Forecasting the Decline
of
Superseded Technologies:

A comparison of alternative methods to forecast the decline phase of technologies

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Abstract

An understanding of the economic life of technologies is important for firms, as new technological diffusion often results in rapid erosion of the market value of a firm's existing technological investments. Little is known about the decline of an older incumbent technology, despite significant effort has been devoted to studying the diffusion of new technologies over the last five decades. There is, it appears, *a pro-innovation bias* (Rogers, 1995), as theory has a singular focus on the growth side of the substitution phenomenon.

Yet to a modern enterprise managing the decline of the older technology may be at least as important as managing the diffusion of the new technology. Consequently, this research takes the first steps towards addressing this gap by investigating how best to predict the decline of an incumbent technology, through an examination of the performance of well-established forecasting methods when applied to the decline phase of a technology life cycle. Interestingly, during the search for historic data it was found that decline series are both rarer than diffusion series, and short, although not as short as diffusion series.

Three studies were undertaken; the first study was a competition of four marketing science diffusion models; the Pearl logistic, Gompertz, Bass, and log-logistic models. The second study tested a pooled analogous series approach against the four models from the first study. Twenty-five decline data series were used in those two studies. The final study applied expert judgment to the task using an online panel of 250 UK managers with forecasting experience. These managers undertook expert judgmental forecasting tasks on 12 of the 25 series, spilt over two cue information treatments. Both absolute and comparative measures of accuracy were deployed along with measures to understand bias and variability. The measures were not always in perfect consensus as to the best models in each study; however, the results in aggregate were conclusive.

It was found that the Bass and the Pearl logistic were consistently the best marketing science models. However, the online panel of forecasting experts provided a pooled estimate that was competitive with those best marketing science models. Importantly, forecasts from presenting data on decline in tabular form to the panel outperformed the same data presented in graphical form, such that tabular presentation was better than any marketing science model. Also well performed was an analogous series model formed from the average value of a normalised pool of the 25 series, as this approach provided forecasts that were within the range of the two best diffusion models. A straight-line model fitted to the last three data points in the estimation data constantly matched or outperformed all three methods over short horizons.

This indicates that simple diffusion models, such as a simple pooled average of available analogous series or even a straight-line model can provide a viable forecast, providing further evidence that simple methods are in general all that is needed to forecast in such situations. Despite laboratory research indicating that individuals are poor at this task, the judgmental study indicates that humans can be successfully used to forecast S-shaped curve trajectories in field trials; however, there are cost and time implications in using a panel that would preclude its use in many situations.

References:

Rogers, E. M. (1995). *Diffusion of innovations* (4th ed.). New York, NY: The Free Press.

Acknowledgments

I want to acknowledge the support of Professor Malcolm Wright in encouraging me to undertake this PhD. I am sure there were times when he regretted the rash suggestion that I take up that opportunity. Malcolm has been a generous mentor by both leaving me be, so as to learn from my own mistakes, but also mentoring me on how to avoid the worst traps for candidates.

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Chapter One: Introduction

This thesis tests the predictive validity of alternative methods for forecasting the decline in demand for superseded technologies.

1.1. Background

From the beginning, technology has formed an important part of the human success story. Initially technology was simple; tools for hunting, cooking, and construction, and over the millennia, the way it underpins the fabric of our society has changed, in terms of our ability to communicate socially, how we produce and consume food, and how we earn to pay for the things of life. Recent advances in *enabling technologies* in areas such as computing, the internet, data storage, nano-scale manufacturing, and social media ensure that technological innovations are arriving more frequently and diffusing globally much faster creating risks for firms. New technological arrivals displace technologies in wide use, those widely used technologies are the backbone of modern commercial endeavours, and firms have invested heavily to design, produce, and market them. While the risk from emerging technology is growing, in seems that during tough times firms tend to focus on eking out the last possible sales dollar from current assets, rather than ensuring investment is following emerging technology trends, with the result that those firms fall behind in the race to remain competitive (Bers & Dismukes, 2007). The majority of the literature tends to focus on new technology entering markets, not decline, and the risks it brings to a firm's market competitiveness. Moreover, the literature is also mostly silent on the issue of predicting the impact of the new technological innovation on an incumbent technology. It is the need for accurate forecasts of the decline in demand due to these forces and their impacts that motivates this thesis

It is reasonable to assume that prevailing forecasting methods can be used for prediction of technology decline, but that potential has yet to be investigated and tested. Fortunately, there is a substantial body of knowledge on forecasting the diffusion of new technology, which can serve as a starting point for this technology decline investigation.

The next section (1.1.1) examines how lack of foresight of technology decline undermines the market value to a firm of its technology. Following on in section 1.1.2 is a discussion on how the introduction rate of technological innovation and the speed with which technologies diffuse affects a firm's profitability. That leads to an outline of the gap in the literature on the phenomenon of decline, and the objectives of this investigation,

1.1.1. Competitive advantage and the need for foresight

Technology is central to maintaining competitive advantage (Clark, 1987; M. E. Porter, 1985; Sethi & King, 1994). Competitive advantage develops when firms are in a position to respond to emerging market needs. Competitive advantage is often transient. Fine (1998) suggests that the ability of firms to build sustained competitive advantage has all but disappeared. He argues that firms increasingly rely on solving yet another new challenge to remain competitive. Fine's observation places even more pressure on the need for technology foresight in a firm, because technology assets now appear destined to have shorter lives than in the last century, and when decline does start, it will progress more rapidly (Van den Bulte, 2000). The critical importance to firms of retaining competitiveness is illustrated in the 2015 KPMG survey of 1,200 global C.E.O.s (KPMG, 2015, p. 6) in which the top four concerns raised by C.E.O.s were:

- "new entrants disrupting our business model" - 74 percent;
- "keeping current with new technologies" - 72 percent;
- "competitors' ability to take business away from our organization" - 69 percent;
- "my company's products/services relevance three years from now" - 66 percent

These concerns are all interlinked and centre on the importance of understanding the diffusion of new technology and the subsequent decline of existing technologies to stay competitive.

There is evidence that incumbent firms are slow to recognise threats and even when risk is recognised, they tend to be muted in their response (Pistorius & Utterback, 1995; Utterback, 1994). Significantly, despite the importance of having foresight of technology decline, Foster (1986) observed that firms tend to strengthen their current, potentially maturing technologies, while exhibiting an inability to spot new superior technologies in time. One reason is that the current market players do not generally introduce radically new technologies, new entrant firms generally do this, and thus current market players need to look beyond their own activities for indications of decline in their technologies (Cooper & Schendel, 1976; Henderson & Clark, 1990). The arrival of a new technology only signals potential initiation of substitution however, and to have a true understanding, firms need to track category level data for the types of technological products upon which they rely. Category level data is resistant to product line sales variation, and hence more likely to pick up the emergence of a decline trend. In summary and as Tellis (2013) observed, businesses are increasingly unable to deal with the pace of innovation and risk losing market position because they do not have foresight of things outside their domain. A technique that allowed forecasting within their domain might well help alleviate this concerning situation.

1.1.2. The relevance of the rapidity and frequency of diffusion to firms

Any market competitiveness based on technology appears destined to be short lived. Those technologies will increasingly decline rapidly giving very little forewarning (Van den Bulte, 2000). The impact is that the value of marketing assets will decline as their market relevance fades. In the mobile device market for example, there have been two striking examples of the impact of insufficient foresight of the lifespan of a technology. Nokia and Sony-Ericsson, both previously industry giants, are now minnows in the mobile devices market (Woods, 2016). Both companies lost out in the race to adopt touchscreen smartphones to replace key driven mobile phones. Blackberry, another mobile device manufacturer, was initially a leader in smart phones with their Blackberry operating system and proprietary hardware. The company also lost out in an equally dramatic way to the widespread adoption of touchscreens (Gillette, D., & Winter, 2013; Statista, 2016). Over the last three decades, we have repeatedly seen this *failure to foresee decline* story unfold. Sony created the mobile music market in the 1970s with its Walkman technology. However when MP3 player technology arrived, this dominance was lost to Apple, who had introduced technology that allowed easy transfer of music files from hard media via MP3 encoding (Tellis, 2013), whereas Sony, who also had a strong presence in the music production industry, resisted allowing users to rip and move their music between media.

These four businesses, Nokia, Sony-Ericsson, Sony, and Blackberry lost their dominance for the most part, due to lack of foresight of the lifespan of the technologies that were their key profit sources. Knowing when to abandon a current technology and reach out to the new technology is important (Bergek, Berggren, Magnusson, & Hobday, 2013; Guiltinan, 2009). While these illustrations involve large firms, it is arguably even more important to smaller firms as they tend to invest in a narrower portfolio of technologies and therefore do not have the diversity of investment to buffer any technology decline shocks.

The impact on a firm by not abandoning old technology in time is demonstrated by the example in Figure 1, where, in just one decade, IBM and DEC transferred market value from mini computer technology, to the personal computer (PC) technologies of Intel and Microsoft. It is possible that IBM thought that when they introduced the first IBM PC that they had all bases covered in the small computing market; however they misjudged the value of their part in the Intel, Microsoft, and IBM PC partnership. Their P.C. technology became rapidly commoditised consequently, while also undermining their minicomputer business. In this case, IBM understood the new technology was coming but misread where the value would lie.

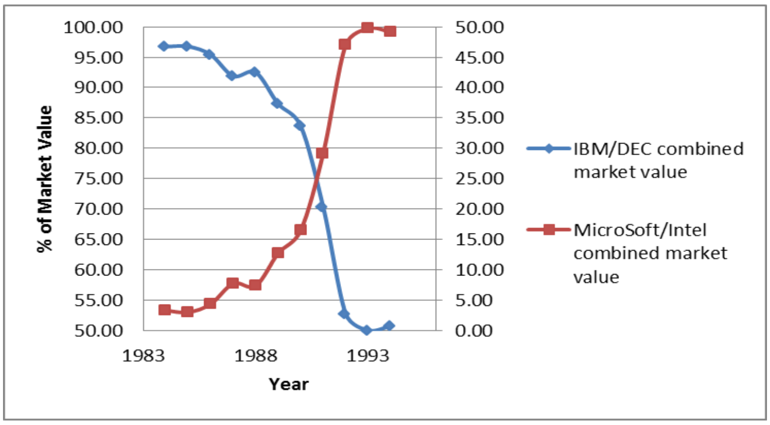


Figure 1. Value transfer - IBM & DEC to Microsoft & Intel (Modis, 1998, p. 204).

The profitability of firms relies in part on the economic life of their invested technologies being longer than the time in which it takes to get payback on that investment. Unexpectedly rapid decline to obsolescence of a technology potentially undermines the payback from that investment (Achilladelis & Antonakis, 2001; Frankel, 1955; Van den Bulte, 2000). This makes forecasting the future prospects for incumbent technologies of critical importance.

There is evidence that the occurrence of substitution of incumbent technologies through technological innovations is more frequent than in the past (Danneels, 2004). Furthermore, the speed with which electrical household durables diffuse in the US appears on average to be accelerating at a compound rate of two percent per annum, and correspondingly the typical rate of cumulative discontinuance is also accelerating with time, although at a slightly slower rate (Van den Bulte, 2000). At the same time the lifespan of technology products seems to be getting shorter perhaps as a result of the increased rate of technology introductions combined with the more rapid speed of their diffusion (Chandrasekaran &

Tellis, 2008; Stremersch, Muller, & Peres, 2010). There are some dissenting views on this acceleration of innovation. Huebner (2005) for example, believes we passed *peak innovation growth* about 100 years ago and we are in the slowdown portion of a total technology diffusion trajectory; however, the risks to firms of rapid decline still exist today, with firms needing to keep foresight over the earning prospects for their technologies.

The challenges for technology lives described above, are compounded for global firms because of a phenomenon called leapfrogging. Leapfrogging is where an adopting entity does not take up an early technology but adopts a later one, thereby skipping a generation (Davison, Vogel, Harris, & Jones, 2000; Jiang & Jain, 2012). This is most obvious in developing economies, which are today tending to buy the latest technology, whereas in the past they may have purchased an older generation of technology (Fong, 2008; James, 2009). Leapfrogging reduces the potential for firms to extend the life of their important market assets (technologies) by exporting to emerging economies as decline occurs in the markets of early release. Combining leapfrogging effects with the observed shortening of product lives, the increased rate of new technology introductions, and also the accelerating diffusion of those introductions, all paint a picture of firms needing prompt and effective foresight over technology use decline. In summary, increasingly technology is superseded earlier in its life, displaced from the market more rapidly, and the opportunities for extending its life are diminished. These all affect the quality of marketing investments and the value of marketing assets. The next section draws together the discussion to this point into a description of the specific problem this thesis addresses, and lays out the research questions.

1.2. The Problem Statement

There is a scarcity of proven techniques for forecasting this decline in the marketing literature. This is important because technology is at the heart of the customer value delivery capability (marketing capability) of most firms. This research is motivated by a desire to fill the knowledge gap in how best to forecast the decline of a technology and to provide guidance for managers of firms experiencing this situation. It could also lay the foundation for further study of decline and discontinuance of technology, an area in the marketing literature barely explored so far (see Chapters Two and Three).

1.3. Objective and Approach

The objective of this research is to apply proven techniques from the forecasting literature to a new problem, that of forecasting rapid technology decline; and to determine which provides the most accurate predictions, and if there are any possible universal patterns that might provide reusable knowledge for managers and academics.

Because forecasting decline has not been investigated in any substantial way, and little has been said about decline in the literature, the survey of the literature is wide-ranging. Within the literature exploration, the objective is to both synthesise what is a sparse literature on decline and to identify suitable forecast methods, and approaches to their application to decline forecasting. Intrinsic in that approach will be both an identification of gaps in the literature, and the relative strength and weakness of theory to explain decline. This thesis is driven by a an empirical generalist's framed approach, that is, "Empirical then Theoretical" (Ehrenberg, 1994), thus the literature review is broad but developed in depth only to the extent required to support the chosen forecasting method approaches.

The theme throughout this thesis is one of applying simple understandable methods validated in the forecasting literature, as discussed in Chapter Five, to the problem of forecasting demand for superseded technologies. An important assumption is that enabling better forecasting of the decline of technologies, will improve managers' capability to make decisions with confidence in situations of rapid technology decline. Accordingly, the following research questions have been formulated.

1.4. Research Questions:

Can decline trajectories be forecast using validated forecasting methods? Specifically:

- Of the approaches chosen, which provides the most accurate forecasts?
- What are the unique considerations of technique required to forecast decline trajectories?
- What potentially generalizable patterns exist?

Another substantial issue but secondary to the primary questions above is:

- To what extent does the choice of forecasting error measures affect our understanding of the performance of the chosen methods, in decline situations?

1.5. Structure of this Thesis

The balance of this thesis consist of nine chapters. Chapters Two through Four review the literatures on diffusion and discontinuance, while Chapter Five reviews the relevant forecasting literature. Chapter Six explains the choice of forecasting methods for the three studies described in this thesis. Chapters Seven, Eight, and Nine describe the three studies and their findings, and Chapter Ten provides a summary and conclusions.

Readers interested in a high-level summary of the literature findings and the outcomes of the three studies described above are directed to Chapter Ten. Included in Chapter Ten is a discussion of the effects on forecast accuracy from method choice, measures used, and from the judgmental study, the impacts of data presentation format. I draw conclusions about the relative performance of the different forecasting methods and about other influences on forecast accuracy. This chapter concludes with a discussion of the implications and limitations of the research, as well as suggestions for further research.

Chapter Two: Technology Diffusion Theory

2.1. Introduction

The substitution of a new technology with perceived superior utility for an older technology is the predominant paradigm in contemporary diffusion theory. Rogers provides the most frequently used definition of technology diffusion;

> *"Diffusion is the process by which an innovation is conveyed to a social group, through certain channels over time"*
>
> (Rogers, 1995, p. 5)

However, because Rogers' definition uses the expression 'convey' indicating a communication focus rather than adoption focus, the definition used in this thesis is adapted from Katz, Levin, and Hamilton (1963, p. 240) to explicitly recognise the role of adopters:

> *Diffusion is the acceptance over time of some specific technology, by individuals, groups, or other adopting units, in a social structure.*

When technologies are introduced into a market, initially they diffuse slowly, then accelerate (if successful), at near exponential rates, later slowing down as a ceiling is reached (Modis, 2002; Rogers, 1962). This S-shaped trajectory formed by the summation over time of individual adoptions, is similar in form; across consumers (Gatignon & Robertson, 1985); inside and between firms (Bass, 1969; Mansfield, 1963; Norton & Bass, 1992); and inside and between countries (Soete & Turner, 1984).

Once an innovation is introduced, how fast does it *diffuse*? What determines the speed of diffusion? These two questions were posed by Edwin Mansfield in the opening paragraph of his famous article in *Econometrica* on technology diffusion (Mansfield, 1961). The answers lie in the bell shape curve of individual adoption behaviour *the rate of adoption curve,* and the S-curve of *cumulative adoption,* described in detail later in this chapter.

The usefulness of the S-curve in describing diffusion is supported by both observation and a sustaining theoretical explanation. The theoretical models are based on analogies from other phenomena such as biological growth, social communication networks, and spread of epidemics in a population. It is commonly observed that technology grows to saturation in a market, similar to the way biological growth follows an S-shaped trajectory (Griliches, 1957; Rogers, 1962). This S-curve is demonstrated in populations as they grow to the maximum carrying capacity of their environment (Pearl, 1927) and in the growth of individual animals and plants as they grow to their genetic potential (Woolston, 1929).

The growth of epidemics in populations provides an alternative platform of understanding for the modelling of diffusion (Karshenas & Stoneman, 1993) and underpins the most famous of the marketing science models, the Bass model. Marketing science models are described in Chapter Three: A second theme that of social communication network theory, and its explanation of the spread of ideas in a society, is also fundamental to the description of diffusion (Granovetter, 1973; Simmel, 1955a; Tarde, 1903).

Diffusion theory from the marketing perspective is discussed in Section 2.2, along with the origins of the theory in section 2.2.1. Roger's theories on adoption by market players, and how this accumulates by information diffusion across a market is described in section 2.2.2, along the way the linkages to contemporary marketing theory are signposted. Sections 2.2.3 to 2.2.4, discuss the literature on determinants of adoption. Section 2.2.5 covers substitution, while section 2.2.6 discusses the extent to which S-curves are seen as empirical generalisations. Finally, section 2.3 explores potential weaknesses in the current diffusion theory, with particular focus on discontinuance. First, the concepts behind mainstream diffusion theory are surveyed.

2.2. Diffusion Theory

In social science, the meaning of diffusion is embedded in the concept of the communication of an idea within and between social groups over time (Katz et al., 1963; Rogers, 1962). Diffusion theory's importance to marketers is grounded in Rogers' five stage explanation of how customers undertake adoption, from the first step of acquiring knowledge, through persuasion, decision, implementation, and finally to confirmation (Rogers, 1976), and the way it sits with the theory of planned behaviour (Ajzen, 1985). Critically important at the individual adoption level is Rogers' determinants of; *suitability, compatibility*, *complexity*, *trialability*, and *observability* which assist marketers in defining the suitability of their products. Likewise the way which advertising and word-of-mouth affects product acceptance is very important in the way marketing communication strategies are developed (Arndt, 1967; Dodson & Muller, 1978), and Rogers' innovativeness categories assist understanding the type of groups that buy products and the sequence in which they purchase relative to others (Martinez, Polo, & Flavian, 1998). Within marketing practice; developing new products, evaluating them and the profiling of target markets are all dependent on diffusion theory (Baker & Saren, 2016), but also the steady state management of products to lengthen a product's life relies on those same concepts. Rogers' theories on diffusion are deeply integrated into marketing principles. Similarly, the forecasting of product sales relies heavily on the models developed as a result of diffusion theory, the Bass model being a well-known example (Bass, 1969).

2.2.1. A brief history of technology diffusion and substitution theory

Innovation, adoption, and market diffusion theories grew out of rural and medical sociology studies from the U.S., in the 1920s and 1930s. Those studies were informed by the earlier work of Tarde (1903), but only in the 1940s did an integrated conceptual framework for technology diffusion start to emerge. The observation of S-curve diffusion growth in the study of the adoption of hybrid corn seed by farmers in three American states was a critical milestone in diffusion theory development (Griliches, 1957; Ryan & Gross, 1943, 1950). Griliches (1957) recognised the S-curve diffusion pattern, and Ryan and Gross (1943) published an integrated theory of technology adoption. Most current diffusion research is influenced by Rogers' model of innovation diffusion, popularised in his book "*Diffusion of Innovations" (renamed "Communication of Innovations"* for the 1971 2nd edition) (Rogers, 1962, 1983, 1995, 2003; Rogers & Shoemaker, 1971).

Rogers describes innovation diffusion as having five components: (1) a communication process, (2) about an innovation, (3) though certain channels, (4) across a social network, (5) over time. Rogers' theory synthesised ideas from many authors, in particular, the work of the early social network theorists Simmel (1955a) and Tarde (1903). Tarde observed diffusion as:

> *A slow advance in the beginning, followed by rapid and uniformly accelerated progress, followed again by progress that continues to slacken until it finally stops: These are the three ages of...invention.(that) if taken as a guide by the statistician and by the sociologists, would save many illusions*
>
> (Tarde, 1903, *p. 127).*

Tarde speculated that the level of interaction in a social group affected diffusion of an innovation and that the process of imitation was critical to the diffusion rate. He emphasised communication and social hierarchy in his model and saw an elite group who guided the initial uptake in society through a process of example and imitation (Kinnunen, 1996). He also observed that innovations have a geographic source and they ripple out and grow in a population following an S-curve. Tarde's hierarchical social model has a parallel in the later *two-step flow of communication* hypothesis, formulated by Lazarsfeld, Berelson, and Gaudet (1948), where information does not diffuse directly but rather via an opinion leader who influences others.

More recently, communication models have moved towards non-hierarchical and more networked model frameworks (Castells, 1996). However, the influence of opinion leaders is still seen as a critical element in the practice of marketing innovations (van Eck, Jager, & Leeflang, 2011). van Eck et al. (2011) found that opinion leaders increase the speed of the information stream and the adoption process itself, while also increasing the total adoption percentage. Simmel (1955b) developed a theory that there were ties that bind individuals together and define a group's membership, and that these ties and memberships influence social behaviour. Later Granovetter (1973) proposed the concept of *weak links* between groups as an explanation for how apparently diverse portions of a population start to adopt an innovation. Those independently developed theories all contribute towards an explanation of how the Tarde observation of S-curve diffusion might occur, and why Tarde's insights should be seen as fundamental to technology diffusion theories.

The study of biological growth, and epidemics furnished diffusion theory with mathematical models of diffusion; some of these models closely link to theory, for example, the epidemic based Bass model (Bass, 1969), and some provide only a mathematical fit to the phenomenon, for example the Gompertz (Winsor, 1932) and the biological based logistic (Pearl & Reed, 1920). These models are also described in Chapter 3. The foundation of biological growth theory is in the observation and mathematical modelling of S-curve biological growth. Biological growth model development started with the logistic functional form originally envisaged by Pierre François Verhulst in 1844-1845. Verhulst studied population growth, and applied the model to the growth of laboratory populations of microorganisms. This model was further developed and popularised by Reed and Pearl (1927). Pearl in particular, investigated a range of population growth situations and observed they universally followed an S-shaped or sigmoid curve (Pearl, 1925). Pearl's observations have been replicated literally thousands of times over the ensuing 90 years. These replications led to an acceptance of the Pearl logistic function in modelling applications as diverse as biology and biomathematics (Tjørve, 2003), demography (Wilson, 1994), technological adoption (Ryan & Gross, 1950), and chemistry (Reed & Berkson, 1929). As a result, these models, and their derivatives, including the Bass model became the stalwarts of marketing science diffusion modelling and forecasting, as described in Chapter Three.

2.2.2. Rogers and an integrated theory of diffusion

As noted above, the most accepted model describing technology diffusion is the Rogers (1962) model of innovation diffusion. This theory focus on an individual adopter or population of adopters and a single innovation or technology rather than on system-wide diffusion of multiple innovations. Rogers had been part of a rural sociology team researching diffusion of rural innovations, along with other early pioneers in the field, such as Griliches (1957) and Ryan and Goss (1943, 1950). As mentioned earlier he drew together the threads of observed biological growth, models of diffusion of technologies, along with the theories of diffusion of information, to form his own theoretical model. His model proposed that the rate of adoption follows a *normal distribution curve* and by inference, the accumulated adoption over time follows an S-curve (Rogers, 1962). Rogers' theory was represented in the form of this normal distribution:

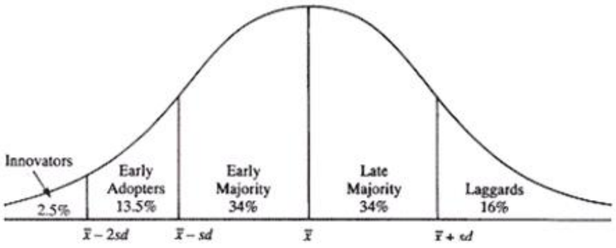


Figure 2. Rogers' diffusion rate model and adopter categories (Rogers, 1983, p. 247).

An important implication of the Rogers' adoption rate curve is the way in which the bell curve represents a chronological progression of the rate of adoption of the technology by individuals. The curve, if represented as a continuous distribution, has a probability density function of *X* with mean of (μ) and variance of (σ^2) as in Equation (1):

$$P_{x(-\infty\ to \infty)} = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-(x-\mu)^2/(2\sigma^2)} \tag{1}$$

Period by period, the accumulated individual adoptions over time presents as an S-curve as in Equation (2) and Figure 3:

$$F_x = \int_{-\infty}^{x} \frac{e^{x^2}/2}{\sqrt{2\pi}} \tag{2}$$

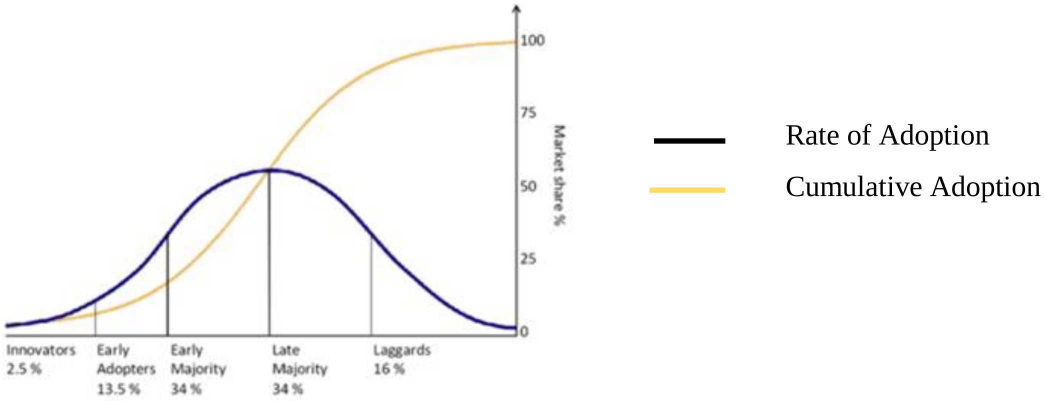


Figure 3. The relationship between rate of adoption and cumulative number of adoptions with time, adapted from (Rogers, 1983, p. 247).

This S-curve representing the accumulated adoption over time has been observed many times and documented initially by Griliches (1957), then Mansfield (1961), Davies (1979), and Gort and Klepper (1982). A primary inflection point exists where the adoption rate curve peaks; this corresponds to the steepest part of the cumulative adoption curve. An important finding is that in practice the typical distribution of adoption rate is often not a smooth bell shaped curve, while the accumulation of adopters in an S-curve is typically smoother as time period variations in adoption rate are absorbed into the accumulated form (Parker, 1994, p. 358).

Rogers’ diffusion theory says that diffusion occurs via the cumulative over time adoption of a specific technology by individuals as they each see value in the new technology. Rogers (2003, p. 177) defines adoption as “an individual decision to make full use of an innovation”. Rogers’ diffusion relies on the actions of five distinct psychographic groups of individuals – see Figure 3. His theory infers levels of *individual innovativeness,* where individuals who are in some way more innovative than others are, adopt earlier in the continuum of diffusion. Rogers derived these from the work categorising adopters by Ryan and Gross (1943). The first group to adopt represented only 2.5 percent of the adoption curve and are notionally those “early influencers” in Tarde’s theories, a category Rogers called *innovators*. Rogers also described four categories of *imitators* which he called *early adopters* (13.5 percent), *early majority, late majority* (both majorities 34 percent), and *laggards* (16 percent) (Rogers, 1958). Rogers' adopter classifications have proven somewhat controversial and are discussed later in this chapter.

His *innovators* are the first to adopt and are characterised by seeking out knowledge about an innovation, and by not being exposed to word-of-mouth. Like all subsequent adopter classes, they go through a five-stage process of individual adoption, a process with stages described as *awareness (or in later editions of his books - knowledge), interest (persuasion), evaluation (decision), trial (implementation), and adoption (confirmation)* (Rogers, 2003, p. 20). During this process, an individual might learn about the innovation, become interested in seeking more information, be persuaded of the value of the innovation, attempt to trial the use of the innovation, decide to adopt, and then implement that decision resulting in continued use.

Information comes to imitators in Rogers' theory from the technology stakeholders, be they owners, sellers, advocates, or earlier adopters. This information arrives as the result of marketing effort directed to the individual, via word-of-mouth and via active searching for information by the potential adopter. According to accepted theory (Rogers, 1962; Simmel, 1955a; Tarde, 1903), the communication of the experiences from those who have adopted already, affect those yet to adopt, and the process continues until few people for whom the technology would be useful and affordable are left who have not adopted. This theory description is critical in the understanding of causal models described in Chapter Five.

Adopters accumulate over time traversing three stages and the trajectory is an S-curve. Stage one is characterised by slow growth, as individuals for whom the technology would have high utility seek out knowledge and evaluate the technology with little word-of-mouth and little experience upon which to base a decision to adopt. If the product has general utility, then with time, the pool of people who know about the technology through personally adopting grows. After an initial period of slow growth, stage two is characterised by a rapid increase in the number of adopters at a nearly exponential rate, as information is shared and the perceived risk of adoption is reduced for those who observe others using the technology. Finally, the number of people who find the technology useful starts to dry up and the diffusion rate slows and becomes asymptotic to a ceiling. Frequently during this process, an earlier adopted technology is divested to make way for a newly adopted technology, through the process of substitution (Fisher & Pry, 1971). Substitution is discussed further in a later section of this chapter.

2.2.3. Factors determining adoption by individuals

Adoption determinants for individuals fall into one of two categories, individual utility, and network effects. In individual utility, the new technology is considered across many criteria on its relative merit compared with the incumbent technology in use. Rogers' (1962) *framework of perceived attributes* provides the most widely cited model for evaluating the utility of technology innovations. The framework characterises innovation as assessable by its:

- relative advantage over an incumbent technology;
- compatibility with the current infrastructure and user experiences;
- relative complexity, in terms of the need to learn new things to adopt the innovation;
- trial-ability prior to purchase;
- observability, which he saw as an interaction with our social networks as we observe the innovation in use

(Rogers, 2003, pp. 15-16; 219-233)

These five characteristics set two boundaries: the effort, and the risk of adoption.

Network effects have traditionally been considered as existing primarily in the *communication dimension*, and to a lesser extent in the *social pressure to adopt* dimension (Rogers & Shoemaker, 1971). In that tradition, social network effects drive social contagion of information about a new technological innovation, for example, in the Bass marketing science model, two modes of communication, that of an advertising effect direct from the innovations' makers and sponsors and a word of mouth effect from those who have experienced the advertising effect and the innovation itself. Increasingly however, communication and network effects are thought more complex than this. For example it is thought that the size of the user base has an important effect, by improving the utility of a technology for adopters as it grows (Z. Katona, Zubcsek, & Sarvary, 2011), in what Cronrath and Zock (2007) describe as *the infrastructure effect*. This concept has taken hold through the study of the adoption of networked technologies, where if there are choices of networked technologies, an adopter might choose a network based on the benefits of the scale of the technology network (*the critical mass effect*) (Cronrath & Zock, 2007; Majumdar & Venkataraman, 1998), and the number of individuals from their social group that already use that network (Cronrath & Zock, 2007; Van Slyke, Ilie, Lou, & Stafford, 2007).

There would appear to be a variant to this network effects concept where the ownership pool of a discrete technology such as mobile phones, tablets, or game consoles, drives complimentary products in a networked way. In this variant, the number of *apps* for a mobile operating system (platform) or games for a gaming platform relates to the size of the population of adopters of the products running that operating system. They form a social network of easily served customers, via the store selling apps for that product (Zhu & Iansiti, 2007). It is possible that the scale of the adopter base stimulates the growth of new apps in proportion to that installed base. In turn the availability of apps, itself a function of installed base of the operating system, might drive further adoption of that platform.

2.2.4. Factors determining adoption by firms

No discussion of technology adoption or discontinuance would be complete without an examination of the ways firms are affected by those processes, particularly given the limited understand of discontinuance in any context. While there is no attempt in this thesis to fill the theory gaps, a knowledge of current state set the scene for the methodological approaches discussed later. There is disagreement on what factors determine how firms adopt individually. Classical economic theory says that profit maximization motivates firms to seek out new technologies that perform better, and abandon older technologies in the process (Jevons, 1879, p. 289; Veblen, 1900). However increasingly, researchers think that this neoclassical theory does not explain how technological diffusion occurs. Rather, evolutionary theory appears to provide a more useful explanation (R. R. Nelson & Winter, 1982). The foundation of evolutionary theory is an analogy to biological competition (R. R. Nelson, 1987). Here, firms, which have adopted a new technology, may have a competitive advantage, in the same way a new species with an adaptation may have an advantage in an environment. In the literature on consumer adoption theory, utility is the primary determinant, however, in evolutionary theory, a different sort of external factor applies pressure on adoption and abandonment, one that is about survival, not just improved utility of a technology, or the maximisation of profit (R. R. Nelson, 1987).

In the evolutionary model, firms are driven to adopt new technology because of a potential or actual shrinkage of the addressable market for the outputs of their older technology. A firm under competitive pressure, is driven both by the functionally superior products entering the market as a result of the new technology held by competitors, and/or by the need to adopt a new technology to improve their financial performance on products that are still functionally viable choices for consumers (Osterman, 1994). Internally, a firm's adoption process and those of an individual can be described similarly, via the five-stage adoption process proposed by Rogers of *awareness, interest, evaluation, trial, and adoption*, via a process of acquisition of knowledge, through persuasion, decision, implementation, and finally to confirmation.

Adoption, or indeed divestment, of industrial technology by a firm is arguably harder, than the same actions for an individual, as industrial technology is often heavily integrated into a firm's process and thus difficult to divest. Moreover, integrating newer technology, which might not be compatible across all its interfaces, is often costly. This can result in resistance to adoption, hence creating the potential for a competitive risk from holding obsolete assets. Without foresight as to the competitiveness of those technologies, over time, firms are at great risk in the market place.

There are other determinants of adoption at the firm level: management's attitudes to risk (Blair & Romano, 1988), and the firm's ability to adapt current technology to meet the new threat. The ability to adapt existing technology is important to protect a firm's technology investments from obsolescence, but it runs the risk of making subsequent abandonment of the incumbent technology more difficult (Veblen, 1915). This obsolescence of technology is discussed across a range of literatures: including the impact of tax and depreciation (Stanback, 1969); the current technological capability of the firm (Santhanam & Hartono, 2003); and management's skills in managing technology assets (Khalil, 2000; Veblen, 1915).

In summary, contemporary diffusion theory as synthesised by Rogers is built on the process of individual adoption, while the adoption of products, services, and technology by firms is very important, and not addressed in that theory in any cohesive way. The same comment applies to discontinuance within firms, with the exception of some work to describe discontinuance theory in terms of integrated information systems, where the embeddedness of the technology in business process ensures that the progression of discontinuance is often bound to a complex process of change (Pollard, 2003; Recker, 2016). What this highlights is a need, when envisaging the use of models, that if their parameters have causal roots such as in the communication modes of the Bass model (Bass, 1969), (described later), then it is not realistic to extend those models into discontinuance for firms. Specifically, the parameters of the Bass model for example are those specified for individual adoption, not those of firms. Fortunately, because of the absence of data representing these determinants in most practical forecasting situations, even models with strong theoretic links to these determinants such as in the Bass Model tend to be used in a naïve fitted model way, rather, than use actual data about determinants in their estimation of phenomena, this sort of approach avoids issue of misspecification based on theoretical frameworks. Thus until we learn more about firms and the adoption process that characterises them, models should probably only be applied in a fitted model (naïve fitting) context.

2.2.5. The substitution of earlier technologies

As mentioned earlier, substitution theory suggests a continued battle between the old and the new technologies. The new technology arrives providing some sort of extra utility over the old technology and so drives users to purchase and use this new technology. The emergence of new technologies is at the expense of the abandonment of incumbent technology in the market (Fisher & Pry, 1971; Norton & Bass, 1987). Critical in conventional theory is that the new and the old compete for share from the beginning of the diffusion of the new technology. However, Foster postulated that the threat of substitution becomes salient at the point where the new technology's *performance S-curve* grows to exceed (intersects) with the older technology's performance curve (Foster, 1986) and an example is illustrated in Figure 5. Christensen (1997a) felt substitution might even occur in situations where consumers are already well served (over served) in the key performance aspects. His argument was that, having become well served overall by the old technology, they may adopt the new technology based on its performance in a dimension not part of the traditional feature and performance set of the technology category, and such a point might be below the performance curve of the earlier technology on its traditional performance dimension.

Adner (2002) established that this progression of substitution can be explained in terms of price and cost asymmetries, effectively the value of the features, and performance of the new technology is becomes superior to the older technology allowing diffusion to take off. Others have demonstrated that new technologies might incubate in one market (niche), and emerge in the broader local market as a threat when they achieve a threshold performance (Adner & Levinthal, 2001; Levinthal, 1998). Sometimes the trigger for adoption of a technology might be a shift in social preferences, that is, a social discontinuity that brings the features of the technology into line with the market (Tripsas, 2008). Not always mentioned but considered by some as important are "management capacity decisions related to product availability", availability is not generally considered a constant force (Jain, Mahajan, & Muller, 1991, p. 90). In this thesis the definition of substitution is:

A process where a technology or generation of product class is displaced by a more useful, newer, and (sometimes) more available candidate for the required use.

Figure 4 illustrates a typical example of substitution, showing how decline of the older fixed line telephone incumbent technology is linked, via substitution, to diffusion of an emerging superior mobile cellular technology. Here the incumbent technology falls rapidly in response to substitution through a point at 50 percent share where it loses dominance in the market. The fixed telephone series can be seen slowing to an asymptote at or near zero share and thus would over time trace the familiar S-curve.

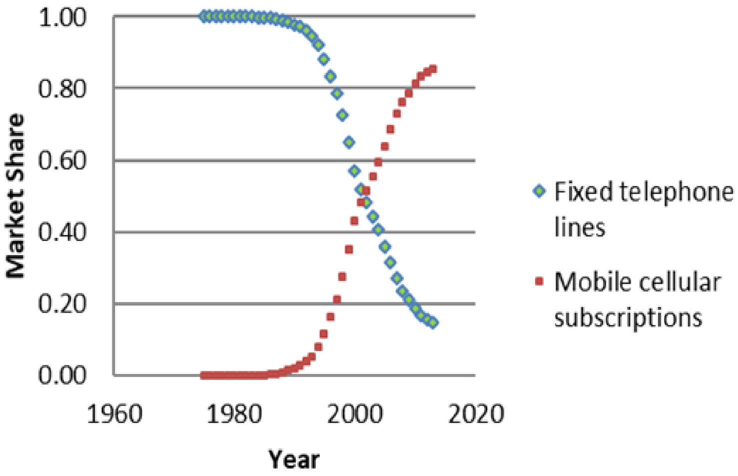


Figure 4. Global substitution of fixed telephone by mobile (International Telecommunications Union, 2013).

The substitution relationship is not always one for one, although Rogers does not mention this. Referring to Figure 4, we might expect more mobile phones adopted for every fixed line abandoned, given the size and make-up of households for example, illustrating a challenge to theory as substitution is not one for one. The performance of a technology frequently improves following an S-curve, before being substituted by a new technology that goes on to improve in the same way as illustrated in Figure 5. Christensen (1997b) observed that a new technology is introduced with lesser performance to the older technology, but with the promise of better performance, it then starts to diffuse as performance improves and acceptance and thus adoption takes off.

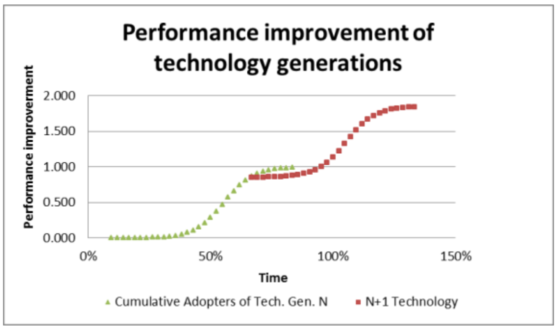


Figure 5. Performance improvement illustrated with synthetic data (MacRae, 2018b).

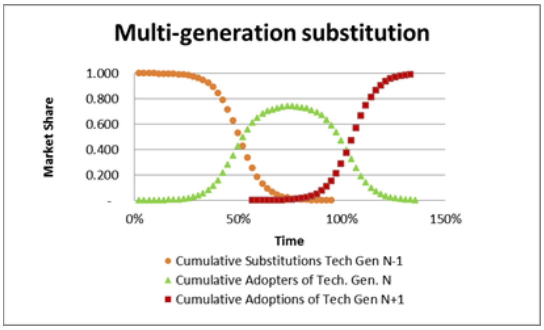


Figure 6. Multiple generation substitution illustrated with synthetic data (MacRae, 2018a).

Sometimes new technologies emerge so quickly that the older has not completely diffused into the market before it comes under substitution pressure as demonstrated in Figure 6. Here a third generation of a technology, or a good substitute, takes off before an earlier technology has reach a saturation point, although depending on the relative timing of the three diffusion trajectories, might still trace an S-curve.

2.2.6. Technology diffusion curves as empirical generalisations

Rogers' diffusion theory relies on accepting that technology diffusion always follows an S-curve, and some researchers believe that an empirical generalisation of this phenomenon does exist (Mahajan, Muller, & Bass, 1995a). Support for this empirical generalisation of S-curve diffusion pattern can be seen graphically in Parker (1994, p. 354, Fig. 1.), where the accumulated adoption (diffusion) curves of many technologies follow well-formed S-curves in almost every case. However, it is important to recognise that the coefficients of models describing the adoption rate curve or in its accumulation S-curve form are not always the same, even in apparently similar markets and with similar products (Massiani & Gohs, 2015). This ability for very similar looking curves to be described by very different specified models is important to the understanding of why modelling diffusion is such a challenge. Parker (1994, p. 358, Fig. 2.), illustrates the potential for variations in the adoption rate to skew or generate inconsistency to the bell curve in some way, even when the cumulative adoption is very clearly a uniform S-curve. Seasonal effects, word of mouth, and the nature of the innovation also affect the speed and shape of the adoption (Cho, Hwang, & Lee, 2012; Gatignon & Robertson, 1985; Mahajan, Muller, & Bass, 1990). Also, the effect of Schumpeter's business cycles (Schumpeter, 1939) over the longer term and competitive effects over the shorter term are thought to be important in the variability of diffusion rate from theoretical norms (Robertson & Gatignon, 1986).

2.3. Exploration of Selected Weaknesses in the Theory

Rogers' theory of technological diffusion is critical to the understanding of discontinuance and technological decline; however, the weaknesses in the theory are equally important, as they are in areas where decline links to diffusion theory. Hence, an awareness of these weaknesses is important in understanding decline from the firm's perspective.

2.3.1. The acceptance of the S-curve as universal

There are many hundreds of examples of the S-curve cumulative adoption (diffusion) curve, but there are situations when this pattern does not occur. Often but not always this is because of the arrival of a better technology which draws away potential adopters, or current users before a saturation level is reached. Sometimes diffusion is impacted by significant local or global events, such as world wars, which alter the diffusion of many things. For example from World War Two for about 10 years the US armed forces purchased vast quantities of non-filter cigarettes delaying decline by about 15 years and altering the pattern of diffusion for filter cigarettes in the US market (Maxwell, 1994).

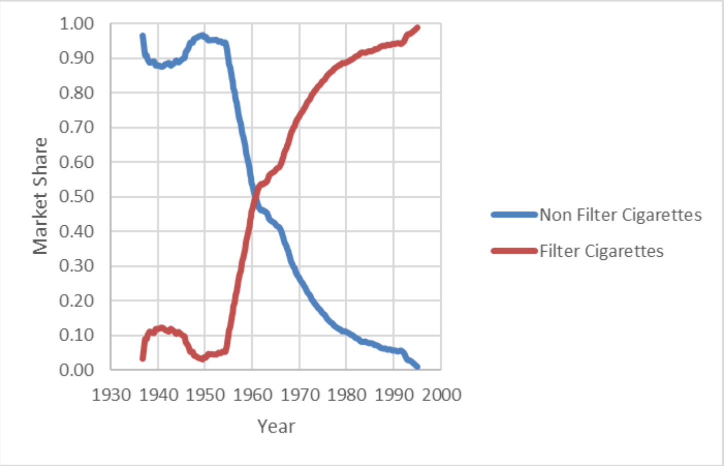


Figure 7. Influence of US war department purchases on sales of nonfilter cigarettes.

Sometimes the defensive surge of an incumbent technology delays the diffusion of the newer technology, the so-called *sailing ship effect* (De Liso & Filatrella, 2008; Howells, 2002; Mendonça, 2013) where rapid advances in sailing ship hulls and sailing rigs, allowed the sailing ships to serve bulk commodities. The tea clippers, for example, kept steam ships at bay for decades (Howells, 2002; Mendonça, 2013). It is also thought that potential sample selection bias in the use of historical cases might exist, giving the impression that the S-curve is universal (Dattee, 2007; Green, 2014), although there seems little empirical evidence to support or refute this argument.

2.3.2. Rogers' theory on adopter types

Rogers' five distinct adopter groups has been criticised at a theoretical level for being a tautology, at least in terms of the ability to attribute individuals to identifiable groups (M. J. Wright & Charlett, 1995). This criticism extends to the application of the theory in marketing practice due to the observed difficulty in identifying innovativeness (Cho et al., 2012; Goldsmith & Reinecke Flynn, 1992). The difficulty in identifying innovativeness in consumers is reviewed in Roehrich (2004). At the same time, it is clear that the first adopters of an innovation are different from those that are last to adopt, in ways that causes them to adopt at different times. What is not clear is if the determining factors are from their environmental exposure, or from their predilection to adopt, or from the psychographic innovation factor of Rogers' theory. For example, Stern and Wright (2016) demonstrated that in drug prescribing, the determinant of early prescribing was the *prescribing rate prior to introduction*, perhaps indicating that *heavy users seek better solutions*, as often hypothesised in the technology innovation literature (Von Hippel, 1986).

2.3.3. Assumes "full use" not limited adoption

As mentioned earlier, Rogers (2003, p. 177) defines adoption as "an individual decision to make full use of an innovation". Rogers excludes situations where people take up the use of an innovation, but not exclusively. A very good example is the non-exclusive adoption of the use of microwave ovens, today most households have a microwave oven, but then most of these households also have some kind of conventional oven. Using Rogers' definition, one would see only a small number of adopters meeting the criteria of true adopters, those that took on the use of a microwave oven and abandoned the use of conventional cooking technology. Given that this definition limits the application range of the Rogers defined term, for the purposes of this thesis, adoption is defined as:

> *A decision to go on to use the innovation for the majority of the tasks for which it was designed to be used.*

2.3.4. Technologies compete from the start

There is some evidence that competition does not always start until later in the diffusion process and that the earliest use is often because of new capability in the new technology rather than an improvement in performance factor, or where a minor capability of the older technology has been achieved more effectively by the new technology. Take the emergence of the motor car for example, which is thought of as a direct substitution of horses as transport (Grübler, 2003; Nakicenovic, 1986). However, the first motor cars were in a narrow niche of appeal around both touring (from which the word tourist comes) and motor racing. The cars' initial niches were in pleasure and excitement: niches previously only partially served by horses. Meanwhile, electric trams, trains, and bicycles were very much more influential in the decline of the use of horses which were at the time seen as the primary transport alternatives (Geels, 2005).

Scholars have tended in the past to think of new technology as having a uniform purpose across all those that adopt it, and that this utility was the same from the first adoption through the full diffusion trajectory. However, there is some thought that new technologies often first diffuse into niches, then upon dominating those early niches, grow to fill larger mainstream market opportunities as described by Levinthal (Adner & Levinthal, 2001; Levinthal, 1998). For example, the availability of maps and navigation software resulted in stand-alone single purpose geographic positioning systems (GPS) devices serving hikers, surveyors, and the military, however, these niches filled quickly, and via software on smart phones, this technology entered a new niche, that of motorists needing to find destinations. The concept of *path dependence* in diffusion incorporates this important role of the niches served by competing technologies (W. B. Arthur, 1988; David, 1985). Significantly, this multiple niche concept undermines the classical diffusion concept of a single pair of technologies competing from the start over a single market need.

2.3.5. There are early and late fluctuations from the expected pattern

There are fluctuations in the data describing diffusion trajectories at the point established technologies reach a peak. This behaviour is predicted by model theory where it is seen as an equilibrium seeking stage (Peitgen & Richter, 1986) in Modis (2002), and as a chaos stage by others. Modis (2002, p. 238) had observed random fluctuating sales at the beginning of diffusion and at the end. This has been demonstrated in a study of a saturated plywood market (Montrey & Utterback, 1990). It seems reasonable to assume that this might also occur in the substituted technology (Modis & Debecker, 1992). Why this occurs is not clear. Is this the result of competitive responses of the incumbent technology? There appears to be no evidence as to the cause, or as to the regularity of the pattern (Modis, 2002), although the *sailing ship effect* has been postulated by some as a possible reason (De Liso & Filatrella, 2008; Howells, 2002; Mendonça, 2013).

2.3.6. There is only one technology competitor

Conventional thinking on substitution assumes that one technology directly substitutes for another, and that there is a very direct link between the rise of use of a new technology and a fall-off in an incumbent older technology’s use (Dosi, 1982). This sense is reinforced by the practice of treating sales as a portion of a market, which is the sum of the older and newer technologies’ market shares. Such practices bring the risk of biasing thinking towards the impact of a single emerging technology, whereas there might well be many emerging technologies, as Amankwah-Amoah (2016) demonstrated in a study of the technologies current during the decline of the floppy disc. This bias towards the idea of single competing pairs of technologies might tend to divert focus from the decline of the incumbent technology, particularly in the early diffusion phases. Additionally, the common practices of representing data in an aggregated form where many similar technologies are considered part of a generation, tends to mask that intermediate or alternative technologies existed, and that they were a substantial part of the process of substitution in the earlier stages of substitution. This illustrates the need for care when collecting data to avoid miscategorising multiple generations of technologies.

2.4. Summary and Conclusions

Although illustrating important weaknesses in diffusion and substitution theory, this thesis is structured to avoid the impact of many of the issues, by focusing only on data for the mature dominant technology presented as a share of all technologies in the market. Hence, the impacts of early diffusion of multiple technologies and multiple niches are subsumed into the aggregated data of the declining dominant incumbent technology. The reason this approach is taken is that as mentioned earlier, the focus and the resources of managers is on technology that are incorporated in their products or are intrinsic in the delivery of their products or services. These weaknesses in the diffusion theory build a case for the focus on decline being forecast exclusively from the decline data, rather than in conjunction with the diffusion generations as proposed by models such as the Norton and Bass (1987) model. The consequence of this approach is the relegation of the diffusion data to an indicator role. Chapter Four introduces discontinuance and decline, both in the practical sense of their implications in the market place and in terms of the links into the established diffusion theory. The concepts that differentiate discontinuance and decline from diffusion theory as currently described by Rodgers are explored. No attempt is made here to develop new theory that more clearly links discontinuance into current diffusion theory. The modelling of diffusion trajectories is a critical part of the diffusion and substitution story. The use of fitted models for forecasting originates in the modelling of diffusion for explanatory purposes, and helps with the understanding of discontinuance, so is covered in the next chapter.

Chapter Three: Fitting Diffusion Models in Management and Marketing

3.1. Introduction

Diffusion models are typically but not always, simulate the S-curve of cumulative adoption of durable technology product formats, rather than the rate of adoption's bell curve. Mahajan and Peterson (1985), frame diffusion models with three classifications:

- Fundamental diffusion models (internal, external and mixed influence);
- Flexible inflection point diffusion models;
- Refinements and extensions, sub-categorized as:
    - Dynamic ceiling diffusion models
    - Multi innovation diffusion models
    - Space (and time) diffusion models
    - Multistage process diffusion models
    - Multi adoption (repeat purchase or sales) models
    - Diffusion models with coefficients as a function of technology specific environmental parameters.

This thesis focuses on exploring technology decline an area where these models have been tested only rarely, if ever. Thus, there are two important assumptions underlying model choice. First, that those simple fundamental models are a good starting point for investigation, because they most closely link to the simple diffusion analogies described in Chapter Two. Second, that many of the later models are attempts to provide improved fit to diffusion growth, and may be so specific to growth situations that they might be incorrectly specified when fitted to decline data. Another influence is the need for a strong focus on parsimony because of the short length of typical series and the risk of overfitting that would result from more complex models. This is a classic situation when Occam's Razer applies (Blumer, Ehrenfeucht, Haussler, & Warmuth, 1987). It is also likely that simple models have less variance at the expense of bias and are a sound starting point in any context (Brighton & Gigerenzer, 2015) This chapter reviews only those simple fundamental models; others provide a review of a broader range of models (see Bridges, Coughlan, & Kalish, 1991; Mahajan et al., 1990; Mahajan, Muller, & Wind, 2000; Meade & Islam, 2006; Peres, Muller, & Mahajan, 2010).

While the analogy of biological growth of individuals and populations appears to be the most commonly used framework to describe diffusion, the concept of an epidemic growing is the starting point of most model developments (Geroski, 2000). Therefore, all the models reviewed assume single purchase (adoption), and have an epidemic growth mechanism. At the upper limit of complexity, the original Norton and Bass (1987) multigenerational substitution model is explained. The Norton and Bass model helps us understand why multi-generational effects in data are so critical when data series are selected and cleaned as is done in Chapter Six, but this model is also included so that the impact of multiple pathways to discontinuance can be discussed.

Only a small number of the many diffusion models have been applied effectively to forecasting tasks, and many published models are rarely used, thus providing little understanding of their forecast performance, and what determines that performance (Armstrong, Brodie, & McIntyre, 1987; Meade & Islam, 2001). Additionally, models appear to provide inconsistent results across any selection of situations presented to them, resulting in there being no universally accepted diffusion model (Cetron & Ralph, 1971; Newell, Genschel, & Zhang, 2014; M. R. Young, 1993). While S-curve diffusion models are typically used in the cumulative form, they are explained in the adoption rate (differential) form as it helps understanding of their behaviour. The customary differential equation that describes the rate of change of adoption is Equation (3):

$$\frac{dY_{(t)}}{d_{(t)}} = (bY_{(t)})(L - Y_{(t)}) \tag{3}$$

Where $Y_{(t)}$ is penetration at time (t), "L" is the maximum expected adoption level and "b" is a coefficient describing the diffusion speed.

In this differential equation, adoption rate is proportional to the population that has already been adopted, represented by the residual market potential denoted by (L - $Y_{(t)}$). However, in prediction, the functions are typically used in a cumulative form as a function of time where (as a simple logistic) diffusion ($Y_{(t)}$) at a given time can be expressed as Equation (4):

$$Y_{(t)} = \frac{L}{1 + e^{-(a+bt)}} \tag{4}$$

Where: "t" is time, "a" reflects the speed of adoption, "b" is a constant of integration that positions the curve on the time scale, and "L" is the long-run outcome, ceiling or asymptote, "e" is Euler's Number (2.7183)

While, the coefficients "L", "a", and "b" can be estimated via market surveys, management judgments, or analogous models (for examples see: Heeler & Hustad, 1980; Mesak & Mikhail, 1988; Oliver, 1987; Souder & Quaddus, 1982), in practice, access to independent observations of parameter measures of the model coefficients is uncommon, or difficult. Thus, it is very common to create the model by fitting the model to data for the variable of interest, that data is generally the only type of data available for historical diffusion series. Consequently, in this investigation, any approach selected will use data from the variable of interest only. The next section starts a review of the diffusion forecasting task context and the following sections describe the marketing science models and methods used in diffusion forecasting.

3.2. Background

Diffusion forecasting is undertaken primarily with marketing science models that trace out an S-curve when suitably specified in their parameters. Many of them as discussed in Chapter Two are based on the Pearl logistic functional form of Equation (5).

$$Y_{(t)} = \frac{L}{1 + e^{-(a+bt)}} \tag{5}$$

These models are used to estimate future values of a historic data series after being fitted to any available historic data. In diffusion forecasting, the historic data available is often from series sampled only annually, and thus have few data points available to estimate parameters through model fitting. This restricts the types of models that can be utilised in modelling or forecasting to those simple models with few parameters. Just like in growth forecasting, in decline forecasting the forecaster is reliant on the extent of the series' progression and the sampling rate of the data. Working with this early data creates two problems for the forecaster. First, discovering if this is truly a decline phase rather than just a variation in an existing trend: a question that can only be answered by determining if the characteristic monotonic decline has started. Second, the difficulty of determining suitable coefficient values for a model's parameters, given the lack of data points in a typical diffusion series (Goodwin, Dyussekeneva, & Meeran, 2013). Because of the limited data points available for the variable of interest, functional forms need to be simple as to fit those data (Mulaik, 1998) and provide stable parameter estimates (Joo & Jun, 1996; Meade & Islam, 1998; Tigert & Farivar, 1981). Another issue is that with decline data, as with diffusion data, related environmental factor data suitable to derive parameters is unlikely to exist, and can constrain the development of a suitable causal model.

One important aspect of forecasting diffusion, and consequently forecasting decline, is establishing when the variable of interest is entering a period of sustained single direction movement, in the case of decline, that is when monotonic decline is indeed underway. With diffusion data, there is typically marketing activity directed at the diffusing technology thereby providing a direct signal of that initial growth. With declining technology, there is no such directed activity to observe, thus forecasters are more reliant on observing the change directly in the data for the target variable. Managers might use the data from the new diffusing technology that has the potential to stimulate a decline, as a leading indicator. The pre-warning aspect of the forecast process is not part of this study; rather, it focuses on identifying monotonic decline in the target data series and predicting forward from that decline. The next sections describe the foundational marketing science (diffusion) models using in diffusion forecasting.

3.3. The Foundational Models

Zvi Griliches (1957) was possibly the first to model technology diffusion with an S-curve function. Griliches studied lags in the development of adapted corn hybrids for specific climatic zones within Ohio and the delay in the entry of producers of the localised hybrids into these areas. Fitting data for different areas with the Pearl logistic growth function, he observed the differences between areas in his estimates of the coefficients of that logistic function. That is, variation in the origin, the slope, and the ceiling (upper asymptotic limit). When looking at differences in the origins (the start points) of the data for the different areas, he believed the differences were explained by different profitability of entry, market density, innovation, and marketing cost. Similarly, he concluded that differences in the long-term saturation usage level (the ceiling) and in the slopes of the growth to that ceiling could be explained, in part, by variation in profitability of adoption in those zones.

Griliches started with the cumulative logistic function, Equation (6) as follows:

$$Y_{(t)} = \frac{L}{1 + e^{-(a+bt)}} \tag{6}$$

Where: $Y_{(t)}$ is the percentage planted in hybrid corn at time t, $L$is the ceiling or equilibrium penetration of the hybrid, and a is a constant of integration that positions the curve on the time scale, while b is the rate of growth coefficient.

He transformed the S-curve growth data to a linear function of a and b, in Equation (7):

$$a + bt = log\, e\, [\frac{Y_{(t)}}{L - Y_{(t)}}] \tag{7}$$

He then took a linear weighted least squares regression, and estimated the value of L by plotting the data on log paper while varying values of L until the resulting graph approximated a straight line. At the time, this method was the easiest as it avoided exhaustive iterative estimation and highlighted visually any gross deviation from the logistic form. It was the standard method for many years. He chose to use the Pearl logistic function more for convenience rather than any inference of perfection of fit and saw its role as a summariser or descriptive vehicle for his results, rather than for its potential as a predictive tool. Rather than use this transform, today one might use software to iterate in estimating a and b.

Griliches (1957, p. 504) discarded the first 5 percent (left truncating) and last 5 percent (right truncating) of the diffusion data on the basis that it should be considered as having very high percentage errors and would have lightweight importance in "any reasonable weighting scheme". This trimming was to become common practice over time (Fisher & Pry, 1971; Lenz & Lanford, 1972). However, because the left truncating of data in this manner can cause bias effects, some authors recommend against this trimming (Jiang, Bass, & Bass, 2006).

Most diffusion models are derived from the cumulative logistic functional form. In logistic curve growth, the change in share per time-period at any given time-period will be proportional to the penetration to date, the percentage left, and a parameter that manages the shape of the curve. In differential form, this is expressed as Equation (8):

$$\frac{dY_{(t)}}{d_{(t)}} = \left(bY_{(t)}\right)(1 - Y_{(t)}) \tag{8}$$

In that form, there is no time frame defining when growth starts, and for how long growth takes place. By integrating the equation with respect to a new parameter a, that is defined as the time when $Y_{(t)}$ = 50 percent of share, then it is possible to develop a number of cumulative closed solutions of the logistic differential equation. The most common expression of this function being, the following three-parameter cumulative form in Equation (9), attributed to Pearl and Reed (1923);

$$Y_{(t)} = \frac{L}{1 + ae^{-bt}} \tag{9}$$

Where L and a are positive constants, with L representing the upper limit asymptote, a representing the number of times the $Y_{(t=0)}$ value needs to grow to reach L. The parameter b represents the rate and direction of the growth with a positive value indicating growth and a negative value decline. Of course, with manipulation this function can look different for example, equations (10) and (11):

$$Y_{(t)} = \frac{L}{1 + e^{-(a+bt)}} \tag{10}$$

Or

$$Y_{(t)} = \frac{L}{1 + e^{(a-bt)}} \tag{11}$$

Both Equations (10) and (11) are described as the Mansfield-Blackman function (Blackman, 1971b; Mansfield, 1961), and are the form used by Griliches. The literature often describes these models by the authors' name, inferring they are different from other forms, despite, if given the same data, and fitted similarly, the forecasts generated would be similar for all four forms.

A number of characteristics of the logistic function are important. First, it is a simple function and summarizes the technology diffusion process in only three factors (L, a, and b). All these formulations of the logistic have the advantage that, given share data normalised to a peak share of 100 percent, L the saturation value (the market size) need not be known, nor considered.

Second, a special feature of these logistic forms is that they have an inflection point at 50 percent of the L value and rotationally symmetrical on its point of inflection, the point of inflection on the y-axis occurs at a point where:

$$Y_{(t)} = \frac{L}{2}$$

, and:

$$t = \frac{-b}{a}$$

Additionally, the logistic is asymptotic to zero when t goes to negative infinity and asymptotic to L when t goes to positive infinity, providing an intuitive sense of a floor and a ceiling at the two asymptotes. As a commonly used symmetrical model of great simplicity, the logistic is a natural candidate for selection in this study.

