The Mechanisms that Drive Disruptive Innovation

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Abstract

Disruptive innovation as a theory lacks concrete definition and is often misinterpreted in the literature. Previous studies dealing with the phenomenon largely focus on the process of market disruption and the factors that drive the process. However, little research exists that seeks to quantitatively validate existing theory. In response to these problems, we develop a market growth model that is capable of analysing multiple market segments and innovations. Building on existing models of consumer choice and innovation diffusion, we develop a utility-based model that considers the effects of preference structure, demand structure, and development dynamics on market disruption. The model is simulated using data on worldwide shipments of hard disk drives (HDD) across four market segments, namely: mainframe, minicomputer, desktop computer, and portable computer markets.

Results show that the proposed model is capable of estimating successive waves of disruptive technological innovation experienced in the HDD industry. Furthermore, qualitative analysis of differing preference structures, demand structures, and development dynamics provide significant insights into how the process occurs. We find that the distance between market segment preferences, the magnitude of optimal demand, and growth rates in technological improvement and absorptive capacity directly influence the speed and likelihood of market disruption. Findings suggest that disruption is not always absolute. Disruptive and disrupted innovations can coexist in the market under certain conditions. Thus, the structure of the market and competition determine the diffusion behaviours of disruptive innovations.

Table of Contents

Table of Tables

Table of Figures

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Author's Declaration

I hereby declare that this thesis entitled 'The Mechanisms that Drive Disruptive Innovation' represents the results of my own work except where specified in the thesis.

Matthew Paul Mount

Author's Publications

MOUNT, M. P. & FERNANDES, K. F. 2011. The Adoption of Free and Open Source Software within High-Velocity Firms. *Behaviour and Information Technology*

MOUNT, M. P. & MILEWSKI, S. 2012. The mechanisms in open innovation intermediaries for facilitating the commercialization of nanotechnology. *R&D Management Conference*

1. Introduction

The purpose of this Chapter is to provide background and context to the intended research. Firstly, we introduce the importance of innovation for sustained economic growth and its relationship with organisational performance. Specifically we focus on the notion of disruptive innovation and the growing need for firms to harness and exploit disruptive technological threats in order to remain competitive. We explicitly identify the gaps in knowledge that became the focus of this investigation, and present a clear research question and objectives. The Chapter concludes with the theoretical framework driving the research process and research contributions.

1.1. Background

Innovation is often attributed as being the primary source of economic growth, industrial change, and competitive advantage (Damanpour et al. 2009, Schumpeter, 1934). As a result, researchers from diverse backgrounds such as sociology, engineering, economics, marketing, and psychology are interested in the outcome of innovations research (Gopalakrishnan and Damanpour, 1997). Firms pursue innovation in order to improve performance, both financial and operational. The suggested link between iterative organisational innovative activity and firm performance is well established in the literature (Cohen and Levinthal, 1990, Damanpour et al. 2009, Roberts and Amit, 2003, Wolfe, 1994). Roberts and Amit's (2003) study of Australian retail banking organisations concludes that firms with greater innovative intensity experience improved financial performance. They state, "*a firm's competitive position is a function of its unique history and innovative activity*" (2003; 118). Furthermore, Damanpour et al. (2009) support this proposition in their study of UK service organisations. They conclude that firms that engage in diversified innovative activity experience improved organisational performance.

Disruptive innovation is emerging as an innovation of strategic importance for both incumbent and entrant firms (Yu and Hang, 2010). Generally, they are defined as innovations that dramatically disrupt the market and change the bases of competition (Schmidt and Druehl, 2008). The importance of disruptive innovation is widely recognised in both academic and practitioner literature (Linton, 2002), and at the core of dynamic organisational capabilities and continuous economic development (Keller and Hüsig, 2009). The Schumpeterian (1942) ideal of '*creative destruction*' captures this concept and the importance of disruptive innovation in modern society. Schumpeter (1942) believes that innovation is the cause for existing ideas and technologies becoming obsolete, thus '*creative destruction*' is the catalyst for sustained economic growth.

Disruptive innovations are a powerful means for broadening and developing new markets and providing new functionality in existing market segments (Govindarajan and Kopalle, 2006a, Di

Stefano et al., 2012). They create growth in the industries they penetrate, or create entirely new industries through the introduction of products and services that transform the existing dynamics of competition (Adner, 2002, Danneels, 2004, Kostoff et al. 2004). As coined by Clayton, M. Christensen (1997), disruptive innovation is defined by the outcome of a specific process, characterised by: (1) a transformation of existing competitive dynamics; and (2) the failure of incumbent firms. For example, Bower and Christensen (1995) document the disruption experienced in the hard disk drive (HDD) industry (Christensen and Bower, 1996). They state (1995; 45) that "*not one of the independent disk-drive companies that existed in 1976 survives today*". Furthermore, the dynamics of competition shifted from overall '*storage capacity*' to performance dimensions such as '*physical size*' and '*price*' (Bower and Christensen, 1995, Danneels, 2004).

Growing competitive pressures and market forces are increasing the importance of innovation as a source of competitive advantage (Descza, 1999; 613). However, management myopia towards future emerging markets and organisational core rigidities such as '*employee knowledge and skills'*, '*technical systems'*, '*managerial systems'*, and '*values and norms'* (Leonard-Barton, 1992), directly inhibit a firm's response to disruptive technological change. The pursuit of disruptive innovation is a strategic imperative for firms seeking long-term competitive advantage and financial performance. Lucas Jr and Goh (2009) find that dynamic capabilities and management propensities for change are essential in the pursuit of disruptive innovation. However, there exists no framework for the ex-ante identification of potentially disruptive innovations. Consequently, organisational capability to respond to disruptive change is limited.

Despite how widespread Christensen's seminal work on disruptive innovation has become in business circles, there seems to be lack of definition regarding the core concept of the theory. In Danneels' reconsideration of disruptive innovation theory, he concludes, "*Christensen does not establish clear-cut criteria to determine whether or not a given technology is considered a disruptive technology*" (2004; 247). Such lack of definition has caused a separation of the term from its theoretical basis. Specifically, he asks such questions as:

- "*What exactly is a disruptive technology"?*
- *"What makes a technology disruptive"?*
- *"What are the exact criteria for identifying a disruptive technology"?*
- *"Is disruption the outcome of structure, size, heterogeneity, and evolution of market segments"?*

Similarly, Tellis (2006) identifies limitations regarding the definition of disruptive innovation. Insight from the literature reveals a plethora of disruptive characteristics including: *low-cost*, *technically simple*, *low-profit margins*, *inferior performance*, *mainstream customer rejection*, *performance* *oversupply*, *preference overlap*, and *asymmetric competition*, among others. As a result, the literature is flooded with conflicting and contradictory definitions of the concept, thereby limiting the advance of future research. Thus, this research aims to bridge this gap in knowledge through the identification of *essential* vs. ancillary characteristics of disruptive innovation (Danneels, 2004).

Similar to the language problems inherent in general innovations research (Linton, 2009), disruptive innovation suffers from similar inconsistencies in definition (Danneels, 2004, Tellis, 2006). Garcia and Calantone (2002) demonstrate how inconsistencies in labelling innovations have hindered academic advancements for identifying new product development (NPD) processes of different innovation types. Existing definitions of disruptive innovation include effects relating to ***market dynamics*** (disruptive vs. sustaining); ***organisational competencies*** (competence destroying vs. competence enhancing), and ***technological discontinuities*** (discontinuous vs. continuous). The diverse opinion surrounding the definition of disruption hinders future development of the phenomena. According to Adner (2002), the underlying theoretical drivers of technology disruption and diffusion remain largely unknown.

Far from exhibiting static equilibrium, the diffusion of disruptive innovation is characterised by high complexity and influenced by unpredictable internal and external dynamics. These include a mixture of competitive (Adner, 2002), technological (Christensen, 1997, Hüsig et al. 2005), and environmental dynamics. Thus, there is a need for a multi-dimensional consideration of such interactions to understand the complexity involved in the emergence of disruptive innovations.

With this in mind, the overall objective of this research is to provide a deeper understanding of how disruptive innovations emerge in the market. Christensen's offers a qualitative case based explanation to disruptive innovation theory, thus the theory lacks quantitative validation. The aim of this research is to both validate a theory of disruption and provide a clearer understanding of the mechanisms that drive the diffusion process of disruptive innovations in established mainstream markets. The research delivers three significant contributions:

1. Provides clarity to the definition of disruptive innovation and the factors that influence the process.
2. Provides empirical validation to the theory of disruptive innovation
3. Identifies and models the competitive dynamics and market conditions that enable disruptive diffusion.

Results of the study provide a rich foundation for understanding the conditions that facilitate disruptive diffusion. Furthermore, we add clarity to the research themes identified by Danneels (2004) through testing the effects of differing dynamics on competitive outcomes – i.e. consumer preference structure, demand structure, and development dynamics. The model will provide practitioners with a tool to help inform future innovation strategies and innovation investment decisions, improve and optimise firm-level segmentation strategies, and to forecast the success of potentially disruptive innovations and emerging competitive threats.

1.2. Research Questions and Objectives

To address the highlighted gaps in knowledge, we develop an overarching research question. The primary objective of the research is to derive a diffusion model that explicates the conditions that enable disruption. The question is decomposed into five sub-questions outlined in Table 1.A; this allowed for a systematic approach to solving the identified problem.

Table 1.A Research Questions

Research Question:	**What are the key mechanisms that drive the diffusion process of disruptive innovation in established mainstream markets?**
Sub-Question 1	*1. Define the disruptive innovation process;*
Sub-Question 2	*2. What are the factors that affect the disruptive innovation process and their relationships to disruption;*
Sub-Question 3	*3. Understand and explain the relationship(s) between the 'factors' of disruption and the diffusion process;*
Sub-Question 4	*4. Use the information obtained from 2 and 3 to Model the process of disruption and provide explanation of the key mechanism(s) that drive the process;*
Sub-Question 5	*5. Explain the diffusion pattern of disruption and demonstrate the differences between disruption and other competitive outcomes.*

1.3. Research Framework

The relationship between the literature and research questions is illustrated in Figure 1.A. The literature review covers three broad areas: innovation, disruptive innovation, and the diffusion of innovations and consumer choice. The primary aim of the literature review is to provide a better understanding of: (1) how disruption is operationalised and defined; (2) how disruptive innovations invade and diffuse in mainstream markets; and (3) how the process of disruption can be modelled?

- *Innovation (Chapter 2)*

We review the literature on definitions of innovation and the relationship between innovation and firm performance. The Chapter identifies innovation characteristics: – competence-enhancing vs. competence-destroying; discontinuous vs. continuous; and disruptive vs. sustaining, and evaluate their impact on three primary dimensions: organisational, technological, and market dimensions respectively.

- *Disruptive Innovation (Chapter 3)*

When considering disruptive innovation we review the existing theory as coined by Christensen (1997), and explore wider definitions and critiques of the theory proposed by Hüsig et al. (2005) and Keller and Hüsig (2009) among others. The initial review helps to answer the following three questions:

1. *What is disruptive innovation*: *How does disruption occur?* An analysis of existing definitions and measures of disruptive innovation help to identify the factors of disruption synonymous with Sub-Question 1.
2. *What are the measures of disruptiveness: What are the factors of disruptive innovation: Are existing measures reliable?* We identify the essential and ancillary characteristics of disruptive innovation to derive an objective definition of the concept. A review of the relationship between disruptive innovation and incumbent firm failure is explored and re-evaluated.
3. *What is the relationship between disruptive innovation and incumbent firm failure*? *Are they dependent or independent events*? Finally, a discussion on responding to disruptive innovation and a critique of existing theory is conducted. Consideration of these points will assist in achieving Sub-Questions 1 and 2.

- *Models of Diffusion and Consumer Choice (Chapter 4)*

Disruptive innovations emerge from successive incremental improvements in innovation generations, and are influenced by consumer preferences, market structure, and technology development. With the aim of trying to consolidate diffusion, consumer choice effects, and factors of disruptive innovation into an integrated model, we examine previous modelling approaches to derive an optimal strategy.

A review of existing diffusion models are presented and evaluated from the management literature, namely *agent-based models, probit models, epidemic models,* and *disruptive innovation models* of diffusion. We consider models that include multiple markets, technology generations, marketing mix variables, and multiple agents. A review of existing consumer choice models that utilise the principles of *MAUT (Multi-attribute utility theory)* is also provided. We limit our analysis to choice models that are based upon the MNL (multinomial logit) and LOGIT formulation. In addition, we evaluate existing models that combine diffusion effects, consumer choice dynamics, and preference heterogeneity.

- *Model of Disruptive Innovation (Chapter 5)*

We present both the modelling framework and model specification that considers the choice effects and diffusion dynamics in a single process. In the model framework, the factors – *preference structure, demand structure*, and *development dynamics,* and their relationships to market disruption are identified. A series of propositions are developed relative to the identified factors for subsequent testing. In the model specification, the mathematical underpinnings of the model are presented and defined sequentially based upon models of consumer choice and diffusion reviewed in Chapter 4.

Finally, we nest the model in a real world application using the case of the HDD industry. We use the HDD industry as it is recognised as the benchmark example of disruptive innovation by Christensen and colleagues. Four independent market segments are identified (mainframe, minicomputer, desktop, and portable) served by four specific innovations (14-inch, 8-inch, 5.25-inch, and 3.5-inch respectively). The proposed model seeks to explain the disruption as experienced in the four aforementioned market segments and innovations.

- *Research Methodology (Chapter 6)*

In this Chapter, we present the research strategy, research design, and research methods used in the study. The research strategy introduces the two-phase approach adopted to address the research question. Phase one is a confirmatory quantitative investigation used to validate the proposed model of disruptive innovation. Phase two is an exploratory qualitative investigation of the dynamics that drive the process of disruption i.e. – preferences, demand, and development dynamics. We document the data considerations for each phase in Section 6.1. The agent-based modelling (ABM) methodology used for quantitative and qualitative investigation is introduced in the research design section. Finally, in the research methods section we document the tools used for data analysis.

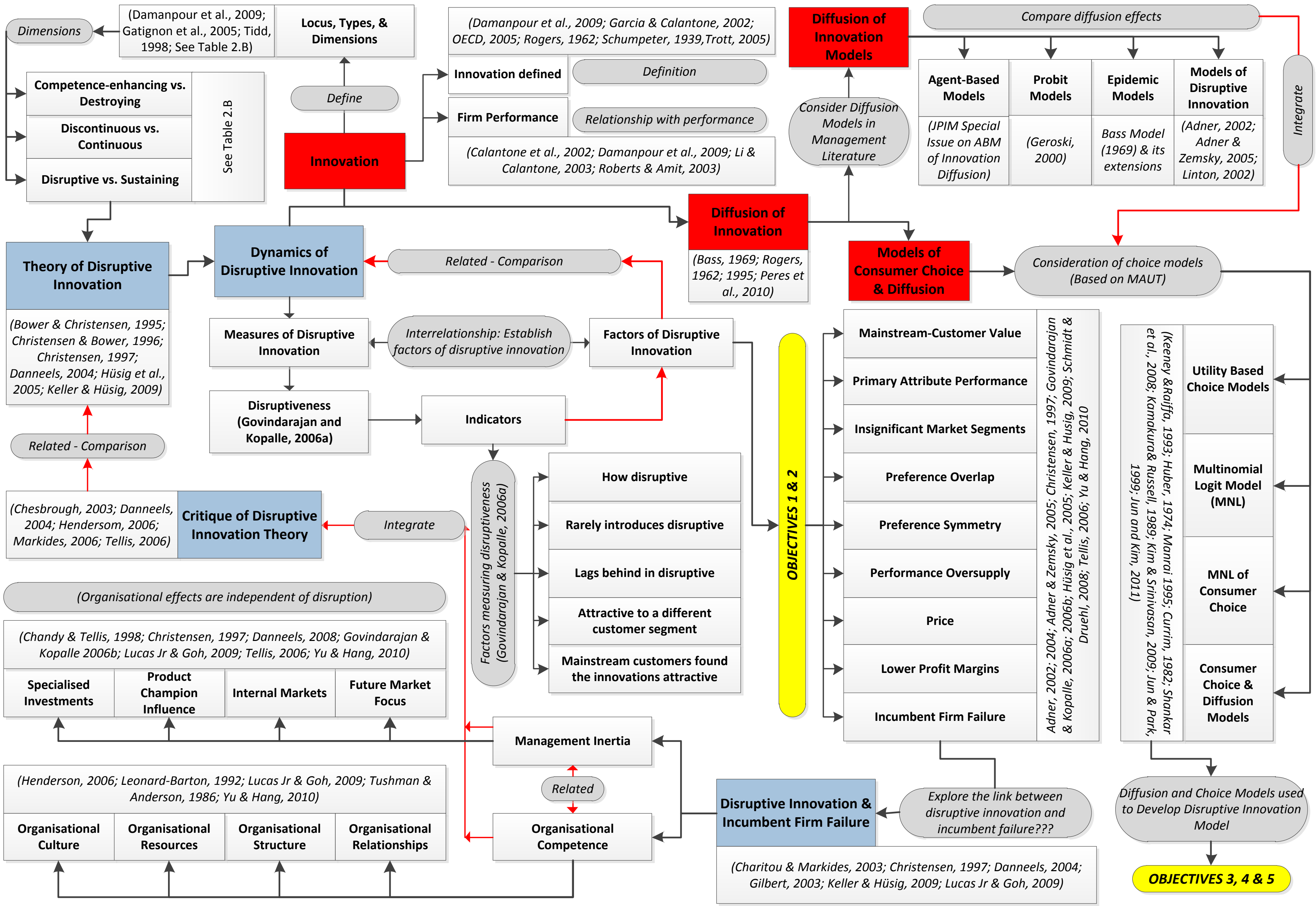
- *Analysis and Results (Chapter 7)*

In the first stage of our analysis we validate the quantitative model with real data from the HDD industry and present the results. In the second stage of our analysis, we modify the model inputs in order to evaluate the impact of preference structure, demand structure, and development dynamics on market disruption. Qualitative analysis of these factors allows us to derive further insights into the mechanisms that drive the process of disruption, thus leading to an improved understanding of the phenomenon. Based upon the model results we document the managerial implications and develop a managerial response and initiation framework for disruptive innovation.

- *Conclusions (Chapter 8)*

The final Chapter summarises the key contributions of the study in the context of academic theory, methodology, and managerial practice and policy. Furthermore, we address the key limitations of the study and provide direction for potential future research.

Figure 1.A Research Framework



1.4. Research Contribution

The contribution of this research is threefold. Firstly, we aim to define disruptive innovation and establish the factors that influence the process (Chapter 3). Disruptive innovations are game changing technologies that transform competition and the structure of market demand (Danneels, 2004), thus providing a catalyst for new growth and industry creation (Lucas Jr and Goh, 2009). As a result, understanding disruptive innovation, market environments, and technology development is important for remaining competitive. Established factors from Chapter 3 form the basis for deriving a diffusion model of disruptive innovation.

The second most influential contribution is the development of a disruptive innovation diffusion model that quantitatively validates the theory of disruptive innovation. Currently the theory is only supported with qualitative case based findings, and disruptive innovations are only labelled as such in hindsight (Sood and Tellis, 2011). The proposed model further develops the theory introduced by Christensen (1997) by providing a quantitative empirical validation of market disruption and qualitative investigation of how the process occurs. The model can be adapted and used by managers as a tool to evaluate the disruptiveness of innovations in their own competitive marketplace. Furthermore, the model can be used to simulate multiple hypothetical scenarios in the context of different market structures and innovation development dynamics. Therefore, managers can use the model to derive optimal innovation, R&D, and segmentation strategies based on the scenario that provides the preferred organisational outcome. We derive a utility-based diffusion model of disruption and develop a series of testable propositions regarding how consumer preferences, demand structure, and development dynamics influence disruption (Chapter 5).

Finally, the proposed model will contribute to existing theory by extending the works of Christensen (1993, 1997) and other popular proponents of disruptive innovation theory (Hüsig et al., 2005, Keller and Hüsig, 2009), to derive a more coherent concept of market disruption. Many researchers have commented on the lack of understanding with regards to the underlying factors that drive the process of market disruption (Danneels, 2004; Sood and Tellis, 2011). Therefore, the results that emerge from this research will provide a significant contribution to knowledge with regards to the development and refinement of existing theory.

The proposed quantitative model will be used to conduct a qualitative investigation of the underlying mechanisms that drive the process of market disruption to assist in the development of new theory. By adjusting the quantitative model inputs, new insights are developed with regards to the impact of differing market and development dynamics on market disruption. Currently, there exists no model that simultaneously considers macro-level diffusion factors and micro-level preference, demand, and development interactions (Section 4.2). Adner (2002; 667) states that:

> "*Understanding the theoretical drivers and conditions that give rise to market disruptions is fundamental to assessing the pervasiveness of the phenomenon and for guiding strategic responses to potentially disruptive threats*".

The model will provide practitioners with an improved tool for forecasting the demand of disruptive innovations and evaluating the potential invasion capability of new innovations in mainstream markets.

2. Innovation and Diffusion of Innovation

In this Chapter we present an extensive review of the literature regarding innovation, types of innovation, and characteristics of innovation. The innovation literature is expansive and diverse, but two important streams can be distinguished: (1) theories of innovation type (typologies, dimensions, characteristics and their impacts); and (2) the diffusion of innovations, which concerns the spread of innovations in markets (Lyytinen and Rose, 2003). The focus of this Chapter is the first stream, whereas the second stream is addressed in Chapter 4.

Innovation and technical change are at the core of dynamic organisational capabilities (Gatignon et al., 2002, Teece and Pisano, 1994, Teece et al., 1997). As such, the importance of innovation and its relation to organisational performance is well documented in the literature. In this Chapter, we define ‘innovation’ and consider the different types and characteristics of innovation from the perspective of three primary dimensions – organisational, technological and market. Based on the outcome of the literature review we developed an innovation framework for analysing the cumulative impact of new innovations. The Chapter is organised as follows:

1. Section one provides a definition of innovation, and highlights the relationship between innovation and organisational performance.

2. Section two considers the different types, dimensions, typologies and characteristics of innovation evident from the literature. Fundamental concepts of innovation are often confused and/ or ambiguous due to the voluminous nature of innovations research and inconsistencies in existing classifications (Garcia and Calantone, 2002, Gatignon et al., 2002). From an extensive review of previous classifications (Table 2.B), we distinguish between innovation ‘types’ and ‘characteristics’, and develop a framework for integrating existing innovation categorisations into a single structure to analyse the cumulative impact of innovations along three dimensions: organisational competence, technological base, and market dynamics.

2.1. Innovation

Innovation and innovative capability are important to organisations seeking to improve performance. The link between innovation and firm performance is well established in the management literature (Crossan and Apaydin, 2010). By adopting innovations over time, organisations intend to adjust their external and internal functions so that they can respond to environmental demands, operate efficiently and effectively, and maintain or improve overall performance. Empirical evidence suggests that organisational level engagement in innovative activity improves overall performance. Table 2.A summarises some of the explored linkages between innovative activity and firm performance from existing literature:

Table 2.A Relationships between Innovation and Firm Performance

Dimension	Performance Measure	Sample & Method
	(Calantone et al., 2002)	
Firm Innovativeness – propensity to engage in innovative activity	Return on Investment (ROI), Return on Assets (ROA), Return on Sales (ROS), and Overall Profitability	US Technology Firms Confirmatory Factor Analysis
	(Li and Calantone, 1998)	
New Product Advantage	Before-tax Profit, Return on Investment (ROI), Product Market Share, and Pre-tax Profit Margin on Product.	US Software Industry Confirmatory Factor Analysis
	(Roberts and Amit, 2003)	
Innovative Activity[1]	Return on Assets (ROA)	Australian Banks Least-Square Regression
	(Damanpour et al., 2009)	
Innovation Types	Service Performance: Quantity of Outputs, Quality of Outputs, Efficiency, Formal Effectiveness, Equity, and Consumer Satisfaction.	UK Public Service Organisations Time Series Regression Models

Calantone et al., (2002) conclude that firm innovativeness is positively related to a firm's financial performance. As a result, an organisation's capacity to understand customers, competitors, and engage in technological development facilitates sustained competitive advantage. Li and Calantone (1998) support this conclusion, they find that a firm's existing market knowledge i.e. market information, tacit knowledge structures, and R&D capabilities, contribute towards new product advantage and innovation. More recent studies (Damanpour et al., 2009) suggest that a firm's engagement with diversified innovative activity and history of innovative activity improve overall performance (Roberts and Amit, 2003). Roberts and Amit (2003; 118) state that: "*firms that are more active and consistent in their innovative activity tend to experience superior financial performance*".

Thus, winners in the global marketplace are firms that engage in consistent innovative activity, exhibit strong R&D capabilities, and demonstrate timely responsiveness to changes in the environment with rapid and flexible innovation (Teece and Pisano, 1994, Teece et al., 1997). As a result, it is important to understand the dynamics of innovation, innovation types and characteristics, and the mechanisms and processes that drive innovative activity.

[1] Reader is referred to Roberts, P. W. and Amit, R. (2003). The Dynamics of Innovative Activity and Competitive Advantage: The Case of Australian Retail Banking, 1981 to 1995. *Organisational Science*, 14, 107-122.

2.1.1. Definition of Innovation

Innovation has been studied in many disciplines and has been defined from many different perspectives. Traditionally, Schumpeter (1939; 59) defines innovation from a broad range of events that include:

> "*The introduction of new commodities, technological change in the production of commodities already in use, the opening up of new markets or of new sources of supply, improved handling of material – in short, any form of 'doing things differently' in the realm of economic life*".

In its simplest form, an innovation is defined as "*an idea, practice, or object that is perceived as new by an individual or other unit of adoption*" (Rogers, 1962; 12). A new idea can be a product, service or process. However, such ideas only become innovations when they have been commercialised to market. Often the terms *invention* and *innovation* are misconstrued and used interchangeably in the literature, although a clear demarcation exists. Invention is the conception of an idea or prototype, whereas innovation is the process under which inventions are successfully commercialised (Trott, 2005). More comprehensive definitions state that innovation is an iterative process initiated from the conception of a new idea to the production and marketing of that idea to market (OECD, 2005; Myers and Marquis, 1969). According to Garcia and Calantone (2002; 112), this definition addresses two important distinctions:

1. *"The innovation process comprises the technological development of an invention and market introduction of that invention to end-users."*
2. *"The innovation process is iterative in nature and thus, automatically includes the first introduction of a new innovation and re-introduction of an improved innovation".*

Three common underlying elements emerge from the literature that forms the basis of a widely accepted definition of innovation: *newness*, *implementation*, and *iterative process*. Newness can refer to the individual adopter, firm, sector, industry, market, or innovation itself (Damanpour et al, 2009; Garcia and Calantone, 2002). Rogers (1962) stresses that an innovation encompasses the implementation of an idea that is perceived as new by the relevant unit of adoption (Calantone et al., 2002). The differentiating factor is the degree of newness to the adopter. Although subtle differences exist between definitions of innovation, 'newness' emerges as a common characteristic. Implementation refers to the process associated with commercialising an innovation i.e. the development process of an invention through to its commercialisation as an innovation in the marketplace (Trott, 2005; OECD, 2005; Rogers, 1962). Iterative process is best understood from differentiating between the concepts of invention and innovation: Inventions must be commercialised through an iterative development process i.e. a transformation before they are operationalised into a commercial innovation. Processes include R&D, manufacturing, commercialisation, and marketing.

2.2. Types, Dimensions, and Typologies of Innovation

Innovations are often categorised into types, dimensions, and typologies as a means of identifying their innovative characteristics or degree of innovativeness (Garcia and Calantone, 2002). Such categorisations help us to understand the effects and characteristics certain innovations possess. For example, Abernathy and Clark (1985) evaluate the impact of technological innovations from two dimensions; (1) *technology and production*, and (2) *market* and *consumer linkages*. Technology and production refers to the effects an innovation has on the design and embodiment of existing technologies and an organisation's production inputs i.e. "*skills*, *knowledge*, *systems* and *supplier networks*". Market and consumer linkages refer to the effects an innovation has on the dynamics of competition and an organisation's customer base, including existing customer knowledge and relationships. They propose four typologies of innovation based upon how they map across these two dimensions; (1) *Architectural*, (2) *Niche Creation*, (3) *Revolutionary*, and (4) *Regular* innovations (Abernathy and Clark, 1985).

In contrast, Tushman and Anderson (1986), and Anderson and Tushman (1990), evaluate innovations relative to their impact on existing organisational capabilities: *competence enhancing* vs. *competence destroying* (organisational competence), and technological platforms – *continuous* vs. *discontinuous*, in order to establish patterns of technological change. Table 2.B provides an analysis of existing innovation classifications in terms of type, dimensions, characteristics, and typologies of innovation that are evident from the literature.

Due to the complexity of categorising innovation, a plethora of typologies have emerged that describe and classify innovations in terms of their associated characteristics and effects. Such categorisations include: *"administrative, architectural, technical, fundamental, minor, continuous, discontinuous, normal, routine, incremental, enabling, disruptive, sustaining, revolutionary, process, product, generational, and evolutionary"* (Linton, 2009; 729). Table 2.B illustrates that the differences between innovation type, dimension, and typology are often perplexing, thus causing ambiguity in definition. Lack of standards across definitions often makes it difficult to be clear about how innovations are classified (Garcia and Calantone, 2002, Linton, 2009). In some cases differing terminology is applied to the same innovation. For example, what is the difference between '*radical'*, '*discontinuous*', '*highly innovative*', '*radically new*' and '*really new*' innovations (Garcia and Calantone, 2002)? In each of the aforementioned cases the classification refers to a technological discontinuity i.e. a departure away from the existing technological standard. Gatignon et al., (2002; 1103) state:

> "*Innovation research often confounds innovation characteristics, innovation types, and the hierarchical locus of the innovation. With greater clarity on units of analysis and on innovation concepts and measures, research on innovation and organisational outcomes might be more cumulative and impactful*".

As a result, fundamental concepts are confused or ambiguous, thereby limiting the development of future innovations research. Table 2.B presents a summary of previous innovation classifications. We distinguish between innovation ***dimensions*** – the foundations from which the innovation is evaluated; ***characteristics*** – the magnitude of effect along certain dimensions; ***typologies*** – author classifications of innovation; and ***type*** – the specific form of innovation i.e. product, process, or service innovations etc. We identify three primary dimensions: (1) technological base; (2) organisational competence; and (3) market dynamics, where:

1. **Technological Base:** – refers to an innovation's impact on existing technological standards.
2. **Organisational Competence:** – refers to an innovation's impact on existing organisational competencies.
3. **Market Dynamics:** – refers to an innovation's impact on existing market and competitive dynamics.

INNOVATION CLASSIFICATIONS					
Author(s)	**Innovation Dimension**	**Innovation Characteristics**	**Typology**	**Examples**	**Innovation Type**
Single Dimension Classifications					
Robertson (1967)	Technological Base	Continuous (I) Discontinuous (R)	Continuous [I] Dynamically Continuous [I→R] Discontinuous [R]	Office 2007 → Office 2010 Normal Toothbrushes → Electric Colour TV → Digital TV	End-product Innovations
Kleinschmidt and Cooper (1991)		Low Innovativeness (I) High Innovativeness (R)	Low Innovativeness [I] Moderate Innovativeness [I→R] Highly Innovative [R]	Ford Fiesta Mark V → Mark VI DVD → Blue Ray DVD Cassette Tape → CD → MP3	
Wheelwright and Clark (1992)		Incremental (I) Radical (R)	Incremental [I] New Generational [I→R] Radically New [R]	Successive iPhone generations Branch Banking → Internet Banking Nintendo Wii	
Freeman (1994) Lee and Na (1994) Atuahene-Gima (1995) Balachandra and Friar (1997) Kessler and Chakrabarti (1999) Sheremata (2004)			Incremental [I] Radical [R]	MS Xbox → Xbox 360 PlayStation → PlayStation 2 → PlayStation 3 Film Cameras → Digital Cameras Fordism → Toyota Production System (Lean Manufacturing)	
Garcia and Calantone (2002)			Incremental [I] Really New [I→R] Radical [R]	Windows Vista → Windows 7 Hybrid Automobiles WWW.	

Christensen and Bower (1996) Bower and Christensen (1995) Christensen (1997) Christensen and Raynor (2003) Govindarajan and Kopalle (2006a) Keller and Hüsig (2009) Lucas Jr and Goh (2009)	Market Dynamics		Sustaining (I) Disruptive (R)	Sustaining [I] Disruptive [R]	Pentium III → Pentium IV Generic MP3 Players → IPod→ New Generation IPods FM / AM Radio → DAB Radio	End-product Technological
					Closed Source Software → Open Source Software (Business Models) Landline → Mobile Phone 8-inch Disc Drives → 5.25-inch → 3.5-inch Microsoft Office → Google Office Applications	End-product Business Model
Henderson and Clark (1990)	Technological Base	Core Component	Reinforced (I_{core}) Overturned (R_{core})	Modular [$I_{linkages}$ / R_{core}] Radical [R_{core} / $R_{linkages}$] Incremental [I_{core} / $R_{linkages}$] Architectural [I_{core} / $R_{linkages}$]	The authors use the example of the room air fan. If the established technology is a large, electrically powered fan mounted in the ceiling, improvement in blade design → **Incremental**. A shift to central air conditioning → **Radical**. New components e.g. compressors/ refrigerants → **Modular**. Introduction of a portable fan that changes component interaction → **Architectural**.	Sub-system –Core vs. Peripheral
		Component Linkages	Unchanged ($I_{linkages}$) Changed ($R_{linkages}$)			
Multi-Dimension Classifications						
Abernathy and Clark (1985)	Market Dynamics and Technological Base		Disrupt (R_{market}) Conserve (I_{market}) Disrupt ($R_{technology}$) Conserve ($I_{technology}$)	Architectural [R_{market} / $R_{technology}$] Niche Creation [R_{market} / $I_{technology}$] Revolutionary [I_{market} / $R_{technology}$] Regular [I_{market} / $R_{technology}$]	Ford Model T (1908) Ford Model A (1927) Closed Steel Body (1923) Lacquer Painting System (1923)	Product and Process Innovations
Veryzer (1998)			Same ($I_{technology}$)	Continuous [$I_{technology}$ / I_{market}]	Office 2007 → Office 2010	End-product

		Advanced ($R_{technology}$) Same (I_{market}) Advanced (R_{market})	Technologically Discontinuous [I_{market} / $R_{technology}$]	Vacuum Tube TVs → Solid State TVs	
			Commercially Discontinuous [$I_{technology}$ / R_{market}]	SONY Walkman	
			Technologically & Commercially Discontinuous [$R_{technology}$ / R_{market}]	First introduction of PCs and Pagers	
Benner and Tushman (2003)		Incremental (I) Radical (R)	NA	NA	
Beverland, Napoli and Farrelly (2010)[2]		Incremental ($I_{technology}$) Radical ($R_{technology}$) Market Driven (I_{market}) Driving Markets (R_{market})	Follower Brands [$I_{technology}$ / I_{market}]	Fast Grip; Fish Co	Brand
			Craft-Designer Led Brands [$I_{technology}$ / R_{market}]	Z-Bikini; Claret; Bubble	
			Category Leader Brands [$R_{technology}$ / I_{market}]	Spring Cheese; Red+White; Zesty Ci	
			Product Leader Brands [$R_{technology}$ / R_{market}]	Home Living; Shizuka; Milk Co	
Tushman and Anderson (1986) Anderson and Tushman (1990)	Technological Base and Organisational Competence	Incremental ($I_{technology}$) Radical ($R_{technology}$) Competence-enhancing ($I_{organisational}$) Competence-destroying ($R_{organisational}$)	Competence-enhancing discontinuity [$I_{organisational}$ / $R_{technology}$]	Mechanical → Electric Typewriters	End-product
			Competence-destroying discontinuity [$R_{organisational}$ / $R_{technology}$]	Steam → Diesel Locomotives	
			Incremental, Competence-enhancing [$I_{technology}$ / $I_{organisational}$]	PDP-8 Minicomputer → PDP- 11	
			Incremental, Competence-destroying [$I_{technology}$ / $R_{organisational}$]	8-inch Disc Drives → 5.25-inch → 3.5-inch	

Table 2.B Innovation Classification Table

[2] Beverland et al., (2010) use a typology of brand positioning to establish a firms' innovation orientation – they use examples of firm-level brand identity to categorise firms in terms of their innovation orientation along two dimensions: (1) technological innovativeness; and (2) market orientation. As such, the examples provided represent brands – reader is referred to Beverland, M. B., Napoli, J. and Farrelly, F. (2010). Can All Brands Innovate in the Same Way? A Typology of Brand Position and Innovation Effort. *Journal of Product Innovation Management*, 27, 33-48.

In Table 2.B we integrate existing classifications of innovation in order to illustrate how innovations are categorised and defined. Innovations are evaluated along specific dimensions relative to the magnitude of their impact. New innovations can either incrementally (**I**) or radically (**R**) affect the innovation dimensions: Organisational Competence (*competence-enhancing* (**I**) vs. *competence-destroying* (**R**)); Technological Base (*continuous* (**I**) vs. *discontinuous* (**R**)); and Market Dynamics (*sustaining* (**I**) vs. *disruptive* (**R**)). However, literature suggests that innovations can also occupy a position between incremental and radical effects (**I→R**). Researchers use these distinctions to create typologies of innovation that reflect an innovation's impact.

For example, Robertson (1967) classifies innovation from a technological perspective: "*Continuous*" innovations incrementally effect existing technology, reaffirming the existing technological standard; "*discontinuous"* innovations radically affect existing technology, shifting technological standards towards a new paradigm; and "*dynamically continuous innovations have more radical effects than a continuous innovation, but do not alter the existing technological paradigm*" (Robertson, 1967; 15). Garcia and Calantone (2002), Kleinschmidt and Cooper (1991), and Wheelwright and Clark (1992) among others, provide similar distinctions to Robertson (1967), but use conflicting terminology. Such lack of standardisation causes ambiguity in how innovations are defined (Linton, 2009). As a result, we propose a new framework for assessing the aggregate level impact of new innovations. We integrate existing typologies and dimensions of innovation into a single framework for assessing the impact of innovations, thus making future research more cumulative and impactful.

2.2.1. Innovation Locus and Unit Level of Analysis

We define innovation locus as the point from which the innovation process originates. Crossan and Apaydin (2010) differentiate between closed (internally driven) and open processes (network driven) of innovation, whereas Gatignon et al., (2002) focus on a more internal, mirco-level approach that differentiates between core and peripheral subsystem processes. From this perspective innovations are composed of hierarchically ordered subsystems or modules (Abernathy and Clark, 1985, Gatignon et al., 2002, Henderson and Clark, 1990, Tidd, 1995). For example, the automobile is characterised by an order of subsystems that comprise both engineering systems (e.g. the engine) (Abernathy and Clark, 1985) and on-board computer systems.

Gatignon et al., (2002; 1106) define core subsystems as "*those that are tightly coupled to other subsystems"*; whereas peripheral subsystems *"are weakly coupled to other subsystems*". As a result, technological change experienced in core subsystems will directly influence the composition and linkages between other integrated peripheral subsystems. Shifts in core subsystems will have cascading effects throughout the whole product or process due to the increased connections of subsystem interactions. This can be the driver of radical technological change (Gatignon et al., 2002, Henderson and Clark, 1990, Tidd, 1995). In contrast, technological change experienced in peripheral subsystems may be more indicative of incremental innovation. The impact of subsystems level innovation in complex products depends both on the degree of coupling and the linking mechanisms between subsystems. Coupling is the measurement of dependence of one system on another system. Tidd (1995; 308) identifies three characteristics of complex product systems:

1. *"Systemic – consists of numerous components and subsystems;*
2. *Multiple interactions across different components, subsystems, and levels;*
3. *Nondecomposable – cannot be separated into its components without degrading performance".*

In addition to locus, the unit level of analysis is also important when assessing the impact of innovations. Gatignon et al., (2002; 1104) state "*innovation is often measured and conceptualised at the product level of analysis even when the empirical referent has been at the subsystem level of analysis*". Differences in perspective can change the degree of impact observed along different dimensions of innovation. For example, a radical change in technological subsystems may only be experienced as an incremental change at the higher systems level. For example, oscillation in watches is a change in the subsystem that has little effect on the performance of the end product (Gatignon et al., 2002). Similarly, the disruption experienced by firms in the US hard disk drive (HDD) industry was not replicated in Japanese firms (Chesbrough, 2003). This is because innovation is a relative phenomenon. Therefore, unit level of analysis is an important distinction when evaluating the impact of new innovations. Product, process, subsystems, business model, industry, firm, or individual, are just a few of the referent levels from which to analyse innovation (Linton, 2009; Markides, 2006).

2.2.2. Innovation Type

Traditionally, Schumpeter (1939) defines innovation as any means of doing something new for economic development, this includes: the introduction of new products, new production processes, and technical and subsystems developments. Innovation researchers have introduced many such conceptual '*type*' classifications of based on an innovation's characteristics and environmental and organisational factors (Damanpour et al., 2009). For example, *technical*, *administrative*, *disruptive*, *sustaining*, *continuous*, *discontinuous* are to name but a few.

In Section 2.2, we demonstrate that current classifications confound innovation type with characteristics, dimensions, and typologies (Garcia and Calantone, 2002; Gatignon et al., 2002). However, academics generally define innovation type based upon their form (Crossan and Apaydin, 2010) i.e. product, process, service, and technical innovations (architectural and modular). To retain parsimony, we refer to architectural and modular subsystems level innovations as '*technical innovations*'. We demonstrate three dominant types of innovation that formulate the PPT (Process, Product & Technical) classification. Utterback and Abernathy (1975) originally distinguish between product and process innovations:

Process Innovations are a means of doing something better. Utterback and Abernathy (1975; 641) define process innovations as the "*system of process equipment, workforce, task specifications, material inputs, work and information flows that are employed to produce a product or service*". Process innovations aim to improve an organisation's efficiency and effectiveness of internal resources and skills. These include; manufacturing configurations, new technological processes, and production processes that are central to the technological core of the organisation (Gopalakrishnan and Damanpour, 1997, Damanpour et al., 2009). Damanpour et al. (2009) label process innovations that impact the technological core of organisations – "*technological process innovations*". However, new processes are also associated with the administrative core of the organisation. Whereas technological process innovations are directly related to the organisation's operating systems, "*administrative process innovations"* are indirectly related to the organisation's operating systems (Damanpour and Evan, 1984; Damanpour et al., 2009).

Administrative processes involve: The reconfiguration of organisational structures; new knowledge used in performing the work of management; new approaches and practices to motivate and reward organisational members; new strategies and structure of tasks and units; modifications of the organisation's management processes; and the implementation of new managerial skills that enable the organisation to function and succeed by using its resources effectively (Damanpour and Gopalakrishnan, 1998; Damanpour et al., 2009). Similarly, business model innovations fall into this category. They redefine the delivery of existing products and services to the end-customer. Markides (2006; 20) defines a business model innovation as "*the discovery of a fundamentally different business model in an existing business or industry*". For example, EasyJet and Jet2 compete in fundamentally different ways from traditional airline suppliers such as British Airways. The unit level of analysis used here is not necessarily the firm, but rather the overall production process or administrative processes that are employed to create a new product or service.

Product Innovations: Utterback and Abernathy (1975) relate product innovation to stages of the product life cycle and a firm's decision to either innovate or imitate. As such, Utterback and Abernathy (1975) inherently include technological radicalness in their definition, as a new product innovation initiates a new technological trajectory. They define new product innovations as "*a new technology or combination of new technologies introduced commercially to meet a user or a market need*." (1975; 642). The Schumpeterian (1942) perspective of new product innovations includes both new products and services. As a result, we adopt the view that a new product innovation compromises a new technological advancement or combination of technological advancements that result in new products or services to end-users.

Other innovation type classifications also exist in the literature. For example, Gatignon et al., (2002) and Henderson and Clark (1990) differentiate between innovation types from a subsystems perspective. Different types of innovations are derived based on changes in these subsystems and the mechanisms that link them together, which we term '*technical innovations'*.

Technical Innovations include technological advancements in products, processes and technologies that are used to produce and deliver products and services (Gopalakrishnan and Damanpour, 1997). Many researchers differentiate between '*architectural*' and '*generational (modular)*' technical innovations (Henderson and Clark, 1990; Gatignon et al., 2002; Tidd, 1995). These classifications emerge from the notion of innovations being nested within hierarchies of subsystems and linking mechanisms. Henderson and Clark (1990; 12) provide a matrix for defining innovation from this perspective (Figure 2.A):

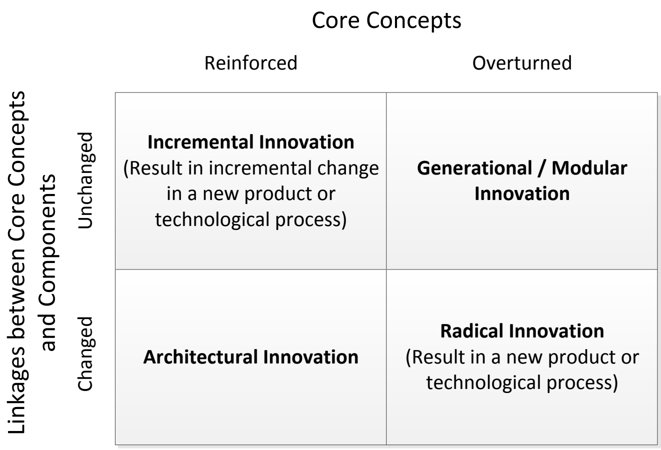


Figure 2.A Technical Innovations Matrix

Architectural innovation involves the reconfiguration of an established system to link together existing components in a new way i.e. changes between the linkages of existing subsystems (Gatignon et al., 2002, Henderson and Clark, 1990). This creates new interactions and new linkages with other components in established products and technological processes (See Table 2.B. for the example of the room air fan – Henderson and Clark, 1990). Generational innovations involve changes in the core design concepts and subsystems without changing the product's technological architecture or linkages (Gatignon et al., 2002; Henderson and Clark, 1990).

Evidently, there is a strong interrelationship between the different type classifications of innovation. For example, the combination of *architectural* and *generational* technical change can result in radically new products and processes (Figure 2.A). However, it is imperative that the unit level of analysis is determined before evaluating the impact of new innovations and technological change. Researchers have introduced many such conceptual types of innovation that can be broadly categorised as subtypes of product, process, and technical innovations (**PPT**). Therefore, we adopt this broad categorisation of innovation in our definition of innovation type.

2.2.3. Innovation Characteristics

Distinct from the structural factors of innovation (*locus of innovation* and *innovation type*) are the innovation's characteristics (Gatignon et al., 2002). These include the innovation's magnitude of change (radical vs. incremental) and the effects on firm competencies, existing technological standards, and market dynamics. When considered simultaneously, these three fundamental dimensions of innovation formulate an aggregate level analysis of an innovation's impact and characteristics. Each innovation dimension is independent of the other. From this perspective an innovation's characteristics are defined by a function of its impact along the three identified dimensions: (1) how an innovation impacts firms' existing competencies; (2) how an innovation impacts the existing technological standards in a product, process or technical innovation; and (3) how an innovation impacts existing market dynamics and competitive structure in established market segments.

As a result, a new innovation will impact all three dimensions simultaneously. The magnitude of effect is dependent upon the unit level of analysis. For example, "*an innovation can be competence enhancing to one firm but competence destroying to another*" (Gatignon et al., 2002). Many categorisations of innovation exist in the literature constructed from the characteristics innovations possess. In this research, we adopt the following categorisation: competence enhancing vs. competence destroying (Tushman and Anderson, 1986); continuous vs. discontinuous[3] (Garcia and Calantone, 2002); and sustaining vs. disruptive (Christensen, 1997), in order to represent the organisational, technological, and market based dimensions of innovation respectively.

***Technological Dimension*:**

The technological dimension (continuous vs. discontinuous) of innovation is well established in the literature (Atuahene-Gima, 1995, Damanpour, 1991, Sheremata, 2004). Generally, discontinuous innovations are characterised by fundamental changes in technology (Dewar and Dutton, 1986) that represent a departure from existing technological trajectories and a movement towards new technological trajectories of improvement. Dosi (1982; 148) defines a technological trajectory as "*the direction of advance within a technological paradigm"*, i.e. a technological outlook, knowledge and set of procedures that influence technological improvement. Similarly, Garcia and Calantone (2002; 120) define discontinuous innovations as "*innovations that embody a new technology"*.

[3] We adopt '*continuous vs. discontinuous*' as the categorisation for an innovation's impact on existing technological standards, and '*incremental vs. radical*' as the scale to measure the magnitude of impact along the three primary dimensions. It is important to make this distinction so the reader does not confuse '*incremental vs. radical*' as the categorisation for an innovation's impact on existing technological standards, as this categorisation is often used in the literature.

In contrast, continuous innovation involves the refinement, improvement and exploitation of an existing technological trajectory for the *continuous* improvement of products and processes (Gatignon et al., 2002). As a result, continuous innovations represent minor increments or simple adjustments in current technologies. The major difference captured by the technological dimension is the perceived degree of technological discontinuity embodied in a new innovation from a particular unit level of analysis. The dimension measures the extent to which a new innovation embodies a new technological paradigm (Dewar and Dutton, 1986, Gatignon et al., 2002). Gatignon et al., (2002) develop a scale for measuring the technological dimension of innovation:

Table 2.C Technological Dimension Scale (Gatignon et al., 2002)

Technological Radicalness Items
INNOVATION is a minor improvement over the previous technology (Reversed)
INNOVATION was a breakthrough innovation
INNOVATION led to products that were difficult to replace with substitute using older technology
INNOVATION represents a major technological advance in SUBSYSTEM

***Organisational Dimension**:*

The organisational dimension introduced by Tushman and Anderson (1986) distinguishes between competence enhancing and competence destroying innovations. The organisational dimension is an innovation characteristic rooted in a firm's particular history (Gatignon et al., 2002). For example, organisational resources, skills, knowledge, competencies, and their assimilation influence a firm's ability to respond to and initiate certain innovations. Competence destroying innovations fundamentally alter the required set of competencies, whereby the existing technological capabilities, production skills and tacit knowledge are disadvantageous to the firm (Tushman and Anderson, 1986). Gatignon et al., (2002; 1107) state, "*competence destroying innovation obsolesces and overturns existing competencies, skills, and know-how*".

In contrast, competence enhancing innovations build on existing competencies such that the inherent technological capabilities, production skills, and tacit knowledge are advantageous to the firm (Tushman and Anderson, 1986). Competence enhancing innovations are complementary to existing firm competencies and help to strengthen the technical and management systems of the firm. Gatignon et al., (2002; 1107) illustrate how the organisational dimension of innovation is independent of the technological dimension using the example of the Swiss watch industry and innovation in oscillation mechanisms: They state:

"*Some discontinuous innovations are competence destroying (e.g. quartz movement for the Swiss in the 1970s) while others are competence enhancing (e.g. automatic movements for the Swiss in the 1970s)*"

As a result, the organisational impact of an innovation is independent of an innovation's technological characteristics i.e. continuous vs. discontinuous. The characteristic captured by the organisational dimension can be summarised as the perceived degree in which a new innovation affects the existing competencies of the firm. The impact of innovation from this perspective is dependent on the firm's existing menu of competencies. Competence destroying to one firm may be experienced as enhancing to another (Gatignon et al., 2002; Tripsas, 1997). Tripsas (1997) concludes that the commercial performance of incumbents and new entrants is driven by the balance and interaction of three factors: (1) *investment in developing new technology* – i.e. the allocation and acquisition of new resources; (2) the *technical capabilities* of the firm; and (3) the ability to appropriate the benefits of technological innovation through *specialised complementary assets*.

Specialised complementary assets refer to "*specialised manufacturing capability, access to distribution channels, service networks, and complementary technologies*" for a given innovation (Tripsas, 1997; 122). Using the example of the typesetting industry, Tripsas demonstrate that incumbent firms with valuable specialised complementary assets did not suffer in the market when faced with competence destroying innovation. Gatignon et al., (2002) develop a scale for measuring the organisational dimension of innovation:

Table 2.D Organisational Dimension Scale (Gatignon et al., 2002)

Competence Enhancing/ Destroying Items
INNOVATION built a great deal on BUSINESS UNIT'S prior technological skills
INNOVATION built heavily on BUSINESS UNIT'S existing experience base
INNOVATION rendered BUSINESS UNIT'S experience base obsolete (Reversed)
INNOVATION built heavily on BUSINESS UNIT'S existing technological knowledge
INNOVATION rendered obsolete the expertise that was required to master the older technology (Reversed)
Mastery of the old technology did not help BUSINESS UNIT master INNOVATION (Reversed)

Market Dimension:

The market dimension of innovation was first introduced by Abernathy and Clark (1985). They evaluate an innovation's impact on the demand dynamics of market segments using the following factors: *relationship with customer base*, *customer applications*, *channels of distribution and service*, *customer knowledge*, and *modes of customer communication*. Table 2.E provides a breakdown of these factors and their incremental and radical effects:

Table 2.E Market Dimension Range of Impact (Abernathy and Clark, 1985; 5)

Domain of Innovation	Incremental Effect	Radical Effect
Relationship with Customer Base	Strengthens ties with established customers	Attracts extensive new customer group/ create new market
C*ustomer Applications*	Improves service in established application	Creates new set of applications/ new set of customer needs
Channels of Distribution and Service	Builds on and enhances the effectiveness of established distribution network/ service organisation	Requires new channels of distribution/ new service, after market support
Customer Knowledge	Uses and extends customer knowledge and experience in established product	Intensive new knowledge demand of customer; destroys value of customer experience
Modes of Customer Communication	Reinforce existing modes/ methods of communication	Totally new modes of communication required.

More recently, Christensen's (Bower and Christensen, 1995, Christensen and Bower, 1996, Christensen, 1997) popular classification of disruptive vs. sustaining innovation has been applied to evaluate impact on existing markets and incumbent firms. Market dynamics refer to the structure of market demand and existing dynamics of competition experienced in a particular market or market segment. Christensen (1997) introduced the concept of disruptive innovation to characterise transformations in competitive structures towards new dimensions of customer value. Disruptive innovations introduce a very different value proposition from the existing paradigm of competition expected. Thus, shifting customer expectations and competition towards new dimensions of performance (Bower and Christensen, 1995, Christensen and Overdorf, 2000, Keller and Hüsig, 2009). For example, the revolution of digital photography transformed the major customer processes associated with traditional film processing (Lucas Jr and Goh, 2009). Failure to respond to such change ultimately lea to the failure of incumbent firms e.g. Kodak.

In contrast, sustaining innovations improve performance along existing dimensions of customer value expected in mainstream markets (Christensen, 1997, Christensen and Overdorf, 2000). That is, they give customers something more or better in the attributes they already value (Bower and Christensen, 1995). For example, new generations of iPods and iPhones replace each other by providing similar but enhanced functionality, thus sustaining the current product-performance paradigm expected by end-users. The characteristic captured by the market dimension is the perceived degree of *disruption* experienced in a given market segment embodied by a new innovation, i.e. the degree of change experienced in competitive dynamics. Govindarajan and Kopalle (2006a) develop a scale to measure the disruptiveness of innovation, however their scale confuses organisational effects with market effects[4].

2.2.4. Conclusion

This section demonstrates that it is important to differentiate between innovation locus, referent, type, dimensions, and characteristics in order to avoid confusion when classifying and evaluating the impact of new innovations. Existing literature has permeated through these boundaries, thus limiting the future integration of research in the domain. Lack of continuity in terminology and confusion of type and characteristics (Garcia and Calantone, 2002; Gatignon et al., 2002) inevitably causes problems. The locus, type, dimensions, and characteristics of innovation are inextricably related, but yet independent concepts. We have identified why it is important to specify the level of analysis due to the relative nature of new innovation. A radical change in a product's component infrastructure or linking mechanisms may result in only an incremental change in the performance or function of the end product (Gatignon et al., 2002; Henderson and Clark, 1990). As a result, it is important to specify the analytical perspective, as the associated characteristics of innovation are dependent on the unit level of analysis. An innovation's characteristics refer to the extent to which an innovation affects technological, organisation and market dimensions.

We propose a new framework to identify and evaluate the cumulative impact of new innovations in Figure 2.B. The framework integrates existing literature into a unified conceptual model that distinguishes between core concepts, while simultaneously providing a tool to analyse the aggregate level impact of new innovation. The proposed framework encompasses locus, referent, type, magnitude, dimensions, and characteristics. Furthermore, existing categorisations of innovation in the literature focus only on single or dual dimensions, thus neglecting a holistic perspective with regards to impact.

The ability to evaluate innovations along all three dimensions will provide organisations and researchers alike with a tool to more effectively capture the effects associated with new innovation. Gatignon et al., (2002) provide measurement scales to evaluate the impact of innovation on organisational (competence enhancing vs. destroying) and technological (continuous vs. discontinuous) dimensions. However, the disruptiveness measure of innovation that evaluates an innovation's impact on market dynamics is not yet adequately established in the literature. Problems with defining disruptive innovation cause confusion in how *disruptiveness* is operationalised. Existing measures of *disruptiveness* (Govindarajan and Kopalle, 2006a) do not effectively capture the essence of the concept. In the following Chapter, we aim to bridge this gap in knowledge with an exhaustive review of the literature.

[4] See Section 3.2 for an analysis of disruptive innovation

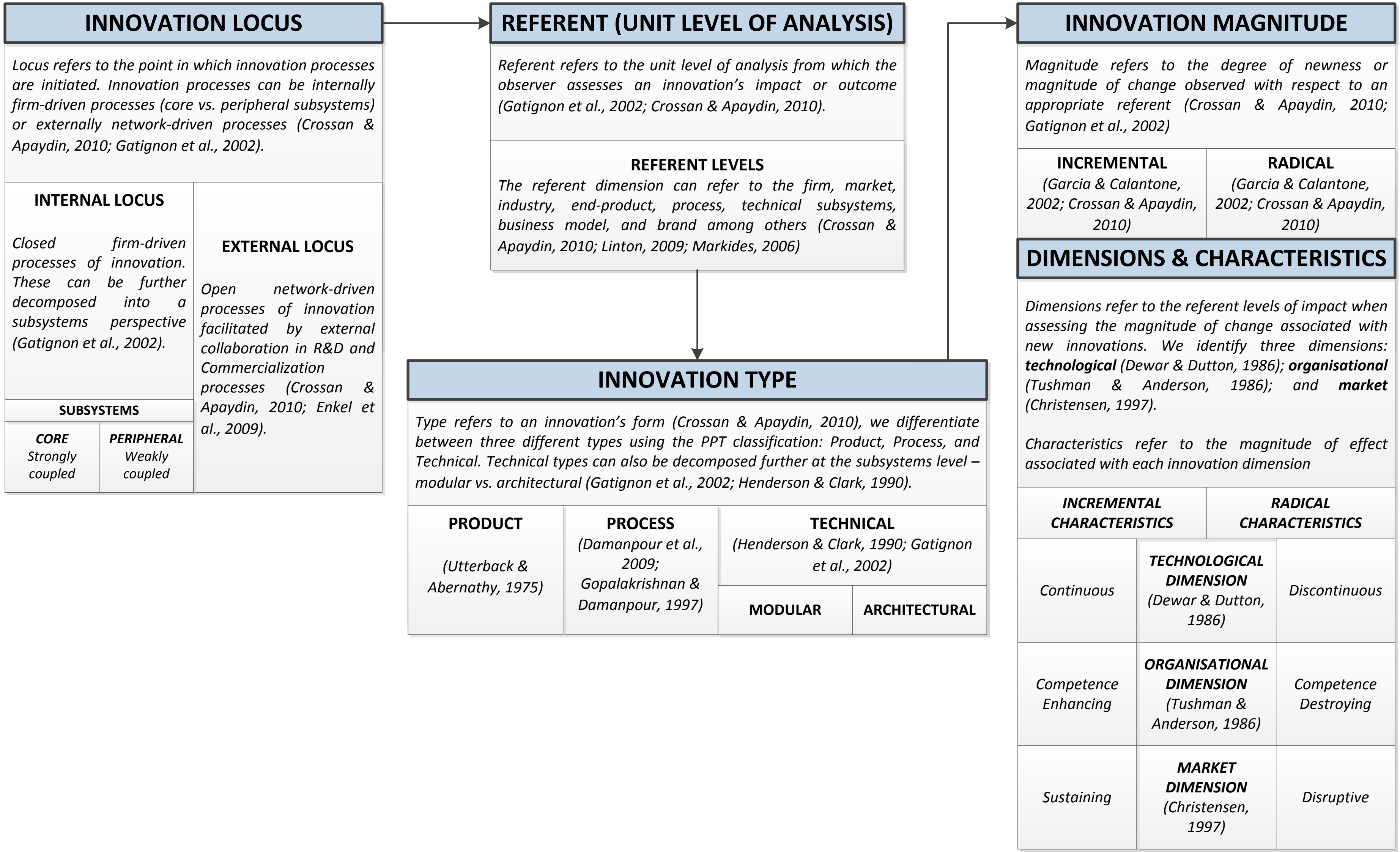


Figure 2.B A Framework for Assessing the Aggregate Impact of New Innovations

3. Disruptive Innovation

The purpose of this Chapter is twofold: (1) to provide a review of the existing literature regarding the theory of disruptive innovation; and (2) to explicitly identify the gaps in knowledge that were the catalyst for this research. As a result, a high level of understanding was developed central to the concept in order to establish a clearly defined research question and objectives. We first introduce the theory and origins of disruptive innovation as introduced by Clayton M. Christensen and document its proliferation in mainstream innovations research. Market disruption occurs as the outcome of a specific process. We examine the process from a multivariate perspective and identify the common underlying factors that emerge in the literature. Identification of disruptive factors helps us to establish a more clear definition of the concept both at the micro (interactions of preference, demand and development dynamics) and macro-level.

Macro-level effects refer to the factors that influence the diffusion of disruptive innovation in mainstream markets e.g. word-of-mouth effects and opinion leadership. In this respect, they are common to all firms. Micro-level effects refer to the interactions between different factors in the system that influence market disruption in different ways depending on the structure of these interactions. That is, they are not common to all firms. These factors include preference, demand, and development dynamics and their interactions.

Danneels' (2004) review of disruptive innovation theory concludes that the current state of research regarding definition, dynamics, and criteria for identifying disruptive innovation needs further clarification. An extensive review of the literature will provide a solid foundation towards achieving these aims. Furthermore, clarification of common factors will provide a reliable way of assessing the potential '*disruptiveness*' of new innovations and aid in the ex-ante identification of potentially disruptive technologies. The Chapter is organised into the following four sections – Figure 3.A illustrates the structure of the Chapter and topic linkages:

1. Section one provides a summary of the theory behind disruptive innovation and documents the process from which disruptive dynamics emerge.

2. Section two identifies the main factors that influence the process of market disruption evident from existing literature. We identify both the direct determinants (essential) of disruptive innovation and moderating factors (ancillary) that affect the speed at which disruption occurs.

3. Section three explores the link between disruptive innovation and incumbent firm failure. We consider three sources of firm failure and analyse their connection to market disruption, these include: (1) the value network, (2) organisational capabilities, and (3) management propensities.

Finally, we examine the importance of identifying disruptive patterns of technological change and the strategies for effective firm response.

4. Section four provides a critique of the current theory and illustrates the relative nature of the phenomenon. As identified in Chapter 2, the impact of innovation is dependent on the unit level of analysis. The section concludes by explicitly identifying the research gaps and defines disruptive innovation in the context of this research.

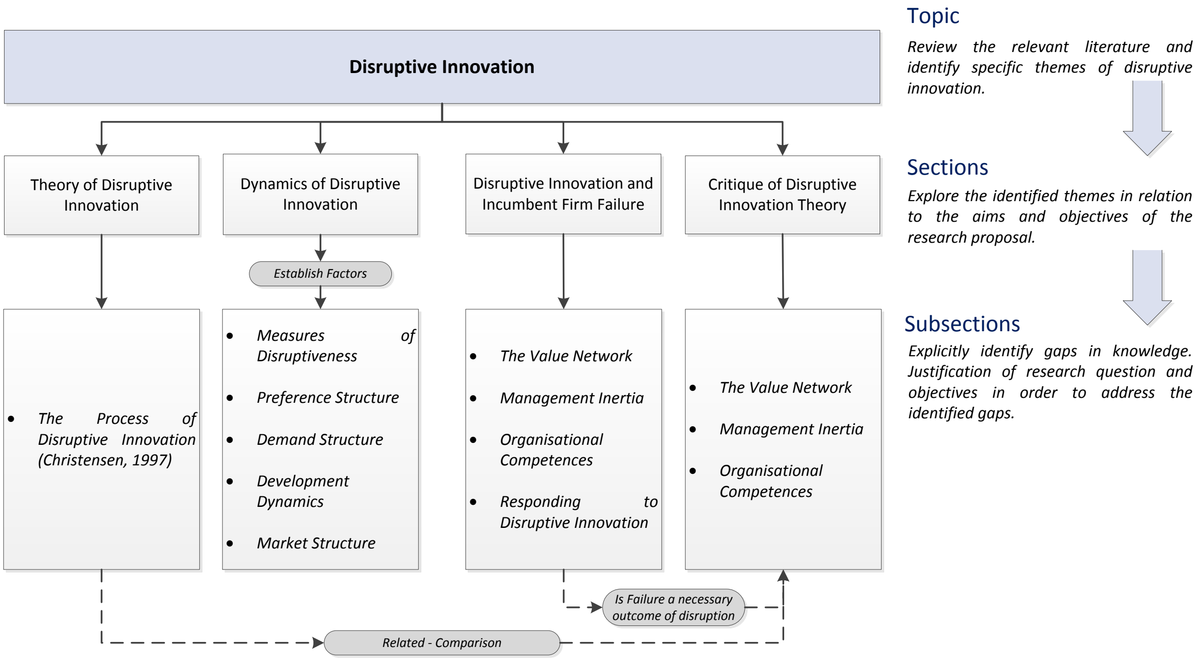


Figure 3.A Structure of Chapter and Topic Linkages

3.1. Theory of Disruptive Innovation

The term '*disruptive technology*' as popularised by Clayton Christensen was first introduced in the article "Disruptive Technologies: Catching the Wave" (Bower and Christensen, 1995). The concept was used to describe technologies that transform existing markets and consumer expectations towards new dimensions of performance. The term disruptive innovation was adopted in later publications to extend the scope of disruptive technologies to include technological, product, process and business model innovations (Christensen and Overdorf, 2000, Christensen and Raynor, 2003). Christensen claimed that when faced with the threat of disruptive change, almost all incumbent firms were displaced from their industries because of organisational and management inertia towards the adoption of new innovation[5] (Christensen, 1997, Henderson, 2006).

[5] The failure of incumbent firms is discussed in detail in Section 3.3

Christensen presents a theory that divides all technological and innovative progression into two categories: 'sustaining' and 'disruptive' innovation. Sustaining innovations are simply innovations that sustain and reaffirm the current paradigm of competition and technological progression expected in a given market. He states that:

> *"Sustaining innovations improve the performance of established technologies, products, processes and business models along the dimensions of performance that mainstream customers in major markets have historically valued*" (Christensen, 1997; xvii).

Conversely, disruptive innovations are defined as those that disrupt and transform the current paradigm of competition expected in a given market segment towards new dimensions of innovation performance (Kassicieh et al., 2002, Kostoff et al., 2004, Walsh, 2004). Disruptive innovations create new markets and stimulate new growth by changing the underlying value proposition expected by mainstream customers. Value in this sense, refers to the unique rank ordering of various innovation attributes in a given market segment (Christensen, 1997).

The work of Christensen and colleagues' has rapidly proliferated in academic and management literature. Inspired from the book '*The Innovator's Dilemma'* (1997), disruptive innovation has created a whole new stream of innovations research and by 2004 had sold over 200,000 copies (Danneels, 2004). Further publications extend the theory to include the management and organisational strategies related to the exploitation of disruptive innovation, and the strategic direction, internal focus, resources, processes, and management values related to driving disruptive innovation (Christensen and Overdorf, 2000, Christensen et al., 2001, Christensen and Raynor, 2003). Consequently, there have been a growing number of research papers appearing in academic circles as illustrated in Table 3.A that explore the topic.

Table 3.A Emergence of Disruptive Innovations – Frequency of Academic Papers

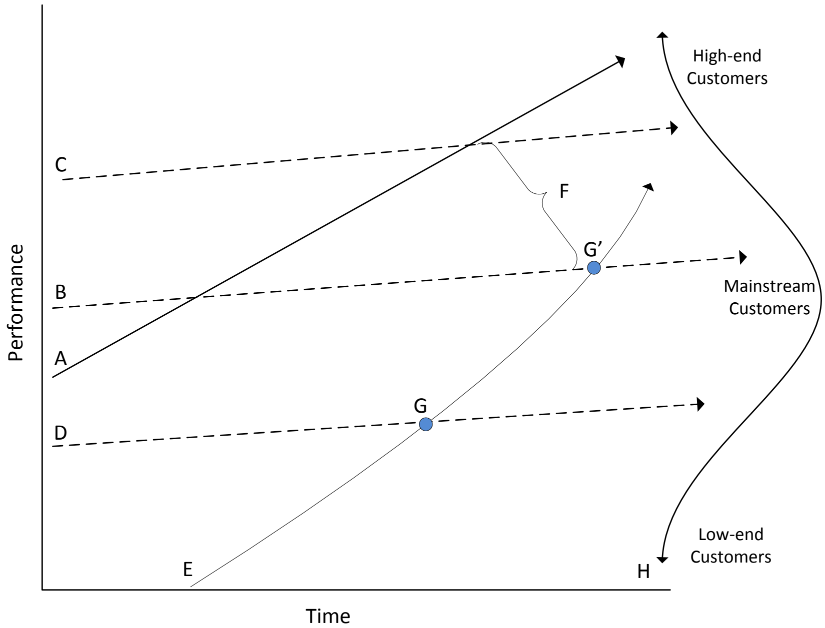
Database / ***Search Period***	**Science Direct**	**EBSCO**	**Emerald**	**JSTOR**
1995-1999	14	8	1	4
2000-2004	40	78	16	7
2005-2009	86	146	33	5
2010-Present	73	110	25	1

**(Search Criteria: 'disruptive innovation' OR 'disruptive technology', within 'article title', 'abstract' or 'key words')*[6]

[6] Database search criteria were limited to: (1) Science Direct – abstract, title and key words (2) EBSCO – abstract and scholarly journals (3) Emerald – abstract (4) JSTOR – abstract.

