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FORECASTING CONSUMER ADOPTION OF
TECHNOLOGICAL INNOVATION:
choosing the appropriate diffusion models for new
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Lance Cameron Gentry

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FORECASTING CONSUMER ADOPTION OF TECHNOLOGICAL INNOVATION:
choosing the appropriate diffusion models for new products and services before launch

By

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ABSTRACT

FORECASTING CONSUMER ADOPTION OF
TECHNOLOGICAL INNOVATION:
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Within the vast literature on various forecasting models, there is consensus that no single diffusion model is best for every situation. Experts in the field have asked for studies to provide empirically based guidelines for recommending when various models should be used. This research investigates multiple diffusion models and provides recommendations for which diffusion models are appropriate for radical and really new products and services before the launch of the innovation. In addition, a forecasting classification grid is proposed.

DEDICATION

This dissertation is dedicated to my family, my committee, and the wonderful people in N370. I greatly appreciate the extra effort my wife, Allison, has put forth to ensure I had uninterrupted time to work on this project. Luke, Charles, Leah – you are the primary reasons why I went back to school and pursued my doctorate. I hope and expect that the life of an academic will provide ample opportunity to get to know you even better as your mother and I lead you to adulthood.

Professor Calantone – Many thanks for your guidance over the last few years. I appreciated the opportunity to get to know you better and I am grateful you made time to serve as my chair. Professor Droge – Thank you for your lessons on focus and your remarkable editing. I hope that I learn to teach my students with the same clarity that you bring to your classes. Professor Bohlmann – I appreciate your suggestions. Your assistance provided reassurance when I had doubts about the output of some of the diffusion models. Professor Page – You are a large part of the reason my research is aimed at the diffusion of innovation among consumers. Thank you for making the study of consumer behavior so interesting. Professor Levine – Thank you for your willingness to serve on my committee even though the timing did not work out. Professor Hoagland – Many thanks for your support, your stories, and the benefit of your vast experience in forecasting.

I also want to thank all of those in N 370. You have made it easier to succeed over the last four years and I appreciate it.

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First and foremost, I would like to thank those at the Consumer Electronics Association. I was first introduced to you while serving at Philips and was favorably impressed by your professionalism and effectiveness. I am pleased that I was responsible for bringing Intel into your organization and believe this was a win-win scenario for both Intel and the CEA. And I greatly appreciate your willingness to give me access to your data for this study. The people at the CEA have always been very friendly and helpful. I would especially like to thank Sean Wargo for his diligence and patience in this project. Despite the number of questions I asked about minutia (e.g., was the AVCO Cartrivision system included in the 1974 VCR data?), he managed to get back to me in a prompt and courteous manner.

I would also like to thank Richard Zwetchkenbaum (Intel), Angela Hearn (Satellite Broadcasting and Communications Association), and Ron Christianson (Cyber Telephone Museum) for their help in obtaining data for this project.

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LIST OF ABBREVIATIONS/DEFINITIONS

Abbreviations

B	Bass model – see page 57
BnC	Box and Cox model – see page 59
Bv	Bass model variant – see page 57
G	Gompertz model – see page 58
GB	Generalized Bass model (Price) – see page 57
GBv	Generalized Bass model (Price) variant – see page 57
SL	Simple Logistic model – see page 58

Definitions

Forecast	"a statement about a condition in the future, arrived at through a system of reasoning consciously applied by the forecaster and exposed to the recipient" (Bright, 1978).
Prediction	"a statement about the future based on rationale, if any, that the predictor has not made known" (Bright, 1978).
Radical Innovation	Radical innovations cause both macro-marketing and macro-technological disruptions (Garcia and Calantone, 2002).
Really New Innovation	Really new innovations cause either a macro-marketing or a macro-technological disruption (Garcia and Calantone, 2002).

Chapter 1

WHAT THIS RESEARCH WILL ACCOMPLISH

The Research Problem

How does one know when or if consumers will accept a technological innovation before the innovation hits the market? This research will evaluate techniques for forecasting consumer adoption of really new and radical technological innovations and develop a methodology for selecting the most appropriate techniques. The focus is on the consumer adoption of a product or service itself, not on the success or failure of a particular firm (e.g., will high-definition televisions be adopted by most consumers, not will Philips capture 20% of the HDTV market).

Forecasting is used in many contexts including predicting the weather, the economy, the advancement of technology, the effect of medicine on a patient, and even changes in fashion. A review and evaluation of the general forecasting methods is necessary to determine which tools are appropriate for forecasting the consumer demand for an innovation.

Is Forecasting Part of Marketing?

The core values of marketing state consumer "welfare is the ultimate goal of all marketing activities" (Achrol and Kotler, 1999). Thus, forecasting would be part of the marketing process if the ability to forecast consumer adoption of a technological innovation benefits consumers. Perhaps the most basic consumer benefits are the economic gains provided by forecasting. Forecasting improves both effectiveness and efficiency in the production of goods.

Effective production – producing the right things – depends upon manufacturers knowing what to produce. If firms produce the wrong product (i.e., products that fail), resources are wasted and losses are imposed on the firm. Consumer welfare is reduced when the firm recoups this cost by increasing the price of successful products. If a forecast dramatically underestimates the market, manufacturers may decide not to meet this need at all. For example, Univac pioneered commercial computers, but forecast a limited market potential for this innovation because they thought computers would only be used for scientific purposes. Based upon this assumption, Univac's market research predicted that there would be a total of a thousand computers in use in the year 2000. Initially they were not even concerned when IBM developed a computer platform designed for business applications (Schnaars, 1989).

Efficient production – producing things right given that the decision to produce has been made – depends upon manufacturers knowing how much to produce. If a forecast is too large, firms waste resources by over-investing in the new offering. Likewise, if the forecast underestimates demand, firms waste resources by catching up to the demand and consumers pay more for the product and/or have to do without it for some time.

The more accurate the forecast, the more effectively and efficiently an innovation may be brought to market. The more effectively and efficiently an innovation is brought to market, the greater the consumer welfare. The greater the increase in consumer welfare, the greater the marketing contribution of forecasting.

Why is This an Important Problem for Academics & Managers?

Academics are in the business of creating knowledge. In other words, researchers exist to reduce uncertainty. Gerwin (1988) listed three types of uncertainty that he found useful in investigating technology: technical uncertainty, financial uncertainty, and social uncertainty. Forecasting consumer adoption of technological innovations – and assigning probabilities to these estimates – is a necessary part of evaluating the technological, business, and social implications of innovation.

Managers who can better understand the range of potential futures should be better prepared for whatever future occurs. As previously discussed, forecasts enable managers to more effectively and efficiently manufacture the right products in the right quantities. In theory, firms with managers who better prepare their firms for these future needs should have a competitive advantage over firms whose managers did not foresee what might lie ahead. However, this presumes that the forecasts do not lead the managers astray. According to Hoagland (2001), false predictions of a Y2K disaster disrupted the supply chain as firms and individuals stocked up on inventories as insurance for the expected disruption. Hoagland's research led him to conclude that the actions taken to hedge against the predicted Y2K disruption actually caused the recent recession.

Academics and managers clearly need to know how much confidence they should have in a forecast. It is likely that the need for a higher level of confidence is related to the height of the barriers of entry and exit of a market. For example, the barriers of entering the suborbital tourism market are very high as there are significant technological, regulatory, market, and capital issues to overcome. Before any reasonable firm would risk the vast amounts of resources needed to serve this market, they need to be extremely confident that a viable market truly exists.

The Research Questions

RQ1. ***Which forecasting methods should be used for forecasting consumer adoption of radical technological innovations?***

RQ2. ***Which forecasting methods should be used for forecasting consumer adoption of really new technological innovations?*** The answer to this question may be the same as RQ1, but this research may show that radical and really new technological innovations should use different forecasting techniques.

RQ3. ***Does an innovation's price affect which methods should be used to forecast consumer adoption of technology innovations?*** In other words, does price affect forecasting accuracy for various methods? If so, what forecasting methods should be used for low and high priced innovations?

The Research Context

This study will evaluate the diffusion of the innovations shown in Figure 1. That is, this research is looking at the diffusion of radical and really new innovations intended for use in the home. The innovations will be classified as either high priced or low priced.

Figure 1: Initial Classification of 8 Consumer Electronic Innovations

	Innovations for Consumers	
Price Level	Radical Innovation	Really New Innovation
High	**PCs (1980 – 2000)** **Satellite Receivers (1986 – 2000)**	**Camcorders (1985 – 2000)** **Projection TVs (1984 - 2000)**
Low	**VCR (1974 - 2000)** **CD Players (1983 - 2000)**	**Cordless Phones (1980 – 2000)** **Telephone Answering Device (1982 – 2000)**

To reduce confounds and to simplify the data-collection process, only the U.S. market will be considered. Likewise, only consumer electronic innovations will be studied in this research.

Data Sources

This study used secondary data for the eight data sets shown in Figure 1. The overwhelming majority of the data was obtained from the Consumer Electronics Association. The CEA, formerly the Consumer Electronic Manufacturers Association, includes more than a thousand companies within the U.S. consumer technology industry. They are the best possible single source for industrial level U.S. sales of consumer electronics.

As shown in Figure 1, the eight data sets were initially selected to include two samples in each cell of consumer electronic innovations. Only data sets with a reasonable history were considered. Newer innovations were not feasible as one would have to wait at least 10 years before comparing the results of the various forecasts with actual results.

Greater detail about each data set is provided in Chapter 3.

Chapter 2

LITERATURE REVIEW

Forecasting: Techniques and Methods

Bright (1978) defined a forecast as "a statement about a condition in the future, arrived at through a system of reasoning consciously applied by the forecaster and exposed to the recipient." Jantsch (1969) first differentiated between two general approaches to forecasting: exploratory and normative. Exploratory forecasting utilizes relevant historical records to project parameters and/or functional capabilities into the future. Normative forecasting starts with future goals and works backwards to identify what barriers must be overcome in order to obtain these goals. Armstrong (2001) considered normative forecasting as synonymous with planning. Lenz (1971) noted that these distinctions are not absolute. All forecasters bring some normative thinking into their forecasts simply by what assumptions they make and what factors they select as important. Conversely, all normative forecasts use exploratory techniques as the starting points for their assumptions. Nevertheless, the distinction between exploratory and normative forecasts is a useful one. All of the forecasts in this study are exploratory forecasts.

Classification Schemes in the Literature

Brucks (1986) stated that a good typology should have three objectives:

> 1) *The typology and coding scheme should be easy to use and seem logical to people who are using the coding scheme.*
>
> 2) *The typology should cover as many of the subjects' statements as possible while remaining relatively parsimonious.*
>
> 3) *The categories in the typology should be as distinct from each other as possible.*

In other words, a good classification system should be exhaustive, exclusive, and concise. Exhaustive means that the classification system should cover every potential option. Exclusive means that anything that belongs into one category should clearly not belong in another category. These criteria will be used to evaluate the various classification schemes that researchers have created to compartmentalize technological forecasting methods.

There are many ways to classify forecasts, all of them at least somewhat arbitrary. The ones more frequently used in the literature are discussed. The classification systems are listed in chronological order as this approach allows the reader to see how subsequent classifications built upon earlier classification methods.

Cetron and Ralph, 1971 – summary

Cetron and Ralph grouped forecasting techniques into five categories: intuitive methods, trend extrapolation, trend correlation, analogy, and dynamic predictive models. This classification system appeared to have been largely based upon the chapter headings of Lenz's 1962 landmark work on technological forecasting, but Cetron and Ralph did place some new methods within some of the classifications.

Intuitive methods include: individual forecasting, polls, panels, and the Delphi technique. Cetron and Ralph's reasoning for grouping these methods together was that all were based upon opinions. Ideally, these opinions were well-educated estimates made by experts, but they were all based upon the intuition of the forecaster.

Trend extrapolation is simply forecasting based upon the continuation of existing trends. It includes: simple extrapolation, substitution, and modified curve-fitting. Cetron and Ralph found that the general opinion in 1971 was that trend extrapolation was widely used due to its ease-of-use rather than due to any accuracy advantages (echoing an observation made a decade earlier by Lenz in 1962). The two key assumptions of trend extrapolation are:

1) the factors which caused the prior pattern of progress will continue;

2) the combined effect of these factors will continue the same pattern of progress.

In a substitution forecast, one measures the rate of substitution, with time, of a new innovation over an older innovation. While the relative increase in performance is presumably the reason for the substitution, this performance increase is reflected in the rate of substitution. The key assumption of substitution is that the process will continue until the new innovation has completely replaced the older innovation if at all possible.

Since technological progress typically advances slowly, reaches a critical mass, accelerates exponentially, and then slows as it reaches limitations, one can expect a given innovation to fit a type of trend curve. Cetron and Ralph distinguished between five types of trend curves: linear with flattening, exponential with no flattening, s-shaped, double exponential, gradual-rapid-subsequent flattening.

In **trend correlation**, the forecaster assumes that "one factor is the primary causal influence in the advancement of the technological parameter of interest." Trend correlation analysis is optimal for situations where the development of a certain innovation lags the development of another innovation.

Analogy forecasting simply looks for another pattern that should be similar to the pattern to be forecast. These are typically classified as growth or historical analogies. Forecasters have used growth formulas (e.g., the rate of cell increase within a rat) and historical patterns (e.g., GE looked at fossil fuel and hydroelectric power development to successfully forecast nuclear power development).

Dynamic predictive models are based upon work initially done by Forrester (1958), the chair of Lenz's thesis. Lenz built upon Forrester's modeling structure to simulate the impact of important causal factors. Over time, these models became more sophisticated. Currently, these types of models are most frequently referred to as structural models.

Cetron and Ralph, 1971 – strengths and weaknesses

Cetron and Ralph's original contributions are largely in the area of intuitive methods, in the addition of historical analogies to the analogy classification, and in incorporating previous research into a formal classification system. Their taxonomy is concise, but neither exhaustive nor exclusive. It is not exhaustive as it does not consider techniques such as forecasting by role-playing. It is not exclusive as their definition of trend correlation specifically incorporates causality. Thus, one could reasonably say that trend correlation – as defined by Cetron and Ralph – is a subset of their dynamic predictive model classification.

Martino, 1972 – summary

Martino discussed five types of forecasts: intuitive, consensus, analogy, trend extrapolation, and structural models.

Intuitive forecasts are obtained by simply asking an expert. Martino wryly noted that "even though an expert may be wrong, his intuitive forecast may still be the best forecast available." He then cited Ralph C. Lenz's quip that intuitive forecasting's real problem is it is "impossible to teach, expensive to learn, and excludes any process of review."

Consensus methods obtain results by asking multiple experts. These experts typically meet together, but this is not a requirement. The positive aspects of this method are:

- that any fact that is known to one expert becomes available to all;
- multiple heads are less likely to overlook something;
- chances are that biases will balance out;
- opportunities for experts to see how others think and thus revise estimates with new input.

The negative aspects of this method include:

- all the problems associated with group dynamics (the Delphi technique is a consensus method that tries to eliminate/reduce these problems);
- any misinformation known to one is known by all.

The **forecasting analogy method** compares a known event (historical event, physical/biological process, etc.) with the event to be forecasted. Growth curves are often used to predict the advance of some technology. The S-curve has been found in many living species for both individual and population growth curves. The adoption of many technological innovations follows a similar pattern - starting slow, followed by a rapid rise, then a leveling off that leads to obsolescence. "The major strength of this method is that it eliminates much of the subjectivity of either intuitive or consensus methods of forecasting. Its major weakness, however, is that the exact extent of the analogy between the model and the thing to be forecast is often not evident until it is too late to do any good" (Martino, 1972).

Trend extrapolation avoids the problem of estimating changes in specific S-curves. Instead of focusing on a single device - or technology - trend extrapolation considers a series of devices that perform the same function. Successive devices usually have major differences in performance (on the order of 100% or more), while improvements to a single device are usually on the order of a few percent.

Structural models create an analytical model of the technology-generation process. "A characteristic feature of such models is they tend to be abstractions; certain elements are omitted because they are judged to be irrelevant, and the resulting simplification in the description of the situation is intended to be helpful in analyzing it and understanding it" (Martino, 1972).

Martino, 1972 – strengths and weaknesses

Martino's classification system is concise and easily understood. His lexicon is a bit confusing, as intuitive forecasts do not consist of all intuitive forecasts, but merely those that are from the opinion of a single expert. He reserves the classification *consensus methods* for the opinions of multiple experts. As his boundaries are quite clear for all five categories, Martino's classifications are exclusive.

One might question the need for dividing subjective techniques into two categories based upon whether a single or multiple number of experts contributed toward it. This distinction does not seem useful and Martino is the only one to have made such a division. Further, the preciseness with which Martino defined his two expert classifications actually precluded both of these categories from incorporating non-expert intuitive forecasting methods such as role-playing. Thus, Martino's taxonomy is not exhaustive.

Bright, 1978 – summary

Bright developed and used eight categories of forecasting: intuitive forecasting, trend extrapolation, dynamic modeling, morphological analysis, normative forecasting, monitoring, cross-impact analysis, and scenarios. As one would expect from their names, Bright's **intuitive forecasting**, **trend extrapolation**, and **dynamic modeling** categories are virtually identical to their Cetron and Ralph (1971) counterparts: respectively, intuitive methods, trend extrapolation, and dynamic predictive models.

Bright's classification of **morphological analysis** was for techniques that created a matrix of all theoretically possible combinations of technological approaches and configurations. He admitted that for morphological analysis to be considered forecasting, "one must argue that morphological analysis identifies known technology and predicts future technology by displaying possibilities that are not yet in use or even explored." Bright stated that in 1942, Zwicky used morphological analysis of the jet engine to conceptualize the terra-jet, the hydra-jet, and the ram-jet.

However, granting Bright's assumption that morphological analysis allows one to identify future possibilities does not make morphological analysis a forecasting technique. Since morphological analysis does not mention the timing of a new innovation, but rather the potential for its existence, it falls short of Bright's own criteria for a forecast. This is not to say morphological analysis has no place, but rather, morphological analysis may help the forecaster conceive of some new technology. Then the forecaster can determine the appropriate method to forecast the adoption of this innovation.

Bright categorizes forecasts that assume new technology will materialize to meet a specific need as **normative forecasting**. However, the distinction between a normative forecast and an exploratory forecast does not change how forecasts are done. Rather, it changes the rate-of-progress assumptions for the forecast and normative forecasts should obviously show a faster rate-of-progress than exploratory forecasts.[1] Thus, while it is important to understand the distinction between normative and exploratory forecasting, normative forecasting is a *type* of forecasting, not a *method* of forecasting.

Bright stated that **monitoring** is based upon assessing events in process and included four activities:

1) Searching the environment for signals that may be the forerunners of significant technological change;
2) Identifying possible alternative consequences if these signals are not spurious and if the trends that they suggest continue;
3) Choosing those parameters, policies, events, and decisions that should be followed in order to verify the true speed and direction of technology and the effects of employing that technology;
4) Presenting the data from the first three steps in a timely and appropriate manner for management's use in decisions about the organization's reaction.

Bright (1978) believed the essence of monitoring is "evaluation and continuous review." Like his mistake with normative forecasting, Bright is confusing a goal of the forecast (monitoring) with the forecast itself. Monitoring is simply a way of using forecasts, but is not a forecast in itself. Indeed, monitoring more accurately

[1] An exception to this expectation would be in the theoretical case where the demand was to slow down progress (e.g., Luddites making policy decisions).

describes a way in which one may wish to use forecasting techniques to incorporate data as it becomes available.

Bright stated that **cross-impact analysis** “attempts to do in fact what is implied in all forecasting -- to provide a prediction of future conditions with allowance for all the interacting forces that will shape that future." Cross-impact analysis is a technique for building a matrix from the opinions of experts. It has some similarities to the Delphi technique and Bright mentioned that cross-impact analysis could complement the Delphi technique. So, cross-impact analysis should be more properly considered as a technique within the intuitive forecasting classification.