3.3.1. The logistic model is inexplicably popular

Why these logistic functional forms are so popular is not clear, because as Pearl and Reed (1920) cited in Vieira and Hoffmann (1977) observed, the Pearl logistic' symmetric growth rate is not universally present in growth processes, that is, the inflection point in actual data is frequently much earlier than 0.5. The Pearl logistic does have slightly slower decline in the tail regions (thicker tails) than the well-known normal distribution, but there is no recorded reason in the literature why that would make it more suitable than the better-known normal distribution. There does not seem to be a theoretical reason other than the analogy to biological growth, for which it was initially conceived. Perhaps it is just that the mathematical form of the Pearl logistic is easier to manipulate than other distributions. The symmetrical property of the simple logistic has been criticised as not suitable for diffusion (Chow, 1967; Dixon, 1980). Dixon (1980) suggests that diffusion processes often exhibit growth rates that are higher at an early stage and show a left skew overall growth rate. Bain (1964) in a study on the diffusion of television sets also noted, that diffusion was not symmetric but biased to early growth. The choice of both Chow (1967) and (Dixon) was the Gompertz function because it has a left skewed growth rate.

3.3.2. Gompertz model

The Gompertz function named after Benjamin Gompertz, an English mathematician and actuary who developed it as a law of mortality (Gompertz, 1825), is another very commonly used functional form. The validity of the Gompertz function as a growth curve model has been mathematically rationalised by Winsor (1932), and initially demonstrated in diffusion growth by M. R. Young (1993). As a differential equation (12), the Gompertz is:

$$\frac{dY_{(t)}}{d_{(t)}} = \left(bY_{(t)}\right)ln(\frac{1}{Y_{(t)}}) \tag{12}$$

Although, the Gompertz is typically formulated as a three-parameter cumulative function, Equation (13).

$$Y_{(t)} = Le^{-ae^{-bt}} \tag{13}$$

Where *L* is again the upper asymptote, *b* and *a* are positive, with *b* setting the displacement along the x axis, and *a* setting the growth rate on the y axis, and *e* is Euler's Number (2.7183)

Of course, this functional form can be manipulated and is often seen in the following form of Equation (14):

$$Y_{(t)} = Le^{-e^{a-bt}} \tag{14}$$

The Gompertz has an inflection point fixed like the Pearl logistic but at about 36.8 percent of the ceiling asymptote with corresponding higher rate of change before that point, that is, the right hand (ceiling) asymptote of the curve is approached more gradually than the left-hand (floor) asymptote (Winsor, 1932). The point of inflection on the y-axis occurs when:

$$y = \frac{L}{e}$$

When fitting to and predicting from data that tends to grow very fast initially, rather than growing and declining symmetrically, this model's earlier inflection point will make a better fit to that early data. This model's asymmetry, along with common usage of this functional form, determined its consideration for selection in this study.

3.3.3. An internal, external and mixed influence model perspective

Around the same time as Rogers published his theories (1962), two important papers were also published: that of Fourt and Woodlock (1960) who described a mathematical model of new repeat purchases, based primarily on the influence of the (external) mass media; and Mansfield (1961) who described a mathematical model of technology diffusion but driven primarily by (internal) word-of-mouth. Rather than the discrete exponential form of

Equation (10) cited earlier, both Mansfield, and Fourt and Woodlock use the differential form of the Pearl logistic in Equation (15):

$$\frac{dY_{(t)}}{d_{(t)}} = g_{(t)}\left(L - Y_{(t)}\right) \tag{15}$$

Where $Y_{(t)}$ represents the cumulative number of adopters at time *(t)*, L is the ceiling or ultimate potential number of adopters, and $g_{(t)}$ is a coefficient of the rate of diffusion. The differential form is frequently used in diffusion modelling perhaps because it makes the relationship between parameters easier to express. From this generic differential form, the coefficient of diffusion $g_{(t)}$ can be re-formulated to provide three types of models:

- An external influence model where the coefficient of diffusion $g_{(t)}$ is a constant, for example (p)
- An internal influence model where the coefficient of diffusion $g_{(t)}$ is a product of a constant, for example q times $N_{(t)}$
- A mixed influence model that incorporates both forms to create a coefficient of diffusion $g_{(t)}$p+q$N_{(t)}$

The first of these model types, an external influence model, is best illustrated by the Fourt and Woodlock (1960) formulation in Equation (16):

$$\frac{dY_{(t)}}{d_{(t)}} = p\left(L - Y_{(t)}\right) \tag{16}$$

Here the external influence coefficient p is called the coefficient of innovation. This model is applicable when communication is direct from an agent of the technology to the adopter via formal rather than word-of-mouth communication. Such models are sometimes called pure innovation models, because their function is derived from a theoretic pure innovation function. This model can be expressed as the negative exponential Equation (17):

$$S_{(t)} = Le^{-pt} \tag{17}$$

Where S is the rate of diffusion at any period (t), L is the ceiling on potential adopters, and p is the coefficient of innovation.

The most notable of the internal influence models, frequently called purely imitative models, is that proposed by Mansfield (1963), which when expressed as a differential equation is Equation (18):

$$\frac{dY_{(t)}}{d_{(t)}} = qY_{(t)}\left(L - Y_{(t)}\right) \tag{18}$$

Where q is the coefficient of imitation, $Y_{(t)}$ is the penetration level at time (t), and L is the market potential.

In the internal influenced model, the constant q reflects the interaction of prior adopters with yet to be adopters. It is characterised as the coefficient of imitation, or sometimes as the coefficient of word-of-mouth. An internal influence model is considered useful where the social system is homogenous and closely linked, and there is a need for legitimizing information.

3.3.4. The mixed influence Bass model

Frank Bass (1969) was one of the first to embrace Rogers' theoretic foundation to develop a quantitative model of diffusion. His model proposed Rogers' classes of adopters be limited to two classes by collapsing the last four classes of Rogers' adoption classification into one, yielding two classes, innovators and imitators. Bass described innovators as independent choosers of product with no ability to be influenced and imitators as relying on social pressure from those that have already chosen, to adopt to guide their adoption.

Combining the concept of external mass media (advertising and news) communication and word-of-mouth into a single simplified model, the primary mechanism in Bass' model is word-of-mouth from existing customers. However, it is the actions of earlier adopters, who get their information from outside, which starts the process by seeding the market with their purchases, experiences, and word-of-mouth. These early adopters are adopting based on external information via a coefficient of innovation (sometimes referred to as the coefficient of promotion or advertising). Conversely, word-of-mouth drives the imitators to adopt in Bass's model and is described by a coefficient of imitation. The two classes in Bass's model are different from Rogers' classes in that they are defined post-hoc by the source of their information not defined prior by their psychographic or demographic profile as inferred in Rogers' model, however the conceptual theory of innovators and imitators is consistent across Rogers' theory and the Bass model.

The Bass model is a mixed influence model and merges intrinsically internal influences with external influencing factors. This is a model where both a p and a q influence exist. In differential equation form, this model is expressed as Equation (19):

$$\frac{dY_{(t)}}{d(t)} = \left[p + \frac{q}{L}Y_{(t)}\right]\left(L - Y_{(t)}\right), \tag{19}$$

Assuming that the ceiling is constant, then integrating this equation gives us Equation (20) a cumulative function for adopters ($Y_{(t)}$ at time (t)):

$$Y_{(t)} = \frac{l - \frac{p(l-Y)}{p + \frac{q}{L}Y} e^{-(p+q)t}}{1 + \frac{\frac{q}{L}(L-Y)}{p + \frac{q}{L}Y} e^{-(p+q)t}} \tag{20}$$

When the coefficient of innovation (p) is zero (a special case), Bass' mixed influence model becomes the differential form of the logistic in Equation (21):

$$\frac{dY_{(t)}}{d_{(t)}} = \left[\frac{q}{L}Y_{(t)}\right]\left(L - Y_{(t)}\right) \tag{21}$$

By integrating that equation, we get Equation (22) a cumulative form of the logistic:

$$Y_{(t)} = \frac{L}{1 + \frac{L-Y}{Yo} e^{-qt}} \tag{22}$$

This delivers a similar function to the Fisher and Pry, and Mansfield models (a purely imitative model). Likewise, in the special case where the coefficient of imitation q is zero, Bass' model defaults to the form of the Fourt and Woodlock model (a purely innovative model). There are various derivations of the above available (Bass, 2010; Mahajan & Peterson, 1985; Meade & Islam, 2001). In common with most popular models in diffusion, the Bass model assumes:

- There will be only L purchases of the product.
- They will all be initial or first purchases

There is evidence of the Bass model fitting historical data from different situations over numerous datasets (Heeler & Hustad, 1980). Heeler and Hustad (1980) observed such results were improved when external sources were used to estimate L; this is also the case with other simple diffusion models. They also thought that fluctuations early in the diffusion process are likely to produce unstable parameter estimates.

Like other diffusion models, the original Bass model can be expressed several ways. As a differential, in Equation (23).

$$\frac{dY_{(t)}}{d_{(t)}} = \left(a + bY_{(t)}\right)\left(p + qY_{(t)}\right)(1 - Y_{(t)}) \tag{23}$$

Although a more familiar form, is Equation (24):

$$\frac{dY_{(t)}}{d_{(t)}} = p\left(L - Y_{(t)}\right) + \frac{q}{L}Y_{(t)}(L - Y_{(t)}) \tag{24}$$

Where $Y_{(t)}$ is the cumulative number of adopters of a new product at time t, parameter $L > 0$ is the total market potential for the new product, and parameters $p > 0$ and $q \geq 0$ are the coefficients of innovation and imitation, respectively.

The adoption rate $\frac{dY_{(t)}}{d_{(t)}}$ is determined by two additive terms: the first term, $p\left(L - Y_{(t)}\right)$ represents adoptions due to innovators, whereas the second term, $\frac{q}{L}Y_{(t)}\left(L - Y_{(t)}\right)$, represents adoptions due to imitators. This model presents the adoption process as in continuous time. In practice, modelling takes place using observed discrete points in time, thus Bass (1969) suggests the following model, Equation (25):

$$Y_{(t)} = Y_{(t-1)} + p(l - Y_{t-1}) + \frac{q}{L}Y_{(t-1)}(L - Y_{(t-1)}) \tag{25}$$

The most useful and commonly recommended [as described in Meade and Islam (1995)] form for discrete time period modelling is the following cumulative form of Equation (26), solved from the differential equation above (sometimes called the *extended logistic curve*):

$$Y_{(t)} = (L)\,\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \tag{26}$$

Where, when q is greater than p, then the point of inflection occurs at:

$$t_{inflection} = \frac{1}{p - q}ln(\frac{q}{p})$$

$$Y_{inflection} = l\frac{(q - p)}{2q}$$

When p is greater than or equal to q, the point of inflection occurs at a negative value of t.

The Bass model has an inflection point at 0.5 of penetration up to 2t* where t* is the time for peak adoption rate. Beyond that point, it is not symmetrical. Thus the Bass model is generally described as symmetrical although not by Bass (Mahajan et al., 1990, p. 12).

The Bass model enjoyed early acceptance because it generalised the Fourt and Woodlock and the Mansfield models. Over time, the Bass model has been successfully fitted to diffusion processes for retailing, agriculture, industrial processes, medical equipment, telecommunications, and consumer durable goods as reviewed by Mahajan et al. (1990, 1995a; 2000). It represented an attractive model alternative to simple extrapolation, and simple fundamental models because of its theoretical underpinnings (Bass, 1969). Today the Bass model is arguably the most widely used model in diffusion growth modelling, and forecasting.

3.3.5. An attempt to improve on the Bass model

The Bass model is criticised for not containing marketing variables such as price and because it relies heavily on the contagion portion of the model, (reviewed in Krishnan, Bass, & Jain, 1999). In response to those criticism Bass, Krishnan, and Jain (1994) included variables, such as price and advertising to generalize the standard Bass model, they also ensured the model had a closed time domain form to ensure theoretical validity. Their model, [Equation (27)] included a new item $x_{(t)}$ to represent all marketing activities. One might call this the marketing effort variable.

$$\frac{Y_{(t)}}{1-Y_{(t)}} = \left(p + qY_{(t)}\right)x_{(t)} \tag{27}$$

Where $x_{(t)}$ is a function of percentage change in the decision variables of price and other marketing efforts, this model collapses back to the standard Bass model when $x_{(t)}$ is a constant over time. In testing, Bass et al. (1994) were able to demonstrate that they did not need these additional variables to describe a market, hence the title of the paper "*Why the Bass Model fits without decision variables*". Whether their model predicted better was not expressly confirmed nor discounted, although recently Dalla Valle and Furlan (2011) were able to show that model's superiority in a cross country wind power diffusion study. Thus, we have mixed support for the simpler original Bass model.

3.3.6. Log-logistic model

Here, Equation (28) is the log-logistic form seen in Meade and Islam (2010b) and as initially proposed by Tanner (1978):

$$Y_{(t)} = \frac{L}{1 + ae^{(-bln(t))}} \tag{28}$$

This function has the b in the simple logistic replaced by the natural log of b thus providing an accelerating impact of that parameter with time. Like the Gompertz, it was originally envisaged as a mortality model, and it brings an inflection point that is flexible between 0 and 0.5 of share.

3.3.7. Extending the logistic to substitution situations

The type of technological decline of technology investigated in this thesis is that linked to the diffusion of new technology with superior utility. Two well-known models are linked in the literature to this substitution effect. The Fisher and Pry (1971) model described in this section and the Norton and Bass (1987) model described in Section **Error! Reference source not found.**, which follows on from this section. Both models link diffusion and decline directly. Fisher and Pry (1971) working with the linear form of the simple logistic model, developed the first generally recognised model of substitution of one technology for another. Their model was an internally influenced model unlike the Bass model's mixed-influence foundations, so was less linked to Rogers' theories than the later Norton and Bass model built on the mixed-influence Bass model. They demonstrated useful accuracy and consistency of performance in technology underpinning product categories such as paint, cleaning products, and building materials. Fisher and Pry made three important assumptions, which constitute rules for their method, assumptions that today are integrated into the thinking of forecasters (Fisher & Pry, 1971):

- Many technological advances are primarily competitive substitutions of one method of satisfying a need with another.
- If substitutions progressed to "a few percent", then they will progress to completion.
- That fractional rate of (fractional) substitution of new for old is proportional to the remaining amount of the old not yet substituted (a special form of a law developed by Raymond Pearl (1925)).

Fisher and Pry used the linear form of the logistic function described by Equation (29):

$$f = \frac{1}{2}[1 + tanh\alpha(t - t_0)] \tag{29}$$

Where: *f* is the fraction of takeover by the new technology, *tanh* is the hyperbolic tangent function, α= ½ the initial annual exponential takeover rate, and T_0 is the year in which the new technology captures 50 percent of the usage or *f* = ½.

Their method involved transforming the data via a log-linear transform to a reasonably straight line, although Griliches and others did similar transforms. The functional form is in Equation (30):

$$\frac{f}{1 - f} = e^{2\alpha(t - t_0)} \tag{30}$$

Fisher and Pry pointed out that population growth and per capita consumption were not included directly in the model and that understanding the unit of substitution required significant thought for the model to be calibrated correctly. Their observations are significant because almost all subsequent models require the same assumptions, although it is often implicit. The area of time dependent market size has been addressed by a range of authors (Centrone, Goia, & Salinelli, 2007; Kalish, 1985; Mahajan & Peterson, 1978; Sharif & Ramanathan, 1981), but models with adjustable market size capability have not come into common use.

Fisher and Pry demonstrated the model's potential effectiveness at predicting the future with historical data for 17 substitution situations, for example: synthetic versus natural fibres, plastic versus leather, and synthetic versus natural rubber. They noted that progress of the substitution to a few percent market share penetration was a critical requirement. Mathematically, this was required to deal with their function, which starts at some infinite time in the past. From a pragmatic perspective, it probably allows the data of substitution to become *viably visible*. This viably visible test is important because you need a viable trend in order to recognise that diffusion is indeed following the trajectory of a successful technology. Moreover, you need to get above the noise floor to the extent that the data of interest is at a stronger level than measurement and stochastic noise levels in the data. In their case, they believed that between diffusion = 10 percent share and diffusion = 90 percent share their model functioned well. Much earlier, Griliches similarly trimmed the two asymptotes but to share = five percent and share = 95 percent. Fisher and Pry (1971) felt in their method, that their forecasts could be relied on if used after an initial 10 percent market share diffusion (effectively left truncating the data).

The trimming of the upper limit (right truncating) is rarely if ever mentioned, and is important because beyond 90 percent, a typical S-curve function takes a very long time to approximate 100 percent and data can vary extensively from pattern as it moves asymptotic to that limit. Hence including the last 10 percent of growth in your forecast can often make the forecast errors appear very large in the time domain. Despite the limited discussion in the literature, the practice of trimming out a portion of the top and bottom data has become common practice. This is discussed in detail section 6.4.5.

3.3.8. Substitutions over successive generations

A significant body of the literature on modelling successive generations of technology (one substituting for the other over time) builds on Frank Bass' model of growth for consumer durables (Bass, 1969), in particular on Norton and Bass (1987). (Norton & Bass) sought to provide a predictive model for initial diffusion and subsequent waves of substitution of products into a market. It is a model focusing on the growth of the technologies in a category over time. As in the earlier Bass diffusion model (Bass, 1969), at their model's foundation is the impact of innovators which diminished with time and the role of the imitators, who rely on promotion and word-of-mouth for confirmation of the suitability of their purchase and whose impact on diffusion rises over time to become dominant. Additionally, the Norton and Bass model also incorporates substitution theory, where those later generations compete with earlier generations. Their model does this by using a concept of generations of innovation, each generation modelled as gaining from substitution of the earlier generation and losing to the later generation by its substitution.

Three of their generations are expressed in Equations (31), (32), and (33) below.

Modelled for three generations it is:

1st Generation.

$$S_{1(t)} = F_{(t1)} l_1 [1 - F_{(t-t2)}] \tag{31}$$

2nd Generation.

$$S_{2(t)} = F_{(t-t2)} [l_2 + F_{(t1)} l_1][1 - F_{(t-t3)}] \tag{32}$$

3rd Generation.

$$S_{3(t)} = F_{(t-t3)} \Big[l_3 + F_{(t-t2)} \big[l_2 + \ F_{(t)} l_{(1)}\big]\Big] [1 - F_{(t-t4)}] \tag{33}$$

Where: $S_{i(t)}$ is the shipments (sales) of generation i at time (t-t_i) being the time since introduction of generation i, l_i i = the incremental potential served by the ith generation, not capable of being served by any earlier generation (Norton & Bass, 1987).

Where:

$$F_{(t)} = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \tag{34}$$

Equation (34) is the cumulative distribution from the original Bass model and assumes that p and q are the same value across the generations (Bass, 2004).

In a more generalised variant of the Norton and Bass model (Norton & Bass, 1987), p and q could be varied by generation. However, Bass (2004) said of that model, that it did not appear to be much of an improvement, consequently, providing some support for the use of the simple version. While there are many substitution models that operate with share of the market as the unit of diffusion, the Norton and Bass model gives us insight into the size of the market. Norton and Bass demonstrated the usefulness of this model through the fitting of their model to early data for the diffusion and subsequent substitution of dynamic RAM and static RAM memory, and microprocessor and microcontroller technologies. They predicted the growth of that technology from this early data and compared it with the data they held for later years, in what is now the tradition of technology forecasting model testing. Norton and Bass noted two behaviours not covered by their model. First, the identification of those that were late adopters and opted for a later generation technology rather than the first generation (the leapfrogging phenomenon). Second, those adopters that switched or substituted their earlier choice for a later generation (another form of leapfrogging but perhaps also characterised as switching). Furthermore, they felt there was potential for adapting the model to deal with the situation where only partial substitution takes place even after extended periods. Most recently, Jiang and Jain (2012) have addressed both generational leapfrogging and switching while still retaining a model that simplifies to the original Norton and Bass model. This model has yet to be demonstrated as a superior forecasting tool compared to the original Norton and Bass models by anyone else.

3.4. Important Assumptions Related to Diffusion Models

There has developed a tradition of technology diffusion forecasting where diffusion environments are assumed to have the following characteristics (for a review, and more comprehensive explanation see Mahajan et al., 1990; Meade, 1984; Meade & Islam, 2006):

- Prospective adopters have a binary choice

  Their choice is to take on the new technology or not, with only the old and the new in the frame. No intermediate state exists.

- A ceiling on the number of potential adopters in a given situation exists, and is both constant and distinct.

  In other words, the pool of potential adopters is static during the diffusion process. In the literature this assumption is often challenged, because market ceiling can grow or shrink; however, the assumption does make modelling simpler, and is commonly used even in markets that appear to be growing. The majority of diffusion models apply this assumption.

- There is no discontinuance of the technology during the modelling period,
- If a technology has progressed a few percent, it will progress to saturation,
- In the case of the internal influence models and mixed influence models, there is an assumption of complete mixing of all social system members and one-to-one communication relationships exist.

  This is an unrealistic assumption, but one required by the mathematical forms used.

- The measure of diffusion used is the market proportion of adopters.

This is the traditional model where diffusion is described as:

$$Y_{(t)} = \frac{l_{(t)}}{L}$$

Where L is a fixed number representing potential adopters (equivalent to market size) and $l_{(t)}$ is the number of adopters of the technology at time *(t)* (Bass, 1969; Winsor, 1932). Rarely is there any ability to decompose the data into the various adoption stages/states (Midgley, 1976; Silver, 1984), although sales forces typically do develop pipeline estimations for the stages of adoption for product sold by personal selling. Conversely and much less commonly seen, are prelaunch test market models, which often use panel data to predict sales, sometimes tracking panel members through the stages of adoption, thus effectively decomposing the adoption process to something similar to Rogers' psychographic profiled stages (Ettlie, 1980; Narasimhan & Sen, 1983). Diffusion modelling approaches also seem to perform well in such situations (Hardie, Fader, & Wisniewski, 1998; M. J. Wright & Stern, 2015).

- Adopting entities will only adopt the technology once.

Models assume non-repeat purchase data, making them ideal for forecasting durables and not for repeat purchase products. Defining the unit of adoption can assist in ensuring the data accessed is of single purchases or adoptions. Take for example the adoption of a new pharmaceutical product, sales will typically be repeated so prescriptions will not be a suitable measure; however, customer numbers or individual names would be suitable. In a similar way, doctors' adoption of prescribing a drug would be suitable whereas the number of prescriptions by a doctor would not. Models that recognise repeat purchase estimation procedures for diffusion models (J. Olson & Choi, 1985; A. G. Rao & Yamada, 1988) and more recently an agent based approach have been proposed (Stummer, Kiesling, Günther, & Vetschera, 2015), these approaches are not yet commonly described as in use by practitioners or researchers within the literature.

- The technology remains unchanged throughout the diffusion period.

This is really a matter of ensuring that what you are measuring is the same. At the product level, this is relatively easy to see when collecting data. At system and platform levels, this is a little harder as various sub parts of a technology might change without being obvious. The same applies to any processes surrounding technology, as it is not always clear when a change has taken place and if the data records this change. Grouping then defining a number of technologies as a discrete technology is common. Many grouped technologies have followed the typical trajectory of diffusion we have come to expect. Defining what the technology does and does not include is important in the process of describing diffusion.

- The spatial/geographic boundaries of the market (social system) are constant.

  The definition of the market does not change is reasonable, importantly when defining diffusion care should be taken to capture a whole market.

- The past can predict the future.
- The model captures all of the “information” about the diffusion situation.

  Diffusion theory assumes diffusion tracks an S-curve. Thus, diffusion is considered cumulative, incremental, and path dependent (Dosi, 1982; Rosenberg, 1972, 1982). The cumulative adoption curve smooths out with period-by-period adoption rate fluctuations. The most commonly used diffusion models are in this cumulative form, protecting forecasting by utilising this cumulative data and thus mitigating the effects of volatile adoption rates particularly in situations where sample rates are low.

3.5. The Current State of Diffusion Forecasting

Many functional forms that generate S-curves have been proposed, many of them like the Bass model have been extended further. Moreover, because of this proliferation of underlying functional forms and their more complete higher order variants, the number of described models is in the many hundreds, covering a wide range of determinants and including many elements that make fitting to data more precise.

However, from the early study by Ryan and Gross (1943) right into the peak years of diffusion model development in the 1990s, the number of models proposed has outstripped the pace of empirical application and validation of the usefulness of these models (Mahajan et al., 1990). Chatfield (2007) is particularly concerned about this issue. The notable exception is the empirical support for the basic Bass model, which is well tested and interestingly performs better in many situations than its enhanced variants (Bass, 1969). The fundamental diffusion models as described by Mahajan and Peterson (1985) have been widely adopted, but also have been extensively adapted in attempts to describe the diffusion phenomenon better, particularly in terms of controllable variables. These enhancements are trying either to improve the fit performance of forecasts, or to provide a better linkage of the model to theoretic foundations, and those theoretic determinants of diffusion growth. It could be said that this process has moved diffusion research themes away from parsimony in model specification. Today the limited empirical evaluation of new model variants continues as observed earlier by Mahajan et al. (1990), although there are some notable exceptions (Fichman, 1992; Hardie et al., 1998; Lomax, Hammond, Clemente, & East, 1996; Meade & Islam, 1995; Parker, 1993; M. R. Young, 1993).

The progression to increasingly sophisticated models begs the question: Are these models useful and practical? With each extra parameter added, not only do they become more complex, but also the process of finding parameter data to allow the estimation of coefficient values becomes more arduous for the forecaster, a point made by Goodwin et al. (2013). Sometimes using these models requires an impractical, if not impossible amount of work, because of the low likelihood of finding suitable environmental data reflecting the parameters, and thus the high search effort to seek them out. Moreover, with each additional coefficient presented there is introduced a point of human intervention to the forecasting process that is adding errors, as each coefficient has the hand of the forecaster impressed on its value, something about which Martino (1993) warns.

3.6. Summary

This chapter laid out the way the chosen models fit into the literature and the characteristics they possess; in fact, the only characteristic that matters to a forecaster is how well a method works in accurately generating a forecast. Statistical goodness of fit is not as critical in terms forecasting as it is in modelling data, because the test of a good forecast is not the fit to the estimation data, but the fit to the out-of-sample data. For example, Armstrong (2001b, p. 461) reviewed six studies on the usage of R^2, and found little association with forecast accuracy. Earlier, M. R. Young (1993) observed a similar lack of relationship. The next chapter looks at discontinuance as a concept and its linkages to contemporary diffusion theory.

Chapter Four: Discontinuance Theory

4.1. Introduction

Chapter two introduced diffusion theory and described some of the weaknesses in that theory with respect to describing individual and cumulative discontinuance (decline). The purpose of this chapter is to define this decline phenomenon, and to survey and synthesise the literature on discontinuance from a technology decline perspective, noting that discontinuance of use is linked to the concept of adoption into use. There is coverage of the relationship of discontinuance to the concepts of *dispossession*, *disadoption*, and *disposal*, accompanied with a defined set of terms for the topics covered. A short discussion on factors that drive individual discontinuance, along with concepts not well integrated in the current theory follows, to assist recognition of the differences between the concepts of cumulative adoption (diffusion) and cumulative discontinuance (decline), all with a focus on the multiple pathways to discontinuance that exist for users. Finally, there is a short section on the shape of decline curves.

4.2. Mixed Terms: Disadoption, Discontinuance, Dispossession

Ekerdt (2009) describes two ways to frame the matter: one centred on the individual user and one on the object technology. This thesis frames discontinuance decline in the first of these ways, that is, as a progression of usage, from common use to rare use in the same way that diffusion implies a growth from rare use to near universal use. Technology decline is defined in this thesis *as a progression from common use to rare use by members of a market*, with discontinuance at the individual level being the opposite to adoption of use as it is defined in section 2.3.3 earlier. However, both the conceptualisation of technology discontinuance and the terminology in use around a technology's fall from use are varied and inconsistently applied in the literature. This results in different descriptors for the same activity and different meanings for the same term, depending upon the context and author (Fenech & Longford, 2014; Lastovicka & Fernandez, 2005). Those concepts and their related terminologies deserve clarification. Table 1 defines situations and terms linked to discontinuance based on general usage, both in society and in the literature.

Table 1

Common Terms Related to Discontinuance

Term	User perspective	Technology availability perspective
Disposal - Typically used in a situation where the technology has already fallen from use. A term linked mostly with waste disposal.	The act of getting rid of an object from one's possession.	Disposing of final stocks of the technology product.
Dispossession - A term that links the parting of people and their things (Ekerdt, 2009).	The feelings about getting rid of an object from one's possession.	Not Applicable.
Discontinuance – a term linked implicitly to ceasing of use (Black, 1983; Rogers, 2003).	Stopping using an object, so that it falls into disuse.	Stopping production of a technology, so that it becomes unavailable (removal from catalogue).
Disadoption - linked to adoption and implicitly to ceasing of use (Prins, Verhoef, & Franses, 2009).	Not generally used but infers a disadoption process exists.	Not generally used.
Abandonment - linked again to parting of people and things (Berger & Le Mens, 2009).	An emotively laden term with meanings of both disregarding and stopping use.	Sometimes used to express a drop from use of a production technology.

One can interpret from the analysis of Table 1 that the two terms: *disadoption* at an individual level and *discontinuance* at a market cumulative level are linguistically suitable. As disadoption is not in common use, the expressions *discontinuance*, *individual discontinuance*, and *cumulative discontinuance* are the terms employed in this thesis, when required cumulative discontinuance is described by its outcome *decline*. Next is a summary of the literature across the terms *disposal*, *dispossession*, and *discontinuance*, as much of what has been written about ceasing to use a technology is spread across these three terms.

4.2.1. Disposal

Disposal is a post-use activity, which would seem important in the new green marketplace because of its links to "total life cycle cost" and "end of life disposal", but to date has had little attention in the marketing literature. The concept of disposal is out of scope for this thesis, however, there are some studies, that cover the reasons people discontinue use that discuss disposal (for example: Antonides & Van Raaij, 1998; Burke, Conn, & Lutz, 1978; Jacoby, Berning, & Dietvorst, 1977; Roster, 2001). Burke et al. (1978) in extending Jacoby et al. (1977) uncovered demographically different tendencies for disposal, with early replacement of goods linked to younger users and later failure-based replacement linked to older users.

4.2.2. Dispossession

Dispossession is covered in the diffusion literature, however it is defined as the emotional or psychological impact and pressures associated with separation (Roster, 2001). Roster (2001) proposes a model for a process of dispossession and identifies three factors: critical events, distancing behaviours, and performance and value assessment. Dispossession seems to have concentrations around four areas of experience: (1) the events that stimulate disposal, (2) the emotions associated with disposal decisions, (3) the symbolic meanings the objects have and (4) the goals and tactics of disposal (Rucker, Balch, Higham, & Schenter, 1992; M. M. Young & Wallendorf, 1989). There do not appear to be any studies with empirical evidence of the relative strength of these factors; however, the concept of emotional ties to things is well understood. Dispossession seems to bring emotional determination to the discontinuance process contrary to the mainstream model, which focuses on economic utility. But is also clearly linked to the disposal process, through a motive of rejection linked perhaps to Rogers (1962) disenchantment discontinuance. The implications of rejection as a potential determinant of discontinuance is discussed further in Section 4.7.8.

4.2.3. Discontinuance

Black (1983) investigated the general process post-purchase and provides both a cross-disciplinary assessment of literature post-adoption and a conceptual framework for the post-adoption period. E. G. Porter (1984) provides an excellent summary of the importance of post adoption dissonance and communication processes on the discontinuance process within individuals. The earliest studies of discontinuance appear to be by Silverman and Bailey (1961) and Bishop and Coughenour (1964) who found those that adopted many innovations went on to discontinue a smaller proportion of those adopted innovations compared to those that adopt fewer innovations. Leuthold and Wilkening (1965) as cited in Black (1983), and Leuthold (1967) all felt the demographic profile of individuals with a low discontinuance rate were similar to that of those considered highly innovative. Ahl (1970) investigated repeat purchase rates across categories of individuals similar in definition to Rogers' adopter classes, and found a higher degree of continuation of use among the earlier adopters, and amongst adopters who had a higher usage overall. These collective findings perhaps indicating that those that recognise high utility early and who demonstrate high usage, in itself an indicator of high utility, are more likely to continue use, when others are discontinuing (Ahl, 1970; Leuthold, 1967).

Tellis and Fenech (2016) attempted to characterise discontinuance behaviour based on the introduction date of a new technology and *time to dive*. They see this dive as opposite in direction but similar in character to the *take-off* observed in successful technology diffusion in the early stages (Peres et al., 2010). Across countries, Tellis and Fenech were able to predict the time when the technology started to decline from observed norms for the period *date of introduction* though to *date to dive* in situations where a new technology was substituting for an old, thus providing a leading indicator of the onset of decline. Additionally, Fenech and Longford (2014) observed that those countries that start a technology decline later, decline faster in a kind of catching up process, potentially placing further pressure on technology investment paybacks. Importantly they felt that a direct positive relationship between the rate of adoption of new technologies and discontinuance of the old ones was not supported and they recommended that discontinuance be modelled directly as a result. This thesis takes that path.

Additionally, there is some indication that discontinuers have more influence than adopters do over the outcomes of technology diffusion. Leuthold (1967, p. 105) described this negative interaction effect where:

> "*...the influence of those who discontinue an improved practice… may be greater than the influence of those who continue in promoting adoption*".

He also found evidence that:

> "*practices with high discontinuance rates nearly always exhibit low adoption rates, but practices exhibiting low discontinuance rates less frequently exhibit high adoption rates*".

Newell et al. (2014) explored the use of the S-curve models to model decays in the availability or usage of traditional media. They observed decline often following a steeper downward path than seen in media undergoing growth.

It seems that, as in diffusion, there is a tipping point in discontinuance (Gladwell, 2015; Tellis & Fenech, 2016). Later discontinuers are influenced by earlier discontinuers in a way that appears to reflect what proportion have discontinued to date, and as Markus (1987) notes the benefits to remaining users falls away as the number of discontinuers grows. This is probably exacerbated where network effects influence the uptake, use, and continued viability of the technology (Z. Katona et al., 2011). However, there is likely a proviso: that the rate of discontinuance is exceeding the rate of adoption, so that the active users of the technology are falling, although there is an alternative scenario, where people are adopting the new before discontinuing the old. That is, they hold onto the older technology for a transition period, while they adjust or replace behaviours reliant on the earlier technology, generating a momentary blip of growth in apparent market size and delaying the discontinuance trajectory. In the case of recording media, this would be the retention of recordings on an older technology and the related player technology. This phenomenon does not appear to be discussed in the literature.

A number of conclusions might be drawn from this literature. That earlier and later adopters are different in their rates of discontinuance (Ahl, 1970; Burke et al., 1978). Specifically, later adopters discontinue at a higher rate than do early adopters (Bishop & Coughenour, 1964; Leuthold & Wilkening, 1965), and that heavy and light adopters discontinue at different rates (Bishop & Coughenour, 1964; Silverman & Bailey, 1961).

4.3. Rogers' Diffusion Theory and Discontinuance

In Rogers' theory, a single technology solution emerges and diffuses, to displace and dominate all alternatives, old and new technologies co-exist in the market during this process. Sometimes the new technology does not displace the old completely (Peres et al., 2010), resulting in the old technology retaining a residual share in the market. From the early days of diffusion research, it was observed in *equilibrium type markets* that the decline curve of the displaced technology was somewhat like a mirror image of the new technology's diffusion S-curve (Fisher & Pry, 1971; Griliches, 1957; Mansfield, 1961). This one on one relationship has the implicit suggestion that the inverse of the diffusion curve is a proxy for substitution decline trajectory, with the substituted technology falling to an asymptote of end of life obsolescence as the new technology moves to saturation (Bartels, Ermel, Sandborn, & Pecht, 2012). For example, this happened with the development of antibiotics in bacterial infection control, when after antibiotics were introduced, many other methods were abandoned. While technology frequently diffuses because of technological superiority, such as jet engines replacing turboprop engines in large passenger aeroplanes (Leyes & Fleming, 1999), sometimes new technologies might supplant others due to superior availability, as occurred with VHS over Beta max tape formats in the 1980-1990s, or due to superior compatibility, as in GSM mobile technology in the 1990/2000s (Hillebrand, 2001).

Implicit in this early theory and empirical work is the one to one linkage of the diffusion and the decline curves, a notion accepted widely via the work of Rogers (1962, 1983, 1995, 2003; 1971), Fisher and Pry (1971) and Bass (1969; 1987). While having the appeal of simplicity, this concept disregards the potential for multiple conduits to individual discontinuance via multiple substitution paths and changes in overall demand. Even demand being satisfied unevenly in the market across substitutes undermines the one to one linkage concept. Given these challenges, the assumption of a one to one relationship of old and new technologies in diffusion theory becomes risky. These uncertainties are covered in more detail later in this chapter.

Rogers' (1962) theories do include the concepts of rejection and discontinuance, however, while the mechanisms of rejection and discontinuance are as integral to the theories as is adoption; they are treated in the theory as a by-product of a single substitution. Consequently, little understanding of the mechanisms driving decline is provided. Rogers (2003, p. 190) defines discontinuance as "a decision to reject an innovation after having previously adopted it". He describes two kinds of discontinuance, one that results from dissatisfaction with the experience of using the technology, that is, *disenchantment discontinuance*, and the other one being *replacement discontinuance* where, despite satisfaction with the current experience, a user is prepared to discontinue the technology in favour of what they perceive to be a better technology. Intuitively disenchantment discontinuance may tend to occur early in the diffusion process, as the expectations of a new adopter are not met. There is some anecdotal evidence for this hypothesis, where the diffusion of highly innovative technologies that did not reach the utility and value expectations of consumers has occurred. For example the first smart organisers, such as the Palm Pilot, the introduction of 2G mobile services in some markets, see examples in Xu, Thong, and Tam (2017), and some aspects of agriculture sprinkler irrigation see Rasouliazar and Fe'li (2011) all show substantial diffusion but a stall in growth and a fall away as the promise of the technology is not met in use.

Nevertheless, how to describe best discontinuance and decline in an adoption and diffusion frame? One issue is Rogers' use of the concept of rejection, described above. In an attempt to embrace Rogers' work, a definition could be developed using a frame similar to replacement discontinuance (Rogers, 2003, pp. 190-191). The definition proposed below does this, and retains links to the concept of usage and thus substitution. Additionally, the definition captures the accumulated action of many, rather than just that of an individual, so describes decline:

> *Discontinuance decline is a cessation of the use of a technology, over time, after its substitution by some newer technology diffusing into a social system.*

However, while this definition deals with the issue of rejection, it does not totally resolve the potential scenario of multiple new technologies being the substituting technology, however, that challenge is beyond the remit of this study.

At the individual level, this discontinuance of use behaviour is more easily defined as:

> *A cessation of the use of a technology, by an adopting unit within a social system.*

4.4. How Discontinuance Rates Interact with Adoption Rates

A technology's current market share is the accumulated sum of its historic rates of adoption and discontinuance, compared with that of its competitors. Any future market share is also determined through its current rate of adoption and discontinuance, a situation rarely mentioned in the literature (Black, 1983; Leuthold, 1967). These two mechanisms drive the ultimate market share. If the rate of adoption exceeds the rate of discontinuance, then the technology grows, and if they are in equilibrium, a technology might have a relatively stable market share. In a similar manner, if discontinuance takes dominance over the adoption rate, then that technology's market share will report decline.

While we know a significant amount about the rate of diffusion across technologies, the interaction of the rate of discontinuance across a technology's life with the rate of diffusion is not well understood and there has been little investigation of rates of discontinuance over a product's life. A recent exception investigates decline to obsolescence and describes the trajectory of an incumbent technology as a competition of adoption rate versus discontinuance rate (Fenech & Longford, 2014). Fenech and Longford (2014) compared the rate of discontinuance of old (declining) products internationally, and found that those countries that start to discontinue later, discontinue faster. Moreover, it seemed to those authors that emerging economies discontinue faster. They concluded that assuming that adoption and discontinuance have similar dynamics was a flawed framework, as earlier discussed in section 4.2.3.

4.5. A Growth Only Perspective in Diffusion Research

From the beginning of innovation diffusion research, the focus has been on how innovations grow in society. This paradigm holds technological innovations as both implicit improvements and direct replacements for a single older technology. This worried early researchers such as De Fleur (1966, p. 318) who observed a pattern of decline in newspaper media that motivated him to call for an investigation of “curves of abandonment”. Despite De Fleur’s call, and periodic calls of others (Black, 1983, p. 357; Leuthold, 1967; Rogers, 2003) for a widening of focus, discontinuance of an earlier technology and its decline are rarely reflected on in the literature.

The literature on diffusion of technology implies that a new technology, once introduced and set on its path will successfully diffuse into the market and substitute totally for an incumbent technology. Rogers (1995, p. 129) had an expression for this perspective: that an innovation should be totally adopted, that it should diffuse rapidly, and that it should be considered so good that it be “…neither re-invented nor rejected…”. He called it *Pro Innovation Bias*. This bias concentrates thinking onto the rate of penetration and the early period just after introduction, thus giving a focus on shorter time frames. This focus precludes the study of those longer processes in technologies that are fully diffused, and are subject to user churn. Early models of diffusion require the process to be seen as adoption and devoid of re-purchase behaviour, perhaps reinforcing a concentration on early phases where repeat purchase or defections would not occur. Interestingly, the use of aggregate models in forecasting has arguably resulted in a distancing of the technology user from the diffusion process, and positioned the technology as the focal point, rather than adoption behaviours. While individual adoption and cumulative adoption in the market has been extensively studied in the literature (see Chapter Two), it is the product life cycle (PLC) that forms the primary framework for technology decline (Golder & Tellis, 2004). In the PLC, technology is viewed as progressing through phases with time: from introduction through growth, maturity, and decline to obsolescence. A notable absence from the diffusion literature is an understanding of what drives discontinuance, the underlying mechanism of accumulation, and how best to model and predict the resultant decline.

4.6. Changes in the Drivers of Discontinuance

As discussed earlier, some users discontinue technology because it is worn. These users discontinue by replacement with the attractive technology of the day, taking little consideration of an intrinsic technology advantage, their driver being dissatisfaction with the impact of wear. The new technology may or may not have performance advantages but it might have a perceived longer life in the market and be attractive on that basis.

Sometimes, and this is the most commonly discussed case in the literature (Sood, James, Tellis, & Zhu, 2012; Sood & Tellis, 2005), there is a performance improvement in a technology which becomes, by definition, the new technology. It is generally accepted in the substitution literature that this process is the dominant one for discontinuance and occurs when the new technology has sufficient perceived total utility advantage over an older technology. Perhaps when this utility advantage is low, then discontinuance of the old technology only occurs under replacement requirements.

However, we are increasingly seeing a new phenomenon that blurs this definition, where products designers are integrating the capabilities of many technologies into their products. This is influencing discontinuance in two ways: first, over time we are seeing the gradual incremental influence of multiple new technologies absorbing one aspect of the capability of the older technology, effectively allowing new products from other categories to substitute for the older technology even though this is not their core capability. This creates a fragmentation of that older technology's utility, because as time goes on many other new technologies absorb parts of the functions of the older one, and then collectively serve to drive the older technology to become redundant. For example, the desktop personal computer has virtually gone from the home, replaced by E readers, smart phones, tablets, and laptops. Even the laptop is fast disappearing as increasing capability is appearing in smartphones, media players, smart televisions, and tablets. This trend further undermines the traditional definition of technology competition as being generational in character, rather than species in nature.

Second, some products are aggregating the capabilities of multiple technologies inside one multifunctional entity. We see aggregation in telephones, which are now mobile in the way only two-way radio once was and they integrate music players, calendars, and mobile internet news. Today mobile phones have the potential to make mobile radio, MP3 players, diaries, newspapers, and printed maps redundant.

Finally, we have discontinuance of technologies that did not deliver on expectations. For example, early smart phones, which were difficult to master, and were frequently abandoned until they started to have touchscreen gesture-based capabilities. Sometimes technologies can have unforeseen and unfavourable consequences that take a long time to appear, for example herbicides such as DDT which have been progressively discontinued as their unsavoury and unforeseen side effects come to be understood.

4.7. Gaps in the Discontinuance Theory

Comprehensive as the work of Rogers is, in drawing together the theory on communication, innovation, adoption and diffusion, there are a number of gaps in the theory. These have been discussed in section 4.3 on the Rogers theory and its links to discontinuance theory. Seven of those gaps related to discontinuance are explored below.

4.7.1. Discontinuance is not always because of obsolescence

Obsolescence is not generally the reason for discontinuance (DeBell & Dardis, 1979; Hoffer & Reilly, 1984; Jacoby et al., 1977; Pickering, 1981), even if substitution with a newer technology is the motivator (DeBell & Dardis, 1979; Jacoby et al., 1977; Pickering, 1981). Wear is an obvious case, when a technology is worn out it is often replaced with a different technology with little consideration of the additional utility benefits, instead, the focus is on the renewal of utility loss due to wear. It also seems that consumers are most likely to replace their technologies for reasons other than failure to perform (Bayus, 1991; DeBell & Dardis, 1979). They replace technology while it still is working for style and fashion reasons (DeBell & Dardis, 1979; Hoffer & Reilly, 1984; Khetriwal & First, 2012), technological advances not related to obsolescence (Jacoby et al., 1977; G. Katona, 1960), or because of a change in situation (Pickering, 1981). These are all forms of discontinuance originating in reduced utility, but not of obsolescence. In the industrial setting, there is evidence that firms replace information technology systems to stay similar to the industry standard and to that technology used by customers and competitors, once again not directly linked to obsolescence (Furneaux & Wade, 2010). Sometimes discontinuance can be a reversion to an older practice, frequently seen as a form of disenchantment discontinuance (see section

4.3). This is often seen post adoption of a new agricultural practice, (Bello, Salau, & Ezra, 2012; Nnadi & Akwiwu, 2007), where the practices of the past and the utility of the new technology clash, or where the environmental requirements in some way are not compatible with the adopted technology. A similar behaviour can be seen in assistive medical device and medicines where discontinuance is frequently part of a reversion to a past practice (Federici, Meloni, & Borsci, 2016; Simons, Levis, & Simons, 1996). It seems social media might also be subject to this same phenomena (S. Zhang, Zhao, Lu, & Yang, 2016).

From a more general perspective on reversion to an earlier technology, Recker (2014) argues that discontinuance intentions are predisposed towards the status quo, and away from change. This indicates perhaps that reverting to an older technology is a signal of significant incompatibility of the technology to the situation. Clearly if the technology is still current then obsolescence is not part of the influence, as by definition if it was obsolete the decision would be to adopt the newer technology not to revert. This is a very important point, as the current diffusion and substitution paradigm is predicated on the insufficiency of the utility of the old over the new, yet reversion includes no new adoptable technology. Although it could be argued that if reversion took place soon after adoption then it is a rejection of that new technology. It is clear from the literature on obsolescence that it is not the reason for discontinuance in the majority of cases.

4.7.2. The role of lead users as co-creators

We know from Rogers that sometimes an independently innovative consumer, on realising a deficiency of performance in a technology, product, or method they currently use, will seek out a better solution. These are Rogers' *innovators*, and on finding and evaluating such a solution, they adopt it by substituting out their old technology, product, or method. However, there is some thought that these early *discontinuers* are heavily engaged users and they actively seek to solve a problem they see with their current technology (Von Hippel, 2007). These innovative *lead users* are often interacting with the new developments around the technology and interacting with designers, which reinforces their enthusiasm. The new technological innovation might come from an in-house solution (firm perspective) or a personally developed (consumer perspective) solution, or from an early commercial (market perspective) solution. This behaviour encompasses three popular theories. The well-known adoption process for individual consumers described by the theory of technology substitution first popularised by Rogers (1962) but established in the work of Ryan and Gross (1943) and

Griliches (1957). The concept of lead-user working on modification of early innovations (Von Hippel, 1986), a concept which is not intrinsic in the Rogers framework, but does have some parallel to the innovator adopter category. Finally there is the concept of evangelising, where once initial solutions are found and verified by these lead-users, they start a process of evangelism, based on the weaknesses of the old and championing the appeal of the new (Dodson & Muller, 1978; Lehrer, 2015). While there seems no empirical evidence for this process, lead users are assumed to advocate at a higher level than do other adopters because of their deeper engagement with the technology during the process of adoption. Current diffusion theory does not recognise this co-creation process as a pathway to new technology adoption, whilst in the software industry in particular, lead user involvement in development of innovations and in evangelising is commonplace and an important part of the agile development process. Increasingly, this co-creation paradigm is part of new marketing theory (Payne, Storbacka, & Frow, 2008).

4.7.3. Choosing from multiple solutions

In the contemporary theory of substitution originating with Rogers' diffusion theory and modelled by Norton and Bass (1987), discontinuance is described as the result of a single new technology, but little is said of multiple substitution paths. There is only allowance for successive generations. Significantly, at the cumulative level of discontinuance (decline), Black (1983, p. 357) considered the exclusion of discontinuance from the main discourse as obscuring the very dynamic nature of diffusion and decline as a continuous mix of adoptions and discontinuances, not exclusively between two technologies.

We know new technologies often arrive in swarms as Schumpeter describes (Schumpeter, 1934, pp. 219-255). Multiple technologies appear to respond to a commonly recognised problem, often in times of good opportunity, and then go on to vie for dominance over time. We often cannot predict with certainty which technology will be successful (Foster, 1986; Rogers, 1995). Thus, it is possible that the impact on an incumbent technology is a result of the aggregation of all the diffusion from the technology swarm, and consequently, we could be misled if we attempted to make a prediction of decline from the diffusion data of a single new technology. This issue is important in those early times before one diffusing technology becomes highly dominant, because individual discontinuances might well be driven by substitution from many sources. Moreover, the early source of adopting individuals for any new technology might not be solely defectors from the incumbent technology but defectors from a number of niches attracted to the new technology's capability (Geels, 2005).

Sometimes many technology solutions compete for the right to solve the needs of consumers for a considerable time, each solution tends to gain its own early adopting and advocating lead users, who have discontinued use of the earlier technology. A useful example of the availability of multiple solutions is the evolution of smart mobile devices. When the Apple iPhone^{tm} was introduced, there were other viable technologies. Nokia, Sony Ericsson, and others were providing more intelligent work tools but with a concentration on developing phones with small footprints, long battery life, and a real focus on ease of use, whilst Blackberry was less focused on size and developed intelligent work tools that provided functions beyond a phone with what now might be termed smartphone features. All those innovations were based on the button driven QWERTY keyboard user interface, as they did not see the emerging touchscreen technology as viable at that time. Apple however, saw the technology benefits to the user of their gesture based touchscreen and provided a smart phone that was easy to use, and it was valued by consumers over other's technologies despite its novelty of interface, large size, and high battery drain (Agar, 2003). During those early years user input to smart phones was provided across proprietary operating systems Blackberry OS, Windows OS, and Apple IOS), and two user interface technologies, keyboard and gesture based touch screen. While it could be argued that this was a strong brand winning over weaker brands and the technology is irrelevant, it is more likely that it was the extra utility created when two innovations combined that of touch screens and of gesture based input protocols, which determined the outcome. There were influential shares for these technologies for a period of time, indicating those moving from a purely mobile phone technology to the multi-use platforms offered by smart phones had substantial choice. Predicting conventional mobile phone technology decline from a single diffusing technology would not have been possible until the decline was driven by the eventual dominance of gesture phones. As late as 2009 gesture based phones held only about 25 percent of the market (Pettey, 2010).

4.7.4. Choosing a portfolio of technologies

It is also possible that individual discontinuance is a result of the distribution of the user's needs across multiple new technological possibilities, a situation seen in the decline of traditional mass media where defection from newspapers, radio, or television was not to a single new media innovation, but rather to a new portfolio of media (Newell et al., 2014). This portfolio is made up of social media such as Facebook, personal news feeds such as Twitter, or opinion leader blog media. In some cases, the portfolio might include an online (new media) version of the old media, for example, on demand TV news or podcast radio (Newell et al., 2014). Here current theory does not allow for the discontinuance to be in favour of a portfolio of technologies.

4.7.5. Competing social groups in a system

When multiple new technology solutions are competing in the market, advocacy by lead users triggers and goes on to reinforce the classic word-of-mouth process that underlies diffusion theory. Competing technologies are diffusing into the market via the Rogers' classic theory of diffusion of information within a social system over time (Rogers, 1962); however, independent social groups linked to each technology, while internally bound by the internally tight links between each advocate within the social group, are also bound by weak links to other social groups (Granovetter, 1973). Thus, diffusion between groups is potentially constrained where competing groups are connected by weak links and are advocating for different technologies. Competing advocacy across groups does not appear central in contemporary marketing theory.

4.7.6. Adoption is defined as "full use" and "complete abandonment"

Rogers' "full use" definition of adoption as mentioned in Chapter 2, and the theory of substitution (see, Fisher & Pry, 1971) has probably contributed to the almost universal understanding that diffusion and substitution are binary, occurring across pairs of technologies, one completely replacing another as technology advances. However, adoption can be full while the consequential use is far from full, as in the example of microwave ovens. We adopted microwave ovens, but do not use them for every cooking task, that is, we do not completely abandon conventional ovens, nor earlier fast cooking methods such as pressure cookers. Current theory does not allow for *reduction in use* only for full abandonment.

4.7.7. Discontinuance is described as a permanent act

Rogers' theory assumes that individual discontinuance will be permanent, however, this is not always the case, for example, social media platforms illustrate *temporary discontinuance* behaviour, the so-called "Facebook vacation" (Maier, Laumer, Weinert, & Weitzel, 2015; York & Turcotte, 2015). York and Turcotte (2015) found that socioeconomic status and geographical location explained little of Facebook's temporary discontinuance, rather users reported leaving because of the burden on their cognitive and social resources and time. This vacation from services may well have been with us historically, in less obvious ways, as those vacating rented homes for a period over university summers have relinquished power, broadband, and telephone services. In this case and in the case of the discontinuance of optional services such as pay-to-view TV, it might be that while temporary discontinuance exists, it is seasonal and not an indicator of long term decline. However, this sort of temporary discontinuance does seem to be primarily related to services.

4.7.8. Implications of these gaps in common theory

Rogers recognises substitution and discontinuance but does not describe the mechanism that underlies these phenomenon. We might consider a social perspective where users seek to discontinue, thus make discontinuance intrinsically a process of seeking alternatives. There are many substitute options when discontinuing, so the information received by a prospective discontinuer comes from many social networks, each associated with one of the multiple alternatives. This makes the choice to discontinue a natural process of identifying alternatives and choosing between options. It seems the act of discontinuing is binary, in that there is a choice to stay with the current technology or to go to a new one, just as in the Rogers model of individual adoption. However, the consumer understands there are many solutions and thus the choice and the paths to disadoption are multiple. Every person adopting a technology is adopting that specific technology; however, every person abandoning is not adopting the same technology.

It is not realistic to consider that a singular choice is the norm in the discontinuance of a dominant incumbent technology as in the classic model described by Rogers (1962). It could be contended that any treatment of discontinuance must frame discontinuance as emanating from the users of the incumbent technology and should recognise the paths to discontinuance are many. Helpfully, Rogers has some support for this modified paradigm in his framing of adoption and discontinuance in terms of a common concept of rejection. Rogers talks of rejection in two ways: as the process of not adopting, and also as the process for discontinuing use of a previously adopted technology (Rogers, 2003, p. 190). With a rejection reference then it becomes natural to frame discontinuance so the incumbent technology is the focus in the rejection situation. The implication of this framing of discontinuance is the need to recognise the potential for multiple discontinuance paths, and the undermining of those implicit one-to-one relationships of one diffusing technology and one substituted technology so common in the diffusion and substitution literature. At the individual level, recognising discontinuance as a portfolio choice between multiple alternatives becomes important. In addition, considering Rogers' adoption stage model as selecting from options is critical. Finally, the recognition that sometimes more than one technology takes the burden of solving what one technology once did, makes a perspective where individual discontinuance behaviour is closely linked to the dominant existing technology, rather than a dominant new technology, appear appropriate.

4.7.9. The shape of decline curves

Not only is it accepted that the diffusion process follows an S-curve, but theory says (Rogers, 1962), and observation records (Fisher & Pry, 1971), that technology decline follows a similar sigmoid shaped (S-shaped) trajectory as diffusion, except that there is a fall from a point of saturation rather than a rise to a ceiling. We know that the market is not always made of just two technologies. Multi-generational models of diffusion were developed because we understand that markets often have a declining technology, a current technology and an emerging technology present at the same time. Chapter Three covers the ways in which Rogers' theory holds true and the ways in which it might not hold true in discontinuance situations. In particular, how discontinuance accumulates to force a technology into decline and what factors influence the rates of individual discontinuance beyond the binary model of substitution are areas in which Rogers' theory is mostly silent. At a decline modelling and forecasting level, this absence has some implications. One of them is that models that were designed to quantify diffusion theory thus use determinants of diffusion in their specification. Given the potential differences in determinants of discontinuance, such models can only be justified for use in discontinuance studies as fitted models in decline studies as the theory of how discontinuance and its accumulation to cause decline is driven, is potentially not the same, or at least is not known to be the same, as that of diffusion. This concern is expressed in Newell et al. (2014) where they observe that decline has some characteristics that are different from diffusion, and this drove their modelling of decline directly, rather than as part of the diffusion process.

As one might expect, however, there are a number of weaknesses in the argument that decline from substitution is simply derived from the inverse of diffusion growth of some defined single technology. For example, the early portions of diffusion data series are highly noisy and are frequently not suitable even for diffusion modelling and forecasting, yet it is at this early stage of a technology's substitution that managers wish to be informed of their technology's decline (Fisher & Pry, 1971; Modis & Debecker, 1992). The predominant theory (Rogers, 1962) and the related literature emphasises substitution decline as a one-for-one inverse relationship with diffusion, although subsequent and overlapping generations are recognised (see Norton & Bass, 1987). Swarms of new technologies contesting at the point of diffusion onset to be an ultimately successful technology are not covered in classical diffusion theory of one to one competition (Schumpeter, 1939, 1947; Ziman, 2003).

In addition, growth model theory typically does not take account of the potential impact of changes in demand over time and the possibility that these demands are satisfied unevenly amongst substitutes across the market (Peres et al., 2010; Schumpeter, 1927, 1947).

As mentioned earlier in this chapter, little work has been done on fitting to the decline phase data or on undertaking decline forecasting. This is surprising given the close theoretical relationship between diffusion, substitution, and discontinuance. Decline is typically represented as a mirrored relationship to substitution by a single diffusing technology (Fisher & Pry, 1971; Nakicenovic, 1986). Recently Newell et al. (2014) fitted data on eight older mass media technologies that had fallen into decline and observed that indeed the pattern was consistently S-shaped, and that those classic simple S-curve models do fit and describe the data well, supporting the potential progression to forecasting. They found, just as in diffusion studies (M. R. Young, 1993), that no universal decline model fits all data sets.

4.8. Summary

From this chapter we understand that a diffusion based theoretic framework for decline can be problematic. Many factors influence decline via discontinuance that are not linked to a single diffusing technology, making a one-to-one relationship between diffusion data and discontinuance data an unhelpful starting point for modelling decline curves. However, the decline process, no matter how poorly specified in theory, does exhibit the classic S-curve in practice. Thus, the models generated by a diffusion researcher may be empirically suitable for decline. However, models that have variables specifically tailored to diffusion theory might be incorrectly specified in the decline domain. Therefore, less fully specified models, which are flexible and general enough to suit observed decline processes, are more appealing. The next chapter describes the literature on, and the challenges of forecasting diffusion, and describes how that literature might translate to decline forecasting.

Chapter Five: Methodological issues

5.1. Introduction

Chapter Two laid out the literature on diffusion theory and described some of the weaknesses in that theory with respect to describing individual and cumulative discontinuance (decline), while Chapter Three indicated how mathematical models can describe, or model, historic diffusion. Chapter Four described the discontinuance literature. The purpose of the current chapter is to describe how forecasting of diffusion is typically done and how such methods might work when applied to decline data, noting once again that discontinuance of use is linked to the concept of adoption into use, and this underpins all diffusion theory. Forecasting is different to modelling in a critical way; with forecasting the objective is to predict the future for a situation of interest, yet typically, little is known about that future, whereas in modelling, as described in Chapter Three, all the data of interest is available. The current chapter lays out the challenges for forecasting in general and then for discontinuance in particular. The chapter begins with a section explaining why forecasters struggle to be accurate and consistent. This is followed by a section covering critical principles that might guide forecasters to better performance. A section introducing selected differences between the notions of diffusion (growth) curves and of discontinuance (decline) curves follows. Then forecasting in the diffusion and discontinuance context is covered. Diffusion models are used to explain the challenges of model estimation methods. Popular forecast error measures and their advantages are explained.

5.2. General Issues

5.2.1. Forecast accuracy

The literature assessing the accuracy and consistency of diffusion model forecasts (Parker, 1994; S. K. Rao, 1985; M. R. Young, 1993) indicates that diffusion model forecast performance is deficient, bringing calls for research to improve model overall accuracy and consistency performance (Fildes & Kumar, 2002). However, attempts to do so are limited, with rare examples being the work of Meade (Islam, Fiebig, & Meade, 2002; Meade & Islam, 1995, 1998). Those studies use few data series (typically under 50) and provide limited understanding of the potential sources and magnitude of prediction error. Rarely mentioned in this context, are the management implications of diffusion forecast performance. Putsis (1998) observed that an improved fit can be found by adjusting parameters for time, but it seems to offer little to no value to a prediction, because fit is not well correlated with prediction performance, a commonly observed phenomenon. Similarly, it is invalid to use model fit to historic data as a proxy for forecast performance (Armstrong & Collopy, 1992; Hyndman & Koehler, 2006). In her competition of forecasting models, M. R. Young (1993) noted that diffusion models that fit well to the early data do not always provide the best forecast. Young also found that models perform better or worse depending on the situation, thus implying that one model does not fit all, and choosing the correct forecast model is critical. Importantly, error measures used to evaluate models have diverse characteristics and show different relative performance based on model, method, and data series in forecasting situations (Armstrong & Collopy, 1992). This is covered in detail in section 6.3.

One further issue in evaluating forecasts is the topic of fixed versus rolling (multiple) origin forecasts. The former is where standing at time T (usually the last point in the estimation sample) forecasts are generated for time periods T+1, T+2 out to T+n periods, versus the concept of rolling forward the origin by one time-period after each forecast (multiple origin forecast evaluation). Forecasts from a single origin are prone to influence from incidents related to just that origin. Moreover, when used with single series many horizons are required to provide a pattern of the viability of the method (Tashman, 2000). A process of updating the forecasting origin after each forecast can reduce the effects of those three problems, but does require more out-of-sample data than a fixed origin test. However, in many situations there is insufficient out-of-sample data to use a rolling origin with all series. Thus, the fixed-origin evaluation can play a useful role where test data is limited and also in evaluation of judgmental forecasts, when we do not know or cannot replicate the underlying forecasting methodology (Tashman, 2000). Armstrong and Collopy (1992) observe that making conclusions about the accuracy of various forecasting methods requires assessment across many time series. Applying tight conditions to specifying that analogous situation makes it often difficult to obtain a large number of series, thus generalising from a single study is risky.

5.2.2. Problems in achieving consistently accurate forecasts

There are many reasons why forecasters are unable to provide perfect accuracy. Martino (1993) describes how forecasts are subject to four key problems:

- *Because there is a lack of inherent necessity,* that is, historical outcomes are not completely determined by observable physical factors; some things just happen by chance, or are influenced by chance happenings. Consequently, each outcome is unique even though the observed situation was apparently identical. Forecasting in such situations is challenging;
- *Because, each event is historically unique,* then understanding the dissimilarities is important. An analogy is strengthened if there are several historical cases with parallel outcomes that can be compared, and found identical at their start points, with the situation of interest;
- *Historically conditioned awareness* means that when people are aware of what happened last time, and armed with that knowledge, they tend to act to achieve a different outcome "this time around". This violates the forecasting principle that people will act in the same way every time;
- *Any causal analogy* assumes that not only are the observed parameters similar but that the cause and effects will play out in the same way.