3.1.1. The Process of Disruptive Innovation

According to Christensen's (1997) theory, disruptive innovations emerge as an outcome of a specific process (Hüsig et al., 2005). He states that disruptive innovations initially underperform established innovations along the dimensions of performance most valued in mainstream markets (Christensen and Raynor, 2003; Christensen et al, 2004). However, in order to compete they offer alternative performance in attributes that are valued in low end, fringe, detached, or niche market segments (Danneels, 2004, Druehl and Schmidt, 2008, Schmidt and Druehl, 2008). Successive performance improvements in primary attributes allow disruptive innovations to gradually move upmarket towards established segments. The process is best understood by the joint consideration of performance supply vs. performance demand trajectories as illustrated in Figure 3.B. The point in which these two trajectories intersect is the point of market disruption (Christensen, 1997).



KEY

A = Performance trajectory of existing innovation driven by sustaining innovations

B = Performance demanded of mainstream customers

C = Performance demanded of high-end customers

D = Performance demanded of low-end customers

E = Performance trajectory of disruptive innovation

F = Performance oversupply of existing innovation

G/G’ = Points of invasion into respective market segments

H = Normal distribution of customers by performance demanded

Figure 3.B Intersecting Trajectories of Market Segment Demand vs. Performance Supplied (Adapted from Christensen 1997)

Figure 3.B. illustrates the trajectories of performance demand for various customer segments (Lines 'B', 'C', and 'D') and trajectories of performance supply for dominant (Line 'A') and disruptive

innovations (Line ‘E’). Initially disruptive innovations do not satisfy the performance demanded by low end, mainstream, or high end customers. Thus, customers in established markets consider them inappropriate. However, over time, performance improvements are made by the disruptive innovation enough to satisfy the performance demanded in the established market i.e. low end (Point ‘G’) and mainstream (Point ‘G’’) in Figure 3.B. Furthermore, the performance improvements made by the dominant innovation that exceed a customer’s demand requirements are subject to diminishing marginal utility, which translates into a decreasing willingness to pay for dominant innovations (Adner, 2004; Danneels, 2004). As a result, customers are driven towards the additional performance offered by the disruptive innovation. Such performance oversupply occurs due to continuous sustaining performance improvements that exceed a market segment’s absorptive capacity to realise such improvements.

Cohen and Levinthal (1990; 128) define absorptive capacity from the perspective of the firm as the “*ability to recognise the value of new information, assimilate it, and apply it to commercial ends”*. In the context of this research, we define absorptive capacity from the perspective of the customer or market segment adopting a new innovation as:

> *‘The ability of the adopter (e.g. customer or market segment) to recognise and internalise the value of performance provided by new innovations in specific attributes, and apply it into a functional benefit’*.

Performance oversupply occurs when technological improvements exceeds a customer’s or market segment’s absorptive capacity to apply such improvement into a functional benefit. As a result, performance oversupply (Point ‘F’) creates a vacuum in the market for the entrance of lower performing disruptive innovations (Hüsig et al., 2005).

Low end customers are the most susceptible to disruptive innovations, as they have the least capacity to absorb sustaining performance improvement. In contrast, high end customers are the least susceptible as they have the highest capacity to absorb sustaining performance improvements (Druehl and Schmidt, 2008, Schmidt and Druehl, 2008). When the performance supply trajectory of a disruptive innovation intersects the performance demand trajectories of different market segments, the disruptive innovation can invade i.e. ($E \cap D$ (G), and $E \cap B$ (G’), in Figure 3.B). These are the points of invasion (Hüsig et al., 2005), in which market segment preferences shift towards the additional performance offered by the disruptive innovation (Adner, 2002, Keller and Hüsig, 2009)[7]. As a result, the competitive dynamics of the market are transformed.

[7] The additional performance of the disruptive innovation cannot be mapped on the performance trajectories of established innovations, as disruptive innovations initially compete on different dimensions of performance than those measured in mainstream markets (Christensen, 1997).

Christensen's model of disruptive innovation assumes that the levels of performance demanded by customers within existing market segments are normally distributed between the extremities of low end and high end customers. Mainstream customers represent the average (μ= mainstream consumers – see Point 'H' in Figure 3.B) level of performance demanded in a given market or market segment (Thomond, 2004). Similarly, Rogers (1962, 1995) uses the normal distribution to differentiate between different adopter categories, which include: *innovators*, *early adopters*, *early majority*, *late majority*, and *laggards*.

3.2. Dynamics of Disruptive Innovation

The primary aim of studies relating to disruptive innovation involves the identification and exploration of factors that influence the process of disruption (Adner, 2002; Adner and Zemsky, 2005; Govindarajan and Kopalle, 2006a; Hüsig et al., 2005). These include the direct determinants of disruption and potential moderating influences that affect the rate in which disruption occurs i.e. *disruption catalysts*. Other research streams examine the relationship between disruptive innovation and incumbent firm failure (Christensen, 1997; Henderson, 2006; Garrison, 2009; Ansari and Krop, 2012) and methods of how to harness and respond to potentially disruptive threats (Lucas Jr and Goh, 2009; Dewald and Bowen, 2009). Limited research exists that addresses the diffusion of disruptive innovation and the mechanisms that drive the process. Adner (2002) offers a demand-based perspective of competition that leads to the emergence of three competitive outcomes: *convergence*, *isolation*, and *disruption*. However, he only considers single preference dimensions between competitive market segments and fails to include other influential dynamics such as development structure.

As a result, very little is known with regards to the dynamics that drive the process of market disruption (Danneels, 2004). When does disruption occur? What are the mechanisms behind the process? How do they contribute towards disruption? These are just a few of the questions raised in the literature (Danneels, 2004). The following section provides a review and summary of the common underlying factors that facilitate disruptive dynamics.

3.2.1. Overview of Disruptive Dynamics

There are a number of consistent characteristics that emerge in the literature argued to be a precursor to market disruption. Originally, Christensen (1997) identified disruptive innovations as initially lower performing, cheaper, and technically simpler, offering alternative performance dimensions to mainstream innovations. Adner (2002) adds preference overlap and preference asymmetry to the original determinants as important factors (Section 3.2.3). Moreover, recent developments have provided contradictory determinants and or anomalies with respect to the original theory. For example, Schmidt and Druehl (2008) provide evidence of disruptive innovations being both more expensive and technologically more advanced than mainstream innovations e.g. mobile phones vs. cell phones and digital cameras vs. film cameras. Consequently, it is important to differentiate between essential and ancillary characteristics of disruption.

Govindarajan and Kopalle (2006b) establish a scale to measure the '*disruptiveness*' of innovations based on the descriptions by Abernathy and Clark (1985), Adner (2002), Christensen (1997), and Christensen and Raynor (2003). However, the scale is derived from the perspective of the firm, and mainly focuses on ability to introduce disruptive innovations, demonstrated in Table ***3.B***.

Table 3.B Measure of Disruptiveness (Govindarajan and Kopalle, 2006a)

Items	Measures
1. How disruptive	• In your opinion, how disruptive were your SBU's new product introductions during the past 5 years? Not Very Disruptive/ Very Disruptive.
2. Rarely introduces disruptive	• This SBU rarely introduces products that are disruptive in nature.
3. Lags behind in disruptive	• This SBU lags behind in introducing disruptive product innovations.
4. Attractive to a different customer segment	• During the past 5 years, the new products that were introduced by this SBU were very attractive to a different customer segment at the time of product introduction.
5. Mainstream customers found the innovations attractive	• During the past 5 years, the new products that were introduced by this SBU were those where the mainstream customers found the innovations attractive over time as they were able to satisfy the requirements of the mainstream market.

From Table 3.B. it is evident that Govindarajan and Kopalle (2006a) consider disruption from the perspective of the organisation's SBU (Items 1 – 3) and the competitive market (Items 1 and 5). As a result, confusion in operationalising a definition of disruption is exacerbated i.e. from what perspective do we analyse disruption? Is disruption a function of the firm, the market, or both? Sood and Tellis (2011; 340) argue that the tautological nature of the concept causes confusion in its interpretation; "*the same term is used to describe the causative agent (disruptive) and its effect (disruption)*". In his original theory, Christensen (1997) relates disruptive innovations to both firm failure and market transformation, thus causing ambiguity as to which domain the theory applies (Danneels, 2004; Markides, 2006).

However, Henderson (2006) demonstrates how incumbent failure is an outcome of organisational incompetence when faced with disruptive technological threats (Section 3.3). She concludes that failure may be attributed to an organisation's inability to adapt and acquire organisational capabilities to harness disruptive change (Lucas Jr and Goh, 2009). As a result, there needs to be a re-evaluation of existing definitions and determinants of disruptive innovation in order to establish the mechanisms that drive the process. Table 3.C provides an overview of disruptive characteristics identified in the literature.

Table 3.C Literature Overview: Characteristics of Disruption

Author(s)	Characteristics
• (Adner, 2002)	(1) Preference overlap; and (2) Preference symmetry
• (Christensen, 1997)	(1) Inferior performance; (2) Offer alternative performance; (3) Cheaper, smaller, and technically simpler; (4) Niche market segments; (5) Performance oversupply; and (6) Incumbent failure
• (Hüsig et al., 2005)	(1) Cheap, simple, initially lower performing and then fast improving; (2) Performance oversupply; (3) Leading customer rejection; (4) Lower margins and profits; (5) Emerging market success; (6) Asymmetrical preference overlap; and (7) Intersecting trajectories
• (Keller and Hüsig, 2009)	(1) The innovation allows for a product with a new combination of performance attributes; (2) The innovation misses main market expectations in one or more established attributes and therefore targets insignificant markets; (3) Incumbents ignore niche; (4) Innovation improves on mainstream attributes; and (5) Incumbent failure
• (Tellis, 2006)	(1) Disruptive technologies underperform on mainstream dimensions; (2) Disruptive technologies offer alternative performance; (3) Developed in insignificant markets; (4) Innovation's performance improves on mainstream attributes; and (5) Incumbent failure

Four factors emerge that appear common to the process of market disruption, these include: *preference structure*, *demand structure*, *development dynamics*, and *market structure*. These four factors can be further categorised into eight characteristics of disruptive innovation:

- **Preference Structure**:
  1. *Mainstream customer preferences*
- **Demand Structure**:
  2. *Preference overlap*
  3. P*reference asymmetry*
- **Development Dynamics**:
  4. *Primary attribute performance*
  5. P*erformance oversupply*
  6. *Low price*
- **Market structure**:
  7. *Insignificant market segments*
  8. *Low end encroachment*

Figure 3.C. illustrates the interactions between the aforementioned factors of disruptive innovation. The following discussion provides and in-depth analysis of these factors and their proposed impact on market disruption.

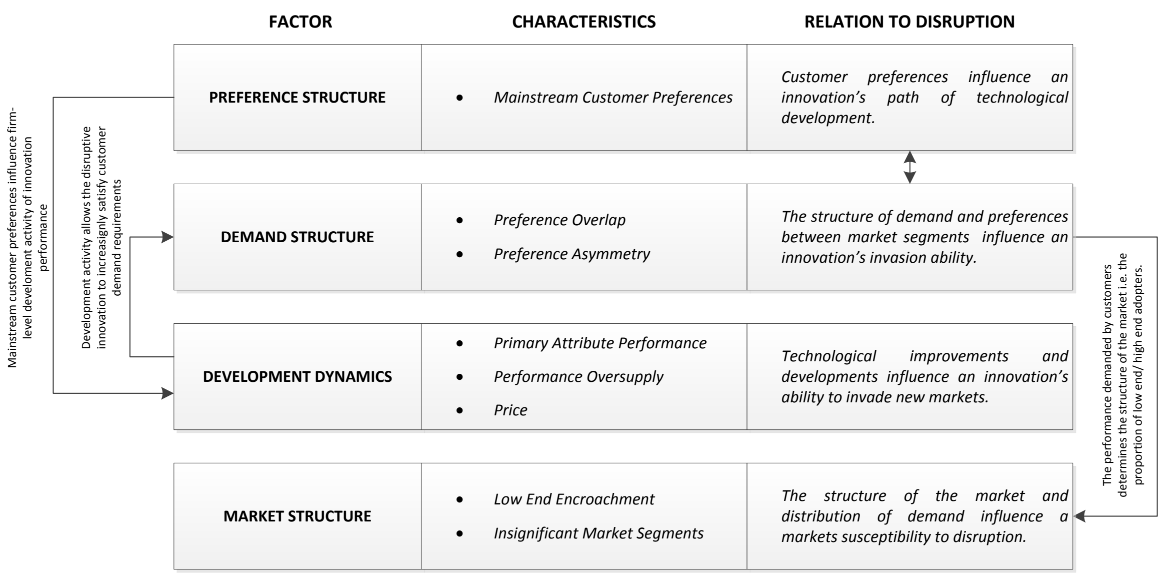


Figure 3.C Summary of Disruptive Factors and Characteristics

3.2.2. Preference Structure

Preference structure refers to the structure of consumer preferences that exist within competitive markets and market segments. Consumer preferences directly influence an innovation's ability to invade new markets. This is because preferences for certain attributes influence the buying behaviour of consumers. Christensen (1997) demonstrates that disruptive innovations are initially constrained to compete in low end and peripheral market segments. However, as disruptive innovations are developed, they start to satisfy the demand requirements of mainstream customers and gradually build momentum to invade upstream markets (Christensen and Bower, 1996). As a result, the structure of mainstream customer preferences between markets and market segments directly affect the invasion capability of new innovations (Hüsig et al., 2005).

Mainstream customer preferences refer to the dimensions of performance that are most valued by the mainstream market. Value in this sense is characterised by the underlying performance metric(s) from which mainstream customers gain most utility. The basis of customer satisfaction is dependent on an innovation's ability to satisfy demand in terms of their preferences (Anderson and Sullivan, 1993). Generally, the incumbent firm's most valuable customers initially reject disruptive innovation as they do not satisfy the performance preferences or demand requirements of their mainstream customers (Hüsig et al., 2005). Central to the '*Innovator's Dilemma'* is the notion that firms typically become industry leaders by continually satisfying mainstream customer preferences (Christensen, 1997, Slater and Mohr, 2006). Sustaining innovations are concerned with improving performance along such established metrics. Christensen and Overdorf (2000; 7) state that "*sustaining innovations are innovations that make a product or service perform better in ways that customers in the mainstream* *market already value*". As a result, incumbent firms that operate in established markets intensify their investments towards sustaining innovation (Hüsig et al., 2005).

Paradoxically, disruptive innovations do not reinforce the established trajectories of product-performance improvement as expected by the mainstream market (Christensen, 1997). Thus, incumbent firms initially have very little incentive to invest in apparently unattractive technological opportunities (Danneels, 2004, Hüsig et al., 2005). A disruptive technology introduces a competing set of features and performance dimensions relative to the existing dominant standard, a combination that is not valued by mainstream customers upon initial introduction (Adner, 2002; Govindarajan and Kopalle, 2006a). Therefore, the performance trajectories of disruptive innovations cannot be plotted on the same performance trajectories as sustaining innovations in established value networks. This is because the vertical axes are measuring different metrics of performance (Christensen, 1997). Figure 3.D illustrates this concept. If an innovation improves enough to satisfy the performance demanded in mainstream markets, then the disruptive innovation can invade. At the point of invasion (Figure 3.D), the dynamics of competition are transformed to new metrics of performance.

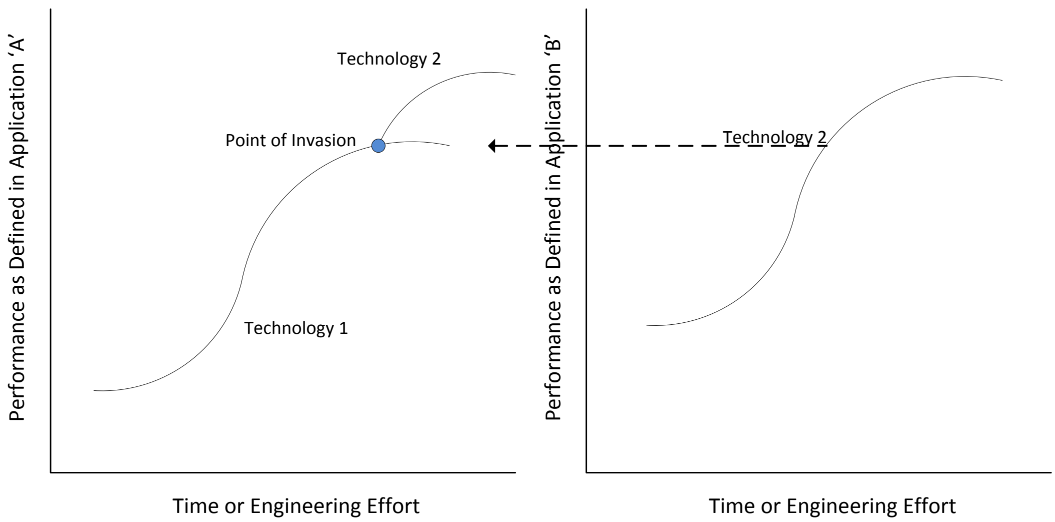


Figure 3.D Disruptive Innovation S-Curve (Christensen, 1997).

Consider the introduction of the mobile phone relative to the landline. The mobile phone offered performance in *portability* over performance in *reception quality* (the attribute most valued by mainstream customers) as an initial basis of competition (Druehl and Schmidt, 2008; Schmidt and Druehl, 2008). If a firm is committed to satisfying mainstream customer preferences, its innovation activity is geared towards sustaining the current product-performance paradigm (Christensen, 1997, Lucas Jr and Goh, 2009). Disruptive innovations change the direction of technological progression, thereby challenging the current boundaries of mainstream customer preferences (Danneels, 2004). Mainstream customer preferences determine an innovation's ability to satisfy the needs of the mainstream market. As a result, the structure of market segment preferences will directly influence the disruptive capability of new and developing innovations.

3.2.3. Demand Structure

Demand structure refers to the magnitude and composition of customer demand for innovation attributes, both within and between competitive market segments. Demand and preference structure are very closely related, such that consumers demand performance on their preferred attributes (Adner, 2002). As illustrated in Figure 3.B, disruptive innovations emerge once the functional demand thresholds of the mainstream market are satisfied. As a result, preference overlap and preference asymmetry between competitive markets directly affect the invasion capability of new innovations (Hüsig et al., 2005).

In response to the question '*when are technologies disruptive*'? Adner (2002) identifies the demand conditions that enable disruptive dynamics, characterised by two elements: *preference overlap* and *preference symmetry*. The interplay of these two factors captures the parallels between different market segment preferences. Preference overlap refers to the extent in which performance improvement in one market segment is also valued in another market segment (Adner, 2002, 2004). He (2002; 672) states that:

> *"The preference overlap between these segments is the degree of similarity between their functional preferences. The greater the preference overlap, the closer the value trajectories, and the greater the segments agreement on the level of product performance".*

Adner (2002) extends Lancaster's characteristics approach (1966) in assuming that utility is derived from the rank ordering of innovation attributes. New innovations are evaluated indirectly through the attributes they possess. Under conditions of increasing preference overlap, the distance between disruptive and dominant innovations is smaller due to similarities in market segment preferences. As a result, performance improvements allow disruptive innovations to enter established markets more easily. When the value trajectory of the disruptive technology intersects the demand thresholds of mainstream customer segments, the new technology can invade (Christensen and Bower, 1996; Govindarajan and Kopalle, 2006b; Tellis 2006; Govindarajan et al., 2011).

Performance improvements in the established technology that surpass the demand thresholds of the mainstream market are subject to diminishing marginal utility. Consequently, the utility derived from the additional performance offered by disruptive innovations eventually shifts market competition to new dimensions of performance, thus causing disruption (Adner, 2002; Keller and Hüsig, 2009). However, under demand conditions of low or zero preference overlap, market segment preferences are completely divergent, which leads to competitive isolation[8] (Adner, 2002). As a result, the functional preferences of independent market segments are purely satisfied by performance improvements of the resident innovation, thereby reducing the likelihood of disruption. However, under conditions of increasing market segment preferences an innovation's ability to invade rival market segments is enhanced.

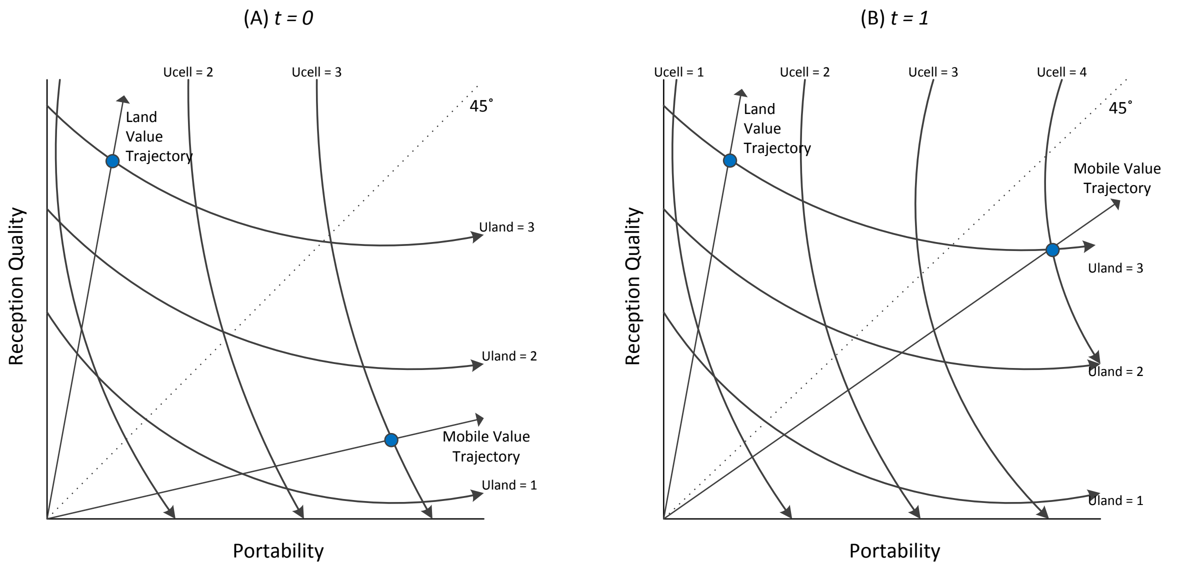


Figure 3.E Indifference Curves (A) Competitive Isolation (B) Competitive Disruption (Adapted from Adner, 2002)

Figure 3.E. theoretically depicts the indifference curves of consumers in the landline and mobile phone market segments. Depending upon the technology's value trajectory, each point on the curve illustrates a consumer's preference for one technological innovation in relation to another. Figure 3.E(A) shows the levels of utility gained by consumers in the market for mobile (*Ucell*)[9] and landline technologies (*Uland*) at time zero ($t = 0$), where ($t = 0$) refers to the market introduction of the mobile phone. Landline consumers only gain a utility level of 1.4 (*Uland*) from mobile phone technologies, and mobile phone consumers only gain a utility level of 1.4 (*Ucell*) from landline technologies. However, the value trajectories indicate that both mobile and landline segments derive a utility level of 3 from their resident technology, thus indicating competitive isolation i.e. no shared functional preferences between market segments. Hence, each technology only has the capability to satisfy its home market segment.

Over time ($t = 1$), performance improvements of the mobile phone increase its disruptive capability and reduce the initial distance between market segment preferences (Adner, 2002). Figure 3.E(B)

[8] Competitive Isolation: represents a partitioning of the market between technologies, such that each focuses exclusively on its own segment (Adner, 2002; 678).
[9] (1) **Ucell**: Utility derived from the mobile phone. (2) **Uland**: Utility derived from the landline

illustrates this concept. As the value trajectory of the mobile phone converges towards the preferences of landline consumers, the initial distance between competitive markets decreases[10] i.e. the invasion capability of mobile phone technologies increase. Landline consumers now gain a utility level of 3 (*Uland*) from the mobile phone offering, while simultaneously gaining a utility level of 4 (*Ucell*) from the additional performance dimension '*portability*'. In contrast, stagnating performance improvements of landline technologies show that consumers only gain a utility level of 1.4 (*Ucell*), and 3 (*Uland*).

Consequently, the increased utility in '*reception quality*' of the mobile phone offering (*Uland = 3*) and additional performance in '*portability*' (*Ucell* = 4) shifts competitive dynamics towards new dimensions of performance. Evidently, increasing degrees of preference overlap facilitate competitive disruption and break the initial isolation between market segments as functional preferences converge (Adner, 2002). However, under conditions of instantaneous preference overlap, the new technology is primarily concerned with enhancing the existing paradigm of product-performance improvement expected by mainstream customers. As a result, such conditions are indicative of sustaining innovation.

DeSarbo et al., (2006) define a competitive market structure as the competition between firms who provide substitutable goods. They state that "*competitive market structures capture the configuration of firms that compete with one another at a given level of the value chain*" (2006; 103). Preference symmetry refers to the symmetry of preference overlap that exists between competing market structures (Adner, 2002; 2004). This can be analysed at both the firm or market level. For example, preference asymmetry exists when the degree of competition between two firms is not equal: "*Firm A competes more intensely with Firm B, than Firm B competes with Firm A*" (DeSarbo, 2006; 103). Conversely, Adner (2004; 34) defines preference asymmetry at the market level as "*whether or not buyers in segment A discount offers from segment B to the same extent that buyers in segment B discount offers from segment A*".

The symmetry of preference overlap and underlying development dynamics between market segments leads to the emergence of two distinct classes of competition: "*competitive convergence*" and "*competitive disruption*" (Adner, 2002). Greater preference asymmetry indicates competitive disruption, in which one innovation is better equipped to invade new market segments than its counterpart as performance improves. Theodore Levitt (1960) in his famous article "Marketing Myopia" supports this proposition. He concludes that the inability to identify future market segments hinders management's perceptions of competitive market structures, thus leaving them more susceptible to disruptive threats. Adner (2002; 678) states:

[10] Figure 3.E(B) is a hypothetical indifference curve at a discrete future time point denoted by *t=1*, whereby the improvement of the disruptive innovation facilitates the technology's invasion capability into established markets.

"When segment preferences are asymmetric we observe competitive disruption, in which one firm maintains dominance of its home market while displacing its rival from the rival's market".

As illustrated in Figure 3.E(B), increasing asymmetric preference overlap of the mobile phone segment over the landline segment (*Uland = 3*, for both mobile and landline value trajectories, and *Ucell = 4*, and *Ucell = 1.4*, for mobile and landline value trajectories respectively) indicates competitive disruption. The example illustrates that the mobile phone offering can invade rival landline market segments while maintaining dominance of its home market. Conversely, under conditions of increasing preference overlap and symmetric preferences, we observe dynamics of competitive convergence (Adner, 2002). In this case technological progression of the new innovation converges towards the established market's preferences to form a single segment (Adner, 2002). Consequently, in the case of convergence, technology development activity of each innovation is geared towards sustaining the current product–performance paradigm characteristic of sustaining innovations.

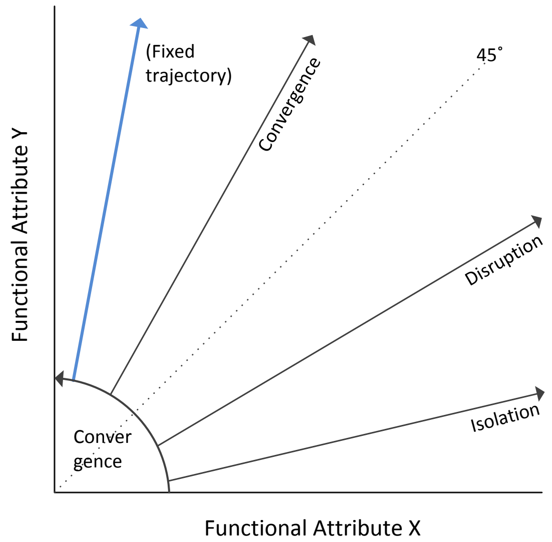


Figure 3.F Preference Relationships and Competitive Regimes (Adner, 2002)

Figure 3.F. summarises the relationship between increasing degrees of preference overlap and the different competitive regimes that emerge. Adner (2002) identifies three competitive outcomes mapped relative to the fixed value trajectory of a given innovation. These include competitive *convergence*, *disruption*, and *isolation*. Increased convergence of functional preferences between market segments leads to the formation of a single unified segment concerned with satisfying the performance requirements of the mainstream market.

3.2.4. Development Dynamics

Firms engage in technology development activity to improve an innovation's performance in certain attributes over time. Adner (2002) differentiates between product and process improvement. Product improvement refers to an upgrade in an innovation's functional attributes, whereas process improvement refers to a reduction in cost. Process improvement allows firms to produce innovations more cost effectively, thus reducing their sale price. Such technological developments shape an innovation's competitive trajectories and influence their ability to invade upstream or downstream market segments.

In addition to technological improvement, a market segment's absorptive capacity to realise such improvement also determines the competitive trajectories of innovations. As previously stated, absorptive capacity in the context of this research refers to '*the ability of the adopter (e.g. customer or market segment) to recognise and internalise the value of performance provided by new innovations in specific attributes, and apply it into a functional benefit'*. This definition provides a new perspective of absorptive capacity that encompasses a consumer's (or market segment's) ability to absorb and assimilate the performance improvement of an innovation. Traditionally scholars define absorptive capacity from the perspective of the firm i.e. the ability of the firm to learn, internalise, and exploit new and external knowledge into a commercial advantage (Cohen and Levinthal, 1990, Van den Bosch et al., 1999, Tsai, 2001).

Primary attribute performance, *performance oversupply*, and *low price* are common characteristics of development dynamics that are argued to influence the disruptive capability of new innovations. Primary attribute performance refers to the extent to which an innovation performs on a specific attribute or combination of attributes most valued by mainstream customers. Common conjecture dictates that disruptive innovations initially underperform established innovations on the metrics of performance most valued by the mainstream market (Adner, 2002, Christensen, 1997, Christensen and Raynor, 2003, Tellis, 2006, Yu and Hang, 2010). Therefore the performance supply trajectories of disruptive innovations initially do not satisfy the performance demanded by mainstream customers. As a result, disruptive innovations are often perceived as inferior when compared with sustaining innovations (Hüsig et al., 2005).

Christensen and Bower's (1996) study of the U.S. HDD industry illustrates this concept. Initially 5.25-inch disk drives could not satisfy the mainframe market demand for *memory capacity* unlike the 8-inch disk drive. Thus, mainstream customers perceived the 5.25-inch disk drive as inferior. Similarly, the mobile phone was initially perceived as inferior in terms of high *reception quality* attributed to traditional landline services (Druehl and Schmidt, 2008; Schmidt and Druehl, 2008;

Govindarajan *et al*., 2011). However, both 5.25-inch disk drives and mobile phone technologies were disruptive to the disk drive and telecommunications markets respectively.

Performance is measured in terms of how well an innovation performs on attributes most valued by mainstream customers. Performance is thus a subjective measure, determined by mainstream customer preferences. Danneels (2004) suggests that customers trade off the performance package of competing innovations in order to optimise their adoption decision based on a complex interplay of multiple performance dimensions. However, imperfect information and effects of bounded rationality often force consumers to trade off only the essential most valued performance dimension(s) (Ratchford, 1982, Williamson, 1981). As such, disruptive innovations are perceived as inferior on the attributes most valued by mainstream customers.

The technological short sightedness of staying close to one's customers, termed '*marketing myopia*' (Levitt, 1960), inspires the drive for continual performance improvement geared towards satisfying existing market segments. Often the rate of technological improvement in established innovations exceeds the absorptive capacity of the market segments they serve (Point 'F', in Figure 3.B). This allows for the entrance of new potentially disruptive innovations into over-served market segments. Hüsig et al., (2005; 21) state that "*new attributes become more valued and a vacuum can emerge at the low end of the established market*".

Performance oversupply is the label applied to the concept of over-serving mainstream customer requirements. It generally occurs when the rate of technological improvement exceeds the growth rates in absorptive capacity. Yu and Hang (2010) state that performance oversupply by the dominant innovation in primary attributes is a necessary condition for the existence of market disruption. However, Adner and Zemsky (2005) conclude that while performance oversupply facilitates disruption, it is not necessary for it to occur. They model performance oversupply by "*reducing the established technology's rate of utility improvement relative to that of the new technology"* (2005; 231). They use a model of horizontal and vertical differentiation[11] in order to explore the emergence of competitive dynamics based upon market boundaries, consumer preferences and firm behaviour.

In this research, we assume that performance oversupply is a sufficient but not necessary condition of market disruption. Although it may act a catalyst for the entry of lower performing disruptive innovations, performance oversupply has little effect on the final outcome. Whether or not a market segment is over-served, disruption will still occur. Assuming a disruptive innovation's performance on mainstream attributes satisfies the demand thresholds of the established market, additional utility is then derived from the alternative performance offered by the disruptive innovation (Keller and Hüsig,

[11] Vertical differentiation is characterised by consumer unanimity over the rank order of product attributes offered at equal price, hence all consumers buy the same variant. Horizontal differentiation is characterised by the heterogeneity of consumer preference even if prices are equal (Cremer and Thisse, 1991)

2009). As a result, customers will switch to the disruptive innovation irrespective of the level of performance oversupply created by dominant innovations.

Consumer utility is derived from the assimilation of product characteristics rather than intrinsically attributed to the product itself (Lancaster, 1966). This information is communicated through the social structures and interaction of competitive market segments (Rogers, 1995). While we assume that performance oversupply has little effect on the outcome, we do believe it may increase the speed in which disruption occurs. This is due to the fact that a consumer's willingness to pay for performance improvement that exceeds their requirements decreases once thresholds of demand are satisfied. This is then communicated through the market's social structures, and, as a result, consumers are more susceptible to substitutable goods in the form of disruptive technologies.

A common thread when exploring the characteristics of disruptive technologies is the role of *price* in driving and defining the disruptive process. When defining disruptive technologies, Christensen (1997) states that they are generally cheaper than established mainstream technologies. This proposition is widely supported in the literature and considered an axiom to the theory. Adner (2002) concludes that once consumer demand requirements are satisfied, absolute lower unit cost becomes a critical adoption characteristic facilitating disruption. He states that "*while disruption is enabled by sufficient performance, it is enacted by price*" (2002; 686). Furthermore, Adner and Zemsky (2005) conclude that disruption arises from firms pursuing a low price, high volume strategy to penetrate mainstream market segments. However, certain anomalies arise in the literature in which the theory cannot account for, and higher priced disruptive technologies successfully invade mainstream segments (Christensen, 2006, Govindarajan and Kopalle, 2006b).

Consider the introduction of digital photography (Lucas Jr and Goh, 2009) and mobile phones (Schmidt and Druehl, 2008). Both technological innovations were higher priced relative to the existing dominant standard in the market at that time i.e. film photography and landline telephones respectively. Furthermore, both innovations were transformational and served as paradigm shifting technologies. Lucas Jr and Goh (2009; 52) state that "*digital cameras changed more than the physical artefact, they changed the process of photography*". Similarly, mobile phones transformed market expectations and consumption patterns of traditional landline telecommunications services. Consequently, Schmidt and Druehl (2008; 359) state:

> *"There are exceptions to Christensen et al.'s (2004) rule that disruptive new-market innovations are low priced: Low end encroachment is possible even when the new product starts out as being high priced"*

We adopt the perspective proposed by Schmidt and Druehl (2008) and conclude that price is not a necessary condition for market disruption to occur. However, price can be conceptualised as an important innovation attribute as opposed to an independent factor. We assume that absolute low cost will increase the speed in which disruption occurs, particularly if price is considered a primary attribute in a consumer's or market segment's adoption decision.

3.2.5. Market Structure

Market structure refers to the size, heterogeneity, and segmentation of markets. Traditional diffusion of innovations literature differentiates between five different classes of adopter: innovators, early adopters, early majority, late majority, and laggards (Rogers, 1995). Danneels (2004) suggests that disruption may be the outcome of market structure i.e. the size, distribution, and segmentation of consumers in different adopter categories. For example, market segments with lower average demand thresholds will be more susceptible to market disruption. In this respect, market structure can act as natural entry barrier for new innovations. In the following discussion, we examine *low end encroachment* and *insignificant market segments* as potential factors influencing disruption.

All potential adopters of a new innovation do not adopt the innovation at the same time. Traditionally, Rogers (1962) distinguishes between different adopter categories based upon their adoption time. The identification of adopter categories is important because they assist in developing market segmentation strategies for targeting different types of customers and penetrating specific market segments (Mahajan et al., 1990). With the case of disruptive innovation, Schmidt and Druehl (2008) and Druehl and Schmidt (2008) use the distinction of low end, mainstream, and high end adopter categories. Customers are segmented into the aforementioned categories based on their demand requirements for innovation performance and willingness to pay (WTP) for various attributes.

Low end customers have the lowest demand requirements and WTP for performance improvements of dominant innovations. Thus, upon introduction, disruptive innovations will always invade mainstream market segments from the low end, as low end customers are more susceptible to the performance proposition offered by the innovation (Hüsig et al., 2005). Schmidt and Druehl (2008; 350) state that:

> *"The low end of a product's market is defined to consist of those customers with the lowest willingness to pay for the product (they have the lowest demand for the product's key performance attributes)"*.

In contrast, high end customers have the highest demand requirements and WTP for performance improvements. As a result, high end customers are generally the last adopters of disruptive innovation since they have the highest capacity to absorb performance improvements of dominant innovations. Mainstream customers occupy a position between the two extremes of low end and high end customers, and represent the average level of demand and WTP for performance improvements observed in a market segment.

The encroachment framework proposed by Druehl and Schmidt (2008) and developed further by Schmidt and Druehl (2008), describes the process in which sustaining innovations progressively move downstream towards low end market segments, and disruptive innovations move upstream towards high end market segments. They state that "*disruptive innovations encroach from the low end upward, while sustaining innovations encroach from the high end downward*" (Druehl and Schmidt, 2008; 46). Table 3.D. documents the different encroachment patterns of sustaining and disruptive innovations:

Table 3.D Mapping Innovation to Diffusion Patterns (Adapted from Schmidt and Druehl, 2008)

Innovation Type	Diffusion Trajectory	Description	Example
Sustaining Innovation	High end encroachment	The new product first encroaches on the high end of the existing market then diffuses downward.	Pentium IV relative to Pentium III
Disruptive	Low end encroachment	The new product first encroaches on the low end of the existing market and then diffuses upward.	
• New-Market Disruption	Fringe-market low end encroachment	Before encroachment begins, the new product opens up a fringe market (where customer needs are incrementally different from those of current low end customers).	5.25 inch disk drives relative to 8 inch drive
	Detached-market low end encroachment	Before encroachment begins, the new product opens up a detached market (where customer needs are dramatically different from those of current low end customers).	Mobile phone relative to land line
• Low end Disruption	Immediate low end encroachment	Low end encroachment begins immediately upon introduction of the new product.	Discount relative to department stores

From Table 3.D. we can see that disruptive innovation maps to low end encroachment, whereas sustaining innovation maps to high end encroachment. The concept is best considered from the visualisation of performance trajectories of different technological offerings illustrated in Figure 3.G. Initially, the mobile phone could not satisfy the levels of performance demanded in reception quality. However, performance in portability enabled the mobile phone to established detached market linkages (Hüsig et al., 2005; Druehl and Schmidt, 2008; Schmidt and Druehl, 2008). Subsequent R&D investments improved the disruptive technology's performance in primary attributes enough to satisfy low end, mainstream and high end demand requirements (Danneels, 2004; Yu and Hang, 2010). Despite the mobile phone's initial high price and technological radicalness, "*the first major group of users to drop the landline in favour of the cell phone was the landline's low end market*" (Schmidt and Druehl, 2008; 351).

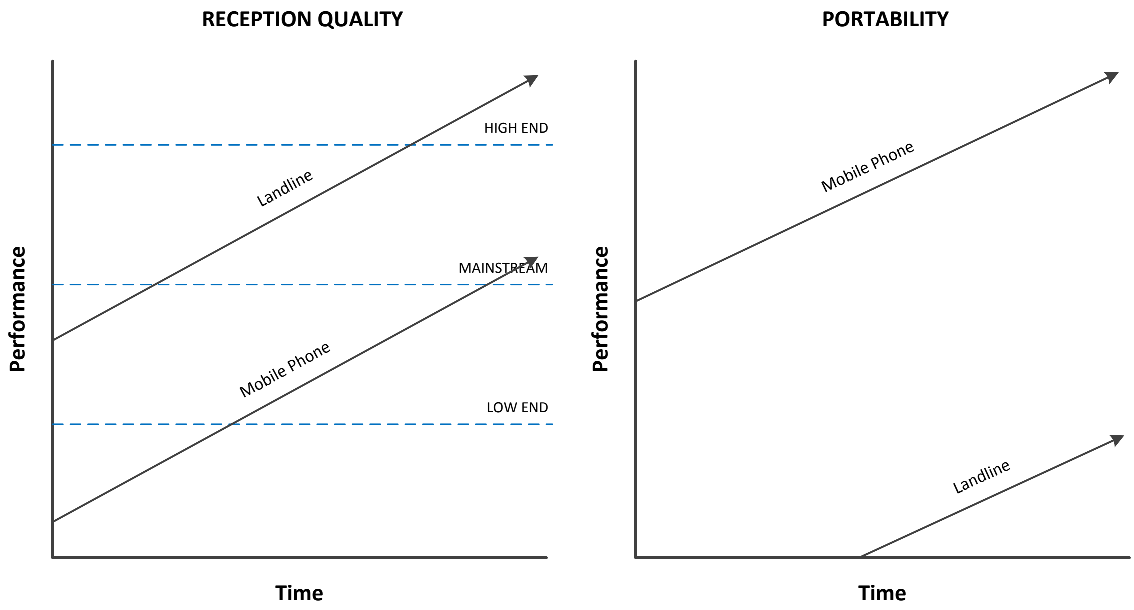


Figure 3.G Performance Trajectories of Landline and Mobile Phone Technologies for Portability and Reception Quality

As discussed in Sections 3.2.1 and 3.2.2, the combination of inferior primary attribute performance and undesirable performance attributes render disruptive innovations unattractive to both mainstream customers and incumbent firms for investment (Govindarajan and Kopalle, 2006a; 2006b; Lucas Jr and Goh, 2009). As a result disruptive innovations are first introduced in emerging or insignificant market segments that do value the performance features offered (Danneels, 2004, Tellis, 2006). Disruptive innovations emerge through successive generations as they improve performance in key attributes to progressively move upwards towards mainstream market segments. Schmidt and Druehl (2008) distinguish between three types of low end encroachment from which disruptive innovations emerge (Table 3.D): detached-market, fringe-market, and immediate low end disruption.

- Detached-market low end encroachment refers to the scenario where disruptive innovations are first introduced in a market detached from the established segment. Detached markets are created when the disruptive innovation introduces a new or alternative performance dimension that is dramatically different from that expected in established markets (Druehl and Schmidt, 2008). For example, mobile phones created a new detached market for customers that valued the high performance provided in portability (re Figure 3.G). As a result, the new innovation served a different purpose from that of the established innovation. However, performance improvements enable the new innovation to eventually become a replacement for the established innovation. (Schmidt and Druehl, 2008).

- Similarly, fringe-market low end encroachment opens up a new market that is detached from the established market. However, the disruptive innovation only introduces a performance dimension that is incrementally different from those in the established market e.g. less of a traditional attribute and some added benefit or feature (Schmidt and Druehl, 2008). For example, free online office applications such as Google Apps provide fringe-market customers with less functionality in exchange for a free service.

- Finally, immediate low end encroachment is the scenario where the disruptive innovation immediately sells to the low end of the established market before diffusing upwards (Schmidt and Druehl, 2008). From this perspective, the new innovation offers an inferior product or service at a lower cost that appeals to the low end of the established market.

Incumbent firms tend to compete in upmarket regions such as mainstream and high end market segments that promise higher profit margins, thereby ignoring apparently insignificant market segments (Christensen, 1997, Hüsig et al., 2005). Consequently, disruptive innovations always emerge from a bottom-up perspective, as they are initially undesirable to established markets and high end segments.

3.2.6. Conclusion

It is evident from the previous discussion that disruptive innovation is a multifaceted phenomenon and encompasses multiple factors and interactions. Moreover, existing definitions do not adequately address the concept. Researchers differ in their assumptions regarding the factors that define and enable the process of disruption (Adner, 2002; Govindarajan and Kopalle, 2006a; Hüsig et al., 2005). However, mainstream customer preferences, preference overlap, preference asymmetry, primary attribute performance, performance oversupply, low price, low-end encroachment, and insignificant market segments emerge as the most consistent characteristics across the extant literature. Results of the literature review suggest that both price and performance oversupply may be overestimated predictors of disruptive innovation, as certain anomalies arise in the theory. For example, Ander (2002) concludes that market disruption is generally enacted by price, whereas Schmidt and Druehl (2008) demonstrate through their encroachment framework that price is independent of disruption. They use the example of digital photography and mobile phone technologies as higher priced disruptive innovations.

Contrary to popular proponents of the theory (Christensen, 1997; Hüsig et al., 2005; Yu and Hang, 2010), we demonstrate how the effects of performance oversupply may have been inflated in the literature, such that the characteristic is a sufficient but not a necessary condition for disruption. Although, we assume that both price and performance oversupply will directly influence the speed of diffusion it is important to consider the impact of preference structure, demand structure, and development dynamics on market disruption.

The combination of these factors forms the basis of the proposed diffusion model that underlies the dynamics that facilitate market disruption (Chapter 5). The factor 'Market Structure' is purposely omitted from our analysis, as the main focus of this research is concerned with analysing the innovation supply and market demand dynamics that enable disruption. However, analysis of market structure provides a potential area for future research.

3.3. Disruptive Innovation and Incumbent Firm Failure

While a disruptive innovation in its simplest form is an innovation that dramatically disrupts the market (Schmidt and Druehl, 2008) i.e. transforms the underlying competitive dynamics to new metrics of performance. Christensen's definition of '*disruption'* implicitly provides a duality of disruptive outcomes. These are: (1) market disruption, which refers to the transformation of competitive dynamics; and (2) organisational disruption, which refers to the disruption experienced by incumbent firms when faced with disruptive threats. In relation to the theory of disruptive technology, Tellis (2006) supports this proposition, stating that:

> *"Two of its premises are important. These deal with the performance path of a disruptive technology and its impact on dominant incumbents who ignore it in favour of listening to current customers*."

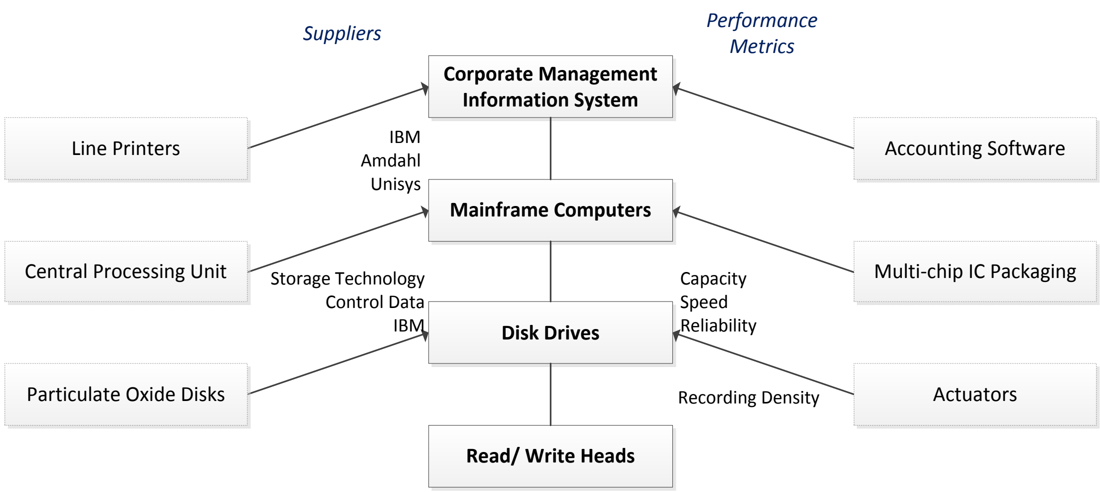
From the above explanation it can be concluded that market disruption and incumbent firm failure are interdependent events (Charitou and Markides, 2003, Gilbert, 2003). However in reality, these two important pillars of Christensen's theory of disruptive innovation represent fundamentally different phenomena (refer to Section 2.2, Table 2.B*)*. Incumbent failure is attributed to organisational and management factors, and are independent of an innovation's effect on existing market dynamics and technological base, whether they are radical, revolutionary, or disruptive (Tellis, 2006). Rather, success or failure is the result of "*internal cultural aspects*", "*organisational competencies*" and "*senior management cognitive failures*" (Christensen, 1997, Henderson, 2006, Tellis, 2006). Christensen and Rosenbloom (1995) argue that the success and failure of entrants and incumbents is attributed to three interlocking sets of forces: (1) the magnitude of technological innovation on firm capabilities; (2) managerial processes and organisational dynamics; and (3) the value network.

In this section, we identify and evaluate the different modes of organisational failure when faced with disruptive technological change. In each case the drivers of success/ failure can be categorised as an outcome of an organisation's value network (Christensen and Rosenbloom, 1995), competencies, and management inertia, rather than attributed to external factors.

3.3.1. The Value Network

Christensen and Rosenbloom (1995) consider firm failure from the perspective of the value network. Christensen (1997; 36) defines a firm's value network as "*the context within which a firm identifies and responds to customer needs, solves problems, procures input, reacts to competitors, and strives for profit*". Firms are embedded in value networks because the products and services they provide are comprised of hierarchically nested subsystems and components that relate to each other in design architecture (Christensen, 1997; Gatignon et al., 2002; Henderson and Clark, 1990).

A firm's unique history and market position influence how they access resources and evaluate the economics of alternative technological investments. The dominant technological paradigm and the corresponding technological trajectory set the scope and boundary of a firm's value network (Christensen and Rosenbloom, 1995). Lettice and Thomond (2008) conclude that path dependencies and prevailing mental models underpin resource allocation. Organisations focus on historically dependent technological, product, or customer-related paths which support the development of sustaining innovations in a given market context. Figure 3.H. illustrates the value network infrastructures of corporate management information systems (MIS), and portable personal computing markets:



(a). Corporate MIS Value Network

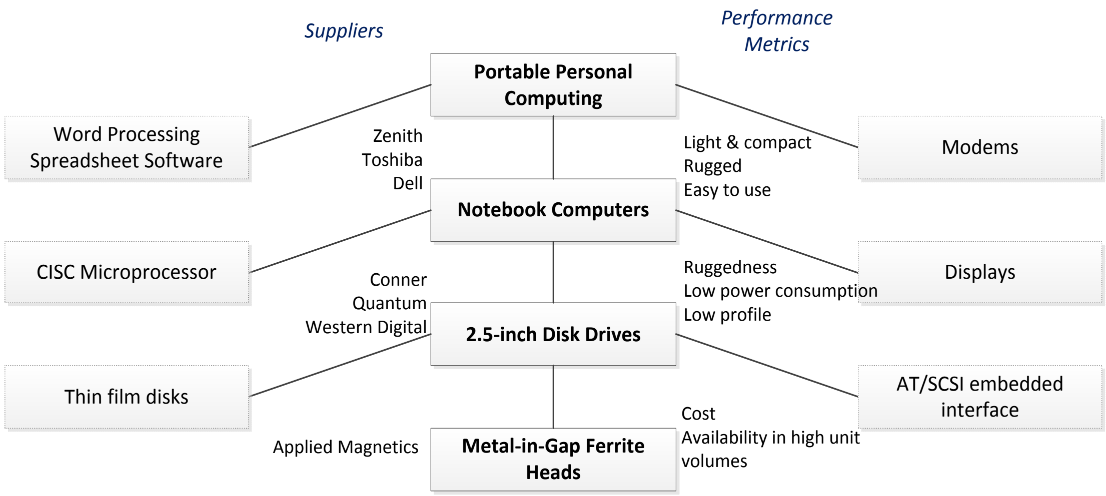


Figure 3.H(a). Corporate MIS Value Network (b). Portable Personal Computing Value Network: Example of Value Networks – (Christensen and Rosenbloom, 1995)

The metrics in which value is assessed differs between value networks. For example, the disk drives used in corporate MIS networks create value from *capacity*, *speed* and *reliability*, whereas the 2.5-inch disk drives used in the portable personal computing networks create value from *ruggedness*, *low power consumption* and *low profile* (Christensen and Rosenbloom, 1995). The firms that supplied these disk drives specialise in providing performance most valued in that network. The firms Storage Technology, Control Data, and IBM, all specialised in supplying disk drives for MIS mainframe markets; whereas Conner, Quantum, and Western Digital specialised in providing disk drives for portable computing markets (Figure 3.H).

The rank ordering of various performance attributes differs across value networks. Furthermore, the value network dictates the trajectory of product-performance improvement and influences investment strategies for future sustaining innovation. Figure 3.H. illustrates both the physical architecture of a product system and the network of producers and markets that comprise a product system (Christensen, 1997). Christensen and Rosenbloom (1995; 242) state:

> "*As firms gain experience within a given network, they are likely to develop their capabilities, structures and cultures to 'fit' that position better by meeting that network's distinctive requirements*".

A firm's position in the value network and connection with upstream and downstream suppliers influences the nature of operation and the impetus for certain technological developments. As a result, established firms become primarily concerned with satisfying the needs associated with the value network within which they compete. This limits a firm's mobility to pursue innovations in other value networks and hence the ability to pursue disruptive innovation (Christensen and Rosenbloom, 1995; Christensen, 1997).

3.3.2. Management Inertia

In the Innovator's Dilemma, Christensen (1997) concludes that incumbent firm failure is attributed to the fact that these firms were held captive by their customers, and thus unresponsive to future emerging markets. Using the example of incumbent firms operating in the HDD industry, Christensen states that:

> *"They were technologically capable of producing these drives. Their failure resulted from the delay in making the strategic commitment to enter the emerging market in which the 8-inch drives initially could be sold"* (1997; 19-20).

Resource dependency (Pfeffer and Salancik, 1978) theory posits that an organisation is dependent upon its economic environment, such that the allocation of a firm's resources is limited to satisfying the demands of that firm's most important revenue stream i.e. mainstream customers (Lettice and Thomond, 2008, Sandström et al., 2009). Such dependencies limit a management team's freedom of action to satisfy the needs of future mass markets and limit the scope for developing and harnessing disruptive change. Popular proponents of the theory focus on the cognitive failures of managers and technological myopia of the senior management team pursuing short-term success when examining why and how firms fail when faced with disruptive technologies (Govindarajan and Kopalle, 2006b).

Lucas Jr and Goh (2009; 48) state that "*management propensities determine the outcome of the battle between dynamic capabilities and core rigidities in responding to a transformational technology*". From this perspective, the success or failure of incumbent firms is an outcome of visionary leadership and management level propensities in response to disruptive technology. Willingness to cannibalise current assets to build future markets is a well-established concept in the literature for pursuing radical innovation (Chandy and Tellis, 1998, Tellis, 2006):

> "*Willingness to cannibalise is critical because firms that dominate markets often are reluctant to embrace or foster radical innovations in their markets. Their reluctance derives from the established base of specialised investments with which they serve such markets.*" (1998; 475)

Disruptive innovations require a firm to reconfigure their current investments towards future emerging markets. As such, willingness to cannibalise is an important management propensity. Chandy and Tellis (1998) identified four variables that directly influence a firm's willingness to cannibalise, these include: "*specialised investments*", "*internal markets*", "*product champion influence*", and "*future-market focus*". Results showed that *specialised investments, internal markets, product champion* and *future-market focus* all had a direct influence on a firm's willingness to cannibalise current assets. In particular, future-market focus was the biggest predictor of a firm's willingness to cannibalise. Tellis (2006; 37) states that "*firms' future market orientation positively* *drives their willingness to cannibalise assets, which in turn drives radical innovation*" (Tellis, 2006; 37). Figure 3.I. illustrates the determinants of willingness to cannibalise and provides a brief description of each construct:

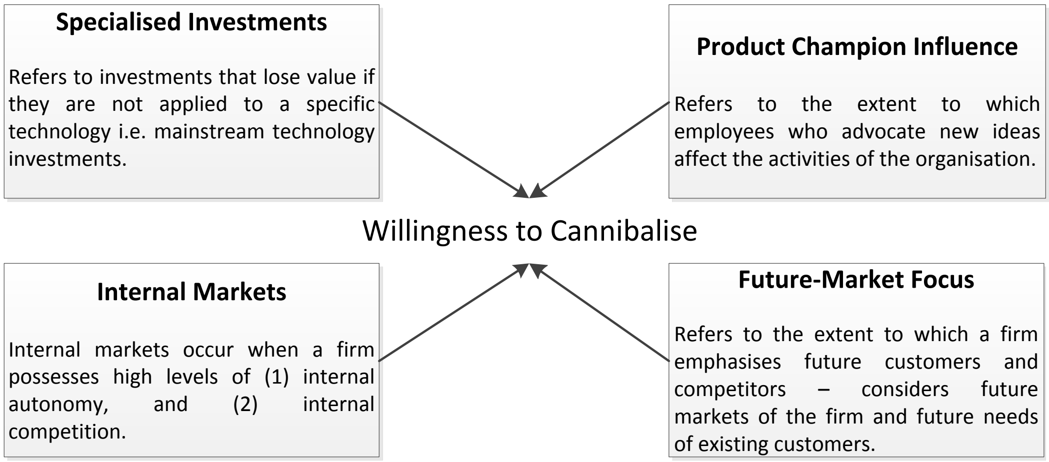


Figure 3.I Determinants of Willingness to Cannibalise (Adapted from Chandy and Tellis, 1998)

Below we adapt the four constructs of willingness to cannibalise from Chandy and Tellis (1998) relative to the pursuit of disruptive innovation and incumbent firm failure:

1. **Specialised Investments**: managers develop a strong professional and personal commitment to existing investments, which can lead to sub-optimal investments e.g. continually investing in sustaining technologies. Specialised investments have a direct negative impact on a firms' willingness to cannibalise current resources, thereby increasing the chances of incumbent firm failure.

2. **Internal Markets**: increased internal competition can increase a firm's willingness to cannibalise in order to remain competitive within the internal and external market structure. As a result, management inertia towards the cannibalisation of existing resources is reduced, thereby increasing a firm's activity in environmental scanning. Danneels (2008; 524) defines environmental scanning as "*the extent to which organisational members devote their efforts to learning about emerging events and trends in their organisation's environment*". Firms with less internal competition are more likely to fail when faced with disruptive change.

3. **Product Champion Influence**: top management actively support the activities of product champions. Similar to an opinion-leader a product champion is an individual who plays a dominant role in the innovation process (Chakrabarti, 1974). The influence of product champions has a positive influence on a firms' willingness to cannibalise current resources. Consequently, firms with influential product champion support will have a lower probability of failure.

4. **Future-Market Focus**: future market orientation of decision makers increases firm-level activity in environmental scanning, and in-turn environmental scanning enhances the firm's ability to recognise new opportunities, markets, technologies and potentially disruptive threats (Danneels, 2008). As a result, managers are not overtly committed to the existing and historic investments of the firm and are more willing to cannibalise current resources.

(Adapted from Chandy and Tellis, 1998)

Consideration of the above points illustrates that the success or failure of incumbent firms is attributed to management propensities that can identify, anticipate and harness disruptive change. From this perspective incumbent firm failure is an outcome of the internal skills and knowledge inherent in human resources. More specifically, senior management's lack of vision towards emerging technologies and markets, and their unwillingness to cannibalise current resources leads to firm failure. Consequently, incumbent failure is independent of the innovation itself (Tellis, 2006). Yu and Hang (2010) summarise incumbent firm failure from an internal human resource perspective in the following Table:

Table 3.E Human Resource Inhibitors (Yu and Hang, 2010; 14)

Perspective	Aspects	Sub-aspects	Inhibitors
Internal	Human Resources	Managers	1. Senior managements are limited by their current experiences. 2. Senior managers were trained to manage well-defined product lines. 3. Middle managers have the most to lose in disruptive change (Try to bolster current investments) 4. Professional managers follow routines to manage established business
		Employees	1. Knowledge lack and risk-averse attitude of employees. 2. Rely on analyst laden corporate strategy to collect or create disruptive ideas 3. Disruption from outside due to brain drain of talent and disruptive ideas

3.3.3. Organisational Competence

Existing organisational competence is another perspective that emerges in the literature that scholars identify as a factor influencing a firm's ability to pursue disruptive innovation. Organisational competencies refer to the resources, skills, and knowledge that are at the firm's disposal. Henderson (2006) believes that the complexity of the role played by embedded organisational competencies is understated when considering incumbent firm failure when confronted with disruptive innovation. She states:

"*The focus entirely on cognitive failures in the senior management team obscures the critical role played by deeply embedded customer or market-related competencies in shaping the ways firms respond to disruptive innovations*" (Henderson, 2006; 5)

Leonard-Barton (1992) introduces the idea of core rigidities, in which the core capabilities of the firm become so rigid that they become *competency traps*. For example, engrained habits, processes and technologies can limit a firm's ability to respond appropriately to disruptive threats (Henderson, 2006, Lucas Jr and Goh, 2009). She identifies such deeply rooted competencies across four dimensions: "*employee knowledge and skills*", "*technical systems*", "*managerial systems*", and "*values and norms*". Pursuing disruptive and radical technological change requires new skills, abilities and knowledge in both the development and production processes of the organisation across these dimensions. However, reconfiguring an organisation towards assimilating new competencies is extremely difficult, particularly if the disruptive technology requires new production capabilities, new logistics or involves a new value network (Henderson, 2006, Tushman and Anderson, 1986).

Established competencies in production and marketing are both difficult to change and act as a barrier for development. Core capabilities are thus institutionalised and idiosyncratic to a firm's tacit and causally ambiguous knowledge structures that span across the four dimensions (Leonard-Barton, 1992). Casual ambiguity refers to the ambiguity that stems from the origins of a firm's capabilities, including skills, technologies, knowledge and information (Barney, 1991). Barney (1991; 109) states that:

"*Causal ambiguity exists when the link between the resources controlled by a firm and a firm's sustained competitive advantage is not understood or understood only very imperfectly"*

Such resources are a source of competitive advantage, as firms cannot duplicate successful strategies and core capabilities that are difficult to imitate. Barney's (1991) resource-based view (RBV) identifies four attributes that firm resources should hold in order to be a source of competitive advantage. These attributes form the common VRIN characteristics: (1) valuable; (2) rare; (3) inimitable; and (4) non-substitutable.

According to the RBV, resources are institutionalised, path dependent, and embedded in a firm's unique history (Chesbrough, 2003). Skills, technologies, knowledge and information are thus developed over time through experience and are not freely available on the market (Teece et al., 1997). However, such institutionalised capabilities can lead to incumbent inertia when faced with radical and disruptive technological change. Tushman and Anderson (1986) state that "*the mastery of new technology fundamentally alters the set of relevant competencies within a product class*". They conclude that technological discontinuities can enhance or destroy existing competencies within the firm. As such, the core capabilities of the firm can also act as core rigidities that inhibit individual and organisational change when confronted with technological and market disruption (Lucas Jr and Goh, 2009). Leonard-Barton (1991) defines a core capability as an interrelated interdependent knowledge system.

Figure *3.J* provides a summary of the four dimensions of core capabilities:

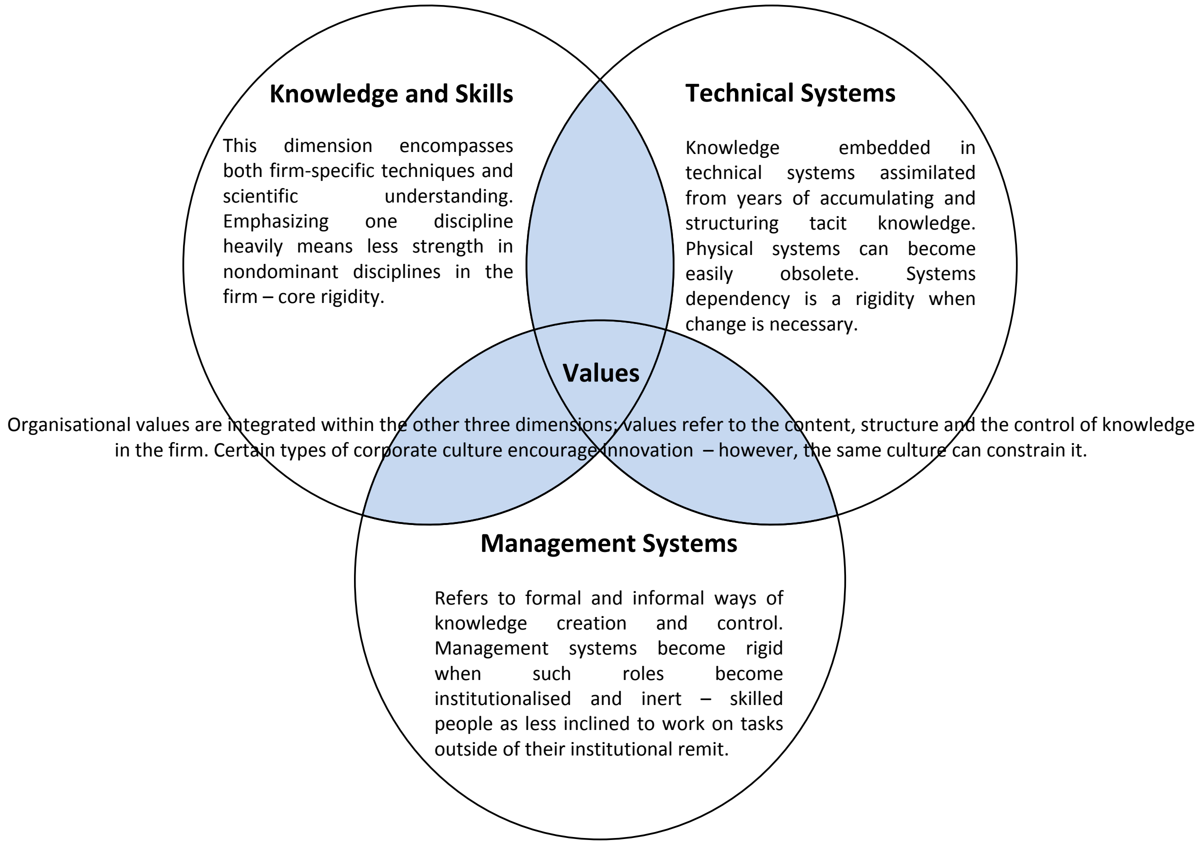


Figure 3.J Four Dimensions of Core Capabilities – Rigidities (Leonard-Barton, 1992)

The four dimensions of a core capability represent an interrelated, interdependent knowledge system (Leonard-Barton, 1992) that directly affect a firm's ability to assimilate the resources to pursue and/ or react to disruptive technological change. The internal influence between the four dimensions is strong, such that the dimensions form a closed loop of complementary and coercive relationships. Values are infused throughout the other three dimensions. Values influence how knowledge is collected, assimilated, and controlled, even physical systems embody values (Leonard-Barton, 1991).

However, core capabilities of the firm can become core rigidities when faced with disruptive change (Henderson, 2006, Lucas Jr and Goh, 2009) and technological discontinuities (Tushman and Anderson, 1986). For example, over emphasis of a particular skill set, attribute or scientific discipline significantly limits the scope of the organisation to a small subset of knowledge. Such organisational myopia restricts a firm's ability to identify and harness disruptive technological change that exists outside the direct remit of a firm's dominant skills domain.

Similarly, a firm's technical systems and management systems can become institutionalised and rigid, especially when they have been coded, configured and structured tacitly to satisfy the dominant discipline and culture (values) of the firm (Leonard-Barton, 1992, Lucas Jr and Goh, 2009). Consequently, when faced with disruptive technological change that requires significant reconfiguration of core capabilities, the probability of incumbent firm failure increases. Table 3.F considers some of the organisational inhibitors to harnessing and developing disruptive innovation organised in terms of *culture*, *resources*, *structure* and *relationships* of the organisation:

Table 3.F Organisational Competence Inhibitors (Adapted from: Henderson, 2006; Lucas Jr and Goh, 2009; Yu and Hang, 2010)

Perspective	**Aspects**	**Sub-aspects**	**Inhibitors**
Internal	Organisation Competence	Organisational Culture	1. The cumulative culture becomes cultural inertia which so difficult to overcome 2. Fail to link the development of technological advances to changes in the market 3. Focus too much on existing customers that encompass existing remit of the organisation – closed loop culture
		Organisational Resources	1. Structured routines are used to evaluate both emerging disruptive projects and existing businesses 2. Financial results are a bad tool for managing disruption, as disruptive technologies initially offer lower profit margins 3. Resource dependence locked firms into existing business and push firms to invest more on conventional business when threatened from low end 4. Non-dynamic capabilities and core rigidities inhibit a firms response to disruptive innovation
		Organisational Structure	1. The size and structure of the firm and business units will directly impact a firms' ability to assimilate resources to respond to disruptive change – bureaucracy and hierarchy support the status quo.
		Organisational Relationships	1. Organisations locked into the relationship with resource providers and suppliers prevent disruptive project development 2. Organisations can find it difficult to change their existing value network – depending on the locus of innovation

Henderson (2006) also poses the question as to whether it is rational for firms to respond to disruptive innovation. This is especially true when the pursuit of disruptive innovation requires the development of new production capabilities, distribution systems, market linkages, labour and skill. Under such conditions, the reconfiguration of existing capabilities and resources towards more appropriate competencies may not be a rational decision. Linton (2009; 732) states:

> "*A firm with a structure that better supports innovation will have greater reach than a firm without. If we consider a series of innovations from the perspective of two different firms: Firm A that has inherent rigidities that make integrating innovation into organisational routines difficult, versus Firm B, an organisation that is better at evolving incorporate innovations – we find that Firm B is able to more easily integrate innovations with large input magnitudes than Firm A does.*"

Input magnitude is the degree of change required in organisational resources to pursue new technological innovation. Innovations that require a larger magnitude of change deviate further away from the existing status quo. A positive magnitude involves reinforcing or extending existing practices and competencies, whereas negative magnitudes represent a departure from organisational strengths and trajectories. As a result, negative magnitudes are more difficult to incorporate (Linton, 2009). When considering the impact of organisational competencies, embedded organisational capabilities and routines may be much more central to incumbent firm failure than is generally acknowledged when faced with disruptive innovation.