Bright (1978) uses the term **scenario** to describe a detailed description of a possible future. “In effect, the planner concedes he cannot predict the 'real' future, so he looks at several possible futures with the idea of being prepared for any uncertainty (the usual military goal) or of coming up with a plan that best accommodates the variety of uncertainties ahead (the usual industrial goal).” This was indeed a new technique that does not readily fall into any of the previously discussed classifications. One might force it to fit into a loose definition of an intuitive forecast, but as Bright used them, scenarios were meant to cover the entire range of foreseeable options with little thought given to which scenario was most probable.

Bright, 1978 – strengths and weaknesses

Bright was a strong advocate of the use of scenarios in forecasting and this was one of his main contributions to the field. He also distinguished between forecasts, predictions, and speculations. Bright (1978) defined a forecast as "a statement about a condition in the future, arrived at through a system of reasoning consciously applied by the forecaster and exposed to the recipient." He defined a prediction as "a statement about the future based on rationale, if any, that the predictor has not made known." And Bright defined speculation as "a statement about the future in which the predictor admits high uncertainty and/or admits lack of a highly supportive rationale." By these definitions, one cannot make an intuitive forecast, but merely an intuitive prediction or speculation.

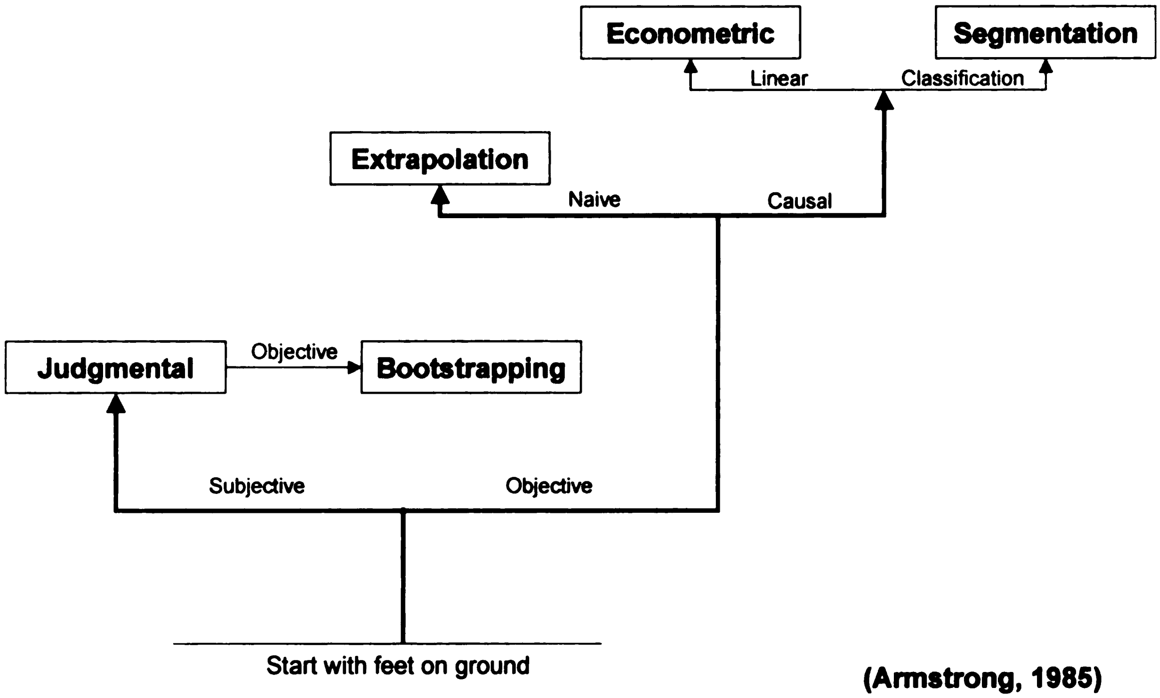
With eight classifications, Bright's taxonomy is hardly concise. However, three of Bright's categories – morphological analysis, normative forecasting, and monitoring are not actually forecasting classifications at all. In addition, the cross-impact analysis is a subset of his intuitive forecasting classification, so his classifications are not exclusive. His classification system is one of the more exhaustive systems and it would not take much redefining to incorporate newer techniques such as forecasting by role-playing into his scenario classification.

Armstrong, 1985 – summary

Armstrong (1985) said that research for analyzing data has historically been organized along three continuums: subjective vs. objective, naive vs. causal, and linear vs. classification methods. He then placed five forecasting methods within these continuums to develop a methodology tree (Figure 2) that also provided guidance as to when various methods should be used. The heavier lines represent the key decisions that need to be made by the forecaster;

the decisions in turn will help determine which methods should be used. Armstrong's five classifications were: judgmental, bootstrapping, extrapolation, econometric, and segmentation.

Figure 2: Forecasting Methodology Tree (1985)



(Armstrong, 1985)

The subjective methods are those using implicit (i.e., vague) processes for data analysis. Naive methods only use data on the variable of interest; causal models use additional variables. Causal models ask "why?" and use these factors to make forecasts. “Linear” is used by Armstrong as meaning a formula. Armstrong preferred linear models as they are both simpler and - in his experience - more accurate than non-linear models. The other side of the linear continuum is classification (segmentation).

Armstrong stated that there are three main decisions to be made when making a forecast. The primary decision is to select intuitive or objective methods. If objective methods are chosen, then Armstrong says another choice must be made between naive and causal approaches. And if a causal approach is selected, the forecaster must then decide between linear and classification approaches.

The **judgmental** classification in Armstrong's lexicon is synonymous with his use of the term subjective. In his words, "These methods are also called implicit, informal, clinical, experienced-based, intuitive methods, guestimates, WAGs (wild-assed guesses), or gut feelings." This category may be considered equivalent to Cetron and Ralph's (1971) intuitive methods. Likewise, Armstrong's **extrapolation** classification is similar to Cetron and Ralph's use of trend extrapolation. The only difference of note is that Armstrong included analogies within his extrapolation category.

Bootstrapping methods are ways of explicitly capturing the subjective processes used by an intuitive forecaster. Direct bootstrapping involves input from a forecaster on how an intuitive forecast was made. In many cases, the predictor is unable to produce an algorithm for producing his forecast. Indirect bootstrapping is used to reverse engineer the rules the forecaster is intuitively using, thus making these rules explicit.

All of the previous classifications schemes placed all explicit models into one category. Armstrong divided his into two categories: econometric and segmentation. The **econometric** classification is used for linear[2] representations of causal models that summarize existing knowledge within the models themselves. The **segmentation** methodology "attempts to find behavioral units that respond in the same way to the causal variables and to group these units." For example, a very basic forecast about the initial acceptance of a new innovation may use a gender segmentation scheme and assume that five percent of males and three percent of females will adopt the innovation in the first year.

Armstrong, 1985 – strengths and weaknesses

Armstrong's Forecasting Methodology Tree provided guidance that better enabled a forecaster to understand what elements went into determining which forecasting method(s) to use. Armstrong's suggestion and use of the naive/causal continuum was also quite useful and built upon the traditional subjective/objective distinction. However, his linear/classification distinction seems questionable. Not only does this distinction include a bias against non-linear methods, it seems to serve little purpose.

For example, the resulting classifications – econometric and segmentation – are not exclusive (e.g., econometric models can easily incorporate multiple segments with their models). One might even say that segmentation is not a forecasting method per se; rather, segmentation techniques may be used to complement most forecasting methods. Forecasters may create forecasts from aggregate data or they may first segment the data, create individual forecasts for

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[2] As discussed earlier, Armstrong saw little point in non-linear econometric models and his nomenclature reinforced his bias.

each segment, and then sum these forecasts. Table 1 shows some of the empirical results from using segmentation.

Table 1: Segmentation's Effectiveness in Forecasting

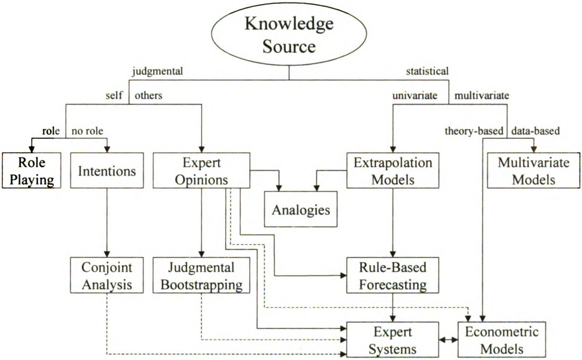
Source	Finding(s)
Armstrong and Andress, 1970	When comparing forecasts of gasoline sales, a regression technique had a 58% error rate. By using segmentation, a forecast was created with only a 41% error rate.
Dunn, William, and Spiney, 1971	Found that additive decomposition forecasts (i.e., summing segments) were superior to a top-down approach for forecasting demand for telephones.
Dangerfield and Morris, 1992	Found that additive decomposition forecasts (i.e., summing products) were superior to a top-down approach for forecasting demand for a product class (used over 15,000 aggregate series created by combining individual series from the M-competition database).

In addition, the models that result from bootstrapping might be viewed as econometric and/or segmentation models. Armstrong's (1985) classification scheme is concise, but is neither exhaustive nor exclusive.

Armstrong, 2001 – summary

Fortunately for the progress of forecasting, Armstrong did not stop with his initial Forecasting Methodology Tree. Armstrong's (2001) Methodology Tree is a much revised version of his earlier classification scheme. It also provides guidance to which method(s) should be used in a given situation.

Figure 3: Armstrong's Methodology Tree (2001)



Dashed lines represent possible relationships.

Armstrong (2001) believed there are eleven types of forecasting methods: role playing, intentions, conjoint analysis, expert opinions, judgmental bootstrapping, analogies, extrapolation methods, rule-based forecasting, expert systems, econometric models, and multivariate models. Armstrong placed these eleven categories into a Methodology Tree (see Figure 3) where the first branch separates judgmental methods from statistical methods. Judgmental methods are then subdivided into those that predict one's own behavior (self) and those where experts predict how others will behave (others). The self methods are further subdivided into roleplaying (where people are placed in a role and asked to act accordingly) and intentions (where people predict their own behavior in various scenarios). Conjoint analysis examines how different scenarios affect intentions. Along the "others" branch, expert opinions are used to make forecasts. Judgmental bootstrapping uses regression analysis to infer experts' rules for forecasting based upon the information that the experts use to make forecasts. Analogies are typically used when few, or no, observations are available (e.g., the introduction of a completely new innovation like holographic television).

The statistical side of the methodology tree first splits into univariate and multivariate branches. The univariate branch is also known as "extrapolation methods" since it uses values of a series to predict other values. Rule-based forecasting is a type of expert system that integrates forecasting methodology with domain knowledge. Expert systems represent rules that the experts use. The multivariate branch subdivides into theory-based (econometric) and data-based (multivariate) models.

Armstrong, 2001 – strengths and weaknesses

Armstrong's scheme is more useful than the older schemes as it provides guidance as to when to use various techniques. However, it is also a very flawed classification system. It is neither exhaustive, exclusive, nor concise. It is not exhaustive because certain classifications are not listed (e.g., where do non-expert opinions about the behavior of others go?). It is not exclusive since he has a classification for extrapolation models, yet all forecasts are extrapolations in one sense or another and some of his classifications are really subsets of a more general classification that he also listed. For instance, he stated that judgmental bootstrapping and rule-based forecasting were expert systems, yet he listed these as unique types along with expert systems. And with eleven non-exhaustive classifications, his system was hardly concise.

A Forecasting Typology is Proposed

The existing classification schemes have made great contributions to the development of forecasting, especially technological forecasting. The earlier typologies (Cetron and Ralph 1971; Martino, 1972) were most useful in determining what was – and was not – forecasting. The later ideas (Armstrong, 1985, 2001) took a step forward by also providing guidance as to when certain classifications should be used. Unfortunately, these taxonomies were neither exhaustive, exclusive, nor concise (Table 2).

Table 2: Summary of Forecasting Classification Schemes

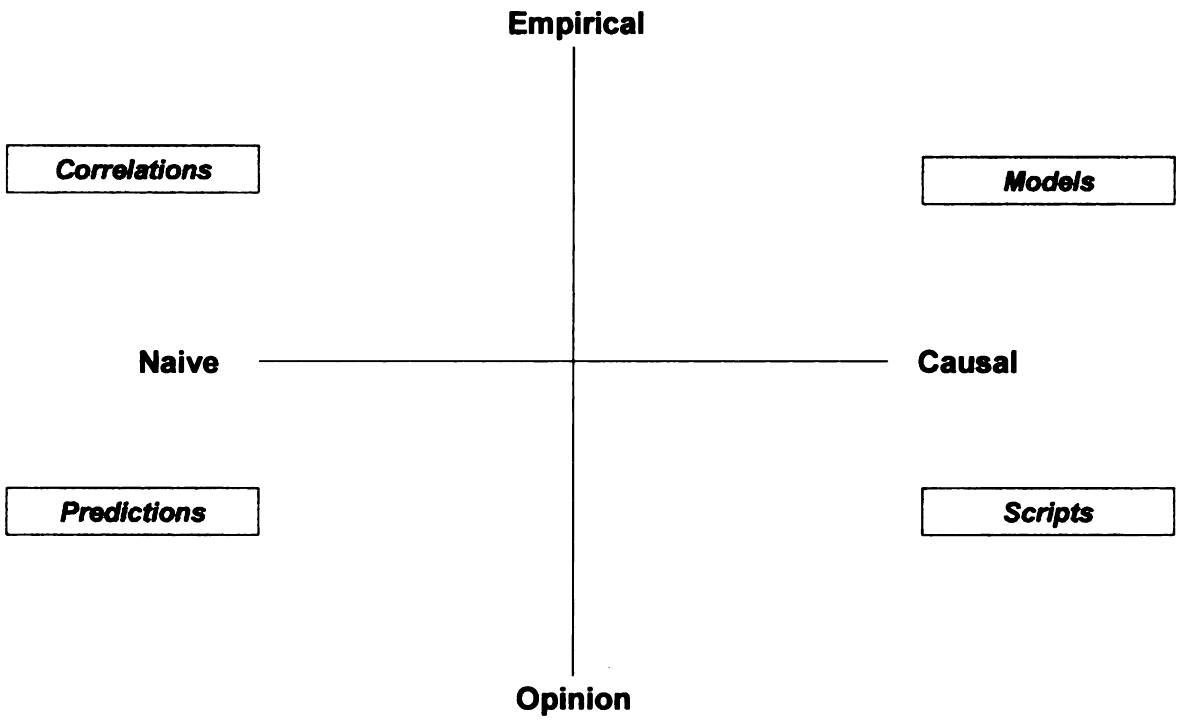
Source	Classifications		Strength(s)	Weakness(es)
Cetron and Ralph, 1971	5	intuitive methods, trend extrapolation, trend correlation, analogy, and dynamic predictive models	concise	neither exhaustive nor exclusive
Martino, 1972	5	intuitive, consensus, analogy, trend extrapolation, and structural models	concise and exclusive	not exhaustive
Bright, 1978	8	intuitive forecasting, trend extrapolation, dynamic modeling, morphological analysis, normative forecasting, monitoring, cross-impact analysis, and scenarios	added concept of scenarios, could be considered exhaustive with a liberal interpretation	neither exclusive nor concise; also included some categories that were inappropriate
Armstrong, 1985	5	judgmental, bootstrapping, extrapolation, econometric, and segmentation	concise, added naive/causal continuum, provided guidance to which forecast should be used	neither exclusive nor exhaustive

Source		Classifications	Strength(s)	Weakness(es)
Armstrong, 2001	11	role playing, intentions, conjoint analysis, expert opinions, judgmental bootstrapping, analogies, extrapolation methods, rule-based forecasting, expert systems, econometric models, and multivariate models	provides guidance to which forecast should be used	flawed classification system (neither exclusive, exhaustive, nor concise).

As per Korchia (1999), "If a typology does not satisfy any of Brucks' three criteria (1986), it must be modified and improved." Therefore a simpler forecasting typology is proposed. As it only has four classifications, it is unquestionably the most concise scheme yet discussed. Thus it should be evaluated to see if it is more exhaustive and exclusive than the other classifications. Figure 4 shows the Forecasting Classification Grid (hereafter, simply the "Grid"). Like all the other classification schemes, it recognizes the importance of distinguishing between opinion and ideas that can be empirically evaluated. It also includes Armstrong's naive/causal distinction. This typology assumes that these two continuums are independent. Given this assumption, four exclusive categories logically follow: predictions, scripts, correlations, and models.

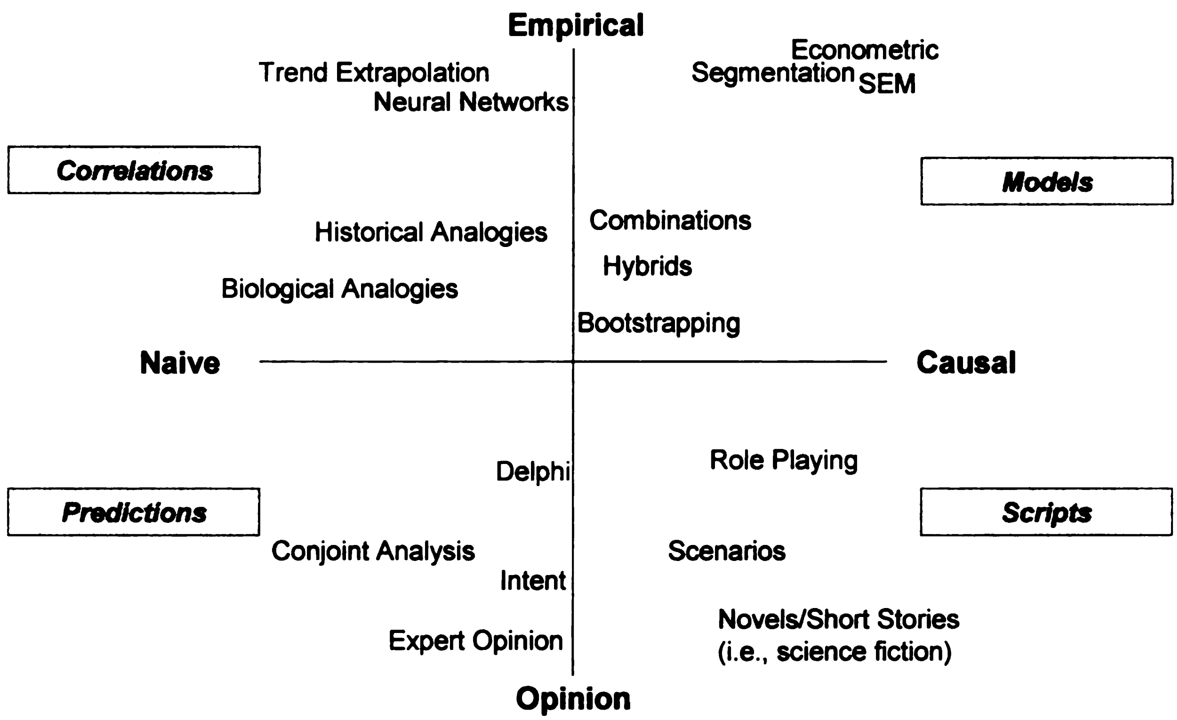
Predictions are defined as explicit forecasts that are based upon opinions whose assumptions have not been made explicit. Scripts are defined as made up scenarios in which a potential future is described and causal assumptions are made. Correlations are defined as forecasts based upon the performance of another factor without any causal assumptions. Models are defined as any forecast with explicit causal assumptions that may be mathematically stated.

Figure 4: Forecasting Classification Grid



One of the attractions of the Forecasting Classification Grid is its simplicity relative to the other ways of classifying forecasts. However, even if the grid is concise, exclusive, and exhaustive, it needs to also fit well with the existing forecasting techniques. Figure 5 shows how the existing techniques fit within the proposed classification scheme. The various techniques and their applicability to forecasting as noted in the literature are discussed using the Grid classifications (predictions, scripts, correlations, and models).

Figure 5: Existing Forecasting Techniques and the Grid



Predictions

By definition, predictions are opinion-based speculation with no explicit causal assumptions. Techniques in this classification include methods such as intentions, conjoint analysis, and expert opinion practices (e.g., Delphi).

