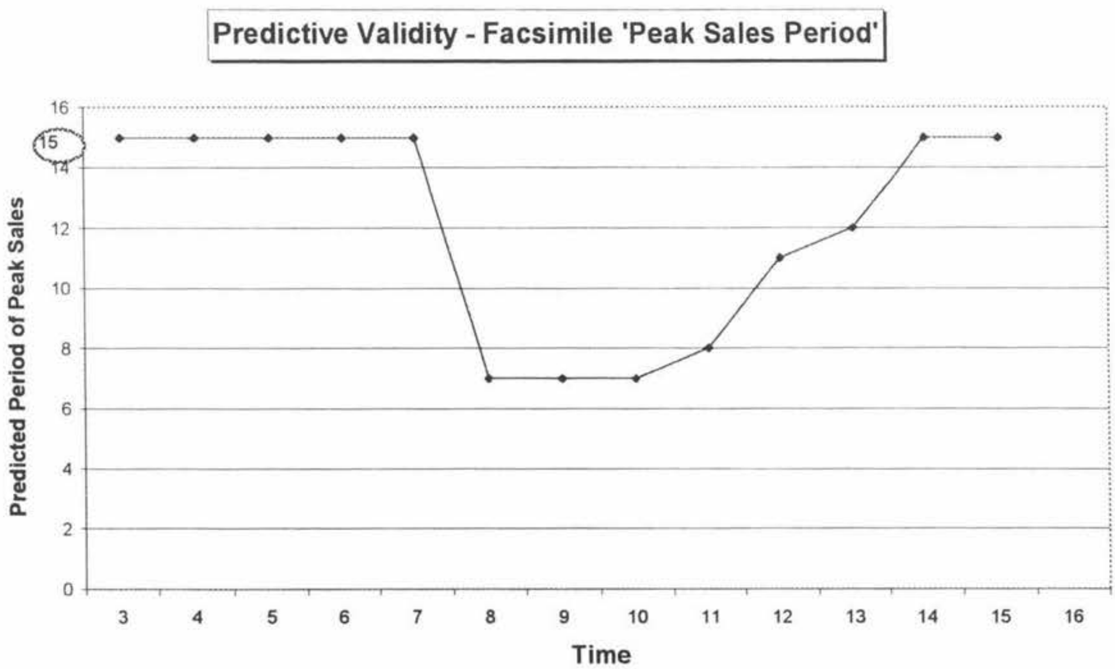

Predictive Validity - Clothes Dryer 'Next Period Sales'
% difference between actual and predicted next perioc sales
6000%
4000%
2000%
0%
-2000%
-4000%
-6000%
-8000%
-10000%
-12000%
-14000%
-16000%
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Time

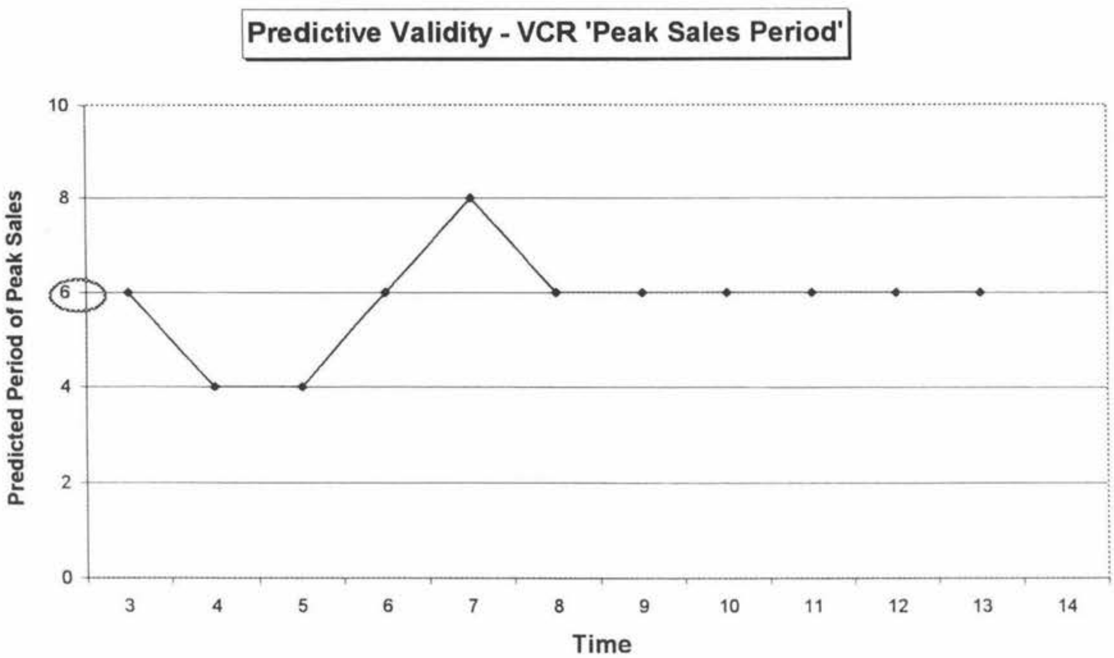


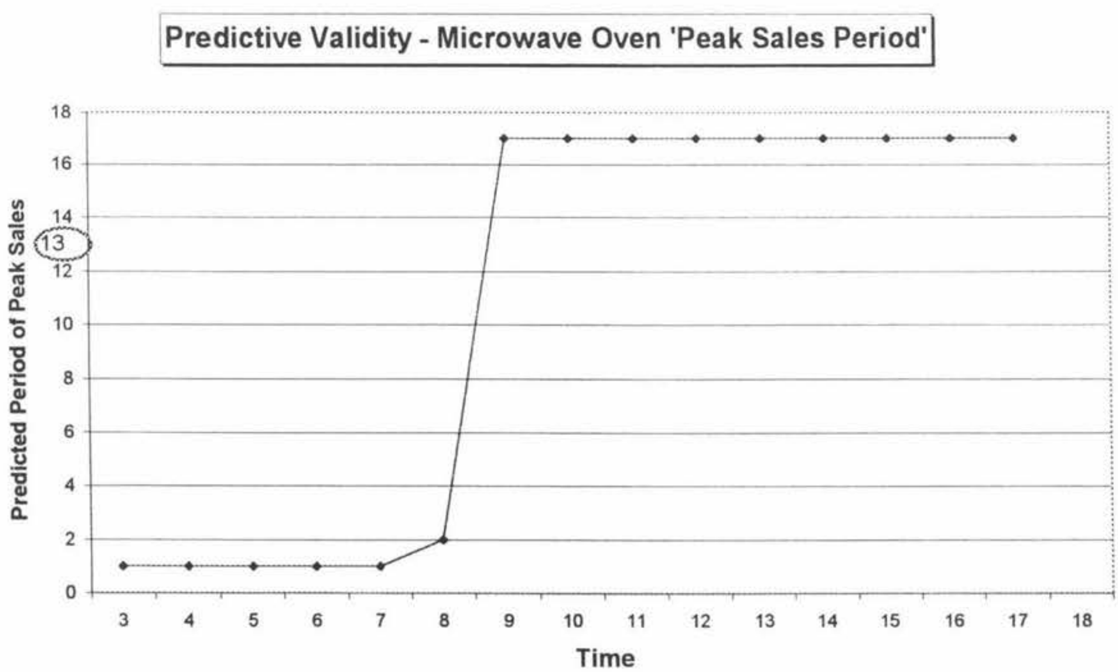
9.3.9 Peak Timing - Japan

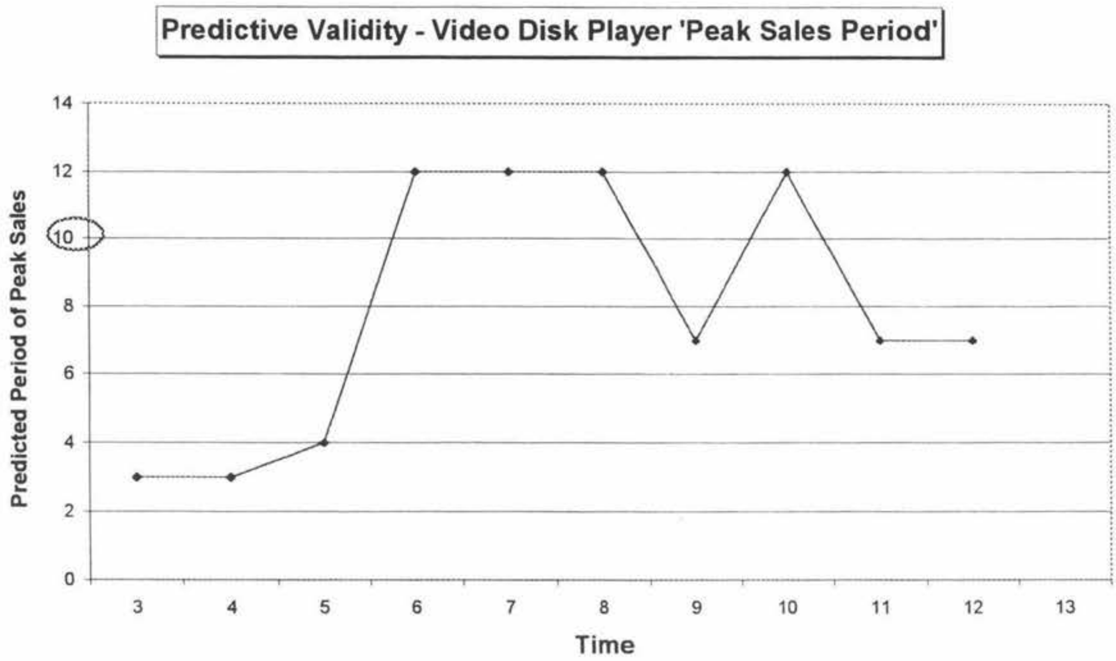



Predictive Validity - Personal Computer 'Peak Sales Period'
Predicted Period of Peak Sales
0
2
4
6
8
10
12
13
14
3
4
5
6
7
8
9
10
11
12
13
14
Time