These four problems remind us of two things. First, that one should control what is controllable, but also be aware that in forecasting some future conditions are uncontrollable and unpredictable.

In addition, forecasters must meet the needs of their audiences. For example, managers are cautious of forecasts produced by models they do not understand (Taylor & Thomas, 1982). Likewise, forecasting practitioners appear to rate sensibility (believability) above accuracy in forecasts (Huss, 1987), while academics rate accuracy higher than believability (Carbone & Armstrong, 1982). Yokum and Armstrong (1995)observed that managers consider flexibility, ease of use, and ease of implementation nearly as important as prediction accuracy in choosing a forecast approach. Mahajan, Muller, and Bass (1995b) observe that model selection involves a trade-off between fit and parsimony, this observation has support in model validity theory, through the concept of allowable degrees of freedom, which, when breached, leads to model overfitting (Babyak, 2004; Everitt & Skrondal, 2002). The principle that, given two explanations and all other things being equal, the simple explanation is the best, has become generally accepted by scientists developing theories and models (Hawking, 2003, p. 371). There is also empirical support for the principle of parsimony in the form of a comprehensive review of experiments that compared the accuracy of forecasts from simple methods and models with that of forecasts from more complex ones. Forecasts from the simpler methods were as or more accurate, and often substantially so (Green & Armstrong, 2015). The approach taken in the research described in this thesis, then, has been to use simple explainable methods that can be assessed using simple explainable measures.

Recently, a principle of conservatism has been proposed, the so-called g*olden rule of forecasting* (Armstrong, Green, & Graefe, 2015). This principle is broad based, where to be conservative means; "adhering to cumulative knowledge about the situation and about forecasting methods" (Armstrong et al., 2015, p. 1781). As a useful illustration, one might think forecasting a small change is conservative, however, if the indicators point to a large change, then assuming no change, which is a common approach, is not conservative (Batchelor & Dua, 1992). Comprehensive reviews of evidence on forecasting principles can be found in Armstrong (1985), and Armstrong (2001d). This next section introduces selected differences between the notions of diffusion (growth) curves and of discontinuance (decline) curves.

5.2.3. The suitability of diffusion models for discontinuance curves

As mentioned in Chapters Two and Three, when discontinuance rates in a market exceed adoption rates, the incumbent technology declines with an S-curve. Rogers' theory implicitly specifies this as a binary process with only the one new and the one old technology involved. On the surface, decline (cumulative discontinuance of use) curves look to be the inverse of diffusion curves. Fisher and Pry demonstrated this with their logarithmic translation of the data and application of a linearised logistic function to both diffusing and substituted technologies. However, this observation only holds true at a theoretical level if the one to one binary substitution process described by Rogers (1962) holds true.

Thus, models built on an understanding of diffusion determinants might well be incorrectly specified, given potentially different determinants of decline, over diffusion. Such incorrect specification could, for example, stem from not reflecting that while diffusion is linked to sales and how these are echoed in market share, decline is affected by a range of dis-adoption and abandonment mechanisms, and therefore not directly by sales. Consequently, there is little to link the market diffusion defined parameters of the more refined marketing science diffusion models to the decline process. Fortunately, a naïve model fitted to data for declining technology will always reflect the impact of those determinants of decline even if the individual level discontinuance mechanisms driving decline are not understood, and the theoretical backing for the parameters used is not confirmed as suitable for a decline situation.

The lack of a strong assessment of the decline mechanisms from a modelling perspective precludes considering causal models for decline. Technology decline modelling research is relatively rare, (for exceptions see Newell et al., 2014; Norton & Bass, 1992). Importantly, when any attempts to model decline take place, they are predominantly undertaken from a growth or diffusion perspective, and forecast from growth onwards into a decline phase, an unnatural process as the modelling does not link with how a manager would commission a forecast. Typically, such studies include the substituted component in the diffusion stream, in order to show cumulative growth of the new technology, such that any decline prediction is a by-product of the single diffusing technology, and any parallel market size expansion (Fisher & Pry, 1971; Marchetti & Nakicenovic, 1979; Norton & Bass, 1987, 1992).

To see if decline forecasting had been attempted, in March 2017, (and again in April 2018), a systematic search was undertaken of Google Scholar, Scopus and Web of Science (seeking sources 10 pages deep in each database (20 entries a nominal page)), this search found no studies directly investigating forecasting of technology decline. There is substantial literature in the area of human capability to undertake decline curve estimation (Best, Smith, & Stubbs, 2007; Ebersbach, Lehner, Resing, & Wilkening, 2008; Wagenaar & Timmers, 1979) and in the area of resource depletion and in particular oil reserves and oil extraction decline (Fetkovich, Fetkovich, & Fetkovich, 1996; Höök, 2009). There was also work on species decline (Duffy et al., 2009). There is perhaps an assumption that the work on decline forecasting has already been done, because substitution research implicitly includes the substituted technology. There are some studies that attempt the modelling of decline curves; their number is however, limited, as is their scope, which is restricted to demonstrating the potential to model (Marchetti & Nakicenovic, 1979; Norton & Bass, 1992). In the context of such limited knowledge, there is a good case for using the accumulated data for the decline of a technology for forecasting rather than working with the growth data of the new technology.

5.2.4. Heteroscedastic forecast errors

The S-curve trajectory of typical diffusion means forecast residual errors can be heteroscedastic. That is, relatively small at the beginning, become large in the middle, and then reduce again at the end, as a simple artefact of the rate of the change in diffusion over time. Moreover, if measured as percentage error this heteroscedacity of errors is further expanded by the S-curve change in the magnitude of the actual values over time.

As a typical S-curve diffusion time-series grows over time, the S-curve pattern becomes more discernible, allowing better model calibration and thus better representing the underlying trend. In fact, the risks associated with not recalibrating the model, as new data become available are high in diffusion studies. This is because the rapid change in the rate of diffusion, observed in the region from take-off until growth slows to a ceiling, means small inaccuracies in the model specification will generate substantial forecast errors in this region of the curve. Hence, the potential gains from updating the calibration of the model each time period and getting an improved prediction are arguably higher than in any other situation where constant updating might be possible, because of the rapid rate of change data level in the middle portion of diffusion curves, where data points by definition are at their scarcest.

5.2.5. The length of diffusion data series

Logging of diffusion data is typically annually or quarterly and, very rarely, monthly. This means there are often few data points available in typical diffusion data series. Emmanouilides (2006) sought a wide range of diffusion time-series with more than seven observations. In the 926 series from 50 countries covering household appliances, home electronics, and telecommunication equipment, all introduced after the year 1950, Emmanouilides found 39 percent of his series only had his minimum of seven observations, 54 percent had between eight and 19 observations, and only eight percent had 20 or more observations. The diffusion literature rarely mentions this lack of length in diffusion series. Such scarcity of data points means that there will often be insufficient data for other than simple models, particularly when attempting to forecast rapidly diffusing technology or when early phase only data is available. Often in such situations, choosing an S-curve model will be difficult to justify on the data alone and models will struggle to fit the data well.

The literature describes several ways of dealing with insufficient data. Sometimes the problem is insufficient target variable data to support models, but elsewhere there might be similar data that can be used as a surrogate (analogous data). Sometimes the data is not adequate for any form of model even when analogous data is sought. In such cases, judgment might need to be applied to augment the data points, augment the models, or predict future data points directly. For example, researchers recognise that knowledge of the intentions of consumers and the opinions of experts can improve model choice and model specification when there is only limited information (Armstrong & Collopy, 1998; Lawrence, Goodwin, O'Connor, & Önkal, 2006). Moreover, even when the S-curve pattern is emerging (becoming recognisable), expert judgment might still be valuable, through some form of *bootstrapping* (Armstrong, 2001c) and by providing input to forecasting models via some form of forecast adjustment. The potential benefits of adding judgmental input to forecasts might be high. Armstrong and Brodie (1999) and Armstrong et al. (1987), observed the benefits of judgment with limited data when they observed that a progression from judgmental methodologies to quantitative models improves forecasts as more data becomes available.

Debecker and Modis (1994) note that the *quality* of the early data and the portion of the growth curve covered by that data substantially affect prediction accuracy from diffusion models. They undertook over 35,000 fits to artificial data series and they were able to establish the uncertainties, confidence intervals, and systematic bias of the S-curve in forecasts for different densities of data. They advocated two simple rules: first, if there is access to a minimum of 20 percent of the full range of the likely diffusion curve, then it is possible to deliver an adequate forecast through fitting using Equation (35.

$$Y(t) = \frac{M}{1 + e^{-a(t-t0)}} \tag{35}$$

Second, if diffusion has passed 50 percent, then a forecast of the ceiling value should be within 20 percent of the actual value, with a 95 percent confidence level. Additionally they demonstrated, consistent with previous researchers (e.g. Fisher & Pry, 1971), that the extremities of a curve, in their case below 5 percent and above 95 percent, could not be expected to fit well, supporting the Fisher and Pry recommendation to trim early and late data, an action that limits the shortest series that can be used. If data series are short then testing models with a rolling origin forecast become problematic as described earlier in section 5.2.1.

5.2.6. Identifying the start of a decline pattern is a challenge

The completion of an S-curve trajectory is what defines successful diffusion. However, there are inherent problems with universally attributing this S-curve pattern to early data, because until the S-curve is well established, the use of an S-curve model is not fully supported. That is, early diffusion data give little indication of the later S-curve growth phase trajectory that regularly follows technology introduction. This lack of indication is because of two factors. The first is the low number of initial adopters and their limited ability to communicated benefits in adoption resulting in low levels of penetration. The second is the issue of noise in the diffusion data, in a large market, small market variations often swamp the low levels of data for the diffusing technology (Davies, 1979; Girifalco, 1991; Modis & Debecker, 1992), and this issue is covered in detail in Section 6.3. The same problem occurs with decline when only a small portion of the decline data has emerged, and there is a lack of an established trend. The forecaster is faced with three questions: first, has the decline process really started? This is critical to apply any further forecasting assumptions. Second, will this decline follow an S-curve? This question could be answered by watching the data progress until the series' shape was evident. The third question: What does the first half of the decline curve say about the second half? These questions form part of tests for the analogy assumptions of S-curves, and are critical to the use of marketing science diffusion models. If the two halves are symmetric, then a symmetric S-curve model can be deployed. If not then a suitable asymmetric model is required. The problems outlined in the three questions manifest themselves in the fitting to early data of models, which is potentially not representative of the trend to come, but also in the choice of models with respect to their points of inflection. Diffusion in the early stage is slow; this slow growth region is extremely variable in length and can go on for weeks, months, or years (Dattee, 2007; Parker, 1994). Decline is similar to diffusion in this respect and during this time, the falls in the data are relatively small in magnitude and could be subject to random or seasonal fluctuations. Accordingly, judgment is required to identify the emergence of an S-curve, and a rule of some kind is needed to attribute the S-curve growth analogy to the data. Once that pattern is accepted, the common observation of S-curve diffusion trajectories allows us to accept the use of models based on this shape.

5.3. Marketing Science Diffusion Model Issues

5.3.1. The diffusion model forecasting process

The process of running a classic diffusion model forecast is straightforward and is well described in the literature (Armstrong, 1985, 2001d; Mahajan & Peterson, 1985). First, a mathematical functional form is selected to suit the expected shape of the curve. Choosing the parameters of that functional form that best estimate the expected curve is the next step. This becomes the parameterised model, which is then run across future time periods to produce a series of point estimates of the variable of interest.

Intuition might suggest that forecasters try a series of predictions, based on a range of values of a model's parameters. Unfortunately, spreading of parameter values across a range, frequently gives vastly different shaped curves with only slightly different parameter values (Steffens & Murthy, 1992), and is unsuccessful in providing realistic estimations of the variable of interest, even in the case of the Bass model where banks of parameters for many different situations exist (Massiani & Gohs, 2015). Forecasters might also compare the forecast with those from other methods, combine forecasts, or use expert intervention to bootstrap the model in search of better forecasts (Armstrong, 2001d). This type of process is suitable for any S-curve prediction task.

5.3.2. Is the model naïve or causal?

It is important to note that one can develop two types of diffusion models. *Naïve models* whose structures are not supported by theory and rely on just fitting the data for the situation of interest (Armstrong, 1968). Alternatively one can develop *causal models* where the parameters are considered representative of real data on specific causal factors from the environment, and those parameters, in principle, can be determined from environmental data (Armstrong, 1968).

There are also two methods for calibrating diffusion models. One method relies on fitting a candidate model to historical data representing the variable of interest; this method is called *naïve modelling*. The second one estimates a model based on parameters derived externally to the variable of interest (Armstrong, 1968). This method of fitting is *causal modelling*.

The implication is that models may be causal at conception but not causal in use, a distinction not often made in the literature. Models loaded with causal factor data are considered causal in this thesis, and all others are described as naïve (or sometimes fitted) models for the reasons outlined, no matter what the theoretical foundation.

5.3.3. The availability of data and naïve fitting

Factors such as marketing spend, competitive pressure, and pricing are often recorded differently from firm to firm and across industries. Frequently such information is not available at all. Thus, the calibration of models using these determinant data is difficult and models are typically curve fitted, where estimates of the parameters come from the observed data on the variable of interest, rather than from market data on the parameters of the model. In other words, whether the model was designed to be one of internal or external influence, was conceived as causal, or was chosen as a purely mathematical form with no basis in theory, suitable parameter values to fit the model to data are derived from fitting the model to the currently available data on the variable of interest.

This process of curve fitting, to which forecasters are frequently driven, is an iterative fitting (naïve) activity, and is so easy with modern software, that it can, ironically, lead forecasters to include more parameters in an attempt to further improve fit. More parameters absorb more degrees of freedom in the data and can result in a model becoming *over-fitted* if there are too many model parameters relative to the number of data points. This situation is critical in situations where data series are short or sparsely sample a phenomenon or both.

In improving the fit there are some limits to the gains from adding parameters, as Parker (1993) demonstrated there is little value in going beyond four parameters (including the ceiling parameter), notwithstanding any difficulties in explaining the model's theoretical base. This provides an upper limit that a forecaster should not exceed, in the interests of parsimony.

5.3.4. Principles that apply in diffusion model forecasting

There are few universal rules in applying diffusion models; however, there are three critical principles. The primary principle is the identification and/or acceptance of an S-curve pattern of diffusion to allow the deployment of marketing science diffusion models. Meade (1984) argues that this aspect of *context validity* is a critical principle in diffusion forecasting. The second principle is the single purchase proposition, where the technology is purchased only once, at adoption. This is the requirement for most diffusion models to have *face validity*: Meade's face validity test is that the curve should have an obvious ceiling (Meade, 1984). The third principle is not to use the model to estimate the ceiling "L" (market potential), as well as the "a" and "b" (shape and rate parameters) as notated in a typical three parameter model such as Equation (10) repeated below.

$$Y_{(t)} = \frac{L}{1 + e^{-(a+bt)}}$$

Debecker and Modis (1994) also support this view, that the ceiling must be estimated separate to the model, as does M. R. Young (1993) who demonstrated that the two most popular S-curve functional forms, the Pearl logistic and the Gompertz, will give poor forecast accuracy when used to forecast without knowing the upper limit. Additionally, Modis (2007) notes that fitting programmes generally yield fits that are biased towards low ceilings. Modis also described a heightening of this bias through permitting larger margins for the determination of the model parameters. Finally, some error measures can influence the predicted ceiling negatively (Miyazaki (1994) cited in Tofallis, 2014), as discussed further in this chapter's section on error measures (section 6.3). In decline forecasting as proposed in this thesis, the peak is determined as unity and fitting to the data will produce a model which will predict a floor. That floor would seem to be unknown to managers as it is some residual, which will be unclear until it becomes identified. This is different from the concept of rising to saturation in the diffusion case, where total market size might well be understood ahead of time.

5.3.5. Selecting between diffusion models

Beyond the provision of some generic guidelines, (see Armstrong & Green, 2011; Meade & Islam, 1998), guidance for the selection of diffusion model functional forms is extremely limited; a well-recognised but ongoing gap in the literature (Riikonen, Smura, Kivi, & Töyli, 2013). The rarely cited U. Kumar and Kumar (1992) provides some guidance. They observe that to select effectively between the many diffusion of innovation models one needs to understand four facets of the models:

- the motivation and assumptions of the model's designers;
- the prime analytical characteristics of each model;
- the relationships that exist between models;
- the behaviour of the model when tested (empirically on a data set)

However, these rules are hard to operationalise without extensive knowledge. U. Kumar and Kumar (1992), recognising this point, propose a framework for model selection based on what they see as important model characteristics:

- The number of parameters and their ranges;
- The point of inflection's location;
- The observation of symmetry or non-symmetry around the point of inflection.

The criteria have their own problems. Criteria One requires great skill and experience. The second criterion requires the passing of between 40 and 60 percent of the diffusion for the inflection point to be recorded before an empirically sound guess as to the likely pattern can be made prior. The third criterion requires that diffusion is close to completion or that an empirically sound guess can be made as to the symmetry. Despite these limitations, the framework is useful in directing the forecaster's focus onto the issues of suitability. Suitability can be assessed with the expected shape of the data series determined from analogous data. Both the inflection point location and the symmetry/asymmetry about that point are important in this regard. As a principle, functional forms with a similar shape to the data should be chosen to be the foundation of a model.

Sharif and Kabir (1976) observed that unless the diffusion and substitution process had nearly been completed, some models overestimate the level of diffusion, for example the Fisher and Pry (1971) and Blackman (1971a) models, while others give an underestimated growth forecast, such as the Floyd (1968) flexible model. Implicit in these biases is the observation that most simple models need at least 20 percent of the S-curve to be recorded, before an acceptable forecast of the growth rate can be achieved. For example Heeler and Hustad (1980) and Srinivasan and Mason (1986a) suggest 10 years' worth of data for optimum performance with the Bass model. These general rules apply in ideal situations where there are no discontinuities in the curve. With very little literature to guide them and given the challenges in selecting models, forecasters generally use the most popular model (Armstrong, 2001e).

5.3.6. Model parameterisation and over-fitting in models

It is always necessary to have more observations than parameters. In theory, only one more point than the number of parameters is required. From statistical theory, any less than this and the parameter's estimated values will have infinite standard error, and the resultant prediction interval is infinitely wide (Hyndman & Kostenko, 2007). When data contain substantial random variation from trend, more data is needed to estimate stable parameters for a model. Conversely, when the variation is small, it is possible to estimate with fewer data points. Given that, if the data from Emmanouilides (2006) and from Parker (1993) are typical, that is, diffusion series are typically short but follow a smooth highly correlated progression (indicating low random variation relative to the trend magnitude) then it should be possible to estimate parameters for models, provided degree of freedom requirements are met.

From a statistical validity perspective, there seems to be no rule of thumb on model parsimony and data sufficiency (the degrees of freedom problem), although regression texts quote ten observations per parameter in a model (Harrell, 2015). However, given the Emmanouilides (2006) data then it seems diffusion forecasters are often working with less than this minimum and thus could be accused of violating many of the basic rules of model validity. Helpfully, Vittinghoff and McCulloch (2006) have demonstrated many situations where this rule can be justifiably relaxed.

As discussed in Chapter Two, the diffusion of technologies is driven by external factors, such as the degree of word of mouth communication or advertising about the technology, the social structure of the market and the availability, utility, and cost of the technology.

The literature demonstrates two divergent philosophical approaches to specifying models. One approach is to develop parsimonious models with a minimum of parameters to avoid overfitting to the data. The other approach comes out of the desire of model developers to include all possible determining factors into a comprehensive model to describe all the available historic data (Neal, 2012, pp. 103-104). There are enticing arguments for both parsimonious and comprehensive model approaches, some of which are discussed in the following sections. A comprehensively specified model does well at describing the ins and outs of data points in the estimation data, because it becomes a very good fit to the random (stochastic) components of the historical data. The concern is that this fitting to the stochastic component is at the expense of fitting to any important and useful underlying trend in the data generation process. This state of *fitting to the noise* in the data is commonly called *over-fitting* (Babyak, 2004). However, as mentioned earlier overfitting risks becoming the norm if data points are sparse in the estimation period. The low density of diffusion data limits the practical permitted complexity of models. So, the theoretical ideal (to use a comprehensive model to fully describe the phenomena) and the best practice (to ensure the methods suit the data available) need to be traded off (Babyak, 2004).

5.4. Analogies in Forecasting Issues

5.4.1. Introduction

Forecasting uses analogies in three important ways: in providing justification for use of models, in providing analogous data for forecasting, and in providing analogous situations for judgmental forecasts (Green & Armstrong, 2007; Lee, Goodwin, Fildes, Nikolopoulos, & Lawrence, 2007).

Sometime there are insufficient data to run diffusion models. When there are little or no data available, predictions in technology diffusion can be based on analogous technologies (Easingwood, 1989; Thomas, 1985). While new products and technologies can conceivably follow a wide variety of diffusion patterns, within that variety there are technologies that demonstrate similar diffusion characteristics to each other (Easingwood, 1989; Parker, 1994). Direct use of diffusion data is the most common way analogies are used in diffusion forecasting, allowing data series to provide a pattern to predict new diffusion. There is also indirect analogy via bibliometric and internet search data (Jun, Sung, & Park, 2017). This indirect process draws an analogy from growth in precursor information such as scientific literature and patent applications (Ernst, 1997). These analogies are applied via the development of scenarios and diffusion model forecasts (Daim, Monalisa, Dash, & Brown, 2007; Daim, Rueda, Martin, & Gerdsri, 2006). Such indirect analogy via plotting internet traffic and bibliographic search information can be used to provide leading indication of diffusion. The use of analogy in decision-making is common (Greenberg & Root, 1995;

Kokinov, 2003). Analogies can help in identifying surrogate data for model fitting (Harijan, Uqaili, Memon, & Mirza, 2011; Thomas, 1985). There are some challenges to using analogies.

5.4.2. Challenges of using analogies

It is common for people to think about each situation as being unique, thus undermining the potential of analogy based decisions (Kahneman & Lovallo, 1993).

Also defining suitable analogous series is a challenge for forecasters as the situations they want to forecast is unique, and of course, has yet to unfold, so it is unclear what the true nature of the situation will be. Martino (1993) discusses the wide range of knowledge that is needed to have a realistic understanding of how things will unfold. The judgment of the forecaster comes into play; to decide which series best represents the situation we wish to forecast where they are seeking a single data series to represent the situation, and in the case of the pooled series approach, which series should belong in the pool, and which series should be excluded. Unlike in individual analogy selection, in a pooled process there is an argument that the hand of the forecaster has less influence on the outcome (Martino, 1993, pp. 37-54).

There is a concern about the unstructured nature of many analogy judgments in forecasts (Green & Armstrong, 2007; Lee et al., 2007), but also that the usefulness of single analogies relies on profound structural matches between the analogy and any (naturalistic) scenarios developed for the problem situation (Gentner, Holyoak, & Kokinov, 2001). Psychology laboratory experiments confirm that people frequently use analogies in generating solutions to decision problems (Gentner et al., 2001; Holyoak & Thagard, 1995), but also that participants tend to choose superficial features to group their analogies (Gick & Holyoak, 1980, 1983; Holyoak & Thagard, 1995). Some research suggests that superficial analogies are more readily drawn from memory and tend to overly influence decisions (Gilovich, 1981). Fortunately in real life, people tend to choose analogies with deep seated structural similarities (Dunbar, 2001). We also know people tend to have over-optimistic and unrealistic views of their capabilities, thus the formalised use of analogies can operate as a frame for expert judgment forecasts, and consequentially may reduce the resultant bias in judgmental forecasts (Armstrong, 2001d, p. 193; Kruger & Dunning, 1999; K. Nikolopoulos, Litsa, Petropoulos, Bougioukos, & Khammash, 2015).

When seeking analogues, it is important to recognise people's tendency to only look for recent or easily recalled situations as possible analogies (Green & Armstrong, 2007; Lee et al., 2007), which is a form of availability bias (Tversky & Kahneman, 1973). Bolton (2003) noted that people who have made a choice are resistant to changing from their initial choice even when later provided with better analogies. It is also possible that analogies people choose are those that confirm their initial beliefs about a situation (Tversky & Kahneman, 1975a), therefore understanding the important parameters of, and the extent of similarity across those parameters is critical to choosing a good analogy (Green & Armstrong, 2007). Unfortunately, there are few examples of analogy approaches to time-series forecast problems to give guidance to decline forecasting (Lawrence et al., 2006), one exception being M. J. Wright and Stern (2015).

5.4.3. Choosing suitable analogous technologies

There are two philosophical approaches to choosing analogies. One commonly discussed approach is to choose a single technology based on some predetermined criteria that most represents the situation of interest (Bass, Gordon, Ferguson, & Githens, 2001). The historic series for that analogous technology then becomes the analogy to represent the outcome you wish to predict (Thomas, 1985). This approach requires judgment and a great deal of care is needed to determine the criteria for choosing the most similar situation, and in applying those criteria. Inherent to this process is the collection of a great deal of information about the situation represented by the series. In the other main approach, pooled and averaged data across many analogies is used to provide the prediction.

In this method, the researcher recognises little is known of the unfolding situation and that a grouping of series that represent the situation in some broad way is more likely on average, to represent the situation to be forecast, than would any single series. The rationale is that an average of a pool of series represents the typical observation in situations of this type, and can be used as the estimation for the situation of interest (Duncan, Gorr, & Szczypula, 2001; Goodwin et al., 2013; M. J. Wright & Stern, 2015). Typically but not always, there is an attempt to select a sub-pool of analogous series from a larger pool, by judgmental or nearest neighbour analysis (Goodwin et al., 2013) and described in section 5.4.4 below.

The literature emphasises that success in forecasting by analogy requires choosing truly analogous situations and that having structured rules to support the choice helps (Lee et al., 2007). However, understanding what is sufficiently similar is the challenge, because forecastable situations differ across a range of dimensions including technological, economic, political, social, cultural, managerial, religious, and ecological. The natural tendency is to look for similarity at the technology level, for example to compare autonomous ride-share cars with the introduction of the first cars. A better approach is use a broader perspective with which to investigate. Perhaps the technology challenge is similar, for example is the new technology going to be as easy to manufacture as its predecessor was at the same stage? Does the entire complementary infrastructure exist in a similar way to the past? Perhaps the market acceptance challenge is similar, or the scale of the overall project is similar (Martino, 1993). It has been suggested that when selecting analogues, the similarity of the market behaviours is often a better base for selection than the similarity of the product (Lilien, Rangaswamy, & Van den Bulte, 2000), although empirical evidence of this seems missing. Other factors that might be considered are market structure, buyer behaviour, and marketing mix strategies (Thomas, 1985). However, approaches like Thomas' often assume criteria are equally important, and brainstorming and interviews of field experts are common, but are both expensive and subject to a variety of personal and social bias. Cronrath and Zock (2007) extended Thomas's approach with system dynamic modeling of the diffusion process to identify model parameters. Unfortunately, Thomas' (1985) process and as extended in Cronrath and Zock (2007) provides a heavy cognitive load and relies on consumers or experts to determine the analogous product. In effect placing what might be interpreted as a systematic approach over an essentially arbitrary choosing process. Thus, one might conclude that choosing analogies is challenging and by definition, no analogy will be perfect. Pooling analogies offers one solution.

5.4.4. Pooling analogous data series

Finding a single historic series that is sufficiently similar to the situation of interest is often a challenge, usually because not enough is known about the current situation of interest, but also little might be known about the available pool of historic candidate situations. Accordingly, suitable series are sometimes pooled, and averaged in some way to provide a suitable analogy, with the goal of improving forecasting accuracy over a less than ideal single analogy (Duncan et al., 2001). Convention says that in seeking a group of analogies, it is important that many similarities exist and that the time-series selected co-vary over time. One might call groups with many such similarities an equivalence group and such groups make good candidates for forecasting (Duncan et al., 2001). However, it seems more advanced statistical methods, such as factor analysis used for grouping analogous series, do not improve forecast accuracy (Duncan et al.). Duncan et al. proposed a Bayesian pooling technique to provide analogous series and since they proposed this structured method of doing this, many of the texts used to teach forecasting have included derivatives of this method. Yet at the same time, there has been limited reported research on the use or performance of the method, with a few exceptions (see Goodwin et al., 2013; M. Kumar & Patel, 2010; M. J. Wright & Stern, 2015). Goodwin et al. (2013) investigated four methods to identify a suitable analogy for forecasting the annual sales of new electronic goods. They used:

- the mean of published values of the Bass model for analogous products;
- the mean of the p and q parameters derived from fitting to a randomly selected analogous data series;
- the mean of the parameters of a group of analogies selected from the nearest neighbour analysis of the pool;
- linear regression using *Ordinary Least Squares* (OLS) onto the transformed analogous data series

They found that the worst performing method was using the mean of the published Bass model p and q parameters. That result is consistent with our knowledge of the diverse shapes that can come from only small differences in p and q values (Massiani & Gohs, 2015). The next worst was a random single analogy from the pool. Interestingly, whether it was selected randomly or via the nearest neighbour method, the outcome was not changed. The best methods were pooled analogies and there appeared to be little to no difference between the actual methods of selection, as they all performed similarly. Goodwin et al. (2013) found pooling five or six analogies provided the maximum improvement in errors over a single analogy.

It is known that the sum, or the average, of several Pearl logistic or Gompertz function curves will not be a Pearl logistic or a Gompertz curve. However, in practice the sum of a number of such curves often closely approximates the function curve type. Reed and Pearl (1927) demonstrated this with the logistic function. It seems the general theory of averaging growth curves worked out by Merrell (1931) and applied by her to the Pearl logistic function, can be applied without modification to both the Pearl logistic and the Gompertz functions. In this vein M. J. Wright and Stern (2015) forecast early sales of new products with analogous series, by comparing diffusion models against analogous series normalised to suit the target situation, they found that their analogous series outperformed yardstick diffusion models already proven best performing in a similar situation by Fader, Hardie, and Zeithammer (2003).

Typical data series often come with little information recorded about the context that generated the data, and when there is information recorded, the likelihood that the parameters recorded are similar across series is low. This limits the ease with which good analogies can be selected from the pool, and makes the unscreened or pooled set of series attractive as an estimator.

5.4.5. Analogies and expert judgment in forecasting

There are many methods proposed for identifying analogies for use in forecasting. Tversky (1977) proposed the similarity matching method, and Sternberg (1977) suggested the proportion method. Another approach first demonstrated by Klein (1986) for getting early predictions, is to ask those expert in the situation, although he observed little can be understood of the basis for their estimates, and one cannot evaluate their predictions prior to the event. Klein demonstrated the importance of expert judgment in using historical analogies. In a method described as *comparison based prediction,* he developed the concept of using experts to make model adjustments when the analogue is not a perfect match to the forecast situation. He found that his comparison based prediction method (using historical analogues) gave improved error performance over existing predictions. The focus of his comparison across analogies was to direct the experts to select the best analogy and then to predict target performance based on the use of known causal factors.

5.4.6. Forecasting with analogous series

The use of analogous times series data in forecasting is founded in the principle outlined by Armstrong, that time series data, which are expected to be correlated, are conceptually similar and can be expected to be affected by similar factors (Armstrong, 2001d, p. 764). It is possible to use a single time series for an analogous technology diffusion situation to forecast a target technology directly. In this method, the analogous data series becomes the forecast after suitable adjustment for time scale and magnitude of the variable of interest.

When a single closely similar analogous series cannot be found, broadly similar analogous time series can be pooled to provide an average diffusion curve.

5.4.7. Using analogous data series to estimate model parameters

Sometimes an analogous series or a pooled set of series is used indirectly, with a diffusion model generated by fitting a suitable functional form to that analogous data and the resultant model is used to forecast. In that vein, the Bass model has a range of loose analogies available through the publication of many set of parameters for historical data series, although in this case pooling has not been done rather individual series are used to generate the parameters (Sultan, Farley, & Lehmann, 1990). Thomas (1985) looked at the estimation of market growth for new products in a prelaunch context using the diffusion data of similar products, and proposed an approach for diffusion modelling using analogies. He located data for similar products, and used a structured procedure of scoring analogies on economic, situation, marketing strategy, and buyer behaviour, to find those as similar to the target situation as possible. Thomas estimated the market potential parameter L from a market study, and the coefficients of a Bass model by fitting to series for analogous products. Consumer evaluation of the underlying attributes defining the new product and existing products determined the products chosen. Estimates of parameters for the target product were derived by taking a weighted average of the parameters for models fitted to the selected analogies. The weights were based on the extent that consumers thought the products had attributes in common with the target. The Thomas method is a form of the nearest neighbour approach (K. Nikolopoulos, Goodwin, Patelis, & Assimakopoulos, 2007). Nearest neighbours are obtained by ranking the historical analogies on their similarity to the target situation. Sometimes, researchers use many neighbours, each weighted by their closeness at other times researchers use the closest neighbour. The Thomas process has become a common process for selecting analogous situations (Bass et al., 2001; Tigert & Farivar, 1981), despite concerns as to the limited similarity of curves generated with only slightly different model parameters, and criticism of the vague definition of Thomas’ similarity criteria (Goodwin et al., 2013).

5.4.8. Analogy data scaling

It is often necessary to scale data when using analogies. Using a common example, geographic separation results in spatial diffusion of technologies starting in a certain type of location, for example in major cities, and then diffusing out to smaller cities. In each location, the growth tends to follow an S-curve, with diffusion being faster in larger cities and slower in smaller ones, indicating a need to scale the rate of change for the size of the city used as an analogue. Once again, such analogues are potentially useful (Golub, Gorr, & Gould, 1993). Occasionally, adoption lag might exist between markets, so to use this sort of data the standardisation of the variables' magnitudes and synchronisation of the time periods is required.

5.4.9. Summary

It appears from the literature that analogous series have been little used in diffusion forecasting. It also appears that when developing analogies for forecasting tasks, simple choosing, and pooling processes work as well as ones that are more complex. From the limited literature analogous series look promising for forecasting in the diffusion and decline domains (M. J. Wright & Stern, 2015). The next section synthesises the forecasting and psychology literature on judgment and in particular expert judgment in forecasting, with respect to the highly trended nonlinear context of diffusion and decline.

5.5. Judgmental Forecasting Issues

5.5.1. Introduction

This section focuses on the judgmental forecasting of a falling S-curve time series by direct extrapolation, outlining the knowledge relevant to judgmental forecasting of nonlinear time series. The challenge involved in decline forecasting is mainly related to the lack of data to undertake forecasts and the challenges of model fitting in sparse data situations. Judgment is able to recognise discontinuity in curves, while models only respond mechanistically to those discontinuances, thus the innate knowledge and understanding of experts, hints at attractive properties of judgment. Judgmental forecasting appears to be the most commonly used forecasting method in industry (Lawrence et al., 2006; Sanders & Manrodt, 1994). For example, Sanders and Manrodt (2003) demonstrated that in the US the use of software to forecast was relatively rare, with only 11 percent reporting using software out of 240 corporations surveyed. No doubt since 2003, more forecasting software has come into use, nevertheless, given the high use of judgment as the sole method of forecasting in industry, it is important to understand how effective judgment is when applied to forecasting tasks.

There is a bias in research into forecasting accuracy towards the numerical statistical side of the discipline (G. Wright, Lawrence, & Collopy, 1996), despite every step of a forecast, even a statistically based one, requiring the input of judgment. Furthermore, completed statistical forecasts are frequently adjusted post-hoc through expert input (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009; Petropoulos, Fildes, & Goodwin, 2016). This further indicates the value of researching judgment in forecasting.

Sometimes data are insufficient to produce an acceptable forecast. It might be that a new situation is so foreign to the forecaster that models cannot be envisaged; or the situation involves either fast growing trends or a great deal of variability. In these types of situations, judgment is necessary to augment, or replace empirical models in forecasting. The main benefit of judgmental input into forecasting is the inclusion of a forecaster's domain knowledge, particularly special insights into unusual pieces of information that are not conducive to modelling despite their importance. For a business context such domain data might include sales promotions, competitor activity, economic trends and manufacturing or supply data (Lawrence et al., 2006).

5.5.2. Using judgment in time series forecasting

Domain knowledge can be used in three ways. The first way being judgment input into statistical models where a model is designed, and/or calibrated with parameters judged suitable by an expert. However, this is rare, perhaps because of concerns about double counting of correlated factors already included in a model and the difficulty in integrating such data. The second and more common, way is to include domain knowledge via judgmental adjustments to forecasts. In the third way, the domain data provides cues to the expert who uses their experience, not to aid the model, but to replace the model. Situations of insufficient data to allow models to be used, force forecasters to use judgment in this way.

The use of analogous situations to provide a context frame along with historic data for the variable of interest and a structured forecasting process is a recognised way to improve direct judgmental forecasts. This is the approach used in Study Three. To understand how to apply analogies and structure to judgmental forecasting it is useful to understand judgmental approaches in forecasting, along with their accuracy and bias.

5.5.3. Structuring judgmental forecasts through analogy

Perhaps forecasters could better use information they possess if required to work within a framework. There is sparse evidence in the literature of an improvement in judgmental forecasts through providing a structured judgmental process, although what exists tends to support the notion that structuring a judgment process improves forecasts (Armstrong, 1985, Chapter 6; Green, 2005; Lawrence et al., 2006). Armstrong (2001d, p. 193) observed that the structured use of analogies reduces bias in judgmental forecasts. Green and Armstrong (2007) suggest that a structured approach mitigates the natural bias in drawing conclusions from personally generated analogies, this approach has been incorporated in recommended rules for forecasting that is; *use structured analogies* (Armstrong et al., 2015). Armstrong (2001d) advocates using analogies in expert forecasting where the anchoring impact of the historical facts would reduce optimistic bias or unrealistic views.

5.5.4. Combining judgment forecasts

There is evidence of the value of combining forecasts, particularly if the task, method or forecaster are different (Armstrong, 1989; Goodwin, 2009). Useful improvements in judgmental forecasts can be made by combining forecasts, with seven percent improvement observed by Winkler and Makridakis (1983), and 12 percent observed by Armstrong (2001a) over 35 studies. Improvement can occur even when the methods are very similar as in Graefe, Armstrong, Cuzán, and Jones (2009)

There is little agreement on how to combine forecasts, although a mechanical approach is recommended over subjective inclusion (Goodwin, 2000; Goodwin & Wright, 1993). Some recommend a simple average of the forecasts (Bunn & Wright, 1991), whilst others recommend regression based weights (Lobo, 1991; Newbold, Zumwalt, & Kannan, 1987). There is empirical evidence that simple average weighting is consistently as good as, if not better than methods that are more sophisticated. Nonetheless, perhaps because this concept goes somewhat against the intuitive response that averaging forecasts gives average performance, it has not been widely adopted (for a review of the evidence see A Graefe, H Küchenhoff, V Stierle, & B Riedl, 2014). Although simple averages of estimates seems promising (Armstrong, 1989; A. Graefe, H. Küchenhoff, V. Stierle, & B. Riedl, 2014), as in other forecasting domains there is a lack of agreement on the combining together of judgmental forecasts, (Önkal-Atay, Thomson, & Pollock, 2007). In combining judgment forecasts simple averaging appears to be a better approach (Lawrence, Edmundson, & O'Connor, 1986). In contrast, statistical grouping of forecasts provides potentially better forecasting outcomes in both combining individual's statistical forecasts (Hogarth, 1978) and in combining interactive group's statistical forecasts, through such methods as *Delphi* (Ang & O'Connor, 1991). Harvey and Harries (2004) recommend that if a forecaster is involved in the process of combining forecasts they should have their own forecast removed from that pool. Combining of methods while valuable is excluded from the studies in this thesis for primarily brevity reasons.

5.5.5. Judgmental extrapolation in time series forecasting

The process of extrapolation seems to underlie the cognitive activity that drives our intuitive expectations of the future, because human expectations for the future are often influenced by perceptions of past behaviour (Andreassen & Kraus, 1990). The thinking processes that drive our instinctive expectation of the future are thought of as happening in only one way, that of simple linear extrapolation (Andreassen & Kraus, 1990). Consequently, it could be argued that a forecasting method based on extrapolation rather than judgmental input into a model better aligns with the human cognitive processes. Wagenaar and Timmers (1978a) believe that this extrapolation is a two-stage cognitive process, one first identifies the series' underlying properties, that is, the trend and the acceleration etc., and then one extrapolates from that knowledge.

Where judgment is concerned there will potentially be biases. Human judgment can be easily biased (Haselton & Funder, 2006). While it is not clear if judgmental forecasters' judgmental biases are rational (De Bondt, 1993; Van den Steen, 2004), or irrational (Anderson & Goldsmith, 1994), there is some empirical evidence that human "intuitive statisticians" are quite capable of being accurate (Cosmides & Tooby, 1996), and given suitable situations can be as accurate as the best statistical methods (Lawrence et al., 2006). L. D. Brown and Rozeff (1978) identified how investment analysts were consistently more accurate than Box-Jenkins forecasts of earnings per share. Ashton (1984) found a similar result for executives estimating advertising sales compared with a regression model forecast. The consensus amongst those researchers tends toward accepting that short-term judgmental forecasts are more accurate than statistical models. Examples are in Lawrence et al. (1986) who investigated combining forecast methods; Braun and Yaniv (1992) who looked at experts' short-term econometric predictions and Clemen and Murphy (1986) who observed weather forecasters.

However, there is also significant evidence that there are factors that work to weaken that capability (Tversky & Kahneman, 1975b), such as situations where variability in the data is high or if there are spikes or bumps within the overall trend, then humans struggle to give good forecasts (Best et al., 2007; Furlong & Wampold, 1982; Ottenbacher, 1986). Similarly, if the data display method is inappropriate for the context (Chambers, Cleveland, Kleiner, & Tukey, 1983; Cleveland & McGill, 1984; Harvey & Bolger, 1996), or if there is insufficient data presented (Park, Marascuilo, & Gaylord-Ross, 1990), then judgmental forecasting capability will be weak.

5.5.6. Judgment in forecasting is historically discouraged

In the past, direct forecasting with judgment has been seen as both inaccurate and unreliable, in comparison to numerical (statistical) methods (Makridakis et al., 1982). Much of the evidence on the accuracy of judgmental accuracy and consistency performance is mixed (Adam & Ebert, 1976; Eggleton, 1982), or negative (Hogarth & Makridakis, 1981; Lorek, Holland, & Bathke, 1992; Makridakis, 1988; P. Tetlock, 2005). Carbone and Gorr (1985) found judgment consistently less accurate than quantitative methods for smoothing time series, and Sanders (1992) found both bias and accuracy deficiencies in judgmental forecasting. Hence, the use of judgmental methods has, historically been actively discouraged (Hogarth & Makridakis, 1981; Makridakis, 1988; Makridakis et al., 1982; Webby & O'Connor, 1996). However, it has been suggested that the practical situations in which such tasks take place are substantially different to those reported and the literature might have limited implications (Doherty & Balzer, 1988; Sanders, 1997).

Interestingly, the recommendations to avoid judgmental forecasting is founded on a large body of work in psychology using simple two state, that is, yes-no, or win-lose situations. Moreover, in other psychology literature, humans have been found to be limited in their ability to learn functional forms, in understanding uncertainty, and in dealing with noise while learning about functional forms (Klayman, 1988). Lawrence, Edmundson, and O'Connor (1985) observe that this body of research typically uses cues (stimulus) that are serial uncorrelated, thus making much of the findings unlikely to be applicable to the highly correlated world of time series forecasting.

5.5.7. Judgmental forecasting accuracy research is mostly econometric

In those studies that have looked at judgmental forecasting of time-series, complexities such as seasonality and large spikes in a trend have been associated with poorer judgmental forecasting accuracy (Lawrence et al., 1985; Sanders, 1992). It seems participants often see noise as part of a trend, resulting in overreaction behaviour, particularly to recent noise (Klayman, 1988). Furthermore, many of the studies are conducted with high levels of induced noise, see for example Sanders (1992) and also Best, Smith, Frey, and Stubbs (1998), see section 5.5.10. Many studies include data with complex seasonality combined with low underlying trends, particularly in econometric literature. That complexity and noise relative to trend level brings additional cognitive load and consequential potential for decreases in accuracy and consistency of performance of judgmental predictions. However, Lawrence et al. (1985) when extrapolating with judgment, found the forecasts appear to be as accurate as their extrapolative statistical model counterparts, although the studies that they reported were primarily of econometric data (Ashley, 1988; Ashton, 1984; L. D. Brown & Rozeff, 1978). In summary, much of the judgmental forecast literature including that in econometrics (see for example; Camerer, 1981), where typical contexts are linear low trend, are investigations with often high signal to noise ratios. This is in stark contrast to the highly trended, highly correlated non-linear nature of decline curves, making much of this literature of limited direct relevance, given the difference in the cognitive task.

The M1 competition (Makridakis et al., 1982) demonstrated that in econometric environments, that is, where economic data series with low trends and moderate variance are common, that simple methods work better. Deseasonalised single level exponential smoothing was superior to all other methods overall (Makridakis et al., 1982). Using the same M1 data, Lawrence et al. (1985), were able to conclude that judgmental forecasts were at least as accurate and sometimes more accurate than statistical methods. Importantly, the standard deviation of their judgmental estimates was less than that of the statistical model methods indicating the possibility that judgmental forecasts were more consistent. There is, further evidence supporting judgment in forecasting (Goodwin & Wright, 1993; Lawrence et al., 1985). In the M2 forecasting competitions data, Makridakis et al. (1993) demonstrated that judgmental forecasting could be at least as accurate as statistical forecasts, and that in some situations was the best method. Other studies using the same or similar data have shown that judgmental forecasts can be poor in comparison to statistical forecasts, and infer that the accuracy demonstrated by Makridakis et al. (1982) was seemingly related to the type of data being forecast (Carbone & Gorr, 1985; Sanders & Ritzman, 1992).

5.5.8. Judgmental forecasts are generally underestimates

When participants are tasked to extrapolate data, accuracy is frequently low and underestimation is common (Bailey & Gupta, 1999; Keren, 1983; Timmers & Wagenaar, 1977). It seems that the underestimation can be found across many formulations of the forecasting task (Mullet & Cheminat, 1995). Generally, this underestimation does not appear to be driven by the method used to present the data, or the wording used in task description (Lawrence et al., 1985, 1986; Lawrence & Makridakis, 1989), nor is it improved by an awareness of humans' propensity to underestimate (Andreassen & Kraus, 1990). The expertise of the judge also seems not to effect outcomes (Sanders & Ritzman, 1992; Wagenaar & Sagaria, 1975).

Some authors (Eggleton, 1982; O'Connor, Remus, & Griggs, 1993), believe there are some consistent biases in judgmental forecasting of trends: forecasters tend to dampen rising and falling trends, with falling trends suffering more than rising trends, although Lawrence and Makridakis (1989) found the dampening was even. Lawrence and Makridakis (1989) also observed that on falling forecasts, forecasters were less confident in their forecasts and widened the bounds of their estimates. This finding was confirmed by O'Connor, Remus, and Griggs (1997). Making forecasts from noisy series is associated with this phenomenon, (see this explained in; Andreassen & Kraus, 1990; Keren, 1983, 1984; Lawrence & Makridakis, 1989; O'Connor et al., 1993). In practice, this means their forecasts lie below upward trend lines but above downward ones. That is, forecasters tend to underestimate the steepness of trends in data series.

5.5.9. Exponential trends are grossly underestimated by humans

Phenomena displaying exponential type growth or decline have important impacts on human life (Wagenaar & Timmers, 1979), beyond diffusion growth models, and analogous series models judgmental methods could be used to investigate these phenomena, however this has not been done often. In a general sense of judgmental forecasting, Lawrence et al. (2006) provide a useful review of judgmental forecasting and sources of the bias, and argue that even experts with experience with growth processes did not do significantly better than amateurs.

More specifically, the ability of humans to judgmentally forecast in exponential growth and decline situations has been investigated in the psychology literature (Best, 2008; Best et al., 2007; Timmers & Wagenaar, 1977; Wagenaar & Timmers, 1978a, 1978b, 1979) and in the financial literature (McKenzie & Liersch, 2011). In exponential growth prediction, judgmental extrapolation has been far from successful. Uniformly, humans substantially underestimate the rate of growth of exponential series when tasked to extrapolate from early data (Timmers & Wagenaar, 1977; Wagenaar & Sagaria, 1975), even providing more data points doesn't help (Wagenaar & Timmers, 1978a, 1978b). Keren (1984) found that people when faced with historical exponential data, were not able to predict an exponential trajectory, although those with experience with exponential growth did better. All these authors reason that the underlying extrapolation model used by people does not allow for such fast moving changes. However in contrast, Bailey and Gupta (1999) while investigating learning curves, which have a declining exponential form, observed that human forecast accuracy was statistically superior to fitted curve models when few data points were available.

The shape of the trend is important, with exponential trends much more poorly forecast than linear trends (Wagenaar & Timmers, 1978a, 1978b) and Best (2008) noted that falling trends were forecast more accurately than growing trends. It has been observed that asymptotic exponential decline is marginally better predicted than exponential growth (Timmers & Wagenaar, 1977; Wagenaar & Sagaria, 1975). This is important because the last half of a decline curve follows a similar trajectory to a declining asymptotic exponential.

Best (2008) hypothesised, based on her findings, that underestimation bias found by previous researchers such as Wagenaar and Timmers (1978b) might depend on the expertise and experience of the forecaster. She found when experienced forecasters have information about the time series presented in a graph, they tended to substantially overestimate, while inexperienced forecasters tend to underestimate slightly. Lawrence and Makridakis (1989) observed that on falling forecasts, forecasters were less confident in their forecasts over growing curves and widened the bounds of their estimates. This finding was confirmed by O'Connor et al. (1997).

5.5.10. Extrapolating exponential trends: The effect of noise

Random noise effects, what one might call variability away from the trend (Adam & Ebert, 1976; O'Connor et al., 1993; Sanders, 1992), and seasonality effects (Adam & Ebert, 1976; Sanders, 1992) appear to cause deterioration in judgmental forecasts. When faced with high variability and significant discontinuities in trends, a type of step function noise, judgment performs worse than statistical models (O'Connor et al., 1993). In addition, even when the information about a curve shape discontinuity improved, individuals tended to overreact to immediate past information on the discontinuity, seemingly reacting to the noise rather than the trend signal (Andreassen, 1988; O'Connor et al., 1993).

Best et al. (2007) investigated if people can discriminate between different trends, under various noise levels. They found that participants chose correctly in 67 percent of exponential examples, and in 65 percent of asymptotic exponential examples. When the variability in the trend data was low and the sample size (data density) was high, they found the ability to discriminate the type of trend was high. The ability to identify trends that had many of the characteristics of diffusion and decline curves was still in the region of 48 percent when the noise (variance) was high. Success was significantly higher than chance, although noise increased the difficulty of identifying trends, something observed earlier (Goodwin & Wright, 1994). It seems that participants react excessively to series noise, especially where there are recency issues (Klayman, 1988). However, while increases in the variability of data greatly diminishes the ability for humans to perceive trends (Best et al., 2007; Goodwin & Wright, 1994; Sanders, 1992), it has been suggested that these findings might have limited application in the real world where access to aids are not so restricted as in laboratory tests (Hammond, 1986; Sanders, 1997).

5.5.11. Data density (sample rate) effects on nonlinear estimation

The evidence of the impact of data point density in the judgmental extrapolation literature is contradictory. Best et al. (2007) found the number of data points presented from the historic series made no difference when identifying nonlinear trends. They used six people knowledgeable about the nature of exponential curves, and previously briefed on the character of the data to be presented. In investigating the effect of the amount of presented data on extrapolation tasks, they found in judgmental extrapolation of exponential trends that overestimation increased as the data density (number of data points) presented increased. At low data densities there were low estimates (underestimation). Critically as data density presented increased, the estimates grew relative to actual, crossing over from underestimates to become overestimates. The Best et al. (2007) findings contrast with two earlier studies where participants were asked to extrapolate from exponential curves. In those studies, Wagenaar and Timmers (1978a, 1979) had found that the judgment accuracy of participants attempting a forecasting task was higher, when they were presented with fewer points. Investigating the Wagenaar and Timmers studies (1977; 1978a, 1978b, 1979), Andreassen and Kraus (1990) did an experiment with 77 undergraduate students that supported the Wagenaar and Timmers (1978a) findings. They hypothesised that a salience effect was at play; that is, when there are fewer data points the focus of the participant goes on to the larger gaps between points and thus to the rate of change of those gaps. Moreover, they discovered that drawing attention to the trend greatly increased the recognition of the magnitude of the trend in forecasting tasks, compared with the substantial underestimation of the trend when only the data was provided. These two observations provide some additional support for the use of judgmental extrapolation when there is a low sampling rate in the data. The contrary results of Best (Best, 2008; 1998; Best et al., 2007) on the impact of data density indicate the need for further investigation of this issue.

5.5.12. The impact of experience and expertise on nonlinear estimation

Lawrence et al. (2006) provide a useful review of judgmental forecasting and in particular the determinants of bias in the outcomes. They argue that even experts with experience with growth processes do not do significantly better than amateurs (Lawrence et al., 2006). Wagenaar and Sagaria (1975) observed that this underestimation of the growth rate was not related to mathematical skills or to experience with exponential growth series.

Best (2008) investigated the impact of expertise on the ability to forecast exponential data. She used six students who had been participants in an earlier investigation and were familiar with exponential and asymptotic exponential curves types, in both growth and decline formats. These participants were briefed as to the nature of the curves they were about to extrapolate. The curves were presented with and without added noise. Their forecasts were compared with those of four un-briefed undergraduate students. Each participant did 36 sessions of 54 trials for a total of 1944 trails each. She found that for both declining exponentials and declining asymptotic exponentials, the experienced (i.e. briefed) participants substantially outperformed the inexperienced (un-briefed) participants.

Experienced participants tended to underestimate by between five and ten percent while inexperienced participants overestimated by between 40 and 60 percent. The overestimation result is somewhat contrary to the consensus view that experts are only marginally more accurate and that humans generally grossly underestimate exponential patterns (Keren, 1984; Timmers & Wagenaar, 1977; Wagenaar & Sagaria, 1975; Wagenaar & Timmers, 1978a, 1978b).

5.5.13. Providing additional information on the series to be forecast

Libby (1976) suggested that a judgmental forecaster's performance might be improved by providing feedback on performance, or by improving the cues on which predictions are based. Some researchers feel that feedback to forecasters on their performance does not help them be more accurate in their judgmental forecasts (Benson & Onkal, 1992; Goodwin & Wright, 1993). However, the benefit of providing cue information as to the nature of the series to forecasters has been shown in a limited number of studies to be effective in improving forecast accuracy of simulated monthly sales data with seasonality (Sanders, 1997), and in forecasts of students asked to rate bonds (Kessler & Ashton, 1981). Remus, O'Connor, and Griggs (1996) found that providing ques as to the underlying structure of a series to participants gave substantially better performance than feedback on the forecaster's performance to date. This study investigates cue information as part of its investigations.

5.5.14. Visual presentation effects

One way to provide cue information is to present data graphically. Graphical presentation of time series data helps participants see phenomena that change with time, changes that might be much harder to detect in for example tabular form. Graphical presentation makes noticeable any changes in the trend recorded in the data (Best, 2008). As Bolger and Wright (1994) observe that if the task has high ecological validity, then judgmental performance is a "function of the interaction between the dimensions of ecological validity and learnability". Also, it seems useful to plot auto-correlated cues in a graph allowing eye-balling, a strong skill in humans (Lawrence & Makridakis, 1989). The literature on the potential of graphical presentation types on judgmental estimation is inconclusive; it seems presenting the data graphically rather than in tabular form does little to aid better estimations (Timmers & Wagenaar, 1977; Wagenaar & Sagaria, 1975). Decline curves are better predicted than growth curves no matter if the historical data is presented in numerical or graphical form

(Timmers & Wagenaar, 1977; Wagenaar & Timmers, 1978b). Although in those studies, numerical presentation resulted in better prediction of decline than graphical presentation. There is however, a significant weakness in these findings, as it is clear that in the Timmers and Wagenaar (1977) study, that both a rising and a falling exponential was presented on the same chart and participants were exposed to more of the trajectory for the declining curve than they were to the growing exponential. This undermines the strength of their often accepted and cited findings and signals the potential for better results in predicting decline in the proposed judgmental study. Additionally, it seems that humans might even predict exponential trajectories better when fewer data points are presented (Wagenaar & Timmers, 1978a).

In the graphical presentation context Best et al. (2007) observed that line graphs conveyed linear trends better while suspended bar graphs were superior in presenting nonlinear trends. It is possible that while line graphs are more effective when discriminating between patterns, other graph presentation formats may be superior when the forecaster must predict data points (Wallgren, Wallgren, Persson, Jorner, & Haaland, 1996). Best 2008 identified that those with experience forecast exponentials better when cue information was provided in bar graphs confirming a similar finding from Culbertson and Powers (1959). This signals that bar graphs are preferable in expert situations.

5.5.15. Forecasting exponential time-series: Limitations of the literature

Much of the body of work in the area of judgmental forecasting has been on two state predictions (see Lawrence et al., 1985). When time series is the focus of the literature, most studies are based on linear low trend econometric environments so has limited relevance to highly trended diffusion forecasting. Importantly, the small literature corpus that does investigate judgmental extrapolation of exponential trends is focused on the understanding of the process used by participants, for example; are participants using a linear or an exponential cognitive model (Keren, 1983; Wagenaar & Sagaria, 1975)? The psychology studies have for the most part focused on cognitive model identification, rather than on the task of prediction and the achievement of prediction accuracy. As a consequence of this cognitive model focus the horizons to be predicted, the contexts presented, and the supporting aids offered in those studies, are not generally optimised with forecasting in mind, (for illustrations see Andreassen & Kraus, 1990; Timmers & Wagenaar, 1977; Wagenaar & Timmers, 1978a).

5.5.16. Summary

How to improve judgmental forecasting has been explored extensively in the forecasting literature, although, much of this exploration has been in linear data contexts. While, the studies of methods exponential data contexts tend to come from psychology and focus on internal validity rather than on supporting best extrapolation behaviour. Thus, the literature leaves open the opportunity to investigate the how to improve judgmental exponential extrapolation forecasts. Doing this by recognising suitable learnings from the linear research in forecasting. Specifically the findings in the use of:

- more structure (Green & Armstrong, 2007)
- better cue information (Lawrence et al., 1985; Lawrence & Makridakis, 1989)
- more realistic contexts (Hammond, 1986; Sanders, 1997)
- a focus on combining forecasts by individuals (Armstrong, 1989; A. Graefe et al., 2014)

The proposed study on judgmental forecasting looks at the impact of tabular versus graphical cue information (Best et al., 2007) in exponential decline judgmental forecast contexts. It brings together the experimental behaviour psychology stream (Best et al., 2007; Timmers & Wagenaar, 1977; Wagenaar & Timmers, 1979), with the judgmental forecasting literature (Lawrence et al., 1985; Lawrence et al., 2006). It seems that there have been no published attempts to use judgmental extrapolation of diffusion or decline in forecasting.

As discussed in the section on analogies in this chapter, the use of an analogy within a structured process is a recognised way to improve judgmental forecasts; this is the approach to providing cues used in Study Three. The following chapter lays out the process of collecting and trimming the time series data for the three studies. However first the research objectives are restated to set the scene for the studies.

5.6. Revisiting the Research Objectives.

The objective of this research is to apply validated techniques from the forecasting literature to the problem of rapid technology decline, to determine which provides the most accurate forecasts, and if there are any universal patterns that might provide reusable knowledge for managers and academics. The literature search confirms that the marketing science diffusion model, analogous series methods are likely to perform on decline data, while the expert judgment method is highly speculative. It is clear from the literature that the theme throughout this thesis; of simple understandable investigation processes is very suitable at this early stage of a programme looking at technology decline.

Research questions:

Can decline trajectories be forecast using validated forecasting methods?

Specifically:

- Of the approaches chosen, which provides the most accurate forecasts? –Three approaches were chosen: fitted marketing science diffusion models, analogous decline series, and expert judgmental forecasting are validated methods, and provide a wide view, a triangulation perhaps of the topic.
- What are the unique and special considerations of technique required to forecast decline trajectories? - Little was learnt of substance from the literature about special considerations for decline; however, it is likely that knowledge from diffusion will be useful, with suitable interpretation.
- What potentially generalizable patterns exist?

Another substantial issue but secondary to the primary questions above is:

- To what extent does the choice of forecasting performance measures affect our understanding of the performance of any method in decline situations (highly trended situations)?, a selection of measures have been chosen that will provide a varied view of performance.

Chapter Six: Method and Data

6.1. Introduction

The earlier chapters have covered the literature on diffusion and discontinuance theory, and the practices of marketing science models, analogous series forecasting and judgmental forecasting. This chapter discusses the methods chosen, the error measures to be used, and the process of locating and cleaning the data collected for the three studies.

6.2. The Chosen Forecasting Methods

An important aspect of selecting a forecasting approach is the knowledge that managers seem sceptical of predictions from methods they do not understand, independent of how well a method might perform (for example, see Taylor & Thomas, 1982). The importance placed on understanding by managers underpins much of good forecasting practice (Armstrong, 2001e, p. 369). Marketing science diffusion models are the most common approach in diffusion forecasting. It is for this reason and their intrinsic ability to be understood in their basic forms that they were chosen as part of this investigation. The diffusion models selected are discussed next. This is followed by an explanation of why analogous series forecasting should be tested. The use of expert judgment is then described. Model parameter estimation is discussed, and then forecast error measures are discussed.

6.2.1. Criteria for the choice of diffusion models

Only *foundational diffusion models* (internal, external, and mixed influence) were considered (for examples see Mahajan & Peterson, 1985). The rationale for this is based on the lack of a general theory on technology decline, and the focus on models that are simple, less reliant on externally defined market determinants, and suitable for naïve data fitting methods. The choice of functional forms for this study was guided by two factors:

- the intention to set a yardstick of simple foundational models in decline studies, in a similar approach to that of Hardie et al. (1998) to support Studies Two and Three;
- the desire to understand the requirements of those models with respect to the often short data series (both in terms of completion of the decline process but also in terms

of the sparsity of data points within the estimation area) as observed (Christodoulos, Michalakelis, & Varoutas, 2010, 2011; Sultan et al., 1990)

The most commonly used models were screened against the following criteria:

- that they represent cumulative diffusion as a function of time;
- that they have no more than three (adjustable) parameters to ensure they are suitable for the short length data series available for this study, and were able to easily translate into a form with a market ceiling set to a normalised level of unity;
- that they were representative of models used extensively in diffusion research;
- that they were not a reformulation of another model already included in the study

6.2.2. Diffusion models selected for use in the three studies

Arguably the three most commonly used diffusion models are the Pearl logistic (Pearl & Reed, 1923), the Gompertz (Gompertz, 1825) and the Bass (Bass, 1969). They are parsimonious in parameter count and are potentially attractive for use in this study because they are simple to understand and are not tied too closely through their parameters to concepts related to growth, which might make them potentially incorrectly specified for this new application. However, despite being the most tested and used models their overall diffusion forecasting performance is reported as inconsistent (Meade & Islam, 2001; M. R. Young & Ord, 1989). Despite inconsistent evidence of performance, simple models are still appealing over complex models. In an investigation of early trial of various products by consumers, Hardie et al. (1998) found that out of eight relatively simple functional forms, simpler models when used to predict product trial outperformed more complex models with both 13 and 26 weeks of estimation data. One of the poorer performing models was the Bass model, despite it being so extensively used that it is considered an empirically generalised model (Mahajan et al., 1995a). The Bass model has however, a reputation for being unstable when applied to short data series (Heeler & Hustad, 1980; Mahajan et al., 1990).