Intentions

Since intentions have been shown to influence behavior (Fishbein and Ajzen, 1975; Ajzen, 1991), polling purchase intentions of potential consumers is used by many firms to develop market forecasts. Jamieson and Bass (1989) found that 70% to 90% of market-research clients use purchase intentions data on a regular basis. Table 3 summarizes the major empirical finding on using purchase-intentions data for forecasting.

Table 3: Summary of Intentions Findings

Source	Finding(s)
Juster 1966	Found that purchase intentions data for durable goods *underestimates* actual purchasing
McNeil 1974	Found that purchase intentions data for durable goods *underestimates* actual purchasing
Theil and Kosobud, 1968	Found that purchase intentions data for durable goods *underestimates* actual purchasing
Bird and Ehrenberg, 1966	Found that purchase intentions data for nondurable goods *overestimates* actual purchasing
Morrison, 1979	Concluded that intentions are imperfect measures of behavior and that intention-based predictions should be adjusted
Morwitz and Schmittlein, 1992	Found that by segmenting households before creating intention-based predictions, they were able to reduce forecasting error by more than 25% compared to comparable aggregate forecasts. This was only true for segmentation methods that distinguished between dependent and independent variables – that is, methods using discriminant analysis or CART (Classification And Regression Trees).
Bemmaor, 1995	Created a model that used intentions to bound forecasts that was accurate for existing consumer products, but not new products.
Lee, Elango, and Schnaars, 1997	Found that extrapolation of past sales provided *more* accurate forecasts than intention-based forecasts
Armstrong, Morwitz, and Kumar, 2000	Found that extrapolation of past sales provided *less* accurate forecasts than intention-based forecasts
Morwitz, 2001	Showed how to use historical intention and behavior data to adjust for bias in future predictions. Using Theil and Kosobod's (1968) data, her method reduced the absolute percent error of intention-based predictions from 17.2% to 9.7%.

Conjoint Analysis

In a search of literally hundreds of conjoint analysis articles, only a single peer-reviewed article could be found where conjoint analysis was used to forecast the acceptance of a really new innovation. Vavra, Green, and Krieger (1999) describe how conjoint analysis was used to help determine commuter demand for the EZPass system throughout the Northeast corridor. Even in this instance, similar systems had been available in other states for years. There are innumerable articles on how conjoint analysis was used to forecast the acceptance of new products, but the "new" products were invariably incremental innovations (e.g., faster cars in Steckel, DeSarbo, and Mahajan, 1991). One of the few times conjoint analysis was used to evaluate a really new innovation (e.g., on-line shopping in Talaga and Tucci, 2001), the researcher used the technique to determine what features are important to the consumer after the consumer has already adopted the innovation.

After discussing the theory and history of conjoint analysis, Wittink and Trond (2001) concluded that conjoint analysis should not be used for discontinuous innovations. If a forecaster strongly desired to use conjoint analysis to make a forecast about "new-to-the-world types of products", Wittink and Trond recommended first educating respondents about the category. Even then, they had limited hope for the accuracy of such a forecast. This author's own experience with professional market-research firms' attempts to forecast consumer demand for radical and really new products in the consumer electronic and PC industry supports their recommendation and conclusion.

Expert Opinion

Table 4 summarizes some of the empirical findings on how expert opinions are used in forecasting.

Table 4: Summary of Expert Opinion Findings

Source	Finding(s)
	Use of information
Ebbesen and Konecni, 1975	Experts (judges) did not base their judgments on all the available relevant information.
Gaeth and Shanteau, 1984	Agricultural experts were influenced by irrelevant factors when making soil quality judgments.
Brockhoff, 1984	Additional information did not increase the accuracy of experts forecasting interest rates.
Lusk and Hammond, 1991	Additional information did not increase the accuracy of meteorologists forecasting microbursts.
	Overconfidence Bias
Lawrence and Makridakis, 1989	When forecasters were asked to place 95% confidence intervals around their forecast ranges, the ranges were about 10% narrower than they should have been.
O'Conner and Lawrence, 1989	When forecasters were asked to set 50% and 75% confidence intervals around their own forecasts, only 37.3% and 63.3% of outcomes fell within the respective intervals.
	Delphi Technique
Brockhoff, 1975	Found no significant difference in accuracy between panels with five, seven, nine, and eleven panelists.
Boje and Murnighan, 1982	Found no significant difference in accuracy between panels with three, seven, and eleven panelists.
Brockhoff, 1975	Accuracy of Delphi results increased for first three rounds with a loss of accuracy for additional rounds.
Erffmeyer, Erffmeyer, and Lane, 1986	Accuracy of Delphi results increased for first four rounds with no benefit for additional rounds.

Harvey (2001) recommended that experts use a checklist when making their forecast in order to minimize the problems with judgments (i.e., experts not using information that they should use while using information that they should not). Given the evidence that expert forecasters are overconfident, Harvey found it reasonable to allow for an overconfidence bias of approximately 10 to 14 percent.

Scripts

Scripts are opinion-based speculation with detailed causal assumptions described in writing. Techniques in this classification include role-playing, scenarios, and the traditional writings of many hard science fiction[3] authors and futurists.

Role Playing

In role playing, subjects are asked to take on roles and act accordingly. Researchers use their decisions as forecasts.

Table 5: Summary of Role Playing Findings

Source	Finding(s)
Cyert, March, and Starbuck, 1961	Subjects made significantly different forecasts depending upon the role they were given (cost analyst vs. market analyst).
Statman and Tyebjee, 1985	Replicated findings of Cyert, March, and Starbuck (1961)
Mandel, 1977	Concluded that researchers would obtain similar results using experts or students as subjects
Babcock et al, 1995	Found significantly different outcomes depending upon instructions given to subjects: "Ask the role players to act as they themselves would act given the role and the situation, or ask them to act as they believe the persons they represent would act."[4]
Armstrong, 2001	In reviewing the role playing literature, "role playing was effective in matching results for seven of eight experiments" and in "five actual situations, role playing was correct for 56 of 143 predictions while unaided expert opinions were correct for 16 percent of 172 predictions."

Armstrong (2001) concluded, "Experts are probably better at identifying what *should* happen than what *will* happen. Role playing should be more accurate as to what will happen."

[3] Hard science fiction is the subset of the genre that limits itself to known facts and possibilities.
[4] There does not yet appear to be any strong evidence to show which question leads to more accurate results.

Scenarios

Schnaar (1989) noted that Herman Kahn popularized the scenario technique in the 1950s when he worked at the Rand Corporation. Bright (1978) advocated the use of scenarios, but sometimes referred to them as an anti-forecast. In his thinking, scenarios were important tools for contingency planning; but the probabilities of each scenario were of little import. Bright's focus was on the benefits of planning for all reasonable outcomes.

Table 6: Summary of Scenario Findings

Source	Finding(s)
Carroll, 1978	Found that scenarios only increased expectancies of the described event when the subject did not have a preconceived preference for an alternative forecast in an election context.
Gregory, Cialdini, and Carpenter, 1982	Found that scenarios influenced behavior – 47% of subjects exposed to scenarios about subscribing to cable TV subscribed shortly thereafter, compared to 20% of the control group.
Schoemaker, 1991	Advocated scenarios for contingency planning ("bounding the uncertainity")
Goodwin and Wright, 1997	Recommend using scenarios for contingency planning.
Gregory and Duran, 2001	In their review of the scenario literature, Gregory and Duran concluded that every use of scenarios "enhance a person's expectancies of the likelihood of the event depicted in the imagined scenario."

Correlations

Correlations are defined as forecasts based upon the performance of another factor without any causal assumptions. Techniques in this classification include methods such as extrapolation, analogies, and neural networks.

Extrapolation

In his review of the literature, Armstrong (2001) found that the appropriateness of the data source used for extrapolation depended upon the goals of the forecasters (see Table 7).

Table 7: Ranking of Data Sources for Extrapolation by Intended Use (Armstrong, 2001)

	Intent (1 = most appropriate or most favorable, 4 = least appropriate or least favorable.)				
Data Source	**To reduce cost of forecasts**	**To control for effects of researcher's bias**	**To estimate current status**	**To forecast effects of small changes**	**To forecast effects of large changes**
Historical	1	1	1	1	4
Analogous situation	2	2	2	4	3
Laboratory experiment	3	4	4	3	2
Field experiment	4	3	3	2	1

Armstrong concluded that there were five conditions that favored the use of extrapolation.

1) when a large number of forecasts is needed;
2) when the forecaster is ignorant about the situation;
3) when the situation is stable;
4) when other methods would be subject to forecaster bias; and/or
5) as a benchmark in assessing the effects of policy changes.

Table 8 summarizes some of the major empirical findings on using extrapolation for forecasting. Findings suggest that simpler extrapolation methods are more accurate than complex extrapolations and that the Box-Jenkins method of extrapolation – which uses autoregressive integrated moving averages to provide time-series forecasts – should be avoided, as better methods are available.

Table 8: Summary of Extrapolation Findings

Source	Finding(s)
Simple Extrapolation vs. Complex Extrapolations	
Dorn, 1950	Found that simple extrapolations were more accurate than complex extrapolations.
Makridakis et al. 1982	Found that simple extrapolations were generally as or more accurate than complex extrapolations.
Makridakis et al. 1993	Found that simple extrapolations were generally as or more accurate than complex extrapolations.
Makridakis and Hibon, 2000	Found that simple extrapolations were generally as or more accurate than complex extrapolations.
Use of Box-Jenkins	
Armstrong, 1985	In reviewing 14 studies, Box-Jenkins was less accurate than other extrapolation methods 71% of the time.
Makridakis et al. 1993	Found that Box-Jenkins was one of the least-accurate methods.

Analogies

Analogies were originally simply used as patterns for growth models. No causal reasoning was desired; forecasters simply selected a pattern that they thought – or hoped – would be appropriate (Cetron and Ralph, 1971; Martino, 1972). Forecasters sometimes used biological analogies for growth models – Cetron and Ralph even discussed how one firm created forecasts based upon the growth rate of a rat's cell. As can be seen in Tables 9 and 10, Lentz (1962) developed an extensive set of biological analogies to facilitate the use of biological growth formulas.

Table 9: Cellular Analogy (Lenz, 1962)

BIOLOGICAL GROWTH	TECHNICAL IMPROVEMENT
Initial Cell	Initial Idea or Invention
Cell Division	Inventive Process
Second Generation Cell	"New" Idea or Invention
Cell Division Period	Time Required for Initial Invention to Initiate "New" Invention
Nutrient Media	Economic Support for Invention
Cell Lifetime	Useful Life of Invention
Cell Death, Normal	Obsolescence of Invention
Cell Mass	Technical Area or Machine Class
Volume Limit of Cell Mass	Limits of Economic Demand for Invention in Given Technical Area
Size of Cell Mass	Total of Existing, Non-Obsolescent Inventions in Technical Area
Strength of Cell Mass	Performance Capability

Table 10: Bisexual Reproduction Analogy (Lenz, 1962)

BIOLOGICAL GROWTH	TECHNICAL IMPROVEMENT
Male Parent, or Parent Cell	Existing Invention or Discovery
Female Parent	Inventor
Opportunity for Fertilization	Communication of Knowledge
Conception	Origination of Idea
Embryo	Evidence of Growth of Idea
Gestation Period	Period Required for Invention
Birth	Disclosure of Invention
Nutrition	Economic Support
Maturation Period	Reduction to Practice
Maturity	Operational Use of Invention
Lifetime	Period from Disclosure to Obsolescence
Death, Normal	Obsolescence
Total Male Population	Total Inventions Disclosed Minus Obsolete Inventions
Total Work Force	Total Operational Inventions
Total Strength of Work Force	Performance Capability

The main problem with forecasting by analogy is that the proper analogy is usually not known until after the new opportunity unfolds – at which point the researcher is using hindsight (Martino, 1971). Naive analogies are rarely seen in the current literature. This may be due to the academic bias toward theory-based solutions.

This is not to say analogies are no longer used. However, researchers now pick an analogy and use the parameters in explicit growth curve models. These hybrids are explicit models, not analogies or correlations, and give the appearance of being more scientific. However, the historical problems related to analogies still apply to these models. For example, the author of the most widely used forecasting model, the Bass Model, still struggles with the same problems the perplexed users of analogies: "Choosing the appropriate analogy of previously introduced new products is important for the Bass model. However, little is known about the best way to guess by analogy other to say that it depends on judgment" (Bass et al, 2001). Armstrong (2001) also found it "surprising that little research has been done on such topics as how to select analogies...and how much gain one might achieve by pooling data from analogies."

Neural networks

Forecasts produced by neural networks are commonly perceived as a "black box" production – examining the model parameters does not indicate why the model makes good predictions (Remus and O'Conner, 2001). Given this lack of explicit causal assumption, neural network forecasting is classified as a correlation method. However, any neural network forecasts that explicitly documents its causal assumption should be considered a model, not a correlation. If causal assumptions are someday routinely included in neural network forecasts, then the method should be reclassified as a model at that time.

Remus and O'Conner (2001) recommended using traditional models if the data fit the assumptions for those models. In theory, the neural network forecast should be as accurate as the traditional models. In practice, Remus and O'Conner concluded that the traditional model was much easier to develop and use in these circumstances. Table 11 summarizes some of the major empirical findings on forecasting with neural networks.

Table 11: Summary of Neural Network Findings

Source	Finding(s)
Sharda and Patil, 1990	Found neural networks were as accurate as Box-Jenkins.
Foster, Collopy, and Ungar, 1992	Found neural networks comparable to traditional methods on quarterly data, less accurate on annual data.
Kang, 1991	Found neural networks to be superior to Box-Jenkins (Autobox) when data included trend and seasonal patterns. Otherwise, Kang found Box-Jenkins to be same or better than neural networks.
Hill, O'Connor, and Remus, 1996	In their comprehensive evaluation study, they found that neural networks were more accurate than any other tested method when using quarterly and monthly data. Other methods were more accurate when using annual data; however, neural networks were more accurate than Box-Jenkins even with annual data.

Models

Models are defined as forecasts with explicit causal assumptions that may be mathematically stated. These models could also be known as rule-based forecasting, but at least one forecasting expert (Armstrong, 2001) reserved this term for forecasts of time series data. Techniques in the "model" classification include expert systems, econometric models, and structural models (e.g., the Bass 1969 model).

Expert Systems

Armstrong (2001) sometimes distinguished between judgmental bootstrapping and expert systems, but was inconsistent in his descriptions (e.g., on page 188 he stated bootstrapping is a "type of expert system," but on page 283 he introduced an article on expert systems by contrasting bootstrapping methods with expert systems). In this document, expert systems are systems that use a model of how an expert would act in making a forecast. Judgmental bootstrapping is a subset of expert systems that infers the rules an expert uses by reverse engineering these rules from the results. Forecasters who desire to create expert systems that directly ask experts how they make their forecasts should ensure the availability of experts with a lot of time (Collopy, Adya, and Armstrong, 2001).

In theory, expert systems should be most useful when experts are making repetitive forecasts (e.g., analyzing traffic patterns to determine where to put a fast-food restaurant) and when problems are semi-structured.[5] After reviewing

[5] Use econometric techniques for very structured problems and judgmental techniques for unstructured problems.

the expert system literature between 1977 and 1993, Wong and Monaco (1995) found that prediction was only the fifth most common use of expert systems (behind planning, monitoring, design, and implementation) and that there were not many research articles about the accuracy of expert systems in a forecasting context. When using expert systems as a replacement for judgmental forecasts, Collopy, Adya, and Armstrong (2001) recommended using a Turing test to check face validity. The following tables summarize some of the empirical findings on how expert systems compare to other forecasting methods.

Table 12: Summary of Expert Systems vs. Judgmental Forecasts

Source	Finding(s)
Yntema and Torgerson, 1961	Found that bootstrapping resulted in an accuracy of .89 while the accuracy of judges was .84 in a simple evaluation of geometric shapes (180 judgments by 6 judges).
Kleinmuntz, 1967	Found expert systems to be more accurate than expert judgments in a counseling setting (the expert system was wrong 28.8% of the time vs. the judgmental error rate of 34.4%).
Goldberg, 1970	Developed bootstrapping models more accurate than 79 percent of the clinicians in a mental health context (123 cases).
Dawes, 1971	Found that bootstrapping predictions for the performance of incoming doctoral students was more accurate than the admission's committee predictions (19 students).
Wiggins and Kohen, 1971	Found that 100% of the derived bootstrapping models were more accurate than the judgments of 98 experts in forecasting the GPA of incoming graduate students (110 judgments).
Michael, 1971	Developed an expert system that was better than the expert in forecasting catalog sales in terms of both unit sales and dollar sales.
Libby, 1976	Concluded that experts were more accurate than bootstrapping in predicting whether or not a large corporation would declare bankruptcy (60 companies).
Goldberg, 1976	Used Libby's (1976) data to show that Libby's results were due to severe skewness in data. By correcting for this skewness, the revised bootstrapping model was more accurate than the experts 72% of the time (vs. the previous 23%).
Roose and Doherty, 1976	Despite some questionable methodology that violated accepted bootstrapping principles (i.e., they used stepwise regression), they found that bootstrapping was slightly more accurate in forecasting the success of life insurance agents than forecasts made by managers (200 judgments).
Ebert and Kruse, 1978	In forecasting future returns of securities, bootstrapping models were more accurate than financial analysts for 72% of the comparisons (15 new securities were evaluated by 5 analysts). Note: they also used stepwise regression.
Abdel-Khalik, Rashad and El-Sheshai, 1980	Bootstrapping models and lending officers were equally accurate in prediction loan defaults (28 loan officers).

Source	Finding(s)
Camerer, 1981	After reviewing the bootstrapping literature, Camereer concluded that that the empirical evidence clearly showed that bootstrapping should improve expert judgments.
Dougherty, Ebert, and Callender, 1986	Developed bootstrapping models for three expert interviewers and predicted the future job performance of applicants. The bootstrapping models were much better than two of the experts and tied the third (120 taped interviews).
Stewart et al, 1989	Found mixed results in comparing an expert system with seven meteorologists. The human judgments were slightly better at forecasting hail and the expert system was slightly better at forecasting severe hail.[6]
Silverman, 1992	Developed an expert system that helped military planners spot biases in their own forecasts. When using expert system, new forecasts did not contain these biases (and will presumably be found to be more accurate).
Ashton, Ashton, and Davis, 1994	In an artificial advertising context, experts were required to forecast annual sales. Use of a bootstrapping model resulted in 6.4% less errors than the expert judgments (13 judges).
Reagan-Cirincione, 1994	Found expert systems to be much more accurate than judgments in two experiments (forecasting teachers' salaries and baseball team records).
Leonard, 1995	Developed an expert system for detecting bank fraud. The judges were *better* than this expert system (80% detection of actual frauds vs. 71%).
Smith et al, 1996	Found that an expert system used by British Gas was more accurate than human experts at forecasting short-term gas demand.
Ganzach, Kluger, and Klayman, 2000	Global judgments of military conscripts' probability of success were made by experts and bootstrapping. Experts were slightly more accurate than bootstrapping (116 interviews). Note: success was judged by absence of failure.

[6] In reviewing the literature on expert systems, there seems to be a tendency for expert systems to improve their accuracy on the more extreme forecasts (e.g., severe hail vs. hail).

Table 13: Summary of Expert Systems vs. Econometric Forecasts

Source	Finding(s)
Stewart et al, 1989	Found mixed results in comparing an expert system with econometric methods for forecasting hail. The econometric forecasts were slightly better at forecasting hail and the expert system was better at forecasting severe hail.
Moninger et al, 1991	Found mixed results in comparing several expert systems with several econometric models in a meteorological context.
Leonard, 1995	Found that an expert system for detecting fraud was more accurate than an econometric model (71% of actual frauds detected vs. 66%).

Econometric Forecasts

The distinction between econometric models and structural models is vague. Technically, it is difficult to create a definition that would differentiate the two techniques – which is one of the reasons against using the term econometrics as one of the four proposed forecasting classifications. In practice, econometrics usually refers to the use of regression analysis. As such, econometrics is a forecasting technique within the proposed model classification.