3.3.4. Responding to Disruptive Innovation

Christensen (1997) offers different management strategies for harnessing disruptive change and the scenarios in which incumbent firms survived. He states (1997; 113) that successful firms "*embedded projects to develop and commercialize disruptive technologies within an organisation whose customers needed them*". Managers need to match an innovation's offering with the demand requirements of the customer or market segment. Christensen (1997) suggests that creating an independent SBU or organisation embedded within a different value network to pursue disruptive innovation helped firms to overcome barriers of resource dependency. By creating an independent entity utilising the resources from new value networks incumbents can pursue emerging markets with disruptive innovation.

However, the smaller profits offered in such markets is an additional factor that limits a firm's ability to recognise their potential (Christensen, 1997). As a result, established firms cannot muster the rationale for entering emerging markets in the crucial early stages, as they work to maintain high growth rates in established markets. He suggests three approaches to deal with this problem (1997; 148):

1. *Try to affect the growth rate of the emerging market, so that it becomes big enough, fast enough, to make a meaningful dent on the trajectory of profit and revenue growth of a large company.*
2. *Wait until the market has emerged and become better defined, and then enter the market.*

3. *Place responsibility to commercialise disruptive technologies in organisations small enough to pursue disruptive innovation.*

Christensen (1997) concludes that the third approach has the most promise. Established firms through collaboration or acquisition can delegate the responsibility of pursuing disruptive innovation to smaller better equipped organisations. Incumbents need to identify appropriate incubation firms with complementary assets, embedded in the relevant value network in order to successfully respond to disruptive innovation.

Ansari and Krop (2012) establish a generic framework of incumbent challenger dynamics from the perspective of the firm (incumbent), the industry setting, and the challenge. Several constructs and their interactions are identified that effect firm performance when faced with disruptive technological change. They state that "*when radical innovations impact an industry, established incumbents are sometimes displaced by new challengers, yet at other times they survive and proposer*". The proposed framework helps firms to develop better strategies for responding to disruptive change through the understanding of different incumbent challenger dynamics.

The Industry Setting:

The industry setting refers to the public and private sector actors that exist within a given firm's value network (Ansari and Krop, 2012). These include suppliers, customers, competitors, and complementary products or services. As illustrated in Section 3.3.1, incumbent firms are influenced by a value network's architecture that determines a firm's ability to respond to disruptive innovation. The structure of specialised complementary assets (Tripsas, 1997), complementary markets, the institutional environment, demand factors, supply factors, and rivalry and turbulence experienced by incumbent firms all influence their reaction to technological threats (Ansari and Krop, 2012). Ansari and Krop (2012) use the example of mobile telephony. They state:

> "*In mobile telephony, challengers did not disrupt incumbents who controlled access to spectrum, networks and mobile phones on which the service is heavily dependent*".

As a result, knowledge of the value network can help firms to build better strategies for dealing with potentially disruptive threats. For example, incumbent firms need to make strategies to enter or create new value networks when challengers develop new innovations that render their existing value network or entire business model obsolete. Conversely, incumbents may exploit challengers that require their well evolved value network in order to compete, thereby negating the threat of disruption e.g. new mobile telephony operators need to rent spectrum from incumbents (Ansari and Munir, 2008).

Hüsig et al., (2005) provide an overview of the management processes involved with responding to disruptive technologies from the context of the value network. (1) Disruptive technology scanning, (2) developing the opportunities and business models for disruptive innovation, and (3) building strategies for harnessing disruptive potential, are the three stages illustrated in Figure 3.K. that are embedded in the value network.

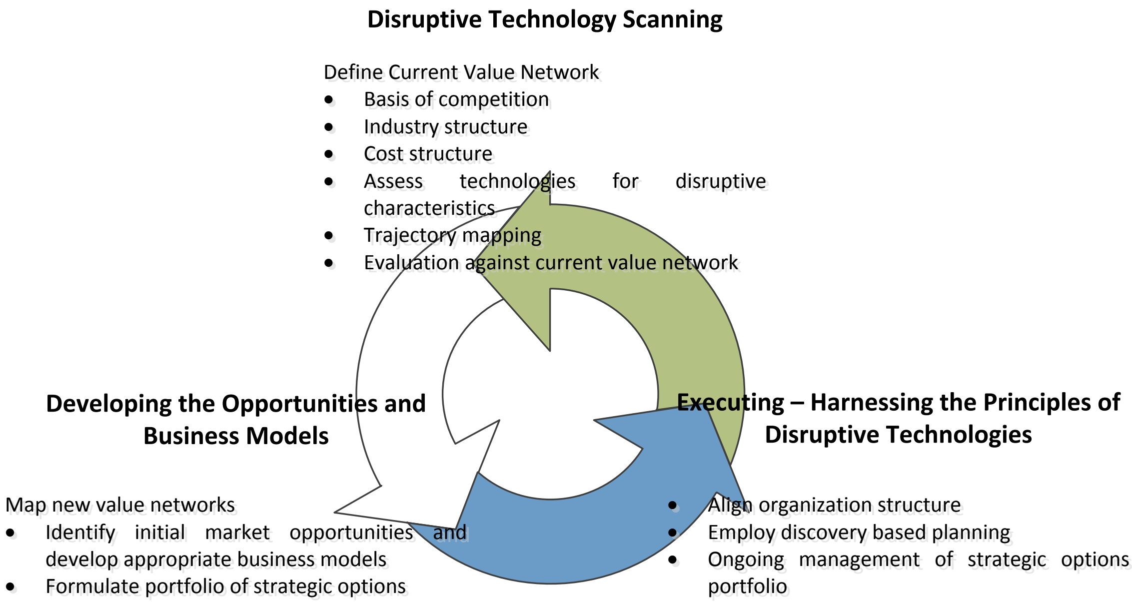


Figure 3.K Management Processes for Disruptive Technologies (Hüsig et al., 2005)

The Incumbent Firm:

In addition to the industry, Ansari and Krop (2012) argue that the incumbent itself and its related constructs: *boundary management* – the firm's interactions with its environment; *firm configuration* – the structure and form of the firm; and *complementary capabilities* – the capabilities used to commercialise or develop new innovations all influence incumbent challenger dynamics. Incumbent firms can effectively manage disruptive threats that emerge in the environment through the development of effective strategies. For example, incumbents in the nanotechnology and biotechnology industries reduce the threat of disruption through the acquisition of challengers and start-ups (Rothaermel and Thursby, 2007). They in turn provide complementary capabilities such as distribution and commercialisation channels (Ansari and Krop, 2012). Organisational strategies include collaboration through joint ventures, partnerships, and alliances, outsourcing, and acquisition. Such strategies improve an incumbent's chances of survival when faced with disruptive innovation.

Firm configuration and complementary capabilities also influence a firm's ability to survive disruptive innovation. The structure of internal processes and organisational culture determine how firm's manage technological change and pursue innovation. Ambidexterity refers to a firm's ability to pursue strategies for both radical and incremental innovation (Tushman and O'Reilly, 1996). Ansari and Krop (2012) conclude that firms with ambidextrous processes are better equipped in responding to disruptive innovation. Adopting both mainstream customer and emerging market orientations (Govindarajan et al., 2011) is important for the ambidextrous firm. Govindarajan et al., (2011) show that mainstream customer and emerging market orientation is positively related to the development of radical and disruptive innovations respectively. Similarly, complementary capabilities such as access to commercialisation channels and capability embedded in the value network insulate incumbents from disruption.

The Challenge:

The challenge refers to the challenge posed by new entrants. Ansari and Krop (2012) identify innovation type, commercialisation requirements, and firm incubation period[12] as the related constructs. New innovations that destroy the complementary assets or value network connections of the firm e.g. access to suppliers and customers, carry more disruptive capability. In addition to innovation type Ansari and Krop (2012) argue that the commercialisation needs of innovations determine their disruptiveness. For example, entrants can easily obtain generic commercialisation assets in the market, whereas specific assets are a source of competitive advantage. As a result, incumbent firms should try to build strategic complementary assets as they can effectively act as an entry barrier for new firms, thereby negating disruptive threats. Finally, the incubation period of the challenge affects a firm's response. The longer the incubation period the higher the likelihood of incumbent firm survival (Ansari and Krop, 2012). Incumbent firms need to build strategies to effectively identify emerging trends while they are still in their incubation period.

3.3.5. Conclusion

From the previous discussion it is evident that incumbent firm failure and market disruption are independent events. Firm failure when faced with disruptive change is a complex phenomenon involving management propensities, organisational competencies, and culture (Lucas Jr and Goh, 2009). Such organisational factors are independent of an innovation's impact on the market and underlying technology. Although disruptive change can be the catalyst for firm failure, failure itself is attributed to an organisation's reaction to and capacity to respond to market changes. When building strategies for responding to disruptive innovations, firms must consider the industry setting, internal structure and capabilities, and the challenge posed by entrants (Ansari and Krop, 2012).

[12] The period between incumbents' awareness of the innovation and its profitable commercialisation (Ansari and Krop, 2012; 18)

Dynamic capabilities are essential when confronted with disruptive technology. They facilitate a firm's ability to reconfigure current processes (Lucas Jr and Goh, 2009). Furthermore, senior management must be willing to cannibalise current resources to initiate the change effort. For example, visionary leaders focus intently on future emerging markets and innovation activity towards satisfying emerging market needs (Tellis, 2006). The danger of focusing too tightly on current customers increases the risk of ignoring potentially disruptive technologies. Similarly, the inability to reconfigure organisational competencies towards developing disruptive innovation directly impacts a firm's ability to respond (Henderson, 2006, Lucas Jr and Goh, 2009, Yu and Hang, 2010). Lucas Jr and Goh (2009) provide a framework for responding to disruptive change illustrated in Figure 3.L that summarises the relationship of dynamic capabilities and core rigidities with a firm's capacity to change:

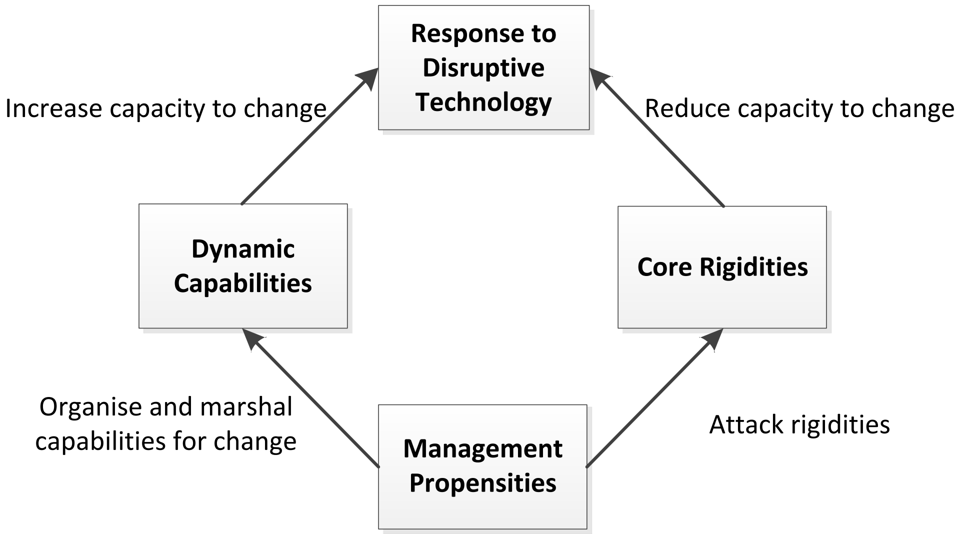


Figure 3.L Framework for Responding to Disruptive Change (Lucas Jr and Goh, 2009; 47)

Separating the duality of disruptive outcomes from Christensen's theory of disruptive innovation significantly helps us to understand the concept of market disruption. Market disruption is facilitated by a transformation of market segment preferences towards new dimensions of performance (Danneels, 2004, Schmidt and Druehl, 2008). In contrast, organisational disruption i.e. incumbent firm failure, is attributed to the combined effects of organisational competence and management propensities (Henderson, 2006, Lucas Jr and Goh, 2009, Tellis, 2006, Tushman and Anderson, 1986). Chesbrough (2003; 659) states:

> "*Firms need to access skills, capital and customers to enter into an industry initially, and the choices they make to access these resources are likely to exert path dependent influences over the subsequent entry behaviour into new submarkets.*"

Using the example of the HDD industry in Japanese and US firms, Chesbrough (1999, 2003) illustrates that the effect of technological innovation on markets and organisations is a relative phenomenon. The disruption experienced by US firms in the HDD industry was not replicated in Japanese firms. He (2003) demonstrates that the initial configuration of the firm i.e. – *management vision*, *institutional environment* and access to *skills*, *capital* and *customers* exerts strong path dependent effects over a firm's response to disruptive change. For example, Japanese firms linked to a keiretsu[13] exhibit a "*lower risk*" of failure, and experienced increased "*longevity*" in the HDD industry when compared to US counterparts (Chesbrough, 2003).

He concludes that firms need to configure themselves to access skills, capital and customers in order to respond to disruptive change in their respective environment (Chesbrough, 2003). Christensen (2006) later reaffirms the proposition that "*relativity is a crucial concept in the theory of disruption*"; disruption can only be measured from the perspective of a single market. Similarly, the effect of disruption on organisational competencies can also only be measured from the perspective of the single firm. In the following section we build a new definition of disruptive innovation based upon the extensive literature review. The definition addresses some of the major critiques to the theory and provides a stepping stone for future research.

3.4. Building a New Definition of Disruptive Innovation

Christensen's (1997) definition of disruptive innovation refers to a specific process (Section 3.1), relating to how new innovations impact existing markets and organisational competencies. Christensen offers an intricate picture of how firms react to shifts in competitive dynamics that ultimately lead to the failure of incumbent firms. However, his definition regarding the process of disruption has caused confusion, specifically in defining the term. Section 3.3 illustrates the duality implicitly present in the existing theory of disruption: (1) market disruption; and (2) incumbent firm failure.

As a result, the innovations literature consists of conflicting definitions regarding the concept. Markides (2006) illustrates that lumping categories of innovation together with different competitive effects simply mixes "*apples with oranges*". Danneels (2004) among others concludes that insights regarding disruptive innovation are ambiguous (Markides, 2006; Tellis, 2006; Sood and Tellis, 2011) and in need of further development. Specifically he asks the questions:

1. *What actually is a disruptive technology/ innovation?*
2. *What makes a technology/ innovation disruptive?*
3. *What are the exact criteria for identifying a disruptive technology/ innovation?*

[13] Keiretsu refers to the interlocking relationships among a corporate group of Japanese firms integrated along the value chain both horizontally and vertically

(Danneels, 2004; 247)

In this section we offer a critique of Christensen's theory based on an extensive review of the literature in Sections 3.2 and 3.3. We identify three problem areas associated with the current concept: (1) definition; (2) association of incumbent firm failure; and (3) relativity of disruptive outcomes. The section concludes with a new definition of disruptive innovation that addresses the specific nature of the concept, and a summary of the gaps in knowledge that directed the research.

3.4.1. Problems of Definition

The lack of concrete definition regarding the concept of disruptive innovation significantly limits future research. Evident from Section 3.3 the process defined by Christensen can be conceived across two dimensions: disruption to the market and disruption to incumbent firms (Danneels, 2004). Christensen does not establish clear-cut criteria to determine whether or not a given technology is considered a disruptive technology. Danneels' (2004) review and critique of disruptive technology provide valuable insights and identifies specific themes for improving the theory. We provide a critique of the existing theory across three key questions concerning definition:

1. *What actually is a disruptive innovation?*

Problems with definition have caused common misconceptions of disruptive technology. Often disruption is applied as an umbrella term and attributed to: Discontinuous technological change (Kassicieh et al., 2002, Linton, 2002, Walsh, 2004) – where innovations are based on a different technological base; or Competence-destroying organisational change (Christensen, 1997, Walsh et al., 2002) – where existing manufacturing practices and technological capabilities are disrupted. Christensen (2006; 42) states that: "*the term disruptive has many prior connotations in the English language, such as "failure" and "radical," in addition to the phenomenon to which I applied it*". However, his definition includes two fundamentally different concepts and categorically links disruptive innovation to incumbent firm failure.

The problem here lies with the consolidation of independent innovation effects, more specifically – '*Technological*', '*Organisational*', and '*Market*' based effects. Disruptiveness is a measure of an innovation's impact on existing markets and should not be confused with technological and organisational based innovation dimensions. Christensen fails to make this distinction, thus causing confusion in definition. In this research we adopt Danneels' (2004) definition of disruptive technology (i.e., one that dramatically disrupts the current market (Schmidt and Druehl, 2008):

> "*A disruptive technology is a technology that changes the bases of competition by changing the performance metrics along which firms compete*" (2004; 249).

2. What makes an innovation disruptive?

Christensen fails to address the issue of what makes an innovation disruptive. Inconsistent terminology and lack of definition make it difficult to operationalise *disruptiveness* or *disruption* to any specific perspective. Is disruptiveness a function of the firms subject to it? Or is disruption a function of the market in which an innovation competes or invades (Danneels, 2004)? From a market perspective disruptive innovation transforms existing metrics of competition towards new dimensions of performance (Keller and Hüsig, 2009), whereas from an organisational perspective a disruptive innovation causes firm failure. The key problem here is the tautological explanation of the phenomenon, the same term is used to describe the process (disruptive) and the outcome (disruption) (Sood and Tellis, 2011).

3. What are the exact criteria for identifying a disruptive innovation?

Section 3.2 is concerned with establishing the factors that lead to disruptive innovation. Christensen's definition of the concept provides no indication towards the exact criteria. He (1997; xviii) states that "*disruptive technologies are typically simpler, cheaper, and more reliable and convenient than established technologies*". Furthermore, Yu and Hang (2010) conclude that "*performance oversupply*" and "*asymmetric competition*" are two essential preconditions of disruption. However, none of these characteristics are quantitatively validated, and thus may not be necessary characteristics of market disruption (Danneels, 2004).

Anomalies with regard to the theory such as the mobile phone and digital cameras were both higher priced and technologically more complex, yet they still dramatically disrupted established markets (Druehl and Schmidt, 2008, Schmidt and Druehl, 2008). Furthermore, Christensen neglects to fully explain how disruptive innovations emerge and encroach upon established mainstream markets: high end vs. low end encroachment (Section 3.2.2). Schmidt and Druehl's (2008) encroachment framework successfully resolves the anomalies of high end vs. low end encroachment. However, an important question still remains: what are the exact criteria for identifying disruptive technologies (Danneels, 2004)?

3.4.2. Problems with the Failure Framework

In The Innovator's Dilemma, Christensen (1997) attributes the failure of established firms to the concept of the value network. Managerial decisions are centred on satisfying the elements of the firm's existing value network, such that innovation and R&D activity is geared towards satisfying current rather than future emerging markets. Christensen's explanation neglects the perspective of organisational competence. He concludes that established firms had the resources and capability to develop disruptive technology (Danneels, 2004), however it was the cognitive failures of senior managers in allocating resources to disruptive change that caused failure.

With reference to the US HDD industry he states (1997; 48) that "*prototypes of the new drives had often been developed before management was asked to make a decision*". To only focus on the impact of managerial propensities is very one dimensional and neglects a wide body of literature that can help explain why and how firms fail when faced with disruptive technological change. Furthermore, Christensen's (1997) definition of the value network can also be seen as a problem of organisational competence, whereby how a firm "*responds to customers' needs, solves problems, procures inputs, reacts to competitors, and strives for profit"* is influenced by the configuration of the organisation across the four dimensions of core capabilities/ rigidities (Leonard-Barton, 1992).

With reference to Figure 3.L, it is evident that resources, processes and management propensities are not independent of one another, but interdependent factors. The complex interplay of organisational competencies and management propensities determine a firm's ability to change. The embedded organisational processes and competencies both shape and are shaped by the people that utilise them (Leonard-Barton, 1992, Lucas Jr and Goh, 2009). Therefore to purely take a resource or process based perspective of the firm is to neglect the holistic view of an organisations' capability to react to disruption. Deszca et al., (1999) identify five factors that enable breakthrough NPD: (1) the organisation; (2) skills and competencies; (3) technology, systems and tools; (4) measurements; and (5) funding and governance.

Christensen's theory lacks analysis from differing theoretical perspectives such as *dynamic capabilities* (Teece et al., 1997), *RBV* (Barney, 1991) and *core capabilities* (Leonard-Barton, 1992). A holistic consideration of the factors that cause established firm failure would further develop our understanding of the barriers to disruption. However, such developments are independent of the concept of market disruption and will not be covered in this research.

3.4.3. Problems of Relativity

The unit level of analysis is important when determining the effect an innovation has across differing dimensions. For example, what is experienced as incremental competence-enhancing technological change in one firm, maybe experienced as radical competence-destroying technological change to another? Chesbrough's (1999, 2003) analysis of the US and Japanese HDD industry illustrates the underlying differences in disruptive effects that can be experienced internationally in different market contexts. He states that:

"*The ability of a firm to reconfigure themselves to acquire new competencies, access skills, capital and customers depends on the "menu" of configuration options available to the firms*" (2003; 675)

It is evident that how firms configure the menu of choices i.e. technical skills, capital and customers differs between countries, both at the international level in terms of institutional environments (Chesbrough, 2003) and at the inter-firm level through organisational capabilities (Leonard-Barton, 1992). A firm's configuration of organisational capabilities and institutional environment within which it operates has path dependent impacts. Chesbrough (2003; 660) states that such configurations "*direct firms along particular paths of development, but constrain the choice of other paths*".

As a result, disruption is a relative phenomenon (Christensen, 2006). What is disruptive in one market may be experienced as sustaining in another. Furthermore, innovation can be thought of as nested within the hierarchy of the supply chain and can be evaluated at the system and sub-systems level (Gatignon et al., 2002, Thomond, 2004). Product, process and technical innovations are composed of hierarchically ordered subsystem innovations or modules (Gatignon et al., 2002). Figure 3.M illustrates that disruptiveness is a product of perspective and location. For example, disruptive change can occur at the individual sub-systems level, multiple sub-systems level, or the whole system level, at different stages of the supply chain. Disruption is thus a matter of perspective and depends on the unit level of analysis.

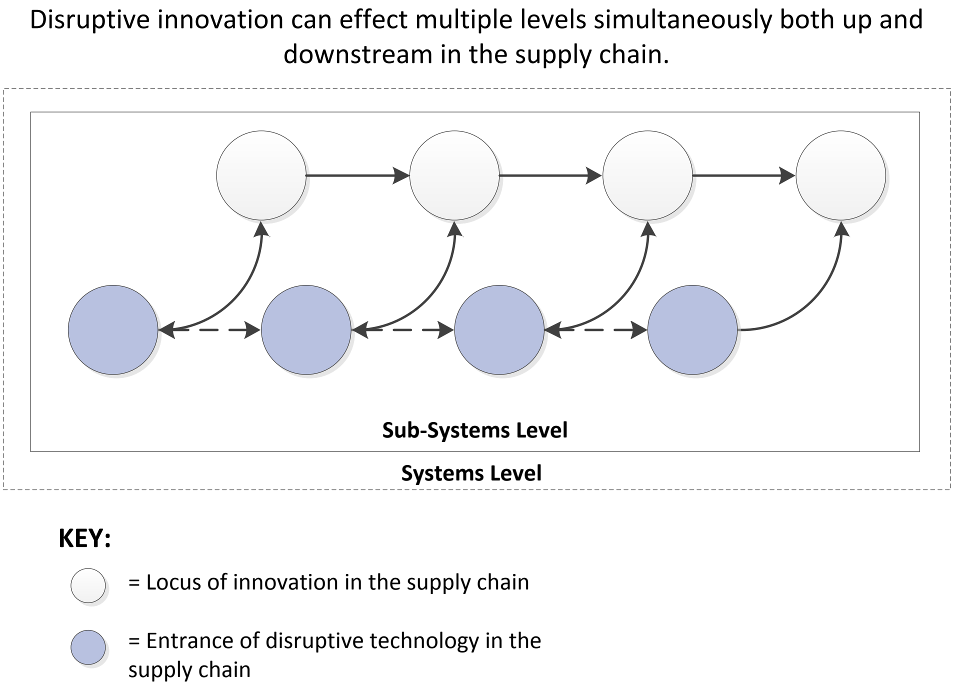


Figure 3.M Hierarchy of Supply Chain

Linton (2009) for example, differentiates between technical and social perspectives of innovation. Technical perspectives relate to products, processes, and subsystems; and social perspectives relate to individual customers, users, business units, firms, industries, and supply chains. As a result, an innovation is able to have a positive or negative effect depending on the perspective an innovation is being considered from (Linton, 2009). He (2009; 730) states that "*the greatest potential source of confusion regarding the language of innovation appears to be that of perspective.*" Existing definitions of disruption fail to address issues of relativity in terms of their referent level. Consequently it is important that the nature of the innovation and the perspective being considered is clearly stated in order to fully understand an innovation's impact.

3.4.4. A New Definition of Disruptive Innovation

The results of the literature review show the common misinterpretation of disruptive innovation used to describe incumbent firm failure (re Section 3.3). We find that when faced with disruptive change, firm failure is attributed to an organisation's ability to react (Henderson, 2006, Lucas Jr and Goh, 2009). Therefore, firm failure is an issue of organisational competence, management propensities, and culture, rather than an issue of innovation itself. In this research we adopt the perspective that disruptive innovation refers to a market-based phenomenon that is independent of technological and organisational dimensions. We define disruptive innovation as:

> *'An innovation that radically transforms existing markets and/ or creates new markets through the introduction of alternative performance dimensions that redefine customer value.'*

This transformation process changes the bases of competition expected in mainstream markets to new dimensions of performance (Danneels, 2004). As demonstrated in Section 3.2, there are many factors that influence the process of market disruption, namely *preference structure*, *demand structure*, *development dynamics*, and *market structure*. Consequently, the interactions between these factors and their initial composition lead to the emergence of different competitive regimes i.e. convergence, isolation, and disruption (Adner, 2002). Thus, market disruption is a complex and multifaceted phenomenon. However, little is known with regards to the factors that drive the process (Danneels, 2004). This research aims to bridge this gap and refine existing theory through the identification of the mechanisms and interactions that facilitate market disruption. Results of which will significantly improve our understanding of the concept.

4. Models of Diffusion and Consumer Choice

In this Chapter, we review theories and models of consumer choice and innovation diffusion in order to establish a solid theoretical background for model development. We consider the factors that influence diffusion and consumer choice at the macro and micro-level, and provide an analysis of competing models. These include: *epidemic*, *probit*, and *agent-based* diffusion models; and MAUT (multi-attribute utility theory) models. MAUT models analyse choice situations and create consumer choice processes (Gumasta et al., 2012). We consider the composition of different consumer choice models that adopt the additive utility method and the multinomial logit (MNL) formulation. Finally, we consider approaches that incorporate both consumer choice and diffusion effects in a single model. The Chapter is organised as follows:

1. Section one provides an introduction to classical diffusion of innovations (DOI) theory and DOI modelling, and highlights the importance of DOI.

2. Section two provides a comparative review of the different types of diffusion and consumer choice models in the management science literature. The basis of this comparison is to establish the most suitable technique for developing a model of disruptive innovation diffusion.

3. Section three considers existing models of disruptive innovation and focuses on the environmental factors that influence the diffusion process. The aim of this section is to provide an overview of the potential dynamics that influence disruption for subsequent model development.

4.1. Introduction

Research on DOI is concerned with understanding the process in which innovations spread in a given market. Rogers (1995) defines DOI from the perspective of four main elements. He states that: (1) an *innovation*; (2) is *communicated* through certain *channels*; (3) *over time*; (4) among members of a *social system* (1995; 11). The effects of social contagion are particularly prominent in traditional definitions of innovation diffusion. Firms and individuals imitate influential others in order to reduce the risks associated with adoption and due to pressures of social conformity. Peres et al. (2010) definition of diffusion considers social interdependencies of all kinds. They state that:

> *"Innovation diffusion is the process of the market penetration of new products and services, which is driven by social influences. Such influences include all of the interdependencies among consumers that affect various market players with or without their explicit knowledge"* (2010; 92).

Diffusion is an important requirement for the realisation of social and economic benefits of innovation, such as increased financial performance of the firm (Damanpour et al., 2009; Roberts and Amit, 2003). As a result, understanding the diffusion process helps us to realise the social and economic benefits attributed to innovation adoption and diffusion. **Communication dynamics** – *group affiliates*, *word-of-mouth* (WOM), *mass media* and *opinion leadership* (Bass, 1969; 2004; Belenzon and Berkovitz, 2010; Van Den Bulte and Joshi, 2007); **innovation dynamics** – *relative advantage*, *compatibility*, *complexity*, *trialability*, and *observability* (Rogers, 1995); and **market dynamics** – *market segment competition* and *consumer preferences* (Adner, 2002) all affect the diffusion potential of new innovation. Consequently, the diffusion processes of new products and services have become increasingly complex and multifaceted in recent years (Linton, 2002). Originally Rogers (1995) provides a conceptual model of innovation diffusion. He concludes that diffusion is the outcome of a communication process that dependents on an innovation's intrinsic characteristics; *relative advantage*, *compatibility*, *complexity*, *trialability*, and *observability*:

- **Relative Advantage**: *the degree to which an innovation is perceived as being better than its precursor;*
- **Compatibility**: *the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters;*
- **Complexity**: *the degree to which an innovation is perceived as being difficult to use;*
- **Trialability**: *the degree to which the results of an innovation are observable to others; and*
- **Observability**: *the degree to which an innovation may be experimented with before adoption.*

(Rogers, 1995; Moore and Benbasat, 1991)

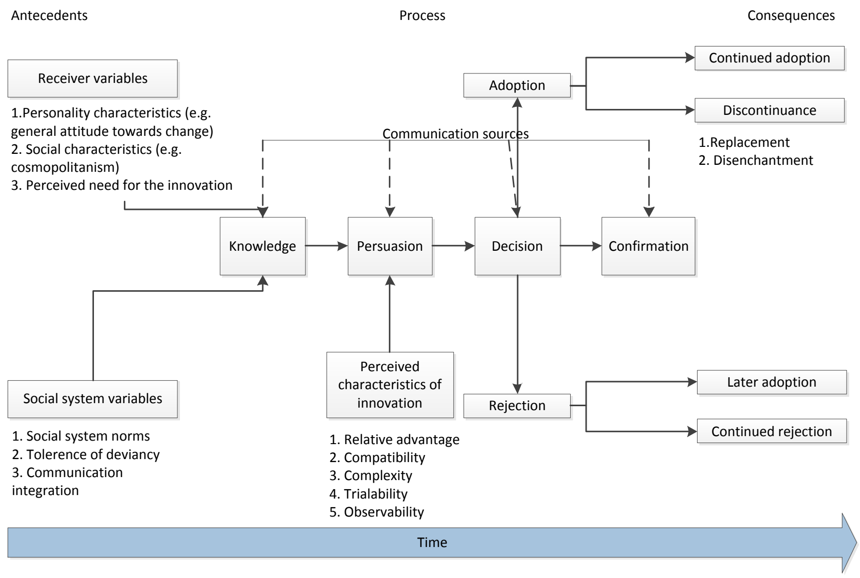


Figure 4.A Rogers' (1995) Diffusion of Innovation Model

Rogers (1995) concludes that adoption is the outcome of an innovation's characteristics and diffusion is the process of communicating an innovation to members of a social system. Diffusion modelling research seeks to understand the spread of innovations throughout their lifecycle from the perspective of communications and consumer interactions. Rogers' model of innovation diffusion focuses on both the micro and macro-level processes that influence adoption and diffusion respectively. Individual adopters of a population are assumed to be heterogeneous in their adoption preferences. However, diffusion is the outcome of social interactions that affect information transmission (Geroski, 2000), such as WOM communications, opinion leadership, network externalities, and social signals (Peres et al., 2010), which are irrespective of individual differences. These models are termed *epidemic models*, which focus on macro-level diffusion characteristics.

In contrast, *probit models* (micro-level) focus micro-level factors such as heterogeneity of goals, capabilities or actions of individual members of the population that influence the adoption decision (Geroski, 2000). Geroski (2000; 610) states that: "*it follows that differences between individuals may have a potentially important role to play in explaining patterns of diffusion*". Finally, agent-based diffusion models encompass both macro and micro-level influences and focus on the interactions of multiple agents in a system. It is expected that using an agent-based approach is superior as it encompasses both macro-level diffusion factors and micro-level interactions that account for individual differences to provide a holistic perspective of diffusion.

4.2. Diffusion of Innovation Models

Diffusion models are primarily used as a forecasting tool to predict the market share of new innovation and to evaluate the influence of specific environmental factors. Forecasting models for new innovations are based on models from diverse fields such as biology, epidemiology, ecology, and management. Traditional management models of innovation diffusion follow the distinctive S-shaped curve that depicts the cumulative number of adopters plotted over time (Bass, 1969; Rogers, 1995). However, disruptive innovations are more difficult to predict and provide a major problem for the technological forecaster. The performance attributes they offer differ from the performance expected by mainstream markets, as such disruptive innovations create new markets and industries (Kostoff et al., 2004; Linton, 2002). In this section we provide a comparison of the identified diffusion models of innovation: *epidemic*, *probit*, and *agent-based* models. Furthermore, we consider the diffusion patterns of disruptive innovations and the models used to explain the phenomenon (Adner, 2002; Adner and Zemsky, 2005; Linton, 2002).

4.2.1. Epidemic Diffusion Models

Epidemic diffusion models are the most widely used to explain DOI in management literature e.g. the Bass model (1969). Epidemic and differential equation (DE) diffusion models are macro-level interpretations of diffusion phenomena that explore the factors that cause innovations to spread in a given system. They emphasise the effects of social contagion and assume agent homogeneity in the population (Moore and Benbasat, 1991, Mahajan et al., 1990). Such models abstract from differences in the goals, capabilities or actions of individual agents in order to focus on diffusion processes from a simple rather than complex perspective (Geroski, 2000). The logic of epidemic models stem from diffusion being a function of information flow within a system, such that knowledge of an innovation results in adoption. The amount of available information is directly proportional to the number of adopters in a given system at a given time. Cantono and Silverberg (2009; 488) state that "*the S-shaped diffusion models and the epidemic models stem from two lines of research originating from Griliches (1957) and Mansfield (1961)*". Griliches' (1983) model fits a logistic growth function:

$$P = \frac{K}{1 + e^{-(a+b(t))}}$$

The function produces a distinctive S-shaped diffusion curve to data representing the percentage of all corn acreage planted using hybrid corn seed by state and years in the US agricultural industry. Overall model fit is excellent, with all R^2 calculations being ≥ 0.90. Similarly, Mansfield (1995) concludes that the rate of innovation diffusion when plotted against time approximately follows a logistic S-shaped function:

$$m_{ij}(t) = n_{ij}\left[1 + e^{-(l_{ij}+\phi_{ij}t)}\right]^{-1}$$

The basic premise of the model is that the proportion of firms that will introduce a new innovation is an increasing function of the proportion of firms already using it and the profitability of doing so, but a decreasing function of the size of investment required (Mansfield, 1961; 762).

Based on the models of Griliches (1957) and Mansfield (1961), and mathematical contagion models found in epidemiology, Frank Bass (1969) developed one the most popular and widely proliferated diffusion models in management science. In the following section, we provide the rationale and a brief mathematical summary of the Bass model and its extensions, including: market mix models and multiple product models (Linton, 2002; Norton and Bass, 1987).

***Bass Model and Extensions*:**

The main thread of epidemic diffusion models in the management science literature have been developed from the new product growth model introduced by Frank Bass – commonly known as the *Bass Model*. The Bass model considers the aggregate first-purchase growth of an innovation (including products, services and technical innovations (Bass, 2004)) introduced into a market with a constant market potential 'M'. Rogers' (1962) classifies adopters of an innovation into five classes according to the timing of adoption: (1) innovators; (2) early adopters; (3) early majority; (4) late majority; and (5) laggards. Bass used these classifications to differentiate between '*innovators*' and '*imitators*'; an innovator's adoption decision is independent of the decisions of other members of the social system. In contrast, imitators are influenced in the timing of adoption by the pressures of other members of the social system. In the formulation of the theory, Bass aggregates groups (2) through to (5) from Rogers' (1962) classifications and defines them as '*imitators*'. He states that:

> "*Apart from innovators, adopters could be said to be influenced by imitation in varying degrees; the pressure increasing for later adopters with the number of previous adopters*" (Bass, 2004; 1834).

Bass suggests that potential adopters are influenced by either a desire to innovate or a desire to imitate influential others in the population (Huber, 1974). He (2004; 1826) states that: "*initial purchases are made by both 'innovators' and 'imitators', the important distinction between an innovator and imitator being the buying influence*". The model assumes that a potential adopter will adopt an innovation through one of two channels: (1) due to internal influences, and (2) external influences.

Imitation is often called the contagion effect, where imitators learn from previous adopters who communicate information to other members of the social system (Bass, 1969; Meade and Islam, 2006). Internal influence refers to the effects of social contagion exerted by previous adopters and communicated through WOM effects and opinion leadership. Opinion leaders spread information in a social system by giving advice and directions to other consumers via WOM. Their innovative behaviour exerts social pressure to non-adopters to adopt (Rogers, 1995, McFadden, 1976). Potential adopters are rational in the consideration of economic and cost benefits from the adoption of a new innovation. As a result, firms tend to imitate influential others in order to minimise the risk of adoption. The information cumulated from increased adoption reduces risk and speeds up the diffusion process. In contrast, forces external to the social system such as mass media effects influence innovators. It follows that the diffusion process is initially driven by external influences (mass media). As the number of adopters increases the diffusion process is driven by internal influences (WOM and opinion leadership). The model is written as:

$$S(t) = \left(a + b\left(\frac{N(t)}{m}\right)\right) \times \left(m - N(t)\right)$$

Where:

$S(t) =$	*number of new adoptions at time (t)*
$a =$	*coefficient of innovation (environmental effect)*
$b =$	*coefficient of imitation (social contagion)*
$N(t) =$	*number of cumulative adopters at time (t)*

$m =$ *market size*

The coefficient a represents the external environmental influence for potential adopters to innovate. Consumers are assumed to be homogenous and the coefficient of innovation is constant over time. The function $b\left(\frac{N(t)}{m}\right)$ represents the increasing effect of social contagion (b), as more consumers adopt the innovation over time ($\frac{N(t)}{m}$). The Bass model is widely used as a strategic aid for forecasting the diffusion potential and diffusion patterns of new innovations in retail service, industrial technology, agricultural, educational, pharmaceutical, and consumer durable goods markets (Ansari and Krop, 2012).

However, the model receives criticism in the literature for the static nature of the coefficients of innovation (a) and imitation (b), particularly with reference to WOM effects (Mahajan and Muller, 1983). Extensions of the Bass model are used in the management literature for various reasons (Ansari and Krop, 2012): to improve sales forecasting estimations using flexible diffusion models (Kim and Srinivasan, 2009); to consider diffusion processes in different contexts e.g. technology generations and multi-product models, multi-market models, and geographical location and cross-country models (Linton, 2002; Norton and Bass, 1987); and to optimise strategy e.g. marketing mix strategies (Jun and Park, 1999, Jun et al., 2002, Jun and Kim, 2011).

***Technology Generations and Multi-Product Models*:**

Technology generations and multi-product diffusion models consider the introduction of new generations of innovation and multiple product competition in the market. New technology generations are improvements of existing technologies that replace older technologies (Norton and Bass, 1987) characteristic of incremental technological innovation. For example, the iPod has multiple generations – $1^{st} \rightarrow 2^{nd} \rightarrow 3^{rd}$ and 4^{th} generations. Furthermore, many new innovations are introduced into competitive markets where there are two or more competing standards. Meade and Islam (2006; 532) state that an innovative product may be available under separate sub-categories such as brands, e.g. mobile phones. The inclusion of competing products and technological generations into diffusion models facilitates our understanding of diffusion under different competitive conditions.

Norton and Bass (1987) proposed an adaptation of the Bass model that considers multiple generations of a technology. In the Norton and Bass (NB) model each generation of the technology attracts new adopters through expanded application and successive generations that cannibalise earlier generations' market potential (Meade and Islam, 2006; Norton and Bass, 1987). Thus, diffusion is the outcome of the number of initial adopters of each generation and new adopters that are attracted from alternative innovations. Namwoon et al., (1988) further extend the NB model to include dynamic market potential, substitution, complementary and competitive effects of successive generations, and multiple product categories.

While developing a forecasting model for the diffusion of disruptive and discontinuous innovation, Linton (2002) introduces a generalisation of the Bass model for multiple products. He states that the number of adoptions during a time period $S(t)$ is the sum of all the products market potential across multiple markets, given by:

$$\sum_i n \left(a_i + b_i \left(\frac{N_i(t)}{c_i m_i(t)}\right)^{(l+d_i)}\right)\text{-}\left(c_i m_i(t) - N_i(t)\right):$$

Where:

$a_i =$	*coefficient of innovation (environmental effect), for market i*
$b_i =$	*coefficient of imitation (social contagion), for market i*
$N_i(t) =$	*number of cumulative adopters at time (t), for market i*
$m_i(t) =$	*market size, for market i*
$c_i(t) =$	*coefficient of potential adopters, for market i*
$d_i(t) =$	*nonuniform influence parameter, for market i*
$n =$	*number of markets*

***Marketing Mix Models*:**

Extensions of the Bass model incorporate marketing mix variables to examine the impact of various marketing strategies on the diffusion process. In order for firms to optimise profitability and marketing strategy, several researchers have incorporated the impact of *price*, *advertising, promotional activity* and *media availability* in innovation diffusion models (Mahajan et al., 1990). Table 4.A. illustrates a few extensions of the Bass model that incorporate marketing mix variables.

Robinson and Lakhani (1975) were the first to introduce price into the probability rate of adoption in the Bass model: $\left(-\beta_2 P(t)\right)$, where $P(t)$ is price and β_2 is a sensitivity parameter. They examined optimal pricing strategies associated with the diffusion of new products. The model shows that an optimal constant price or initially lower prices are favourable pricing strategies to enable diffusion (Meade and Islam, 2006).

The impact of media availability on innovation diffusion, such as *newsprint consumed*, *newspaper circulation*, *television*, and *radio,* has been tested by Tellefsen and Takada (1999). The regression equation presented in Table 4.A. was used to explain the variation in the coefficients of innovation and imitation in the Bass model, the formula can be stated as follows:

"Coefficient p (innovation) or q (imitation) = f (newsprint, newspapers, radios, television, product, country" (Tellefsen and Takada, 1999; 87).

The results show that access to mass media has a positive effect on the influence of the diffusion parameter 'p' – coefficient of innovation. The effects of television ownership are significantly related to 'p' due to the broad penetration of advertising through this medium (Peres et al, 2010; Tellefsen and Takada, 1997). Similarly, Talukdar et al., (1988) also find that mass media effects have a positive influence on the coefficient of external influence (innovation).

Tsai et al. (2010) examine the impact of price on imitative behaviours of consumers to buy LCD TVs. They state that: "*price reduction is the key factor to strengthen the imitating behaviours of potential LCD TV adopters*" (2010; 556). The coefficient of imitation is modified to include $(P_0 - P_t)^{\delta}$, which represents the price gap between $[0, t]$, and 'δ' is the parameter of price elasticity, which represents the marginal effect of price reduction on internal influence 'q_1'. Results show that consumer's imitating tendencies increase with price decline and the coefficient of imitation is much greater than the coefficient of innovation.

***Cross Country and Multiple Market Models*:**

Modelling the effect of different national cultures on the diffusion process gives insight into the effects of national differences on the rate of innovation adoption, and provides insight into the global spread of new technologies. Understanding cross-country differences in the context of normative managerial decisions in multinational markets is important (Peres et al., 2010). For example, exploring optimal modes of market entry and examining the effects of cross-country marketing mix strategies. Table 4.A. provides an example of a popular cross-country extension of the Bass model and a generalisation of multi-market diffusion models.

Gatignon et al., (1989) propose an adaptation of the Bass model to consider the effects of country characteristics on the diffusion process. The cultural variables to capture national differences included: *cosmopolitanism* – the level of engagement with external information outside of the immediate social system; *mobility* – the level of mobility of a population; and the role of *woman in society* – the number of women working outside the home (Gatignon et al., 1989). The three aforementioned characteristics are incorporated into the coefficients of internal '$q(i) = Z'(i)g_q + e_q(i)$' and external influence '$p(i) = Z'(i)g_p + e_p(i)$'. Where g_p and g_q are vector coefficients of innovation and imitation respectively. Peres et al. (2010) formulate a generalisation of a multi-market diffusion model with cross country influences (Kumar and Krishnan, 2002, Putsis Jr et al., 1997). They conclude that cross-country effects result from two types of influences, *weak ties* – the level of influence from adopters in one country to non-adopters in another; and *signals* – the level of adoption in one country is a signal to imitate in another. The parameter 'δ_{ij}' is incorporated into the Bass model to reflect the strength of relationship between two countries (i and j) in order to examine cross-country effects on innovation diffusion.

Table 4.A Summary of Bass Model Extensions

Author(s)	Model Specification	Extension
	Multi-Generation and Multi-Product Models	
Norton and Bass (1987)	$S_1(t) = F_1(t)m_1 - F_2(t-\tau_2)F_1(t)m_1$, for $t > 0$ $S_2(t) = F_2(t-\tau_2)(m_2 + F_1(t)m_1)$, for $t > \tau_2$	• Extends Bass model to include multiple technology generations
Linton (2002)	$S(t) = \sum_i n\left(a_i + b_i\left(\frac{N_i(t)}{c_i m_i(t)}\right)^{(l+d_i)}\right)\left(c_i m_i(t) - N_i(t)\right)$	• Extends Bass model to include multiple products in different markets n=number of markets; c_i=coefficient for market (i) of potential adopters
	Marketing Mix Models	
Robinson and Lakhani (1975)	$h(t) = \left(\beta_0 + \beta_1 F(t)\right)e\left(-\beta_2 P(t)\right)$	• Extends Bass model to include a price index
Tellefsen and Takada (1999)	$lnY_{jk} = a + \sum_{i=1}^{4} b_i M_{ij} + \sum_{j=1}^{j-1} c_j N_j + \sum_{k=1}^{k-1} d_k P_k + U_{jk}$	• Extends Bass model to text the impact of media availability on diffusion
Tsai et al., (2010)	$n(t) = \left(p + q_1 \times (P_0 - P_t)^{\delta} \times \frac{N_{(t)}}{M}\right)\left[M - N_{(t)}\right]$	• Extends Bass model to include the coefficient of imitation as a function of price
	Cross Country & Multiple Market Models	
Gatignon et al (1989)	$x(i,t) - x(i,t-1) = \left(p(i) + q(i)x(i,t-1)\right)\left(1 - x(i,t-1)\right) + u(i,t)$ $p(i) = Z'(i)g_p + e_p(i)$ $q(i) = Z'(i)g_q + e_q(i)$	• Extends Bass model to include the effects of country characteristics
Peres et al (2010)	$\frac{dx_i(t)}{dt} = \left(p_i + q_i x_i(t) + \sum_{j \neq i} \delta_{ij} x_j(t)\right)\left(1 - x_i(t)\right)$	• Extends Bass model to formulate a generalisation of cross country diffusion models

4.2.2. Probit Diffusion Models

Epidemic models abstract from the heterogeneity of individual differences in decision making, demand characteristics, goals, capabilities and actions, in order to model diffusion in a simple homogenous setting (Geroski, 2000). Probit models effectively capture the individual differences in agent characteristics, but neglect the effects of social contagion and interaction effects among individuals (Cantono and Silverberg, 2009). However, Geroski (2000; 610) states that: "*the differences between individuals have a potentially important role to play in explaining patterns of diffusion*". Considering the differences in individual adoption behaviour is an important prerequisite for understanding the diffusion process, as consumers and firms make different choices to satisfy individual needs. Probit models of diffusion focus on differences in specific characteristics e.g. *firm size*. Adoption occurs when certain conditions of the agent are satisfied. For example, individuals differ in some characteristic 'x_i'; and an individual's adoption threshold is 'x^*' adoption occurs when: $x_i \geq x^*$ (Geroski, 2000).

4.2.3. Agent-Based Diffusion Models

Definition of an Agent and Multi Agent System (MAS):

> "*An agent can be a physical or virtual entity that can act, perceive its environment and communicate with others, is autonomous and has skills to achieve its goals and tendencies. It is in MAS that contains an environment, objects and agents, relations between all the entities, a set of operations that can be performed by the entities and the changes of the universe in time and due to these changes*" (Ferber, 1999).

Agent-based modelling (ABM) is a methodology rooted in complexity theory. ABM offers a promising methodology to capture the complex nature of innovation diffusion without abstracting from individual differences (Kamakura and Russell, 1989). Macro-level diffusion models aggregate the potential adopter population assuming consumer homogeneity. However, in reality individual differences play an important role in the adoption decision and diffusion outcomes (Geroski, 2000). ABM can effectively incorporate micro-level simulations such as social interactions and heterogeneity in individual attributes, preferences, and market structures into the modelling process to explain macro-level diffusion (Garcia and Jager, 2011; Rahmandad and Sterman, 2008).

Garcia and Jager (2011) state that, "*phenomena at the macro-level can be understood as emerging from the interactions between agents at the micro-level*". ABM effectively integrates the effects of social contagion and interactions between consumers and firms in markets to provide a holistic model of innovation diffusion. The interaction effects between heterogeneous agents are modelled at the micro level, but provide deep insights into macro-level diffusion and highlight the complex nature of diffusion processes and dynamics. Table 4.B. introduces a few examples of agent-based diffusion models from the management literature[14]:

Table 4.B Agent Based Models of Innovation Diffusion

Author(s)	**Model**	**Parameters Tested**
van Eck et al (2011)	*Utility Function*: $U_{i,t} = \beta_i x_{i,t} + (1-\beta_i) y_{i,t}$ *Individual Preference*: $q \geq p_i \rightarrow y_{i,t} = 1$, and $q < p_i \rightarrow y_{i,t} = 0$ *Normative Influence*: $x_{i,t} = \frac{adopting\_neighbours_{i,t}}{total\_neighbours_{i,t}}$	• Innovativeness of opinion leader (OL) • Weight of normative influence OL • Weight of normative influence non-leader (NL) • Quality of product judgement (OL) • Number of OLs in network • Reach of mass media
Zhang et al (2011)	*Manufacturer Agents*: $\Pi_k = \left(\sum_{j \in J_k} q_j \cdot (p_j - z_{2,j}) - c^I\right) - c_k^R$ *Consumer Agents*: $P_{ij} = \frac{exp(u_{ij})}{exp(u_i^{NONE}) + \sum_{j' \in C_a} exp(u_{ij'})}$ *Government Agent*: $c_k^R = max\left(0, \sum_{j \in J_k} pq_j(Z_{CAFE} - Z_{1j})\right)$	• Vehicle parameters: body type; fuel type; engine power; motor power; battery capacity; aluminium share; and fuel economy • Cost and price parameters: mark-up; manufacturing cost; vehicle cost; price; and investment cost per vehicle • Government parameters: CAFE standard and CAFE penalty rate

van Eck et al., (2011) create an ABM in order to investigate the effects of opinion leadership on the diffusion process. The model distinguishes between informational and normative influences. Opinion leaders and non-leaders are introduced as agents into the model. Individual adoption is based upon the information received through informational influence and normative social pressures. The variable parameters illustrated in Table 4.B are simulated to explore their effects on the diffusion process. An individual's adoption decision depends on the utility that they receive from adopting at time 't' and their utility threshold $(U_{i,min})$. Therefore, an individual will adopt if $U_{i,t} \geq U_{i,min}$. Similarly, Zhang et al., (2011) model DOI using a likelihood function that considers the interactions between manufacturers, consumers, and government agents. Consumers adopt the innovation that maximises their utility from a given product set 'C_a'.

[14] The reader is referred to Special Issue on ABM for DOI modelling for a broader spectrum of models: Special Issue on Agent-Based Modeling of Innovation Diffusion. *Journal of Product Innovation Management*, 28(2), 146-318, March 2011

4.2.4. Models of Disruptive Innovation

There have been very few attempts to model the diffusion of disruptive innovation in the literature. The complex nature of the process and ambiguous definition of the phenomena make modelling extremely difficult (Linton, 2002). Disruptive innovations can serve multiple markets and market segments and transform the demand structure of existing markets that they invade. The diffusion of disruptive innovations results from a combination of micro-level interactions that determine the invasion capability of new technologies. *Preference structure*, *demand structure*, *price* and *technological improvement* interactions directly impact the diffusion capability of disruptive innovation (Adner, 2002; Adner and Zemsky, 2005).

Adner (2002) demonstrates how micro-level development interactions can lead to the emergence of different competitive regimes, namely *disruption*, *convergence* and *isolation*. However, how such micro-level interactions translate into macro-level diffusion is not addressed in the literature. Existing models of disruptive innovation focus on the micro (Adner, 2002) and macro-level (Linton, 2002) effects individually, but fail to provide a holistic perspective of how micro-level interactions lead to disruptive innovation diffusion. Examples of disruptive innovation diffusion models are illustrated in Table 4.C:

Table 4.C Diffusion Models of Disruptive Innovation

Author(s)	**Model**
Linton (2002)	*(1) Multiple Products and Constant Markets:* $$S(t) = \sum_i n \left(a_i + \ b_i \left(\frac{N_i(t)}{m_i}\right)^{(l+d_i)}\right) \times \left(m_i - N_i(t)\right)$$ *(2) Learning Curve Effect:* $$S(t) = \sum_i n \left(a_i + \ b_i \left(\frac{N_i(t)}{m_i}\right)^{(l+d_i)}\right) \times \left(m_i - N_i(t)\right) \left(\frac{N_i(t)}{N_i(0)}\right)^{-f}$$
Adner (2002)	***Consumer Choice*** *Market space:* $B_{ij} = \left(F_{jX} - F_{iX}\right)^{\gamma} \left(F_{jY} - F_{iY}\right)^{1-\gamma}$ *Utility:* $U_{ij} = U_i\left(F_j, P_j\right) = \left(B_{ij}\right)^{\alpha} \left(\frac{1}{P_j}\right)^{1-\alpha}$ *Price:* *Min:* $P_{i0} = (U_{i0})^{\frac{1}{(\alpha-1)}}$ *Max:* $P_{ij} = P_{i0}\left(B_{ij}\right)^{\frac{\alpha}{(1-\alpha)}}$ ***Demand Structure*** $U_A = (F_X)^{\gamma A} (F_Y)^{1-\gamma A}$ $U_B = (F_X)^{\gamma B} (F_Y)^{1-\gamma B}$ *Preference overlap* $= 1 - \lvert\gamma_A - \gamma_B\rvert$ *Preference symmetry* $= \lvert 0.5 - \gamma_A\rvert - \lvert 0.5 - \gamma_B\rvert$ ***Technology Development*** *1. Product innovation:* *Performance improvement:* $F_{j,t+1} = \left(F_{jX,t} \Delta F_X\right), \left(F_{jY,t} + \Delta F_Y\right)$ *where:* $[(\Delta F_X)^2 + (\Delta F_Y)^2]^{\frac{1}{2}} = \lvert F^{prod}\rvert$ *Cost increase:* $C_{j,t+1} = C_{j,t} + C^{prod}$ *2. Process Innovation:* *Performance unchanged:* $F_{j,t+1} = F_{j,t}$ *Cost decrease: :* $C_{j,t+1} = C_{j,t}(1 - \Delta_c)$

Linton (2002) extends the Bass model to develop a macro-level model for forecasting the market diffusion of disruptive innovations. Building on the notion that disruptive innovations serve multiple markets, the model incorporates a coefficient 'c_i' to represent the portion of each market or market segment 'i' that consists of potential adopters for the disruptive innovation. The effect of social contagion becomes: '$\frac{N_i(t)}{c_i m_i(t)}$' (See Table 4.A). Equation (1) from Table 4.C considers multiple products in constant markets. Diffusion is calculated as the sum of the number of adopters $S_{(t)}$ in each market m_i for a specific innovation. Equation (2) incorporates the impact of learning curve effects on the diffusion potential of disruptive innovations into equation (1) '$\left(\frac{N_i(t)}{N_i(0)}\right)^{-f}$'. Learning curve effects represent the impact of technological improvement on the sales potential of disruptive innovations.

Where:

$S(t) =$	*number of new adoptions at time (t)*
$a_i =$	*coefficient of innovation (environmental effect), for market i*
$b_i =$	*coefficient of imitation (social contagion), for market i*
$N_i(t) =$	*number of cumulative adopters at time (t), for market i*
$N_i(0) =$	*number of products made prior to product launch, for market i*
$m_i(t) =$	*potential market size, for market i*
$d_i =$	*nonuniform influence parameter, for market i*
$n =$	*number of markets*
$f_i =$	*coefficient of learning curve effects for market i*

Similarly, Georgantzas and Katsamakas (2009) develop an eight sector macro-level model extended from the Bass model to capture the dynamics of disruptive innovation diffusion:

1. $markets\ sector_{i,d}$,
2. $switch\ contemplation\ sectors_{i,d}$,
3. $tactics\ sector_{i,d}$, and
4. $financial\ accounting\ sectors_{i,d}$

They differentiate between high end [HeM], low end [LeM] and non-consumer markets [NcM] in order to establish market sector equations i.e. determination of potential market size or *strategic business area* [SBA]. Switch contemplation equations capture the cognitive processes of switching from incumbent to disrupter '$i \longrightarrow d$', and disrupter to incumbent '$d \longrightarrow i$'. Tactics sector equations determine the competitive actions of retaliation of incumbents and disrupters as a function of its o*ffer appeal* and *price appeal*. Finally, financial accounting sectors are incorporated to evaluate the performance (EBITDA – earnings before interest, taxes, depreciation and amortization, and market share) of incumbents and disrupters based upon their respective competitive strategy.

However, both of the aforementioned models of disruptive innovation abstract from the differences between market segment preferences, technological performance, demand structure, and their interactions. Adner (2002) develops a micro-level simulation model of the competitive dynamics that facilitate disruptive diffusion. The model considers competition between two market segments (A and

B) and has two basic components: (1) a characterisation of consumers and consumer preferences, and (2) the mechanism by which products move through the market space. The market space is defined by two functional attributes X and Y; consumers adopt the innovation that maximises their utility. Utility 'U_i' is determined by a product's performance 'F_j' and price 'P_j'. Over time, the innovation engages in both process and product innovation that improves the price and product performance of the innovation respectively. Product Innovation enhances performance along functional attributes (F^{prod}) but increases cost (C^{prod}), given by:

$$F_{j,t+1} = \left(F_{jX,t} + \Delta F_X\right), \left(F_{jY,t} + \Delta F_Y\right)$$

$$C_{j,t+1} = C_{j,t} + C^{prod}$$

Process Innovation improves the cost effectiveness of the innovation, but leaves the performance unchanged, given by:

$$C_{j,t+1} = C_{j,t}(1 - \Delta_c)$$

$$F_{j,t+1} = F_{j,t}$$

Consumer demand is determined by the relationship between consumer's relative preferences 'γ', for attributes X and Y. Members of the same market segment have the same relative preferences, such that:

$$U_A = (F_X)^{\gamma A}(F_Y)^{1-\gamma A}$$

$$U_B = (F_X)^{\gamma B}(F_Y)^{1-\gamma B}$$

Adner and Zemsky (2005) develop a model of vertical and horizontal differentiation to further consider the impact of consumer preferences and the effect of pricing strategies on market boundaries between segments. They consider the conditions that lead to isolation and disruption.

4.3. Consumer Choice Models

Models of consumer choice and preference seek to understand consumer behaviour towards the design or characteristics of innovations with multiple attributes. As a result, choice models are useful in providing input for key marketing decisions such as pricing, advertising, and segmentation (Currim and Sarin, 1983). Such models are generally based on the economic principle of utility maximisation, although some models are derived using the attribute-based processing method whereby innovations are assessed on an attribute-by-attribute basis (Manrai, 1995). In this research we only focus on models developed from the perspective of additive utility with a MNL/ logit formulation of choice probabilities. This is because these models form the basis of development in Chapter 5. Furthermore, Currim and Sarin (1983) demonstrate that there is little difference between the performance of additive and multiplicative utility models. In utility based models, consumers adopt the innovation that maximises their utility across a given choice set of innovations.

Generally, utility based consumer choice models differ in their composition. For example, additive and multiplicative utility models, derivation of consumer preferences using different methods (i.e. conjoint analysis – *statistical methods*, *heuristics*; algebraic, and lottery-based procedures (Currim and Sarin, 1983; Keeney and Raiffa, 1993) and the degree of aggregation (Currim, 1982). Furthermore, different types of model formulations exist: LOGIT, MNL, PROBIT, negative exponential and extreme value models among others. However, a comparative analysis of different model choice formulations is not within the remit of this study, the reader is referred to Currim (1982) and Manrai (1995) for a more in-depth consideration. Each procedure has the common goal of deriving a utility function that best specifies a consumer group's preferences. In this section we provide a comparison of the different choice models based upon the MNL formulation evident from management science, operations research, and decision science literature. In addition, we consider models that include dynamics of both consumer choice and diffusion in a single model, with the aim of deriving a diffusion model of disruptive innovation that considers market segment choice heterogeneity.

4.3.1. Utility Based Consumer Choice Models

MAUT models are designed to obtain the utility of innovation alternatives that have more than one valued dimension, and therefore must be evaluated on more than one criterion (Huber, 1974). The information processing procedure that is prevalent in marketing suggests that consumers use a process of abstraction to reduce a large number of physical attributes to a few key dimensions that are most important in the adoption decision (Manrai, 1995). Consumers then assign a preference or attractiveness weight for each of the specified attributes as a ranking mechanism. The most widely used additive form of the utility function states that the utility of an alternative is the weighted sum of the conditional utilities of the alternative's attributes x_{jk}, given by:

$$u(j) = \sum_{k=1}^{K} w_k x_{jk}$$

Where u is the multi-attribute utility function and w_k's are the individual attribute utility functions for alternative j. There are different methods for deriving estimates of w_k as previously mentioned e.g. statistical estimation, heuristics, or purely explorative measures. Additive independence is a key condition for the additive utility function model. Attributes are considered additive independent if preferences over the attribute space K are independent i.e. not based on the joint probability distribution of attributes. Standard convention dictates that the preference rates sum to one and the conditional utility functions are normalised on the interval [0,1] (Rüdiger von and Weber, 1993).

Consumers are generally segmented based upon their preferences for product attributes or buyer background variables such as demographics (Green and Krieger, 1991, Kamakura and Russell, 1989). Multi-attribute utility theory (MAUT) has been widely used to model complex decision-making problems and generate solutions based on the derived utility from alternative outcomes.

A key issue in formulating multi-attribute problems is the identification of utility functions of consumers and the estimation of parameters for utility functions. There are several methods for identifying key preference parameters and important innovation attributes e.g. using mathematical techniques such as linear programming, maximum likelihood (MLE), and regression / least squares estimation when data is available. Huber (1974) differentiates between explicated qualitative methods and derived quantitative methods for deriving parameter estimates for MAUT problems. He suggests that derived or observed measures offer better performance compared with explicated measures when exponent parameters are required. However, Keeney and Raiffa (1993) suggest that when objective or data driven measures of preferences and attributes are unavailable, subjective measures derived by the researcher can effectively capture attribute scales.

Although, such scales require the following desirable properties: "*completeness*", so that it covers all important aspects of the decision; "*operational*", so that it can be meaningfully used in analysis; "*decomposable*", so that evaluation can be simplified and broken down; "*nonredundant*", to avoid confounding decision effects; and *minimal*, to retain relative simplicity (Keeney and Raiffa, 1993; 50). The parameter estimation techniques used in this study are documented in the Research Methodology (Chapter 6).

4.3.2. Multinomial Logit Model

The independent MNL model is an example of a model driven by the principle of utility maximisation. McFadden (1976) provides us with a model of choice that takes the additive utility form given in Section 4.3.1. The model assumes that utility is derived from the summation of individual attributes plus some error term, given by:

$$u(j) = \sum_{k=1}^{K} w_k x_{jk} + \varepsilon_j$$

The utility of each alternative can be divided up into a deterministic component $w_k x_{jk}$ and a random component ε_j. Error ε_j arises from random error in the model due to unobserved attributes. The model structure assumes that a consumer selects the innovation from which s/he derives the highest utility. A consumer defines some set J, that includes all potential innovation alternatives j for a homogeneous market segment i. In the decision horizon, consumer i considers all innovations $j \in J$ before adopting the innovation that maximises their utility. The probability that consumer i adopts innovation j, is given by:

$$P_{ij} = P\left(U_{ij} \geq U_{iJ}, \forall j \in J\right)$$

Such that the probability of consumer i choosing alternative j is equal to the probability that the utility consumer i derives from innovation j (U_{ij}), is greater than or equal to the utility of all other alternatives (U_{iJ}) offered in the set J [$\forall j \in J$]. Furthermore, by the LOGIT formulation we assume that errors ε_j are independently distributed according to the type I extreme value distribution or Gumbel distribution (Shankar et al., 2008; Manrai, 1995; Currim, 1982). The independently and identically distributed (iid) property is an assumption regarding the joint distribution of two or more random variables ε_j, indicating that they are independent and thus not correlated. The assumption holds when two or more innovation attributes k are evaluated independently of other innovation attributes i.e. the performance of one has no impact on the other. As a result, the model takes the form of the ubiquitous MNL model (Shankar et al., 2008):

$$P_{ij} = \frac{exp \sum_{k=1}^{K} w_k x_{jk}}{\sum_{j}^{J} exp \sum_{k=1}^{K} w_k x_{jk}}$$

Where:

$j \in J =$	*innovation alternative* $j = 1, 2, \ldots J$
$P_{ij} =$	*probability consumer* i *adopts innovation j*
$k \in K =$	*innovation attributes* $k = 1, 2, \ldots K$
$w_k =$	*preference weight for attribute* k*, for market segment/ consumer* i
$x_{jk} =$	*performance supplied by innovation* j *on attribute* k

For the MNL model to hold, the Luce axiom of irrelevance of independent alternatives (IIA) must be satisfied. According to Manrai (1995; 5) the IIA axiom states that the preference scale values of an individual innovation depends solely on the attributes of that innovation and not on the attributes of other competing innovations. For example, if a new innovation is introduced or performance improvements of existing innovations are undertaken, then there is a uniform pattern of response to changes in market share. However, according to Currim (1982) this is not always desirable, as new innovations will consequently cannibalise more share from higher performing innovations rather than lower performing innovations. Therefore, the IIA assumption may not be always realistic in all economic or marketing decisions. The main advantage of the IIA axiom is that allows for the consideration of a large set of innovations due to economies in data processing (Manrai, 1995).

4.3.3. Multinomial Logit Models of Consumer Choice

MNL models are used to analyse and explain situations nested within the MAUT and multi-criteria decision making (MCDM) paradigm. They provide a simplified mechanism for the analysis of choice situations and are widely used in the decision sciences, and applied to diverse situations including analysing financial risks, economic utility, and aiding decisions in production and operations management. Specifically, MNL models are used in marketing and management literature to perform segmentation analyses (Kamakura and Russell, 1989; Mantrala et al., 2008), examine brand choice and brand equity (Srinivasan et al., 2005; Shankar et al., 2008), and evaluate technology choice scenarios and upgrade purchase behaviours of consumers (Kim and Srinivasan, 2009).