Beyond the Bass, the Pearl logistic and the Gompertz models, a variety of other functional forms are also somewhat popular. However, many of them, as indicated in Chapter Five in the section on diffusion models, are effectively the same function but in a different form. Other models do not easily provide a solution giving universal and logical parameter values, or do not scribe an S-curve but assume exponential curve growth. Further, some are over-parameterised for the short data series typically available in diffusion prediction tasks. Of the more popular secondary models notable examples include, in no particular order: Von Bertalanffy (Von Bertalanffy, 1957), Richards (Richards, 1959), the family of flexible logistic (FLOG) models (Bewley & Fiebig, 1988) and the log-logistic model (Tanner, 1978). The foundational and other extended models are extensively reviewed in Mahajan et al. (1995a) and Meade and Islam (2010b). The model formulations are presented in Table 2.

Table 2

Models Selected for Testing

Name (typically called)	Function	Comments
Pearl logistic (often called the simple logistic) - In form used by Meade and Islam (2001), see Equation (9)	$Y_t = \frac{L}{1+ae^{-bt}}$	Where *L* and *a* are positive constants, with *L* representing the upper limit asymptote, *a* representing the number of times the $Y_{(t=0)}$ value needs to grow to reach *M*, *b* representing the rate and direction of the growth with a positive value indicating growth and a negative decline.
Gompertz - In a three-parameter cumulative function form (Sood et al., 2012), See Equation (13).	$Y_t = Le^{-ae^{-bt}}$	Where *L* is the upper asymptote, *b* and *a* are positive, with *b* setting the displacement along the x axis, and *a* setting the growth rate on the y axis.
Bass - In cumulative density form (Meade & Islam, 2010a), See Equation (26).	$Y_{(t)} = (L)\,\frac{1-e^{-(p+q)t}}{1+\frac{q}{p}e^{-(p+q)t}}$	Where *L* is the upper asymptote, *q* is *the coefficient of innovation p is the coefficient of imitation.* When q is greater than p then the point of inflection occurs at $t_{inflection} = \frac{1}{p-q} ln(\frac{q}{p})$ $N_{inflection} = L\frac{(q-p)}{2q}$ When p is greater than or equal to q then the point of inflection occurs at a negative value of *t*.
log-logistic - (Tanner, 1978), see Equation (28)	$Y_{(t)} \ \frac{L}{1+ae^{(-bln(t))}}$	An asymmetric function formed by inserting the natural log (ln) of time in place of time *(t)* in the simple logistic.
A model representing a straight line.	$Y_t = aX + bt$	Where *a* = the rate of descent and *b* = the time displacement of the descent from *t*=0

Formulations of the models for this study has been selected because their saturation value L, the market size, need not be known nor considered given share data normalised to a peak share of 100 percent. Setting L as fixed, is supported by the principle that a fixed saturation level model is difficult to beat by a model that adjusts for market growth over time (Meade & Islam, 2001).

There are many other potential approaches to forecasting beyond diffusion models. The two primary groups are the use of analogies, and judgmental methods. In the next section, the rational for deciding on an analogical method is described.

6.2.3. The rationale for the analogical approach chosen

In this current study, a simple method that overcomes challenge with choosing the best analogy was sought. This problem is described in depth in Chapter Five in the section on analogies in forecasting. With the focus on simple methods, an *analogous series* approach was chosen see (M. J. Wright & Stern, 2015). They had used this method on similar nonlinear series, to predict early trial sales of new products. Their method appeals for being both simple and tested. In the current study, a simple average of all series became an analogous series predictor.

6.2.4. The rationale for the judgmental approach chosen

For the third approach the investigation turns to expert judgment, an approach which has an inconsistent history in the literature but which when implemented as *structured judgmental forecasting* (Green & Armstrong, 2007; Rowe & Wright, 2001), shows some promise. In the proposed approach, experts would be canvassed via a panel and asked to judge the future data series outcomes directly. The literature on these three methods was covered in Chapter Five.

6.2.5. Model Parameter Estimation Methods

Having chosen a model and with empirical data available, it is possible to estimate the parameters’ values that provide the best fit of the model to that empirical data. This procedure is *parameter estimation*, and results in a model that estimates the data to which it is fitted. There are several approaches to parameter estimation proposed in the marketing literature (Mahajan, Mason, & Srinivasan, 1985; Mahajan & Sharma, 1986). The most common methods and the context in which they are used are presented in Table 3.

The methods used in marketing studies, tend to be dominated by model based estimation techniques for estimating the parameters, primarily by fitting to historical data, and have been generally limited to Ordinary Least Squares Estimation (OLS) (M. R. Young & Ord, 1989), Maximum Likelihood Estimation (MLE) (Schmittlein & Mahajan, 1982), and

Nonlinear Least Squares Estimation (NLLS) (Mahajan et al., 1985). Today these three methods are easy with the availability of computer programmes, which implement the complex routines to iterate the methods. The amount of data available and the functional form being assumed (and used), determines the procedure that should be used.

Table 3

Common Methods of Parameter Estimation and Their Application

Concept	Method	Used when/ requires
Judgment or observation based	Informed guess	Little data exists, or as a starting estimate in models
	Expert judgment from direct observation of parameter values	Requires current observations and market expert availability
Combined judgment and model based estimation	Estimation by experts with judgmental fore-casts (bootstrapping with time-series model forecasts)	As a reference point to test alternative situations, to evaluate published parameters, or to modify published parameters in the light of observations.
Model based estimation	By formal estimation from historical data	Parameter values from the literature are already available or direct estimation from data by fitting iteratively is possible.
	By using an analogue series to parameterise the model	Using data from a similar situation, the validity of the analogue selected is critical.

Source: Adapted from D. W. J. Arthur (2006)

The following section provides some guidance on the selection of a model based iterative technique for estimating model parameters.

Early diffusion research used *Ordinary Least Squares* (OLS), also known as *Linear Least Squares*, as the estimation technique (Fisher & Pry, 1971; Griliches, 1957; Mansfield, 1963). OLS relies on transforming the data to a linear form via a log-linear transform and applying a linear regression model to estimates the parameters. OLS minimizes squared differences between the transformed data and the prediction from a linear function that is fitted to estimate that data. This log-linear transformation method is still quite common despite the ease with which modern software can fit non-linear functions to S-curve growth, and is favoured by statisticians because it frequently results in a close to normal distribution of errors, and thus supports the use of statistical tests relying on normality. OLS has the following practical advantages:

- Transforming helps compare different scaled time series;
- Any significant deviation from the transformed function is easier to see and to locate, by measuring the deviation of the target data from a linear logistic model;
- A simple linear regression can be applied to fit the transformed data;
- It tends to minimise the effects of stochastic variation in the original data.

If we can assume that the fit errors are distributed normally, then the OLS estimator is also the maximum likelihood estimator. Most statisticians would view OLS as only useful for fitting linear regression models, because parameter estimates are unstable when few data points exist, a standard error of the OLS model parameters cannot be derived, and there is a time interval bias in estimating parameters for some models (Putsis, 1996).

Maximum Likelihood Estimation (MLE) is frequently used to estimate parameters and make inferences in statistics. Schmittlein and Mahajan (1982), who proposed MLE in Bass model studies, demonstrated how under a wide range of conditions MLE is consistent, asymptotically normal, and asymptotically efficient. MLE has the following characteristics: sufficiency (complete information about the parameter of interest contained in its MLE estimator); consistency (true parameter values that generated the data recovered asymptotically, i.e. for data of sufficiently large samples); efficiency (lowest-possible variance of parameter estimates achieved asymptotically); and parameterization invariance (same MLE solution obtained independent of the parameterisation used). Further, many of the inference methods in statistics are developed based on MLE. For example, MLE is a prerequisite for the chi-square test and many model selection criteria, such as the *Akaike Information Criterion* (AIC) (Akaike, 1973). However, MLE requires assumptions on distribution not supported in diffusion models, and a solution appears readily available for the Bass model only.

Srinivasan and Mason (1986a) observed that MLE seriously underestimated the standard errors of parameters and introduced *Non-Linear Least Squares* (NLLS) estimation to diffusion research. Putsis and Srinivasan (2000, p. 269) observe that the NLLS approach, when used in a noncumulative context, "…will do well in most settings and may be preferred to MLE"; subsequently NLLS has become the standard estimation technique in diffusion research. Both MLE and NLLS methods do not suffer from the time-interval bias problem that exists in OLS, and they can provide standard errors for the parameters.

Most of the research into estimators is directed at the Bass model and compares the OLS, MLE, and NLLS approaches. Putsis and Srinivasan (2000) warns that if nonlinear models have covariates, it is not clear which one is preferred, MLE or NLLS. Van den Bulte and Lilien (1997) demonstrated that although NLLS is favoured over OLS and MLE, it is not exempt from bias in parameter estimation (referring to how it understates "L" and "p" and overstates "q" in Bass model parameter estimation). Dekimpe, Parker, and Sarvary (1998) observed that problems primarily occur when estimation is done without placing external constraints on the parameter ranges. When constraints are used, the problem was largely eliminated (Dekimpe et al., 1998). NLLS requires a 'good' initial estimate of parameter values; otherwise, it might converge on a local, rather than a global, optimum. NLLS is implemented in most simple fitting software and has many of the advantages of MLE. A multi start algorithm based on NLLS built into Microsoft Excel's Solver add-in, became the parameter estimation tool used to minimise the sum of the squared errors in forecasts.

6.3. Measures of Forecast Accuracy

Which forecasting approach is best is a vexing question in forecasting. Are we interested in absolute accuracy, or is bias important? In forecasting understanding what measure is describing a manager's sense of *what is best* is important (Chatfield, 2007). In their survey of practitioners, Yokum and Armstrong (1995) found that expected forecast accuracy is the most important criterion for a manager selecting a forecasting method. However, research reports different forecast accuracy depending on the error measure used (Makridakis & Hibon, 2000). Much of the difference stems from poor immunity to outliers and scale dependence, issues described in detail in this section. Moreover, according to Meade (1984), forecasts are frequently reported without any supporting statements.

Meade went on to develop the following three principles for ideal reporting of forecasts:

- statistical validity: subject all estimations of model parameters to significance tests
- demonstrable forecasting ability
- accompany forecasts with some measure of uncertainty, ideally a prediction interval

These principles are frequently violated, at least in published literature, where significance tests on parameters are not published and uncertainty intervals are not included, particularly when reporting on model performance. Why is not clear, however some expansion on the issue is needed. A common theme in forecasting is a fixation on absolute accuracy. Some authors (Koning, Franses, Hibon, & Stekler, 2005) keenly recommend the use of statistical tests. However, samples of time series are not a random sample (Chatfield, 2007), and contrary to Meade's requirements, Armstrong (2007a) and Kostenko and Hyndman (2008) argue that significance tests tend to damage improvements in forecasting, and Chatfield (2007) tends to agree and firmly states, "..significance tests are not valid to tackle this question". So while those authors were talking about significance testing of relative forecast accuracy, their comments also apply to Meade's first requirement. Meade's comments point out that we are never sure how close our model specification is to the true model specification. On the other hand, while Meade infers the need for a statistical test to identify a problem with a forecast, Chatfield (2007), is interested in solving the problem and draws attention to Draper (1995) and combining methods to incorporate issues of model specification uncertainty. The Draper/ Chatfield perspective is the one taken in relation to this investigation, although formal assessment of the combining of forecasts is not in the scope of this thesis.

With regard to Meade's second requirement, there are many challenges. At the heart of Meade's assertion is the need to demonstrate an empirical generalisation related to the models on the target data, of the kind envisaged by Mahajan et al. (1990) when they discuss the validation of the Bass model. The very limited amount of validation undertaken on models and the great variation in data series types makes this an unrealistic requirement. There are other ways to think of forecast-ability. For example, is it related to the volatility of a series, and reduces with reductions in series variability, as described in section 5.5.10, and by Catt (2009)? Alternatively is forecast-ability linked to the best possible forecast error, that is, linked to the model not the data a perspective subscribed to by Boylan (2009), and taken in this thesis.

Meade's third requirement is also vexing. What determines a suitable method to set an interval for a forecast which starts out as a point estimate, as most do? Returning to Chatfield (2007), the lack of support for the concept of a random sample from a large population in most time series, removes the opportunity to use a normal distribution of errors approach. What is possibly a better approach is to consider best possible and worst possible type scenarios as ways to set bounds (Boylan, 2009). The setting of upper and lower bounds in this way might be a better approach but is situation specific, and has no place in this thesis where generalisation based on mean performance across series is the context.

This thesis takes advice from Armstrong (2007a), Kostenko and Hyndman (2008), and Chatfield (2007) and presents performance relative to a benchmark but also with a selection (basket) of suitable measures and with identification of models on a ranked basis whilst at the same time respecting the observation that measures of error have characteristics that suit them to certain aspects of error reporting.

Kitchenham, Pickard, MacDonell, and Shepperd (2001) observed that for any given situation alternative accuracy statistics frequently give conflicting results, because these measures do not measure the same facet of prediction accuracy. Therefore, while the normalising of the variable of interest removes data scale related issues from the choice of measure, error magnitude, and error sign effects are still critical, particularly given the nonlinear, highly trended nature of the decline data.

Evaluation of forecast performance is proposed via a basket of measures. MAPE is proposed because MAPE is a frequently recommended measure, but has some limitations that impact in diffusion research, a point it seems is not made in the literature but is discussed below. It is proposed that *relative accuracy* is evaluated using CumRAE and UMBRAE as these two measures work in similar ways but have different requirements for the management of outliers. UMBRAE is reportedly less sensitive to outliers and thus should show different results to CumRAE if the data is sufficiently impacted by outlier data. Evaluation of *bias* of model forecast is to be assessed by illustrating the mean residual error, which both indicates the magnitude and the sign of any error and when plotted gives a visual indication of the forecast's fit overall. *Forecast consistency* of the models is demonstrated with provision of a *parametric estimate interval* and *percentage times better than the naïve benchmark.* These measures are described in the following sections.

6.3.1. Mean absolute percentage error measures

Percentage error based measures are scale independent and ensure that error measures are suitable to compare forecast error performance across data sets with different scales. *Mean Absolute Percent Error* (MAPE), also sometimes known as *Mean Absolute Percentage Deviation* (MAPD), or the *Mean Magnitude of Relative Error* (MMRE), is the most popular for these measures. It is usually expressed as a percentage as demonstrated in Equation (36) below (Gneiting, 2011):

$$MAPE = mean\ (|p_t|) \tag{36}$$

Where:

$$p_t = \frac{100\%}{n}\sum_{i=1}^{n} |\frac{X_{actual} - X_{forecast}}{X_{actual}}| \tag{37}$$

, and X_{actual} is the actual value, $X_{forecast}$ is the forecast value and p_t is the percentage error. Multiplying by 100 makes it a percentage error.

MAPE was included because it tells a manager a lot about the error as a percentage of the value of the variable of interest. Managers often prefer measures based on percentages (Goodwin et al., 2013). MAPE is a commonly used measure in forecasting.

Mean Absolute Percentage error (MAPE) is calculated as follows in Equation (38):

$$MAPE = mean\ (\frac{100\%}{n}\sum\nolimits_{i=1}^{n} \left|\frac{X_{actual} - X_{forecast}}{X_{actual}}\right|) \tag{38}$$

Where X_{actual} is the actual value, $X_{forecast}$ is the forecast value and multiplying by 100 makes it a percentage error.

Measures like MAPE have three drawbacks in practical application. When used with *low-values* data, then calculating the MAPE value for those observed (actual) small values, very large changes in the Absolute Percentage Error (APE) can occur from a small deviation in actual error. This scale sensitivity makes the MAPE very challenging as an error measure where great variation in scale exists. Makridakis (1986) proposed that reporting the MAPEs with and without outliers as a solution to this, where an outlier can be defined as; *any value greater than the MAPE plus some value*, and suggested that outliers be values three standard deviations or more out from the mean. In another attempt to solve this issue, Makridakis (1993) proposed eliminating from the process of averaging of absolute percentage errors, any series that have values of less than some cut-off value and suggested that cut-off be values less than “1.00”.

In the use of MAPE, the impact of errors is asymmetrical about the real value. That is, errors above the actual value result in a greater APE than a similar value below the actual value. The result outcome is that when used to select among competing prediction methods it systematically selects those whose predictions are too low (Miyazaki (1994) cited in Tofallis, 2014). This observation led to the use of symmetric measures, for example, *Symmetrical Mean Absolute Percentage Error* (sMAPE) for forecasts with values at/or near zero. Symmetric Mean Absolute Percentage Error (sMAPE) is a variation on MAPE and is calculated using the average of the absolute value of the actual and the absolute value of the forecast in the denominator. It was originally proposed by Armstrong (1978, p.348), and was preferred by Makridakis (1993). Goodwin and Lawton (1999) observe that it is far from symmetric, particularly if errors have large absolute values. Foss, Stensrud, Kitchenham, and Myrtveit (2003) found that MAPE (they call it MMRE) consistently selects inferior models when used in model selection. Thus, the decision was made to select MAPE, despite that when used with falling or rising S-curves, because it tends to overstate the management impact of errors as the curve falls in an exponential-like way, while it understates this impact on rising curves.

6.3.2. Relative error based measures

Relative accuracy is important if the scatter (variation in the data) grows as the value of the dependent variable grows (heteroscedacity). In relative measures, a benchmark is set by having a standardised method as a comparator as described in Equation (39). Typically, this benchmark forecasting method is the Random Walk (RW); where all forecasts are equal to the last observation. For example, in the case of annualised data, forecasts for any February is equal to the last February observation. There needs to be a measure and a benchmark selected within this framework.

$$Relative\ measure = \frac{measure\ method}{measure\ benchmark} \tag{39}$$

For example, if the preferred measure were MAE then a suitable relative measure would be MAE/MAE benchmark. As Hyndman and Koehler (2006) point out, these relative measures can be developed from RMSEs, MdRAEs, MAPEs, while the method preferred by Armstrong and Collopy (1992) is the Relative MAE, although they call it Cumulative RAE (CumRAE). Just as with other relative error measures, the benchmark is usually an appropriate naïve forecast model. It is not obvious from the literature how common the use of any relative measure is, because they are described with a variety of nomenclature. *Relative Absolute Error* (RAE) is the simplest relative error measure. Each error is divided by the error obtained from a naïve benchmark forecast which is typically The Random Walk (Armstrong & Collopy, 1992). The Relative Error (r_t) is defined in Equation (40) as:

$$r_t = \frac{e_t}{e *_t} \tag{40}$$

Where $e*_t$ is the forecast error obtained from the benchmark method Thus:

$$RAE = /r_t/ \tag{41}$$

Or expanded as:

$$RAE = \frac{|F_{m,h,s} - A_{h,s}|}{|F_{rw,h,s} - A_{h,s}|} \tag{42}$$

Where *m* = method, *h* = time horizon for the forecast, *s* = data series being examined, *rw* = random walk, *F* = forecast and *A* = actual. This formulation delivers the RAE for one horizon, one method, and one series.

Using RAE based measures for providing a scale-less measure of forecast accuracy addresses some of the issues of the percentage error based measures. RAE measures are recommended by both Armstrong and Collopy (1992) who favour the GMRAE, and Fildes (1992) who recommends a method that is equivalent to the GMRAE, the Geometric RMSE (GRMSE). Hyndman and Koehler (2006) and Armstrong and Collopy (1992) suggest, when looking at the errors across many series, then taking the geometric mean of all the series for that horizon and that method. They prefer GMRAE because the geometric mean is appropriate for averaging relative numbers, and is useful for measuring forecast error performance on a single forecast time horizon (point estimate) with a single method across many series (sets of data) (Armstrong & Collopy, 1992). GMRAE is however a less common error measure in comparison to MAPE and CumRAE, and is the reason why it was not selected for this investigation.

CumRAE is defined as the sum across all forecast horizons of the unsigned errors from the method under evaluation, divided by the sum of benchmark errors over those horizons, and is useful when we want to assess the error performance of a forecast made for a time period, across many horizons, using a particular data series, and one particular model. Then *Cumulative Relative Absolute Error* (CumRAE) is appropriate, according to Armstrong and Collopy (1992), where CumRAE is described mathematically as Equation (43):

$$CumRAE = \frac{\sum_{h=1}^{H} |F_{m,h,s} - A_{h,s}|}{\sum_{h=1}^{H} |F_{bm,h,s} - A_{h,s}|} \tag{43}$$

Where: m is the forecasting method, bm is the naïve forecast benchmark method, h is the horizon being forecast, s is the series being forecast, $F_{m,h,s}$ is the forecast from method m for horizon h of series s. $A_{h,s}$ is the actual value at horizon h of series s, and *h* is the number of horizons to be forecast.

CumRAE is easier to understand compared with other relative measures, for example, a CumRAE of 1.0 indicates that the sum of the absolute errors of the forecasts from the model being evaluated and the sum of the absolute errors of the forecasts from the benchmark model were the same. Similarly, a CumRAE of 0.7 would indicate that the sum of the evaluated method absolute errors was 30 percent below the sum of benchmark absolute errors.

As a relative error, CumRAE is less scale sensitive than the MAPE, but can require the Winsorising of data to remove outliers as recommended by Armstrong (Armstrong & Collopy, 1992). Winsorising was not used in this study because the impact of outlier removal was thought to penalise the outcomes, given how short and how sparse data series were. Midway through the investigation a new measure of error was published that was similar to CumRAE but with less sensitivity to outliers. The new measure is incorporated into this study because of its apparently superior qualities.

By placing bounds on RAE and creating a bounded RAE (BRAE) the issues of RAE being potentially very large or undefined are resolved (Chen, Twycross, & Garibaldi, 2017). Chen et al. (2017) start with the relative error as in Equation (40), where et* is the forecast error obtained from the benchmark method this allows them to define BRAE as:

$$BRAE = \frac{|e_t|}{|e_t| + |{e^*}_t|} \tag{44}$$

Adding $|e_t|$ to the denominator ensures that it will never be less than the numerator, ensuring BRAE will have a maximum value of 1 while the minimum value is 0 when $|e_t|$ equals zero. Any accuracy measure based on BRAE will be resistant to outliers in the data. To avoid being undefined when $|{e^*}_t|$ = $|e_t|$ = zero, BRAE is defined as 0.5 for that case.

Mean Bounded Relative Absolute Error (MBRAE) can be defined as Equation (45):

$$MBRAE = \frac{1}{n}\sum_{t=1}^{n} \frac{|e_t|}{|e_t| + |{e^*}_t|} \tag{45}$$

Though MBRAE has better characteristics in comparing forecasting methods, like many measures it is a scaled error measure that cannot be directly interpreted in terms of error size. A simple transformation can be made to MBRAE to obtain a more interpretable measure which Chen et al. (2017) term the Unscaled MBRAE (UMBRAE) characterised as Equation (46).

$$UMBRAE = \frac{MBRAE}{1 - MBRAE} \tag{46}$$

When UMBRAE is equal to 1, the proposed method performs about the same as the benchmark method; when UMBRAE < 1, the proposed method performs about (1 - UMBRAE) * 100 percent better than the benchmark method; and when UMBRAE > 1, the proposed method is about (UMBRAE – 1) x 100 percent worse than the benchmark method.

One critical aspect of using these relative measures is the choice of benchmark. An investigation of benchmarks was undertaken with respect to suitability. Both UMBRAE and CumRAE use comparison between the diffusion model forecasts and a naïve benchmark model. The UMBRAE removes the problem that relative measures can become large or undefined for very small values of benchmark forecast error.

It is important to note that relative measures can only be computed where there is a number of forecast points rather than a single point in each series (Hyndman & Koehler, 2006). Armstrong and Collopy (1992) and Hyndman and Koehler (2006) favour relative error measures, because these measures are only infinite or undefined when all the historical observations are of the same value, a rare occurrence in forecasting situations. However, as they point out, if all data are positive and much greater than zero, then using MAPE is simpler.

Often a one step ahead naïve *random walk* forecast benchmark is used in forecasting (Armstrong & Collopy, 1992; Kilian & Taylor, 2003). In this study, an equivalent naïve benchmark is used. Because the origin of the forecast remains stationary then so does the naïve benchmark's location, becoming a fixed origin single point as the estimate for all horizons. It was expected that all methods would have produced much smaller errors than either of these potential naïve benchmarks; thus, an extrapolation of a straight line applied to the last three data points of the estimation data and fitted with linear regression was also assessed as a naïve benchmark (Chen et al., 2017; MacRae, Wright, Green, & Hodis, 2015). Earlier tests not reported here had identified that point fitted lines were too sensitive to non-trend variations and four point fitted lines lagged the data curves significantly

In the three studies, the cumulative errors across each horizon were assessed with these measures, that is: from zero to one period, from zero to two periods, out to four periods. They are reported as means across all series.

6.3.3. The performance of two possible naïve benchmarks

Two basic strategies can be applied to a benchmark for relative measures. One is to apply a completely naïve benchmark that holds no pretence to fitting the theory or the empirical evidence on the form of the phenomena. This sort of benchmark would not compete with any model under assessment; rather it would provide a somewhat distant and impartial reference, the random walk is the most popular (C. R. Nelson & Plosser, 1982), and despite its pretensions to be naïve is very well performing in many situations primarily because of its typical application within a one step ahead protocol. (Kilian & Taylor, 2003). Another approach not mentioned in the literature is a benchmark that is deliberately chosen for competitiveness. Such a benchmark is closer to the everyday understanding of a benchmark as a standard, which sets a level of performance that is currently the best and which any other model needs to beat to be given the benchmark title. This study demonstrates the use of relative measures with both types of benchmark.

In forecasting decline, as defined in this study, a random walk with drift might seem the best approach (Haldrup & Hylleberg, 1995), however, because of the restrictions placed on the study to use fixed origin forecasts see section 5.2.1, two alternatives were considered. A straight line fitted to the last three estimation points, and a stationary point benchmark representing the last point in the estimation data.

The single stationary point is a traditional naïve standard, given the use of a single origin for all forecasts, this benchmark is the equivalent of the random walk naïve model. The forecasts from this model are simply the last known value of the variable of interest, thus it does not represent the S-curve decline very well, because it does not follow the curve, as the classic naïve model, the random walk, would do with step ahead forecasting tests.

A simple investigation of how the stationary point benchmark performed was undertaken by plotting MAPE, the results are presented in Figure 8. Clearly, the stationary benchmark is not a competitive forecast method, so is a conceptually poor benchmark, its MAPE error rate growth mirroring the rate of decline in the data series it measures. It does however, remove the benchmark duties from the straight-line model, allowing it to be assessed as a model alongside the classic marketing science diffusion models, because all models are then measured relative to this stationary point benchmark.

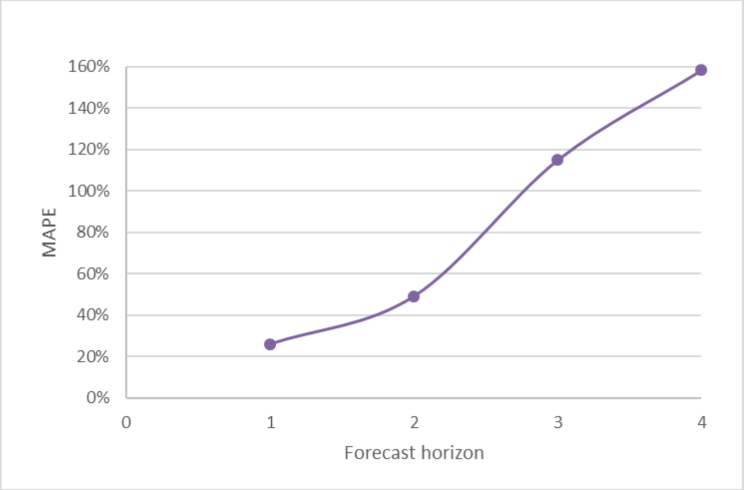


Figure 8. Mean forecast MAPE of the stationary point benchmark model.

The straight-line model fitted to and then extrapolated from, the last three estimation data points is demonstrated fitted to a series with a non-ideal curve in Figure 9.

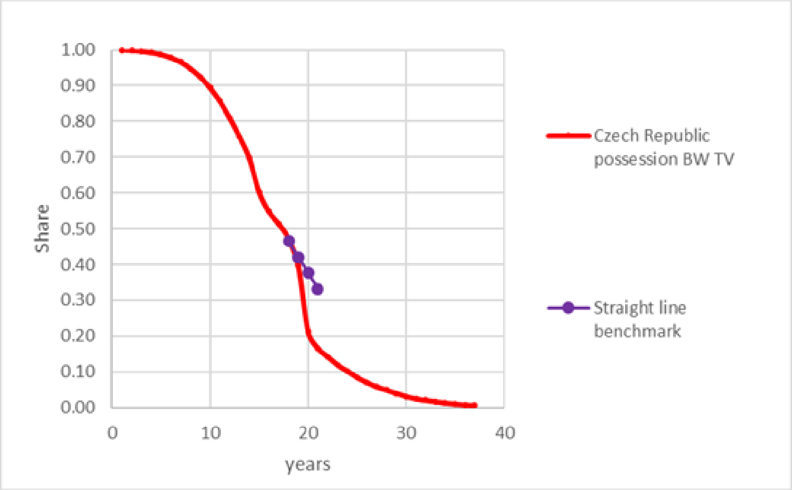


Figure 9. Simulated fit of the straight-line to an example decline data series.

Even when applied to a series with a local non S-curve slope, this model is still a reasonable model, in its expression of the slope of the last three data points and of the central part of the curve in general. It is clear that on an empirical basis, and in the restricted context of this study, the straight-line model makes a better benchmark for S-curve decline in the context of this study, than does the naïve stationary point benchmark. Figure 10 demonstrates that MAPE for the straight-line model is predictably lower than the stationary point model, see Figure 8, but also confirms that the benchmark's MAPE performance deteriorates in some

S-curve fashion reminding us that one might expect the S-curve model's MAPE error performance to deteriorate in a much more linear fashion.

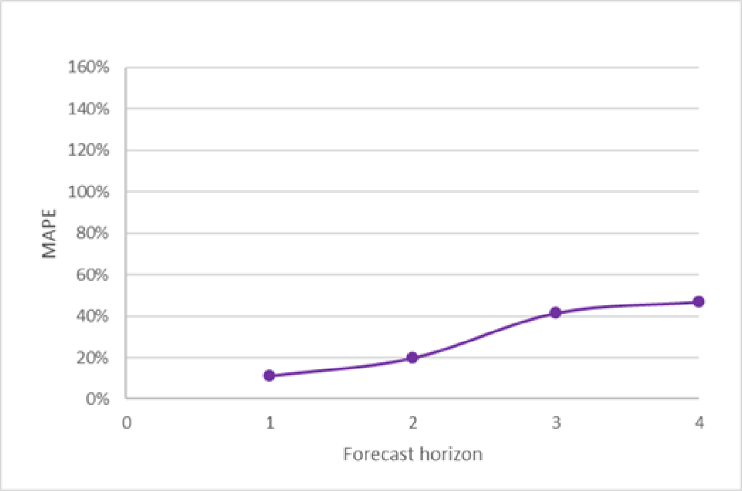


Figure 10. Mean forecast MAPE of the straight-line model.

All the above indicators, point to the straight-line model being the better benchmark. However, when the straight-line was utilised as a benchmark in early investigations in CUMRAE, the models under investigation performed similarly to the straight-line model. This caused a problem, as sometimes the performance was worse sometimes better. Consequently, as work progressed these observations became increasingly difficult to explain in a simple understandable manner, because across the horizons any given model might be better or worse than the straight-line at any given horizon. Whereas when the models were compared with the stationary point (a less competitive benchmark), it was easy to explain the situation as in most estimates the models beat the naïve stationary point benchmark, greatly enhancing understanding. As a result, it was decided to use the less competitive benchmark but to include the straight-line model into the pool of models investigated. The challenges in multi horizon forecasting of using a competitive benchmark versus a weaker benchmark is not mentioned in the forecasting literature, although the limited usefulness of linear models is mentioned by Meade and Islam (2001). They warn against the blind adoption of the *simpler models forecast better than more complex models* premise, because linear models will not model saturation, and will only be competitive short term as a result.

6.3.4. Residual forecast error as a measure of forecast bias

Understanding bias is very useful in assessing forecast methods, the mean residual errors in prediction (variation from a perfect fit) do provide means of easily explaining bias in the predictions. The limitation with the use of residual errors is that in S-curve situations, errors rise exponentially as a percentage of actual decline, as decline progresses but they are not represented by simple residual errors. One solution to this is to use the Mean Percentage Error (MPE) represented as in Equation (47).

$$MPE = \frac{100}{n}\sum_{t=1}^{n}\frac{(a_t - f_t)}{a_t} \tag{47}$$

Where a is the actual value and f is the forecast value. However this measure has two disadvantages, first it becomes undefined if the actual value is ever zero, and significantly for managers produces in S-curve situations errors which grow exponentially in percentage terms as decline progresses potentially overemphasising error levels of later periods [(which potentially) managers are not so concerned with], compared with near term errors. Thus, for the three studies the decision was made to stay with residual forecast errors rather than go with MPE.

6.3.5. Forecast consistency

Significantly, the presentation of forecast performance via accuracy focused means of error measures such as MAPE, CumRAE and UMBRAE used in this thesis can distort perceptions of performance. Because there may be a few extreme performances existing in a set of performance data, such that it is not clear how consistently the mean performance level is achieved (Armstrong & Collopy, 1992; Chen et al., 2017; Hyndman & Koehler, 2006). The use of medians instead of means may not solve the problem, as it is not clear from the literature if median based measures are better than mean based measures (Adhikari & Agrawal, 2012). Thus, it is important to understand the consistency of forecasting performance. So after an adequate level of relative accuracy is achieved, the focus of forecasters and managers might naturally fall to the consistency of the method in reaching that level. Also, the standard deviation of measures like CumRAE and UMBRAE are not likely to be useful as their distribution is very unlikely to be normally distributed. Early exploratory data analysis indicated that this was so, but that forecast errors could be expected to be normally distributed. Thus a different approach is needed. Traditionally, parametric forecast intervals are taken as a way of expressing forecast variability (Goodwin, 2014), thus this became one approach to describing variability via a plotting/ranking of the interval size for models.

Another one way to describe forecast consistency is to assess what proportion of time one method's forecasts are better than a benchmark (Armstrong & Collopy, 1992). This measure was also adopted in the spirit of the basket of measures approach. Both of these measures by their very nature do take the emphasis off the level of accuracy performance.

6.3.5.1. Forecast interval estimate

A simple way is to generate such an interval is to use a parametric estimate of the forecast interval (forecast uncertainty). The Shapiro and Wilk (1965) test is the most powerful of all normality tests in general use so this was used to indicate forecast error normality of distribution. With data sets of less than 30 series, to construct the estimate interval the *t* distribution should be used, as prescribed in Equation (48).

Where:

$$Interval\ Estimate = \bar{x} \pm t\frac{SD}{\sqrt{n}} \tag{48}$$

The *t* values are acquired by consulting a *t* table, *t* distribution tables require the availability of degrees of freedom (*n-1*), along with α. Calculation of α is covered in Equation (49).

Where:

$$\alpha = \frac{1-(confidence\ level)}{2} \tag{49}$$

The degrees of freedom and α allow the looking up of the t statistic. With the *t* statistic, the calculation of the forecast interval estimate is possible.

6.3.5.2. Forecast consistency – percent of times better than the benchmark

Another way of looking at forecasting performance is to assess what *proportion of times one method's forecasts are better than a benchmark's estimate* (Armstrong & Collopy, 1992). This measure focuses on the consistency of the model's forecast superiority, rather than absolute accuracy levels. Because the presentation of the means of error measures can distort perceptions of error performance where a few extreme performances exist in a set of data. This presentation format of performance avoids this problem.

Both CumRAE and UMBRAE have been implemented with a stationary point forecast naïve benchmark, making the process of assessing consistency as easy as calculating the number of times the models' CumRAE (or UMBRAE) betters unity with the naïve benchmark value of 1.0.

6.3.6. Summary

Section 6.3 highlighted important challenges in selection of error measures. The forecast measures of MAPE, CumRAE and UMBRAE, use means of error measures and can distort perceptions of performance where a few extreme performances exist in a set of data, such that it is not clear how consistently the mean performance level is achieved (Armstrong & Collopy, 1992; Chen et al., 2017; Hyndman & Koehler, 2006). The presentation of performance via a proportion of times better than a benchmark, can improve understanding of the consistency of performance, although it does take the emphasis off the level of accuracy performance.

This review of the chosen error measures demonstrates that no one measure can be relied upon to give a clear picture of the accuracy of a forecast method, hence the choice of multiple measures, to provide a range of lenses on the error structure of a forecast in the manner that might aid a manager. The next section describes the processes of collecting, screening, and trimming the data are described. A list of the selected data series is provided.

6.4. Data

6.4.1. Seeking data

Data series for the studies were sought for technologies with no limitations on the nature of the data set, other than that the technology was declining under obvious substitution. Seminal articles and books, as well as journals and conference proceedings related to technology substitution research were surveyed. These initial sources were used to conduct a reference tree search, that is, the search went through the sources' content, and from there, on to review the works cited within. Keyword searches were also undertaken on Scopus, Google Scholar, and the general Google internet search engine including, but not limited to the terms, *technology decline* - *innovation diffusion* - *technology diffusion* - *technology substitution* - *technology disadoption*, and *technology discontinuance*, and combinations of the individual words. To minimise the effect of any potential selection bias that might have existed in the academic literature in the acquisition of data, the on-line publications of selected US, Japanese, and global industry bodies, and selected government statistic offices were also searched to identify data series for technology that had declined. These searches were limited to sources where data were available for no fee. Finally, subscribers of a popular academic website (ResearchGate.net) were canvassed (twice, one year apart) to uncover any unpublished data series. This latter action yielded no additional data.

6.4.2. The potential for selection bias in seeking data

In seeking data series, it quickly became obvious that in contrast to diffusion growth data, technology decline data series are scarce. In addition, it became clear that available decline data series were very consistently S-shaped and were typically very short. Notably series were usually recorded only annually, with data from earlier publications tending to be reported only every five years, and data that are more recent sometimes reported quarterly. This low sampling rate meant that many of the data series had few observations overall, and this scarcity greatly influenced data density in the rapidly changing portion of their S-curve decline. This problem was exacerbated if the technology was fast diffusing. Finding only short S-curve data series created concerns about selection bias in the data collection process. In response to this concern, and to ensure that the research was tapping the sources of data in a thorough manner, a search of the literature was undertaken to investigate the typical size of diffusion data sets. It was found that data sets for diffusion are indeed relatively short. Of nearly 1,000 diffusion series collected, Emmanouilides (2006) observed that only around 39 percent of series had seven or more observations, thus supporting the findings of this study on the shortness of decline phase data series. After all series that had not provided at least three data points beyond the point of 50 percent market share fall, were removed, the remaining decline data series collected had an average 20 data points. These data series were not as long as they might appear as many series had several data points beyond the flat floor point of complete obsolescence. This inflated the number of data points in the series somewhat.

In respect to initial concerns that there was selection bias and that data series that did not confirm to the S-curve decline pattern were not being represented in research, articles were sought voicing the existence of such phenomena and surveyed for suitable data series. In addition, a question was posted on a popular global academic website (ResearchGate.net), asking for examples of such non-conforming data series. One conference paper (Dattee, 2007) challenged the prevalence of the diffusion S-curve, however, on deeper investigation was found to be discussing deviations from a pure shape and this discussion tended to confirm the S-curve model by the nature of the rarity of those exceptions.

6.4.3. The data collection criteria used

As a first step, two criteria for collection were employed; the first was that data sets should include unit sales, subscription, ownership, or usage data for both the new and the old technology, and that data were presented as penetration data, that is, as a proportion of households or population. No distinction was made between industrial or consumer products; however, any series representing a consumable product was not collected. No data that relied on revenues were included to avoid price effects on data.

Data were only collected for data sets where *a clear social system structure* could be identified. Where this was not possible they were not collected, for example, technology production figures do not link tightly to a social system adopting the technology. Similarly, global adoption is across many countries and is not linked to a single social system, and has potentially many different start dates for diffusion. One exception accepted into these data sets was the data on Global DRAM production where the shipments were to industrial businesses, but who were seen as tightly linked into a social system even across country borders, because their use of the technology started as soon as a factory was able to ship. Amongst the collected series if there were multiple generations acting in the market together over short time-frames, all generations' data were captured to allow correction for multigenerational effects.

As data were sometimes expressed in the form of a proxy for penetration data, care was taken to ensure that the proxy was a realistic model of the underlying social system, for example, some proxies were relatively strongly linked to the underlying technology. Take for example the licence subscriptions for television (TV) in Japan; they were considered a strong indication of current penetration of either black and white (BW) or colour TV technologies in households. A slightly weaker argument supported the sales of music media; however, as the alternative of *playing devices sold* only reflected the adoption of technology and gave no signal of the decline of the intrinsic media technology, this was considered a good proxy for penetration. This approach is a significant difference from the way data are accepted when researching a diffusion situation. In some older cases, data series were only available in graphical form and consequently needed to be extracted using calibrated scanning and plotting software designed for the purpose (Engauge Digitizer version10.2). In attempting to represent the plotted data accurately, this process had the potential to generate artificially high numbers of data points, so the data were filtered to exclude all but the reported observation rate. This process does perpetuate errors in the original graphical process and can introduce plotting measurement errors. Decline data series were scarce requiring all efforts to utilise those series that were uncovered. Because diffusion data are usually reported in both an aggregated across technology and cumulative across time form, with a resultant level of resolution that is often surprisingly low (rounded to the unit of reporting), this process was deemed acceptable, at least prior to screening. Diffusion researchers report, if the data time series data do not include observations covering the start of diffusion (left-hand data truncation), then there can be problems in fitting and testing forecasting models. Data with left hand truncation were avoided in the collection process. Twenty-three data sets were found, containing more than 250 data series.

6.4.4. The data screening process

To be accepted, data series had to show a clear sign of a new technology displacing the incumbent one. The data was only accepted if significant literature existed supporting the substitution of the declining technology or there was a data matching two technologies as growing and declining together and their use context was similar

Data reported less than annually for the later periods required for forecasting were excluded, as were short series with five or fewer years reported. If there were obvious multigenerational effects, or adjustments could not be made across a data set for the effects, the series was excluded. If the declining technology was not a clearly dominant technology form (operationalised as a saturation ceiling of at least 70 percent share of the market), it was not accepted. To avoid left truncated data issues that might have led to underestimation of the time to reach the floor, the data series had to present a ceiling peak rather than just have data that were above 70 percent share (Jiang et al., 2006).

Newell et al. (2014) set their limit for inclusion as having more than 50 percent fall from the peak and required an undetermined number of data points in the series. In this study, series that that did not provide three data points between the peak, and the last data point before the 50 percent fall point, were discarded as being too short for consideration. To allow forecasting, a substantial progression towards a floor of complete disuse and sufficient data to test a model's forecast accuracy was required. This was operationalised as; *at least two data points on or beyond the 50 percent fall point*. These criteria still allowed selection of short sparsely populated series, thus reflecting the typical data series available, as noted by Emmanouilides (2006).

A data series that showed significant impact from a global phenomenon such as a world war or the Great Depression were also eliminated. This culling process does raise the question of introducing selection bias; however, it involved only one data series. This was a series recording the decline of unfiltered cigarettes, which was dramatically affected by military purchasing during World War II.

6.4.5. The data, its translation and trimming

Practitioners will always wish to forecast as soon as adequate data are available, and as the estimation data changes in an S-curve, continuous re-forecasting each time more data is available is highly valuable, more so than in classic equilibrium economic modelling. Thus, they can start forecasting as soon as some minimum requirement is reached and re-estimate the model parameters as each new measurement arrives. This reforecasting is advantageous in situations where sampling rates are low relative to the rate of change of a technology's market share, or where the data series has significant noise.

In this study, all possible estimation observation points were included in a single estimation, because in typical series there were so few data points, prior to the fall to 50 percent share that viable one step ahead forecasting was possible before that point only on a small majority of the series. Another perspective was that in a large minority of the series, a practitioner would have to wait until close to the 50 percent point to obtain sufficient data points to calibrate their model. Beyond the 50 percent fall point few series had sufficient data points to allow a viable one step ahead forecast regime to be instigated, that is, the typical data series length prevented attempts to assess the impact of different estimation periods as is typical (see Hardie et al., 1998). These observations pose the question; should synthetic data be generated to allow both step ahead forecasting and estimation from early in the progress of decline? The approach taken was that the valuable insights to be gained from using this real life data outweighed any value in generating data to conform to conventional practice.

When choosing forecast horizons for this study, the working assumption was that managers are mostly interested in the simple question: what will the market share be for this technology next year and over the following few years? So horizons at one, two, three, and four were envisaged, with measurement across the horizon i.e. total error for the horizon forecasts were contemplated. Whereas researchers might look to use a standardised one step ahead process to be consistent with the literature.

All data were presented in cumulative form to minimise the impact of noise in the periodic reported data, and to conform to convention. The data existed sometimes as units sold, and sometimes as units in use, to remove issues of scale, each decline data series was normalised to a market share proportional to the total sales for all technologies in that market. To convert data to a market share, all data for the relevant growing and declining technologies were used. This was not required where the data already existed as share or penetration. In multigenerational cases, this earlier technologies and later technologies were summed to avoid multigenerational effects.

Some of the selected data series represented technologies that had long periods of stable penetration at 100 percent saturation, or if not saturated were market dominant at some obvious plateau, while others had grown to saturation or some other obvious peak, and then had gone rapidly into decline. Thus, to ensure the models reacted similarly to all data series, the early data needed to be truncated on the left to make the starting data point similar for all series. As the first step in that process, all data sets were trimmed of any monotonic growth data points up to a point of peak market share. Then all data were assessed for any steady state period prior to the start of monotonic decline and trimmed for the second time; this time to the last point prior to the onset of obvious monotonic decline. Monotonic decline was defined as three consecutive falls. This left only the decline data in all data series. Some of the data series had regular reporting dates that changed by a few months at some time in the reported period. Where this change occurred in the estimation period, the data were interpolated using a simple linear method to ensure the observations were consistently spaced over time, utilising the most frequently reported month as the starting point. These imputed data were only used for model fitting, and not for forecast performance assessment.

It is a common practice in diffusion research to trim initial data to exclude the first five to ten percent of the diffusion share measured from unset of diffusion, as recommended by Fisher and Pry (1971). This is due to competitive response to substitution by the older technology, diffusion data is thought to be prone to oscillations at the point of initial diffusion. Furthermore, measurement noise is a large percentage of the early observation value in diffusion of the new technology (Davies, 1979; Girifalco, 1991; Modis & Debecker, 1992) and the substitution of the older technology (Modis & Debecker, 1992). However, measurement noise is a much smaller proportion of share in decline data, because decline is starting from a relatively substantial market share in any dominant technology. Given this reduced effect of noise compared with diffusion data at the start of the forecasting, the trimming of the first five or ten percent results in *left hand truncated data* (Jiang et al., 2006), the recommended practice of removing the first five or ten percent of share level was not carried out. This helped retain what few data points existed in the shorter series. The final requirement was that the data series, after trimming, had at least three data points in the calibration sample and a minimum of two data points remaining available (withheld) for forecasting. The resulting datasets are listed in Table 4.

Table 4

The Data Series Investigated

	Description (all expressed as mkt share)	Source
1	Iowa non-hybrid seed corn[1]	Ryan and Gross (1943)
2	Australian dial-up internet subscribers[2]	Australian Bureau of Statistics (various years)
3	New Zealand dial-up internet subscribers[3]	Statistics New Zealand (various years), (OECD, 2005)
4	US steam locomotives[4]	U.S. Bureau of the Census (1975)
5	US BW TV households[5]	Girifalco (1991, p. 477)
6	Japanese BW TV households[6]	Ministry of Internal Affairs and Communications (2012), and Statistics Japan (various years)
7	Australian CD albums sold[7]	Australian Recording Industry Association (various years)
8	Japanese vinyl disks sold[8]	Recording Industry Association of Japan (various years)
9	Global 256K DRAM memory shipments[9]	Victor and Ausubel (2002)
10	Global 4M DRAM memory shipments[10]	Victor and Ausubel (2002)
11	Azerbaijan possession BW TV[11]	Euromonitor (2016b)
12	Czech Republic possession BW TV[11]	Euromonitor (2016b)
13	Estonia possession BW TV[11]	Euromonitor (2016b)
14	Lithuania possession BW TV[11]	Euromonitor (2016b)
15	Slovakia possession BW TV[11]	Euromonitor (2016b)
16	Ukraine possession BW TV[11]	Euromonitor (2016b)
17	Thailand possession cassette/radio playe[11]r	Euromonitor (2016c)
18	Russia possession cassette/radio player[11]	Euromonitor (2016c)
19	Egypt possession cassette/radio player[11]	Euromonitor (2016c)
20	Jordan possession cassette/radio player[11]	Euromonitor (2016c)
21	Morocco possession cassette/radio playe[11]r	Euromonitor (2016c)
22	Taiwan possession videotape recorder[11]	Euromonitor (2016d)
23	Australia possession videotape recorder[11]	Euromonitor (2016d)
24	Denmark possession videotape recorder[11]	Euromonitor (2016d)
25	Spain possession videotape recorder[11]	Euromonitor (2016d)

Note: The majority of the data series are from large scale government agency series and the sample size is large and would be considered a census, the sample size in those cases is likely to be different from year to year, although often sample sizes are not reported. Below are sample sizes for the full market (all technology competing) for each series.

Note No.

1. n=257 farmers (sometimes reported as 259)
2. N= 3.9M subscribers growing to 12.5M over the period
3. N= 0.5M subscribers growing to 2M over the period
4. N =47K locomotives falling to 30K over the period
5. N = 53M households growing to 86M over the period
6. N= 20K households growing to 37K over the period
7. N = 56M at peak
8. N = 338K album equivalents at the peak
9. N = 2.7MB at end of period
10. N = 81,000MB at end of period
11. N = not known but assumed to be full census

To ease the modelling process, after trimming and normalising, the recorded dates for observations in each series were converted to years and then translated so each series started at a standardised year one. From this point on in the study, the explanatory variable of *time passed* was defined as the number of periods past the peak of usage, sales or subscription, and year one in the data was set at the year of the observed peak. The independent variable of *market share* was defined as a proportion of the peak and described as the fall in share from that observed peak. The normalising of the independent variable data to unity resulted in year one of the transformed data, starting at a level of unity and declining from that point. This process corresponds to the method used by Newell et al. (2014), and yielded 25 data series from the initial set of more than 250 series. Given discussions in the forecasting literature advocating for presentation of results based on small samples even in the absence of rigorous statistical tests this small data set was accepted (Armstrong, 2007a, 2007b; Goodwin, 2007).

6.5. Summary

This current chapter described the collection and cleaning of the data, to obtain a set of 25 data series suitable for decline forecast model testing. The chapter also described the suitability of individual error measures in forecasting decline. The following three chapters are the three studies that make up this thesis.

Chapter Seven: Fitted Model Forecasting Study

7.1. Introduction

This chapter is devoted to an empirical investigation of four simple functional forms, representing popular marketing science models, applied to 25 historical decline data series to determine their relative performance in predicting the data trajectory beyond the estimation data to which they are fitted. Studies, aimed directly at forecasting decline appear to be rare, although Fisher and Pry (1971), Kucharavy and De Guio (2011) and Fenech and Longford (2014) modelled (fitted) the decline phenomena in relation to growth in the process of assessing models in the substitution process. Some researchers have predicted decline as an ancillary activity to demonstrating the fit of diffusion models a notable example being Norton and Bass (1992). In general there is little consideration of decline in the literature; the limits of the current knowledge are described earlier (see Chapter Four describing discontinuance decline, and also Chapters Two, Three and Five which provide extensive coverage of the theory, the mathematics and the application of classic S-curve marketing science models used in This study.

To deploy fitted marketing science models for decline forecasting data should be assumed S-curve shaped. S-curve shapes in decline have been demonstrated (Fisher & Pry, 1971; Kucharavy & De Guio, 2011; Newell et al., 2014). Also important is that there are sufficient data points available to both estimate model parameters, but also to withhold to test their prediction capability. Early in the investigation, it was clear that decline data series were S-curve shaped, but also that they were short in length. Indicating that predicting with early data might be a challenge. Meade and Islam (2006) called for investigations of forecasting with limited data. It is not clear however, if they were calling for research on data restricted by limited completion of the diffusion process, or on the limitations imposed by short low sample rate series. Interestingly, it turned out as data was collected that both issues exist from time to time in decline and diffusion data. Data sparsity is often driven by sampling rate and its interaction with diffusion rate, the extent of this in diffusion data is alluded to by Emmanouilides (2006). The implication is that until sampling rates increased to adequately sample the decline trajectories, then models might need to be simple fundamental models to meet data adequacy requirements This issue is a primary reason why their performance on short series is emphasised in this and the subsequent studies.

7.2. Aim of This Study

This investigation aims to determine the suitability of four marketing science models; the Pearl logistic, Gompertz, log-logistic and Bass Models, in decline forecasting. This study also aims to discuss the characteristics of the decline trajectories of technologies, as they might affect forecasting marketing science models.

The first objective is to determine what procedures are required at a methodological level to routinely use S-curve models on early, and thus, short decline data, given little, or no, suitable guidance in the literature. Some of the important methodological issues that come from the characteristics of the identified data are described in sections 6.4.4 and 6.4.5. The second objective is to set out how diffusion models perform against such typical decline data, thus empirically validating the support for the use of the S-curve model by analogy in respect to decline. The outcome of addressing this issue would be an indication of the viability of typical diffusion models in predicting decline from early data. The presentation of results will focus on graphical information, backed up by measures of relative performance in a commitment to the third objective: to facilitate readers' understanding of the process and findings, by concentrating on simple understandable methods (section 6.2.1) and measures (section 6.3).

7.3. Data, Models, and Methods

7.3.1. Data

The implementation of any decline forecast relies on the prior identification of monotonic decline in the target data series, and predicting forward from that decline. Refer to Chapter Six for a description of the decline identification procedure used in this thesis. There was a need to accumulate target series data for estimation purposes. The issues associated with this are varied and covered in Chapters Three and Five. The pool of technology data series candidates were all assumed to be suitable on the basis that they were from a similar data generating process, that is, they were all decline curves from substitution processes, and they are listed in Table 4 in section 6.4.5. While the functional forms used were selected for their parsimony, many data series were very short, having much less than 10 data points per model parameter. With no apparent rule to guide the number of data points needed for diffusion model viability, the number of estimation points were set at a minimum of 3 points, and this resulted in minimum points per parameter as low as 1.5. That is an extreme ratio and indicates potential overfitting, however, given the reality of forecasting, that is, you can get more data, but only by waiting for more periods to pass. Hence, overfitting was accepted on the assumption that managers are not prepared to wait. To allow for the data fitting recommendations for such models described throughout Chapters Five and Six, forecasting is delayed until after the series had fallen to a point on or before 0.50 share fall in this Study.

7.3.2. Models

This study is based on the assumption that an initial investigation should start with simple models, therefore four foundational diffusion models (marketing science models) were chosen (Mahajan & Peterson, 1985). They are the Gompertz (Gompertz, 1825) Pearl logistic (Pearl & Reed, 1923), Bass (Bass, 1969) and the log-logistic (Tanner, 1978). The selection process is outlined in Section 6.1. A model created by a straight-line fitted to the last three data points in the estimation data is also tested as a prospective competitor to the diffusion models after initially being considered as the naïve benchmark for the relative accuracy measures. The rationale and the choosing process are described in Section 6.3.3.

7.3.3. Forecast method and notes

7.3.3.1. Fitted model parameter value estimation

To test forecasting performance the models (more correctly termed functional forms unless fitted to data), were fitted to estimation data selected from the first half of the series of interest until fit was optimised. Removal of the estimation data from each trimmed data series (trimming is described in Section 6.4.5) was according to the following rules defining the upper and lower limit to the estimation data. The first data point in the estimation data was the first point in the post-trimmed data series, the final data point included was the last data point with a market share higher than, or equal to, 50 percent share. This rule ensured that the ending point was close to but never beyond the 50 percent share point. This rule increased the potential the curve inflection point was included. Its inclusion greatly improves prediction and it is frequently just below 50 percent share (Heeler & Hustad, 1980;

Pearl, 1925; Srinivasan & Mason, 1986b). The low sample rate of many series meant the last data point was often some distance before 50 percent. See Appendix A.

All remaining data were withheld for forecast performance testing, although only the first four observations of the remaining data were allocated to forecast performance assessment. Few series could contribute more points than those four, because many series fell to a floor rapidly or terminated early, leaving no further points. As described later (in section 7.3.3), three cases had only three data points and two cases only two data points available for assessing forecast performance. Because many series had low sampling rate not all series provided sufficient estimation points, before the 50 percent share decline point restricting the opportunity for a realistic test of the performance of models earlier in the decline process. Early estimations of model parameter values were made by altering model parameter values manually until the model produced output that was a good visual fit to the estimation data.

With initial values in the model, iterative fitting with the Solver add-in within Microsoft Excel refined the parameter values. This relied on minimising the sum of the squared residuals between the model predictions and the actual estimation data across the estimation points using a nonlinear least squares (NLLS) routine contained in the software. The software contained a multi-start point routine that ran many iterations of the fitting process for a designated number of attempts, and then chose automatically the best fit. With such highly trended and highly correlated data, the multi start routine would have avoided any local minima rendered our visual inspection stage redundant; however it was retained as a double check. R^2, Adjusted R^2, SSE, and MAPE were used to evaluate fit quality.

All functional forms in all specifications (models) had a good fit to their estimation data. R^2 values were typically 0.99, or better, with mean R^2 values of 0.98 or better. The worst model being the Gompertz model fitted to series 18 at R^2 0.89. MAPE values were typically less than three percent. The worst was less than seven percent; the mean was less than two point five percent. A summary of the model fit statistics from the estimation of the fitted models is provided in Table 5.

Table 5

Marketing Science Model Fit Statistic Summary –Study One

	Pearl logistic			Gompertz			Bass			Log-logistic		
	R2	SSE	MAPE %	R2	SSE	MAPE %	R2	SSE	MAPE %	R2	SSE	MAPE %
Min	0.90	0.00	0.02	0.89	0.00	0.06	0.96	0.00	0.00	0.96	0.00	0.09
Max	1.00	0.03	6.17	1.00	0.04	6.98	1.00	0.02	5.10	1.00	0.04	5.14
Mean	0.98	0.01	1.99	0.98	0.01	2.32	0.99	0.00	1.52	0.99	0.00	1.64
SD	0.02	0.01		0.03	0.01		0.01	0.00		0.01	0.01	

After applying a penalty by using adjusted R^2 for the number of parameters in the models most Adjusted R^2 values were above 0.95. The three series with poor initial fit and two data series (9 and 10) where there were only three data points available for estimation were exceptions. When the denominator in the Adjusted R^2 function fell to zero (only three estimation points) making the adjusted fit undefined, R^2 was recorded as in the same way, as a negative Adjusted R^2 would be, that is, as zero. Failing this statistical goodness of fit is not, critical in terms of forecasting because the test of a good forecast is not the fit to the estimation data but the fit to the out-of-sample data (as described in section 3.5). Moreover, the majority of fits had Adjusted R^2 within 0.005 of the unadjusted values with a mean adjustment of 0.01. The largest adjustment was just 0.03. Despite the weakness of model fits to the three series with weak adherence to the S-curve shape and the two series with only three estimation points, each model specification was considered an apt representation of the decline process, given acceptable R^2, SSE and MAPE. As these series are representative of data found in the wild it was deemed necessary to retain them even if their R^2 had been poorer than they were. The three data series (18, 21, and 24) that were fitted less well by all models have their R^2 and SSE values presented in Table 6.

Table 6

Marketing Science Model Fit Statistics of the Least S-Curved Data – Study One

	Pearl logistic			Gompertz			Bass			Log-logistic		
Series No.	R2	SSE	MAPE %	R2	SSE	MAPE %	R2	SSE	MAPE %	R2	SSE	MAPE %
18	0.90	0.03	4.36	0.89	0.03	4.61	0.96	0.01	2.98	0.96	0.01	2.97
21	0.94	0.01	5.59	0.92	0.02	6.37	0.96	0.01	4.65	0.98	0.00	2.95
24	0.93	0.03	6.17	0.91	0.04	6.98	0.96	0.02	5.10	0.98	0.01	3.52

A visual investigation of the graphical fits to data showed that the poorer fits were explained by the shape of the original data. Series number 18 (Russian Radio Cassette possession) appeared to have measurement noise as the data stepped up and down in an unusual way contrary to other series, indicating possible irregularities in the reporting process. Series 21 (Morocco Radio Cassette possession) fell asymptotic to a floor much above zero share (28 percent in 2016). Series 24 (Danish Videotape recorder possession) also fell asymptotic to what appeared to be a floor much above zero share (47 percent in 2016).

7.3.3.2. The forecasting process

Using the optimised (parameterised/fitted) models, forecasts were made by inserting into the model values of *t* representing predictions for horizons of one, two, three, and four periods ahead, across all of the 25 data series.

7.4. Results

7.4.1. The evaluation criteria

Model forecasting performance was assessed on four criteria;

- *magnitude of the errors* with MAPE. MAPE has some limitations that impact in decline research, specifically around interpreting results as discussed in section 6.3.1 but not it seems mentioned in the literature;
- *relative accuracy* using CumRAE and UMBRAE. The two measures work in similar ways but have different approaches to dealing with outliers. UMBRAE is reportedly less sensitive to outliers and thus should show different results to CumRAE if the data is affected by outlier data. Both CumRAE and UMBRAE have been implemented with a stationary point forecast naïve benchmark, making the process of assessing consistency as easy as calculating the number of times the models' CumRAE (or UMBRAE) betters unity with the naïve benchmark value of 1.0
- *bias* of the models forecast is assessed using the mean error, which both indicates the magnitude and the sign of any error and when plotted give a visual indication of the errors across horizons and bias
- *forecast consistency* of the models is demonstrated with provision of a *parametric estimate interval* and *percentage times better than the naïve benchmark;* these measures are described in sections 6.3.5 and 6.3.5.2 respectively, particularly the need

for sufficient data, their relevance as a measures and assumptions to be met. Results were recorded and are presented throughout this chapter. All measures used to present the results are summing the performance of the model across all prior horizons, so a forecast is across an horizon, rather than an estimation at a point in time.

7.4.2. Preliminary assessment of model performance

Mean absolute error in forecast share is presented as a preliminary to the formal measure results. Figure 11 demonstrates rising mean absolute forecast error as the forecast horizons lengthen. The poorest performing model is the Gompertz with mean absolute error of forecast share of about 0.10 of share at Horizon One rising to about 0.14 of share at Horizon Four.

Of the three better marketing science models there is little to choose between them at Horizons One to Two. At Horizons Three and Four, the log-logistic deteriorates slightly leaving the Bass and the Pearl logistic as the two best marketing science models. The straight-line model, is the best performer at Horizons One, and Two, going on to deteriorate in a similar manner to the log-logistic at Horizons Three and Four.

These absolute errors in predicting share are useful to get, in management terms, a sense of the scale of the error. While what is an acceptable measurement error for such forecasts does not appear to be recorded in the literature, the better models all had on average, absolute prediction errors less than nine percent market share even at Horizon Four.