Table 14: Summary of Econometric Findings

Source	Finding(s)
Lutkepohl, 1991	Said the maximum number of variables should not be greater than the cube root of total observations.
Neter et al, 1996	"A general rule of thumb states that there should be at least 6 to 10 cases for every variable in the pool."
Grove and Meehl, 1996	Given a good measure of success and ample historical data, econometric approaches are virtually always more accurate than judgmental forecasts.
Allen and Fildes, 2001	After reviewing the literature – over 30 comparisons of judgmental and econometric forecasts – Allen and Fildes concluded that econometric models "appear to be gaining over extrapolative or judgmental methods, even for short-term forecast, though much more slowly than their proponents had hoped."

Structural Models

Researchers have concluded that little empirical research has been done to investigate the comparative forecasting performance of demand forecasting in various settings (Armstrong, Brodie, and McIntyre, 1987; Meade and Islam, 2001). The following table lists various models that have been used to predict the adoption of an innovation.

Table 15: List of Growth Curve Models[7]

Source	Model
Gregg, Hassel, and Richards, 1964	Modified Exponential
Gregg, Hassel, and Richards, 1964	Logarithmic Parabola
Gregg, Hassel, and Richards, 1964	Simple Logistic
Gregg, Hassel, and Richards, 1964	Gompertz
Rogers, 1962	Cumulative Normal
Bain, 1963	Cumulative Lognormal
Bass, 1969	Bass Model
Bass, 1969	Extended Logistic
Bass, Krishnan, and Jain, 1994	Generalized Bass Model
Tanner, 1978	Log-Logistic
Easingwood, Mahajan, and Muller, 1981	Nonsymmetric Responding Model
Bewly and Fiebig, 1988	The Flexible-Logistic (FLOG) Model: Inverse Power Transfer (IPT)
Bewly and Fiebig, 1988	The flexible-logistic (FLOG) Model: Exponential (ELOG)
Bewly and Fiebig, 1988	The Flexible-Logistic (FLOG) Model: Box and Cox
Meade, 1985	Observation-Based Modified Exponential (Local Logistic)
Mar-Molinro, 1980	Auto-Regressive Error Term

[7] Many of growth models in this list were first tabulated by Meade and Islam (2001).

Summary of Literature Review

The review of the literature led to three main points of interest to this research. First, the consensus of forecasting experts was that no single forecasting method can obtain both accurate and valid forecasts over various conditions. In other words, various forecasting methods have unique strengths and weaknesses in the context of different conditions.

Second, an enduring research question has been asked for decades: How can we demonstrate (empirically) some guidelines for the selection of forecasting approaches under different environmental conditions? This research addresses this question for pre-launch forecasts (i.e., forecasts made without the benefit of market data obtained from actually seeing the innovation in the market) for various innovation and price level contexts as described in Chapter 3.

Third, a systematic way to organize the literature is proposed. The forecasting classification grid is based upon the work of earlier forecasters (largely Armstrong, 1985). The difference in approach may be due to the differing purpose of this research from that of earlier classification proposals.

Chapter 3

METHOD

This research determined which forecasting methods are most appropriate for forecasting consumer adoption of radical and really new technological innovations. This research also investigated the impact of pricing on these determinations. While the questions are general, this research focused on consumer electronic innovations and evaluated five well-established models of innovation diffusion. Two model variants were also evaluated.

In this research, it was useful to visualize a quadrant consisting of two continuums – the level of innovation (radical vs. really new) and the price level.(high vs. low). The terms same, horizontal, vertical, and opposite were used to describe how similar or different one innovation was from another. If an innovation was from the same quadrant, this meant that the innovations shared both the same level of innovation and the same price level. If an innovation was said to be from a horizontal quadrant, then it belonged to a different innovation classification, but stayed within the same price level. Likewise, if an innovation was said to belong to a vertical quadrant, it had the same innovation classification, but had a different price level. Finally, if an innovation was in an opposite quadrant, then both the innovation and price levels were different. Figure 6 shows how these terms are used in reference to the Personal Computer (radical, high-price) innovation.

Figure 6: How Descriptive Terms (*Same, Horizontal, Vertical, & Opposite*) Are Used

	Example: Forecasting PCs	
Price Level	Radical Innovation	Really New Innovation
High	**PCs** **Satellite Receivers** **(*same* quadrant)**	**Camcorders,** **Projection TVs** **(*horizontal* quadrant)**
Low	**CD Players** **(*vertical* quadrant)**	**VCR,** **Cordless Phones,** **Telephone Answering Devices** **(*opposite* quadrant)**

These descriptive terms are used to separate innovations into four analogous groups. An analogous group is a collection of innovations that share both the same price level and innovation level. For example, VCRs, Cordless Phones, and Telephone Answering Devices belong to the same analogous group.

Hypotheses

While this research was largely exploratory research aimed at providing guidance for the three general research questions discussed in Chapter 1, some specific hypotheses were developed. These hypotheses were created to either provide confirmatory support or falsify assumptions behind the research questions.

Hypothesis 1. Forecasts using parameters from the same quadrant for a dataset will be more accurate than forecasts using parameters from other quadrants.

a. Forecasts using parameters from the same quadrant will be significantly more accurate (have less error) than forecasts using parameters from the opposite quadrant.

b. Forecasts using parameters from the same quadrant will be significantly more accurate than forecasts using parameters from horizontal quadrants.

c. Forecasts using parameters from the same quadrant will be significantly more accurate than forecasts using parameters from vertical quadrants.

d. This will be most apparent in comparison to forecasts using parameters from opposite quadrants.

   i. $Z_{H1a} > Z_{H1b}$

   ii. $Z_{H1a} > Z_{H1c}$

Hypothesis 2. Forecasts using parameters from adjacent (horizontal and vertical) quadrants for a dataset will be more accurate than forecasts using parameters from opposite quadrants.

a. Forecasts using parameters from a vertical quadrant will be significantly more accurate than forecasts using parameters from the opposite quadrant.

b. Forecasts using parameters from a horizontal quadrant will be significantly more accurate than forecasts using parameters from the opposite quadrant.

Hypothesis 3. The level of innovation will have a greater impact on the accuracy of a forecast than the price level. (i.e., forecasts using parameters from a vertical quadrant will be significantly more accurate than forecasts using parameters from horizontal quadrants.)

Data Sources

In many cases, when an innovation was first made available is largely a matter of interpretation. For the purposes of this diffusion research, an innovation was considered to be first available when it met the following conditions.

1) The innovation had to be available to consumers nationwide.
2) The innovation should be available as a complete product – not merely plans or parts to be assembled by a skilled hobbyist.
3) The innovation had to free of burdensome regulations that would inhibit adoption of the innovation.

With the exception of the CD Player dataset, the CEA data started several years after the introduction of the product. Other sources were obtained to fill in the missing data wherever possible. In some cases, the missing data had to be partially extrapolated. These extrapolations are described for each innovation.

Personal Computers (PCs)

One could argue that the 1949 Simon was the first personal computer, although it was never sold as a product and thus fails to meet the criteria used in this research. Rather the plans to the Simon were sold to hobbyists who built their own computer. The 1955 GENIAC was the first pre-assembled computer sold to consumers. It was followed by the Heathkit EC-1 (1959), the Honeywell Kitchen Computer[8] (1966), the DEC PDP-8 desktop model (1968), the Arkay CT-650 (1969), the Imlac PDS-1 (1970), the Kenbak-1 (1972), the HP 9830 (1972),

[8] The Honeywell Kitchen Computer even included a cutting board.

the French Micral (1973)[9], the Scelbi-8H (1973), the Mark-8 (1974), the Altair (1975), the IBM 5100 (1975), the Pro Tech SOL Computer (1977), the Commodore PET (1977), the Apple II[10] (1977), the Radio Shack TRS-80 (1977) and the 1981 introduction of the IBM PC. Several sources were used to compile this list, but the Blinkenlights (2002) timeline was especially useful.

In 1977 several new computers were made available to the public. Not only did these computers meet the innovation criteria used in this research, but all of them included a keyboard and output to a video display (e.g., a monitor or television). Thus 1977 was selected as the starting point for the diffusion of the personal computer. Personal computers being defined as programmable devices complete with a keyboard for input and a video port for output.

The CEA dataset started in 1980, the data from 1977-1979 were created by a combination of extrapolation, various references, and judgment. Specifically, an average price of $1,000 was used for these three years based upon known prices for personal computers in 1977 and the CEA average price of $1,000 for 1980. While the CEA's data started in 1980, it did not show a penetration of 1% until 1981. Since the data was rounded, a zero % penetration rate in 1980 meant that the consumer penetration was actually between 0% and .49%. Given that 500,000 units were sold in 1980 to businesses and households, a consumer household penetration rate of .4% was estimated for

[9] The Xerox Alto was also created in 1973, yet it cannot be considered as a personal computer for this research since Xerox made their infamous decision not to market it.
[10] The Apple I (1976) was sold as a motherboard only and may be considered a prototype since only about 200 were made.

1980. This number was repeatedly halved for 1979 (.2%), 1978 (.1%), and for 1977 (.05%).

DBS Satellite Receivers

According to the Satellite Broadcasting & Communications Association (SBCA), the first Direct Broadcast Satellite receiver was built by Taylor Howard in 1976 after the FCC declared smaller, personal satellite receivers would be allowed. In 1978, Howard published a manual to enable hobbyists to build their own systems. In 1979, manufacturers first sold complete systems to consumers, 5,000 units were shipped including a $36,000 version by Scientific Atlanta that made the cover of the Nieman Marcus catalog.

The CEA dataset started in 1986. The SBCA was able to provide information from 1979-1986, so there was perfect overlap between the two datasets. Both datasets included quantities for 1986 and the data matched perfectly. While the price points and unit penetration were available from SBCA, the consumer home penetration had to be derived from SBCA data. This was done by dividing unit sales by the number of households for all years except 1984 and 1985. Since the CEA consumer penetration started in 1986 at 1%, the penetration for earlier years were capped below 1%. .8% was used for 1984 and .9% was used for 1985.

CD Players

Philips invented the Compact Disc and teamed with Sony to bring it to market. Since both firms are important members of the Consumer Electronic Association, the CEA dataset tracked the diffusion of CD players since its US introduction in 1983. During the first year of US sales, 30,000 CD players were sold along with 800,000 CDs – almost 27 CDs sold for every player.

Camcorders

A camcorder is defined as an integrated camera that records video into a video cassette. According to the CEA, the first camcorder hit stores in May, 1983. Interestingly enough, it was a Beta camcorder.

The CEA dataset starts with 1985. The data for years 1983-84 were created by a combination of extrapolation, various references, and judgment. Specifically, the average prices of $2,950 (1983) and $2,000 (1984) were chosen by looking at press releases, consumer reviews, and advertisements from 1983 and 1984. The consumer penetration data was derived by repeatedly halving the CEA consumer penetration data. Since the CEA showed that 1% of consumer households owned a camcorder in 1985, 0.5% household penetration was used for 1984 and 0.25% household penetration was used for 1983.

Projection Televisions (PTVs)

According to the CEA, the first rear projection television (PTV) was sold in 1982 and this date is used for the diffusion study.[11] The CEA dataset starts with 1984. The data for years 1982-83 were created by a combination of extrapolation, various references, and judgment. Specifically, the average prices of $2,177 (1982) and $2,073 (1983) were obtained using the consumer electronic industry rule of thumb of assuming an annual 5% price reduction and working backwards from the CEA average price of $1,974 in 1984[12]. The consumer penetration data was derived by repeatedly halving the CEA consumer penetration data. Since the CEA showed that 1% of consumer households owned a projection television in 1984, 0.5% household penetration was used for 1983 and 0.25% household penetration was used for 1982.

VCRs

The first video cassette recorder for the home market was the 1972 AVCO Cartrivision System.[13] To reinforce the cliché that those who forget history are doomed to repeat it, their business model was later reinvented by DIVX. Two types of cassettes were available. Black ones for recording – that could be reused – and red ones that could be rented. The red cassettes could only be viewed once and could only be rewound by a special machine owned by the company that offered rentals. By the time the Betamax product was released in

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[11] In point of fact, the first rear projection set was introduced by RCA in 1947 – the 648PTK. However, it suffered from a dim image and was a market failure. Rear projection televisions were not available for another 35 years.

[12] The average PTV price was derived by multiplying the following year's price by 1.05. So the actual decrease was .0476, not .05.

1975, AVCO was no longer manufacturing units. The first stand-alone VHS VCR in the US was available in 1977.

The CEA dataset starts in 1974. The data for years 1972-73 were created by a combination of extrapolation, various references, and judgment. Specifically, the average prices of $1,600 (1972) and $1,000 (1973) were chosen by looking at press releases, consumer reviews, and advertisements from 1972 and 1973. Zero percent consumer penetration was assumed for 1972-1973 as the CEA data showed zero percent consumer penetration from 1974-1978.

Cordless Phones and Telephone Answering Device (TADs)

In 1976, the Federal Courts agreed with the FCC and permanently halted the practice of requiring consumers to insert special "safety" devices between telephones (and telephone devices such as answering machines and modems) and the phone lines so long as these devices met FCC regulations. This decision put a stop to burdensome regulations that were dissuading consumers from connecting telephony innovations to their lines. While both cordless phones and telephone answering devices (TADs) predate 1976, their home penetration was insignificant (less than .5% of households). Thus, for the purposes of this research, 1976 was selected as the start of the diffusion process for these innovations.

[13] The Sony U-matic (1970) was actually the first VCR and was initially intended for the home market. However, its costs were too great so Sony decided to market it to corporations instead.

The CEA datasets start with 1980 for cordless phones and 1982 for the TADs. The information from 1976 until the CEA data started was created by a combination of extrapolation, various references, and judgment. Specifically, the average prices of were obtained using the same methods employed to extrapolate the missing PTV prices. The consumer penetration data was derived by repeatedly halving the CEA consumer penetration data which measured consumer household penetration of cordless phones at 0% in 1980[14] and consumer household penetration of TADs at 1% in 1982.

Revised Classification of Innovations

While reading sources to aid in the extrapolation of the two years of data for the VCR case not included in the CEA dataset, the author discovered a consumer electronic innovation that is no longer in use. Video Tape Recorders (VTRs) were available to consumers in the sixties and some were specifically aimed at home consumers. The existence of these products falsified the assumption that the VCR was the first innovation that consumers could purchase to record television shows. Thus, VCRs were a really new innovation, not a radical innovation.

[14] Similar to the extrapolation used for the PC data, a household penetration of 0.4% was used for 1980.

Figure 7: Revised Classification of 8 Consumer Electronic Innovations

	Innovations for Consumers	
Price Level	Radical Innovation	Really New Innovation
High	**PCs (1977 – 2000)** **Satellite Receivers (1979 – 2000)**	**Camcorders (1983 – 2000)** **Projection TVs (1982 - 2000)**
Low	**CD Players (1983 - 2000)**	**VCR (1972 - 2000)** **Cordless Phones (1976 – 2000)** **Telephone Answering Device (1976 – 2000)**

Figure 7 shows the revised classification of the innovations in this research. The reclassification of the VCR provided a third innovation for low-priced, really new innovations. However, this resulted in only one low-priced, radical innovation being used in this research.

Models

Many diffusion models have been used in various contexts. Throughout the forecasting literature, one common refrain was repeatedly stressed – no single forecasting method was appropriate for every situation (Cetron and Ralph, 1971; Armstrong, 2001). While there were many well-known models from which to choose, the following seemed most represented in the literature (Table 16).

Table 16: Diffusion Models Initially Considered

- Logarithmic Parabola (Gregg, Hossel, & Richardson, 1964)
- Modified Exponential (Gregg, Hossel, & Richardson, 1964)
- Observation-Based Modified Exponential (Meade, 1985)
- Bass model (Bass, 1969)
- Generalized Bass model (Bass, Krishnan, and Jain, 1994)
- Simple Logistic (Gregg, Hossel, & Richardson, 1964)
- Gompertz (Gregg, Hossel, & Richardson, 1964)
- Extended Logistic (Bass, 1969)
- Log-logistic (Tanner, 1978)
- Flexible Logistic (FLOG) – Inverse Power Transform (Bewley & Fiebig, 1988)
- FLOG – Box & Cox (Bewley & Fiebig, 1988)
- FLOG – Exponential (Bewley & Fiebig, 1988)

From these models, it was desired to select a manageable number of diffusion models for the purposes of this research. Meade and Islam (2001) strongly recommended that, "A reasonable initial set of models should include the [simple] logistic, Gompertz, and Bass models." Given the interest in price, the Generalized Bass model (price only) was appropriate. Some exploratory research was done with all of the models and the FLOG Box & Cox seemed more robust within the consumer electronic context than the other models (APPENDIX A).

In the process of setting up all the models, the author became intrigued by Bass assumption that *m* should remain constant. In the market of interest, the number of US households is continually expanding. Therefore two variant models, a Bass variant and a Generalized Bass (Price) variant, were also developed.

Table 17: Diffusion Models used in Research

- Bass model (B)
- Generalized Bass model - Price (GB)
- Bass model variant (Bv)
- Generalized Bass model (Price) variant (GBv)
- Simple Logistic model (SL)
- Gompertz model (G)
- FLOG – Box & Cox model (BnC)

While supported by the literature and some exploratory research, the decision of which models to select for the research was based upon the author's judgment. As a check on this selection, two forecasting experts were consulted.[15] After review, both experts concurred with the decision.

Bass Model (B)

The Bass 1969 model has been stated in many forms. This research used the Lilien, Rangaswamy, and Van Den Bulte's (2000) transfiguration of Bass $x(t) = \left[p + q(\frac{X(t-1)}{m}) \right] \left[m - X(t-1) \right]$ as it is common in the literature and since Lilien et al. also provided a large list of Bass parameters.

Bass Model Variants

The Generalized Bass model (Bass, Krishnan, and Jain, 1994) was developed to consider the impact of price and advertising in forecasts. Since the datasets provided by the CEA were industry data, information on average pricing was available, but individual firms did not share their related advertising expenditures. Thus a Price-only variant of the Generalized Bass model was

[15] Professors Roger Calantone and Jon Bohlmann.

used. This equation $x(_t) = \left[p + q(\frac{X(_{t-1})}{m})\right][m - X(_{t-1})][1 + B(\frac{\Pr(_t) - \Pr(_{t-1})}{\Pr(_{t-1})})]$ is a subset of the complete Generalized Bass model (GB).

Both the Bass model and the Generalized Bass model constrain *m* to be constant. However, it is common for the actual *m* to change over the period to be forecast. Therefore a changing *m* variant was created by the author for both the Bass model and Generalized (Price) Bass model. The equation for the Bass model variant (Bv) used is $x(_t) = \left[p + q(\frac{X(_{t-1})}{m(t)})\right][m(t) - X(_{t-1})]$ and the equation for the Generalized Bass (Price) model variant (GBv) is

$$x(_t) = \left[p + q(\frac{X(_{t-1})}{m(t)})\right][m(t) - X(_{t-1})][1 + B(\frac{\Pr(_t) - \Pr(_{t-1})}{\Pr(_{t-1})})].$$

The author investigated changing *m* variants for the other models, but given how the other three models were structured, allowing *m* to change with *t* had zero impact on the results.