One of the most useful concepts in marketing is segmentation, as it allows for the analysis of consumer heterogeneity in preferences. Therefore, the application of the MNL model can be used to identify brand or attribute preferences, product switching behaviours that occur through successive innovation generations or technological developments, and examine the impact of market mix variables on choice probabilities. Kamakura and Russell (1989) develop a market segmentation model that examines the price elasticity of demand for changes in brand's price and its impact on competitors. The model assumes that consumers can be categorised by a small number of segments in order to sufficiently account for preference heterogeneity. Market segments are characterised by a vector of mean preferences u_{jk} and a price sensitivity parameter β_k. Where u_{jk} is the utility of product j for consumer k. The basic structure of the model is given by the MNL formulation:

$$P_j(u_k, \beta_k, X_{jkt}) = \frac{exp(u_k + \beta_k X_{jkt})}{\sum_{j'} exp(u_{j'k} + \beta_k X_{j'kt})}$$

The equation states that the probability of choosing brand j at time t is equal to the utility that consumer group k derives from the brand $exp(u_k + \beta_k X_{jkt})$, divided by the sum of all the utilities of brand alternatives j' $\sum_{j'} exp(u_{j'k} + \beta_k X_{j'kt})$. Where X_{jkt} is the available price of brand j. In their analysis, Kamakura and Russell (1989) examine the price elasticities across heterogeneous market segments. Similarly, the MNL formulation is used as a baseline model to examine the choice situation in many other marketing papers. For example, Mantrala et al., (2006) examine optimal pricing strategies for automotive aftermarket retailers selling component parts. The MNL develops a consumer's probability of choosing product i in a certain subclass, at store s, at time t (Pr_{ist}), from a collection of alternatives N. Where N refers to the ranked quality variants within a certain subclass N = [Good, Better, Best, None], and none is a no-purchase option. The MNL formulation of product choice is given by:

$$Pr_{ist} = \frac{exp(V_{ist})}{\sum_{j \in N} exp(V_{ist})}$$

Where:

$V_{ist} =$	$\alpha_i + \beta P_{ist} \;\; \forall i \in N$
$\alpha_i =$	*consumer preference for a product* i
$\beta =$	*price sensitivity parameter*
$P_{ist} =$	*price of product* i *in store* s *at time* t

Other extensions of the MNL formulation include approaches for the measurement and analysis of brand equity, where brand equity refers to the added value to a product that can be attributed to the brand. Srinivasan et al., (2005) propose a model to predict a brand's equity in a product market. They differentiate between sales that are derived from the base product and sales derived from the brand to assess the impact of brand equity. Brand equity e_{ij} in their modelling framework is a function of customer loyalty q_i, incremental brand choice probability Δp_{ij} i.e. the difference between base product and brand choice probabilities ($p - p'$ respectively), and brand contribution margin g_j, where i is the customer and j is the brand, is given by:

$$e_{ij} = q_i \Delta p_{ij} g_j \qquad \textit{individual level brand equity}$$

$$e_j = (T/Q) g_j \sum_{i=1}^{N} q_i \Delta p_{ij} \qquad \textit{aggregate level brand equity}$$

At the aggregate level, individual level responses are summed over N, and (T/Q) is a scale factor where T is the total product category sales and Q is the total quantity sales. If g_j is different for customers then g_{ij} goes into the summation. To measure the model they use a MNL formulation to determine customer choice probabilities, given by:

$$P_{ij} = \frac{\left(A_j/100\right)^{\gamma} exp\left(\alpha u_{ij}\right)}{\sum_{k \in C_i}\left(A_j/100\right)^{\gamma} exp\left(\alpha u_{ij}\right)}$$

Where:

$C_i =$	*set of brands customer* i *is aware of*
$u_{ij} =$	*customer preference for a product j*
$\alpha, \gamma =$	*Scale parameters*
$A_j =$	*availability factor of brand j*

Similarly, Shankar et al., (2008) develop a model to estimate brand equity for multi-category products and apply it to a specific case. In their model brand equity has two primary components: offering value OV and relative brand image RBI. Where OV is the net present value of a brand offering, and RBI is a measure that includes brand image and other marketing mix variables. Brand equity BE_{it}, for brand i at time t is measured over all product categories $j \in J$ that carry brand i's name, given by:

$$BE_{it} = \sum_{j=1}^{J} OV_{ijt} RBI_{ijt}$$

In their paper Shankar et al., (2008) isolate the effects of brand name in order to measure the contribution of brand image on consumer utility using RBI as the appropriate measure. They use the MNL formulation to derive a measure of brand image and its contribution towards consumer utility relative to other marketing mix factors. Factors include: brand image B; product quality Q; price P; distribution D; sales force S; and communication C, $[B, Q, P, D, S, C \in \boldsymbol{X}]$. Brand image's contribution for individual k, where β is a vector of coefficients associated with variables in the set $\boldsymbol{X}$, and X is a vector of product j's offering that carries brand name i is given by:

$$RBI_{ijkt} = \frac{\beta_{Bj} X_{Bijkt}}{\beta_{Bj} X_{Bijkt} + \beta_{Qj} X_{Qijkt} + \beta_{Pj} X_{Pijkt} + \beta_{Dj} X_{Dijkt} + \beta_{Sj} X_{Sijkt} + \beta_{Cj} X_{Cijkt}}$$

Similar to the MNL, Kim and Srinivasan (2009) apply a LOGIT formulation to assess the timing of innovation upgrade and the proportion of sales attributed to each upgrade with regards to the price paths and product specification (attributes) of alternative innovation offerings. Using the example of the PDA (personal digital assistant) they examine the upgrade purchase behaviours of students from the perspective of utility maximisation. Consumers upgrade when:

$$u_t - u_0 > u_t^*,$$

Do no upgrade if: $u_t - u_0 \leq u_t^*$

Where u_t is the utility derived from upgrading, u_0 is the utility derived from the existing product, and u_t^* is the reservation utility that acts as a threshold for upgrading. The probability of upgrading at time t, where b is a time unit dependent scale parameter, is given by the LOGIT formulation:

$$P_t = \frac{exp[b(u_t - u_0 - v_0 - u_t^*)]}{1 + exp[b(u_t - u_0 - v_0 - u_t^*)]}$$

The model was applied to assess the impact of pursuing a penetration pricing strategy on upgrade behaviours of consumers. As demonstrated, the application of the MNL and LOGIT formulations can be used in the analysis of multiple scenarios. Furthermore, the application of the MNL with added diffusion characteristics has the benefit of evaluating consumer choice dynamics and innovation diffusion behaviours in a single model or process. In the following section, we examine such models that are evident from the literature.

4.3.4. Models of Consumer Choice and Diffusion

Models of consumer choice and diffusion combine the effects of an innovation's characteristics and consumer choice with market diffusion dynamics. Generally, such models capture innovation sales growth as an innovation develops over time and improves performance in key characteristics or attributes. Jun and Park (1999) provide a multi-generational choice based diffusion model that examines consumer choice behaviour and the diffusion and upgrade purchases of high-tech products. Consumers are assumed to adopt the innovation generation k that maximises their utility on a given attribute set V_t^k at time t. Consumer choice is formulated using the MNL and diffusion effects are considered in the model with the incorporation of market size at time t $(N_t - Y_{t-1})$, where N_t is the market potential at time t, and Y_{t-1} is the number of cumulative sales recorded in the previous time period $t - 1$. Modelling diffusion this way assigns a proportion of the market to the choice probability of adoption given by the MNL, such that:

$$(N_t - Y_{t-1}) \frac{exp(V_t^k)}{exp(c) + exp(V_t^1) + (V_t^2) + \cdots (V_t^n)}$$

The consumer considers all the available generations $k \in n$, in addition to a non-purchase decision $exp(c)$. Jun has several extensions of the original model proposed above, used to forecast service subscribers in the Korean mobile telecommunications market (Jun et al., 2002). The model reports R^2 levels of over 0.7 for analog, digital cellular, and personal communication services (PCS) markets. More recently, Jun and Kim (2011) propose a model of multi-product diffusion that incorporates replacement demand. Unlike the original model, to simultaneously consider choice and diffusion effects, the proposed model takes a two-stage procedure with the consideration of a Bass diffusion process followed by a consumer choice scenario that takes the LOGIT formulation. The Bass process is given again below (See Section 4.2.1):

$$\textbf{Bass Process}: \left(a + b\left(\frac{N(t)}{m}\right)\right)\left(m - N(t)\right)$$

The Bass process assigns the proportion of potential adopters into the next stage of the procedure. In the next stage the consumer decides whether to buy (b) or not to buy (n). Consumer i makes a purchase decision based on the choice that maximises utility $[b, n]$. When consumer i is in state b, they make a category purchase from $k \in K$ that maximises utility. When consumer i is in state n i.e.

chooses not to purchase then they re-enter the market potential in the Bass process given as m above. The choice probability in the model is as follows:

$$Pr_{it} = \frac{\sum_{k=1}^{K} exp\left(V_{it}^{b} + V_{it}^{k}\right)}{exp\left(V_{it}^{n}\right) + \sum_{k=1}^{K} exp\left(V_{it}^{b} + V_{it}^{k}\right)}$$

Where:

$V_{it}^{n} =$	*non purchase state n with components V for consumer i*
$V_{it}^{b} =$	*purchase state b with components V for consumer i*
$V_{it}^{k} =$	*category purchase k with components V for consumer i*
$Pr_{it} =$	*choice probability of consumer i at time t*

Similarly, Lee et al. (2006) and Kim et al. (2005) model consumer choice and diffusion dynamics as a two-stage procedure, differentiating between a Bass process and a choice process in order to model the diffusion and future demand of large screen TV sets. Focusing on the model proposed by Lee et al. (2006), the Bass process is used to define the number of TV set adopters and the choice process to assign market share to product j. They use a LOGIT formulation to determine the probability that consumer i will choose product j, where $j = 1,2,3 \dots J$, such that:

$$\frac{exp^{X_{ij}\beta}}{\sum_{j=1}^{J} exp^{X_{ij}\beta}}$$

Where X_{ij} refers to the attributes of product j and individual specific variables i, and β is a preference parameter. To calculate market share at time S_{jt}, they take the average of each consumer $i = 1,2, \dots, N$ choice probability as follows:

$$S_{jt} = \frac{\sum_{i=1}^{N}\left(\frac{exp^{X_{ij}\beta}}{\sum_{j=1}^{J} exp^{X_{ij}\beta}}\right)}{N}$$

To incorporate effects of consumer choice and innovation diffusion two different modelling procedures emerge from the literature. The first approach being to use market size variables as means of distributing market share. Market share is derived from applying the choice probabilities (MNL) to the available market size at a specific point in time. Jun and Park (1999) adopt this first perspective and use the variables N_t (market size) and Y_{t-1} (previous adopters) to define the market potential at time t. The second perspective follows a two-step approach: Step one is to apply a Bass diffusion process to define the market of potential adopters in any given time period. Similar to the first approach, market share of an innovation is then calculated through the application of a LOGIT or MNL choice scenario (Kim et al., 2005; Jun et al., 2002; Jun and Kim, 2011) to the potential adopters defined in the first stage.

4.3.5. Conclusion

In this section, we have reviewed the different approaches evident from the literature used to model diffusion of innovations, consumer choice, and consumer choice and diffusion. Models of DOI include both macro and micro-level approaches, with macro-level models focusing on aggregate impacts such as the effects of social contagion. For example, mass media, WOM, and opinion-leadership effects that are well established in literature (Meade and Islam, 2006; Tellefsen and Takada, 1999; van Eck et al, 2011). However, macro-level models abstract from individual preferences and neglect adopter heterogeneity (Geroski, 2000) in attribute, brand, or innovation preferences. As illustrated in the review of choice models, heterogeneity in consumer preferences, brand equity, and innovation attributes are essential in determining adoption behaviours of consumers. Probit models address issues of heterogeneity but neglect to consider macro-level effects and diffusion. As a result, an approach that considers both macro-level and micro-level effects is preferred.

Agent-based models provide an effective method for the consideration of both micro-level interactions and macro-level impacts of innovation diffusion in order to provide a holistic perspective of diffusion phenomena. Adner (2002) illustrates how the structure of the market and technological development interactions can lead to different competitive regimes, including market disruption (

Figure 3.F). Therefore, it is important to consider how market structure and technological developments influence consumer choice scenarios at the micro-level, which in turn influences macro-level diffusion. Incorporating consumer choice and diffusion effects is essential for understanding the dynamics of disruption, as it allows for an assessment of the underlying mechanisms behind the process.

Understanding how micro interactions influence market disruption will help in the identification and evaluation of such mechanisms. ABM allows for the integration of such complexities in the modelling process and simulation of interactions among key agents that can explain disruption. However, Garcia and Jager (2011; 148) state that "*criticism has arisen about ABMs being toy models and unrepresentative of real phenomena*." To alleviate this problem ABMs should be grounded within a real market issue, and inputs and parameters of the model based upon solid theoretical assumptions or driven by real data to go beyond the level of toy models (Garcia and Jager, 2011). A more in-depth analysis of ABM and its implications is provided in the methodology Chapter (Chapter 6).

5. Model of Disruptive Innovation

In this Chapter, we develop an agent-based diffusion model of disruption that can be used to assess the disruptive potential of new innovations in multiple markets. We develop a diffusion model to address the key question of this study: *What are the key mechanisms that drive the diffusion process of disruptive innovations in established mainstream markets*? The factors that emerged in the literature review (Chapter 3, § 3.2) common to disruptive innovation are used to construct a model that includes: consumer preference structure, demand structure, and development dynamics. Specifically, we use the case of the HDD industry as the benchmark example in order to model successive waves of market disruption. The Chapter is organised into four main sections:

1. Section one introduces the background of inter-market innovation diffusion that is characteristic of market disruption, and defines the aims and purpose of the model relative to disruptive innovation.

2. Section two documents the modelling framework from the perspective of consumer preference structure, demand structure, and development dynamics, and highlights their impact on the disruptive potential of new innovation. A series of testable propositions are developed that we intend to test on the disruptive patterns experienced in the HDD industry.

3. Section three introduces the main model and its mathematical structure.

4. Finally, section four applies the model developed in the previous section to the case of the HDD industry, which is generally used as the benchmark example for defining disruptive innovations (Christensen and Bower, 1996; Christensen, 1997). We define four market segments: – *Mainframe*, *minicomputer*, *desktop*, and *portable*; four innovations – *14-inch, 8-inch*, *5.25-inch,* and *3.5-inch;* and three attributes – *capacity*, *size*, and *price*, that form the basis of our analysis. We document the utility formulations for each market segment and innovation with real data in Chapter 6.

5.1. Introduction

The agent-based model proposed in this study is developed on the basis of consumer choice, demand structure, and development dynamics. We combine the effects of consumer choice and innovation diffusion analysed in Chapter 4 into a single model. Consumers are assumed to adopt the innovation among a given choice set that maximises their utility. Utility is derived from the levels of performance supplied in certain attributes by an innovation considered in that choice set. Different market segments differ in how they rank innovation attributes and are thus served by different innovations that satisfy their demand requirements. For example, the mainframe computer market segment was initially served by the 14-inch disk drive; the minicomputer segment by the 8-inch disk drive; desktop segment by the 5.25-inch disk drive; and portable segment by the 3.5-inch disk drive. However, successive technology developments facilitate in reducing the barriers that exist between seemingly independent market segments to enable the invasion of new potentially disruptive innovation. Following the theories and empirical findings in the literature review (Section 3.2), we propose that consumer preferences, demand structure and development dynamics all influence the disruptiveness of new and developing innovations.

The rapid growth in market size and the pace of technological evolution in high technology markets (e.g. IT markets) make the boundaries between segments more permeable. For example, in the IT sector there are mainframe, minicomputer, desktop, and portable market segments (Namwoon et al., 2000). Other examples of inter-category disruptive innovation diffusion include Microsoft Office vs. free online office solutions such as Google Apps. The improvement in functionality of online applications such as Google Apps has enabled them to move into other markets such as low end business segments and student users (Keller and Hüsig, 2009). As a result, it is often difficult to define an innovation's competitive marketplace as high-tech products from different segments that provide similar functionality can pose competitive threats that rival those from direct competitors (Namwoon et al., 2000) For example, Namwoon et al. (2000) state that:

> "*IT sectors are undergoing dramatic changes in their market structures requiring a broader concept of the 'competitive market', which includes not only the innovations in one category but related-competing innovations in other categories as well*" (2000; 496)

The concept of '*fuzzy*' product market boundaries has been a consistent issue that requires a deeper understanding, especially in the context of high technology markets. The purpose of this model is to capture the disruptive waves of innovation as experienced in the HDD industry and provide a generalised diffusion model that can be applied to other potentially disruptive cases.

Disruptive innovations introduce a different attribute structure when compared with sustaining innovations. Consequently, they are initially de-rated along dimensions of performance that are valued by mainstream customers (Adner, 2002; Christensen, 1997). Through successive technological generations they improve performance in key attributes in order to progressively invade more significant higher end market segments that offer increased market potential. The emergence of disruptive innovation in established markets shifts consumer expectations towards new dimensions of product performance (Keller and Hüsig, 2009). Adner (2002) demonstrates how the structure of market demand from the perspective of preference overlap and preference symmetry directly influences the disruptive capability of new innovations (§ 3.2). Thus, we propose to capture the competitive interactions affecting the market growth of different product categories from the perspective of consumer preferences, demand, and development dynamics. The possibility of assessing individual and system level preference characteristics points to the potential application of the model to evaluate the disruptiveness of new innovations. The model will provide a rich foundation for developing future organisational R&D strategies and firm-level segmentation strategies. Furthermore, it will help firms to target markets with most growth potential relative to the product offering.

5.2. Model Framework

We propose a model of consumer choice based on the composition of consumer preferences, both at aggregate and market segment level of analysis. The aim of the model is to understand how disruptive innovations emerge in the market through successive performance improvements. We specifically examine the enabling preference and demand structures, and development dynamics that facilitate disruption. At the aggregate level, we consider the diffusion trends that emerge across all market segments in a single trajectory. At the market segment level, we consider the individual market segment diffusion trends for each individual innovation in each market segment. The model considers the diffusion of potentially disruptive innovations given the existence of a dominant innovation in the market. Innovation attributes and market demand for attributes influence the disruptive potential of new innovations. The goal of the model is to understand the preference structure, demand structure, and development dynamics that lead to the emergence of disruptive innovations. Figure 5.A illustrates the modelling framework and outlines the research propositions (arrows *a*-*e*) and interactions between different agents (arrows *f*, and *g*).

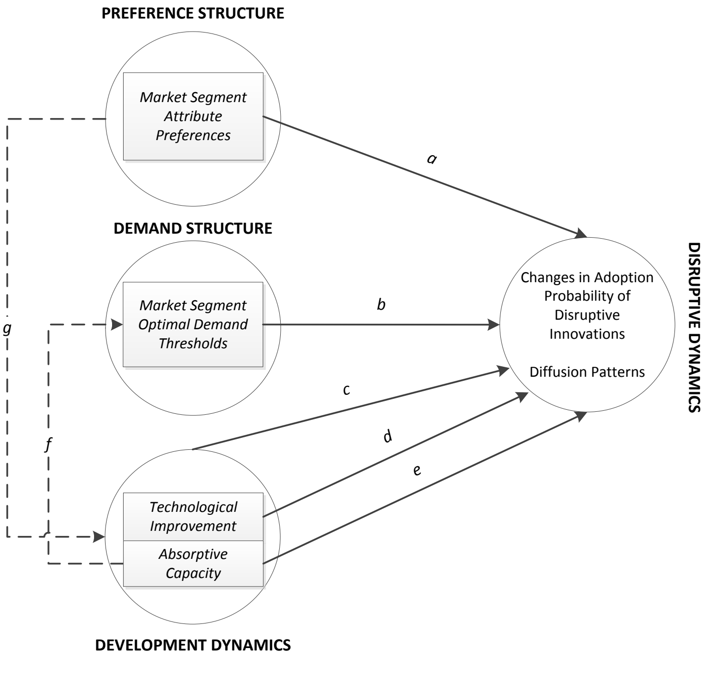


Figure 5.A Proposed Modelling Framework

5.2.1. Consumer Preference Structure

Consumer preferences drive firm-level development initiatives (arrow a) and guide the decision making process in providing potential customers with a heuristic to differentiate between different product offerings. We assume that consumers adopt the innovation that maximises their utility among a choice of innovation alternatives $[j \in J]$. The principle of utility maximisation postulates that a consumer uses all relevant information and selects the innovation that maximises his/her utility. Here the basic choice process assumes that all of the attributes are considered in a simultaneous compensatory structure, thus assigning a utility value to each innovation alternative. After that, the innovations are compared and the innovation with highest utility is selected. However, as Namwoon et al., (2000) point out, market segment boundaries are becoming increasingly '*blurred*' (Adner, 2002) and consumers now consider innovations from external market segments in addition to their internal direct competitors.

The degree of overlap in preference structure between independent market segments for innovation attributes $[k = 1,2 \dots K]$ directly influences an innovation's ability to invade external market segments (Adner, 2002; Hüsig et al, 2005). Adner (2002) defines preference overlap as the extent to which attribute performance in one market segment is also valued in another market segment. He states that "*the greater the preference overlap, the closer the value trajectories of consumers, and the greater the segments' agreement on the level of product performance*" (2002; 672). In other words, due to the small relative distance between market segment preferences, consumers' utility functions are similar on an inter-market level. As a result, the boundaries that exist between market segments become more permeable allowing for the entrance of new disruptive innovations. This leads to our first proposition:

> PROPOSITION 1A (P1A): *The lower (higher) the degree of preference overlap between market segments for innovation attributes, the slower (faster) the speed and likelihood of market disruption*

However, if market segment preferences are homogenous and converge towards a one-dimensional preference structure (Adner, 2002), disruptive innovations will find it difficult to invade mainstream markets, and, in turn, exhibit a lower adoption probability (arrow a). Under such conditions consumers have no preference for the alternative performance offered by disruptive innovations (Adner, 2002). Thus:

> PROPOSITION 1B (P1B): *Convergence towards a one-dimensional homogeneous preference structure for primary attributes will result in a slower speed and likelihood of market disruption*

5.2.2. Optimal Demand Structure

Consumers use preference structure to rank and assign value to an innovation's attributes (Christensen and Rosenbloom, 1995), taken relative to the optimal demand requirements specified by a market segment (arrow b). Optimal demand is defined as the average threshold of performance from which consumers in a given market segment gain maximum utility. Consumers gain maximum utility from performance that either satisfies or exceeds their optimal demand for certain attributes. The optimal functional demand threshold determines the utility ceiling from which no further utility is gained from performance improvements i.e. where $x_{jk(t)} \geq O_{ik(t)} = 1$. Where $x_{jk(t)}$ denotes the performance supplied by innovation j on attribute k at time t, and $O_{ik(t)}$ denotes the optimal threshold of market segment i for attribute k at time t.

We introduce an optimal threshold to reflect issues of performance oversupply and diminishing marginal utility for improvements that exceed a consumer's demand requirements. Performance that exceeds a market segment's optimal demand for primary attributes are subject to diminishing marginal utility (Adner, 2002; Adner and Zemsky, 2005; Adner and Zemsky, 2006) and help to create a vacuum for lower performing disruptive innovations to enter the market (Yu and Hang, 2010). Market segments characterised by high (low) average optimal demand will be harder (easier) to disrupt, as innovations have to attain a higher (lower) level of performance before being considered in the adoption decision (arrow b). For example, consider the revolution of digital photography (Lucas Jr and Goh, 2009): Digital cameras were able to invade mainstream film camera segments as the average level of performance demanded in terms of picture quality was easily attained. Similar disruptive patterns were observed in the HDD industry (Christensen, 1997; Christensen and Bower, 1996). This suggests our second proposition:

> PROPOSITION 2 (P2): *The lower (higher) the average optimal demand thresholds for attribute performance, the faster (slower) the speed and likelihood of market disruption*

At the market segment level, optimal functional demand thresholds are assumed to be homogenous and measured as the average threshold value for all consumers in a given market segment [$\bar{O}_{ik(t)}$]. As an innovation improves its performance over time, a consumer's preference structure relative to the innovation's attributes impact the utility a consumer derives from the innovation (arrow a). Utility is thus a function of both the innovation's performance in certain attributes over time, and how market segments trade-off such attributes (Adner, 2002). Similarly, Christensen (1997) uses performance trajectories of supply and demand for different innovations and market segments respectively, to determine how, and if in fact when, an innovation can invade new market segments (arrow b).

5.2.3. Development Dynamics

Development dynamics are decomposed into technological improvements in innovation attributes and a market segment's absorptive capacity to exploit improvements in innovation attributes (§ 3.2). Optimal demand is determined by a consumer's absorptive capacity for performance improvements. In this context, absorptive capacity refers to the degree in which consumers have the ability to acquire, assimilate, and transform knowledge (Cohen and Levinthal, 1990; Zahra and George, 2002) for the exploitation of innovation performance improvements. Over time, expectations and demand for innovation performance change; technological advancements and learning increase consumers' ability to create new knowledge (Kankanhalli et al., 2012). As a result, optimal demand is dynamic, shaped by market segment growth rates in absorptive capacity. We assume that optimal demand and absorptive capacity are homogeneous and measured at the market segment level.

Market segments that exhibit slow growth rates in absorptive capacity are more susceptible to disruptive threats, as new innovations can more easily satisfy optimal demand thresholds of mainstream customers (arrow *e*). Once optimal demand thresholds of performance are satisfied, additional utility is derived from the alternative performance offered by disruptive innovations (Keller and Hüsig, 2009). In contrast, high growth rates in absorptive capacity (γ_{ik}) inflate optimal demand, which helps to create market entry barriers, thus reducing the risk of market disruption. This suggests our third proposition:

> PROPOSITION 3A (P3A): *The faster (slower) the growth rate in absorptive capacity for performance improvements in primary attributes, the slower (faster) the speed and likelihood of market disruption*

Technology development also determines the rate in which disruptive innovations can improve performance in order to satisfy the optimal demand requirements of established market segments (arrow *d*). Technological improvements in innovation attributes emerge through successive architectural and modular advancements (Henderson and Clark, 1990) that increase an innovation's disruptive capability (Christensen, 1997). Analogously, market segments' absorptive capacity for performance improvements also increases as consumers learn to assimilate and transform knowledge into benefit. Theories of absorptive capacity (re: Cohen and Levinthal, 1990; Tsai, 2001; Zahra and George, 2002) state that the ability to exploit such knowledge, directly influences competitive advantage and the performance of innovations.

However, development asymmetries that exist between technological improvement and absorptive capacity can lead to the emergence of different competitive regimes (arrow *c*) – *disruption*, *isolation*, and *convergence* (Adner, 2002). Christensen and Bower (1995) demonstrate that rates of technological improvement in excess of a market segment's absorptive capacity lead to competitive disruption in the HDD industry. Performance oversupply occurs when dominant innovations improve at a faster rate than the market can absorb, allowing for the entrance of inferior disruptive innovations at the low end of the market (Hüsig et al., 2005). As a result, market disruption is driven by slower growth rates in absorptive capacity relative to technological improvements of the dominant innovation (arrow c). Thus:

> PROPOSITION 3B (P3B): *The higher the positive (negative) asymmetry in technology development relative to absorptive capacity, the faster (slower) the speed and likelihood of market disruption*

Consequently, utility is dynamic and a function of an innovation's performance and technology development relative to a consumer's optimal demand threshold and growth rates in absorptive capacity for technological improvements. We define these observed differentials between growth rates in technology development and market segment absorptive capacity as development asymmetries, where:

> Positive development asymmetry refers to a faster growth rate in technological development relative to absorptive capacity i.e. $\alpha_{jk} > \gamma_{ik}$, and
>
> Negative development asymmetry refers to a slower growth rate in technological development relative to absorptive capacity i.e. $\gamma_{ik} > \alpha_{jk}$.

5.3. Model Specification

Our modelling approach rests on the assumption that consumers can be segmented into their respective market segments based on their preference structure. Consumer choice is characterised by preferences and demand for innovation attributes (demand-side) and the performance supplied in such attributes by an innovation over time (supply-side). We assume that consumers adopt the innovation that maximises utility among a given choice set of innovation alternatives. A market segment's utility function determines the amount of pay-off derived from a given product or innovation.

In this study, we adopt the common additive utility function (Currim and Sarin, 1984; Roberts and Urban, 1988; Shankar et al., 2008) expressed in Equation 1 to determine the amount of pay-off market segments derive from a given innovation. The composite utility of each innovation alternative $j \in J$ is represented by a vector of preference weights w_{ik} and levels of performance supplied x_{jk} for each attribute $k = 1,2...K$. The utility a market segment derives from an innovation is given by the sum of the individual preference parameters w_{ik}, multiplied by the performance supplied by that innovation, plus a random error term ε_{kj}, such that:

$$U_{ij} = (w_{ik1}x_{j1} + w_{ik2}x_{j2}+, \dots, w_{ikn}x_{jk}) + \varepsilon_{kj(t)}$$

Equation 1

$$U_{ij(t)} = \sum_{k=1}^{K} w_{ik}x_{jk(t)} + \varepsilon_{kj(t)}$$

where $U_{ij(t)}$ denotes the utility market segment i derives from innovation j at time t. The utility equation comprises of a deterministic component $\beta_i X_{jK(t)}$ and stochastic component $\varepsilon_{ij(t)}$. Where $X_{jK(t)}$ is a vector that defines the k-dimensional attribute space of observed attributes $[k = 1,2, \dots K]$ for innovation j; and β_i is the vector notation for measured attractiveness assigned by market segment i to attribute k $[w_{ik}]$. More specifically, β_i represents the column vector of attribute importance weights determined by heterogeneous consumer preferences, and X_{jKt} is the k-dimensional row vector of attributes for all innovation alternatives $[j = 1,2 \dots J]$. Utility is derived from the sum of the individual partworths for each of the identified attributes, denoted as $\beta_i X_{jK(t)}$ in vector notion, where $\varepsilon_{ij(t)}$ is the error term representing misspecifications in unobserved attributes.

$$U_{ij(t)} = \beta_i X_{jK(t)} + \varepsilon_{ij(t)}$$

Where:

$$i = 1, \dots I; j = 1, \dots J; t = 1, \dots T$$

$$\beta_i = (w_{ik1}, w_{ik2}, \dots, w_{ikn})$$

$$X_{jK(t)} = (x_{jk1(t)}, x_{jk2(t)}, \dots, x_{jK(t)})$$

The utility $U_{ij(t)}$ consumers derive in a given market segment i from innovation j is measured in the model as the amount of performance supplied $x_{ik(t)}$ relative to a consumer's optimal demand threshold $O_{ik(t)}$. We propose that utility is inversely proportional to optimal demand since higher levels of O_{ik} are harder to attain, thus resulting in a lower utility pay-off.

Both the rate of technological advancement by innovation j on attribute k (α_{jk}), and increases in a market segment's absorptive capacity for attribute k (γ_{ik}) directly influence utility over time. Where α and γ are scale parameters that determine the growth rate in technology development and absorptive capacity respectively. Subsequent technological improvements and new generations of innovation change the utility outcomes of consumers over time. Furthermore, the extent to which a market segment can realise such performance improvements in terms of their absorptive capacity also influence a market segment's derived utility (§ 5.2.2). As a result, utility is dynamic, and determined by the interplay between development dynamics and optimal demand thresholds, given by:

Equation 2

$$U_{ij(t)} = \sum_{k=1}^{K} w_{ik} \left(\frac{\alpha_k \left(x_{jk(t)} \right)}{\gamma_{ik} \left(O_{ik(t)} \right)} \right) + \varepsilon_{kj(t)}$$

Assuming that the error arising from random individual behaviour or unobserved attributes ε_{kj} has a standard type I extreme value distribution, the adoption probability of an individual in market segment i takes the ubiquitous MNL formulation (Shankar et al., 2008)[15]. At the aggregate level, the MNL gives the total conditional probability of all market segments $i \in I$ adopting innovation j [Pr_j] at time t, given the existence of potential innovation alternatives $j = 1,2, \ldots J$. The great popularity of the MNL stems from the fact that they generate simple closed form expressions that represent consumer choice probabilities, such that:

Equation 3

A. At the aggregate level;

$$Pr_{j(t)} = \frac{exp\left(\sum_{i=1}^{I} \sum_{k=1}^{K} w_{ik} \left(\frac{\alpha_{k(x_{jk(t)})}}{\gamma_{k(o_{ik(t)})}} \right) \right)}{\sum_{j}^{J} exp\left(\sum_{i=1}^{I} \sum_{k=1}^{K} w_{ik} \left(\frac{\alpha_{k(x_{jk(t)})}}{\gamma_{k(o_{ik(t)})}} \right) \right)}$$

B. at the market segment level;

$$Pr_{ij(t)} = \frac{exp\left(\sum_{k=1}^{K} w_{ik} \left(\frac{\alpha_{k(x_{jk(t)})}}{\gamma_{k(o_{ik(t)})}} \right) \right)}{\sum_{j}^{J} exp\left(\sum_{k=1}^{K} w_{ik} \left(\frac{\alpha_{k(x_{jk(t)})}}{\gamma_{k(o_{ik(t)})}} \right) \right)}$$

Equation 3A gives the cumulative conditional probability of all market segments i adopting innovation j at time t. To assess this at the market segment level the summation of $i \in I$ in Equation 3B is omitted in order consider market segments independently. This allows for the independent examination of an individual market segment's susceptibility to potentially disruptive threats.

Diffusion patterns of disruptive innovations emerge from the choices made by consumers taken over time. By studying the choice behaviours of consumers, we can understand the sales patterns of new innovations (Jun and Park, 1999; Jun et al., 2002; Jun and Kim, 2011). The proposed model extends this knowledge in order to understand the sales patterns of disruptive innovations from the perspective of preference structure, optimal demand structure, and development dynamics. To incorporate diffusion effects in the model we make the following assumptions: new generations of an innovation

[15] Refer to Section 4.3.2

are captured in a single diffusion trajectory; and (2) a consumer's choice in a given time period is determined by the utility derived from an innovation j, and taken independently of the choices made in previous time periods.

Two basic components comprise our approach: the total market potential $M_{(t)}$ at time t; and the adoption probability $Pr_{j(t)}$. Sales $S_{j(t)}$ (or market share) for innovation j are calculated by multiplying the cumulative conditional purchase probability $Pr_{j(t)}$ with the total market potential at time t (Equation 4). This calculation gives the proportion of adopters for an innovation across all market segments at a specific point in time, which when taken longitudinally gives the diffusion patterns of that innovation. At the market segment level of analysis, market size and sales are taken to be segment level variables $M_{i(t)}$ and $S_{ij(t)}$; where $M_{i(t)}$ is the market size for segment i at time t, and $S_{ij(t)}$ is the sales of innovation j in market segment i at time t. The adoption probability takes the form of equation 3B at the market segment level.

Equation 4

$$S_{j(t)} = \left(M_{(t)}\right) \cdot \left(\frac{exp\left(\sum_{i=1}^{I}\sum_{k=1}^{K} w_{ik}\left(\frac{\alpha_{k}(x_{jk(t)})}{\gamma_{k}(o_{ik(t)})}\right)\right)}{\sum_{j}^{J} exp\left(\sum_{i=1}^{I}\sum_{k=1}^{K} w_{ik}\left(\frac{\alpha_{k}(x_{jk(t)})}{\gamma_{k}(o_{ik(t)})}\right)\right)} \right)$$

$$= \left(M_{(t)}\right) \cdot \left(Pr_{j(t)}\right)$$

Sales are affected by technological improvements undertaken by the firm and a market segment's absorptive capacity. These new generations of innovation have the potential to invade established market segments dependent upon: preference structure, optimal demand structure, and development dynamics. The competitive landscape defined by $j \in J$ is also dynamic, with new innovations entering and old innovations leaving the competitive marketplace over time. As a result, both the growth effects that influence the rate of diffusion, and market saturation effects that gradually slow the rate of diffusion are considered in the proposed model. As new generations of innovations are introduced, consumers' expectations of performance changes, thus changing a market segment's evaluations of an innovation's performance. In the following section, we apply the derived model to the HDD industry and define the market segments, innovations, and attributes for subsequent model estimation. Table 5.B provides a summary of the notation used in this Chapter:

Table 5.A Summary of Notation

Symbols	Definition
j	Innovation
k	Attribute
i	Market segment
c	Adopter category
$x_{jk(t)}$	Performance supplied by innovation j on attribute k at time t
$O_{ik(t)}$	Optimal demand threshold of market segment i for attribute k
w_{ik}	Preference weight of market segment i assigned to attribute k
$U_{ij(t)}$	Utility market segment i derives from innovation j at time t
α_{jk}	Growth rate parameter in technology development for innovation j on attribute k
γ_{ik}	Growth rate parameter in absorptive capacity for market segment i on attribute k
$Pr_{j(t)}$	Probability of adopting innovation j at time t
$M_{(t)}$	Total market size available at time t
$S_{j(t)}$	Sales of innovation j at time t

5.4. Model Application to Hard Disk Drive (HDD) Industry

The rapid growth and pace of technological development experienced in the HDD industry over the last 30 years has made it one of the most dynamic and turbulent to date. Such high-velocity environments are characterised by rapid and discontinuous change in demand, competitors, technology or regulation (Bourgeois and Eisenhardt, 1988). The HDD industry has seen exponential growth (McKendrick, 2001) and documented a high turnover of firms both entering and leaving the industry resulting from successive waves of disruptive innovation as demonstrated by Christensen (1993). These multiple waves of disruptive innovation have consistently transformed the industry and led to incumbent firm failure. Christensen and Bower (1996) demonstrate the disruption experienced in the HDD industry from the perspective of four market segments, namely: *mainframe, minicomputer*, *desktop* and *portable* market segments.

The HDD industry is characterised by multiple sub-markets that have emerged over time. According to Chesbrough (2003), a new sub-market is created when a technology offering causes of group of customers within an existing market to behave differently from the mainstream customers in that market. Christensen's seminal works demonstrate the transitions from different form factors in hard disk drives, ranging from the original 14-inch disk drives, to 8, 5.25, and 3.5. Each of these drives initially served a distinct market segment. The 14-inch drive served the requirements of the mainframe computer market segment (Christensen and Bower, 1996). The 8-inch drive served the requirements of the minicomputer market segment; the 5.25-inch served the requirements of the desktop market segment; and the 3.5-inch disk drive served the requirements of the portable market segment (Chesbrough, 2003).

Specifically associated with each market segment is a unique rank ordering of the importance of various performance attributes, which rank order differs from that employed in other market segments (Christensen and Rosenbloom, 1995). In the case of mainframe computer markets, consumers prefer reliability, greater capacity, and faster access time provided by the 14-inch drives (Christensen, 1993); Minicomputer market segments value lower cost per megabyte, in addition to the capacity and access time provided by 8-inch drives (Christensen and Bower, 1996). In contrast, desktop market segments preferred the attributes – volume, weight, and lower total cost of 5.25-inch drives as they provided sufficient capacity for the required application (Christensen and Bower, 1996). Furthermore, Christensen and Rosenbloom (1995; 243) state that:

> "*In the architecture used for portable segments – size, weight, and ruggedness of 3.5-inch drives were all important attributes but none of these attributes were critical in the architectures of mainframe or minicomputer*".

Note how each market segment exhibits a different rank ordering of important product attributes. Rank ordering of preferred attributes differs according to the application sought by each type of customer. Rank order implies that a key determinant of market disruption is the degree to which it addresses the needs of customers both in its own value network and competing value networks (Christensen and Rosenbloom, 1995). Performance improvements enable innovations to migrate into other market segments: 14-inch drives were driven from the mainframe market, 8-inch from the minicomputer, and 5.25 from the desktop by smaller sized disk drives as they developed over time. The key question for assessing the overlap between market segments is whether or not the performance in attributes provided by an innovation will be valued in other market segments?

5.4.1. Conclusion

In this section, we have developed a choice based diffusion model that encompasses consumer preference structure, optimal demand structure, and development dynamics. A series of testable propositions are developed based on the literature that specifies the relationships and interplay of the aforementioned factors and their impact on market disruption. The model specification documents the mathematical underpinnings that are used to test the propositions developed in the model framework. We aim to test the model in a real world application using secondary data collected from the HDD industry over a 20 year period (1979-1998). The seminal works of Christensen and colleagues form the basis of our analysis and help identify the structure of the HDD industry, market segments, rank order of market segment preferences, and innovation attributes.

The proposed model provides a quantitative mechanism to test the theory of disruption proposed by Christensen. We build on his previous qualitative case based findings and observations to validate the theory of market disruption using a mathematical model. Based upon a clearer definition of the concept established in Chapter 3, the model will help develop new insights into the theory and identify the underlying factors that drive the process of disruption. Existing research documents the transition that occurs from the introduction of disruptive innovation, however little is known with regards to ‘how’ this transition occurs.

In our analysis, we consider three attributes, namely – *capacity*, *price*, and *size*, and the distribution of consumer preferences over this attribute space in the context of four market segments – *mainframe*, *minicomputer*, *desktop*, and *portable*. We only consider capacity, size, and price in the attribute set as they are considered the most important attributes that consumers trade-off between market segments. Furthermore, consumers generally only consider a few key attributes in the adoption decision in order to make the decision process simpler (Ratchford, 1982; Williamson, 1981). As a result, capacity, size, and price are used as the attributes in which consumers differentiate between different product offerings. Based on secondary data collected over a 20 year period (1979 – 1998) in the HDD industry, we formulate attribute utilities from the perspective of four innovations – 14-inch, 8-inch, 5.25-inch, and 3.5-inch. We document the utility formulation procedures for attributes – capacity, price, and size that are applied in our model in the Methodology Chapter that follows.

6. Research Methodology

This Chapter discusses the proposed research methodology designed to answer the research question and objectives defined in Chapter 1. More specifically, we document the practical steps undertaken during the research endeavour that were used to examine the impact of different factors, namely – *preference structure, demand structure*, and *development dynamics* on the disruptiveness of innovations. We develop and present a systematic research strategy, design methodology, and research methods for the purpose of data collection and analysis. We primarily adopt an objectivist quantitative approach in order to model the disruptive waves of innovation experienced in the HDD industry. However, we also use qualitative analysis to examine the impact of differing supply-side and demand-side dynamics with respect to the aforementioned factors. The objective here is to address some of the key research areas outlined by Danneels (2004; 248) regarding the definition of disruptive innovation:

> "*Does the impact of technological disruption depend on the structure (i.e., size, heterogeneity, evolution) of the market segments?*"

Addressing these areas will contribute towards extending the theory of disruptive innovation and help to build a better understanding of existing theory. The Chapter proceeds in three primary sections, namely: Research Strategy, Research Design, and Research Methods as advised by Bryman (2008).

1. Section one introduces the two-phase research strategy adopted in this study to address the identified research gaps and question. We document the primary methodological approach that drives the study and the practical considerations for adopting the proposed strategy.

2. Section two introduces the research design framework used to drive the collection and analysis of data. Specifically, we introduce our modelling approach.

3. Finally, section three introduces the research methods (semi structured survey and software used) and procedures employed for data collection and analysis.

6.1. Research Strategy

We develop a two-phase mixed methods research strategy utilising a mixture of both quantitative and qualitative approaches with the aim of addressing the research question posed in Chapter 1. The current state of research with regards to the theory of disruptive innovation requires both quantitative validation and further qualitative investigation to provide clarity to existing concepts. We initially propose a quantitative investigation to develop a model of disruptive innovation based upon the factors developed in Chapter 3. Using the model, we extend existing theory through qualitative investigation of differing dynamics to resolve issues of ambiguity (Danneels, 2004). In particular, we extend theory through the qualitative investigation of the mechanisms underlying the process of market disruption*: consumer preferences*, *optimal demand structure*, and *development dynamics*, using a quantitative agent-based modelling approach. In the following sections we introduce the practical steps taken during each phase and link research strategy with the research objectives and research focus. Figure 6.A presents a summary of the research strategy.

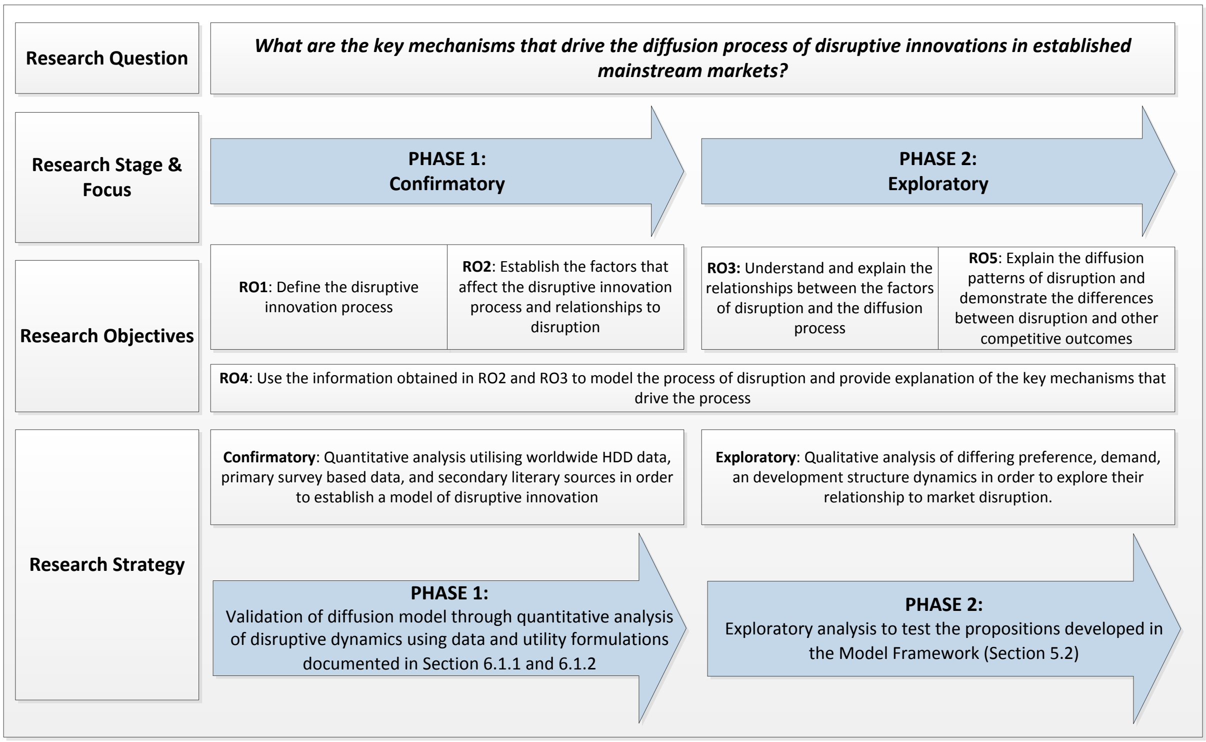


Figure 6.A Summary of Research Strategy

6.1.1. Phase One: Quantitative Investigation

We propose an agent-based diffusion model of disruptive innovation that considers consumer preferences, demand, and development dynamics as model inputs. Diffusion processes vary depending upon their impact and due to the characteristics of different contexts and innovations. The diffusion curves of disruptive innovations can be both positively and negatively skewed and demonstrate different forms of kurtosis. For example, faster speeds and market entry timing of disruptive innovations will result in a more peaked and negatively skewed diffusion curve. Disruptive innovations emerge from a complex interplay of various agents specified in the model framework (Chapter 5).

The aim of the quantitative investigation is to validate Christensen's theory of disruptive innovation through replication of the disruptive trends observed in the HDD industry (Christensen, 1993, Christensen and Bower, 1996). However, it is expected that the proposed approach can be modified to assess all possible disruptive situations to measure the overall disruptiveness of new and developing innovations. The proposed modelling approach uses real empirical data collected from the HDD industry, supported by primary and secondary sources. Table 6.A illustrates the different data sources used as model inputs in our quantitative investigation.

Table 6.A Model Data Sources

	Model Inputs	Source
Empirical Data	Attribute Performance ($x_{jk(t)}$) • Disk drive storage capacity • Price • Size (Form Factor) Technology Development (α_j)	DISK/TREND Inc. HDD Annual Report Data (1979 – 1998).
Primary Data	Preference Weight (w_{ik}) Attribute Ranking	Survey data from small panel of industry experts (Discussed in § 6.3).
Secondary Data	Market segment optimal demand ($O_{ik(t)}$) Absorptive Capacity (γ_i) Attribute Ranking	Model inputs obtained from Christensen's performance supply vs. demand trajectories illustrated in Figure 6.B (Christensen, 1993; Christensen and Bower, 1996; Christensen, 1997).

As is evident from Table 6.A., we use a mixture of real data, subjective survey based data and secondary data sources to derive model inputs for subsequent quantitative investigation. Huber (1974) and Keeney and Raiffa (1993) suggest that management scientists can use both subjectively and objectively defined measures and parameter estimates as inputs to solve problems that involve multiple attributes.

We obtained empirical data in the form of paper reports of the worldwide disk drive industry from DISK/TREND Inc. DISK/TREND Inc. is a market research company founded in 1977 by Jim Porter that specialises in providing expertise on HDDs. They produce specific market reports and annual reports of worldwide disk drive trends, providing information on total unit shipments, form factors (size), storage capacity, and price. While Christensen used HDD data to examine the transition between different disk drive sizes and the failure experienced by incumbent firms using case narratives and descriptive statistics, we develop a unique dataset of worldwide shipments of HDD and HDD attributes (capacity, size, and price) to mathematically model the transitions and their effect on different market segments. A major contribution of the research is the development of a new dataset and its application to validate a theory of disruption.

The new dataset spanned a 20-year period ranging from 1979 to 1998 of worldwide HDD shipments. Data was filtered in terms of the three aforementioned attributes – capacity, price, and size. We coded disk drives into 14 discrete capacity groups so that they could be more easily categorised (see below). By coding the data in such a way we could easily see the rates in which technology developed for each size of disk drive over the 20-year period. The dataset was further categorised into their respective size brackets – 14-inch, 8-inch, 5.25-inch, and 3.5-inch HDDs, sale price and whether there was a category purchase.

Capacity Groups

1. <30MB
2. 30-60MB
3. 60-100MB
4. 100-300MB
5. 300-500MB
6. 500-1GB
7. 1-2GB
8. 2-3GB
9. 3-5GB
10. 5-10GB
11. 10-20GB
12. 20-40GB
13. 40-80GB
14. 80+GB

Figure 6.B illustrates Christensen's performance supply vs. demand trajectories for each disk drive innovation *j* and market segment *i* (Christensen, 1993; Christensen and Bower, 1996; Christensen, 1997).

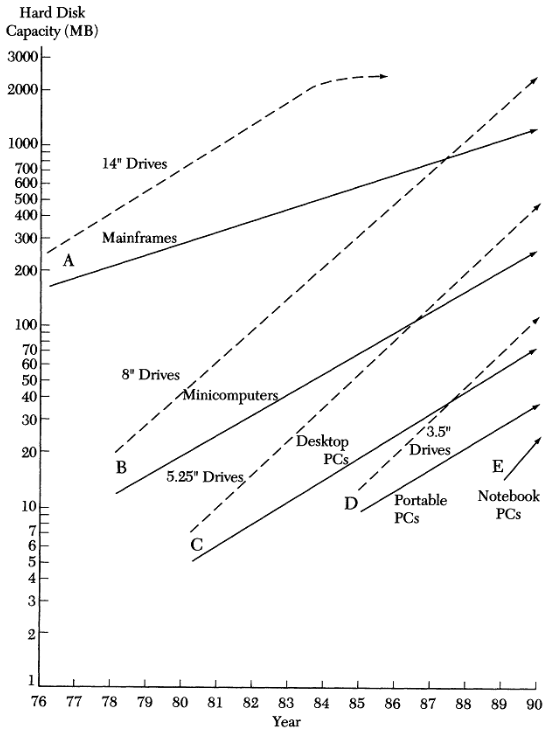


Figure 6.B Christensen's Supply vs. Demand Trajectories of HDD Industry (Christensen, 1993; 559)

The dataset was used to compute parameter estimates to model the successive waves of market disruption as experienced in four market segments – mainframe, minicomputer, desktop, and portable. In terms of secondary data, we utilise Christensen's seminal works to derive the model inputs defined in Table 6.A. In particular, the demand trajectories illustrated in Figure 6.B were used to derive model inputs for market segment optimal demand thresholds. By extrapolating the demand trajectories for each market segment, we were able to derive estimates for market segment growth rates in performance demanded in terms of storage capacity. Furthermore, we use primary data collected through the administration of a semi-structured survey[16] to a small panel of HDD industry experts for model input. The panel comprised three industry experts working for a leading market research consulting firm with clients visible in the U.S., Japan, Asia, and Europe. The company specialises in data storage expertise, this includes knowledge of HDD technologies and the HDD supply chain. In the following sub-sections, we provide a more detailed analysis of how the data described in Table 6.A. was used to derive different model inputs for quantitative (Section 6.1.2) and qualitative investigation (Section 6.1.3).

6.1.2. Phase One Data and Utility Formulations

In this section, we introduce how different data sources were used to derive utility formulations for the Phase One quantitative investigation of market disruption. We derive model inputs for preference, demand and development dynamics.

***Preference Structure*:**

Each market segment (*mainframe*, *minicomputer*, *desktop*, and *portable)* has a unique rank ordering regarding the importance of various innovation attributes determined, which are determined by w_{ik}, where $\sum w_{ik} = 1$. To obtain the attributes and rank order of attribute preferences across market segments, we used a combination of primary and secondary data sources (Christensen, 1993; Christensen and Bower, 1995; Christensen and Rosenbloom, 1995; inter alia). We used a semi-structured survey (Appendix 2) to ask a small panel of industry experts:

> "*In your opinion, what would have been the essential attributes and rank order of such attributes that market segments trade-off?*"

Experts with over 25 year's global experience in consultancy within the HDD industry were used to verify the attributes different market segments consider in the adoption decision and the rank order of such attributes (Table 6.B). The attributes and rank order defined by the panel of industry experts largely verified the secondary sources identified in Section 5.4. Keeney and Raiffa (1993) state that when objective or data driven measures of preferences are unavailable, subjective measures based on

[16] Refer to Section 6.2

expert judgments can effectively capture attribute scales. However, the subjective nature of the derived estimates should be acknowledged as a key limitation in the study.

Table 6.B Rank Order and Preferences of HDD Attributes

	Mainframe		Minicomputer		Desktop		Portable	
Attributes	*Rank*	w_{ik}	*Rank*	w_{ik}	*Rank*	w_{ik}	*Rank*	w_{ik}
• *Capacity*	*1*	*0.5*	*1*	*0.5*	*3*	*0.2*	*1*	*0.2*
• *Price*	*2*	*0.3*	*3*	*0.2*	*1*	*0.5*	*2*	*0.3*
• *Size*	*3*	*0.2*	*2*	*0.3*	*2*	*0.3*	*3*	*0.5*

Demand Structure

Using the unique dataset of worldwide shipments of HDDs and secondary data sources, we establish model inputs for innovation performance supply $x_{jk(t)}$[17] and market segment demand $O_{ik(t)}$ for the attributes identified in Table 6.B: $k =$ *capacity*, *price*, and *size*. Secondary data sources were used to calculate market segment demand with respect to (w.r.t hereafter) capacity for each segment i. We extrapolate the demand trajectories developed by Christensen in Figure 6.B (re Christensen, 1993; Christensen and Rosenbloom, 1995; Christensen and Bower, 1996)[18], where the optimal demand threshold for capacity for each market segment $i =$ *mainframe*, *minicomputer*, *desktop* and *portable,* is taken to be numerically equal to the capacity derived from extrapolation. Performance supplied $x_{jk(t)}$ w.r.t. capacity for each innovation $j =$ *14-inch*, *8-inch*, *5.25-inch*, and *3.5-inch* is derived from the unique dataset. We take the average level of capacity supplied $\bar{x}_{jk(t)}$ for each innovation in each year as the level of performance supplied. Model input figures and utility formulations for disk drive capacities are documented in Appendix 1 (Table 1 and 2).

Optimal demand w.r.t. price for each market segment is equal to the cheapest disk drive available at time t that also satisfies market segment i's demand threshold for capacity. We use capacity in the formulation as a mechanism to differentiate between the differences in market segment demand for price. We define performance supplied w.r.t. price as follows:

$$x_{jk(t)} = \sum\left(\left(\frac{O_{ik(t)}}{p_{j(t)}}\right)^2 * s_{j(t)}\right)$$

[17] Note. For all $x_{jk} \geq O_{ik}$ we assign a value of 1 (i.e. maximum utility), as consumers gain no more utility from performance improvements that exceed their optimal demand threshold

[18] Figure 5 (Christensen, 1993); Figure 4 (Christensen and Rosenbloom, 1995); and Figure 2 (Christensen and Bower, 1996)

where $p_{j(t)}$ is the price of disk drive j at time t, and $s_{j(t)}$ is a dummy variable related to observed sales ($s_{j(t)} = 1$) or no observed sales ($s_{j(t)} = 0$) of a specifically priced innovation $p_{j(t)}$ at time t. We use a dummy variable to account for the birth and death of innovations in the market. In our formulation price is inversely proportional to optimal demand, as higher prices reduce the level of utility derived. Thus, performance supplied is taken as the sum of the price performance for each innovation, relative to the optimal demand threshold of segment i. Price is modelled this way as to discount higher priced disk drives at a greater rate than lower priced disk drives. Model input figures and utility formulations are documented in Appendix 1 (Tables 4–8).

In terms of size, we assume that given the choice all market segments prefer smaller sized disk drives as opposed to larger sized disk drives. Thus, the optimal demand threshold w.r.t. size is equal to the smallest sized disk drive available at time t, which we assign a score of 1. Since all market segments prefer smaller size, scores are homogenous across all market segments. To calculate performance supplied (x_{jk}) w.r.t. size for disk drive j larger sized disk drives are discounted as new smaller sized drives emerge in the market, such that:

$$x_{jk(t)} = b_j$$

where b_j is the score assigned to disk drives of size j. Scores are assigned according to the timeline of market introduction given in Table 6.C. From the unique dataset we were able to observe at which points new sized disk drives entered the market. From the data we observe that the 14-inch drive was introduced in 1976; 8-inch in 1979; 5.25-inch in 1980; and 3.5-inch in 1983. Primary data in the form of a semi-structured survey was used to derive a discount factor of 0.3 and applied to score disk drives based on their market introduction (highlighted in green Table 6.C). Utility formulations for size are documented in Appendix 1 (Table 9). We used the semi-structured survey to ask the panel of experts:

> *"In your opinion, what would be the discount rate applied to a larger sized disk drive across market segments as new smaller sized disk drives emerged in the market?"*

Table 6.C Timeline of Disk Drive Introduction to Market

Disk Drive	**Year of Introduction**					
	1978	**1979**	**1980**	**1981**	**1982**	**1983+**
14"	*1*	*0.7*	*0.4*	*0.4*	*0.4*	*0.1*
8"	*0*	*1*	*0.7*	*0.7*	*0.7*	*0.4*
5.25"	*0*	*1*	*1*	*1*	*1*	*0.7*
3.5"	*0*	*1*	*1*	*1*	*1*	*1*

Development Dynamics:

We consider absorptive capacity and technological improvement from the perspective of a single attribute capacity. This is because in the HDD industry, technological improvement in capacity is the primary focus of development activity (Christensen, 1997). Furthermore, since size is constant within innovation categories j and price is a non-technological performance dimension, we only focus on the development of memory capacity in our analysis. From the unique dataset we establish parameter estimates for α_{jk} in capacity, by maximizing the likelihood function for performance improvements of innovation j through time i.e. $x_{jk(t)}/x_{jk(t-1)}$. Maximum likelihood estimation (MLE) is an unbiased method of parameter estimation that makes the observed data "*most likely*" (Myung, 2003). Results of the MLE are illustrated in Table 6.D.

Table 6.D Estimated Parameters for Growth in Technological Improvement (Capacity)

	μ	σ
14_Inch	0.23 (0.63)	0.14 (0.03)
8_Inch	1.57 (0.24)	0.97 (0.18)
5.25_Inch	1.55 (0.15)	0.37 (0.07)
3.5_Inch	1.56 (0.09)	0.37 (0.07)

Notes. Means μ and standard deviations σ of the estimated parameters for each innovation j = *14-inch*, *8-inch*, *5.25-inch*, and *3.5-inch* over the period 1979-1998 are given with standard errors in parentheses. These are estimates of α_{jk} for capacity, the parameters for *8", 3.5"* are normally distributed, *14"* log-logistically distributed, and *5.25"* logistically distributed.

Parameter estimates for absorptive capacity γ_{ik} were derived using secondary sources. Borrowing heavily from Christensen's work, we take the growth rates in absorptive capacity for each market segment to be numerically equal to the observed growth rates in the demand trajectories illustrated in Figure 6.B. The values derived for each segment i are as follows: = 1.17; and minicomputer, desktop, and portable = 1.33.

6.1.3. Phase Two: Qualitative Investigation

In our qualitative investigation, we use the quantitative model to analyse the impact of differing preference, demand, and development structures to provide new insights and development to the theory of disruptive innovation. The propositions developed in Section 5.2 form the basis of our investigation. We develop a series of differing 'what if' situations by modifying model inputs to conduct a qualitative investigation. Such analysis will help to address current shortcomings of Christensen's theory identified by Danneels (2004). Next we discuss how we modified model inputs in the ABM to conduct our qualitative analysis, and document the resulting data and utility formulations.

Preference Structure:

We modify market segment preference structure to reflect dynamics of preference isolation and preference convergence. Under conditions of preference isolation, market segments are divergent in their preferences for innovation attributes (Adner, 2002) i.e. each market segment values a different attribute. We examine the conditions whereby market segments only value their highest ranking attribute i.e. $w_{ik} = 1$, as demonstrated in Table 6.E. This is to impose inter-market conditions of low preference overlap across market segments. In contrast, convergence refers to homogeneous preferences for innovation attributes across all market segments. We examine the conditions whereby market segments only value a single attribute – i.e. *capacity*. This is to reflect conditions of high preference overlap. Qualitative analysis of differing preference conditions will help to identify the preference dynamics that facilitate market disruption (P1A, P1B).

Table 6.E Preference Isolation

	Mainframe		**Minicomputer**		**Desktop**		**Portable**	
Attributes	*Rank*	w_{ik}	*Rank*	w_{ik}	*Rank*	w_{ik}	*Rank*	w_{ik}
• *Capacity*	*1*	*1*	*1*	*1*	*N/A*	*0*	*N/A*	*0*
• *Price*	*N/A*	*0*	*N/A*	*0*	*1*	*1*	*N/A*	*0*
• *Size*	*N/A*	*0*	*N/A*	*0*	*N/A*	*0*	*1*	*1*

Demand Structure:

In the analysis of demand structure, we modify optimal demand conditions for capacity for each market segment. This allows us to examine the effects of high and low optimal demand thresholds on inter-market disruption (P2). Under conditions of high optimal demand, a market segment's demand threshold for primary attribute performance is high, whereas under conditions of low optimal demand, a market segment's threshold for primary attribute performance is low. To reflect such conditions, we positively and negatively scale optimal demand thresholds derived from Christensen's performance supplied vs. demand trajectories illustrated in Figure 6.B. Model input figures for qualitative analysis of demand structure are provided in Appendix 1 (Table 10).

Development Dynamics:

In our analysis of development dynamics, we examine the effects of high and low growth rates in absorptive capacity in order to test Proposition 3A. Furthermore, we scale the differences between growth rates in technological improvement 'α_{jk}' (Table 6.D) and absorptive capacity 'γ_{ik}' to reflect conditions of positive and negative development asymmetries. Development asymmetry is a measure of difference between how fast an innovation improves and how capable a market segment is in absorbing such improvements. The differences observed in growth rates for absorptive capacity and technological development determine development asymmetry. Negative asymmetry refers to conditions in which market segment growth rates in absorptive capacity exceed growth rates in technological improvement ($\gamma_{ik} > \alpha_{jk}$). In contrast, positive asymmetry refers to conditions in which growth rates in technological improvement exceed growth rates in absorptive capacity ($\alpha_{jk} > \gamma_{ik}$).

Qualitative analysis of positive and negative development asymmetries between technological improvement and absorptive capacity will help us to identify the development conditions that lead to market disruption. Model inputs for high and low growth rates in α_{jk} and γ_{ik} for capacity are documented in Appendix 1 (Tables 11 and 12). Furthermore, market segment utility formulations for positive and negative development asymmetries are documented in Appendix 1 (Tables 13–16).

6.2. Research Design

Agent-Based Modelling (ABM):

Complexity in innovation research has largely been neglected in favour of simplicity. As a result, the interaction effects among various 'agents' are ignored. Agents have behaviours described by simple rules and interactions with other agents. Agent-based modelling (ABM) and simulation offers a relatively new approach to studying complex adaptive systems (Garcia, 2005), such as market disruption and disruptive innovation diffusion. ABMs are widely used in computer science, biology, economics, finance and operations management to investigate complex phenomena (Macal and North, 2010; Rahmandad and Sterman, 2008). For example, the Journal of Product Innovation Management (JPIM) devoted a special issue to agent-based modelling of innovation diffusion. In this issue, van Eck et al., (2011) examined the role of opinion leadership; and Zhang et al., (2011) the diffusion of alternative fuel vehicles.

A typical ABM has three elements: (1) a set of agents, their attributes and behaviours; (2) specification of agent interactions i.e. how preferences, demand, and development structures are related; and (3) the agent's environment i.e. the market and market structures in which agents interact with other agents and their environment (Macal and North, 2010). ABMs differ from traditional modelling techniques such as differential equation models that generally aggregate agent effects (Rahmandad and Sterman, 2008). In contrast, ABMs consider individual behaviours of heterogeneous agents and their interactions that lead to macro-level diffusion (Garcia and Jager, 2011). Garcia (2005; 381) states: "*it is from the interactions between agents that aggregate macro-scale behaviours* *emerge"*. Rahmandad and Sterman (2008) conclude that ABM offers a more realistic methodology for the examination of micro-level interactions that lead to aggregate behaviours. We specify the agents for market disruption and their interactions in the Model Specification in Section 5.3. ABMs are particularly useful in simulating the dynamic interactions between agents that both directly and indirectly influence consumer utility as in Equation 3.

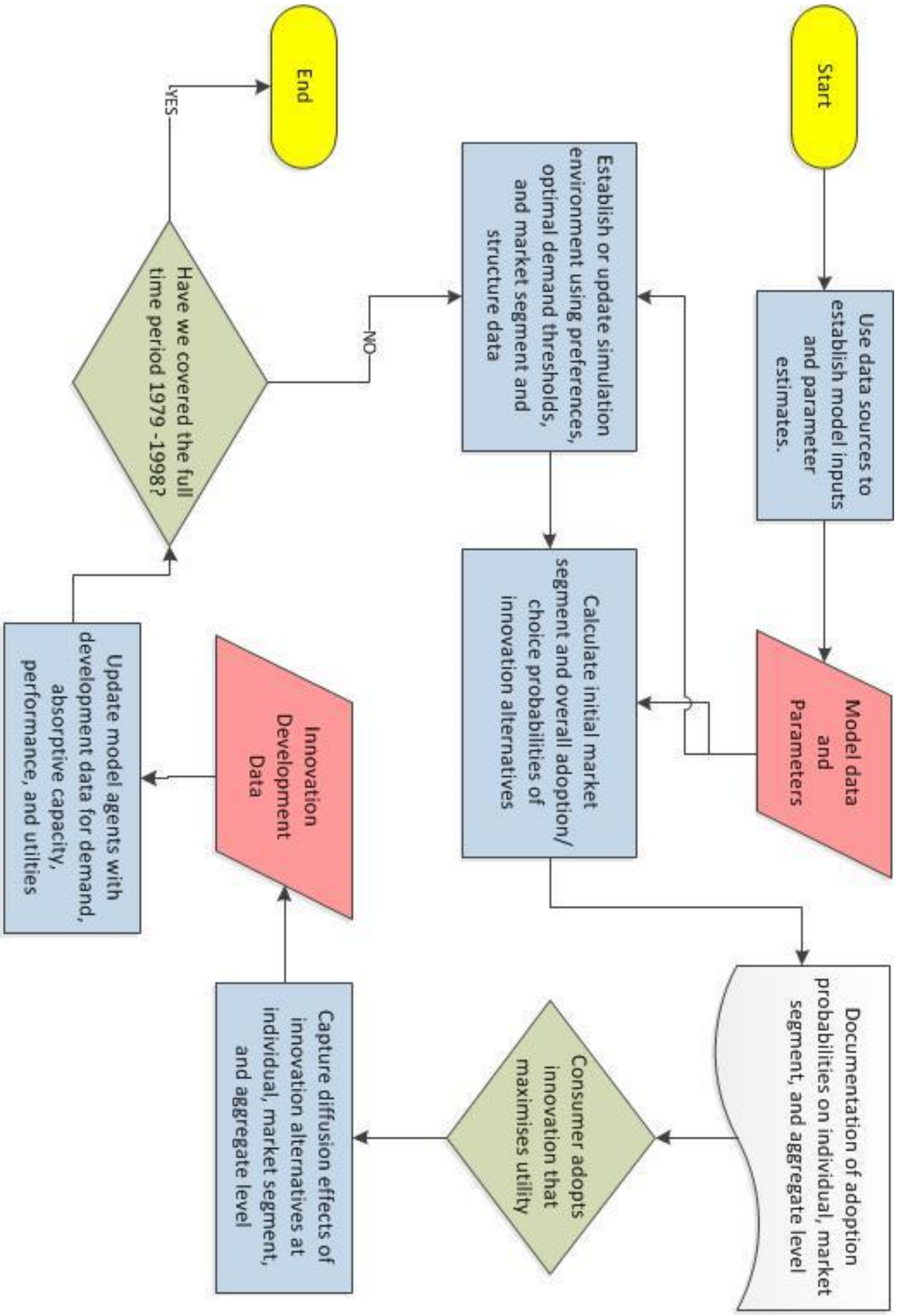


Figure 6.C Model Simulation Procedure

Figure 6.C illustrates the simulation procedure adopted in this study. We first create and operationalise model variables and parameters using the input data and parameter estimates

documented in Section 6.1. In the second stage, we specify the simulation environment in terms of market structure, market segment preferences, and optimal demand thresholds. We then calculate the initial adoption/ choice probabilities $Pr_{ij(t)}$ of consumers in each market segment for each innovation using the MNL model. Consumers adopt the innovation that maximises their utility $U_{ij(t)}$. In the next stage, we establish the diffusion effects by multiplying the adoption probability by the market potential $M_{(t)}$ to give the distribution of adopters for each innovation. Over time, development dynamics improve both an innovation's performance and consumer's absorptive capacity for performance improvements. Subsequent agent and environment interactions in preferences, demand, and development change consumer utility over time, thus creating a feedback loop to update the initial adoption/ choice probabilities. Consumers are assumed to adopt an innovation in every model cycle as the market size data in the unique dataset represents the number of new adopters each time.

Benefits and Limitations of ABM

According to Bonabeau (2002), simulation provides an excellent tool for the refinement of existing theory. As a result, it provides us with a methodology to clarify the theory of disruptive innovation. By simulating an approximation of real-world behaviour that can be difficult to capture in more static differential equation models, ABM focuses on how certain phenomena emerge over time and how certain activities or policies influence different outcomes (Garcia, 2005). We start in Section 5.2 with a set of explicit propositions to induce new insights into the theory of disruptive innovation. ABM allows us to manipulate agents in the validated model to analyse certain 'what-if' scenarios to develop new theory from micro-level interactions (Axelrod, 1997). In our qualitative analysis we isolate the effects of single agents by changing the rules and inputs which they act upon, which leads to new insights. Garcia (2005; 384) summarises situations in which ABMs are useful for innovations research (we link these situations to the objectives of this study):

- When both macro- and micro-levels of analyses are of interest (e.g., adoption [micro] and diffusion [macro])
- When social systems can be described by 'what-if' scenarios but not by differential equations (e.g., market structures of disruptive innovations)
- When emergent phenomena may be observed (e.g., emergence of disruptive innovations)
- When coevolving systems interact in the same environment (e.g., competitive market segments – mainframe, minicomputer, desktop, and portable)
- When learning or adaptation occurs within the system (e.g., performance improvement and absorptive capacity)
- When the population is heterogeneous or the topology of the interactions is heterogeneous and complex (e.g., market structures and optimal demand thresholds)

ABMs also have limitations. Garcia and Jager (2011) state that "*criticisms have arisen about ABMs as being toy models and unrepresentative of real phenomena*". A model has to serve a specific purpose, general purpose models do not work. As a result, to alleviate this problem they recommend that ABMs are grounded within a real market problem using empirical data. In addition, since ABMs aim to model complex systems their derivation is not easy. Bonabeau (2002; 7287) states that complex systems with human agents are difficult to quantify and calibrate and can sometimes give incorrect quantitative outcomes. However, they can still provide new qualitative insights. Finally, Bonabeau (2002) concludes that the use of many micro-level interactions is computationally intensive and can be extremely time consuming. As a result, it is best to start with a simple model and gradually increase its complexity.

