Organisational Innovativeness and Diffusion of Innovation

Xiaohui Shi

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Abstract

In the existing literature, studies of innovativeness usually focus on individual characteristics with little concern for aggregated behaviour; the central role of innovativeness, opinion leadership, and geographic location have not been fully reflected in diffusion models; most diffusion models either make simplified assumptions to model aggregated trends or concern individual behaviours excessively as being 'toy models'; understandings of the diffusion forces bifurcate into explanations on social contagion effect and self-conformity effect and few diffusion models have tried to combine these two streams of thinking. In order to contribute knowledge to these fields, this study seeks to model the diffusion process from an agent-based perspective, with a specific focus on the effects of organisational innovativeness, opinion leadership, and geographic location. The proposed model is a focusing tool that helps interpret and organise the empirical observation. In turn, the model's results could raise further questions for empirical exploration.

The result from the model simulation echoes a number of existing works on innovation strategies with further quantitative implications for both industry policy makers and managers in organisations. It is found that the statistical distributions of organisational innovativeness and opinion leadership are both important factors in diffusion; the level of information flow between organisations with different innovativeness levels influences the diffusion process significantly; to cluster organisations in one area changes the interactions between them and increases the diffusion rate, even when the average interaction level of the system is controlled. The model also indicates that organisations' self-effort is the only way for being innovators; that factors that are related to interactions with others are more important for laying in the majority category; and that laggards normally adopt innovations by 'luck'.

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Preface

The work described in this thesis was carried out between 2009 and 2011 at the York Management School, University of York. This research topic was initially offered by my supervisor Professor Kiran Fernandes with a practical question that was, *'how will an innovation diffuse in a system, if organisations change their innovation strategies constantly?'* At first glance, the answer to this question seemed to be easy by simply incorporating a measure of organisational innovativeness into an appropriate diffusion model. However, to implement this research is no bed of roses. First, it is not easy to measure organisational innovativeness, especially to do so on a continuous basis. Second, it is not easy to meaningfully incorporate organisational innovativeness into diffusion models, since innovativeness not only has a direct impact on diffusion, but also closely relates to and influences other factors of diffusion. Third, there are other interesting and inter-related issues around this topic that needs to be considered such as 'what is the natural driver(s) of a diffusion process and how to model diffusion?', 'what is the role of opinion leadership in diffusion and how to model opinion leadership in a diffusion model?', etc. Because of these reasons, I finally developed an agent-based diffusion model in order to better understand the diffusion phenomenon in a more comprehensive manner.

After this agent-based diffusion model was initially proposed, I started to suffer from thinking about how to validate and analyse the model. The model proposed in this study desires a set of real world data which is difficult to obtain. Additionally and more importantly, I was thinking whether it would be worthy to stick to the real world data, since the data from a few cases could only partially reveal the diffusion phenomena, and thus would be difficult to assist a generalised understanding. This is the key reason that I decided to introduce a simulation approach into my study.

As I did not go for real data collection, I invested my time to explore diffusion theories and models from various disciplines such as management, marketing, biology, economics, and sociology; to play with these models; and to find the linkages between these models. As this work is not limited to specified cases, I could simulate and explore all the scenarios I like. After I finished the draft of this thesis, I started to consider a few other topics. By simply modifying and extending the ideas and models in this thesis, I quickly generated one more papers, to model the multi-generation diffusion problem. This work is attached as an appendix in this thesis. I like this very much, as the result of the model matches the real world data extraordinarily well.

Writing this thesis has been hard. While in the process of writing I feel I have learned a lot, my knowledge of innovation and diffusion has broadened, and my initial conceptions on this topic have certainly changed. I attempted to give this thesis a broad perspective on organisational innovativeness and diffusion, thus combining ideas from management, marketing, biology, economics, and sociology. As a result, I hope that this thesis will bring benefits to both academics and practitioners who are keen to understand the nature of diffusion.

Acknowledgements

Considering that doing research in operations research requires strong and sincere assistance, this study is carried out with extraordinary help from my supervisor, Professor Kiran Fernandes, whose guidance and support added many aspects of value to this study. His confidence in my work enabled me to change direction several times without feeling lost and to finally arrive at the right place.

I would like to offer special thanks to Professor David Higgins, for his invaluable support and comment throughout my PhD study. My thanks also go to Dr Harry Venables, for reading my thesis at the final stage.

During my PhD life in York, I received support and help from my friends, PhD student fellows, and staff in the school: Ken Chen, Do-Kyu Lee, Pattarin Chumnumpan, Matthew Mount, Michael Perkins, Dian Ekowati, Helen Geddes, Wendy Tomlinson, and Terry Chen.

This thesis is dedicated to my parents, who brought me up with their endless love, gave me the freedom to learn, encouraged me to pursue this degree and constantly support me in everything I do; to my brother and sister in law, for their understanding, encouragement and their belief in me; and to Xiuxiu, for her love.

Author's Declaration

I hereby declare that this thesis entitled 'Organisational Innovativeness and Diffusion of Innovation' represents the results of my own work except where specified in the thesis.

Xiaohui Shi (Leo)

Chapter 1 Introduction

"There is nothing more difficult to plan, more doubtful of success, nor more dangerous to manage than the creation of a new order of things… whenever his enemies have the ability to attack the innovators, they do so with the passion of partisans, while the others defend him sluggishly, so that the innovators and his party alike are vulnerable"

(Machiavelli 1513)

1.1 Background - Innovation

Innovation is a phenomenon that is as old as mankind itself, as it is related to the human tendency of doing things in a better way (Fagerberg 2005). Although the topic of innovation did not receive considerable academic attention in the early stages, the situation has changed greatly over the last century. Currently, about 10,000 academic articles with the topic of 'innovation' are published each year (Figure 1) covering various research fields.

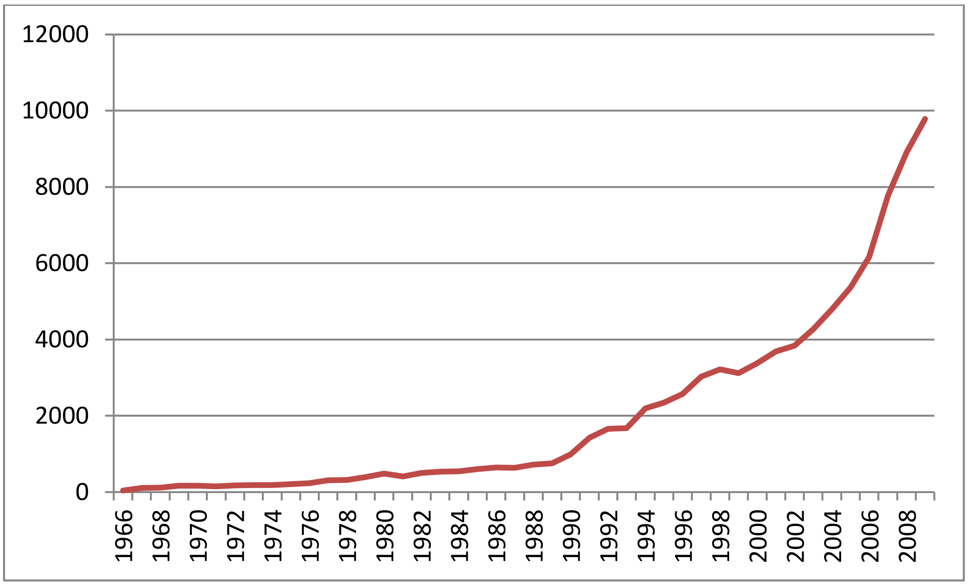

Figure 1: Number of Academic Articles that Fall into the Topic of 'Innovation' (The source is from the ISI Web of Knowledge, Social Sciences Citation Index)

1.1.1 Definition of Innovation

Innovation is a broad concept that has been studied in many disciplines and defined from different perspectives. There are many debates on its nature, originality, extent, determinants, and consequences. Joseph Schumpeter (1883-1950) is usually considered as the first economist to highlight the meaning of innovation. In an early study, Schumpeter (1934) lists five types of activities that can be considered as innovations: the introduction of a new product; the introduction of a new method of production; the introduction of a new market; the conquest of a new source of supply of raw materials or half-manufactured good; the carrying out of the new organisation of any industry. Later Mansfield (1963) generalised Schumpeter's idea to define innovation as an organisation's first ever use of a new product, process, service, or idea. As Mansfield's definition only considers the first introduction of these items or activities as innovations and names all subsequent usages as imitation, Thompson (1965) modifies the scope of this concept to the first time within an organisational setting. Similar descriptions have been followed by most consequent studies. For instance, Damanpour and Evan (1984) consider an innovation as the implementation of a new idea at the time of adoption; Van de Ven (1986) considers innovation as the process of generating a new idea and putting the following translation and implementation process into practice. In practical terms, the term 'innovation' has similar definitions but with specific focus on product, process, and organisational innovation activities. In the innovation guideline of the OECD (2005, p. 46), innovation is defined as "*the implementation of a new or significantly improved product (good or service) or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations*".

Based on the above reviews, it is concluded that those widely accepted definitions of innovation usually consist of three fundamental elements: newness, implementation, and process. First, newness usually means new to the organisation, but not necessarily new to the whole world. It is only important that the potential adopter perceives the innovation as new. Also, researchers sometimes specify the meaning of newness as new to the industry, new to the market, new to the organisation, and new to the customer due to their specific research contexts[1]. Furthermore, newness can also be considered from the perspective of whether the innovation is developed inside or outside the unit of analysis (creative innovation vs. adaptive innovation). Second, implementation is introduced to differentiate innovations from inventions. It is widely agreed that innovation does not occur when a new idea is generated, but rather when the new idea is implemented (Damanpour & Evan 1992). Sometimes, people even tend to use a more constrained term, commercialization, to explain innovation in order to state that innovation should be a profit-driven activity (Fagerberg 2005). The use of the term 'commercialization' is fairly appropriate in private sectors where organisations are all pursuing profit, although in public sectors not all the innovations are profit focused. Third, process means innovation is usually a long and continuous process that covers both the initialization and implementation stages, with one innovation usually involving many interrelated innovations (Fagerberg 2005). Kline and Rosenberg (1986) argue that a successful innovation needs consistent support and all a company's abilities geared towards this innovation, which could be either a sequential linear function or a complex process with convergent, parallel, and divergent activities[2] (Kline & Rosenberg 1986).

Moreover, it is significant for one to understand the different types of innovation, since previous works have found that the results of innovation studies are largely influenced by innovation types. First, innovations can be differentiated in terms of their output, for instance, Schumpeter's original definition of innovation is rightly proposed based on the results of innovation. In both academic and practi-

[1] Readers are referred to read the work of Garcia and Calnatone (2002) for a comprehensive study on the newness of innovation.

[2] However, according to Kimberly and Evanisko (1981), cited in King (2000), many studies also see innovation as a discrete item. Typical examples are the various innovations studied in diffusion research: a new product for customers, news from newspapers, and an ISO standard for firms. As in the book 'Diffusion of Innovation', Rogers (2003, p. 12) defines innovation in the field of diffusion as "*an idea, practice, or object that is perceived as new by an individual or other unit of adoption*", without clearly emphasising that it must be a process.

cal fields, more interest is generated either within product innovations that represent new products; within service innovations that have been introduced to meet the market need; or process innovations that represent the new elements introduced into an organisation's production or service operations to improve operational efficiencies or enable the production of new products (Damanpour 1991). Therefore, product and service innovations are there to satisfy organisations' outside customers while process innovations aim to increase the efficiency and effectiveness of the internal organisational process (Damanpour & Avellaneda 2009). The second commonly used classification for innovations is the typology of administrative innovation and technological innovation (Daft 1978). At the management level of organisations, innovation is about the change of organisational structure and administrative processes that are indirectly related to the basic work of organisations (Kimberly & Evanisko 1981), while at the organisation level, people care more about new technologies that are embedded in products, services, and production process (Damanpour 1991). Damanpour (1987) also advances ancillary innovations that are described as new services provided to communities, such as library services, career development programs, and tutorial services as an complement to the above typology. Third, people also distinguish innovations by considering the degree of change associated with them. Incremental innovations represent those changes exploited from existing products, ideas, and technologies, while radical innovations are used to represent fundamental changes. Ettilie et al. (1984) point out that radical and incremental innovations require different business strategies and structures to deal with. This area has received even more attention since the introduction of the concept of disruptive innovations (Bower & Christensen 1995; Christensen 1997). Other innovation classifications include the level of innovation (industry level, organisational level, departmental level, innovation level) (Gopalakrishnan & Damanpour 1997) and the originality of innovation (creative and adoptive) (Van de Ven & Rogers 1988).

1.1.2 Importance of Innovation

The ultimate goal for organisations in terms of introducing innovations is to improve the organisation performance. A significant correlation between innovative activities and organisation performance has been found (Damanpour, Szabat & Evan 1989; Damanpour & Avellaneda 2009; Hult, Hurley & Knight 2004; Hurley & Hult 1998; Sivadas & Dwyer 2000; Subramanian & Nilakanta 1996) and a survey of more than 700 of the Fortune 1,000 companies indicates that over one third of their profits over the next five years will come from new products (Hamilton 1982). Furthermore, innovation is significant to those followers who have the ambition to catch-up or even replace the current economic leaders. According to Freeman and Soete (1997) and Freeman and Louçã (2001), the fast economic growth of the United States and Germany in the second half of the nineteenth century, when compared to the United Kingdom, is because they didn't simply imitate the innovations already being used, but rather developed their own ways of organizing production and distribution. Also the way Japan caught-up with the West after the Second World War depended very much on its own organisational innovations. A few scholars further argue that innovation is vital to an organisation's survival (Crespell, Knowles & Hansen 2006; Frambach 1993) and that it is one of the key factors, along with marketing, for an organisation's long-term health (Drucker 1973). This is since innovation is a source of competitive advantage (Tidd 2001) and a way of defending against market entry (Hauser, Tellis & Griffin 2006).

However, the innovation journey is not easy. First, truly innovative organisations are those that exhibit innovative behaviours consistently over time (Subramanian & Nilakanta 1996). Second, a typical innovation process consists of a set of activities running from design to adoption, and to diffusion. Risk or even failure can occur at every step. Therefore, it is estimated that the majority of the inventions recorded at the US patent office are never introduced to the market at all (Kline

& Rosenberg 1986). It is also reported that nearly 50% of the new products that are introduced each year finally failed (Sivadas & Dwyer 2000).

1.1.3 Innovation Studies: an overview

Innovation studies cover a wide range of topics across a variety of disciplines. Some of these studies are practical and based on real world phenomena, while others are very theoretical with or without empirical support. Hauser (2006) identifies these topics and classifies them into five categories with corresponding achievements and research gaps in each: consumers' responses to the innovation that includes organisational innovativeness and diffusion of innovation; organisations and innovation that explains why organisations adopt innovations; market entry strategies that suggest direction on innovation generation for organisations; prescriptions for product development; and outcomes from innovation. Also Fagerberg (2005) argues that there has been a large amount of research on the consequences of innovation in the last past one century, but people still lack an understanding about why and how innovation occurs.

1.2 Background – Diffusion

According to Rogers (2003), the roots of diffusion theory can be traced back to three early thinkers: Gabriel Tarde (1843-1904) who observed S-shaped phenomena and proposed the concept of opinion leadership; Georg Simmel (1858-1918) who emphasised the importance of communication networks in diffusion; and those German-Austrian diffusionists who raised the importance of diffusion to the attention of scientists in other social fields. Later Rogers (1962) summarised the knowledge in order to make diffusion study systematic. Although criticisms exist[3], diffusion research is one of the most important issues in business research nowadays.

[3] These criticisms include the pro-innovation bias of diffusion research, the individual-blame bias in diffusion research, the recall problem in diffusion research, and the issue of equality in the

1.2.1 Definition of Diffusion

Diffusion is a generalised term for a set of processes including "*embracing contagion, mimicry, social learning, organized dissemination, and other family members*" (Strang & Soule 1998, p. 266). The term 'diffusion' in academic works is usually used to demonstrate the spread of an innovation between members of a system through certain channels over time (Rogers 2003). In practical terms, diffusion is defined as "*the spread of innovations, through market or non-market channels, from first implementation anywhere in the world to other countries and regions and to other markets and firms*" (OECD 2005, p. 78).

In the Rogers' definition above, diffusion has four key elements: innovation, communication channel, time, and social system (see Table 1). Among these elements, it should be emphasised that the definition of innovation used in diffusion studies is normally narrower than the general definition of innovation that is discussed in Section 1.1.1. This is since diffusion usually focuses on the adoption decision of individuals/organisations without too much concern for their exact adoption processes. Therefore, the targeted innovations in diffusion studies are usually those that take a short time for adoption.

Element	Definition
Innovation	*"An innovation is an idea, practice, or object that is perceived as new by an individual or other unit of adoption"*
Communication Channel	*"A communication channel is the means by which messages get from one individual to another"*
Time	*"The innovation-decision period is the length of time required to pass through the innovation-decision process"*
Social System	*"A social system is defined as a set of interrelated units that are engaged in joint problem solving to accomplish a common goal"*

Table 1: Elements of Diffusion
(Source is from Rogers (2003, pp. 12-31))

diffusion of innovations. Readers are referred to Rogers' (2003) book for a detailed discussion of these issues.

In the areas of management and marketing, diffusion research has been growing considerably since the early twentieth century as researchers study the process whereby a new product (or process, technology, service, etc.) is communicated through mass media and word of mouth and thus spread in a market or system. Also in a few other fields, diffusion has long been studied. For instance, sociologists started to investigate the spread of agricultural ideas decades ago; teaching/learning innovations are analysed in the area of education; researchers in public health and medical sociology are always keen to understand how new medicines and health treatments can be utilised through the whole social system; news, technological innovations, and new communication technologies are studied in communication studies; technological innovations in geography also raised people's interest decades ago. Furthermore, there is similar, although sometimes unrelated interest in this concept from other fields. For instance, the term 'technological change' when used in economics represents the change of goods and services produced and the means by which the change is diffused (Stoneman 2002); in biology, epidemic studies tend to model the spread of certain diseases that transfer between individual people via direct or indirect contact, which share the similar characteristics of innovation diffusion.

1.2.2 Importance of Diffusion

As a research field, diffusion is relevant to many disciplines such as anthropology, sociology, education, public health and medical sociology, communication, marketing and management, and geography. This multi-disciplinary nature has made diffusion into a bridge that links various disciplines and methodologies and thus utilises the research results from different fields (Rogers 2003).

In the real world, it is argued that innovation has little social or economic impact without diffusion (Hall 2005), as it is commonly observed that for most innovations it takes a long time for the extent of ultimate use to be attained and it is only when innovations are widely used in an economy that any real welfare gains arise from those innovations. A typical example is the use of communication tools (such as mobile phones, emails, and so on), in which cases the tools can achieve the best performance only when most people have adopted these products. Another example could be that the price of the innovation will decrease along with the decreased cost of producing the innovation due to the economies of scale. Therefore, to understand the diffusion process is to also understand how innovations generate economic benefits.

1.2.3 Diffusion Studies: an Overview

Explanations of diffusion can be broadly categorised into two streams regarding the processes leading to adoption (Ansari, Fiss & Zajac 2010). The first group of explanations mostly adopted by management and marketing researchers, which argue that potential adopters are rational and that they consider the economic benefits/cost resulting from the adoption of the innovation. Organisations tend to imitate the actions of others to minimize search costs and to avoid the risk of adoption. Therefore, the information cumulating from the increasing number of adopters will reduce the uncertainty of the innovation and the risk of adoption and therefore speed up the diffusion process. The second group of explanations have solid roots in sociology studies, which argue that potential adopters tend to face growing levels of pressure from the increasing number of existing adopters. Different from the first explanation, organisations in the second, observe others, not for lowing the cost and risk of adoption, but to appear legitimate and conform to norms.

A broad concept of diffusion theory covers a wide range of subjects such as communication channels, diffusion networks, opinion leadership, change agent, and innovativeness, which all have the potential to influence the diffusion process. The following paragraphs list the factors of diffusion that are proposed by a number of scholars.[4]

[4] It should be noted that, although some of these frameworks are developed on the basis of diffusion between individual people, they can also be used to analyse the diffusion between organisations. As mentioned in the work of Hauser et al. (2006), innovation studies usually focus on

Rogers (1962) explains the factors of diffusion starting from a few intrinsic characteristics of innovation including: the relative advantage of the innovation, which explains how the improved innovation is over the previous one; compatibility, the ease of which the innovation can be adopted with the potential adopter's current way of doing things and with social norms; the complexity of the innovation, which explains whether the innovation is difficult to use; the trialability of the innovation, which explains the ease with which the innovation can be tested by a potential adopter; the observability of the innovation, which explains the ease with which the innovation can be evaluated after trial, and the degree that the innovation is visible to others. In conclusion, organisations will be more likely to adopt the innovation, if the innovation has improved from the previous version, is more compatible to the organisation's current context, is easier to use, and can provide good experiences in the trial stage, helping communications spread among organisations through the network effect.

Another contribution in this area is made by Hall (2005), who proposes to classify these factors of diffusion into five groups: those that are related to the benefit derived from the innovation, those that determine the cost of adopting the innovation, those that influence the information and uncertainty of the innovation, those that affect the environment of diffusion including market size, market structure, and industry environment, and those that contribute to the communication channels and network effect between organisations. Specifically, the first category focuses on the characteristics of innovation itself; the second and third category needs analysis of both innovation and organisation; the fourth one represents the diffusion environment; the final group emphasises the interactions between organisations within the diffusion process. In conclusion, the key reason for an organisation to adopt an innovation is that the benefit of the innovation minus the cost of the innovation is more than the organisation's expectation,

specific targets such as individuals, households, organisations, and institutions, while the theories and concepts behind those studies are actually similar. The above explanation also applies to the rest of this thesis.

and the way to know this fact is through information about the innovation that comes through certain channels from existing adopters.

The final framework discussed here is proposed by Gatignon and Robertson (1985). They argue that diffusion is the output of the sum of individual adoption decisions, which are influenced by: the characteristics of the innovation, the characteristics of individual adopters, the characteristics of the system, and the inter-influence between individual adopters. Specifically the studies of innovation characteristics are based on Rogers' (1962) early work; the studies of individual characteristics are naturally innovativeness studies; the social system, or the environment context, is determined by a number of sub-factors such as geographical settings, societal culture, political conditions, global uniformity (Wejnert 2002), and market/system competition; the inter-influence between individual adopters is closely related to the term 'opinion leadership', which investigates the role of opinion leaders in diffusion.

To sum up, Gatignon and Robertson's (1985) framework can be considered as a combination of Rogers' (1962) framework and Hall's (2005) framework but utilised in a more structural way. The three frameworks show that a diffusion process is not a simple phenomenon that can be determined by one or a few factors. Instead, it is influenced by the characteristics of the innovation, the characteristics of the potential adopters, the characteristics of the environment, and the complex relationships between them.

1.3 Research Motivation

The current study was initially motivated by Gatigon and Robertson's (1985) diffusion framework, as presented in Section 1.2.3: when a particular diffusion process is targeted, the characteristics of the innovation and the diffusion environment are basically fixed within a certain range; then the characteristics of each organisation (typically organisational innovativeness) and the inter-organisational relationship become the main interests in understanding the diffusion phenomenon. By further extending the above idea, it is concluded that this study is mainly motivated from the following perspectives:

First, organisational innovativeness has been studied excessively, with decent knowledge on its factors and measures. However, there remains a gap in the research literature in terms of incorporating measures of organisational innovativeness into diffusion models (Hauser, Tellis & Griffin 2006). According to Rogers (2003), unlike most existing studies that try to understand the variables that relate to innovativeness, future research needs to use innovativeness as a predictor to study the consequences of diffusion. Furthermore, although organisational innovativeness is usually heterogeneous and dynamic, this nature has not been fully reflected in diffusion models. Therefore, the author suggests that to use innovativeness as a variable to model diffusion will be beneficial in terms of understanding the nature of diffusion.

Second, as a closely related concept to organisational innovativeness and one of the main factors in diffusion, the role of opinion leadership has been studied extensively. However, most of the existing studies on opinion leadership analyse the role of only a few key opinion leaders in the diffusion process, without including a macro view on the distribution of all organisations' opinion leadership. Additionally, opinion leadership as a variable in diffusion models has rarely been studied. Although a recent study by van Eck et al. (2011) tries to contribute to this topic, it simply models opinion leadership as an independent factor and ignores the links between opinion leadership and other factors of diffusion. Therefore, the author believes that to model the relationship between organisational innovativeness and opinion leadership and their respective roles in diffusion will provide implications for better understanding and managing the diffusion process.

Third, most existing diffusion models are either macro models (usually epidemic diffusion models) that use equations to represent the homogeneous effect of information flow between members in the system, or micro models (usually probit diffusion models) that study the role of individual organisational characteristics in innovation adoption (Geroski 2000). Therefore, the author believes that an agent-based diffusion model, which considers both an organisation's individual characteristics and their interactions, is desirable in order to combine the ideas from both epidemic diffusion models and probit diffusion models.

Fourth, as mentioned in Section 1.2.3, the diffusion forces are either explained from a social contagion perspective that focuses on the growing level of general information about the value of the innovation, or argued from a self-conformity perspective that tends to emphasise the growing level of social pressure toward social conformity (Ansari, Fiss & Zajac 2010). Therefore, the author believes that a model that combines these two streams of understanding will enrich the current knowledge on the explanations of diffusion forces.

Finally, the literature of diffusion models has been growing considerably in the last fifty years. Models with various factors are developed from various perspectives to understand this phenomenon. However, each model normally addresses just one or a few factors at a time and the links between these models are not fully clarified. Therefore, the author believes that it will be valuable to develop a diffusion model with a good extendibility, so all of these factors (such as organisational geographic location) can be combined.

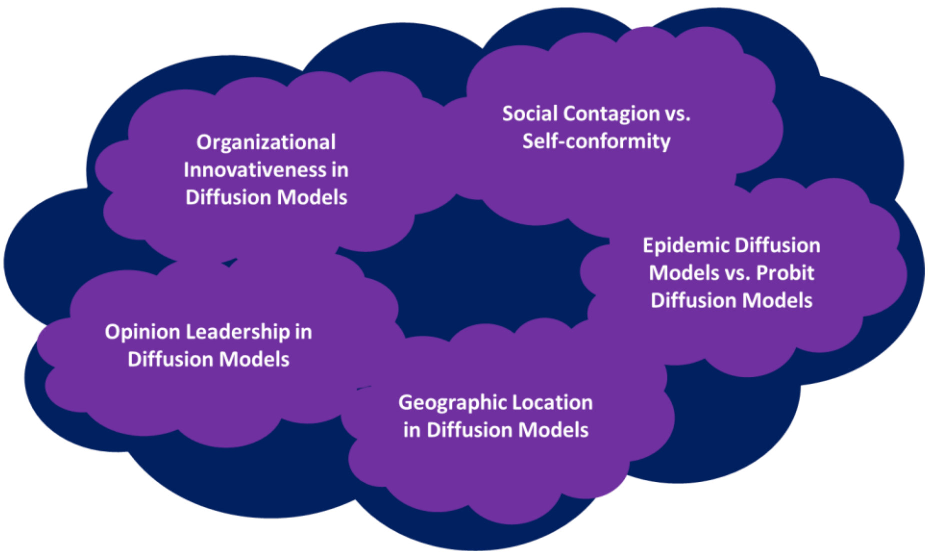

Figure 2: Research Motivations

1.4 Research Aim and Questions

The aim of this study is *to understand the impact of organisational innovativeness, organisational opinion leadership, and organisational geographic location on the diffusion process, with a specific focus on the heterogeneous and dynamic nature of these three factors, in order to imply managers in organisations and industry policy makers in making innovation and diffusion strategies and policies*.

In this study, organisational innovativeness is defined as the ability of an organisation to adopt an innovation relative to other organisations within a given system, and organisational opinion leadership is the specific role of an organisation that can influence others to adopt an innovation. The opinion leadership of an organisation is indicated by the innovativeness level of the organisation and the geographic location between two organisations is represented by the physical distance between them. As shown in the research framework below (Figure 3), all three factors are considered as heterogeneous and two of them are considered as dynamic in the diffusion process. Consequently, each of the factors leads to a question that needs to be answered by this study in order to achieve the overall research aim:

1. How is an innovation diffused in an environment where the organisational innovativeness is heterogeneous and dynamic?
2. How is an innovation diffused in an environment where the organisational opinion leadership is heterogeneous and dynamic?
3. How is an innovation diffused in an environment where the physical distance between organisations is heterogeneous?

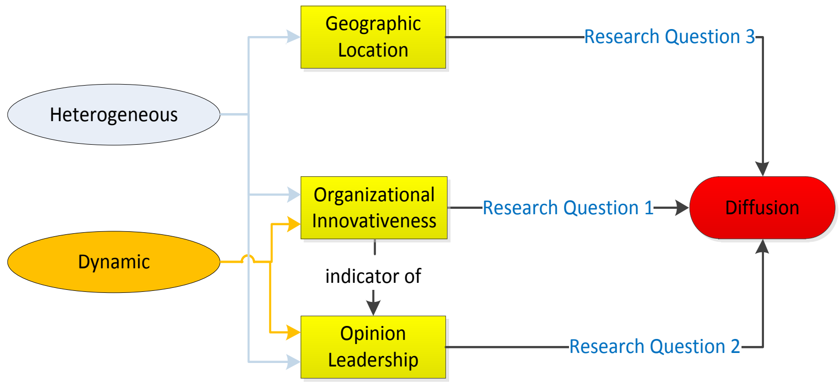

Figure 3: Research Framework

An ideal approach for this study is to develop a diffusion model that considers both the characteristics of individual organisations and their interactions, covers diffusion forces from both social contagion and self-conformity perspectives, incorporates the diffusion factors of interests (organisational innovativeness, opinion leadership, and geographic location), and has both theoretical and empirical supports. Then by analysing the proposed diffusion model, the research questions can be answered and the research gaps can be fulfilled.

1.5 Potential Contributions

In the existing literature, the diffusion phenomenon is understood from different perspectives: forces of diffusion are explained from either social contagion effect or self-conformity effect; models of diffusion can be developed based on either aggregated trend or individual behaviour. Additionally, factors of diffusion are normally analysed separately in diffusion studies for reducing the complexity of analysis. The author agrees with the contributions of these previous studies. While in this study the author is more interested to explore the situation when all these perspectives and factors are combined together.

Therefore, this research will be developed to contribute to the existing body of knowledge by incorporating innovativeness, opinion leadership, and geographic location into a diffusion model that is capable to both demonstrate the aggregated diffusion trend and reflect the role of individual behaviour, with a synthesised view on the forces of diffusion. This proposed model is expected to reexamine the role of organisational innovativeness, opinion leadership, and geographic location in a more comprehensively defined diffusion environment, and thus provide a better understanding on the nature of the diffusion process. Additionally, analysing the proposed model with real world data only can demonstrate a few specific diffusion cases, and thus the result will be limited. Therefore, this study will introduce a simulation approach, in which, the proposed model can be tested and analysed with a wide range of possible inputs.

The result of this study is also expected to contribute to the knowledge in the theory of practice. Specifically, by understanding the role of innovativeness, opinion leadership, and geographic location from an aggregated level, this study is expected to help industry policy makers audit the diffusion speed of an innovation; by understanding the role of these factors from an individual level, this study is potentially beneficial for managers in organisations to make innovativeness and location strategies.

1.6 Structure of This Thesis

This section outlines this thesis and explains the content and purpose of each chapter. Figure 4 shows the questions to be answered in each chapter.

Chapter 1 - Introduction

The present chapter provides a background to the study, followed by the motivations of the research, a description of the research objective and questions, some potential contributions, as well as an outline of the thesis.

Chapter 2 – Organisational Innovativeness and Diffusion Models

Having introduced the research background and research objectives, the second chapter aims to summarise the current knowledge on the relative topics. Chapter 2 consists of three separate sections that dig into the existing literature and summarise the knowledge on organisational innovativeness, models of diffusion, and their relationship. The section on organisational innovativeness provides a critical analysis on its definition, factors, and measures. The section on diffusion models reviews these models in order to express a view on their historical development. The final section emphasises models of adopter-categories, as they could be a potential link between the studies of organisational innovativeness and diffusion models.

Chapter 3 – The Modified Bass Model

Chapter 3 proposes a new diffusion model that will be further extended in the following chapter. This chapter first analyses the Bass model and points out its limitations. Then the new model is developed by combining the ideas of the Bass model and the Von Neumann-Morgenstern Framework. The performance of the proposed model is assessed based on a new parameter estimation technique.

Chapter 4 – Proposed Agent-Based Model of Diffusion

Based on the model proposed in the previous chapter, Chapter 4 develops an agent-based diffusion model to solve the research questions of this study. The author develops the model following a set of general rules of 'diffusion model design'. A short literature review and discussion is given before each part of the model, to ensure that the model is developed rationally.

Chapter 5 – Simulation Design

Before simulating and analysing the proposed agent-based diffusion model, Chapter 5 addresses and discusses the simulation context. This chapter aims to answer a number of questions: Why is a simulation study used here? What software is used for the simulation study? How is the simulation context defined? How is the simulation procedure designed? How is the simulation to be analysed? In Section 5.7 of this chapter, a case study is conducted in order to show how the proposed agent-based diffusion model and the simulation design can be used to fit real world data.

Chapter 6 – Results and Implications

Chapter 6 simulates the proposed agent-based diffusion model under the context defined in Chapter 5, discusses the result of the simulation, and provides a few managerial implications to both industry policy makers and managers in organisations.

Chapter 7 – Conclusions

The final chapter re-emphasises the key theories used in the proposed diffusion model, re-visits the content of each chapter, highlights the key findings from this study, summarises the research contributions, states the research limitations, and directs possible future studies in this area.

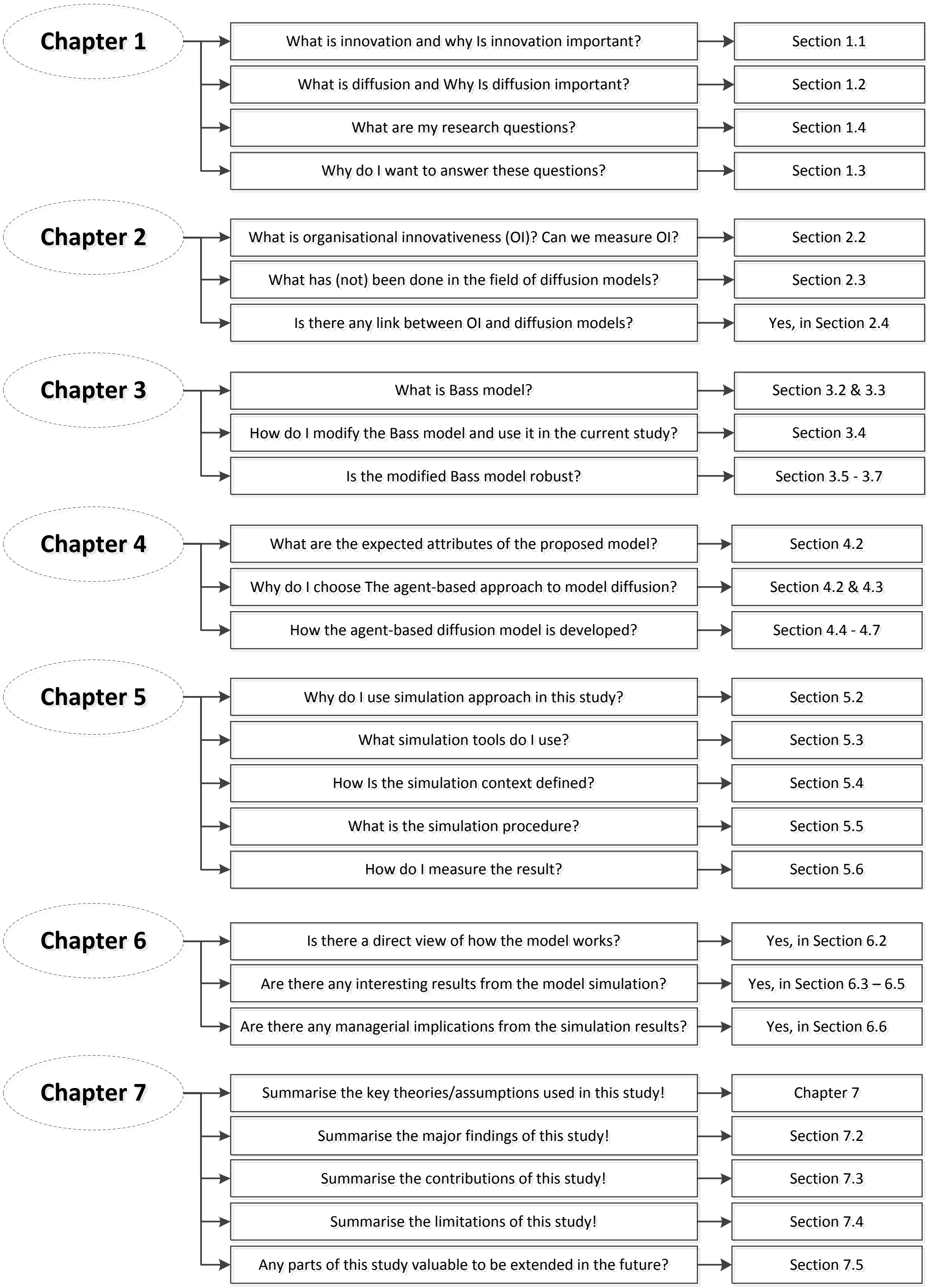

Figure 4: Thesis Structure

Chapter 2 Organisational Innovativeness and Diffusion Models

"Be not the first by whom the new is tried, nor the last to lay the old aside"

(Pope 1771)

"A beautiful management model should match well with the phenomenon being studied, and they can be further enhanced if the parameters have intuitive interpretations."