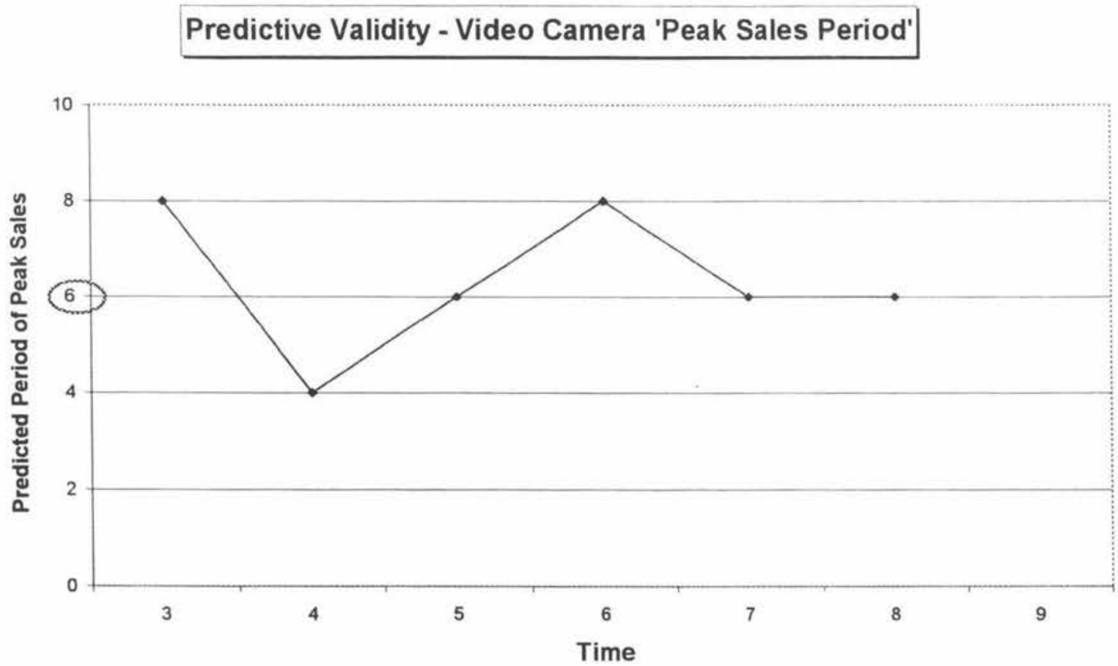

Predictive Validity - Facsimile 'Peak Sales Period'
Predicted Period of Peak Sales
0
2
4
6
8
10
12
14
15
16
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Time


Predictive Validity - VCR 'Peak Sales Period'
Predicted Period of Peak Sales
Time
0
2
4
6
8
10
3
4
5
6
7
8
9
10
11
12
13
14


Predictive Validity - Microwave Oven 'Peak Sales Period'
Predicted Period of Peak Sales
Time
13
0
2
4
6
8
10
12
14
16
18
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18

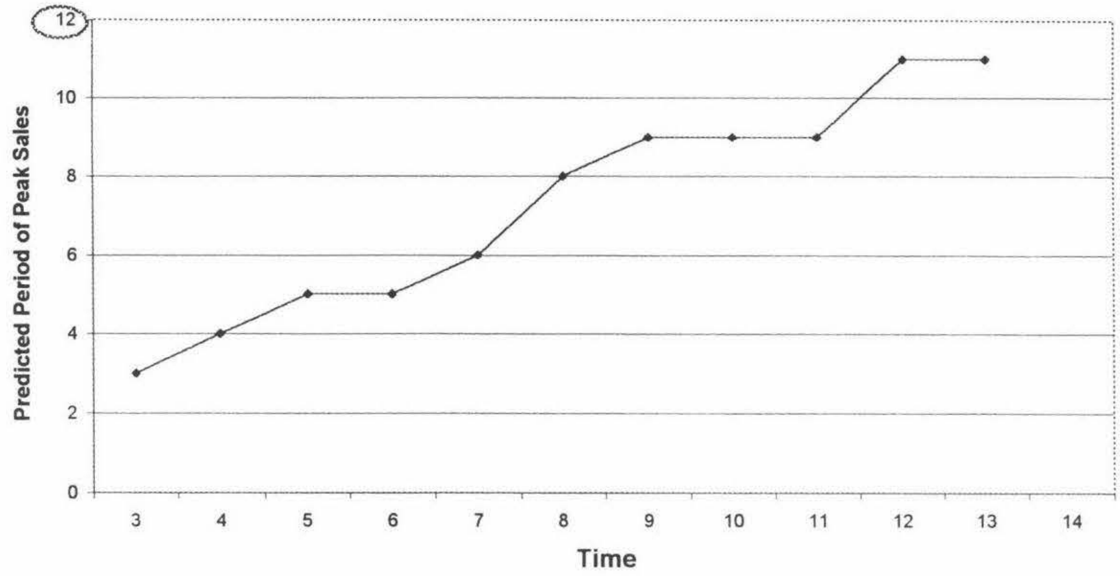


Predictive Validity - Video Disk Player 'Peak Sales Period'
Predicted Period of Peak Sales
Time
14
12
10
8
6
4
2
0
3
4
5
6
7
8
9
10
11
12
13

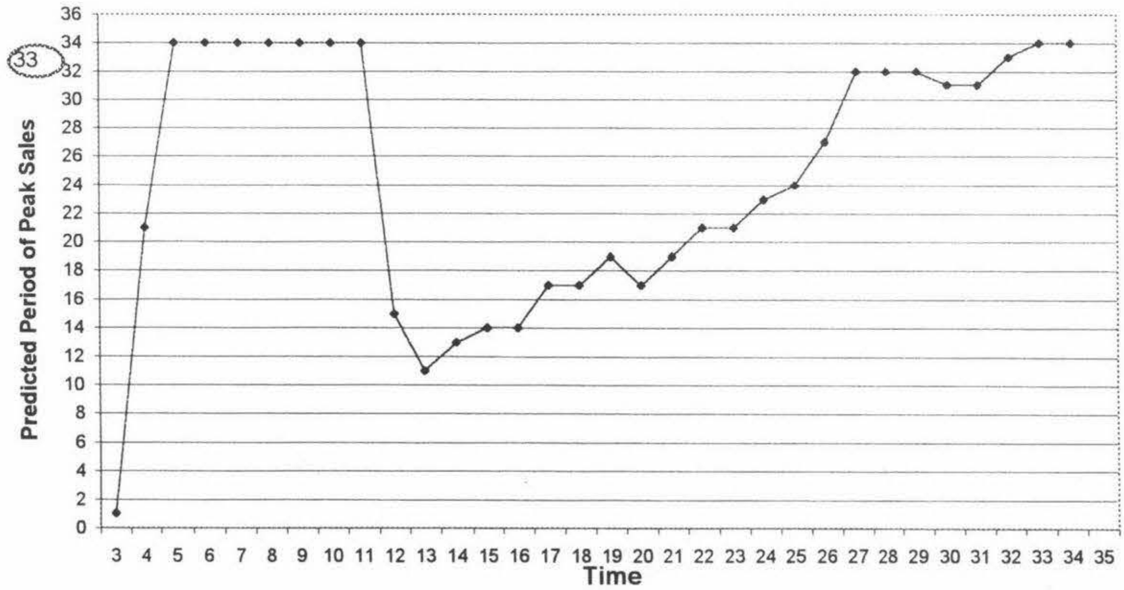


Predictive Validity - Video Camera 'Peak Sales Period'
Predicted Period of Peak Sales
Time
10
8
6
4
2
0
3
4
5
6
7
8
9

Predictive Validity - Digital Audio Disk Player 'Peak Sales Period'

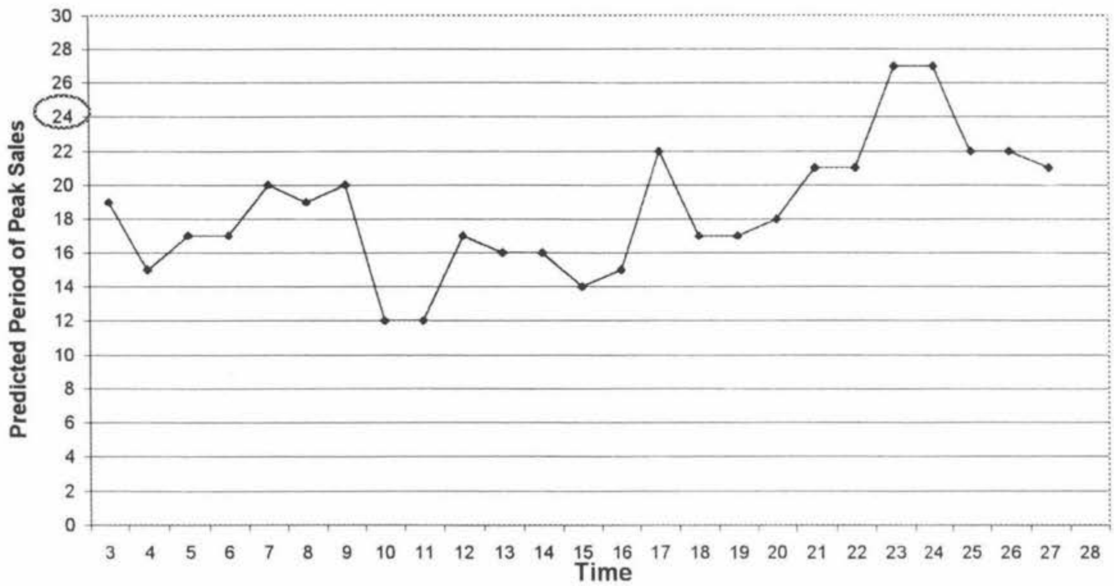


Predictive Validity - Vacuum Cleaner 'Peak Sales Period'