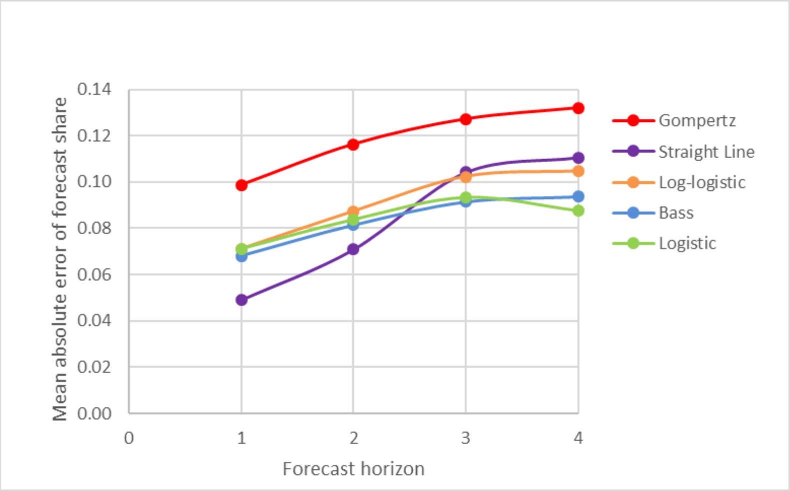


Figure 11. Mean absolute error of forecast share for the marketing science models.

7.4.3. Model forecast absolute percentage accuracy

MAPE (refer to Figure 12 and Table 7) indicates, that the best two marketing science diffusion models are the Pearl logistic and the Bass. Across Horizons One to Three, they are the best and are narrowly beaten by the Gompertz at Horizon Four. There is little to choose between those two; they are about 16 percent and 15 percent MAPE respectively at Horizon One and grow to 39 percent and 40 percent MAPE respectively at Horizon Four. The Gompertz and the log-logistic are the two worst marketing science models. The Gompertz improves from about 4.5 percent MAPE poorer than the best at Horizon One to having slightly better MAPE to the best by Horizon Four (about 3.5 percent MAPE better) in a smooth progression of improvement. The log-logistic on the other hand, deteriorates from near identical MAPE to the best models at Horizons One and Two to about 10 percent MAPE inferior to the best by Horizon Four. The Gompertz and log-logistic MAPE performances' cross over at about half way between Horizons Two and Three where both are inferior to the two best models by about 4-5 percent MAPE. The straight-line model is the best predictor at Horizon One and matches the best two diffusion models at Horizon Two. For later horizons, the superior match of the marketing science models to the decline curve shape, shows in three models; with the Pearl logistic, the Gompertz, and Bass models all being better than the straight-line model. The straight-line model's forecast errors, as expected, trace an S-curve of MAPE reflecting how it is not a realistic model of the decline data generating process, despite its competitive MAPE levels.

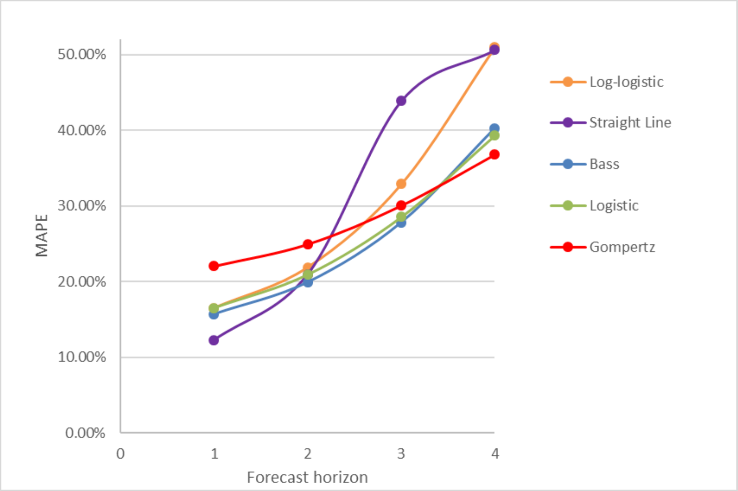


Figure 12. Mean forecast MAPE of the marketing science models.
Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

Table 7

Mean Forecast MAPE of Marketing Science Models

Horizon	Pearl logistic %	Gompertz %	Bass %	Log-logistic %	Straight-line %
1	16.54	22.04	15.72	16.54	12.28
2	20.95	24.94	19.94	21.92	20.99
3	28.55	30.06	27.85	32.90	43.88
4	39.35	36.81	40.31	51.01	50.64

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

In summary, all models including the straight-line model, have deteriorating MAPE as the horizons extend, and the straight-line deteriorates quicker, because it is not reflecting S-curve decline, the typical pattern in the data. As the MAPE measure is burdened with expressing the errors as a percentage of a rapidly falling variable of interest, it tends to overemphasise error levels at the expense of an understanding of a more general understanding of forecast performance of the model. In the next section, the relative performance of the models is investigated, using the naïve benchmark, based relative measures.

7.4.4. Model relative forecast accuracy

The primary performance measure in this study is the relative measure CumRAE, a related but bounded variant published during this study is also utilised to explore the their relative performance, when faced with various levels of variation in error range (Chen et al., 2017) see section 6.3.2. Table 8 shows the percentage difference between the two relative error measures. As can be seen, these differences are mostly small except in the case of the performance of the straight-line model, which generated sufficiently large errors at longer horizons to produced large differences between CumRAE and UMBRAE see Table 8. It indicates that there are outliers in error magnitude generated by the straight-line model forecasts, which are being removed by the bounding process in the UMBRAE measure. However, if the aim was to test the forecast capability of a model one might well be interested in seeing the performance when dealing with outliers (poorer forecast) and CumRAE provides that when the Winsorising process is omitted from data preparation. However, to understand the effect those outlier forecasts they would need to be removed in some way. This could be done by deleting forecasts, Winsorising the error data or undertaking a comparison with UMBRAE, making UMBRAE useful to a forecast research in ways not envisaged by Chen et al. (2017), and arguably easier to execute than the Winsorising process which involves trimming the data.

Figure 13 and Figure 14 illustrate the virtually identical results for diffusion models with those two measures. Table 9 and Table 10 list the CumRAE and UMBRAE for the models' forecast performance. Because of this strong similarity of result, they are reported together and any differences are analysed at the end of this section.

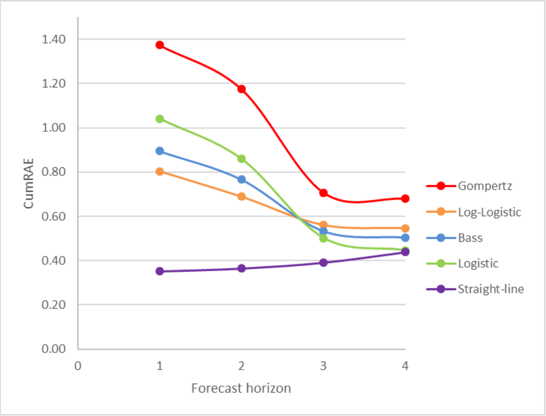
Table 8

Absolute Percentage Difference of Mean CumRAE and Mean UMBRAE for Marketing Science Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	2.71	1.92	2.35	1.55	2.02	1.73	2.45	1.11	2.57	0.60
3	2.30	2.43	4.05	3.75	2.03	1.88	2.44	0.20	8.89	8.19
4	2.50	3.01	1.45	3.52	1.95	2.82	3.30	1.36	15.31	13.84

Note: Number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20
Note: Percentage difference calculated with respect to CumRAE

Measuring relative accuracy with CumRAE and UMBRAE, the three better models were the log-logistic, the Bass and the Pearl logistic. Their performance was closely grouped, with the Pearl logistic the worst of that group, at early horizons, being worse that the CumRAE benchmark at Horizons One (CumRAE 1.04) and only being about fourteen percent better than the naïve benchmark (CumRAE 0.86) at Horizon Two. The log-logistic was the best model at the first two horizons and bettering the naïve benchmark by 20 percent and 30 percent respectively over those horizons. Over those same horizons, the Bass was halfway between. By the last two horizons, the log- logistic and the Pearl logistic had swapped positions of best and worst. By Horizon Four, the three models had remarkable similar performance with the log-logistic performing the worst with performance 45 percent better than the naïve benchmark. The Pearl logistic was the best performing of all models at that horizon (55 percent better). The Bass model continued to be placed between those two models. Of the four marketing science models, the worst performing was the Gompertz that performed substantially worse than the naïve benchmark measure over Horizons One and Two, and at no time bettered any of the other models. The straight-line is the best predictor overall with performance about 67 percent better than the naïve benchmark across all horizons. The straight-line model's performance is critically, linked to the location of the fixed origin for the forecasts at, or just before, the 50 percent share fall point. This is because this is an area where the rate of change in decline rate is at its lowest (the curve is most linear like).



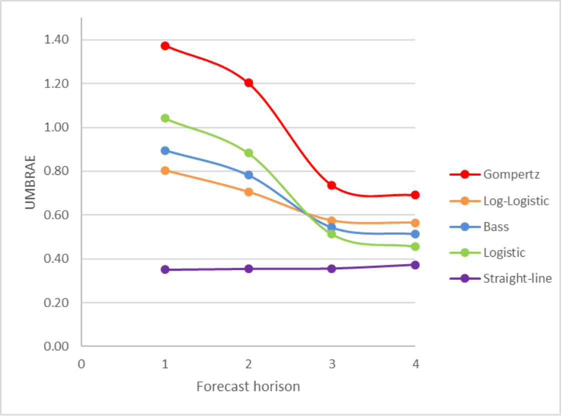


Figure 13. Mean CumRAE of marketing science models.

Figure 14. Mean UMBRAE of marketing science models.

Table 9

Mean CumRAE of Marketing Science Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	1.04	1.57	1.37	1.87	0.90	1.28	0.80	0.89	0.35	0.33
2	0.86	1.39	1.17	1.71	0.77	1.14	0.69	0.80	0.36	0.32
3	0.50	0.52	0.71	0.66	0.53	0.63	0.56	0.52	0.39	0.33
4	0.45	0.49	0.68	0.63	0.50	0.59	0.55	0.48	0.44	0.39

Note: Normal distribution plots of the CumRAE and UMBRAE indicated that outcomes were not normal; despite this and as is common practice the standard deviation (SD) dispersion statistic is presented along with the mean.
Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

Table 10

Mean UMBRAE of Marketing Science Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	1.04	1.57	1.37	1.87	0.90	1.28	0.80	0.89	0.35	0.33
2	0.88	1.42	1.20	1.74	0.78	1.16	0.71	0.81	0.35	0.32
3	0.51	0.54	0.74	0.68	0.54	0.64	0.57	0.52	0.36	0.30
4	0.46	0.51	0.69	0.65	0.51	0.61	0.56	0.49	0.37	0.34

Note: Normal distribution plots of the CumRAE and UMBRAE indicated that outcomes were not normal; despite this and as is common practice the standard deviation (SD) dispersion statistic is presented along with the mean.
Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

In summary, at no time was the Gompertz competitive with any of the models, and would have been rejected as a suitable model based on the CumRAE and UMBRAE measures, even though it beat the naïve benchmark in the last two horizons. At no time did the diffusion models beat the straight-line model. The three better performing diffusion models, perform such that you would choose the log-logistic if you were interested in early horizons, the Pearl logistic if you were interested in later horizons and the Bass if you needed the best performer across the horizons on average. If the length of the series limited you to forecasting after getting to this 50 percent fall point then the best model by a substantial margin is the straight-line drawn through the last three points prior to the 50 percent point. It is interesting to note the swapping of ranking of the two best models from that provided by MAPE to that provided by these two measures. This is difficult to explain simply but is most likely related to three things; The difference in sensitivity to scale between MAPE which is highly sensitive as described in section 6.3.1, and the two relative measures which are largely insensitive. The scale issue is related to the generation of errors, and the level of the actual data. When data is falling away then a given magnitude of effort becomes a larger percentage error. Also in data with substantial changes in both scale and rate of change (as are decline curves), then a fitted model will generate a wide error distribution in terms of magnitude variation. These three factors drive the different rankings from the different measures.

7.4.5. Model forecast bias

Sometimes the focus of interest is the direction of the error in forecasts. Figure 15 and Table 11 present the mean error in market share terms. Table 11, also includes the standard deviations of the errors in prediction. Those errors demonstrate that the Bass model forecasts close to neutral performing best, indicating little bias over many series and across all horizons. The Bass model performs best with on average only one percent overestimation of market share, that is, predicts more rapid decline than the actual market. The standard deviation of the Bass estimates are about 11 percent market share across all horizons. The Pearl logistic, the next best model, also overestimates decline, but by between two and five percent as the horizon extends and has a worst case standard deviation of eleven percent market share. The straight-line model underestimates over the first three horizons and over estimates at Horizon Four, and is competitive with the best two target diffusion models and betters the Pearl logistic model across the last three horizons. However, its performance is be deteriorating rapidly by Horizon Four. The log-logistic performs competitively with the Pearl logistic in terms of error level at early horizons but deteriorates to be the third worst at Horizons Three and Four, it underestimates rather than over estimates as do the other models. On this measure, the Gompertz performs very poorly and would be rejected.

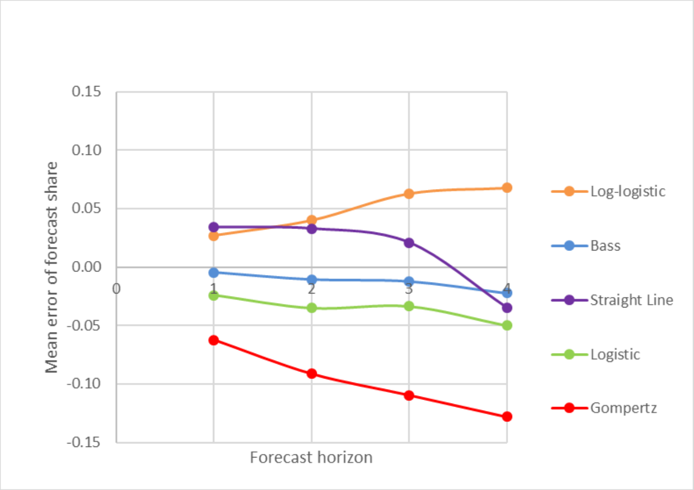


Figure 15. Mean error of forecast share for the marketing science models.

Table 11

Mean Share Error of Forecast of the Marketing Science Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	-0.02	0.09	-0.06	0.11	0.00	0.10	0.03	0.09	0.03	0.08
2	-0.04	0.11	-0.09	0.12	-0.01	0.11	0.04	0.10	0.03	0.10
3	-0.03	0.12	-0.11	0.12	-0.01	0.11	0.06	0.11	0.02	0.13
4	-0.05	0.12	-0.13	0.11	-0.02	0.12	0.07	0.11	-0.03	0.15

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

In summary, the size of the mean errors and the standard deviation of errors (see Table 11) indicate that the mean forecast error of the models appear to give good (relatively unbiased) forecasts.

7.4.6. Model forecast variability

Taking the perspective that an adequate level of relative accuracy is achieved, and then the focus might naturally fall to the consistency of the method in reaching that level. Two ways to express forecast variability are explored. The first is the range of variation that might occur in an estimate based on the probability distribution for a normally distributed sample. The second is the proportion of times a models forecasts better than a benchmark. Both methods are used to identify model superiority.

7.4.6.1. Parametric estimation of the forecast interval

Data error distribution normality for models was indicated across the 25 series, at all horizons, with stronger normality indicated at longer horizons. The Shapiro Wilks (1965) test used is the most powerful normality test but like all such tests is weaker in power on small samples (Razali & Wah, 2011). Differences between the mean and the median at some model/horizon estimates indicated the weakness of the test on this sample. However, assuming error distribution normality, parametric estimation of forecast uncertainty were calculated as described in section 6.3.5.

Charting forecast estimation intervals via fan charts assists in demonstrating the potential variation in a model's forecast. An example of this at 80 percent and 95 percent confidence levels with respect to the mean estimate error is provided in Figure 16. The values for all model forecast intervals are presented in Table 12 and Table 13. Presenting error (bias) and forecast interval together provides a summary of the overall performance of models, and answers the question for managers: How good will that forecast likely to be? For example, it demonstrates that the Pearl logistic, Bass, straight-line models all exhibit low bias, and that the predictions for the Gompertz and the log-logistic are highly biased, and thus the range of the estimate intervals also represent strong bias in the forecast. Managers are often interested in the risks and opportunities at those outer limits of the estimate, and this presentation shows the limits of potential forecasts. However, as a way to present the relative variability performance of each of the models it fails because it places the interval on a biased origin making interpretation of relative intermodal interval challenging.

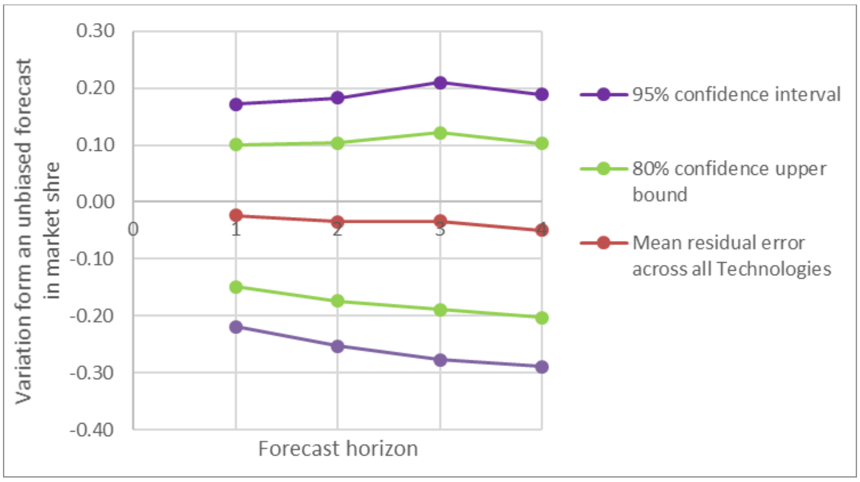


Figure 16. Logistic model mean prediction error (forecast interval) - Study one.

Table 12

The 80 Percent Confidence Bound for the Mean Value of the Marketing Science Model Forecasts

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line	
Horizon	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd
1	-0.15	0.10	-0.21	0.09	-0.14	0.13	-0.09	0.14	-0.07	0.13
2	-0.17	0.10	-0.25	0.06	-0.15	0.13	-0.10	0.18	-0.10	0.17
3	-0.19	0.12	-0.27	0.05	-0.16	0.14	-0.08	0.20	-0.16	0.20
4	-0.20	0.10	-0.28	0.02	-0.18	0.14	-0.08	0.21	-0.23	0.16

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

Table 13

The 95 Percent Confidence Bound for the Mean Value of the Marketing Science Model Forecasts.

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line	
Horizon	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd
1	-0.22	0.17	-0.30	0.17	-0.21	0.20	-0.16	0.21	-0.12	0.19
2	-0.25	0.18	-0.33	0.15	-0.23	0.21	-0.17	0.25	-0.18	0.24
3	-0.28	0.21	-0.36	0.14	-0.25	0.23	-0.15	0.28	-0.26	0.30
4	-0.29	0.19	-0.36	0.10	-0.27	0.23	-0.16	0.30	-0.34	0.27

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

So a presentation based on a zero biased forecast is required, to demonstrate the relative variation performance of the models. The relative size of the models' parametrically estimated 80 percent forecast intervals (with respect to an unbiased forecast) are recorded in Figure 17 and Table 14. Here we can see how the marketing science models have very similar size estimated forecast intervals at each of the four horizons. Interestingly, the Bass scribes a different shape curve to the others, one more linear that the other marketing science models illustrating its consistency of performance across horizons. Importantly from a managerial point of view, the marketing science models have very similar variability in forecast performance.

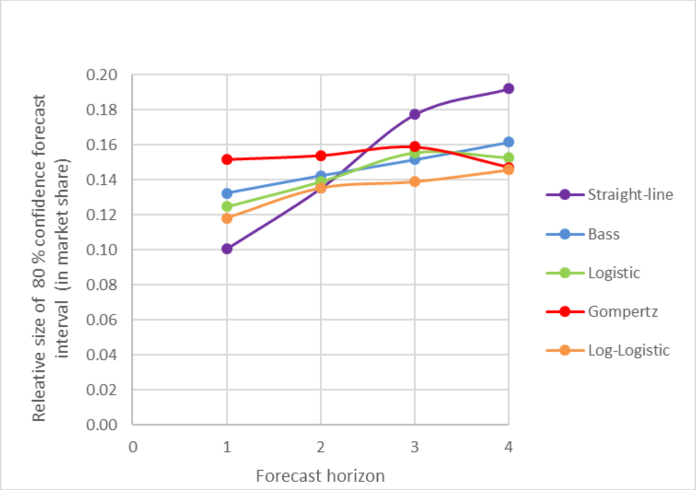


Figure 17. Relative size: 80 percent confidence intervals for marketing science models.

Table 14

Relative Size of Forecast Intervals (80 Percent) for Marketing Science Model Forecasts

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line	
Horizon	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd
1	-0.12	0.12	-0.15	0.15	-0.13	0.13	-0.12	0.12	-0.10	0.10
2	-0.14	0.14	-0.15	0.15	-0.14	0.14	-0.14	0.14	-0.14	0.14
3	-0.16	0.16	-0.16	0.16	-0.15	0.15	-0.14	0.14	-0.18	0.18
4	-0.15	0.15	-0.15	0.15	-0.16	0.16	-0.15	0.15	-0.19	0.19

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

Overall, there is little to separate the marketing science models' forecast intervals. The straight-line model is better earlier and deteriorates to be worse than the marketing science models in later horizons. Therefore, in summary the marketing science models demonstrate uniform level of consistency while the poor ability of the straight-line to replicate the data generating process of decline means its variance increases with horizon length.

7.4.6.2. Model forecast proportion of times better than benchmark

Another way to consider forecast consistency is to assess what proportion of time one method's forecasts are better than a benchmark. Figure 18 and Table 15 demonstrate how frequently each model forecasts better than the naïve benchmark. With regard to bettering the naïve benchmark, the straight-line model is consistently better than the other models, across horizons. The log-logistic is the next most consistent model, bettering or equalling all models except the straight-line across all horizons. The Pearl logistic is worse earlier in the horizons and better in later horizons than the Bass. The worst performer, the Gompertz, is the worst performer at all horizons, and at its best only beats the naïve benchmark 81percent of the time and then only at Horizon Three.

That the straight-line model is substantially more consistent in bettering the naïve benchmark than the others is interesting. It betters the scores of all models, at all horizons. In the first two horizons, it is substantially better. The log-logistic is consistently the best of the marketing science models, only being matched by the Pearl logistic in the fourth horizon.

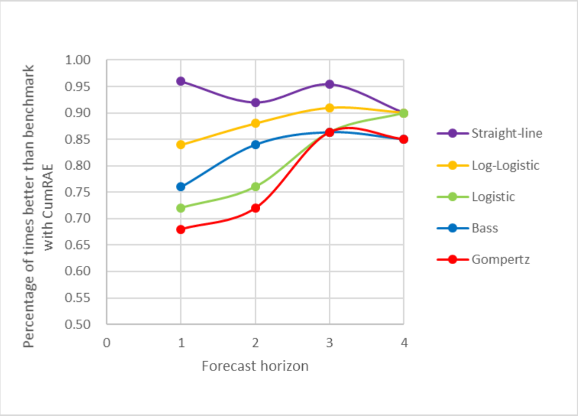


Figure 18. Proportion of times marketing science models are better than the naïve benchmark.

Table 15

Proportion of times Marketing Science Models are better than the Naïve Benchmark

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line	
Horizon	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE
1	0.72	0.72	0.68	0.68	0.76	0.76	0.84	0.84	0.96	0.96
2	0.76	0.76	0.72	0.72	0.84	0.84	0.88	0.88	0.92	0.92
3	0.86	0.86	0.86	0.82	0.86	0.86	0.91	0.91	0.95	0.95
4	0.90	0.90	0.85	0.85	0.85	0.85	0.90	0.90	0.90	0.95

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

7.5. Summary

This study investigated the performance of functional forms developed for modeling diffusion when applied to forecasting decline. The Bass and the Logistic model are the best performing of the marketing science models. Models that performed well had the same results with CumRAE and UMBRAE indicating they dealt with outlier curve shapes better than the weaker performing models. Interestingly the worst performing models registered better UMBRAE than CumRAE figures indicating their poor performance on outlier curve shapes, was an issue.

The log-logistic and the Gompertz appear to be weak in comparison to the Bass and Pearl logistic in terms of mean relative accuracy, however on this set of data and under this restricted test, the log-logistic, did beat the other marketing science models when the consistency of the performance (percent better) was considered. This apparent contradiction of being worse on a mean relative accuracy perspective but being more consistently better on a proportion of forecasts basis shows the importance, when evaluating models, of looking at their performance on a variety of measures.

Chapter Eight: Analogous Series Forecasting Study

8.1. Introduction

This chapter describes an investigation into predicting decline with analogous series. It is the second of three studies focussing on identifying the best performing method for predicting technology usage decline. The principles of forecasting with analogies is covered in Chapter Four.

A summary of issues particular to this current study follows. The study uses the 25 series from the first study, normalised for time. The models assessed in Study One are fitted, and then used to forecast these temporally adjusted series, to provide a comparison of performance with the analogous series model developed in the current study.

Forecasting cumulative discontinuance (decline) can be problematic because forecasting is often required before much data has accumulated, a situation where the shortness of the data series makes determining suitable coefficient values for a classic diffusion model's parameters difficult (Goodwin et al., 2013). Green and Armstrong (2007) and others (Martino, 1993; Thomas, 1985) suggest that analogies from one situation can be used to analyse, explain and predict other similar situations. This brings the potential to solve the short data series problem and to forecast when very little data has accumulated.

When identifying suitable analogies new technologies are compared to similar technologies that have gone before, in terms of performance, development cost, and market risk (Martino, 1993). When an analogy is using data distributed over time, the forecasting method is called *analogous series forecasting.* Analogous series forecasting depends on the assumption that two different situations of interest share *equivalent models of behaviour,* sometimes called *the data generating process.* Analogous series forecasting relies on first recognising that the S-curve decline pattern is commonplace and second; that it makes for a useful analogy for the trajectory of the target variable, recognising that a new situation is similar to typical historic situations is critical. The assumption in the technology decline situation, given the decline trajectories of historic technologies, is that it will be possible to identify a suitable analogy for a current day technology decline situation (Bass et al., 2001; Thomas, 1985).

In new product sales, analogies have been shown to be useful guidance for a target's diffusion trajectory, providing superior prediction performance to classic marketing science models (Goodwin et al., 2013; M. J. Wright & Stern, 2015). Finding very similar situations when seeking analogous series can be difficult. First, as discussed in section 5.4.3, deciding on what criteria to measure similarity by is fraught with challenges. Second, the available pool of suitable analogous series may shrink rapidly as you tighten the criteria to better match your situation. These two issues are important because many of the recommended techniques for analogous series forecasting focus on finding the best single analogy (Martino, 1993; Thomas, 1985). One way to deal with this is to recognise many technologies have been shown to have similar shaped decline patterns, and that by extension, the pattern of historic data from analogous situations that represent completed decline processes across many technologies might provide a suitable analogue of the target technology's future behaviour. In a simple example, when listing a house for sale, a bundle of similar properties that have sold recently are used to determine the price for the house to be sold. This bundling underlies the method for this study.

While marketing science diffusion forecasting requires considerable diffusion data, for model parameter estimation, analogous series models require little from the current technology decline data to allow an analogous series forecast. Once the analogy of an S-curve progression can be accepted, and the initiation of monotonic decline is observed, then forecasting can go ahead for the series of interest despite any data series shortness. Interestingly, because the analogous data series model relies on similar data it creates a complete representation of the target technology's decline trajectory, thus the prediction model might be available ahead of any observation of the expected decline start. Thus, hypothetically an analogous model forecast might sit in the hands of a forecaster who only needs to recognise the start of the decline, and have a sense of the likely time to decline completely to provide a forecast. If such forecasts were proven to be a suitable technique of prediction, a forecast of the time to obsolescence is potentially always at hand, just waiting the assignment of a decline start date, an advantage that does not appear to be suggested in the literature. Also, analogous data series when applied in a pooled manner has local anomalies smoothed out, by averaging so that only typical discontinuances in curves are reflected substantively in the analogue, and thus in the prediction. This is, potentially at least, more effective than is the case of fitting to discontinuances with a statistical model.

This concept is not covered in the literature, possibly because a concerted empirical programme of study would be required to prove its veracity.

So in summary, both the initiation of an analogous series forecast can be earlier, curve discontinuances and the sample rate of the series do not limit the forecast process. The only conditions are; the universal requirement to identify the start of decline for applying the technique, and the availability of analogous technology decline data.

8.2. Aim of This Study

As in Study One, the first objective is to determine, at a methodological level, what procedures are required to routinely use analogous series with only early, and thus short decline data, given little or no suitable guidance in the literature. Many of the important methodological issues that come from the characteristics of the identified data are described in sections 6.4.4 and 6.4.5. The issues specific to the normalising of data and building an analogous series model are covered in section 8.3.3.

The second objective is to confirm how the proposed analogous series model performs in predicting on the 25 decline data series, thus empirically validating the support for the use of the model in decline forecasting.

8.3. Data, Models, and Methods

8.3.1. Data

As in Study One, the execution of the method in the current study relies on the prior identification of monotonic decline in the target data series, and predicting forward from that decline, as described in section 6.4.5. Unlike diffusion model forecasting, there is no need to accumulate target series data for estimation purposes, only to the extent it is needed to identify the decline process. Instead, the data from other analogous decline series is the source of prediction information for the target situation.

The pool of technology data series candidates used in this study are those from Study One, and are listed in section 6.4.5. The normalising process described in section 8.3.3, to follow, was undertaken to achieve time equivalence across the disparate data series. The data series were all assumed suitable analogies on the basis that they were from a similar data generating process, that is, they were all decline curves from substitution processes. It was further assumed that little was known about the target situation to either make a judgment for selection of a single series to represent the target situation, or to cull outlier series from the pool to make the pool more representative. This aligns with the typical requirement of a forecaster needing to make a prediction early in an unfolding situation and with little sense of the likely outcome. The proposed method can be implemented by a practitioner with little recourse to information with which to accurately match current and past situations, both speeding up forecasting, but also removing the risk of forecaster bias in series selection.

Because forecasting is delayed until after the series had fallen to 0.50 share in this study, to align with the limitations of diffusion models and the protocol in Study One, it is conceptually possible to undertake a nearest neighbour selection or culling of the pool method to be instigated, based on the data evidence for this early decline. However, Goodwin et al. (2013) observe that selecting analogies is neither trivial, nor easy, and that forecast results from such endeavours are prone to high error levels. For the current study, a test of an analogous series predictor without culling was considered the most rigorous.

8.3.2. Models

An initial objective of this current study was to deploy the best performing of the models from Study One as a form of standard against which the analogous series method could be compared. This was to be in a similar way to M. J. Wright and Stern (2015) and their use of the best performing model from Hardie et al. (1998). The results in Study One were somewhat inconsistent across the error measures employed, with no single diffusion model consistently standing out as performing better than any other on all measures. While it could be argued that this was because MAPE is not a relevant measures in this context, and that the straight-line was the clear winner, it has been previously discussed in the literature that different error measures deliver different apparent outcomes, dependent on both model and data use (Armstrong & Collopy, 1992). The resultant potential issues have been discussed by Ahlburg (1992), Armstrong and Collopy (1992), and Fildes (1992). This inconsistency means, that unlike M. J. Wright and Stern (2015), it was thought not possible to decide on one superior model, although two models stood out over the worst two. As a consequence, and given the differences in the treatment of the data series between the two studies, it was decided to run the full set of Study One models across each of the data series normalised for time. It was decided that a pool including all the series would be used as an analogue as follows;

> *n-S of the pool would be used to forecast the series (S). S being each series withdrawn from the pool (n) consecutively to serve as the candidate for forecasting by the pool n-S.*

Thus, analogous series forecasts are created using a pool of all the data series from Study One, each time less the series of interest, as laid out in the following sections.

8.3.3. Forecast method and notes

The analogous series model was compared with the marketing science diffusion models from Study One, because there must be *format congruence* between the outcomes of the current study and of Study One. This is so that performance of marketing science models and of the proposed analogous series model can be measured in the same way. Also, to aid understanding, the evaluation process and presentation of results focus on uniformity with Study One.

In Study One, it was observed that not all series fell directly to a floor on or about zero market share, raising the need for a forecasting assumption to be made. That is, to decide if a floor substantially above zero will be reached or if the target technology's decline will be complete and full obsolescence will occur. These two situations require slightly different approaches. Both situations, however, are easily facilitated by analogous series methods. Implicit in these two situations is the observation that while managers will know what market conditions exist today, determining which scenario will play out is fraught with uncertainty. However, there is a convention in diffusion forecasting research to assume full saturation will be achieved, along with complete substitution of the older technology, resulting in total obsolescence (see Fisher & Pry, 1971).

8.3.3.1. Method assuming complete obsolescence

An assumption that a technology will decline to a floor at zero or close to zero requires a different forecasting approach to assuming a floor typically observed in the data. Such an approach could be based on an assumption that decline data is rotationally symmetrical around a primary slope inflection point in the decline series (assumed to be 0.50 market share). That is, the first 50 percent of the analogous series could be rotated through 180 degrees to provide a symmetrical S-curve.

If symmetry around the inflection point is defined as:

$$|y_{t50} - y_{t50+i}| = |y_{t50} - y_{t50-i}|$$

Where *t50* is the time corresponding to the inflection point, at 50 percent share, and *i* is any normalised period from 0 to n where n is the number of normalised periods up to and including 0.50*t.*

Then Equation (50) demonstrates how knowing y_{t50} *and* y_{t50-I} you can know y_{t50+i}:

$$y_{t50+i} = y_{t50} + (y_{t50} - y_{t50-i}) \tag{50}$$

Thus providing cumulative decline level predictions for the future periods beyond 0.50 market share in normalised time. Although described here for completeness it is not the method used in this study. To do this, an interpolation to identify a time representing the 0.50 market share level is required similar to that in this Study, and the series trimmed to that point; then the standardised averages can be rotated.

8.3.3.2. This study assumes typical obsolescence levels

For this study, it was assumed that the forecaster had no knowledge to support the choice of a specific floor level, thus an approach using the average level of a series pool including technology with floors above zero, was utilised. That is, that decline will be to a typical level of obsolescence, rather than the full obsolescence that the diffusion saturation assumption might indicate. This assumption links to the concept that typically managers have little or no information to assume anything other than typical behaviour for their target. While it is possible to use nearest neighbour (K. Nikolopoulos et al., 2007) and other structured methods (Thomas, 1985) to select a single analogy series, it has been shown that in new product starts, a simple average of a pool of series performs well compared with diffusion models (M. J. Wright & Stern, 2015). A simple average is the approach taken here, with no attempt to cull series in line with the method used by M. J. Wright and Stern (2015). There is support for this approach in the findings of Goodwin et al. (2013).

8.3.3.3. Normalising the series on the time scale

Although the 25 data series were across different technologies and from different geographies with implicitly different social contexts, they were accepted as similar because of the same substitution driven data generation process that made them acceptable in Study One. To generate an analogous series as an estimator of a series, the average of the values across all the series for any period i_t is used as an estimate of the proportion of cumulative decline attained by the focal series by period i_t. This process uses all the available data to recognize the empirical pattern. In order to implement the proposed analogous series forecasting model, all the data series are required to be made directly comparable on the time scale. They had already been normalised to their peak market shares during the preliminary data trimming process described in Chapter Six.

However, in the pool of data series used, not all series were represented by the same sample rate and they differed in duration from start to completion, additionally some series were not complete, in that they appeared to be still progressing towards an asymptote (floor). Normalising of the series to a standard sample rate and duration was required but because of the inconsistent state of completeness of some series, normalising the series using data from start to finish of each series was not practical. Accordingly, the duration of the first half of the process was used to normalise each series, that is, from 0.95 to 0.50 market share was used, then the time periods beyond the 0.50 market share point were scaled with the normalising ratio calculated for the first half of the curve.

Finding a universal start point across many series is challenging. S-shaped curve data can have long and slow lead-in and lead-out tails, and they are not consistent even in very similar situations because of the slow progress of decline, and the relatively large effect of noise from a variety of sources. Frequently this becomes an issue when comparing many series. In the 25 data series the rate of decline beyond the point at which monotonic decline first occurred, varied because of this effect. For the analogous series method, this variable lead-in tail had the potential to affect attempts to normalise data on the time scale because normalisation requires uniformity of start and finish points across series. Thus, a further trimming of the data down to the 95 percent market share level was undertaken. It is thought that left truncated data series affect the performance of diffusion models (Jiang et al., 2006), and the shortness of many of the 25 series meant that further trimming was likely to result in a marginal number of data points for adequate model parameter estimation. Thus in this study, the normalisation and the fitting processes were monitored for any deleterious effects on the marketing science models when applied to this modified data set.

To set the ceiling at 0.95, interpolations were made to identify a time representing the 0.95 market share level. The data series was then trimmed to that time and level to provide a standardised start point for all series. A similar interpolation was undertaken to locate time at the 0.50 share level. This was done by a simple linear interpolation as described by Equation (51) below:

$$y_{int} = y_1 + \frac{(x_{int} - x_1)(y_2 - y_1)}{x_2 - x_1} \qquad (51)$$

A linear interpolation was seen as simple to implement (and any deleterious effects would be easy to understand and interpret. The standardised start point for each series (0.95 market share) was then set to a normalised time scale point of t = 1. Because of the desire to assign a normalised timescale using only the first half of the data, then interpolations to identify a time representing this 0.50 market share level were required in a similar way as for the 0.95 level.

Also, intermediate points representing an appropriate proportion of time elapsed since $t = 1$ were needed, so that by standardising both the duration between 0.95 to 0.50 and sample rate, all the series could be combined at the same standardised time points along their decline curve. Thus, a standard time scale frame was selected based on a sample rate that produced 10 time periods (time intervals of 0.10 of the original time scale). This scale was organised such that the 0.95 point represented time sample point one and the 0.50 share level represented time sample point eleven. This sample rate was chosen to be typical of the sample rates in the pool of data sets, which had sample rates from three to just over twenty samples, for the duration of fall from 0.95 to 0.50 share. That scaling process provided the standardised intermediate points for the *x* axis values for which market share levels must be interpolated from adjacent points in the existing data. The impact of this choice was that some data series were scaled up to the norm (gained sample points) and many were scaled down to the norm (lost sample points). This process provided a market share level for each standardised point. The interpolations were generated using the same simple linear method used for the two terminal points.

More formally this normalising of time on the x axis was as described in Equation (52) below:

$$t_{i(norm)} = \frac{t_n}{t_N} \times t_i \qquad (52)$$

Where t_n = number of periods in the normalised time scale, t_N is the number of periods (in years) taken for the series to fall from 0.95 to 0.50 market share and t_i is the time period to be scaled.

This scaling of the time domain as described above resulted in series with the same start at 0.95 and finish at 0.50 time points, spread over the same number of time sampling points, but further extending out to the last point in the source series or four points beyond 0.50 share, whichever came first. These series, which had already been normalised on the demand dimension (y axis) by the use of peak market share, became the data series in Figure 19, used for fitting the diffusion models and the basis of analogous series generated in this study. The analogous series model is an average of the values at the normalised time points.

8.3.3.4. *Analogous Series Forecasting*

The averaging across all series at the standardised time points is described formally in Equation (53) below:

$$y_{(i(t)estimate)} = \frac{1}{n}\sum\nolimits_{i=1,n} (Y_{nt_{i(norm)}}) \qquad (53)$$

Where $Y_{(i(t)estimate)}$ = mean share of market still held at time t_i, after cumulative decline attained by time t_i, for a group of data series *1* through n, where i is any time from 0 to x on the standardised scale, n = the number of series. Y_n at *ti* (norm) is the cumulative decline of a technology n at time t.

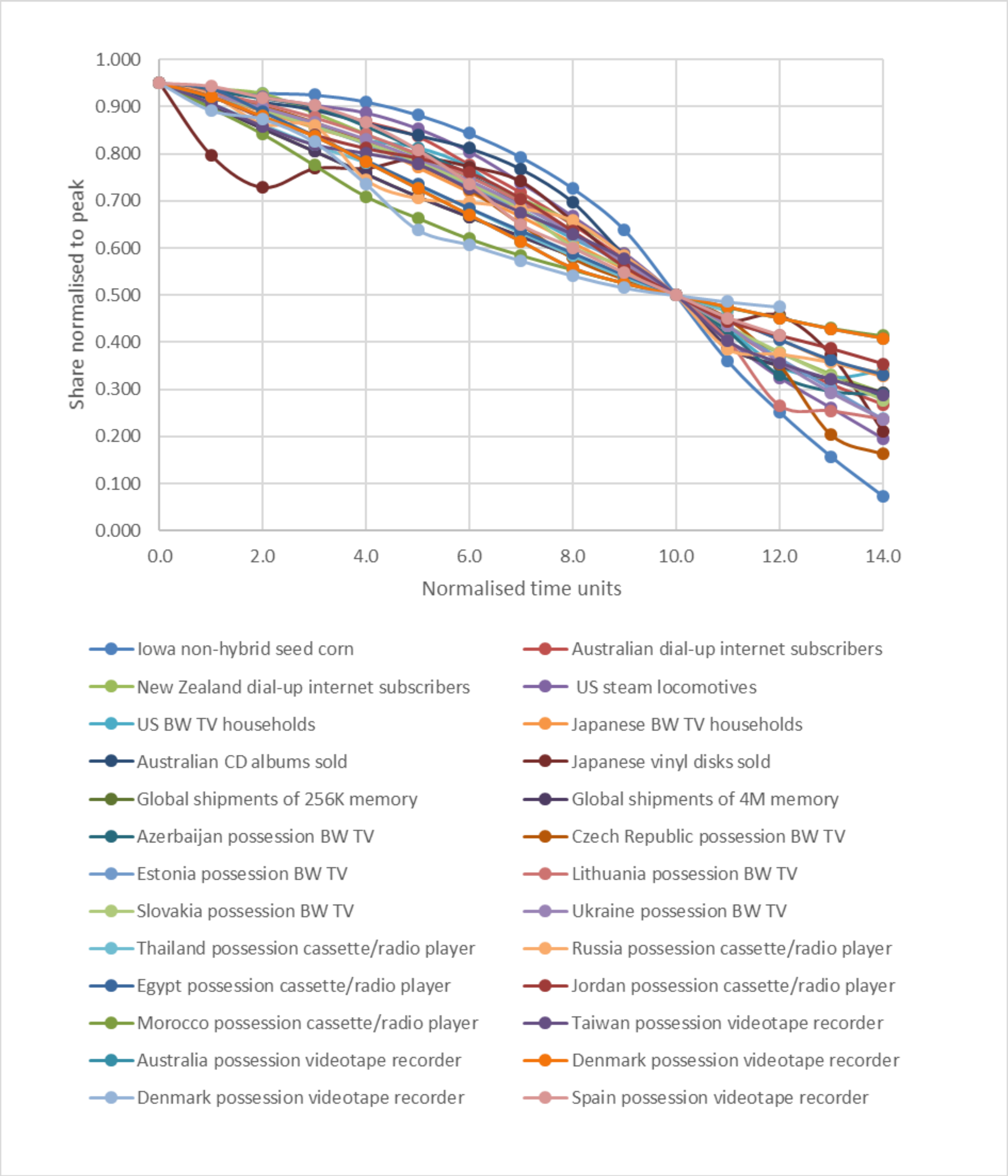


Figure 19. The 25 data series normalised for both level and time.

8.3.3.1. *Analogous series model forecasting process*

However, while the above model does estimate an average decline curve, and is a general predictor of future similar series, it is not suitable for testing forecasting performance, as the series to be forecast is included in the analogous series pool. To test forecast performance, the target series must be omitted. The recognised method is to use a jackknife resampling technique (Tukey, 1958), and generate the prediction estimate at each sampling point (the estimator series forecast), by systematically leaving out one series' observation each time, and calculating the average for the remaining observations, that then becomes an estimate for the removed observation, then taking the average of all the estimates.

The formulation for the estimate of a target series for forecast performance evaluation, is described in Equation (54) below:

$$y_i(t) = \frac{1}{(n-1)} \sum\nolimits_{i=1,n} (Ynt_i) \qquad (54)$$

The result is a series that represents a typical (average) cumulative decline curve, in standardised units, from 0.95 out to the last point at the end of the analogous estimator series. Because the series had varying lengths of tail (the number of sample points beyond the 0.50 share point) at the later points in the estimator series, the number of series from the pool that have input into the average for a sample point fell away as some series terminated early. This means a decision was needed as to when to terminate the analogous series, or to recognise that as the series progresses estimated sample points are backed by a smaller number of series. The estimator series was not truncated in this study, as only four of the 25 series terminated earlier than our four sample points (horizons) beyond 0.50 share, rather all four horizons were accepted in a similar manner to the approach in study one.

With a standardised time sample rate decided and a ratio based on that, and the actual sample rate over the first portion of the curve set, then that ratio can be applied to provide a forecast that is at standardised time periods beyond the fall to 0.50 point. Once again, interpolation of the actual share level for these scales points was required to provide standardised time point versions of the actual data to support testing against the model predictions.

For a manager, to obtain a forecast from this average scaled estimator (time normalised series), there is a need to rescale the analogous series model back to real time. For forecasting performance testing purposes, the time scales were kept in their normalised form, to assist with result interpretability. It was considered that while translating the data back to an un-normalised time frame form would provide apparent comparability with the other two studies, there were some concerns about the changes in the data error distribution under this process that would have offset benefits of comparability.

8.3.3.2. Fitted model parameter value estimation

As in Study One, the marketing science diffusion models were first fitted to data from the first half of the series of interest, and used to estimate the parameters of the functional form and thus create the model. The difference from Study One is that the marketing science diffusion models were applied to the analogous series rather than the raw data.

The first estimation data point was the interpolated 0.95 share point and the last estimation data point was the interpolated 0.50 share point. The scaling of the decline duration resulted in additional interpolated data points being added to the parameter estimation data of shorter data series, and removed from longer series. The resultant normalised estimation data series were short at 11 observations. This resulted in about five data points per model parameter, much better than the 1.5 minimum points per parameter for the shortest series in Study One. In Study One, the first point utilised for model parameter estimation was the first one of the sequence in which monotonic decline is observed, and the last data point was the last point available, at or just before 0.50 share, resulting in two issues. First, for some series, the last estimation data point was far before the 0.50 share level, consequently presenting less of the shape of the unfolding curve to the model. Secondly, also in Study One the series all had their native sampling rate. These sampling rates varied considerably and depending on the decline rate for the technology gave a wide range of total estimation data points. The use of an interpolated data point for the 0.50 point removed the first problem and inserted some presumably small amount of estimation error. The trimming of early data to 0.95 share would have reduced some but not all of that gain, resulting in potential to improve the fit of the marketing science models to the trend. The move to a time standardised sampling rate also provided a consistent sampling rate, at the expense of a reduction in the mean sampling rate. Just as in Study One, the first four points in the series data beyond the 0.50 share point became the data points to be forecast. In all other respects, the model parameter values were estimated as in Study One. Table 16 is a summary of the fit statistics.

Table 16

Marketing Science Model Fit Statistic Summary - Study Two

	Pearl logistic			Gompertz			Bass			Log-logistic		
Series No.	R2	SSE	MAPE %	R2	SSE	MAPE %	R2	SSE	MAPE %	R2	SSE	MAPE %
Min	0.92	0.00	0.27	0.90	0.00	0.71	0.96	0.00	0.17	0.93	0.00	0.76
Max	1.00	0.03	6.03	1.00	0.03	6.83	1.00	0.01	3.43	1.00	0.02	4.96
Mean	0.98	0.01	1.99	0.98	0.01	2.39	0.99	0.00	1.65	0.98	0.01	2.50
SD	0.02	0.01		0.03	0.01		0.01	0.00		0.02	0.00	

N=25 fits per model

All functional forms in all specifications (models) had a good fit to their data, with R^2 values typically 0.97 or better, with a mean better than $R^2 = 0.98$ for each functional form. The worst fit was the Gompertz model to series 24 at $R^2 = 0.91$. Residual fit MAPE values were typically less than three percent, with the worst being less than seven percent (Gompertz), and a mean of less than three percent across the functional forms. Just as in Study One, three data series (18, 21, and 24) were fitted less well by all functional forms, their weaker fit can be explained by the shape of the data trajectory in those particular series as described in Study One.

As in Study One, despite the penalty of adjusting the R^2 values for number of parameters in the models, adjusted R^2 values above 0.95 were achieved for all models across all series, except the three series (18, 21, 24), and except for the log-logistic model, and for all models across the three series with poor initial fit the fits for adj. R^2 were better than 0.90. We know fit is not a good predictor of forecasting performance (Armstrong, 2001b; M. R. Young, 1993). Thus, despite the weakness of model adjusted R^2 fits to the three series, each model specification was considered a suitable representation of the decline process, given acceptable R^2, SSE, and MAPE.

8.3.3.3. The fitted model forecasting process

Using the optimised (parameterised/fitted) models, forecasts were made by inserting into each model, values of *t* representing horizon predictions for one, two, three, and four periods ahead, across all of the 25 data series.

8.4. Results

8.4.1. The evaluation criteria

Again as in Study One, MAPE, CumRAE, and UMBRAE were recorded for all series and are reported throughout this chapter in summarised form. Also reported was the mean error as an indicator of forecast bias, a forecast interval, and the percentage of times the estimator was better than the naïve benchmark. These measures are described in section 6.3. The cumulative errors across each horizon were assessed with these measures, that is: from zero to one period, from zero to two periods, out to four periods. They are reported as means across all series.

8.4.2. Preliminary assessment of model performance

Just as in Study One, mean absolute forecast share error is presented as a preliminary to the formal measure results. Figure 20 demonstrates rising absolute forecast share error as the forecast horizons lengthen. This was also observed in Study One, but with normalised data, it seems the pattern of rise and the relative absolute forecast share error levels are more consistent within and across models. The two poorest performing models are the log-logistic and the Gompertz with mean absolute forecast share errors of about 0.06 of share and 0.05 of share respectively at Horizon One rising to about 0.12 and 0.125 of share respectively at Horizon Four. Of the two better marketing science models, the Bass is the weaker, having performance similar to the Gompertz at Horizon One and improving to have performance similar to the Pearl logistic the best model at Horizon Four. The analogous series performs well and there is little to choose from the Pearl logistic and the analogous series at Horizons Two and Three. The analogous series performs slightly better at Horizon One and Horizon Four than the Pearl logistic model. The straight-line model is the clear best performer across all horizons.

While what is an acceptable measurement error for such forecasts does not appear to be recorded in the literature, the better models all had, on average, absolute prediction errors less than 8 percent share even at Horizon Four. These mean absolute errors in predicting share are useful in management terms to get, a sense of the scale of the error.

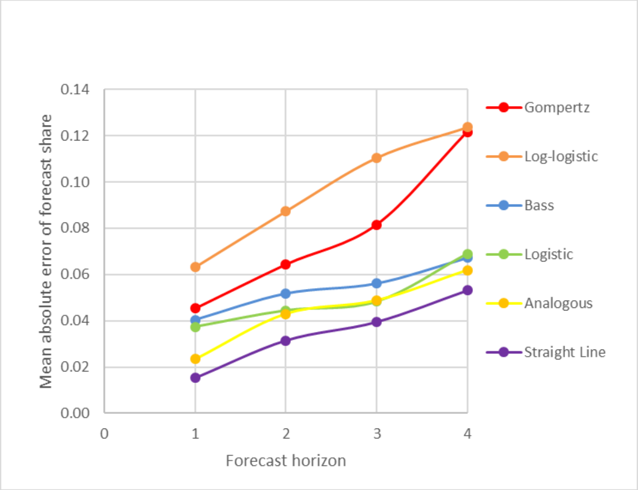


Figure 20. Mean absolute error of forecast share for the analogous series vs. marketing science models.

8.4.3. Model forecast absolute percentage accuracy

The attraction of MAPE is that it provides a sense of the forecast error as a percentage of the actual level at each sample point. Referring to Figure 21 and Table 17, the worst model continues to be the log-logistic with MAPE of 15.17 percent at Horizon One about five percent (MAPE) worse than the Gompertz which is the next worst at Horizon One. The log-logistic rapidly deteriorates in performance from this point, growing to a MAPE of 36 percent and substantially worse than the Gompertz, which is still the next worst model out at Horizon Four. The Bass is slightly better than the Gompertz model across all horizons. The Bass is one percent MAPE better at Horizon One with a MAPE of about ten percent and gradually improves with respect to the Gompertz to be three percent MAPE better by Horizon Four with a MAPE of 19.5 percent. The analogous series and the Pearl logistic model both perform well, under assessment from MAPE. The analogous series model delivered a slightly better prediction on average, at Horizons One (5.5 percent MAPE, 3 percent better MAPE) and Two (9 percent MAPE, about 1 percent better MAPE) and slightly worse predictions compared with the Pearl logistic at Horizons Three (12 percent MAPE, 1.5 percent worse MAPE) and Four (18 percent MAPE, 3.5 percent worse MAPE). The straight-line model out performs the marketing science models at all horizons.

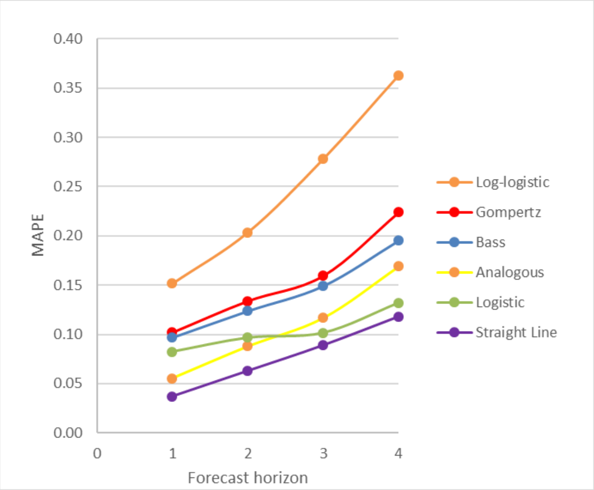


Figure 21. Mean forecast MAPE - the analogous series vs. marketing science models.

Table 17

Mean Forecast MAPE - Analogous Series vs Marketing Science Models

Horizon	Pearl logistic %	Gompertz %	Bass %	Log-logistic %	Straight-line %	Analogous %
1	8.24	10.21	9.67	15.17	3.72	5.54
2	9.66	13.40	12.36	20.36	6.31	8.79
3	10.16	15.96	14.91	27.82	8.92	11.68
4	13.20	22.40	19.51	36.31	11.83	16.92

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

8.4.4. Model forecast relative accuracy

The primary performance measure in this study is CumRAE, a bounded variant (UMBRAE) was also used (Chen et al., 2017), see section 6.3.2. Just like in Study One, the results from using UMBRAE were similar to CumRAE. This was not unexpected given the similarity of the two measures' with a base in RAE, and the normalised levels and time scales in the pool of series. Clearly, the differences are a result of poorer performing models registering higher errors that are bounded at a limit by the UMBRAE. Only the straight-line generated sufficiently large errors at longer horizons to produce large differences between CumRAE and UMBRAE, see Table 18. Because of this strong similarity of result, they are reported together and any differences are analysed at the end of this section. Once again, it appeared that despite the sensitivity of CumRAE to forecast error outliers, the improvement from using UMBRAE is modest.

Table 18

Absolute Percentage Difference of Mean CumRAE and Mean UMBRAE for Marketing Science Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Analogous	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	%	%	%	%	%	%	%	%	%	%	%	%
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	1.44	2.49	1.64	2.31	2.18	1.39	2.00	1.32	9.59	19.77	0.90	1.98
3	3.52	5.48	2.12	4.67	5.42	6.62	4.16	9.31	7.56	11.30	6.80	3.76
4	2.64	6.31	0.13	5.29	7.81	12.95	6.15	21.42	9.98	6.80	5.17	3.17

Note: Normal distribution plots of the CumRAE and UMBRAE indicated that outcomes were not normal; despite this, because it is common practice, the standard deviation (SD) dispersion statistic is presented along with the mean.
Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20
Note: Percentage difference calculated with respect to CumRAE

Figure 22and Figure 23 illustrate the virtually identical results for diffusion models with those two measures. Table 19 and Table 20 list the CumRAE and UMBRAE for the models' forecast performance. Using CumRAE, the ranked performance of the best models is changed from that of MAPE. Specifically, the best formal models are the Bass and the analogous series model. At Horizon One, the analogous series model is just a little worse than the Bass with a performance, that betters the naïve benchmark by 26 percent (CumRAE of 74), at Horizon Two the analogous series model just betters the Bass with performance that improves on the naïve benchmark by 43 percent. At Horizon Three, the analogous series model continues to better the Bass by now a miniscule margin with a performance that beats the benchmark by 63 percent. At Horizon Four, the Bass and the analogous series model have virtually identical results beating the benchmark by about 63 percent. The straight-line outshines all marketing science models by a considerable margin with a performance that is very consistent and betters the naïve fixed origin benchmark by more than 70 percent at all horizons.

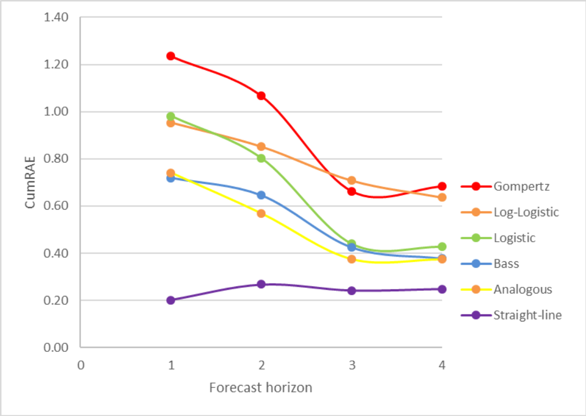


Figure 22. Mean CumRAE - analogous series vs. marketing science diffusion models.

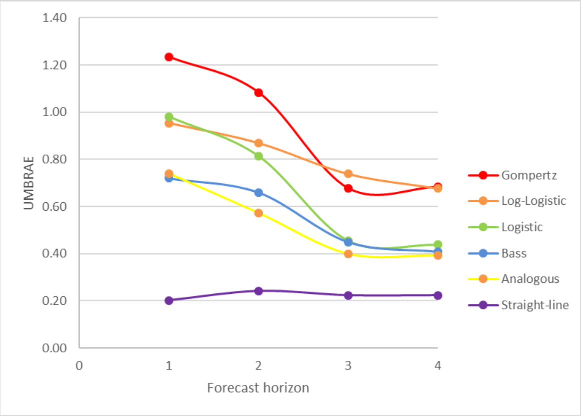


Figure 23. Mean UMBRAE - analogous series vs. marketing science diffusion models.

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

The two worst models swapped places, with the Gompertz model becoming the worst performer overall, and not able to better the naïve benchmark at Horizons One and Two, although it matched the next worst, the log-logistic, at Horizon Three with performance that was 30 percent better than the naïve benchmark. The log-logistic managed to beat the naïve benchmark at all horizons improving progressively from five percent better to 32 percent better from Horizon One to Horizon Four. The Pearl logistic, which had performed well on MAPE, is worse than the log-logistic and the Bass at Horizon One (just beating the naïve benchmark; at Horizon One two percent better) and improves to match the Bass, and beat the naïve benchmark by 57 percent. The Pearl logistic's performance nearly matches the performance of the best two models at Horizon Four (3 percent MAPE worse).

Table 19

Mean CumRAE - Analogous Series vs. Marketing Science Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Analogous	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	0.98	1.67	1.23	1.94	0.72	0.84	0.95	0.64	0.20	0.16	0.74	1.25
2	0.80	1.48	1.07	1.75	0.65	0.79	0.85	0.60	0.27	0.31	0.57	0.92
3	0.44	0.65	0.66	0.82	0.43	0.40	0.71	0.33	0.24	0.26	0.37	0.46
4	0.43	0.60	0.68	0.77	0.38	0.34	0.64	0.25	0.25	0.20	0.37	0.46

Note: Normal distribution plots of the CumRAE and UMBRAE indicated that outcomes were not normal; despite this, because it is common practice, the standard deviation (SD) dispersion statistic is presented along with the mean.
Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

Table 20

Mean UMBRAE - Analogous Series vs. Marketing Science Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Analogous	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	0.98	1.67	1.23	1.94	0.72	0.84	0.95	0.64	0.20	0.16	0.74	1.25
2	0.81	1.52	1.08	1.79	0.66	0.80	0.87	0.61	0.24	0.25	0.57	0.90
3	0.45	0.68	0.68	0.86	0.45	0.43	0.74	0.36	0.22	0.23	0.40	0.48
4	0.44	0.64	0.68	0.81	0.41	0.38	0.68	0.30	0.22	0.18	0.39	0.47

Note: Normal distribution plots of the CumRAE and UMBRAE indicated that outcomes were not normal; despite this, because it is common practice, the standard deviation (SD) dispersion statistic is presented along with the mean.
Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

8.4.5. Model forecast bias

Sometimes the focus of interest is the direction of the error in forecasts. That some models have a tendency towards bias in their estimates is illustrated in Figure 24 and Table 21 where it can be seen that on average, the Gompertz model will overestimate decline by a substantial margin and this bias increases with horizon length. While the log-logistic and the Bass models will on average, underestimate the decline, once again with increasing bias with advancing horizons. The log-logistic does this with by a similar margin to the Gompertz.

The Pearl logistic overestimates decline by a small amount (about 1.5 to 2.5 two market share). The analogous series does better than this on average, being bias free at all horizons. This bias free character is as expected, given the mathematical basis of the analogous series.

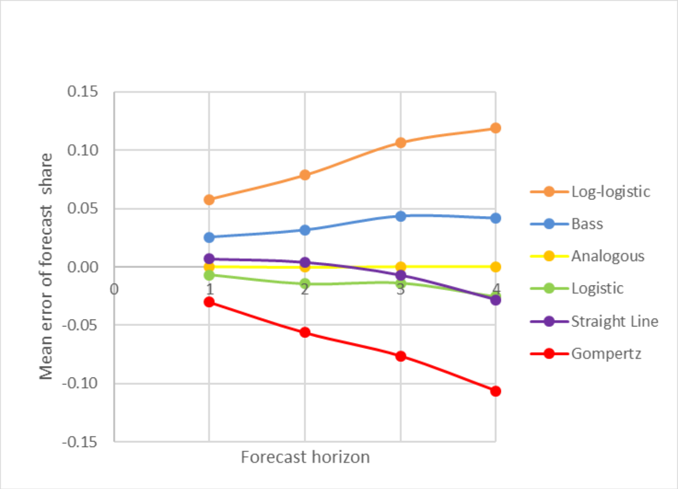


Figure 24. Mean forecast share error - analogous series vs. marketing science models.

Table 21

Mean Forecast Share Error - Analogous Series vs. Marketing Science Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Analogous	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	-0.01	0.05	-0.03	0.05	0.03	0.05	0.06	0.05	0.01	0.02	0.00	0.03
2	-0.01	0.06	-0.06	0.06	0.03	0.06	0.08	0.06	0.00	0.04	0.00	0.06
3	-0.01	0.06	-0.08	0.06	0.04	0.06	0.11	0.06	-0.01	0.06	0.00	0.07
4	-0.03	0.08	-0.11	0.08	0.04	0.08	0.12	0.08	-0.03	0.07	0.00	0.08

Note: Normal distribution plots of the CumRAE and UMBRAE indicated that outcomes were not normal; despite this, because it is common practice, the standard deviation (SD) dispersion statistic is presented along with the mean.
Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

8.4.6. Model forecast variability

Taking the perspective that an adequate level of relative accuracy is achieved, the focus might naturally fall to the consistency of the method in reaching that level.