6.3. Research Method

MATLAB:

To simulate the proposed ABM we use MATLAB (Matrix Laboratory), a numerical computation, visualisation and programming environment. MATLAB is used due to its powerful computing power and user-friendly interface and toolboxes (e.g., statistics, curve fitting, and distribution fitting toolbox). Furthermore, MATLAB offers an extensive library of online tutorials and examples to guide users in the coding and programming of different functions for data analysis. Variables in MATLAB are specified as vectors and matrices and defined in the environments workspace. In this section, we document the practical steps taken to operationalise model variables for subsequent data analysis in MATLAB.

We first define model variables in MATLAB:

1. Market segment utility variables for capacity;
   - **capacity_AbG_main**
   - **capacity_AbG_mini**
   - **capacity_AbG_desk**
   - **capacity_AbG_port**
2. Market segment utility variables for price;
   - **price_AbG_main**
   - **price_AbG_mini**
   - **price_AbG_desk**
   - **price_AbG_port**
3. Market segment utility variables for size (assumed homogeneous refer to Section 6.1.1);
   - **size_AbG**

4. Market segment preference weights for innovation attributes: – capacity, price, and size;
    - **weight**
5. Market size variable;
    - **market_size**
6. Original unit shipment data of HDDs: - 14-inch, 8-inch, 5.25-inch, and 3.5-inch
    - **Orig**
7. Market segment adoption probabilities for each disk drive innovation
    - **adoption_probability**
8. Market segment preference weights for innovation attributes: – capacity, price, and size;
    - **weight**
9. Market segment and aggregate utility scores for each disk drive innovation
    - **util**

Second, we normalise all the utility formulations in the first step on the interval [0,1]. We normalise in order to standardise the metrics of measurement across innovation attributes. For example, capacity is measured in megabytes (MB), price in US Dollars ($), and size in terms of a subjectively operationalised score. To aggregate unstandardised utility scores is infeasible as the underlying metrics differ across innovation attributes. Thus, normalisation is an essential procedure in order to aggregate attribute utility scores. Finally, we operationalise the adoption/ choice probabilities and diffusion behaviours of each disk drive innovation by coding the MNL model equation expressed in Section 5.3. The coding procedure in MATLAB is simplified by predefining the model input variables for each time period during the simulation (1979 – 1998). As a result, only the MNL model needs to be programmed for numerical computation.

Summary of Data and Data Sources

Empirical data was collected and collated from numerous paper-based sources from DISKTREND Inc. These were organised to form a unique dataset that comprised worldwide unit shipments of HDDs based upon their capacity by group (groups 1-14), size (14-inch, 8-inch, 5.24-inch, and 3.5-inch), and price (organised by group and size) over a 20-year period (1979 – 1998). The dataset goes beyond the narrative and descriptive case based findings proposed by Christensen (1997) and encompasses a full time series dataset for multiple attributes in order to mathematically model the phenomenon. Empirical data was used to derive all initial model inputs and parameter estimates for the quantitative investigation, apart from market segment optimal demand thresholds and growth rates in optimal demand (i.e. absorptive capacity). Use of only the HDD industry is a key limitation of the data that restricts the ability to provide generalisation and validation of the theory. However, it provides a significant milestone towards achieving a generalised validation of disruptive innovation.

Secondary data in the form of Christensen's demand trajectory in Figure 6.B was used to derive model inputs for optimal demand thresholds and growth rates in optimal demand. This graph was used to extrapolate individual market segment demand trajectories, from which inputs for mainframe, minicomputer, desktop, and portable market segments were established. However, using Christensen as the only point of reference is an observed limitation and we acknowledge the possibility of bias in the results.

Finally, we collected primary data through the administration of a semi-structured survey to a small focus group of HDD experts from an internationally recognised market research/ consultancy firm that specialise in HDD trends. We intentionally leave the survey semi-structured to keep the focus group on the tightly defined topic, while simultaneously leaving some questions open-ended. The aim of the focus group survey was to define model inputs for the rank order, attribute structure, and preference structure of market segments. We chose a firm based upon two key characteristics '*breadth*' and '*depth*': Breadth refers to the scope of operations: we preferred a specialised firm with a small breadth of expertise that purely focused on the trends of the HDD industry. Depth refers to the level of experience: we preferred a firm with more years' experience as opposed to less. Based upon these criteria we were able to easily identify the most appropriate firm as our focus group. We contacted the firm directly via email and they agreed to contribute to the research by completing the survey. As the location of the case firm was outside the UK, the survey was administered to three analyst participants via email. The firm and focus group participants wished to remain anonymous; the survey is documented in Appendix 2. It is recognised that using subjectively derived measures and a small focus group is a limitation of the data.

7. Analysis and Results

In this Chapter we simulate the proposed agent-based model developed in Chapter 5. Firstly, the proposed model is validated with real data from the HDD industry. We analyse model fit with aggregate level diffusion trends for 14-inch, 8-inch, 5.25-inch, and 3.5-inch disk drives observed between 1979 and 1998. Based upon the validated model, we then conduct qualitative analysis of preference structure, optimal demand structure, and development structure in order to derive new insights with regards to the underlying mechanisms that drive the process of disruption. Results of the simulation are presented both at the aggregate market and individual market segment level to provide a more rich understanding of the phenomena. We simulate the effects of each factor in isolation as to avoid issues of multicolinearity and examine their impact on market disruption. The Chapter proceeds in five sections:

1. Section one presents the aggregate model simulation results with real HDD data. We the analyse goodness of fit statistics and test statistics for each disk drive innovation to validate the proposed model. The simulated results are presented and disruptive trends are then discussed.
2. Section two, three, and four present the simulation results for qualitative analysis of preference structure, optimal demand structure, and development structure, respectively. In this section, we evaluate the influence of the aforementioned factors on market disruption. Specifically, we aim to test the propositions developed in Section 5.2 in order to develop new understanding with regards to the underlying mechanisms that drive the process of disruption. We discuss the results at both the aggregate and individual market segment level.
3. Section five discusses the novelty of the research findings and their contribution to the concept of market disruption. We emphasise the new insights developed from the perspective of the preferences, demand, and development and organise these in a clear and coherent way that leads to an improved theory. Furthermore, we provide a summary and table of the model results and research findings.
4. Finally, section six discusses the managerial implications of our results and potential applications of the model. Furthermore, we introduce organisational response strategies for firms seeking to respond to potentially disruptive threats and firms seeking potentially disruptive opportunities. We link the derived strategies to existing management practices and capabilities to provide a response framework.

7.1. Model Estimation

To determine a diffusion model of disruptive innovation across multiple market segments, we estimate the MNL choice model using the case of the HDD industry. Following the Model Framework and Model Specification defined in Chapter 5, we simulate the agent-based diffusion model using the data inputs and utility formulations identified in Section 6.1. Before being able to conduct any qualitative analysis we must first validate the general quantitative model using empirical data. As a result, we first estimate the model at the aggregate level and examine overall model fit for each disk drive innovation across all market segments with real data from the HDD industry. The model must first be validated as to make the qualitative analysis more robust. As Garcia and Jager (2011) point out, if ABMs are not nested within a real-world problem using real data, then the model is just a "toy-model" and results have no meaning.

In the first step, we simulate the aggregate model using MATLAB. Table 7.A. provides overall model fit statistics with empirical diffusion (unit shipment) data for HDDs taken over a twenty year period (1979 – 1998). Results show that overall model fit and correlation was very good. The model reports R^2 levels of 0.99, 0.65, and 0.64 for 3.5-inch, 8-inch, and 14-inch disk drives respectively, and an overall R^2 of 0.68. These results demonstrate a large correlation effect with real diffusion data ($r \geq 0.5$), accounting for 68% of the overall variance (Field, 2005). However, model fit of unit shipments is slightly lower for the 5.25-inch disk drive ($R^2 = 0.45$), which shows a medium effect accounting for over 45% of the variance. We believe that this is due to the price competitiveness of the 5.25-inch disk drive in the model compared with the 3.5-inch disk drive.

Table 7.A Model Fit Statistics with Empirical Data

	$\mathbf{R^2}$	**RMSE**	**F(S_j)**	**T(S_j)***
14_Inch MNL	0.64	123.18	0.83* (0.12, 5.61)	0.25 (-47.75, 54.86)
8_Inch MNL	0.65	384.52	0.54* (0.10, 2.84)	0.17 (-114.9, 126.3)
5.25_Inch MNL	0.45	32462.42	0.12 (0.05, 0.31)	-1.16 (-9.31, 4.75)
3.5_Inch MNL	0.99	32466.80	1.41* (0.23, 8.83)	0.21 (-4.39, 4.93)
Total MNL	*0.68*	*16359.23*		

Notes. Model fit statistics to empirical data. F = f-test and T = t-test results for total sales (S_j) over time period 1979-1998 for each innovation. *Significant at the 0.001 level (99.99%). Confidence intervals (95%) are illustrated in parenthesis for t-test and f-test results.

We perform independent two-sample t-tests and f-tests to examine the differences in the mean and variance of estimated vs. observed data. Such analysis allows us to test the hypothesis of whether the results of the model estimation for each innovation and actual unit shipment data are statistically different. Results in Table 7.A. show that there is no significant difference between the model estimation and empirical data for the diffusion curves of each disk drive: 14-inch t-test ($p = 8009$), f-test ($p = 0.7336$); 8-inch t-test ($p = 8670$), f-test ($p = 0.2058$); 5.25-inch t-test ($p = 0.2537$); and 3.5-inch t-test ($p = 0.8345$), f-test ($p = 0.5141$). All results were significant at the 99.99% level (p >0.001), which indicated no statistical difference between the actual and estimated diffusion patterns of HDDs across the aggregate market. Only the f-statistic for 5.25-inch disk drive showed significant difference in variance from the observed data.

We also report the RMSE (root mean square error) of disk drive diffusion curve estimates as a benchmark for future model or model extension comparisons. RMSE is good for measuring the performance of competing models; however, it is not such a good indicator of model fit as it is scale-dependent. As a result, RMSE results for 5.25-inch and 3.5-inch are much larger due to exponential growth in market size during the time of market introduction.

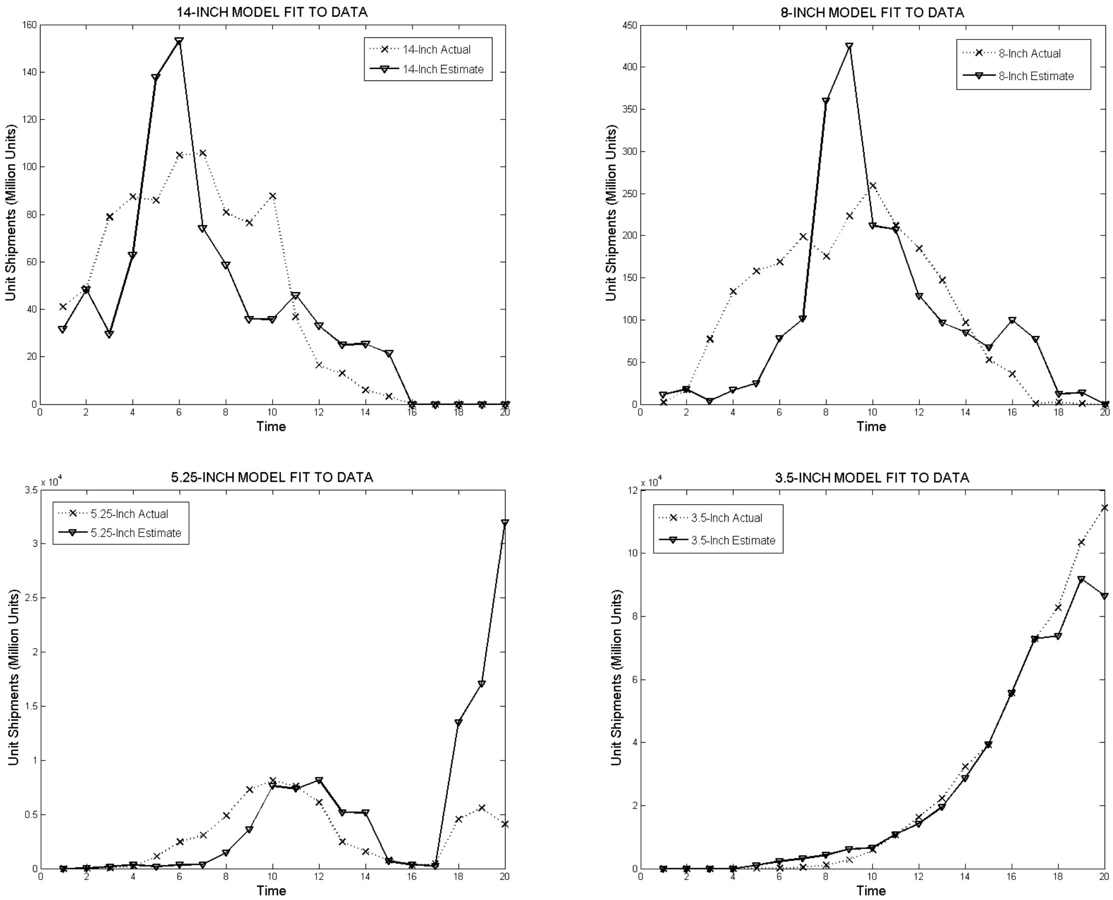


Figure 7.A. Aggregate Model Estimation Results

Figure 7.A. shows the similarities between the estimated diffusion trends for each disk drive and empirical data. Disruptive trends can be visualized between each graphical frame. The decline of the 14-inch disk drive occurred during the growth phase of the 8-inch disk drive – time point 6 (1984). This pattern was repeated as new smaller sized innovations of HDDs emerged: 8-inch declined during growth phase of 5.25-inch – time point 10 (1988); and 5.25 inch declined during an increase in growth rate of 3.5-inch drives – time point 12 (1990). However, due to exponential growth in market size of HDDs, sales of the 5.25-inch showed growth again in 1995 – time point 17. At this point (17 – 20), the model estimation results for 5.25-inch disk drives deviate drastically from observed trends. We

believe that this is due to the price competitiveness of the 5.25-inch drive i.e. sales start to increase again since the product is more attractive to price sensitive market segments. As a result, sales of the 5.25-inch drive are inflated. Furthermore, we believe that much of these sales would normally be attributed to the 2.5-inch drive as it was introduced in 1988. However, data constraints limit our analysis to only 14-inch, 8-inch, 5.25-inch, and 3.5-inch disk drives. Limitations of the model are addressed further in Chapter 8.

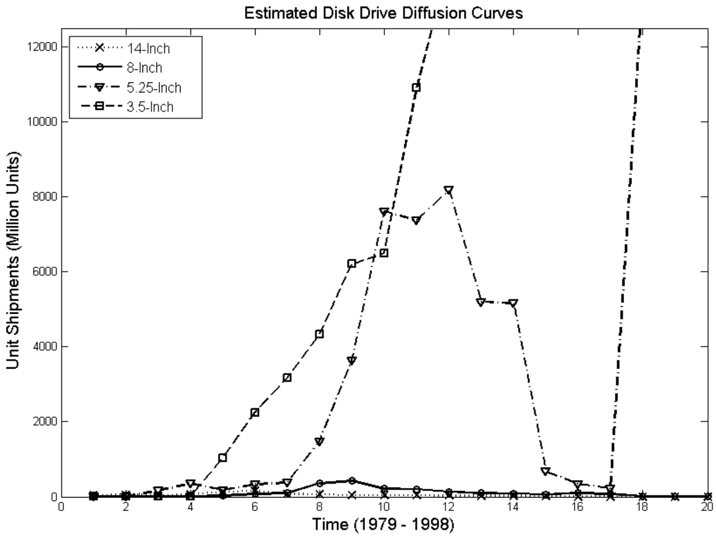


Figure 7.B. Estimated Disk Drive Diffusion Curves

Figure 7.B illustrates the estimated diffusion curves from Figure 7.A. in a single plot. The general trend captured by the proposed ABM largely reflects the disruptive patterns experienced in the HDD industry as depicted by McKendrick (2001)[19]. Having presented and validated the aggregate level diffusion patterns of disk drive innovations with real data, we are now able to use the model to qualitatively analyse disruption at the market segment level for mainframe, minicomputer, desktop, and portable segments. It is with the qualitative assessment that new significant insights can be developed with regards to the underlying mechanisms that drive the process of market disruption.

7.1.1. Market Segment Level Analysis

Using MATLAB to simulate the preference structures documented in Table 6.B., we demonstrate the diffusion of disk drive innovations across independent market segments. In our analysis, we assume that there is an equal distribution of customers in each segment i.e. preferences w_{ik} are equally distributed across the total market. Although market segments may die out as new disruptive innovations emerge, we assume that customer preferences for that segment remain constant. For example, although today the mainframe and minicomputer markets are in decline, we assume that

[19] Reader is referred to Figure 2 from McKendrick (2001). Global strategy and population-level learning: the case of hard disk drives. *Strategic Management Journal,* 22, 307-334.

previous market segment's consumers have the same preference structure, but have simply switched to alternative innovations to satisfy their requirements. Following this assumption, we simulate the disruption experienced at the market segment level.

Figure 7.C. illustrates the market segment level diffusion curves for each disk drive. Results show that consistent with the literature (Christensen and Rosenbloom, 1995) sales of higher capacity 14-inch and 8-inch disk drives were primarily attributed to mainframe and minicomputer market segments. This is because these segments preferred the higher performance in capacity provided by such drives. In contrast, desktop and portable market segments preferred the smaller size and lower price provided by the 5.25-inch and 3.5-inch disk drives (Christensen and Bower, 1996; Christensen, 1997). As Christensen's theory suggests, each graphical frame in Figure 7.C. (clockwise from top left) illustrates the gradual disruptive transitions of disk drive innovations towards higher end market segments. These results support Druehl and Schmidt's (2008) finding that disruptive innovations follow a low end encroachment pattern, gradually diffusing from lower demanding to higher demanding market segments.

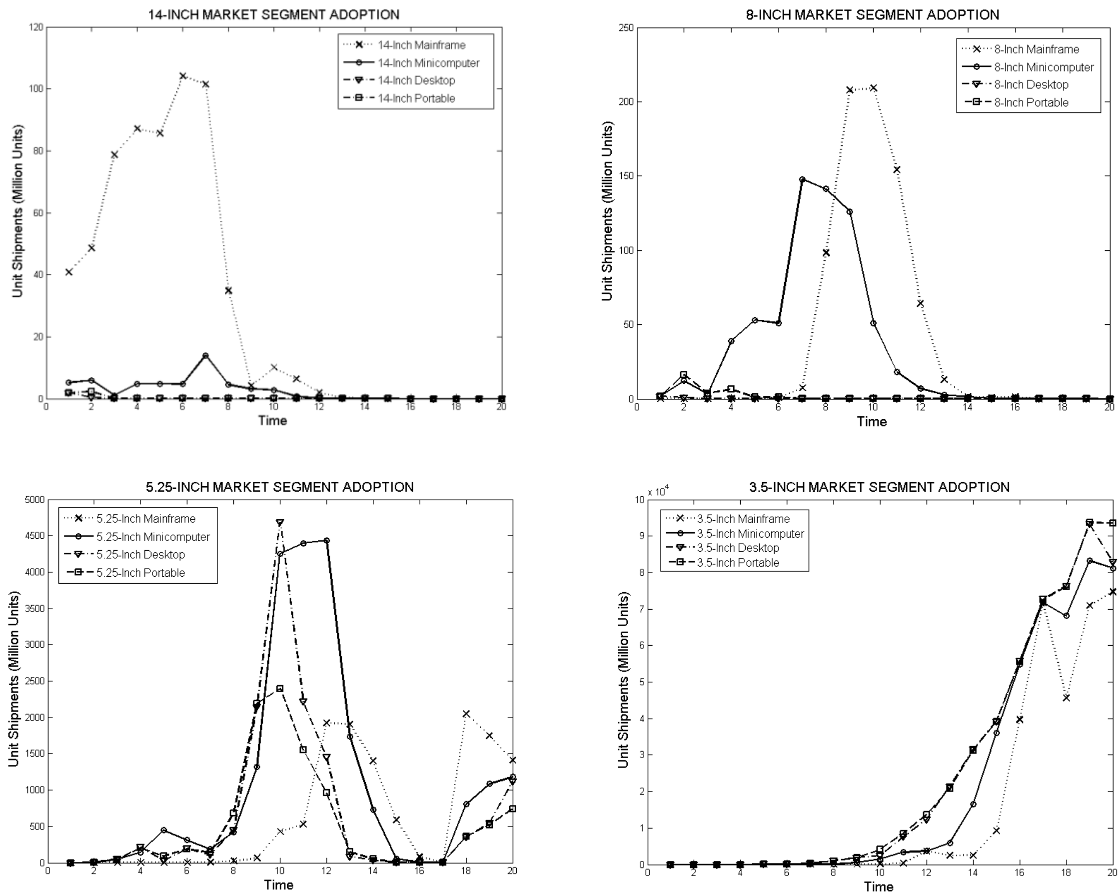


Figure 7.C. Market Segment Diffusion Curves

The simulation shows that mainframe consumers started to shift from 14-inch to 8-inch disk drives in 1985 (point 7) as sales declined due to performance improvements in capacity of 8-inch offerings.

Similar disruptive patterns were observed for 5.25-inch and 3.5-inch disk drives as they improved performance in capacity enough to satisfy the demand requirements of the mainframe market. These results generally reflect the estimates proposed by Christensen's intersecting technology trajectories depicted in Figure 6.B (Christensen and Bower, 1996). For example, our model also estimates that 3.5-inch disk drives started to invade desktop segments in 1988. However, slight discrepancies exist. According to our results, minicomputer consumers started to switch from 8-inch to 5.25-inch disk drives in 1986 (point 8) rather than 1987, as sales of 8-inch drives started to rapidly decline. We supplement graphical results in Table 7.B. with a summary of the changes in mainframe and minicomputer market segment adoption probabilities $Pr_{ij(t)}$ for each disk drive innovation over time:

Table 7.B Market Segment Adoption Probabilities (Mainframe and Minicomputer)

	MAINFRAME				**MINICOMPUTER**			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*99.7%*	*0.3%*	*0.0%*	*0.0%*	*12.6%*	*87.4%*	*0.0%*	*0.0%*
1980	*99.7%*	*0.3%*	*0.0%*	*0.0%*	*12.2%*	*70.8%*	*17.1%*	*0.0%*
1981	*99.9%*	*0.1%*	*0.1%*	*0.0%*	*1.3%*	*4.5%*	*94.1%*	*0.0%*
1982	*99.7%*	*0.2%*	*0.1%*	*0.0%*	*5.6%*	*29.2%*	*65.2%*	*0.0%*
1983	*99.7%*	*0.1%*	*0.1%*	*0.1%*	*5.7%*	*33.5%*	*40.0%*	*20.8%*
1984	*99.3%*	*0.5%*	*0.1%*	*0.1%*	*4.5%*	*30.2%*	*12.7%*	*52.6%*
1985	*95.9%*	*3.7%*	*0.2%*	*0.1%*	*13.3%*	*74.5%*	*6.1%*	*6.2%*
1986	*43.2%*	***56.1%***	*0.5%*	*0.2%*	*5.6%*	*80.7%*	*8.7%*	*5.0%*
1987	*5.4%*	*93.0%*	*0.8%*	*0.7%*	*4.2%*	*56.4%*	*18.2%*	*21.2%*
1988	*11.4%*	*80.7%*	*5.3%*	*2.6%*	*3.2%*	*19.6%*	***52.4%***	*24.8%*
1989	*17.2%*	*72.8%*	*6.9%*	*3.0%*	*2.0%*	*8.5%*	*57.8%*	*31.6%*
1990	*11.6%*	*34.7%*	*31.4%*	*22.3%*	*0.9%*	*3.7%*	*72.5%*	*22.8%*
1991	*2.2%*	*8.7%*	***78.1%***	*11.0%*	*0.5%*	*1.8%*	*71.0%*	*26.7%*
1992	*0.5%*	*1.3%*	*90.2%*	*7.9%*	*0.3%*	*1.3%*	*47.3%*	***51.0%***
1993	*0.5%*	*2.0%*	*74.2%*	*23.3%*	*0.2%*	*0.7%*	*7.2%*	*91.8%*
1994	*0.0%*	*3.6%*	*25.2%*	***71.2%***	*0.0%*	*0.5%*	*1.4%*	*98.1%*
1995	*0.0%*	*0.2%*	*1.3%*	*98.5%*	*0.0%*	*0.4%*	*1.0%*	*98.6%*
1996	*0.0%*	*0.0%*	*44.8%*	*55.2%*	*0.0%*	*0.0%*	*17.6%*	*82.4%*
1997	*0.0%*	*0.0%*	*31.3%*	*68.7%*	*0.0%*	*0.0%*	*19.5%*	*80.5%*
1998	*0.0%*	*0.0%*	*34.7%*	*65.3%*	*0.0%*	*0.0%*	*29.1%*	*70.9%*
AVERAGE	***52.4%***	***18.9%***	***22.4%***	***26.9%***	***4.8%***	***26.5%***	***33.6%***	***49.1%***

We can see from the highlighted adoption probabilities the years in which new disruptive innovations started to dominate higher end market segments: 8-inch disk drives started to dominate the mainframe market from 1986, 5.25-inch in 1991; and 3.5-inch in 1994. Similarly, in the minicomputer market 5.25-inch disk drives started to dominate in 1988, and 3.5-inch in 1992. Table 7.C. documents the changes in adoption probabilities for desktop and portable market segments. We can see that the 5.25-

inch disk drive was particularly short-lived in the desktop market with 3.5-inch disk drives emerging as a dominant design just three years after market introduction.

Performance improvements facilitate in increasing the adoption probabilities ($Pr_{ij(t)}$) of new innovations over time, thus leading to the emergence of competitive disruption. Similar to the arguments proposed by Anderson and Tushman (1990), we can see that technological advancements of new innovations result in coexistence during eras of ferment. An era of ferment is characterised by intense competition between and within market segments, in which there is a coexistence of technologies until a dominant design emerges (Anderson and Tushman, 1990; Nair and Ahlstrom, 2003). For example, between 1983 and 1989 there was intense competition between 5.25-inch and 3.5-inch disk drives in the desktop market. These results suggest that disruption is not an absolute phenomenon (Sood and Tellis, 2011). We observe multiple crossings of paths between the adoption probabilities of competing innovations during periods of intense competition until a winner emerges. Table 7.C. illustrates that in 1988 5.25-inch disk drives regained technological leadership in the desktop market, only to lose it again in 1989. These results suggest that eras of intense competition are often a precursor to disruption, whereby resident innovations fight drastically to retain dominance.

Table 7.C Market Segment Adoption Probabilities (Desktop and Portable)

	DESKTOP				**PORTABLE**			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*4.7%*	*95.2%*	*0.0%*	*0.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1980	*0.8%*	*5.0%*	*94.2%*	*0.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1981	*0.1%*	*0.3%*	*99.6%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*	*0.0%*
1982	*0.1%*	*0.2%*	*99.7%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*	*0.0%*
1983	*0.0%*	*0.1%*	*2.7%*	***97.2%***	*0.1%*	*0.7%*	*7.8%*	*91.5%*
1984	*0.0%*	*0.1%*	*7.9%*	*92.0%*	*0.1%*	*0.7%*	*7.8%*	*91.5%*
1985	*0.0%*	*0.1%*	*3.6%*	*96.3%*	*0.0%*	*0.1%*	*4.5%*	*95.4%*
1986	*0.0%*	*0.1%*	*9.3%*	*90.6%*	*0.0%*	*0.1%*	*14.1%*	*85.8%*
1987	*0.0%*	*0.1%*	*29.3%*	*70.6%*	*0.0%*	*0.1%*	*30.1%*	*69.7%*
1988	*0.0%*	*0.0%*	*57.7%*	*42.2%*	*0.0%*	*0.1%*	*29.5%*	*70.3%*
1989	*0.0%*	*0.0%*	*29.2%*	*70.7%*	*0.0%*	*0.1%*	*20.4%*	*79.5%*
1990	*0.0%*	*0.0%*	*23.8%*	*76.1%*	*0.0%*	*0.1%*	*15.8%*	*84.1%*
1991	*0.0%*	*0.0%*	*3.4%*	*96.5%*	*0.0%*	*0.1%*	*6.1%*	*93.8%*
1992	*0.0%*	*0.0%*	*2.2%*	*97.7%*	*0.0%*	*0.1%*	*3.2%*	*96.7%*
1993	*0.0%*	*0.0%*	*0.2%*	*99.8%*	*0.0%*	*0.1%*	*0.4%*	*99.5%*
1994	*0.0%*	*0.0%*	*0.1%*	*99.9%*	*0.0%*	*0.1%*	*0.3%*	*99.6%*
1995	*0.0%*	*0.0%*	*0.1%*	*99.9%*	*0.0%*	*0.1%*	*0.2%*	*99.7%*
1996	*0.0%*	*0.0%*	*7.6%*	*92.3%*	*0.0%*	*0.0%*	*7.9%*	*92.0%*
1997	*0.0%*	*0.0%*	*9.8%*	*90.2%*	*0.0%*	*0.0%*	*9.3%*	*90.6%*
1998	*0.0%*	*0.0%*	*27.5%*	*72.5%*	*0.0%*	*0.0%*	*18.2%*	*81.8%*
AVERAGE	***0.4%***	***5.3%***	***26.7%***	***86.5%***	***0.7%***	***10.7%***	***19.2%***	***88.8%***

Our analysis extends Christensen's technology trajectories to document the disruption experienced in each individual market segment for each disk drive innovation. From the diffusion curves in Figure 7.C. we can see that mainframe consumers started to adopt 5.25-inch drives in 1989 (point 11) as sales of 8-inch drives declined. This pattern was mirrored by 3.5-inch drives in 1992 (point 14) as sales of 5.25-inch drives declined due to performance improvements in capacity of 3.5-inch drives. These multiple waves of market disruption were repeated in minicomputer and desktop market segments (Christensen and Bower, 1996). For example, the desktop market segment was initially served by 5.25-inch disk drives. However, sales started to rapidly decline after 1988 (point 10) as 3.5-inch drives started to supersede 5.25-inch drives in the market. Positive development asymmetries allowed the 3.5-inch disk drive to continually encroach up market towards high end segments. In 1990 (point 12) the 3.5-inch further disrupted the minicomputer market.

We observe that new potentially disruptive innovations can invade new markets when they are able to satisfy optimal demand thresholds for primary attributes. Additional utility is then derived from the alternative performance offered by the disruptive innovation (Keller and Hüsig, 2009). Thus, we can conclude that disruptive innovations follow a low end encroachment pattern as proposed by Druehl and Schmidt (2008) and Schmidt and Druehl (2008). However, before disruption occurs there is intense competition between the resident and invading innovation in a battle for market dominance. This provides new insight into the theory, suggesting that disruption occurs through intense competition and a series of successive incremental generations to finally dominate the market. Similar to Anderson and Tushman (1990), our analysis shows that during eras of ferment innovations engage in intense competition until a clear winner emerges. In the following sections, we focus our attention towards the underlying mechanisms that drive this process and provide evidence of the propositions developed in § 5.2.

7.2. Analysis of Preference Structure

In this section we simulate the effect of preference structure on market disruption. Model inputs derived in § 6.1.3 are used for qualitative analysis of two different inter-market preference structures, namely: *preference convergence* and *preference isolation*. We examine the aggregate and market segment level effects of preference structure on market disruption by changing the rank order and weight w_{ik} of market segment preferences for disk drive attributes. We change the preference structures in order to reflect competitive conditions of convergence and isolation.

7.2.1. Effect of Preference Convergence

Competitive convergence refers to dynamics of symmetric attribute preferences across market segments. To reflect these conditions, we converge all market segment preferences towards capacity

($w_{ik} = 1, \forall i \in I$) so that consumers only value a single '*primary*' attribute and no other. Figure 7.D. illustrates the aggregate level diffusion curves for each disk drive innovation under conditions of preference convergence. We can see that higher performing 14-inch and 8-inch disk drives experience increased sales and market longevity. This is because consumers preferred the higher capacity provided by such drives, thus preventing the entrance of lower performing disruptive innovations.

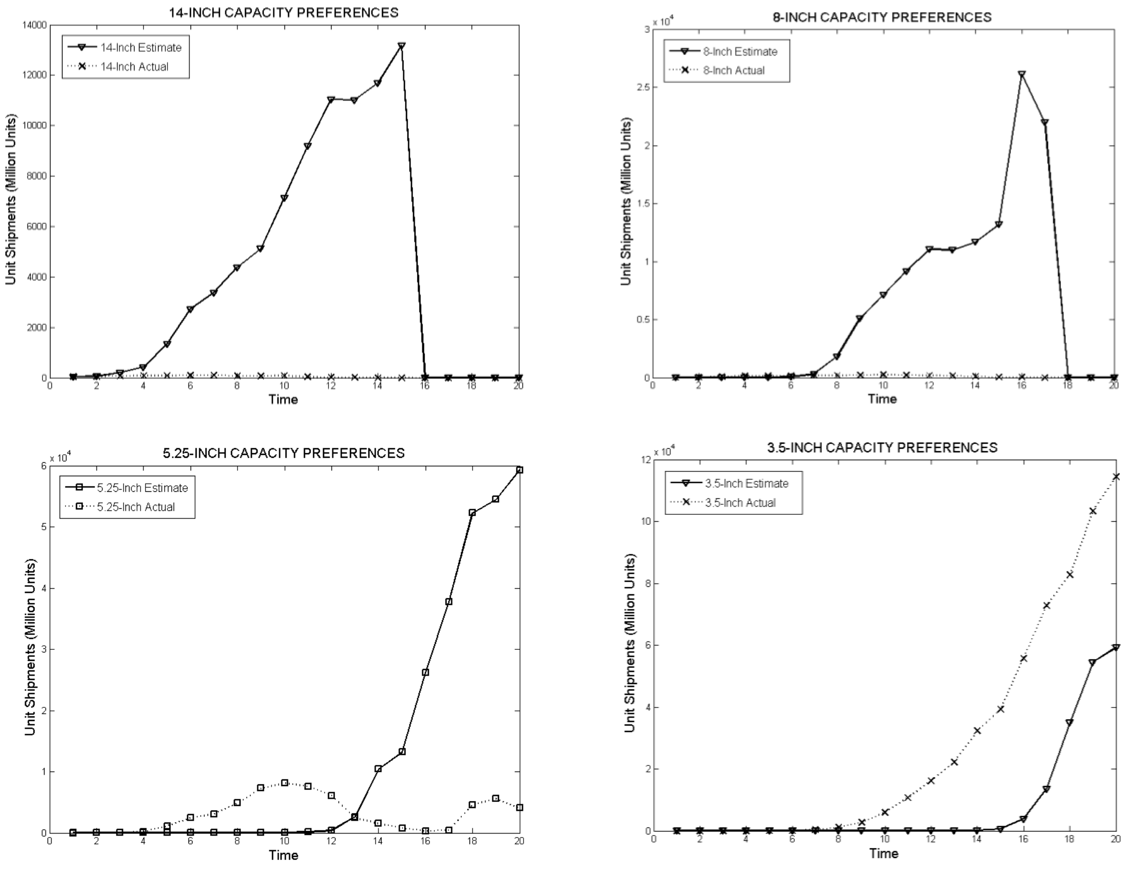


Figure 7.D. Aggregate Diffusion Curves for Preference Convergence (Capacity)

Results from Figure 7.D. show that in each case, market entry of smaller sized disk drives was delayed, which led to a slower speed and likelihood of market disruption. Comparison of Figures 7.A. and 7.D. show that 8-inch disk drives were delayed by 3 years; 5.25-inch by 4 years; and 3.5-inch by 10 years. Similarly, analysis of simulated adoption probabilities for each disk drive in Appendix 3 (Tables 1 and 2) support these findings. We see that the average adoption probability of 14-inch disk drives increases by approximately 58%, whereas the adoption probability of the 3.5-inch disk drive decreases by approximately 66%. These results support *Proposition 1B*, as higher average adoption probability indicates increased market longevity of the 14-inch drive and lower average adoption probability of the 3.5-inch drive indicates a slower speed of market disruption. Comparison of aggregate level adoption probabilities shows that the disruptive capability of smaller sized disk drives significantly reduced when preferences converge to a single attribute. For example, the 3.5-inch disk drive was not visible in the aggregate market until 12 years later (1995) when compared with the adoption probabilities of the validated model.

The results suggest that inferior performance in capacity reduces the disruptive capability of new innovations, as consumers do not value alternative performance offered in the form of smaller size or lower price. However, once optimal demand thresholds for capacity are satisfied, homogeneous preferences across market segments result in consumer indifference between innovation alternatives. Consumer indifference results in a coexistence of innovations in the market with identical adoption probabilities (Nair and Ahlstrom, 2003). For example, Figure 7.D. shows that 14-inch and 8-inch disk drives coexisted between 1987 (point 9) and 1993 (point 15), and 8-inch and 5.25-inch between 1993 (point 15) and 1994 (point 16). The adoption probabilities in Appendix 3 (Table 2) support these results and highlight the coexistence of innovations during eras of intense competition. Similar to the conclusions of Anderson and Tushman (1990), we can see that multiple innovations compete in the market simultaneously, thus prolonging disruption until a dominant design emerges. Consequently, the structure of attribute preferences across market segments can act as a natural barrier for disruptive innovation. Therefore, we can conclude that homogeneous preferences for primary attributes result in a slower speed and likelihood of market disruption (P1B).

Market Segment Analysis of Preference Convergence:

Analysis of market segment diffusion curves gives further insight into the influence of preference convergence on patterns of market disruption. Figure 7.E. illustrates the diffusion patterns of disk drive innovations at the individual market segment level. When compared with the simulation output in Figure 7.C. similar patterns of disruptive lag can be observed. For example, market entry of the 5.25-inch and 3.5-inch disk drives was delayed in the mainframe market by 8 (1992) and 11 years (1994) respectively. These patterns were replicated in the minicomputer market segment with an 8 and 9 year delay in entry of 5.25-inch and 3.5-inch disk drives. These disruptive lags occur, as higher demanding mainframe and minicomputer consumers prefer the increased performance in capacity provided by 14-inch and 8-inch disk drives. As a result, lower performing disruptive innovations find it difficult to penetrate the market.

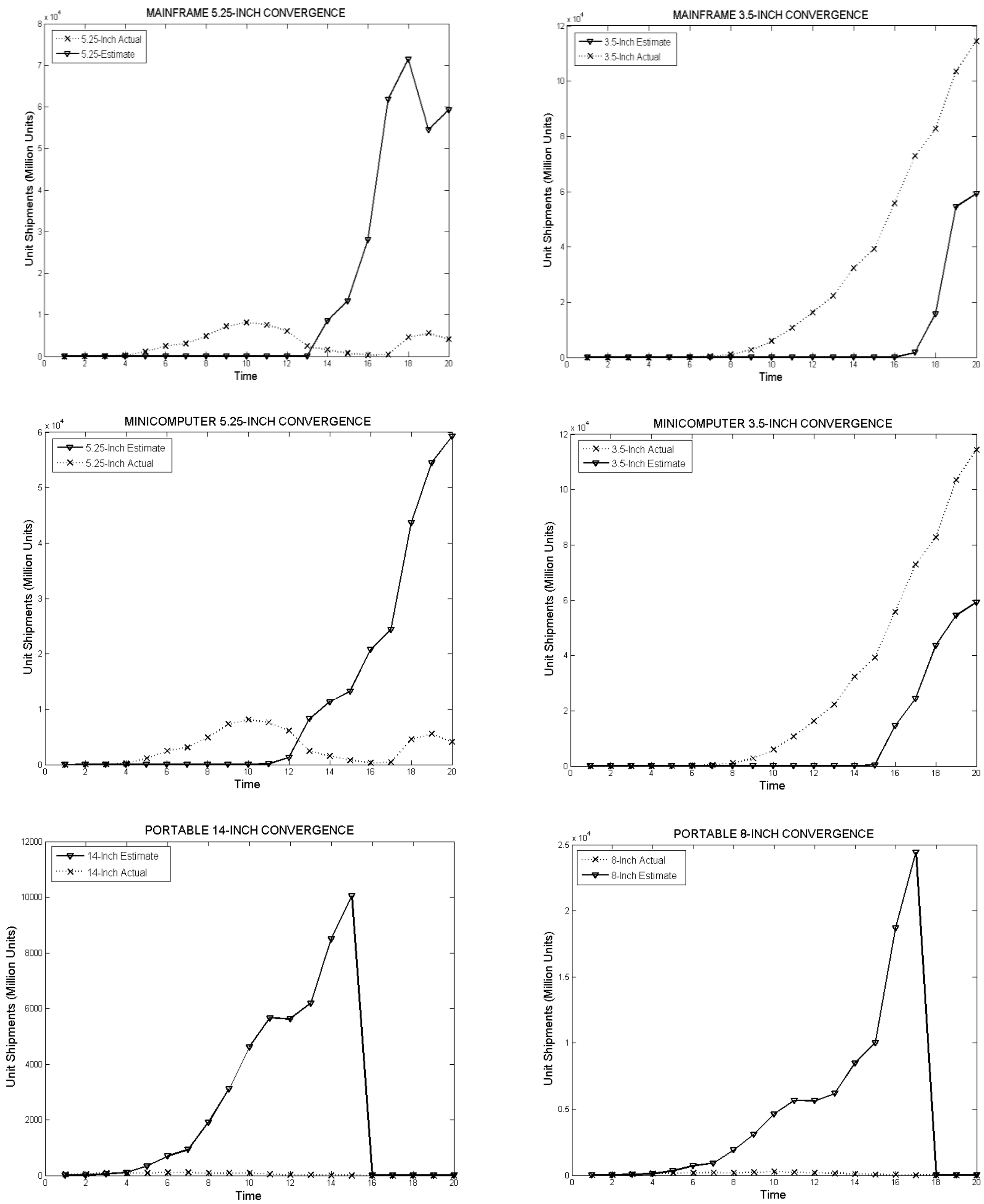


Figure 7.E. Market Segment Diffusion Curves for Preference Convergence (Capacity)

The bottom two frames in Figure 7.E. illustrate the diffusion curves of 14-inch and 8-inch disk drives in the portable market segment. Results show that under conditions of preference convergence for capacity, both 14-inch and 8-inch disk drives experienced significant increases in sales and market longevity. Furthermore, analysis of adoption probabilities in Appendix 3 (Tables 3 and 4) support *Proposition 1B* and demonstrate that the speed and likelihood of market disruption decreases when market segments converge towards a primary attribute. The average adoption probability of 14-inch drives increases by over 20% in the mainframe market, while the average adoption probability of 3.5-

inch drives decreases by over 60% (re Appendix 3 (Table 3)). Therefore, results suggest that the structure of market segment preferences directly influences the disruptive capability of new innovations. In particular, preference convergence slows the speed of disruption as consumers do not value the alternative performance offered by disruptive innovations.

7.2.2. Effect of Preference Isolation

In addition to preference convergence, we examine the conditions of preference isolation across market segments. Preference isolation refers to demand conditions of divergent preference overlap in innovation attributes across market segments (Adner, 2002). To reflect these conditions we simulate dynamics whereby consumers only value their highest ranking attribute from Table 6.B: mainframe – *capacity*; minicomputer – *capacity*; desktop – *price*; and portable – *size*. Figure 7.F. illustrates the aggregate level diffusion curves for each disk drive innovation under conditions of preference isolation.

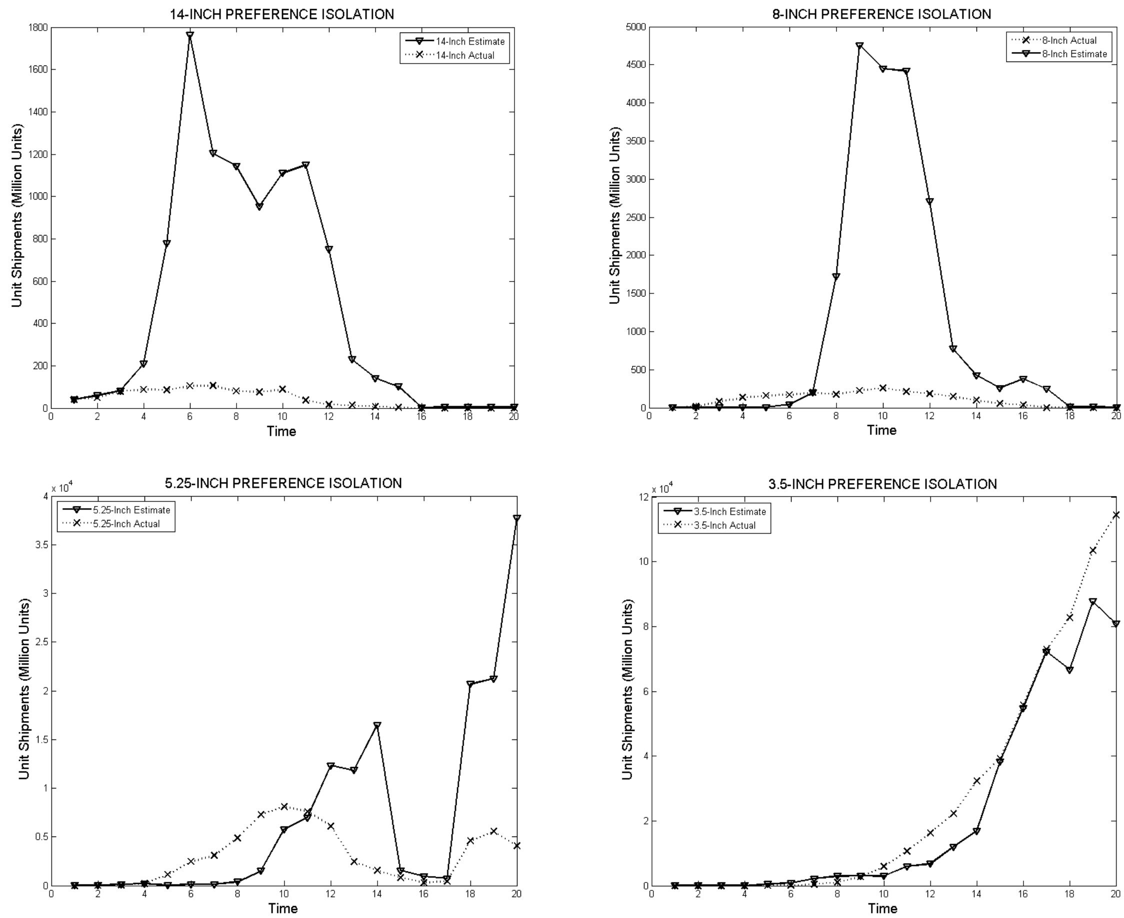


Figure 7.F. Aggregate Diffusion Curves for Preference Isolation

Results of the aggregate diffusion curves show that under conditions of isolation, sales of 14-inch, 8-inch, and 5.25-inch disk drives significantly increase. In comparison, sales of 3.5-inch disk drives decrease. This suggests a slower speed and likelihood of market disruption. Since market segment preferences are divergent, each innovation is superior on a certain attribute that satisfies the need of a specific segment. As a result, disk drive innovations compete in isolation of each other. For example, high capacity 14-inch and 8-inch disk drives serve mainframe and minicomputer market segments; whereas lower priced 5.25-inch disk drives serve the desktop segment and the smaller sized 3.5-inch the portable market segment. Due to the low degree of preference overlap between segments, customers in each market do not value the performance offered by potentially disruptive innovations that compete in other market segments. Consequently, the aggregate diffusion curve of the 3.5-inch disk drive is more negatively skewed, as disruption occurs at a slower rate due to divergent preferences across markets.

Analysis of aggregate level adoption probabilities in Appendix 3 (Table 2) supports this conclusion. We can see that the average adoption probability of 14-inch disk drives increases by 19%, thus indicating a lower likelihood and speed of market disruption. Similarly, the average adoption probability of 3.5-inch disk drives decreases by 21%. It is also observed that there is a more equal distribution of adoption probabilities across each disk drive. This indicates a lower susceptibility to market disruption, as 14-inch, 8-inch, and 5.25-inch disk drives experience increased market longevity. As the distance between market segment preferences increase and become more divergent, a market's susceptibility to disruption decreases (P1A). In the next sub-section, we analyse the effects of preference isolation at the individual market level.

Market Segment Analysis of Preference Isolation:

Analysis shows that under conditions of isolation, market segments experience decreased competitive turbulence and disruption from external threats. This is because each innovation is solely concerned with satisfying its home market's primary attribute. Mainframe and minicomputer market segments document significant increases in sales and extended lifecycles for 14-inch and 8-inch disk drives, thus reducing the likelihood of market disruption from 5.25-inch and 3.5-inch alternatives. Simulation results provide partial support for Adner's (2002) conclusion that isolation leads to a partitioning between market segments, leading to lower probability of inter-market disruption.

Results from Figure 7.G. illustrate that mainframe and minicomputer diffusion curves are more negatively skewed for 5.25-inch and 3.5-inch disk drives when compared with the original market segment diffusion curves in Figure 7.C. This difference indicates a time lag in the entrance of smaller sized disruptive innovations. Disruption of the 8-inch disk drive into the mainframe market segment was delayed by a year (1984), whereas 5.25-inch (1991) and 3.5-inch (1994) disk drives were both delayed by 5 years. These lags in disruption were replicated in the minicomputer market segment, where entrance of the 5.25-inch drive was delayed by 9 years (1989) and 3.5-inch innovations by 7 years (1993). Analysis of adoption probabilities also shows that preference isolation reduces the threat of disruption. For example, the average adoption probability of 3.5-inch drives decreases by 20% for mainframe and 36% for minicomputer market segments (see Appendix 3 (Table 5)).

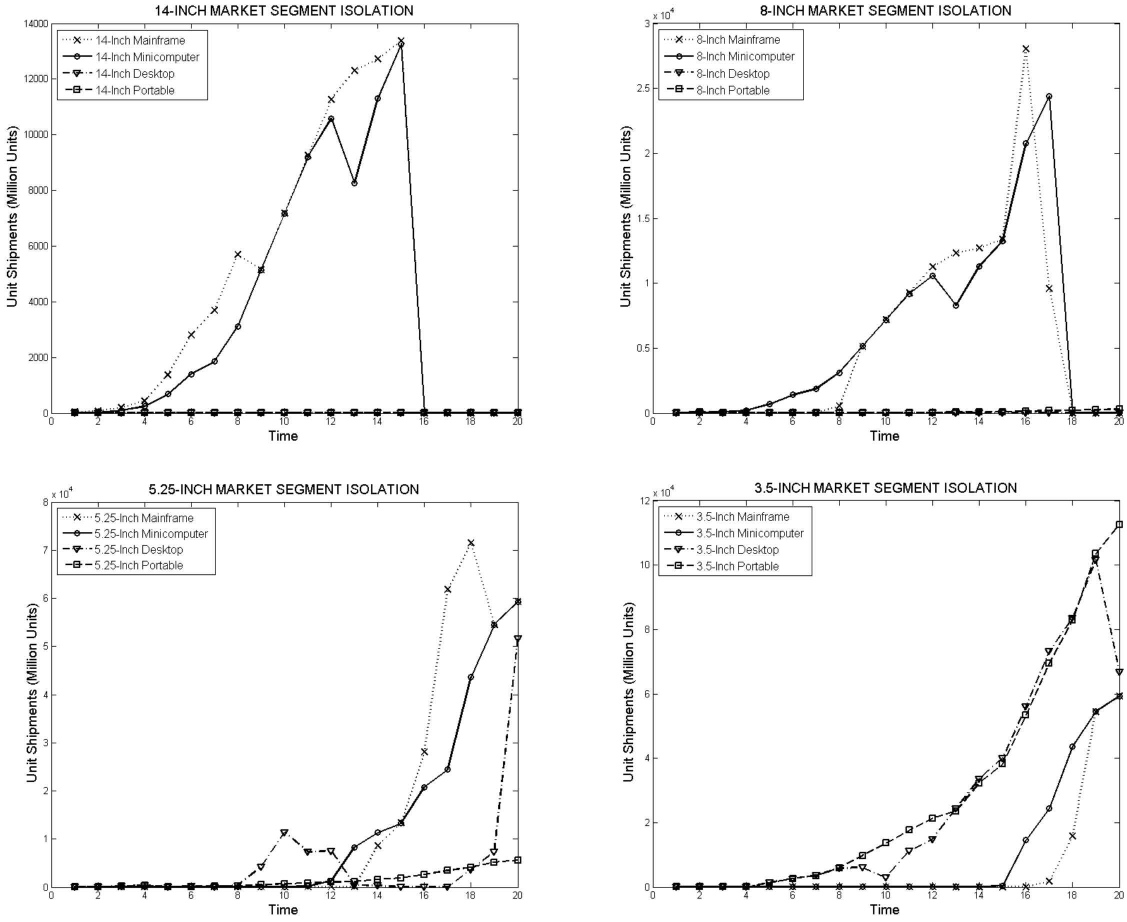


Figure 7.G. Market Segment Diffusion Curves for Preference Isolation

Evidently, preference isolation results in market entry lags, thus slowing the speed and likelihood of market disruption. Isolation insulates market segments from disruptive threats as consumers do not value the performance offered by alternative innovations. Disruptive innovations can only invade external competitive markets when optimal demand thresholds for primary attributes are satisfied. This leads to a coexistence of innovation alternatives in the marketplace. Results of the simulation provide support for Proposition 1A i.e. lower degrees of preference overlap between competitive market segments reduce a market's susceptibility to disruptive threats. However, competitive convergence towards a single attribute also slows the speed and likelihood of market disruption. In both cases, the structure of market segment preferences act as a market entry barrier for lower performing disruptive innovations (P1A, P1B).

In conclusion, disruption occurs when there is a higher degree of overlap in preferences, but not to the extent whereby they converge towards a single dimension. Market segments that share preference similarities with other external markets are more susceptible to disruption. This is because the competitive boundaries that exist between segments are less defined and thus more vulnerable to external threats. In the case of convergence and isolation, preference boundaries are structured and well defined, which effectively reduces a market's susceptibility to disruptive innovation. Under such conditions, markets have no competition in the form of external markets that offer technologies, products, or services that the home market could potentially value. In the case of convergence, external threats are consolidated into a single market, whereas in the case of isolation, segments are so far away in terms of preferences that mainstream markets are insulated from disruption.

Sensitivity to changes in market segment preferences demonstrates the general robustness of these results. By changing market segment preferences we can see the model's sensitivity to new inputs. For example, when market segments have zero preferences for innovation attributes consumers become totally indifferent to innovation alternatives. As a result, all innovations coexist in the aggregate marketplace simultaneously with identical adoption probabilities. Figure 7.H. illustrates the diffusion curves sensitivity to zero preference structures. In the next section, we focus our analysis towards the effects of optimal demand on market disruption.

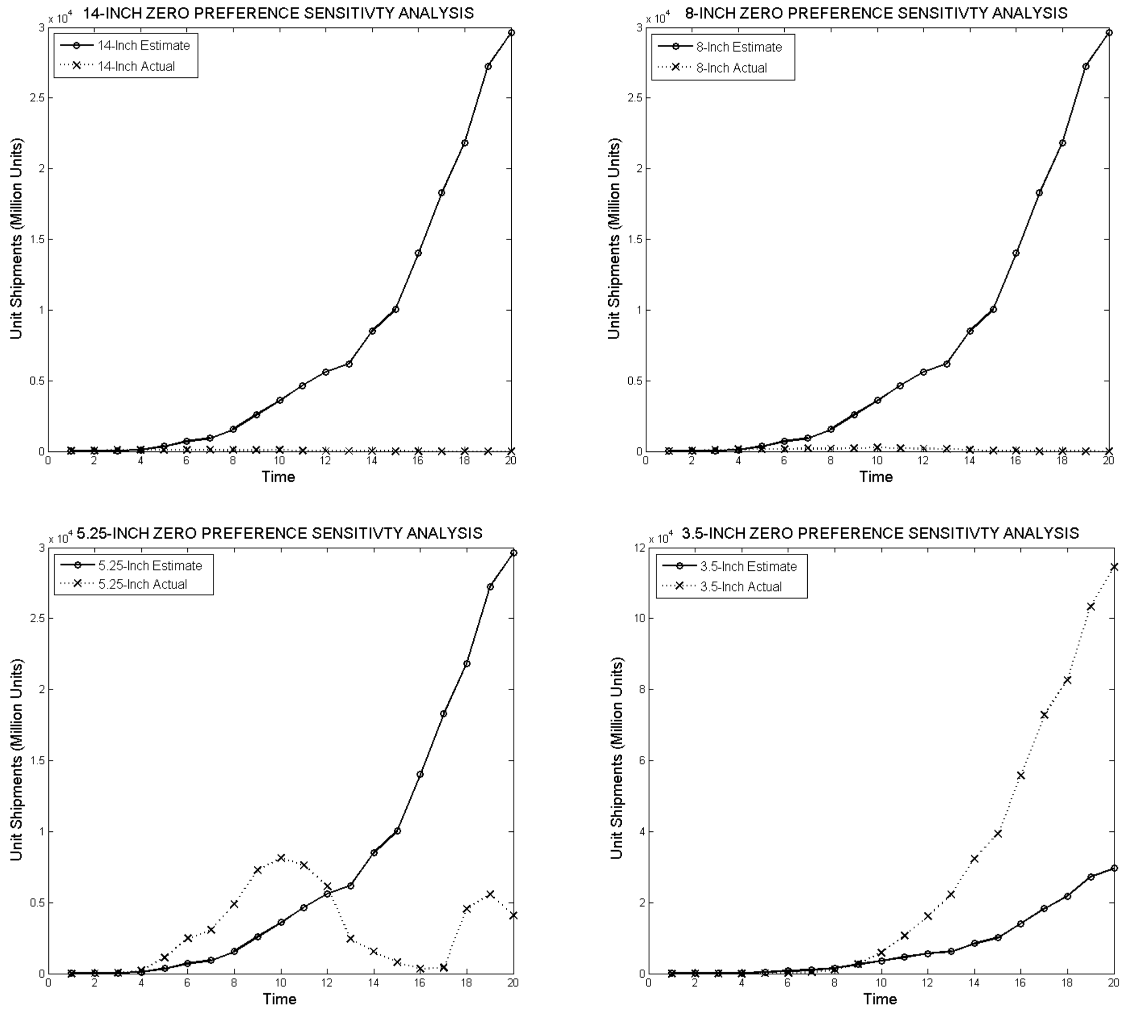


Figure 7.H. Market Segment Diffusion Curves for Zero Preference

7.3. Analysis of Demand Structure

To analyse the effects of optimal demand on market disruption, we positively and negatively scale market segment demand thresholds for capacity by a factor of ± 2. Model inputs for the analysis of optimal demand are documented in Appendix 1 (Table 10). We propose that the initial size of a market segments' optimal demand threshold will directly influence the disruptive capability of new innovations. In our analysis, we scale optimal demand (O_{ik}) for capacity in order to evaluate the effects of high and low demand thresholds on market disruption. Results are presented at both the aggregate and individual market segment level.

7.3.1. Effect of High and Low Optimal Demand

High and low optimal demand thresholds create different competitive landscapes for existing and new innovations. For example, high demand thresholds mean that disruptive innovations will struggle to compete in the market due to the increased performance requirements of consumers. Results in Figure 7.I. show the aggregate level diffusion curves for each disk drive innovation under conditions of high and low optimal demand.

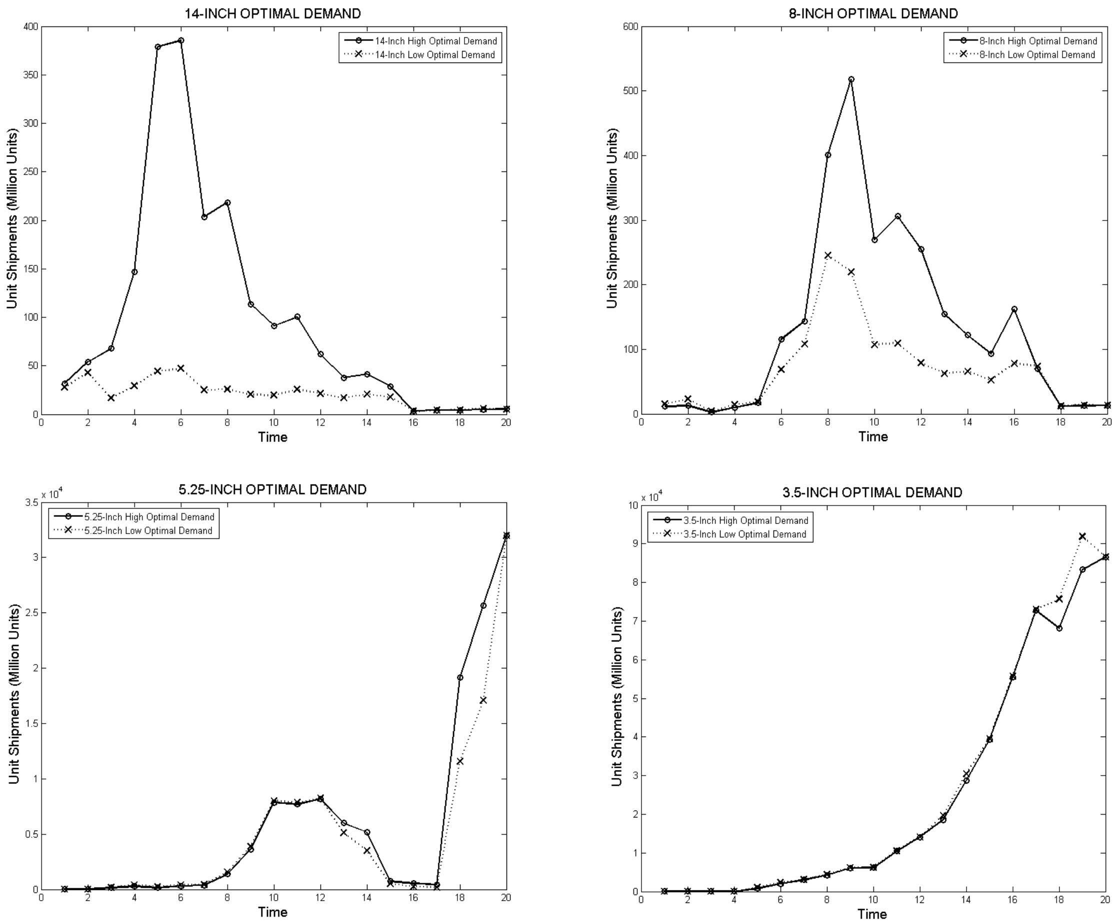


Figure 7.I. Aggregate Diffusion Curves for High and Low Optimal Demand

Simulation results demonstrate that under conditions of high optimal demand, the speed and likelihood of market disruption decreases. Sales of the 14-inch disk drive are much higher since the average demand needs of the market can only be satisfied by higher performing 14-inch drives. However, the difference between high and low thresholds gradually decreases in each graphical frame as we move towards the diffusion curves of the 3.5-inch disk drive, at which point the relationship is reversed. This suggests that as optimal demand increases, sales of higher performing disk drives also increases but at a slower rate as we move towards lower performing innovations. For example, sales of the 14-inch, 8-inch, and 5.25-inch disk drive are higher under conditions of high optimal demand (HOD) when compared with low optimal demand (LOD). However, this relationship is reversed for 3.5-inch disk drives i.e. LOD>HOD. This suggests that HOD conditions slow the speed of disruption for the 3.5-inch drive, as lower performing innovations find it difficult to compete due to increased demand conditions. Conversely, under LOD conditions the disruption speed of 3.5-inch disk drives increases as the innovation can more easily satisfy mainstream market demand requirements, thus providing support for *Proposition 2*.

These results are supported by the analysis of adoption probabilities in Appendix 3 (Table 7). We can see that under conditions of HOD the market lifecycle of 14-inch disk drives increases. Furthermore, the initial speed of 3.5-inch disruption is approximately 20% lower upon market introduction in 1983. Analysis of average adoption probabilities shows that 14-inch disk drives increase by 8%, whereas the average adoption probability of 3.5-inch drives decreases by 4% under HOD conditions. Consequently, we can conclude that the initial magnitude of market segment optimal demand has a direct impact on the disruptiveness of innovations. In the next sub-section, we analyse these effects at the market segment level.

Market Segment Analysis of High and Low Optimal Demand:

Market segment analyses of high and low optimal demand thresholds produce similar results. We find that that under conditions of HOD, the speed and likelihood of disruption decreases. Lower performing disruptive innovations are unable to satisfy the increased levels of performance demanded by upmarket segments, thus limiting their disruptive capability. Comparison of average adoption probabilities for HOD and LOD shows that market segments experience increased (decreased) sales and lifecycles for higher performing disk drive innovations when optimal demand is high (low). For example, mainframe and minicomputer market segments experience increased sales and adoption probabilities for 14-inch (23.25%) and 8-inch (17.75%) disk drives respectively. This is because consumers in these markets have a higher absorptive capacity for performance improvements, thus preventing the entry of lower performing disruptive innovations. Market segment adoption probabilities are documented in Appendix 3 (Tables 8–11).

Figure 7.J. illustrates the effect of optimal demand on the disruptiveness of innovations. Each graphical frame documents the changes in adoption probabilities for home market innovations. Results suggest that HOD thresholds lead to a lower risk of disruption. In the first frame we can see that the adoption probability and lifecycles of 14-inch disk drives increases in the mainframe market under HOD conditions. Furthermore, the adoption probability of 3.5-inch disk drives decreases in the portable market segment, thus indicating a slower speed and likelihood of market disruption. In contrast, when optimal demand is low (LOD), these effects are reversed i.e. the adoption probability of 14-inch disk drives decreases, whereas the adoption probability of 3.5-inch disk drive increases. These results provide support for *Proposition 2*. However, the effects of optimal demand are relatively small in some years. For example, the differences observed in the desktop market for 5.25-inch disk drives shows little variability.

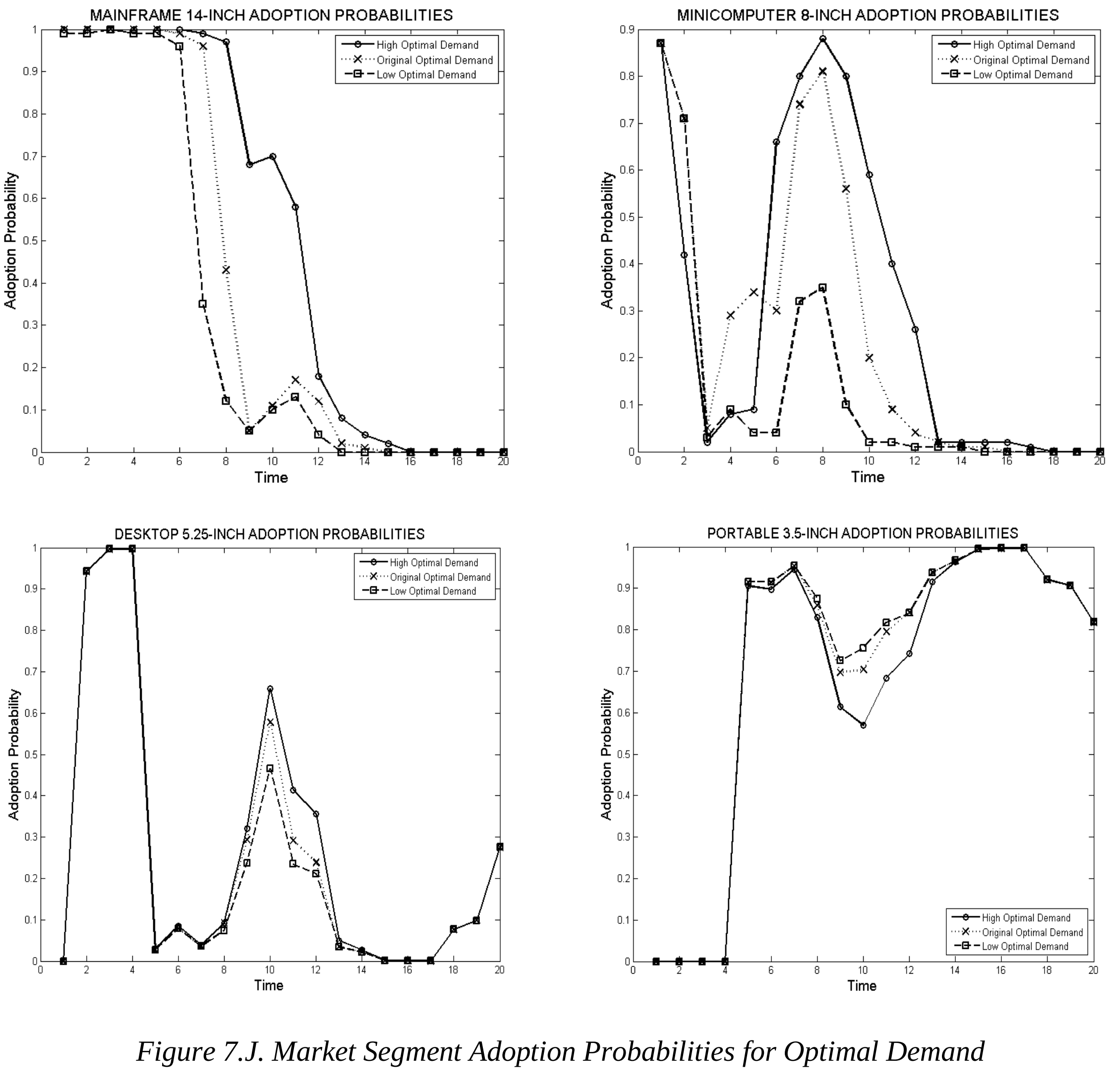


Figure 7.J. Market Segment Adoption Probabilities for Optimal Demand

Analysis of market segment diffusion curves for HOD vs. LOD thresholds support these findings (Figure 7.K.). Simulation results show that when optimal demand is high market entry of the 8-inch disk drive was delayed by 4 years in the mainframe market; 5.25-inch by 3 years, and 3.5-inch by 7 years. Similar results were observed in the minicomputer market segment. High optimal demand delayed market entry of the 5.25-inch disk drive by 6 years and the 3.5-inch by 4 years. Under such conditions, high levels of O_{ik} facilitate in creating market entry barriers for lower performing disruptive innovations. In contrast, low levels of O_{ik} result in a faster speed and likelihood of market disruption, as new innovations can more easily satisfy a market segment's demand requirements. Thus, optimal demand levels can both expose and protect markets from lower performing disruptive innovations (P2).