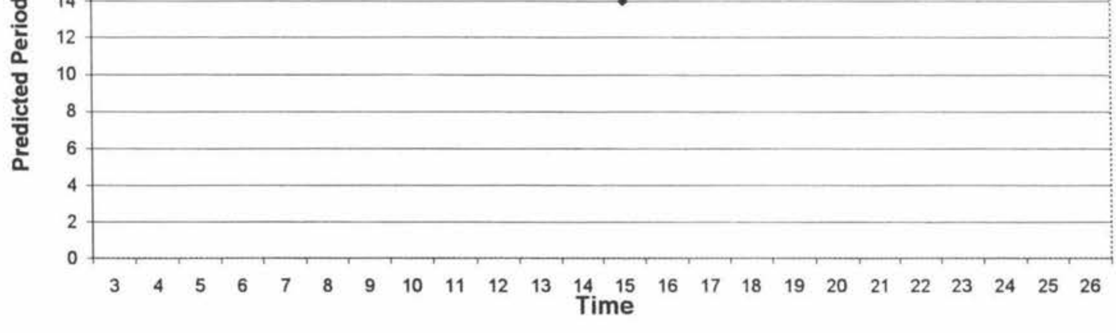


9.3.10 Peak Timing - Taiwan

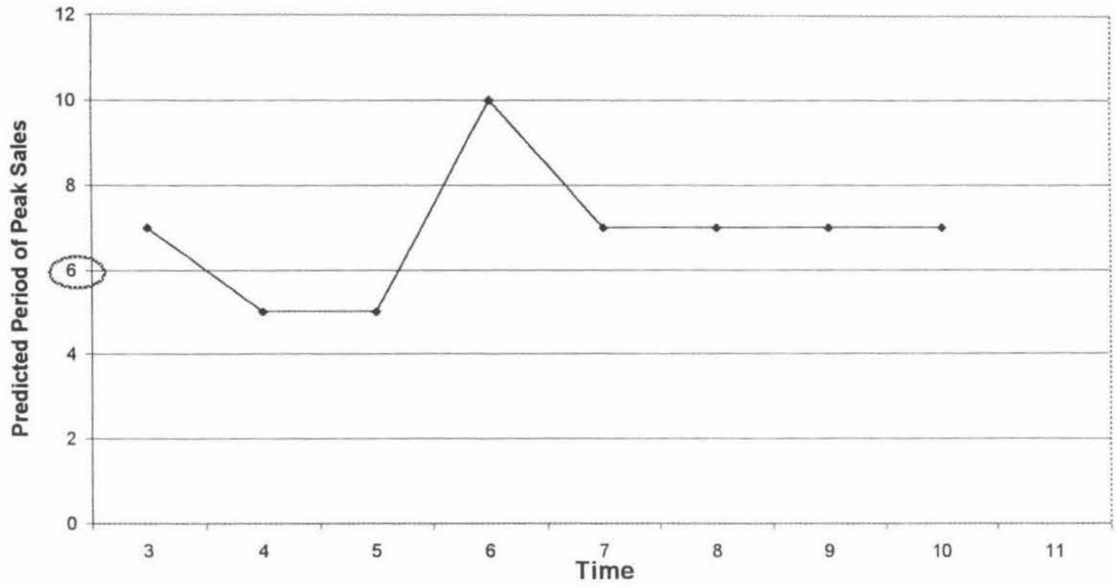
Predictive Validity - Air Conditioner 'Peak Sales Period'



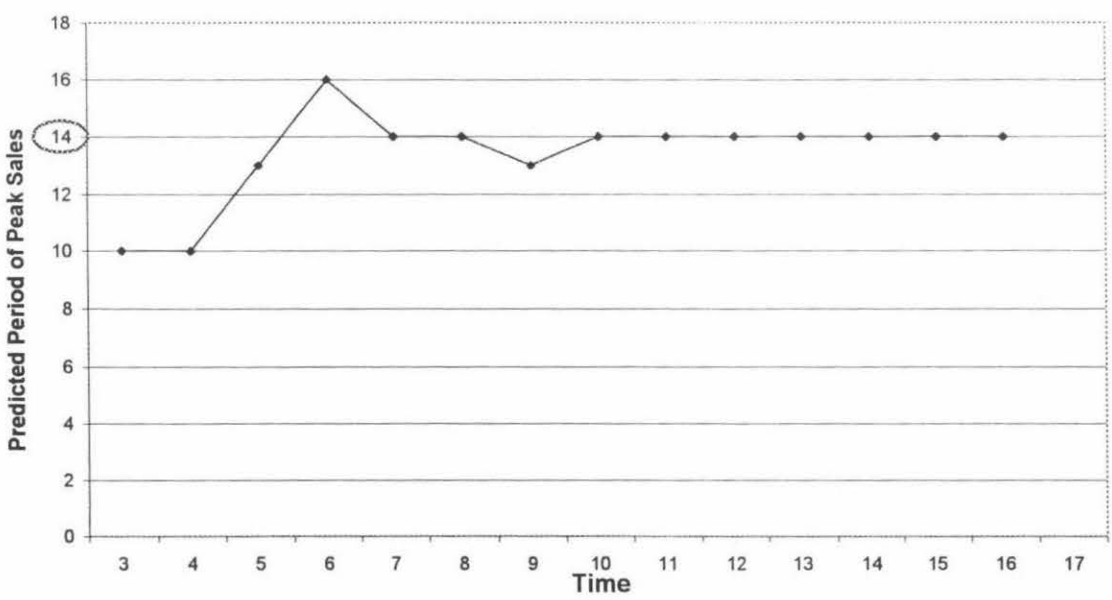
Predictive Validity - Personal Computer 'Peak Sales Period'

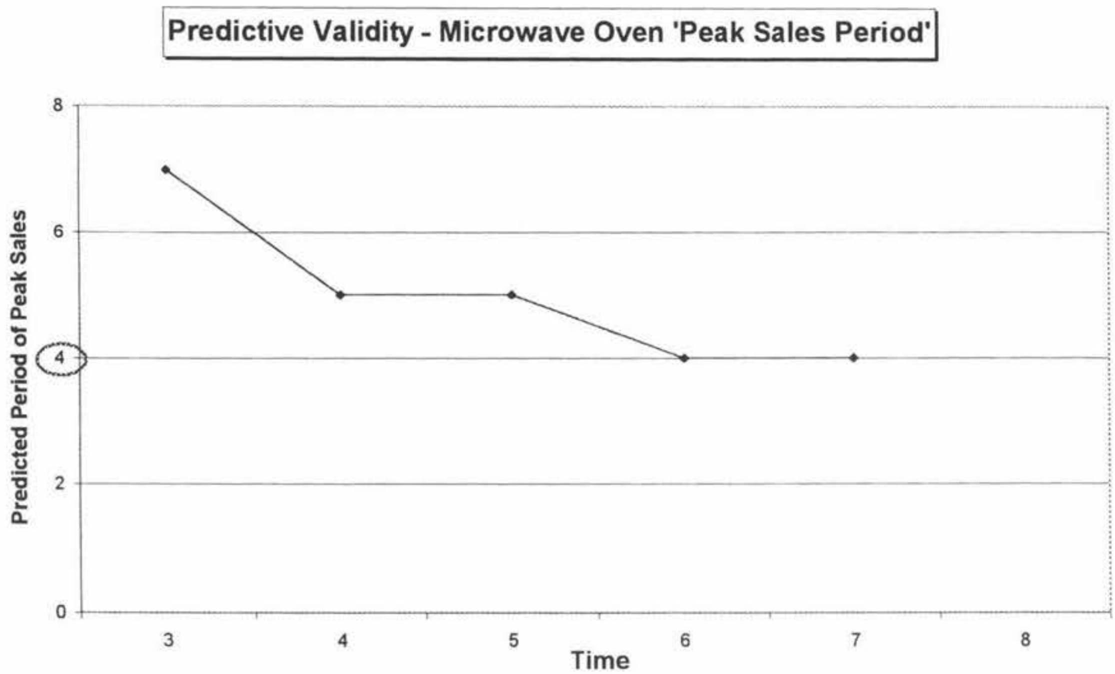


Predictive Validity - Facsimile 'Peak Sales Period'

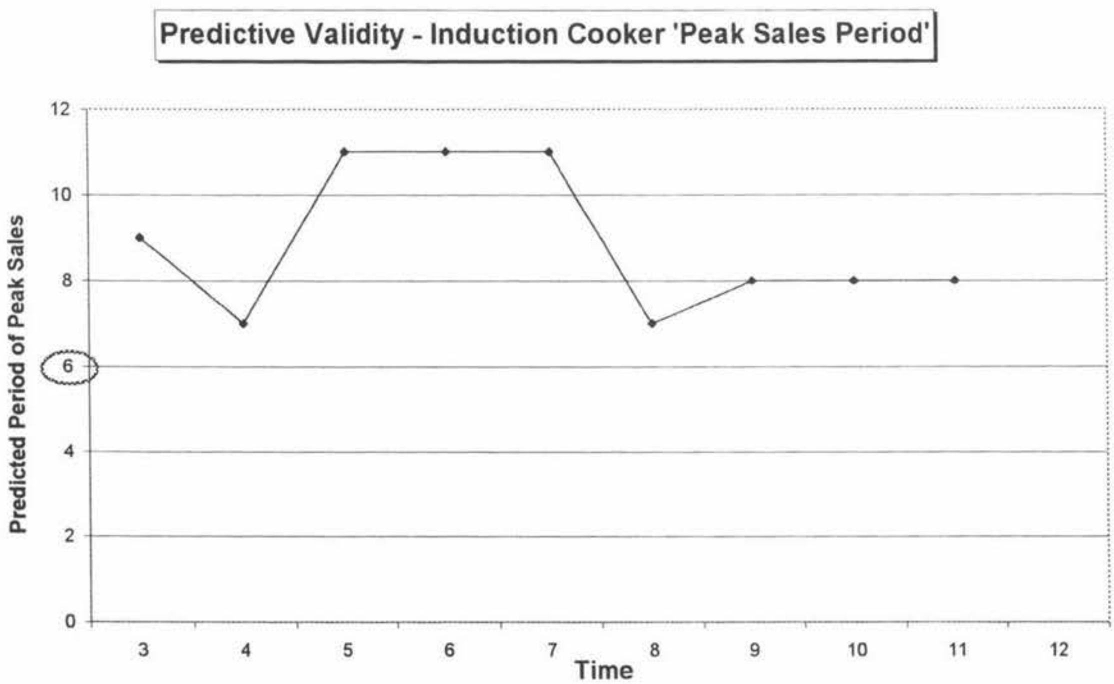


Predictive Validity - VCR 'Peak Sales Period'