8.4.6.1. Parametric estimation of the forecast interval

Data normality is critical to the use of this test. This method was able to be implemented because, with the exception of the straight-line model, histogram plots and Shapiro and Wilk (1965) tests indicated normality in the error distribution across the 25 series, at all horizons, with stronger normality indicated at longer horizons. The Shapiro Wilks test is the most powerful normality test but like all tests of normality are weaker in power at small sample sizes (Razali & Wah, 2011). Significant differences between the mean and the median in some of the model/horizon situations indicated the weakness of that test on this sample. However, assuming error distribution normality, parametric estimations of forecast uncertainty were calculated as described in section 6.3.5. The presentation of the error (bias) and the forecast interval together is a very useful summary of the overall performance of the models, and is important for managers. An example of this presentation at 80 percent and the 95 percent confidence levels with respect to the mean estimate error is provided in Figure 25. The numerical values for all models are presented in Table 22 and Table 23.

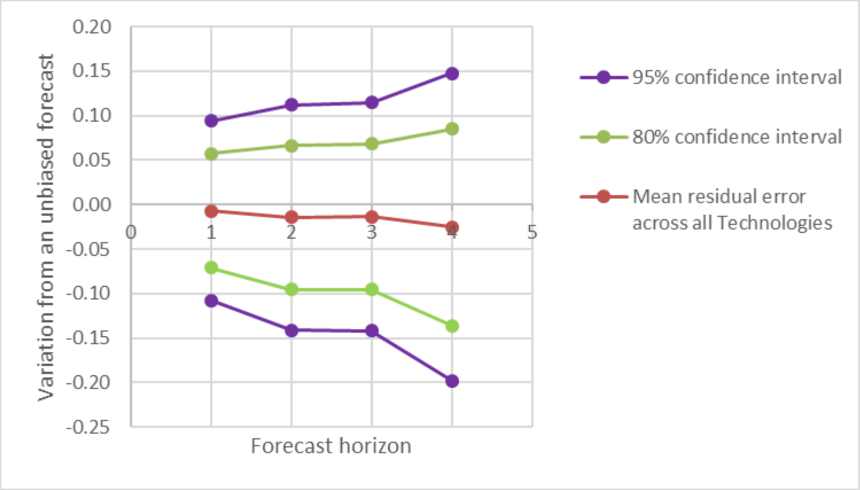


Figure 25. Logistic model mean prediction error (forecast interval) - Study two.

Table 22

The 80 Percent Confidence Bound for the Mean Error - Analogous Series vs. Marketing Science Model Forecasts

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Analogous	
Horizon	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd
1	-0.07	0.06	-0.09	0.03	-0.04	0.09	-0.01	0.12	-0.02	0.03	-0.04	0.04
2	-0.10	0.07	-0.13	0.02	-0.04	0.10	0.00	0.16	-0.05	0.06	-0.08	0.08
3	-0.10	0.07	-0.15	0.00	-0.05	0.12	0.03	0.19	-0.09	0.07	-0.09	0.09
4	-0.14	0.09	-0.22	0.00	-0.07	0.15	0.01	0.23	-0.12	0.06	-0.11	0.11

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

Table 23

The 95 Percent Confidence Bound for the Mean Error - Analogous Series vs. Marketing Science Diffusion Model Forecasts

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Analogous	
Horizon	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd
1	-0.11	0.09	-0.13	0.07	-0.07	0.12	-0.04	0.16	-0.04	0.05	-0.06	0.06
2	-0.14	0.11	-0.18	0.06	-0.08	0.15	-0.05	0.20	-0.09	0.10	-0.12	0.12
3	-0.14	0.11	-0.20	0.04	-0.10	0.17	-0.02	0.23	-0.13	0.12	-0.14	0.14
4	-0.20	0.15	-0.28	0.06	-0.13	0.22	-0.05	0.29	-0.17	0.11	-0.17	0.17

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

As noted in Study One, as a way to present the relative variability performance of each of the models, this approach fails as it presents the interval referenced to a biased estimate, making interpretation of relative interval size across models difficult. A presentation based on a zero biased forecast is required, to demonstrate the relative variation performance of the models. The relative size of the models' parametrically estimated 80 percent forecast intervals (with respect to an unbiased forecast based on CumRAE) are recorded in Figure 26 and Table 24.

Here we can see how the marketing science models have very similar size estimated forecast intervals at each of the four horizons. Interestingly the Bass scribes a different shaped curve to the others, one closer to linear than the other marketing science models, illustrating its consistency of performance across horizons. Importantly from a managerial point of view, the marketing science models have very similar variability in forecast performance, so this would seem to suggest this is not a reason to choose one over another. While the analogous series has much lower variability at early horizons it is similar to the marketing science models in most respects, thus variability is not a reason to choose analogous series over marketing science models. The straight-line model has lower variability than all other models.

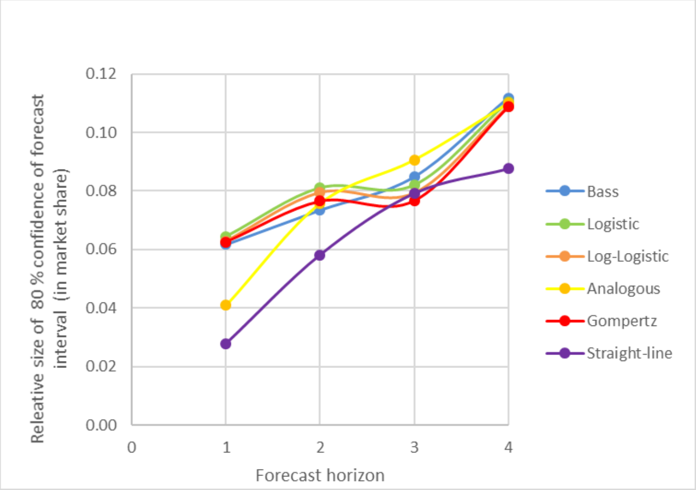


Figure 26. Relative size of forecast intervals (80 percent) - analogous series vs. marketing science models.

Table 24

Relative Size of Forecast Intervals (80 Percent) of Analogous Series vs. Marketing Science Diffusion Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Analogous	
Horizon	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd
1	-0.06	0.06	-0.06	0.06	-0.06	0.06	-0.06	0.06	-0.03	0.03	-0.04	0.04
2	-0.08	0.08	-0.08	0.08	-0.07	0.07	-0.08	0.08	-0.06	0.06	-0.08	0.08
3	-0.08	0.08	-0.08	0.08	-0.08	0.08	-0.08	0.08	-0.08	0.08	-0.09	0.09
4	-0.11	0.11	-0.11	0.11	-0.11	0.11	-0.11	0.11	-0.09	0.09	-0.11	0.11

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

Overall, the analogous series model’s forecast interval has equivalent range to the marketing science models at Horizons Two through Four and betters the range of all marketing science models at Horizon One. The straight-line continues to better the marketing science models, having the lowest overall range of all models.

8.4.6.2. Model forecast proportion of times better than naïve benchmark

Figure 27 and Table 25 demonstrate how frequently each model forecasts better than the naïve benchmark. With regard to bettering the benchmark, the straight-line model is consistently better than the other models, across horizons. It betters all models at all horizons, except for being equalled by the log-logistic model at Horizon Three. The Bass is the next most consistent model, bettering or equalling all models except the straight-line across all horizons, and the log-logistic at Horizons Three and Four. The analogous series estimator betters the Pearl logistic, log-logistic, and Gompertz at Horizon One. It betters the Gompertz, matches the log-logistic, and Pearl logistic at Horizon Two. The analogous series matches the Bass, and the Pearl logistic at Horizons Three and Four. The straight-line, the Bass and the analogous series all beat the benchmark at least 80 percent of the time across all of the horizons. The worst performer, the Gompertz, is the worst at all horizons and when at its best only beats the threshold 81percent of the time and then only at Horizon Three.

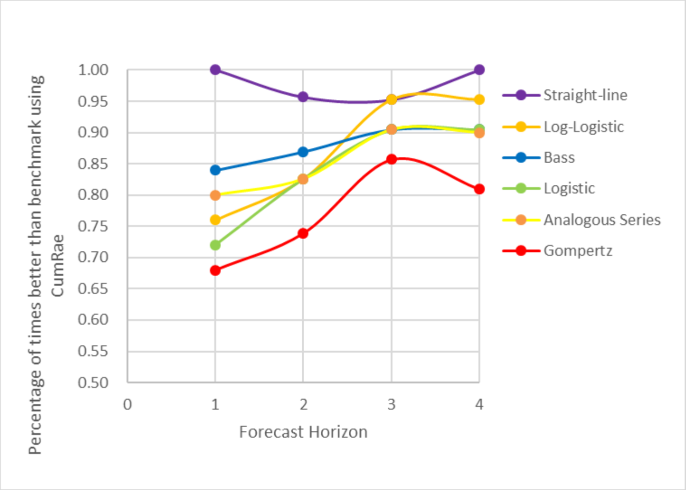


Figure 27. Proportion of times analogous series model forecasts are better than the naïve benchmark.

Table 25

Proportion of Times Analogous Series and Marketing Science Models are better than the Naïve Benchmark.

Horizon	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Analogous	
	Cum RAE	UMB RAE	Cum RAE	UMB RAE	Cum RAE	UMB RAE	Cum RAE	UMB RAE	Cum RAE	UMB RAE	Cum RAE	UMB RAE
1	0.72	0.72	0.68	0.68	0.84	0.84	0.76	0.76	1.00	1.00	0.80	0.80
2	0.83	0.83	0.74	0.74	0.87	0.87	0.83	0.83	0.96	0.96	0.83	0.83
3	0.90	0.90	0.86	0.86	0.90	0.90	0.95	0.95	0.95	0.95	0.90	0.86
4	0.90	0.90	0.81	0.86	0.90	0.90	0.95	0.95	1.00	1.00	0.90	0.86

Note: number of forecasts for each model horizon are H1-H2 n = 25, H3 n= 22, H4 n= 20

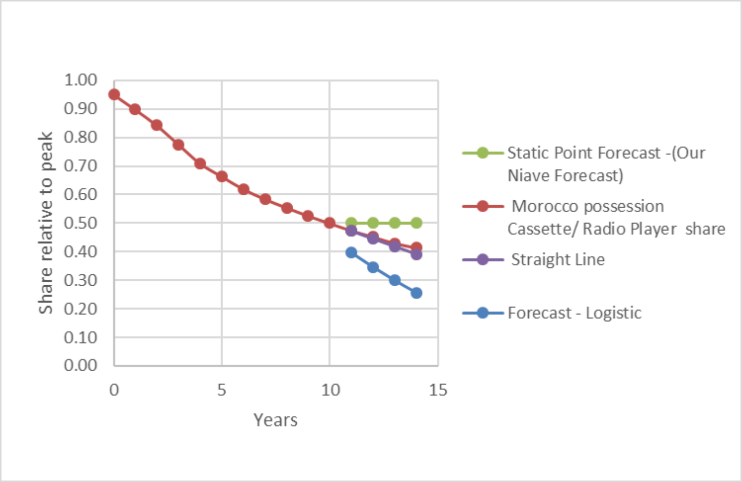


Figure 28. An illustration of why "proportion of times better" was low for models.

What is not obvious from these results is the impact of series that were trending towards floors significantly above zero. Illustrated in Figure 28 is a typical series that exhibited this trajectory and shows why the percentage of times better is low for marketing science models.

It is clear that the illustrated series is either incomplete or asymptotic to a floor higher than zero. Consequently, the static point forecast is a better representation of that trend than is the Pearl logistic; interestingly, on average the straight-line model is the best model, again with the observation that the straight-line is fitted to just the last three points of the estimation data. The pattern of not performing on series that were incomplete or falling to an asymptote (floor) above zero was repeated for all models, and across the four series related to possession of Radio Cassette (Morocco) or Video Cassette Recorder (Australia, Denmark, Spain). This undermined the absolute levels of *times better* performance however, these series were retained to provide a more generalizable result. The impact on forecast performance can be seen in Table 26.

Table 26

Relative Accuracy of Models (Series Asymptotic to Floors Higher than Zero)

Horizon	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Analogous	
	Cum RAE	UMB RAE	Cum RAE	UMB RAE	Cum RAE	UMB RAE	Cum RAE	UMB RAE	Cum RAE	UMB RAE	Cum RAE	UMB RAE
Morocco cassette radio player												
1	3.02	3.02	3.61	3.61	0.79	0.79	0.44	0.44	0.08	0.08	1.70	1.70
2	2.50	2.57	3.08	3.17	0.65	0.67	0.34	0.36	0.13	0.12	1.67	1.67
3	2.19	2.30	2.79	2.91	0.56	0.60	0.28	0.31	0.15	0.14	1.73	1.73
4	2.06	2.18	2.69	2.80	0.54	0.57	0.26	0.28	0.20	0.17	1.71	1.71
Australia videotape recorder												
1	3.33	3.33	4.15	4.15	1.64	1.64	0.61	0.61	0.20	0.20	1.75	1.75
2	2.75	2.84	3.54	3.64	1.39	1.43	0.52	0.54	0.21	0.21	1.68	1.68
3	2.42	2.55	3.21	3.35	1.24	1.31	0.46	0.49	0.22	0.21	1.71	1.71
4	2.24	2.38	3.03	3.18	1.17	1.24	0.43	0.46	0.24	0.23	1.65	1.65
Denmark videotape recorder												
1	7.85	7.85	9.03	9.03	4.01	4.01	3.04	3.04	0.64	0.64	4.07	4.07
2	6.74	6.89	7.97	8.13	3.50	3.58	2.62	2.68	0.72	0.70	4.13	4.13
3												
4												
Spain videotape recorder												
1	1.23	1.23	1.77	1.77	0.59	0.59	0.11	0.11	0.06	0.06	0.41	0.41
2	1.15	1.16	1.7	1.72	0.59	0.59	0.05	0.06	0.14	0.12	0.43	0.43
3												
4												
Mean												
1	3.86	3.86	4.64	4.64	1.79	1.79	1.02	1.02	0.24	0.24	1.98	1.98
2	3.28	3.37	4.07	4.16	1.56	1.60	0.88	0.90	0.30	0.29	1.98	1.98
3	2.31	2.43	3.00	3.13	0.90	0.95	0.37	0.40	0.19	0.18	1.72	1.72
4	2.15	2.28	2.86	2.99	0.85	0.91	0.34	0.37	0.22	0.20	1.68	1.68

The marketing science models reacted very differently to these four series that fell to a floor above zero. The Bass model and the log-logistic both performed well on those series, and beat the naïve Benchmark on the last two and last three horizons respectively. Both the Pearl logistic and the Gompertz model were unable to be competitive on these series performing two to four times worse than a stationary point naïve benchmark across the horizons. With the analogous series being in the region of 1.6 to 2.0 times worse than the naïve benchmark, this reflects how far from the typical decline series these four series were. It is worth remembering that these series are normalised for time so have different shapes to their parent series. The straight-line was the best performing model.

8.5. Summary

While the concept of analogy is deeply embedded in the theory, modelling and forecasting of phenomena, it is not commonly used directly in the form of analogous series forecasting, notable exceptions being Duncan et al. (2001) and M. J. Wright and Stern (2015). Given this gap in knowledge, this study investigated the performance of a simple analogous series model for predicting substitution driven technological decline. By comparing the performance of foundational marketing science diffusion models with the analogous series model, the relative performance of the simple new method of using analogous series was compared to the most well-known diffusion models when applied to decline situations. A number of interesting findings came from this investigation, and these are discussed in Chapter 10. Key amongst them is that the analogous series model used in the study is highly competitive with marketing science models, in terms of relative mean accuracy, bias, and variability. Also that a straight line fitted to the last three points before the 50 percent share, betters all other models for relative accuracy, and is very competitive for bias and variability over all horizons relative to the models assessed.

Chapter Nine: Judgment Forecasting Study

9.1. Introduction

This chapter investigates predicting decline with judgmental forecasts, the third and last study in this thesis. The first study looked at the forecast performance of simple marketing science whilst the second investigated the use of analogous series as a forecast tool. These two methods both produced viable forecasts on decline data, however on average, a simple straight-line model fitted to the last three points leading up to the primary inflection point, performed better. This suggests potential to improve on the performance of these two methods.

An alternative to marketing science models and analogous series is direct forecasting with judgment. A literature search indicates that this forecasting approach has not yet been applied to diffusion growth nor to technology decline. The approach in this study was to obtain many judgmental forecasts from an on-line panel of experts. The experts were asked to use their best judgment to estimate the next four points in six out of twelve randomly presented historic decline data series. The forecasting model was the arithmetical mean of all participant forecasts for each data series, an approach recommended by Bunn and Wright (1991). This provided a simple way to forecast with the judgment of a panel of experts. Konstantinos Nikolopoulos, Buxton, Khammash, and Stern (2016) found that such pooling of expert forecasts provides useful improvements over individual expert's forecasts. The judgmental forecast model is then compared to the diffusion models from Study One.

As discussed in the full review of judgmental forecasting literature in section 5.15, there is limited forecasting literature on judgmental estimation of diffusion curves. However, in the psychology literature there are studies reporting on the performance of participants in judgmental extrapolation of exponential curves, both growing and declining (Best et al., 2007; Jones, 1977; Wagenaar & Timmers, 1979). The evidence is contradictory concerning estimation accuracy, although it seems that falling curves are forecast better than growth curves. In general, it appears that judgmental estimation of *exponential-like* curves is highly inaccurate (Best et al., 2007; Jones, 1977; Wagenaar & Timmers, 1979). In the judgmental forecasting literature reviewed in section 5.5.7, the evidence on the relative performance of judgment over statistical models is mixed. Significantly, it appears that no judgmental forecasting of diffusion curves has been reported.

In the psychology literature there is a stream of investigation into the relative effectiveness of tabular and graphical presentation of data. There is however, little consistency in support for one method being better than the other (Best et al., 2007; Jones, 1977; Wagenaar & Timmers, 1979). The forecasting literature does not help either, in terms of deciding if tabular or graphical presentation approaches are best (Lawrence et al., 2006), although guidance as to the relative performance of different types of graphical treatments exist (Harvey, 2001). An important issue in forecasting, and also in surveys when feedback is not possible, is the type of supplementary information available to provide cues on the task properties. It seems that information explaining the task's characteristics is beneficial in improving judgmental prediction accuracy (Wagenaar & Timmers, 1979), as is the provision of structure around the information such that any analogous situation presented, is equally well understood by participants.

Ironically when experts make decisions, their accuracy has been found to be generally low and in many domains of expertise, lengthier professional experience has not been associated with better decisions (Armstrong, 1980). There are those that argue that there is a *contra expertise effect*, such that beginners perform as well or better than do experts (Önkal & Muradoğlu, 1995; Thomson, Pollock, Henriksen, & Macaulay, 2004; Wilkie-Thomson, Önkal-Atay, & Pollock, 1997).

This current study is based on collecting estimates via an on-line survey using a commercial panel with paid membership. Since the forecasting tasks had potentially high cognitive load, the estimates were expected to be impacted by the issue of speeding, a phenomenon where some survey participants take implausibly short times to complete tasks in a survey, typically by using some sort of heuristic shortcut when responding (J. N. Bassili & Scott, 1996; Greszki, Meyer, & Schoen, 2015; Kaminska, McCutcheon, & Billiet, 2010). This shortcutting activity, dubbed *survey satisficing*, is thought to occur where surveys have significant cognitive load (Krosnick, 1991). In those situations, a portion of participants might develop strategies to ease the effort expended in completing the task. While there are methods to detect some satisficing behaviours, not all behaviours are detectable, because it is possible for satisficing behaviour to result in answers which are plausible, and hence look acceptable, but which may not be optimal compared with a conscientious respondent's response (for examples see, Cannell, Miller, & Oksenberg, 1981). Speeding is considered to be at its worst when participants are reluctant, the cognitive load is high, or the respondent's ability to answer is low (Krosnick, 1991; Krosnick, Narayan, & Smith, 1996).

However, short completion times might also reflect a respondent's motivation to perform the task correctly, that is, reflect their accessible attitude as described by Grant, Mockabee, and Monson (2010). Short completion times could also potentially be related to higher knowledge (Heerwegh, 2003). Higher cognitive abilities are also thought to correlate with higher speed (John N. Bassili, 1996; Couper & Kreuter, 2013). In contrast, the K. Olson and Bilgen (2011) study found that higher-educated participants take longer, possibly because in controlled situations experts are thought to gain from using a more deliberative process (Moxley, Anders Ericsson, Charness, & Krampe, 2012). Thus, it might be reasonable to expect that those that are deliberative in the tasks of this experiment might provide better forecasts, equally the less experienced might gain most from this deliberative action (Cokely et al., 2017; Moxley et al., 2012).

Another important factor is reading speed. It is possible to find literature mentioning generally accepted maximum reading rates of 200 to 400 words per minute, (Rayner, Schotter, Masson, Potter, & Treiman, 2016), or describing a maximum of 500 words per minute as proposed by Rayner (1998). However, there is the notion that some readers can get a quick intuitive understanding of things, and investigators of expertise (Benner & Tanner, 1987; Dreyfus & Dreyfus, 2005) argue rapid expert decision making is principally the result of accumulated experience, which often leads to quick intuitive decisions, and reading speed is an indicator of this intuition. Herbert Simon wrote that intuition was "nothing more and nothing less than recognition" of prior learnt patterns (Simon, 1992, p. 155). Thus, experts can make rapid "intuitive" responses to problems (Simon, 1987; Usher, Russo, Weyers, Brauner, & Zakay, 2011). Hence, reading speed is not a good indicator of perfunctory thinking, as a quick intuitive reaction might well be founded in deep experience and understanding, in fact many researchers argue that heuristics and intuition even typify decision making by experts (Kahneman & Frederick, 2005).

9.2. Aim of This Study

The focus of this chapter is on validating the performance of judgmental estimation in forecasting decline in the use of technologies, testing the hypothesis in simple terms: *Is pooled judgmental estimates of S-curve decline series by experts better or worse than marketing science diffusion models estimates?* To investigate this there must be *format congruence* between the outcomes of this study and Study One, that is, the judgmental forecasting task must deliver outcomes comparable with that earlier study, so that performance of marketing science models and of judgmental estimation can be directly compared. In addition, to aid understanding, the evaluation process and presentation of results focus on uniformity with the first two studies.

9.3. Data, Models, and Methods

9.3.1. Data

As in the first two studies, the execution of the method in the current study relies on the prior identification of monotonic decline in the target data series, and predicting forward from that decline, referred to in section 6.4.5. While judgmental extrapolation does not necessarily have the same requirements for trimming and scaling as the marketing science diffusion model method of Study One, it was decided that the diffusion model estimation data from Study One (post trimming) be used as the estimation data for the judgmental forecasting task. However, the number of series used in the study was reduced to twelve series to keep the survey response load to reasonable limits given cost constraints on the number of participants. The selection was via three steps:

- First, outlier series were trimmed based on their variation from the S-curve trajectory. Using the data series normalised for both level and time from Study Two (both the estimation and the withheld portions), the absolute variance for all the series from the average value of all the series was assessed. To do this the focal series’ total deviation from the mean of all the deviations (variance data) was ordered by magnitude, to allow eyeballing of the deviations, at the same time a box-and-whisker analysis of the variance data was undertaken(McGill, Tukey, & Larsen, 1978). This analysis indicated two series that were substantially outside the upper outer fence. The two series eliminated by this outlier trimming were Morocco - Possession of cassette/radio player and Iowa non - hybrid corn growers.

- Series that did not have at least three data points available to be withheld were removed, as they would have wasted opportunities to obtain estimates from the participants. This factor was not a problem with the earlier two studies using numerical methods, where there was no monetary or respondent fatigue cost implications, and where their inclusion strengthened the data. The three series removed were Australia - CD albums sold, Denmark - Possession of videotape recorder, Spain - Possession of videotape recorder, Thailand - Possession of cassette/radio player. This left 19 series available.
- Finally, using magnitude ranked absolute variance data, the remaining series were sampled using the following sampling rules; four series were chosen centred on the mean deviation, and four series were chosen each from the series that were most close to the upper or lower first standard deviation bounds (from the mean deviation). This gave 12 series; four from B/W TV, two from DRAM, two from video recorder, plus one radio cassette player series and a series on US steam locomotives. That resulted in an oversampling of B/W TV so Russia – Possession of cassette/radio player was included as the next most close series and Czech Republic - Possession of B and W TV was removed, as the least close series in that technology. The datasets are listed in Table 27.

Table 27

The Data Series Investigated

Series No.	Original series No.	Description	Source
1	2	Australian dial-up internet subscribers	Australian Bureau of Statistics (various years)
2	3	New Zealand dial-up internet subscribers	Statistics New Zealand (various years),(OECD, 2005)
3	4	US steam locomotives in use	U.S. Bureau of the Census (1975)
4	9	Global 256K DRAM memory shipments	Victor and Ausubel (2002)
5	10	Global 4M DRAM memory shipments	Victor and Ausubel (2002)
6	13	Estonia possession BW TV share	Euromonitor (2016b)
7	14	Lithuania possession BW TV share	Euromonitor (2016b)
8	15	Slovakia possession BW TV share	Euromonitor (2016b)
9	18	Russia possession cassette/radio player share	Euromonitor (2016c)
10	20	Jordan possession cassette/radio player share	Euromonitor (2016c)
11	22	Taiwan possession videotape recorder share	Euromonitor (2016d)
12	23	Australia possession videotape recorder share	Euromonitor (2016d)

9.3.2. Survey sample

The three primary constraints on sample size were: the budget limit of $5,000 NZD, respondent acquisition costs in the region of $20 NZD per completed survey, and the need to operate an effective two by two experiment. Negotiations with the panel provider, Survey Sampling International (SSI) resulted in a commitment to deliver 250 completed surveys for that budget. The provider described the panel as *business decision makers in the UK*. No pre-screening by the panel provider was undertaken; the size of the panel sampled was described as greater than 150,000.

9.3.3. Forecast method and notes - survey experimental design

9.3.3.1. Introduction

The study was designed to test how well experts can forecast a decline trajectory. Estimation capability is tested for participants randomly allocated to incomplete data series presented in either tabular or graphical format. There appears to be no recognised thresholds for respondent *survey taking fatigue* (Rolstad, Adler, & Rydén, 2011) in the literature. However, to minimise potential fatigue, the participants' survey completion times (a proxy for task load during design) was actively minimised. The effort resulted in the following respondent workload; two screening questions, six forecasting tasks and a short section of seven demographic style questions.

9.3.3.2. Basic experimental design

Respondents were randomly allocated to one of the two treatments. Bar graphs were the graphical data presentation. Bar graphs were chosen over other graphical presentation formats because it is thought that bar graphs are superior when presenting nonlinear trends (Best et al., 2007), when a forecaster must predict data points (Wallgren et al., 1996), and when forecasters are experienced (Best, 2008; Culbertson & Powers, 1959). An alternative data presentation was a vertical two column table form. The amount of cue information was held constant across the two treatments and at a level that represented what a forecaster might be expected to know if their job involved forecasting technological decline, and they had investigated the literature around typical decline trajectories.

Participants were offered on rotation all three of the control series and then randomly one series each from three sets of three experimental series, to avoid resampling effects. This resulted in each respondent being offered six tasks from the same treatment representing six different data series out of a total of 12 series. To ensure the three control series were representative of the twelve series, they were selected one each from the lower standard deviation, the median of series and the upper standard deviation series groups. Each control series was chosen for its placement nearest to the mean deviation of that group, to allow for further analysis beyond the scope of this thesis.

9.3.3.3. Survey design

Given that this survey was to a commercial paid panel, the tasks in the survey were thought to have the potential to trigger four behaviours:

- Survey abandonment,
- Question skipping,
- Inattention indicated by long completion times,
- Speeding by satisficing - answering via straight-lining the answer (for examples and an explanation see, Vandenplas, Loosveldt, Beullens, & Denies, 2017);
- Speeding by satisficing - via a rule providing a suitable but suboptimal answer (Krosnick, 1991).

The first of these actions, abandonment, was considered natural and unavoidable given the nature of the participants, the context, and the task, so little was done to mitigate abandonment other than efforts to reduce to a minimum, the total cognitive load, and time effort to complete the survey. The survey had two screening questions, in the first; participants were asked if they forecasting experience, and those that responded “no” were screened out of the survey by the software. A second question asked their relative experience, permitting further screening if required. Placing this question early was intentional to further indicate the importance of expertise and experience, with an expectation that some participants would abandon on the second question.

Skipping questions, the second of the undesirable behaviours, was avoided by forcing participants to answer each question in the survey. The rationale was that given the participants were business decision makers and they received a small remuneration, the gains from this strategy would outweigh any potential risk of increasing abandonment, or satisficing rates.

The third undesirable behaviour, that of inattention, was not specifically controlled for in the survey design, because other than extremely long completion times little potential for identification of this behaviour existed. Often instructive tasks are included in survey questions to assist in the isolation of inattentive participants at design time, this was not done in this survey, because of a belief that the tasks compelled attention, and thus inattention would be obvious in the responses. Interestingly this proved not to be the case.

The fourth issue that of speeding is complex. The identification of speeders was considered important despite the evidence in Greszki et al. (2015), and Sauro (2014) that speeders add noise rather than bias. Speed alone does not directly indicate inattention to a task, nor indicate satisficing via the use of a rule to provide an adequate but suboptimal answer. The forecasting tasks in this study were very different to typical survey questions and were expected to provide a high cognitive load even for experienced participants, leading to the potential for satisficing behaviour. Therefore, one identifiable behaviour, that of completion times, was considered as a way to detect both inattention and satisficing. Timers were placed in each prediction task in the survey along with click counters to allow post-hoc identification (Osborne, 2012).

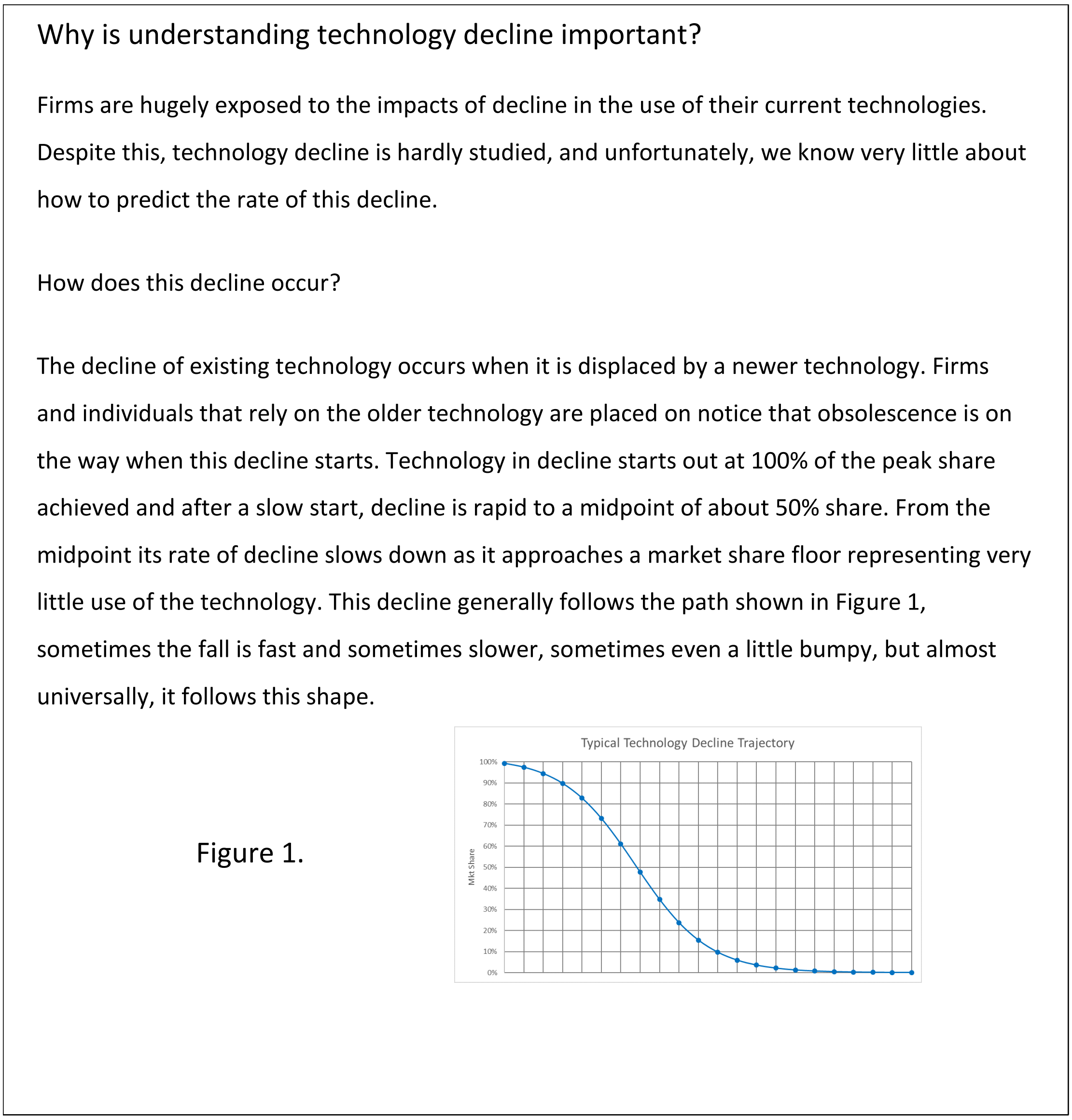
Typically when researchers undertake a comparison between judgment and statistical models, the forecaster would be deliberately isolated from any information not included in the models, to “effect a fair comparison” (Lawrence et al., 1985). Lawrence et al. (1985) contest that this creates a level playing field by improving the level of *internal control* in the research and much of the literature on predicting exponentials is so focused. However, there is a counter argument, that any forecasting performance test should reflect the capability of typical forecasters. In applied judgmental time series, forecasting the forecaster has much more information available than the laboratory tested studies allow. They have an understanding of character of the time period involved, an understanding of type and nature of the data series, and of other factors contributing to the formation of the series not included in a typical statistical model. To retain external validity (realism) with respect to information held by forecasters, the information was made available via a process that structured the presentation of this information consistently for each forecaster across each treatment, albeit within the limitation of an email survey, in line with the philosophy of Armstrong and Green (Armstrong, 2006; Green & Armstrong, 2007).

9.3.4. Testing and implementation of the survey

Because of concerns about the impact of cognitive load (Krosnick, 1991; Krosnick et al., 1996), extensive focus was placed on the initial experimental design and conceptual testing. First, two experts in forecasting research guided initial design, then the survey was implemented using Qualtrics' on-line survey tool and set up for distribution via an email link to participants. It was then pretested with those same two experts plus a small group of five market research practitioners and researchers. After refinement of the survey based on feedback from this group, it was sent out to a pilot group of 20 PhD students from a range of disciplines. Further refinement was undertaken. The survey was then soft launched to 56 panel members and 30 valid surveys were obtained and those responses were analysed in Microsoft Excel^{TM} and SPSS^{TM} to identify if any design problems existed. After that final test, the survey was released to the full panel via an email invitation to obtain the quota of 250 randomly selected panel members, all of whom were paid a small standard incentive by the panel provider. The survey ran November 22 to 29, 2017.

9.3.5. Survey flow

The survey script started with a Massey University standardised survey introduction, which described the level of ethical approval, how to ask the researcher questions and where a participants could, with confidentiality, express concerns about the survey. The participants were presented with a broad definition of forecasting and then a simple in-survey screening question was used to exclude those that had never, "*made forecasts, met with others to make forecasts, reviewed forecasts, or used forecasts in any role*" current or past. Participants were then asked, with that same broad definition in mind, to assess on a 10-point scale, their experience in forecasting relative to others in their industry. This question served to identify if the survey invitation may be disproportionately taken up by either expert or novice forecasters, resulting in unrepresentative results, given the difference in performance of those groups in other studies, another validity threat. This question also facilitates a future investigation of the impact of experience on forecast accuracy. They were then briefed on the typical reason for technological decline and the typical trajectory of that decline. The typical series used was the series closest to the mean trajectory of the normalised data from study, presented in the form of the actual data series used in study one and three. Participants were informed of this typical trajectory via a textual description, and a visual presentation of a typical pattern of technology decline. This briefing information is presented in Figure 29 below.



Why is understanding technology decline important?

Firms are hugely exposed to the impacts of decline in the use of their current technologies. Despite this, technology decline is hardly studied, and unfortunately, we know very little about how to predict the rate of this decline.

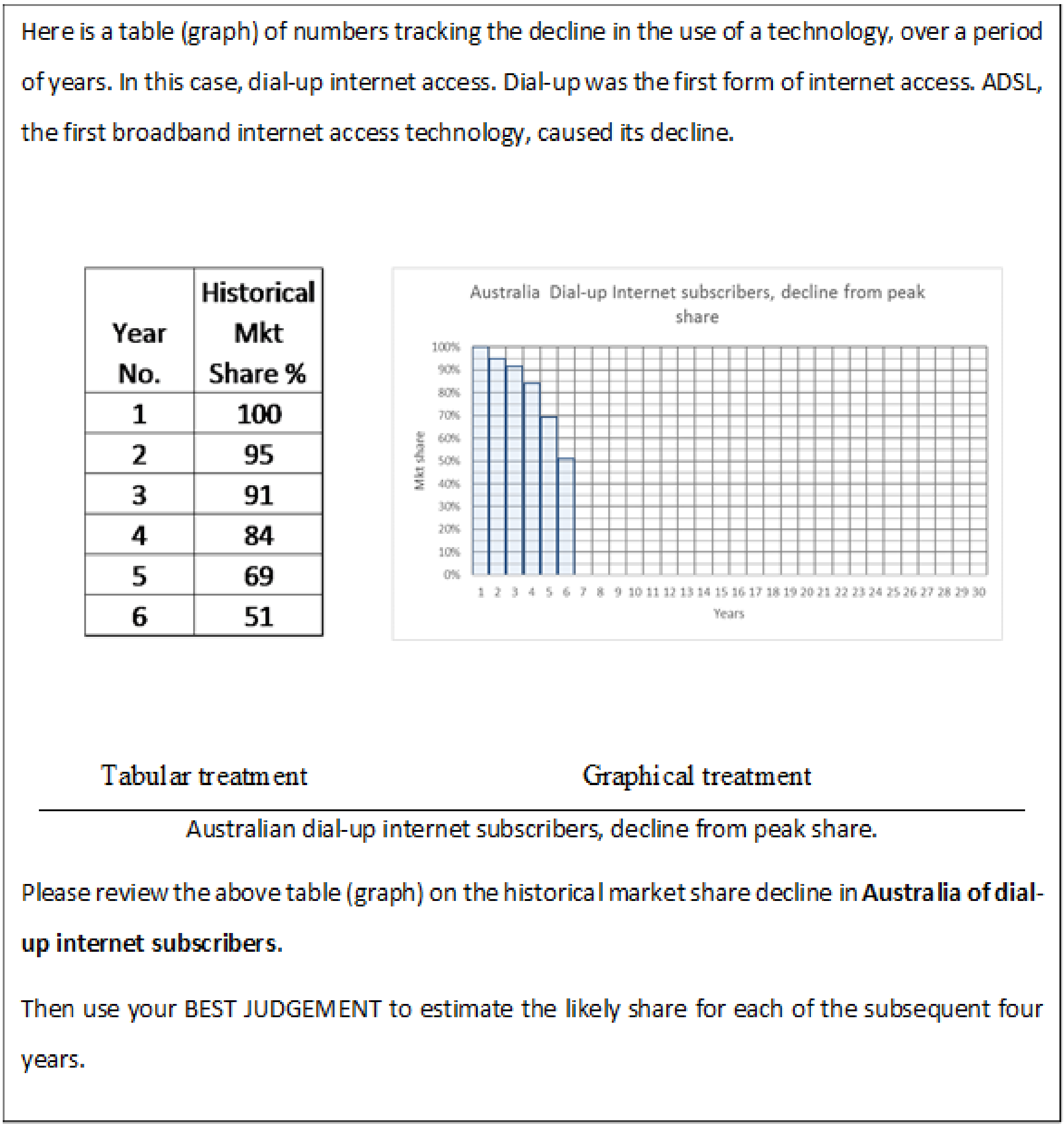
How does this decline occur?

The decline of existing technology occurs when it is displaced by a newer technology. Firms and individuals that rely on the older technology are placed on notice that obsolescence is on the way when this decline starts. Technology in decline starts out at 100% of the peak share achieved and after a slow start, decline is rapid to a midpoint of about 50% share. From the midpoint its rate of decline slows down as it approaches a market share floor representing very little use of the technology. This decline generally follows the path shown in Figure 1, sometimes the fall is fast and sometimes slower, sometimes even a little bumpy, but almost universally, it follows this shape.

Figure 1.

Figure 29. The information presented to brief all participants to the same level.

Participants were then advised of the number of tasks they would be undertaking, the nature of those tasks, and that it was expected to take approximately nine minutes to complete the survey. Participants were requested to apply the knowledge provided from the briefing information to extrapolate an uncompleted historical technology decline process out four more time periods. The form of the tabular treatment and the graphical treatment for a typical data series can be seen in Figure 30.



Here is a table (graph) of numbers tracking the decline in the use of a technology, over a period of years. In this case, dial-up internet access. Dial-up was the first form of internet access. ADSL, the first broadband internet access technology, caused its decline.

Year No.	Historical Mkt Share %
1	100
2	95
3	91
4	84
5	69
6	51

Tabular treatment

Graphical treatment

Australian dial-up internet subscribers, decline from peak share.

Please review the above table (graph) on the historical market share decline in **Australia of dial-up internet subscribers.**

Then use your BEST JUDGEMENT to estimate the likely share for each of the subsequent four years.

Figure 30. A typical forecast task but showing both treatments for illustration.

Having completed their six forecasting tasks, participants were then asked in what industry they were employed, their years of management experience, prevalence of forecasting tasks in their current role, year of birth, gender, education level, and size of their employing organisation. The full survey instrument can be found in Appendix A.

9.3.6. Models

9.3.6.1. Fitted model forecasting

As in Study One and Two, four marketing science models and the straight-line model were used as comparisons in a competition of performance. The results from these models serve as a benchmark for the judgmental approach, by being re-run on the 12 series selected for the current study. This ensured model performance was directly comparable within the current study, avoiding differences caused by selecting a subset of the 25 series. The procedures used to fit and forecast with the marketing science models, were identical, and generated identical predictions to that of Study One, although the results from each series in the data set when summed within the measures were, as expected, different from Study One.

9.3.6.2. Model parameter value estimation

As in the first two studies, the four marketing science diffusion functional forms were first fitted to data from the first half of the series of interest, and used to estimate the parameters of the functional form and thus create the model. The difference from Study One is that the marketing science diffusion models were applied to only 12 of the set of 25 series. Just as in Study One, the first four points in the series data beyond the 0.50 share point became the data points to be forecast. The model parameter values were estimated as in Study One. Table 28 is a summary of the fit statistics.

Table 28

Marketing Science Model Fit Statistic Summary – Study Three

	Pearl logistic			Gompertz			Bass			Log-logistic		
	R2	SSE	MAPE %	R2	SSE	MAPE %	R2	SSE	MAPE %	R2	SSE	MAPE %
Min	0.90	0.00	0.00	0.89	0.00	0.00	0.96	0.00	0.00	0.96	0.00	0.00
Max	1.00	0.03	0.04	1.00	0.03	0.05	1.00	0.01	0.03	1.00	0.01	0.03
Mean	0.98	0.00	0.01	0.98	0.00	0.02	0.99	0.00	0.01	0.99	0.00	0.01
SD	0.03	0.01	0.00	0.03	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00

N =25 fits per model

All functional forms in all specifications (models) had a good fit to their data, with R^2 values typically 0.97 or better, with a mean better than $R^2 = 0.97$ for each functional form. The worst fit was the Gompertz model to series 18 at $R^2 = 0.89$. Residual fit MAPE values were typically less than three percent, with the worst being less than seven percent, and a mean of less than three percent across the functional forms. Just as in Study One, data series number (18) was fitted less well by all functional forms. As described in Study One the weaker fit can be explained by the shape of the data trajectory. As in Study One, despite the penalty of adjusting the R^2 values for number of parameters in the models adjusted R^2 values above 0.95 were achieved for all models across all series, but for the Gompertz model across series 18. We know fit is not a good predictor of forecasting performance (Armstrong, 2001b; M. R. Young, 1993). Thus, despite the weakness of model fits to the three series with adjusted R^2, each model specification was considered a suitable representation of the decline process, given acceptable R^2, SSE and MAPE, and thus also suitable for forecasting future values of the variable of interest.

9.3.6.3. The fitted model forecasting process

Using the optimised (parameterised/fitted) models, forecasts were made by inserting into the model values of t representing horizon predictions for one, two, three, and four periods ahead, across the 12 selected data series.

9.3.7. The judgmental forecast estimate

9.3.7.1. Judgmental model forecasting

The estimates of all valid survey participants form the basis of the judgmental forecasting model used in this study. A simple mean of the estimates of all participants for each treatment became the forecast of the judgmental forecasting at each horizon. The judgmental model estimates were compared with the marketing science diffusion model estimates and those provided by the straight-line model.

As noted in section 5.5.4 on combining forecasts, this simple average has been found to be as effective as other methods. This averaging across all participants at each judgmental estimation point (horizon) is described formally in Equation (55) below:

$$y_{i_{(t)}estimate} = \frac{1}{n}\sum\nolimits_{i=1,n} (Y_{nt_i}) \qquad (55)$$

Where $Y_{i(t)estimate}$ = mean share of market still held at time t_i, after cumulative decline attained by time t_i, for a group of judgmental estimates *1* through *n*, where *i* is any time from 0 to *x*, *n* = the number of judgmental estimates. Y_n at *ti* is the cumulative decline of a technology *n* at time *t*.

Tactics that minimised validity issues associated with the study were implemented, to control for confounding influences. The first action was careful data series selection via a structured statistical process to ensure as much as possible the data series in this study were representative of the full data set as far as possible. The participants were randomly selected from a large sample of a large population. Further, the participants were screened for experience and replaced, until a quota of experienced forecasters was reached. As described earlier, psychology literature indicates that forecast bias is significant in judgmental forecasting of exponential-like trajectories, and is sensitive to noise (see section 5.5.10), experience (see section 9.1), cues, and cognitive load (Krosnick et al., 1996). Noise is not a significant issue other than at the initiation of an S-curve trend because as mentioned earlier the signal to noise ratio rapidly improves as decline progresses. Given the findings in studies of an inverse expertise effect, respondent experience was recorded and analysed to ensure representative experience distribution, (but also to allow investigation for this phenomenon later). Given that this study took place outside a laboratory, many information cues might affect validity, the primary ones of data presentation and scenario-briefing cues were controlled, and the other uncontrollable issues were recognised by adopting a large sample strategy. The study was repeated twice: once with responses trimmed for implausibly rapid completion times, and once trimmed for potential satisficing through observed forecast pattern differences from the pattern briefed and the data presented. Finally, to avoid the influence of a narrowly specified assessment measure, a basket of measures was instigated to allow analysis of multiple aspects of model forecast performance, including bias, accuracy, and consistency, in particular the implementation of naïve benchmark based error measures.

9.3.8. The evaluation criteria

The evaluation criteria were the same as the first two studies; Mean forecast share error, MAPE, CumRAE, and UMBRAE are reported for all series. Also reported was the mean absolute forecast error in share as an indicator of forecast bias, a forecast interval, and the percentage of times the estimator was better than the naïve benchmark across all forecasts. These measures are described earlier, in section 6.3. The measures utilised the cumulative errors across each horizon, that is: from zero to one period, from zero to two periods, out to four periods. The results are reported summarised as means across all series.

9.3.9. Exploratory data analysis

9.3.9.1. Incomplete responses

The survey automatically screened out respondents reporting no forecasting experience. By survey close off time, 36.6 percent of all those offered the survey were terminated in this way. A second question asked their relative experience and seven participants abandoned the survey at that point. Those responses with the experience response field empty were removed (they represented surveys where no forecasting task was undertaken). This left 354 participants (62.2 percent) available to attempt the forecasting tasks. The breakdown of numbers offered the survey is presented in Table 29.

Table 29

Breakdown of Participants Screened Out on Experience Basis

Screen into survey?	Respondent (n)	Percent of responses	Comment
Experience = “yes”	354	62.2	Screened in
Experience = “no”	208	36.6	Screened out
Experience = empty	7	1.2	Failed before screen
Total responses	569	100.0	Offered survey

There were 41 percent females and 59 percent males, participants ranged in age from 18 to 74 years with a mean age of 44 years old. They represented a range of industries and levels of forecasting expertise as presented in Table 30 and Figure 31 below. The propensity for people to estimate themselves as better than average was recognised in formulating the relative experience; however, a comprehensive assessment of experience was outside the scope of this study.

Table 30

Industries Represented in the Participants

Industry	Percent
Other service industries	22.3
Selling, distribution and retailing	16.8
Manufacturing	14.7
Finance and banking	11.6
Professions in private practice	9.9
Education	8.6
Transportation	7.2
Civil Service and local government	6.5
Primary (farming, fishing, mining, etc.)	2.4
Total	100.0

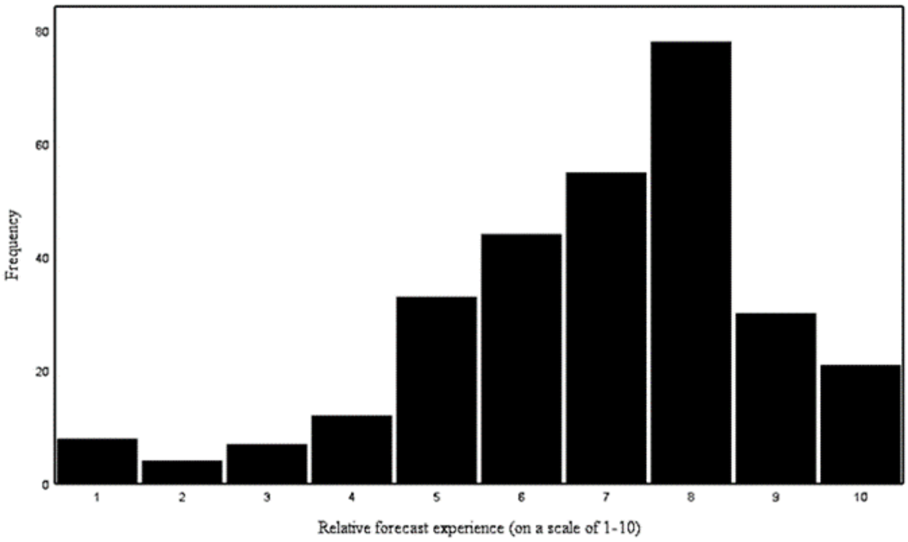


Figure 31. Self-reported experience level of participants.

9.3.9.2. *Low quality responses, speeding, and satisficing*

Next, the preliminary data analysis process moved to the issue of low quality responses. First, all participants who abandoned the survey, after being screened in, were removed. Of the 354 responses screened in and thus available to complete the survey, 64 were removed from further analysis because they had not completed the survey sufficiently. They had generally completed two or fewer of the six tasks and had not completed the demographic section. Only one of the 62 participants removed had answered more than 50 percent of the survey, but they had skipped a forecasting task and the demographic section. Two participants provided implausible values, that is, above 100 percent market share, and were removed. The breakdown is illustrated in Table 31.

Table 31

Breakdown of Participants Removed for Providing Incomplete Responses

		Respondent (n)	Percent of total screened in
Survey uncompleted			
	No Data	1	0.3
	Only screen answered	48	13.6
	Screen +1 answered	8	2.3
	Screen +2 answered	3	0.8
	Screen +>2 answered	2	0.6
	Improbable answers	2	0.6
	Total uncompleted	64	17.5
Survey Completed		290	82.5
	Total responses	354	100

This left 290 survey responses determined as completed, 40 more than the contracted 250 completed surveys. Early exploratory data analysis had uncovered a pattern of rapid survey completions indicating the potential for low quality responses from this speeding behaviour in some individuals, the panel provider offered additional participants to increase the chance that after trimming, 250 participants would remain.

Participants with extremely long times to complete, were considered inattentive. That some participants were very slow can be seen in the time spent on questions in Figure 32.

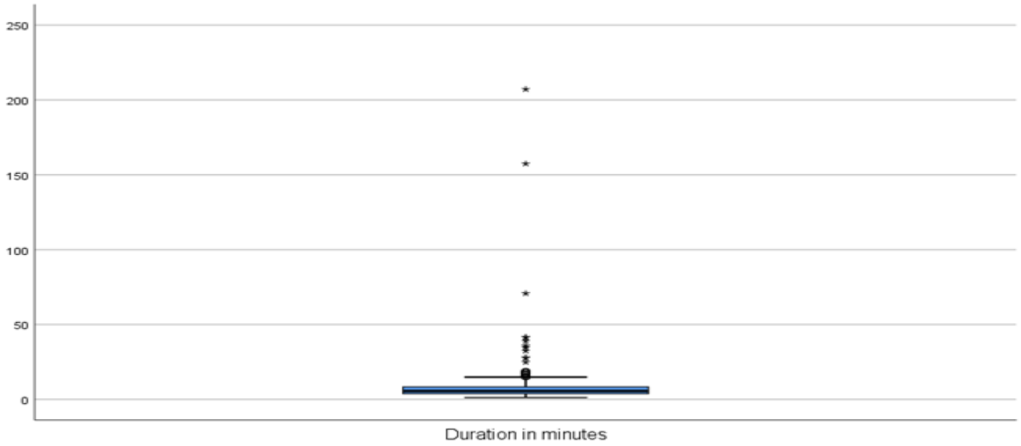


Figure 32. Distribution of time to complete speed of participants.

Participants who took more than two hours to complete the task were considered likely to have been distracted and inattentive. That decision removed six participants who took variously 2.6, 3.5, 62.9, 70.7, 120.8 and 143.7 hours to complete. After removing those ultra-slow responders, the maximum time for the tabular treatment became 41.6 minutes and 149 participants remained, and for the graphical treatment the maximum duration was 70.8 minutes and 135 participants remained. The average time to complete was then seven point four minutes. The tabular treatment average was seven and a half minutes and the graphical presentation average time to complete was seven point two minutes. The reduction in the number of participants is illustrated in Table 32.

Table 32

Breakdown of Participants (Screened for slow Responses - greater 2.5 hours)

	Respondent (n)	Percent of total screened in
Survey completed	290	NA
Less Ultra Slow	6	NA
Treatment 1 remaining	149	52
Treatment 2 remaining	135	48
Total remaining	284	100

Calculating for reading speed but making no allowance for any cognition and execution activity, many participants recorded reading speeds exceeding 500 words per minute, which is often thought as the upper limit for understanding of text where there is not significant redundancy (Rayner, 1998; Rayner et al., 2016). Many of those fast responses were less than half the mean time to complete for participants. Many participants had speeds beyond 600 words per minute (four times the trimmed mean) as illustrated in Figure 33.

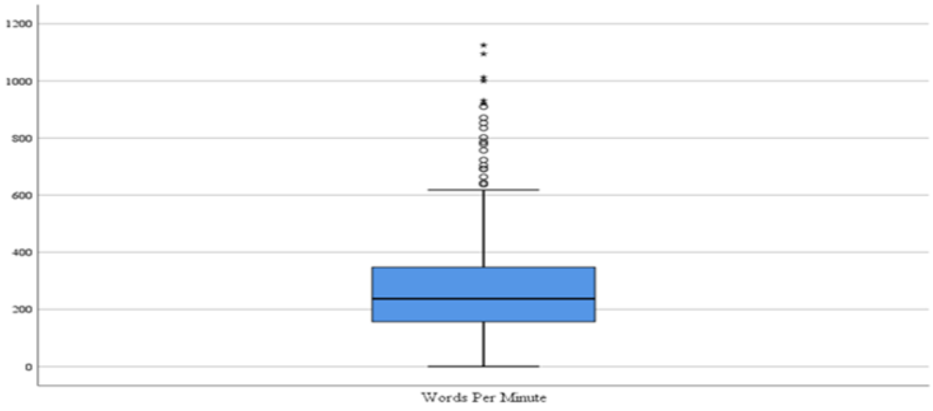


Figure 33. Distribution of word per minute speed of participants (both treatments).

The exploratory data analysis also uncovered two prediction behaviour patterns not linked to the S-curve decline paradigm presented in the information cues of the survey: first, that of *flat-lining* predictions across the four prediction time periods within each task, and second, that of providing an exponential growth prediction against the historic S-curve decline trend data provided. In forecasting there are well-known prediction strategies that correspond with these two response patterns.

In the case of flat-lining, a recommendation followed by many forecasters is to use the last recorded data point as the next one-step ahead data point prediction. This recommendation is generally in low drift (low trend) economic series and has become a stalwart in forecasting theory (Gardner, 2015; Green & Armstrong, 2015; Moosa & Burns, 2016). While this approach is well known, it has specific application; in series where often trend is indistinguishable from noise, and generally only in single step ahead situations. In the context of this study, that approach would have generated a flat-line response across all horizons. Unfortunately, it was not possible to identify if the observed flat-lining was satisficing behaviour or a legitimate forecasting strategy. Conrad, Tourangeau, Couper, and Zhang (2017, p. 46) observe how difficult it is to separate a legitimate from a satisficing response.

Predictions with growth trajectories were initially thought as being the result of participants not understanding the task context, potentially but not exclusively, the result of speeding. However, there is a strong theme in economic literature that supports the idea of cycles of growth (Schumpeter, 1939; Tinbergen, 1981), and these might well have been on the minds of the participants when they answered. Perhaps asking a question in the survey on the forecasting approach used, could have identified a respondent's underlying strategy, however, the survey did not do this. Thus, screening out such responses as low quality was not possible on any intentions basis, as they may well have been using the random walk theory despite its lack of applicability in this case, or using an economic growth cycle forecasting strategy.

Given that speed domain, and prediction pattern behaviour domain outliers existed in the data, it was decided to identify the effect of those outliers on forecast accuracy. A simple strategy of testing estimation performance with and without outliers was put in place. Established protocols for identifying outliers (described in sections, 9.5.1 and 9.5.2) were used to develop methods of identifying and removing outliers identified by speed, and those identified by respondent prediction behaviour. The data was first analysed without any trimming for speed or outlier behaviours.

9.4. Results: Judgmental Performance without Trimming Data

9.4.1. Preliminary assessment of model performance

Just as in the earlier studies absolute forecast share error is presented as a preliminary to the formal measure results. Figure 34 demonstrates a relatively flat absolute forecast share error for the diffusion models as the forecast horizons lengthen. This indicated a more consistent forecasting capability for the models with this smaller set of data series tested in this study compared with the observation of Study One and Study Two,. The improved performance is likely the result of removing series, which may have had non-smooth and weak adherence to S-curve shapes. Series that had large deviations from the mean shape of the normalised series were trimmed in the first step of reducing the number of series to 12 from 25, because they would have represented a large portion of any variance in the reduced data set.

Absolute errors in predicting share are useful to get a sense of the scale of the error in management terms. Figure 34 shows that the Bass and Pearl logistic, the two best marketing science models both had on average absolute prediction errors less than 0.10 share even at Horizon Four. This is a slight deterioration on the worst case horizon 0.08 share for the better models in Study Two on analogous data, and similar to those of Study One.

From the absolute error in predicting share perspective expert judgments might perform better than expected, being very competitive with the marketing science models. Expert judgments have lower error than all models in the first two horizons, only being bettered by the Bass and Pearl logistic models across the later two horizons. The Gompertz and the log-logistic are the worst of the marketing science models on this measure by a substantial margin. Because of this performance and their performance in earlier studies, the Gompertz and log-logistic models are not presented beyond this point. The straight-line model continues to be competitive with the diffusion models on this set of data, which is a subset of those used in the two earlier studies.

That the expert judgment estimates have much lower mean absolute forecast share errors than the diffusion models in early horizons, and are competitive even at later horizons, is very surprising. The literature's description of judgmental forecasting in general and exponential judgments in particular is that they are highly biased (see the review in section 5.5).

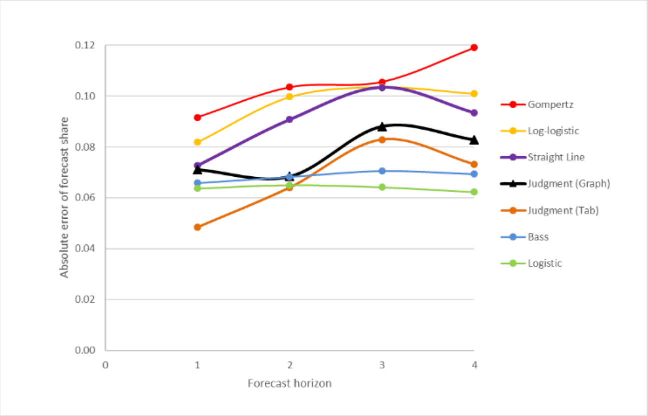


Figure 34. Mean absolute error of forecast share for the judgmental models.

9.4.2. Model forecast absolute percentage accuracy

Referring to Figure 35 and Table 33, it can be seen that the straight-line model has an S-shaped MAPE indicating a poor fit to the decline data generating process. The same is true of the two judgment treatments as the forecast horizons lengthen. This signals the likelihood of experts using a linear judgmental estimate process even when briefed to expect an S-shaped trajectory. The Pearl logistic and the Bass models are the best marketing science diffusion models with near identical performance, in terms of level of MAPE and also in the consistency of the MAPE over the four horizons.

At the first horizon, judgment models are competitive with the Pearl logistic and the Bass model, which are the best performing marketing science model, the tabular treatment is better by five percent MAPE, and graphical treatment is worse by about one percent MAPE at Horizon One. Judgment under both treatments was competitive with the two marketing science models at Horizon Two, with tabular presentation of the data worse than both the logistic and the Bass with a MAPE of 21 percent (about 2 percent worse) and the graphical presentation of data having MAPE two percent higher than that. Both judgment approaches rapidly deteriorate, and are uncompetitive at the last two horizons; being bettered by all models except the straight-line by Horizon Four see Figure 35. Interestingly, by comparing graphs of the judgmental models' prediction errors (MAPE), with those of the straight-line model it seems that the judgmental models' responses have a distribution over the horizons similar to a straight line.

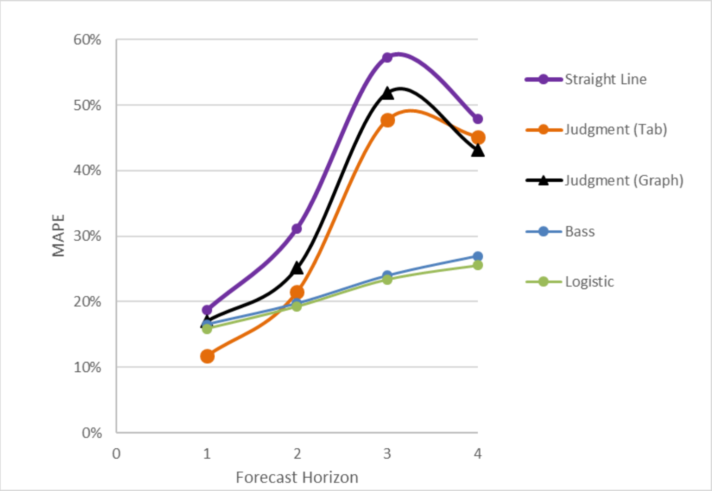


Figure 35. Mean forecast MAPE of judgment compared with the two best models.