(Bass 2004)

2.1 Introduction

In order to better summarise and benchmark the achievements of diversified innovation studies, Wolfe (1994) categorises organisational innovation studies into three streams: process theory research, organisational innovativeness research, and diffusion research. Process theory research studies the nature of the innovation process and tries to understand how and why innovation develops over time in organisations. Organisational innovativeness research investigates the drivers that are related to organisations' intention and ability regarding innovative activities. Diffusion research views the consequences of innovation from a macro level and studies how an innovation is diffused in a system (industry, country, etc.). Although these streams specialise in different aspects of organisational innovation activities, the interests within these streams are somehow closely linked with each other.

On the basis of the proposed research aim and research questions, the current research is designed as shown in Appendix 1.[5] After briefly introducing innova-

[5] This study covers two broad research topics: organisational innovativeness and diffusion models. Specifically, organisational innovativeness studies can be either considered as one of the main streams of innovation studies (readers are referred to read the work of Wolf (1994)) or as part of the diffusion research (readers are referred to the work of Rogers (2003)), because innovation,

tion studies and diffusion studies in the introduction chapter, the current chapter bifurcates into the literature of organisational innovativeness and diffusion models, respectively. The former part of the literature review is to summarise the factors and measures of organisational innovativeness with the following aims: factors of organisational innovativeness give readers implications for understanding their effects on the adoption time of organisations and thus the overall diffusion process; the review regarding measures of organisational innovativeness is to show that organisational innovativeness can be assessed and thus can be the input for diffusion models. The literature review of diffusion models aims to give readers a general view on the development of diffusion models and inspire the author to model the diffusion process with the desired properties. Finally, although the relationship between organisational innovativeness and diffusion models has not been studied in a direct manner, a potential contribution in this area can be referred to the models of the adopter-category: these models normally categorise adopters on the basis of their innovativeness levels, and in turn they can be used to model the diffusion process. To sum up, this chapter will be divided into five sections. Specifically, Section 2 reviews the literature on organisational innovativeness to clarify its definition and summarise the drivers and measures of innovativeness that have been studied; Section 3 illustrates a picture of the historical development of diffusion models; Section 4 summarises and discusses models of adopter-category, which could make a link between organisational innovativeness and diffusion models; Section 5 provides a summary of the current chapter.

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organisational innovativeness, and diffusion of innovation are three concepts that are closely related to each other. In Appendix 1, organisational innovativeness studies and diffusion studies are placed as two separated topics.

2.2 Organisational Innovativeness

Standing out among other topics in diffusion research, innovativeness is one of the earliest and largest streams, since it is the fundamental behaviour of organisations in the diffusion process and the main objective of innovation based organisations. Actually, early studies of organisation innovation research are mainly studies of variables related to organisational innovativeness (Van de Ven & Rogers 1988). Works in this area focus on the characteristics of organisations that can differentiate potentially early as well as late adopters in order to understand why a few organisations adopt innovations relative to others (Wolfe 1994). From the organisation level, the aim of this steam is to better understand the factors that help organisations introduce innovations efficiently and effectively. From the industry level, it studies how to distinguish and characterise early adopters from a population of firms (Stendahl & Roos 2008). In order to achieve these goals, scholars usually consider the relationship between one dependent variable (organisational innovativeness) and a few independent variables (factors of organisational innovativeness) through regression analysis (Wolfe 1994). Furthermore, one of the primary issues in studying organisational innovativeness is how to measure the innovativeness level of organisations. Kuznets (1962) points out that the greatest obstacle of understanding the role of technological change is the scholars inability to adequately measure innovations. The reason for the insufficiency can be varied: it can be because of inconsistency or there may even be conflicting definitions of innovation studied, lack of precise and consistent measurement, and so on. (Juslin, Knowles & Hansen 2007).

2.2.1 Definition of Innovativeness

Innovativeness is a term that is closely related to innovation, but has a different construct. A common understanding of innovativeness is that, the earlier one adopts an innovation, the more innovative it is. Therefore, Rogers (2003, p. 267) defines innovativeness as "*the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than any other members of* *the system*". Rogers' definition is based on the result of an innovation diffusion process, because he uses individual adoption time to calculate innovativeness, and this data is only available when all individuals have adopted the innovation. Therefore, people are usually more interested in the attitude or overall capability of individuals to create or adopt innovations. First, innovativeness can be thought of as an attitude and it is especially obvious when economists use R&D intensity as an indicator of innovativeness. Under this concept, Hurley and Hult (1998) define it as the degree of openness to new ideas as a type of firm's culture. Second, innovativeness is related to a firm's capacity to engage in innovative activities for the introduction of new processes, products, or ideas in an organisation (Damanpour 1991; Glynn 1996; Hult, Hurley & Knight 2004; Hurley & Hult 1998).

Innovativeness can be viewed from different perspectives based on innovation outputs. According to Schumpeter's definition (page 2), each innovation activity can lead to a specific innovativeness dimension. Product innovativeness represents an organisation's overall capacity towards a new product; process innovativeness represents an organisation's overall capacity for developing or introducing a new business process, etc. As the research literature has increasingly expanded, more innovativeness dimensions have been proposed. After summarising previous studies (Avlonitis, Kouremenos & Tzokas 1994; Capon et al. 1992; Hurley & Hult 1998; Lyon, Lumpkin & Dess 2000; Miller & Friesen 1983; North & Smallbone 2000; Rainey 1999; Subramanian & Nilakanta 1996), Wang and Ahmed (2004) classify five main dimensions of innovativeness: product innovativeness, market innovativeness, process innovativeness, behaviour innovativeness, and strategic innovativeness, which are expected to give an overall view of organisational innovativeness. Additionally, organisational innovativeness can be differentiated by the categories of 'creative' and 'adoptive,' similar to the classification of innovations by their originality. The former focuses on the capacity to develop an innovation within organisations, while the latter focuses on the capacity of adopting an innovation from the outside. Combining the ideas above, ten dimensions of organisational innovativeness are summarised in Table 2.

	Creative	Adoptive
Product	Capacity of organisations to create new products	Capacity of organisations to adopt new products
Process	Capacity of organisations to create new processes	Capacity of organisations to adopt new processes
Market	Capacity of organisations to create new markets	Capacity of organisations to adopt new markets
Behaviour	Capacity of organisations to create new behaviours	Capacity of organisations to adopt new behaviours
Strategic	Capacity of organisations to create new strategies	Capacity of organisations to adopt new strategies

Table 2: Dimensions of Organisational Innovativeness

2.2.2 Factors of Organisational Innovativeness

The main objective of organisational innovativeness studies is to search and identify a range of variables that are related to an organisation's propensity to adopt innovations (Lam 2005; Wolfe 1994). First and most obviously, the characteristics of the innovation itself have a direct influence on the organisation's attitude towards innovation (Rogers 2003). Beside this, Baldredge and Burnham (1975) attempt to classify other factors of organisational innovativeness through a factor analysis of three categories: individual factors, organisational factors, and environmental factors. This classification is applied by most scholars when conducting research in this field. Therefore, the following paragraph summarises the factors of organisational innovativeness from four aspects: innovation, the organisation, the individual, and the environment.

2.2.2.1 Characteristics of Innovation

Following the early attempt of Rogers (1962) on adopters' perceived innovation attributes,[6] Tornatzky and Klein (1982) conducted a meta-analysis of organisational innovativeness and found a number of innovation characteristics related to innovation adoption and implementation in an organisation. The majority of the following studies do not exceed this range. Among these factors, the initial five factors proposed by Rogers (1962) plus another five (cost, communicability, divisibility, profitability, and social approval) are mostly addressed in the literature.

However, it should be stated that although the characteristics of innovation can influence an organisation's decision regarding innovation adoption, they actually do not influence the organisation's capability of adopting innovations. Therefore, Damanpour (1991) points out that the influence of innovation attributes on organisational innovativeness will decrease when multiple innovations are studied.

2.2.2.2 Organisational Factors of Organisational Innovativeness

Scholars have long considered the relationship between organisational attributes and the adoption of innovation in order to understand what inner factors of organisations cause earlier adoption of innovations. Due to the large number of factors in this construct, the author categorises these factors into three subgroups: those that are related to organisational structure; those that are related to organisational strategy and resources, and those that are related to organisational culture and psychographics.

<u>Organisational Structure</u>

As summarised by Wolfe (1994), organisational structure is the most dominant determinant of organisational innovativeness and has attracted the most attention since its emergence. An early work by Thompson (1965) tries to examine the

[6] Readers are referred to Section 1.2.3, which provided a discussion on this issue.

relationship between the bureaucratic structure of organisations and their innovative behaviours. The result suggests that the increased professionalism, the loose and untidy structure, the decentralised administration, the free communications within an organisation, the rotation of assignments, the greater reliance on group processes, the attempts at continual restructuring, the modification of the incentive system, can all influence organisational innovativeness to a certain degree. Another early significant attempt in this area is Mintzberg's (1979) work, in which he suggests that the simple structure, professional bureaucracy, divisionalised form, and adhocracy are the desired attributes of organisations with regard to breeding innovations. Then, Damanpour (1991) summarises a few influential characteristics of organisational structure that could influence organisational innovativeness: specialisation, functional differentiation, professionalism, formalisation, centralisation, internal communication, and vertical differentiation. The above factors have been validated by most of the following research literature: (Frambach & Schillewaert 2002; Kimberly & Evanisko 1981; Pierce & Delbecq 1977; Wan, Ong & Lee 2005).

Furthermore, a few scholars also believe that certain relationship exists between the age of an organisation and its innovativeness level. According to Pierce and Delbecq (1977), age will add to an organisation's complexity and bureaucracy, and so hinder its capacity for innovation. On the other hand, older organisations usually have a well-defined resource base and high survival potential that can assist innovative activities (Kimberly & Evanisko 1981). These arguments further lead to the study of a company's life cycle towards innovation: organisations should have different strategies towards innovations at different stages of their life (Miller & Friesen 1984).

Finally, size is also believed to have a strong effect on organisational innovativeness, although the effect is still uncertain. Some researchers state that bigger organisations are considered to have more resources to support innovative activities, while some others point out that small organisations are more flexible in their ability to adopt innovations (Rogers 2004). Therefore, Damanpour (1992) concludes that to understand the effect of size on innovativeness should not ignore the role of those control variables such as types of organisation and types of innovation.

Organisational Strategy and Resources

Innovation process is often considered as an element of organisational strategy (Capon et al. 1992). If organisations have a consistent strategy and make continuous attempts towards innovation, their innovativeness will increase correspondingly. And the clearest way to view how much effort an organisation is trying to put into innovation activities is by assessing the R&D investment and acquisition expenditure of the organisation (Acs & Audretsch 1988). Furthermore, competent resources are also significant to the innovative activities of organisations. For instance, Nonaka (1991) presents a framework to explain how innovations can be developed through a continuous spiral knowledge creating process; Damanpour (1991) reports that innovations tend to be developed within organisations with more technical resources; especially in high-tech industries, a positive relationship is found between innovativeness and the number of specialists and professionals in the organisation (Damanpour 1991).

Organisational Culture and Psychographics

The culture and psychographic aspects of organisational innovativeness have recently attracted increasing attention (Hult, Hurley & Knight 2004; Hurley & Hult 1998; Ozsomer, Calantone & Bonetto 1997; Wang & Ahmed 2004). In a recent study on the innovation culture of organisations, Dobni (2008) argues that an innovation culture scale might best be represented through a structure that consists of seven factors: innovation propensity, organisational constituency, organisational learning, creativity and empowerment, market orientation, value orientation, and implementation context. For studies of organisational psychographics, Robertson and Wind (1980) summarise six factors: direction, decision centrality, openness of communication, achievement motivation, resistance to change, and conflict, which are closely related to the attitude of organisations to engage in innovative activities.

2.2.2.3 Individual Factors of Organisational Innovativeness

Rogers (1962) points out that the leaders' attitude toward change has a dominant role in how organisations conduct innovative activities. A few other scholars (Hage & Dewar 1973; Miller, Vries & Toulouse 1982) also recognise that people who lead innovation activities in organisations, play an important role for innovation creation and adoption. Actually, leaders in organisations are not only responsible for encouraging the starting of innovation, but also sustaining innovative activities through the whole innovation process (Borins 2001).

After classifying leaders of organisations into 'administrative' or 'professional,' the study results show that organisations with both cosmopolitan professionals and local administrators have the highest innovativeness level, and that the lowest innovativeness level is exhibited by organisations with local professionals and local administrators (Robertson & Wind 1983).

As summarised and discussed by a number of scholars (Damanpour 1991; Meyer & Goes 1988), if administrators have long tenure and a higher educational background (Meyer & Goes 1988), they are likely to exert more positive influences on innovative activities. These two factors (tenure and education) are not limited to administrators, but also to regular staff (Kimberly & Evanisko 1981).

To sum up, if individuals have a strong managerial attitude toward change (Damanpour 1991), have a higher job satisfaction and job involvement (Pierce & Delbecq 1977), have a strong belief that innovation is important (Meyer & Goes 1988), and are willing to take risks and exchange ideas (Wan, Ong & Lee 2005), they will have more motivation to make changes.

2.2.2.4 Environmental Factors of Organisational Innovativeness

About half a century ago, Terreberry (1968) noticed that certain environments promote organisational evolution. He also stated that an organisation's adoption of innovation was just an ability to learn and perform according to changes in the environment. The environmental factors listed in this study are the characteristics of the organisation's particular circumstance, for example, social, cultural, political, economic as well as technological support, and the networks an organisation using for interacting with other members of the system including its competitors, collaborators, and subcontractors.

Among other various environmental factors, environmental uncertainty and environmental competition are the most persuasive. This is because organisations would feel that there is no need to innovate when they are in a less competitive environment. Similar results are supported by other researchers such as Pierce and Delbecq (1977), Kimberly and Evanisko (1981), and Frambach and Schillewaert (2002). By using the term, 'market turbulence', Hult et al. (2004) argue that the effect of innovativeness on business performance is greater under high market turbulence than under low market turbulence. Ozsomer et al. (1997) also find that environmental hostility will lead to environmental uncertainty and further influence firms' strategy to innovate.

Beside environmental competition and uncertainty, social network also plays an important role for innovations. Pierce and Delbecq (1977) figure out that inter-organisational interdependence hinders organisational innovativeness. Rogers (1962) also reports that networks could promote innovations and that this is especially important for SMEs. The importance of social networks is also summarised and emphasised by Damanpour (1991) and Frambach and Schillewaert (2002). Other less studied environmental factors may include the size of the industry or market, the earnings of local people (Meyer & Goes 1988), and the marketing activity of suppliers (Frambach et al. 1998; Frambach & Schillewaert 2002).

Table 3 lists the factors of organisational innovativeness that are discussed in this study.

Factors of Organisational Innovativeness

		Factors	***References***
Individual		Attitude toward change	(Rogers 1962)
		Job satisfaction and involvement	(Pierce & Delbecq 1977)
		Cosmopolitan	(Robertson & Wind 1983)
		Tenure and educational background (both leaders and non-leaders)	(Kimberly & Evanisko 1981; Meyer & Goes 1988)
		Belief that innovation is important	(Meyer & Goes 1988)
		Willing to take risks and exchange ideas	(Wan, Ong & Lee 2005)
Environmental		Competitive environment (environmental complection, uncertainty, hostility, etc.)	(Pierce & Delbecq 1977)
		Network (inter-firm independence)	(Damanpour 1991; Frambach & Schillewaert 2002; Pierce & Delbecq 1977; Rogers 2004)
		Size of the industry/market, degree of wealth	(Meyer & Goes 1988)
		Supplier's marketing activity (targeting, communication, risk education)	(Frambach et al. 1998; Frambach & Schillewaert 2002)
Organisational	***Structure***	Specialisation; functional differentiation; professionalism; formalisation; centralisation; internal communication; vertical differentiation	(Damanpour 1991)
		Size	(Damanpour 1992)
		Age (life-cycle)	(Kimberly & Evanisko 1981; Miller & Friesen 1984; Pierce & Delbecq 1977)
	Strategy / Resource	R&D and acquisition expenditure	(Acs & Audretsch 1988)
		Slack (knowledge, technology, and human resources)	(Damanpour 1991)
	Culture / Psycho-graphics	Innovation propensity; organisational constituency; organisational learning, creativity, and empowerment; market orientation; value orientation; implementation context	(Dobni 2008; Hult, Hurley & Knight 2004)
		Direction; decision centrality; openness of communication; achievement motivation; resistance to change; conflict	(Robertson & Wind 1980)

Table 3: Factors of Organisational Innovativeness

2.2.3 Measures of Organisational Innovativeness

Although significant and requisite, it is difficult to measure organisational innovativeness directly, because a standard definition of organisational innovativeness does not actually exist and the contexts of innovation activities are diverse (Välimäki et al. 2004). Various approaches for assessing organisational innovativeness have been proposed in both academic and practical fields, but no single one provides a perfect solution. For instance, Geroski (1994) lists R&D expenditure, number of patents, and counts of major/minor innovations as three main ways of assessing an organisation's innovation performance, and Smith (2005) promotes R&D data, patent counts, and bibliography data. However, they both notice that each approach has its advantages and disadvantages.

This section reviews the measures of organisational innovativeness and attempts to make a comparison between them. These measures are presented from four perspectives: the innovation-based approach, the self-evaluation approach, the input and output approach, and the size-based approach. Corresponding indicators used in each approach are also listed and discussed.

2.2.3.1 Innovation-Based Approach

Innovativeness measures can be divided into two types: objective approaches that focus on innovations directly, and subjective approaches that analyse an organisation's innovation behaviour towards innovation. Actually, the innovation-based approach can also be categorised within the input and output approach (section 2.2.3.2), if the innovations are considered as output from an organisation's innovative activities. The reason why it is separated and explained first is because this approach is the most straightforward way of assessing organisational innovativeness, and the only way that focuses on innovations directly (Smith 2005).

According to Midgley and Dowling (1978), most studies use an innovation-based approach to assess innovativeness, if the research target are human-beings. The innovation-based approach is also widely used in organisational studies (Wolfe 1994). In this construct, organisational innovativeness can generally be measured through four indicators: the adoption time of a single innovation, the number of total innovations each organisation has at a given time period, the literature-based innovation output indicators, and the composite methods.

Based on Rogers' (2003) statement of innovativeness, one simple way of assessing organisational innovativeness is to compare the adoption time of each organisation for a given innovation, since the earlier one adopts the innovation, the higher its innovativeness is. The advantage of this method is it can be easily understood and applied, while its major shortcoming is that it only focuses on one innovation without supporting an overall view of organisation's innovation performance.

Another innovation-based indicator is the number of innovations each organisation has adopted within a specific time period, since the more innovative organisations will normally have more innovations (Robertson 1971). This indicator improves the above method by using more than one innovation to measure innovativeness, and thus the bias can be reduced. However, it is constrained by the difficulties of selecting proper innovations, since innovations are usually weakly defined by surveyors and different innovations are generally considered to have the same impact on the result.

Literature-based innovation output indicators measure organisational innovativeness by surveying the product announcement sections of technical and trade journals (Coombs, Narandren & Richards 1996; van der Panne 2007; Walker, Jeanes & Rowlands 2002). Compared with questionnaire and interview based innovation evaluation approaches, the literature-based innovation output approach does not suffer from a recall problem and a low response rate from organisations. However, it also has a few shortcomings: it only focuses on product innovations, and a few organisations may try to capture customers by advancing non-innovative products as innovations.

Finally, an example of composite methods can refer to the work of Fell et al. (2003), which is designed to examine a list of pre-defined innovations and accounts for the time of adoption. This method considers both the number of innovations and the time of adoption. The result shows that this composite method can capture elements of both methods well and should thus be more accurate than any of the others.

2.2.3.2 Input and Output Approach

From its literal meaning, the input and output approach evaluates organisational innovativeness through assessing input activities towards innovations and the output resulting from those innovative activities. This is a widely-accepted approach in the literature and it consists of a number of indicators. Among them, R&D data and patent data[7] are the most significant and widely used.[8]

R&D and patent data are both easily accessible and well understood. Also they are both comprised of archived number-based values that can be used in subsequent analysis (Rogers 1998). As examined and reviewed in a few influential articles, R&D data is believed to have significant correlations with improvement of market share (Ettlie, Bridges & O'Keefe 1984) and organisational innovativeness (Acs & Audretsch 1988). Correlations have also been observed between patent data and innovation activities. For instance, Mansfield (1986) finds that there are many innovations that will not be commercialised unless they are patented, with this being especially common in a few specialised industries such as those involving pharmaceuticals and chemicals; even in industries where patents are not

[7] R&D data here refers to either personnel or non-personnel data that can describe an organisation's investment towards research and development activities. In OECD (2005, p. 92), R&D is defined as "*creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture, and society, and the use of this stock of knowledge to devise new applications*". And a patent is to "*protect new inventions and covers how things work, what they do, how they do it, what they are made of, and how they are made. It gives the owner the right to prevent others from making, using, importing, or selling the invention without permission*" (UK.Patent.Office 2009).

[8] Other indicators within the input and output approach include: net profits, revenue growth, share performance, market capitalisation and productivity (Rogers 1998). However, they are less popular in organisational innovation research compared with R&D and patent data.

considered very important, such as the motor vehicle industry, over 60% of patentable inventions seem to actually have been patented.

R&D and patent data are also closely related to each other. An early study by Pakes and Griliches (1984) shows a strong correlation between R&D expenditure and the number of patents in organisations, even at the cross-sectional level. Basberg (1987) also reports that the positive relationship between R&D and patent is empirically well documented, since many studies consider patent as an output indicator of R&D. In order to explain the correlation between R&D and patent, Griliches (1990) argues that parallel changes will occur within patent data soon after organisations change their R&D expenditure. Though there are certain degrees of lag effects, they are usually small and not well-estimated.

However, both R&D data and patent data have major shortcomings. According to Kleinknecht et al. (2002), cited by Smith (2005), R&D just measures input, and it only can represent a partial view of an organisation's investment towards innovations. Therefore, an important recent modification is to further measure *acquired R&D data*, which is calculated by using the capital good's value multiplied by the R&D intensity of the supply industry (Smith 2005). Patent data can either overestimate or underestimate organisational innovativeness (Nelson 2009). On the one hand, many patents also represent inventions that have not been commercialised, while on the other, many innovations are not patented because of different patent laws in different countries, cost consideration, because it is easy for competitors to invent around the patent, and other reasons (Basberg 1987). Basberg (1987) also points out that the patent-based approach will introduce bias to the measurement result, since radical or minor innovations cannot be distinguished in aggregated patent data. Furthermore, patent data is a poorer indicator for the short-term analysis of innovative activities (Griliches 1990) and it is especially weak in the within-firm time series dimension (Pakes & Griliches 1984).

It should also be noticed that both R&D and patent data are influenced by a few moderators (control variables) such as size and type of organisation (Alcaide-

Marzal & Tortajada-Esparza 2007; Smith 2005). Industry effects could take on an important role in the variance of R&D intensity between different organisations (Cohen, Levin & Mowery 1987) and the correlation between innovations and R&D is greater for large organisations than for small ones (Acs & Audretsch 1988). Acs and Audretsch (1988) further point out that, organisational innovativeness would increase with increased R&D expenditures, but more and more slowly. Griliches (1990) also finds that small organisations tend to be more efficient in receiving patents with the same amount of R&D expenditure, and small organisations are more likely to receive innovation spill-over from large ones that have larger R&D centres such as large organisations and universities (Acs, Audretsch & Feldman 1994). According to Cohen and Klepper (1996), the propensity to invest in R&D activities and the amount of R&D conducted by organisations, are closely related to size, and R&D productivity seems to decline with organisation size.

2.2.3.3 Self-Evaluation Approach

The third approach for assessing organisational innovativeness is to ask organisations to rate themselves as innovative or not. This is usually processed by using questionnaire surveys with interval scale questions. A few examples can be referred to the works by Capon et al. (1992), Green and Aiman-Smith (1995), Wang and Ahmed (2004), and Crespell et al. (2006).

The self-evaluation approach is easily applied and it can directly reach those people who are already familiar with these organisations. Furthermore, this approach can assess all dimensions of organisation innovativeness including innovation, the innovative activities of an organisation, environmental effect, and individual attitude towards innovation. However, since data is generally subjective, that is, shaped by the opinions of individual people, the results would introduce considerable bias. Moreover, researchers would usually fail to get desirable data because of the recall problem.

2.2.3.4 Size

Although many scholars use size as a control variable when assessing organisational innovativeness, a few others consider it as a direct indicator. However, a clear relationship between size and organisational innovativeness has not yet been agreed upon in the current literature, although Damanpour (1992) does provide a few guidelines for examining the relationships between size and innovativeness. First, size is more effective in assessing innovations in manufacturing and profit-making organisations than in service and non-profit-making organisations. Second, non-personnel data is more reliable than personnel data in assessing firm size, and thus serves as a better indicator of innovativeness (However, OECD (2005) holds an opposite view about this issue and suggests using the number of employees to measure firm size). Third, data with logarithm transformations is more reliable, since innovativeness will increase more and more slowly when the size is increasing. Fourth, the type of innovations does not have a considerable moderating effect on the relationship between size and innovation. Finally, size is more strongly related to implementation than to the initialisation of innovation in organisations.

There are various ways for measuring the size of organisations. Kimberly (1976) summarises four aspects of size that include: the physical capacity of an organisation, personnel available to an organisation, organisational inputs or output, and resources available to an organisation. Relevant indicators are available for each aspect.

Table 4 lists the measures of organisational innovativeness that are discussed in this study.

Measures of Organisational Innovativeness		
	Indicator(s)	***Comments***
Innovation based	*Adoption time of innovation(s)*	To compare the adoption time of each individual for a given innovation (Rogers 1962);
	Number of Innovations	To compare the number of innovations each individual adopts/has within a specific time period (Robertson 1971);
	Literature-based output indicators	To measure innovativeness through surveying product announcement sections of technical and trade journals (Coombs, Narandren & Richards 1996; van der Panne 2007; Walker, Jeanes & Rowlands 2002).
Input / Output	*R&D data*	1. R&D and patent data are both easily accessible, well understood, and easily used in subsequent analysis (Rogers 1998); 2. R&D has significant correlations with innovative activities (Ettlie, Bridges & O'Keefe 1984; Acs & Audretsch 1988); and so does patent data (Mansfield 1986); 3. R&D and patent data are closely related to each other (Pakes & Griliches 1980), though certain degrees of lag effect exist (Griliches 1990). However: 1. R&D only measures input, and only shows a partial view of innovation activities (Kleinknecht, Montfort & Brouwer 2002); 2. Patent data can either overestimate or underestimate organisational innovativeness (Nelson 2009); 3. Patent data is a poor indicator for short-term analysis of innovativeness activities (Griliches 1990); it is also weak in a within-firm time series dimension (Pakes & Griliches 1984).
	Patent number	
	Others	Net profits; revenue growth; share performance; market capitalization or productivity, etc. (Rogers 1998)
Self-Evaluation	*Various Indicators*	Asking people in organisations to rate themselves as innovative or not, is done usually through surveys with interval scale questions.
Size	*Physical capacity, personnel data, organisation inputs and outputs, organisational resources (Kimberly 1976)*	According to Damanpour (1992): 1. Size is more effective in assessing innovations in manufacturing and profit-making organisations than in service and non-profit-making organisations; 2. Data with logarithm transformations is more reliable; 3. Size is more strongly related to implementation than to initialisation of innovation in organisations.

Table 4: Measures of Organisational Innovativeness

2.2.3.5 Single-indicator Approach vs. Multi-indicator Approach

Organisation innovation performance is a complex phenomenon that is determined by many factors. Although a number of approaches and indicators are available, each of them only can explain it from a partial view. Therefore, to use a number of indicators seems sensible, as it allows us to explain organisational innovativeness from more perspectives and thus increases the credibility of the result. However, debate exists on this issue. For instance, Hagedoorn and Cloodt (2003) use R&D data, patent data, and the number of announced innovations to conduct an innovativeness study. Although the result shows that this multi-indicator based approach does catch the latent variable of organisational innovativeness, to use any of these indicators also provides a good result. The work further argues that it is typical that these indicators have great correlations with each other, so introducing all of them is not necessary.[9]

2.3 Models of Diffusion Process

Science is the process where data and theories are generalised to explain different types of phenomena (Bass & Wind 1995), which are the patterns or regularities that repeat over different situations and that can be described by mathematical, graphical, or symbolic methods (Bass 1995). Among these methods, the mathematical model is particularly useful and widely-used in management studies (Leeflang & Wittink 2000). As one of the three pillars in the successful introduction of an innovation (the other two are creation of an innovation and commercialisation of an innovation), diffusion could be the easiest to study because it is more predictable from observable factors than the other two, and the most popular technique to predict this process is the diffusion model (Hall 2005, p. 478): *"In fact, for such decision, diffusion or growth models are the only analytical tools available to study the life-cycle analyses and their impact on strategic decisions".*

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[9] The author made a trial analysis of the organisational innovativeness indicators. Readers are referred to Appendix 2 for details of this experiment.

It is well acknowledged that the resulting curve of a typical diffusion process is normally an S-shape curve, where the adopter of an innovation is plotted versus the time. Following this observation, a number of models have been proposed to match this S-shape phenomenon, some of them originating from the desire to provide a mean that better understands the phenomena, others simply driven from the desire to fit the real data. It is believed that good diffusion models should be able to capture the fundamental nature of the diffusion process, and thus can be used to understand the phenomena and forecast the future demand of the innovation. By reviewing and extending the studies of Eliashberg and Lilien (1993) and Montgomery (1973), Leeflang and Wittink (2000) conclude five model building eras in marketing research in the last century. The history starts from direct applications of existing operation research and management science methods to newly designed models that can simply capture the management reality. In fact, diffusion models in management studies also follow such traits. This section tries to summarise a few influential diffusion models from the existing literature.

2.3.1 Epidemic Diffusion Models

The most popular explanation of a general diffusion process is the family of epidemic diffusion models. This type of model is based on the assumption that the reason why individuals have not adopted the innovation is because they have not known about it. Therefore, epidemic diffusion models largely focus on the information/knowledge transfer between members of the diffusion environment.

The basic understandings embedded in epidemic diffusion models were mostly proposed half a century ago and consequent models are usually just modifications based on these fundamental works. It has been documented that the natural growth of many phenomena can be depicted by using an S-shape curve (Meade & Islam 1998), and Griliches (1957) is usually considered as the pioneer, who observe that the penetration of innovations also follows an S curve. Another early attempt is from Fourt and Woodlock (1960), who propose a simple model with a linear relationship between the number of new adopters and the number of potential adopters at each time point. However, as the result of Fourt and Woodlock's (1960) model does not represent a classical S-curve, it has not received considerable academic praise. Despite this, the model is still important in diffusion literature, because it points out that the number of new adopters at each time point should be someway related to the number of potential adopters. From this point onwards, scholars have tried to adopt and propose various models to fit and explain this phenomenon. For instance, Mansfield (1961) introduces a logistic function between the number of existing adopters and the number of potential adopters in order to describe the diffusion process. This model is still widely-used today especially for the studies where the effect of the mass media is not significant. Among these early diffusion models, the Bass model (1969) is the most influential one. By reconsidering the diffusion process alongside managerial meanings, Frank Bass (1926 - 2006) proposed the Bass model, which went on to become one of the most important models in marketing and management. Based on the two-step flow theory, the Bass model assumes that a potential adopter will adopt an innovation under either of two effects: the external effect (or environmental effect, mass media effect as commonly accepted) and the internal effect (or inter-influence effect between members of the system, social contagion effect as commonly accepted). Specifically, the former effect means that the information of the innovation from the environment and the latter represents the information of the innovation that comes from other members in the system. Taking the individual view to explain the Bass model, Meade and Islam (2006) state that individuals are influenced by either a desire to innovate or a need to imitate others. Most epidemic diffusion models that have been developed are based on the concept of the Bass model.

In this study, these important epidemic diffusion models after the Bass model are summarised and classified into four streams: diffusion models with marketing-mix variables; multi-category and multi-generation diffusion models; global diffusion models; and dual-market diffusion models.

2.3.1.1 *Diffusion Models with Marketing-Mix Variables*

One of the major shortcomings of the Bass model is its lack of managerial variables. Therefore, scholars have always been trying to fill this gap and their contributions start with the introduction of marketing-mix variables. These modified models have successfully turned the Bass model from a simple forecasting tool into a managerial aid (Roberts & Lattin 2000). Table 5 below lists a few influential models in this category.

The model developed by Robinson and Lakhani (1975) is one of the earliest attempts to introduce managerial parameters into the Bass model. This model is based on a basic assumption that, the lower the price is, the more quickly the innovation is diffused. Therefore, a learning curve function, $e^{-kPr(t)}$, is introduced to modify the sum of the environmental effect and inter-influence effect. Related to Robinson and Lakhani's (1975) model, Simon and Sebastian (1987) consider that advertisements can influence either the environmental effect or the inter-influence effect. Therefore, they introduce an implicitly-defined function $A(t)$ to modify the parameters of the two effects, respectively.

It can be seen that the models of Robinson and Lakhani (1975) and Simon and Sebastian (1987) both make modifications to the two parameters of the Bass model without considering that the size of the market is also influenced by marketing-mix variables. Therefore, Kamakura and Balaubramanian (1988) introduced a function $Pr(t)^{\eta_2}$ to modify the size of the *total market* with Jain and Rao (1990) further proposing an alternative by using a similar function to modify the size of the *potential market*.

The last model listed in this category is proposed by Bass et al. (1994), with a design of a generalized Bass model to solve the marketing-mix issues in the diffusion model. This model uses the changing price and advertisement rate to update the environmental and inter-influence effects in the Bass model. Compared with other models in this category, the generalised Bass model has a few merits.

First, it includes both price and advertisement effects. Second, it is the first model to use explicit and comparable functions to define the effects of price and advertisement.[10] Third, the model can perfectly reduce to the Bass model when the value of price and advertisement do not change though time.