Simple Logistic (SL) & Gompertz (G)

The Simple Logistic and Gompertz models (Gregg, Hossel & Richardson, 1964) are some of the earliest and simplest diffusion models. Meade & Islam's (2001) transfigurations were used. The equation for the Simple Logistic is

$X(_t) = \frac{m}{1 + c\exp(-bt)}$ and the equation for the Gompertz is

$$X(_t) = m\exp(-c(\exp(-bt))).$$

Flexible logistic (FLOG) – Box and Cox (BnC)

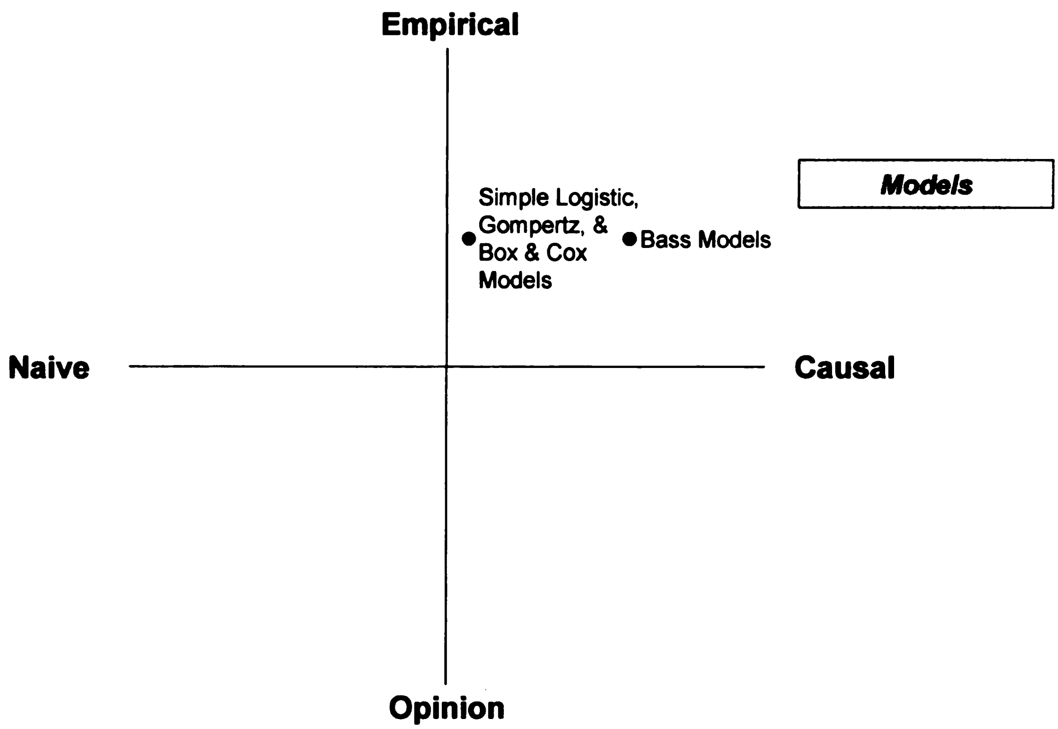
Bewley and Fiebig (1988) developed several flexible logistic models that used the base equation $X_t = \frac{m}{1 + c\exp-(B(t))}$. Multiple variants use different formulas for *B*(*t*). The Box and Cox model uses $B(t) = (b\frac{(1+t)^k - 1}{k})$.

The Box and Cox model has a tendency for one of its variables (*c*) to tend to infinity in some cases. Since using such extreme values would cause the parameters to give poor results for other cases, a cap of 100,000 was placed on the *c* variable in this research. This value allowed the BnC model to be viable with all the datasets.

Selected Models and Proposed Forecasting Classification Grid

Using the proposed classification grid, all seven forecasting methods are models (Figure 8). Most of the models barely meet the minimum definition of a model, but all of these forecasting methods explicitly express their causal assumptions mathematically. Since the Bass Models also provide a deeper theoretical reasoning as to why they work, these models are farther to the right on the Naïve/Causal continuum.

Figure 8: Classification of Research Models



Verification of Models

Once the Lilien, Rangaswamy, and Van Den Bulte's (2000) Bass model was working, an attempt was made to verify it by comparing it to Meade and Islam's (2001) transfigured Bass formula: $x(t) = pm + (qp)X(t-1) - \frac{q}{m}\left[X(t-1)^2\right]$. The results did not match. A third Bass model was created, based upon the original article (Bass, 1969) with the equation $x(t) = pm + (q-p)X(t-1) - \frac{q}{m}\left[X(t-1)^2\right]$. The results from this model perfectly matched that of the Lilien et al. transfiguration, validating both models and served as an indication that there was a problem with the Meade and Islam variant that turned out to be a typographical mistake.[16]

[16] There should be a minus sign between the *q* and *p* in the Islam and Meade paper.

Since the Bass model was going to serve as the benchmark for the other models, additional testing was done to ensure the Bass models were working as expected. The innovations listed by Lilien et al. (2000) overlapped with four of the datasets being used in this study. All data sets used penetration data for tracking diffusion. By reducing the CEA datasets to the same periods covered by the Lilien et al. datasets, it was possible to compare the Bass parameters listed by Lilien et al. to those obtained by this research. As shown in Table 18, the parameters obtained by this method differed from those described by Lilien et all.

Table 18: Minding p's and q's

		Lilien et al. (2000)			Gentry (2003)		
Product	Years	*p*	*q*	*m*	*p*	*q*	*m*
Camcorders	1986-96	0.044	0.304	30.5	0.022	0.035	100
CD Player	1986-96	0.055	0.378	29.6	0.034	0.246	100
Cordless Telephone	1984-96	0.004	0.338	67.6	0.034	0.136	100
VCR	1981-94	0.025	0.603	76.3	0.029	0.299	100

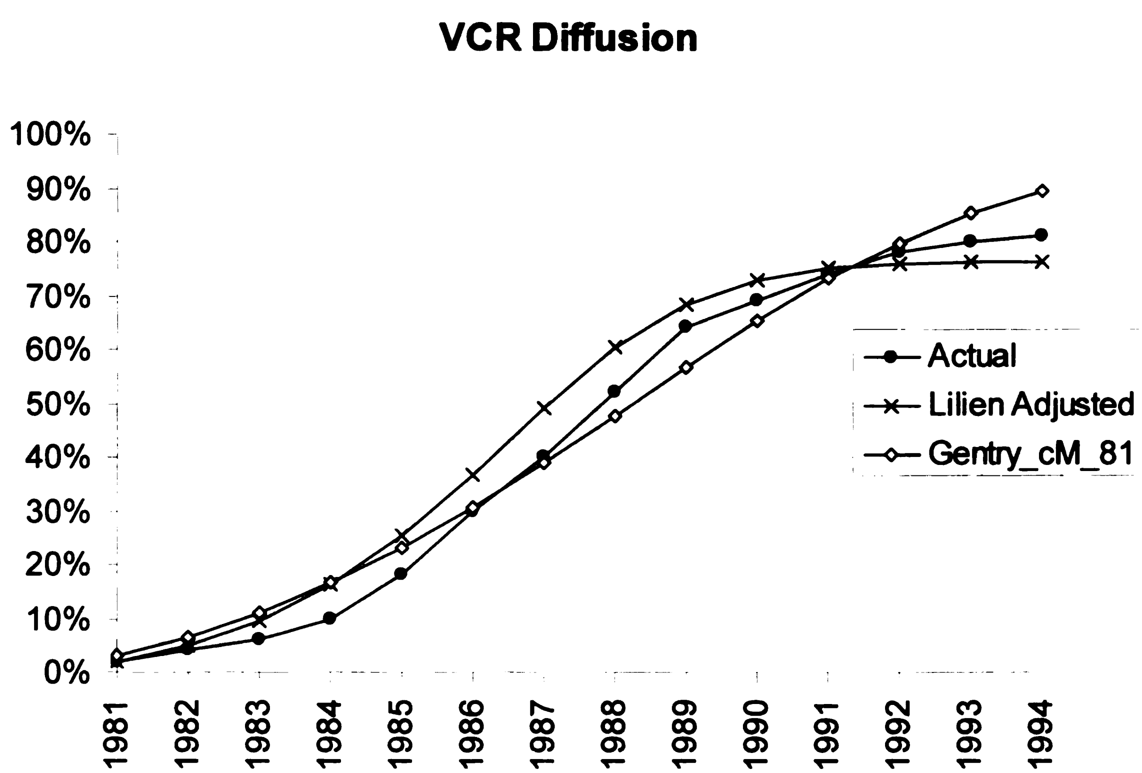
It would be understandable for some of the parameters to differ since the data came from different sources. However it seemed unlikely that all four datasets would significantly differ. After analyzing the Bass model itself, the conundrum was resolved. Changing the size of *m* within the Bass formula, when using discrete time notation, does not directly affect the percentage of those who adopt so long as *m* remains constant as specified. It plays a significant role when one is interested in the amount of units to be purchased, but has no impact on the percentage of adopters. If one multiplies the percentage of adopters obtained by the Lilien et al. parameters by the *m* given by Lilien et al, the results approached those obtained by the Gentry parameters in two of the four cases.

Table 19: Camcorder Diffusion with Lilien Adjustment

Year	Actual	Lilien et al	Gentry	Lilien Adjusted
1986	2%	4%	2%	1%
1987	4%	10%	4%	3%
1988	5%	17%	7%	5%
1989	8%	24%	9%	7%
1990	11%	33%	11%	10%
1991	15%	43%	14%	13%
1992	18%	53%	16%	16%
1993	19%	63%	18%	19%
1994	21%	71%	21%	22%
1995	22%	79%	23%	24%
1996	25%	85%	25%	26%

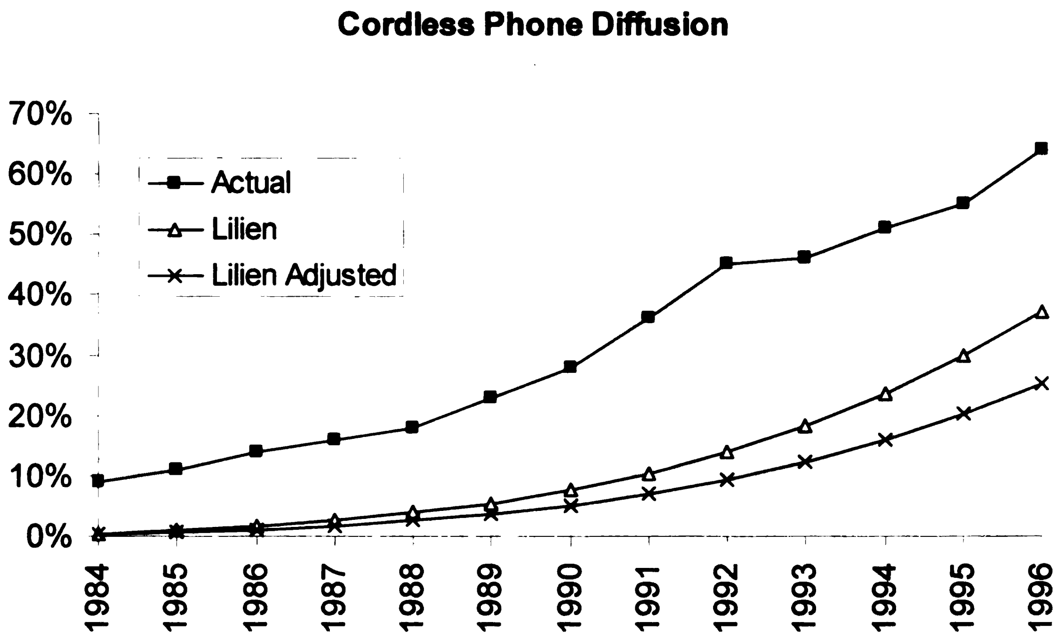
When using both the Lilien et al. coefficients and adjusting for m leads to very similar results compared to the Gentry parameters for both the Camcorder and VCR products.

Figure 9: VCR Diffusion with Lilien Adjustment



Even with the adjustments, the Bass parameters obtained with the Gentry datasets were significantly different that those obtained by the Lilien et al. datasets for cordless phones and CD players. However, Figure 10 clearly demonstrates that is due to differences in the data as the Lilien et al. curves greatly differ from the actual data provided by the Consumer Electronics Association. Thus, it appears that the Bass models are valid in all cases and any true discrepancies between the Lilien results and the results of this research are due to differences in the data.

Figure 10: Cordless Phone Diffusion



The other models used in this research were basic implementations of standard formulas. Perhaps because they were not as famous as the Bass model, it was not necessary to choose from many variants. After reviewing to ensure that these additional models were working as expected, their results were compared to the Bass model. As expected, all models gave results similar to the Bass model. No additional validation procedures were performed.

Process

Curve Fitting

In order to calculate which seven diffusion models had the potential to work best, all seven models were run with the eight innovation datasets provided by the CEA. Only the CEA datasets were used as they contained perfect (non-extrapolated) information for these fifty-six models.

The curve fitting exercise was then duplicated with the extended datasets. The extended datasets cover the time period of interest for the forecasting.

Forecasting

The model parameters obtained through extended curve-fitting procedures were used to create the forecasts. The parameters from each of the 8 innovations were used to forecast the diffusion of the other 7 innovations. This was done for each of the seven models. Thus, a total of 392 forecasts were created. As part of the forecasting analysis, it was clear that the Generalized Bass models were not as well suited for diffusion forecasts as the other models (see APPENDIX B), so the GB models were not used for the quadrant analysis.

Hypotheses Testing (Quadrant Analysis)

Using the squared sum of errors obtained by the forecasting models, the results for each forecast were used to compare the relative importance of price level and innovation type. This was done in two ways. First, each forecasting method was reviewed as a whole and segmented by the two price levels and two innovation levels.[17] Then the specific hypotheses were tested by seeing how many results predicted by the hypotheses were actually correct. This provided two distinct methods of looking at the price levels, innovation levels, and forecast method.

While analyzing this information, it became clear that forecasts based upon the PC parameters did not work as well as the parameters from other innovations. A posteriori, this may be because PCs may have been purchased for reasons other than home entertainment. Many may have been purchased for home offices. The PC may be used for educational purposes as well as entertainment. The home office purchases and educational consideration may explain why the PC diffusion differed than that of the other innovations. Given the unique characteristics of the personal computer diffusion curve, the quadrant analyses were repeated without using the PC dataset.

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[17] It may prove helpful to have Figure 6: How Descriptive Terms (*Same, Horizontal, Vertical,* & *Opposite*) Are Used (page 46) at hand.

Chapter 4

RESULTS

Table 20: Model Abbreviations

B	Bass model
Bv	Bass model variant
GB	Generalized Bass model (Price)
GBv	Generalized Bass model (Price) variant
SL	Simple Logistic model
G	Gompertz model
BnC	Box and Cox model

Potential Fit of Models

After determining and using the optimal parameters for seven models, the sum of the squared errors (SSE) were obtained by subtracting the curve-fitting results from the actual results in order to show how well each model did in comparison to one another for each innovation. One can make a case for measuring the best and worse models by either the total SSE (Table 21) or by their cumulative placement rankings (Table 20).

Table 21: Curve Fitting Results

Innovation (data starts)	e^2 of B	e^2 of Bv	e^2 of GB	e^2 of GBv	e^2 of SL	e^2 of G	e^2 of BnC
PCs (1980)	0.011	0.012	0.007	0.007	0.016	0.015	0.013
Sat. Receivers (1986)	0.001	0.001	0.001	0.001	0.001	0.001	0.001
VCRs (1974)	0.074	0.063	0.036	0.029	0.055	0.017	0.027
CD Players (1983)	0.038	0.033	0.035	0.031	0.047	0.016	0.008
Camcorders (1985)	0.002	0.002	0.002	0.002	0.007	0.004	0.003
PTVs (1984)	0.000	0.000	0.000	0.000	0.001	0.000	0.001
Cordless Phones (1980)	0.005	0.005	0.005	0.005	0.007	0.012	0.005
TADs (1982)	0.021	0.018	0.011	0.011	0.042	0.012	0.006
Total:	0.153	0.135	0.097	0.087	0.177	0.077	0.064

Table 22: Curve Fitting - Comparative Placement

Innovation (data starts)	B	Bv	GB	GBv	SL	G	BnC
PCs (1980)	3	4	1	2	7	6	5
Sat. Receivers (1986)	4	5	2	3	1	6	7
VCRs (1974)	7	6	4	3	5	1	2
CD Players (1983)	6	4	5	3	7	2	1
Camcorders (1985)	3	4	1	2	7	6	5
PTVs (1984)	5	4	3	2	7	1	6
Cordless Phones (1980)	4	2	3	1	6	7	5
TADs (1982)	6	5	2	3	7	4	1
Total:	38	34	21	19	47	33	32

Judging by total SSE, the Box and Cox model is the best potential model (.064) given perfect information. However, if one uses the comparative placement method, the Generalized Bass variant is the best potential model. In either case, the Simple Logistic model is clearly the worse potential model. However, it is important to note that even the Simple Logistic model only had a total SSE of 0.177 for all eight innovations. Since this was a curve-fitting exercise, not a forecast, the accuracy of the various diffusion models is not surprising. At the .05 level of testing, there were no significant differences between any of the seven models.

Optimal Parameters

The curve fitting exercise was duplicated with the extended datasets to determine the optimal parameters for each model.

Table 23: Curve Fitting - Optimized Parameters for B Model

Innovation	p	q
PCs (1977-2000)	0.0076	0.1267
Satellite Receivers (1979-2000)	0.0003	0.2604
VCRs (1972--2000)	0.0014	0.3554
CD Players (1983-2000)	0.0170	0.2230
Camcorders (1983-2000)	0.0088	0.1329
PTVs (1982-2000)	0.0054	0.0515
Cordless Phones (1976-2000)	0.0039	0.2313
Telephone Answering Devices (1976-2000)	0.0049	0.2175

Table 24: Curve Fitting - Optimized Parameters for Bv Model

Innovation	p	q
PCs (1977-2000)	0.0076	0.1453
Satellite Receivers (1979-2000)	0.0003	0.2771
VCRs (1972--2000)	0.0013	0.3871
CD Players (1983-2000)	0.0164	0.2494
Camcorders (1983-2000)	0.0087	0.1499
PTVs (1982-2000)	0.0054	0.0651
Cordless Phones (1976-2000)	0.0038	0.2552
Telephone Answering Devices (1976-2000)	0.0048	0.2418

Table 25: Curve Fitting - Optimized Parameters for GB Model

Innovation	p	q	B
PCs (1977-2000)	0.0075	0.1401	-1.5073
Satellite Receivers (1979-2000)	0.0005	0.2586	1.0531
VCRs (1972--2000)	0.0017	0.2243	-8.5919
CD Players (1983-2000)	0.0160	0.2603	1.5604
Camcorders (1983-2000)	0.0023	0.1195	-8.9563
PTVs (1982-2000)	0.0060	0.0547	4.2393
Cordless Phones (1976-2000)	0.0041	0.2360	0.7047
Telephone Answering Devices (1976-2000)	0.0053	0.2188	0.4371

Table 26: Curve Fitting - Optimized Parameters for GBv Model

Innovation	p	q	B
PCs (1977-2000)	0.0074	0.1604	-1.5360
Satellite Receivers (1979-2000)	0.0005	0.2747	1.0545
VCRs (1972--2000)	0.0017	0.2530	-7.7575
CD Players (1983-2000)	0.0154	0.2889	1.5009
Camcorders (1983-2000)	0.0022	0.1319	-9.1342
PTVs (1982-2000)	0.0059	0.0691	3.5670
Cordless Phones (1976-2000)	0.0039	0.2607	0.7328
Telephone Answering Devices (1976-2000)	0.0036	0.2352	-1.6927

Table 27: Curve Fitting - Optimized Parameters for SL Model

Innovation	b	c
PCs (1977-2000)	0.1599	35.2554
Satellite Receivers (1979-2000)	0.2403	1016.7619
VCRs (1972--2000)	0.3705	632.6383
CD Players (1983-2000)	0.2839	30.4163
Camcorders (1983-2000)	0.1828	38.4293
PTVs (1982-2000)	0.1236	54.1284
Cordless Phones (1976-2000)	0.2431	95.7757
Telephone Answering Devices (1976-2000)	0.2377	78.5701

Table 28: Curve Fitting - Optimized Parameters for G Model

Innovation	b	c
PCs (1977-2000)	0.0865	4.9556
Satellite Receivers (1979-2000)	0.0856	12.1903
VCRs (1972--2000)	0.2566	55.7292
CD Players (1983-2000)	0.1877	6.2126
Camcorders (1983-2000)	0.0898	4.6937
PTVs (1982-2000)	0.0458	4.4081
Cordless Phones (1976-2000)	0.1530	11.5618
Telephone Answering Devices (1976-2000)	0.1543	11.0536

Table 29: Curve Fitting - Optimized Parameters for BnC Model

Innovation	b	c[18]	k
PCs (1977-2000)	0.8919	224.3901	0.3748
Satellite Receivers (1979-2000)	1.2582	26500.0001	0.4417
VCRs (1972--2000)	2.2013	100000.0000	0.3718
CD Players (1983-2000)	6.3438	100000.0000	-0.2766
Camcorders (1983-2000)	2.7401	2118.1201	-0.0818
PTVs (1982-2000)	2.4619	1560.3284	-0.1931
Cordless Phones (1976-2000)	0.7533	534.4088	0.6042
Telephone Answering Devices (1976-2000)	3.8056	100000.0000	0.0193

Actual Fit of Models (Forecasting)

For the purposes of forecasting the consumer adoption of innovations, the Generalized Bass models were not as reliable as the other five diffusion models (APPENDIX B). Therefore, only the results of the other five models were presented here. For each of the eight innovations, forecasts were created by using the optimal parameters of the other seven innovations. The results for the five diffusion models still of interest were tabulated by both sum of the squared errors and by the comparative placement method (Tables 30 to 45 and Tables 56-64).