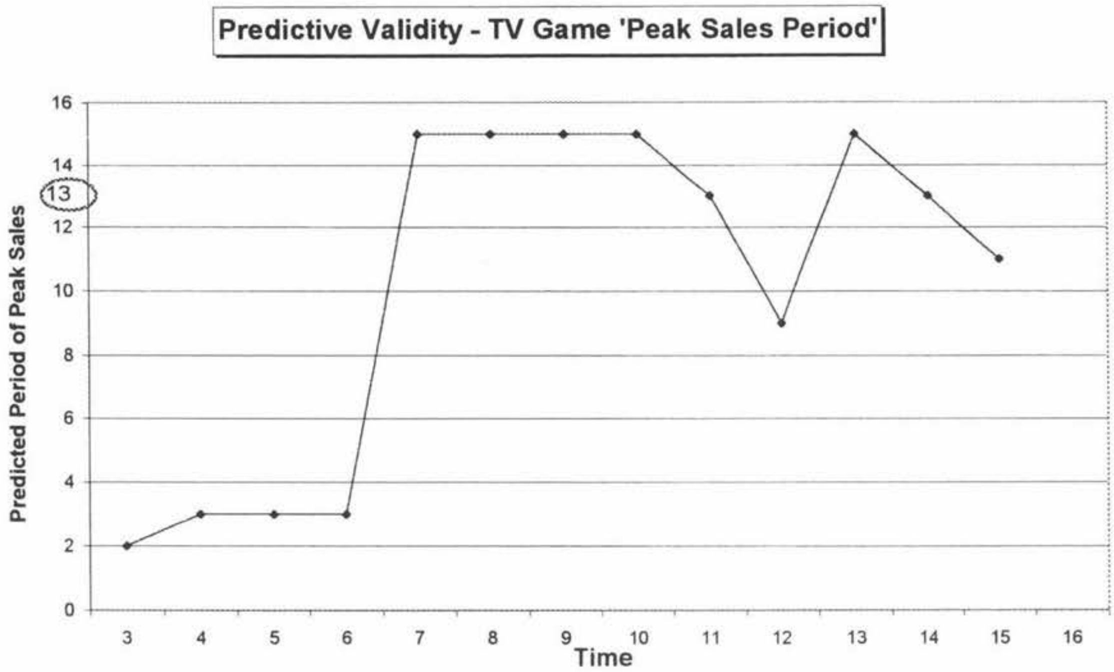


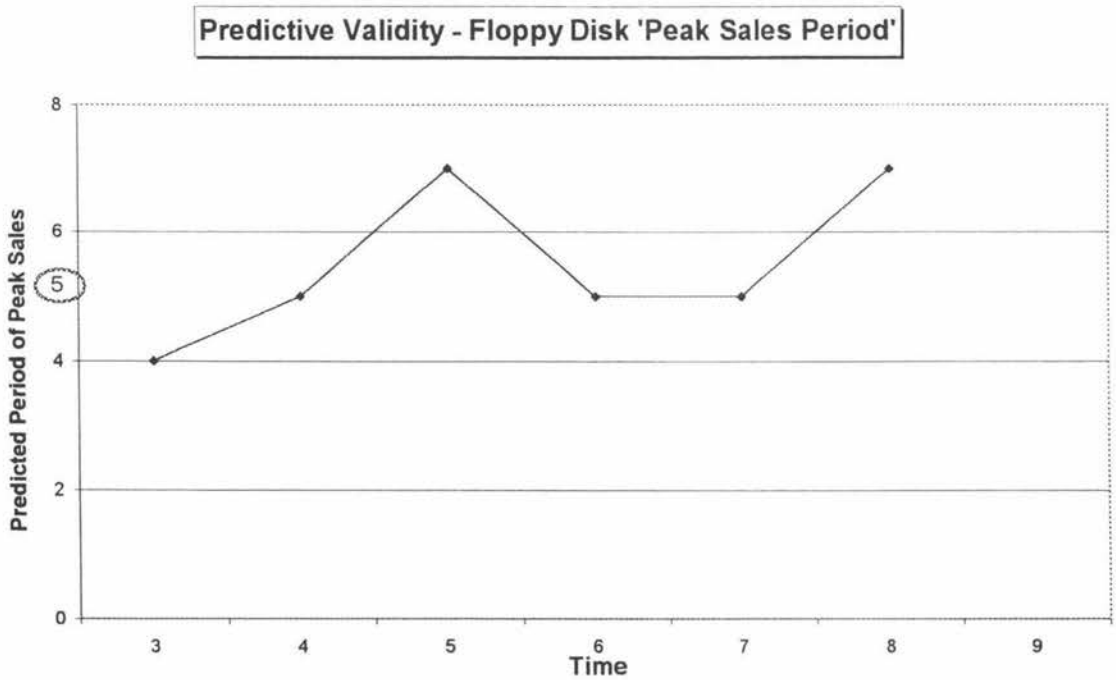


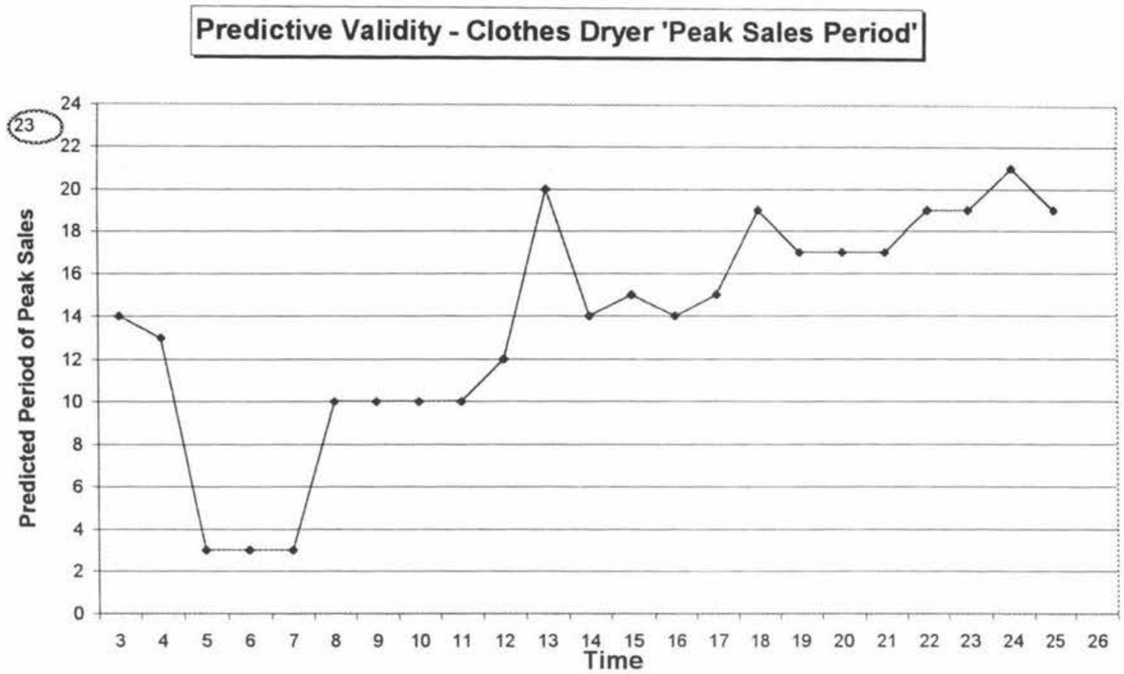
Predictive Validity - Microwave Oven 'Peak Sales Period'
Predicted Period of Peak Sales
0
2
4
6
8
3
4
5
6
7
8
Time



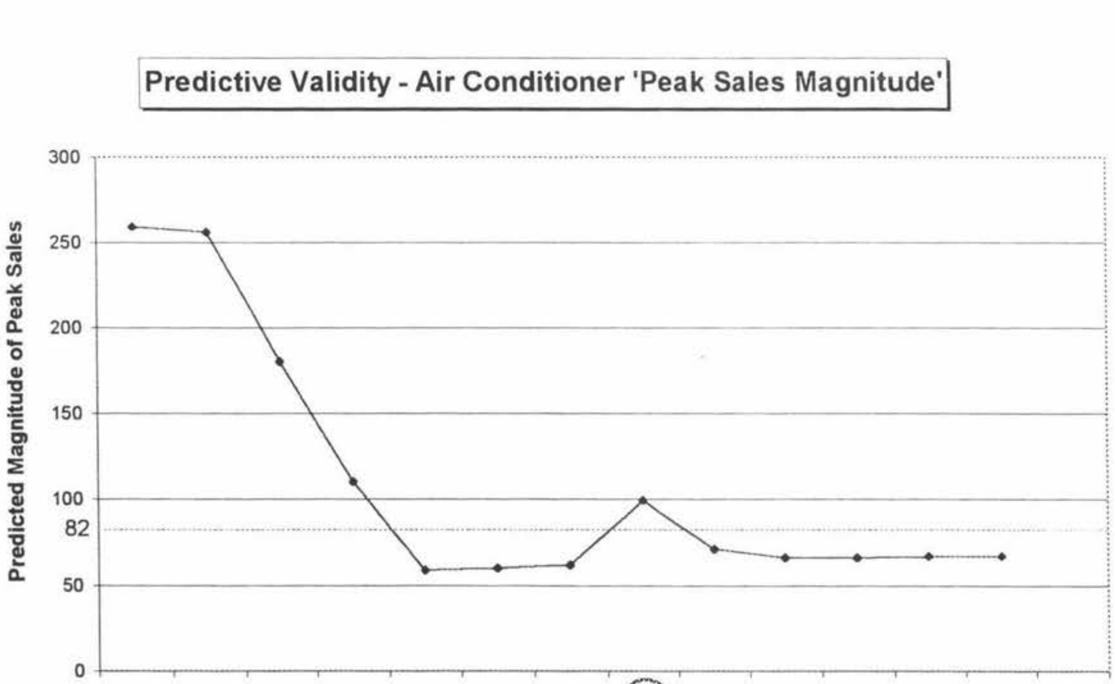
Predictive Validity - Induction Cooker 'Peak Sales Period'
Predicted Period of Peak Sales
0
2
4
6
8
10
12
3
4
5
6
7
8
9
10
11
12
Time


Predictive Validity - TV Game 'Peak Sales Period'
Predicted Period of Peak Sales
Time
0
2
4
6
8
10
12
13
14
16
3
4
5
6
7
8
9
10
11
12
13
14
15
16