Table 33

Mean Forecast MAPE of Judgmental Models vs. Marketing Science Models

Horizon	Pearl logistic %	Gompertz %	Bass %	Log-logistic %	Straight-line %	Judgment Tabular %	Judgment Graphical %
1	15.89	21.53	16.53	20.28	18.72	11.72	17.04
2	19.27	23.11	19.73	28.74	31.19	21.52	25.19
3	23.39	27.16	23.97	41.56	57.25	47.74	51.87
4	25.55	34.82	26.97	34.77	47.94	45.17	43.10

Note: number of forecasts for each model horizon are H1-H3 n = 12, H4 n= 11

9.4.3. Relative performance

The primary performance measure in this study is the relative measure CumRAE. UMBRAE, a related but bounded variant published during this study is also utilised to explore their relative performance when faced with various levels of variation in error range (Chen et al., 2017). At all times the naïve benchmark used in the CumRAE and UMBRAE measures is fixed as the last point in the estimation data, see section 6.3.2 .

As with the two earlier studies the UMBRAE performs similar to CumRAE in this study as demonstrated in Table 34. With the data series purged of outlier series as described in section

9.3.1, the worst case (graphical presentation at Horizon Four) had slightly greater than eight percent and differences were generally less than three percent.

Table 34

Absolute Percentage Difference of Mean CumRAE and Mean UMBRAE for Models – Study Three

Horizon	Pearl logistic	Gompertz	Bass	Log-logistic	Straight-line	Judgment Tabular	Judgment Graphical
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	1.63	0.80	0.51	2.44	0.69	3.96	4.52
3	0.65	0.25	0.60	3.41	3.39	4.12	6.81
4	0.81	0.63	0.21	4.28	6.39	3.97	8.33

Note: number of forecasts for each model horizon are H1-H3 n = 12, H4 n= 11
Note: Percentage difference calculated with respect to CumRAE

The main findings are as follows:

- Figure 36 shows that the judgment model with tabular presentation of data is the most accurate of all the models at all horizons, except Horizon Four where it matches those models, and Horizon One where it is bettered by the straight-line model.
- The Pearl logistic is the best of the marketing science models, bettering the Bass by 6 percent at Horizon One and falling to only 2 percent advantage at Horizon Four.
- The judgment model with graphical presentation of data is significantly poorer than all models; being worse than the Pearl logistic, the Bass, the log-logistic and the straight-line model. Looking at Table 35, it does beat the Gompertz at Horizon One and does improve to match the Bass at Horizon Two and beats it by a small margin at Horizons Three and Four.
- The Gompertz and the log-logistic perform substantially poorer than the Bass and the Pearl logistic.
- Figure 36 also shows that mean model CumRAE (relative performance) improves for all marketing science and judgmental models with longer horizons. Table 35 also shows that standard deviations also diminish as horizons extend.
- The performance of the straight-line model is substantially unchanged across the time horizons, and is competitive with the best two marketing science models at all horizons. It beats the marketing science models at Horizon One and Two, and matching them at Horizon Three while only slightly worse at Horizon Four.

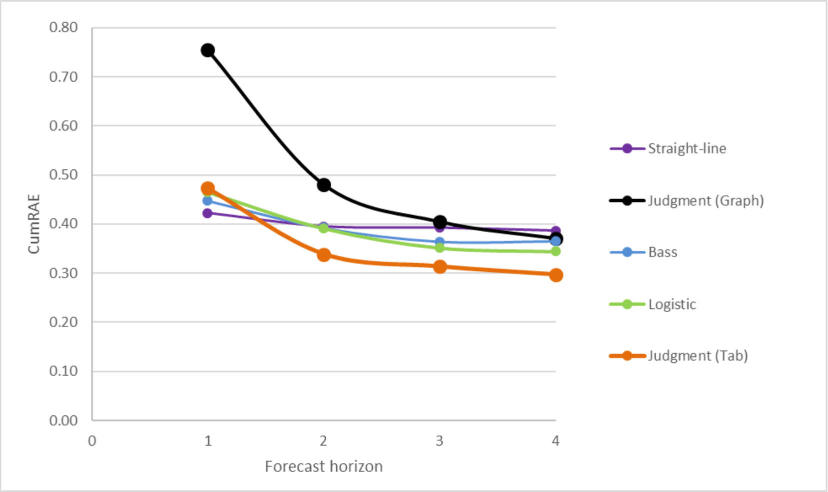


Figure 36. Mean relative accuracy of judgmental models vs. the three best models.

Table 35

Mean CumRAE Judgmental Models vs. Marketing Science Diffusion Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Judgment-Tabular		Judgment-Graphical	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	0.46	0.60	0.69	0.80	0.45	0.62	0.65	0.31	0.42	0.36	0.47	0.44	0.75	0.64
2	0.39	0.53	0.63	0.74	0.39	0.55	0.56	0.29	0.40	0.34	0.34	0.27	0.48	0.39
3	0.35	0.48	0.60	0.66	0.36	0.50	0.50	0.28	0.39	0.36	0.31	0.25	0.40	0.32
4	0.34	0.47	0.62	0.61	0.37	0.48	0.49	0.28	0.39	0.43	0.30	0.26	0.37	0.30

Note: Normal distribution plots of the CumRAE and UMBRAE indicated that outcomes were not normal; despite this, because it is common practice, the standard deviation (SD) dispersion statistic is presented along with the mean.
Note: number of forecasts for each model horizon are H1-H3 n = 12, H4 n= 11

9.4.4. Model forecast bias

Sometimes the focus of interest is the direction of the error in forecasts. To aid understanding of model prediction bias, Figure 37 and Table 35 present the mean forecast share error, which illustrates bias. Figure 37 shows that the Bass model forecasts close to neutral and performs best of all marketing science models, indicating little bias over many series and across all horizons. The Bass model has a bias towards overestimating decline on average of less than about one point five percent and predicts more rapid decline than the actual market, with a standard deviation that is on average between nine and twelve percent market share across the horizons. The Pearl logistic, the next best model, consistently overestimates decline by between three and five percent market share and has a worse case standard deviation of ten percent market share.

Judgment estimation with graphical presentation tends to overestimate at early horizons before transitioning to underestimating then reverting to overestimation. Judgment with graphical treatment is competitive with the best two target diffusion models and betters the Pearl logistic model across all horizons and is competitive with the Bass at all horizons. Judgment estimates from tabular presentation always underestimate, but by a small amount, being less than one percent share at Horizons One and Four but rising to about three percent share across Horizons Two and Three.

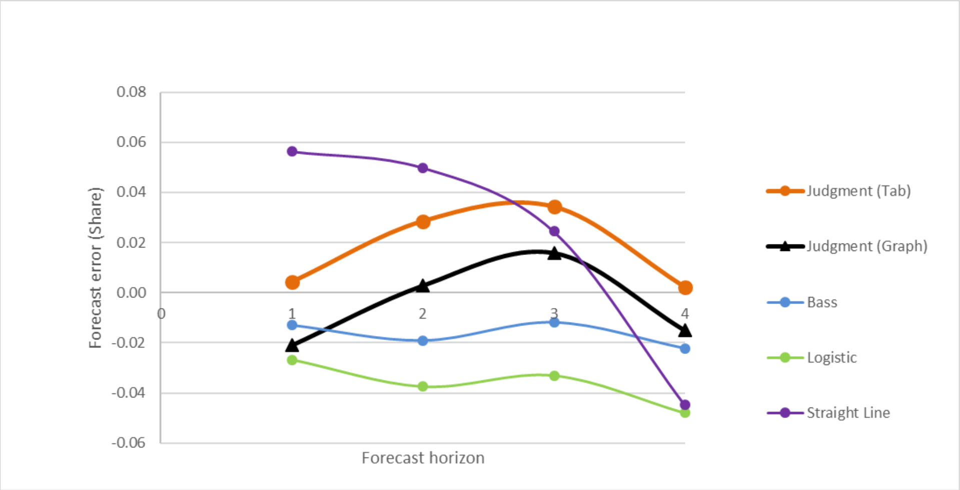


Figure *37. Mean forecast share error - judgmental models vs. the best marketing science models*

Table 36

Mean Forecast Share Error - Judgmental Models vs. Marketing Science Models

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Judgment-Tabular		Judgment-Graphical	
Horizon	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	-0.03	0.10	-0.07	0.12	-0.01	0.11	0.04	0.09	0.06	0.09	0.00	0.06	-0.02	0.08
2	-0.04	0.09	-0.09	0.10	-0.02	0.10	0.05	0.10	0.05	0.12	0.03	0.09	0.00	0.10
3	-0.03	0.09	-0.10	0.11	-0.01	0.10	0.07	0.10	0.02	0.14	0.03	0.10	0.02	0.11
4	-0.05	0.09	-0.12	0.09	-0.02	0.11	0.06	0.10	-0.04	0.14	0.00	0.10	-0.01	0.10

Note: number of forecasts for each model horizon are H1-H3 n = 12, H4 n= 11

The size of the standard deviation of errors indicates that while the mean in forecast share shows the models appear to give relatively unbiased forecasts, there is a substantial spread in errors of prediction for individual series within the pool of series studied. Interestingly, the spread of estimates from the experts is narrower than that for the marketing science models.

9.4.5. Model forecast variability

When evaluating models, once an adequate level of relative accuracy is achieved, the focus might naturally fall to the consistency of the method in reaching that level. Model estimate variability is the focus of this section.

9.4.5.1. Parametric estimation of the forecast interval

Data normality is critical to the use of this test. Despite the small number of series (N=12), two-tailed tests of normality tests (Shapiro & Wilk, 1965) generally indicated normality in the error distribution across all judgment treatments and the marketing science model forecasts. There were exceptions with the Pearl logistic and the Gompertz failing at Horizon Four. The Shapiro Wilks test is the most powerful normality test but like all tests of normality are weaker in power at small sample sizes (Razali & Wah, 2011). Significant differences between the mean and the median in some of the model/horizon situations indicated the weakness of that test on this sample. However, error distribution normality was assumed and parametric estimation of forecast certainty was calculated as described in section 6.3.5. Charting forecast estimation intervals via simple fan charts greatly assists in understanding the potential variation in a forecast generated by a model. An example of this presentation at 80 percent and the 95 percent confidence levels with respect to the mean estimate error are provided in Figure 38. The numerical values for all models are presented in Table 37 for the 80 percent interval and Table 38 for the 95 percent interval.

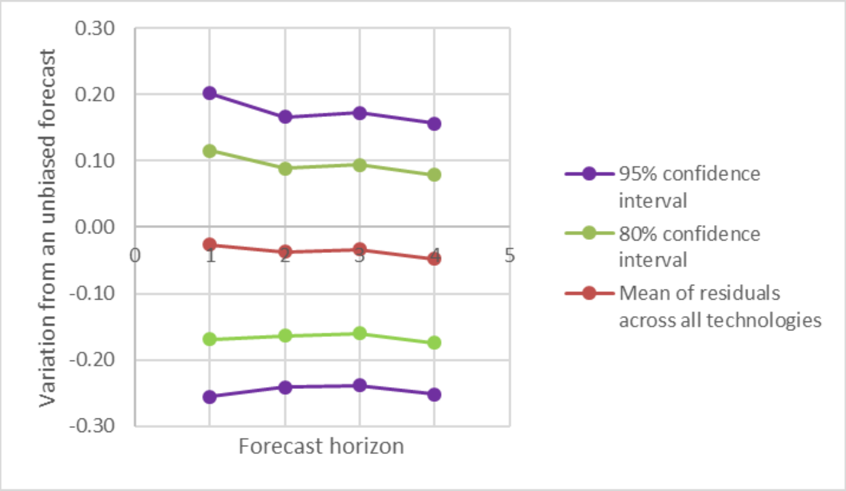


Figure 38. Logistic model mean prediction error (forecast interval) - Study three.

Table 37

The 80 Percent Confidence Bound for the Mean Error - Judgmental Models vs. Marketing Science Model Forecasts

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Judgment-Tabular		Judgment-Graphical	
Horizon	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd
1	-0.17	0.11	-0.24	0.10	-0.17	0.14	-0.09	0.16	-0.07	0.18	-0.08	0.09	-0.14	0.09
2	-0.16	0.09	-0.24	0.05	-0.16	0.12	-0.09	0.19	-0.11	0.21	-0.09	0.15	-0.14	0.14
3	-0.16	0.09	-0.24	0.05	-0.15	0.13	-0.07	0.20	-0.16	0.21	-0.11	0.18	-0.14	0.17
4	-0.17	0.08	-0.24	0.01	-0.17	0.12	-0.08	0.20	-0.24	0.15	-0.13	0.13	-0.14	0.12

Note: number of forecasts for each model horizon are H1-H3 n = 12, H4 n= 11

Table 38

The 95 Percent Confidence Bound for the Mean Error - Judgmental Models vs. Marketing Science Model Forecasts

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Judgment-Tabular		Judgment-Graphical	
Horizon	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd
1	-0.26	0.20	-0.34	0.21	-0.26	0.24	-0.16	0.24	-0.15	0.26	-0.13	0.14	-0.21	0.16
2	-0.24	0.17	-0.32	0.14	-0.25	0.21	-0.17	0.27	-0.22	0.32	-0.16	0.22	-0.22	0.23
3	-0.24	0.17	-0.33	0.14	-0.24	0.22	-0.15	0.28	-0.28	0.32	-0.19	0.26	-0.23	0.27
4	-0.25	0.16	-0.32	0.08	-0.26	0.21	-0.17	0.28	-0.36	0.27	-0.20	0.21	-0.22	0.19

Note: number of forecasts for each model horizon are H1-H3 n = 12, H4 n= 11

The above approach, that of presentation of the error (bias) and the forecast interval together is a very useful summary of the overall performance of the models, and is important for managers. However, as noted in Study One, as way to present the relative variability performance of each of the models it fails because it places the interval on a biased origin making interpretation of relative interval challenging. So a presentation based on a zero biased forecast is required, to demonstrate the relative variation performance of the models. This is simply presented using the positive portion of the interval calculated with zero as the mean error deviation. The models' parametrically estimated 80 percent forecast intervals (with respect to an unbiased forecast) are recorded in Figure 39 and Table 39. Here it can be seen how the marketing science models have very similar size estimated forecast intervals at each of the four horizons, and indicates that the marketing science models have very similar variability in forecast performance. The Bass and Pearl logistic are the most consistent. Overall, judgmental with graphical presentation model's forecast interval is as good as the marketing science models. The judgmental with tabular presentation model, is generally better at all horizons only being beaten by the Pearl and log-logistic at Horizon

Three. However, their variability is not as stable over the four horizons as are the marketing science models.

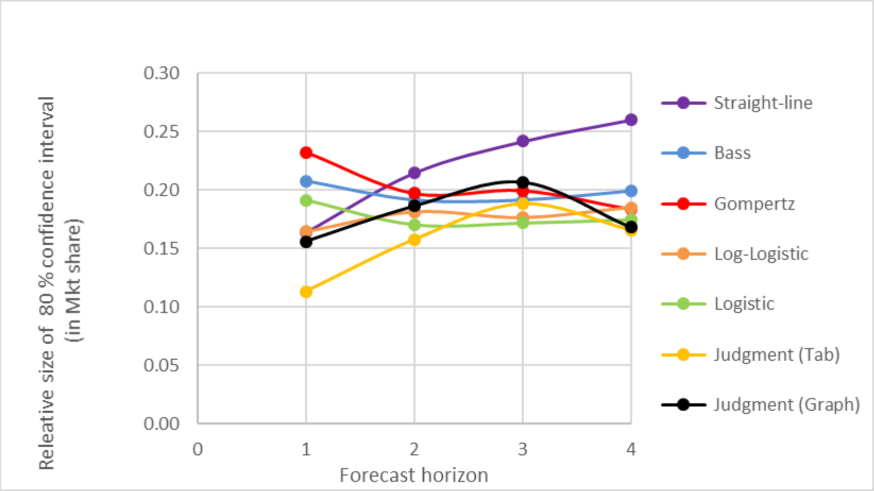


Figure 39. Relative size of 80 percent intervals for judgmental models.

Table 39

Relative Size of Forecast Intervals (80 Percent) - Judgmental Model vs. Marketing Science Model Forecasts

	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Judgment-Tabular		Judgment-Graphical	
Horizon	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd	Lwr-Bnd	Upr-Bnd
1	-0.19	0.19	-0.23	0.23	-0.21	0.21	-0.16	0.16	-0.16	0.16	-0.11	0.11	-0.16	0.16
2	-0.17	0.17	-0.20	0.20	-0.19	0.19	-0.18	0.18	-0.21	0.21	-0.16	0.16	-0.19	0.19
3	-0.17	0.17	-0.20	0.20	-0.19	0.19	-0.18	0.18	-0.24	0.24	-0.19	0.19	-0.21	0.21
4	-0.17	0.17	-0.18	0.18	-0.20	0.20	-0.18	0.18	-0.26	0.26	-0.17	0.17	-0.17	0.17

Note: number of forecasts for each model horizon are H1-H3 n = 12, H4 n= 11

9.4.5.2. *Model forecast proportion of times better than naïve benchmark*

Another way to consider forecast consistency is to assess what proportion of time one method’s forecasts are better than a benchmark.

Figure 40 shows the forecast consistency performance of the marketing science models and the two judgmental approaches. On this small set of data series, all the marketing science models had identical proportion of times when they beat the naïve benchmark at each of the horizons. This unusual situation is most likely linked to the close-to-ideal S-shaped curves offered to the models, because outlier series (in terms of their normalised for time trajectories) were trimmed during the reduction from 25 to 12 series. Judgment with tabular treatment performed the most consistently, beating the marketing science models on the last three horizons and being worse about five percent of the time at Horizon One. Judgment with graphical treatment was the weakest overall being worse than the naïve benchmark 25 percent more often than the marketing science models at Horizon One matching the marketing science models over horizons two and three and matching the best model, Judgment with tabular treatment, at Horizon Four.

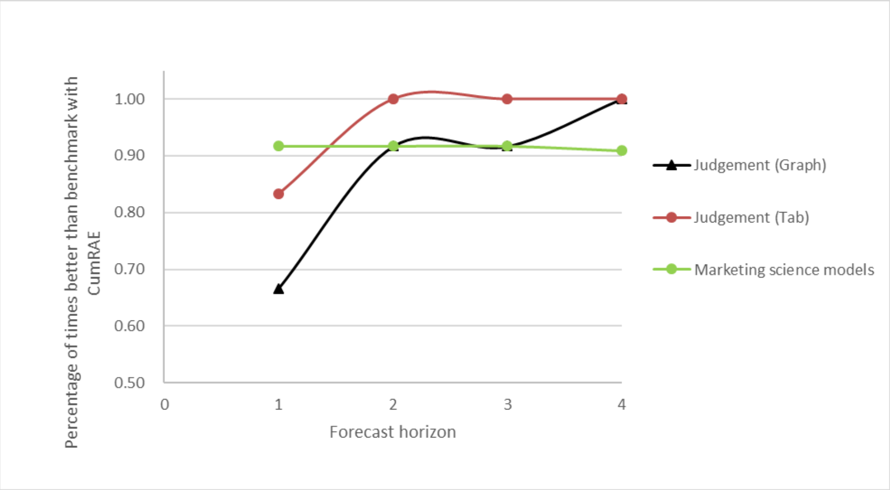


Figure 40. Proportion of times judgmental models are better than the naïve benchmark

Table 40

Proportion of times Judgmental Model Forecasts are better than the Naïve Benchmark

Horizon	Pearl logistic		Gompertz		Bass		Log-logistic		Straight-line		Judgment-Tabular		Judgment-Graphical	
	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE	Cum-RAE	UMB-RAE
1	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.83	0.83	0.67	0.67
2	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	1.00	1.00	0.92	0.92
3	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	1.00	1.00	0.92	0.92
4	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	1.00	1.00	1.00	0.92

Note: number of forecasts for each model horizon are H1-H3 n = 12, H4 n= 11

9.5. Results: Judgmental Performance and Trimming Data

The expectation early in the investigation was that the use of an on-line panel of experts would mean a wide range of satisficing and inattention behaviours might present in the data for this study. Measures were put in place in the survey to both mitigate and to allow post-hoc identification of such behaviours. However, during analysis it became clear that trimming data because of a behaviour that was assumed, rather than proven to exist, was not an appropriate approach. As a consequence of the difficulty in justifying the removal of flat-liners, inattentive, and other forecast behaviours that appeared to be outliers from median behaviour, the primary investigation described in section 9.4, was done without removing any of those types of responses. To confirm that this was the best strategy, an investigation of the impact of trimming the data based on speeding and observed behaviour was undertaken. The data was coded to allow a comparison between the mean prediction performance of the trimmed and untrimmed data. This trimming based investigation is described below.

9.5.1. Defining outliers by speed.

As a respondent may be fast because of either satisficing or experience driven intuitive decision-making, a conservative coding approach was needed. This coding could be done on a question-wise or case-wise basis, as these capture different behaviours (Greszki et al., 2015). For example, participants might be either on a learning curve about their task, or alternatively simply random in their response, a pattern well recognised as deliberate satisficing rather than answering optimisation in speeders (Greszki et al., 2015; Malhotra, 2008). However for simplicity, speeders were identified on a case-wise basis, as C. Zhang and Conrad (2014) had observed that participants if they speed on one question tend to speed on all. Thus, the respondent completion time for all the forecast tasks was assessed using timers designed into the survey. The median time to complete the whole survey was used as a benchmark, due to the median's insensitivity to the positively skewed shape of the response time curve. Using the classification thresholds used by Greszki et al. (2015), cases that took less than half, a third and a quarter of the median time were identified (see Table 41). To retain conservativism, those that were at least twice as fast as the median speed to complete the whole survey were coded as speeders. This cut-off level was cross validated as suitable because it matched typical incidence levels described in other studies of from ten to fifteen percent speeders (see for example Conrad et al., 2017). For the tabular treatment, just under 13 percent of the remaining participants were coded speeders. The slowest respondent coded as a speeder averaged just under 20 seconds per forecasting task, and took 2.8 minutes for the whole survey, compared to pre-release testers who took on average 9 minutes. The tabular treatment after speeder coding and removal had 130 participants.

For the graphical treatment just under 15 percent of the remaining participants were coded as speeders. The slowest respondent coded as a speeder averaged just under 18 seconds per forecasting task, and 2.9 minutes for the whole survey. The graphical treatment after speeder coding and removal had 115 participants.

Table 41

Breakdown of Ultra-fast Responses

Tabular treatment	Participants (n)	Percent of responses
Median time = 5.75mins		
0.50 of median time	19	12.75
0.33 of median time	6	4.03
0.25 of median time	2	1.34
Total responses	149	
Graphical treatment		
Median time = 5.52mins		
0.50 of median time	20	14.81
0.33 of median time	8	5.93
0.25 of median time	2	1.48
Total responses	135	1

9.5.2. Defining outliers by behaviour

Because it is not possible to determine if a prediction was because of a considered action or just a satisficing behaviour based on insufficient attention to the task, there is no justification for removing the prediction, just because it was implausible within the S-curve decline paradigm. Therefore, the coding for outliers/speeders needed to be conservative. To allow for a comparison of performance with and without trimming, responses were coded based on observed behaviour, based on three different response patterns:

- Respondent predictions that on average grew rather than declined (growth)
- Respondent predictions that on average were flat rather than declining (flat-lining)
- Respondent predictions that on average were declining (decline)

Classification was of the averaged response at each horizon for each respondent across each series. These average responses were normalised to zero at the first horizon, then the slope from first to last horizon of those normalised points became a case wise classification of behaviour. Because of the need to remain conservative the thresholds for coding were:

- Growth: those that grew by more than 5 percent share
- Flat-lining: those who fell or grew by less than 5 percent share
- Decline: those that fell by more than 5 percent share

In the tabular treatment, 20 responses were coded as flat-lining and 11 responses coded as growth. In the graphical treatment, 26 responses were coded as flat-lining and 10 responses coded as growth. Both types were collectively excluded from further analysis under the *trimmed by behaviour* category in this portion of the study. This left 118 cases (79.2 percent of the untrimmed) defined as having normalised average slopes that met the definition of decline forecast in the tabular treatment, and 99 cases (73.3 percent of the untrimmed) in the graphical treatment. The results with and without trimming are presented in the section below. For simplicity, the results are presented only with CumRAE, the primary measure in the earlier studies.

Table 42

Breakdown of Behaviour Based Responses Removed

Tabular treatment	Respondent (n)	Percent of responses
Flat-liners	20	13.42
Growth strategy	11	7.38
Total after trimming	118	79.19
Total responses	149	100.00
Tabular treatment		
Flat-liners	26	19.26
Growth strategy	10	7.41
Total after trimming	99	73.33
Total responses	135	100.00

9.5.3. Tabular presentation of the data

When trimming of the tabular presentation treatment data is undertaken, for speed or for behaviour, there is a deterioration in the prediction performance of participants. This is demonstrated in Figure 41. Trimming by either means provides a slight improvement in estimates performance at Horizon One, consequentially indicating no support for trimming the data based on speeding nor trimming the data based on unexpected prediction behaviours. Although undertaking it might cause no substantial harm to the prediction either.

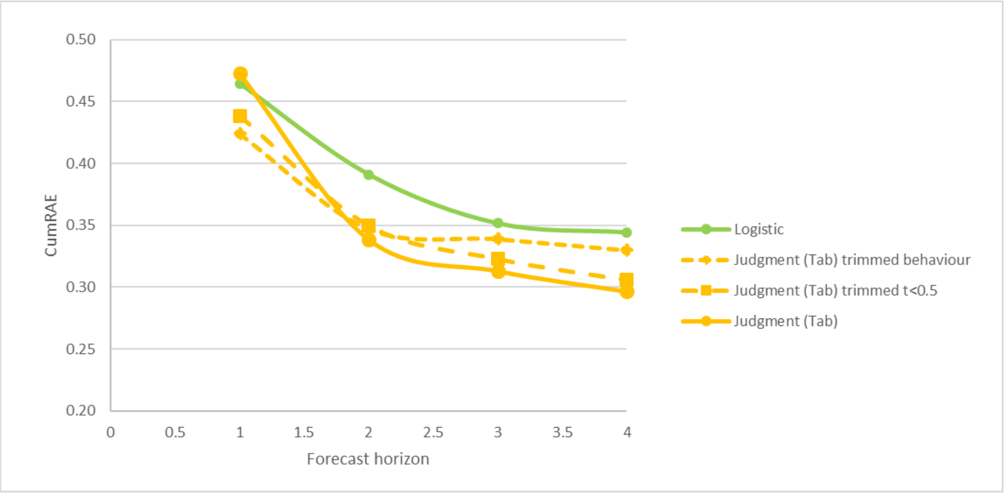


Figure 41. *Impact on forecast performance of trimming the tabular presentation data.*

9.5.4. Graphical presentation of the data

When trimming of the graphical presentation treatment data is undertaken, for speed or for behaviour there is a substantial improvement in the prediction performance of participants. This is demonstrated in Figure 42. Trimming by either means provides a substantial improvement in the model's performance across all Horizons. At early Horizons judgment with graphical presentation is moved from being much poorer than the best marketing science model (Pearl Logistic), to matching it in the case of *trimmed for time* and being substantially better in the case of *trimmed for behaviour*. At the later horizons, both trimming methods deliver similar improvements levels. Thus, overall the *trimming for behaviour* delivers a very consistent estimation performance that is about 65 percent better than the naïve benchmark at all horizons, indicating support for trimming the data based on unexpected prediction behaviours. Even *trimming for speed*, the weaker of the two trimming methods, improved the graphical treatment forecast by enough to make the treatment better than the Pearl logistic.

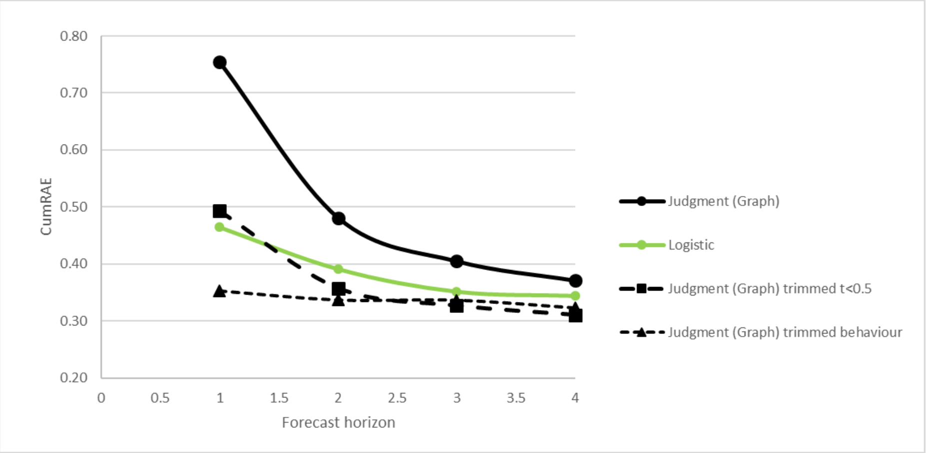


Figure 42. Impact on forecast performance of trimming the graphical presentation data.

Why trimming either way improved the graphical treatment's performance quite substantially but caused a minor deterioration of the forecast performance of tabular treatment is hard to determine. However, it could be surmised that in some way the graphical treatment participants found the task more challenging, such that a higher proportion of the graphical treatment participants undertook satisficing type behaviour which, when removed, provided improved performance on average from the remaining responses. The weaker prediction performance of graphical treatment over the tabular treatment supports this hypothesis to some extent. In terms of managerial practicality, the untrimmed tabular presentation is the easier to implement and has comparable performance to the best marketing science models, while after trimming the graphical result does provide a model with consistently strong accuracy performance over that of the simpler tabular without trimming approach (see Figure 43).

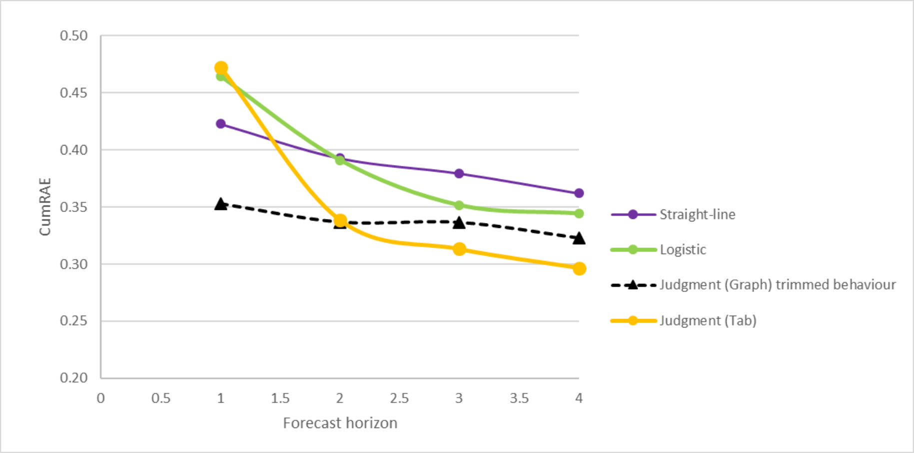


Figure 43. Relative accuracy performance of the two best judgmental model approaches

The judgmental estimation with tabular presentation approach matches the best marketing science model (the Pearl logistic) at Horizon One, matches the judgmental graphical presentation model at Horizon Two and is the best model by a small margin at the last two horizons. As in the other two studies, the straight-line model was competitive, but not superior. It seems possible when series that represent normalised for time trajectory outliers are removed, then relative to the straight-line, the marketing science models improved their performance. For brevity the bias and variability of the trimmed analysis is not presented.

9.6. Summary

This study investigated the potential for a panel of experts to predict technology decline curves, that is, how well experts perform against diffusion models. The study found that humans are on average, good decline curve forecasters when they are aware that the curve is expected to be S-Shaped.

Chapter Ten: Conclusions, Limitations and Implications

10.1. Introduction

This chapter summarises and synthesises the research findings from the three studies and the literature review, as well as presenting other interesting or unexpected observations made during the research process. It discusses the limitations of investigation in some depth as they form a critical part of new knowledge developed through the investigation. The implications of those limitations for researcher and manager alike are laid out. First, however, a brief a personally framed review of the research problem is set out.

10.2. A Personal View of the Research Problem

An interest in the substantial effects on firms of neither recognizing the warning signs of, nor responding sufficiently quickly to the decline of technologies in their domain triggered this investigation. During informal conversations with marketing and market forecast academics, it appeared that there was limited academic interest in this topic. It was argued in some of those exploratory conversations, that academe already offered a substantial corpus of knowledge guiding business in identifying new trends (A. L. Porter & Cunningham, 2004; Yoon & Park, 2005). However, this sits at odds with Christensen (1997a) who observes in his popular book, *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*, that innovations that threaten competitive advantage frequently fall outside the well-honed methods to identify them. The implication of this observation being that conventional methods perpetuate the fallacy that just looking a little harder at your domain was all that was required to understand the impacts on your firm. It was also concerning to discover that firms tend to be subdued in their reaction to any knowledge about decline (Pistorius & Utterback, 1995; Utterback, 1994).

Theory seems poorly adapted to discussing discontinuance decline. Not only does it focus on a single growing technology substituting for an incumbent technology, with little conversation about the decline side of the calculation, but also technology substitution seems increasingly dominated by products that are a strong amalgam of many new technological innovations, smart mobile devices being, at the time of writing, the most prevalent form of this phenomenon. This increasingly difficult task of identifying discrete individual technologies informed the decision to analyse groups of technologies, which on the surface, appeared not to have that much in common. The analogous technology literature also identifies a challenge of understanding what is, or was, a similar or analogous technology, resulting in part a decision to pool disparate technologies when examining model performance.

Given that the focus of this thesis is forecasting, not theory development, activity to develop the theory of discontinuance was curtailed; however, two clear research threads quickly emerged. One is how firms focus on squeezing that last possible dollar from existing assets, thus *trying to avoid the inevitable* decline. Firms seemed to do this rather than ensuring that their investment is following emerging technology trends, and the literature appeared to focus on this as a desirable goal (Bers & Dismukes, 2007). The second theme was *ambulance at the bottom of the cliff* research, describing how to deal with obsolescence, that last step in a technology decline journey (Sandborn, 2015; Solomon, Sandborn, & Pecht, 2000). There was an apparent complete absence of literature investigating the rapid phase of decline between those two thematic foci, meaning that in a practical sense when firms turn from shoring up their older technology investments and recognise the inevitability of decline, there is little in the way of practical tools or theory to guide decisions with respect to the declining sales trajectory.

Knowing the deep foundation of knowledge around forecasting and diffusion, but the dearth of knowledge in decline forecasting, the overall approach was to investigate decline forecasting in a foundational *first survey* way. This had three effects on the investigation process, first a need to draw together disparate literature to form a simple but cohesive story of what aspects of technology decline are important for a forecaster to understand. Second was the requirement to ground this work in relation to the substantial body of growth-orientated diffusion research, a significant challenge given that this was not an investigation into decline theory, and thus the treatment was necessary brief, and curtailed in scope. Third, there was the requirement to find methods and ways to apply those methods that were congruent with how technology decline unfolds. So the literature and the empirical studies are driven by this foundational, first survey approach and the increasing awareness by the author that simple methods had an important part to play as the literature revealed itself.

Sticking with a theme of simplicity; common software (Microsoft Excel^{TM}) and nonlinear least squares was used in the fitting protocols and analysis, to ensure easy understanding and replication of the studies.

10.3. Research Objectives.

The objective of this research was to apply validated techniques from the forecasting literature to the problem of rapid technology decline, as reflected in the research questions.

Research questions:

- Can decline trajectories be forecast using validated forecasting methods? Explicitly:
- Of the approaches chosen, which approach provides the most accurate forecasts?
- What are the unique and special considerations of technique required to forecast decline trajectories?
- What potentially generalizable patterns exist?

Another substantial issue but secondary to the primary questions above was:

- To what extent does the choice of forecasting performance measures affect our understanding of the performance of any method?

To answer those questions it was necessary to understand what accuracy means and how best to measure such things. Additionally, to decide on the best forecasting approaches from arguably hundreds of candidates.

10.4. Measures to Determine Accuracy

While many accuracy measures are seen as better in certain situations, no one measure seems universally useful nor to be in universal use (Armstrong & Collopy, 1992). Furthermore, in the context of S-shaped curves that are found in diffusion and decline data, little has been written about accuracy measures that suited this kind of highly trended, non-linear environment. Thus, an approach based on the use of a basket of measures was taken. First, a relative absolute error measure (CumRAE) was chosen, based on using a naïve benchmark forecast method as a comparator to the method under test. This was supplemented by a very new, bounded relative absolute error measure UMBRAE (Chen et al., 2017), which limits the level of error recognised in a forecast, thus making the sensitivity of this measure to outliers in error distribution lower than CumRAE. The normal implementation of CumRAE includes a suggestion to trim the data of outliers before its use, via the Winsorising procedure (Armstrong & Collopy, 1992). Because that procedure would reduce the number of effective series in the study pool, when that pool was already smaller than ideal, Winsorising was not undertaken with some interesting benefits. Also, the selection of a benchmark, proved problematic as benchmarks for forecasting in exponential-like data did not appear to have been investigated, and so there was no obvious choice for a benchmark in what was found to be a short data series length situation. Early exploratory analysis was undertaken on two benchmarks, a stationary point representing the random walk, and a straight line fitted to the last three data points. That work resulted in a decision to go with the stationary point benchmark and place the straight-line model within the pool of models to be tested. The methodological conundrum in this study as to the suitability of the two benchmarks in this context was not resolved, and this is discussed later in section 10.7.

To complement these two measures of relative absolute error, *Mean Absolute Percentage Error* MAPE was included in the error measure basket. This had some known limitations that might have led to it being excluded as a single error measure; however, its popularity and ease of interpretability helped its inclusion in the basket of measures.

Also included was a simple measure of bias in the form of the *mean error for each* model, as well as two measures of forecast variability. One measure of forecast variability measured the consistency of a model's superiority by *the percentage of times the model beat the benchmark model*. The second measure illustrated the likely variation in any given models forecasts through a *parametric measure of the forecast interval*. The measures chosen were not perfect and their flaws became clearer as the studies progressed. Some of the issues associated with execution of these measures are described here under the findings related to model accuracy, while others are referred to in section 10.8 on interesting and unexpected findings.

10.5. Choosing the Forecasting Approaches

This study investigated and validated three forecasting approaches; market science models, analogous series, and expert judgment. These three studies provide validated forecasting approaches that forecasters or researchers might desire to use, or to combine, to make decline forecasts. Pooling approaches greatly increases understanding in forecasting. The literature on combining forecasts talks about the value of combining forecasts from multiple approaches as particularly useful (Armstrong, 2006).

To choose the first of the three approaches was easy; as marketing science diffusion models are, the single most widely used and validated way to forecast in diffusion situations. But where to enter the stream of forecasting research to best serve technological decline forecasting? A major question given an almost untouched area of enquiry. There are many sophisticated and comprehensive models that could have been applied, but many were not widely used or well validated and may tend to be both difficult to understand from a management point of view as well as challenging to use, even by highly experienced users (Chatfield, 2007). There is a heavy trade-off of understanding and usability with incremental accuracy for forecasting models (Chatfield, 2007). Moreover, because many had several variables in their makeup, they risked *over-fitting* the short data series available (Babyak, 2004). Mahajan et al. (1995b) note that model selection involves a trade-off between fit and parsimony. Oliva and Watson (2006), recognise aspects of these problems with their advice to not consider increasing accuracy as a primary aim of forecasting. Morlidge (2010) suggests a focus on accuracy that is adequate for decision making, inferring excess accuracy is to be avoided. We know management places understanding forecasts very high. Yokum and Armstrong (1995) observe that they consider flexibility, ease of use, and ease of implementation nearly as important as prediction accuracy in choosing a forecast approach. As a result of the preceding advice, and recognising the first survey nature of the investigation, simple popular foundational diffusion models were selected to represent the marketing science diffusion model approach. These models were in many ways not much more than S-curve mathematical functions, with simple or no theoretical connections to the technology growth story. This selection approach fitted well with the empirical observations by marketers that simple models performed equally well and sometimes better than more sophisticated models (Fader et al., 2003; Hardie et al., 1998). There was a theory-backed reason for this desire for simple models, and that was to remove any model that held growth linked variables such as *marketing effort*. The theoretical foundation of such models is not necessarily well specified for the discontinuance situation. The overarching rationale was that the shape of the decline curve was unexplored and those models were by definition specified for a different environment linked directly to a single diffusing technology.

Two other forecasting approaches presented themselves as candidates because of their simplicity of application, but also the opportunity their application offered to provide new knowledge about the methods themselves. Those two methods were predicting with a pool of analogous series, and using judgmental estimates by a panel of experts. The former method had shown some promise (Duncan et al., 2001; Hardie et al., 1998), the latter less so, although the Delphi method had shown some value in combining judgment, but not in the way proposed. Because of the early discovery nature of these studies interactive groups methods (for example Delphi) were not considered so that the focus could stay on the measurement of judgment in falling exponentials an area where the literature indicated performance enhancements were needed. The exploration provided a fascinating journey of discovery. With regard to choosing analogies, there are two conflicting approaches, either to define a suitable single analogy or to use a pooling data approach. With scant literature on the use of analogous series to forecast directly, two studies stood as being simple but rigorous in concept and in execution, thus aligning closely with this thesis, and led to a decision to pool data series (Hardie et al., 1998; M. J. Wright & Stern, 2015). This decision was supported by the work of Goodwin et al. (2013).

The expert judgmental forecasting study uncovered literature that was less than conclusive, around what to expect from judgmental forecasting. The relevant literature for forecasting exponential type growth or decline situations came from small scale experimental laboratory work in behavioural psychology (Best et al., 2007; Sanders, 1992) and the forecasting literature being, in the main, from low trend data in econometric research (Ashley, 1988; Ashton, 1984). Authors had mentioned the potential inapplicability of this low trend work to diffusion forecasting and the laboratory work to real forecasting situations (Hammond, 1986; Sanders, 1997). The opportunity to test on-line survey panels as a tool in forecasting was an interesting emerging area. Fortunately, the general area of methods and how to assess judgment was covered in the psychology literature greatly enabling the development of Study Three’s forecasting approach.

10.6. Answers to the Research Questions

10.6.1. Of the chosen approaches, which provides the most accurate forecasts?

10.6.1.1. Bass and Pearl logistic accuracy performance was best of the diffusion models

Of the four marketing science models tested, the Gompertz, the log-logistic, the Bass, and the Pearl logistic, two models stood out as superior. MAPE consistently placed the marketing science models in rank order from first; Pearl logistic, through Bass, to Gompertz with log-logistic last. This occurred across all three studies, despite the intrinsic differences in the makeup of the data series presented in each study. MAPE placed the Pearl logistic model in first place across all four forecasting horizons in almost all cases, The Bass model is some distance back in second place with a mixture of second and third places across the horizons and studies. The Bass only places first once, in the fourth horizon of Study One. The Gompertz has an overall ranking that places it third, with nearly equal quantities of second, third and fourth placed rankings spread across the horizons and studies. The log-logistic like the Gompertz had a range of second third and fourth rankings but substantially more fourth places and thus was the weakest model when measured by MAPE. Those rankings are presented in detail in Table 43.

Table 43

Relative Ranking with MAPE of the Marketing Science Models

	Horizon	Study One	Study Two	Study Three	Rank Across Studies
Pearl logistic					
	1	2	1	1	1.3
	2	2	1	1	1.3
	3	2	1	1	1.3
	4	2	1	1	1.3
				Mean Rank	1.3
Bass					
	1	1	2	2	1.7
	2	1	2	2	1.7
	3	1	2	2	1.7
	4	3	2	2	2.3
				Mean Rank	1.8
Gompertz					
	1	4	3	4	3.7
	2	4	3	3	3.3
	3	3	3	3	3.0
	4	1	3	4	2.7
				Mean Rank	3.2
Log-logistic					
	1	2	4	4	3.3
	2	3	4	3	3.3
	3	4	4	3	3.7
	4	4	4	4	4.0
				Mean Rank	3.6

The two relative accuracy measures, CumRAE and UMBRAE place the Bass model first with consistently high rankings across all horizons. The Bass scored purely first or second ranks across all horizons and all studies. The Pearl logistic was second achieving first ranking more often than did the Bass model, but third across Horizon One in two studies and Horizon Two in one study. The log-logistic was an erratic performer, placed variously first, second, third, and fourth. Consistently the Gompertz performed poorly across horizons and across studies, and ranked last in all horizons. For simplicity and readability, only the CumRAE results are presented, in Table 44.

Table 44

Relative Ranking with CumRAE of the Marketing Science Models

	Horizon	Study One	Study Two	Study Three	Rank Across Studies
Bass					
	1	2	1	1	1.3
	2	2	1	1	1.3
	3	2	1	2	1.7
	4	2	1	2	1.7
				Mean Rank	1.5
Pearl Logistic					
	1	3	3	2	2.7
	2	3	2	1	2.0
	3	1	2	1	1.3
	4	1	2	1	1.3
				Mean Rank	1.8
Log-logistic					
	1	1	2	3	2.0
	2	1	3	3	2.3
	3	3	4	3	3.3
	4	3	3	3	3.0
				Mean Rank	2.7
Gompertz					
	1	4	4	4	4.0
	2	4	4	4	4.0
	3	4	3	4	3.7
	4	4	4	4	4.0
				Mean Rank	3.9

If evaluating models with CumRAE on average and across horizons, no diffusion model can beat the straight-line model; the best of the diffusion models being the Bass, Pearl logistic, and log-logistic competing for the worst performer.

10.6.1.2. Bass and Pearl logistic had best diffusion model bias performance

The bias in forecast results is a critical aspect of accuracy often seen as secondary to accuracy, however it is very important to the way we interpret performance in many things so deserves equal if not superior attention to absolute accuracy. Mean error is very useful both as a summary measure of error but more importantly as a simple indicator of bias, especially when plotted to indicate trends in bias. In Figure 44, the mean bias for models at each horizon across three studies is displayed. The Bass demonstrates the least bias on average across the studies with a consistent bias towards underestimating the decline by about one percent share across all horizons. The Pearl logistic on the other hand, tends to overestimate the fall on average by about two percent market share at the first horizon and deteriorates to about five percent overestimation of the fall in market share at the fourth horizon. The log-logistic tends to underestimate the decline trajectory between four percent market share at Horizon One and deteriorating to about seven percent market share by Horizon Four. The Gompertz is the worst model and overestimates the market share decline from about five percent at Horizon One to about 12 percent market share by horizon four. Importantly this ranking of the errors from underestimating to overestimating across the models is consistently displayed in the three studies as demonstrated in Table 45.

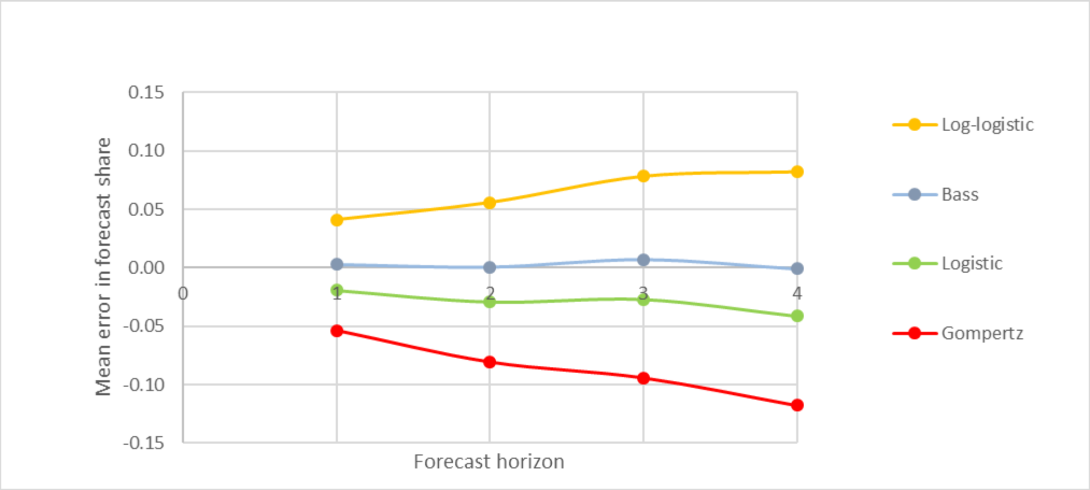


Figure 44. Bias results averaged across the three studies

Table 45

Model Mean Forecast Share Error Averaged Across Studies

	Horizon	Study One	Study Two	Study Three	Error Across Studies
Bass					
	1	0.00	0.03	-0.01	0.00
	2	-0.01	0.03	-0.02	0.00
	3	-0.01	0.04	-0.01	0.01
	4	-0.02	0.04	-0.02	0.00
				Mean Error	0.00
Pearl Logistic					
	1	-0.02	-0.01	-0.03	-0.02
	2	-0.04	-0.01	-0.04	-0.03
	3	-0.03	-0.01	-0.03	-0.03
	4	-0.05	-0.03	-0.05	-0.04
				Mean Error	-0.03
Log-logistic					
	1	0.03	0.06	0.04	0.04
	2	0.04	0.08	0.05	0.06
	3	0.06	0.11	0.07	0.08
	4	0.07	0.12	0.06	0.08
				Mean Error	0.06
Gompertz					
	1	-0.06	-0.03	-0.07	-0.05
	2	-0.09	-0.06	-0.09	-0.08
	3	-0.11	-0.08	-0.10	-0.09
	4	-0.13	-0.11	-0.12	-0.12
				Mean Error	-0.09

10.6.1.3. Analogous series model matches the best marketing science model

The analogous series model is as good as the best of the diffusion models. That is, the mean value of a pool of non-culled (the full 25) series of decline curves normalised for time is a model that can predict diffusion as well as the better of the diffusion models assessed. It is consistently better in terms of *percent of times better* and in terms of relative measures like CumRAE. Section 5.4 illustrates other strengths identified in using analogous series models.

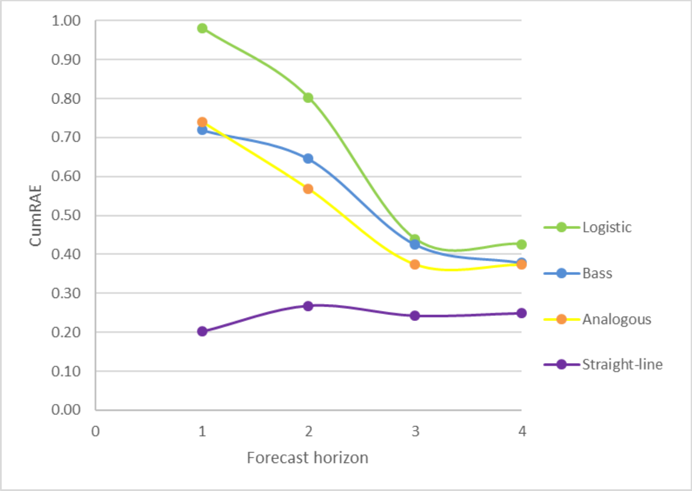


Figure 45. Relative performance of analogous series model

No attempt was made to see if careful selection from the 25 series of a smaller pool would help improve the result. However, because there is always the potential that this result is related to some unique character of the 25 pooled series, there is a strong need to investigate this phenomenon in other areas, perhaps in the diffusion growth situation where the availability of series is not so restricted.

10.6.1.4. The mean prediction from an expert on-line panel presented with data in tabular form matches the best marketing science model

Given that the literature describes large errors in judgmental prediction of exponential-like data trajectories, and judgmental forecasting's poor record on trended data in general, expectations were low. However, it seems that when taken on average, a judgmental model based on a panel of experts provided with a tabular presentation of a data series out to a market share falling to about 0.50, can predict a technology decline out four further periods more accurately on average, than the best marketing science models. The Bass and Pearl logistic models in Figure 46 represent the best two marketing science models to illustrate this finding. Even at Horizon One where the judgmental model is at its weakest, it still matched the best marketing science models.

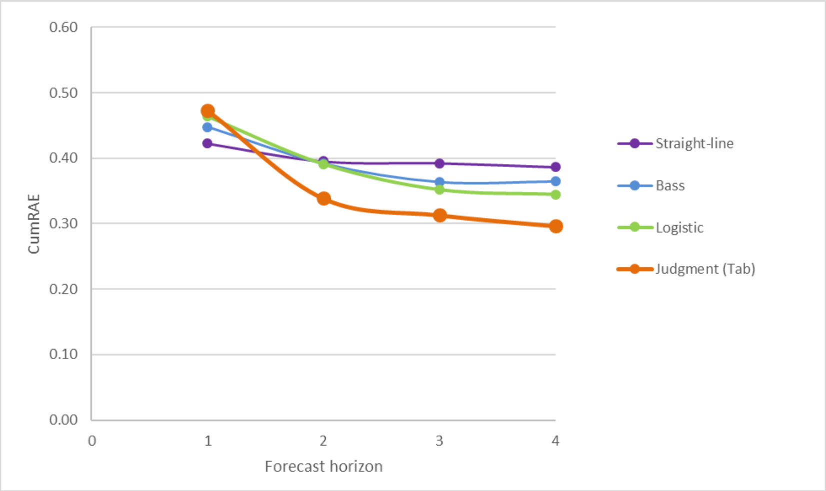


Figure 46. Relative performance of experts presented with data in tabular form

10.7. Considerations of Technique Required to Forecast Decline Trajectories

10.7.1. What is a suitable benchmark for model assessment in decline?

One unexpected problem with measuring accuracy was which benchmark forecast method to include in the relative absolute error measures (CumRAE and UMBRAE). The perfect benchmark is by definition that model which best emulates the phenomenon to be forecast. Yet that phenomenon is essentially unknown in data that exhibits high levels of difference with respect to a linear trend over time. That is why the random walk is so successful as it does not attempt to generate a new data point; it just reflects the last data point forward as its best guess. In the case of S-shaped decline curves, a benchmark needs to capture the character of the decline data to be competitive. Because of the S-curve shape of decline trajectories, the character of a benchmark used in forecast model evaluation needs to be different to that required, in say econometric forecasting. In econometric forecasting situations, data is often without trend or has a low trend, and single step ahead forecasting regimen using the random walk benchmark model is the norm. Even multi-horizon fixed origin rolling forecasts can be undertaken with the random walk benchmark in those environments. However as soon as a highly trended nonlinear situation such as in diffusion or decline is uncovered, then the problem alters. Even single step ahead situations would not be well served by the random walk during those fastest change portions of a trajectory. That is, the random walk loses some of its value as a competitive benchmark. Multiple horizon fixed origin forecasts exacerbate the erosion of competitiveness. After all, the random walk is still a benchmark just not a very good one. Early on the straight-line model was identified as a suitable benchmark for such highly trended data, because it has many of the attributes of a random walk with drift.

However, Meade and Islam (2001) warn against linear models because such models will not model saturation, or in our case the residual share floor, nor the slowing of the decline towards that floor, where it will lag the slowdown significantly. Straight-line models will only be competitive short term as a result, exactly as observed here. Despite its poor match to the process by which a decline S-curve data series is generated (*the data generating process*) it is still a better match than that of a random walk. In early investigations using the straight-line as a benchmark, it was found that its forecasts are so competitive with the marketing science diffusion models that it was difficult to describe the relative performance of those models, as sometimes the models were better and sometimes worse than the straight-line model. This occurred due to the way in which the relative performance of models swaps as the straight-line moves, from a position of being better, to being the same and on to being worse, as the horizons progress compared with the target models. This was visible in the average absolute forecast share errors for the models of Figure 47. This difficulty in providing explainable results and the desire to go on to show the competitiveness of the straight-line model, resulted in the adoption of the stationary point benchmark, allowing the straight-line model to be analysed for the role of a competitive forecasting model.

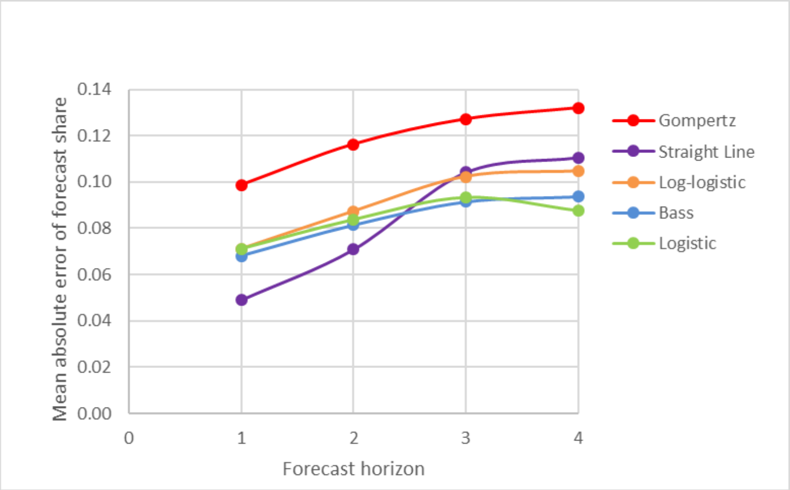


Figure 47. Mean absolute forecast share error of straight-line compared diffusion modes

So while the straight-line provides a viable forecast in its own right in this context, it can mislead as a benchmark in the CumRAE and UMBRAE measures. If a multiple horizon stationary origin periodically updated forecast approach was taken (given suitable data) then the straight-line is still superior to the fixed origin benchmark.

10.7.1. MAPE should be used with caution as it can mislead in this context

Errors from MAPE are easily misinterpreted in both exponential-like growth and decline situations, a point that does not appear to be made in the literature, but is intrinsic in their character. With decline the problem is however, substantially more concerning than in growth. This is because as a percentage of actual share, errors rise exponentially as decline progresses, the reverse is true in growth studies. This is well illustrated by seeing the forecast share error trend versus the MAPE trend in Figure 48 and Figure 49 below.

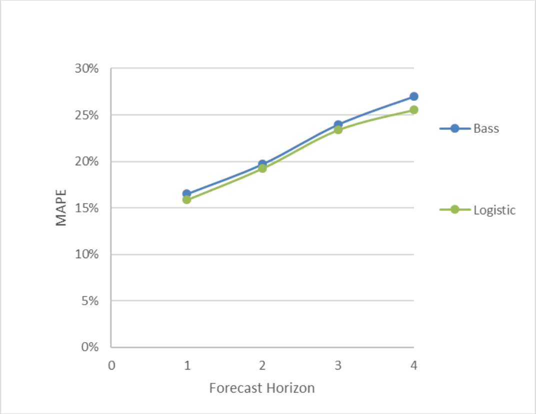


Figure 48. Typical MAPE (decline curve error measurement situation).

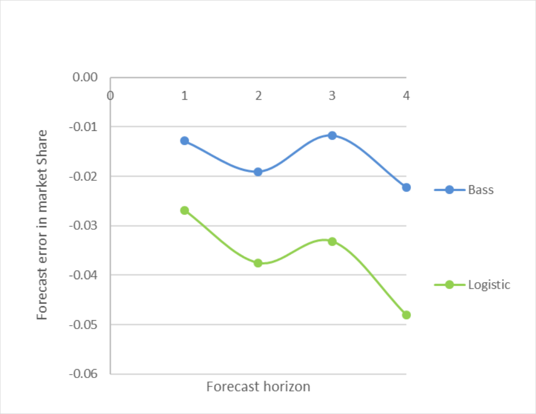


Figure 49. Typical forecast error distribution (decline curve error measurement situation).

10.8. Interesting or Unexpected Elements of the Findings.

The third research question – *what potentially generalizable findings exist* – is addressed by the material already reported, as well as interesting or unexpected findings discussed in this section.

10.8.1. The literature indicates - decline from substitution data is rare

It is clear from the outcome of the data collection process described in section 6.4.1, that decline data series are rarely reported in comparison to their diffusion growth cousins. It was found that diffusion series with no matched decline technology occurred very frequently, as reported by Emmanouilides (2006). Only about 250 series were identified with a decline component, most of these did not reach the relatively unrestrictive criteria for amount of decline progression as described in section 6.4. Data found for this study was, in the main, from long term national organisation programmes e.g. from government statistics offices but also and importantly, from the Euromonitor Passport GMDI series (Euromonitor, 2016a). Little data was found from industry sources, the exception being the recorded music industry globally. It was interesting to discover that some data that had been used in the likes of the Fisher and Pry (1971) study was not now available, or at least could not be located. In addition, there appeared to be some future promise in the Euromonitor data repository given its relative youth in technology life cycle terms. This is because it has many technology series that have been recorded for long enough to be starting to decline, but have not yet recorded an asymptotic floor under that decline. Consequently, it is possible that the proportion of technology decline phase series available will grow with time. This dearth of decline data is not reported in the literature, and neither is technology decline generally discussed in marketing literature with notable exceptions (Black, 1983; Fenech & Longford, 2014). Why this is so, is unclear, perhaps there is some sort of *survivor bias* (Nassim, 2007). The literature records a bias in the survival rates of similar data; in stock market mutual fund and portfolio returns (S. J. Brown, Goetzmann, Ibbotson, & Ross, 1992; Elton, Gruber, & Blake, 1996), in firm survival (Schaffer, 1989) and in entrepreneur survival (Cassar, 2006). One possible reason for a bias in this context is pro-innovation bias, as observed by Rogers (1995). Pro-innovation bias could mean that technology decline was considered not as important as was the emergence of a new technology. Thus reporting of technology series in decline were not undertaken or were not reported in the same proportions as new technologies. Associated with this bias is the possibility that those series that were initially reported were expunged from the records as time went on. That there is a dearth of decline data, and even the absence of literature on decline is of concern for business forecasters and researchers alike is not generally discussed.

10.8.2. Data series found were short

Decline series were found to be short although, not as short as were diffusion growth series reported by Emmanouilides (2006), who found that few data series were longer than 19 observations. However, decline series length was still problematic because, as in growth series, decline is rapid once at observable levels, and given that reported sampling rates are low (the reason why data series are short), there are often few data points before decline is well underway, substantially limiting forecasting in those situations.

The methods and models chosen are critical downstream outcomes of this shortness of data series. The data series used in published studies do not seem to reflect this need to use approaches adapted to short data series perhaps because of a selection bias in publishing studies with longer series because results are less ambiguous when longer series are used.

10.8.3. Models suitable for typical tasks need to be very simple

Given short data in both diffusion and decline series and if diffusion and discontinuance decline speeds are to continue to accelerate then more complex models would in many cases not be able to meet the minimum fitting requirements, recommended on a parameter basis. This is illustrated by considering the global DRAM data series where only three or four data points were available, and arguably, more and more technology will diffuse and decline from use over that sort of short duration life (maybe only 3-7 years). In the case of decline there continues to be a need to use or consider simple models until such time data reported is more regularly based on faster sampling rates. This observation also applies to diffusion series if the findings of Emmanouilides (2006) are accepted. In future model validation, research will need to continue to apply methods such as those applied in this thesis. This is because when dealing with short series, that are not abundant, then complex models can easily be over-fitted to the data, giving misleading results in respect to the potential for generalised forecasting performance.

10.8.3.1. An expert on-line panel tends to predict with a generally linear response despite the cue information indicating an S-curve.

Figure 50 presents the MAPE of the two judgmental models, the straight-line model, and that of the two better marketing science models. As mentioned in the studies the marketing science models tend to have a linear and low deterioration in their forecast MAPE indicating the good match of the model to the validation data out four periods. Also, like the straight-line model, which has no ability to replicate the S-curve shape, and thus generates S-shaped error patterns, the two judgmental methods have a similar error distribution shape, indicating that the judgmental models are presenting something similar to a linear extrapolation of the data provided. Investigations of extrapolation of exponential type trajectories in the psychology literature has focused on an assumption that a polynomial or exponential function underlies participants intuitive extrapolation of such trajectories (Jones, 1977, 1979, 1984; Keren, 1984; Timmers & Wagenaar, 1977; Wagenaar & Timmers, 1978a, 1979). Given the striking nature of this finding, a repeat of the study at a number of other points on the exponential curve might confirm the type of conceptual model used by people in their judgments of decline. The results may also be a feature of study differences, as past research has tended to use a very small set of participants often less than ten persons, and burdening them with often tens if not hundreds of tasks.