Authors(s)	Model Description
(Robinson & Lakhani 1975)	$f(t) = (M - F(t))(p + qF(t))e^{-kPr(t)}$
	This is the first influential diffusion model that introduces the marketing-mix variables. In this model, price ($Pr(t)$) can affect both the environmental and inter-influence effects. p and p here are the parameters of external effect and internal effect respectively; $f(t)$, $F(t)$, and M indicate new adopters, cumulative adopters, and total market. ***These definitions apply to all the models in this section unless specified.***
(Simon & Sebastian 1987)	$\begin{cases} f(t) = (p + pA(t) + qF(t-1))(m - F(t-1) \\ f(t) = (p + (q + qA(t))F(t-1))(m - F(t-1) \end{cases}$
	In this model, the authors propose that advertisement effect ($A(t)$) can either influence the environmental or inter-influence effects
(Kamakura & Balasubramanian 1988)	$f(t) = (p + qF(t))Pr(t)^{\eta_1}(\theta M(t)\, Pr(t)^{\eta_2} - F(t))$
	In this model, the total market $\theta M(t)$ for the innovation is dynamic. Price here affects both the communication channels and the total market with different degrees ($Pr(t)^{\eta_1}$ and $Pr(t)^{\eta_2}$).
(Jain & Rao 1990)	$\begin{cases} S(t) = \left(MPr(t)^{-\eta} - Y(t-1)\right)\dfrac{F(t) - F(t-1)}{1 - F(t-1)} \\ S(t) = (M - Y(t-1))Pr(t)^{-\eta}\dfrac{F(t) - F(t-1)}{1 - F(t-1)} \end{cases}$
	In this model, price ($Pr(t)$) can affect either the total market (M) or potential market ($M - Y(t-1)$).
(Bass, Krishnan & Jain 1994)	$f(t) = (p + qF(t))x(t)\left(1 - F(t)\right), x(t) = 1 + \beta_1\dfrac{Pr'(t)}{Pr(t)} + \beta_2\dfrac{A'(t)}{A(t)}$
	Here both price and advertisement are included as variables. The authors use the relative change of price and advertisement to model their respective impact on diffusion, and introduce two parameters β_1 and β_1 to represent the respective importance of these two factors in diffusion. This model can reduce to the Bass model perfectly when price and advertisement effects remain constants.

Table 5: Diffusion Models with Marketing-Mix Variables

[10] Different to previous models, the generalised Bass model uses the changing rate of price and advertisements as variables. Therefore, products with different price and advertisement inputs become comparable.

2.3.1.2 Multi-Category and Multi-Generation Diffusion Models

The original Bass model was developed within an ideal environment where only one generation of one single innovation exists in the system. In real situations, these innovation providers normally have competitors offering the same or similar innovations to the market. Furthermore, due to their continuous improvement, innovations can exist with different generations. In order to understand these phenomena, scholars have developed a number of multi-category and multi-generation diffusion models. A few of them are highlighted in Table 6.

The first attempt in this category was made by Peterson and Mahajan (1978), with an equation modelling the diffusion of inter-products based on Frank Bass' single product diffusion model. In this model, a number of similar products exist in the same market and the function $C_i F_j(t)$ is used to represent the influence from product j to product i. Then, based on the value of C_i, they identify three types of inter-product relationships as: complementary ($C_i > 0$), substitute ($C_i < 0$), and independent ($C_i = 0$). They further provide a model for contingent product diffusion, in which the total market of the contingent product equals the sales of the focal product.

Another example here represents a special case of the inter-product effect used for the sale of software. The model developed by Bayus (1987) assumes that the sale of software should be determined by the sale of its depending hardware. After calculating the sale of hardware at time t $H_j(t)$,[11] the sale of software in segment j at time t would equal the value of $H_j(t)$ multiply the purchase rate in category j at time t.

It is found that the Bass model is limited when studying the diffusion of certain innovations such as IT technologies, since one IT innovation normally has more than one generation, and it is very common for these generations to be available in the market at the same time. That is why Norton and Bass' (1987) multi-

[11] This can be done by using existing diffusion models such as the Bass model.

generation diffusion model is widely agreed upon as one of the most important extensions of the Bass model in literature (Bass 2004; Meade & Islam 2006). This model divides the sales of each generation into two parts: initial expected sales calculated by the Bass model and sales accrued by inter-generational effect. Specially, the model assumes that the cumulative sales of first generation at time t equals the initially expected sales minus the sales plundered by the sales of the second generation, the cumulative sales of the second generation at time t equals the initially expected sales of the second generation plus the sales plundered from the first generation then minus the sales plundered by the sales of the third generation, and so on so forth.

Finally, the model developed by Kim et al. (2000) combines the effects of the multi-category and multi-generation effect in a single model. However, the concept behind the model is the same as the work of Norton and Bass (1987) and Peterson and Mahajan (1978).

Author(s)	Model Description
(Peterson & Mahajan 1978)	$f_i(t) = (p_i + q_iF_i(t) + c_iF_j(t))(M_i - F_i(t))$ $i, j = 1{,}2; i \neq j$
	This is an early work in the literature of diffusion models, which studies multiple inter-products diffusion. In this model, the diffusion process of product i ($f_i(t)$) is influenced by both the mass media effect of the product, social contagion effect from the current adopters ($q_iF_i(t)$), and previous adopters ($c_iF_j(t)$).
(Bayus 1987)	$S(t) = \sum_j \int_0^t H_j(\tau)\rho_j(t-\tau)d\tau$
	The diffusion of hardware and the diffusion of the hardware's associated software can be considered as a special case of multi-generation diffusion: the sales of software normally come after the sales of its dependent hardware. In this study, the total sales of the software at time t ($S(t)$) is determined by the sales of its dependent hardware $H_j(\tau)$ and the purchase rate τ time period after the hardware was purchased.
(Norton & Bass 1987)	$S_1(t) = m_1F_1(t) - m_1F_1(t)F_2(t-\tau_2)$ $S_2(t) = m_2F_2(t-\tau_2) + m_1F_1(t)F_2(t-\tau_2)$ ……
	This is one of the most influential models in the literature of diffusion studies, as it proposes a direction for solving multi-generation diffusion problems. The basic concept under this model is: first, the diffusion curve of each generation can be initially explained by the Bass model ($m_iF_i(t)$); then it is assumed that some adopters of generation i will become the adopters of the next generation ($m_iF_i(t)F_{i+1}(t-\tau_{i+1})$). Here τ_i is the release time of each generation.
(Kim, Chang & Shocker 2000)	$S_{k,n}(t) = \big[m_{k,n}F_{k,n}(t - t'_{k,n}) + m_{k,n-1}F_{k,n-1}(t - t'_{k,n-1})F_{k,n}(t - t'_{k,n}) + m_{k,n-2}F_{k,n-2}(t - t'_{k,n-2})F_{k,n-1}(t - t'_{k,n-1})F_{k,n}(t - t'_{k,n}) \dots + m_{k,1}F_{k,1}(t - t'_{k,1}) \dots F_{k,n}t - t'_{k,n}\big][1 - F_{k,n+1}(t - t'_{k,n+1})]$
	This is a diffusion model that considers both multi-category and multi-generation problems. Although the model looks complicated, the concept behind this model is the same with Norton's work.

Table 6: Multi-category and Multi-Generation Diffusion Models

2.3.1.3 Global Diffusion Models

Due to the current state of globalisation, organisations are more concerned with diffusion issues within a global context (Dekimpe, Parker & Sarvary 2000). Therefore, a number of global diffusion models have been developed since the late 1980s and a few influential ones are summarised in Table 7.

The first influential contribution in this field was made by Gatignon et al. (1989), who modified the Bass model and endowed new definitions for the parameters of external influence and internal influence in terms of global diffusion attributes. Specifically, three characteristics were introduced to represent the propensity of individual people in different countries to purchase new products: cosmopolitanism, mobility, and the role of women in society. However, the major defect of this model is that it does not account for the inter-influences that occur between the consumers from different countries. In order to implement the above work and model the cross-country effect within global diffusions, Putsis et al. (1997) propose that one country's internal influence can be affected by the number of the adopters in other countries. However, one of the major shortcomings of this model is that only positive cross-country effect is allowed. Therefore, Kumar and Krishnan (2002) further modify Putsis et al.'s (1997) model by defining that the cross-country effect could have either a positive or negative value. Finally, a recent work by Albuquerque et al. (2007) provides a systematic way to combine the ideas of the studies above. Besides the intra-country influences, Albuquerque et al. (2007) assume that the adoption rate of firms in one country can be further affected by the number of adopters in other countries. Then they describe the parameter of inter-country effect by using three main factors: geographical distance, trading between two countries, and culture similarity. This model is a combinational model including most of the existing attributes from global diffusion models in the current literature.

Authors(s)	Model Description
(Gatignon, Eliashberg & Robertson 1989)	$$F_i(t) - F_i(t-1) = (p_i + q_i F_i(t-1))(1 - F_i(t-1))$$ $$\begin{cases} p_i = Z'_i g_p + e_{p,i} \\ q_i = Z'_i g_q + e_{q,i} \end{cases}$$
	This is an early study to investigate the cross country diffusion issues. In this model, the number of new adopters in country i at time t ($F_i(t) - F_i(t-1)$) is influenced by its own mass media effect p_i and social contagion effect q_i. Specifically, p_i and q_i are determined by the characteristics of this country (g_p and g_q). $e_{p,i}$ and $e_{q,i}$ here are the error terms.
(Putsis et al. 1997)	$$f_i(t) = X_i(t)(\alpha_i + \sum_{j=1}^{N} c_i p_{ij} F_j(t))$$ $$p_{ij} \geq 0, \sum_{j=1}^{N} p_{ij} = 1, X_i(0) = T$$
	In this model, α_i is the parameter of external influence, $X_i(t)$ is the potential market, p_{ij} is the parameter of mixing patterns as populations in reality may not mix entirely randomly or be totally segregated, and c_i is the effect contact rate of person of type i.
(Kumar & Krishnan 2002)	$$\begin{cases} f_i(t) = (p_i + q_i F_i(t)) x_i(t)(1 - F_i(t)) \\ x_i(t) = 1 + b_{21} f_2(t) \\ i = 1,2 \end{cases}$$
	In this model, the cross-country effect ($x_i(t)$) can have either positive or negative value, while the model only explains the diffusion environment with only two countries.
(Albuquerque, Bronnenberg & Corbett 2007)	$$f_{i,t} = \left(p_i + q_{ii} \frac{F_{i,t-1}}{M_i} + \sum_{i'=1,\ldots I; i' \neq i} q_{ii'} \frac{F_{i',t-1}}{M_{i'}} \right)$$
	This model combines the attributes of most global diffusion models in the existing literature. $q_{ii'}$ is furthered determined by three factors: geographical distance, trading between two countries, and culture similarity.

Table 7: Global Diffusion Models

2.3.1.4 *Dual-Market Diffusion Models*

Dual-market diffusion models can be considered as a special case of global diffusion models when only two countries are studied. However, by using simplified expressions of global diffusion models, the dual-market diffusion models are useful in exploring a few specific issues. Not all the diffusion processes follow the classical S-curve in the real world. Instead, two thirds of all innovations decline or even fail not long after they are released and this is extremely common in high-tech industries or in the diffusion of discontinuous innovations. Furthermore, for a considerable number of innovations, there is the existence of clear saddle phenomena (Goldenberg et al. 2006; Goldenberg, Libai & Muller 2002).[12] Mahajan and Muller (1998) find that most existing diffusion models seem powerless in explaining these phenomena. Therefore, it is expected that the development of dual-market diffusion models can be a potential way to solve these problems, a reason why these models have become one of the most popular ideas in developing diffusion models over the last decade (Muller & Yogev 2006). This section lists a few dual-market diffusion models in the existing literature and explains them briefly (Table 8).

Around two decades ago, Tanny and Derzko (1988) distinguished the roles of different adopters in the diffusion process. Their work first points out that potential adopters who have higher innovativeness will not be influenced by other members who have lower innovativeness. The model proposed by them shows that it is better to target more valuable customers (those who are more influential), especially at the beginning of the diffusion process, for a rapid take off. Steffens and Murthy (1992) re-consider this issue by classifying adopters in the system into two groups: innovators who adopt the innovation independently without considering others' opinions, and imitators who adopt the innovation either de-

[12] Readers are referred to a discussion between take-off, saddle, size of Rogers' adopter-category model, and change-of-dominance time which can be found in Muller and Yogev's (2006) work.

pendently or independently. In a recent study by Van den Bulte and Joshi (2007), a systematic conceptual foundation for the role of influentials (opinion leadership) is finally given to support dual-market diffusion models. In their work, they define influentials as those who are usually earlier in adopting the innovation and then influence other imitators. From another perspective, this model can also be seen as a generalised extension of Tanny and Derzko (1988) and Steffens and Murthy (1992), since in Van den Bulte and Joshi's model, influential adopters and imitator adopters can exert different influences to imitate potential adopters, while in previous models, this effect is homogeneous.

Authors(s)	Model Description
(Tanny & Derzko 1988)	$\begin{cases} f_1(t) = (p_1 + q_1 F_1(t))(1 - F_1(t)) \\ f_2(t) = q_2(F_1(t) + F_2(t))(1 - F_2(t)) \end{cases}$
	$f_1(t)$ depends on the environmental effect and the number of adopters who are in category 1, and it is not effected by $F_2(t)$; $f_2(t)$ depends on the number of all adopters $(F_1(t) + F_2(t))$, while it is not influenced by the mass media effect.
(Steffens & Murthy 1992)	$\begin{cases} f_1(t) = p_1(1 - F_1(t)) \\ f_2(t) = \left(p_2 + q_2(F_1(t) + F_2(t))\right)(1 - F_2(t)) \end{cases}$
	In this model, $f_1(t)$ solely depends on the mass media effect p_1. $f_2(t)$ depends on the mass media effect p_2 and the social contagion effect based on all adopters $(q_2(F_1(t) + F_2(t)))$.
(Van den Bulte & Joshi 2007)	$\begin{cases} f_1(t) = (p_1 + q_1 F_1(t))(1 - F_1(t)) \\ f_2(t) = (p_2 + q_2[wF_1(t) + (1 - w)F_2(t)])(1 - F_2(t)) \end{cases}$
	This model is used to explain the diffusion process when opinion leaders (category 1) and normal adopters (category 2) are separated. It is more flexible compared with the above two models: the potential adopters in these two categories are influenced by mass media effect and social contagion effect with respective values; opinion leader adopters $(F_1(t))$ can influence all potential adopters, while normal adopters cannot influence potential opinion leaders adopters; the opinion leader adopters and normal adopters have different level of influence on the potential normal adopters ($q_2 w$ and $q_2(1 - w)$).

Table 8: Dual-Market Diffusion Models

2.3.2 Probit Diffusion Models

A leading alternative to the epidemic diffusion models that can also represent the S-curve phenomena is the family of probit diffusion models. Probit diffusion models consider the differences of adoption time between individuals which take place due to their respective goals, needs, and abilities. In other words, the reason why an individual adopts an innovation is because its requirements for adoption are satisfied and the threshold for adoption is triggered (Geroski 2000). Compared with epidemic diffusion models, probit diffusion models emphasise the heterogeneity of individual decision making with factors such as firm size, cost of innovation, and technological expectations. These models capture individual difference, but neglect the role of interactions between individuals (Cantono & Silverberg 2009).

Table 9 lists a few probit diffusion models that have been well praised in literature. These models study the diffusion process using different organisational characteristics. The first model, proposed by von Neumann and Morgenstern (1947), uses information about the innovation as an indicator. It proposes that organisations that receive more information about the innovation are more likely to adopt the innovation earlier. The second model, which is actually a normal distribution (Rogers 1962), presents the adoption time of organisations on the basis of their innovativeness. It proposes that organisations with higher innovativeness are more likely to adopt the innovation, relative to others. The third model (Davies 1979) assumes that an organisation will adopt an innovation, if the return π_i from the innovation is more than its expected return π^*. The model uses firm size as the indicator of return π_i. Then following the equation $\frac{\pi_i}{\pi^*} = \theta S^{\upsilon}$; he proposes that there should be a critical size point S^* that can make $\pi_i = \pi^*$. So if the size of the organisation exceeds S^*, it will adopt the innovation. The final model (Van den Bulte & Stremersch 2004) introduces income as an indicator of an individual's tendency to adopt innovations, and thus their adoption time. It is based on the assumption that individuals with more income are more capable of implementing innovative activities and thus likely to adopt innovations earlier. It uses a Gamma distribution to represent individual income and then draws a diffusion curve in a similar way to the second model in this category.

Author(s)	Model Description
(von Neumann & Morgenstern 1947)	$u(x_i) = 1 - e^{-\eta x_i}$
	The diffusion process is modelled through information about the innovation that the organisation receives. $u(x_i)$ here is defined as the potential adopter's relative satisfaction about the innovation; x_i indicates the information about the innovation that the potential adopters receives; and η is a coefficient.
(Rogers 1962)	$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$ (normal distribution)
	The diffusion process is modelled based on organisational innovativeness. There are two assumptions under this model: first, organisational innovativeness follows normal distribution; second, organisations that have higher level of innovativeness will adopt the innovation earlier. Therefore, the diffusion curve will be the same with the distribution curve of innovativeness, which is a normal distribution curve.
(Davies 1979) cited by (Geroski 2000)	$\frac{\pi_i}{\pi^*} = \theta S^{\upsilon}$
	Diffusion process is modeled through size of organisations. In this model S indicates the size of the organisation, π_i and π^* represent the actual return and expected return from the innovation. θ and υ are parameters.
(Van den Bulte & Stremersch 2004)	$x^{k-1} \frac{e^{(-x/\theta)}}{\Gamma(k)\theta^k}$ (Gamma Distribution)
	The concept under this model is similar with Rogers' model above. The only difference is that, this model uses income as a direct indicator for individual adoption time and incomes is assumed to follow a Gamma distribution.

Table 9: Probit Diffusion Models

2.3.3 Epidemic Diffusion Models vs. Epidemic Models

Most diffusion models are epidemic diffusion models. From their terminology, it is easy to deduce that diffusion of innovation and diffusion of epidemics can share certain similar patterns.[13] For instance, Hivner et al. (2003) try to add managerial meanings to the SEIR (see Glossary) model (Beltrami 1993), although this relationship is not discussed systematically. Another recent study by Bettencourt et al. (2006) develop a new model for the spread of ideas on the basis of the SIR (see Glossary) model. This is done by dividing the idea of a diffusion process into five stages: susceptible, idea incubators, idea adopters, skeptics, and recovered, which is very similar to the concept of multi-category diffusion models in management studies. Therefore, it is assumed that the SIR model and its extensions can be borrowed by the management field if the parameters of these models are endowed with proper managerial meanings. Surprisingly, little of the existing literature has studied this issue systematically. As the Bass model and the SIR model both have a rich literature on their respective theories and implementations, it would be interesting to have a comprehensive re-consideration of these models in order to see whether there are certain potential links between them, and more importantly for future studies, to see whether these links can be further used. The following paragraph and Table 10 list a few potential relationships between diffusion models in management and epidemics studies.

Many epidemic models consider the birth and death rates of the population, which is similar to the dynamic market problem in the Bass model, as discussed in the work of Mahajan and Peterson (1978). In sexually transmitted diseases (STDs), potential adopters can get the disease from adopters while adopters may become potential adopters again after the disease has been cured; in marketing, innovations can be consumables, which are normally purchased repeatedly during a product life-cycle. The spread of disease normally has a number of stages; correspondingly in the management field, multi-category and multi-generation

[13] Readers are referred to Section 3.2, which has a detailed discussion on the relationship between an epidemic model and the Bass model.

innovations are modelled in the form of multi-stage purchase models. Finally, the SIR model and the Bass model both can be extended to explain cross-country diffusion phenomena.

Epidemic Diffusion Models	Epidemic Models
Diffusion Models with Dynamic Market	Epidemic Models with Vital Dynamics
Diffusion Models with Repeated Purchase (Ratchford, Balasubramanian & Kamakura 2000)	SIS model (Keeling & Eames 2005)
Diffusion Models with Multi-Stage Purchase	MSIR Model
	SEIR Model (Gao, Teng & Xie 2008)
	Epidemic Models with Vaccination Effect (Zeng, Chen & Sun 2005)
Diffusion Models with the Role of Market Maven	SIR Model with Carrier State
Cross-Country Diffusion	Epidemic Models on Population-Level (Wang 2008)

Table 10: Epidemic Diffusion Models and Epidemic Model

2.4 Models of Adopter-category

Although the innovativeness and diffusion research are sometimes considered as two different streams in innovation studies, they are actually closely linked. On the one hand, time is one of the key elements in diffusion as mentioned in Section 1.2, because diffusion only happens when the adoption time of individuals is different. On the other hand, innovativeness studies are there to explain the difference between the adoption time of individuals.

A typical example of the link between the two types of studies are those models that fall in the adopter-category. The initial aim of these adopter-category models is to assist further analysis after measuring organisational innovativeness. By using certain classification approaches to categorise organisations into a few compartments, these adopter-category models can help scholars better understand innovativeness from a few aspects such as for mental clarification and communication, to discover new fields of research, to work as a checklist, and to increase fun (Good 1965). Then these models gradually become multi-functional. On the one hand, scholars use adopter-category models to understand individual behaviours due to their levels of innovativeness. On the other, the diffusion process can be explained on the basis of difference between individual adoption time as modelled by adopter-category models.

2.4.1 The Rogers Model of Adopter-Category

The most significant and widely-agreed model for categorising organisations based on innovativeness is the model by Rogers (1962). Rogers uses a normal distribution to classify different adopter-categories based upon an individual's/ organisation's adoption time[14], categories include: innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%). The use of this model is not only limited to categorising and understanding the characteristics of adopters, it also provides a way of understanding and modelling the diffusion process: if the organisations in each category are assumed to adopt the innovation sequentially based on their innovativeness level, this model becomes a typical probit diffusion model, with the number of new adopters following a typical bell-shape curve (Figure 5).

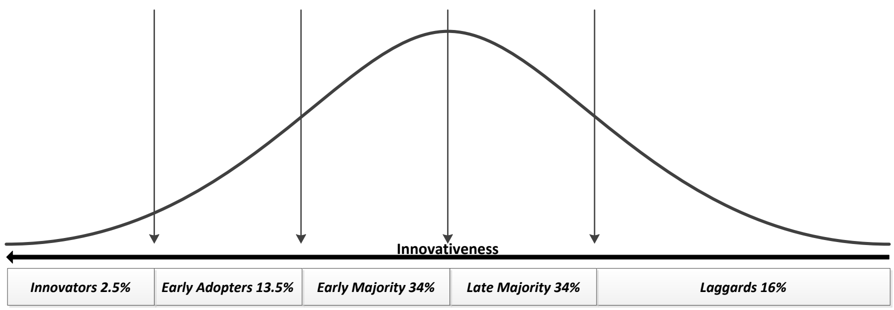

Figure 5: The Rogers Model of Adopter-Category
(The source is from Rogers (1962))

[14] Adoption time, as discussed in Section 2.2, is one of the key indicators for innovativeness.

2.4.2 The Moore Model of Adopter-Category

The second model to be reviewed in this section is famous because of the popularity of the book 'Cross the Chasm' (Moore 1991). This model is a modified version of the Rogers model of adopter-category, which further proposes three cracks and one chasm between the five categories (Figure 6). The central idea of this model is that adopters in different categories require different benefits from an innovation. Therefore, the success of diffusion in one category sometimes does not indicate successive success in other categories.

Although the S-shape diffusion process is dominant in academic literature, it does not fit many real-life cases, especially in high technological fields such as the pharmaceutical industry. History shows that only one third of innovations will finally succeed and progress through the S-curve process, many others will fail at varying stages (Goldenberg et al. 2006; Goldenberg, Libai & Muller 2002). Moore's model is an important complementary for diffusion theory and it is especially useful for understanding the diffusion of disruptive innovations.

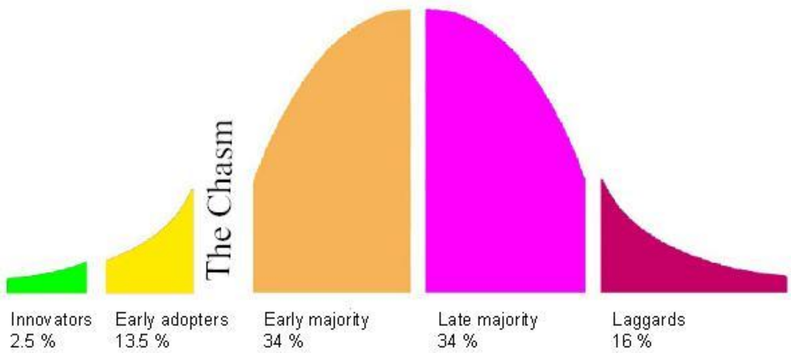

Figure 6: The Moore Model of Adopter-Category
(The source is from Moore (1991))

2.4.3 The Bass Model

Different to the Rogers' model and Moore's model, the Bass model differentiates adopters into two segments: innovators who adopt the innovation independently and imitators who adopt the innovation under the influence of existing adopters. In other words, the two categories are not differentiated by the time of adoption, but rather identified by the reason for the adoption (Figure 7). Therefore, the innovators in the Bass model do not need to be the ones who adopt the innovation earlier than others; also these imitators find it possible to adopt the innovation at the very beginning.

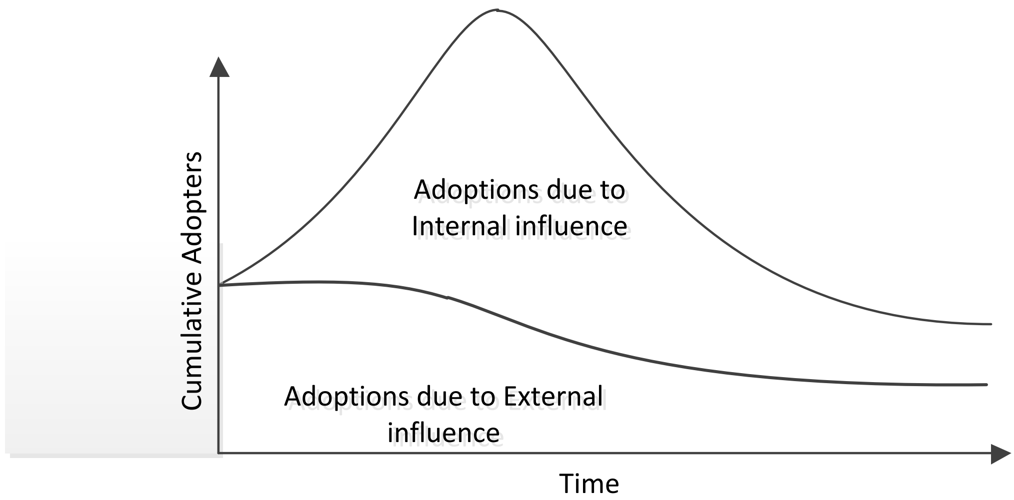

Figure 7: The Bass Model of Adopter-Category
(The source is from Bass (1969))

2.4.4 The Mahajan Model of Adopter-category

Due to the increased popularity of the Bass model in diffusion research, some researchers (Mahajan, Muller & Srivastava 1990) feel it necessary to re-consider the Rogers' adopter-category model by combining it with ideas from the Bass model. Using the bell-shape curve generated from the Bass model, they first find the peak point, and then they divide the curve into four parts. Along with the group of people who adopted the innovation at the beginning of the diffusion, five categories are thus defined: innovators, early adopters, early majority, late majority, and laggards (Figure 8). In this model, the size of each category is not fixed as in the Rogers' model, but is flexible due to the value of the two parameters p and q in the Bass model.

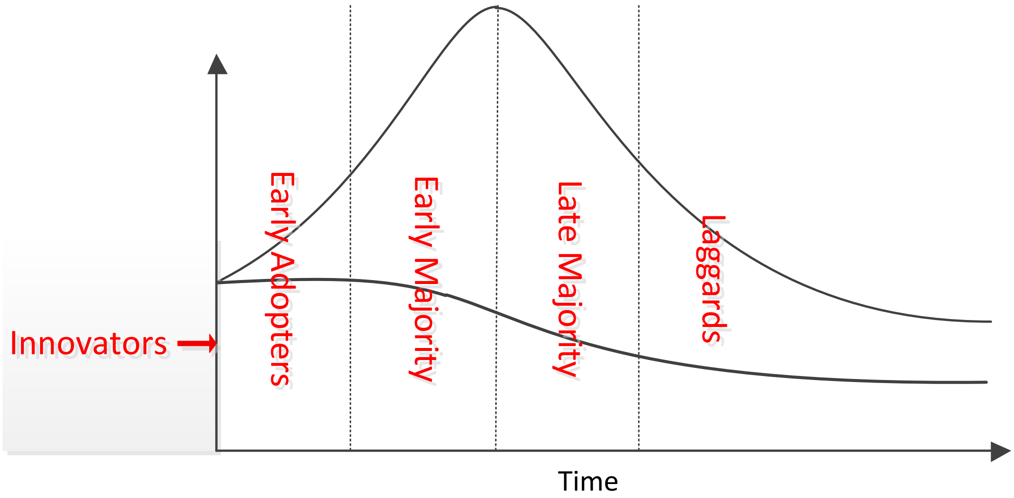

Figure 8: The Mahajan Model of Adopter-Category
(The source is from Mahajan et al. (1990))

2.4.5 Dual-Market Model

Another useful way of categorising adopters is to use a dual structure model. This dual structure can be any type such as innovators vs. non-innovators, influentials vs. imitators, innovators vs. imitators, and so on. For example, in order to emphasise the 'chasm' in his model, Moore (1991) changed it to a dual structure by uniting innovators and early adopters as the early market and leaving the rest as the mainstream market. Furthermore, the concept of the dual-market model is widely used in dual-market diffusion models. For instance, Muller and Yogev (2006) model customers into early adopters and later adopters in order to study when the targeted customers should change from being early adopters to early majorities. Similarly, Van den Bulte and Joshi (2007) used a dual-market model to emphasise the role of opinion leaders in the diffusion process.

2.4.6 Comparison between Adopter-Category Models

The comparison between these models is made from four aspects: the classification philosophy, the number of compartments in each model, ex post or ex ante, and the definition of each compartment (Table 11).

First, the five adopter-category models discussed above are developed based on the three following philosophies: the earlier one adopts the innovation, the more innovative it is (Rogers' model, Moore's model, and Mahajan's Model); innovators tend to be the ones who adopt innovations independently and imitators tend to follow others' opinions (the Bass model); adopters are classified by their social status or attributes such as innovators vs. non-innovators, opinion leaders vs. followers, influential vs. imitators, and so on (dual-market model).

Under the classification philosophies listed above, the five models classify adopters into either two or five categories. The five-category models are all derived or related to the Rogers' model. On the other hand, the Bass model and the dual-market models both propose a two-category structure.

The third attribute of the five models is whether the model can be generated before or after the diffusion process. The Rogers' model and Moore's model can be structured only after the whole diffusion process has finished. Similarly, since innovators in the Bass model and the Mahajan adopter-category model represent the individual who adopts the innovation only through external influence, they also fit into the ex ante model. The only exception is the dual-market model, of which the role of individuals can be differentiated before the diffusion starts.

In these models, each category may represent different types of individuals even if they have the same name. Here the author only takes 'innovators' as an example. In the Rogers' adopter-category model and the Moore's adopter-category model, innovators make up 2.5% of the agents with the highest innovativeness level and who tend to be the earliest adopters. In the Mahajan's adopter-category model, innovators are not only the first group of adopters with the highest innovativeness, but are further defined as those individuals who actually adopt the innovations at the time when the diffusion actually starts. In the Bass model, 'innovators' means the adopters who make the adoption decisions solely by themselves. They do not need to be early adopters and they can even be the last group of adopters. Therefore, the number of innovators in the Bass model can change due to different diffusion processes. For dual-market models, adopters are usually named for their roles within the diffusion process, for instance, a few researchers follow Moore's idea and combine the first two categories of Rogers' Model (innovator and early adopter) as the early market, leaving other categories as the mainstream market (Muller & Yogev 2006).

Model	Classification Philosophy	No. of Categories	Ex post Ex ante	Innovator
(Rogers 2003)	Innovativeness level	5	ex post	First 2.5% adopters
(Moore 1991)	Innovativeness level	5	ex post	First 2.5% adopters
(Mahajan et al. 1990)	Innovativeness level	5	ex post	Individuals who adopt soon after the innovation is released
(Bass 1969)	Communication channels	2	ex post	Individuals who adopt innovations independently
Dual Market	Social status	2	ex ante	Not defined

Table 11: Comparison of Adopter-Category Models

2.5 Summary[15]

This chapter has covered the topics of organisational innovativeness and diffusion models. In addition, a potential link between these two topics and the models of the adopter-category, have been reviewed and compared. This chapter does not intend to list all the contributions that have been made due to the excessive work already undertaken in this field. Instead, the author summarises the key knowledge on the following issues: *what is organisational innovativeness and how can it be measured? What has been (not) known in diffusion models and how these diffusion models are developed? How can organisational innovativeness relate to diffusion models?*

The answer to the first question shows that organisational innovativeness can be measured and quantified, and thus has the potential to be modelled. The answer to the second question can inspire the author as to how to develop diffusion models that answer diffusion related questions. The answer to the third question

[15] Readers are referred to Appendix 1 for a comprehensive framework of the current reviewed literature.

can demonstrate the importance of incorporating innovativeness into diffusion models and inspire the author as to how to do this.

2.5.1 Organisational Innovativeness

Innovativeness is one of the fundamental behaviours of innovation-driven organisations (Rogers 2003) and thus it is mostly the concern of scholars in the realm of diffusion. The current literature has discussed intensively, although not completely, the factors and measures of innovativeness from various perspectives. This section provides a summary of that knowledge.

Factors of organisational innovativeness cover different aspects: innovation itself, individual, environment, organisational structure, organisational strategy and resources, and organisational culture and psychographics. Within each aspect, a number of factors have been found that exert either positive or negative effects on organisational innovativeness. However, three issues should be emphasised here: first, this study only summarises the influential factors. A few specifics that have not been mentioned in this chapter are also valuable for considering in a few particular contexts. For instance, organisations who adopt process innovations may consider the characteristics of the innovation providers (Frambach & Schillewaert 2002; Meyers, Sivakumar & Nakata 1999); customer orientation also influences an organisation's innovative activities (Laforet 2009); in a work by O'Neil et al. (1998), the past success and failure rate of an organisation is valuable for studies into the adoption rate of new strategies. Second, Greenhalgh et al. (2004) point out that no single factor of organisational innovativeness can be isolated and independently quantified when studying the innovative performance of organisations. Therefore, to truly understand the relationship between organisational innovativeness and these factors, a systematic approach that can assess these variables from an overall view is needed. Third, the adoption rate of an innovation can be influenced by many factors, either directly or indirectly. The author does not identify any explicit relationship between organisational innovativeness and any of these factors, since the same factor(s) may produce different results within different contexts. Some examples are: Baldridge and Burnham (1975) do not find any correlation between environmental change and organisational innovativeness, and the role of individual characteristics is also found to be weak in their study; although a few authors argue that type of innovation is not essential in the study of an organisation's innovation performance, Damanpour and Evan (1984) finds that technical innovations are adopted earlier than administrative innovations in public libraries; in the studies of Damanpour (1987) and Kimberly and Evanisko (1981), all factors together are better in predicting technological innovations than administrative innovations, and different influences of each factor vary within different innovations; Damanpour (1992) concludes that size is more useful when used in manufacturing and profit-making organisations than in service and non-profit-making organisations and size is also more effective in assessing the implementation stage of innovation rather than the initiation stage; Rogers (2004) also finds that the network effect only appears in small size groups, since SMEs are more urgent in finding companies that support their innovation activities. Therefore, it is concluded that the validity of these factors depends on many moderators such as different innovations, different stages of innovation, different industries, different organisations, and so on. Researchers should also be reminded to consider the different dimensions of innovation (Damanpour 1991; Subramanian & Nilakanta 1996). Only when these dimensions are distinguished, can the results of these researchers show considerable agreement (Damanpour 1988).