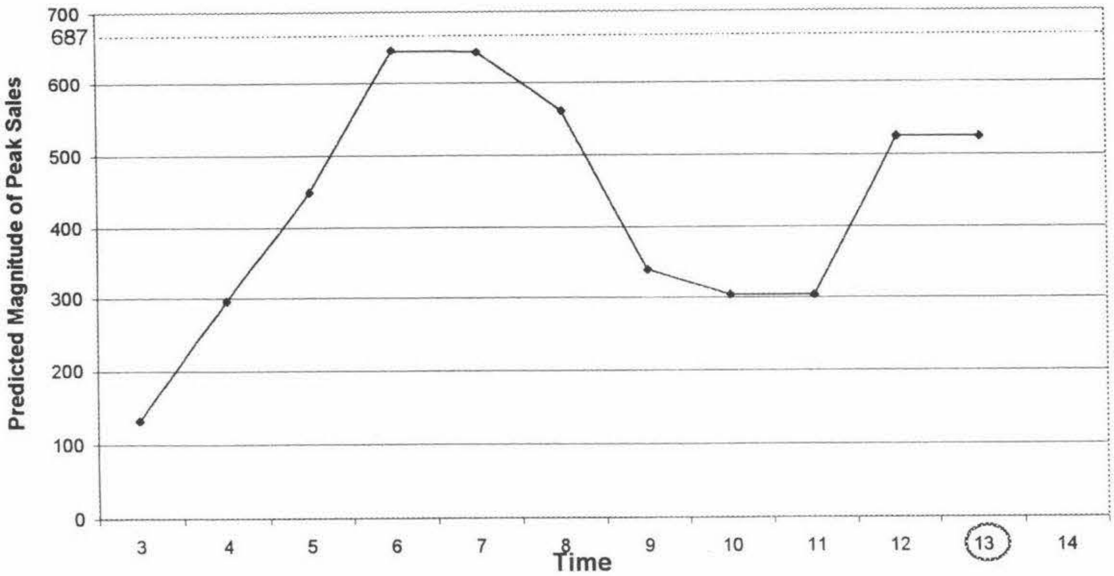

Predictive Validity - Floppy Disk 'Peak Sales Period'
Predicted Period of Peak Sales
Time
0
2
4
5
6
8
3
4
5
6
7
8
9



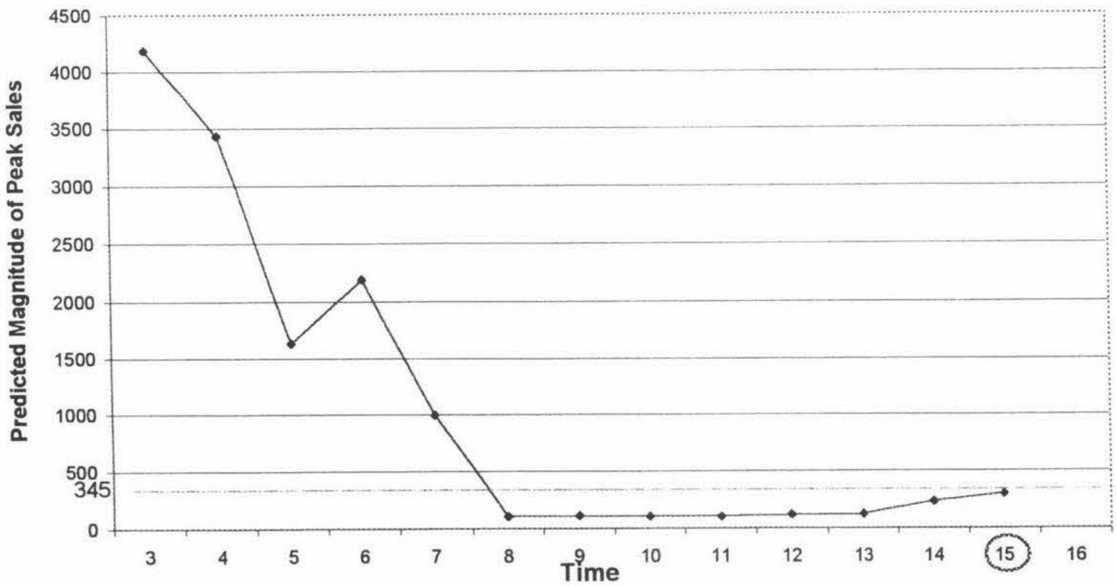
9.3.11 Peak Magnitude – Japan

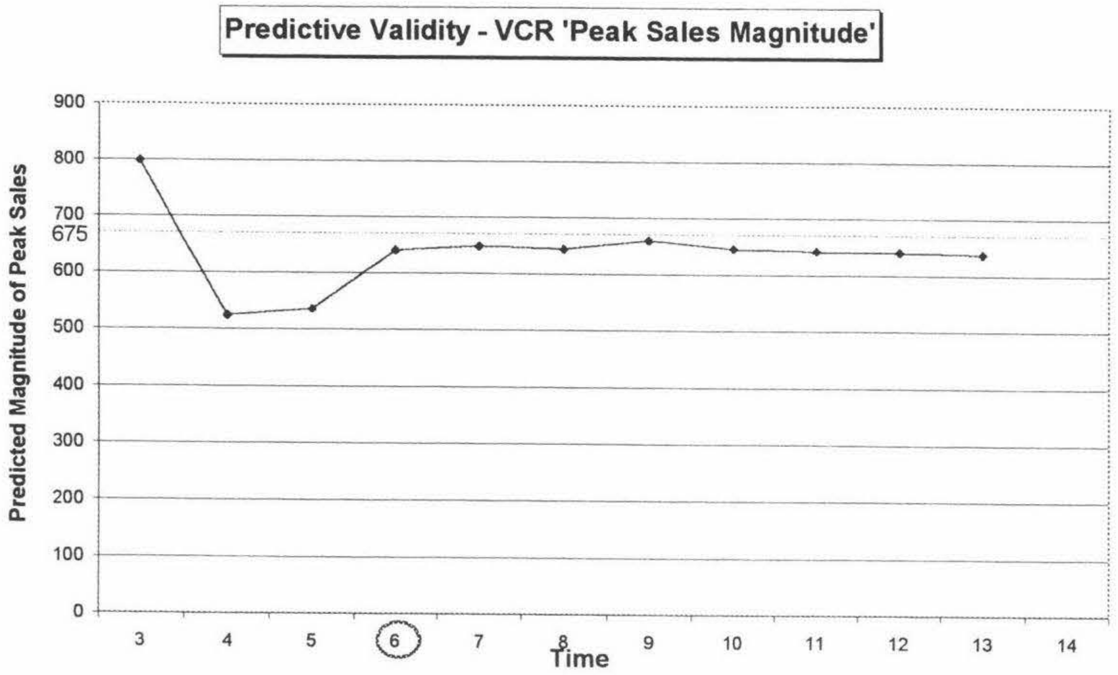


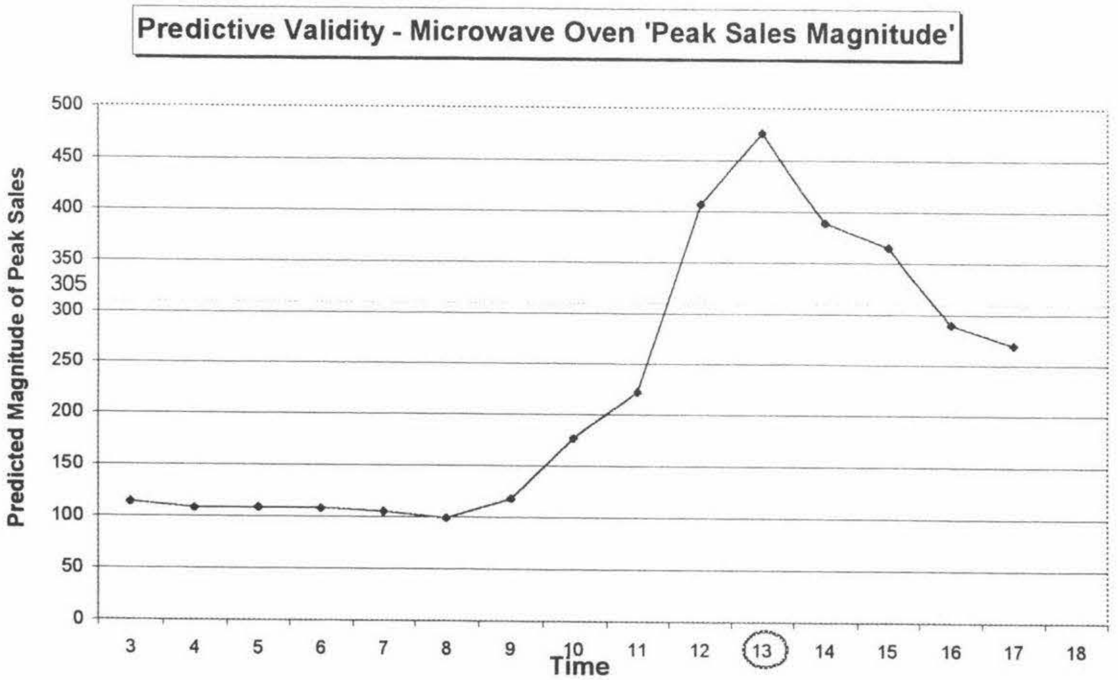
Predictive Validity - Personal Computer 'Peak Sales Magnitude'