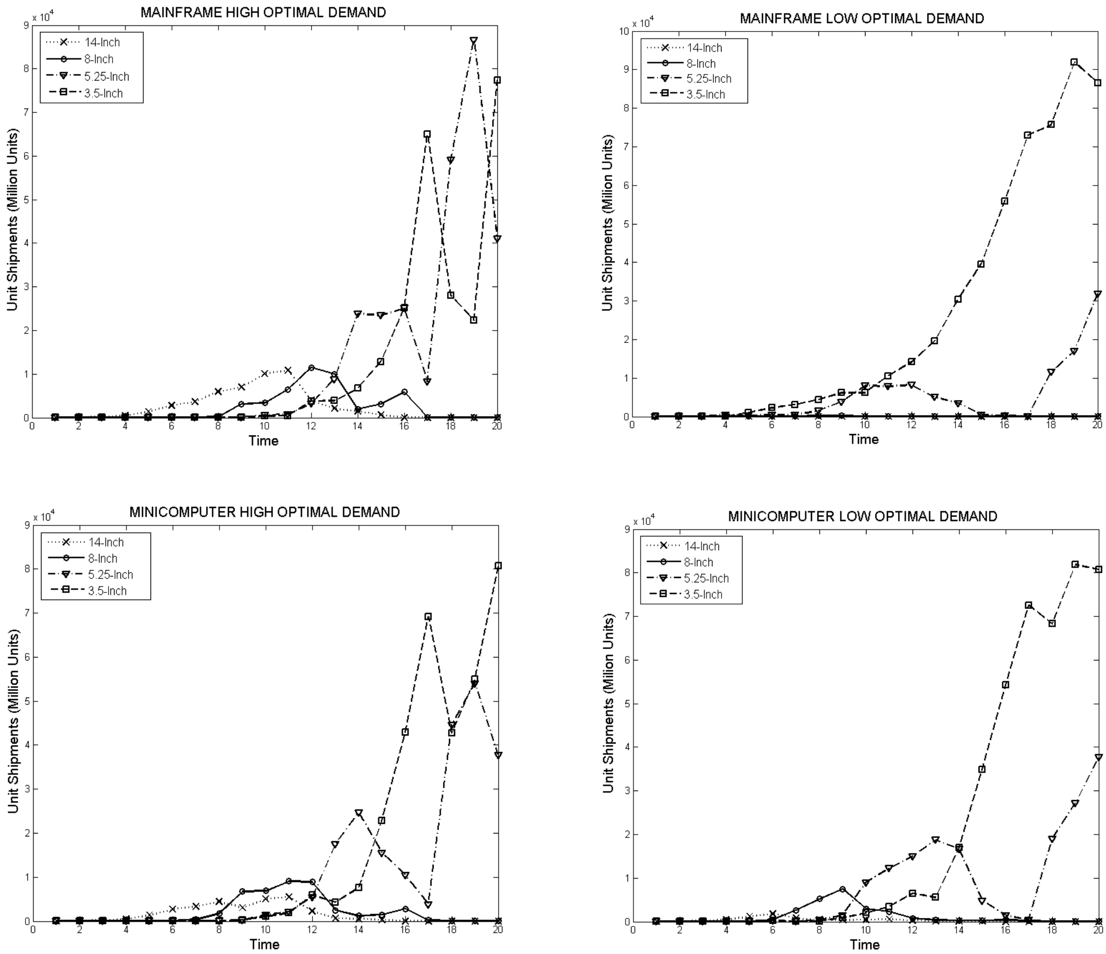


Figure 7.K. Mainframe and Minicomputer Market Segment Diffusion Curves for Optimal Demand

In conclusion, it is evident that market segment optimal demand thresholds for attribute performance directly influence the disruptive capability of new innovations. Market segments that exhibit HOD thresholds for primary attributes are less susceptible to external disruptive threats, as new innovations find it difficult to satisfy the high performance demanded in mainstream markets. Thus, high thresholds can create market entry barriers for lower performing disruptive innovations. Conversely, market segments that are characterised by LOD thresholds are more susceptible to market disruption. This is because new potentially disruptive innovations can more easily satisfy the demand requirements of mainstream customers. As a result, the initial magnitude of $\boldsymbol{O_{ik}}$ can both increase and decrease a market's susceptibility to disruption.

7.4. Analysis of Development Dynamics

We examine the effects of development dynamics on market disruption by changing the growth rates in absorptive capacity (γ_{ik}) and technology development (α_{jk}). Firstly, we consider the effects of differing growth rates in absorptive capacity on market disruption. We then extend our analysis to consider the effects of higher positive and negative development asymmetries between absorptive capacity and technological advancement.

7.4.1. Effect of Absorptive Capacity

Growth rates in absorptive capacity determine a market segment's optimal demand threshold for attribute performance. Consequently, results from the previous section provide partial support for *Proposition 3A*. Slower growth rates in 'γ_{ik}' result in a lower optimal demand threshold, thus enabling the entrance of lower performing disruptive innovations. In contrast, faster growth rates increase optimal demand thresholds and prolong the lifecycles of higher performing dominant innovations. To check the robustness of these results, we analyse the effects of high and low growth rates in absorptive capacity at the aggregate level.

Figure 7.L. illustrates the aggregate level diffusion curves for 14-inch, 8-inch, and 3.5-inch disk drives. Results suggest that higher growth rates lead to a slower speed and likelihood of market disruption. We observe that higher performing 14-inch and 8-inch disk drives experience increased sales and market longevity when growth rates in absorptive capacity are high. For example, sales of 14-inch disk drives are 90% higher and sales of 8-inch disk drives are 81% higher. Furthermore, diffusion curves of 3.5-inch disk drives decrease, which suggests a slower speed and likelihood of market disruption. Higher growth rates increase a market segment's ability to absorb performance improvements of the resident innovation, thus preventing the entrance of lower performing disruptive innovations (P3A).

In contrast, Figure 7.L. illustrates that when absorptive capacity is low, the speed and likelihood of market disruption increases. Results show that sales of 3.5-inch disk drives increase, whereas sales of both 14-inch and 8-inch disk drives decrease, thus indicating a faster speed and likelihood of market disruption (P3A). Analysis of adoption probabilities in Appendix 3 (Table 12) provides further support for these results. We can see that the average adoption probability of 14-inch and 8-inch drives decreases, whereas the average adoption probability for 5.25-inch and 3.5-inch drives increases. This suggests that customers are switching to the disruptive innovation more quickly as they are incapable of absorbing the performance improvements of the resident technology. These results are reversed when growth rates in absorptive capacity are high, thus providing further support for *Proposition 3A*. In the next sub-section we analyse the effect of absorptive capacity at the market segment level.

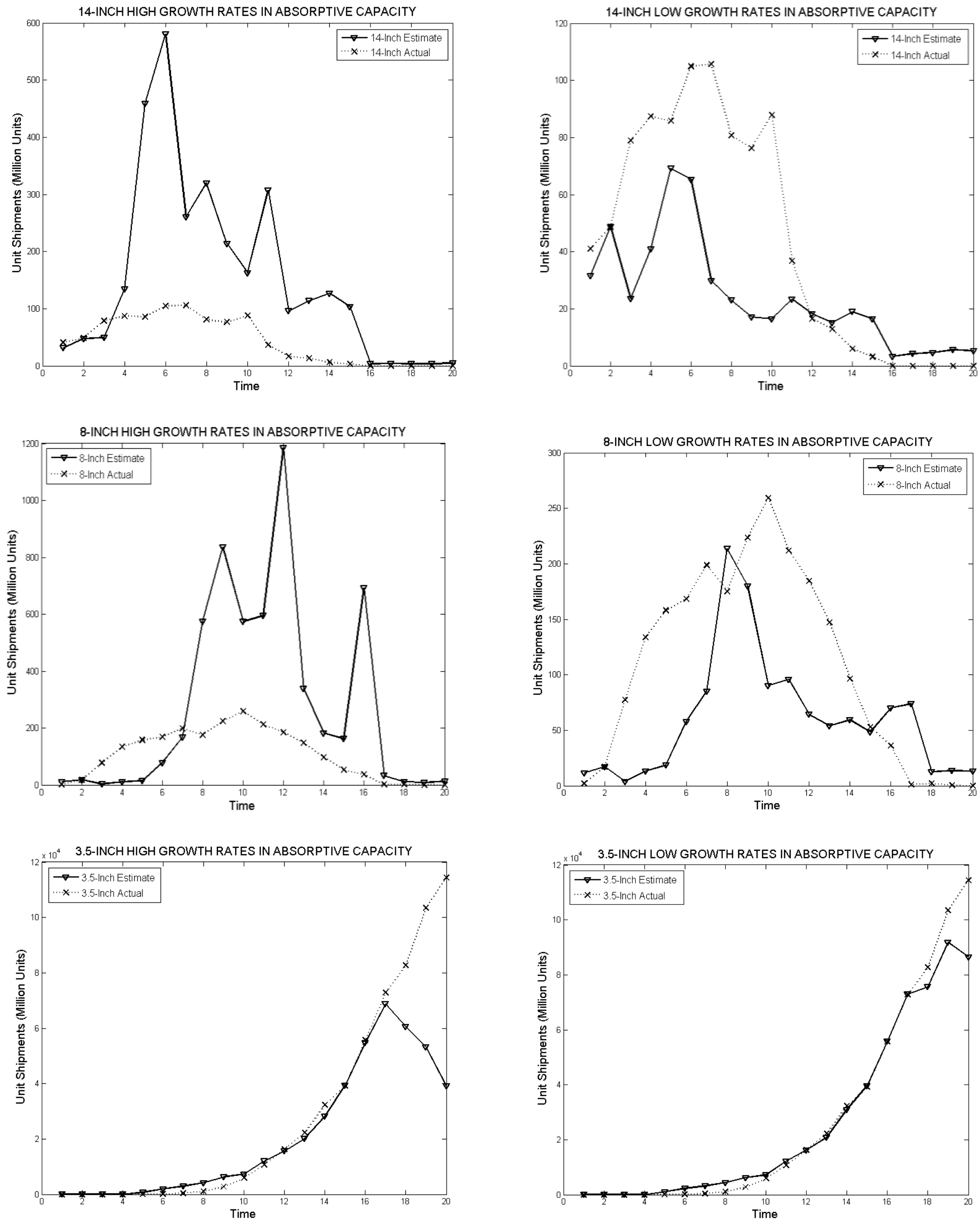


Figure 7.L. Aggregate Diffusion Curves for Absorptive Capacity

Market Segment Analysis of Absorptive Capacity:

At the market segment level similar patterns emerge. Higher growth rates in absorptive capacity lead to time lags in disruption. Comparison of high vs. low growth rates in Figure 7.M. show that the diffusion curves of lower performing 5.25-inch and 3.5-inch disk drives are more negatively skewed when γ_{ik} is high. Thus, market entrance of lower performing disruptive innovations is prolonged. Results suggest that the entrance of 8-inch (point 8 vs. 6), 5.25-inch (point 12 vs. 10), and 3.5-inch (point 12 vs. 10) disk drives were delayed by 2 years in the mainframe market segment. These lags were repeated in the minicomputer market segment, where entrance of the 5.25-inch disk drive was delayed by 4 years (point 10 vs. 6) and 3.5-inch by 2 years (point 10 vs. 8). In conclusion, both aggregate and market segment analysis of absorptive capacity provides support for *Proposition 3A*.

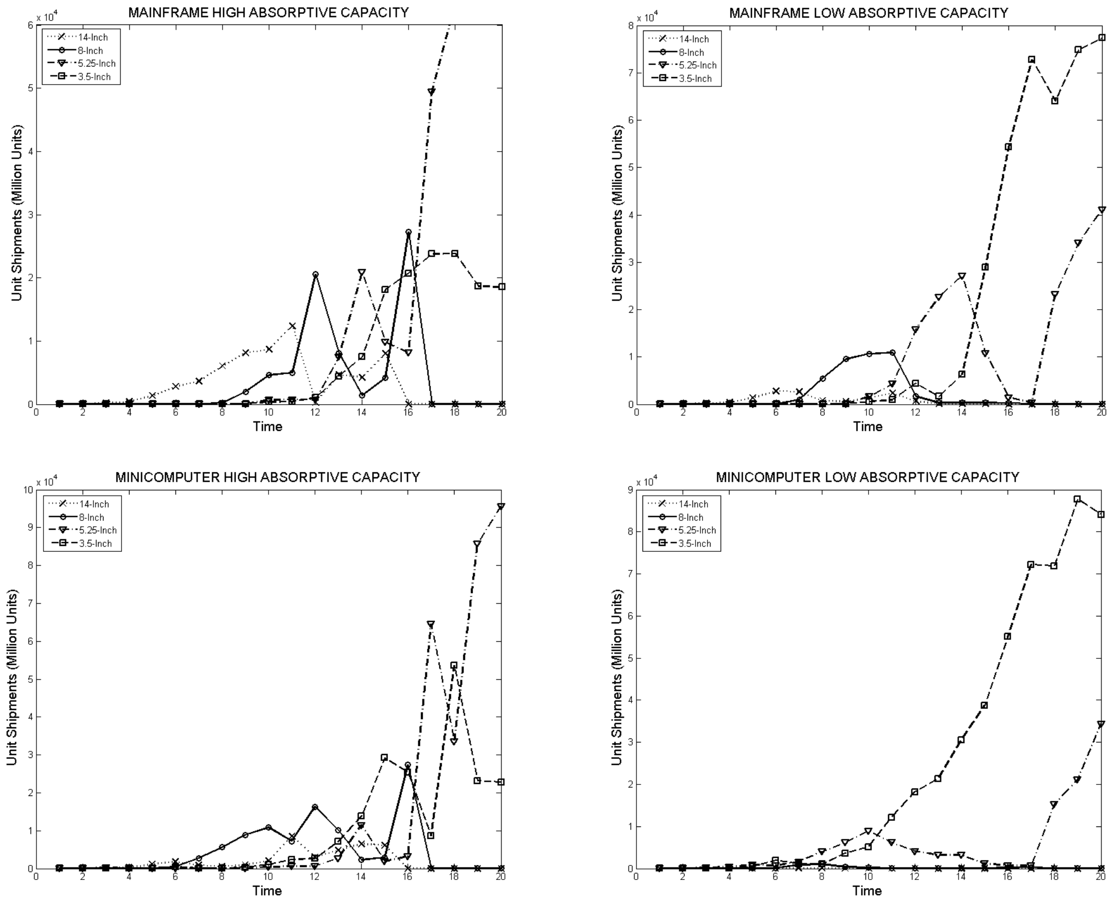


Figure 7.M. Mainframe and Minicomputer Market Segment Diffusion Curves for Absorptive Capacity

7.4.2. Effect of Development Asymmetry

We extend our analysis of development dynamics to include positive and negative development asymmetries between technological improvement and absorptive capacity. We propose that higher growth rates in technological improvement relative to absorptive capacity will result in a faster speed and likelihood of market disruption. Aggregate level results suggest that positive development asymmetries increase the disruptiveness of innovations. Figure 7.N. illustrates that sales of 14-inch and 8-inch disk drives are significantly lower when compared with negative asymmetry. Conversely, sales of 3.5-inch disk drives are higher when compared with negative asymmetry, thus indicating a faster speed and likelihood of market disruption (P3B). Higher positive asymmetries between α_{jk} and γ_{ik} facilitate in creating a vacuum in the market for lower performing disruptive innovations. This is because the rate of advancement in attribute performance exceeds a market segment's ability to absorb such improvements, thereby paving the way for lower performing disruptive innovations to enter the market.

Under conditions of high negative development asymmetry i.e. when $\gamma_{ik} > \alpha_{jk}$ the aforementioned effects are reversed, resulting in a slower speed and likelihood of market disruption (P3B). Higher growth rates in absorptive capacity relative to technological improvement slow the entry time of lower performing disruptive innovations. This is because there is a higher aggregate capability for the market to absorb performance improvements of the resident innovation. Analysis of adoption probabilities provides support for these results (re Appendix 3 (Table 13)). Results show that the adoption probability of 3.5-inch disk drives decreases, while the adoption probability of 14-inch disk drives increases, indicating a lower susceptibility to disruption and longer lifecycles of resident innovations. Market segment analyses provide similar results.

Market Segment Analysis of Development Asymmetry:

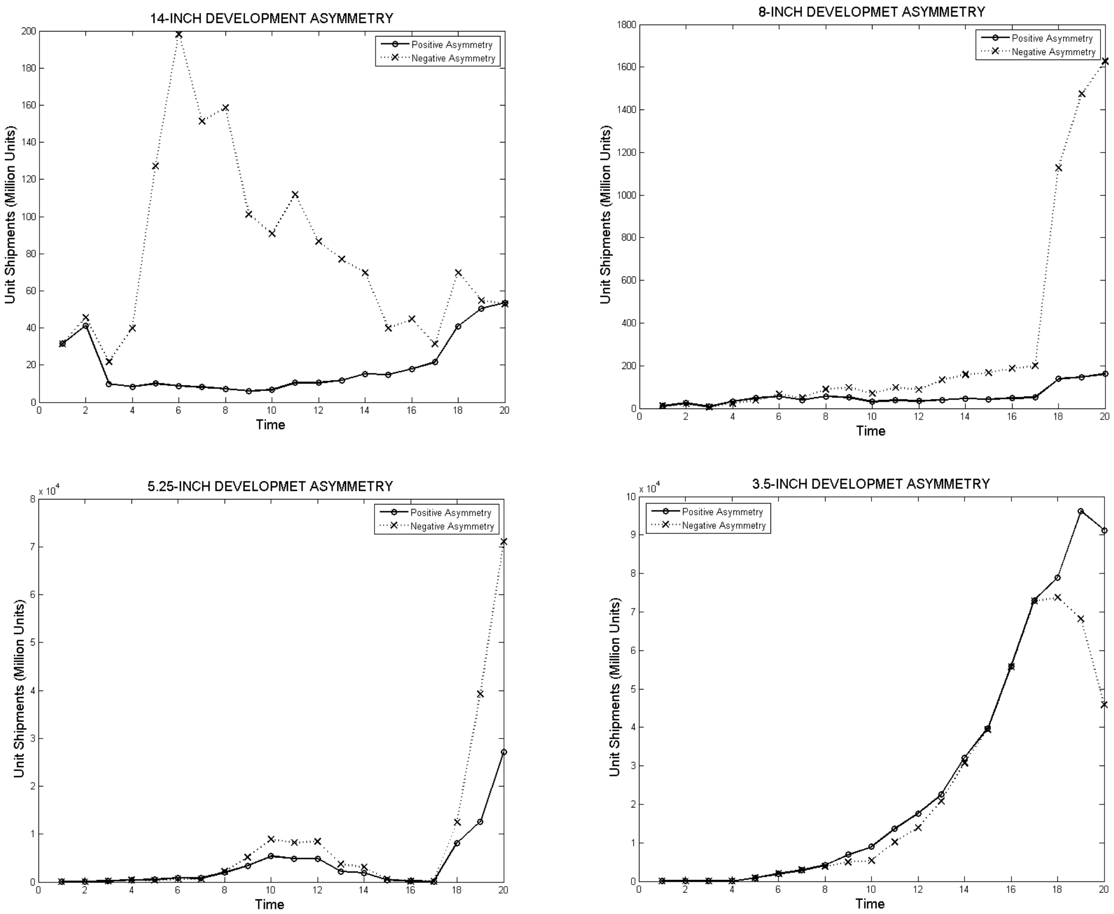


Figure 7.N. Aggregate Diffusion Curves for Development Asymmetry

Analysis of mainframe and minicomputer market segment diffusion curves provides further support for *Proposition 3B*. Similar to Figure 7.M. the diffusion curves of lower performing 5.25-inch and 3.5-inch disk drives in Figure 7.O. are also negatively skewed. Negative development asymmetries increase the lifecycles of 14-inch and 8-inch disk drives in mainframe and minicomputer market segments. Comparison of positive and negative development asymmetries shows that sales of 14-inch and 8-inch disk drives increase under conditions of negative asymmetry. Thus, a market segment's susceptibility to disruptive threats decreases when the difference between $\gamma_{ik} > \alpha_{jk}$ increases. Market entry of the 5.25-inch (point 9 vs. 6) and 3.5-inch (point 11 vs. 8) disk drive was delayed by 3 years in the mainframe market. Furthermore, simulation results of the minicomputer market show that entry of the 5.25-inch disk drive was delayed by 3 years (point 8 vs. 5) and 3.5-inch by 1 year (point 8 vs. 7).

In contrast, positive development asymmetries ($\alpha_{jk} > \gamma_{ik}$) increase a market segment's susceptibility to disruption. Figure 7.O. illustrates that under conditions of positive asymmetry, 3.5-inch disk drives were able to enter and dominate mainframe and minicomputer market segments more quickly. Higher positive asymmetry allows for the entry of lower performing disruptive innovations. This is due to a market segment's inability to absorb the performance improvements of superior technologies.

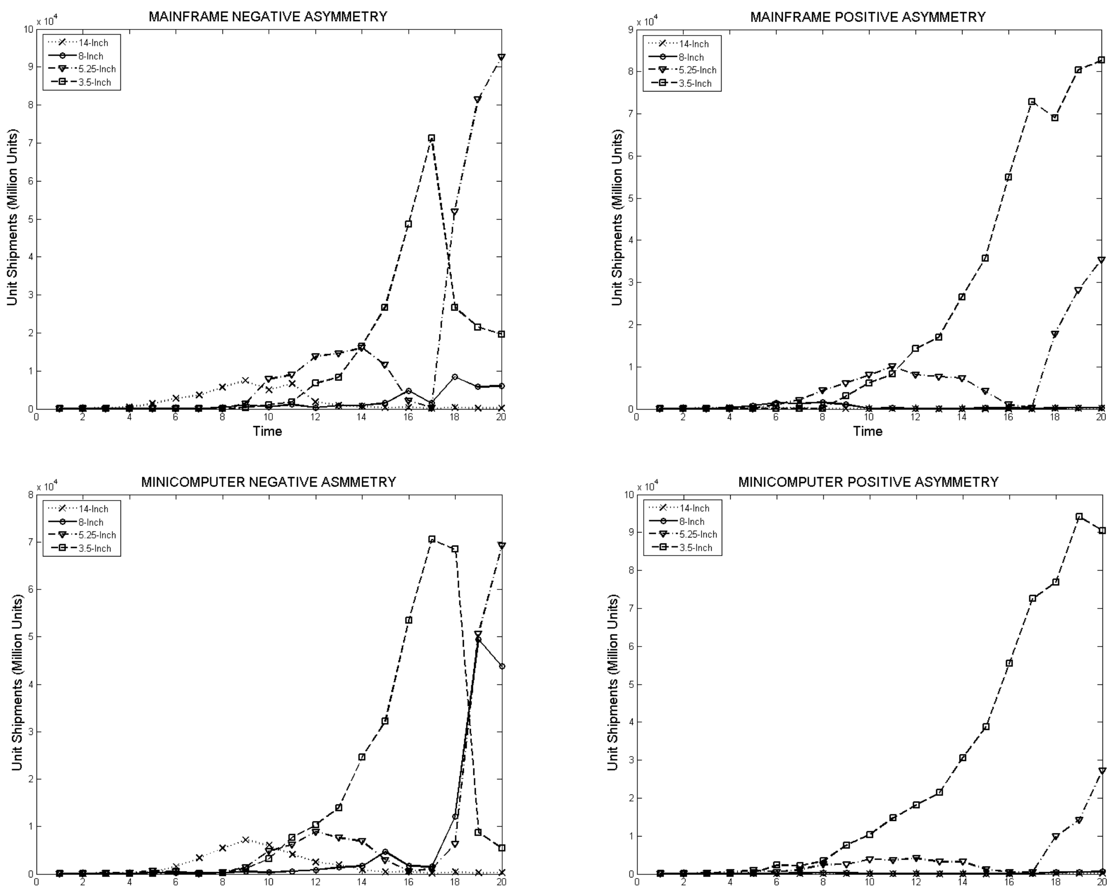


Figure 7.O. Mainframe and Minicomputer Market Segment Diffusion Curves for Development Asymmetry

Comparison of positive and negative adoption probabilities for each market segment provides support for these results (re Appendix 3 (Tables 14–17)). For example, the adoption probability of 14-inch disk drives increases by over 26%, while the adoption probability of 3.5-inch disk drives decreases by over 19%. Similar patterns can be observed for minicomputer, desktop, and portable segments, where the adoption probabilities of 3.5-inch disk drives decrease by 30%, 3.4%, and 3.1% respectively. Results for desktop and portable market segments are significantly lower due to lower optimal demand thresholds. Thus, we can conclude that higher positive (negative) development asymmetry i.e. $\gamma_{ik} > \alpha_{jk}$ ($\alpha_{jk} > \gamma_{ik}$), leads to a faster (slower) speed and likelihood of market disruption (P3B). Therefore, the direction and distance between growth rates can both insulate markets from potentially disruptive threats or create a vacuum for their entrance.

7.5. Summary and Discussion of Research Findings

In this section, we provide a summary of the research findings linking our results to existing literature and then discuss the research findings and their contribution to Christensen's theory. Little research exists that seeks to understand the diffusion of disruptive innovation and the mechanisms that drive the process. In this study we bridge this gap and provide a diffusion model that encompasses preferences, demand, and development dynamics. Using real data from the HDD industry, we simulate different market conditions and analyse their effect on market disruption. In the next sub-section, we summarise the research findings.

7.5.1. Summary of Findings and Literature Links

Similar to Adner (2002), we use consumer preferences to differentiate between market segment boundaries. Our results confirm that the degree of preference overlap and preference symmetry between market segments directly influences the disruptiveness of innovations (Adner, 2002). Adner (2002) concludes that under conditions of preference convergence, the likelihood of disruption decreases as innovations evolve to compete head-on, thus resulting in sustaining innovation. We extend this analysis to consider conditions in which market segments evolve and converge towards an identical preference structure. We also find that the likelihood of disruption decreases as segments converge. However, once potentially disruptive innovations satisfy the demand requirements of the mainstream market, they are able to invade. Simulation results show that under such conditions, market segments become indifferent between innovation alternatives resulting in coexistence. Thus, convergence does not stop disruption, but rather slows the process leading to intensified internal competition in the mainstream market.

Similar results emerge for preference isolation. Adner (2002) concludes that divergent trajectories of innovation performance improvement facilitate in isolating market segments from disruptive threats.

We extend this analysis to consider the influence of divergent market segment preferences. Results show that the speed and likelihood of disruption decreases as preferences diverge. However, as with preference convergence, disruptive innovations can still invade mainstream markets as long as they are able to satisfy demand requirements for primary attributes. Under such conditions, market segments become indifferent between innovation alternatives, thus leading to coexistence. Synonymous with convergence, divergent preferences do not stop disruption, rather they slow the process leading to intensified internal competition.

Our results show that central to the disruptiveness of innovations is the ability to satisfy the optimal demand requirements of the mainstream market. This allows for the entry of new disruptive innovations in the marketplace, which leads to coexistence. Sood and Tellis (2011) provide similar conclusions when analysing patterns of disruption, they state that:

> *"At many points in time, competing technologies coexist. In some cases, disrupted technologies continue to survive and coexist with the new technology by finding a niche…. It is true that some technologies do die, but many continue to survive even after being disrupted (2011; 349)".*

These findings support previous studies that state radical disruptive innovations can sometimes set in motion a battle for dominance between incumbent and invading innovations until a dominant design emerges (Nair and Ahlstrom, 2003; Anderson and Tushman, 1990; Tushman and Anderson, 1986). Consistent with Sood and Tellis (2011), results show that in this battle for dominance there can be multiple disruptions or crossings between paths of innovation. Therefore, disruption is not always permanent, dominant innovations can sometimes regain technological leadership. Results of the study extend these findings through the identification of the conditions that lead to such competition. Our results show that optimal demand thresholds for primary attributes act as a trigger for disruption.

While Adner (2002) concludes that disruption is ultimately enacted by lower price, we conclude that disruption occurs due to market segments gaining a higher utility pay-off from disruptive innovations. Not all disruptive phenomena are initiated by lower price e.g. mobile phone vs. landline (Druehl and Schmidt, 2008; Schmidt and Druehl, 2008). As new innovations improve performance in primary attributes, additional utility is gained from the performance supplied in alternative attributes. Thus, the initial magnitude of optimal demand thresholds directly influences the disruptiveness of innovations. We find that utility is inversely proportional to optimal demand i.e. higher demand thresholds result in a lower utility pay-off, as innovations find it more difficult to attain the levels of performance demanded. Therefore, higher levels of O_{ik} insulate markets from disruption, whereas low levels of O_{ik} leave markets more vulnerable. Simulation results show that disruption occurs once the utility derived from disruptive innovations outweighs the utility derived from dominant innovations.

Finally, we find that the direction and size of development asymmetries that exist between technological advancement and absorptive capacity influences the disruption. Researchers argue that performance oversupply allows for the entry of disruptive innovations (Christensen, 1997; Hüsig et al., 2005; Yu and Hang, 2010). Our results support this claim, as higher positive development asymmetries lead to a faster speed and greater likelihood of market disruption. This is because new disruptive innovations are able to satisfy the demand requirements of mainstream markets faster. Conversely, the speed and likelihood of disruption decreases when growth rates in absorptive capacity exceed technological advancement i.e. $\gamma_{ik} > \alpha_{jk}$. This is because the growth rates in absorptive capacity inflate optimal demand thresholds such that new innovations find it difficult to attain the level of performance demanded in mainstream segments.

However, positive development asymmetries are a sufficient but not necessary condition of market disruption, our results suggest that greater positive asymmetry results in a faster speed and higher likelihood of disruption. Based on the above findings, it is evident that preferences, demand, and development are all influential in driving the process of market disruption. Table 7.D. summarises the research findings in the context of the propositions introduced in Section 5.2.

Table 7.D Summary of Research Findings

Proposition	**Summary of Findings**
P1A	Results confirm (P1A), as market segments with similar preference structures to external segments have a higher susceptibility to disruptive innovation. Simulations show a faster speed of market entry for lower performing innovations and thus higher likelihood of disruption.
P1B	Results confirm (P1B), as convergence towards homogeneous preferences facilitates in creating a single market, thereby reducing susceptibility to disruption. Simulations show slower speed of market entry for lower performing innovations and thus lower likelihood of disruption under homogenous preferences.
P2	Results confirm (P2), as low demand thresholds for primary attribute performance increase the speed and likelihood of market disruption. Simulations show that disruptive innovations can more easily satisfy the demand requirements of the mainstream market.
P3A	Results confirm (P3A), as market segments with higher growth rates in absorptive capacity have a higher capacity to absorb performance improvements of sustaining innovations, thus reducing a market's susceptibility to disruption.
P3B	Results confirm (P3B). Higher positive development asymmetry between growth rates in technological development of disruptive innovations and absorptive capacity of mainstream market results in a higher susceptibility to disruption. Simulations show that as the following differential $\alpha_{jk} > \gamma_{ik}$ increases markets become increasingly vulnerable to disruptive innovations.

7.5.2. Discussion of Results and Impact on Theory

Christensen's (1997) theory of disruptive innovation demonstrated the disruption experienced in the HDD industry at the aggregate market level through the cumulative impact of mainframe, minicomputer, desktop, and portable segments. He uses case narratives and statistics to demonstrate incumbent firm failure when faced with market changing innovations. The theory uses evidence of: (1) Stagnating sales of HDDs and the transitions between 14-inch, 8-inch, 5.25-inch, and 3.5-inch drives; and (2) analysis of incumbent firms leaving and new entrants entering the HDD market to explain the concept. However, the theory address very little with regards to the underlying mechanisms that lead to market disruption and the process from which disruptive innovations emerge (Danneels, 2004, Sood and Tellis, 2011). Results of this study suggest that disruption is a multifaceted phenomenon, subject to a complex interplay of multiple agents.

Analysis of preference structure suggests that disruption occurs somewhere between market isolation and convergence. Under conditions of preference isolation and convergence markets have minimal competition from external markets. When preferences break from such structures the boundaries between external market segments becomes less rigid, as they share common value characteristics. This facilitates inter-market competition, which can lead to the entrance of new disruptive innovations. Figure 7.P. illustrates this concept. Under conditions of isolation we note that market A is completely isolated from market B, as the distance between preferences is large, which reduces the threat of disruption. Similarly, when markets converge they become a single segment with no competition in the form of a disruptive innovation. However, under preference conditions of convergence, firm level competition will increase due to an increase in the number of firms operating in the segment (i.e. A + B). Finally, when the distance between preferences is smaller, markets are similar on an inter-market level which increases the level of competition across markets and their susceptibility to disruption.

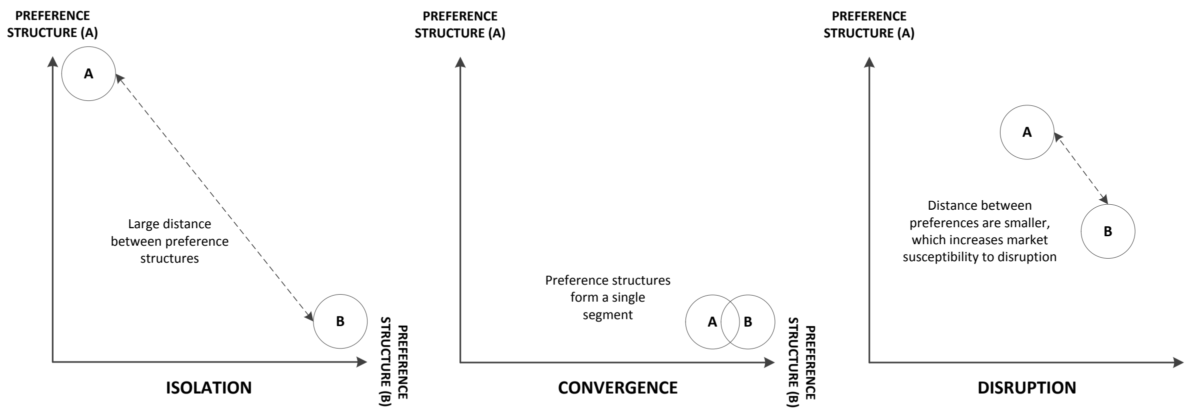


Figure 7.P. Impact of Preference Structure

We find that a market's susceptibility to disruption increases as the distance between consumer preferences becomes small enough so that external innovations can invade, but not so large that a unified market is created with homogenous preferences. This finding adds new insight to the theory. Results suggest that markets in close proximity to external markets are more susceptible to disruption. This is because segments have a higher level of agreement on dimensions of innovation performance. Conversely, markets that operate in isolation, or those that converge to make a single segment, are less susceptible to disruption.

From the perspective of demand structure, we extend Christensen's theory by examining the demand conditions that increase and decrease a market's susceptibility to disruption. We find that markets characterised by high demand for performance in primary attributes are less susceptible to disruptive threats. This is because high-demand conditions create a natural entry barrier for lower performing disruptive innovations. This provides a new perspective to disruptive dynamics that is previously unexplored. However, if the rate of technology improvement (α_{jk}) by the disruptive innovation is fast enough to quickly satisfy the demand conditions of the mainstream market, then HOD has little effect in terms of creating a market entry barrier. Our results suggest that development asymmetries that exist between the rate of technology improvement and absorptive capacity are essential in shaping disruptive outcomes. In particular, a market's susceptibility to disruption increases when the rate of disruptive innovation performance improvement (α_{jk}) exceeds growth rates in absorptive capacity (γ_{ik}) i.e. when $\alpha_{jk} > \gamma_{ik}$. A major contribution to Christensen's theory is the finding that positive development asymmetry is a key mechanism that drives the process of market disruption.

The results showed that higher rates of performance improvement relative to the market's ability to convert such improvement into a functional benefit (absorptive capacity) allowed for the entry of lower performing disruptive innovations. Under such conditions disruptive innovations become increasingly attractive to the mainstream market. Conversely, when the ability of the mainstream market to absorb performance improvements in primary attributes exceeds that of the disruptive innovation's ability to improve, then markets are less susceptible to disruption. This finding significantly improves our understanding of how market disruption occurs. We find that performance oversupply of sustaining innovations is not a necessary condition of disruption as Christensen emphasised. Rather, the differential between performance improvement of the disruptive innovation and mainstream market absorptive capacity is the main driver of disruption.

From this perspective our research confirms the results of Druehl and Schmidt (2008) and Sood and Tellis (2011) that disruption follows a low end encroachment pattern, gradually diffusing upmarket towards high end customers as they improve performance over time. Our results show that during this transition, there is intense competition between the resident and disruptive innovation until a dominant design emerges. As a result, there can be long periods of resident and disruptive innovation co-existence, and depending on the structure of preferences, demand, and development, different competitive outcomes can emerge. Thus, we propose an improved definition of the concept:

> '*Market disruption is the outcome of a complex interplay of preference, demand, and development dynamics that facilitate inter-market competition between independent segments. Disruption occurs when external innovations invade new markets and become the new dominant standard. Periods of intense competition between the disruptive and resident innovations precede disruption, whereby resident innovations fight to retain market dominance*.'

7.6. Managerial Implications

In this section, we link the results of the model and simulated dynamics to managerial practice. We expect that the proposed model can provide meaningful implications and be used in practice to help inform future innovation response and development strategies. In particular, the model can be used to simulate different preference, demand, and development dynamics for various market situations. As a result, the model has the potential to answer multiple 'what-if' scenarios in order to assist in developing firm-level strategies. We discuss several implications of the model from both the aggregate and market segment level, and derive a response framework that is likely to be helpful to organisations, managers, and policy makers alike.

7.6.1. Implications of Preference Structure

Consumer preferences and their influence on shaping the adoption decision of customers are well established in the literature. However, very little is known with regards to the influence of preference structure on the disruptiveness of innovations and the implications for managers. Similar to Adner (2002), we find that the degree of overlap between market segment preferences directly influences the disruptiveness of innovations. In this study, we extend the analysis of preferences to include multiple attributes and market segments. Results from the effects of preference structure show that under conditions of market segment convergence and isolation, the speed and likelihood of market disruption decreases. Thus, disruption occurs somewhere in-between the extremities of convergence and isolation. The closer the distance between market segment preferences the higher the risk of disruption. However, when market segments converge towards an identical preference structure, the risk of disruption decreases (Adner, 2002). This is because innovations that service these segments offer performance that sustains the current product-performance paradigm expected in the mainstream market.

Therefore, managers need to be aware of both their internal and external competitive environments (Namwoon et al., 2000). Market segments that have close external competitors are more susceptible to disruptive threats as they have similar value trajectories. Danneels (2008) suggests that a manager's engagement in environmental scanning enables them to better evaluate their competitive environment. Environmental scanning refers to the extent to which managers engage in learning about events, trends, and patterns in the internal and external marketplace. Thus, firms have a higher capability to identify external disruptive threats. Simulation results show that preference structure is directly related to the disruptiveness of innovations, higher degrees of preference overlap result in a faster speed and likelihood of disruption.

Under such conditions, managers need to effectively engage in environmental scanning in order to identify market segments with similar preference structures. Early identification of disruptive threats allows managers to respond to and harness disruptive potential, thus leading to sustained competitive advantage. Researchers argue that organisational processes of exploration are essential for the identification and pursuit of disruptive radical innovations (Andriopoulos and Lewis, 2009; Benner and Tushman, 2003). Exploration involves the development of new knowledge and capabilities that enable firms to respond to disruptive threats. Results suggest that firms with close external competitors need to be more explorative in their strategy to negate the effects of market disruption on the firm. This is because firms with close external competitors are more susceptible to disruptive innovations.

In contrast, results show that when market segment preferences are divergent, the risk of disruption decreases. Low preference overlap between segments means that markets are more isolated from external disruptive threats. Under such conditions, processes of exploitation allow firms to strengthen their position in the internal marketplace. Exploitation involves the development of existing knowledge and capabilities that facilitate incremental sustaining innovations (Andriopoulos and Lewis, 2009; Benner and Tushman, 2003). Results suggest that when market segments are isolated firms should focus on bolstering their existing position in the internal marketplace, as the threat of disruption from external competitors is lower. Similarly, when market segments converge towards an identical preference structure, the risk of disruption is also lower. Therefore, exploitation is the best strategy for sustaining competitive advantage.

In conclusion, it is important that managers engage in environmental scanning in order to evaluate the firm's competitive landscape. Some researchers suggest that for sustained competitive performance, firms should be ambidextrous and balance both processes of exploration and exploitation (Benner and Tushman, 2003). However, similar to Burgelman (1991), we suggest that temporal differentiation between exploitation and exploration is a more viable approach than the simultaneous pursuit of both (Gupta et al., 2006). The distance of external competitors will directly influence the strategy adopted by the firm. For example, firms with a high degree of preference overlap with external competitors should adopt an exploratory strategy, as the risk of disruption is higher. Conversely, when segments operate in isolation, firms should adopt an exploitative strategy. Therefore, firms follow a punctuated equilibrium approach (Burgelman, 1991) and go through phases of exploration and exploitation independently, depending upon the competitive environment.

7.6.2. Implications of Demand Structure

The notion of demand thresholds as a trigger for adoption is well established in the social sciences (re Kim and Srinivasan, 2009; Adner, 2002). In this study, we introduce the concept of an optimal demand threshold that specifies the level of attribute performance from which consumers gain maximum utility. As such, optimal demand thresholds capture characteristics of performance improvement and diminishing marginal utility for performance that exceeds optimal demand i.e. $x_{jk} > O_{ik}$. Results show that the magnitude of a market segment's optimal demand threshold will directly influence the disruptiveness of innovations. For example, market segments characterised by consumers with high optimal demand are more difficult to invade. Therefore, it is easy to conclude that market segments with lower optimal demand are more susceptible to disruption.

Under such conditions managers need to be more prospective in their approach to innovation. Low levels of O_{ik} allow for the entry of external disruptive innovations. Thus, firms need to be more explorative and dynamic. Exploration allows firms to anticipate potentially disruptive threats, and dynamic capabilities allow firms to effectively respond and redeploy processes to harness disruptive potential. In contrast, high levels of O_{ik} insulate market segments from disruptive threats, as external competitors must attain a high level of performance before being considered in the adoption decision. Under such conditions, managers need to adopt a more defensive approach to innovation in order to satisfy the high demand requirements of customers. Firms exploit existing assets in order to strengthen their position in the internal marketplace and remain competitive in high end segments.

In conclusion, managers seeking new growth in new markets should target segments with low optimal demand thresholds. This is because such markets offer an easier entry route compared with high demanding segments, as innovations can more easily attain the performance requirements of lower demanding customers. For firms operating in such segments, processes of exploration are essential for sustaining competitive advantage, as the risk of market disruption is higher. Thus, managers need to be aware of changes in the internal and external marketplace. Conversely, firms operating in markets with high optimal demand are less susceptible disruption e.g. luxury market segments. Under such conditions managers can adopt an exploitative approach. Similar to the implications of preference structure, engagement in environmental scanning is important for firms to evaluate their internal and external demand environment. The structure of market segment demand directly influences the strategic direction of the firm i.e. exploration vs. exploitation.

7.6.3. Implications of Development Dynamics

In our analysis we consider the effects of development dynamics from the perspective of technological advancement α_{jk} and absorptive capacity γ_{ik}. Results show that development asymmetries that exist between growth rates in α_{jk} and γ_{ik}, directly influence the disruptiveness of innovations. For example, when $\alpha_{jk} > \gamma_{ik}$, the speed of disruption increases. Higher growth rates in technological advancement relative to absorptive capacity mean that disruptive innovations can encroach and invade mainstream markets faster. Similarly, we find that when technological development of the sustaining exceeds absorptive capacity, a vacuum emerges in the market for the entry of lower performing disruptive innovations.

Under conditions of positive development asymmetry, managers should be more prospective and exploratory in their approach to innovation. Faster growth rates in technological advancement relative to absorptive capacity mean that market segments experience increased competition from external threats. Therefore, processes of exploration are more beneficial under such conditions. This is because firms need to be able to anticipate and respond to disruptive changes in the marketplace in order to avoid failure (Lucas Jr and Goh, 2009). A prospective approach allows firms to operate in more dynamic environments where competition and risk of market transformation is higher (Miles and Snow, 1978).

In contrast, under conditions of negative development asymmetry, managers should be more defensive and exploitative in their approach to innovation. Faster growth rates in absorptive capacity relative to technological advancement mean that market segments experience decreased competition from external threats. Higher levels of γ_{ik} facilitate in increasing thresholds of optimal demand, thus lower performing disruptive innovations find it difficult to compete. As a result, market segments are more insulated from external threats of disruption. Processes of exploitation enable firms to leverage existing assets in order to satisfy demand increases of the internal market. Managers defend their market position through incremental sustaining innovation.

In conclusion, managers need to evaluate the trends and patterns of technological improvement and absorptive capacity through engagement in environmental scanning (Danneels, 2008). Knowledge of internal and external market advancements in technology and customer demand are important for firms seeking sustained competitive advantage. Depending on the development asymmetries observed in the market, firms will adopt a different strategy for innovation. When $\gamma_{ik} > \alpha_{jk}$, firms should be more exploitative as customers value more of the attributes already supplied, whereas when $\alpha_{jk} > \gamma_{ik}$ firms should be more exploratory, as customers are more open to disruptive innovations that offer alternative performance.

7.6.4. Managerial Response Framework

In this section, we consider the implications discussed above and develop a managerial response framework for firms seeking to respond to and initiate disruptive innovation. Evident from the previous discussion, firms choose to either engage in exploration or exploitation (Andriopoulos and Lewis, 2009; Benner and Tushman, 2003). We conclude that the simultaneous pursuit of both strategies is not a viable approach for sustained competitive advantage. Rather firms should adopt a punctuated equilibrium approach (Burgelman, 1991), and independently adopt either an exploratory or exploitative strategy dependent upon the structure of preferences, demand, and development. Divergent preferences, high optimal demand, and negative development asymmetries insulate market segments from disruptive innovations, thus competition from internal rivals pose the biggest threat to incumbent firms. Therefore, processes of exploitation are better suited under such conditions. Firms adopt a defensive approach to innovation in order to develop a single core technology and deliver more performance in the attributes that markets traditionally value (Miles and Snow, 1978).

Conversely, higher preference overlap, low optimal demand, and positive development asymmetries expose market segments to disruptive innovations, thus both internal and external competition is intense. Therefore, processes of exploration are essential for firms operating in such environments. According to Miles and Snow (1978), a prospective strategy is better suited under such conditions: They (1978; 553) state that:

> *"Prospector's domain is usually broad and in a continuous state of development. The systematic addition of new products or markets, frequently combined with retrenchment in other parts of the domain, gives the prospectors products and markets an aura of fluidity...... Prospectors must develop and maintain the capacity to survey a wide range of events. This type of organisation invests heavily in individuals and groups who scan the environment for potential opportunities."*

Figure 7.Q. illustrates the managerial response framework developed in this study to assist managers looking to both initiate and respond to disruptive innovation. We extend the frameworks introduced in Section 3.3 to include preference, demand, and development structure, and identify strategies and capabilities associated with different environmental conditions. Furthermore, the framework developed here is based on empirical results and insights derived from the analysis.

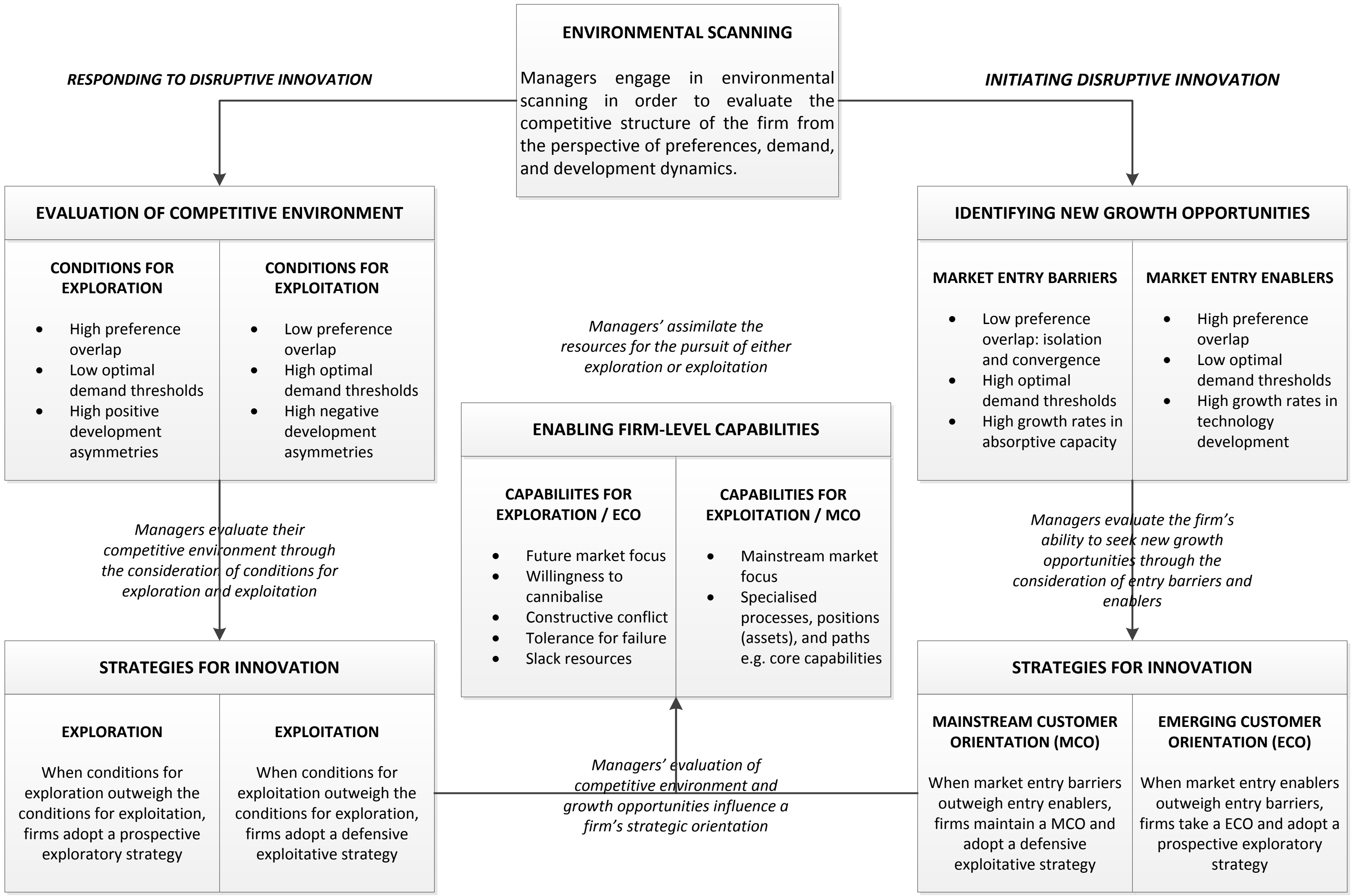


Figure 7.Q. Managerial Framework for Responding to and Initiating Disruptive Innovation

The proposed framework draws on the previous discussion of managerial implications to derive firm-level innovation strategies. Central to the framework is management engagement in environmental scanning (Danneels, 2008; Miles and Snow, 1978). Managers need to be aware of their internal and external competitive environment in order to make informed decisions. For organisations responding to disruptive innovation, managers need to evaluate the competitive environment in terms of preferences, demand, and development dynamics to choose the appropriate strategic direction. A prospective exploratory approach is adopted when conditions of exploration outweigh exploitation. In order to pursue such a strategy, firms require dynamic capabilities characterised by a future market focus, willingness to cannibalise, constructive conflict, tolerance for failure, and slack resources (Chandy and Tellis, 1998; Danneels, 2008) – see Section 3.3.4. Conversely, when conditions of exploitation outweigh exploration, a defensive exploitation approach to innovation is adopted. Firms require a mainstream market focus and possess specialised market, technological or organisational assets e.g. core capabilities (Leonard-Barton, 1992) and VRIN resources (Barney, 1991).

For organisations initiating disruptive innovation, managers seek new growth opportunities in new markets. A mainstream customer orientation (MCO) is adopted when market entry barriers outweigh entry enablers. Govindarajan et al (2011; 123) define MCO as the focus of the firm on serving its most important customers. Under such conditions, capabilities for exploitation are better suited for satisfying existing customers. In contrast, firms adopt an emerging customer orientation (ECO) when market entry enablers outweigh entry barriers. An ECO is characterised by firms focusing on future emerging market segments (Govindarajan et al., 2011). Under such conditions, capabilities of exploration are better suited for firms seeking new market opportunities. Dynamic capabilities such as willingness to cannibalise existing assets, allow firms to realign their processes for the pursuit of disruptive innovation.

8. Conclusions

In this final Chapter, we provide a summary of the research findings identified in Chapter 7 and discuss the major contributions of the study from the perspective of academic theory, methodology, managerial practice and policy. We identify how the study has helped improve our understanding of disruptive innovation theory and provide practical implications for managers to develop better strategies for innovation. We then address the research limitations and the assumptions underlying the study. Finally, we identify potential areas for future research and extensions of the model that could provide further insights. The Chapter proceeds in three sections:

1. Section one provides a summary of the research contributions from the perspective of academic theory, methodologies for innovations research, and managerial practice and policy.

2. Section two addresses the research limitations.

3. Finally, section three identifies potential areas for future research with regards to improving our understanding of disruptive innovation theory.

8.1. Research Contributions

We develop a MNL (multinomial logit) diffusion model that considers consumer choice processes and diffusion phenomena that spans multiple market segments and innovations. Using the example of the HDD industry as the benchmark for disruption (Christensen, 1997) a model is developed that considers mainframe, minicomputer, desktop, and portable computer market segments, and 14-inch, 8-inch, 5.25-inch, and 3.5-inch disk drive innovations. This work is distinguished from that of Christensen's as we provide a quantitative investigation of both an aggregate and individual market segment level analysis of disruption. We move from the case based narratives and descriptive statistics used by Christensen to a quantitative validation of the theory using a new mathematical model of consumer choice and innovation diffusion. Furthermore, a new and unique dataset was developed of worldwide shipments of HDDs that contained information of capacity, price, and size.

The model seeks to understand the micro-level processes and interactions that lead to disruptive diffusion at the macro-level. To achieve this balance we based our approach on existing MNL models of consumer choice and diffusion identified in Chapter 4. We extend Christensen's analysis through the application of a mathematical model using a unique dataset of HDDs spanning a 20-year period. Christensen's theory fails to model the disruptive transitions between different sized disk drives and individual market segment level transitions between such drives. We provide a quantitative validation of the theory to compliment Christensen's case based descriptions to develop new insights to how disruptive innovations emerge.

We adopt a utility-based perspective similar to Adner (2002) and include preference, demand, and development dynamics into the modelling procedure (re Figure 6.C). The model is empirically tested with a unique dataset of HDD shipments and then used to conduct qualitative analysis of differing system dynamics to establish the conditions that facilitate market disruption. New insights are developed by conducting aggregate and individual market segment level analysis of disruptive innovation as in Equations 3A and 3B. Analysis shows that model performance is very good, with an overall R^2 of 0.68, and statistically significant model fit statistics (see Chapter 7).

Results show that the process of market disruption is influenced by preferences, demand, and development dynamics simultaneously. We find that the degree of preference similarity between market segments directly influences an innovation's ability to invade new external markets. Furthermore, the structure of market segment demand and development dynamics from the perspective of absorptive capacity and technological improvement also affect the speed and likelihood of market disruption (re Section 7.6). For example, high demanding market segments with high negative development asymmetries are more difficult to invade. Such segments are difficult to disrupt because high optimal demand thresholds make it hard for disruptive innovations to compete. In addition, negative development asymmetries mean that growth rates in demand exceed an innovation's performance improvement. Thus, disruptive innovations lack the capability to invade market segments under such conditions.

We conclude that rather than emerge from any specific factor alone, disruption occurs from a system of influences. The combination of preferences, demand, and development and their evolution in the internal and external marketplace determine the disruptiveness of innovations. Thus, market disruption is a complex phenomenon. Our results show that disruptive innovations can in some cases coexist with dominant innovations, suggesting that disruption is not always absolute. Systemic influences in the form of preferences, demand, and development shape how innovations compete. In the following subsections we summarise the research findings in terms of the contribution towards academic theory, methodology, and managerial practice.

8.1.1. Contributions to Academic Theory

The new model proposed and simulated in this study has addressed the research gaps identified in Section 1.2. We first addressed the problems that arise with definition and anomalies attributed to current theory. Danneels (2004) suggests that further clarification is required to establish what exactly disruptive innovation is and what are the mechanisms underlying the process? Building on

Christensen's theory, the results of the research reported in this thesis provide new insights to the concept of disruptive innovation:

- Firstly, evident from the literature review, we separate the duality of disruptive outcomes initially proposed by Christensen. We conclude that disruption is purely a market-based phenomenon, whereas firm failure is attributed to the capability of the organisation to effectively respond to disruptive threats.
- Secondly, we develop a new mathematical model and utilise a unique dataset and methodology to derive the mechanisms that drive the process of disruption. Such analysis has previously been neglected in the works of Christensen. Results provide new insights into the theory and identify the preference, demand, and development conditions that lead to disruption (re Section 7.5.2).
- Thirdly, the provision of a mathematical model to Christensen's theory provides a potential tool for estimating the disruptiveness of innovations *ex ante*. A main criticism of Christensen's theory is the retrospective (*ex post*) nature of case analyses to derive the theory (Sood and Tellis, 2011). Although the proposed model uses historical HDD data to provide new insights, the model is capable of analysing any potential disruptive scenario under differing environmental conditions.
- Finally, we propose a new improved definition of disruptive innovation based on the model findings (re Section 7.5.2) to build on Christensen's theory. We find that low preference overlap, low optimal demand, and negative development asymmetries reduce a market's susceptibility to disruption.

Following this, we were able to identify the factors that facilitate the disruptive innovation process and differentiate between essential and ancillary characteristics. Existing studies offer a plethora of contradictory characteristics, thus causing confusion in understanding the process of disruption (Danneels, 2004, Sood and Tellis, 2011). Adner (2002) demonstrates that preference overlap and preference symmetry are important factors in driving disruption. However, the study lacks empirical validation and fails to include other important factors. The results of the study bridge this gap in academic theory through the exploration of preference, demand, and development dynamics with empirical data. Results show that the distance between market segment preferences, consumer demand for attribute performance, and developments in technology and absorptive capacity all drive market disruption.

Finally, we contribute to existing theory by providing an explanation of the diffusion patterns of disruptive innovation. The model shows that disruption occurs when the utility derived from the disruptive innovation exceeds the dominant innovation. Under such conditions, disruptive innovations are capable of invading external market segments and displacing dominant innovations in their respective markets. The speed in which this occurs depends on the rate of technological improvement (α_{jk}) by innovations and absorptive capacity (γ_{ik}) of customers in competitive market segments. These findings provide new insights into existing theory that conclude disruption is enacted by price (Adner, 2002). We find that disruptive innovations are not always capable of displacing dominant innovations. Depending on the structure of preferences, market segments may become indifferent between innovation alternatives leading to coexistence. These findings are consistent with Sood and Tellis (2011), who conclude that disrupted technologies can continue to exist. Results suggest that optimal demand thresholds act as a trigger for market invasion, allowing the entrance of external innovations. The major difference between disruptive and sustaining competition, is that disruptive competition involves internal and external competitors, whereas sustaining competition involves only internal competitors.

8.1.2. Contributions to Methodology

We adopt an empirical approach that integrates aspects of consumer choice and innovation diffusion into a single model. Traditional modelling approaches either focus on the micro-level choice factors that influence consumer adoption decisions or macro-level diffusion behaviours that focus on the spread on innovations in a given social system. However, a number of models in the literature are emerging that integrate both micro and macro-level factors (re Section 4.3.4). Such models have the added benefit of considering consumer choice heterogeneity and innovation diffusion simultaneously. As a result, they are capable of analysing complex phenomena such as disruptive innovation and market disruption.

Agent-based modelling (ABM) has emerged as a flexible tool that is used to model complex phenomena. ABM offers a superior modelling approach to traditional epidemic and probit diffusion models, as they are capable of balancing the benefits of both. However, such models require real data to alleviate problems of being “toy-models” (Garcia and Jager, 2011). The modelling approach in this study utilises ABM and considers both aspects of consumer choice and innovation diffusion using data from the HDD industry. As a result, we demonstrate that ABM is a valid technique for modelling problems associated with innovation diffusion. Due to the complex nature of innovation phenomena, we show that ABM offers a good alterative to traditional methods.

By using ABM we move beyond the case based narratives and descriptive statistics used by Christensen to validate the theory. ABM provides a flexible method to qualitatively analyse numerous ‘what-if’ scenarios by modifying model inputs. Thus, the performance of such models goes beyond quantitative validation and can provide valuable qualitative information too. In this study, we demonstrate that this technique provides a method for developing new and existing theory with regards to disruptive innovation.

8.1.3. Contributions to Managerial Practice

Results of the study provide significant contributions to managerial practice. First, the potential to model the disruptiveness of innovations has significant implications for managers. The ambiguous nature of the concept in terms of definition and domain to which disruption applies, has limited our ability to model the process of disruption (Danneels, 2004). For example, Kostoff et al. (2004; 142) state that "*disruptive technologies can only be revealed as being disruptive in hindsight*". However, the model proposed in this study provides managers with a tool to assess the potential disruptiveness of innovations and can be further modified to predict and forecast future emerging disruptive trends. As a result, managers can use the model to identify external competitive threats in order to negate the effects of disruptive innovation on the organisation.

Second, qualitative analysis of preference structure, demand structure, and development dynamics has significant implications for managers seeking to develop and respond to disruptive innovation. The proposed model provides managers with a flexible tool to analyse different market scenarios. Thus, the model can be tailored to reflect changing market conditions, enabling managers to develop better innovation strategies. For example, the model can be used to analyse the effects of certain innovation development initiatives in order to evaluate which strategy will provide the desired outcome. In addition, the model can be used to evaluate the impact of potential changes in the firm's competitive environment. For example, the model can be used to analyse the effects of changes in preference structure i.e. what are the effects of divergence, isolation or positions in-between these extremities on the firm.

In Section 7.5.4, we introduce a managerial response and initiation framework for disruptive innovation. The framework identifies conditions in which firms should either adopt an exploratory or exploitative strategy. Results of the model simulation were used to construct the framework to provide managers with a useful aid for responding to or initiating disruptive innovation.

8.1.4. Contributions to Policy

Results of the study have significant implications for innovation policy makers and practitioners developing national/ regional systems of innovation. We identify four areas of policy development that practitioners can focus on to improve knowledge on disruptive innovation:

1. Research and Technology Development (RTD) Policy

The findings reported in this thesis suggest that RTD investment that focuses on the continuous development of existing innovation capabilities to satisfy existing market needs, limits the ability to recognise emerging trends and thus increases a market's susceptibility to disruption. Policy makers and practitioners need to nurture the growth and development of new innovation capabilities that expand their existing value network. Practitioners can provide financial incentives to support RTD activity for firms looking to expand their skill set. Thus, firms will be better equipped to respond to and develop disruptive innovations.

2. Education and Entrepreneurship Policy

Recognising new growth potential in peripheral and existing markets broadens organisational capabilities to respond to and harness the power of disruptive innovation. Our results suggest that market failure is attributed to an inability to identify threats from disruptive innovations by continually focusing efforts on sustaining innovation. The literature suggests that management skill in environmental scanning, tolerance for failure, and constructive conflict (Danneels, 2008) positively affects firm level ability to respond to and develop disruptive innovations. As a result, policy makers and practitioners need to focus on promoting education and entrepreneurship policy to equip managers with new skills and empower them in developing disruptive innovation.

3. Interaction Policy

Evidence suggests that large incumbent firms are the most afflicted by disruptive innovation as they have better developed value networks and seek to protect their sources of competitive advantage through developing sustaining innovation (Christensen, 1997). As a result, large incumbents cannot easily change the direction of performance improvement or create links with other value networks. Thus, policy makers can promote processes of open innovation for large incumbents to access a wider breadth and depth of capabilities, value networks, and skills for responding to and developing disruptive innovations. In comparison, SMEs are better equipped to develop disruptive innovation and act as an incubator for nurturing their growth (Ansari and Krop, 2012). In this case, policy makers can provide support for SMEs with access to external expertise to further develop new disruptive innovations and technologies.

4. *Competition Policy*

The findings reported in this thesis suggest that disruptive innovations emerge from the interactions of consumer preferences, demand, and innovation development dynamics. Policy makers and practitioners can use the results of the study to develop new disruptive innovation competition policies, which will lead to the development of superior national systems of innovation. In markets that have a higher susceptibility to disruption, policy makers can advise on strategies that protect firms from disruption (re Section 7.6). Conversely, in markets that have lower susceptibility to disruption, policy makers can advise on strategies that enable firms to develop disruptive innovations (re Section 7.6).

By focusing efforts on the four aforementioned areas of policy development, we believe that superior national/ regional systems of innovation can emerge. Table 8.A. summarises the suggested policy areas and guidelines:

Table 8.A Summary of Policy Areas and Guidelines

Policy Areas	**Policy Guidelines**
RTD Policy	Provide financial incentives for firms to invest in RTD that is geared towards disruptive innovation.
Education and Entrepreneurship Policy	Provide access to education for the labour force in capacities for developing disruptive innovations and support entrepreneurship through promoting creativity and providing access to finance.
Interaction Policy	Promote open innovation through development of expertise networks to partner firms and provide access to wider skills and capabilities (for both incumbent and SMEs). Provide expertise to SMEs and incubate disruptive innovation development.
Competition Policy	Advise on disruptive innovation strategies to stimulate competition in new markets and protect existing markets from threats of disruption.

8.2. Research Limitations

In this section, we address the limitations and assumptions underlying the study. Specifically, we focus on the limitations of the data, model, and assumptions used to facilitate the modelling procedure.

Data Limitations:

Firstly, the proposed model uses data collected from the worldwide HDD (hard disk drive) industry over a 20 year period (1979 – 1998). Synonymous with Christensen and Bower (1996) and Christensen (1997), we used this data as a benchmark example of disruptive innovation in order to quantitatively validate existing theory and provide new insights through qualitative analysis. However, we are aware that given the lack of other disruptive cases, the model results lack generalizability. This represents a key limitation of the study, since our results alone are not enough to validate a general theory. The retrospective nature of the HDD data and lack of other cases to test the model are the sources of this limitation. As a result, future research should aim to replicate our findings using other cases of disruptive innovation.

The subjective nature of primary data collected is also a limitation of the study. The inputs derived in Chapter 6 for attribute rankings, preference weights, and discount rates are not unbiased estimators due to the use of only a single firm and small focus group of respondents (Appendix 2). As a result, the derived parameter estimates cannot be truly representative of mainframe, minicomputer, desktop, and portable computer market segments. Lack of objectively data driven estimates using robust statistical techniques and use of subjective measures in the model specification is an acknowledged limitation of the research. However, Keeney and Raiffa (1993) suggest that subjectively defined measures and parameter estimates from industry experts can be used in cases where objective measures are unavailable. Furthermore, the research borrows heavily from the work of Christensen for secondary HDD data to derive model parameters for market segment thresholds and growth rates in absorptive capacity. This is also acknowledged as a limitation of the research, as these sources cannot be verified or replicated from the original data used by Christensen.

Model Limitations:

In terms of the model, we simplify the complex decision-making processes of consumers down to only a few key attributes that market segments trade-off to inform their adoption decision. However, it is recognised that such simplification is not always the case in reality. Another important limitation of the model arises from the IIA (independence of irrelevant alternatives) axiom (Manrai, 1995; Currim, 1982) assumed in the MNL formulation. According to the axiom, innovations are discounted at a uniform rate as new innovations are introduced in the market. Thus, the derived utility of an innovation depends solely on the attributes of that innovation, thereby ignoring similarities between alternatives. Currim (1982; 201) captures the concept well, he states:

> *"If a product class has two alternatives and their measured attractiveness is 5 and 2, then by equation 3 the probabilities of choice will be .9525 and .0475, respectively. If a new brand introduced is highly correlated with the second but only slightly superior to it, say a measured utility of 2.1, the probabilities of choice are .905, .045, and .05, respectively. The new brand has cannibalised more share from the first brand than from the second, a result which may be intuitively unappealing."*

This property is not always desirable or realistic since competing innovations are not discounted uniformly. As a result, the IIA property facilitates in inflating model estimates of 5.25-inch disk drives between points 17 (1996) and 20 (1998) in Figure 7.A. However, due to the complex nature of the problem the IIA axiom provides a simple way to analyse computationally difficult problems.

Assumption Limitations:

Finally, in the proposed model we consider demand heterogeneity between market segments but not within market segments. We assume that consumers within competitive markets are homogeneous in their demand structure, which is not always a realistic assumption. For example, mainframe, minicomputer, desktop computer, and portable computer segments will differ internally in their demand structure. According to Schmidt and Druehl (2008), markets can be segmented into high end, mainstream and low end customers. Thus, we neglect the influence of different adopter categories on market disruption. Furthermore, preferences for attributes are assumed to be static and non-dynamic, which does not account for switching behaviours or changes in consumer tastes/ preferences over time. By acknowledging these limitations, we can offer potential avenues for future research to overcome these shortcomings and provide suggestions for developing knowledge further.

8.3. Future Research Directions

We address potential future research directions from the perspective of research limitations presented in Section 8.2. Furthermore, we identify areas in which to extend the model in response to other important research streams.

8.3.1. Model Validation

In response to the lack of generalizability offered by the proposed modelling approach, future research should focus on seeking to validate the model through replicating the results using other examples of disruptive innovation. To broaden the scope of the model results, extensions should be data driven and include: disruptive *product*, *service*, and *business model* innovations.

- Potential disruptive product innovations include: mobile vs. landline telephones (Schmidt and Druehl, 2008; Druehl and Schmidt, 2008), digital vs. analogue film cameras (Lucas and Goh, 2009), and internet tablets vs. portable computers.

- Potential disruptive service innovations include: cheap no-frills flights vs. traditional flight providers (Schmidt and Druehl, 2008) e.g. Jet2 vs. British Airways, and Skype vs. traditional telecommunications services (Ansari and Krop, 2012), and Microsoft vs. Google office applications (Keller and Hüsig, 2009).