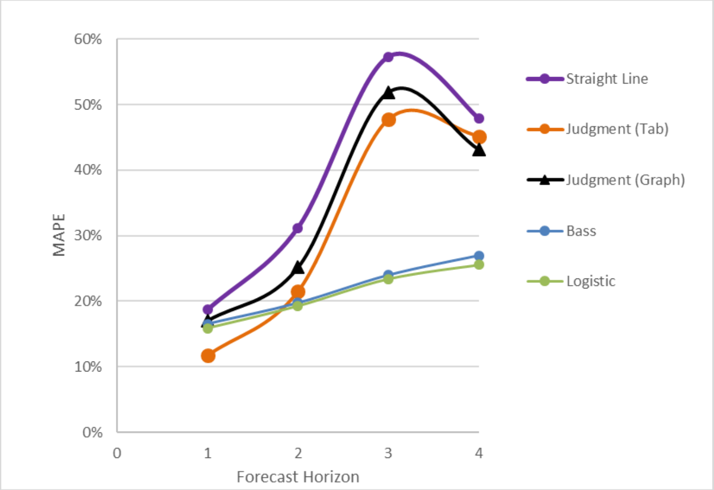


Figure 50. expert on-line panel tends to predict with a generally linear response

10.8.4. Analogous series can potentially forecast earlier than diffusion models

Importantly, according to the diffusion model literature, parameter estimates for marketing science diffusion models tend not to stabilise until approximately half of the process is completed (Heeler & Hustad, 1980; Pearl, 1925; Srinivasan & Mason, 1986b). As already observed, there is very little length in decline series; consequently, on some of the shorter series, even simple models require that a good deal of the decline process has taken place before there is sufficient data to estimate the parameters.

That the analogous series already embodies the information as to the typical trajectory opens up the prospect of forecasting from first recognition of a decline trend. Indeed it appears from the literature that the potential to forecast early has not been explicitly promoted as a benefit of using analogous series methods, although this is implicit in the work of Goodwin et al. (2013), Hardie et al. (1998), and M. J. Wright and Stern (2015). The concept of a typical trajectory as a model for all technology decline should have appeal to managers and set a benchmark for other forecasts, the testing of this concept on early decline data is however, outside of this study

10.8.5. Not all survey participants extrapolated the trend as described

There were prediction behaviours in the judgmental surveys that did not align with the context on which participants were briefed. Some were flat-lining the predictions across the four prediction time periods within each task. Others provided a strong growth prediction against an historic S-curve decline trend. There are well-known prediction strategies that correspond with those two response patterns. Unfortunately, it was not possible to identify if the observed flat-lining is a satisficing behaviour or a legitimate forecasting strategy. In the same vein, those participants providing predictions with growth trajectories were initially thought as being the result of insufficient understanding as to the nature of the task, potentially but not exclusively the result of speeding. However, there is a strong theme in economic literature that supports the idea of cycles of growth (Schumpeter, 1939; Tinbergen, 1981), and these might well have been on the mind of the participants when they answered. However, whether these strategies were used or satisficing behaviour was in play, could not be identified in this investigation.

10.8.6. The judgmental treatments were affected differently by the trimming process.

Trimming the tabular pool of estimates did not improve performance of the models either by trimming for speed or by trimming by behaviour. By comparison, trimming either way substantially improved the performance of the graphical presentation model. It may be that visual presentation encourages quick intuitive decision-making by some participants, and that this intuitive decision making is not suited to the forecasting task. Thus resulting in a wide scatter in estimated level, versus the tabular presentation, which might require a much more deliberative approach both to identify the trend and then to undertake the process of estimating the trajectory. Perhaps part of the differences is that, in the graphical presentation, attempts are made to visually extrapolate the curve shape, whereas in the tabular form, the data is assessed for the numerical change between successive data points.

10.8.7. There is no documented acceptable level of accuracy in technology diffusion or decline forecasting.

As research has been focused on the accuracy dimension alone, arguably managerial understanding has suffered as complexity in models and methods has grown. This focus on accuracy may have dampened the desire to provide in the literature an exposition of management’s threshold of forecast adequacy (Oliva & Watson, 2006), although in this thesis intuitively the levels achieved on average by the best models feel adequate, being less than ten percent market share error, in most forecasts, at most horizons.

10.8.8. CumRAE and UMBRAE - one is not better, they both are useful

CumRAE and UMBRAE generally provide identical numbers for the models when tested in this study. However, given outlier levels of fit to validation data (poor forecast performance), UMBRAE makes models appear better. This is misleading researchers, into thinking that they should use CumRAE because it is sensitive to outlier errors and provides a more realistic picture of performance, Armstrong and Collopy (1992) suggest Winsorising the data to remove those potential outliers as series because they distort the results. However, if this is done on the data series rather than the forecast error series, then there is no test of the sensitivity of models to such outliers. An attractive alternative identified in this study is to use the difference between the CumRAE and UMBRAE results to identify models that fail on outlier data, without resorting to Winsorising the data.

10.8.9. Over short horizons a straight-line model performs well

When evaluating models with CumRAE or UMBRAE, this study shows no diffusion model can beat the straight-line model through the central part of the decline curve. The straight-line model forecasts are so competitive with the marketing science models and the analogous series model, that in the very restricted conditions of this study and across early horizons at least, it is a contender to be the best model.

However, caution is required in interpreting those findings because of the fixed origin forecasting protocol used. That protocol locates the estimation region for the straight-line model at the start of the *slowest rate of change in decline rate* area in the middle of the decline process. In this phase close to the inflection point, the curve demonstrates a trajectory that is “more linear” than elsewhere on the curve as the rate of change in decline rate slows to the main inflection point then speeds up as it moves away. Interestingly, there is some support for seeing this model as a valid predictor, this relates to the data sufficiency issues mentioned throughout the studies. This support comes from the acknowledgment that the quality of estimations from the marketing science diffusion models improves greatly with the inclusion of the inflection point (Heeler & Hustad, 1980; Pearl, 1925; Srinivasan & Mason, 1986b). Similarly, the limited length of the typical decline series uncovered in this thesis means that often most of the aforementioned estimation period up to the inflection point would be required to estimate the model parameters. Thus, the unique conditions that link the straight-line model to its performance may often exist because the classic marketing science models are likely to be unable to be parameterised or be unstable given the limited amount of earlier data points available for them to be calibrated.

There is a strong argument that the rate of decline through the central inflection point is the critical part of the curve, because it sets the general pathway to obsolescence. It could be that a straight line through that region, and extrapolated until it reaches zero market share, is the most realistic path for most firms, because it can be argued that the forecasting task for decline is subtly different. For most firms, the shape of the transition to the floor is less important because as the market for the technology and its product outputs fall, those consumers that are left are likely to be increasingly different from the majority that supported the market in its heyday. Only those firms that were already serving this niche or who can quickly adapt will have any interest in the residual niche that might evolve. It is likely that mainstream firms of any size will be unable to adapt quickly enough to still dominate in a rapidly shrinking and thus overcrowded market.

Moreover, the decision to redirect investment and effort away from an existing technology does not require an estimate of the floor in the same way as diffusion requires knowing the size and timing of the ceiling, to ensure investment in suitable capacity. A dying technology requires a range of decisions that are immediately reactive and by nature brutally absolute, so no granular knowledge is required to decide to abandon a market and remove a technology from a firm's productive assets other than the rate of fall through the region of greatest market share decline. One exception to this rule is if the firm was set up and adequately adaptive to contemplate becoming a small player by addressing any residual niche that might remain.

10.8.10. Over later horizons S-curve models perform better

It was clear in this research that at a managerial level, the straight-line model and all the marketing science diffusion models provide potentially useful predictions, indicating both the trend and the magnitude of the decline at each horizon. This is an important matter as it sets in context the relative accuracy, bias, and consistency of predictions. However, at later horizons the diffusion models are the best regardless of the measure, as they better reflect the data generating process.

10.9. Limitations and Suggestions for Further Research

10.9.1. The over reliance on the simple model premise

Meade and Islam (2001) warn against the premise of simpler models tending to forecast better than more complex models as a principle, because it can lead to the very situation observed here, where a very specific set of forecasting rules led to the straight-line model performing better than models with better theoretical foundations. They argue that linear models will not model saturation, and will only be competitive short term as a result. Thus, the straight-line cannot forecast the floor, and will lag in forecasting the slowing of decline towards that floor. While it can be so argued, the forecasting task for decline is different in that the rate of decline is the critical fact required by management. Further, it can be argued that the decision of redirecting investment and effort away from pre-invested technology does not require an estimate of the floor in the same way as diffusion requires knowing both the size and timing of the ceiling to ensure capacity exists.

10.9.2. The impact of applying multiple horizon forecasts.

At the outset of this research a decision was made that had substantial ramifications to the path this thesis took. An assumption was made that managers were interested in answering the question, where will we be in one year, two years, and three years out from today? Implicit in this assumption is that these forecasts are all done with respect to today. Thus, they are from a fixed origin and stretch out one year, two years, and three years from that point. Managers of course would request that these would be undertaken as early as possible upon observing a need for forecasts. Managers expect them to be updated periodically (a rolling programme of new forecasts every month, quarter, or year in line with a marketing planning cycle). This posed a challenge related to data sufficiency. The data series were so short that the opportunity to have rolling forecasts from an early stage (say from the onset of decline) on past the fall to half peak share was not available. Because early on in the decline trajectory, the shortest series did not provide enough estimation points, and the earlier in the decline trajectory one went the greater this problem became. Beyond the fall to half the peak market share the pool of series holding enough out of sample validation data points fell away due to the number of series that did not represent a technology with a completed discontinuance process. The result was a single origin (single set of) multiple horizon forecasts could be undertaken but no more. Thus this thesis only investigated forecasting decline after market share had fallen below 50 percent.

Those challenges draw attention to the differences between what managers want and what researchers undertake. For example, a researcher might have conceivably reverted to using a single step ahead forecast protocol, or alternatively used longer synthetic series to alleviate the problem. In this thesis, that was not done to ensure that the challenges of forecasting to managers' expectations rather than modifying the approach to get an elegant result were highlighted. The motivation was to keep in stark relief the practical limitations for forecasters rather than work to make the testing of models an elegant procedure. This greatly affected the generalisability of the results, at least on the surface; however, the data available in the wild would tend to match this captive set of 25 data series so the compromises were accepted.

10.9.3. The number of series

The number of series identified for this study limits the findings in several ways. Further data series could allow the reasons for the varying results to be investigated. The generalisability of the results is the most important restriction resulting from this small data set pool. The seeking of extra data is a substantial opportunity to:

- investigate forecasting the early phases of decline when the natural advantage of the analogous series over the diffusion models is high, as undertaken for new product introductions by M. J. Wright and Stern (2015);
- extend this study to investigate predicting residual niches (floors), because a larger pool might contain more series with asymptotes terminating at a floor higher than zero. This is an area of substantial interest, in that these technologies may represent residual niches in the marketplace with important economic value for those that identify and serve them early in the industries' rush to abandon a technology;
- undertake a study to understand the relative symmetry or otherwise of decline data and whether any specific technology environments exhibit a particular bias in symmetry that would aid future forecasting. In the selection of diffusion models, this may allow the choice of suitable diffusion models. The growth model literature already describes methods for identifying asymmetry for the purposes of model

selection however; a more generalised observation of the nature of decline curves is worthy.

- further, if a larger pool of series for decline was available, then testing approaches to selecting series could be evaluated as little seems to have been done on selecting analogous decline situations
- provide a larger pool of data which would be attractive to researchers and practitioners alike in a similar way that the pool of Bass parameters has stimulated research into diffusion

10.9.4. The length of the series

The restricted length of the series constrained the study in many ways similar to the limited number of series found. Most specifically, to a single fixed origin forecast, so that forecasts could be undertaken over longer horizons. With longer series (given they might not exist in any greater proportions than found but if quantities could be found), then periodic reforecast testing could be undertaken, across more of the trajectory, starting early and finishing later. Finding more long series opens opportunities to reformulate all three studies: So as to investigate the effect of data density on decline forecasting model performance, and allow periodic reforecasts to take place using the multi horizon forecasts in this study. Given the limited amount of longer data series, the use of synthetic data might be required; however, this undermines some of the generalisability built up in the studies of this thesis. This process would allow the use of the random walk as a benchmark, as well as testing of the models earlier and later in the decline progression process, with the spin off benefit of the opportunity to confirm the speed at which forecast performance reaches an asymptote as extra data is provided. An important aspect with respect to all three forecasting approaches tested.

The CumRAE and UMBRAE error measures in this study are restricted in their usefulness because of the benchmark used (the fixed-point estimation model). This has tended to undermine its sensitivity, although it has little practical effect on ranked (relative) assessment of models, just on understanding of their absolute performance.

10.10. Summary

In conclusion, managers can have some confidence in using any of the three approaches. The marketing science models can work very well providing forecasts, in the region of the curve tested. However only the Bass and the Pearl logistic model should be used with the proviso that this study is using limited data series and further work might find different ranking of models. It must be said however, that the full 25 series, the trimmed pool of 12 series, and the normalised 25 of Study Two had different pooled variances and proportions of different character curves and the results were consistently in favour of these two models. Marketing science models rely on the availability of a number of data points, which means in practical terms they cannot often be deployed early in the decline process. So managers should be cautious in expecting to use marketing science models on decline data until the decline is close to a fall of 50 percent of peak, where decline is very rapid. This is related to the estimation of parameter requirements for marketing science models. Managers should not contemplate more advanced models in situations where the data is similar to that in the 25 series found for this study. Analogous series data, allows managers who have access to historic series for past declines to use them as a pool of information for determining the typical rate of decline over the whole period from early identification of decline. However, while this study did not test the earlier time frames for methodological reasons, a manager should in the absence of enough data for marketing science models, treat analogous series as useful indicators in those earlier periods given the theoretical support, but with caution. Taking the simple mean of judgment by experts in a panel, as described in this study, might not be something that managers normally consider; however, in the limited testing of the current study, the data indicates that this approach even in relatively uncontrolled situations such as in on-line panels can provide forecasts that are competitive with marketing science models.

Managers have, within the scope indicated in this thesis, three methods that will give strong indications of the trajectory of their technology’s decline. The analogous series indicates potential to forecast from an earlier time, however, none of these three methods have been validated earlier in the decline trajectory. Interestingly, if the data is available up to or near to a 50 percent decline point, a simple straight line through the last three available data points and extrapolated out will tend to be better than any of the three methods. Additionally, there is sufficient evidence in the literature for managers to consider combining the forecasts from the three tested methods in a simple average. An argument could be made for inclusion of the straight-line model into that combining process. The plotting of forecasts from different methods as shown in this study is a powerful tool for understanding those forecasts' relative characteristics. This study indicates the power of such a simple process.

Marketing science researchers will find a full agenda of possible ways to extend these three studies. The first is in the search for more series to pool with the 25 series here to validate or dismiss the findings of the three studies. With the strengthened number of data series, it should be possible to test marketing science models earlier in the decline phase to provide a wider band of confident operating region for managers. There is a caution for researchers, that is, that attempting to work with earlier data is to recognise that the models will not be viable on all series. Thus, the ethos of this study to represent what is easily and universally applicable will be undermined as a way to signal to managers how to identify if the models will suit the data. This search for the operating limits of marketing science diffusion models was not undertaken here beyond providing a safe limit, which provided high certainty to managers.

Analogous series models show great promise. They could provide indications early if required, this study did not test the early decline performance of this approach, but from an intuitive and theoretical perspective, it should be a fruitful investigation. Extra data series will assist in validation of this approach.

Given the finding that expert judgment tends to use a linear extrapolation model, then testing of forecasts earlier in the decline process would be fruitful, at least to see if the linear model is only linked to this region of the decline. It would be interesting to try this work in both a laboratory and field situation to see the impact of satisficing behaviours that should be controllable in the laboratory. Moreover, the Superforecasting hypothesis (P. E. Tetlock & Gardner, 2016) that some forecasters are better judges than others could be investigated both within study three's data but also with further survey work.

In concluding this thesis, it can be said that you can indeed forecast decline in technology with simple but proven methods. If decline series were more prolific and longer, then this statement could be said more emphatically, however, that was not the case.

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Appendix A: Data Series Used

Series No.	Series Name	Source
1	Iowa non-Hybrid Seed Corn	Ryan, (1943)
2	Australian Dial Up Internet Subscribers	Austats series 8153.0
3	New Zealand Dialup Internet Subscribers	Pre 2004 OECD Communications Outlook 2005, post 2003 Statistics NZ internet service provider reports
4	US Steam locomotives (n)	Historical Statistics of the US
5	US BW TV households	Girifalco, (1991)
6	Japanese BW TV households	Japan TV subscriptions 1968-2004 from Japan Statistics Handbook, from Japan year book 2014 and other sources including Japan statistics bureau sources post 2004
7	Australian CD Albums Sold	http://www.aria.com.au/pages/statistics.htm
8	Japanese Vinyl Disks Sold	RIAJ Year Book 2000 Recording Industry Association of Japan
9	Global 256K DRAM Shipments	Victor, (2002)
10	Global 4M DRAM Shipments	Victor, (2002)
11	Azerbaijan possession B and W TV share	Possession of B and W TV set: Euromonitor-International, (n.d.)
12	Czech Republic possession B and W TV share	Possession of B and W TV set: Euromonitor-International, (n.d.)
13	Estonia possession B and W TV share	Possession of B and W TV set: Euromonitor-International, (n.d.)
14	Lithuania possession B and W TV normalised to peak share	Possession of B and W TV set: Euromonitor-International, (n.d.)
15	Slovakia possession B and W TV share	Possession of B and W TV set: Euromonitor-International, (n.d.)
16	Ukraine possession B and W TV share	Possession of B and W TV set: Euromonitor-International, (n.d.)
17	Thailand possession Cassette/ Radio Player share	Possession of Cassette/Radio Player: Euromonitor-International., (n.d.)
18	Russia possession Cassette/ Radio Player share	Possession of Cassette/Radio Player: Euromonitor-International., (n.d.)
19	Egypt possession Cassette/ Radio Player share	Possession of Cassette/Radio Player: Euromonitor-International., (n.d.)
20	Jordan possession Cassette/ Radio Player share	Possession of Cassette/Radio Player: Euromonitor-International., (n.d.)
21	Morocco possession Cassette/ Radio Player share	Possession of Cassette/Radio Player: Euromonitor-International., (n.d.)
22	Taiwan Possession Videotape Recorder Possession share	Possession of Videotape Recorder: Euromonitor-International, (n.d.)
23	Australia Possession Videotape Recorder share	Possession of Videotape Recorder: Euromonitor-International, (n.d.)
24	Denmark Possession Videotape Recorder share	Possession of Videotape Recorder: Euromonitor-International, (n.d.)
25	Spain Possession Videotape Recorder share	Possession of Videotape Recorder: Euromonitor-International, (n.d.)

Year	Year no	Iowa Hybrid Corn Users (n)	Iowa Hybrid corn users (share)	Iowa Non-hybrid users Normalised to peak share	Total MKT
1926	1	259	1.00	1.00	259
1927	2	258	1.00	1.00	259
1928	3	255	0.98	0.98	259
1929	4	250	0.97	0.97	259
1930	5	247	0.95	0.95	259
1931	6	241	0.93	0.93	259
1932	7	240	0.93	0.93	259
1933	8	234	0.90	0.90	259
1934	9	218	0.84	0.84	259
1935	10	197	0.76	0.76	259
1936	11	161	0.62	0.62	259
1937	12	100	0.39	0.39	259
1938	13	56	0.22	0.22	259
1939	14	20	0.08	0.08	259
1940	15	6	0.02	0.02	259
1941	16	2	0.01	0.01	259

Year	Year no	Australian Dial-up Internet Subscribers (n)	Australian Dial-up Internet Subscribers (share)	Aust. Dial-up Internet Subscribers Normalised to peak share	Total MKT
2,001.20	1	3,941,000	0.99	1.00	3,968,000
2,002.20	2	3,991,000	0.94	0.95	4,229,000
2,003.20	3	4,607,000	0.91	0.91	5,077,000
2,004.20	4	4,359,000	0.84	0.84	5,220,000
2,005.20	5	3,709,000	0.69	0.69	5,384,000
2,006.20	6	3,019,883	0.51	0.51	6,028,836
2,007.20	7	2,260,450	0.34	0.34	6,711,600
2,008.20	8	1,707,900	0.23	0.23	7,349,200
2,009.20	9	1,169,700	0.14	0.14	8,227,700
2,010.20	10	834,400	0.09	0.09	9,397,400
2,011.20	11	636,800	0.06	0.06	10,791,000
2,012.20	12	415,700	0.04	0.04	11,765,500
2,013.20	13	258,900	0.02	0.02	12,231,800
2,014.20	14	191,200	0.02	0.02	12,485,200

year	Year no	New Zealand Dial-up Internet Subscribers (n)	New Zealand Dial-up Internet Subscribers (share)	New Zealand Dial-up Internet Subscribers Normalised to peak share	Total MKT
1999.00	1.00	480000	0.99	1.00	482706
2000.00	2.00	542234	0.99	1.00	546890
2001.00	3.00	644500	0.97	0.98	661767
2002.00	4.00	874100	0.95	0.96	917600
2003.00	5.00	969776	0.92	0.93	1052776
2004.00	6.00	900000	0.82	0.83	1091000
2005.50	7.00	838985	0.73	0.73	1150631
2006.67	8.00	773056	0.63	0.63	1235586
2007.00	8.33	654867	0.44	0.44	1487892
2007.00	8.83	517533	0.34	0.34	1530727
2008.00	9.33	412000	0.26	0.26	1609175
2009.00	10.58	309033	0.18	0.19	1677197
2010.00	11.58	174250	0.10	0.10	1682923
2011.00	12.58	115333	0.06	0.06	1786718
2012.00	13.58	84833	0.04	0.04	1904766
2013.00	14.58	60000	0.03	0.03	1980263

year	Year no	US Steam locomotives (n)	US Steam locomotives (share)	US Steam locomotives Normalised to peak share	Total MKT
1937	1	48477	0.98	1.00	47507
1938	2	46923	0.98	1.00	46495
1939	3	46342	0.98	1.00	45122
1940	4	45210	0.97	0.99	44277
1941	5	43604	0.97	0.99	44323
1942	6	42410	0.96	0.98	44625
1943	7	41911	0.95	0.97	45366
1944	8	41755	0.94	0.96	46255
1945	9	41983	0.93	0.94	46204
1946	10	41921	0.91	0.93	45467
1947	11	41018	0.89	0.91	44301
1948	12	39592	0.87	0.89	44429
1949	13	36942	0.83	0.85	43225
1950	14	34581	0.78	0.79	42903
1951	15	30344	0.70	0.72	42421
1952	16	26680	0.62	0.63	39645
1953	17	22590	0.53	0.54	37196
1954	18	16737	0.42	0.43	34966
1955	19	12274	0.33	0.34	33468
1956	20	9041	0.26	0.26	32535
1957	21	6266	0.19	0.19	32342
1958	22	3918	0.12	0.12	31565
1959	23	2608	0.08	0.08	31485
1960	24	1488	0.05	0.05	31112
1961	25	871	0.03	0.03	30817
1962	26	374	0.01	0.01	30634

year	Year no	US TV households with BW TVs (n)	US TV households with BW TVs (share)	US BW TV Households Normalised to peak share	Total MKT
1964	1	51600000	0.97	1.00	53210000
1965	2	49902736	0.94	0.97	52951525
1966	3	53850000	0.91	0.94	59070000
1967	4	55130000	0.86	0.89	64130000
1968	5	56670000	0.81	0.83	70370000
1969	6	58250000	0.78	0.80	74750000
1970	7	38653928	0.63	0.65	60900358
1971	8	33900000	0.55	0.57	61500000
1972	9	27650000	0.44	0.45	63450000
1973	10	19993244	0.31	0.32	65400000
1974	11	22347683	0.33	0.34	67350000
1975	12	21605378	0.31	0.32	70291655
1976	13	14268639	0.20	0.21	70150000
1977	14	12664753	0.18	0.18	71800000
1978	15	9749714	0.13	0.14	73450000
1979	16	7091248	0.09	0.10	75100000
1980	17	12899757	0.16	0.17	80018371
1981	18	9750936	0.12	0.13	79900000
1982	19	10098750	0.12	0.13	83278262
1983	20	9399154	0.11	0.12	83850943
1984	21	8002507	0.09	0.10	85252296
1985	22	7195062	0.08	0.09	86631719

year	Year no	Japanese TV households with BW TVs (n)	Japanese TV households with BW TVs (share)	Japanese BW TV households Normalised to peak share	Total MKT
1967	1	20270	1.00	1.00	20270
1968	2	19532	0.92	0.92	21221
1969	3	18092	0.82	0.82	22088
1970	4	15156	0.66	0.66	22819
1971	5	11726	0.50	0.50	23520
1972	6	8803	0.36	0.36	24433
1973	7	6589	0.26	0.26	24925
1974	8	5210	0.20	0.20	25753
1975	9	4282	0.16	0.16	26545
1976	10	3749	0.14	0.14	27059
1977	11	3346	0.12	0.12	27773
1978	12	3100	0.11	0.11	28394
1979	13	2920	0.10	0.10	28932
1980	14	2777	0.09	0.09	29263
1981	15	2661	0.09	0.09	29789
1982	16	2475	0.08	0.08	30403
1983	17	2264	0.07	0.07	30799
1984	18	2156	0.07	0.07	31062
1985	19	2055	0.07	0.07	31509
1986	20	1955	0.06	0.06	31955
1987	21	1705	0.05	0.05	32397
1988	22	1550	0.05	0.05	32839
1989	23	1447	0.04	0.04	33189
1990	24	1358	0.04	0.04	33543
1991	25	1271	0.04	0.04	33937
1992	26	1126	0.03	0.03	34344
1993	27	1040	0.03	0.03	34701
1994	28	971	0.03	0.03	35027
1995	29	866	0.02	0.02	35377
1996	30	800	0.02	0.02	35816
1997	31	733	0.02	0.02	36283
1998	32	667	0.02	0.02	36597
1999	33	610	0.02	0.02	36878
2000	34	542	0.01	0.01	37274

year	Year no	Aust. CD albums sold (n)	Aust. CD Album (share)	Aust. C D Albums Normalised to peak share	Total MKT
2000	1	43917000	0.99	1.00	45508917
2001	2	49670000	0.97	0.98	52290777
2002	3	46954000	0.94	0.96	50815678
2003	4	50640000	0.91	0.92	56777167
2004	5	48234000	0.90	0.91	54490583
2005	6	46174000	0.89	0.90	51806083
2006	7	49818000	0.87	0.88	57220167
2007	8	44045000	0.84	0.85	52285583
2008	9	38659000	0.82	0.83	47019250
2009	10	39529000	0.80	0.81	49590583
2010	11	33114000	0.76	0.77	43731500
2011	12	30232000	0.70	0.71	43090917
2012	13	27356000	0.60	0.61	45801833
2013	14	19595000	0.52	0.53	37814500
2014	15	12563714	0.43	0.44	29137181
2015	16	11323034	0.38	0.39	29424647

Year	Year no	Japan Vinyl Album equivs.	Japan Vinyl Album equivs. share	Japan Vinyl Album equivs. Normalised to peak share	Total Market Album equivalents
1965	1	27178.4	1.00	1.00	27178
1966	2	37219.7	0.85	0.85	43551
1967	3	47905.5	0.78	0.78	61756
1968	4	58447.3	0.72	0.72	80767
1969	5	67630.7	0.76	0.76	88609
1970	6	70228.3	0.77	0.77	90772
1971	7	87894.1	0.77	0.77	114333
1972	8	93548.1	0.80	0.80	117603
1973	9	93935.6	0.78	0.78	120230
1974	10	105170.1	0.77	0.77	136759
1975	11	101573.5	0.75	0.75	136256
1976	12	103452.4	0.69	0.69	150012
1977	13	99499.8	0.62	0.62	160809
1978	14	101019	0.56	0.56	180984
1979	15	89617.5	0.51	0.51	176397
1980	16	81053.6	0.45	0.45	178658
1981	17	77439.8	0.44	0.44	175171
1982	18	75323.8	0.46	0.46	164579
1983	19	68590.9	0.42	0.42	163749
1984	20	51539.7	0.31	0.31	167532
1985	21	32370	0.19	0.19	172180
1986	22	14785.9	0.08	0.08	186385
1987	23	3144	0.01	0.01	224460
1988	24	886.6	0.00	0.00	232380
1989	25	895.6	0.00	0.00	263624
1990	26	986.1	0.00	0.00	271770
1991	27	773.6	0.00	0.00	276683
1992	28	620	0.00	0.00	283702
1993	29	534	0.00	0.00	314649
1994	30	944	0.00	0.00	319870
1995	31	1034	0.00	0.00	326867
1996	32	1186	0.00	0.00	338772
1997	33	2985	0.01	0.01	309162
1998	34	1914	0.01	0.01	306892
1999	35	1297	0.00	0.00	284806
2000	36	697	0.00	0.00	282362

Year	Year no	Global Shipments of 256K memory (n) Mb	256K share	Global 256K DRAM Shipments Normalised to peak share	Global DRAM Shipments in Mb
1986	1	154.88	0.85	1.00	183.07
1987	2	191.75	0.83	0.98	230.50
1988	3	238.84	0.59	0.70	404.50
1989	4	212.97	0.32	0.37	672.50
1990	5	155.79	0.17	0.21	891.63
1991	6	76.70	0.05	0.06	1486.49
1992	7	50.26	0.02	0.02	2733.24

Year	Year no	Global Shipments of 4M memory	4M share	Global 4M DRAM Shipments Normalised to peak share	Global DRAM Shipments in Mb
1993	1.00	3104.00	0.77	1.00	4020.00
1994	2.00	5016.00	0.70	0.91	7171.04
1995	3.00	6596.00	0.53	0.69	12403.00
1996	4.00	5992.00	0.27	0.35	22284.00
1997	5.00	3772.00	0.09	0.11	43575.00
1998	6.00	2044.00	0.03	0.03	81061.00

Year	Year no	Azerbaijan possession B and W TV share	Azerbaijan Possession of Colour TV Set	Azerbaijan possession B and W TV normalised to peak share	
1986	1	1.00	22.50	1.00	
1987	2	0.99	23.80	0.99	
1988	3	0.99	25.40	0.99	
1989	4	0.99	27.10	0.99	
1990	5	0.98	29.10	0.98	
1991	6	0.98	31.40	0.98	
1992	7	0.97	34.00	0.97	
1993	8	0.96	36.80	0.96	
1994	9	0.95	39.80	0.95	
1995	10	0.93	43.00	0.93	
1996	11	0.92	46.20	0.92	
1997	12	0.90	49.50	0.90	
1998	13	0.85	52.80	0.85	
1999	14	0.79	56.10	0.79	
2000	15	0.73	59.30	0.73	
2001	16	0.66	62.40	0.66	
2002	17	0.59	65.30	0.59	
2003	18	0.52	67.90	0.52	
2004	19	0.44	73.30	0.44	
2005	20	0.33	81.90	0.33	
2006	21	0.30	84.30	0.30	
2007	22	0.29	87.20	0.29	
2008	23	0.25	90.10	0.25	
2009	24	0.24	91.90	0.24	
2010	25	0.18	94.80	0.18	
2011	26	0.11	97.20	0.11	
2012	27	0.09	98.40	0.09	
2013	28	0.06	99.00	0.06	
2014	29	0.05	99.40	0.05	
2015	30	0.04	99.50	0.04	
2016	31	0.03	99.60	0.03	

Year	Year no	Czech Republic possession B and W TV share	Czech Republic Possession of Colour TV Set	Czech Republic possession B and W TV normalised to peak share	
1980	1	77	49.90	1.00	
1981	2	76.9	53.10	1.00	
1982	3	76.7	56.30	1.00	
1983	4	76.4	59.50	0.99	
1984	5	76	62.70	0.99	
1985	6	75.3	65.70	0.98	
1986	7	74.4	68.70	0.97	
1987	8	73	71.50	0.95	
1988	9	71.2	74.20	0.92	
1989	10	68.9	76.70	0.89	
1990	11	66	78.90	0.86	
1991	12	62.4	81.00	0.81	
1992	13	58.4	82.80	0.76	
1993	14	53.8	84.50	0.70	
1994	15	46.5	86.00	0.60	
1995	16	42.2	87.30	0.55	
1996	17	39.6	88.60	0.51	
1997	18	36.4	89.80	0.47	
1998	19	30.5	90.80	0.40	
1999	20	16.4	91.90	0.21	
2000	21	12.8	92.90	0.17	
2001	22	11	93.80	0.14	
2002	23	9.2	94.80	0.12	
2003	24	7.9	95.50	0.10	
2004	25	6.5	96.10	0.08	
2005	26	5.4	96.50	0.07	
2006	27	4.5	97.00	0.06	
2007	28	3.8	97.30	0.05	
2008	29	3.1	97.60	0.04	
2009	30	2.4	97.90	0.03	
2010	31	1.9	98.10	0.02	
2011	32	1.6	98.40	0.02	
2012	33	1.3	98.50	0.02	
2013	34	1	98.70	0.01	
2014	35	0.8	98.90	0.01	
2015	36	0.6	99.00	0.01	
2016	37	0.5	99.10	0.01	

Year	Year no	Estonia possession B and W TV share	Estonia Possession of Colour TV Set	Estonia possession B and W TV normalised to peak share	
1977	1	74	26.70	1.00	
1978	2	74.2	28.70	1.00	
1979	3	73.7	30.60	1.00	
1980	4	72.5	32.50	0.98	
1981	5	71.2	34.40	0.96	
1982	6	69.9	36.40	0.94	
1983	7	68.3	38.40	0.92	
1984	8	66.6	40.50	0.90	
1985	9	64.8	42.80	0.88	
1986	10	62.8	45.20	0.85	
1987	11	60.6	47.90	0.82	
1988	12	58.3	50.80	0.79	
1989	13	55.7	53.80	0.75	
1990	14	53	56.90	0.72	
1991	15	50.1	60.10	0.68	
1992	16	47	63.30	0.64	
1993	17	43.7	66.50	0.59	
1994	18	40.2	69.70	0.54	
1995	19	36.6	72.70	0.49	
1996	20	32.9	75.60	0.44	
1997	21	29.1	78.20	0.39	
1998	22	25.4	82.60	0.34	
1999	23	21.8	85.60	0.29	
2000	24	18.2	91.90	0.25	
2001	25	14.8	92.20	0.20	
2002	26	12	94.10	0.16	
2003	27	9.7	93.90	0.13	
2004	28	7.5	94.60	0.10	
2005	29	5.7	95.30	0.08	
2006	30	4.4	95.00	0.06	
2007	31	3.4	96.00	0.05	
2008	32	2.5	97.10	0.03	
2009	33	1.8	98.20	0.02	
2010	34	1.4	98.60	0.02	
2011	35	1	97.40	0.01	
2012	36	0.7	97.40	0.01	
2013	37	0.5	97.30	0.01	
2014	38	0.4	97.00	0.01	
2015	39	0.3	97.00	0.00	
2016	40	0.2	96.90	0.00	

Year	Year no	Lithuania possession B and W TV normalised to peak share	Lithuania Possession of Colour TV Set	Lithuania possession B and W TV normalised to peak share	
1982	1	77.3	53.00	1.00	
1983	2	76.9	54.10	0.99	
1984	3	76.3	55.20	0.99	
1985	4	75.6	56.40	0.98	
1986	5	74.7	57.60	0.97	
1987	6	73.7	58.70	0.95	
1988	7	72.3	59.60	0.94	
1989	8	70.6	60.40	0.91	
1990	9	68.6	61.20	0.89	
1991	10	66.1	62.00	0.86	
1992	11	63.2	63.00	0.82	
1993	12	59.9	64.20	0.77	
1994	13	56.1	65.70	0.73	
1995	14	51.9	67.60	0.67	
1996	15	47	70.00	0.61	
1997	16	42	74.00	0.54	
1998	17	37	76.00	0.48	
1999	18	29	81.00	0.38	
2000	19	18	89.00	0.23	
2001	20	20	88.00	0.26	
2002	21	18	89.00	0.23	
2003	22	18	90.00	0.23	
2004	23	14	92.00	0.18	
2005	24	9	94.00	0.12	
2006	25	7	96.00	0.09	
2007	26	5	97.00	0.06	
2008	27	3	98.00	0.04	
2009	28	2.2	98.30	0.03	
2010	29	1.7	98.40	0.02	
2011	30	1.3	98.50	0.02	
2012	31	1	98.60	0.01	
2013	32	0.8	98.60	0.01	
2014	33	0.7	98.70	0.01	
2015	34	0.6	98.80	0.01	
2016	35	0.5	98.80	0.01	

Year	Year no	Slovakia possession B and W TV share	Slovakia Possession of Colour TV Set	Slovakia possession B and W TV normalised to peak share	
1981	1	71.4	29.20	1.00	
1982	2	71.1	30.90	1.00	
1983	3	70.7	32.50	0.99	
1984	4	70	33.90	0.98	
1985	5	68.6	35.30	0.96	
1986	6	66.8	37.20	0.94	
1987	7	63.8	39.90	0.89	
1988	8	60.6	43.80	0.85	
1989	9	57.5	50.80	0.81	
1990	10	53.4	57.30	0.75	
1991	11	48.5	63.00	0.68	
1992	12	43	68.50	0.60	
1993	13	37.5	73.50	0.53	
1994	14	31.6	78.00	0.44	
1995	15	26.6	81.90	0.37	
1996	16	21.9	85.00	0.31	
1997	17	17.6	87.50	0.25	
1998	18	14	89.50	0.20	
1999	19	10.8	91.20	0.15	
2000	20	8.9	92.80	0.12	
2001	21	7.2	94.20	0.10	
2002	22	5.9	95.20	0.08	
2003	23	5	96.00	0.07	
2004	24	4.3	96.90	0.06	
2005	25	3.7	97.90	0.05	
2006	26	3.2	99.20	0.04	
2007	27	2.8	99.60	0.04	
2008	28	2.4	99.70	0.03	
2009	29	2.1	99.70	0.03	
2010	30	1.8	99.70	0.03	
2011	31	1.6	99.80	0.02	
2012	32	1.4	99.80	0.02	
2013	33	1.2	99.80	0.02	
2014	34	1.1	99.80	0.02	
2015	35	0.9	99.90	0.01	
2016	36	0.8	99.90	0.01	

Year	Year no	Ukraine possession B and W TV share	Ukraine Possession of Colour TV Set	Ukraine possession B and W TV normalised to peak share	
1980	1	71.2	54.30	1.00	
1981	2	71	55.00	1.00	
1982	3	70.1	55.70	0.98	
1983	4	69.2	56.50	0.97	
1984	5	68.2	57.40	0.96	
1985	6	67	58.30	0.94	
1986	7	65.8	59.30	0.92	
1987	8	64.4	60.30	0.90	
1988	9	62.9	61.20	0.88	
1989	10	61.3	62.20	0.86	
1990	11	59.5	63.00	0.84	
1991	12	57.5	63.80	0.81	
1992	13	55.4	64.50	0.78	
1993	14	53	65.30	0.74	
1994	15	50.4	66.10	0.71	
1995	16	47.6	67.30	0.67	
1996	17	44.7	68.70	0.63	
1997	18	41.5	70.50	0.58	
1998	19	38.2	72.50	0.54	
1999	20	34.7	74.70	0.49	
2000	21	31.6	76.80	0.44	
2001	22	27.8	78.90	0.39	
2002	23	24	80.80	0.34	
2003	24	20.9	82.40	0.29	
2004	25	18.1	83.70	0.25	
2005	26	15.3	85.80	0.21	
2006	27	11.9	88.70	0.17	
2007	28	9.1	91.60	0.13	
2008	29	6.3	93.90	0.09	
2009	30	5	94.70	0.07	
2010	31	4.1	95.00	0.06	
2011	32	3.4	95.40	0.05	
2012	33	2.8	95.60	0.04	
2013	34	2.3	95.60	0.03	
2014	35	1.9	95.60	0.03	
2015	36	1.6	95.70	0.02	
2016	37	1.3	95.70	0.02	

Year	Year no	Thailand possession Cassette/ Radio Player share	Thailand Possession of CD Player	Thailand possession Cassette/ Radio Player normalised to peak share	
1999	1	74.1	4.70	1.00	
2000	2	73.3	4.80	0.99	
2001	3	71.1	5.00	0.96	
2002	4	68.9	5.10	0.93	
2003	5	66.1	5.30	0.89	
2004	6	63.6	5.40	0.86	
2005	7	61	5.50	0.82	
2006	8	59.1	5.70	0.80	
2007	9	56.5	5.60	0.76	
2008	10	53.7	5.50	0.72	
2009	11	50.8	5.60	0.69	
2010	12	47.8	5.50	0.65	
2011	13	44.9	5.50	0.61	
2012	14	42.2	5.50	0.57	
2013	15	39.6	5.50	0.53	
2014	16	37.4	5.50	0.50	
2015	17	35.4	5.40	0.48	
2016	18	33.6	5.30	0.45	

Year	Year no	Russia possession Cassette/ Radio Player share	Russia Possession of CD Player	Russia possession Cassette/ Radio Player normalised to peak share	
1995	1	77	4.10	1.00	
1996	2	72	6.10	0.94	
1997	3	72	7.10	0.94	
1998	4	66	7.10	0.86	
1999	5	67	8.00	0.87	
2000	6	66	8.40	0.86	
2001	7	58	8.90	0.75	
2002	8	54.9	9.60	0.71	
2003	9	53.9	10.00	0.70	
2004	10	53.7	10.50	0.70	
2005	11	53	11.10	0.69	
2006	12	52	11.60	0.68	
2007	13	50	11.30	0.65	
2008	14	45	11.10	0.58	
2009	15	44	11.10	0.57	
2010	16	29	10.90	0.38	
2011	17	30	10.80	0.39	
2012	18	29	10.70	0.38	
2013	19	28	10.60	0.36	
2014	20	27	10.50	0.35	
2015	21	25.5	10.30	0.33	
2016	22	24	10.20	0.31	

Year	Year no	Egypt possession Cassette/ Radio Player share	Egypt Possession of CD Player	Egypt possession Cassette/ Radio Player normalised to peak share	
2005	1	84.8	6.90	1.00	
2006	2	83.9	7.40	0.99	
2007	3	80.5	7.90	0.95	
2008	4	73.3	7.20	0.86	
2009	5	65.6	7.40	0.77	
2010	6	58.2	7.20	0.69	
2011	7	51.2	7.20	0.60	
2012	8	44.4	7.00	0.52	
2013	9	37.7	7.00	0.44	
2014	10	31.1	6.80	0.37	
2015	11	26.6	6.70	0.31	
2016	12	22.7	6.60	0.27	

Year	Year no	Jordan possession Cassette/ Radio Player share	Jordan Possession of CD Player	Jordan possession Cassette/ Radio Player normalised to peak share	
1991	1	88.4	2.60	1.00	
1992	2	88.3	3.10	1.00	
1993	3	87.8	3.70	0.99	
1994	4	87	4.00	0.98	
1995	5	85.8	5.00	0.97	
1996	6	84.2	6.10	0.95	
1997	7	82.2	6.80	0.93	
1998	8	78.3	7.90	0.89	
1999	9	75.1	8.80	0.85	
2000	10	72.5	9.60	0.82	
2001	11	70.5	10.60	0.80	
2002	12	69.2	11.50	0.78	
2003	13	65.4	12.50	0.74	
2004	14	60.2	13.40	0.68	
2005	15	54.2	14.30	0.61	
2006	16	47.8	14.50	0.54	
2007	17	43.3	14.70	0.49	
2008	18	38.7	14.10	0.44	
2009	19	36.5	14.30	0.41	
2010	20	34.2	14.00	0.39	
2011	21	31.5	13.90	0.36	
2012	22	29.3	13.80	0.33	
2013	23	27.1	13.60	0.31	
2014	24	24.9	13.50	0.28	
2015	25	23.1	13.40	0.26	
2016	26	21.4	13.30	0.24	

Year	Year no	Morocco possession Cassette/ Radio Player share	Morocco Possession of CD Player	Morocco possession Cassette/ Radio Player normalised to peak share	
2003	1	81.2	7.50	1.00	
2004	2	79.4	11.20	0.98	
2005	3	69.6	15.70	0.86	
2006	4	57.3	21.00	0.71	
2007	5	49.1	27.10	0.60	
2008	6	43.5	30.60	0.54	
2009	7	38.7	32.40	0.48	
2010	8	34.6	33.70	0.43	
2011	9	31.9	34.10	0.39	
2012	10	29.7	34.10	0.37	
2013	11	28	33.60	0.34	
2014	12	26.5	33.00	0.33	
2015	13	25	32.70	0.31	
2016	14	23.6	32.30	0.29	

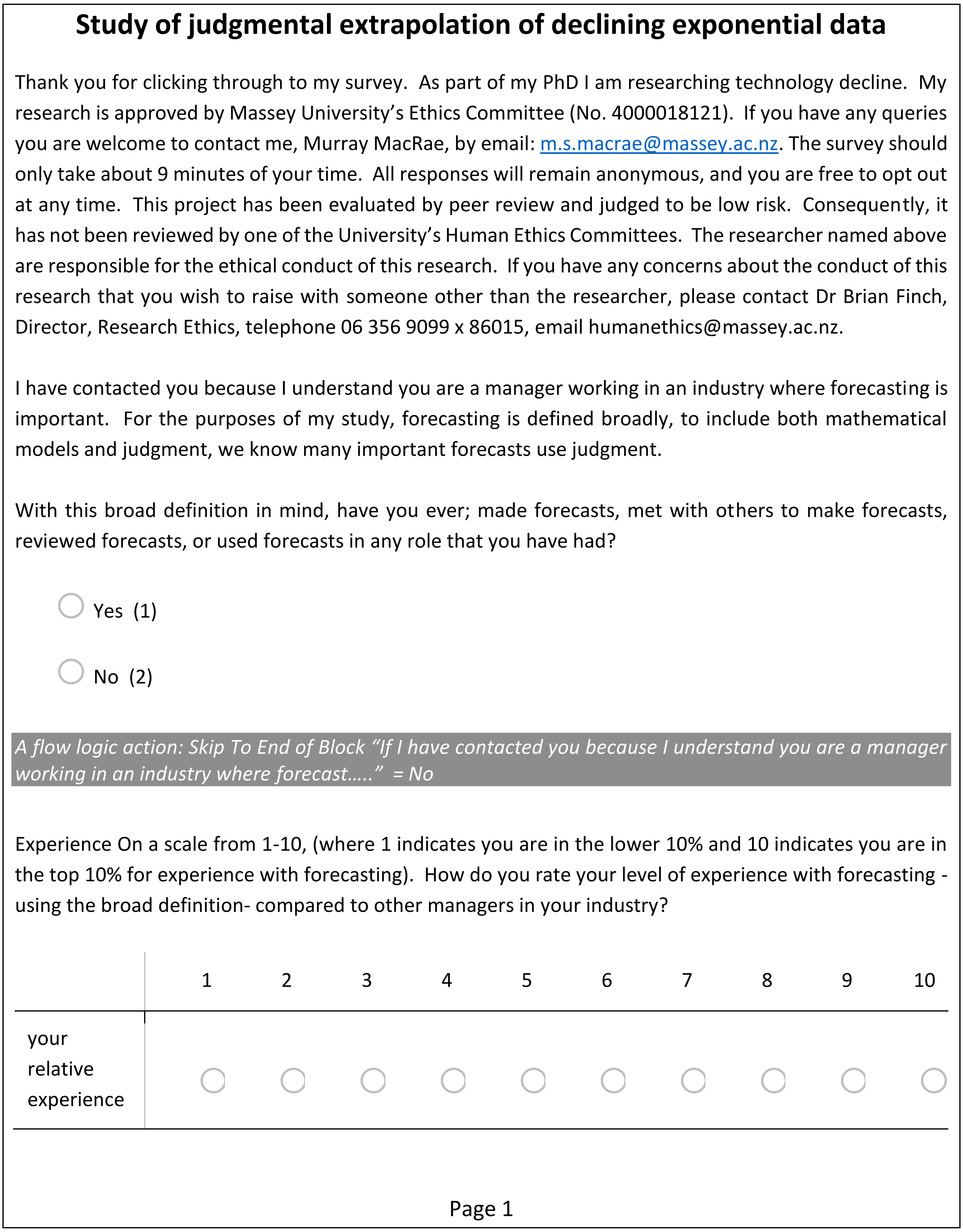
Year	Year no	Taiwan Possession Videotape Recorder Possession share	Taiwan Possession of DVD Player/Recorder	Taiwan Possession Videotape Recorder possession normalised to peak	
1992	1	71.2	2.40	1	
1993	2	69.2	3.20	0.97	
1994	3	66.4	4.00	0.93	
1995	4	62.2	4.20	0.87	
1996	5	58.6	5.10	0.82	
1997	6	57.1	5.70	0.80	
1998	7	55.2	6.40	0.78	
1999	8	50.7	7.30	0.71	
2000	9	46.7	13.50	0.66	
2001	10	43.1	22.50	0.61	
2002	11	37.9	32.90	0.53	
2003	12	29.2	40.10	0.41	
2004	13	25.4	46.00	0.36	
2005	14	22.5	48.60	0.32	
2006	15	19.9	53.50	0.28	
2007	16	18.3	52.70	0.26	
2008	17	17.1	44.10	0.24	
2009	18	16.3	42.20	0.23	
2010	19	15.7	39.40	0.22	
2011	20	15.2	37.70	0.21	
2012	21	14.9	34.30	0.21	
2013	22	14.7	29.80	0.21	
2014	23	14.5	27.70	0.20	
2015	24	14.4	26.00	0.20	
2016	25	14.3	24.60	0.20	

Year	Year no	Australia Possession Videotape Recorder share	Australia Possession of DVD Player/Recorder	Australia Possession Videotape Recorder normalised to peak share	
2002	1	89.1	23.00	1.00	
2003	2	89	44.00	1.00	
2004	3	88	60.00	0.99	
2005	4	83.7	72.00	0.94	
2006	5	74.2	79.80	0.83	
2007	6	61.4	84.60	0.69	
2008	7	48.6	87.30	0.55	
2009	8	42.8	87.60	0.48	
2010	9	37.5	85.70	0.42	
2011	10	33.5	83.00	0.38	
2012	11	31	79.80	0.35	
2013	12	29.1	75.90	0.33	
2014	13	27.6	71.90	0.31	
2015	14	26.7	70.10	0.30	
2016	15	25.9	68.40	0.29	

Year	Year no	Denmark Possession Videotape Recorder share	Denmark Possession of DVD Player/Recorder	Denmark Possession Videotape Recorder normalised to peak share	
2004	1	85.00	54.00	1.00	
2005	2	84.00	68.00	0.99	
2006	3	83.00	83.00	0.98	
2007	4	76.00	84.00	0.89	
2008	5	74.00	84.00	0.87	
2009	6	68.00	86.00	0.80	
2010	7	55.00	85.00	0.65	
2011	8	51.50	78.00	0.61	
2012	9	47.80	68.00	0.56	
2013	10	44.40	65.00	0.52	
2014	11	42.60	61.00	0.50	
2015	12	41.10	53.00	0.48	
2016	13	40.00	52.00	0.47	

Year	Year no	Spain Possession Videotape Recorder share	Spain Possession of DVD Player/Recorder	Spain Possession Videotape Recorder normalised to peak share	
2001	1	76.4	6.70	1.00	
2002	2	75.1	15.80	0.98	
2003	3	72.6	27.40	0.95	
2004	4	72.3	46.40	0.95	
2005	5	70.4	62.90	0.92	
2006	6	69.4	73.40	0.91	
2007	7	67.1	75.60	0.88	
2008	8	62.9	78.30	0.82	
2009	9	58.7	78.80	0.77	
2010	10	50.8	78.40	0.66	
2011	11	47.5	77.90	0.62	
2012	12	43.3	74.40	0.57	
2013	13	39.8	70.30	0.52	
2014	14	36.4	67.10	0.48	
2015	15	32.7	64.10	0.43	
2016	16	30.9	62.40	0.40	

Appendix B: The Survey Instrument



Study of judgmental extrapolation of declining exponential data

Thank you for clicking through to my survey. As part of my PhD I am researching technology decline. My research is approved by Massey University's Ethics Committee (No. 4000018121). If you have any queries you are welcome to contact me, Murray MacRae, by email: m.s.macrae@massey.ac.nz. The survey should only take about 9 minutes of your time. All responses will remain anonymous, and you are free to opt out at any time. This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher named above are responsible for the ethical conduct of this research. If you have any concerns about the conduct of this research that you wish to raise with someone other than the researcher, please contact Dr Brian Finch, Director, Research Ethics, telephone 06 356 9099 x 86015, email humanethics@massey.ac.nz.

I have contacted you because I understand you are a manager working in an industry where forecasting is important. For the purposes of my study, forecasting is defined broadly, to include both mathematical models and judgment, we know many important forecasts use judgment.

With this broad definition in mind, have you ever; made forecasts, met with others to make forecasts, reviewed forecasts, or used forecasts in any role that you have had?

○ Yes (1)

○ No (2)

A flow logic action: Skip To End of Block "If I have contacted you because I understand you are a manager working in an industry where forecast….." = No

Experience On a scale from 1-10, (where 1 indicates you are in the lower 10% and 10 indicates you are in the top 10% for experience with forecasting). How do you rate your level of experience with forecasting - using the broad definition- compared to other managers in your industry?

	1	2	3	4	5	6	7	8	9	10
your relative experience	○	○	○	○	○	○	○	○	○	○

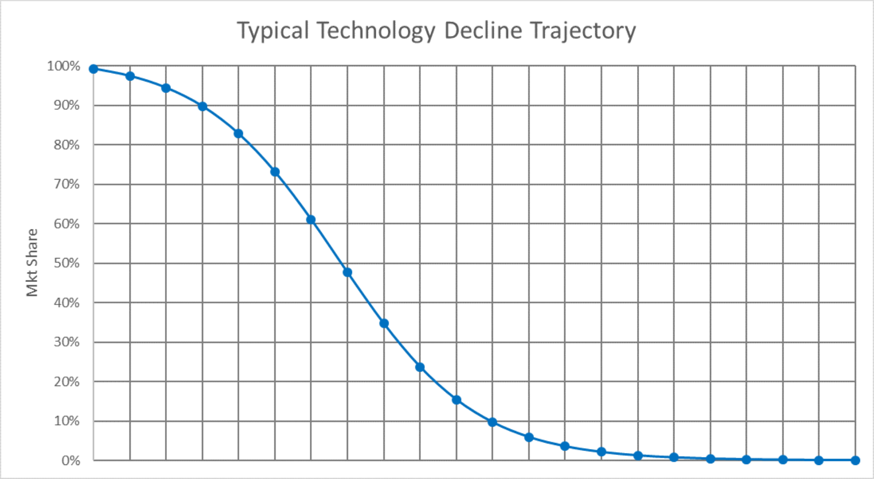
Page 1

Why is understanding technology decline important?

Firms are hugely exposed to the impacts of decline in the use of their current technologies. Despite this, technology decline is hardly studied, and unfortunately, we know very little about how to predict the rate of this decline.

How does this decline occur? The decline of existing technology occurs when it is displaced by a newer technology. Firms and individuals that rely on the older technology are placed on notice that obsolescence is on the way when this decline starts. Technology in decline starts out at 100% of the peak share achieved and after a slow start, decline is rapid to a midpoint of about 50% share. From the midpoint its rate of decline slows down as it approaches a market share floor representing very little use of the technology. This decline generally follows the path shown in Figure 1., sometimes the fall is fast and sometimes slower, sometimes even a little bumpy, but almost universally, it follows this shape.

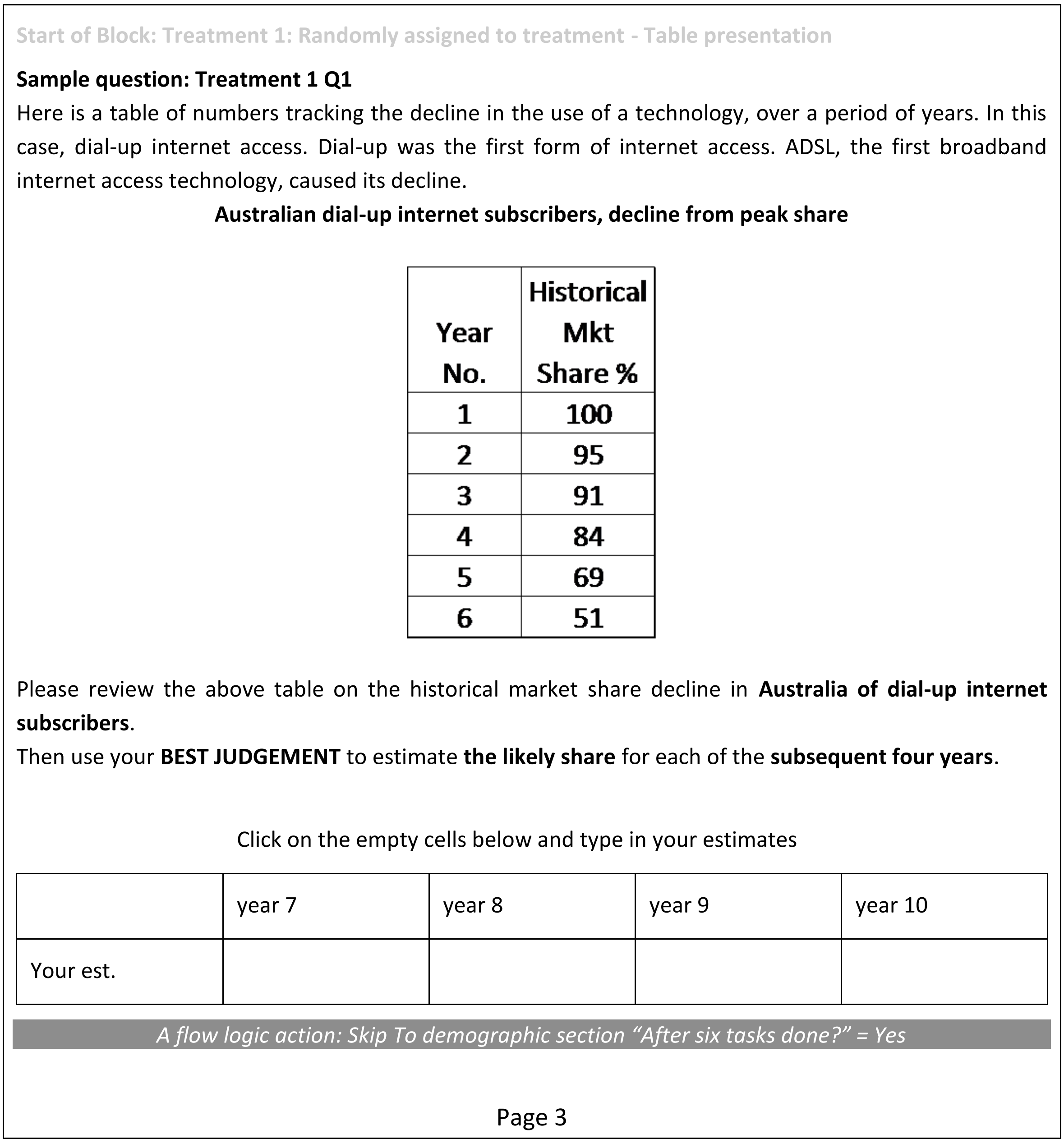
Figure 1.



The survey you are about to take is one of very few studies into the human ability to predict this kind of technology decline, and is part of a bigger study into ways to predict the rate of decline. In the survey you will be presented with 6 tasks where you will predict the market share of a declining technology. These are real technologies selected from the last 100 years. You are given all the available data indicating a fall down to approximately 50% share. In the following pages you will be asked to estimated share over the next 4 years for various technologies.

Click the arrow to begin.

End of Block: Introduction



Start of Block: Treatment 1: Randomly assigned to treatment - Table presentation

Sample question: Treatment 1 Q1

Here is a table of numbers tracking the decline in the use of a technology, over a period of years. In this case, dial-up internet access. Dial-up was the first form of internet access. ADSL, the first broadband internet access technology, caused its decline.

Australian dial-up internet subscribers, decline from peak share

Year No.	Historical Mkt Share %
1	100
2	95
3	91
4	84
5	69
6	51

Please review the above table on the historical market share decline in **Australia of dial-up internet subscribers**.

Then use your **BEST JUDGEMENT** to estimate **the likely share** for each of the **subsequent four years**.

Click on the empty cells below and type in your estimates

	year 7	year 8	year 9	year 10
Your est.				

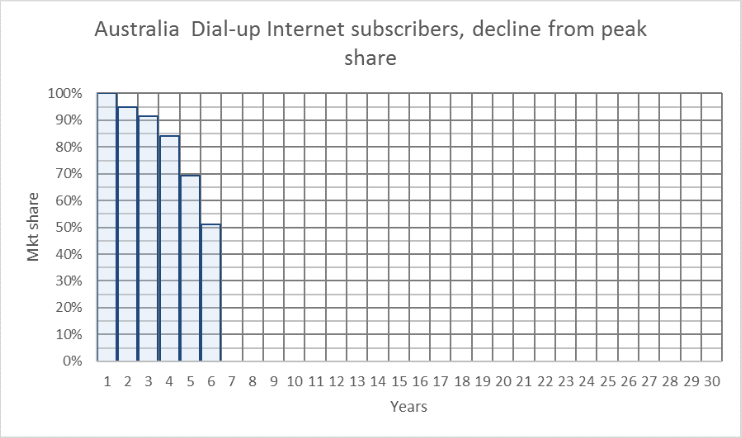
A flow logic action: Skip To demographic section "After six tasks done?" = Yes

Page 3

Start of Block: Treatment 2: Alternative randomly assigned to treatment Graphical presentation

Sample question: Treatment 2 Q1

Here is a graph of numbers tracking the decline in the use of a technology, over a period of years. In this case, dial-up internet access. Dial-up was the first form of internet access. ADSL, the first broadband internet access technology, caused its decline.



Please review the above graph on the historical market share decline in **Australia of dial-up internet subscribers.**

Then use your **BEST JUDGEMENT** to estimate **the likely share** for each of the **subsequent four years**.

Click on the empty cells below and type in your estimates

	year 7	year 8	year 9	year 10
Your est.				

A flow logic action: Skip To demographic section "After six tasks done?" = Yes

Page 4

Start of Block: Demographic Block

I am also interested in; what industry employs you, your experience as a manager how much forecasting work you undertake and a little about you personally.

From the drop down list choice the industry that most suits the one in which you currently work.

- ▼ Primary (farming, fishing, mining, etc.) (1) ... Education (10)

How long across your career have you held management roles (jobs)

○ less than 12 months

○ over 12 months but less than 2 years

○ over 2 years but less than 5 years

○ over 5 years but less than 10 years

○ over 10 years but less than 15 years

○ over 15 years

In your current role how frequently are you involved in preparing or reviewing forecasts

○ At least Annually

○ At least quarterly

○ at least monthly

○ more frequently than monthly

○ never

In what year were you born?

- ▼ 1920... 2000

Are you male? or female?

- ○ Male
- ○ Female

What is the highest level of education you have completed?

- ○ Less than High School
- ○ High School
- ○ Post High School Diploma
- ○ Undergraduate Degree
- ○ Masters Degree
- ○ Doctoral Degree
- ○ Other Degree e.g. professional

Org Size Approximately how many people work for your employer?

- ○ 1 to 4
- ○ 5 to 9
- ○ 10 to 19
- ○ 20 to 49
- ○ 50 to 99
- ○ 100 to 249
- ○ 250 to 499
- ○ 500 to 999
- ○ 1000 or more

End of Block: Demographic Block End of Survey skip to "thankyou" statement