[18] As discussed in Chapter 3, an upper limit of 100,000 was used for variable *c*.

Table 30: Personal Computer Forecasting Results

PC Forecasts	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Using coefficients optimized for Satellite Receivers (1979-2000)	0.983	0.993	0.983	1.023	1.000
Using coefficients optimized for VCRs (1972--2000)	0.803	0.869	0.834	0.849	0.804
Using coefficients optimized for CD Players (1983-2000)	2.770	2.625	2.889	2.620	2.369
Using coefficients optimized for Camcorders (1983-2000)	0.051	0.042	0.100	0.039	0.028
Using coefficients optimized for PTVs (1982-2000)	0.674	0.686	0.581	0.635	0.716
Using coefficients optimized for Cordless Phones (1976-2000)	0.262	0.272	0.271	0.282	0.273
Using coefficients optimized for Telephone Answering Devices (1976-2000)	0.309	0.323	0.328	0.346	0.338
Total	5.865	5.822	6.007	5.809	5.543

Table 31: PC Forecasts – Comparative Results

Ranking of PC Forecasts	B	Bv	SL	G	BnC
Using coefficients optimized for Satellite Receivers (1979-2000)	1	3	2	5	4
Using coefficients optimized for VCRs (1972--2000)	1	5	3	4	2
Using coefficients optimized for CD Players (1983-2000)	4	3	5	2	1
Using coefficients optimized for Camcorders (1983-2000)	4	3	5	2	1
Using coefficients optimized for PTVs (1982-2000)	3	4	1	2	5
Using coefficients optimized for Cordless Phones (1976-2000)	1	3	2	5	4
Using coefficients optimized for Telephone Answering Devices (1976-2000)	1	2	3	5	4
Total	15	23	21	25	21

The Box and Cox Model performed the best overall for forecasting PC diffusion with a SSE of 5.543 and tying for second in the comparative results.

Table 32: DBS Satellite Receiver Forecasting Results

Satellite Receiver Forecasts	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Using coefficients optimized for PCs (1977-2000)	0.773	0.792	0.749	0.792	0.788
Using coefficients optimized for VCRs (1972--2000)	2.205	2.386	2.240	2.246	2.230
Using coefficients optimized for CD Players (1983-2000)	5.885	5.773	6.043	5.724	5.432
Using coefficients optimized for Camcorders (1983-2000)	1.102	1.080	1.208	1.059	0.976
Using coefficients optimized for PTVs (1982-2000)	0.062	0.061	0.067	0.064	0.061
Using coefficients optimized for Cordless Phones (1976-2000)	1.470	1.529	1.476	1.540	1.503
Using coefficients optimized for Telephone Answering Devices (1976-2000)	1.647	1.717	1.656	1.724	1.735
Total	13.145	13.338	13.440	13.150	12.726

Table 33: DBS Satellite Receiver Forecasts – Comparative Results

Ranking of Satellite Receiver Forecasts	B	Bv	SL	G	BnC
Using coefficients optimized for PCs (1977-2000)	2	4	1	5	3
Using coefficients optimized for VCRs (1972--2000)	1	5	3	4	2
Using coefficients optimized for CD Players (1983-2000)	4	3	5	2	1
Using coefficients optimized for Camcorders (1983-2000)	4	3	5	2	1
Using coefficients optimized for PTVs (1982-2000)	3	2	5	4	1
Using coefficients optimized for Cordless Phones (1976-2000)	1	4	2	5	3
Using coefficients optimized for Telephone Answering Devices (1976-2000)	1	3	2	4	5
Total	16	24	23	26	16

The Box and Cox Model performed the best overall for forecasting the diffusion of satellite receivers with a SSE of 12.726 and tying for first in the comparative results.

Table 34: CD Player Forecasting Results

CD Player Forecasts	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Using coefficients optimized for PCs (1977-2000)	1.505	1.476	1.578	1.478	1.485
Using coefficients optimized for Satellite Receivers (1979-2000)	3.407	3.405	3.406	3.426	3.420
Using coefficients optimized for VCRs (1972--2000)	0.076	0.091	0.099	0.177	0.122
Using coefficients optimized for Camcorders (1983-2000)	1.233	1.232	1.260	1.228	1.215
Using coefficients optimized for PTVs (1982-2000)	2.636	2.634	2.674	2.653	2.625
Using coefficients optimized for Cordless Phones (1976-2000)	1.309	1.269	1.332	1.311	1.321
Using coefficients optimized for Telephone Answering Devices (1976-2000)	1.141	1.096	1.182	1.175	1.141
Total	11.345	11.235	11.578	11.464	11.337

Table 35: CD Player Forecasts – Comparative Results

Ranking of CD Player Forecasts	B	Bv	SL	G	BnC
Using coefficients optimized for PCs (1977-2000)	4	1	5	2	3
Using coefficients optimized for Satellite Receivers (1979-2000)	3	1	2	5	4
Using coefficients optimized for VCRs (1972--2000)	1	2	3	5	4
Using coefficients optimized for Camcorders (1983-2000)	4	3	5	2	1
Using coefficients optimized for PTVs (1982-2000)	3	2	5	4	1
Using coefficients optimized for Cordless Phones (1976-2000)	2	1	5	3	4
Using coefficients optimized for Telephone Answering Devices (1976-2000)	3	1	5	4	2
Total	20	11	30	25	19

The Bass Model variant performed the best overall for forecasting the diffusion of CD players with a SSE of 11.235 and placing first in the comparative results.

Table 36: Camcorder Forecasting Results

Camcorder Forecasts	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Using coefficients optimized for PCs (1977-2000)	0.018	0.015	0.030	0.016	0.016
Using coefficients optimized for Satellite Receivers (1979-2000)	0.564	0.564	0.564	0.571	0.569
Using coefficients optimized for VCRs (1972--2000)	0.076	0.091	0.099	0.177	0.122
Using coefficients optimized for CD Players (1983-2000)	1.241	1.244	1.286	1.241	1.218
Using coefficients optimized for PTVs (1982-2000)	0.284	0.283	0.295	0.288	0.281
Using coefficients optimized for Cordless Phones (1976-2000)	0.020	0.022	0.023	0.054	0.032
Using coefficients optimized for Telephone Answering Devices (1976-2000)	0.021	0.026	0.024	0.058	0.053
Total	2.229	2.249	2.329	2.409	2.294

Table 37: Camcorder Forecasts – Comparative Results

Ranking of Camcorder Forecasts	B	Bv	SL	G	BnC
Using coefficients optimized for PCs (1977-2000)	4	1	5	2	3
Using coefficients optimized for Satellite Receivers (1979-2000)	3	1	2	5	4
Using coefficients optimized for VCRs (1972--2000)	1	2	3	5	4
Using coefficients optimized for CD Players (1983-2000)	3	4	5	2	1
Using coefficients optimized for PTVs (1982-2000)	3	2	5	4	1
Using coefficients optimized for Cordless Phones (1976-2000)	1	2	3	5	4
Using coefficients optimized for Telephone Answering Devices (1976-2000)	1	3	2	5	4
Total	16	15	25	28	21

The Bass Model and the Bass variant performed the best overall for forecasting the diffusion of camcorders with respective SSEs of 2.229/2.249 and placements of second/first in the comparative results.

Table 38: Projection Television Forecasting Results

PTV Forecasts	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Using coefficients optimized for PCs (1977-2000)	0.219	0.230	0.200	0.234	0.230
Using coefficients optimized for Satellite Receivers (1979-2000)	0.057	0.057	0.057	0.060	0.059
Using coefficients optimized for VCRs (1972--2000)	0.618	0.709	0.644	0.721	0.682
Using coefficients optimized for CD Players (1983-2000)	3.186	3.168	3.276	3.155	3.067
Using coefficients optimized for Camcorders (1983-2000)	0.360	0.357	0.375	0.357	0.345
Using coefficients optimized for Cordless Phones (1976-2000)	0.423	0.454	0.422	0.496	0.449
Using coefficients optimized for Telephone Answering Devices (1976-2000)	0.518	0.557	0.511	0.586	0.593
Total	5.382	5.531	5.486	5.610	5.426

Table 39: PTV Forecasts – Comparative Results

Ranking of PTV Forecasts	B	Bv	SL	G	BnC
Using coefficients optimized for PCs (1977-2000)	2	4	1	5	3
Using coefficients optimized for Satellite Receivers (1979-2000)	3	2	1	5	4
Using coefficients optimized for VCRs (1972--2000)	1	4	2	5	3
Using coefficients optimized for CD Players (1983-2000)	4	3	5	2	1
Using coefficients optimized for Camcorders (1983-2000)	4	2	5	3	1
Using coefficients optimized for Cordless Phones (1976-2000)	2	4	1	5	3
Using coefficients optimized for Telephone Answering Devices (1976-2000)	2	3	1	4	5
Total	18	22	16	29	20

The Bass model performed the best overall for forecasting the diffusion of projection televisions with a SSE of 5.382 and placing second in the comparative results.

Table 40: Video Cassette Recorder Forecasting Results

VCR Forecasts	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Using coefficients optimized for PCs (1977-2000)	1.176	1.268	1.107	1.266	1.255
Using coefficients optimized for Satellite Receivers (1979-2000)	4.450	4.601	4.492	5.081	4.744
Using coefficients optimized for CD Players (1983-2000)	1.653	1.470	1.688	1.624	1.586
Using coefficients optimized for Camcorders (1983-2000)	0.798	0.928	0.556	0.994	1.376
Using coefficients optimized for PTVs (1982-2000)	4.908	5.027	4.124	4.634	5.250
Using coefficients optimized for Cordless Phones (1976-2000)	0.232	0.252	0.224	0.229	0.219
Using coefficients optimized for Telephone Answering Devices (1976-2000)	0.224	0.237	0.202	0.196	0.216
Total	13.518	13.848	12.449	14.041	14.658

Table 41: VCR Forecasts – Comparative Results

Ranking of VCR Forecasts	B	Bv	SL	G	BnC
Using coefficients optimized for PCs (1977-2000)	2	5	1	4	3
Using coefficients optimized for Satellite Receivers (1979-2000)	1	3	2	5	4
Using coefficients optimized for CD Players (1983-2000)	4	1	5	3	2
Using coefficients optimized for Camcorders (1983-2000)	2	3	1	4	5
Using coefficients optimized for PTVs (1982-2000)	3	4	1	2	5
Using coefficients optimized for Cordless Phones (1976-2000)	4	5	2	3	1
Using coefficients optimized for Telephone Answering Devices (1976-2000)	4	5	2	1	3
Total	20	26	14	22	23

The Simple Logistic model performed the best overall for forecasting the diffusion of VCRs with a SSE of 12.449 and placing first in the comparative results.

Table 42: Cordless Phone Forecasting Results

Cordless Phone Forecasts	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Using coefficients optimized for PCs (1977-2000)	0.305	0.313	0.297	0.316	0.315
Using coefficients optimized for Satellite Receivers (1979-2000)	2.330	2.358	2.333	2.438	2.377
Using coefficients optimized for VCRs (1972--2000)	0.174	0.195	0.184	0.189	0.165
Using coefficients optimized for CD Players (1983-2000)	1.784	1.656	1.860	1.699	1.562
Using coefficients optimized for Camcorders (1983-2000)	0.150	0.175	0.079	0.203	0.319
Using coefficients optimized for PTVs (1982-2000)	2.007	2.034	1.770	1.911	2.107
Using coefficients optimized for Telephone Answering Devices (1976-2000)	0.015	0.014	0.015	0.019	0.019
Total	6.773	6.751	6.546	6.787	6.868

Table 43: Cordless Phone Forecasts – Comparative Results

Ranking of Cordless Phone Forecasts	B	Bv	SL	G	BnC
Using coefficients optimized for PCs (1977-2000)	2	3	1	5	4
Using coefficients optimized for Satellite Receivers (1979-2000)	1	3	2	5	4
Using coefficients optimized for VCRs (1972--2000)	2	5	3	4	1
Using coefficients optimized for CD Players (1983-2000)	4	2	5	3	1
Using coefficients optimized for Camcorders (1983-2000)	2	3	1	4	5
Using coefficients optimized for PTVs (1982-2000)	3	4	1	2	5
Using coefficients optimized for Telephone Answering Devices (1976-2000)	2	1	3	4	5
Total	16	21	16	27	25

The Simple Logistic model performed the best overall for forecasting the diffusion of cordless phones with a SSE of 6.546 and tying for first in the comparative results.

Table 44: Telephone Answering Device Forecasting Results

TAD Forecasts	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Using coefficients optimized for PCs (1977-2000)	0.378	0.384	0.381	0.376	0.377
Using coefficients optimized for Satellite Receivers (1979-2000)	2.511	2.540	2.514	2.609	2.553
Using coefficients optimized for VCRs (1972--2000)	0.195	0.204	0.196	0.170	0.160
Using coefficients optimized for CD Players (1983-2000)	1.622	1.494	1.681	1.536	1.406
Using coefficients optimized for Camcorders (1983-2000)	0.203	0.228	0.135	0.246	0.356
Using coefficients optimized for PTVs (1982-2000)	2.136	2.164	1.909	2.041	2.232
Using coefficients optimized for Cordless Phones (1976-2000)	0.055	0.051	0.055	0.019	0.037
Total	7.147	7.106	6.919	7.010	7.126

Table 45: TAD Forecasts – Comparative Results

Ranking of TAD Forecasts	B	Bv	SL	G	BnC
Using coefficients optimized for PCs (1977-2000)	3	5	4	1	2
Using coefficients optimized for Satellite Receivers (1979-2000)	1	3	2	5	4
Using coefficients optimized for VCRs (1972--2000)	3	5	4	2	1
Using coefficients optimized for CD Players (1983-2000)	4	2	5	3	1
Using coefficients optimized for Camcorders (1983-2000)	2	3	1	4	5
Using coefficients optimized for PTVs (1982-2000)	3	4	1	2	5
Using coefficients optimized for Cordless Phones (1976-2000)	4	3	5	1	2
Total	20	25	22	18	20

The Gompertz model performed the best overall for forecasting the diffusion of telephone answering devices with a SSE of 7.010 (second best) and placing first in the comparative results.

Hypotheses Testing (Quadrant Analysis)

The primary purpose of this research is to provide guidance on which diffusion models should be used in various conditions. While the previous set of tables looked at the forecasts for each innovation, the following set of tables looks at of the forecasts as a whole and then as segments.

Table 46: All Eight Innovations – Comparative Results

	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	65.4	65.9	64.8	66.3	66.0
Total finish score (lower is better)	141	167	167	200	165
Rankings by e^2 sums	2	3	1	5	4
Rankings by finish position	1	3	3	5	2

The Bass model performed the best overall for forecasting the diffusion of *all* innovations with a SSE of 65.4 (second best) and placing first in the comparative results. However, the results are not statistically significant.

Table 47: Radical Innovations – Comparative Results

Personal Computers, Satellite Receivers, CD Players	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	30.4	30.4	31.0	30.4	29.6
Total finish score (lower is better)	51	58	74	76	56
Rankings by e^2 sums	2	3	5	4	1
Rankings by finish position	1	3	4	5	2

The Bass model and the Box and Cox model performed the best overall for forecasting the diffusion of *radical* innovations with respective SSEs of 30.4/29.6 and placements of first/second in the comparative results.

Table 48: Radical/High Priced Innovations – Comparative Results

PCs, Satellite Receivers	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	19.0	19.2	19.4	19.0	18.3
Total finish score (lower is better)	31	47	44	51	37
Rankings by e^2 sums	3	4	5	2	1
Rankings by finish position	1	4	3	5	2

The Box and Cox model performed the best overall for forecasting the diffusion of *radical, high-priced* innovations with a SSE of 18.3 and placing second in the comparative results.

Table 49: Radical/Low Priced Innovations – Comparative Results

CD Players	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	11.3	11.2	11.6	11.5	11.3
Total finish score (lower is better)	20	11	30	25	19
Rankings by e^2 sums	3	1	5	4	2
Rankings by finish position	3	1	5	4	2

The Bass model variant performed the best overall for forecasting the diffusion of *radical, low-priced* innovations with a SSE of 11.2 and placing first in the comparative results.

Table 50: Really New Innovations – Comparative Results

Camcorders, PTVs, VCRs, Cordless Phones, TADs	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	35.0	35.5	33.7	35.9	36.4
Total finish score (lower is better)	90	109	93	124	109
Rankings by e^2 sums	2	3	1	4	5
Rankings by finish position	1	3	2	5	3

The Bass model and the Simple Logistic model performed the best overall for forecasting the diffusion of *really new* innovations with respective SSEs of 35.0/33.7 and placements of first/second in the comparative results.

Table 51: Really New/High Priced Innovations – Comparative Results

Camcorders, PTVs	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	7.6	7.8	7.8	8.0	7.7
Total finish score (lower is better)	34	37	41	57	41
Rankings by e^2 sums	1	3	4	5	2
Rankings by finish position	1	2	3	5	3

The Bass model performed the best overall for forecasting the diffusion of *really new, high-priced* innovations with a SSE of 7.6 and placing first in the comparative results.

Table 52: Really New/Low Priced Innovations – Comparative Results

VCRs, Cordless Phones, TADs	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	27.4	27.7	25.9	27.8	28.7
Total finish score (lower is better)	90	109	93	124	109
Rankings by e^2 sums	2	3	1	4	5
Rankings by finish position	1	3	2	5	3

The Bass model and the Simple Logistic model performed the best overall for forecasting the diffusion of *really new, low-priced* innovations with respective SSEs of 27.4/25.9 and placements of first/second in the comparative results.

Table 53: High Priced Innovations – Comparative Results

PCs, Satellite Receivers, Camcorders, PTVs	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	26.6	26.9	27.3	27.0	26.0
Total finish score (lower is better)	65	84	85	108	78
Rankings by e^2 sums	2	3	5	4	1
Rankings by finish position	1	3	4	5	2

The Bass model and the Box and Cox model performed the best overall for forecasting the diffusion of *high-priced* innovations with respective SSEs of 26.6/26.0 and placements of first/second in the comparative results.

Table 54: Low Priced Innovations – Comparative Results

CD Players, VCRs, Cordless Phones, TADs	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	38.8	38.9	37.5	39.3	40.0
Total finish score (lower is better)	76	83	82	92	87
Rankings by e^2 sums	2	3	1	4	5
Rankings by finish position	1	3	2	5	4

The Bass model and the Simple Logistic model performed the best overall for forecasting the diffusion of *low-priced* innovations with respective SSEs of 38.8/37.5 and placements of first/second in the comparative results.

Cell Testing (Hypotheses Testing)

The specific hypotheses discussed earlier (page 46) were tested by measuring the differences between the sum of squared errors for forecasts using parameters from various quadrants. Since the hypotheses made specific predictions about the accuracy of various comparisons, the total number of successful predictions were simply counted to compute the binomial distribution (Berry and Lindgren, 1996).