Innovation is usually difficult to identify (Gatignon et al. 2002), since innovation is complex, uncertain, somewhat disorderly, and subject to changes of many sorts. Innovation has no obvious or uniform dimensionality and there is no generally agreed way of measuring its importance or impact (Kline & Rosenberg 1986). Therefore, to understand and assess organisational innovativeness needs the analysis of various innovation activities within a clearly defined research context (Van de Ven & Rogers 1988). It should be noted that all the measures listed in this thesis can only show a partial view of the whole phenomenon. Furthermore, types of innovations, cross-industry effect, different approaches or indicators can all influence the final result. Therefore, although scholars have proposed various approaches and indictors to assess organisational innovativeness, no widely-agreed preference of these measures exists. The design of an organisational innovativeness assessment should have a clearly defined research context and serious consideration should be paid to the selection of approaches and indicators.

2.5.2 Models of Diffusion Process

Diffusion models have been used to capture the life-cycle dynamics of an innovation and to forecast the innovation demand. Most influential diffusion models in the existing literature originate from two step flow theory (Katz & Lazarsfeld 1955), which emphasises the role of interactions between potential and existing adopters (epidemic diffusion models). Another important stream of diffusion models, probit diffusion models, seek to model the adoption time of individuals/organisations due to their own characteristics and thus explain the diffusion process. These two streams of models can both illustrate the S-shape curve of diffusion with meaningfully theoretical support. Therefore, they are both widely used.

However, many issues in the arena of diffusion models have not been solved. For instance, Mahajan et al. (2000b) list the five future challenges: the role of market chasm in diffusion, shadow effect in diffusion, strategy-driver diffusion, global diffusion, and diffusion in the internet based environment. Bass (2004) and Meade and Islam (2006) call attention for a wide range of topics including global diffusion models, multi-generation diffusion models, and individual diffusion models. Hauser et al. (2006) further emphasise the demands of future works that can model a network effect and incorporate measures of innovativeness. Additionally, emphases have also been made with regard to the timing of promotional activities through relative diffusion models (Delre et al. 2007; Krishnan & Jain 2006).

2.5.3 Models of Adopter-Category

Adopter-category models are usually developed based on an understanding of innovativeness. The Rogers' adopter-category model, which uses a normal distribution to classify and name potential adopters, is the most widely used one in studying relevant research topics. Most following models are either derived from the Rogers' model (for example, the Moore's adopter-category model) or are inspired by Rogers (the Bass model and the Mahajan's model fall into this category).

On the one hand, categorising individual organisations based on their innovativeness can help us understand the natural characteristics of the system (how many members of the system are innovators, early adopters, laggards, and so on). On the other, the diffusion trend can be captured through those adopter-category models by knowing who are likely to adopt the innovation early and when they are likely to adopt. Therefore, these models can be considered as a bridge between the knowledge of organisational innovativeness and diffusion models. Furthermore, these adopter-category models clearly reveal that innovativeness is one of the key elements in diffusion, since even innovativeness itself can be used to model diffusion.

Chapter 3 The Modified Bass Model

> *"Models are abstractions and implications of reality. Useful models capture the essence of reality in a way that enhances understanding of phenomena. Simple and elegant mathematical models, often referred to as 'beautiful', that match well with the phenomenon being studied will have appeal in the arena of competing ideas about the phenomenon. The appeal of such models is further enhanced if the parameters have intuitive interpretations. I believe that the Bass model has the properties just discussed."*
>
> *(Bass 2004)*

3.1 Introduction

As reviewed and discussed in the previous chapter, diffusion models are usually categorised into two main streams, as epidemic diffusion models and probit diffusion models. The first stream originates from the understanding of diffusion that emphasises the role of interactions between members of a system. These models, such as the Bass model, can produce good fit for real phenomena, from both theoretical and empirical perspectives, and thus have long been used for understanding the diffusion process and predicting future demand. The latter stream, of probit diffusion models, explains the diffusion process on the basis of individual differences towards innovation adoption. These models can also depict the S-curve of the diffusion trend, and can be further used to explain and validate the relationship between organisational innovativeness and diffusion.

This chapter aims to develop a new diffusion model on the basis of the Bass model. It is desirable that the new model fills a few limitations of the Bass model, maintains its empirical accuracy, and be capable of incorporating new factors with greater diversity. Specifically, Section 2 introduces and analyses one of the most important diffusion models in literature, the Bass model; Section 3 provides further discussions on the Bass model by comparing it with a few other classical diffusion models in literature; Section 4 is the key section of this chapter, which proposes a new diffusion model by combining the ideas of the Bass model and the von Neumann-Morgenstern Framework; Section 5 reviews the parameter estimation techniques in the existing literature and then proposes a new way for estimating parameters in diffusion models; Section 6 gathers a set of diffusion data that will be used to assess the performance of the proposed diffusion model; On the basis of the parameter estimation technique proposed in section 5 and the diffusion data gathered in Section 6, Section 7 assesses the model performance of the modified Bass model; Section 8 provides a conclusion of the current chapter.

3.2 Introduction to the Bass Model

The Bass model is named after Frank Bass (1926 – 2006), who is a pioneer in the area of modelling the diffusion phenomenon and one of the founders of marketing science. The Bass model is based on the understanding of two-step flow theory (Katz & Lazarsfeld 1955), which assumes that in a typical diffusion process, the information from the innovation is first passed to a few individuals through the mass media and then spread to many others by word of mouth effect. Based on the above assumption, it is believed that a typical diffusion process normally follows a number of stages: the diffusion rate is low when the diffusion starts, since the adoptions during this time period are mainly driven by external influences (mass media) and thus it very much relies on the high innovativeness of those potential adopters; then the main force of diffusion gradually turn into internal influences (word of mouth), so the diffusion rate will increase gradually due to the increased power of word of mouth until it reaches a peak point; finally the diffusion rate will decline until the innovation has penetrated the whole market because there are less and less potential adopters left in the system.[16]

In the Bass model, the total number of potential adopters is assumed to be a constant that is based on approximation of the system. The diffusion influences are considered to originate from both outside (normally named external influence, mass media effect, or environmental effect) and inside (normally named internal influence, social contagion effect, or inter-influence effect) the population. From a homogeneous point of view, the model assumes that the diffusion environment exerts constant effect on potential adopters over time, and the level of the word of mouth effect depends on the growing number of adopters. Therefore, the model is defined as:

$$f(t) = \left(p + q \times \frac{F(t)}{M}\right) \times \left(M - F(t)\right) \tag{1}$$

where:

$f(t)$	=	*Number of adopters at time t*
$F(t)$	=	*Number of cumulative adopters a time t*
M	=	*Total number of potential adopters*
p	=	*Parameter of environmental effect*
q	=	*Parameter of social contagion effect*

Here, parameter p and function $\mathrm{q} \times \frac{\mathrm{F(t)}}{\mathrm{M}}$ represent how many percentage of potential adopters will adopt the innovation under the influence of the environmental effect and social contagion effect respectively. Specifically, $\frac{F(t)}{M}$ represents the percentage of penetration at time t. Therefore, if the total number of

[16] Scholars also find that the Bass model can be explained through the view of uncertainty and risk that is contained in the innovations. From the inter-organisational level, the use of innovation by one organisation results in reductions in uncertainty and thus increases the adoption probability of the potential adopters (Stoneman 2002).

potential adopters (M) is set as a constant, the Bass model can be re-written as the format in Equation 2 by combining M and q. Furthermore, If $\left(M - F(t)\right)$ is moved to the left hand side, the equation $\frac{f(t)}{M-F(t)}$ becomes the hazard rate[17] (Equation 3).

$$f(t) = \left(p + q \times F(t)\right) \times \left(M - F(t)\right) \tag{2}$$

$$\frac{f(t)}{M - F(t)} = p + q \times F(t) \tag{3}$$

Besides being a good explanation tool of diffusion, the Bass model is also widely used as a prediction tool for innovation demand. One can calculate the number of new adopters within each time period $f(t)$, if the values of M, p and q are available. If the model is used when diffusion has already started, people can use existing data to estimate the values of M, p, and q. However, when the model is used before the diffusion starts, people may need to make an initial guess at these values on the basis of previous diffusion data of similar innovations or even modellers' experiences.

The above discussions show that the Bass model is great value in the practical field. Many empirical studies have shown its good fit to real diffusion phenomena. However, the Bass model has its limitations. First, as a highly aggregated model, it is insufficient to show the adoption probability of individuals, therefore it is difficult to further explore how individuals' adoption probability will change over time, how their actions will change the probability, and how the environment will influence the probability. These issues all lead the development of diffusion models to an individual level (Roberts & Lattin 2000). Second, the Bass model simply sums the environmental effect and the social contagion effect to represent the overall adoption probability. This may underestimate the complex-

[17] A hazard rate studies the probability of a population member performing a certain behaviour. It is based on research of time to failure in statistics (Kalbfleisch & Prentice 1980).

ity of this issue, as adoption probability may not simply increase linearly with the sum of these two effects. For instance, Floyd (1968) points out that to use a decreasing function to modify the social contagion effect will improve model performance.[18] Third, the Bass model cannot be extended to incorporate factors with great diversity because of its region limitation on parameters. For instance, after rewriting the Bass model at an individual level, the authors (Strang & Nancy Brandon 1993; Angst et al. 2010) exponentiate the right-hand side with the simple aim of making the results non-negative, since their model needs to include inputs with negative values. Finally, as a homogeneous model, the Bass model naturally uses a fully connected network,[19] and the information flow between each pair of individuals are the same. Again, this problem only can be solved by modelling diffusion at an individual level.

3.3 Further Discussions on the Bass Model

In this section, the Gompertz model and the G/SG model, which are derived on the basis of different theories, are compared with the Bass model.

3.3.1 The Gompertz Model

The Gompertz model follows the assumption that is *growth rate falls exponentially with current size* (Gompertz 1825). Hence its mathematical expression can be written correspondingly as:

$$K^{\frac{F'(t)}{F(t)}} = \frac{a}{F(t)} \tag{4}$$

where:

$F(t)$ = *Number of cumulative adopters a time t*

K, a = *Parameters*

---

[18] This means an adopter will have gradually decreased influence to potential adopters. The reason for this could be various, for instance, some adopters will turn to adopt other innovations after certain time, and thus lose influence to potential adopters.

[19] A fully connected network is a network in which each of the notes is connected to each other.

Here, function $\frac{F'(t)}{F(t)}$ is the growth rate, which means the percentage of the new adopters over the existing adopters. Therefore, the Gompertz model can also be considered as a self-growing model, which is fundamentally different with the Bass model.

In real practice, the Gompertz model is usually written in the format of the following equation (Equation 5):

$$F(t) = Me^{-\eta e^{-bt}} \tag{5}$$

where:

M	$=$	*Total number of potential adopters*
b	$=$	*Parameter of growth rate (shape parameter)*
η	$=$	*Scale parameter*

The Gompertz model also can be transformed into the format shown in Equation 6 (Dixon 1980). Now the Gompertz model and the Bass model look similar to each other: compared with the Bass model, the Gompertz model does not have a parameter of the environmental effect, and the total market and number of existing adopters (in red colour) are both modified by a logarithm function:

$$F'(t) = log_K^{\frac{M}{F(t)}} \times F(t) = \frac{ln^{\frac{M}{F(t)}}}{ln^K} \times F(t) = \frac{1}{ln^K} F(t)(ln^M - ln^{F(t)}) \tag{6}$$

Another fundamental difference between the Gompertz model and the Bass mode is the initial value of $F(t)$: in the Bass model the range of $F(0)$ is set to be $[0, 1]$ while in the Gompertz model the range of $F(0)$ is set to be $(0, 1]$. This is because the Gompertz model presumes that a number of individuals have already adopted the innovation. As a self-growing model, the Gompertz model needs an initial value so the number of the adopters can 'grow'.

3.3.2 The G/SG Model

The G/SG model (Bemmaor 1994) is a model that mixes a shifted Gompertz distribution (Equation 7) and a Gamma distribution. The idea of this model can be briefly explained in two parts. First, a consumer's tendency to adopt an innovation follows a shifted Gompertz distribution, which is determined by two parameters b and η. Specifically, parameter η is assumed to be the consumer's tendency to adopt late and b is a scale parameter. Second, different consumers' tendencies (parameter η) follow a Gamma distribution with two parameters (one shape parameter and one scale parameter). When the shape parameter in the Gamma distribution equals 1, the Gamma distribution reduces to an exponential distribution and the G/SG model reduces to the Bass model. Therefore, it can be seen that although the G/SG model is derived from the perspective of probit diffusion models, its model structure is closely related to epidemic diffusion models.

$$f(t|\eta, b) = be^{-bt}e^{\left(-\eta e^{-bt}\right)[1+\eta(1-e^{-bt})]} \tag{7}$$

The G/SG model has been proposed for more than fifteen years and empirical studies have demonstrated it can provide even better performance than the Bass model in a few cases (Bemmaor & Lee 2002). However, the model does not raise much attention in management literature due to a few reasons. Most importantly, the existing literature does not provide explicit managerial explanations as to how the G/SG model is derived, and the theories underlying this model are not clear. Therefore, scholars such as Mahajan (1994) argue its weakness in providing meaningful implications for real practice.[20]

3.3.3 The Bass Model and the SIR Model

The SIR model (Kermack & McKendrick 1927) is a classical epidemic model. It classifies the spread process of an epidemical disease into three serial steps: sus-

[20] Readers are referred to Appendix 3, where the author tries to re-analyse the G/SG model and give the model managerial meaning.

ceptible, infectious, and recovered with immunity. 'Susceptible' relates to those who may contract the disease if they are exposed to it, 'infectious' relates to those who have already got the disease and are capable of spreading it to others, and 'recovered with immunity' implies those who have recovered and are immune to the disease. In the SIR model the number of new infections is calculated by the current number of those susceptible and a dynamic infection rate, which is determined by the number of those considered infectious (the more infectious they are, the higher the risk for those considered susceptible to get effected). Also it is assumed that the infectious transfer to recovery at a constant rate. (see Equation 8)

$$\begin{cases} s(t) = -\beta I(t)S(t) \\ i(t) = \beta I(t)S(t) - \gamma I(t) \\ r(t) = \gamma I(t) \\ S(t) + I(t) + R(t) = M \end{cases} \tag{8}$$

where:

M	=	*Total population*
$S(t), I(t), R(t)$	=	*Number of susceptible, infectious, and recovery*
$s(t), i(t), r(t)$	=	*Change of susceptible, infectious, and recovery*
β, γ	=	*Infection rate and recovery rate*

In the Bass models, the number of new adopters is determined by the current number of potential adopters and a dynamic adoption rate, which is determined by the number of existing adopters (the more adopters exist, the higher influence potential adopters suffer). Therefore, the Bass model is theoretically similar to the S-I part of the SIR model.

Additionally, if the recovery rate is set to be 0 in order to exclude the recovery part of the SIR model, ($r(t) = R(t) = 0$), the SIR model can be reduced to:

$$\begin{cases} s(t) = -\beta I(t)S(t) \\ i(t) = \beta I(t)S(t) \\ S(t) + I(t) = M \end{cases} \tag{9}$$

If we introduce a parameter δ and set $\delta = \beta M^2$, we can get Equation 10 from Equation 9

$$i(t) = \beta\big(M - I(t)\big)I(t) = \delta\frac{I(t)}{M}(1 - \frac{I(t)}{M}) \tag{10}$$

Here, $\frac{I(t)}{M}$ means the percentage of infectious people within the whole population at time t, which has the same meaning as $\frac{F(t)}{M}$ in the Bass model. If the value of M is set to be 1, the above equation can be further changed to:

$$i(t) = \delta I(t)(1 - I(t)) \tag{11}$$

So it can be seen that the S-I part of the SIR model is a special case of the Bass model, when $p = 0$. To sum up, the Bass model and the SIR model have great similarities from both theoretical and mathematical aspects.

3.4 The Modified Bass Model

In this section, a modified Bass model is proposed in order to fill the limitations of the Bass model that is listed in Section 3.2.

3.4.1 Risk Attitudes

Innovations contain uncertainties and risk, which result in different perceptions from different potential adopters, even though these potential adopters possess the same amount of information about the innovation. Therefore, before introducing the modified version of the Bass model, it is valuable to spend some time on the concept of risk attitudes.

Different attitudes can be adopted by different individuals during the same situation, with these resulting in different behaviours that lead to different consequences (Hillson & Murray-Webster 2007). There are normally three basic types of risk attitudes that potential adopters may process regarding the level of comfort to risk. These are: risk averse, risk neutral, and risk seeking. Risk averse relates to behaviour exhibited by the person who is uncomfortable with risk, and thus tends to avoid or reduce the uncertainties of the innovation. Risk seeking relates to behaviour exhibited by those who are happy with risk, and thus have no desire to avoid or reduce threats or to exploit opportunities to remove uncertainty. These individuals are happy with an uncertain outcome and happy to see unexpected outcomes from innovations. Finally, risk neutral behaviour straddles the middle, between risk averse and risk seeking: those who exhibit these traits do not have any particular preference between risk averse and risk seeking.

Potential adopters in most existing diffusion models are naturally either risk neutral or risk averse. In most epidemic diffusion models, especially the ones that are directly transformed from the Bass model, the hazard rate normally has a linear relationship with the cumulative amount of information about the innovation. Therefore, the models are proposed on the assumption that the potential adopters in the population are, on average, risk neutral[21]. On the other hand, probit diffusion models normally consider potential adopters as a special case of risk averse: they will only adopt an innovation when the potential benefit from the innovation is more than the cost of adoption, since they do not want to take any risk regarding the innovation.

[21] If we consider utility as a function with a positive first derivate, an agent possesses risk averse if and only if the utility function is concave; an agent possess risk seeking if and only if the utility function is convex; an agent is risk neutral if and only if the utility function is linear.
In the Bass model, it can be considered that potential adopters' relative satisfaction increase linearly with the amount of the information about the innovation.

3.4.2 The Von Neumann-Morgenstern Framework

As proposed by von Neumann and Morgenstern (1947) and used in the study by Chatterjee and Eliashberg (1990), if potential adopters are considered as risk averse in innovation adoption, one potential adopter's uncertain perception of an innovation's performance can be modelled based on the information of the innovation he receives. The above statement can be explained with the following mathematical expression:

$$u(x_i) = 1 - e^{-\eta x_i} \tag{12}$$

where:

$u(x_i)$	=	*Utility function (relative satisfaction)*
x_i	=	*Potential adopter's uncertain perception of the innovation's performance after receiving i 'units' of information of the innovation*
η	=	*Coefficient of risk averse*

Although it seems questionable to consider all potential adopters as risk averse and simply use one single coefficient η to represent the level of risk averse for all of them, this assumption has been validated in a number of empirical studies: Howard (1971), Hauser and Urban (1979; 1977), Currim and Sarin (1984; 1983), and Roberts and Urban (1988), as summarised by Chatterjee and Eliashberg (1990).

3.4.3 The Modified Bass Model

By incorporating the idea from the von Neumann-Morgenstern framework, the modified Bass model is written in Equation 13.

$$P_{k,t} = 1 - e^{(-\eta)(p_k + q_k F_t)} \tag{13}$$

where:

$P_{k,t}$	=	*Adoption Probability of potential adopter k at time t*
F_t	=	*Number of cumulative adopters at time t*
η	=	*Coefficient of risk averse*
p_k	=	*Potential adopter's uncertain perception of the innovation's performance after receiving information of the innovation from environment*
q_k	=	*Potential adopter's uncertain perception of the innovation's performance after receiving information of the innovation from a member of the system*

Instead of using a threshold to represent the adoption decision of the potential adopter *k*, a continuum is introduced to represent its adoption probability. The model can be explained as follows: first, the potential adopter *k* in the system exhibit risk averse, on average. Second, the potential adopter's adoption probability is determined by its uncertain perception of the innovation's performance after information about the innovation is received. Third, information about the innovation can be accessed from both the environment and the existing adopters in the system.

In Equation 13, the potential adopters are assumed as risk averse averagely (see Page 74). However, each individual organisation does not need to be risk averse, since Equation 13 is defined as a probability function. For instance, a potential adopter can adopt an innovation when it receives little information about the innovation, although the probability is low.

Since coefficient η is a constant over time in the above model, it can be absorbed into parameters p_k and q_k. Furthermore, this model can be transformed to an aggregated level (Equation 14).

$$f(t) = \left(1 - e^{(-p-qF(t))}\right)\left(M - F(t)\right) \tag{14}$$

where:

$f(t)$	$=$	*Number of adopters at time t*
$F(t)$	$=$	*Number of cumulative adopters at time t*
M	$=$	*Total market*
p	$=$	*Parameter of environmental effect*
q	$=$	*Parameter of social contagion effect*

Compared with the Bass model, the homogeneous version of the modified Bass model uses an (cumulative) exponential distribution function to modify the part of $p + qF(t)$.

3.5 Data for Assessing the Modified Bass Model

Validation of diffusion models requires good data. However, according to Putsis et al. (2000), until now, few works have discussed this issue except in articles by Heeler and Hustad (1980) and Bulte and Lilien (1997). It is widely agreed that diffusion data is not easy to assemble. For the source of the data, it is common to use data that relies on manufacturer shipments and warehouse withdrawals. For the time range of the data, although it is found that quarterly data can produce a better fit and more accurate forecasting, aggregated annual data is used in most studies and it is recommended that the data should cover at least a ten-year period and include the data on the peak point. Furthermore, since all diffusion models, except those specific diffusion models with replacement and additional adoption effect, are all based on the assumption of first-time adoption, it is impossible to exclude the error data (repeated purchases) completely. It is considered that this problem is not notable shortly after the introduction of the innovation and will grow continuously as time goes by. To minimise the error from this problem requires a proper selection of the diffusion case, a properly defined time period, and additional information from individual organisations.

The data for assessing the modified Bass model in this study is a set of secondary data that is gathered from the previous diffusion study of Bulte and Lilien (1997) (Table 12). The data covers diffusion processes with a variety of innovations from household products (air conditioner, clothes dryer, colour television), agricultural innovations (corn 1943 and 1946), healthcare technologies (tetracycline, ultrasound, mammography, and CT scanning), and educational improvements (foreign languages, accelerated program, and compulsory school). The time periods for these diffusion processes are from 13 years (foreign languages and accelerated problem) to 18 years (CT scanning). The data from Tetracycline covers 17 years, the data of corn (1948) and compulsory school cover 14 years, with the rest based on 15 year results. All this data follows a bell-shape curve. Specifically, the data for corn (1948), ultrasound, mammography, and foreign languages tend to be left skewed (Figure 9); the data for colour television, Tetracycline, CT scanning, accelerated program, and compulsory school tend to be right skewed (Figure 10); while the left two (air conditioner and clothes dryer) are likely to be symmetrical (Figure 11).

One major issue of this data set for a comparison study is that the sample size of these diffusion processes distinguishes from each other due to the methods used to assemble the data. For instance, the sum of the adoptions of air conditioner is only 20.2 within 15 years and the number for the data of corn (1948) is 433 within 14 years. In order to exclude the error resulting from this issue, these samples are unified by defining that the total market of each data set is 100. The way to achieve this goal is for each data set and each year's adoption data to be divided by the final adoption number. The modified data sets are shown in Table 13.

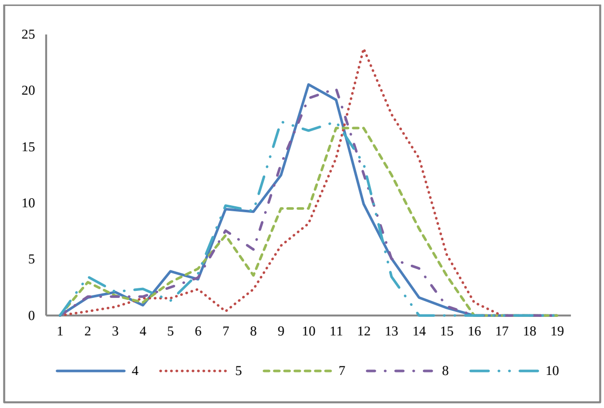

Figure 9: Diffusion Data: Left Skewed

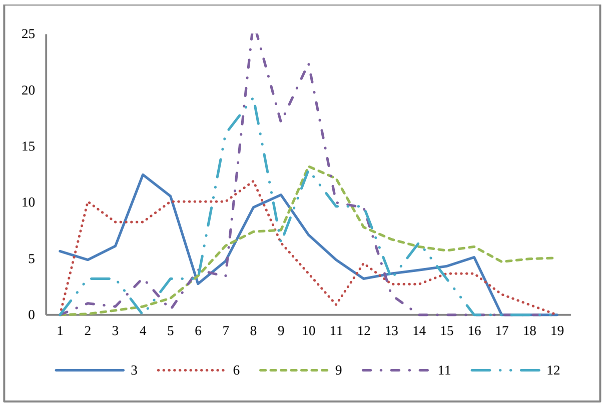

Figure 10: Diffusion Data: Right Skewed

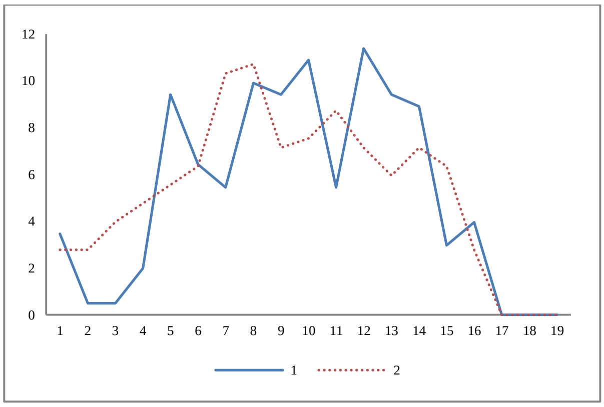

Figure 11: Diffusion Data Symmetrical

Item	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	sum
Air conditioner	0.7	0.1	0.1	0.4	1.9	1.3	1.1	2	1.9	2.2	1.1	2.3	1.9	1.8	0.6	0.8				20.2
Clothes dryer	0.7	0.7	1	1.2	1.4	1.6	2.6	2.7	1.8	1.9	2.2	1.8	1.5	1.8	1.6	0.7				25.2
Color television	5.1	4.4	5.5	11.2	9.5	2.5	4.3	8.6	9.6	6.4	4.4	2.9	3.3	3.6	3.9	4.6				89.8
Corn (1948)	0	7	9	4	17	14	41	40	54	89	83	43	22	7	3					433
Corn (1943)	0	1	2	4	4	6	1	6	16	21	36	61	46	36	14	3				257
Tetracycline	0	11	9	9	11	11	11	13	7	4	1	5	3	3	4	4	2	1		109
Ultrasound	0	5	3	2	5	7	12	6	16	16	28	28	21	13	6					168
Mammography	0	2	2	2	3	4	9	7	16	23	24	15	6	5	1					119
CT scanner	0	1	5	9	18	42	74	89	91	159	146	94	81	73	69	73	57	60	61	1202
Foreign language	0	1.25	0.77	0.86	0.48	1.34	3.54	3.36	6.24	5.95	6.24	4.89	1.25							36.17
Accelerated program	0	0.67	0.48	2.11	0.29	2.59	2.21	16.8	11.04	14.4	6.43	6.15	1.15							64.32
Compulsory school	0	1	1	0	1	1	5	6	2	4	3	3	1	2	1					31

Table 12: Diffusion Data
(The source is from Bulte and Lilien (1997))

Itemt	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	sum
1	3.4653	0.4950	0.4950	1.9802	9.4059	6.4356	5.4455	9.9010	9.4059	10.8911	5.4455	11.3861	9.4059	8.9109	2.9703	3.9604	0.0000	0.0000	0.0000	99.9996
2	2.7778	2.7778	3.9683	4.7619	5.5556	6.3492	10.3175	10.7143	7.1429	7.5397	8.7302	7.1429	5.9524	7.1429	6.3492	2.7778	0.0000	0.0000	0.0000	100.0004
3	5.6793	4.8998	6.1247	12.4722	10.5791	2.7840	4.7884	9.5768	10.6904	7.1269	4.8998	3.2294	3.6748	4.0089	4.3430	5.1225	0.0000	0.0000	0.0000	100
4	0.0000	1.6166	2.0785	0.9238	3.9261	3.2333	9.4688	9.2379	12.4711	20.5543	19.1686	9.9307	5.0808	1.6166	0.6928	0.0000	0.0000	0.0000	0.0000	99.9999
5	0.0000	0.3891	0.7782	1.5564	1.5564	2.3346	0.3891	2.3346	6.2257	8.1712	14.0078	23.7354	17.8988	14.0078	5.4475	1.1673	0.0000	0.0000	0.0000	99.9999
6	0.0000	10.0917	8.2569	8.2569	10.0917	10.0917	10.0917	11.9266	6.4220	3.6697	0.9174	4.5872	2.7523	2.7523	3.6697	3.6697	1.8349	0.9174	0.0000	99.9998
7	0.0000	2.9762	1.7857	1.1905	2.9762	4.1667	7.1429	3.5714	9.5238	9.5238	16.6667	16.6667	12.5000	7.7381	3.5714	0.0000	0.0000	0.0000	0.0000	100.0001
8	0.0000	1.6807	1.6807	1.6807	2.5210	3.3613	7.5630	5.8824	13.4454	19.3277	20.1681	12.6050	5.0420	4.2017	0.8403	0.0000	0.0000	0.0000	0.0000	100
9	0.0000	0.0832	0.4160	0.7488	1.4975	3.4942	6.1564	7.4043	7.5707	13.2280	12.1464	7.8203	6.7388	6.0732	5.7404	6.0732	4.7421	4.9917	5.0749	100.0001
10	0.0000	3.4559	2.1288	2.3777	1.3271	3.7047	9.7871	9.2895	17.2519	16.4501	17.2519	13.5195	3.4559	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	100.0001
11	0.0000	1.0417	0.7463	3.2805	0.4509	4.0267	3.4359	26.1194	17.1642	22.3881	9.9969	9.5616	1.7879	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	100.0001
12	0.0000	3.2258	3.2258	0.0000	3.2258	3.2258	16.1290	19.3548	6.4516	12.9032	9.6774	9.6774	3.2258	6.4516	3.2258	0.0000	0.0000	0.0000	0.0000	99.9998

Table 13: Modified Diffusion Data

3.6 Parameter Estimation Techniques

One advantage of the Bass model is that through certain parameter estimation techniques parameters of the model can be estimated (Bass 2004) on the basis of its analytical solution (Equation 15). Then, the Bass model is able to become a tool for future prediction, that is, after estimating the parameters via knowledge of the diffusion data in the initial years or simply by making an initial guess at the parameter values.

$$\begin{cases} F(t) = \dfrac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \\ f(t) = \dfrac{((p+q)^2/p) e^{-(p+q)t}}{\left(1 + \frac{q}{p} e^{-(p+q)t}\right)^2} \end{cases} \tag{15}$$

However, the result calculated based on guessed parameters is not trust worthy and to estimate the parameters accurately with a limited data set is not easy. Therefore, the study of parameter estimation techniques becomes one of the central issues in diffusion model studies.

3.6.1 Current Parameter Estimation Approach

In the early days, the issue of parameter estimation was solved by using ordinary least square (OLS) (Bass 1969). The original Bass model is able to be further transformed into Equation 16. Then the OLS approach suggests using a discrete analogue of Equation 16 to estimate the parameters M, p, and q (see Equation 17).

$$f(t) = \big(p + qF(t)\big)\big(M - F(t)\big) = pM + (q-p)F(t) - \frac{q}{M}F(t)^2 \qquad (16)$$

$$f_t = a + bF_{t-1} - cF_{t-1}{}^2 \qquad (17)$$

where:

$$M = -b - (b^2 - 4ac)^{0.5}/2c$$

$$p = a/m$$

$$q = -mc$$

OLS is a relatively simple approach with a few shortcomings in estimating the equation parameters. As summarised by Putsis et al. (2000), these limitations include the unstable or even the wrong result where only a few data points exist, and the time-interval bias created by attempting to estimate with discrete time-series data. Thus Maximum likelihood estimation (MLE) and Nonlinear least square (NLLS) are introduced as a direct consequence of these OLS estimator shortcomings. A typical implementation of the MLE can be processed through Equation 18. And NLLS is considered to have even higher performance than MLE. (The NLLS approach will be discussed in details later in Section 3.6.3, since it will become a major part of the proposed parameter estimation approach used by this study). Furthermore, a recent study uses Generic Algorithm (GA) estimation to estimate diffusion models through Equation 19, as NLLS is found to produce inaccurate results under certain conditions: NLLS is sensitive to the value of initial input, and more importantly, NLLS is not a global estimation tool (Venkatesan, Krishnan & Kumar 2004).

$$L(\gamma, \lambda, \mu, s_t) = (1 - G(t_{T-1}))^{S_T} \prod_{i=1}^{T-1} (G(t_i) - G(t_{i-1}))^{S_i} \tag{18}$$

where:

$\gamma \quad = \quad p + q$

$\lambda \quad = \quad q/p$

$\mu \quad =$ *Eventual probability of adoption, so* $E(x(t)) = \mu MF(t)$

$s_t \quad =$ *the numbers of adopters in the corresponding time periods* t_i

$G(t_i) \quad = \quad \mu F(t)$

$$(p, q, m) = \frac{1}{T} \sum_{t=1}^{T} (x(t) - E(x(t)))^2 \tag{19}$$

where:

$p, q, m \quad =$ *Parameters to be estimated*

$T \quad =$ *Diffusion Time*

$x(t) \quad =$ *Actual number of adoption*

$E(x(t)) \quad = \quad m(F(t) - F(t-1))$

One key merit of the above approaches is that, OLS, MLE, NLLS, and GA are all available from software packages. Other than these, a further recent approach is the use of adaptive filter techniques. The benefit of using this approach is the better prediction of future sales, while this approach normally finds difficult to implement due to the technical barrier, with results not being significantly improved. One typical example of this approach is the Augmented Kalman Filter, which is designed by Xie et al. (1997).

Moreover, sometimes little or even no direct data is available for estimating the parameters of a diffusion model. There are basically two ways to solve this problem and in many cases they are used together: one is to use more advanced parameter estimation techniques and the other is to make an initial guess based on previous results. Lenk and Rao (1990) propose a Bayesian-based technique for models where little direct data is available. Another similar case of using Bayesian-based technique in estimating parameters of diffusion models can be found in the work of Albuquerque et al. (2007). Furthermore, a meta-analysis is very useful in estimating models with little or no data, because it can help make an initial guess at parameters (Sultan, Farley & Lehmann 1990). Also Bronnenberg and Sismerio (2002) use multimarket data to make predictions when no or poor data exists.

It can be seen that all the above approaches have been designed to address single-equation models. That's why full-information estimators such as full-information maximum likelihood (FIML) and three-stage least squares (3SLS) are necessary (Putsis, Putsis & Srinivasan 2000). For instance, the multi-generation or multi-category diffusion models normally require a consistent and simultaneous estimation of all equations (each equation may represent one generation or category, respectively).

3.6.2 Numerical Analysis

Epidemic diffusion models are normally in the form of ordinary differential equations. An ordinary differential equation represents a differential relation between an unknown function together with its deviation and a function of a single independent variable. Although many real world phenomena are described in ordinary differential equation(s), many of them cannot be solved analytically. Therefore, people have to satisfy themselves with an approximation of the real results. In addition, even when the analytical solution exists, an approximation can yield sufficiently accurate solution while reducing the complexity of the problem significantly, and is thus preferred.

A number of numerical analysis methods are available for solving ordinary differential equations. These include the Euler method, the exponential Euler method, and so on. Most of them are embedded in certain software packages, so can be easily implemented.