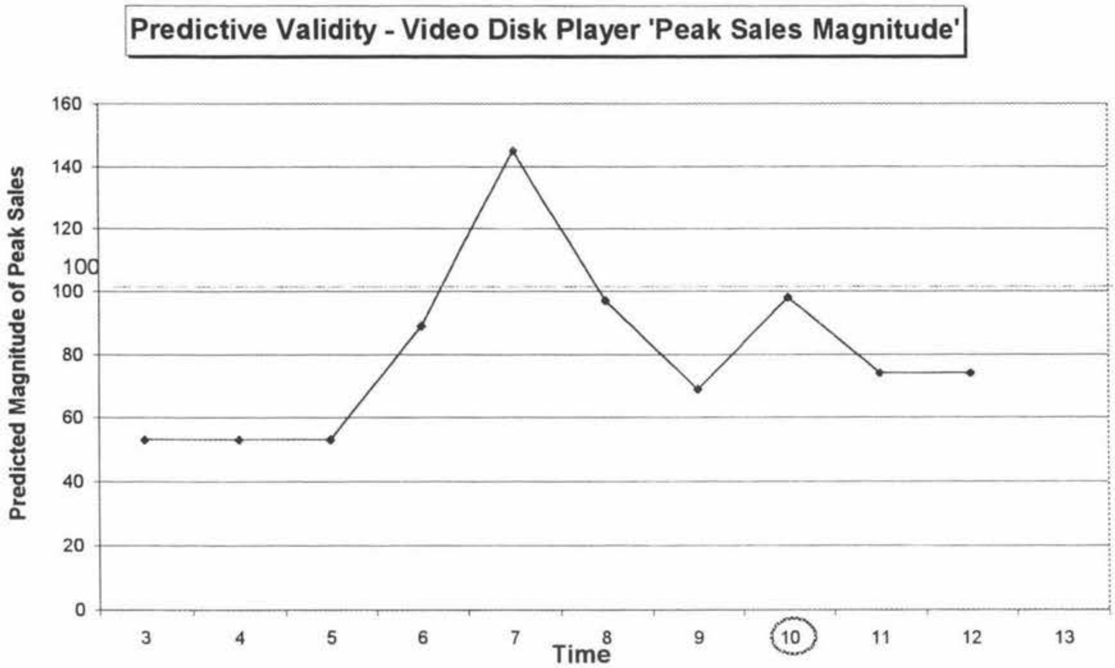


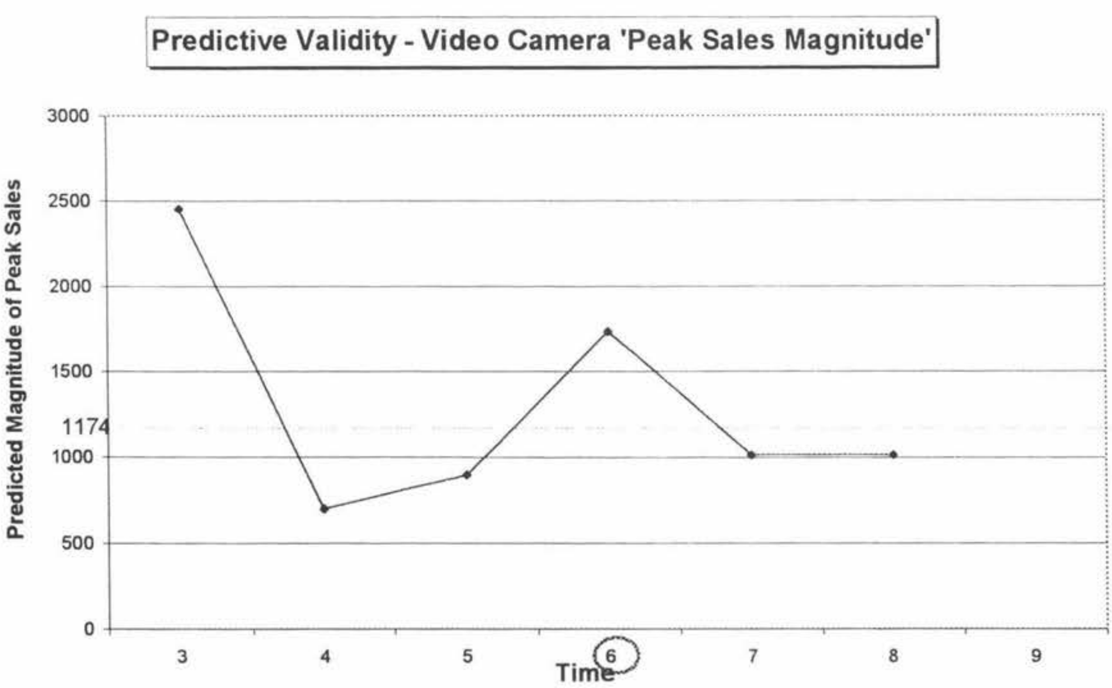
Predictive Validity - Facsimile 'Peak Sales Magnitude'

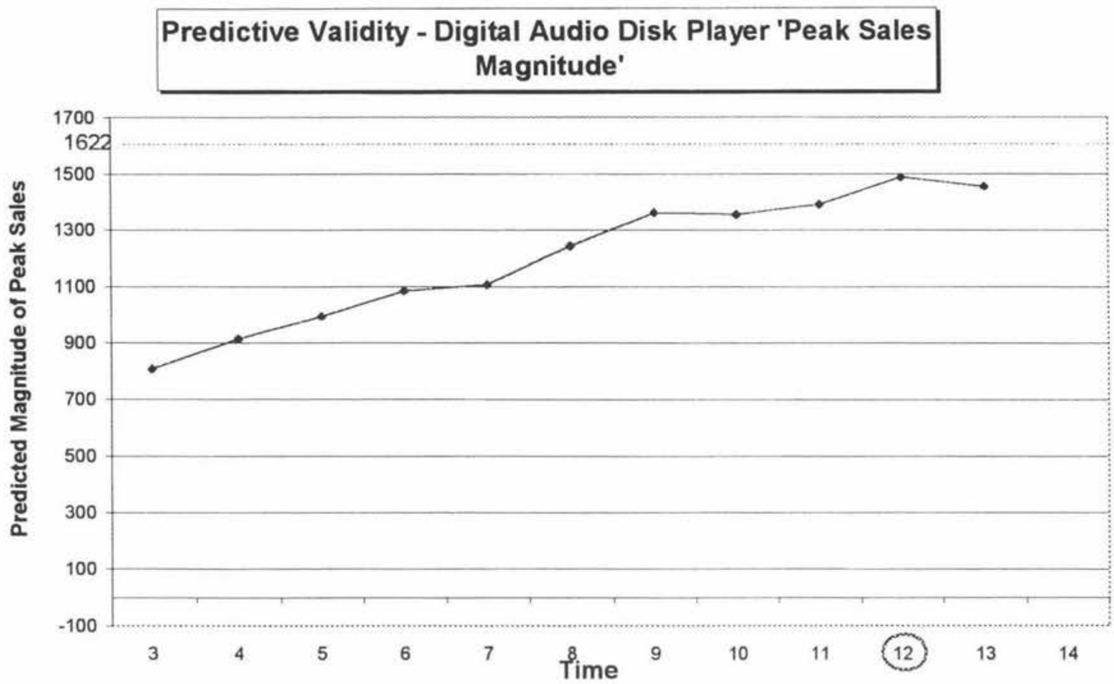


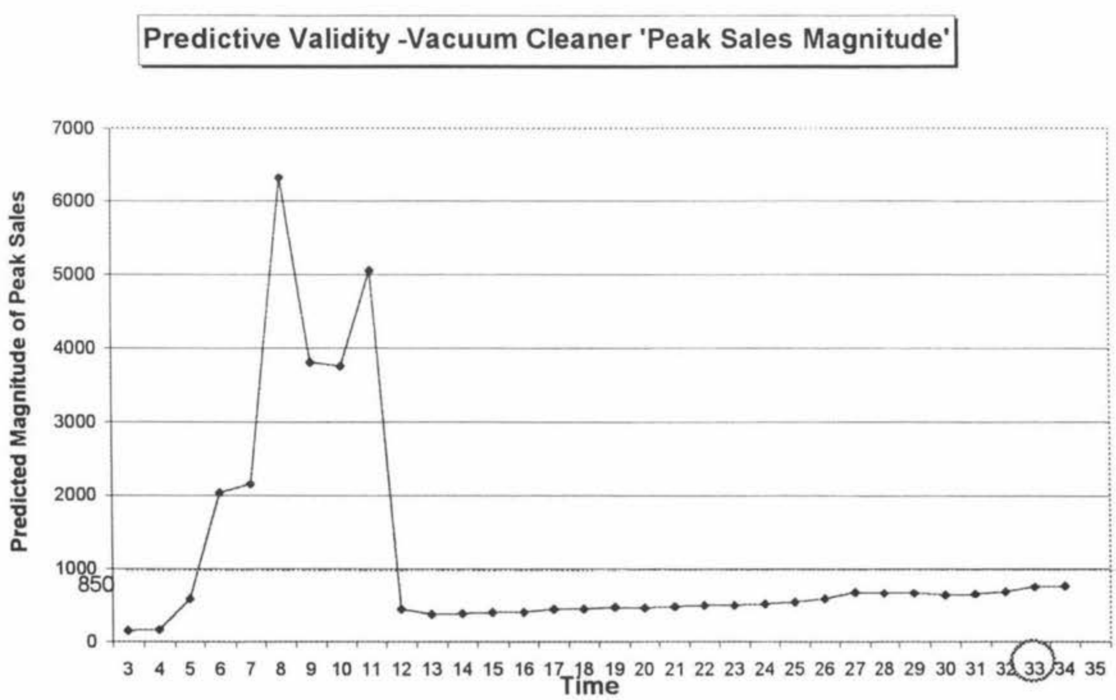

Predictive Validity - VCR 'Peak Sales Magnitude'
Predicted Magnitude of Peak Sales
900
800
700
675
600
500
400
300
200
100
0
3
4
5
6
7
8
9
10
11
12
13
14
Time


Predictive Validity - Microwave Oven 'Peak Sales Magnitude'
Predicted Magnitude of Peak Sales
500
450
400
350
305
300
250
200
150
100
50
0
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
Time