Table 55: Results of Cell Comparisons

	n	number correct	percent correct	z score
H1	270	206	76.3%	8.6**
H1a (opp)	100	85	85.0%	7.0**
H1b (hz)	70	40	57.1%	1.2
H1c (vt)	100	81	81.0%	6.2**
H2	280	173	61.8%	3.9**
H2a (vt vs. op)	140	73	52.1%	0.5
H2b (hz vs. op)	140	100	71.4%	5.1**
H3	140	33	23.6%	-6.3**

**P < 0.01

Strong support for the first two hypotheses was found, although the results for hypotheses H1b and H2a were not significant. Support for H1d (not shown on Table 55) was also found as $Z_{H1a} > (Z_{H1b}; Z_{H1c})$. Not only was support lacking for the third hypothesis, but it was clearly refuted.

Quadrant Analysis without PCs

As discussed in Chapter 3, it became clear that the diffusion of PCs followed a pattern that differed from the other consumer electronic innovations. Therefore the quadrant analysis was repeated without using this dataset.

Table 56: All Seven Innovations – Comparative Results

	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	55.0	55.4	54.2	55.9	55.9
Total finish score (lower is better)	95	108	117	121	99
Rankings by e^2 sums	2	3	1	4	5
Rankings by finish position	1	3	4	5	2

The Bass model performed the best overall for forecasting the diffusion of *all* innovations with a SSE of 55.0 (second best) and placing first in the comparative results.

Table 57: Radical Innovations – Comparative Results

Satellite Receivers, CD Players	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	22.2	22.3	22.6	22.3	21.8
Total finish score (lower is better)	27	29	45	39	25
Rankings by e^2 sums	2	3	5	4	1
Rankings by finish position	2	3	5	4	1

The Box and Cox model performed the best overall for forecasting the diffusion of *radical* innovations with a SSE of 21.8 and placing first in the comparative results.

Table 58: Radical/High Priced Innovations – Comparative Results

Satellite Receivers	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	12.4	12.5	12.7	12.4	11.9
Total finish score (lower is better)	14	20	22	21	13
Rankings by e^2 sums	3	4	5	2	1
Rankings by finish position	2	3	5	4	1

The Box and Cox model performed the best overall for forecasting the diffusion of *radical, high-priced* innovations with a SSE of 11.9 and placing first in the comparative results.

Table 59: Radical/Low Priced Innovations – Comparative Results

CD Players	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	9.8	9.7	10.0	10.0	9.8
Total finish score (lower is better)	13	9	23	18	12
Rankings by e^2 sums	2	1	4	5	3
Rankings by finish position	3	1	5	4	2

The Bass model variant performed the best overall for forecasting the diffusion of *radical, low-priced* innovations with a SSE of 9.7 and placing first in the comparative results.

Table 60: Really New Innovations – Comparative Results

Camcorders, PTVs, VCRs, Cordless Phones, TADs	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	32.8	33.2	31.6	33.6	34.2
Total finish score (lower is better)	68	79	72	82	74
Rankings by e^2 sums	2	3	1	4	5
Rankings by finish position	1	4	2	5	3

The Bass model and the Simple Logistic model performed the best overall for forecasting the diffusion of *really new* innovations with respective SSEs of 32.8/31.6 and placements of first/second in the comparative results.

Table 61: Really New/High Priced Innovations – Comparative Results

Camcorders, PTVs	**e^2 of B**	**e^2 of Bv**	**e^2 of SL**	**e^2 of G**	**e^2 of BnC**
Sum of e^2	7.4	7.5	7.6	7.8	7.5
Total finish score (lower is better)	22	29	32	40	27
Rankings by e^2 sums	1	3	4	5	2
Rankings by finish position	1	3	4	5	2

The Bass model performed the best overall for forecasting the diffusion of *really new, high-priced* innovations with a SSE of 7.4 and placing first in the comparative results.

Table 62: Really New/Low Priced Innovations – Comparative Results

VCRs, Cordless Phones, TADs	**e^2 of B**	**e^2 of Bv**	**e^2 of SL**	**e^2 of G**	**e^2 of BnC**
Sum of e^2	25.4	25.6	24.0	25.8	26.7
Total finish score (lower is better)	46	50	40	42	47
Rankings by e^2 sums	2	3	1	4	5
Rankings by finish position	3	5	1	2	4

The Simple Logistic model performed the best overall for forecasting the diffusion of *really new, low-priced* innovations with a SSE of 24.0 and placing first in the comparative results.

Table 63: High Priced Innovations – Comparative Results

Satellite receivers, Camcorders, PTVs	**e^2 of B**	**e^2 of Bv**	**e^2 of SL**	**e^2 of G**	**e^2 of BnC**
Sum of e^2	19.7	20.1	20.3	20.1	19.4
Total finish score (lower is better)	36	49	54	61	40
Rankings by e^2 sums	2	3	5	4	1
Rankings by finish position	1	3	4	5	2

The Bass model and the Box and Cox model performed the best overall for forecasting the diffusion of *high-priced* innovations with respective SSEs of 19.7/19.4 and placements of first/second in the comparative results.

Table 64: Low Priced Innovations – Comparative Results

CD Players, VCRs, Cordless Phones, TADs	e^2 of B	e^2 of Bv	e^2 of SL	e^2 of G	e^2 of BnC
Sum of e^2	35.3	35.4	34.0	35.8	36.5
Total finish score (lower is better)	59	59	63	60	59
Rankings by e^2 sums	2	3	1	4	5
Rankings by finish position	1	1	5	4	1

The Bass model performed the best overall for forecasting the diffusion of *low-priced* innovations with a SSE of 35.3 (second) and placing first in the comparative results.

Cell Testing (Hypotheses Testing) without PCs

Table 65: Results of Cell Comparisons

	n	number correct	percent correct	z score
H1	170	146	85.9%	9.4**
H1a (opp)	40	40	100.0%	6.3**
H1b (hz)	40	35	87.5%	4.7**
H1c (vt)	90	71	78.9%	5.5**
H2	170	132	77.6%	7.2**
H2a (vt vs. op)	85	57	67.1%	3.1**
H2b (hz vs. op)	85	75	88.2%	7.1**
H3	85	31	36.5%	-2.5**

**P < 0.01

Strong support for the first two hypotheses was found, the results for all sub-hypotheses were significant. Support for H1d (not shown on Table 65) was also found as $Z_{H1a} > (Z_{H1b}; Z_{H1c})$. Not only was support lacking for the third hypothesis, but it was clearly refuted.

Chapter 5

DISCUSSION OF RESULTS

It is important to differentiate between forecasts that are created before an innovation is easily available and forecasts that are created after years of history in the marketplace. The conclusions drawn from this research are appropriate for creating forecasts before the innovation is marketed. This research used datasets from the United States consumer electronic market. The conclusions drawn from this research may be applicable to other industries and other countries, but further research will be needed to determine if generalizations are valid.

Answering the Research Questions

The research questions asked which forecasting method(s) should be used under various innovation levels (radical and really new) and price levels (high and low). The results of the research provided specific answers to these questions. When forecasting the diffusion of a radical high-priced innovation, one should use the Box & Cox model. It is recommended that one also generate a Bass model forecast if a second opinion is desired. When forecasting the diffusion of really new high-priced innovation, one should use the Bass model with the Box & Cox model serving as a backup. The Bass variant model should be used when forecasting the diffusion of low-priced radical innovations, with either the Bass model or the Box & Cox model providing a second opinion. When forecasting the diffusion of low-priced really new innovations, the Simple Logistic model should be used. The robust Bass model may also be used if multiple models are desired. Figure 11 summarizes when various models should be used.

Figure 11: Recommended Models by Context

	Consumers	
Price Level	Radical Innovation	Really New Innovation
High	**Box & Cox** **Bass**	**Bass** **Box & Cox**
Low	**Bass variant** **Bass / Box & Cox**	**Simple Logistic** **Bass**

Lessons From the Hypotheses

Hypotheses 1 and 2 stated that the various combinations of innovation levels (radical and really new) and price levels (high and low) would result in four populations that were significantly different from one another. The research supported these claims. As theorized, parameters from populations that were different in terms of both innovation level and price level did less well than parameters from more similar populations.

Hypothesis 3 presumed that the level of innovation would have a greater impact on the accuracy of a forecast than the price level. This presumption was clearly wrong. Not only did the research falsify it, it did so in such a manner that the opposite statement appears to be true. The price level of an innovation actually has more impact on the accuracy of a forecast than the innovation level.

Models

As discussed in Chapter 4, the Box and Cox and Generalized Bass models were the best models when it came to curve-fitting while the Simple Logistic model did the poorest. Curve-fitting is a very useful tool and may be useful for forecasts when an innovation has already been available in the marketplace. However, the results of the research showed that a curve-fitting advantage did not translate into a forecasting advantage when creating a forecast for an innovation without a market history.

Bass Models

The popularity of the Bass model derives from two unique factors. As this research has reinforced, the Bass model is very robust – working well in all tested contexts. In addition, the Bass model's two coefficients have a theoretical foundation. However, the coefficients of innovation and imitation are only theoretically sound if the model starts from the initial diffusion of the innovation. Otherwise, the model assumes that the innovation first appeared later than it actually did. As shown in Table 66, this false assumption artificially inflates the role of p (the coefficient of innovation) and artificially deflates the role of q (the coefficient of imitation).

Table 66: Watching *p*'s and *q*'s

Description	B *p*	B *q*	B SSE	GB *p*	GB *q*	GB *B*	GB SSE
VCR (1974-2000)	0.003	0.349	0.074	0.010	0.177	-5.000	0.091
VCR (1975-2000)	0.004	0.344	0.073	0.009	0.179	-10.775	0.037
VCR (1976-2000)	0.005	0.337	0.070	0.010	0.180	-10.460	0.036
VCR (1977-2000)	0.008	0.328	0.067	0.014	0.188	-8.197	0.034
VCR (1978-2000)	0.011	0.317	0.063	0.003	0.140	-20.793	0.035
VCR (1979-2000)	0.016	0.301	0.058	0.004	0.145	-18.892	0.034
VCR (1980-2000)	0.023	0.279	0.051	0.007	0.154	-15.614	0.033
VCR (1981-2000)	0.034	0.250	0.043	0.007	0.163	-13.813	0.033
VCR (1982-2000)	0.050	0.211	0.033	0.023	0.177	-6.601	0.028
VCR (1983-2000)	0.075	0.159	0.021	0.056	0.152	-2.670	0.020
VCR (1984-2000)	0.114	0.086	0.011	0.113	0.087	-0.044	0.011
VCR (1985-2000)	0.168	0	0.005	0.171	0	0.201	0.005
VCR (1986-2000)	0.202	0	0.024	0.235	0	2.673	0.022
VCR (1987-2000)	0.245	0	0.065	0.311	0	5.681	0.049
VCR (1988-2000)	0.304	0	0.114	0.356	0	7.382	0.066
VCR (1989-2000)	0.381	0	0.147	0.486	0	6.846	0.117
VCR (1990-2000)	0.465	0	0.137	0.481	0	7.431	0.111
VCR (1991-2000)	0.558	0	0.120	0.488	0	6.848	0.097
VCR (1992-2000)	0.637	0	0.096	0.671	0	7.172	0.038
VCR (1993-2000)	0.694	0	0.068	0.719	0	6.434	0.020
VCR (1994-2000)	0.748	0	0.044	0.778	0	5.621	0.006
VCR (1995-2000)	0.828	0	0.034	0.845	0	5.173	0.003
VCR (1996-2000)	0.850	0	0.022	0.866	0	4.617	0.001

This does not mean that the Bass models cannot be useful if one's data starts after the initial diffusion. On the contrary, the Bass models may still be used for forecasting just as any other model. Rather, this caution is meant for how one interprets the coefficients of innovation and imitation.

Despite the flexibility given by Bass, Krishnan, and Jain (1994) in allowing the sign of the price coefficient (*B*) to fluctuate, researchers who conduct similar experiments are advised to constrain the price variable to be negative. While this will result in sub-optimal curve-fitting, the loss in accuracy should be relatively minor. Conversely, forecasts of other innovations using only negative price variables should see gains in their accuracy. It is expected that research done with the negative constraint on the price coefficient should allow direct comparisons between the Generalized Bass models and the other diffusion models.

The Bass model variants created for this research deliberately violated the assumption of a constant *m*. This resulted in a model (Bv) that outperformed any of the others in the radical low-priced innovation context. Unfortunately, there was just one innovation in this context – additional research is recommended to test the viability of this variation with more datasets in various contexts.

Simple Logistic and Gompertz

The Simple Logistic model is one of the oldest diffusion models known. True to its name, it is a very basic model. However, it clearly outperformed the other models in the context of really new low-priced innovations.

The Gompertz model has also been used for quite a while. Based upon this research, it is not recommended for forecasting the diffusion of really new or radical innovations before the launch of an innovation. However, the Gompertz model may be very well suited for forecasts generated well after the launch of an innovation. While this was not the focus of this research, it was observed that the diffusion of the Projection Television innovation follows a perfect Gompertz curve.

Box and Cox

As discussed in Chapter 3, the Flexible Logistic Box and Cox model has a problem where the *c* variable tends to run to infinity in some scenarios. This was addressed by capping the upper limit of *c* to 100,000. Despite (or because of) this fix, the author must admit to being skeptical as to how well the Box and Cox model would do in comparison to the other models. As it turned out, the Box and Cox was second only to the Bass model in terms of robustness. The Box and Cox was also the best model in the context of radical high-priced innovations.

Contributions

This research has provided the following contributions:

- Support for the use of multiple forecasting methods
- Guidance for when various models should be used
- Guidance for when various models should not be used
- Criteria for when an innovation is released
- Definition of an Analogous Innovation
- Evidence that Analogous Groups Matter
- Superior method for extrapolation
- Evidence that price levels matter more than innovation levels
- A forecasting classification grid was created and proposed

This research has provided additional support for the traditional view that no single forecasting method is best for every situation, although the Bass model comes pretty close. The unique contribution of this forecasting research was in providing guidance for selecting forecasting models in various price and innovations contexts.

This research also provided the first empirical study that suggests the Gompertz Model is not a preferred model for use in pre-launch conditions. While this finding still needs to be verified in other studies, this finding could help forecasters improve their accuracy by guiding them to more appropriate models.

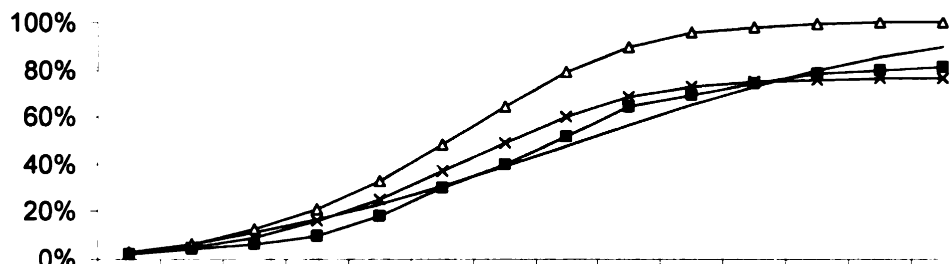
Three specific criteria were proposed as necessary before first counting when an innovation became available. The use of this criteria should allow for researchers to compare forecasting model parameters from one innovation with the same parameters from another innovation.

A definition of an analogous innovation was proposed. This definition was used as the basis for research that provided evidence that analogous innovation groups make an important difference in determining which methods should be used for pre-launch forecasting. It appears likely that the definition may also need to include the industry (e.g., really new innovation, low price level, consumer electronic industry), but this is currently speculation and needs to be tested.

This research provided evidence that the discrete time notation of the Bass Model used by this author was superior for extrapolation than the method employed by Lilien et al. Both methods work approximately the same (see Figure 12) for a given period of time, although the method used here had a slightly lower sum of squared errors.

Figure 12: Comparison of Gentry and Lilien et al. Diffusion Forecasts for VCRs

VCR Diffusion

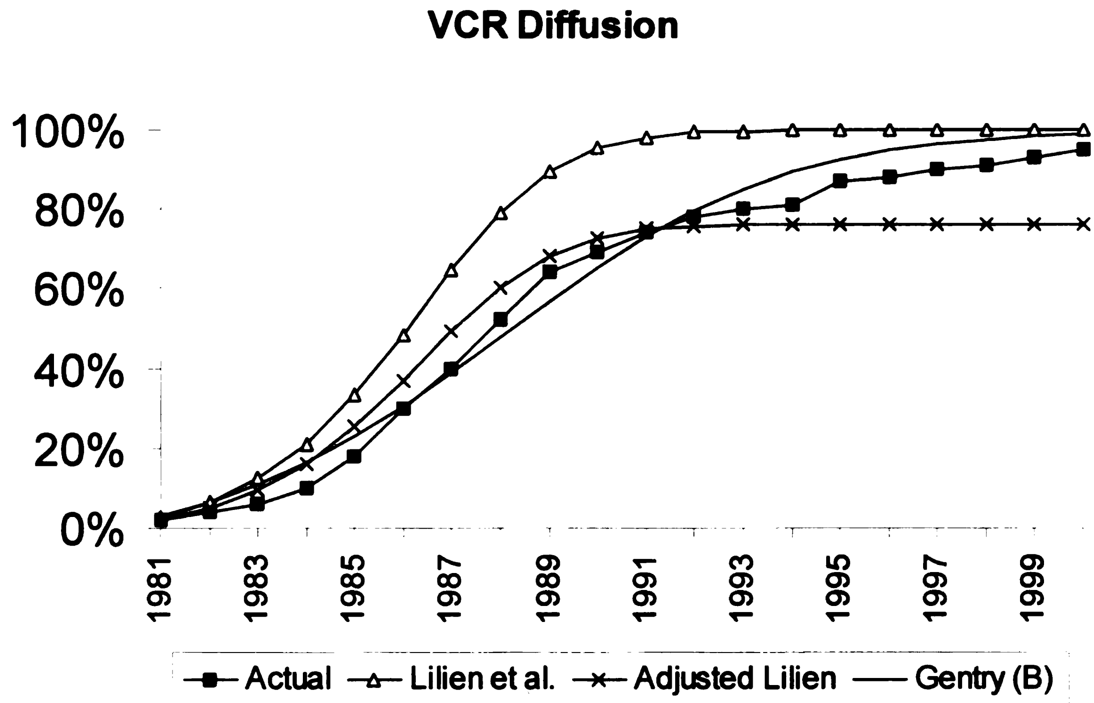


	81	82	83	84	85	86	87	88	89	90	91	92	93	94
Actual	2%	4%	6%	10%	18%	30%	40%	52%	64%	69%	74%	78%	80%	81%
Lilien et al.	3%	6%	12%	21%	33%	48%	64%	79%	90%	95%	98%	99%	100	100
Adjusted Lilien	2%	5%	9%	16%	25%	37%	49%	60%	68%	73%	75%	76%	76%	76%
Gentry (B)	3%	6%	11%	16%	23%	30%	39%	48%	57%	65%	73%	80%	85%	89%

	p	*q*	*m*	SSE
Lilien et al.	0.025	0.603	76.3%	0.521
Adjusted Lilien	n/a	n/a	n/a	0.038
Gentry (B)	0.029	0.299	100%	0.029

However, when the forecast was extended, using the same parameters, the superiority of the method used in this research becomes apparent (Figure 13).

Figure 13: Extended Comparison of Gentry and Lilien et al. Diffusion Forecasts for VCRs



	p	q	m	SSE
Lilien et al.	0.025	0.603	76.3%	0.578
Adjusted Lilien	n/a	n/a	n/a	0.167
Gentry (B)	0.029	0.299	100%	0.049

A forecasting classification grid was also proposed to simply the classification of various forecast models. By revisiting the 1985 findings of Armstrong, the forecasting classification grid provides an exhaustive, exclusive, and concise method for classifying forecasts.