3.6.3 Proposed Parameter Estimation Approach

NLLS is used to estimate parameters for the modified Bass model due to its accuracy and wide acceptance in the literature. Two most commonly used NLLS estimation approaches are those of Srinivasan and Mason (1986) and Jain and Rao (1990). They both use the same statistical estimation technique, but apply it to different model structures. Specifically, the former one uses the model:

$$x(t) = m[F(t) - F(t-1)] \tag{20}$$

And the latter uses the model:

$$x(t) = \frac{[m - X(t-1)][F(t) - F(t-1)]}{[1 - F(t-1)]} \tag{21}$$

where:

$F(t)$ = *Number of cumulative adopters at time t*

m = *Total market*

$x(t)$ = *Number of adopters at time t*

$X(t)$ = *Number of cumulative adopters at time t*

According to Putsis et al. (2000), Sriivasan and Mason‘s approach can provide better fit to the real data, so it is used in this study. However, this modified Bass model cannot be directly estimated by NLLS, since it does not have an analytical solution (Xie et al. 1997; Putsis, Putsis & Srinivasan 2000). As this model is an ordinary differential equation, approximation of the result can be obtained through the numerical methods mentioned in Section 3.6.2. Therefore, a subroutine that uses numerical analysis to approximate $F(t)$ is introduced (a similar use of numerical techniques for the maximum likelihood estimation of diffusion models can be found in the work of Garland and Gallant (2002)). Furthermore, Generic Algorithm estimation (Venkatesan, Krishnan & Kumar 2004) is initially implemented as a trial parameter search, due to the limitations of NLLS discussed in Page 81.

A trial experiment is implemented in order to test the feasibility of the proposed parameter estimation approach. Two parameter estimation techniques are applied to the Bass model: NLLS that uses analytical solutions from the Bass model; NLLS that uses the numerical technique to approximate $F(t)$. And the two approaches are compared using the 12 sets of diffusion data gathered in Section 3.5. The results of these comparisons are listed in Table 14. Data in each cell is the sum of the residual between the real value X_t and the estimated function value $E_t(X)$ at each time point:

$$\sum_{t=1,2,\ldots,T} \left(X_t - E_t(X)\right)^2 \tag{22}$$

The data explains how much the estimated value differs from the real value. The figures in Columns 5 and 6 are also used to measure the performance of this approach. Specifically, it is defined that the ‘difference’ between the values calculated by the two approach is $\Delta \mathrm{x_i}$ for the diffusion process i. In each diffusion process i, let the value calculated by the NLLS with an analytical solution of $F(t)$ be x_i and the value calculated by the NLLS with an approximation of $F(t)$ be $x_{0,i}$, then the ‘relative error’ is defined as $\mathrm{e_i} = \frac{\Delta \mathrm{x_i}}{\mathrm{x_i}} = \frac{\mathrm{x_{0,i}\text{-}x_i}}{\mathrm{x_i}}$.

This shows that the overall performances of the two approaches are basically the same, 949.1815 (approach one) and 949.0889 (approach two). The sum of differences ($\sum \Delta \mathrm{x_i}$) between them is $949.1815 - 949.0889 = 0.092$, which means the relative error $\overline{e_i}$ is $\frac{0.0926}{949.1815} < 10^{-4}$. Also for each individual experiment, the differences $(\Delta\mathrm{x})$ are around 10^{-3} and the relative errors are all around 10^{-4}. Therefore, it can be concluded that the proposed numerical technique based estimation approach has similar, or even the same performance as the analytical solution based estimation approach. To sum up, the proposed approach should be accurate and robust.

Diffusion	NLLS + Analytical Solution	NLLS + Numerical analysis	Difference	Error Percentage	Number of Adopters
1	78.9922	78.9933	0.0011	1.3925E-05	100
2	22.8101	22.8112	0.0011	4.8224E-05	
3	100.4193	100.4191	0.0002	1.9916E-06	
4	55.2700	55.1940	0.076	0.00137507	
5	32.1841	32.1296	0.0545	0.00169338	
6	86.0863	86.0850	0.0013	1.5101E-05	
7	57.6894	57.6950	0.0056	9.7072E-05	
8	38.9604	38.8312	0.1292	0.00331619	
9	58.4962	58.4945	0.0017	2.9062E-05	
10	49.8500	49.8490	0.001	2.006E-05	
11	180.2870	180.4455	0.1585	0.00087915	
12	188.1365	188.1415	0.005	2.6576E-05	
Total	949.1815	949.0889	0.0926	9.7558E-05	
Average	79.09846	79.09074	0.00772	9.76E-05	

Data in Colum 2 and 3 is the sum of the residual between the sample and estimated function value at each time point.

Table 14: Performance of the Proposed Parameter Estimating Approach

3.7 Model Performance on Explaining Diffusion Phenomena

Diffusion models have different performances when explaining the same diffusion phenomenon (Meade & Islam 1998). The figure below (Figure 12) is the result of a simulation, in which case the Bass model, the Gompertz model, and the modified Bass model are used to fit one set of randomly generated diffusion data. Compared with the Bass model (Black curve) and the modified Bass model (Red curve), the Gompertz model (Blue curve) has a lower starting point, a sharper initial trend, and a slower decline after the peak point. Moreover, the peak point in the curve that is produced by the Gompertz model comes earlier than the peak points in the curves of the Bass model and the modified Bass model. Finally, the curve produced by the modified Bass model nearly superposes the curve produced by the Bass model and it is just between the curves of Bass model and Gompertz model.

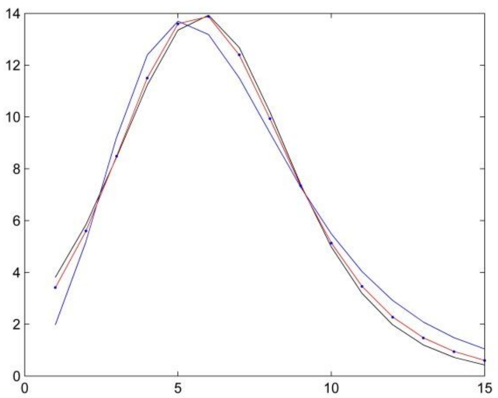

Figure 12: Bass Model, Gompertz Model, and Proposed Models

The comparison is then replicated by using real data of 12 diffusion processes from Table 13. Table 15 shows the result of comparing these three models (see Appendix 4 for the resulting figures). Similar to Table 14, data in each cell is the sum of the residual between the sample X and estimated function value $E(X)$ at each time point. From an aggregated perspective, the results show that the overall performance of the modified Bass model (987.2703) is similar to the Bass model (949.0859) and superior to the Gompertz model (1116.6227). If the performance of the Bass model is set as 1, the ratio between the performances of the Bass model, the modified Bass model, and the Gompertz model is 1:1.0402:1.1765. And the average performance of the 12 diffusion processes is 93.0519, 79.0905, and 82.2725.

To sum up, the performance of the modified Bass model is very close to the performance of the Bass model, and is better than the Gompertz mode at an overall level. If the individual data set is focused, it is found that no single model has the best performance across all data sets. In the diffusion processes of corn (1948), corn (1943), ultrasound, mammography, and foreign languages, where the diffusion data tend to be left skewed, the Bass model can provide the best performances. The Gompertz model provides better fit in relation to the diffusion processes of colour television, Tetracycline, CT scanning, accelerated program, and compulsory school where the diffusion data is likely to be right skewed. And in the other two processes of diffusion (air conditioner and clothes dryer), the three models show a similar performance.

Diffusion	*Gompertz Model**	*The Bass Model**	*The Bass Model***	*The Modified Bass Model**	*Number of Adopters*
1	81.8563	$\boxed{78.9922}$	78.9933	79.20853	100
2	22.7490	22.8101	22.8112	$\boxed{22.2312}$	100
3	$\boxed{98.1849}$	100.4193	100.4191	100.1152	100
4	128.2537	55.2700	$\boxed{55.1940}$	78.7418	100
5	78.9672	32.1841	$\boxed{32.1296}$	46.0935	100
6	$\boxed{75.6258}$	86.0863	86.0850	83.3941	100
7	109.6305	$\boxed{57.6894}$	57.6950	68.4853	100
8	93.8527	38.9604	$\boxed{38.8312}$	55.7452	100
9	$\boxed{34.7480}$	58.4962	58.4945	51.9388	100
10	81.6453	49.8500	$\boxed{49.8490}$	58.3077	100
11	$\boxed{151.9466}$	180.2870	180.4455	164.9737	100
12	$\boxed{159.1632}$	188.1365	188.1415	178.0359	100
Total	1116.623	949.1815	949.0889	987.2709	
Average	93.05193	79.09846	79.09074	82.27258	

Data in each cell is the sum of the residual between the sample and estimated function value at each time point.

Data with boarder indicates the most accurate result to the real data.

* : Parameters in the model is estimated by the NLLS + Numerical approach

**: Parameters in the model is estimated by the NLLS + Analytical solution approach

Table 15: Performance of Diffusion Models

3.8 Summary

The Bass model effectively captures the two main factors in diffusion (environmental effect and social contagion effect); other less important factors are captured by the error term; and thus the model provides a good explanation for the diffusion process from both theoretical and empirical aspects. The model proposed in this chapter is based on the Bass model with further ideas from the von Neumann-Morgenstern framework. It is under the assumption that potential adopters are, on average, risk averse. At an aggregated level, the social contagion effect in the modified Bass model tends to decline through time, which could provide a better fit with the real data in a few diffusion cases. Additionally, the value ranges of the two parameters in the modified Bass model are both $[0, +\infty]$, which means new factors of diffusion can be incorporated with greater diversity, compared with the original Bass model.

During the process of assessing the modified Bass model, one of the key problems in using NLLS estimation is how to calculate the value of $F(t)$ from the diffusion model at each time point. This issue raises the proposition that only diffusion models that have a closed form solution can apply to this approach directly. In this study, the author uses numerical analysis to approximate the value of $F(t)$. The accuracy of the result can ultimately approach the real value if the tolerance of the numerical analysis approaches zero. Additionally, the introduction of the numerical analysis is not only useful for NLLS estimation, but for all the other approaches that require a solution of $F(t)$, such as GA.

The empirical accuracy of diffusion models largely depends on different cases, as no single model can explain all diffusion phenomena perfectly. Through the parameter estimation technique developed in Section 3.6.3, the twelve sets of diffusion data are processed in order to test the performance of the modified Bass model. As a comparison to the Bass model and the modified Bass model, the Gompertz model was chosen for use in this study. This is because the Gompertz model is based on different understandings of diffusion than the Bass model and also because it exhibits a good empirical performance. As shown, the result of the comparison between the three models, the Gompertz model and the Bass model are superior in a few of the diffusion phenomena. Based on the above discussions, it is concluded that: in each diffusion process, the curve of the modified Bass model is just between the Bass model and the Gompertz model; among the three models, the Bass model is superior when the diffusion curve tends to be left skewed; among the three models, the Gompertz model provides a better fit when the curve tends to be right skewed; in the other two processes of diffusion where curves tend to be systematic, all three models do not differ visibly.

To sum up, the modified Bass model aims to fill a few limitations of the original Bass model, to act as an alternative approach for modelling the diffusion process and predicting the future trends, and also serve as the basic structure of the diffusion model that will be developed in the next chapter.

Chapter 4 Proposed Agent-Based Model of Diffusion

"All theory depends on assumptions which are not quite true. That is what makes it theory. The art of successful theorizing is to make the inevitable simplifying assumptions in such a way that the final results are not very sensitive."

(Solow 1956)

"The objective of agent-based models is to build theory rather than to construct a descriptively accurate or predictive model of organisations in contingent environments"

(Garcia 2005)

4.1 Introduction

Simple epidemic diffusion models such as the Bass model can produce diffusion curves with good accuracy. However, they only capture the trend of the diffusion process with a few generalised parameters, so are not capable of explaining the role of other specified factors.

This chapter is the central part of this thesis. It proposes an agent-based diffusion model to answer the research questions of this study. This chapter is divided into the following sections: Section 2 lists a few desirable attributes for designing diffusion models. It provides a guideline for developing the new diffusion model in this study; Section 3 provides a brief discussion on agent-based models and explains why an agent-based model is suited to this work; Section 4 illustrates the mode framework, which contains key factors that will be considered in the proposed model and shows the relationships between these factors and the diffusion; together, Sections 5, 6, and 7 introduce the proposed agent-based diffusion model. Specifically, Section 5 shows the main structure of the model, which is designed on the basis of the modified Bass model in Chapter 3; after clarifying the meaning of organisational innovativeness in this study, Section 6 models the effect of organisational innovativeness onto the main model proposed in Section 5; Section 7 aims to model the inter-organisational influence on diffusion, which consists of the effect of opinion leadership, innovativeness difference, and geographic location; Finally, a summary of this chapter is given in section 8.

4.2 Desired Attributes of the Diffusion Model

Mathematical models can be broadly divided into two constructs in terms of the modelling methods being used: deterministic models and probabilistic models. On the one hand, deterministic models can be explicitly expressed in the form of mathematical equations, and the solutions of these equations are determined once the values of the parameters are specified. On the other hand, probabilistic models can describe the object by using a number of random variables and their probability distributions, and thus their output is rather a set of possibilities. In general, deterministic models depict a trajectory, while probabilistic models yield a set of outcomes. Therefore, deterministic models outperform probabilistic models in capturing the fundamental characteristics of a problem and simplifying the complexity into a few key factors; they are weak in predicting a wide range of result possibilities. However, based on a comparative analysis set, Rahmandad and Sterman (2008) found that the output of deterministic models and the average output of probabilistic models are generally the same, that is, if these two models are designed based on the same concept. In the field of diffusion models, epidemic diffusion models are mainly deterministic models and probit models usually fall into the latter category.

A model should be the abstraction and simplification of a real phenomenon and a good model should help us to better understand this phenomenon (Bass & Wind 1995). Little (1970) argues that many models are not widely adopted in management practice, because good models with good parameterisations are usually difficult to find and managers usually fail to truly understand these models. Then he further proposes a few guidelines for modellers, they should be:

simple, robust, easy to control, adaptive, complete on important issues, and easy to communicate with. These fundamental guidelines have been followed in designing management models since then (Little 2004). Besides the above guidelines, Bass et al. (1994) also discuss a few properties specifically for developing diffusion models, which are listed below.

First, due to the empirical success of the Bass model, it is widely accepted that this model does capture the nature of diffusion and that its output is consistent with reality. Therefore, it is expected that all the diffusion models should be able to reduce to, or be similarly equivalent with, the Bass model curve. Second, a variable changed at one time will not only influence the result at this specific time point, but also impact on all future time periods. In the Bass model, this property is typically represented by $qF(t)$ on the right hand side of the equation, which means the factors that result in the change of the number of adopters at one time point will influence the number of new adopters at the next and all the following time points. Third, models should be capable of empirical estimation. Without this property, the model will become only an explanation tool, in which case its practical value will largely be limited. The attribute of empirical support requires availability of the data and good parameter estimation technique. Forth, the observed data should match the value that the model expects. It is obvious that the proposed model should be a good fit with the real phenomena. Fifth, the diffusion models are expected to have analytical solutions, since this property can help with the further analysis of the models and ease of parameter estimation. Sixth, variables of the models should be interpreted by managerial meanings and provide useful implications for the real world. Finally, the model should be easily implemented, which is consistent with Link's (1970) argument above (Page 93).

The guidelines listed above by Link (1970) and Bass et al. (1994) are all useful for developing new diffusion models. Further referring to the research gaps and questions listed in Chapter 1, the author expects the proposed model in this study to have the following attributes: it is expected that the proposed diffusion model can become a bridge between epidemic diffusion models and probit models; it is expected that the proposed diffusion model can combine the forces of diffusion and thus provide a better understanding of the nature of the diffusion process; it is expected that the proposed diffusion model will be develop based on a solid support from the theories and empirical findings, which means the model is not only an explanation tool, but also a means of further proving these theories and findings; it is expected that the proposed diffusion model has good extensibility, which means the model should be able to further incorporate factors other than the ones discussed in this work, and thus serve as a benchmarking tool for future research.

In terms of all the desired attributes listed above, the author considers that an ***agent-based diffusion model*** would be appropriate for this study and the reasons will be discussed in the following section.

4.3 Introduction to the Agent-Based Model

Epidemic diffusion models and probit diffusion models both have their limitations. Normally in the form of macro models, epidemic models well capture the key diffusion forces and model them on an aggregated basis, but they also ignore or underestimate the importance of individual variations on the overall diffusion process. Probit diffusion models use individual variations to explain the diffusion curve without consideration of the interactions between members of the system. Agent-based models, which stand in the middle between macro diffusion models and micro diffusion models, are expected to combine their merits and cover their limitations. According to Garcia (2005), agent-based models differ from the macro and micro models from a few perspectives. First and the same with the probit diffusion models, the unit of study is the agent (individual or organisation). Also each agent has the unique characteristics and decision-making attitude it follows. Therefore, agent-based models will explain the phenomena by modelling the individual behaviours of the agents. Second, similar to epidemic diffusion models, agent-based models consider agent adaptiveness and interactions, which means the mass media effect and the social contagion effect both can be captured.

Agent-based models are rooted in complexity theory and they offer a promising methodology for capturing the dynamics of diffusion without abstracting individual differences. They are often probabilistic models, of which every simulation is different although the underlining mechanism is the same as with the deterministic models. These models can be either developed independently or developed based on deterministic models (Keeling et al. 2003; Keeling et al. 2001). Agent-based models have become more and more popular because of the development of computing technology and because the modelling idea is not as abstract as in the deterministic models. Several recently published agent-based modelling studies can be found in a special issue of the *Journal of Product Innovation management* (Garcia & Jager 2011). Table 16 presents an agent-based model, which stands as one of the latest progress in understanding the role of innovativeness and opinion leadership in diffusion through an agent-based approach

Authors(s)	Model Explanation
(van Eck, Jager & Leeflang 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*: $x_{i,t} = \frac{adopting\_neighbours_{i,t}}{total\_neighbours_{i,t}}$
	Two main types of interpersonal influence are defined in this work: informational influence refers to the tendency to accept information from others as evidence of reality; normative influence explains the tendency to conform to the expectations of others. The utility function $U_{i,t}$ of agent i at time t is determined by the individual preference (informational influence) $y_{i,t}$ and the social influence (normative influence) $x_{i,t}$ with one parameter β_i that explains their relative importance in the model. The individual preference $y_{i,t}$ is based on the product quality q and the quality threshold p_i. The social influence $x_{i,t}$ is calculated based on one assumption: if more neighbours adopt the product, normative influence in favour of the product increase.

Table 16: An Agent-Based Diffusion Model

Garcia (2005, p. 383) summarises the proper use of agent-based models: "*when both macro- and micro levels of analyses are of interest; when social systems can easily be described by 'what if' scenarios but not by differential equations; when emergent phenomena may be observed; when coevolving systems interact in the same environment; when learning or adaptation occurs within the system; when physical space and temporal space are of interest; when the population is heterogeneous or the topology of the interactions is heterogeneous and complex.*" Considering this study, the expected model will cover both macro level and micro level analysis; the adoption behaviour of each organisation can be described by 'what if' scenarios, for instance, organisations are defined to adopt the innovation when certain conditions are met; in diffusion, organisations interact with each other to transfer the information of the innovation; geographic location is one of the interests of this model. Therefore, an agent-based approach can be appropriate for this study.

4.4 Model Framework

The expected agent-based diffusion model of this study will be developed on the basis of the modified Bass model proposed in Chapter 3. Thus it shares the similar understanding of the diffusion process as the Bass model, which considers that the adoption decision of an organisation is influenced by the amount of the information about the innovation received from the environment and other members in the system.

The amount of information about the innovation is assumed to be constant over time within the environment. However, organisations can have different levels of acceptance for the information due to their innovativeness level, which results in different adoption probability. For inter-organisational influence, it is considered that the influence between two organisations is not the same for all paired organisation, but varies due to the characteristics of the organisations and their relationships. Following the theories and empirical findings from the literature, it is proposed that the power of inter-organisational influence is determined by two factors: opinion leadership and innovativeness difference, which are both modelled on the basis of organisational innovativeness. Additionally, geographic location, specifically the physical distance between two organisations, will make a further impact on inter-organisational influence.

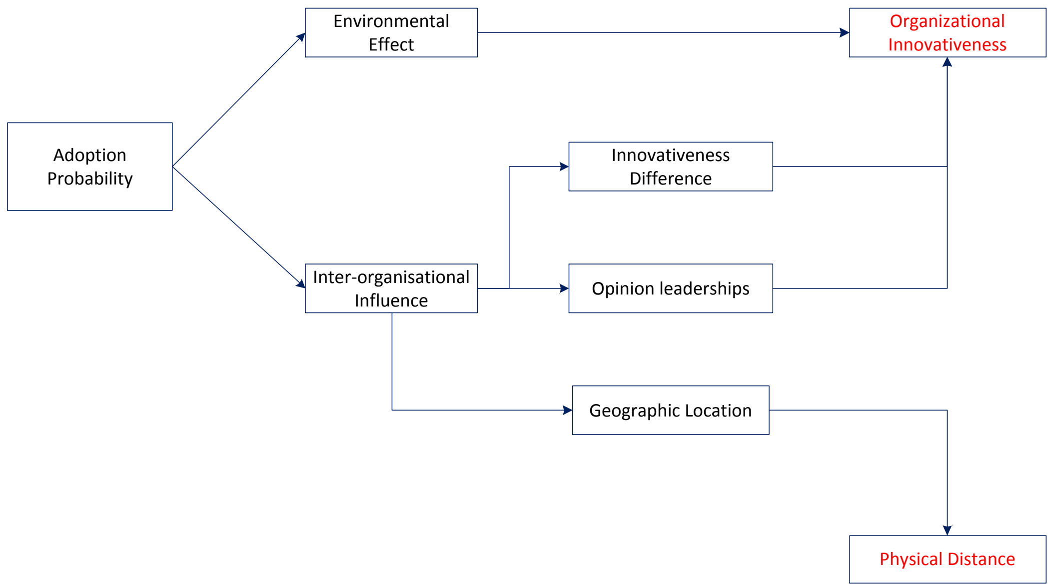

Figure 13: Model Framework

Figure 13 shows the model framework. In the following sections, this framework will be divided into parts, discussed and transformed into corresponding mathematical equations.

4.5 Main Model

It is assumed that an innovation is diffused in an environment with M organisations, which all have the potential to adopt this innovation. For each organisation k at time t, its probability of adoption ($P_{k,t}$) is determined by a von Neumann-Morgenstern framework with the coefficient of risk averse η, which represents its uncertain perception of the innovation's performance after receiving the information of the innovation from both the environment and other members in the system. Specifically, the organisation's uncertain perception of the innovation's performance after receiving the information of the innovation from the environment is assumed to be $p_{k,t}$, that is, it is able to change periodically, and its average level of uncertain perception of the innovation's performance after receiving the information of the innovation from one existing adopter is denoted as $q_{k,t}$ that is also dynamic. The mathematical expression for the above discussion can be written as below (Equation 23). Also it should be noticed that this equation can reduce to the modified Bass model expressed in the Chapter 3, that is, once $p_{k,t}$ and $q_{k,t}$ are considered as constants.

$$P_{k,t} = 1 - e^{\left(\eta \times (-p_{k,t} - q_{k,t} \times F_t)\right)} \tag{23}$$

where:

$P_{k,t}$	=	*The adoption probability of organisation k at time t*
F_t	=	*Number of organisations that have already adopted the innovation at time t*
η	=	*Coefficient of risk averse*
$p_{k,t}$	=	*The organisation's uncertain perception of the innovation's performance after receiving information of the innovation from environment at time t*
$q_{k,t}$	=	*The organisation's uncertain perception of the innovation's performance after receiving information of the innovation from a member of the system at time t*

Additionally, the effect of organisational innovativeness on the uncertain perception of the innovation's performance under environmental effect is represented as function $f_1(OI_{k,t})$, and the effect of inter-organisational influence and geographic location on the uncertain perception of the innovation's performance under inter-influence between members in the system is modelled by $f_2(OI_{k,t}, OI_{k',t})$ and $f_3(PD_{k,k'})$ respectively. Therefore the mathematical equation is extended as:

$$P_{k,t} = 1 - exp\left(\eta \times \left(-p_t \times f_1(OI_{k,t}) - q_t \times \sum_{k' \in K_t} f_2(OI_{k,t}, OI_{k',t}) \times f_3(PD_{k,k'})\right)\right) \tag{24}$$

where:

K_t	=	*Set of organisations that have already adopted the innovation at time t*
p_t	=	*Potential adopters' average uncertain perception of the innovation's performance after receiving information of the innovation from environment at time t*
q_t	=	*Potential adopters' average uncertain perception of the innovation's performance after receiving information of the innovation from a member of the system at time t*
$f_1(OI_{k,t})$	=	*Function that represents the **relative** innovativeness level of organisation k within the system at time t*
$f_2(OI_{k,t}, OI_{k',t})$	=	*Function that represents the **relative** inter-influence between organisations k and k' within the system at time t*
$f_3(PD_{k,k'})$	=	*Function that represents the **relative** effect of geographic location between organisations k and k' within the system*

In this model, any issues that result from a change of information flow at an aggregated level will be reflected in the change of p_t and q_t. Correspondingly, functions $f_1(OI_{k,t})$, $f_2(OI_{k,t}, OI_{k',t})$, and $f_3(PD_{k,k'})$ only represent the relative level of organisational innovativeness, inter-organisational influence, and geographic location effect within the system, which means $\overline{\sum_{\iota=1,2,\ldots,M} f_1(OI_{\iota,t})} = 1$, $\overline{\sum_{\substack{J=1,2,\ldots,M \\ \iota=1,2,\ldots,M \\ \iota \neq J}} f_2(OI_{\iota,t}, OI_{J,t})} = 1$, and $\overline{\sum_{\substack{J=1,2,\ldots,M \\ \iota=1,2,\ldots,M \\ \iota \neq J}} f_3(PD_{\iota,J})} = 1$. For instance, the dynamic change of organisational innovativeness is determined by p_t and $f_1(OI_{k,t})$: p_t represents the change of the average level of organisational innovativeness while the change of $f_1(OI_{k,t})$ reflects the individual change of organisational innovativeness when the system average is fixed. Therefore, the true values of the interested factors in this study (organisational innovativeness, opinion leadership, and geographic location) are all determined by two perspectives: the mean value and the distribution.

There are two reasons for modelling the diffusion process in such a way. First, it is desirable that the proposed model is able to reduce to its homogeneous version and thus maintain its empirical accuracy. Second, it is desirable that the model is able to answer questions raised from both aggregated and individual levels, since these two sets of parameters/functions contribute to the homogeneous and heterogeneous nature of the phenomenon, respectively.

4.6 Environmental Effect

Innovativeness is a concept that is designed specifically for understanding the diversity of an individual's adoption time and it naturally has a positive relationship with early adoption, according to its definition. In this study, organisational innovativeness affects the adoption decision on the basis of information from the environment and other members of the system, but in different ways. Compared with the information from the environment, the information of the innovation that has been transferred between organisations is less risky, as it has already been tested by others. Therefore, the former is directly related to organisational innovativeness while the second is closer to the inter-organisational relation and the self-conformity of organisations. In conclusion, organisational innovativeness in the proposed model of this study influences the environmental effect directly and it has an indirect effect on inter-organisational relations, which will be discussed in Section 4.7.

An organisation with a higher innovativeness level will be more open to the information regarding innovation and thus result a positive effect on its uncertainty perception of adoption. Therefore, a positive relationship is proposed between organisational innovativeness and uncertain perception of the innovation's performance after receiving the information from the environment. Here, the value of organisational innovativeness serves as a bridge between an organisation's capability and its intention towards innovation, and the organisation's uncertain perception of the innovation's performance. This relationship is considered as linear here for simplicity.

As mentioned before (Page 100), function $f_1(OI_{k,t})$ is expected to represent the relative effect of organisational innovativeness. Therefore, the innovativeness of organisation k at time t is divided by the average innovativeness level of the system at time t in order to model this relative effect:

$$f_1(OI_{k,t}) = \frac{OI_{k,t}}{\overline{OI_t}} \tag{25}$$

Where:

$OI_{k,t}$ = *Innovativeness of organisation k at time t* [22]

$\overline{OI_t}$ = *Average innovativeness of all organisations at time t*

4.7 Inter-Organisational Influence

Organisations tend to imitate others, which can be explained from various perspectives (Lieberman & Asaba 2006). This attribute of organisations makes the inter-organisational influence an imperative channel in diffusion, as inter-organisational interactions can disseminate innovation and foster adaption. The study of inter-organisational influence falls into the area of inter-organisational relations (IOR) research, which focuses on the relationship between individual organisations and the environment and relationships between groups of organisations (Johnsen, Lamming & Harland 2008). A number of terms are used to represent inter-organisational relations due to its wide use across different fields (Table 17 and 18).

[22] In real situation, this value can be assessed though measures of organisational innovativeness as listed in Chapter 2.

Names for inter-organisational entities			
An alliance	*An association*	*A cluster*	*A coalition*
A collaboration	*A consortium*	*A constellation*	*A cooperation*
A federation	*A joint venture*	*A network*	*A one stop shop*
A partnership	*A relationship*	*A strategic alliance*	*A zone*
Descriptors for inter-organisational entities			
Collaborative …	*cooperative …*	*Coordinated …*	*interlocking …*
Inter-organisational …	*Inter-professional …*	*Joined-up …*	*joint …*
Multi-agency …	*Multi-party …*	*Multi-organisational …*	*multiplex …*
Trans-organisational …	*virtual …*		
Names for inter-organisational acts			
Bridging	*Collaboration*	*Contracting*	*Cooperation*
Franchising	*Networking*	*Outsourcing*	*Partnering*
Working together			

Table 17: Commonly Used Language in Inter-Organisational Relations (Source is from Cropper et al. (2008))

Tangible and intangible resource
Tacit and explicit knowledge
Different forms of resource interdependence
The intensity and frequency of rouse and information flows among organisations
Trust
Reciprocity and equity as well as other forms of norm-based social exchange
Incentive structures and administrative controls
Various forms of contracts
The diversity of types of relations that exist among the organisations of an IOE
The overall intensity and restrictedness of the relations
Internal clustering that a set of IORs displays

Table 18: Attributes of Inter-Organisational Relations (Source is from Cropper et al. (2008))

In the existing diffusion literature, the effect of inter-organisational influence is usually explained from two perspectives: as social contagion effect and social conformity effect (Ansari, Fiss & Zajac 2010). The former proposes that a potential adopter adopts an innovation, because this potential adopter has more contact with the ones who have already adopted the same innovation. Another concept in diffusion, the information cascade, also can be classified within this category. The latter explains the inter-organisational influence from a psychological point of view, arguing that a potential adopter feels under pressure from those existing adopters who have similar social status to them.

In this study, the modelling of inter-organisational influence follows the following method. First, a fully connected network is introduced for the network structure of the organisations in the system. Additionally, it is specified that inter-organisational influence only exists if a potential adopter and an existing adopter are linked together. Otherwise, the inter-organisational influence equals zero. Then the exact value of the inter-organisational influence between two organisations is decided by two factors. The first determinant of the inter-organisational influence between a potential adopter *k* and an existing adopter *k'* is the opinion leadership of *k'*. Opinion leadership is the specific role of an organisation in influencing others. It decides the credibility of the existing adopter *k'* in the system and the value of the information comes from it. However, the level of inter-organisational influence cannot be identified by this single factor, since the potential adopter *k* may not accept all the information that comes from *k'* due to certain reasons. That is the reason why the model in this study further considers that innovativeness difference between two organisations takes an important role regarding the inter-organisational influence that exists between them.

In conclusion, the level of this inter-organisational influence is determined by how much information the existing adopter can give and how many percentage of the information can be truly passed to the potential adopter. Therefore, the inter-organisational influence between two organisations *k* and *k'* is modelled as:

$$f_2(OI_{k,t}, OI_{k',t}) = f_4(OI_{k',t}) \times f_5(OI_{k,t},\ OI_{k',t}) \quad (26)$$

where

$f_4(OI_{k',t})$	=	*Function that represents the relative opinion leadership of organisation k' at time t*
$f_5(OI_{k,t},\ OI_{k',t})$	=	*Function that represents the relative effect of innovativeness difference on the inter-influence effect between organisation k and k' within the system at time t*

4.7.1 Opinion Leadership

"*Every herd of wild cattle has its leaders, its influential heads*" (Tarde 1903). One fundamental concept in diffusion theory is the two-step flow theory, which proposes that mass media first reaches a few individuals – the ***opinion leaders***, who will later exert influence on many others. It is found that opinion leaders exert more influence on other's opinions, actions, and behaviours than does the media (Belenzon & Berkovitz 2010), and thus have significant influence on diffusion (Valente & Davis 1999). The term 'opinion leader' has a few same or similar concepts in literature. For instance, 'influentials' are usually considered the same as opinion leaders, that is, those individuals who are closer to innovations and who can influence imitators whose own adoption does not affect the influentials (Van den Bulte & Joshi 2007); 'market mavens' are specific individuals *"who have information about many kinds of products, places to shop, and other facets of markets, and initiate discussions with consumers and respond to requests from consumers for market information"* (Feick & Price 1987, p. 85); another similar terminology in literature, 'hubs', represents the individuals who have exceptionally large number of social ties in diffusion and adoptions (Goldenberg et al. 2009). Also in epidemic studies, the concept of super spreading is defined as the event in which a specific few affect a significant number of others, and it has a similar meaning with opinion leadership as discussed above. According to Weimann et al.

(2007) and Rogers (2003), opinion leaders have a few particular characteristics: they have more exposure to mass media and change agents; they undertake more social participation; and they are more cosmopolitan than their followers. These characteristics make opinion leaders adopt innovations earlier and be more willing to pass the information of innovations to others.

As summarised by Weimann et al. (2007) and Rogers (2003), in management, marketing, and sociology studies, measures of opinion leadership such as positional approach, reputational approach, self-designating approach, sociometric approach, observation, and key informant approach, are normally made through observations and surveys with ideas originating from the early works of Rogers and Cartano (1962). In epidemic studies, researchers introduce certain distributions to model super-spreading events[23], using the results as an input of offspring distribution (for instance, Possion distribution), thus generating the process of epidemic spread. However, to borrow this epidemic approach directly assumes opinion leadership as a randomly assigned 'ability', one that is available to every individual, in which case the proposed model of opinion leadership will fail to represent the desired 'link' between opinion leadership and organisational innovativeness.

Although all the above measures can be borrowed in the context of organisations, this study tends to measure the opinion leadership of each organisation, instead of finding specific organisational opinion leaders. Therefore, this study proposes a new way of modelling organisational opinion leadership on the basis of organisational innovativeness. First, innovativeness is positively related to opinion leadership (Grewal, Mehta & Kardes 2000) and this can be explained from a few different perspectives.[24] This positive relationship between innova-

[23] Super spreading events are the epidemics in which certain individuals infect a large number of second cases (Lloyd-Smith et al. 2005). It has the similar concept with opinion leadership.

[24] For instance, this relationship is easy to deduce from the definition of opinion leadership, since an opinion leader will only adopt an innovation earlier before it can pass the information of the innovation to others (van Eck, Jager & Leeflang 2011). Another explanation is based on the understanding that opinion leaders have unique characteristics that differentiate them from other

tiveness and opinion leadership has been found by a few studies with different correlation degrees: 0.65, 0.78 and 0.8, and 0.74 (Flynn, Goldsmith & Eastman 1996; Goldsmith & Hofacker 1991; Ruvio & Shoham 2007). Second, higher innovativeness is an essential, but non-sufficient condition for opinion leaders, for instance, the relationship between innovativeness and opinion leadership varies with product categories of interest (Summers 1971). Based on the Rogers model of adopter-category (see details of this model in Section 2.4.1), Rogers (2003) states that early adopters usually have the highest degree of opinion leadership. And he further argues that the shape of the distribution of opinion leadership depends on the characteristics of the system and innovation: "*if the system favours change, then innovators tend to be opinion leaders*".

Figure 14 draws the curve of opinion leadership based on the discussion above: opinion leadership (red line) increases as innovativeness goes higher, then starts to decrease after reaching a peak point.[25] The blue line here is the curve of a normal distribution, which represents the Rogers model of adopter-category.