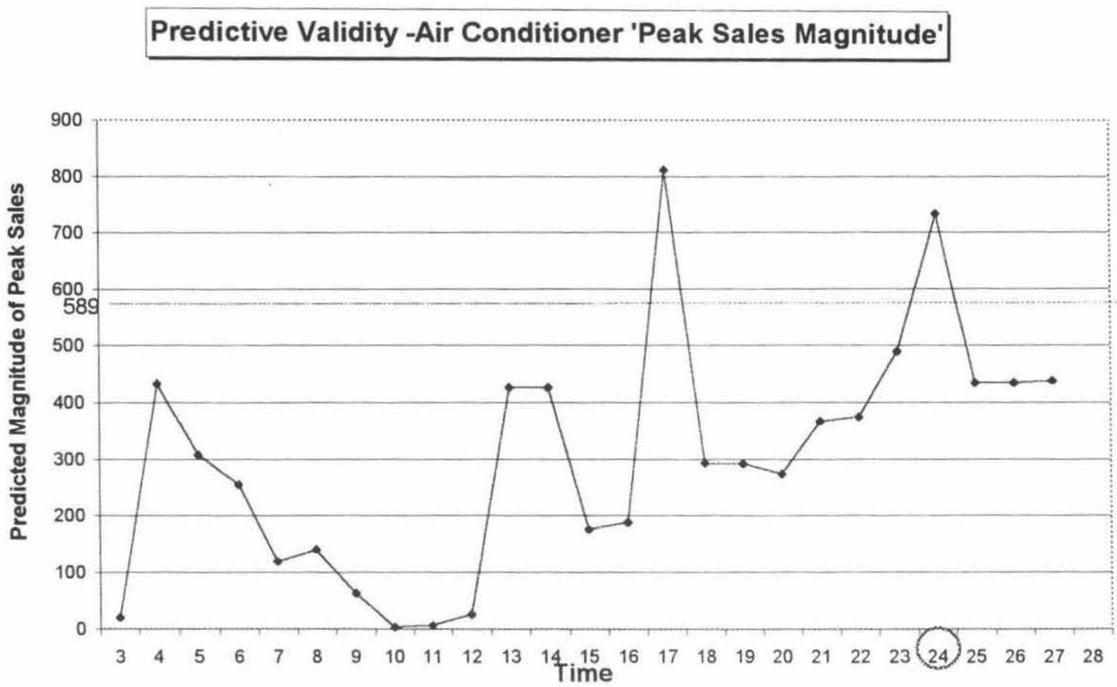

Predictive Validity - Video Disk Player 'Peak Sales Magnitude'
Predicted Magnitude of Peak Sales
160
140
120
100
100
80
60
40
20
0
3
4
5
6
7
8
9
10
11
12
13
Time

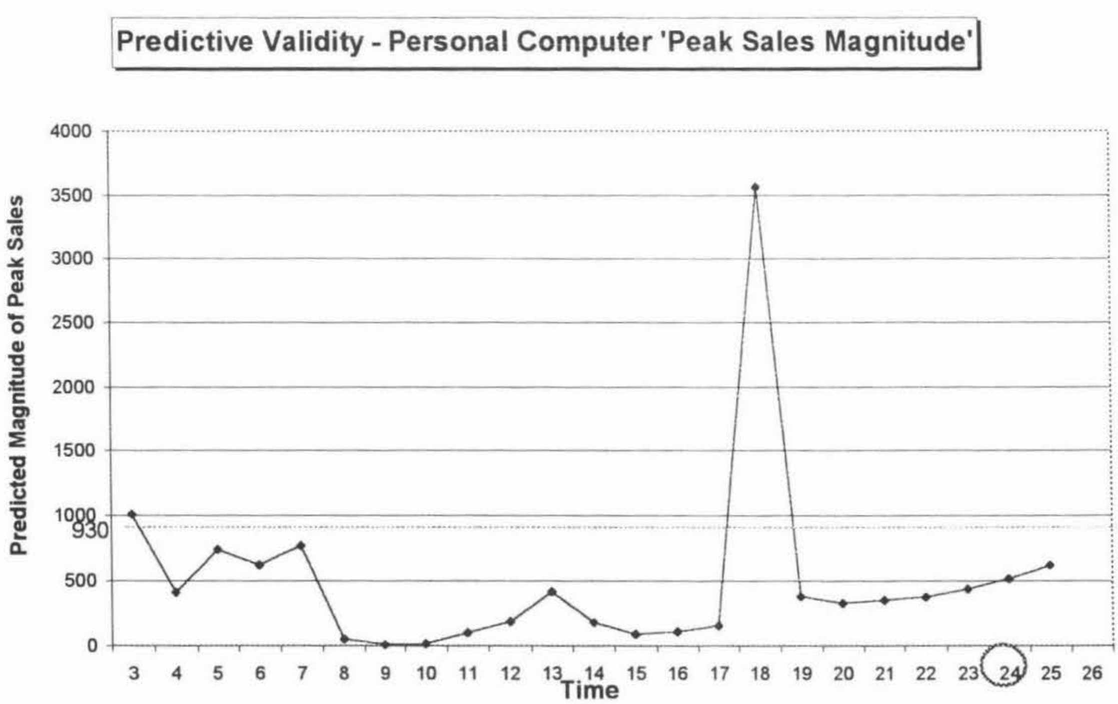

Predictive Validity - Video Camera 'Peak Sales Magnitude'
Predicted Magnitude of Peak Sales
3000
2500
2000
1500
1174
1000
500
0
3
4
5
6
7
8
9
Time


Predictive Validity - Digital Audio Disk Player 'Peak Sales Magnitude'
Predicted Magnitude of Peak Sales
1700
1622
1500
1300
1100
900
700
500
300
100
-100
3 4 5 6 7 8 9 10 11 12 13 14
Time

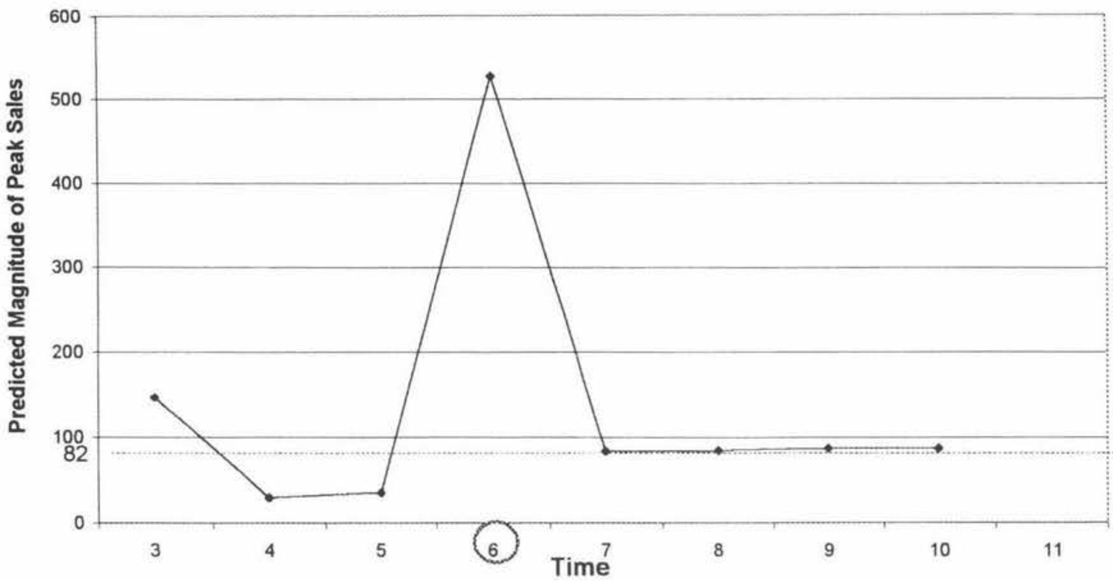

Predictive Validity -Vacuum Cleaner 'Peak Sales Magnitude'
Predicted Magnitude of Peak Sales
7000
6000
5000
4000
3000
2000
1000
850
0
3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35
Time

9.3.12 Peak Magnitude - Taiwan

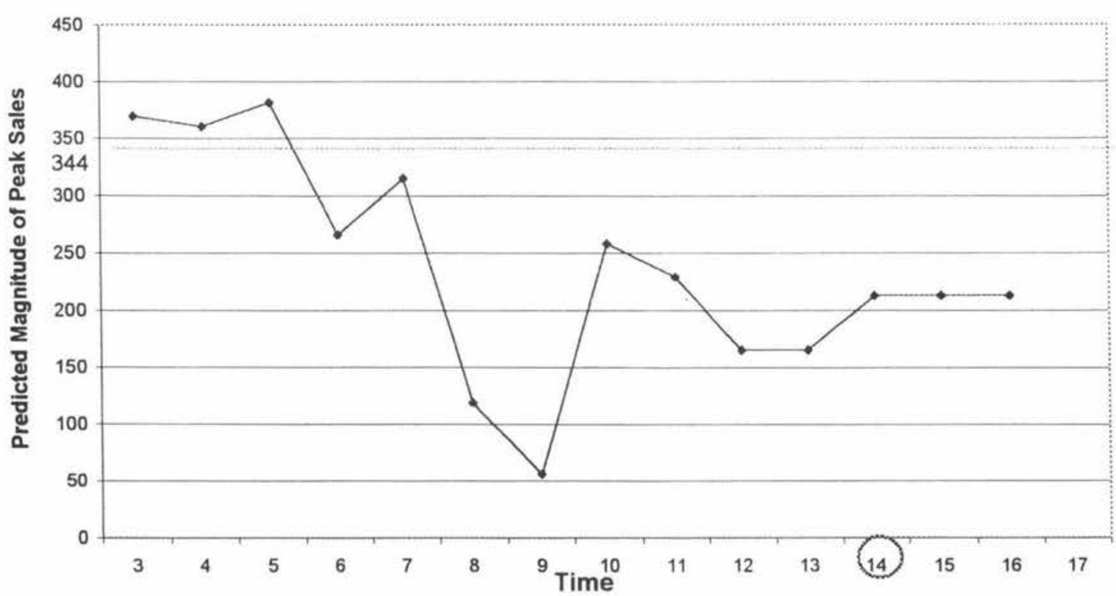




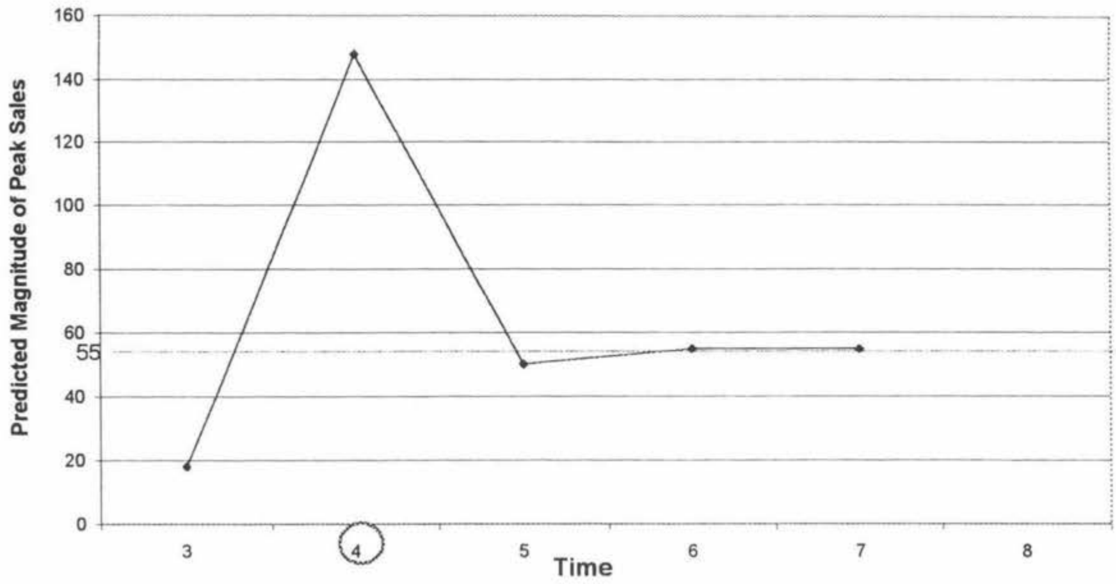
Predictive Validity - Facsimile 'Peak Sales Magnitude'