APPENDICES

APPENDIX A

SELECTING DIFFUSION MODELS

Table 16: Diffusion Models Initially Considered

- Logarithmic Parabola (Gregg, Hossel, & Richardson, 1964)
- Modified Exponential (Gregg, Hossel, & Richardson, 1964)
- Observation-Based Modified Exponential (Meade, 1985)
- Bass model (Bass, 1969)
- Generalized Bass model (Bass, Krishnan, and Jain, 1994)
- Simple Logistic (Gregg, Hossel, & Richardson, 1964)
- Gompertz (Gregg, Hossel, & Richardson, 1964)
- Extended Logistic (Bass, 1969)
- Log-logistic (Tanner, 1978)
- Flexible Logistic (FLOG) – Inverse Power Transform (Bewley & Fiebig, 1988)
- FLOG – Box & Cox (Bewley & Fiebig, 1988)
- FLOG – Exponential (Bewley & Fiebig, 1988)

As discussed in Chapter 3, the Bass model, the Generalized Bass model, the Simple Logistic model, and the Gompertz model were selected on the basis of the research and the literature. As both a check on the literature and an opportunity to see how each model worked, each model was created and plotted against the actual VCR diffusion.

A quick review of the following figures (starting on the next page) revealed that Meade and Islam's recommendation was wise: The parameters of the Simple Logistic, Gompertz, and Bass models were easily adjusted to a shape similar to the actual VCR diffusion curve. The Generalized Bass model was likewise appropriate. This graphical review supported the initial decision to use these four models.

The other models were also reviewed. The Logarithmic Parabola, Modified Exponential, Observation-Based Modified Exponential, and Log-

Logistics models did not lend themselves to a close approximation of the actual VCR diffusion. Thus, these models were removed from consideration. The Extended Logistic model and all three Flexible Logistic models were able to approximate the actual VCR diffusion and all were judged appropriate for use.

Given the amount of modeling required for this research, it was decided to add just one of these four models to those already selected. Since the Extended Logistic model was a variant of the Bass model – which was already selected for the research along with several variants – it was decided to use one of the Flexible Logistic models instead. While all three FLOG models were suitable, it was judged that the Box and Cox model was slightly more appropriate for the VCR diffusion and it was selected for the research.

Figure 14: Initial Look at Logarithmic Parabola Model

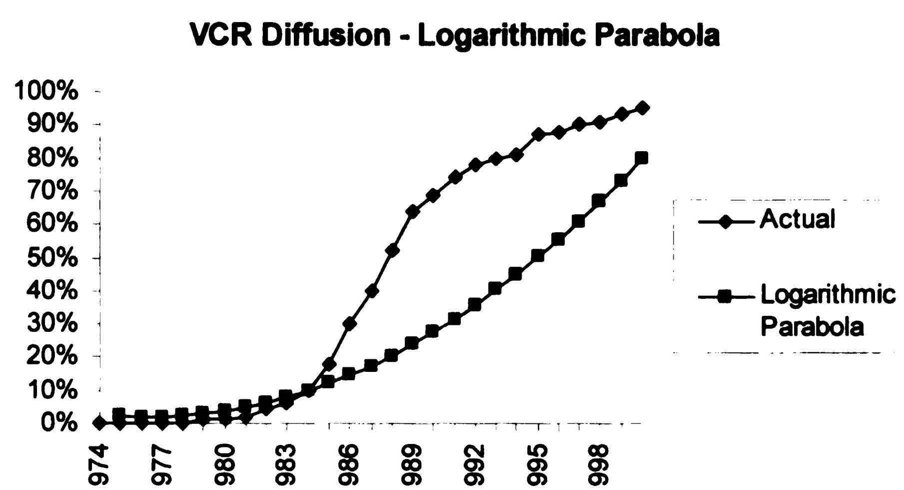


Figure 15: Initial Look at Modified Exponential Model

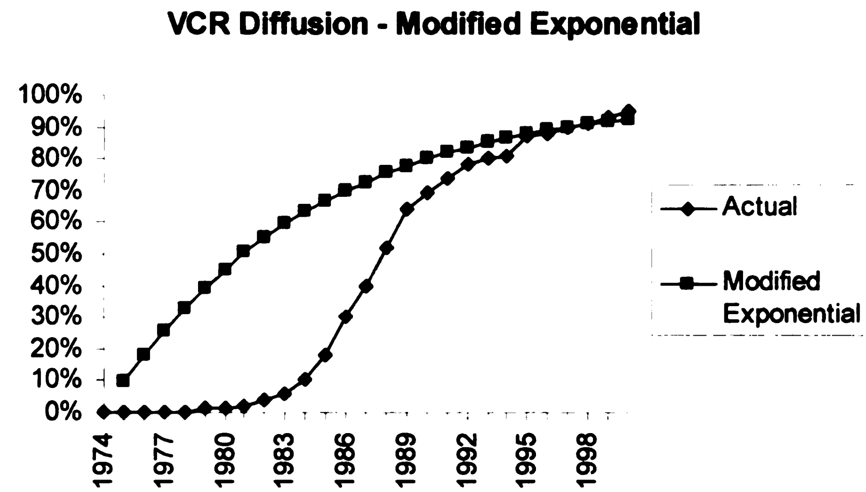


Figure 16: Initial Look at Observation-Based Modified Exponential Model

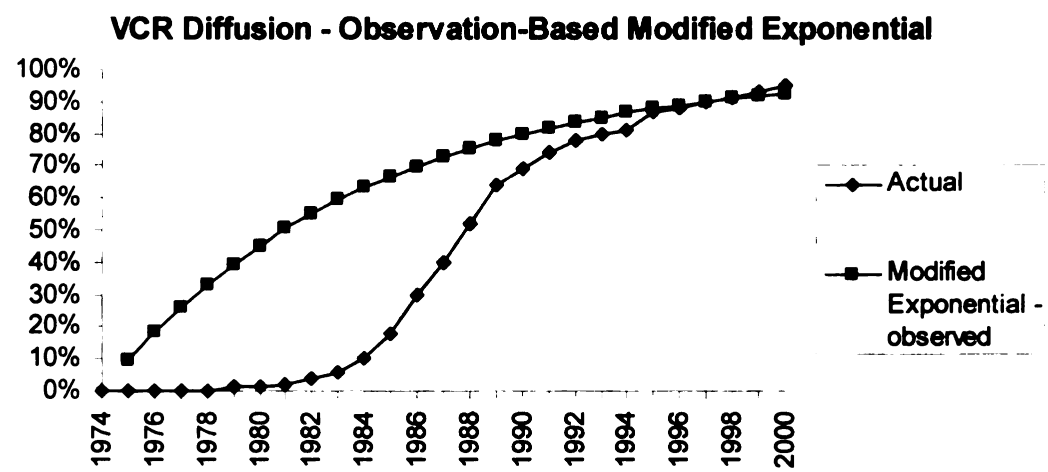


Figure 17: Initial Look at Bass Model

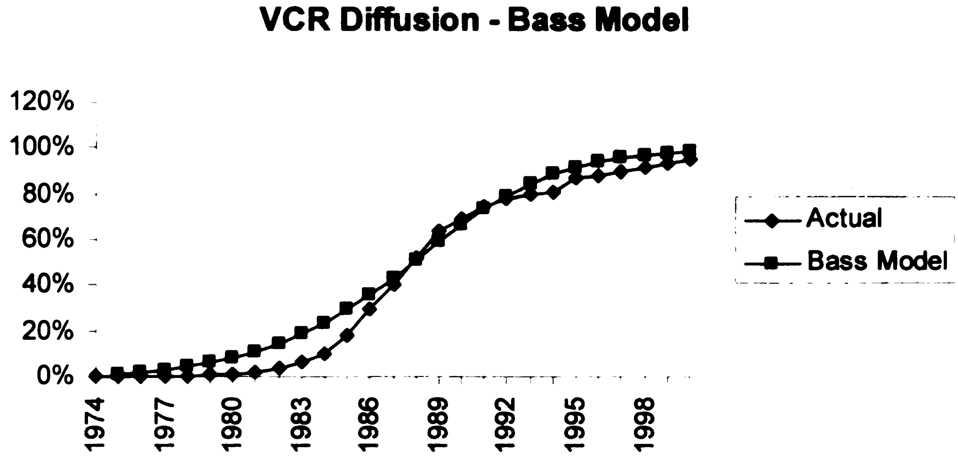


Figure 18: Initial Look at Generalized Bass Model

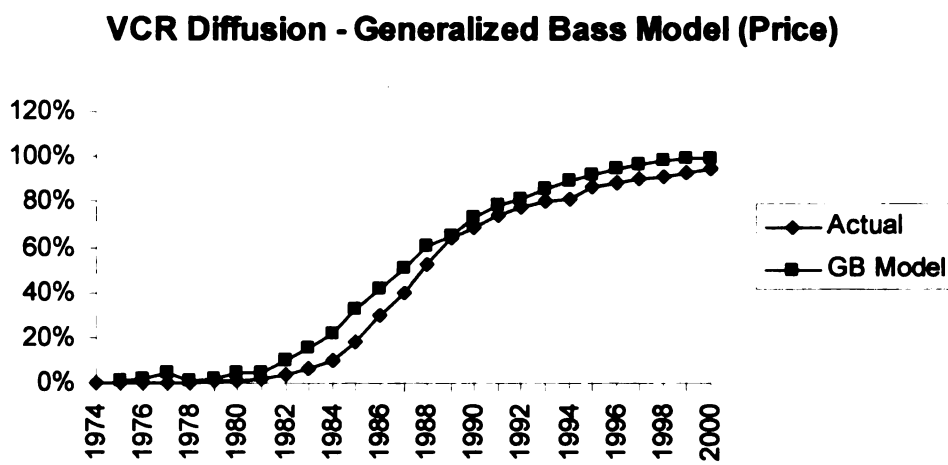


Figure 19: Initial Look at Simple Logistic Model

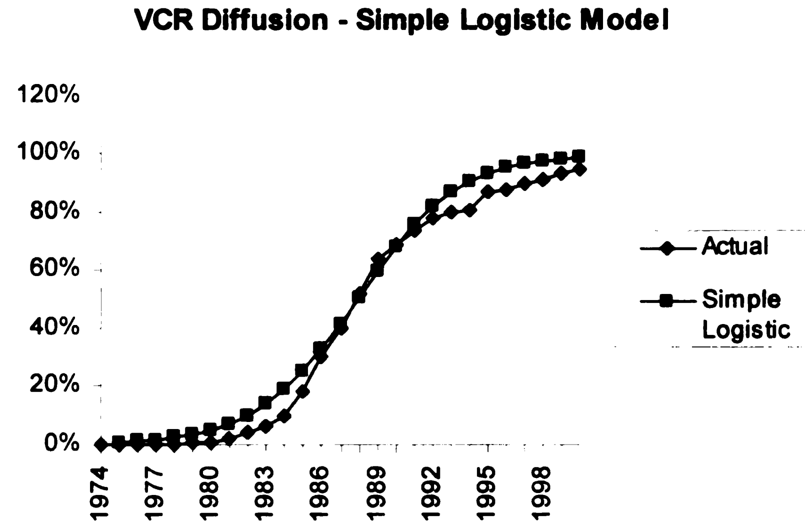


Figure 20: Initial Look at Gompertz Model

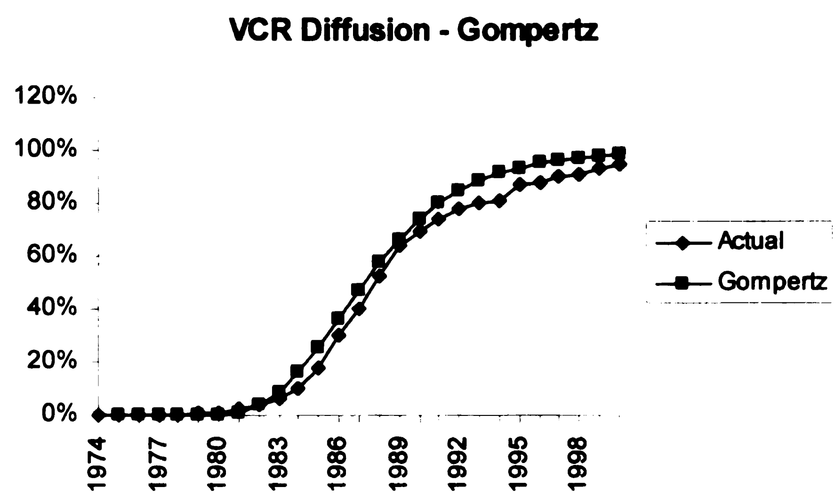


Figure 21: Initial Look at Extended Logistic Model

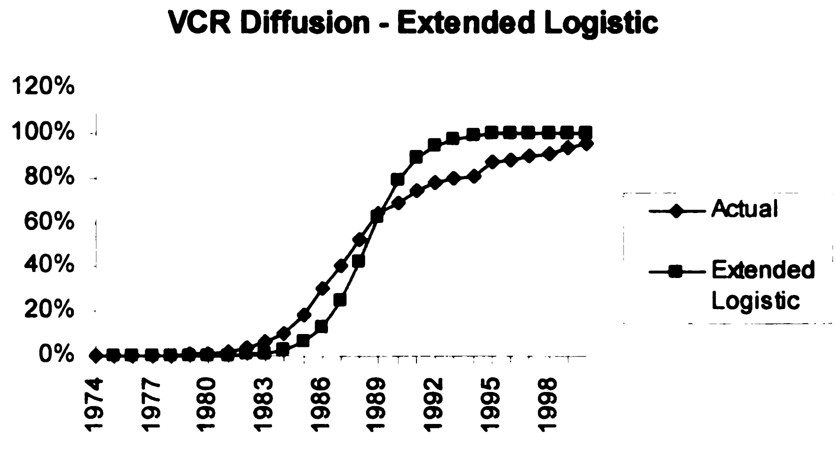


Figure 22: Initial Look at Log-Logistic Model

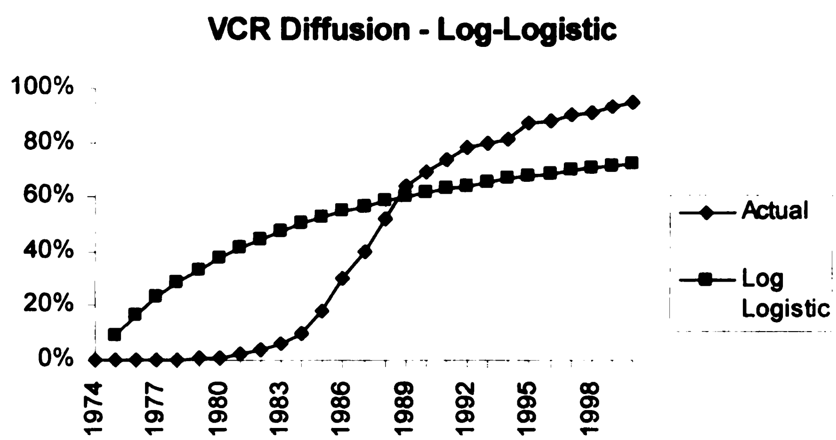


Figure 23: Initial Look at the Flexible Logistic Inverse Power Transform Model

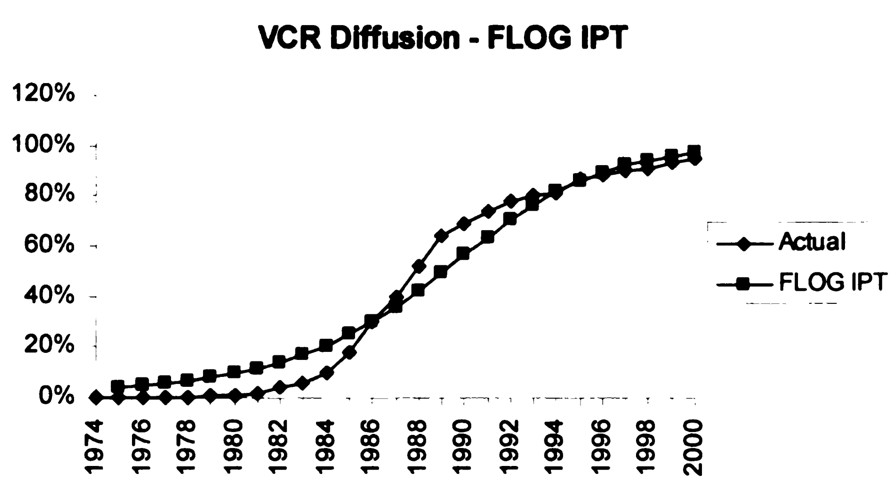


Figure 24: Initial Look at the Flexible Logistic Box and Cox Model

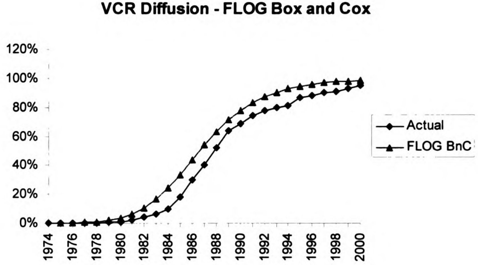
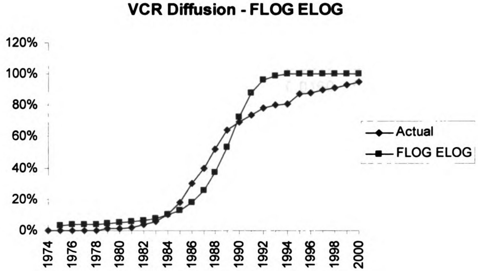


Figure 25: Initial Look at the Flexible Logistic Exponential Model



APPENDIX B

DIFFUSION AND THE GENERALIZED BASS MODEL

Bass, Krishnan, and Jain (1994) created the Generalized Bass model in response to criticism that the Bass model did "not combine contagion effects with traditional economic variables such as price." They expected the price coefficient (*B*) to be negative, but did not constrain the coefficient. As can be seen in Table 25, three of the price coefficients had negative values when the parameters were optimized for curve-fitting.

Table 25: Curve Fitting - Optimized Parameters for GB Model

Innovation	p	q	B
PCs (1977-2000)	0.0075	0.1401	-1.5073
Satellite Receivers (1979-2000)	0.0005	0.2586	1.0531
VCRs (1972--2000)	0.0017	0.2243	-8.5919
CD Players (1983-2000)	0.0160	0.2603	1.5604
Camcorders (1983-2000)	0.0023	0.1195	-8.9563
PTVs (1982-2000)	0.0060	0.0547	4.2393
Cordless Phones (1976-2000)	0.0041	0.2360	0.7047
Telephone Answering Devices (1976-2000)	0.0053	0.2188	0.4371

Ceteris paribus, a negative price coefficient increases diffusion while a positive price coefficient retards diffusion. In five of the studied innovations, a positive price coefficient was found to provide optimal results for curve-fitting. These optimal parameters were used in accordance with the freedom Bass, Krishnan, and Jain (1994) established for the price variable. This did not appear to be a problem when the hundreds of models were generated.

However, during the analysis portion of the research, it became clear that using a mixture of positive and negative price variables was problematic. The

Generalized Bass models (and GB variants) were significantly different from the other models when parameters from an innovation with a positive price coefficient were used with innovations that had an optimized negative price coefficient. These differences resulted in poor showing (Table 67) by the two models that used the price variable (the Generalized Bass model and the GB variant).

Table 67: Sum of Squared Errors for All Forecasts

B	Bv	GB	GBv	SL	G	BnC
65.2	65.7	74.9	75.4	64.6	66.2	65.9

Based upon these results, **the Generalized Bass model and the GB variant were not analyzed further since they were significantly less accurate than the other models by over three standard deviations**. Reliable conclusions about the comparison of the Generalized Bass model with the other five models should not be drawn from this research.

Researchers who conduct similar experiments are advised to constrain the price variable to be negative. While this will result in sub-optimal curve-fitting, the loss in accuracy would be relatively minor. Conversely, forecasts of other innovations using only negative price variables should see gains in their accuracy. It is expected that research done with the negative constraint on the price coefficient would allow direct comparisons between the Generalized Bass models and the other diffusion models.

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