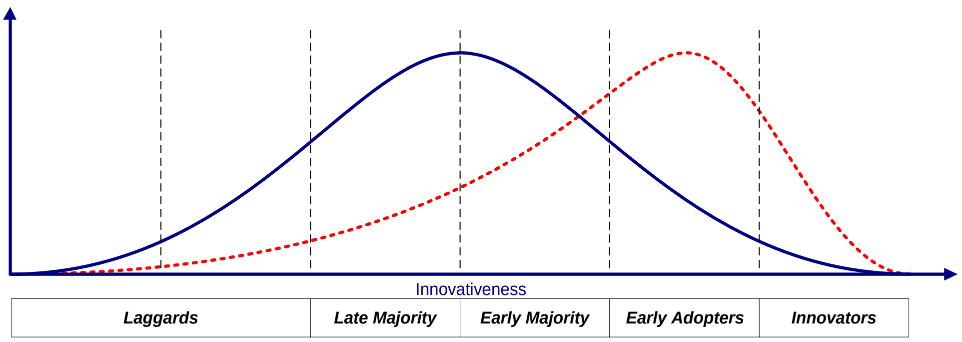

Figure 14: Curve of Opinion Leadership

members in the system. According to Chan and Misra (1990), one of the opinion leaders' personality traits is that they feel different from others and also choose to act differently from others. This trait, to a certain degree, can be represented by innovativeness, since organisations with different levels of innovativeness will tend to act differently in terms of adopting innovations.

[25] Here we assume that the peak point falls into the category of early adopters, which is a common case in diffusion studies.

A discrete function (Equation 27), which is modified based on the function of normal distribution (the blue line in Figure 14), is developed to represent the curve of opinion leadership.

$$OL_{k',t} = \begin{cases} \left(\dfrac{e^{-\left(a \times OI_{k',t} - \overline{OI_t}\right)^2} / 2(\beta_t \sigma_t)^2}{\sqrt{2\pi(\beta_t \sigma_t)^2}} \right), when\ OI_{k',t} < \alpha_t \\ \left(\dfrac{e^{-\left(b \times OI_{k',t} + c - \overline{OI_t}\right)^2} / 2(\beta_t \sigma_t)^2}{\sqrt{2\pi(\beta_t \sigma_t)^2}} \right), when\ OI_{k',t} \geq \alpha_t \end{cases} \tag{27}$$

where

$OL_{k',t}$	=	*Opinion leadership of organisation k' at time t*
$\overline{OI_t}$	=	*Average innovativeness of all organisations at time t*
σ_t	=	*Standard deviation of organisational innovativeness at time t*
α_t	=	*Shape parameter (organisational innovativeness of the organisation with highest opinion leadership)* $\alpha_t \in [0, +\infty]$
β_t	=	*Scale parameter*
a, b, c	=	*Parameters determined by* α_t *and* $\overline{OI_t}$

$a = \overline{OI_t} / \alpha_t,$

$b = \alpha_t / \overline{OI_t},$

$c = \overline{OI_t} - \ b \times \alpha_t$

In this model, the necessary data for the input is only organisational innovativeness. $\overline{OI_t}$ and σ_t can easily be calculated if the data of organisational innovativeness is available. α_t and β_t are the shape parameter and scale parameter of the curve, respectively. The values of a, b, c are determined by α_t *and* $\overline{OI_t}$.

The shape parameter α_t in the Equation 27 determines the location of the peak point of the curve. In other words, it decides who has the highest opinion leadership in the system due to their innovativeness level. The range of α_t is $[0, +\infty)$, which allows anyone in the system has the possibility to be an opinion leader. For instance, if $\alpha_t = \overline{OI_t}$, the distribution of opinion leadership is likely to be a normal distribution, in which case organisations with a mean innovativeness level are opinion leaders; if $\alpha_t = \overline{OI_t} + \frac{3\sigma_t}{2}$, opinion leaders tend to be early adopters, which is a common situation in diffusion literature. The scale parameter β_t ($\beta_t \in [0, +\infty)$) determines the concentration level of the curve of opinion leadership. A smaller β_t indicates that the opinion leadership is held by only a few individuals (opinion leaders) and most others have very little influence on others. In contrast, a bigger value of β_t represents the situation whereby all organisations tend to have equal influence on each other. Ultimately, if β_t approaches $+\infty$, opinion leadership will tend to be equally distributed, it thus goes to the homogeneous level that is the same as the assumption in the Bass model.

Similar to function $f_1(OI_{k,t})$, relative level of opinion leadership is modelled as the quotient of the dividend (the opinion leadership of organisation k' at time t) and divisor (the average opinion leadership level of the system at time t):

$$f_4(OI_{k',t}) = \frac{OL_{k',t}}{\overline{OL_t}} \tag{28}$$

where:

$\overline{OL_t}$ = *Average opinion leadership of all organisations at time t*

4.7.2 Innovativeness Difference

The effect of innovativeness difference is related to the desire for self-conformity by organisations. Moore (1991) states that adopters in higher innovativeness categories may not exert considerable influence on individuals in lower innovativeness categories. This is because individuals who have different innovativeness levels desire different characteristics from the innovation. As summarised in the work of Van den Bulte and Joshi (2007), sociology studies argue that individuals will only imitate others who have a similar social status to them, with examples including the autonomous-inner-directed model (Riesman 1950), status completion and maintenance theory (Bourdieu 1984), and middle-status conformity theory (Homans 1960). Weimann et al. (2007) also summarise that opinion leaders exist at every social level, and in most cases they only influence others from the same social level. Moreover, a few of the diffusion models in the marketing literature notice the importance of this issue and try to differentiate individuals/organisations due to their roles within the system. For instance, global diffusion models normally set different levels of social contagion effect between organisations in different countries (Albuquerque, Bronnenberg & Corbett 2007); dual market models classify potential adopters into two categories due to the level of opinion leadership in the system (Van den Bulte & Joshi 2007); also in probit models, each individual organisation has its own threshold, which is determined by its own characteristics.

In this study, it is assumed that the inter-organisational influence will decrease as the innovativeness difference between the two organisations increases. Therefore, an exponential function is introduced to represent the negative effect between innovativeness difference and its effect on inter-organisational influence. Two scale parameters n_1 and n_2 are used separately when $OI_{k',t} > OI_{k,t}$ and $OI_{k',t} \leq OI_{k,t}$, since an adopter with a lower innovativeness level will find it more difficult to influence a potential adopter with a higher innovativeness level.

$$D_{k,k',t} = \begin{cases} e^{-n_1 \times \left(OI_{k',t} - OI_{k,t}\right)}, when\ OI_{k',t} > OI_{k,t} \\ e^{-n_2 \times \left(OI_{k,t} - OI_{k',t}\right)}, when\ OI_{k',t} \leq OI_{k,t} \end{cases} \tag{29}$$

where:

$D_{k,k',t}$	=	*Effect of innovativeness difference between organisation k and k' at time t*
n_1, n_2	=	*Scale Parameters*

The relative effect of innovativeness difference on inter-influence effect is modelled as:

$$f_5\left(OI_{k,t},\ OI_{k',t}\right) = \frac{D_{k,k',t}}{\overline{D_t}} \tag{30}$$

where:

$\overline{D_t}$	=	*Average innovativeness difference effect in the system at time t*

4.7.3 Geographic Location

Geographic location affects adoption and diffusion by influencing the applicability of innovation based on the characteristics of the ecological infrastructures of the potential adopters, and by exerting the spatial effects of geographical proximity (Wejnert 2002). Furthermore, it is argued that knowledge, which constitutes the most significant basis for innovation related activities, is difficult to exchange over a long distance, because the means for effective knowledge transfer require a highly time and space specific environment (Lam 2000). Therefore, innovation has become increasingly reliant on the interactions and information/ knowledge flow (Asheim & Gertler 2005).

A number of studies have addressed the effect of geographic location on diffusion through either measures of pairwise distances or spatially defined regions. A common finding is that geographically clustered actors tend to influence each other, since geographic location fundamentally alters the flow of information through a network (Jason & Powell 2004). It also enhances the direct observation of competitors, and therefore may try to mimic them. Effect of geographic location in diffusion is discussed from various perspectives in the literature. For instance, Hansen and Løvås (2004) point out that informal ties are more resilient to geographical distance than are formal ties; Bell and Zaheer (2007) find that geographic location plays a different role in knowledge transmission, if networks are differentiated at (institutional, organisational, and individual level); the work of Bell (2005) strongly supports the idea that organisations in a cluster are more innovative than remotes when the network effect is controlled.

As found by a number of studies (Cortright & Mayer 2002; Leyshon & Thrift 1997; Feldman 2000) which are summarised by Asheim and Gertler (2005), an organisation's tendency towards clustering becomes more marked, not less, although the effect of physical distance is weakened by the development of communication technology today (Van Alstyne & Brynjolfsson 2005). Therefore, the author in the current study considers that geographic location is still a good indicator for the likelihood of mutual awareness and interdependence, especially when network relations are not provided directly (Strang & Soule 1998). Although there could be various results from different regions of study, characteristics of successful regional innovation systems within the same context will exhibit certain consistencies from case to case (Asheim & Gertler 2005).

In this study, it is assumed that the physical distance between two organisations has a negative and non-linear relationship with the inter-organisational influence that exists between them. Similar to the function of innovativeness difference, an exponential function that uses physical distance between paired organisations as input is used here to represent the effect of geographic location on inter-organisational influence. The effect of geographic location is modelled as:

$$GL_{k,k'} = e^{-a_{PD} \times PD_{k,k'}} \tag{31}$$

where:

$GL_{k,k'}$	=	*Effect of geographic location between organisation k and k'*
a_{PD}	=	*Scale parameter*
$PD_{k,k'}$	=	*Physical distance between organisation k and k'*

In Equation 31, the only input is the physical distance between each pair of organisations. Physical distance is measurable through Euclidean distance when Geographic Information System (GIS) organisational data is available. The scale parameter a_{PD} indicates the importance of physical distance on inter-organisational influence. Specifically, big value of a_{PD} indicates a weak influence from physical distance. Finally, the relative effect of geographic location is modelled as:

$$f_3(PD_{k,k'}) = \frac{GL_{k,k'}}{\overline{GL}} \tag{32}$$

where:

$\overline{GL}$	=	*Average Geographic location effect of all paired organisations in the system*

4.8 Summary

As identified by Gilbert and Troitzsch (1999), cited by Macy and Willer (2002), there are three periods in the development of social simulation: macro simulation, micro simulation, and agent-based models consecutively. Among them, the macro simulation normally uses mathematical equations, makes simplified assumptions on the homogeneity of phenomena across time and space, and treats these factors of diffusion as invariant; the micro simulation focuses on individuals' behaviour and use equations to represent the behavioural processes of changing though time, without permitting individuals to directly interact with each other; agent-based models, on the basis of micro simulation with further allowance of the interactions between individuals, can be considered as a combination of the macro simulation and the micro simulation. Compared with this model development framework, epidemic diffusion models are normally macro simulations, while probit diffusion models are basically micro simulations, and agent-based diffusion models fall into the last category.

The agent-based diffusion model proposed in this chapter follows two-step flow theory, maintains the basic structure of the Bass model, incorporates diffusion factors of interests (organisational innovativeness, opinion leadership, innovativeness difference, and geographic location) based on the theories and empirical findings from the existing literature, and considers the characteristics of organisations and their interactions. It is expected that the result generated from the model will be able to echo these existing theories and empirical findings, answer the research questions of this study, and further, provide a few implications.

Organisational innovativeness is assumed as having a linear relationship with the adoption probability contributed by the environmental effect, since organisations will be more likely to receive the information of the innovation from their environment if they have high innovativeness levels. The inter-organisational influence in the proposed agent-based model is determined by three factors: the opinion leadership of influentials, innovativeness difference between organisations, and the geographic location of organisations. Specifically, opinion leadership is modelled by a modified normal distribution function following the theories and empirical findings from the literature; the innovativeness difference and physical distance of organisations are both assumed to have a negative and exponential relationship on the inter-organisational influence.

The model in this chapter can be reduced to the modified Bass model proposed in Chapter. Therefore, it also can reduce to the Bass model curve and guarantee a certain level of empirical accuracy. More importantly, the model suggests a way for further extending the basic structure of those classical diffusion models to explore more interesting topics. Further, compared with the other desired properties listed in Section 4.2, this proposed agent-based diffusion model matches the following criteria; first, as it is based on the structure of the Bass model, the proposed model also has a carry-through effect; second, the proposed model can satisfy the need for empirical estimation, by following the approach that has been proposed and used in Chapter 3; third, as each parameter and function is imbued with clear managerial meanings, it is believed that the proposed model can provide good managerial implications. However, there are a few desired attributes that the model does not meet: the model does not have a closed form solution, which may limit its value for further analysis; the model might be difficult to implement due to its complex structure and the difficulty of the data collection issue.

Chapter 5 Simulation Design

"…for Distinction Sake, a Deceiving by Words, is commonly called a Lye, and a Deceiving by Actions, Gestures, or Behavior, is called Simulation…"

(South 1697)

5.1 Introduction

In computer simulation, theorists express their ideas in a programming language and a computer is facilitated to generate results for analysis. Computer simulation has been widely used in the natural science and engineering fields (Zeigler 1985), but was adopted as a methodology in the social sciences a little later. However, the use of simulation in the social sciences has undergone a major growth spurt recently. Now it is considered as the third symbol system for social scientists, besides language and mathematics, and it is especially useful when the complexity of theory expression exceeds the ability of the theorists to hold all relevant postulates in mind (Ostrom 1988).

The proposed agent-based diffusion model in this study only requires two types of inputs (organisational innovativeness and geographic location) which are both measurable through certain approaches as discussed in previous chapters. However, the validity of the model using real data can only show a partial view of the phenomena, since the data will be limited by the sample size and the result will be limited within a particular context. Therefore, a simulation approach is introduced in this work in order to provide a generalised view of the model performance, as simulation can generate inputs from a great range of possible regions.

This chapter defines the context of the diffusion process and discusses how the proposed agent-based diffusion model will be simulated and analysed (see Figure 15). Specifically, Section 2 introduces the concept of the Monte Carlo simulation, discusses its characteristics, and explains why it is applied in the current study; Section 3 lists the software that is used in this study for the model simulation and explains the choice of selection; Section 4 defines the context of the simulation by setting up the characteristics of the environment, the characteristics of the innovation, the means of generating the input, and the initial values of the parameters in the model; Section 5 shows the simulation procedures designed for the respective software environments; Section 6 explains how the result of the simulation will be analysed; Finally, a summary of this chapter is provided.

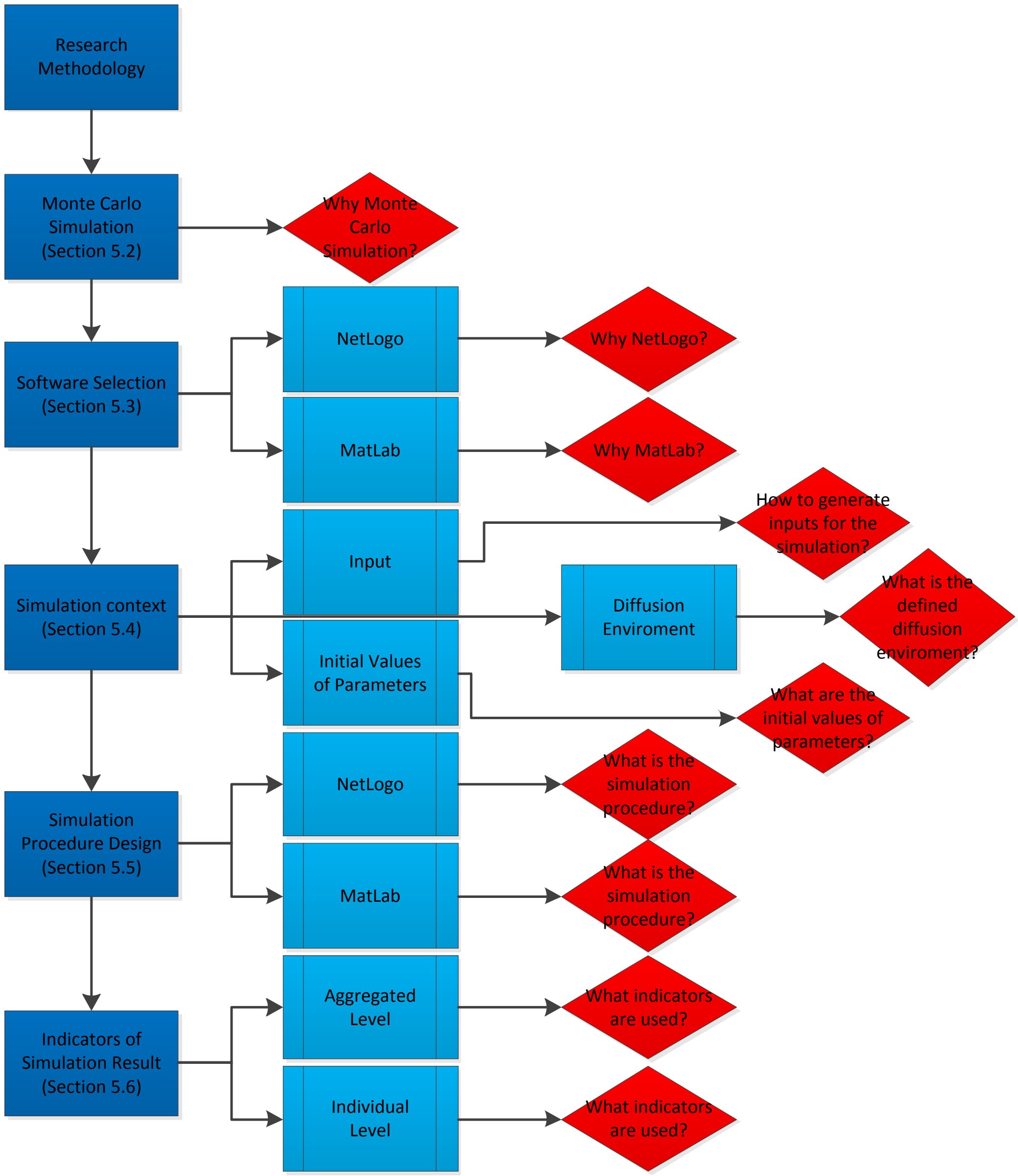

Figure 15: Research Methodology Mind Map

5.2 Monte Carlo Simulation

Diffusion processes vary due to the characteristics of different contexts and innovations. This study does not use real world data from any specific diffusion case. Instead, it is expected that the proposed model can be assessed in all the possible situations in order to measure an overall performance of the proposed model. To achieve this goal, the Monte Carlo method is introduced to generate data for the model.

Monte Carlo simulation, sometimes also referred to as stochastic simulation (Ripley 1987) uses random variables, which are generated on the basis of certain statistical distributions, in order to evaluate mathematical expressions. The Monte Carlo method is a general term for many techniques that approximate solutions to quantitative problems through statistical sampling. A formal definition of Monte Carlo methods is given by Halton (1970, p. 2) as "*representing the solution of a problem as a parameter of a hypothetical population, and using a random sequence of numbers to construct a sample of the population, from which statistical estimation of the parameter can be obtained*". Monte Carlo Simulation is particularly useful for simulating the systems of which inputs have significant uncertainties. Examples of the use of Monte Carlo methods include: stochastic integration, where an integral is evaluated based on a simulation-based method; Monte Carlo tests, where simulation is used to compute the p-value; and Markov-Chain Monte Carlo, which is used for sampling from probability distributions based on constructing a Markov chain.

Compared with analytical methods, Monte Carlo methods can handle very complex and realistic systems. In a typical Monte Carlo simulation, the entire system is simulated a large amount of times. In each simulation, the value of each parameter is selected from the specified distribution that describes the parameter. The output of each simulation is a separate and independent result that represents a possible result for the system. The outputs that result from the large number of simulations together form the overall performance of the model.

Therefore, the result of a Monte Carlo simulation is not a single value, but probability distributions. Monte Carlo methods normally follow a particular pattern: define a domain of possible inputs; generate inputs randomly from a probability distribution over the domain; perform a deterministic computation on the inputs; and aggregate the results. Correspondingly, the current simulation study also follows a similar procedure.

5.3 Software Selection

To simulate the proposed agent-based model only necessitates one basic attribute from those programming languages or software packages: it should be able to provide an agent-based programming environment. Although a number of programming languages or software can fulfil this basic requirement, two of them (NetLogo and MatLab) are selected for this simulation study due to their certain unique characteristics.

5.3.1 NetLogo

NetLogo is the choice for stimulating the proposed agent-based diffusion model. This is because it is capable of producing a vivid view of the diffusion process through its output system. Specifically: as a multi-agent programmable modelling environment (Wilensky 1999), NetLogo is naturally appropriate for simulating agent-based models; NetLogo is particularly powerful in modelling complex systems over time, since modellers can give instructions to agents independently (Wilensky 1999). Therefore, it is easy to explore the relationship between the behaviour of individual agents and the aggregated patterns that emerge from the complex interaction; NetLogo provides an easy to use and vivid output system: users can view the simulation process and the result in either a 2D or a 3D environment; finally, NetLogo is GIS capable, so information regarding geographic location can be imported directly.

5.3.2 MatLab

MatLab stands for Matrix Laboratory. It is a tool for mathematical computing, which allows matrix manipulations, implementation of algorithms, result plotting, and so on. Although its initial aim is simply for numerical computing, MatLab has been becoming increasingly powerful due to its optional toolboxes and packages. MatLab is used for simulation in this study for the following reasons. First, as a 'Matrix Laboratory', MatLab is convenient for creating vectors, matrices, and multi-dimensional arrays. Although these attributes add difficulties to the programming, they can greatly increase the computing speed; second, MatLab has powerful computing capability; third, different to many other programming languages, MatLab has a user-friendly programming environment; forth, MatLab provides intelligent problem-solving tools for specific application areas. For instance, parameter estimation techniques such as NLLS and Generic algorithms are all embedded as toolboxes in MatLab; finally, MatLab is also GIS capable with certain add-ons such as ArcView.

5.4 Simulation Context

Diffusion happens in various contexts. Section 3.5 shows 12 diffusion processes spread across different industries with different types of innovations. The characteristics of each industry and innovation vary, which results in different diffusion curves. Therefore, before simulating the model, the diffusion context should be identified.

First and most important, the organisations targeted in this study are assumed to be in the same industry. Therefore, the biases from cross-industry effect can be ignored. Then the characteristics of the innovation, the environment, and the organisations in this industry can be identified by their respective variables and parameters. Specifically, the variables in this model are typically the data for representing the characteristics of organisations (organisational innovativeness and geographic location), and the use of the parameters are listed as follows: η, p_t, and q_t are used to indicate the generalised level of diffusion forces; α_t and β_t are used to control the distribution of opinion leadership in this system; $a_{PD}$is used to represent the degree of physical distance effect between organisations to their inter-organisational influence; n_1 and n_2 are used to represent the level of innovativeness difference effect to their inter-organisational influence.

5.4.1 Statistical Distributions for Inputs

The model requires two sets of data as input: organisational innovativeness and geographic location, which will be generated through certain pre-defined statistical distributions. Therefore, the first thing is to determine the types of distributions that should be used.

Organisational innovativeness follows a normal distribution (Rogers, 2003) in most cases in this study due to its simplicity and wide-acceptance in the diffusion literature. Normal distribution represents a special case whereby organisations distribute averagely around the average value due to their innovativeness levels. However, in real practice, the distribution of organisational innovativeness is thus usually a right skewed curve. According to the work of McDonald (1984), beta distribution, Singh-Maddala distribution, lognormal distribution, gamma distribution, Weibull distribution, and exponential distribution are all available to represent the distribution of consumers' income (here consumers' income can be considered as an indicator of their innovativeness). In this study, Gamma distribution is used as an alternative to normal distribution in a few cases for generating organisational innovativeness, so the results provided from Normal distribution and Gamma distribution can be compared in order to explain how the distribution of organisational innovativeness can influence diffusion.

Different to organisational innovativeness that is determined by a single value, geographic location should be identified by at least a two dimension coordinates system. Therefore, the geographic location of organisations is generated by multivariate normal distributions.[26] For each multivariate normal distribution, it provides a number of organisations with coordinates that fall into one cluster, which means these organisations are clustered around a central point.

In a real situation, the data of organisational innovativeness can be imported from measures of organisational innovativeness, and the data of geographic locations is assessable from a geographic information system (GIS).

5.4.2 Initial Values of Parameters

Besides the variables in the model, the initial values of parameters also need to be identified before simulation. The proposed agent-based diffusion model contains eight parameters. Coefficient of risk averse η can be absorbed into parameters of p_t and q_t without influencing the model performance. Therefore, the value of η is set to be 1. The initial value of α_t and β_t in the model of opinion leadership is defined as $\overline{OI_t}$ and 1. For the parameters of a_{PD}, n_1, and n_1, their initial values are set to be 0.01, 0, and 0 respectively, for simplicity. Finally, the initial values of p_t and q_t are set as 0.03 and 0.005/0.0025 (0.005 when the system has 100 organisations and 0.0025 when the system has 200 organisations), chosen from a common range of diffusion models (Sultan, Farley & Lehmann 1990), and they are considered as constants throughout the whole diffusion process unless otherwise specified.

5.5 Simulation Procedure Design

Based on the definition of the diffusion context, the way of generating the variables, and the initial values of the parameters, the proposed agent-based diffusion model is simulated through the following procedures in NetLogo and MatLab respectively.

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[26] Multivariate normal distribution is a generalisation of a one dimension normal distribution to higher dimensions. Also it should be noted that using multivariate normal distribution to generate the locations of organisations only produces an ideal environment compared with the real world: the vertical axis and horizontal axis of organisations both follow a normal distribution. However, we propose that this generated environment can be considered as an abstraction of the reality.

5.5.1 NetLogo[27]

In the NetLogo simulation, each organisation is represented as a 'house' with different colours that indicates how many innovations this house has adopted. Organisations are initially painted WHITE (no innovations). As they adopt innovations one by one, the colour changes to ORANGE, YELLOW, GREEN, LIGHT BLUE, DARK BLUE, and PURPLE, consecutively. The whole simulation is divided into a few separated functions and also programmed separately:

- GO: this is the starting point of the simulation. When clicked, this programme first calls the SETUP function to set initial values. Then it goes on to ADOPT INNOVATION, CALCULATION, UPDATE INNOVATIVENESS, and UPDATE NETWORK, consecutively. BIRTH and DEATH OF ORGANIATIONS and PROJECT INNOVATIONS are optional functions in this environment;
- SETUP: this function is used to generate the values of the variables and set the initial values of the parameters;
- ADOPT INNOVATION: this function is used to determine '*which organisations will adopt the innovation at each given point of time*';
- CALCULATION: this function is used to calculate the number of new adopters and the cumulative number of adopters at each time point;
- UPDATE INNOVATIVENESS: this function uses the data of size and R&D expenditure as inputs to update organisational innovativeness;
- UPDATE NETWORK: this function is used to update the inter-organisational influence;
- BIRTH & DEATH OF ORGANISATIONS: this is an optional function that is used to determine how many organisations enter the system and how many organisations leave the system;
- PROJECT INNOVATIONS: this is an optional function that is used to mimic how potential adopters are influenced by existing adopters.

[27] The author adds a few more factors into the proposed model during the NetLogo Simulation. Readers are referred to Section 6.2 to see the detail of this issue.

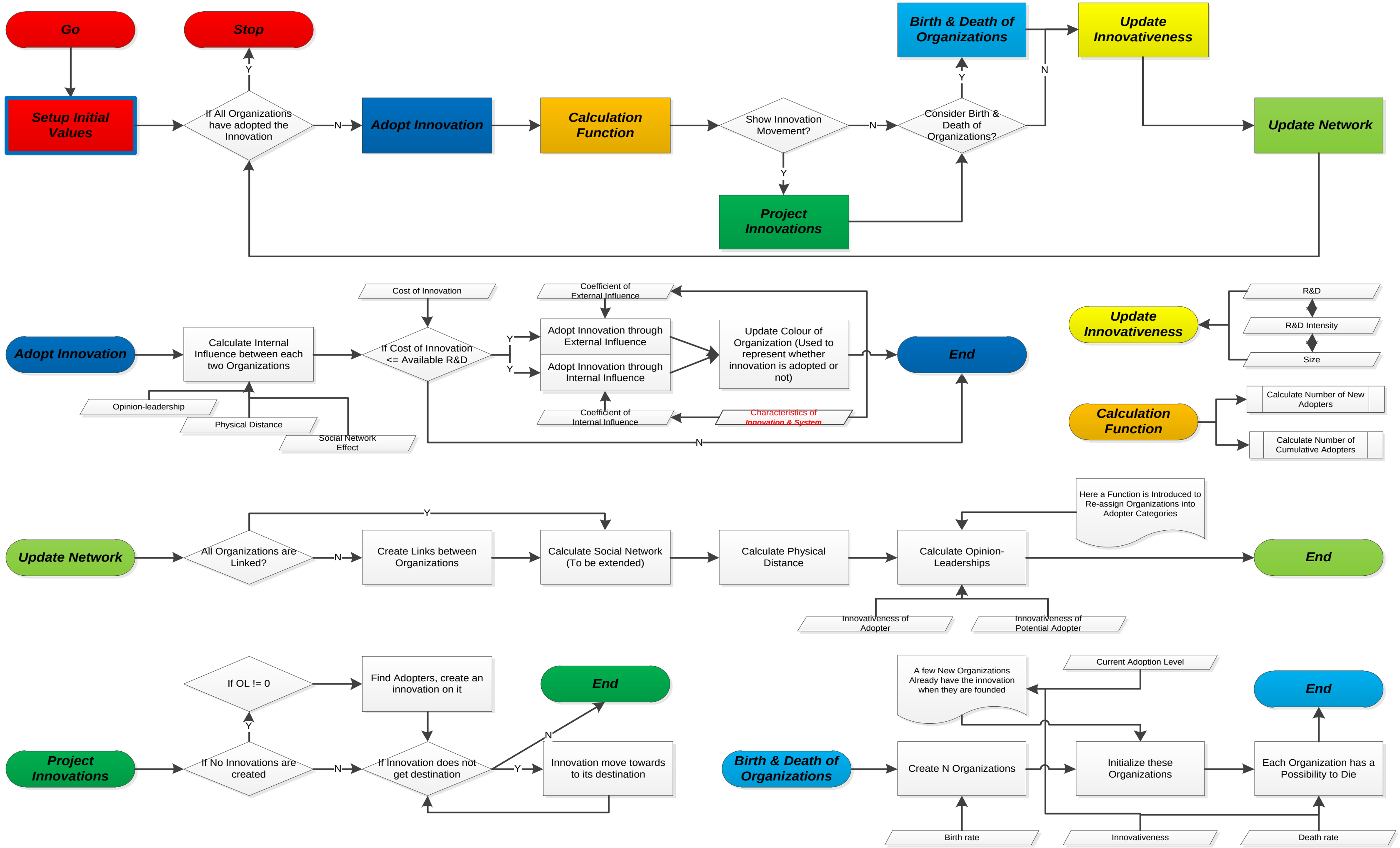


Figure 16: Flow Chart of Model Simulation (NetLogo)

5.5.2 MatLab

The MatLab based simulation has a similar procedure to the NetLogo simulation. Below is the procedure of the MatLab based simulation:

- Declare parameters: this includes a number of parameters such as the parameter of the environment, the parameter of inter-organisational influence, the parameter of physical distance, etc.;
- Initialise and generate the values for the variables. Beside the values of these declared parameters listed above, organisational innovativeness and geographic locations of organisations are also generated by certain statistical distributions.
- Call sub function GEOGRAPHIC LOCATION;
- For each time period:
    - Call sub Function OI UPDATE
    - Call sub function of OPINION LEADERSHIP and INNOVATIVENESS DIFFERENCE, then, based on the values of opinion leadership, innovativeness difference, and geographic location effect, calculate the inter-organisational influence
    - Call function ADOPTION
    - Update variables
    - Generate output. The outputs here are grouped into two parts. The first part uses the result to generate curves for the number of new adopters and the number of cumulative adopters; the second part makes the one way sensitivity analysis and uncertainty analysis, which will be further discussed in section 5.5 of this Chapter.

Below are the explanations of these sub-functions:

- GEOGRAPHIC LOCATION: this function calculates the effect of geographic location between each paired organisation in the system;
- OI UPDATE: this function is used to calculate and update the innovativeness of each organisation at each time point;
- OPINION LEADERSHIP: this function calculates the opinion leadership of each existing adopter;
- INNOVATIVENESS DIFFERENCE: this function calculates the effect of innovativeness difference on the inter-organisational influence between each paired organisation.

5.6 Indicators of Simulation Result

The aim of the NetLogo simulation is simply to show how the model works without further support for the analyses of the model performance. Therefore, the simulation result from NetLogo is just a vivid expression of the diffusion process plus a figure of the corresponding diffusion curve. In the demonstration of the diffusion process, each existing adopter at each time point will inject a point (represent the information of the innovation) that moves to each potential adopter. After receiving information regarding the innovation, the potential adopters evaluate the value of the information, make relative adoption decisions, and update their own status.

The proposed agent-based diffusion model is mostly analysed in MatLab simulation and the result is discussed from both macro and micro levels. From a macro level, the aim of the analysis is to test the overall model performance, together with the effects of the distribution of organisational innovativeness, opinion leadership, and geographic location on the diffusion process. The micro level analysis aims to analyse how the innovativeness and location of an organisation influence its relative adoption behaviour. In each analysis, different approaches and indicators are used.

In the aggregated level analysis, the model is simulated 50,000 times for each set of inputs, and the results are averaged out as the overall performance of the model. We manipulate the values of p_t and q_t, and use different statistical distributions to generate organisational innovativeness, opinion leadership, and geographic locations, respectively, in order to investigate their effects. Sensitivity and uncertainty analysis are used to analyse the results. The former, together with the diffusion curves produced by the simulation, test the effect of each parameter in the diffusion process, and the second checks model stability.[28]

Sensitivity analysis and uncertainty analysis are the studies of the response of the model to uncertainty involved within the value range of variables, the variations of the initial conditions, boundary conditions and model parameters (Buzby et al. 2008). As Saltelli et al. (2000) assert: *"sensitivity analysis is the study of how the variation (uncertainty) in the output of a mathematical model can be apportioned, qualitatively or quantitatively, to different sources of variation in the input of the model"*. Although a variety of possible approaches can be used, for example, local methods, sampling-based methods, emulator based methods, screening methods, variance based methods, high-dimensional model representation methods, and Mote Carlo filtering based methods, they all follow a similar procedure: specify the target function of interest; assign a probability density function to the selected factors; generate a matrix of inputs with that distribution(s) through an appropriate design; evaluate the model and compute the distribution of the target function; select a method for assessing the influence or relative importance of each input factor based on the target function.

In this work, the variance between the curve of the modified Bass model and the average of the 50,000 curves produced by the agent-based diffusion model is used as the result of the one way sensitivity analysis. This result is used to repre-

[28] The aim of the uncertain analysis in this study is to see whether the change of the parameter(s) in the proposed diffusion model will make the model unstable and thus influence the model utility. From the simulation, it is found that the model stability is under a tolerated level, when parameters in the model are changed within the proposed range. Therefore, the result of the uncertain analysis will not be further discussed in the following part of this thesis.

sent the extent of difference between the modified Bass model and the proposed agent-based diffusion model when a variable/parameter changes. The uncertainty analysis is made by the sum of variance between each curve that is produced by the agent-based model and it's average. These two measures follow the equations indicated below. Equation SA is the measure of the one way sensitivity analysis and equation UA is the measure of the uncertainty analysis.

$$SA = \left(\sum_{t \in T} \left(N_1(t) - \overline{N_2(t)} \right)^2 \right) / T$$

$$UA = \left(\sum_{t \in T} \left(\overline{N_2(t)} - N_2(t) \right)^2 \right) / T \qquad (33)$$

where:

$N_1(t)$	$=$	*Number of new adopters or cumulative adopters at time t calculated by modified Bass model*
$N_2(t)$	$=$	*Number of new adopters or cumulative adopters at time t calculated by the proposed agent-based model*
T	$=$	*Period of diffusion process*

On an individual level, the agent-based model is also simulated 50,000 times and the results from the simulations are averaged as its overall performance. Different to the macro level analysis, one single organisation is targeted in order to explore the effect of organisational innovativeness and geographic location on adoption probability at each time point. Two indicators of adoption probability are introduced here: the number of successful adoptions and the average time of successful adoptions. A large number of successful adoptions indicate high adoption probability for the organisation through the whole diffusion process, while early adoption time shows a significant adoption probability starting at the earliest time.