- Potential disruptive business model innovations include: Dell vs. Compaq – Dell challenged existing business models in the home computer industry through selling low-cost PCs over the internet; MP3 vs. record labels (CDs) – the growth in digitised music formats and introduction of iTunes as a business model challenged the dominance of record labels and CDs in the music industry (Ansari and Krop, 2012); and online business schools vs. traditional business schools e.g. Open University vs. traditional universities (Markides, 2006).

Following this, future research on developing a model to understand the disruptiveness of innovations and the mechanisms that drive the process will be more cumulative and impactful. This will assist in the development of a general model and theory. Furthermore, objective data driven measures and parameter estimates for model inputs should be used to avoid limitations of subjective bias as identified in Section 8.2 – *Data Limitations*.

8.3.2. Model Extensions

In this section, we propose numerous model extensions for future research to highlight potential differences in patterns of market disruption, alleviate problems related to the IIA axiom, and examine the effect internal market demand heterogeneity. In addition, we propose other model extensions for future research that can be used to provide further theoretical insights and to forecast and predict the disruptiveness of innovations.

Different Patterns of Market Disruption:

It is recognised that understanding potential differences between patterns of market disruption is a particularly fruitful area for future research. The model and methodology used in this study can be applied to numerous industries to analyse potential differences across industries. For example, there may be underlying differences in patterns of disruption recognised in the manufacturing, pharmaceutical, high-technology, and service industries among others. Understanding such differences will have a significant impact on the development of new differentiated innovation policies (re Section 8.1.4), which can lead to improved national/ regional systems of innovation.

Similarly, the model and methodology used in this thesis can also be applied to examine international differences in patterns of disruption. As Chesbrough (2003) points out, the patterns of firm failure and market disruption recognised in the US hard disk drive industry were not replicated in Japan. Emphasis here should lie on developing an understanding of how country specific institutional factors such as the labour market, competition policies – e.g. intellectual property law, and the economy influence disruptive outcomes. Again, understanding such differences will lead to the development of improved national systems of innovation. Furthermore, such analyses will highlight the potential impact that different innovation policies have on shaping disruptive outcomes.

Non IIA Axiom:

As mentioned in Section 8.2, the proposed model is limited by the IIA axiom and uniformly discounts existing innovations as new innovations emerge in the marketplace. Therefore, an interesting opportunity here would be the introduction of a nested model that groups similar innovations into specific categories as a mechanism to avoid the IIA axiom with correlated innovations. Such a model may provide more robust results.

The nested multinomial logit (NMNL) model assumes that some innovation alternatives share common characteristics leading to a greater cross elasticity between such alternatives. The NMNL model assumes that decision processes are hierarchical and can be nested into specific groups based upon innovation attributes (Manrai, 1995). Such models may provide a solution to the unrealistic IIA axiom and offer increased model fit.

Demand Heterogeneity:

Demand heterogeneity is an important aspect when considering the internal choice behaviours of market segments. This is because the structure of internal market demand can significantly influence a market segment's susceptibility to disruptive threats. For example, a market segment characterised by a high proportion of low end customers will be more susceptible to market disruption. This because lower performing disruptive innovations find easier to attract the market's low end customers (Schmidt and Druehl, 2008). Therefore, a particular area of interest would be to analyse the impact of different adopter categories (i.e. low end, mainstream and high end adopters) on market disruption. These adopter groups can be categorised by certain demand limits that can be randomly assigned different demand thresholds that fall within the limits of each group. By doing this, conditions of true consumer demand heterogeneity can be simulated using the model and methodology developed in this study as a base. The proposed model can be extended to include a number of sub-market segments characterised by different optimal demand thresholds. Such analyses would provide new insights with regards to the effect of market structure and demand heterogeneity on market disruption.

Forecasting Model:

The model can also be extended and used as forecasting tool to measure the potential disruptiveness of new innovations as they emerge in the marketplace. A recognised limitation of the study and that of Christensen is the use of the HDD industry in retrospective to explain disruptive phenomena. However, the model and methodology used in this study can be modified using techniques such as regression / multiple regressions and genetic algorithms to derive new model inputs. These new model inputs can then be used in the proposed ABM (Section 5.3) to evaluate the potential disruptiveness of innovations ex ante. Furthermore, the model can be used to simulate multiple 'what-if' scenarios to evaluate the market conditions in which new innovations have the potential to be disruptive.

Using the model as a forecasting tool would provide managers and researchers alike with a way to predict and evaluate the potential disruptiveness of new innovations in different market conditions ex ante. As a result, managers will be able to develop better innovation strategies and sustain long-term competitive advantage.

8.3.3. Optimisation Problems

The proposed model can be extended to solve multiple optimisation problems related to innovation strategy. Optimisation is a technique used to maximise or minimise mathematical functions given certain conditions. For example, firms may wish to optimise the utility of a given innovation for a certain market segment. Given certain innovation development and budget constraints, optimisation methods can be used to derive superior paths of innovation development that maximise the utility payoff to consumers in a specific segment. Such analyses would have huge impact on the development of improved firm-level R&D and investment strategies, which in turn can reduce the probability of firm failure when faced with disruptive threats. Furthermore, these conditions can be modified depending on preference structure, demand structure, and development dynamics.

Another interesting extension would be to examine optimal innovation strategies for incumbent and disruptor firms under different market conditions. For example:

- *Optimal innovation strategies for incumbent firms under preference isolation and convergence*
- *Optimal innovation strategies for disruptor firms under preference isolation and convergence*

These potential questions can be extended to examine a variety of different market conditions. Such research would help develop better innovation strategies for firms seeking to initiate or respond to disruptive innovation.

Finally, optimisation can be used to evaluate the impact of different policy initiatives on shaping a firm's ability to respond to, or develop disruptive innovations. Future research should focus on which policy initiatives or combination of policy initiatives maximise a firm's ability to develop disruptive innovation; and which policies minimise a firm's susceptibility to disruption in terms of failure rates. This can be assessed in different international and industry contexts as described in Section 8.3.2. Results of such studies will help to develop improved national and industry innovation policies and systems of innovation.

References

ABERNATHY, W. J. & CLARK, K. B. 1985. Innovation: Mapping the winds of creative destruction. *Research Policy,* 14**,** 3-22.

ADNER, R. 2002. When are technologies disruptive? a demand-based view of the emergence of competition. *Strategic Management Journal,* 23**,** 667-688.

ADNER, R. 2004. A demand-based perspective on technology life cycles. *Advances in Strategic Management,* 21**,** 25-53.

ADNER, R. & ZEMSKY, P. 2005. Disruptive Technologies and the Emergence of Competition. *The RAND Journal of Economics,* 36**,** 229-254.

ADNER, R. & ZEMSKY, P. 2006. A demand-based perspective on sustainable competitive advantage. *Strategic Management Journal, 27,* 215-239.

ANDERSON, E. W. & SULLIVAN, M. W. 1993. The Antecedents and Consequences of Customer Satisfaction for Firms. *MARKETING SCIENCE,* 12**,** 125-143.

ANDERSON, P. & TUSHMAN, M. L. 1990. Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. *Administrative Science Quarterly,* 35**,** 604-633.

ANDRIOPOULOS, C. & LEWIS, M. W. 2009. Exploitation-Exploration Tensions and Organizational Ambidexterity: Managing Paradoxes of Innovation. *Organization Science,* 4, 696-717.

ANSARI, S. & KROP, P. Incumbent performance in the face of a radical innovation: Towards a framework for incumbent challenger dynamics. *Research Policy*.

ANSARI, S. & MUNIR, K. 2008. How valuable is a piece of the spectrum? Determination of value in external resource acquisition. *Industrial and Corporate Change,* 17**,** 301-333.

ATUAHENE-GIMA, K. 1995. An Exploratory Analysis of the Impact of Market Orientation on New Product Performance. *Journal of Product Innovation Management,* 12**,** 275-293.

AXELROD, R. 1997. *The Complexity of Cooperation*. Princeton University Press, Princeton

BALACHANDRA, R. & FRIAR, J. H. 1997. Factors for success in R&D projects and new product. *IEEE Transactions on Engineering Management,* 44**,** 276.

BARNEY, J. 1991. Firm Resources and Sustained Competitive Advantage. *Journal of Management,* 17**,** 99-120.

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

BASS, F. M. 2004. A New Product Growth for Model Consumer Durables. *Management Science,* 50**,** 1825-1832.

BELENZON, S. & BERKOVITZ, T. 2010. Innovation in Business Groups. *Management Science, 56,* 519-535.

BENNER, M. J. & TUSHMAN, M. L. 2003. Exploitation, Exploration, and Process Management: The Productivity Dilemma Revisited. *The Academy of Management Review*, 28**,** 238-256.

BEVERLAND, M. B., NAPOLI, J. & FARRELLY, F. 2010. Can All Brands Innovate in the Same Way? A Typology of Brand Position and Innovation Effort*. *Journal of Product Innovation Management,* 27**,** 33-48.

BONABEAU, E. 2002 Agent-Based Modeling: Methods and Techniques for Simulating Human Systems. *Proceedings of the National Academy of Sciences of the United States of America, 99,* 7280-7287.

BOURGEOIS, L. J., III & EISENHARDT, K. M. 1988. Strategic Decision Processes in High Velocity Environments: Four Cases in the Microcomputer Industry. *Management Science,* 34**,** 816-835.

BOWER, J. L. & CHRISTENSEN, C. M. 1995. Disruptive technologies: Catching the wave : Joseph L. Bower and Clayton M. Christensen, Harvard Business Review (January-February 1995), pp. 43-53. *Journal of Product Innovation Management,* 13**,** 75-76.

BRYMAN, A. 2008. *Social Research Methods,* Oxford, Oxford University Press.

BRYMAN, A. & BELL, E. 2007. *Business Research Methods,* Oxford, Oxford University Press.

BURGELMAN, R. A. 1991. Intra-organizational ecology of strategy-making and organizational adaptation. *Organization Science,* 2, 239-262.

BURRELL, G. & MORGAN, G. 1979. *Sociological Paradigms and Organisational Analysis,* London, Heinemann Educational Books Ltd.

CALANTONE, R. J., CAVUSGIL, S. T. & YUSHAN, Z. 2002. Learning orientation, firm innovation capability, and firm performance. *Industrial Marketing Management,* 31**,** 515-524.

CANTONO, S. & SILVERBERG, G. 2009. A percolation model of eco-innovation diffusion: The relationship between diffusion, learning economies and subsidies. *Technological Forecasting & Social Change, 76,* 487-496.

CHAKRABARTI, A. K. 1974. The Role of Champion in Product Innovation. *California Management Review,* 17**,** 58-62.

CHANDY, R. K. & TELLIS, G. J. 1998. Organizing for Radical Product Innovation: The Overlooked Role of Willingness to Cannibalize. *Journal of Marketing Research,* 35**,** 474-487.

CHARITOU, C. D. & MARKIDES, C. C. 2003. Responses to Disruptive Strategic Innovation. *MIT Sloan Management Review,* 44**,** 55-63.

CHESBROUGH, H. 1999. The organizational impact of technological change: a comparative theory of national institutional factors. *Industrial and Corporate Change,* 8**,** 447-485.

CHESBROUGH, H. W. 2003. Environmental influences upon firm entry into new sub-markets: Evidence from the worldwide hard disk drive industry conditionally. *Research Policy,* 32**,** 659-678.

CHRISTENSEN, C. M. 1993. The Rigid Disk Drive Industry: A History of Commercial and Technological Turbulence. *The Business History Review,* 67**,** 531-588.

CHRISTENSEN, C. M. 1997. *The Innovator's Dilemma,* Boston MA, Harvard Business School Press.

CHRISTENSEN, C. M. 2006. The Ongoing Process of Building a Theory of Disruption. *Journal of Product Innovation Management,* 23**,** 39-55.

CHRISTENSEN, C. M., ANTHONY, S. D. & ROTH, E. A. 2004. *Seeing What's Next,* Boston MA, Harvard Business School Press.

CHRISTENSEN, C. M. & BOWER, J. L. 1996. Customer Power, Strategic Investment, and the Failure of Leading Firms. *Strategic Management Journal,* 17**,** 197-218.

CHRISTENSEN, C. M. & OVERDORF, M. 2000. Meeting the Challenge of Disruptive Change. *Harvard Business Review,* March-April**,** 66-76.

CHRISTENSEN, C. M., RAYNOR, M. & VERLINDEN, M. 2001. Skate to Where the Money Will Be. *Harvard Business Review,* 79**,** 72-81.

CHRISTENSEN, C. M. & RAYNOR, M. E. 2003. *The Innovator's Solution,* Boston, Harvard Business School Press.

CHRISTENSEN, C. M. & ROSENBLOOM, R. S. 1995. Explaining the attacker's advantage: Technological paradigms, organizational dynamics, and the value network. *Research Policy,* 24**,** 233-257.

COHEN, W. M. & LEVINTHAL, D. A. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly,* 35**,** 128-152.

CROSSAN, M. M. & APAYDIN, M. 2010. A Multi-Dimensional Framework of Organizational Innovation: A Systematic Review of the Literature. *Journal of Management Studies,* 47**,** 1154-1191.

CROTTY, M. 1998. *The Foundations of Social Research: Meaning and Perspective in the Research Process,* London, Sage Publications.

CURRIM, I. S. 1982. Predictive Testing of Consumer Choice Models Not Subject to Independence of Irrelevant Alternatives. *Journal of Marketing Research (JMR),* 19**,** 208-222.

CURRIM, I. S. & SARIN, R. K. 1983. A Procedure for Measuring and Estimating Consumer Preferences Under Uncertainty. *Journal of Marketing Research (JMR),* 20**,** 249-256.

DAFT, R. L. 1983. Learning the Craft of Organizational Research. *The Academy of Management Review,* 8**,** 539-546.

DAMANPOUR, F. 1991. Organizational Innovation: A Meta-Analysis of Effects of Determinants and Moderators. *The Academy of Management Journal,* 34**,** 555-590.

DAMANPOUR, F. & EVAN, W. M. 1984. Organizational Innovation and Performance: The Problem of "Organizational Lag". *Administrative Science Quarterly,* 29**,** 392-409.

DAMANPOUR, F., WALKER, R. M. & AVELLANEDA, C. N. 2009. Combinative Effects of Innovation Types and Organizational Performance: A Longitudinal Study of Service Organizations. *Journal of Management Studies,* 46**,** 650-675.

DANNEELS, E. 2004. Disruptive Technology Reconsidered: A Critique and Research Agenda. *Journal of Product Innovation Management*, 21**,** 246-258.

DEBRUYNE, M. & REIBSTEIN, D. J. 2005. Competitor See, Competitor Do: Incumbent Entry in New Market Niches. *Market Science, 24*, 55-66.

DESARBO, W. S., GREWAL, R. & WIND, J. 2006. Who competes with whom? A demand-based perspective for identifying and representing asymmetric competition. *Strategic Management Journal,* 27**,** 101-129.

DESZCA, G., MUNRO, H. & NOORI, H. 1999. Developing breakthrough products: challenges and options for market assessment. *Journal of Operations Management,* 17**,** 613-630.

DEWAR, R. D. & DUTTON, J. E. 1986. The Adoption of Radical and Incremental Innovations: An Empirical Analysis. *Management Science,* 32**,** 1422-1433.

DI STEFANO, G., GAMBARDELLA, A. & VERONA, G. Technology push and demand pull perspectives in innovation studies: Current findings and future research directions. *Research Policy*.

DRUEHL, C. T. & SCHMIDT, G. M. 2008. A Strategy for Opening a New Market and Encroaching on the Lower End of the Existing Market. *Production and Operations Management,* 17**,** 44-60.

EISENHARDT, K. M. 1989. Building Theories from Case Study Research. *The Academy of Management Review,* 14**,** 532-550.

ENKEL, E., GASSMANN, O. & CHESBROUGH, H. 2009. Open R&D and open innovation: exploring the phenomenon. *R&D Management, 39,* 311-316.

FERBER, J. 1999. *Multi-Agent Systems: An Introduction to Distributed Artificial Intelligence,* Boston, Addison-Wesley Longman Publishing Co., Inc.

FIEDLER, M. & WELPE, I. M. 2010. Antecedents of cooperative commercialisation strategies of nanotechnology firms. *Research Policy,* 39**,** 400-410.

FIELD, A. 2005. *Discovering Statistics Using SPSS,* Second Edition. London, SAGE Publications

FREEMAN, C. 1994. The economics of technical change. *Cambridge Journal of Economics,* 18**,** 463-514.

GARCIA, R. 2005. Uses of Agent-Based Modeling in Innovation/ New Product Development Research. *Journal of Product Innovation Management, 22,* 380-398.

GARCIA, R. & CALANTONE, R. 2002. A critical look at technological innovation typology and innovativeness terminology: a literature review. *Journal of Product Innovation Management,* 19**,** 110-132.

GARCIA, R. & JAGER, W. 2011. From the Special Issue Editors: Agent-Based Modeling of Innovation Diffusion. *Journal of Product Innovation Management, 28,* 148-151.

GATIGNON, H., ELIASHBERG, J. & ROBERTSON, T. S. 1989. Modeling Multinational Diffusion Patterns: An Efficient Methodology. *MARKETING SCIENCE,* 8**,** 231-247.

GATIGNON, H., TUSHMAN, M. L., SMITH, W. & ANDERSON, P. 2002. A Structural Approach to Assessing Innovation: Construct Development of Innovation Locus, Type, and Characteristics. *Management Science,* 48**,** 1103-1122.

GENET, C., ERRABI, K. & GAUTHIER, C. 2012. Which model of technology transfer for nanotechnology? A comparison with biotech and microelectronics. *Technovation,* 32**,** 205-215.

GEORGANTZAS, N. C. & KATSAMAKAS, E. 2009. Disruptive Internet-service innovation diffusion. *Human Systems Management,* 28**,** 163-181.

GEROSKI, P. A. 2000. Models of technology diffusion. *Research Policy, 29,* 603-625.

GILBERT, C. 2003. The Disruption Opportunity. *MIT Sloan Management Review,* 44**,** 27-32.

GOPALAKRISHNAN, S. & DAMANPOUR, F. 1997. A review of innovation research in economics, sociology and technology management. *Omega,* 25**,** 15-28.

GOVINDARAJAN, V. & KOPALLE, P. K. 2006a. Disruptiveness of innovations: measurement and an assessment of reliability and validity. *Strategic Management Journal,* 27**,** 189-199.

GOVINDARAJAN, V. & KOPALLE, P. K. 2006b. The Usefulness of Measuring Disruptiveness of Innovations Ex Post in Making Ex Ante Predictions*. *Journal of Product Innovation Management,* 23**,** 12-18.

GOVINDARAJAN, V., KOPALLE, P. K. & DANNEELS, E. 2011. The Effects of Mainstream and Emerging Customer Orientations on Radical and Disruptive Innovations. *Journal of Product Innovation Management, 28,* 121-132.

GREEN, P. E. & KRIEGER, A. M. 1991. Segmenting Markets with Conjoint Analysis. *Journal of Marketing,* 55**,** 20-31.

GRILICHES, Z. 1957. Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica, 25,* 501-522.

GUMASTA, K., GUPTA, S. K., BENYOUCEF, L. & TIWARI, M. K. 2011. Developing a reconfigurability index using multi-attribute utility theory. *International Journal of Production Research, 49,* 1669-1683.

GUPTA, A. K., SMITH, K. G. & SHALLEY, C. E. 2006. The interplay between exploration and exploitation. *Academy of Management Journal,* 4, 693-706.

HENDERSON, R. 2006. The Innovator's Dilemma as a Problem of Organizational Competence. *Journal of Product Innovation Management,* 23**,** 5-11.

HENDERSON, R. M. & CLARK, K. B. 1990. Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms. *Administrative Science Quarterly,* 35**,** 9-30.

HOYLE, R. H. 2007. Applications of Structural Equation Modeling in Personality Research. *In:* ROBINS, R. W., FRALEY, R. C. & KRUEGAR, R. F. (eds.) *Handbook of Research Methods in Personality Research.* New York: Guilford Press.

HUBER, G. P. 1974. MULTI-ATTRIBUTE UTILITY MODELS: A REVIEW OF FIELD AND FIELD-LIKE STUDIES. *Management Science,* 20**,** 1393-1402.

HÜSIG, S., HIPP, C. & DOWLING, M. 2005. Analysing disruptive potential: the case of wireless local area network and mobile communications network companies. *R&D Management,* 35**,** 17-35.

JÖRESKOG, K. G. 1993. Testing structural equation models. *In:* BOLLEN, K. A. & LONG, J. S. (eds.) *Testing structural equation models.* Newbury Park, CA: Sage Publications.

JUN, D. B. & KIM, J. I. 2011. A choice-based multi-product diffusion model incorporating replacement demand. *Technological Forecasting and Social Change,* 78**,** 674-689.

JUN, D. B., KIM, S. K., PARK, Y. S., PARK, M. H. & WILSON, A. R. 2002. Forecasting telecommunication service subscribers in substitutive and competitive environments. *International Journal of Forecasting,* 18**,** 561-581.

JUN, D. B. & PARK, Y. S. 1999. A Choice-Based Diffusion Model for Multiple Generations of Products. *Technological Forecasting and Social Change,* 61**,** 45-58.

KAMAKURA, W. A. & RUSSELL, G. J. 1989. A Probabilistic Choice Model for Market Segmentation and Elasticity Structure. *Journal of Marketing Research,* 26**,** 379-390.

KANKANHALL, A., PEE, L. G., TAN, G. W. & CHHATWAL, S. 2012. Interaction of Individual and Social Antecedenta of Learning Effectivenes: A Study in the IT Research Context. *IEEE Transactions on Engineering Management, 59*, 115-128.

KASSICIEH, S. K., WALSH, S. T., CUMMINGS, J. C., MCWHORTER, P. J., ROMIG, A. D. & WILLIAMS, W. D. 2002. Factors differentiating the commercialization of disruptive and sustaining technologies. *Engineering Management, IEEE Transactions on,* 49**,** 375-387.

KEENEY, R., & RAIFFA, L. 1993. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. Cambridge University Press, Cambridge.

KELLER, A. & HÜSIG, S. 2009. Ex ante identification of disruptive innovations in the software industry applied to web applications: The case of Microsoft's vs. Google's office applications. *Technological Forecasting and Social Change,* 76**,** 1044-1054.

KESSLER, E. H. & CHAKRABARTI, A. K. 1999. Speeding Up the Pace of New Product Development. *Journal of Product Innovation Management,* 16**,** 231-247.

KIM, S.-H. & SRINIVASAN, V. 2009. A Conjoint-Hazard Model of the Timing of Buyers' Upgrading to Improved Versions of High-Technology Products*. *Journal of Product Innovation Management,* 26**,** 278-290.

KIM, W.-J., LEE, J.-D. & KIM, T.-Y. 2005. Demand forecasting for multigenerational products combining discrete choice and dynamics of diffusion under technological trajectories. *Technological Forecasting and Social Change,* 72**,** 825-849.

KLEINSCHMIDT, E. J. & COOPER, R. G. 1991. The impact of product innovativeness on performance. *Journal of Product Innovation Management,* 8**,** 240-251.

KOSTOFF, R. N., BOYLAN, R. & SIMONS, G. R. 2004. Disruptive technology roadmaps. *Technological Forecasting and Social Change,* 71**,** 141-159.

KUMAR, V. & KRISHNAN, T. V. 2002. Multinational Diffusion Models: An Alternative Framework. *MARKETING SCIENCE,* 21**,** 318-330.

LANCASTER, K. J. 1966. A New Approach to Consumer Theory. *The Journal of Political Economy,* 74**,** 132-157.

LEE, J., CHO, Y., LEE, J.-D. & LEE, C.-Y. 2006. Forecasting future demand for large-screen television sets using conjoint analysis with diffusion model. *Technological Forecasting and Social Change,* 73**,** 362-376.

LEE, M. & NA, D. 1994. Determinants of technical success in product development when innovative radicalness is considered. *Journal of Product Innovation Management,* 11**,** 62-68.

LEONARD-BARTON, D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal,* 13**,** 111-125.

LETTICE, F. & THOMOND, P. 2008. Allocating resources to disruptive innovation projects: challenging mental models and overcoming management resistance. *International Journal of Technology Management,* 44**,** 140-159.

LEVITT, T. 1960. MARKETING MYOPIA. *Harvard Business Review,* 38**,** 45-56.

LEWIS, M. W. & KELEMEN, M. L. 2002. Multiparadigm Inquiry: Exploring Organizational Pluralism and Paradox. *Human Relations,* 55**,** 251-275.

LI, T. & CALANTONE, R. J. 1998. The Impact of Market Knowledge Competence on New Product Advantage: Conceptualization and Empirical Examination. *The Journal of Marketing,* 62**,** 13-29.

LINTON, J. D. 2002. Forecasting the market diffusion of disruptive and discontinuous innovation. *Engineering Management, IEEE Transactions on,* 49**,** 365-374.

LINTON, J. D. 2009. De-babelizing the language of innovation. *Technovation,* 29**,** 729-737.

LUCAS JR, H. C. & GOH, J. M. 2009. Disruptive technology: How Kodak missed the digital photography revolution. *The Journal of Strategic Information Systems,* 18**,** 46-55.

LYYTINEN, K. & ROSE, G. M. 2003. The Disruptive Nature of Information Technology Innovations: The Case of Internet Computing in Systems Development Organizations. *MIS Quarterly,* 27**,** 557-596.

MACAL, C. M. & NORTH, M. J. 2010. Tutorial on agent-based modelling and simulation. *Journal of Simulation, 4,* 151-162.

MAHAJAN, V., MULLER, E. & SRIVASTAVA, R. K. 1990. Determination of Adopter Categories by Using Innovation Diffusion Models. *Journal of Marketing Research (JMR),* 27**,** 37-50.

MAHAJAN, V. & MULLER, E. 1993. New-product diffusion models. *In Handbook in operations research and management science: Chapter 8. Marketing, vol 5.* Amsterdam, Netherlands: North Holland.

MANRAI, A. K. 1995. Mathematical models of brand choice behavior. *European Journal of Operational Research,* 82**,** 1-17.

MANSFIELD, E. 1961. Technical Change and the Rate of Imitation. *Econometrica, 29,* 741-766.

MANTRALA, M. K., SEETHARAMAN, P. B., KAUL, R., GOPALAKRISHNA, S. & STAM, A. 2006. Optimal Pricing Strategies for an Automotive Aftermarket Retailer. *Journal of Marketing Research (JMR),* 43**,** 588-604.

MARKIDES, C. 2006. Disruptive Innovation: In Need of Better Theory. *Journal of Product Innovation Management, 23,* 19-25.

MCFADDEN, D. 1976. Quantal choice analysis: A survey. *Annals of Economic and Social Measurement,* 5**,** 363-390.

MCKENDRICK, D. G. 2001. Global strategy and population-level learning: the case of hard disk drives. *Strategic Management Journal,* 22**,** 307-334.

MEADE, N. & ISLAM, T. 2006. Modelling and forecasting the diffusion of innovation – A 25-year review. *International Journal of Forecasting, 22,* 519-545.

MILES, R. E., SNOW, C. C., MEYER, A. D., & COLEMAN, JR, H. J. 1978. Organizational Strategy, Structure, and Process. *The Academy of Management Review,* 3, 546-562

MOORE, G. C. & BENBASAT, I. 1991. Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research,* 2**,** 192-222.

MORGAN, G. & SMIRCICH, L. 1980. The Case for Qualitative Research. *The Academy of Management Review,* 5**,** 491-500.

MOUNT, M. P. & FERNANDES, K. 2011. Adoption of free and open source software within high-velocity firms. *Behaviour & Information Technology***,** 1-16.

MYERS, S. & MARQUIS, D. G. 1969. *Successful industrial innovatiobs: A study of factors underlying innovation in selected firms,* Washington, National Science Foundation.

MYUNG, I. J. 2003. Tutorial on maximum likelihood estimation. *Journal of Mathematical Psychology, 47,* 90-100.

NAMWOON, K., CHANG, D. R. & SHOCKER, A. D. 2000. Modeling Intercategory and Generational Dynamics for a Growing Information Technology Industry. *Management Science,* 46**,** 496-512.

NIKULAINEN, T. & PALMBERG, C. 2010. Transferring science-based technologies to industry—Does nanotechnology make a difference? *Technovation,* 30**,** 3-11.

NORTON, J. A. & BASS, F. M. 1987. A Diffusion Theory Model of Adoption and Substitution for Successive Generations of High-Technology Products. *Management Science, 33,* 1069-1089.

OECD. 2005. *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data*.

PERES, R., MULLER, E. & MAHAJAN, V. 2010. Innovation diffusion and new product growth models: A critical review and research directions. *International Journal of Research in Marketing,* 27**,** 91-106.

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

PFEFFER, J. & SALANCIK, G. R. 1978. *The External Control of Organizations: A Resource Dependence Perspective,* New York, Harper & Row.

PUTSIS JR, W. P., BALASUBRAMANIAN, S., KAPLAN, E. H. & SEN, S. K. 1997. Mixing Behavior in Cross-Country Diffusion. *MARKETING SCIENCE,* 16**,** 354-369.

RAHMANDAD, H. & STERMAN, J. 2008. Heterogeneity and Network Structure in the Dyanmics of Diffusion: Comparing Agent-Based and Differential Eqaution Models. *Management Science, 5,* 998-1014.

RATCHFORD, B. T. 1982. Cost-Benefit Models for Explaining Consumer Choice and Information Seeking Behavior. *Management Science,* 28**,** 197-212.

ROBERTS, P. W. & AMIT, R. 2003. The Dynamics of Innovative Activity and Competitive Advantage: The Case of Australian Retail Banking, 1981 to 1995. *Organization Science,* 14**,** 107-122.

ROBERTS, J. H. & URBAN, G. L. 1988. Modeling Multiattribute Utility, Risk, and Belief Dynamics for New Consumer Durable Brand Choice. *Management Science, 34*, 167-185.

ROBERTSON, T. S. 1967. The Process of Innovation and the Diffusion of Innovation. *The Journal of Marketing,* 31**,** 14-19.

ROBINSON, B. & LAKHANI, C. 1975. Dynamic Price Models for New-Product Planning. *Management Science, 21,* 1113-1122.

ROGERS, E. M. 1995. *Diffusion of Innovations,* New York, Free Press.

RÜDIGER VON, N. & WEBER, M. 1993. The Effect of Attribute Ranges on Weights in Multiattribute Utility Measurements. *Management Science,* 39**,** 937-943.

SANDSTRÖM, C., MAGNUSSON, M. & JÖRNMARK, J. 2009. Exploring Factors Influencing Incumbents' Response to Disruptive Innovation. *Creativity and Innovation Management,* 18**,** 8-15.

SCHMIDT, G. M. & DRUEHL, C. T. 2008. When Is a Disruptive Innovation Disruptive?*. *Journal of Product Innovation Management,* 25**,** 347-369.

SCHUMPETER, J. A. 1934. *The Theory of Economic Development* Cambridge, Harvard University Press.

SCHUMPETER, J. A. 1942. *Capitalism, Socialism, and Democracy,* New York, Harper.

SHANKAR, V., AZAR, P. & FULLER, M. 2008. Practice Prize Paper---BRAN*EQT: A Multicategory Brand Equity Model and Its Application at Allstate. *MARKETING SCIENCE,* 27**,** 567-584.

SHEREMATA, W. A. 2004. Competing through Innovation in Network Markets: Strategies for Challengers. *The Academy of Management Review,* 29**,** 359-377.

SILVERMAN, D. 2000. *Doing Qualitative Research,* London, Sage Publications.

SLATER, S. F. & MOHR, J. J. 2006. Successful Development and Commercialization of Technological Innovation: Insights Based on Strategy Type. *Journal of Product Innovation Management,* 23**,** 26-33.

SOOD, A. & TELLIS, G. J. 2011. Demystifying Disruption: A New Model for Understanding and Predicting Disruptive Technologies. *Marketing Science, 30,* 339-354.

SRINIVASAN, V., CHAN SU, P. & DAE RYUN, C. 2005. An Approach to the Measurement, Analysis, and Prediction of Brand Equity and Its Sources. *Management Science,* 51**,** 1433-1448.

TALUKDAR, D., SUDHIR, K., & AINSLIE, A. 2002. Investingating New Product Diffusion Across Products and Countries. *Marketing Science, 21,* 97-114.

TEECE, D. & PISANO, G. 1994. The Dynamic Capabilities of Firms: an Introduction. *Industrial and Corporate Change,* 3**,** 537-556.

TEECE, D. J., PISANO, G. & SHUEN, A. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal,* 18**,** 509-533.

TELEFSEN, T. & TAKADA, H. 1999. The relationship between mass media availability and the multicountry diffusion of consumer products. *Journal of International Marketing, 7,* 77-96.

TELLIS, G. J. 2006. Disruptive Technology or Visionary Leadership?*. *Journal of Product Innovation Management,* 23**,** 34-38.

THOMOND, P. N. 2004. *Exploring and Describing Management Action for the Pursuit of Disruptive Innovation.* Doctor of Philosophy PhD, Cranfield University.

TIDD, J. 1995. Development of Novel Products Through Intraorganizational and Interorganizational Networks. *Journal of Product Innovation Management,* 12**,** 307-322.

TRIPSAS, M. 1997. Unraveling the Process of Creative Destruction: Complementary Assets and Incumbent Survival in the Typesetter Industry. *Strategic Management Journal,* 18**,** 119-142.

TRIPSAS, M. 2009. Technology, Identity, and Inertia Through the Lens of “The Digital Photography Company”. *Organization Science, 20,* 441-460.

TROTT, P. 2005. *Innovation Management and New Product Development,* London, Financial Times Press.

TSAI, W. 2001. Knowledge Transfer in Intraorganizational Networks: Effects of Network Position and Absorptive Capacity on Business Unit Innovation and Performance. *The Academy of Management Journal, 44,* 996-1004.

TSAI, B. H., LI, Y. & LEE, G. H. 2010. Forecasting global adoption of crystal display televisions with modified product diffusion model. *Computers & Industrial Engineering, 58,* 553-562.

TUSHMAN, M. L. & ANDERSON, P. 1986. Technological Discontinuities and Organizational Environments. *Administrative Science Quarterly,* 31**,** 439-465.

TUSHMAN, M. L. & O'REILLY, C. 1996. Ambidextrous Organizations: Managing Evolutionary and Revolutionary Change. *California Management Review,* 38**,** 8-30.

UTTERBACK, J. M. & ABERNATHY, W. J. 1975. A dynamic model of process and product innovation. *Omega,* 3**,** 639-656.

VAN DEN BOSCH, F. A. J., VOLBERDA, H. W. & DE BOER, M. 1999. Coevolution of Firm Absorptive Capacity and Knowledge Environment: Organizational Forms and Combinative Capabilities. *Organization Science, 10,* 551-568.

VAN DEN BULTE, C. & JOSHI, Y. V. 2007. New Product Diffusion with Influentials and Imitators. *Marketing Science, 26,* 400-421.

VAN ECK, P. S., JAGER, W. & LEEFLANG, P. S. H. 2011. Opinion Leaders' Role in Innovation Diffusion: A Simulation Study. *Journal of Product Innovation Management, 28,* 187-203.

VERYZER, R. W. 1998. Discontinuous Innovation and the New Product Development Process. *Journal of Product Innovation Management,* 15**,** 304-321.

WALSH, S. T. 2004. Roadmapping a disruptive technology: A case study: The emerging microsystems and top-down nanosystems industry. *Technological Forecasting and Social Change,* 71**,** 161-185.

WALSH, S. T., KIRCHHOFF, B. A. & NEWBERT, S. 2002. Differentiating market strategies for disruptive technologies. *Engineering Management, IEEE Transactions on,* 49**,** 341-351.

WHEELWRIGHT, S. C. & CLARK, K. B. 1992. *Revolutionizing Product Development: Quantum Leaps in Speed, Efficiency, and Quality* New York, Free Press.

WILLIAMSON, O. E. 1981. The Economics of Organization: The Transaction Cost Approach. *The American Journal of Sociology,* 87**,** 548-577.

WOLFE, R. A. 1994. ORGANIZATIONAL INNOVATION: REVIEW, CRITIQUE AND SUGGESTED RESEARCH DIRECTIONS*. *Journal of Management Studies,* 31**,** 405-431.

YU, D. & HANG, C. C. 2010. A Reflective Review of Disruptive Innovation Theory. *International Journal of Management Reviews,* 12**,** 435-452.

ZAHRA, S. A. & GEORGE, G. 2002. Absorptive Capacity: A Review, Reconceptualization, and Extension. *The Academy of Management Review, 27,* 185-203.

ZHANG, T., GENSLER, S. & GARCIA, R. 2011. A Study of the Diffusion of Alternative Fuel Vehicles: An Agent-Based Modeling Approach. *Journal of Product Innovation Management, 28,* 152-168.

Appendix 1. Calculations and Utility Formulations

Table 1 provides a breakdown of the average amount of capacity supplied in MB for each innovation (14-inch, 8-inch, 5.25-inch, and 3.5-inch) and the amount of capacity demanded for each market segment (mainframe, minicomputer, desktop, and portable) for each year (1979 – 1998). These figures were used to calculate market segment utility for capacity.

Table 1. Capacity Performance Supplied vs. Demanded

PERFORMANCE SUPPLIED CAPACITY (MB)					PERFORMANCE DEMANDED CAPACITY (MB)				
	14”	8”	5.25”	3.5”		MAIN	MINI	DESKY	PORT
1979	*190.41*	*27.00*	*0.00*	*0.00*	**1979**	*231*	*13*	*0*	*0*
1980	*206.27*	*23.71*	*21.00*	*0.00*	**1980**	*270*	*18*	*5*	*0*
1981	*537.76*	*23.64*	*19.36*	*0.00*	**1981**	*316*	*24*	*7*	*0*
1982	*685.33*	*30.70*	*19.70*	*0.00*	**1982**	*370*	*31*	*9*	*0*
1983	*654.27*	*46.65*	*21.02*	*18.50*	**1983**	*433*	*42*	*12*	*10*
1984	*734.64*	*108.23*	*23.17*	*19.69*	**1984**	*507*	*55*	*16*	*13*
1985	*918.00*	*262.74*	*27.29*	*20.47*	**1985**	*593*	*74*	*21*	*18*
1986	*1440.41*	*530.26*	*34.19*	*20.41*	**1986**	*694*	*98*	*28*	*24*
1987	*1784.71*	*942.03*	*49.77*	*27.72*	**1987**	*812*	*130*	*37*	*31*
1988	*1787.74*	*1275.98*	*83.36*	*32.34*	**1988**	*950*	*173*	*49*	*42*
1989	*2322.56*	*1734.25*	*136.37*	*48.18*	**1989**	*1111*	*230*	*65*	*55*
1990	*3396.94*	*7570.95*	*242.78*	*73.83*	**1990**	*1300*	*306*	*87*	*74*
1991	*3852.02*	*3430.60*	*846.39*	*129.00*	**1991**	*1521*	*407*	*115*	*98*
1992	*4409.50*	*3122.20*	*1709.26*	*229.67*	**1992**	*1780*	*542*	*153*	*130*
1993	*8628.33*	*6264.63*	*2777.16*	*467.29*	**1993**	*2082*	*721*	*204*	*173*
1994	*0.00*	*7394.43*	*4384.66*	*924.86*	**1994**	*2436*	*959*	*271*	*230*
1995	*0.00*	*2319.00*	*12441.15*	*1839.82*	**1995**	*2850*	*1275*	*360*	*306*
1996	*0.00*	*0.00*	*4036.57*	*2830.36*	**1996**	*3335*	*1696*	*479*	*407*
1997	*0.00*	*0.00*	*8030.51*	*5022.06*	**1997**	*3902*	*2255*	*637*	*542*
1998	*0.00*	*0.00*	*15620.59*	*9693.83*	**1998**	*4565*	*2999*	*848*	*721*

Source: Obtained from calculations reported on pp. 112 of this thesis

Table 2 below provide a breakdown of the utility payoff for capacity in the mainframe and minicomputer market segments. The figures show the proportion of capacity supplied with respect to that demanded as a decimal, where a value of 1.00 indicates the innovation provides 100% of the capacity demanded. Values are suppressed to 1.00, as consumers cannot gain more than 100% utility.

Table 2. Capacity Utility Formulation for Mainframe and Minicomputer Segments

UTILITY FORMULATION CAPACITY MAINFRAME					**UTILITY FORMULATION CAPACITY MINICOMPUTER**				
	14	**8**	**5.25**	**3.5**		**14**	**8**	**5.25**	**3.5**
1979	*0.82*	*0.12*	*0.00*	*0.00*	**1979**	*1.00*	*1.00*	*0.00*	*0.00*
1980	*0.76*	*0.09*	*0.08*	*0.00*	**1980**	*1.00*	*1.00*	*1.00*	*0.00*
1981	*1.00*	*0.07*	*0.06*	*0.00*	**1981**	*1.00*	*1.00*	*0.82*	*0.00*
1982	*1.00*	*0.08*	*0.05*	*0.00*	**1982**	*1.00*	*0.98*	*0.63*	*0.00*
1983	*1.00*	*0.11*	*0.05*	*0.04*	**1983**	*1.00*	*1.00*	*0.51*	*0.44*
1984	*1.00*	*0.21*	*0.05*	*0.04*	**1984**	*1.00*	*1.00*	*0.42*	*0.36*
1985	*1.00*	*0.44*	*0.05*	*0.03*	**1985**	*1.00*	*1.00*	*0.37*	*0.28*
1986	*1.00*	*0.76*	*0.05*	*0.03*	**1986**	*1.00*	*1.00*	*0.35*	*0.21*
1987	*1.00*	*1.00*	*0.06*	*0.03*	**1987**	*1.00*	*1.00*	*0.38*	*0.21*
1988	*1.00*	*1.00*	*0.09*	*0.03*	**1988**	*1.00*	*1.00*	*0.48*	*0.19*
1989	*1.00*	*1.00*	*0.12*	*0.04*	**1989**	*1.00*	*1.00*	*0.59*	*0.21*
1990	*1.00*	*1.00*	*0.19*	*0.06*	**1990**	*1.00*	*1.00*	*0.79*	*0.24*
1991	*1.00*	*1.00*	*0.56*	*0.08*	**1991**	*1.00*	*1.00*	*1.00*	*0.32*
1992	*1.00*	*1.00*	*0.96*	*0.13*	**1992**	*1.00*	*1.00*	*1.00*	*0.42*
1993	*1.00*	*1.00*	*1.00*	*0.22*	**1993**	*1.00*	*1.00*	*1.00*	*0.65*
1994	*0.00*	*1.00*	*1.00*	*0.38*	**1994**	*0.00*	*1.00*	*1.00*	*0.96*
1995	*0.00*	*0.81*	*1.00*	*0.65*	**1995**	*0.00*	*1.00*	*1.00*	*1.00*
1996	*0.00*	*0.00*	*1.00*	*0.85*	**1996**	*0.00*	*0.00*	*1.00*	*1.00*
1997	*0.00*	*0.00*	*1.00*	*1.00*	**1997**	*0.00*	*0.00*	*1.00*	*1.00*
1998	*0.00*	*0.00*	*1.00*	*1.00*	**1998**	*0.00*	*0.00*	*1.00*	*1.00*

Source: Obtained from calculations reported on pp. 102 (Equation 2) of this thesis

Similar to Table 2, Table 3 provides a breakdown of the utility payoff for capacity in the desktop and portable computer market segments.

Table 3. Capacity Utility Formulation for Desktop and Portable Segments

UTILITY FORMULATION CAPACITY DESKTOP					UTILITY FORMULATION CAPACITY PORTABLE				
1979	*0.00*	*0.00*	*0.00*	*0.00*	**1979**	*0.00*	*0.00*	*0.00*	*0.00*
1980	*1.00*	*1.00*	*1.00*	*0.00*	**1980**	*0.00*	*0.00*	*0.00*	*0.00*
1981	*1.00*	*1.00*	*1.00*	*0.00*	**1981**	*0.00*	*0.00*	*0.00*	*0.00*
1982	*1.00*	*1.00*	*1.00*	*0.00*	**1982**	*0.00*	*0.00*	*0.00*	*0.00*
1983	*1.00*	*1.00*	*1.00*	*1.00*	**1983**	*1.00*	*1.00*	*1.00*	*1.00*
1984	*1.00*	*1.00*	*1.00*	*1.00*	**1984**	*1.00*	*1.00*	*1.00*	*1.00*
1985	*1.00*	*1.00*	*1.00*	*0.98*	**1985**	*1.00*	*1.00*	*1.00*	*1.00*
1986	*1.00*	*1.00*	*1.00*	*0.74*	**1986**	*1.00*	*1.00*	*1.00*	*0.87*
1987	*1.00*	*1.00*	*1.00*	*0.75*	**1987**	*1.00*	*1.00*	*1.00*	*0.89*
1988	*1.00*	*1.00*	*1.00*	*0.66*	**1988**	*1.00*	*1.00*	*1.00*	*0.78*
1989	*1.00*	*1.00*	*1.00*	*0.74*	**1989**	*1.00*	*1.00*	*1.00*	*0.87*
1990	*1.00*	*1.00*	*1.00*	*0.85*	**1990**	*1.00*	*1.00*	*1.00*	*1.00*
1991	*1.00*	*1.00*	*1.00*	*1.00*	**1991**	*1.00*	*1.00*	*1.00*	*1.00*
1992	*1.00*	*1.00*	*1.00*	*1.00*	**1992**	*1.00*	*1.00*	*1.00*	*1.00*
1993	*1.00*	*1.00*	*1.00*	*1.00*	**1993**	*1.00*	*1.00*	*1.00*	*1.00*
1994	*0.00*	*1.00*	*1.00*	*1.00*	**1994**	*0.00*	*1.00*	*1.00*	*1.00*
1995	*0.00*	*1.00*	*1.00*	*1.00*	**1995**	*0.00*	*1.00*	*1.00*	*1.00*
1996	*0.00*	*0.00*	*1.00*	*1.00*	**1996**	*0.00*	*0.00*	*1.00*	*1.00*
1997	*0.00*	*0.00*	*1.00*	*1.00*	**1997**	*0.00*	*0.00*	*1.00*	*1.00*
1998	*0.00*	*0.00*	*1.00*	*1.00*	**1998**	*0.00*	*0.00*	*1.00*	*1.00*

Source: Obtained from calculations reported on pp. 102 (Equation 2) of this thesis

Table 4 below provides a summary of the price performance supplied figures for 14-inch and 8-inch disk drives in each market segment (mainframe, minicomputer, desktop, and portable) as calculated in the equation on page 112. Performance supplied is taken to be the sum of the price difference between the cheapest disk drive available and the price charged for different disk drives of a certain size.

Table 4. Price Performance Supplied for 14-Inch and 8-Inch Disk Drives

14-INCH					8-INCH				
	MAIN	**MINI**	**DESKY**	**PORT**		**MAIN**	**MINI**	**DESKY**	**PORT**
1979	*3.00*	*0.75*	*0.00*	*0.00*	**1979**	*2.00*	*1.32*	*0.00*	*0.00*
1980	*3.00*	*0.11*	*0.48*	*0.00*	**1980**	*2.00*	*0.19*	*0.60*	*0.00*
1981	*4.48*	*0.12*	*0.63*	*0.00*	**1981**	*2.00*	*0.19*	*0.60*	*0.00*
1982	*4.44*	*0.61*	*0.64*	*0.00*	**1982**	*4.00*	*1.01*	*0.77*	*0.00*
1983	*4.46*	*0.85*	*0.50*	*0.00*	**1983**	*4.00*	*1.01*	*0.51*	*0.00*
1984	*3.68*	*0.45*	*0.54*	*0.00*	**1984**	*4.67*	*0.76*	*0.73*	*0.00*
1985	*3.52*	*2.51*	*0.49*	*0.06*	**1985**	*4.52*	*3.10*	*0.69*	*0.12*
1986	*2.02*	*0.77*	*0.40*	*0.02*	**1986**	*3.82*	*2.56*	*0.86*	*0.09*
1987	*0.56*	*0.17*	*0.23*	*0.01*	**1987**	*4.09*	*1.85*	*1.07*	*0.07*
1988	*0.28*	*0.10*	*0.09*	*0.01*	**1988**	*1.55*	*0.55*	*0.54*	*0.06*
1989	*0.91*	*0.09*	*0.34*	*0.02*	**1989**	*1.68*	*0.17*	*0.70*	*0.04*
1990	*0.00*	*0.01*	*0.10*	*0.00*	**1990**	*0.01*	*0.16*	*0.60*	*0.03*
1991	*0.04*	*0.01*	*0.12*	*0.00*	**1991**	*0.73*	*0.14*	*0.61*	*0.02*
1992	*0.01*	*0.00*	*0.03*	*0.00*	**1992**	*0.29*	*0.07*	*0.36*	*0.02*
1993	*0.00*	*0.00*	*0.00*	*0.00*	**1993**	*0.79*	*0.09*	*0.21*	*0.02*
1994	*0.00*	*0.00*	*0.00*	*0.00*	**1994**	*0.67*	*0.06*	*0.27*	*0.02*
1995	*0.00*	*0.00*	*0.00*	*0.00*	**1995**	*0.01*	*0.01*	*0.34*	*0.00*
1996	*0.00*	*0.00*	*0.00*	*0.00*	**1996**	*0.04*	*0.02*	*0.48*	*0.02*
1997	*0.00*	*0.00*	*0.00*	*0.00*	**1997**	*0.00*	*0.00*	*0.04*	*0.00*
1998	*0.00*	*0.00*	*0.00*	*0.00*	**1998**	*0.00*	*0.00*	*0.00*	*0.00*

Source: Obtained from calculations reported on pp. 112-113 of this thesis

Similar to Table 4, Table 5 provides a summary of the price performance suppliedfor 5.25-inch and 3.5-inch disk drives in each market segment (mainframe, minicomputer, desktop, and portable).

Table 5. Price Performance Supplied for 5.25-Inch and 3.5-Inch Disk Drives

	5.25-INCH					3.5-INCH			
	MAIN	**MINI**	**DESKY**	**PORT**		**MAIN**	**MINI**	**DESKY**	**PORT**
1979	*0.00*	*0.00*	*0.00*	*0.00*	**1979**	*0.00*	*0.00*	*0.00*	*0.00*
1980	*1.00*	*1.00*	*1.00*	*0.00*	**1980**	*0.00*	*0.00*	*0.00*	*0.00*
1981	*1.00*	*1.00*	*1.00*	*0.00*	**1981**	*0.00*	*0.00*	*0.00*	*0.00*
1982	*2.00*	*2.00*	*1.46*	*0.00*	**1982**	*0.00*	*0.00*	*0.00*	*0.00*
1983	*3.00*	*2.23*	*1.11*	*0.00*	**1983**	*1.00*	*1.00*	*1.00*	*0.00*
1984	*3.00*	*1.74*	*1.36*	*0.00*	**1984**	*2.00*	*2.00*	*1.44*	*0.00*
1985	*4.00*	*3.24*	*1.56*	*1.08*	**1985**	*2.00*	*2.00*	*1.90*	*1.81*
1986	*4.00*	*3.31*	*1.99*	*1.22*	**1986**	*2.00*	*2.00*	*2.00*	*1.36*
1987	*5.31*	*4.20*	*3.06*	*1.46*	**1987**	*4.00*	*4.00*	*2.86*	*1.20*
1988	*5.36*	*4.30*	*3.07*	*2.36*	**1988**	*4.00*	*4.00*	*2.65*	*2.05*
1989	*6.61*	*3.81*	*4.38*	*2.52*	**1989**	*5.00*	*4.21*	*4.14*	*2.44*
1990	*0.94*	*3.88*	*4.19*	*2.60*	**1990**	*0.89*	*4.44*	*4.31*	*2.66*
1991	*6.45*	*3.37*	*3.57*	*1.38*	**1991**	*6.52*	*4.58*	*4.55*	*2.02*
1992	*5.50*	*2.92*	*3.14*	*1.73*	**1992**	*6.34*	*4.67*	*4.48*	*3.28*
1993	*4.33*	*1.41*	*1.40*	*0.32*	**1993**	*6.44*	*4.48*	*3.80*	*2.21*
1994	*2.15*	*0.33*	*0.77*	*0.13*	**1994**	*6.67*	*4.49*	*3.95*	*2.79*
1995	*0.26*	*0.12*	*0.67*	*0.07*	**1995**	*4.26*	*3.60*	*3.67*	*2.81*
1996	*3.04*	*1.93*	*2.73*	*1.93*	**1996**	*3.56*	*2.81*	*3.57*	*2.81*
1997	*2.85*	*1.70*	*2.65*	*1.70*	**1997**	*3.08*	*2.31*	*3.18*	*2.31*
1998	*2.54*	*2.54*	*3.24*	*2.54*	**1998**	*2.61*	*2.61*	*3.44*	*2.61*

Source: Obtained from calculations reported on pp. 112-113 of this thesis

Table 6 below provides a breakdown of the price performance demanded for each market segment (mainframe, minicomputer, desktop, and portable). Price performance demanded was taken to be equal to the cheapest disk drive available in the market that also satisfied the performance demanded in terms of capacity for each market segment.

Table 6. Price Performance Demanded

	PERFORMANCE DEMANDED PRICE ($)			
	MAIN	**MINI**	**DESKY**	**PORT**
1979	*16922.7*	*1305.8*	*1305.8*	*1305.8*
1980	*14903.5*	*501.4*	*501.4*	*501.4*
1981	*13374.2*	*501.4*	*501.4*	*501.4*
1982	*11114.8*	*1097.1*	*501.4*	*501.4*
1983	*10000*	*1097.1*	*333.3*	*333.3*
1984	*5638.3*	*800*	*352.9*	*352.9*
1985	*4500*	*2216.7*	*341.1*	*341.1*
1986	*2918.6*	*1634.7*	*400.9*	*280.2*
1987	*1992.4*	*1096*	*367.4*	*258.4*
1988	*1435.1*	*853.3*	*273.5*	*273.5*
1989	*1769.9*	*556.3*	*455.2*	*263.4*
1990	*119.4*	*505.5*	*342.3*	*224*
1991	*1080.5*	*469*	*316.9*	*175.8*
1992	*751.9*	*372.3*	*233*	*204.8*
1993	*854.9*	*292.3*	*151.7*	*121.6*
1994	*564.4*	*173.6*	*108.6*	*108.6*
1995	*241.1*	*166.6*	*128.4*	*128.4*
1996	*197.6*	*142*	*142*	*142*
1997	*145*	*112.1*	*112.1*	*112.1*
1998	*103.6*	*103.6*	*103.6*	*103.6*

Source: Obtained from calculations reported on pp. 112 of this thesis

Table 7 below provides a breakdown of the utility payoff for price in the mainframe and minicomputer market segments. The figures show the proportion of price performance supplied with respect to that demanded.

Table 7. Market Segment Price Utility Formulation for Mainframe and Minicomputer Segments

	UTILITY FORMULATION PRICE MAINFRAME					UTILITY FORMULATION PRICE MINICOMPUTER			
	14"	**8"**	**5.25"**	**3.5"**		**14"**	**8"**	**5.25"**	**3.5"**
1979	*0.0001773*	*0.0001182*	*0*	*0*	**1979**	*0.0005773*	*0.0010096*	*0*	*0*
1980	*0.0002013*	*0.0001342*	*6.71E-05*	*0*	**1980**	*0.0002222*	*0.0003876*	*0.0019944*	*0*
1981	*0.0003352*	*0.0001495*	*7.48E-05*	*0*	**1981**	*0.0002489*	*0.0003876*	*0.0019944*	*0*
1982	*0.0003991*	*0.0003599*	*0.0001799*	*0*	**1982**	*0.0005532*	*0.0009244*	*0.001823*	*0*
1983	*0.0004458*	*0.0004*	*0.0003*	*0.0001*	**1983**	*0.0007709*	*0.0009244*	*0.0020304*	*0.0009115*
1984	*0.0006531*	*0.000829*	*0.0005321*	*0.0003547*	**1984**	*0.0005657*	*0.0009548*	*0.0021754*	*0.0025*
1985	*0.0007822*	*0.001004*	*0.0008889*	*0.0004444*	**1985**	*0.0011313*	*0.0013984*	*0.0014628*	*0.0009022*
1986	*0.0006937*	*0.0013103*	*0.0013705*	*0.0006853*	**1986**	*0.0004738*	*0.0015668*	*0.0020271*	*0.0012235*
1987	*0.0002816*	*0.0020525*	*0.0026633*	*0.0020076*	**1987**	*0.0001549*	*0.0016861*	*0.0038312*	*0.0036496*
1988	*0.0001959*	*0.0010788*	*0.0037328*	*0.0027873*	**1988**	*0.0001165*	*0.0006414*	*0.0050428*	*0.0046877*
1989	*0.0005128*	*0.0009514*	*0.0037327*	*0.002825*	**1989**	*0.0001612*	*0.000299*	*0.006851*	*0.0075767*
1990	*3.76E-07*	*8.01E-06*	*0.0008367*	*0.0007973*	**1990**	*1.49E-05*	*0.0003178*	*0.007667*	*0.0087827*
1991	*4.16E-05*	*0.0006792*	*0.005974*	*0.0060332*	**1991**	*1.81E-05*	*0.0002948*	*0.0071802*	*0.0097661*
1992	*8.11E-06*	*0.0003812*	*0.0073107*	*0.0084329*	**1992**	*4.01E-06*	*0.0001888*	*0.0078387*	*0.0125313*
1993	*8.32E-07*	*0.0009185*	*0.0050656*	*0.0075278*	**1993**	*2.84E-07*	*0.0003141*	*0.0048314*	*0.01532*
1994	*0*	*0.0011901*	*0.0038167*	*0.0118191*	**1994**	*0*	*0.0003661*	*0.0018754*	*0.0258731*
1995	*0*	*5.61E-05*	*0.0010741*	*0.0176707*	**1995**	*0*	*3.88E-05*	*0.0007422*	*0.0216196*
1996	*0*	*0.0001792*	*0.0153943*	*0.0180406*	**1996**	*0*	*0.0001288*	*0.0135883*	*0.0197699*
1997	*0*	*8.08E-07*	*0.0196259*	*0.0212245*	**1997**	*0*	*6.24E-07*	*0.0151728*	*0.0205865*
1998	*0*	*0*	*0.0245351*	*0.0251786*	**1998**	*0*	*0*	*0.0245351*	*0.0251786*

Source: Obtained from calculations reported on pp. 102 (Equation 2) of this thesis

Similar to Table 7, Table 8 provides a breakdown of the utility payoff for price in the desktop and portable computer market segments.

Table 8. Market Segment Price Utility Formulation for Desktop and Portable Segments

UTILITY FORMULATION PRICE DESKTOP					UTILITY FORMULATION PRICE PORTABLE				
1979	*0*	*0*	*0*	*0*	**1979**	*0*	*0*	*0*	*0*
1980	*0.000222*	*0.000388*	*0.001994*	*0*	**1980**	*0*	*0*	*0*	*0*
1981	*0.000249*	*0.000388*	*0.001994*	*0*	**1981**	*0*	*0*	*0*	*0*
1982	*0.000253*	*0.000422*	*0.002411*	*0*	**1982**	*0*	*0*	*0*	*0*
1983	*0.000234*	*0.000281*	*0.001666*	*0.003*	**1983**	*0*	*0*	*0*	*0*
1984	*0.00025*	*0.000421*	*0.002487*	*0.003385*	**1984**	*0*	*0*	*0*	*0*
1985	*0.00019*	*0.000347*	*0.003177*	*0.005294*	**1985**	*0.00019*	*0.000347*	*0.003177*	*0.005294*
1986	*0.000116*	*0.000451*	*0.003611*	*0.004989*	**1986**	*8.12E-05*	*0.000316*	*0.004349*	*0.004836*
1987	*5.19E-05*	*0.000565*	*0.006257*	*0.006499*	**1987**	*2.59E-05*	*0.000282*	*0.005637*	*0.004637*
1988	*1.07E-05*	*0.000206*	*0.008639*	*0.007485*	**1988**	*3.73E-05*	*0.000206*	*0.008639*	*0.007485*
1989	*0.000132*	*0.000245*	*0.007784*	*0.008131*	**1989**	*7.63E-05*	*0.000142*	*0.009555*	*0.009269*
1990	*1.01E-05*	*0.000215*	*0.009937*	*0.010662*	**1990**	*6.62E-06*	*0.000141*	*0.011608*	*0.011878*
1991	*1.22E-05*	*0.000199*	*0.007011*	*0.011743*	**1991**	*6.77E-06*	*0.000111*	*0.007827*	*0.01147*
1992	*2.51E-06*	*0.000118*	*0.008329*	*0.015675*	**1992**	*2.21E-06*	*0.000104*	*0.008431*	*0.015999*
1993	*1.48E-07*	*0.000163*	*0.003305*	*0.019027*	**1993**	*1.18E-07*	*0.000131*	*0.002649*	*0.018191*
1994	*0*	*0.000229*	*0.001173*	*0.025714*	**1994**	*0*	*0.000229*	*0.001173*	*0.025714*
1995	*0*	*0.000456*	*0.000572*	*0.021902*	**1995**	*0*	*2.99E-05*	*0.000572*	*0.021902*
1996	*0*	*0.001606*	*0.013588*	*0.01977*	**1996**	*0*	*0.000129*	*0.013588*	*0.01977*
1997	*0*	*1.25E-05*	*0.015173*	*0.020586*	**1997**	*0*	*6.24E-07*	*0.015173*	*0.020586*
1998	*0*	*0*	*0.024535*	*0.025179*	**1998**	*0*	*0*	*0.024535*	*0.025179*

Source: Obtained from calculations reported on pp. 102 (Equation 2) of this thesis

Table 9 below provides a breakdown of the utility payoff for size, which is homogenous across all market segments (mainframe, minicomputer, desktop, and portable). Utility is calculated by dividing the disk drive score by the actual size of the lowest available disk drive at that time. (NB: utility formulations for each attribute are normalised on a scale of [0,1] so that the different metrics can be aggregated i.e. capacity (MB), price ($), and size scores).

Table 9. Size Utility Formulation

	UTILIY FORMULATION SIZE			
	14	**8**	**5.25**	**3.5**
1979	*0.0875*	*0.125*	*0*	*0*
1980	*0.0875*	*0.125*	*0*	*0*
1981	*0.07619*	*0.133333*	*0.190476*	*0*
1982	*0.07619*	*0.133333*	*0.190476*	*0*
1983	*0.028571*	*0.114286*	*0.2*	*0.285714*
1984	*0.028571*	*0.114286*	*0.2*	*0.285714*
1985	*0.028571*	*0.114286*	*0.2*	*0.285714*
1986	*0.028571*	*0.114286*	*0.2*	*0.285714*
1987	*0.028571*	*0.114286*	*0.2*	*0.285714*
1988	*0.028571*	*0.114286*	*0.2*	*0.285714*
1989	*0.028571*	*0.114286*	*0.2*	*0.285714*
1990	*0.028571*	*0.114286*	*0.2*	*0.285714*
1991	*0.028571*	*0.114286*	*0.2*	*0.285714*
1992	*0.028571*	*0.114286*	*0.2*	*0.285714*
1993	*0.028571*	*0.114286*	*0.2*	*0.285714*
1994	*0.028571*	*0.114286*	*0.2*	*0.285714*
1995	*0.028571*	*0.114286*	*0.2*	*0.285714*
1996	*0.028571*	*0.114286*	*0.2*	*0.285714*
1997	*0.028571*	*0.114286*	*0.2*	*0.285714*
1998	*0.028571*	*0.114286*	*0.2*	*0.285714*

Source: Obtained from calculations reported on pp. 102 (Equation 2) and 113 of this thesis

Table 10 below provides a breakdown of the simulated model inputs for high and low optimal demand thresholds for each market segment (mainframe, minicomputer, desktop, and portable) in terms of capacity. This enabled qualitative analysis of demand structure. Original optimal demand thresholds documented in Table 1 are scaled by a factor of + and -2 to derive inputs for high and low optimal demand conditions respectively.

Table 10. Demand Structure Thresholds

CAPACITY									
HIGH OPTIMAL DEMAND					LOW OPTIMAL DEMAND				
	MAIN	**MINI**	**DESKY**	**PORT**		**MAIN**	**MINI**	**DESKY**	**PORT**
1979	*462.31*	*26.60*	*0.00*	*0.00*	**1979**	*115.58*	*6.65*	*0.00*	*0.00*
1980	*540.90*	*35.38*	*10.00*	*0.00*	**1980**	*135.22*	*8.84*	*2.50*	*0.00*
1981	*632.85*	*47.05*	*13.30*	*0.00*	**1981**	*158.21*	*11.76*	*3.33*	*0.00*
1982	*740.43*	*62.58*	*17.69*	*0.00*	**1982**	*185.11*	*15.65*	*4.42*	*0.00*
1983	*866.31*	*83.23*	*23.53*	*20.00*	**1983**	*216.58*	*20.81*	*5.88*	*5.00*
1984	*1013.58*	*110.70*	*31.29*	*26.60*	**1984**	*253.40*	*27.67*	*7.82*	*6.65*
1985	*1185.89*	*147.23*	*41.62*	*35.38*	**1985**	*296.47*	*36.81*	*10.40*	*8.84*
1986	*1387.49*	*195.81*	*55.35*	*47.05*	**1986**	*346.87*	*48.95*	*13.84*	*11.76*
1987	*1623.36*	*260.43*	*73.61*	*62.58*	**1987**	*405.84*	*65.11*	*18.40*	*15.65*
1988	*1899.34*	*346.37*	*97.91*	*83.23*	**1988**	*474.83*	*86.59*	*24.48*	*20.81*
1989	*2222.22*	*460.68*	*130.22*	*110.70*	**1989**	*555.56*	*115.17*	*32.55*	*27.67*
1990	*2600.00*	*612.70*	*173.19*	*147.23*	**1990**	*650.00*	*153.18*	*43.30*	*36.81*
1991	*3042.00*	*814.89*	*230.34*	*195.81*	**1991**	*760.50*	*203.72*	*57.58*	*48.95*
1992	*3559.14*	*1083.81*	*306.35*	*260.43*	**1992**	*889.79*	*270.95*	*76.59*	*65.11*
1993	*4164.19*	*1441.47*	*407.45*	*346.37*	**1993**	*1041.05*	*360.37*	*101.86*	*86.59*
1994	*4872.11*	*1917.15*	*541.90*	*460.68*	**1994**	*1218.03*	*479.29*	*135.48*	*115.17*
1995	*5700.36*	*2549.81*	*720.73*	*612.70*	**1995**	*1425.09*	*637.45*	*180.18*	*153.18*
1996	*6669.43*	*3391.25*	*958.58*	*814.89*	**1996**	*1667.36*	*847.81*	*239.64*	*203.72*
1997	*7803.23*	*4510.36*	*1274.91*	*1083.81*	**1997**	*1950.81*	*1127.59*	*318.73*	*270.95*
1998	*9129.78*	*5998.78*	*1695.62*	*1441.47*	**1998**	*2282.44*	*1499.69*	*423.91*	*360.37*

Source: Obtained from calculations reported on pp. 115 of this thesis

Table 11 below provides a breakdown of the simulated model inputs for high and low growth rates in absorptive capacity (γ_{ik}) for each market segment (mainframe, minicomputer, desktop, and portable). This enabled qualitative analysis of development dynamics in terms of absorptive capacity. Growth rates in absorptive capacity are positively and negatively scaled by a factor of + and – 2 to obtain new thresholds. The original growth rates in absorptive capacity are taken from Christensen (re Figure 6.B p110) with scaled high and low growth rates given in parentheses: Mainframe = 1.17 (1.34; 1.085); and minicomputer, desktop, and portable 1.33 (1.66; 1.165).

Table 11. Development Dynamics Absorptive Capacity

HIGH GROWTH RATES IN ABSORPTIVE CAPACITY					LOW GROWTH RATES IN ABSORPTIVE CAPACITY				
	MAIN	**MINI**	**DESK**	**PORT**		**MAIN**	**MINI**	**DESK**	**PORT**
1979	*231*	*13*	*0*	*0*	**1979**	*231*	*13*	*0*	*0*
1980	*310*	*22*	*5*	*0*	**1980**	*251*	*15*	*5*	*0*
1981	*415*	*37*	*8*	*0*	**1981**	*272*	*18*	*6*	*0*
1982	*556*	*61*	*14*	*0*	**1982**	*295*	*21*	*7*	*0*
1983	*745*	*101*	*23*	*10*	**1983**	*320*	*24*	*8*	*10*
1984	*999*	*168*	*38*	*17*	**1984**	*348*	*29*	*9*	*12*
1985	*1338*	*278*	*63*	*28*	**1985**	*377*	*33*	*11*	*14*
1986	*1793*	*462*	*105*	*46*	**1986**	*409*	*39*	*13*	*16*
1987	*2403*	*767*	*174*	*76*	**1987**	*444*	*45*	*15*	*18*
1988	*3220*	*1273*	*288*	*126*	**1988**	*482*	*53*	*17*	*21*
1989	*4315*	*2113*	*479*	*209*	**1989**	*523*	*61*	*20*	*25*
1990	*5782*	*3508*	*794*	*347*	**1990**	*567*	*71*	*23*	*29*
1991	*7747*	*5823*	*1319*	*577*	**1991**	*615*	*83*	*27*	*34*
1992	*10382*	*9666*	*2189*	*957*	**1992**	*668*	*97*	*31*	*40*
1993	*13911*	*16046*	*3634*	*1589*	**1993**	*724*	*113*	*36*	*46*
1994	*18641*	*26636*	*6032*	*2637*	**1994**	*786*	*131*	*42*	*54*
1995	*24979*	*44216*	*10014*	*4378*	**1995**	*853*	*153*	*49*	*63*
1996	*33472*	*73399*	*16623*	*7268*	**1996**	*925*	*178*	*58*	*73*
1997	*44852*	*121842*	*27594*	*12065*	**1997**	*1004*	*208*	*67*	*85*
1998	*60102*	*202258*	*45805*	*20027*	**1998**	*1089*	*242*	*78*	*99*

Source: Obtained from calculations reported on pp. 114–115 of this thesis

Similar to Table 11, Table 12 provides a breakdown of the simulated model inputs for high and low growth rates in technological improvement (α_{jk}) for each disk drive (14-inch, 8-inch, 5.25-inch, and 3.5-inch). This enabled qualitative analysis of development dynamics in terms of technological improvement.