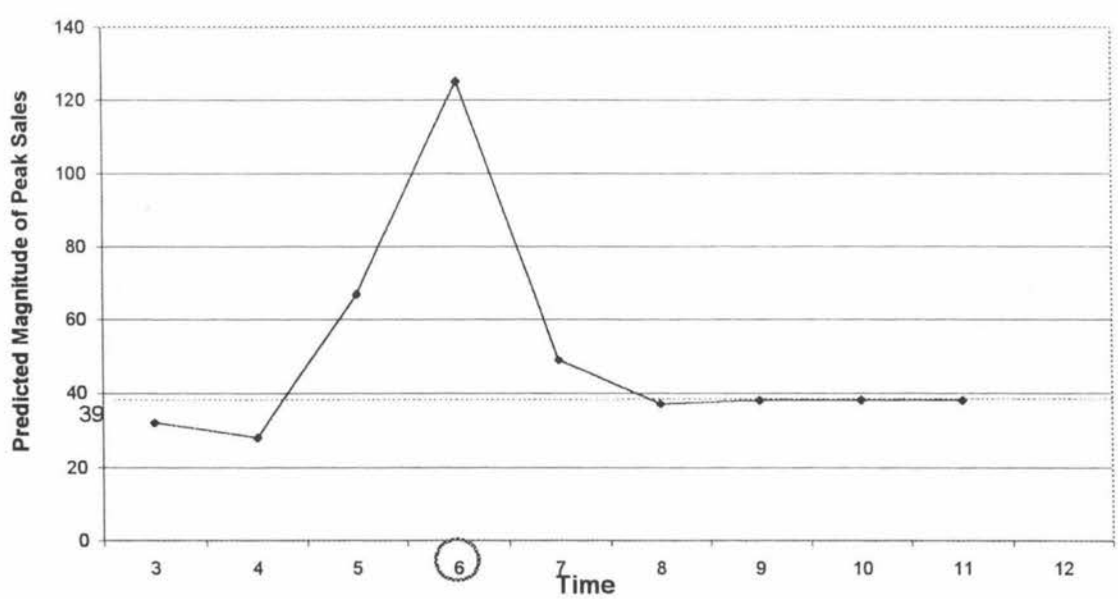
Predictive Validity - VCR 'Peak Sales Magnitude'



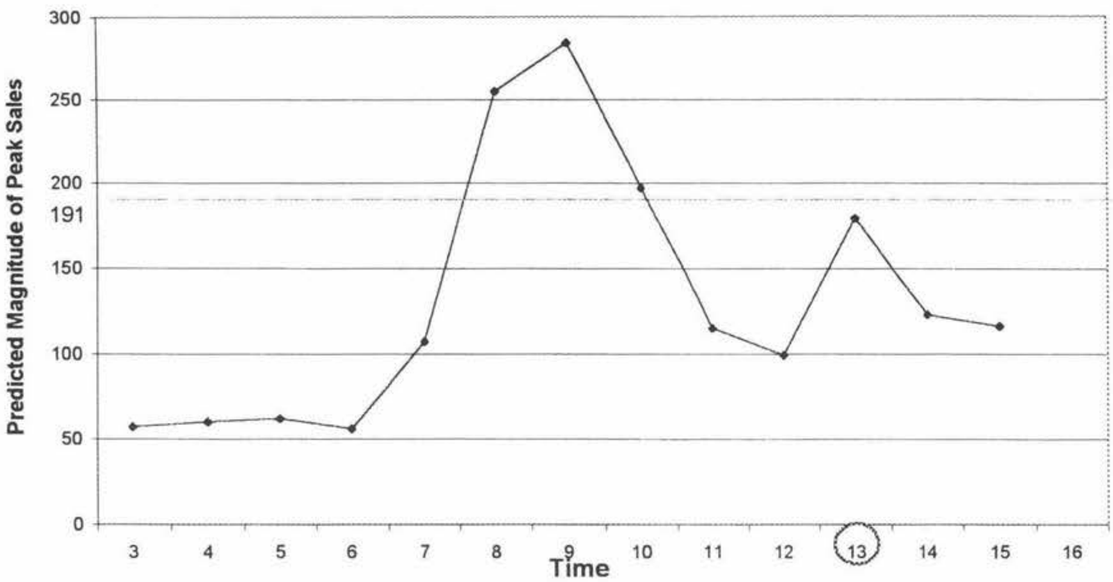
Predictive Validity - Microwave Oven 'Peak Sales Magnitude'



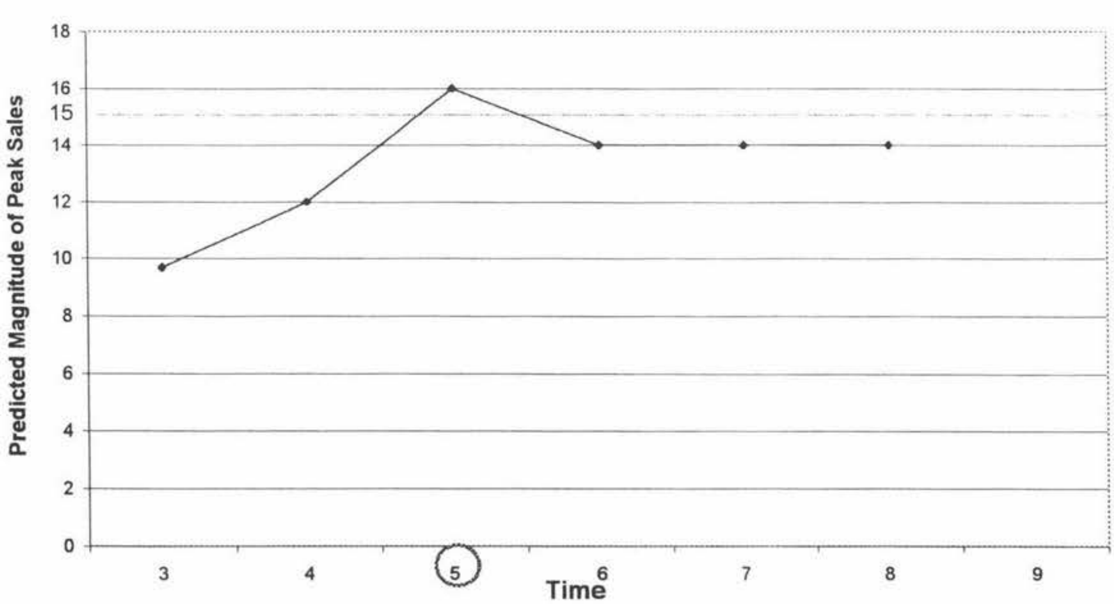
Predictive Validity - Induction Cooker 'Peak Sales Magnitude'

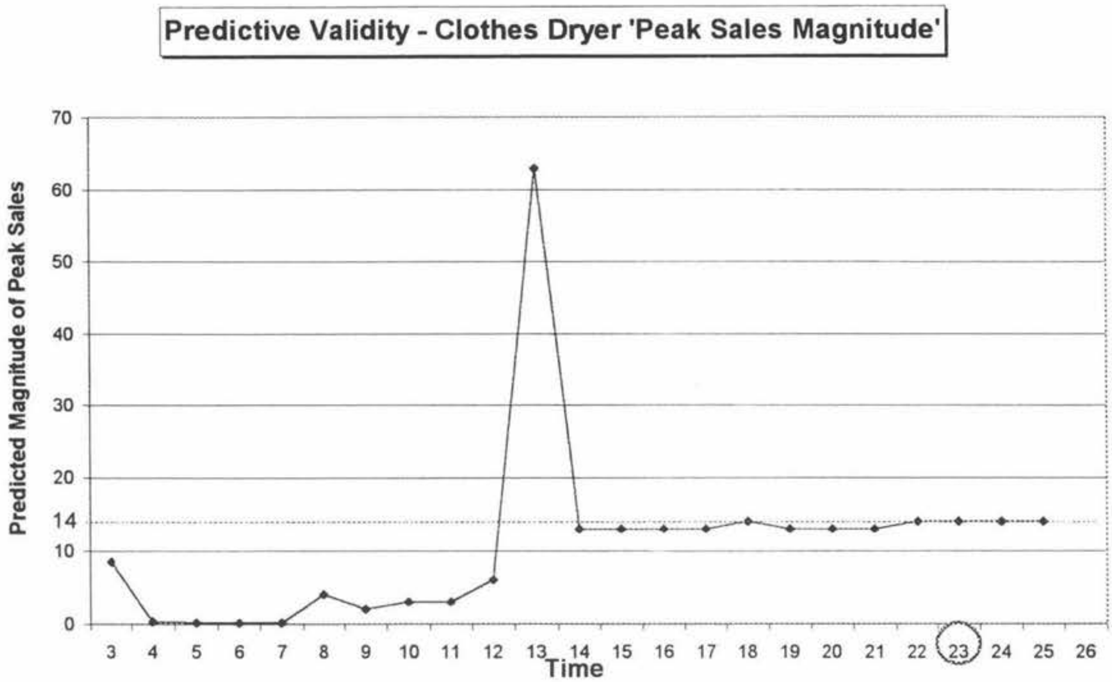


Predictive Validity - TV Game 'Peak Sales Magnitude'



Predictive Validity - Floppy Disk 'Peak Sales Magnitude'




Predictive Validity - Clothes Dryer 'Peak Sales Magnitude'
Predicted Magnitude of Peak Sales
70
60
50
40
30
20
14
10
0
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
Time