5.7 Model Implementation: A Case of Japanese 3G Mobile Service

Before simulating and analysing the proposed agent-based diffusion model, this section applies the model to a real world case, in order to show how the model operates and how well it can explain the real diffusion phenomenon. The case used here is not an innovation for organisations, but is a service product that is sold to and used by individual customers. However, as innovation studies that focus on different targets normally share the similar theories and concepts (see Footnote 4, page 9), we believe this case study can provide some implications on the model implementation within organisational settings.

5.7.1 3G Mobile Service in Japan

The case that is introduced here is the third generation of standards for mobile phones and mobile telecommunication services in Japan.

5.7.1.1 Overview of Japan

Japan is an island nation in East Asia. The country is a major economic power in the world today with a population that is estimated at around 127 million (CIA 2012). Japan is one of the more wealthy countries in the world. Although the grow rate has been fluctuating (see Figure 17), the GDP per capital of Japan reaches 42,831 US dollars in 2010, according to the data of The World Bank (2010).

The inequity of income in Japan has been rising since 1980s due to the increasing dualism in the labour market: the proportion of non-regular workers (who only earn 40% as full-time workers on average) has risen to over 30% of employees from 19% one decade ago (OECD 2006). Japan's recent published Gini coefficient (see Glossary) is 37.6, with a poverty line at 13738.25 US dollars, according to the data of CIA (2012).

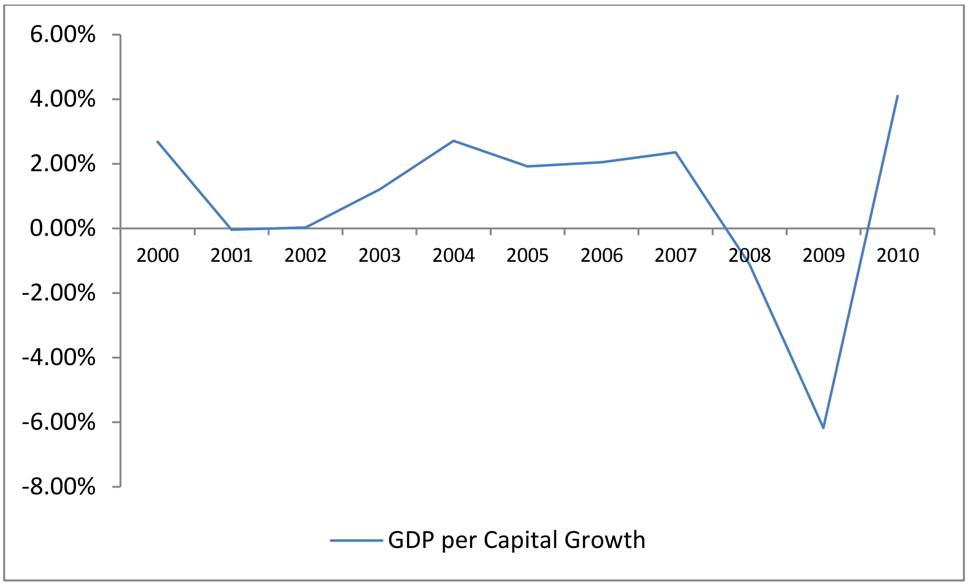


Figure 17: GDP per Capital Growth - Japan

5.7.1.2 3G Mobile Service in Japan

NTT DoCoMo Inc. is the predominant mobile phone operator in Japan with more than half the Japanese cellular market. The companies' 3G mobile service, Freedom of Mobile Multimedia Access (FOMA), is the first commercialised one among its type in the world. This service product was launched in October 2001 and has been used since then.

The data used in the current section is the monthly subscription number of the company's FOMA service between October 2001 and November 2011 (122 data points in total) in the Japanese market (DoCoMo 2011). The number of the new FOMA service subscribers in each month (see Figure 18) shows a bell-shape curve, which is consistent with the finding in diffusion literature, but with has many fluctuations.

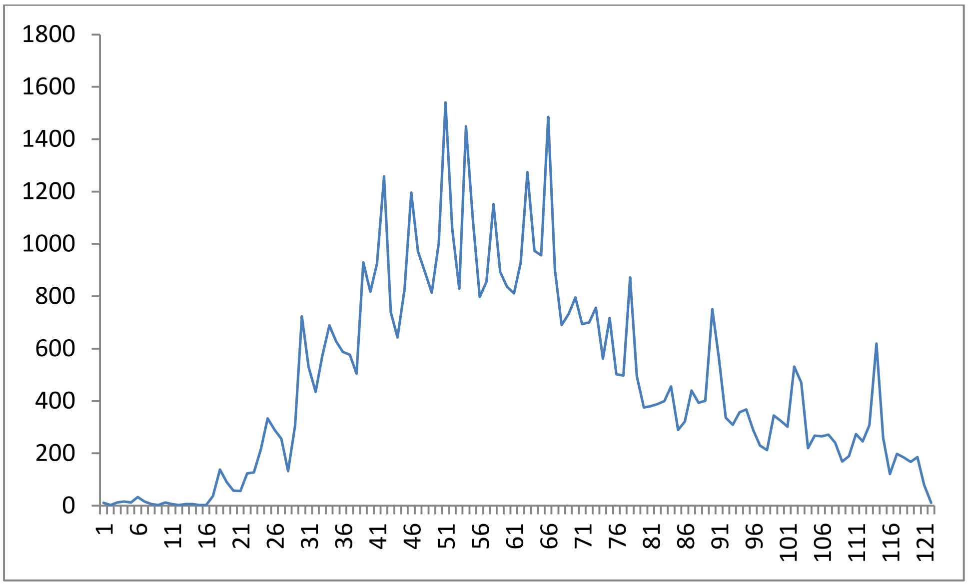


Figure 18: Number of New FOMA Service Subscribers (Thousands)

5.7.2 Model Implementation and Result

We first fit the modified Bass model to the data using the proposed parameter estimation technique in Section 3.6.3 and the resulted curve is drawn using the dotted red line in Figure 19. The result shows that the modified Bass model can capture the diffusion trend of the FOMA service. The estimated parameter values in the modified Bass model are $p = 0.00112$, $q = 0.07196$, and $m = 57374000$, indicating that this service product has been approaching its saturation point (the actual cumulative number of subscribers is 579530000 by the end of 2011).

5.7.2.1 Agent Define

In this section, the agent in the proposed agent-based model does not represent an organisation, but represent an individual potential subscriber of the FOMA service in Japan. Therefore, there are 57.374 million agents in the system, which equals to the overall market of this product. Each agent has three attributes in this case study: customer's innovativeness that is indicated by the customer's income, customer's opinion leadership that is calculated based on his/her innovativeness level, and customer's location that is indicated by the area where the customer lives.

The country of Japan is divided into eight regions: Chubu, Chugoku, Hokkaido, Kansai, Kanto, Kyushu, Shikoku, and Tohoku. Table 19 below shows the region population of Japan in 2008. This set of figure is used to calculate the ratio of each region' population and we consider this ration does not change through time. Then the ratio is used to generate agents. For instance, among 127 million agents, 17.04% of the agents in the model are generated and located in Chubu, 6.09% of the agents in the model are generated and located in Chugoku, and so on.

Region	Chūbu	Chūgoku	Hokkaidō	Kansai	Kantō	Kyūshū	Shikoku	Tōhoku
Population	21,627,390	7,732,440	5,682,950	22,712,756	40,428,553	14,763,963	4,153,946	9,817,290
Ratio	17.04%	6.09%	4.48%	17.90%	31.85%	11.63%	3.27%	7.74%

Table 19: Japanese Population Subject to Regions

5.7.2.2 Innovativeness

Here customers' income is used as the indicator of customers' innovativeness. It is assumed that the Gini coefficient of Japan is not changed between 2001 and 2011. The GDP per capital of 2001 and the Gini coefficient are used to calculate the initial income distribution using the method in the study of Van den Bulte and Stremersch (2004). Then the GDP per capital growth (see Figure 17) is introduced to update customers' income through time.

5.7.2.3 Geographic location

Here it is considered that individual customer's range of activities is fixed within the cities they live; therefore, the physical distance of each pair of customers is determined by the distance of the location they live. We choose the city that has the biggest population in each region as the 'capital' of the region. Then we use the geographic distance between each pair of the 'capital' cities to represent the geographic distance between the two customers who live in the corresponding regions. A similar measurement of the geographic distance can be found in the study of Albuquerque, Bronnenberg and Corbett (2007). Then the geographic distance between these cities can be calculated through Google Map (see the result in Table 20).

For instance, the geographic location between two customers who live in the same region will be 0; the geographic location between customers who live in Chubu and Chugoku will be 301 miles.

Region		Chūbu	Chūgoku	Hokkaidō	Kansai	Kantō	Kyūshū	Shikoku	Tōhoku
	City	Nagoya	Hiroshi-ma	Sapporo	Osaka	Shinjuku	Fukuoka	Matsu-yama	Morioka
Chūbu	Nagoya	0	301	921	111	221	475	322	555
Chūgoku	Hiroshi-ma	301	0	1117	206	508	176	47	837
Hokkaidō	Sapporo	921	1117	0	927	705	1291	1138	371
Kansai	Osaka	111	206	927	0	318	380	202	647
Kantō	Shinjuku	221	508	705	318	0	683	530	339
Kyūshū	Fukuoka	475	176	1291	380	683	0	196	1012
Shikoku	Matsu-yama	322	47	1138	202	530	196	0	858
Tōhoku	Morioka	555	837	371	647	339	1012	858	0

Table 20: Distances between Cities (miles)

5.7.2.4 Model Parameters

The initial values of parameters p and q are set as 0.00112 and 0.07196, which are from estimating the Modified Bass model. Then we run the model repeatedly to calibrate the value of the two parameters, and finally get $p = 0.00051$ and $q = 0.10565$.

We consider the opinion leadership distribution follows a typical manner as discussed in Section 4.7.1, and thus $\alpha_t = \overline{OI_t}$ and $\beta = 1$.

For the value of a_{PD}, we consider that the two customers who live in the two most distanced cities have only half of the inter-influence compared with the ones who live in the same city. Therefore, following Equation 31 we can have $e^{-a_{PD} \times 1291} = 0.5$, and thus $a_{PD} = 6.2054e - 004$.

For the value of n_1 and n_2, we consider that the customers who earn the average income only exert half of the inter-influence to the customers who are under the poverty line, comparing with the inter-influence between the two customers who both earn the average income, and the customers who are under the poverty line only can exert one quarter of the inter-influence to the ones who have the average income, comparing with the inter-influence between the two customers who both earn the average income. Following the same way of calculating parameter a_{PD}, we have $n_1 = 2.6035e - 005$ and $n_2 = 5.2070e - 005$.

5.7.2.5 Result

The model operates by using Matlab, following the similar procedure defined in Section 5.5.2. As the proposed model is an agent-based one, it does not produce a fixed result and thus the output of each simulation is different even with the same input. The green line in Figure 19 shows one of the produced curves based on the above setting. It can be seen that the curve produced by the agent-based diffusion model is also capable to capture the trend of the real diffusion process. Additionally it can simulate the fluctuations like the ones in the real diffusion curve.

Furthermore, the values of parameters p and q are not the same in the modified Bass model and the proposed agent-based diffusion model, indicating that the three factors (innovativeness, opinion leadership, and geographic location) do have an impact on the diffusion process. Their role will be analysed in Chapter 6.

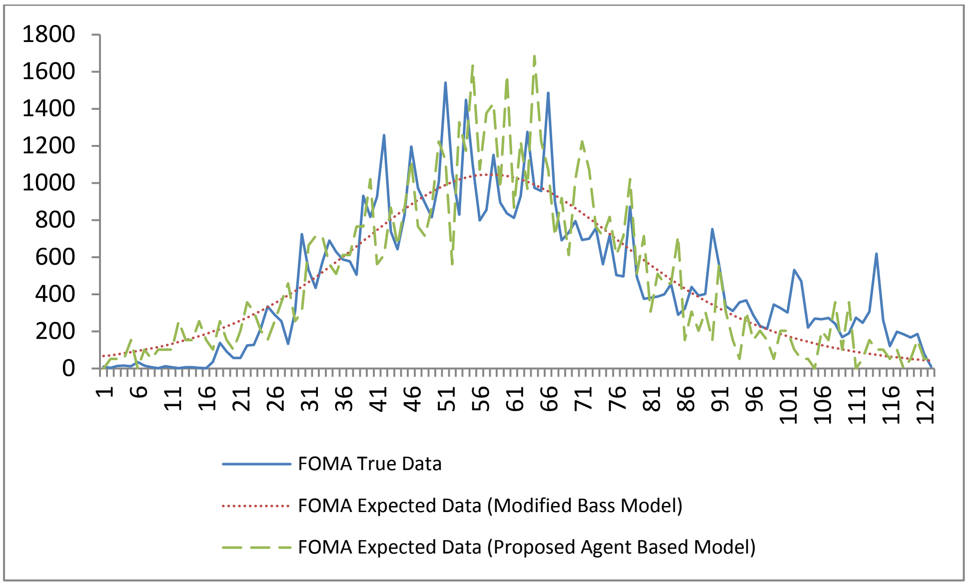


Figure 19: Result - Japan 3G Mobile Subscription (Thousands)

5.8 Summary

Simulation is the imitation of the appearance or character of something. The simulation of the diffusion processes within dynamic contexts can produce insights unavailable from other approaches (Gibbons 2004). By creating a virtual context on the basis of empirically validated theories and rules, simulation study is able to explore the effects of the interested factors in diffusion. Furthermore, a view of the full range of the outcomes (that is, throughout the diffusion) reveals a comprehensive view with regard to model performance and diffusion phenomena.

Simulation is used in this study mainly for two reasons. First, real data is limited by its sample size while the sample size can be ultimate in a simulation study. Therefore, the performance of the proposed model can be tested easily through a simulation study. Second, a large number of simulations can cover most possibilities for real phenomena, and thus provide a generalised view of the diffusion process. Input of the simulation is generated based on the existing theories and findings. For instance, it is widely agreed that organisational innovativeness can be explained by a normal distribution, so a normal distribution is used to generate organisational innovativeness as the input of the model in most cases. It is expected that the input data generated by this study should be rational.

Two software types feature in this study for the simulation of the proposed agent-based model. NetLogo is used to give an initial screening of the model performance and mimic the diffusion process through a 2D plotting. MatLab is used as the main tool for simulating and analysing the proposed model; this is because of its high computing performance and its flexible programming environment. Results of the MatLab simulation will be analysed from two perspectives with different indicators that deal with the aggregated level and individual level analysis, respectively. A number of indicators are introduced for the result analysis: direct observation from the produced curve, one-way sensitivity analysis, and individual adoption rate/time.

Section 5.7 is a case study showing how the proposed agent-based diffusion model can implement and fit the real world data. Although the case used here is to study a service product for individual customers, it still can provide implications on understanding and implementing the proposed agent-based diffusion model, as the diffusion processes in organisational and individual settings normally share the same theories and concepts. The result of the case study indicates that the proposed agent-based model can capture the diffusion trend like those homogeneous diffusion models, and can further explain the fluctuations within the diffusion process.

Chapter 6 Results and Implications

> *"Although articles like … excite me intellectually, I am concerned about the utility and real world applications of diffusion models in marketing…, the mathematical developments in the diffusion modelling area have surpassed the practical utility and applicability of diffusion models…, My criticism is meant to challenge all of us involved in this area to reflect on how we can further develop these models so that they can be applied meaningfully in the real world"*
>
> *(Mahajan 1994)*

6.1 Introduction

The volume of diffusion research has expanded tremendously in the last fifty years. Modelling activities, in particular, have attracted much attention as being an explanation tool and prediction tool of diffusion. These models originate from different understandings of diffusion forces, emphasise different aspects of diffusion, and have been applied in various diffusion contexts. Especially in organisational studies, diffusion models are useful in analysing the strategic decisions that explicitly require consideration of the diffusion process over time. Therefore, it is argued that good diffusion models should not only have a good fit with real diffusion phenomena, but also be capable of solving real world problems and providing meaningful implications.

The agent-based diffusion model in this study is proposed on the basis of the Bass model and incorporates factors of diffusion including organisational innovativeness, opinion leadership, innovativeness difference, and geographic location. Based on the simulation context defined in Chapter 5, the current chapter aims to simulate the agent-based model, analyse the results, and provide implications for both academic and practical fields. Specifically, Section 2 presents the result of the model simulation on NetLogo. The model used in this simulation has a few extended functions compared with the agent-based model proposed in Chapter 4. The aim of this simulation is to provide a direct view of how the model works; it does not support any further analysis. The following three sections (3, 4, and 5) are the simulation results based on MatLab and they aim to analyse the model performance; following the context defined in Chapter 5, the simulation in Section 3 tries to answer three questions: how is diffusion influenced by the parameter p_t in the model (the generalised level of environmental effect)?; how is diffusion influenced by the parameter q_t in the model (the generalised level of inter-organisational influence)?; and how is diffusion influenced by the distribution of organisational innovativeness? The above three issues are all discussed at an aggregated level. Under the same context that is used in Section 3, Section 4 further explores the effect of opinion leadership and geographic location in the diffusion process from an aggregated level. Different to Section 3 and Section 4 that both view the effect of respective factors on an aggregated level, Section 5 discusses the effect of organisational innovativeness and geographic location at the individual level. Section 6 tries to link the result of the simulation study to real phenomena in order to provide a few managerial implications for both industry policy makers and mangers in organisations. Section 7 is summary of the current chapter.

6.2 Simulation on NetLogo

Due to the weak computing power of NetLogo, the agent-based diffusion model will only be simulated once per experiment. The author only wants to generate a demonstration of the diffusion process.

In addition to the proposed agent-based diffusion model in Chapter 4, a few more factors are introduced here in order to make the diffusion process closer to processes in the real world. These newly introduced factors increase model complexity and make the result difficult to analyse. In other words, the author further sacrifices the analytical usage of the model in order to make the result more vivid. These factors are explained below.

6.2.1 *Birth and Death of Organisations*

In the real world, the number of organisations in a system is normally dynamic: new organisations may come to the system and existing organisations may leave the system at any point of time, for a number of reasons. In diffusion models, authors such as Mahajan and Peterson (1978) also notice that the potential market for a new product should be considered as dynamic. In this NetLogo simulation, the birth and death rates of organisations are introduced following the ideas from epidemic studies. For the birth of new organisations, a linear relationship[29] between the number of new organisations $M_{Birth,t}$ and the total number of organisations M_{t-1} at time $t-1$ is proposed. A parameter b (birth rate) is introduced to represent this linear relationship:

$$M_{Birth,t} = b \times M_{t-1} \tag{34}$$

One issue that should be emphasised here is that organisations may already have the innovation before they first enter this system. In order to cover this issue, the author proposes that the probability that an organisation k already has the innovation when they enter the system is determined by the penetration rate of the innovation at time t, which is calculated by using the number of existing adopters of this innovation (F_t) divided by the total number of organisations (M_t). In other words, the more organisations who have adopted the innovation, the higher probability that 'newcomers' already possessed the innovation before they entered the system:

$$P_k = F_t / M_t \tag{35}$$

[29] This relationship can be various types. A linear relationship is used here just for simplicity.

For the death of existing organisations, it is assumed that each organisation has got a probability of d to leave this system at time t, and the relationship is modelled as:

$$M_{Death,t} = d \times M_{t-1} \tag{36}$$

After determining the value of $M_{Birth,t}$ and $M_{Death,t}$, the total number of the organisations in the system at time t can be represented in Equation 37:

$$M_t = M_{t-1} + M_{Birth,t} - M_{Death,t} = M_{t-1} \times (1 + b - d) \tag{37}$$

6.2.2 R&D Budget in a Multi Innovation Diffusion Process

In real situations, it is more than common for one innovation to be diffused in the system at the same time. For instance, multi-product diffusion models or even multi-generation models (see Section 2.3 for a detailed discussion) can be classified in this category. Furthermore, organisations normally do not have enough resources to engage in all these innovation activities. The pipeline theory is one of the means to explore this issue: according to Ding and Eliashberg (2002), innovation investment is risky due to the uncertainty of the innovation process, and thus no single investment can guarantee a success of the final result. Therefore, due to budgetary constraints, organisations normally select only a few innovation activities. In the current NetLogo simulation, it is assumed that organisations have a limited budget for purchasing innovations. Of course, organisations cannot adopt an innovation if they do not have enough money.

Subsequently, the author considers the situation whereby s innovations are diffused in the system at the same time. For organisation k at time t, its total R&D budget is denoted as $R\&D_{k,t}$. However, organisation k normally cannot use all the money to purchase innovations, so a random function (f_6) [30] is used to simulate the available budget of organisation k for purchasing innovations ($R\&D_{Available,k,t}$):

$$R\&D_{Available,k,t} = R\&D_{k,t} \times f_6 \tag{38}$$

The adoption process only happens when organisation k has enough available budget to purchase the innovation:

$$P_{k,t} = 0, if\ Cost_s > R\&D_{Available,k,t} \tag{39}$$

Finally, after the innovation is adopted by organisation k, the cost of adopting the innovation is automatically deducted from the R&D budget and the R&D budget is updated:[31]

$$R\&D_{k,t} = R\&D_{k,t-1} - Cost_s \tag{40}$$

6.2.3 Result of NetLogo Simulation

In each experiment, the software simulates the model once and produces a corresponding demonstration and curves. Beside the demonstration of the diffusion process, the main output of the simulation is two curves: the number of new adopters through time and the cumulative number of adopters through time. As the model is stochastic, curves produced from each simulation are not the same. However, in most cases, the number of new adopters through time is a bell-

[30] Here, the random function f_6 could be any type. In this study, the author uses a random normal function.

[31] However, the author senses a few limitations in this part, which also leave opportunities for future studies. First, various issues are involved in the diffusion of multi-innovations, for instance, multi-generation diffusion is one of the demanding research areas in the diffusion model; certain innovations may also have positive or negative effects to each other. Second, organisations are keen to know how to make decisions when they are available to purchase some of the innovations but not all of them. In this study, the author simply uses a first-come-first-adopt logic to simulate this process.

shape curve and the cumulative number of adopters through time maintains an S-curve, which is consistent with the findings in the existing literature.

Figure 20 is a screenshot from the NetLogo simulation. As can be seen, users can set up the value of the parameters for the model. Houses (organisations) in the demonstration area (right hand side of the figure) are painted different colours to represent how many innovations they have adopted. The small green points in the demonstration represent the information of the innovations that transferred from existing adopters to potential adopters.

The following three sets of figures (Figure 21, 22, 23) show the result of the NetLogo simulation. In this simulation, 6 innovations are diffused within the system. The cost for adopting these innovations is 0, 0, 0, 100, 50, and 5. For each diffusion process, the value of parameters p and q are set respectively (p = 0.02, 0.03, 0.05, 0.02, 0.03, and 0.05; q = 0.6, 0.3, 0.4, 0.6, 0.3, and 0.4). The release time of each innovation is 0, 0, 0, 8, 8, 8. In addition, the initial number of organisations is set to be 100; the birth rate and death rate of the organisations are set as 4% and 1%, so the number of the organisations will increase slightly from a long-term view. The overall budget of each organisation is randomly generated by a normal distribution. At each time point, another normal distribution is introduced to generate the percentage of the available R&D budget that an organisation can actually use for adopting these innovations.

Figure 21 is the result of NetLogo Simulation without considering the birth rate, death rate, and cost of innovations. The number of new adopters follows a bell-shape curve and the number of cumulative adopters follows an S-shape curve. Figure 22 is the result of the NetLogo simulation that considers the effect of birth and death rates. Compared with Figure 21, the curves in Figure 22 do not show a significant difference, because although some organisations leave the system and some new organisations enter, the total number does not change significantly. Figure 23 is the result of the NetLogo simulation in which all factors are triggered. Compared with Figure 21 and Figure 22, the most significant difference is that innovations with high cost (light blue and dark blue curves) diffuse very slowly, since most of organisations do not have enough capability to adopt them. What they can do is wait until they have cumulated enough R&D budget.

After presenting an initial view of the model in this section, the simulation study in the following three sections will be made on MatLab.

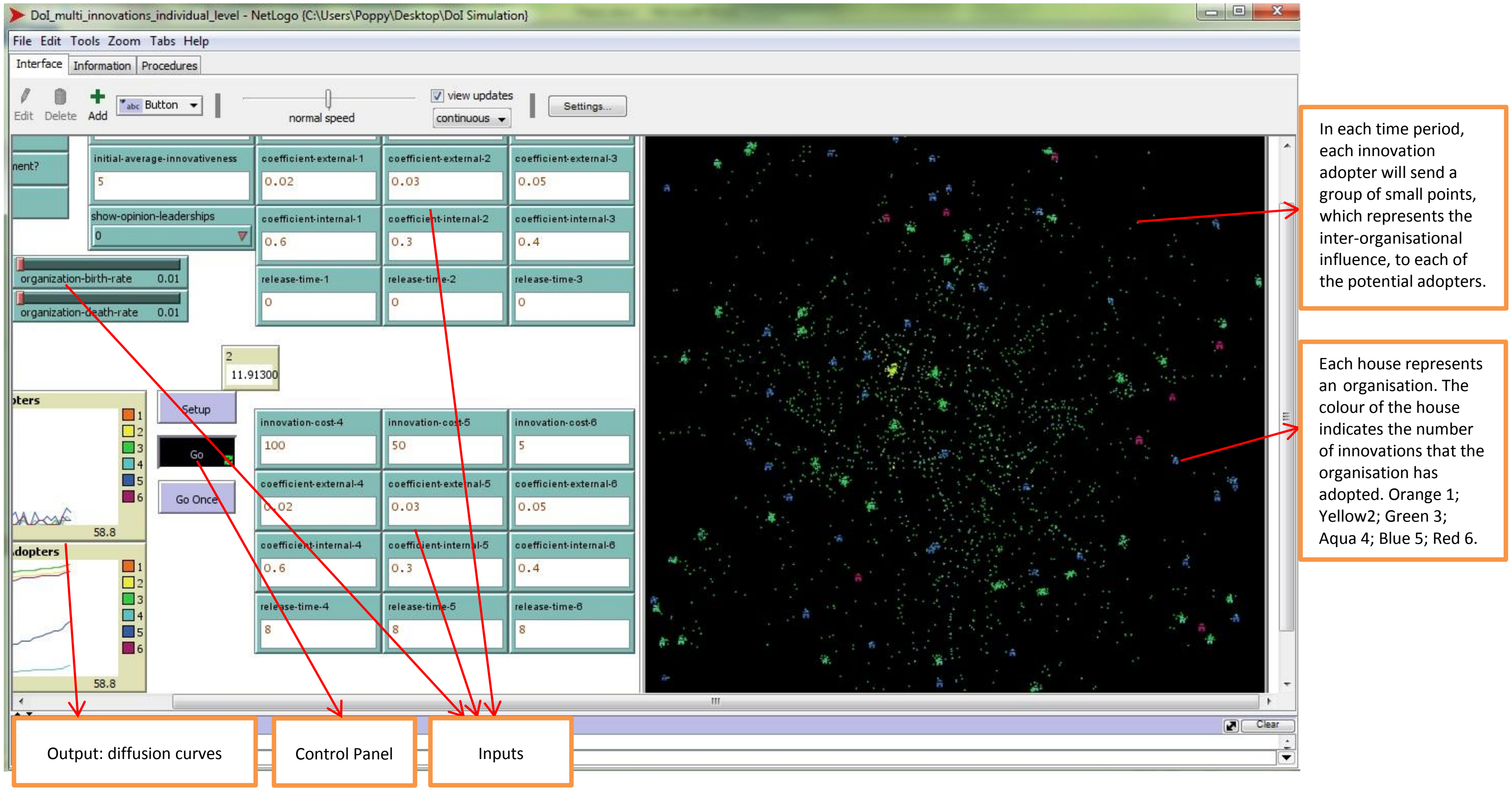


Figure 20: NetLogo Simulation

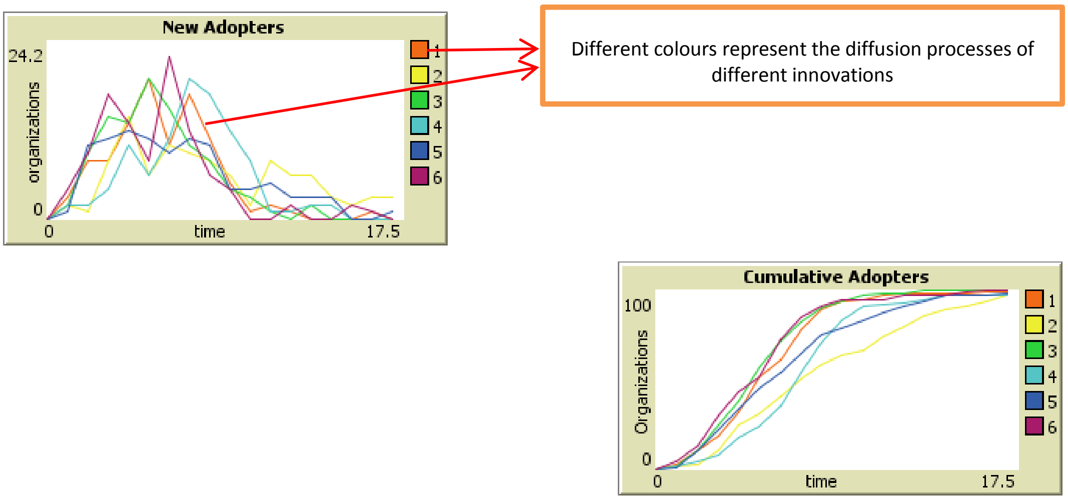


Figure 21: Result - NetLogo Simulation (1)

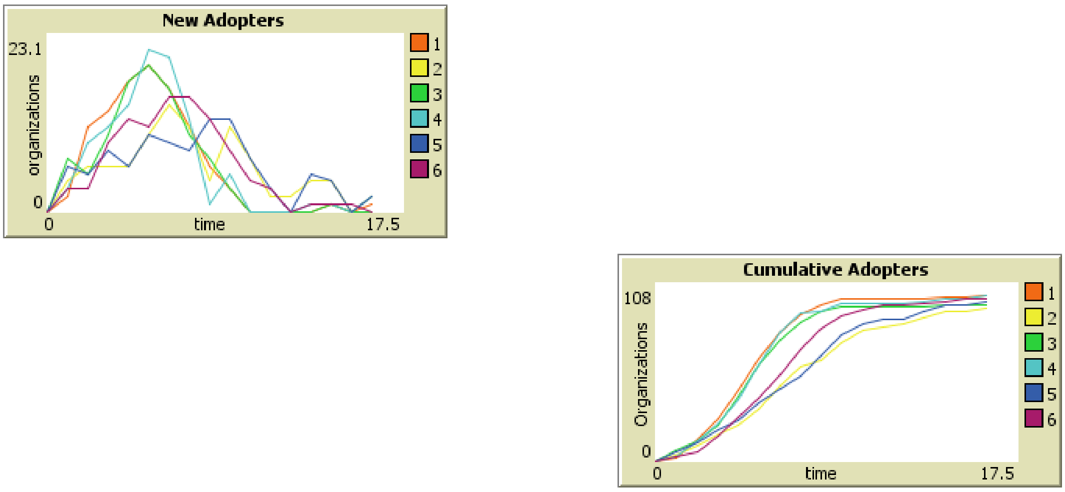


Figure 22: Result - NetLogo Simulation (2)

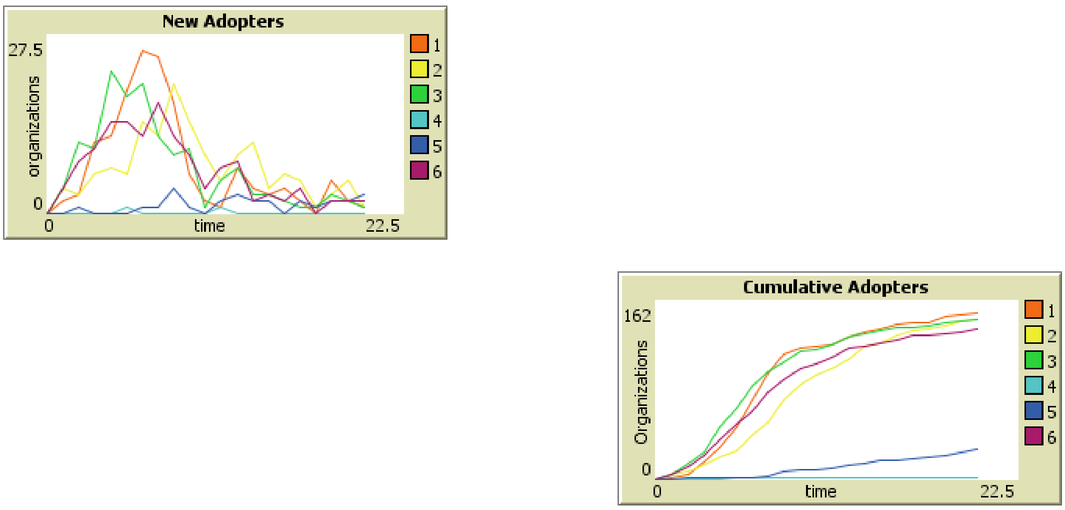


Figure 23: Result - NetLogo Simulation (3)

6.3 p_t, q_t and Organisational Innovativeness[32]

Following the simulation context defined in Chapter 5, the agent-based diffusion model is simulated in a 200-organisation system by using MatLab. The reason why the sample size is doubled here compared with the diffusion data used in Chapter 3 is to make the result more robust.

In the first step, the author intends to focus on the generalized level of the environmental effect (p_t) and the inter-organisational influence (q_t), as well as the role of organisational innovativeness in diffusion. Therefore, the inter-organisational influence is set to be homogeneous ($f_2(OI_{k,t}, OI_{k',t}) = f_3(PD_{k,k'}) = 1$), which means each paired organisation has the same level of inter-influence and thus the effect of function $f_2(OI_{k,t}, OI_{k',t})$ and function $f_3(PD_{k,k'})$ can be excluded.

The result from simulating the agent-based model is compared with the result from simulating the modified Bass model (see Table 21, page 153).

6.3.1 Effect of p_t and q_t

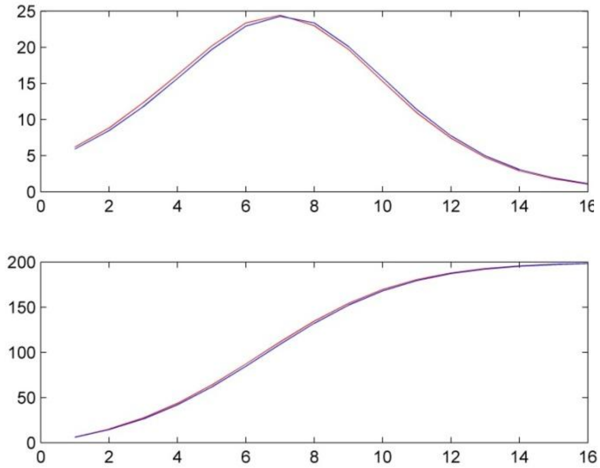
The result in Row 1 of Table 21 relates to the investigation of the generalised level of the environmental effect (p_t) and the inter-organisational influence (q_t) in diffusion. The value of the two parameters is changed and the corresponding results observed. When the value of p_t increases by 5% and 10%, diffusion speed increases according to the observation of the produced curves (Figure 24). The corresponding results of the one-way sensitivity analysis (cumulative number of

[32] Four groups of outputs are listed as: Sensitivity analysis based on the number of new adopters; Uncertainty analysis based on the number of new adopters; Sensitivity analysis based on the cumulative number of adopters; Uncertainty analysis based on the cumulative number of adopters. Because of the reasons mentioned in Footnote 28, the result of the uncertain analysis will not be discussed in this thesis.
The two groups of sensitivity analysis both can reflect the impact of changed parameter(s) on diffusion. During the discussion, the author uses the result from sensitivity analysis based on the cumulative number of adopters most of the time, for simplicity.
The above explanations apply to all the following sections in this Chapter unless specified.
The raw data of the simulation result can be found in Appendix 5.

adopters) are 2.3766 and 9.2636, which shows a considerable difference compared with the benchmarking model (the modified Bass model). Also the result indicates that the diffusion speed does not increase linearly with the increase of p_t. This is because p_t also enhances the social contagion effect indirectly: the bigger value of p_t can result in an early take-off of the diffusion, which makes the adopters cumulate faster, thus increasing the power of the social contagion effect in the system.