Table 12. Development Dynamics Technological Improvement

HIGH GROWTH RATES IN TECHNOLOGICAL IMPROVEMENT					LOW GROWTH RATES IN TECHNOLOGICAL IMPROVEMENT				
	14	**8**	**5.25**	**3.5**		**14**	**8**	**5.25**	**3.5**
1979	*190*	*27*	*0*	*0*	**1979**	*190*	*27*	*0*	*0*
1980	*278*	*58*	*21*	*0*	**1980**	*212*	*35*	*21*	*0*
1981	*406*	*124*	*44*	*0*	**1981**	*237*	*45*	*27*	*0*
1982	*593*	*265*	*93*	*0*	**1982**	*264*	*57*	*34*	*0*
1983	*865*	*566*	*194*	*19*	**1983**	*294*	*74*	*44*	*19*
1984	*1263*	*1212*	*408*	*39*	**1984**	*328*	*95*	*55*	*24*
1985	*1844*	*2593*	*858*	*83*	**1985**	*366*	*122*	*71*	*30*
1986	*2693*	*5550*	*1801*	*176*	**1986**	*408*	*156*	*90*	*39*
1987	*3931*	*11876*	*3782*	*374*	**1987**	*455*	*201*	*115*	*50*
1988	*5740*	*25415*	*7943*	*792*	**1988**	*507*	*258*	*147*	*64*
1989	*8380*	*54388*	*16680*	*1680*	**1989**	*566*	*331*	*187*	*81*
1990	*12234*	*116390*	*35028*	*3561*	**1990**	*631*	*426*	*238*	*104*
1991	*17862*	*249074*	*73558*	*7548*	**1991**	*703*	*547*	*304*	*133*
1992	*26079*	*533019*	*154472*	*16003*	**1992**	*784*	*703*	*388*	*171*
1993	*38075*	*1140661*	*324392*	*33926*	**1993**	*874*	*904*	*494*	*218*
1994	*55590*	*2441015*	*681223*	*71923*	**1994**	*975*	*1161*	*630*	*280*
1995	*81161*	*5223771*	*1430569*	*152476*	**1995**	*1087*	*1492*	*803*	*358*
1996	*118495*	*11178870*	*3004194*	*323250*	**1996**	*1212*	*1917*	*1024*	*458*
1997	*173002*	*23922782*	*6308808*	*685289*	**1997**	*1351*	*2464*	*1306*	*586*
1998	*252583*	*51194754*	*13248497*	*1452813*	**1998**	*1506*	*3166*	*1665*	*750*

Source: Obtained from calculations reported on pp. 114–115 of this thesis

Table 13 below provides a breakdown of the utility payoff for mainframe and minicomputer market segments under simulated conditions of higher positive development asymmetry i.e. where rates of technological improvement (α_{jk}) are faster than absorptive capacity (γ_{ik}). We use higher rates of technological improvement and lower rates of absorptive capacity from (Tables 11 and 12) to compute new utility values.

Table 13. Positive Development Asymmetry Utility Formulations for Mainframe and Minicomputer

UTILITY FORMULATION MAINFRAME					UTILITY FORMULATION MINICOMPUTER				
	14	**8**	**5.25**	**3.5**		**14**	**8**	**5.25**	**3.5**
1979	*0.82*	*0.12*	*0.00*	*0.00*	**1979**	*1.00*	*1.00*	*0.00*	*0.00*
1980	*1.00*	*0.23*	*0.08*	*0.00*	**1980**	*1.00*	*1.00*	*1.00*	*0.00*
1981	*1.00*	*0.45*	*0.16*	*0.00*	**1981**	*1.00*	*1.00*	*1.00*	*0.00*
1982	*1.00*	*0.90*	*0.31*	*0.00*	**1982**	*1.00*	*1.00*	*1.00*	*0.00*
1983	*1.00*	*1.00*	*0.61*	*0.06*	**1983**	*1.00*	*1.00*	*1.00*	*0.76*
1984	*1.00*	*1.00*	*1.00*	*0.11*	**1984**	*1.00*	*1.00*	*1.00*	*1.00*
1985	*1.00*	*1.00*	*1.00*	*0.22*	**1985**	*1.00*	*1.00*	*1.00*	*1.00*
1986	*1.00*	*1.00*	*1.00*	*0.43*	**1986**	*1.00*	*1.00*	*1.00*	*1.00*
1987	*1.00*	*1.00*	*1.00*	*0.84*	**1987**	*1.00*	*1.00*	*1.00*	*1.00*
1988	*1.00*	*1.00*	*1.00*	*1.00*	**1988**	*1.00*	*1.00*	*1.00*	*1.00*
1989	*1.00*	*1.00*	*1.00*	*1.00*	**1989**	*1.00*	*1.00*	*1.00*	*1.00*
1990	*1.00*	*1.00*	*1.00*	*1.00*	**1990**	*1.00*	*1.00*	*1.00*	*1.00*
1991	*1.00*	*1.00*	*1.00*	*1.00*	**1991**	*1.00*	*1.00*	*1.00*	*1.00*
1992	*1.00*	*1.00*	*1.00*	*1.00*	**1992**	*1.00*	*1.00*	*1.00*	*1.00*
1993	*1.00*	*1.00*	*1.00*	*1.00*	**1993**	*1.00*	*1.00*	*1.00*	*1.00*
1994	*1.00*	*1.00*	*1.00*	*1.00*	**1994**	*1.00*	*1.00*	*1.00*	*1.00*
1995	*1.00*	*1.00*	*1.00*	*1.00*	**1995**	*1.00*	*1.00*	*1.00*	*1.00*
1996	*1.00*	*1.00*	*1.00*	*1.00*	**1996**	*1.00*	*1.00*	*1.00*	*1.00*
1997	*1.00*	*1.00*	*1.00*	*1.00*	**1997**	*1.00*	*1.00*	*1.00*	*1.00*
1998	*1.00*	*1.00*	*1.00*	*1.00*	**1998**	*1.00*	*1.00*	*1.00*	*1.00*

Source: Obtained from calculations reported on pp. 102 (Equation 2) of this thesis

Similar to Table 13, Table 14 provides a breakdown of the utility payoff for desktop and portable computer market segments under simulated conditions of higher positive development asymmetry.

Table 14. Positive Development Asymmetry Utility Formulations for Desktop and Portable

UTILITY FORMULATION DESKTOP					UTILITY FORMULATION PORTABLE				
1979	*0.00*	*0.00*	*0.00*	*0.00*	**1979**	*0.00*	*0.00*	*0.00*	*0.00*
1980	*1.00*	*1.00*	*1.00*	*0.00*	**1980**	*0.00*	*0.00*	*0.00*	*0.00*
1981	*1.00*	*1.00*	*1.00*	*0.00*	**1981**	*0.00*	*0.00*	*0.00*	*0.00*
1982	*1.00*	*1.00*	*1.00*	*0.00*	**1982**	*0.00*	*0.00*	*0.00*	*0.00*
1983	*1.00*	*1.00*	*1.00*	*1.00*	**1983**	*1.00*	*1.00*	*1.00*	*1.00*
1984	*1.00*	*1.00*	*1.00*	*1.00*	**1984**	*1.00*	*1.00*	*1.00*	*1.00*
1985	*1.00*	*1.00*	*1.00*	*1.00*	**1985**	*1.00*	*1.00*	*1.00*	*1.00*
1986	*1.00*	*1.00*	*1.00*	*1.00*	**1986**	*1.00*	*1.00*	*1.00*	*1.00*
1987	*1.00*	*1.00*	*1.00*	*1.00*	**1987**	*1.00*	*1.00*	*1.00*	*1.00*
1988	*1.00*	*1.00*	*1.00*	*1.00*	**1988**	*1.00*	*1.00*	*1.00*	*1.00*
1989	*1.00*	*1.00*	*1.00*	*1.00*	**1989**	*1.00*	*1.00*	*1.00*	*1.00*
1990	*1.00*	*1.00*	*1.00*	*1.00*	**1990**	*1.00*	*1.00*	*1.00*	*1.00*
1991	*1.00*	*1.00*	*1.00*	*1.00*	**1991**	*1.00*	*1.00*	*1.00*	*1.00*
1992	*1.00*	*1.00*	*1.00*	*1.00*	**1992**	*1.00*	*1.00*	*1.00*	*1.00*
1993	*1.00*	*1.00*	*1.00*	*1.00*	**1993**	*1.00*	*1.00*	*1.00*	*1.00*
1994	*1.00*	*1.00*	*1.00*	*1.00*	**1994**	*1.00*	*1.00*	*1.00*	*1.00*
1995	*1.00*	*1.00*	*1.00*	*1.00*	**1995**	*1.00*	*1.00*	*1.00*	*1.00*
1996	*1.00*	*1.00*	*1.00*	*1.00*	**1996**	*1.00*	*1.00*	*1.00*	*1.00*
1997	*1.00*	*1.00*	*1.00*	*1.00*	**1997**	*1.00*	*1.00*	*1.00*	*1.00*
1998	*1.00*	*1.00*	*1.00*	*1.00*	**1998**	*1.00*	*1.00*	*1.00*	*1.00*

Source: Obtained from calculations reported on pp. 102 (Equation 2) of this thesis

Table 15 below provides a breakdown of the utility payoff for mainframe and minicomputer market segments under simulated conditions of higher negative development asymmetry i.e. where rates of absorptive capacity (γ_{ik}) are faster than technological improvement (α_{jk}). We use higher rates of absorptive capacity and lower rates of technological development from Tables 11 and 12 to compute new utility values.

Table 15. Negative Development Asymmetry Utility Formulations for Mainframe and Minicomputer

UTILITY FORMULATION MAINFRAME					UTILITY FORMULATION MINICOMPUTER				
	14	**8**	**5.25**	**3.5**		**14**	**8**	**5.25**	**3.5**
1979	*0.82*	*0.12*	*0.00*	*0.00*	**1979**	*1.00*	*1.00*	*0.00*	*0.00*
1980	*0.69*	*0.11*	*0.07*	*0.00*	**1980**	*1.00*	*1.00*	*0.95*	*0.00*
1981	*0.57*	*0.11*	*0.06*	*0.00*	**1981**	*1.00*	*1.00*	*0.73*	*0.00*
1982	*0.47*	*0.10*	*0.06*	*0.00*	**1982**	*1.00*	*0.94*	*0.56*	*0.00*
1983	*0.39*	*0.10*	*0.06*	*0.02*	**1983**	*1.00*	*0.73*	*0.43*	*0.18*
1984	*0.33*	*0.09*	*0.06*	*0.02*	**1984**	*1.00*	*0.56*	*0.33*	*0.14*
1985	*0.27*	*0.09*	*0.05*	*0.02*	**1985**	*1.00*	*0.44*	*0.25*	*0.11*
1986	*0.23*	*0.09*	*0.05*	*0.02*	**1986**	*0.88*	*0.34*	*0.20*	*0.08*
1987	*0.19*	*0.08*	*0.05*	*0.02*	**1987**	*0.59*	*0.26*	*0.15*	*0.06*
1988	*0.16*	*0.08*	*0.05*	*0.02*	**1988**	*0.40*	*0.20*	*0.12*	*0.05*
1989	*0.13*	*0.08*	*0.04*	*0.02*	**1989**	*0.27*	*0.16*	*0.09*	*0.04*
1990	*0.11*	*0.07*	*0.04*	*0.02*	**1990**	*0.18*	*0.12*	*0.07*	*0.03*
1991	*0.09*	*0.07*	*0.04*	*0.02*	**1991**	*0.12*	*0.09*	*0.05*	*0.02*
1992	*0.08*	*0.07*	*0.04*	*0.02*	**1992**	*0.08*	*0.07*	*0.04*	*0.02*
1993	*0.06*	*0.06*	*0.04*	*0.02*	**1993**	*0.05*	*0.06*	*0.03*	*0.01*
1994	*0.05*	*0.06*	*0.03*	*0.01*	**1994**	*0.04*	*0.04*	*0.02*	*0.01*
1995	*0.04*	*0.06*	*0.03*	*0.01*	**1995**	*0.02*	*0.03*	*0.02*	*0.01*
1996	*0.04*	*0.06*	*0.03*	*0.01*	**1996**	*0.02*	*0.03*	*0.01*	*0.01*
1997	*0.03*	*0.05*	*0.03*	*0.01*	**1997**	*0.01*	*0.02*	*0.01*	*0.00*
1998	*0.03*	*0.05*	*0.03*	*0.01*	**1998**	*0.01*	*0.02*	*0.01*	*0.00*

Source: Obtained from calculations reported on pp. 102 (Equation 2) of this thesis

Similar to Table 15, Table 16 provides a breakdown of the utility payoff for desktop and portable computer market segments under simulated conditions of higher negative development asymmetry.

Table 16. Negative Development Asymmetry Utility Formulations for Desktop and Portable

UTILITY FORMULATION DESKTOP					UTILITY FORMULATION PORTABLE				
1979	*0.00*	*0.00*	*0.00*	*0.00*	**1979**	*0.00*	*0.00*	*0.00*	*0.00*
1980	*1.00*	*1.00*	*1.00*	*0.00*	**1980**	*0.00*	*0.00*	*0.00*	*0.00*
1981	*1.00*	*1.00*	*1.00*	*0.00*	**1981**	*0.00*	*0.00*	*0.00*	*0.00*
1982	*1.00*	*1.00*	*1.00*	*0.00*	**1982**	*0.00*	*0.00*	*0.00*	*0.00*
1983	*1.00*	*1.00*	*1.00*	*0.81*	**1983**	*1.00*	*1.00*	*1.00*	*1.00*
1984	*1.00*	*1.00*	*1.00*	*0.62*	**1984**	*1.00*	*1.00*	*1.00*	*1.00*
1985	*1.00*	*1.00*	*1.00*	*0.48*	**1985**	*1.00*	*1.00*	*1.00*	*1.00*
1986	*1.00*	*1.00*	*0.86*	*0.37*	**1986**	*1.00*	*1.00*	*1.00*	*0.85*
1987	*1.00*	*1.00*	*0.66*	*0.29*	**1987**	*1.00*	*1.00*	*1.00*	*0.65*
1988	*1.00*	*0.89*	*0.51*	*0.22*	**1988**	*1.00*	*1.00*	*1.00*	*0.50*
1989	*1.00*	*0.69*	*0.39*	*0.17*	**1989**	*1.00*	*1.00*	*0.89*	*0.39*
1990	*0.79*	*0.54*	*0.30*	*0.13*	**1990**	*1.00*	*1.00*	*0.69*	*0.30*
1991	*0.53*	*0.41*	*0.23*	*0.10*	**1991**	*1.00*	*0.95*	*0.53*	*0.23*
1992	*0.36*	*0.32*	*0.18*	*0.08*	**1992**	*0.82*	*0.73*	*0.40*	*0.18*
1993	*0.24*	*0.25*	*0.14*	*0.06*	**1993**	*0.55*	*0.57*	*0.31*	*0.14*
1994	*0.16*	*0.19*	*0.10*	*0.05*	**1994**	*0.37*	*0.44*	*0.24*	*0.11*
1995	*0.11*	*0.15*	*0.08*	*0.04*	**1995**	*0.25*	*0.34*	*0.18*	*0.08*
1996	*0.07*	*0.12*	*0.06*	*0.03*	**1996**	*0.17*	*0.26*	*0.14*	*0.06*
1997	*0.05*	*0.09*	*0.05*	*0.02*	**1997**	*0.11*	*0.20*	*0.11*	*0.05*
1998	*0.03*	*0.07*	*0.04*	*0.02*	**1998**	*0.08*	*0.16*	*0.08*	*0.04*

Source: Obtained from calculations reported on pp. 102 (Equation 2) of this thesis

Appendix 2. Focus Group Survey

The aim of the survey is to specify attribute ranking, attribute structure, and preferences for 4 different market segments, namely: *Mainframe Computer*, *Minicomputer, Desktop Computer,* and *Portable Computer Segments*. Preferences refer to the degree of preference a market segment places on one attribute over other attributes. (ALL ANSWERS PROVIDED ARE BASED ON PERSONAL JUDGMENT AND EXPERTISE).

STEP 1.***Attribute Ranking and Structure*******

In your opinion, what would have been the essential attributes and rank order of such attributes that market segments trade-off? We propose that there are 3 main attributes that customers consider in their adoption of HDDs:

1. Capacity
2. Size (Form Factor)
3. Price
4. …
5. …

If there are any other attributes that you consider important to a market segment's adoption decision then please specify any additional attributes that you believe should be included in the above list. Once a list is formalised, examine the list of attributes and rank them in order of their importance for each market segment.

New innovations of disk drive that emerge over time reduce their form factor from 14-inch – 8-inch – 5.25-inch – 3.5-inch. In your opinion, what would be the discount rate applied to a larger sized disk drive across market segments as new smaller sized disk drives emerged? For example, if size is an important factor then customers will discount larger sized drives as new smaller disk drives are introduced.

STEP 2.***Attribute Importance*******

Examine the table below that includes each of the attributes specified above, how important is each of these factors from the perspective of each market segment based upon your expert judgements? In other words, how important is one attribute relative to the others?

You have a total of 100 points to allocate to the specified attributes for each market segment. If you believe one attribute is twice as important as another for a specific market segment, then you will assign it twice as many points (Please include any additional attributes in the blank spaces in the "Attribute" column).

Market Segment	**Attribute**	**Points Allocation**
Mainframe	Capacity	
	Size (Form Factor)	
	Price	
	…	
	…	
Mini-computer	Capacity	
	Size (Form Factor)	
	Price	
	…	
	…	
Desktop	Capacity	
	Size (Form Factor)	
	Price	
	…	
	…	
Portable	Capacity	
	Size (Form Factor)	
	Price	
	…	
	…	

Appendix 3. Adoption Probabilities

Table 1 below provides a breakdown of the aggregate market adoption probabilities (i.e. across all segments) for each disk drive innovation. The figures show the percentage of total market adopters for each disk drive in each year.

Table 1. Aggregate Level Adoption Probabilities

AGGREGATE LEVEL ADOPTION PROBABILITIES				
	14	**8**	**5.25**	**3.5**
1979	*73.7%*	*26.3%*	*0.0%*	*0.0%*
1980	*72.1%*	*26.3%*	*1.6%*	*0.0%*
1981	*14.4%*	*2.0%*	*83.6%*	*0.0%*
1982	*14.5%*	*3.8%*	*81.7%*	*0.0%*
1983	*10.1%*	*1.8%*	*13.2%*	*74.9%*
1984	*5.5%*	*2.8%*	*11.9%*	*79.9%*
1985	*2.0%*	*2.7%*	*10.1%*	*85.1%*
1986	*0.9%*	*5.8%*	*23.9%*	*69.4%*
1987	*0.3%*	*4.1%*	*35.2%*	*60.3%*
1988	*0.2%*	*1.5%*	*53.0%*	*45.2%*
1989	*0.2%*	*1.1%*	*39.8%*	*58.9%*
1990	*0.1%*	*0.6%*	*36.3%*	*63.0%*
1991	*0.1%*	*0.4%*	*21.0%*	*78.5%*
1992	*0.1%*	*0.2%*	*15.2%*	*84.5%*
1993	*0.1%*	*0.2%*	*1.7%*	*98.1%*
1994	*0.0%*	*0.2%*	*0.6%*	*99.2%*
1995	*0.0%*	*0.1%*	*0.3%*	*99.6%*
1996	*0.0%*	*0.0%*	*15.5%*	*84.5%*
1997	*0.0%*	*0.0%*	*15.7%*	*84.3%*
1998	*0.0%*	*0.0%*	*27.0%*	*73.0%*
AVERAGE	**12.95%**	**4.21%**	**25.65%**	**77.40%**

Source: Obtained from calculations reported on pp. 102 (Equation 3A) of this thesis

Table 2 below provides a breakdown of the aggregate market adoption probabilities (i.e. across all segments) for each disk drive innovation under simulated conditions of preference convergence and preference isolation. The figures in the table below show the percentage of total market adopters for each disk drive in each year under conditions of isolation and convergence for each disk drive. The highlighted percentages illustrate points in time where disk drive innovations co-existed in the market with equal adoption probability i.e. consumers were indifferent between disk drive alternatives.

Table 2. Aggregate Adoption Probabilities for Convergence and Isolation

	PERFERENCE ISOLATION				**PREFERENCE CONVERGENCE**			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*96.1%*	*3.9%*	*0.0%*	*0.0%*	*99.6%*	*0.4%*	*0.0%*	*0.0%*
1980	*90.0%*	*4.7%*	*5.3%*	*0.0%*	*98.6%*	*0.7%*	*0.7%*	*0.0%*
1981	*40.3%*	*0.8%*	*58.9%*	*0.0%*	*99.1%*	*0.5%*	*0.3%*	*0.0%*
1982	*48.0%*	*0.9%*	*51.1%*	*0.0%*	*99.2%*	*0.6%*	*0.2%*	*0.0%*
1983	*57.0%*	*0.5%*	*2.2%*	*40.3%*	*98.3%*	*1.1%*	*0.3%*	*0.3%*
1984	*62.8%*	*1.6%*	*4.2%*	*31.4%*	*97.1%*	*2.4%*	*0.3%*	*0.2%*
1985	*32.4%*	*5.3%*	*3.5%*	*58.7%*	*91.0%*	*8.4%*	*0.3%*	*0.2%*
1986	*18.4%*	*27.7%*	*6.3%*	*47.6%*	*70.3%*	*29.3%*	*0.4%*	*0.1%*
1987	*9.3%*	*46.2%*	*14.8%*	*29.8%*	*49.8%*	*49.8%*	*0.4%*	*0.1%*
1988	*7.7%*	*31.0%*	*40.3%*	*21.0%*	*49.7%*	*49.7%*	*0.5%*	*0.1%*
1989	*6.2%*	*23.8%*	*37.6%*	*32.4%*	*49.5%*	*49.5%*	*0.8%*	*0.1%*
1990	*3.3%*	*12.1%*	*54.7%*	*30.0%*	*49.0%*	*49.0%*	*1.7%*	*0.2%*
1991	*0.9%*	*3.1%*	*47.7%*	*48.2%*	*44.4%*	*44.4%*	*10.7%*	*0.4%*
1992	*0.4%*	*1.3%*	*48.5%*	*49.8%*	*34.4%*	*34.4%*	*30.6%*	*0.6%*
1993	*0.3%*	*0.6%*	*3.8%*	*95.3%*	*32.8%*	*32.8%*	*32.8%*	*1.5%*
1994	*0.0%*	*0.7%*	*1.7%*	*97.7%*	*0.0%*	*46.6%*	*46.6%*	*6.9%*
1995	*0.0%*	*0.3%*	*1.0%*	*98.7%*	*0.0%*	*30.0%*	*51.5%*	*18.5%*
1996	*0.0%*	*0.0%*	*23.7%*	*76.3%*	*0.0%*	*0.0%*	*59.9%*	*40.1%*
1997	*0.0%*	*0.0%*	*19.5%*	*80.5%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
1998	*0.0%*	*0.0%*	*31.8%*	*68.2%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
AVERAGE	**31.5%**	**8.7%**	**24.0%**	**56.6%**	**70.8%**	**22.6%**	**17.8%**	**11.3%**

Source: Obtained from calculations reported on pp. 102 (Equation 3A) of this thesis

Table 3 below provides a breakdown of the market segment adoption probabilities for mainframe and minicomputer segments under conditions of preference convergence. The figures show the individual market's adoption probabilities for each disk drive innovation in each year.

Table 3. Market Segment Adoption Probabilities for Convergence – Mainframe and Minicomputer

	MAINFRAME				MINICOMPUTER			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.0%*	*0.0%*
1980	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*	*0.0%*
1981	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*46.1%*	*46.1%*	*7.8%*	*0.0%*
1982	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*54.0%*	*44.7%*	*1.3%*	*0.0%*
1983	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*49.7%*	*49.7%*	*0.4%*	*0.2%*
1984	*99.9%*	*0.0%*	*0.0%*	*0.0%*	*49.9%*	*49.9%*	*0.1%*	*0.1%*
1985	*99.6%*	*0.4%*	*0.0%*	*0.0%*	*49.9%*	*49.9%*	*0.1%*	*0.0%*
1986	*91.3%*	*8.7%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.1%*	*0.0%*
1987	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*49.9%*	*49.9%*	*0.1%*	*0.0%*
1988	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*49.9%*	*49.9%*	*0.3%*	*0.0%*
1989	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*49.6%*	*49.6%*	*0.8%*	*0.0%*
1990	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*47.0%*	*47.0%*	*5.9%*	*0.0%*
1991	*49.7%*	*49.7%*	*0.6%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*	*0.0%*
1992	*37.4%*	*37.4%*	*25.2%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*	*0.1%*
1993	*33.3%*	*33.3%*	*33.3%*	*0.0%*	*33.0%*	*33.0%*	*33.0%*	*1.0%*
1994	*0.0%*	*49.9%*	*49.9%*	*0.1%*	*0.0%*	*37.0%*	*37.0%*	*26.0%*
1995	*0.0%*	*13.1%*	*84.5%*	*2.4%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*
1996	*0.0%*	*0.0%*	*81.9%*	*18.1%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
1997	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
1998	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
AVERAGE	**74.1%**	**20.7%**	**19.8%**	**7.5%**	**45.3%**	**38.9%**	**19.5%**	**13.2%**

Source: Obtained from calculations and parameters reported on pp. 102 (Equation 3B) and 114 of this thesis

Similar to Table 3, Table 4 provides a breakdown of the market segment adoption probabilities for desktop and portable segments under simulated conditions of preference convergence.

Table 4. Market Segment Adoption Probabilities for Convergence – Desktop and Portable

	DESKTOP				**PORTABLE**			
1979	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1980	*33.3%*	*33.3%*	*33.3%*	*0.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1981	*33.3%*	*33.3%*	*33.3%*	*0.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1982	*33.3%*	*33.3%*	*33.3%*	*0.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1983	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1984	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1985	*26.0%*	*26.0%*	*26.0%*	*22.1%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1986	*32.5%*	*32.5%*	*32.5%*	*2.4%*	*30.6%*	*30.6%*	*30.6%*	*8.1%*
1987	*32.4%*	*32.4%*	*32.4%*	*2.7%*	*30.1%*	*30.1%*	*30.1%*	*9.6%*
1988	*33.0%*	*33.0%*	*33.0%*	*1.1%*	*32.2%*	*32.2%*	*32.2%*	*3.5%*
1989	*32.5%*	*32.5%*	*32.5%*	*2.4%*	*30.5%*	*30.5%*	*30.5%*	*8.4%*
1990	*31.0%*	*31.0%*	*31.0%*	*7.1%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1991	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1992	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1993	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*25.0%*
1994	*0.0%*	*33.3%*	*33.3%*	*33.3%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*
1995	*0.0%*	*33.3%*	*33.3%*	*33.3%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*
1996	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
1997	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
1998	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
AVERAGE	**29.2%**	**26.5%**	**33.1%**	**23.7%**	**26.6%**	**24.5%**	**31.1%**	**26.3%**

Source: Obtained from calculations and parameters reported on pp. 102 (Equation 3B) and 114 of this thesis

Table 5 below provides a breakdown of the market segment adoption probabilities for mainframe and minicomputer segments under conditions of preference isolation. The figures show the individual market's adoption probabilities for each disk drive innovation in each year.

Table 5. Market Segment Adoption Probabilities for Isolation – Mainframe and Minicomputer

	MAINFRAME				**MINICOMPUTER**			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.0%*	*0.0%*
1980	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*	*0.0%*
1981	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*46.1%*	*46.1%*	*7.8%*	*0.0%*
1982	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*54.0%*	*44.7%*	*1.3%*	*0.0%*
1983	*100.0%*	*0.0%*	*0.0%*	*0.0%*	*49.7%*	*49.7%*	*0.4%*	*0.2%*
1984	*99.9%*	*0.0%*	*0.0%*	*0.0%*	*49.9%*	*49.9%*	*0.1%*	*0.1%*
1985	*99.6%*	*0.4%*	*0.0%*	*0.0%*	*49.9%*	*49.9%*	*0.1%*	*0.0%*
1986	*91.3%*	*8.7%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.1%*	*0.0%*
1987	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*49.9%*	*49.9%*	*0.1%*	*0.0%*
1988	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*49.9%*	*49.9%*	*0.3%*	*0.0%*
1989	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*49.6%*	*49.6%*	*0.8%*	*0.0%*
1990	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*47.0%*	*47.0%*	*5.9%*	*0.0%*
1991	*49.7%*	*49.7%*	*0.6%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*	*0.0%*
1992	*37.4%*	*37.4%*	*25.2%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*	*0.1%*
1993	*33.3%*	*33.3%*	*33.3%*	*0.0%*	*33.0%*	*33.0%*	*33.0%*	*1.0%*
1994	*0.0%*	*49.9%*	*49.9%*	*0.1%*	*0.0%*	*37.0%*	*37.0%*	*26.0%*
1995	*0.0%*	*13.1%*	*84.5%*	*2.4%*	*0.0%*	*33.3%*	*33.3%*	*33.3%*
1996	*0.0%*	*0.0%*	*81.9%*	*18.1%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
1997	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
1998	*0.0%*	*0.0%*	*50.0%*	*50.0%*	*0.0%*	*0.0%*	*50.0%*	*50.0%*
AVERAGE	**74.1%**	**20.7%**	**19.8%**	**7.5%**	**45.3%**	**38.9%**	**19.5%**	**13.2%**

Source: Obtained from calculations and parameters reported on pp. 102 (Equation 3B) and 115 of this thesis

Similar to Table 5, Table 6 provides a breakdown of the market segment adoption probabilities for desktop and portable segments under simulated conditions of preference isolation.

Table 6. Market Segment Adoption Probabilities for Isolation – Desktop and Portable

	DESKTOP				**PORTABLE**			
1979	*25.0%*	*25.0%*	*25.0%*	*25.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1980	*0.0%*	*0.0%*	*99.9%*	*0.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1981	*0.0%*	*0.0%*	*99.9%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*	*0.0%*
1982	*0.0%*	*0.0%*	*100.0%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*	*0.0%*
1983	*0.0%*	*0.0%*	*1.2%*	*98.8%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1984	*0.0%*	*0.0%*	*6.6%*	*93.4%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1985	*0.0%*	*0.0%*	*1.8%*	*98.2%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1986	*0.0%*	*0.0%*	*5.9%*	*94.0%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1987	*0.0%*	*0.0%*	*40.8%*	*59.2%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1988	*0.0%*	*0.0%*	*79.2%*	*20.8%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1989	*0.0%*	*0.0%*	*39.5%*	*60.5%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1990	*0.0%*	*0.0%*	*33.6%*	*66.4%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1991	*0.0%*	*0.0%*	*1.7%*	*98.2%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1992	*0.0%*	*0.0%*	*0.9%*	*99.1%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1993	*0.0%*	*0.0%*	*0.0%*	*100.0%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1994	*0.0%*	*0.0%*	*0.0%*	*100.0%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1995	*0.0%*	*0.0%*	*0.0%*	*100.0%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1996	*0.0%*	*0.0%*	*4.2%*	*95.8%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1997	*0.0%*	*0.0%*	*6.7%*	*93.3%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
1998	*0.0%*	*0.0%*	*43.6%*	*56.4%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*
AVERAGE	**1.7%**	**1.3%**	**29.8%**	**83.4%**	**0.7%**	**10.7%**	**14.0%**	**95.0%**

Source: Obtained from calculations and parameters reported on pp. 102 (Equation 3B) and 115 of this thesis

Table 7 below provides a breakdown of the aggregate market adoption probabilities (i.e. across all segments) for each disk drive innovation under simulated conditions of high (HOD) and low optimal demand (LOD). We use the figures for HOD and LOD as documented in Appendix 1 (Table 10) for qualitative analysis. The percentages show the proportion of total market adopters for each disk drive innovation.

Table 7. Aggregate Adoption Probabilities Optimal Demand

	AGGREGATE ADOPTION PROBABILITIES							
	LOW OPTIMAL DEMAND				HIGH OPTIMAL DEMAND			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*64.6%*	*35.4%*	*0.0%*	*0.0%*	*73.7%*	*26.3%*	*0.0%*	*0.0%*
1980	*64.1%*	*34.0%*	*1.9%*	*0.0%*	*80.4%*	*18.4%*	*1.1%*	*0.0%*
1981	*8.3%*	*2.0%*	*89.8%*	*0.0%*	*32.8%*	*1.3%*	*65.9%*	*0.0%*
1982	*6.7%*	*3.3%*	*90.0%*	*0.0%*	*33.8%*	*2.3%*	*64.0%*	*0.0%*
1983	*3.2%*	*1.4%*	*15.9%*	*79.5%*	*27.7%*	*1.3%*	*10.7%*	*60.4%*
1984	*1.7%*	*2.5%*	*14.0%*	*81.9%*	*13.7%*	*4.1%*	*10.5%*	*71.7%*
1985	*0.7%*	*2.9%*	*11.7%*	*84.7%*	*5.5%*	*3.9%*	*9.6%*	*81.0%*
1986	*0.4%*	*3.9%*	*25.3%*	*70.4%*	*3.5%*	*6.4%*	*22.3%*	*67.8%*
1987	*0.2%*	*2.1%*	*37.8%*	*59.9%*	*1.1%*	*5.0%*	*35.2%*	*58.7%*
1988	*0.1%*	*0.7%*	*55.8%*	*43.3%*	*0.6%*	*1.9%*	*54.6%*	*42.8%*
1989	*0.1%*	*0.6%*	*42.4%*	*56.8%*	*0.5%*	*1.6%*	*41.6%*	*56.3%*
1990	*0.1%*	*0.4%*	*36.7%*	*62.9%*	*0.3%*	*1.1%*	*36.3%*	*62.3%*
1991	*0.1%*	*0.3%*	*20.6%*	*79.1%*	*0.2%*	*0.6%*	*24.2%*	*75.0%*
1992	*0.1%*	*0.2%*	*10.3%*	*89.5%*	*0.1%*	*0.4%*	*15.2%*	*84.3%*
1993	*0.0%*	*0.1%*	*1.2%*	*98.6%*	*0.1%*	*0.2%*	*1.8%*	*97.9%*
1994	*0.0%*	*0.1%*	*0.5%*	*99.4%*	*0.0%*	*0.3%*	*0.9%*	*98.8%*
1995	*0.0%*	*0.1%*	*0.3%*	*99.6%*	*0.0%*	*0.1%*	*0.6%*	*99.3%*
1996	*0.0%*	*0.0%*	*13.2%*	*86.7%*	*0.0%*	*0.0%*	*22.0%*	*78.0%*
1997	*0.0%*	*0.0%*	*15.7%*	*84.3%*	*0.0%*	*0.0%*	*23.5%*	*76.5%*
1998	*0.0%*	*0.0%*	*27.0%*	*73.0%*	*0.0%*	*0.0%*	*27.0%*	*73.0%*
AVERAGE	***10.0%***	***4.7%***	***26.8%***	***78.1%***	***18.3%***	***4.0%***	***24.6%***	***74.0%***

Source: Obtained from calculations and parameters reported on pp. 102 (Equation 3A) and 115 of this thesis

Table 8 below provides a breakdown of the mainframe market segment adoption probabilities for each disk drive under conditions of high (HOD) and low optimal demand conditions (LOD). The figures show the adoption probabilities for each disk drive innovation in each year. These were calculated using new model parameters for HOD and LOD documented in Appendix 1 (Table 10). The percentages show the proportion of individual market adopters for each disk drive innovation.

Table 8. Market Segment Adoption Probabilities Optimal Demand for Mainframe

	MAINFRAME HIGH OPTIMAL DEMAND				**MAINFRAME LOW OPTIMAL DEMAND**			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*99.7%*	*0.3%*	*0.0%*	*0.0%*	*99.3%*	*0.7%*	*0.0%*	*0.0%*
1980	*99.7%*	*0.3%*	*0.0%*	*0.0%*	*99.5%*	*0.5%*	*0.0%*	*0.0%*
1981	*99.9%*	*0.1%*	*0.0%*	*0.0%*	*99.8%*	*0.1%*	*0.1%*	*0.0%*
1982	*99.8%*	*0.1%*	*0.1%*	*0.0%*	*99.5%*	*0.4%*	*0.1%*	*0.0%*
1983	*99.8%*	*0.1%*	*0.1%*	*0.0%*	*99.4%*	*0.4%*	*0.2%*	*0.1%*
1984	*99.6%*	*0.2%*	*0.1%*	*0.1%*	*95.7%*	*3.9%*	*0.2%*	*0.2%*
1985	*98.9%*	*0.8%*	*0.1%*	*0.1%*	*35.3%*	*64.1%*	*0.4%*	*0.2%*
1986	*96.6%*	*2.9%*	*0.3%*	*0.2%*	*11.8%*	*87.2%*	*0.7%*	*0.3%*
1987	*67.5%*	*30.8%*	*0.9%*	*0.8%*	*5.0%*	*92.6%*	*1.4%*	*1.0%*
1988	*69.9%*	*23.4%*	*4.3%*	*2.5%*	*9.7%*	*74.1%*	*12.2%*	*4.1%*
1989	*58.3%*	*34.9%*	*4.4%*	*2.4%*	*13.2%*	*60.8%*	*21.0%*	*5.1%*
1990	*17.9%*	*51.0%*	*14.2%*	*16.9%*	*3.9%*	*10.5%*	*64.2%*	*21.3%*
1991	*8.3%*	*40.5%*	*35.6%*	*15.6%*	*0.4%*	*1.4%*	*92.7%*	*5.5%*
1992	*4.3%*	*5.8%*	*70.0%*	*19.8%*	*0.4%*	*1.0%*	*85.3%*	*13.3%*
1993	*1.6%*	*7.9%*	*58.5%*	*32.0%*	*0.3%*	*1.2%*	*47.7%*	*50.8%*
1994	*0.0%*	*10.5%*	*44.7%*	*44.8%*	*0.0%*	*1.0%*	*5.3%*	*93.7%*
1995	*0.0%*	*0.1%*	*11.2%*	*88.7%*	*0.0%*	*0.2%*	*0.4%*	*99.4%*
1996	*0.0%*	*0.0%*	*67.8%*	*32.2%*	*0.0%*	*0.0%*	*26.6%*	*73.4%*
1997	*0.0%*	*0.0%*	*79.5%*	*20.5%*	*0.0%*	*0.0%*	*31.3%*	*68.7%*
1998	*0.0%*	*0.0%*	*34.7%*	*65.3%*	*0.0%*	*0.0%*	*34.7%*	*65.3%*
AVERAGE	***68.13%***	***11.04%***	***22.45%***	***21.36%***	***44.88%***	***21.05%***	***22.35%***	***31.39%***

Source: Obtained from calculations and parameters reported on pp. 102 (Equation 3B) and 115 of this thesis

Table 9 provides a breakdown of the minicomputer market segment adoption probabilities for each disk drive under conditions of high (HOD) and low optimal demand conditions (LOD).

Table 9. Market Segment Adoption Probabilities Optimal Demand for Minicomputer

	MINCOMPUTER LOW OPTIMAL DEMAND				MINICOMPUTER LOW OPTIMAL DEMAND			
1979	*12.6%*	*87.4%*	*0.0%*	*0.0%*	*12.6%*	*87.4%*	*0.0%*	*0.0%*
1980	*51.6%*	*42.3%*	*6.1%*	*0.0%*	*12.2%*	*70.8%*	*17.1%*	*0.0%*
1981	*16.3%*	*2.4%*	*81.3%*	*0.0%*	*0.8%*	*2.7%*	*96.5%*	*0.0%*
1982	*62.3%*	*7.9%*	*29.8%*	*0.0%*	*1.9%*	*8.8%*	*89.3%*	*0.0%*
1983	*69.3%*	*8.8%*	*13.7%*	*8.2%*	*0.8%*	*3.7%*	*63.7%*	*31.8%*
1984	*12.3%*	*65.5%*	*3.9%*	*18.2%*	*0.7%*	*4.0%*	*24.5%*	*70.7%*
1985	*16.4%*	*80.3%*	*1.4%*	*1.8%*	*4.6%*	*32.0%*	*37.6%*	*25.8%*
1986	*7.5%*	*88.4%*	*2.2%*	*1.9%*	*1.9%*	*34.6%*	*49.0%*	*14.5%*
1987	*7.3%*	*80.1%*	*4.5%*	*8.1%*	*0.9%*	*10.4%*	*56.0%*	*32.7%*
1988	*9.6%*	*58.5%*	*15.2%*	*16.7%*	*0.5%*	*2.3%*	*81.0%*	*16.2%*
1989	*8.1%*	*40.2%*	*20.7%*	*31.0%*	*0.4%*	*1.5%*	*72.3%*	*25.8%*
1990	*4.8%*	*25.5%*	*35.2%*	*34.5%*	*0.3%*	*1.3%*	*63.7%*	*34.6%*
1991	*0.6%*	*2.3%*	*83.9%*	*13.2%*	*0.3%*	*1.0%*	*34.9%*	*63.9%*
1992	*0.6%*	*2.2%*	*73.0%*	*24.2%*	*0.2%*	*0.6%*	*13.9%*	*85.3%*
1993	*0.5%*	*1.7%*	*21.8%*	*76.0%*	*0.1%*	*0.4%*	*2.9%*	*96.6%*
1994	*0.0%*	*2.0%*	*7.0%*	*91.0%*	*0.0%*	*0.4%*	*1.3%*	*98.3%*
1995	*0.0%*	*0.6%*	*2.3%*	*97.1%*	*0.0%*	*0.4%*	*1.0%*	*98.6%*
1996	*0.0%*	*0.0%*	*33.6%*	*66.4%*	*0.0%*	*0.0%*	*17.6%*	*82.4%*
1997	*0.0%*	*0.0%*	*19.5%*	*80.5%*	*0.0%*	*0.0%*	*19.5%*	*80.5%*
1998	*0.0%*	*0.0%*	*29.1%*	*70.9%*	*0.0%*	*0.0%*	*29.1%*	*70.9%*
AVERAGE	***18.65%***	***31.38%***	***25.49%***	***39.99%***	***2.55%***	***13.81%***	***40.57%***	***58.03%***

Source: Obtained from calculations and parameters reported on pp. 102 (Equation 3B) and 115 of this thesis

Table 10 provides a breakdown of the desktop computer market segment adoption probabilities for each disk drive under conditions of high (HOD) and low optimal demand conditions (LOD).

Table 10. Market Segment Adoption Probabilities Optimal Demand for Desktop

	DESKTOP HIGH OPTIMAL DEMAND				**DESKTOP LOW OPTIMAL DEMAND**			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*4.7%*	*95.2%*	*0.0%*	*0.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1980	*0.8%*	*5.0%*	*94.2%*	*0.0%*	*0.8%*	*5.0%*	*94.2%*	*0.0%*
1981	*0.1%*	*0.3%*	*99.6%*	*0.0%*	*0.1%*	*0.3%*	*99.6%*	*0.0%*
1982	*0.1%*	*0.2%*	*99.7%*	*0.0%*	*0.1%*	*0.2%*	*99.7%*	*0.0%*
1983	*0.0%*	*0.1%*	*2.9%*	*97.0%*	*0.0%*	*0.1%*	*2.7%*	*97.2%*
1984	*0.0%*	*0.1%*	*8.5%*	*91.4%*	*0.0%*	*0.1%*	*7.9%*	*92.0%*
1985	*0.0%*	*0.1%*	*3.9%*	*96.0%*	*0.0%*	*0.1%*	*3.6%*	*96.4%*
1986	*0.0%*	*0.1%*	*9.1%*	*90.7%*	*0.0%*	*0.1%*	*7.4%*	*92.6%*
1987	*0.0%*	*0.1%*	*32.0%*	*67.8%*	*0.0%*	*0.1%*	*23.8%*	*76.1%*
1988	*0.0%*	*0.1%*	*65.8%*	*34.1%*	*0.0%*	*0.0%*	*46.6%*	*53.3%*
1989	*0.0%*	*0.1%*	*41.4%*	*58.6%*	*0.0%*	*0.0%*	*23.4%*	*76.5%*
1990	*0.0%*	*0.0%*	*35.5%*	*64.4%*	*0.0%*	*0.0%*	*21.1%*	*78.8%*
1991	*0.0%*	*0.0%*	*5.0%*	*95.0%*	*0.0%*	*0.0%*	*3.4%*	*96.5%*
1992	*0.0%*	*0.0%*	*2.7%*	*97.3%*	*0.0%*	*0.0%*	*2.2%*	*97.7%*
1993	*0.0%*	*0.0%*	*0.2%*	*99.8%*	*0.0%*	*0.0%*	*0.2%*	*99.8%*
1994	*0.0%*	*0.0%*	*0.1%*	*99.9%*	*0.0%*	*0.0%*	*0.1%*	*99.9%*
1995	*0.0%*	*0.0%*	*0.1%*	*99.9%*	*0.0%*	*0.0%*	*0.1%*	*99.9%*
1996	*0.0%*	*0.0%*	*7.6%*	*92.3%*	*0.0%*	*0.0%*	*7.6%*	*92.3%*
1997	*0.0%*	*0.0%*	*9.8%*	*90.2%*	*0.0%*	*0.0%*	*9.8%*	*90.2%*
1998	*0.0%*	*0.0%*	*27.5%*	*72.5%*	*0.0%*	*0.0%*	*27.5%*	*72.5%*
AVERAGE	***0.4%***	***5.3%***	***28.7%***	***84.2%***	***0.4%***	***5.3%***	***25.3%***	***88.2%***

Source: Obtained from calculations and parameters reported on pp. 102 (Equation 3B) and 115 of this thesis

Table 11 provides a breakdown of the portable computer market segment adoption probabilities for each disk drive under conditions of high (HOD) and low optimal demand conditions (LOD).

Table 11. Market Segment Adoption Probabilities Optimal Demand for Portable

	PORTABLE LOW OPTIMAL DEMAND				**PORTABLE LOW OPTIMAL DEMAND**			
1979	*4.7%*	*95.2%*	*0.0%*	*0.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1980	*4.7%*	*95.2%*	*0.0%*	*0.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1981	*0.2%*	*4.7%*	*95.0%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*	*0.0%*
1982	*0.2%*	*4.7%*	*95.0%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*	*0.0%*
1983	*0.1%*	*0.7%*	*8.7%*	*90.5%*	*0.1%*	*0.7%*	*7.8%*	*91.5%*
1984	*0.1%*	*1.0%*	*9.3%*	*89.7%*	*0.1%*	*0.7%*	*7.8%*	*91.5%*
1985	*0.0%*	*0.2%*	*5.2%*	*94.6%*	*0.0%*	*0.1%*	*4.5%*	*95.4%*
1986	*0.0%*	*0.2%*	*16.8%*	*83.0%*	*0.0%*	*0.1%*	*12.5%*	*87.4%*
1987	*0.0%*	*0.2%*	*38.4%*	*61.4%*	*0.0%*	*0.1%*	*27.4%*	*72.5%*
1988	*0.0%*	*0.1%*	*42.9%*	*56.9%*	*0.0%*	*0.1%*	*24.3%*	*75.6%*
1989	*0.0%*	*0.1%*	*31.5%*	*68.3%*	*0.0%*	*0.1%*	*18.2%*	*81.7%*
1990	*0.0%*	*0.1%*	*25.7%*	*74.2%*	*0.0%*	*0.1%*	*15.8%*	*84.1%*
1991	*0.0%*	*0.1%*	*8.3%*	*91.6%*	*0.0%*	*0.1%*	*6.1%*	*93.8%*
1992	*0.0%*	*0.1%*	*3.5%*	*96.3%*	*0.0%*	*0.1%*	*3.2%*	*96.7%*
1993	*0.0%*	*0.1%*	*0.4%*	*99.5%*	*0.0%*	*0.1%*	*0.4%*	*99.5%*
1994	*0.0%*	*0.1%*	*0.3%*	*99.6%*	*0.0%*	*0.1%*	*0.3%*	*99.6%*
1995	*0.0%*	*0.1%*	*0.2%*	*99.7%*	*0.0%*	*0.1%*	*0.2%*	*99.7%*
1996	*0.0%*	*0.0%*	*7.9%*	*92.0%*	*0.0%*	*0.0%*	*7.9%*	*92.0%*
1997	*0.0%*	*0.0%*	*9.3%*	*90.6%*	*0.0%*	*0.0%*	*9.3%*	*90.6%*
1998	*0.0%*	*0.0%*	*18.2%*	*81.8%*	*0.0%*	*0.0%*	*18.2%*	*81.8%*
AVERAGE	***0.7%***	***10.7%***	***21.9%***	***85.6%***	***0.7%***	***10.7%***	***18.6%***	***89.6%***

Source: Obtained from calculations and parameters reported on pp. 102 (Equation 3B) and 115 of this thesis

Table 12 below provides a breakdown of the aggregate market adoption probabilities (i.e. across all segments) for each disk drive innovation under simulated conditions of high and low growth rates in absorptive capacity. We use the figures in Appendix 1 (Table 11) as inputs to derive new aggregate market adoption probabilities for qualitative analysis. The percentages show the proportion of total market adopters for each disk drive innovation.

Table 12. Aggregate Adoption Probabilities Absorptive Capacity

ADOPTION PROBABILITIES – HIGH ABSORPTIVE CAPACITY					ADOPTION PROBABILITIES – LOW ABSORPTIVE CAPACITY				
	MAIN	**MINI**	**DESK**	**PORT**		**MAIN**	**MINI**	**DESK**	**PORT**
1979	*73.2%*	*26.8%*	*0.0%*	*0.0%*	**1979**	*73.2%*	*26.8%*	*0.0%*	*0.0%*
1980	*71.5%*	*26.9%*	*1.5%*	*0.0%*	**1980**	*72.7%*	*25.7%*	*1.6%*	*0.0%*
1981	*23.8%*	*1.5%*	*74.6%*	*0.0%*	**1981**	*11.4%*	*1.8%*	*86.8%*	*0.0%*
1982	*30.7%*	*2.5%*	*66.8%*	*0.0%*	**1982**	*9.4%*	*3.0%*	*87.6%*	*0.0%*
1983	*33.6%*	*1.0%*	*9.8%*	*55.6%*	**1983**	*5.1%*	*1.4%*	*15.2%*	*78.4%*
1984	*20.7%*	*2.8%*	*8.9%*	*67.6%*	**1984**	*2.3%*	*2.1%*	*13.7%*	*81.9%*
1985	*7.0%*	*4.5%*	*8.8%*	*79.7%*	**1985**	*0.8%*	*2.3%*	*11.8%*	*85.1%*
1986	*5.1%*	*9.2%*	*19.1%*	*66.6%*	**1986**	*0.4%*	*3.4%*	*26.1%*	*70.1%*
1987	*2.1%*	*8.1%*	*29.0%*	*60.8%*	**1987**	*0.2%*	*1.7%*	*38.1%*	*60.0%*
1988	*1.1%*	*4.0%*	*44.3%*	*50.6%*	**1988**	*0.1%*	*0.6%*	*49.1%*	*50.2%*
1989	*1.7%*	*3.2%*	*30.2%*	*65.0%*	**1989**	*0.1%*	*0.5%*	*33.6%*	*65.8%*
1990	*0.4%*	*5.3%*	*24.9%*	*69.4%*	**1990**	*0.1%*	*0.3%*	*27.3%*	*72.3%*
1991	*0.5%*	*1.4%*	*17.0%*	*81.1%*	**1991**	*0.1%*	*0.2%*	*15.7%*	*84.0%*
1992	*0.4%*	*0.5%*	*16.1%*	*83.0%*	**1992**	*0.1%*	*0.2%*	*8.8%*	*91.0%*
1993	*0.3%*	*0.4%*	*1.4%*	*97.9%*	**1993**	*0.0%*	*0.1%*	*1.1%*	*98.7%*
1994	*0.0%*	*1.2%*	*1.2%*	*97.6%*	**1994**	*0.0%*	*0.1%*	*0.4%*	*99.5%*
1995	*0.0%*	*0.0%*	*6.0%*	*93.9%*	**1995**	*0.0%*	*0.1%*	*0.3%*	*99.6%*
1996	*0.0%*	*0.0%*	*30.7%*	*69.3%*	**1996**	*0.0%*	*0.0%*	*13.2%*	*86.7%*
1997	*0.0%*	*0.0%*	*51.3%*	*48.7%*	**1997**	*0.0%*	*0.0%*	*15.7%*	*84.3%*
1998	*0.0%*	*0.0%*	*66.9%*	*33.1%*	**1998**	*0.0%*	*0.0%*	*27.0%*	*73.0%*
AVERAGE	***18.14%***	***5.23%***	***26.77%***	***69.99%***	**AVERAGE**	***11.73%***	***3.70%***	***24.90%***	***80.03%***

Source: Obtained from calculations reported on pp. 102 (Equation 3A)

Table 13 below provides a breakdown of the aggregate market adoption probabilities (i.e. across all segments) for each market segment under simulated conditions of higher positive and negative development asymmetry. We use the figures in Appendix 1 (Table 11) as inputs to derive new aggregate market adoption probabilities for qualitative analysis. The percentages show the proportion of total market adopters for each disk drive innovation.

Table 13. Aggregate Adoption Probabilities Development Asymmetry

AGGREGATE ADOPTION PROBABILITIES									
POSITIVE ASYMMETRY					**NEGATIVE ASYMMETRY**				
	MAIN	**MINI**	**DESK**	**PORT**		**MAIN**	**MINI**	**DESK**	**PORT**
1979	*73.2%*	*26.8%*	*0.0%*	*0.0%*	**1979**	*73.2%*	*26.8%*	*0.0%*	*0.0%*
1980	*61.7%*	*36.9%*	*1.4%*	*0.0%*	**1980**	*67.8%*	*30.6%*	*1.5%*	*0.0%*
1981	*4.8%*	*3.5%*	*91.8%*	*0.0%*	**1981**	*10.5%*	*2.8%*	*86.7%*	*0.0%*
1982	*1.9%*	*7.4%*	*90.7%*	*0.0%*	**1982**	*9.1%*	*5.1%*	*85.8%*	*0.0%*
1983	*0.7%*	*3.4%*	*32.9%*	*62.9%*	**1983**	*9.3%*	*2.7%*	*23.4%*	*64.6%*
1984	*0.3%*	*2.0%*	*31.4%*	*66.3%*	**1984**	*7.1%*	*2.3%*	*22.1%*	*68.5%*
1985	*0.2%*	*1.1%*	*21.6%*	*77.2%*	**1985**	*4.1%*	*1.3%*	*16.7%*	*77.9%*
1986	*0.1%*	*0.9%*	*32.0%*	*67.0%*	**1986**	*2.5%*	*1.4%*	*34.7%*	*61.3%*
1987	*0.1%*	*0.5%*	*32.6%*	*66.9%*	**1987**	*1.0%*	*0.9%*	*50.0%*	*48.1%*
1988	*0.0%*	*0.2%*	*37.3%*	*62.5%*	**1988**	*0.6%*	*0.5%*	*61.6%*	*37.3%*
1989	*0.1%*	*0.2%*	*26.2%*	*73.5%*	**1989**	*0.6%*	*0.5%*	*44.2%*	*54.6%*
1990	*0.0%*	*0.2%*	*21.7%*	*78.1%*	**1990**	*0.4%*	*0.4%*	*37.6%*	*61.6%*
1991	*0.0%*	*0.2%*	*9.0%*	*90.8%*	**1991**	*0.3%*	*0.5%*	*15.1%*	*84.0%*
1992	*0.0%*	*0.1%*	*5.7%*	*94.1%*	**1992**	*0.2%*	*0.5%*	*8.9%*	*90.4%*
1993	*0.0%*	*0.1%*	*0.9%*	*98.9%*	**1993**	*0.1%*	*0.4%*	*1.3%*	*98.2%*
1994	*0.0%*	*0.1%*	*0.3%*	*99.6%*	**1994**	*0.1%*	*0.3%*	*0.3%*	*99.3%*
1995	*0.0%*	*0.1%*	*0.2%*	*99.7%*	**1995**	*0.0%*	*0.3%*	*0.2%*	*99.5%*
1996	*0.0%*	*0.2%*	*9.3%*	*90.5%*	**1996**	*0.1%*	*1.3%*	*14.2%*	*84.4%*
1997	*0.0%*	*0.1%*	*11.5%*	*88.3%*	**1997**	*0.1%*	*1.4%*	*36.0%*	*62.6%*
1998	*0.0%*	*0.1%*	*22.9%*	*77.0%*	**1998**	*0.0%*	*1.4%*	*59.9%*	*38.6%*
AVERAGE	***7.2%***	***4.2%***	***24.0%***	***64.7%***	**AVERAGE**	***9.4%***	***4.1%***	***30.0%***	***56.5%***

Source: Obtained from calculations reported on pp. 102 (Equation 3A)

Table 14 below provides a breakdown of the mainframe market segment adoption probabilities for each disk drive under conditions of higher positive and negative development asymmetry. The figures show the adoption probabilities for each disk drive in each year. These were calculated using the utility formulations in Appendix 1 (Tables 13–16). The percentages show the proportion of individual market adopters for each disk drive innovation.

Table 14. Market Segment Adoption Probabilities Development Asymmetry - Mainframe

	MAINFRAME POSITIVE ASYMMETRY				**MAINFRAME NEGATIVE ASYMMETRY**			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*99.7%*	*0.3%*	*0.0%*	*0.0%*	*99.7%*	*0.3%*	*0.0%*	*0.0%*
1980	*99.3%*	*0.7%*	*0.0%*	*0.0%*	*99.6%*	*0.4%*	*0.0%*	*0.0%*
1981	*98.8%*	*1.0%*	*0.1%*	*0.0%*	*99.7%*	*0.2%*	*0.1%*	*0.0%*
1982	*53.8%*	*45.5%*	*0.7%*	*0.0%*	*99.2%*	*0.6%*	*0.2%*	*0.0%*
1983	*35.1%*	*58.2%*	*6.6%*	*0.1%*	*99.1%*	*0.6%*	*0.3%*	*0.1%*
1984	*10.1%*	*52.3%*	*37.2%*	*0.4%*	*98.3%*	*1.1%*	*0.4%*	*0.2%*
1985	*6.9%*	*34.2%*	*58.2%*	*0.7%*	*97.2%*	*1.7%*	*0.8%*	*0.2%*
1986	*2.4%*	*25.2%*	*70.1%*	*2.3%*	*92.3%*	*4.6%*	*2.6%*	*0.5%*
1987	*0.4%*	*10.5%*	*59.6%*	*29.5%*	*72.5%*	*10.3%*	*14.0%*	*3.2%*
1988	*0.2%*	*1.1%*	*56.1%*	*42.6%*	*34.6%*	*3.3%*	*54.7%*	*7.4%*
1989	*0.3%*	*1.0%*	*54.4%*	*44.4%*	*35.7%*	*6.1%*	*48.2%*	*10.0%*
1990	*0.1%*	*0.3%*	*36.3%*	*63.3%*	*7.9%*	*1.3%*	*61.1%*	*29.8%*
1991	*0.1%*	*0.4%*	*30.8%*	*68.6%*	*3.8%*	*3.5%*	*59.2%*	*33.5%*
1992	*0.1%*	*0.3%*	*21.5%*	*78.1%*	*1.9%*	*2.7%*	*47.3%*	*48.1%*
1993	*0.1%*	*0.5%*	*10.5%*	*88.9%*	*0.8%*	*3.8%*	*28.7%*	*66.7%*
1994	*0.1%*	*0.3%*	*1.8%*	*97.8%*	*0.7%*	*8.6%*	*4.0%*	*86.7%*
1995	*0.1%*	*0.1%*	*0.3%*	*99.5%*	*0.2%*	*2.1%*	*0.4%*	*97.3%*
1996	*0.1%*	*0.3%*	*20.5%*	*79.1%*	*0.4%*	*9.7%*	*59.4%*	*30.5%*
1997	*0.1%*	*0.3%*	*25.8%*	*73.8%*	*0.2%*	*5.3%*	*74.8%*	*19.7%*
1998	*0.1%*	*0.3%*	*29.9%*	*69.7%*	*0.2%*	*5.1%*	*78.1%*	*16.6%*
AVERAGE	***20.4%***	***11.6%***	***26.0%***	***41.9%***	***47.2%***	***3.6%***	***26.7%***	***22.5%***

Source: Obtained from calculations reported on pp. 102 (Equation 3B)

Table 15 provides a breakdown of the minicomputer market segment adoption probabilities for each disk drive under conditions of higher positive and negative development asymmetry.

Table 15. Market Segment Adoption Probabilities Development Asymmetry - Minicomputer

	MINCOMPUTER POSITIVE ASYMMETRY				MINICOMPUTER NEGATIVE ASYMMETRY			
1979	*12.6%*	*87.4%*	*0.0%*	*0.0%*	*12.6%*	*87.4%*	*0.0%*	*0.0%*
1980	*12.2%*	*70.8%*	*17.1%*	*0.0%*	*12.7%*	*73.1%*	*14.2%*	*0.0%*
1981	*0.8%*	*2.7%*	*96.5%*	*0.0%*	*1.8%*	*6.2%*	*92.0%*	*0.0%*
1982	*1.9%*	*8.8%*	*89.3%*	*0.0%*	*7.7%*	*33.1%*	*59.3%*	*0.0%*
1983	*1.0%*	*4.4%*	*73.4%*	*21.2%*	*28.1%*	*19.4%*	*47.3%*	*5.2%*
1984	*0.4%*	*1.7%*	*17.8%*	*80.1%*	*54.1%*	*7.5%*	*17.6%*	*20.8%*
1985	*1.3%*	*7.5%*	*32.2%*	*59.0%*	*90.9%*	*4.2%*	*3.2%*	*1.7%*
1986	*0.4%*	*5.8%*	*38.9%*	*54.8%*	*87.1%*	*4.3%*	*6.1%*	*2.5%*
1987	*0.2%*	*1.9%*	*24.6%*	*73.2%*	*69.6%*	*4.3%*	*14.2%*	*11.8%*
1988	*0.2%*	*0.8%*	*27.2%*	*71.9%*	*41.8%*	*2.4%*	*33.6%*	*22.3%*
1989	*0.2%*	*0.6%*	*19.7%*	*79.5%*	*22.3%*	*2.9%*	*33.3%*	*41.5%*
1990	*0.2%*	*0.5%*	*18.4%*	*80.9%*	*11.0%*	*3.7%*	*39.4%*	*45.9%*
1991	*0.2%*	*0.5%*	*13.0%*	*86.3%*	*7.6%*	*5.5%*	*30.7%*	*56.3%*
1992	*0.2%*	*0.5%*	*9.4%*	*90.0%*	*2.6%*	*4.8%*	*20.3%*	*72.3%*
1993	*0.1%*	*0.4%*	*2.9%*	*96.6%*	*1.0%*	*11.6%*	*7.3%*	*80.1%*
1994	*0.1%*	*0.3%*	*0.9%*	*98.8%*	*0.9%*	*3.0%*	*1.0%*	*95.1%*
1995	*0.1%*	*0.2%*	*0.7%*	*99.0%*	*0.2%*	*2.1%*	*1.4%*	*96.3%*
1996	*0.2%*	*0.5%*	*11.3%*	*88.1%*	*0.4%*	*13.9%*	*7.2%*	*78.4%*
1997	*0.2%*	*0.5%*	*13.0%*	*86.3%*	*0.2%*	*45.3%*	*46.5%*	*8.0%*
1998	*0.2%*	*0.5%*	*23.0%*	*76.3%*	*0.2%*	*36.9%*	*58.3%*	*4.5%*
AVERAGE	***1.6%***	***9.8%***	***26.5%***	***62.1%***	***22.6%***	***18.6%***	***26.6%***	***32.1%***

Source: Obtained from calculations reported on pp. 102 (Equation 3B)

Table 16 provides a breakdown of the desktop computer market segment adoption probabilities for each disk drive under conditions of higher positive and negative development asymmetry.

Table 16. Market Segment Adoption Probabilities Development Asymmetry - Desktop

	DESKTOP POSITIVE ASYMMETRY				DESKTOP NEGATIVEASYMMETRY			
	14	**8**	**5.25**	**3.5**	**14**	**8**	**5.25**	**3.5**
1979	*4.7%*	*95.2%*	*0.0%*	*0.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1980	*0.8%*	*5.0%*	*94.2%*	*0.0%*	*0.8%*	*5.0%*	*94.2%*	*0.0%*
1981	*0.1%*	*0.3%*	*99.6%*	*0.0%*	*0.1%*	*0.3%*	*99.6%*	*0.0%*
1982	*0.1%*	*0.2%*	*99.7%*	*0.0%*	*0.1%*	*0.2%*	*99.7%*	*0.0%*
1983	*0.0%*	*0.1%*	*2.7%*	*97.2%*	*0.0%*	*0.1%*	*3.2%*	*96.7%*
1984	*0.0%*	*0.1%*	*7.9%*	*92.0%*	*0.0%*	*0.1%*	*11.3%*	*88.6%*
1985	*0.0%*	*0.1%*	*3.6%*	*96.4%*	*0.0%*	*0.1%*	*5.7%*	*94.2%*
1986	*0.0%*	*0.1%*	*7.4%*	*92.6%*	*0.0%*	*0.1%*	*12.0%*	*87.8%*
1987	*0.0%*	*0.1%*	*23.8%*	*76.1%*	*0.0%*	*0.1%*	*34.9%*	*65.0%*
1988	*0.0%*	*0.0%*	*46.6%*	*53.3%*	*0.0%*	*0.1%*	*60.2%*	*39.7%*
1989	*0.0%*	*0.0%*	*23.4%*	*76.5%*	*0.0%*	*0.1%*	*31.0%*	*68.9%*
1990	*0.0%*	*0.0%*	*21.1%*	*78.8%*	*0.0%*	*0.1%*	*27.7%*	*72.2%*
1991	*0.0%*	*0.0%*	*3.4%*	*96.5%*	*0.0%*	*0.1%*	*4.1%*	*95.8%*
1992	*0.0%*	*0.0%*	*2.2%*	*97.7%*	*0.0%*	*0.1%*	*2.7%*	*97.2%*
1993	*0.0%*	*0.0%*	*0.2%*	*99.8%*	*0.0%*	*0.0%*	*0.2%*	*99.8%*
1994	*0.0%*	*0.0%*	*0.1%*	*99.9%*	*0.0%*	*0.0%*	*0.1%*	*99.9%*
1995	*0.0%*	*0.0%*	*0.0%*	*99.9%*	*0.0%*	*0.0%*	*0.0%*	*99.9%*
1996	*0.0%*	*0.1%*	*6.0%*	*94.0%*	*0.0%*	*0.2%*	*7.9%*	*91.9%*
1997	*0.0%*	*0.0%*	*7.9%*	*92.1%*	*0.0%*	*0.1%*	*12.1%*	*87.8%*
1998	*0.0%*	*0.0%*	*25.4%*	*74.6%*	*0.0%*	*0.1%*	*36.8%*	*63.1%*
AVERAGE	***0.3%***	***5.1%***	***23.8%***	***70.9%***	***0.3%***	***5.1%***	***27.2%***	***67.4%***

Source: Obtained from calculations reported on pp. 102 (Equation 3B)

Table 17 provides a breakdown of the portable computer market segment adoption probabilities for each disk drive under conditions of higher positive and negative development asymmetry.

Table 17. Market Segment Adoption Probabilities Development Asymmetry - Portable

	PORTABLE POSITIVE ASYMMETRY				PORTABLE NEGATIVE ASYMMETRY			
1979	*4.7%*	*95.2%*	*0.0%*	*0.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1980	*4.7%*	*95.2%*	*0.0%*	*0.0%*	*4.7%*	*95.2%*	*0.0%*	*0.0%*
1981	*0.2%*	*4.7%*	*95.0%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*	*0.0%*
1982	*0.2%*	*4.7%*	*95.0%*	*0.0%*	*0.2%*	*4.7%*	*95.0%*	*0.0%*
1983	*0.1%*	*0.7%*	*7.8%*	*91.5%*	*0.1%*	*0.7%*	*7.8%*	*91.5%*
1984	*0.1%*	*0.7%*	*7.8%*	*91.5%*	*0.1%*	*0.7%*	*7.8%*	*91.5%*
1985	*0.0%*	*0.1%*	*4.5%*	*95.4%*	*0.0%*	*0.1%*	*4.5%*	*95.4%*
1986	*0.0%*	*0.1%*	*12.5%*	*87.4%*	*0.0%*	*0.1%*	*14.3%*	*85.5%*
1987	*0.0%*	*0.1%*	*27.4%*	*72.5%*	*0.0%*	*0.1%*	*37.1%*	*62.7%*
1988	*0.0%*	*0.1%*	*24.3%*	*75.6%*	*0.0%*	*0.1%*	*38.4%*	*61.4%*
1989	*0.0%*	*0.1%*	*18.2%*	*81.7%*	*0.0%*	*0.2%*	*30.2%*	*69.6%*
1990	*0.0%*	*0.1%*	*15.8%*	*84.1%*	*0.0%*	*0.2%*	*24.1%*	*75.7%*
1991	*0.0%*	*0.1%*	*6.1%*	*93.8%*	*0.0%*	*0.2%*	*8.1%*	*91.7%*
1992	*0.0%*	*0.1%*	*3.2%*	*96.7%*	*0.0%*	*0.2%*	*4.0%*	*95.8%*
1993	*0.0%*	*0.1%*	*0.4%*	*99.5%*	*0.0%*	*0.1%*	*0.5%*	*99.4%*
1994	*0.0%*	*0.1%*	*0.2%*	*99.7%*	*0.0%*	*0.1%*	*0.3%*	*99.6%*
1995	*0.0%*	*0.1%*	*0.2%*	*99.7%*	*0.0%*	*0.1%*	*0.2%*	*99.6%*
1996	*0.0%*	*0.1%*	*6.2%*	*93.7%*	*0.0%*	*0.3%*	*8.9%*	*90.8%*
1997	*0.0%*	*0.1%*	*7.4%*	*92.5%*	*0.0%*	*0.3%*	*11.0%*	*88.7%*
1998	*0.0%*	*0.1%*	*15.7%*	*84.2%*	*0.0%*	*0.3%*	*22.3%*	*77.3%*
AVERAGE	***0.5%***	***10.1%***	***17.4%***	***72.0%***	***0.5%***	***10.2%***	***20.5%***	***68.8%***

Source: Obtained from calculations reported on pp. 102 (Equation 3B)