In Figure 24, the red curve is produced by the proposed agent-based model in this study; the blue curve is produced by the homogeneous version of the modified Bass model ($p = 0.03$, $q = 0.0025$, and $M = 200$); the bell shape curves represent the number of new adopters; the S-shape curves illustrate the cumulative number of adopters.

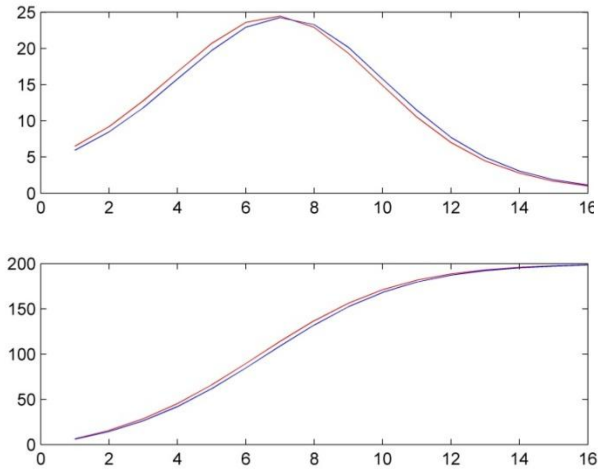
(The above explanations apply to all the following figures in this section)



p_t increases by 5%;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



p_t increases by 10%;

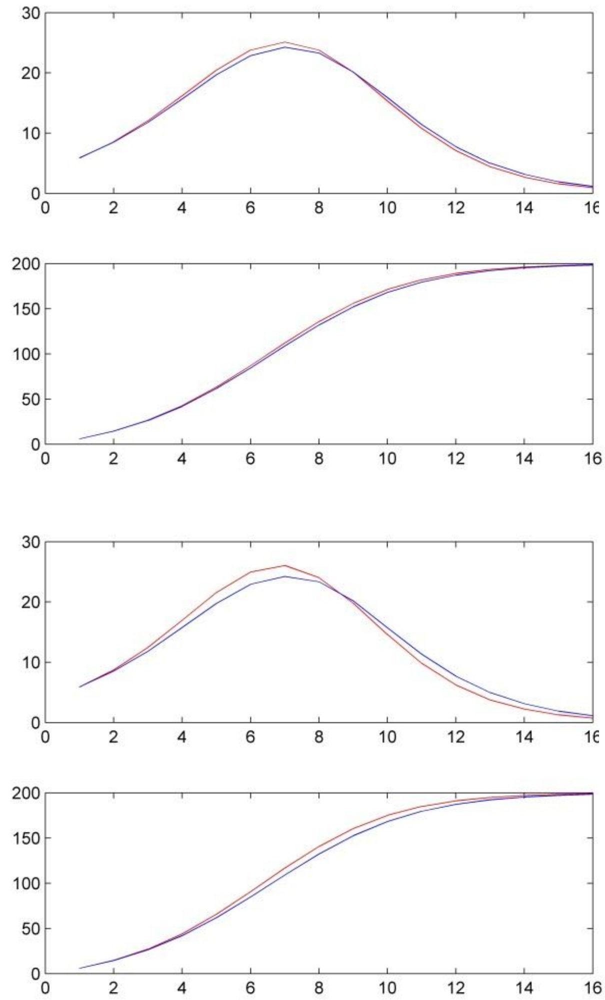
Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 24: Result – p_t increases by 5% and 10%

Then the generalised environmental effect p_t is fixed, and the value of q_t is managed to increase by 5% and 10%. The resulting curves show an increased diffusion speed (Figure 25). While different to the curves resulting from the change of p_t, the initial stage of diffusion does not change much and the curves only show a significant increase sometime after the start. It is typically because there are few adopters at the beginning of diffusion, that the social contagion effect does not affect the diffusion visibly. Also the result of the sensitivity analysis indicates an increase with the modified Bass model, and even compared with the resulting change of p_t at 5% and 10%.

Therefore, it can be concluded that p_t and q_t are both positively related to the speed of diffusion. The effect of q_t is more important than p_t from a long term view, if they are increased by the same percentage value. However, p_t has an immediate effect at the initial stage of diffusion, while q_t tends to have a clear influence only after adopters have reached a certain number.



q_t increases by 5%;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters.

q_t increases by 10%;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 25: Result – q_t increases by 5% and 10%

In diffusion, there are various reasons for a continuously changed environmental effect, for example, the dynamic price of the innovation, the dynamic promotion for the innovation, and so on. Furthermore, it should be noted that the change of the average level of organisational innovativeness is also reflected by the value of the parameter p_t (see Section 4.5). In this experiment, it is assumed that other factors of the environmental effect are all set as constants, and thus the experiment is only designed to understand the role of dynamic innovativeness in diffusion of innovation. Here the value of p_t is set to increase continuously at constant rates in each time period (5% and 10%). As shown in the result, the diffusion speed increases as observed in the curves (Figure 26) and shown in the sensitivity analysis (8.7059 and 38.6208) as expected. Additionally, the sensitivity analysis indicates that continuously[33] increasing the value of parameter p_t by 5% only has a similar effect to increasing it 10% when the diffusion starts. This further suggests that to increase the average level of organisational innovativeness in the early stage is more important to diffusion speed.

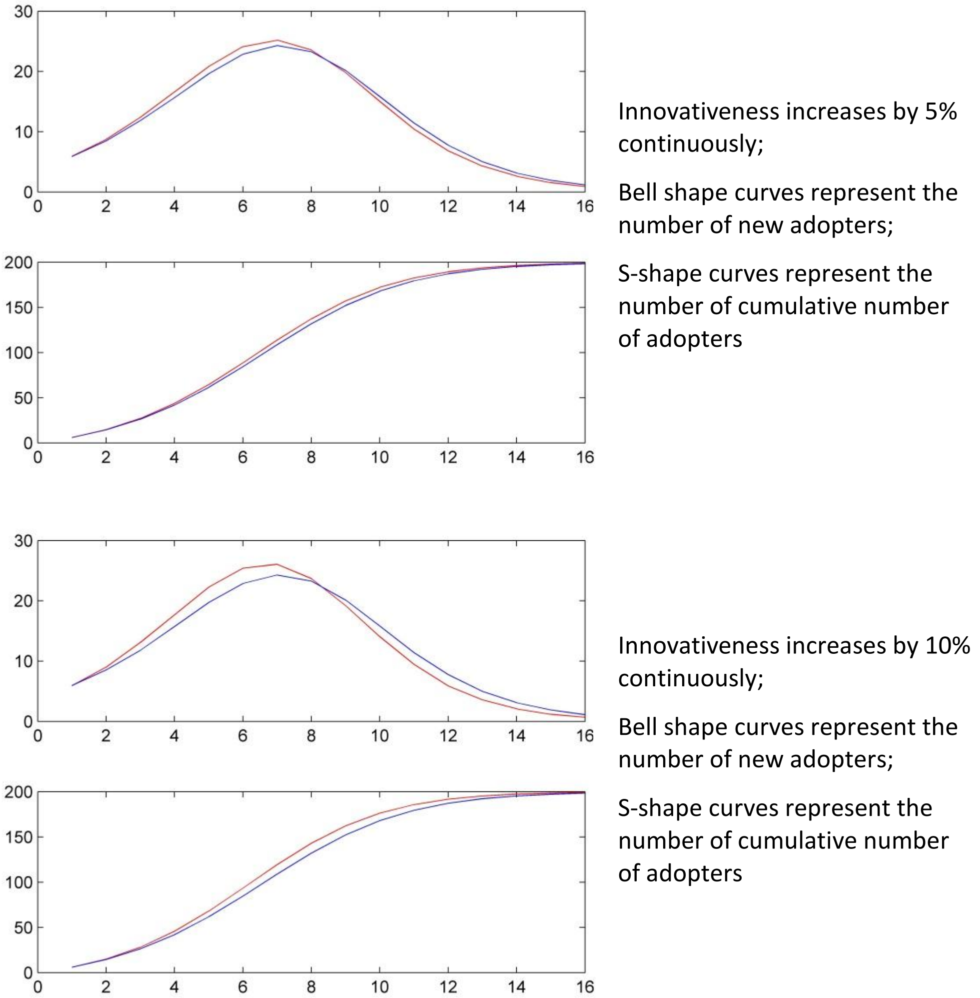


Figure 26: Result – Innovativeness increases continuously by 5% and 10%

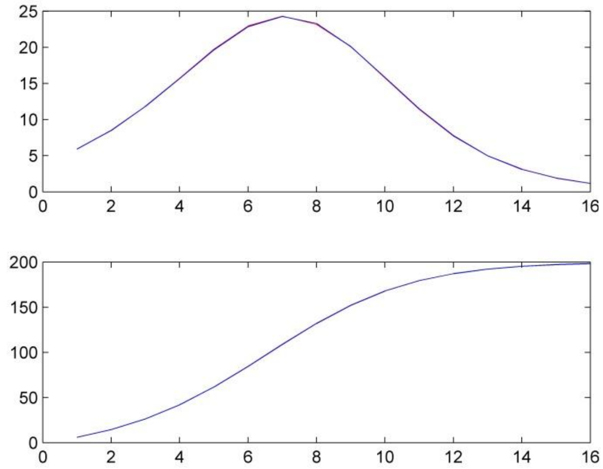
6.3.2 Effect of Organisational Innovativeness Distribution

Organisations normally have different levels of innovativeness in the real world, and the distribution of organisational innovativeness can be of various types due to the characteristics of the system. For instance, if income is used as an indicator for consumers' adoption tendencies (Van den Bulte & Stremersch 2004), its

[33] The value of parameter p_t will increase $(1.05)^{15}$-1 $\approx 107.9\%$ after 15 time periods

value can be represented by different distributions such as beta distribution, Singh-Maddala distribution, lognormal distribution, gamma distribution, Weibull distribution, and exponential distribution (McDonald 1984). In the current stage of the experiment, the values of p_t and q_t are maintained as constants and different statistical distributions are used to generate organisational innovativeness. The result shows that when organisations have the same level of innovativeness, the model has the same performance as its homogeneous version - the modified Bass model (Figure 27), which is consistent with the finding of Rahmandad and Sterman (2008). Then two normal distributions with mean = $\overline{OI_t}$ and standard deviation = $\frac{\overline{OI_t}}{3}$ and $\frac{\overline{OI_t}}{6}$ are used to generate organisational innovativeness as input (Figure 28).[34] The diffusion curve changes slightly when the organisational innovativeness changes from equally distribution to normal distribution with standard deviation = $\frac{\overline{OI_t}}{6}$, and to normal distribution with standard deviation = $\frac{\overline{OI_t}}{3}$ (The author believes that the difference represents a slightly faster diffusion speed, and it is a result of the issue discussed in Footnote 34). Finally, it is found that the diffusion delays when gamma distribution is used to generate the input. That is because Gamma distribution is right skewed, which means the innovativeness of most organisations is lower than the mean value (Figure 29). Therefore, although a few organisations may adopt the innovation very early, the adoption time of most organisations tends to be late.

[34] If $\sigma_t = \mu_t/3$, then for 98.5% of organisations, innovativeness will fall into the set of $[0, +\infty]$. For the other 1.25% of organisations, whose innovativeness is below 0, the absolute value of their innovativeness is used in the model instead, since innovativeness cannot be negative. Therefore, the average level of organisational innovativeness is actually slightly bigger than the expected value of $\overline{OI_t}$.
However, it is tested that the relative difference is very small when the data set is big enough, so it will not influence the simulation result significantly.

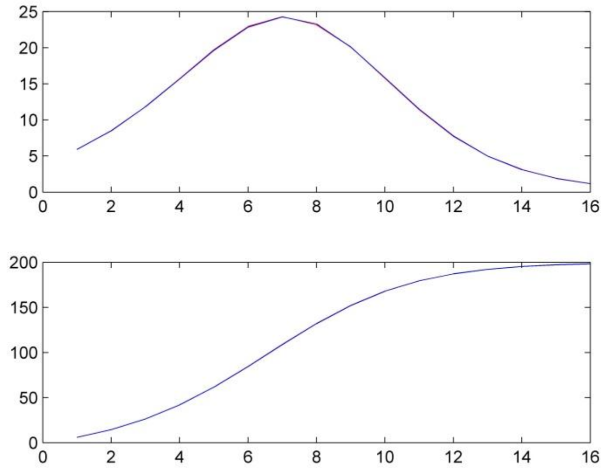


Innovativeness is equally distributed;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 27: Result – Innovativeness is Equally Distributed



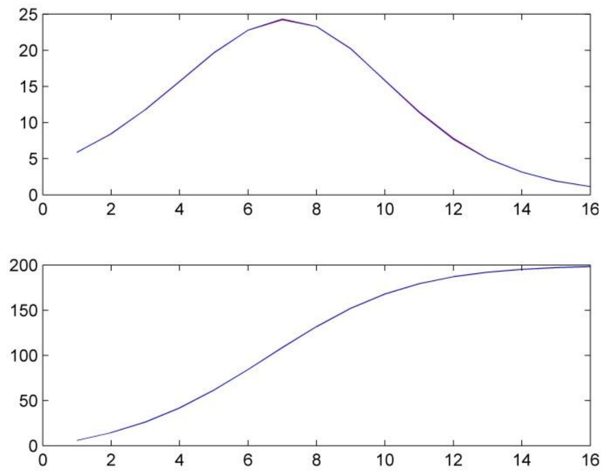
Innovativeness follows a normal distribution (1);

Mean = $\overline{OI_t}$;

Standard deviation = $\frac{\overline{OI_t}}{3}$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



Innovativeness follows a normal distribution (2);

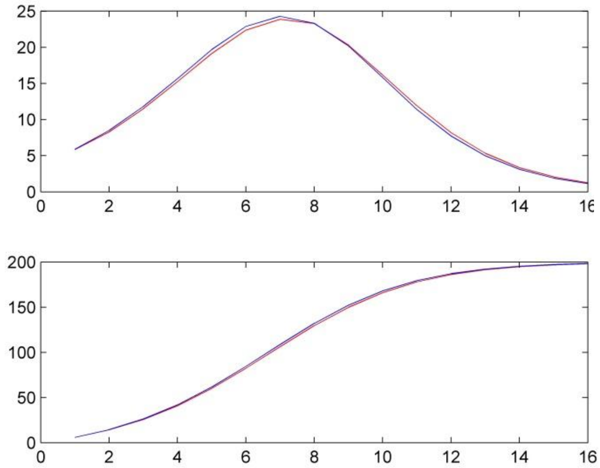
Mean = $\overline{OI_t}$;

Standard deviation = $\frac{\overline{OI_t}}{6}$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 28: Result – Innovativeness follows Normal Distributions with different Standard Deviation



Innovativeness follows a Gamma distribution;

Shape parameter equals 1.5;

Scale parameter equals $\frac{\overline{OI_t}}{1.5}$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 29: Result – Innovativeness follows Gamma Distribution

From the above discussions, it is also easy to deduce that the overall diffusion process will increase if organisational innovativeness follows a left-skewed distribution. However, this part of the simulation and discussion are excluded in this study, since the author considers innovativeness following a left-skewed distribution is not a common phenomenon in the world.

Input				Output			
Row	p_t	q_t	***OI***	***SA***	***UA***	***SA 2***	***UA 2***
1	+5%	=	Normal Distribution	0.1328	13.3315	2.3766	84.5498
	+10%	=		0.5045	13.1523	9.2636	80.5793
	=	+5%		0.3278	13.6289	5.5171	87.1057
		+10%		1.4013	13.7539	22.5224	85.7690
2	+5% (annually)	=		0.5138	13.2707	8.7059	76.7012
	+10% (annually)			2.3097	12.8531	38.6208	67.9410
3	=	=	Equally	0.0028	13.4999	0.0137	86.7180
			Normal Distribution $\sigma_t = \frac{\overline{OI_t}}{6}$	0.0083	13.3941	0.1034	69.9607
			Normal Distribution $\sigma_t = \frac{\overline{OI_t}}{3}$	0.0035	13.3741	0.0416	86.8970
			Gamma Distribution (shape parameter equals 1.5)	0.1464	13.3076	2.6203	87.5551

Table 21: Simulation Result (1)

6.4 Inter-Organisational Influence

Consistent with section 6.3, the simulation in this section is also made in an environment with 200 organisations. As discussed in Section 4.7, the inter-organisational influence between two organisations in the proposed agent-based model consists of three factors: the opinion leadership of the existing adopter that is calculated on the basis of innovativeness; the effect of innovativeness difference used to represent the force of the self-conformity of the potential adopter; and the physical distance between two organisations. In this section, the simulation will focus on these three aspects and explore how they impact the inter-organisational influence and thus the diffusion process.

In the current stage of the experiment, the values of p_t and q_t are fixed as 0.03 and 0.0025. The mean and standard deviation of the normal distribution for generating the innovativeness of organisations are denoted as $\overline{OI_t}$ and σ_t (here $\sigma_t = \frac{\overline{OI_t}}{3}$). So the effects of p_t, q_t, and organisational innovativeness are all excluded. Table 22 (Page 167) summarises the findings of this section (Section 6.4).

6.4.1 *Effect of Opinion Leadership*

After the data of organisational innovativeness is ready, nine curves of opinion leadership are generated following function $f_4\left(OI_{k',t}\right)$ with different values of the scale parameter ($\beta_t = 1.0$, 1.1, and 0.9) and the shape parameter ($\alpha_t = \overline{OI_t} + 1.5 \times \sigma_t$, $\alpha_t = \overline{OI_t}$, and $\alpha_t = \overline{OI_t} - 1.5 \times \sigma_t$). The three scale parameters represent the concentration level of the opinion leadership in the system. The three shape parameters represent the cases where opinion leaders tend to be early adopters, organisations with an average system innovativeness level, and laggards.[35] Figure 30 below shows three curves corresponding with the opinion leadership along with three shape parameters. The experiment regarding the effect of opinion leadership is made on the basis of the data generated from these inputs.

[35] In the real world, the situation where opinion leaders have low innovativeness is not so common. Here the reason why this situation is introduced is simply for the following comparison and discussion.

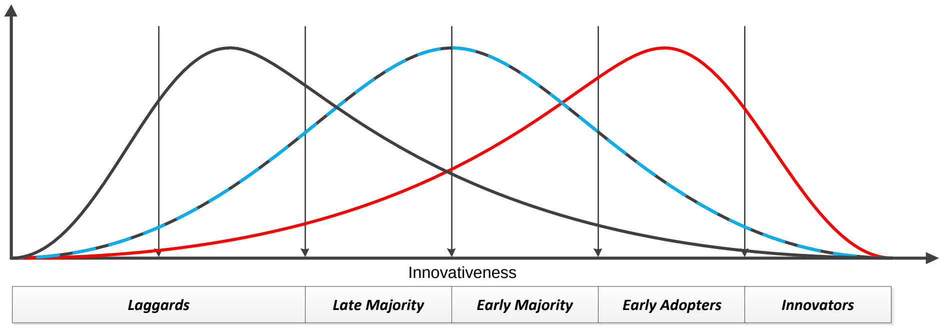
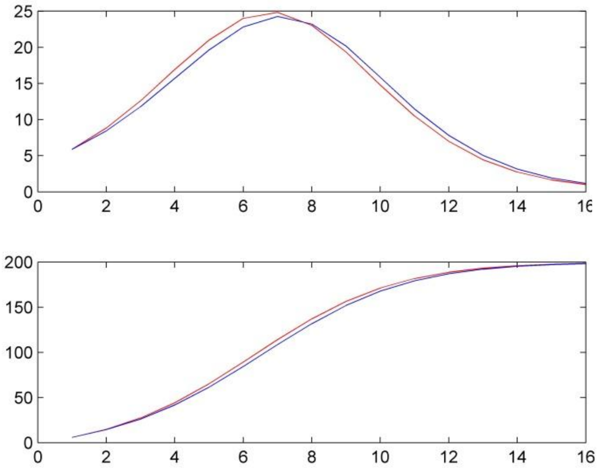


Figure 30: Curves of Opinion leadership

The result in Row 1 (Table 22) is from the simulation of the proposed agent-based model with different values of α_t and a fixed value of β_t, that tests how the location of the peak point in the curve of opinion leadership will influence the diffusion process. It suggests the shape of the opinion leadership curve as an important factor to diffusion: compared with the curve produced by the modified Bass model, diffusion rate increases when opinion leaders tend to be early adopters, decreases when opinion leaders tend to be late adopters, and does not change visibly when opinion leaders are the ones with an average innovativeness level (Figure 31). The result of the sensitivity analysis also indicates that to change the shape of the opinion leadership curve by changing the value of α_t from $\overline{OI_t}$ to $(\overline{OI_t} + 1.5 \times \sigma_t)$ has a similar result to increasing the value of p_t by 10% when the diffusion starts, increasing the value of q_t by 5% when diffusion starts, or increasingly p_t by 5% continuously (7.2004 : 9.2636 : 8.7059).

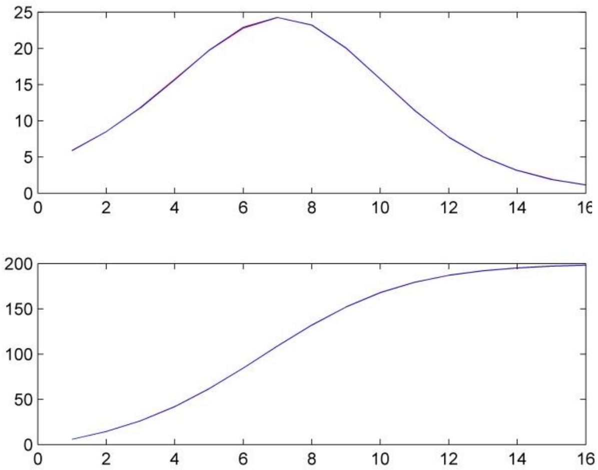


$\alpha_t = \overline{OI_t} + 1.5 \times \sigma_t$;

$\beta_t = 1$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

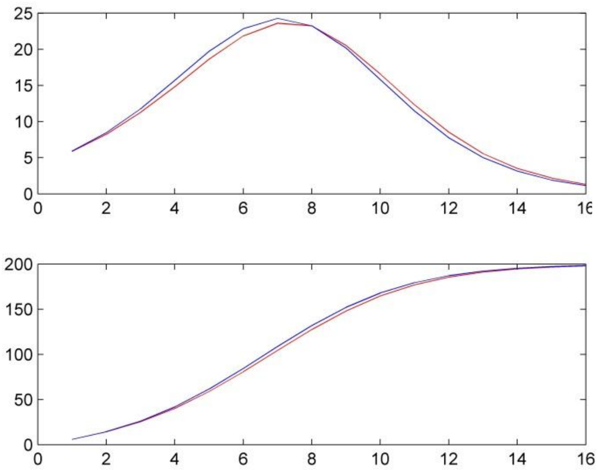


$\alpha_t = \overline{OI_t}$;

$\beta_t = 1$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



$\alpha_t = \overline{OI_t} - 1.5 \times \sigma_t$;

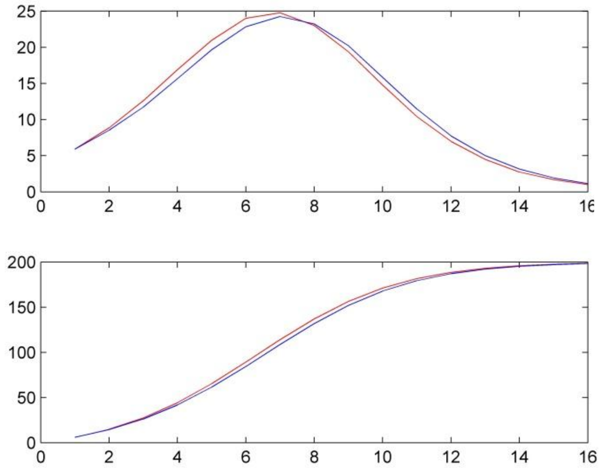
$\beta_t = 1$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 31: Result – Effect of α_t

In the following row (Row 2) of the table, the scale parameter β_t is changed relatively in order to see if the concentration level of the opinion leadership curve will influence the diffusion speed. From the resulting figures (Figure 32 and 33) and sensitivity analysis, when the curve of opinion leadership tends to be symmetrical, the scale parameter does not influence the diffusion process significantly (the result is 0.16442 when the scale parameter equals 1.1 and 0.1223 when the scale parameter equals 0.9). However, when the curve of opinion leadership is not symmetrical, the scale parameter can further influence the effect of the shape parameter. Specifically, when the value of the scale parameter β_t increases, opinion leadership tend to distribute equally among individuals, and the effect of the shape parameter (α_t) is reduced; contrastingly, the effect of the shape parameter is further enlarged if the value of β_t decreases.

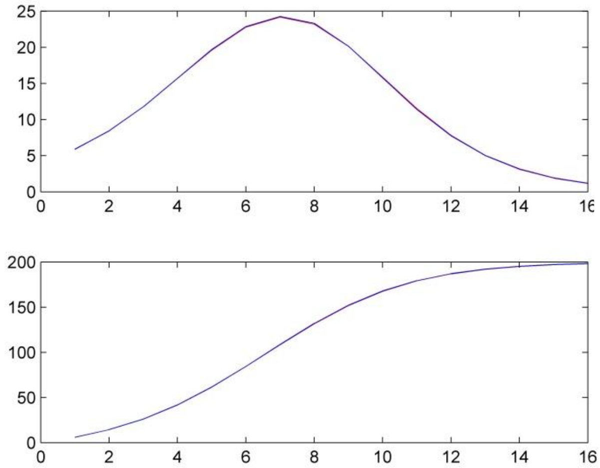


$\alpha_t = \overline{OI_t} + 1.5 \times \sigma_t;$

$\beta_t = 0.9;$

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

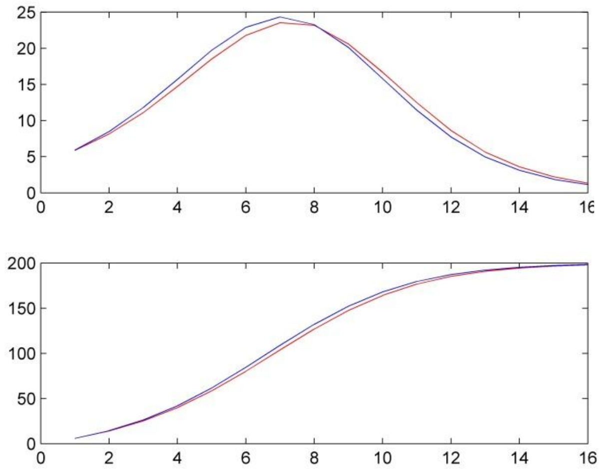


$\alpha_t = \overline{OI_t};$

$\beta_t = 0.9;$

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



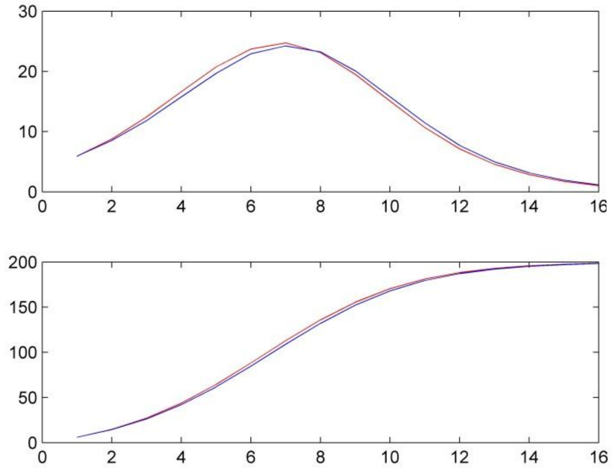
$\alpha_t = \overline{OI_t} - 1.5 \times \sigma_t;$

$\beta_t = 0.9;$

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 32: Result – Effect of β_t (1)

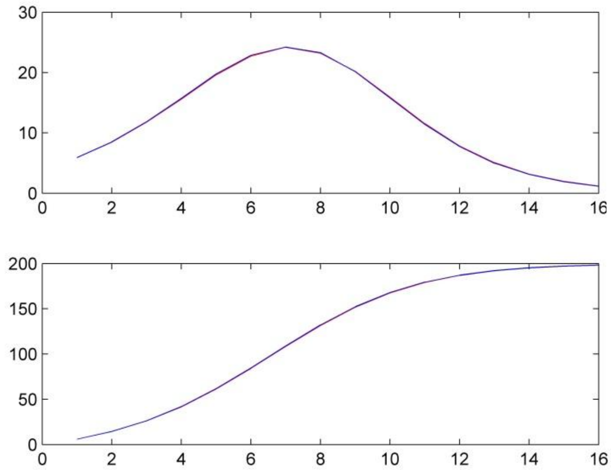


$\alpha_t = \overline{OI_t} + 1.5 \times \sigma_t$;

$\beta_t = 1.1$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

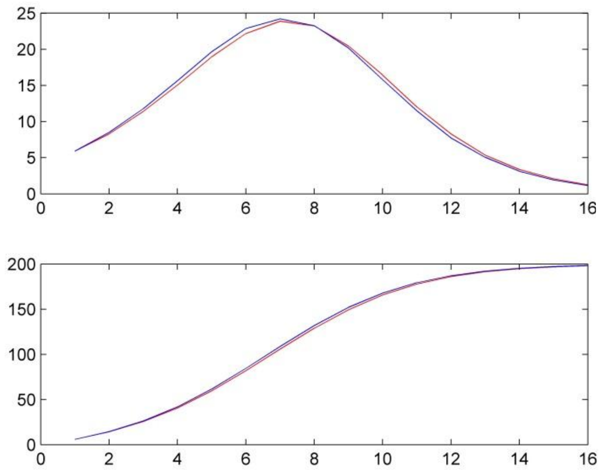


$\alpha_t = \overline{OI_t}$;

$\beta_t = 1.1$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



$\alpha_t = \overline{OI_t} - 1.5 \times \sigma_t$;

$\beta_t = 1.1$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

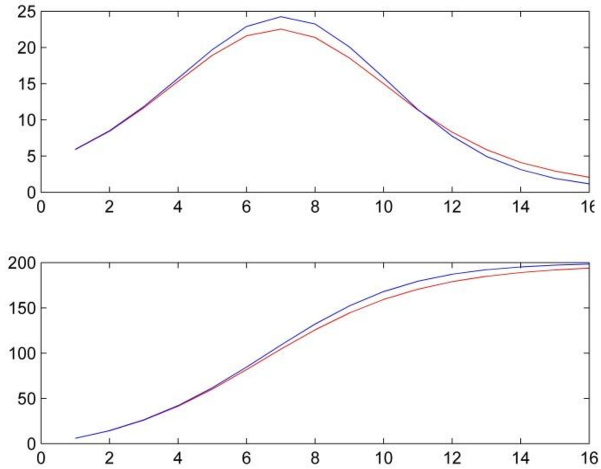
Figure 33: Result – Effect of β_t (2)

6.4.2 *Effect of Innovativeness Difference*

Following on, the effect of innovativeness difference is then investigated. The result is shown in Row 3 and 4 of Table 22 with corresponding curves in Figure 34, 32, and 33. Here the opinion leadership is generated three times, from function $f_4(OI_{k',t})$ with $\beta_t = 1$ and $\alpha_t = \overline{OI_t}, \overline{OI_t} + 1.5 \times \sigma_t,$ and $\overline{OI_t} - 1.5 \times \sigma_t$. Additionally, Row 3 is the result where only one of the scale parameters (n_1 or n_2) is triggered and Row 4 indicates the integrated effect when they are both triggered.

On the one hand, the single consideration of the scale parameter n_1 delays the diffusion process (Figure 34), typically because those early adopters will exert less influence on their followers based on this setting. In addition, this phenomenon will be even more obvious when opinion leaders are more innovative, since these opinion leaders will adopt the innovation early and lose influence to most of their follower quickly. On the other, the single consideration of the scale parameter n_2 speeds up the diffusion process (Figure 35), as the information transferred from high-innovativeness adopters to low-innovativeness potential adopters is relatively enhanced, and thus the former ones will adopt innovations early and exert more influence on the followers. Similarly, this phenomenon will be more obvious when opinion leaders are more innovative. Finally, when these two effects are combined, the information transferred from high-innovativeness adopters to low-innovativeness potential adopters and the opposite information transfer channel are both weakened. If the two scale parameters are set with the same value ($n_1 = n_2 = 0.15$), the resulting curves (Figure 36) are similar with the ones when only n_2 is considered (the diffusion speed increases), while differently, the increase rate is more visible when the opinion leaders tend to be late adopters and is less visible when opinion leaders tend to be early adopters.

An adopter with low innovativeness normally finds it more difficult to influence a potential adopter with higher innovativeness in the real world ($n_1 < n_2$). Therefore, the diffusion will speed up compared with the modified Bass model, if the effect of innovativeness difference is considered in this proposed model.

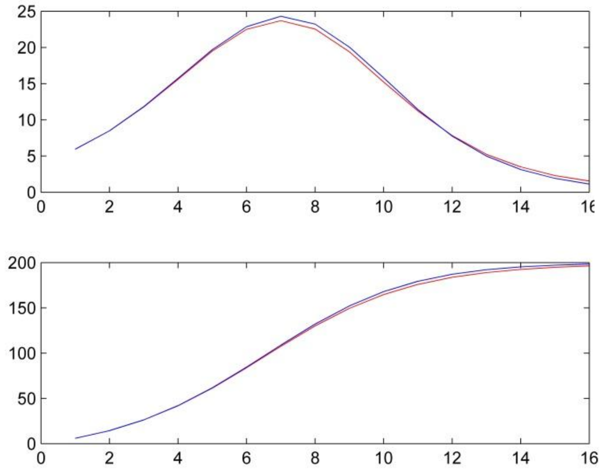


$\alpha_t = \overline{OI_t} + 1.5 \times \sigma_t$;

$n_1 = 0.15$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

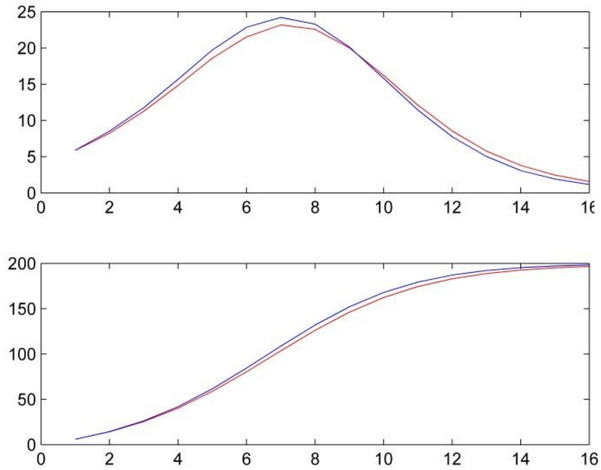


$\alpha_t = \overline{OI_t}$;

$n_1 = 0.15$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



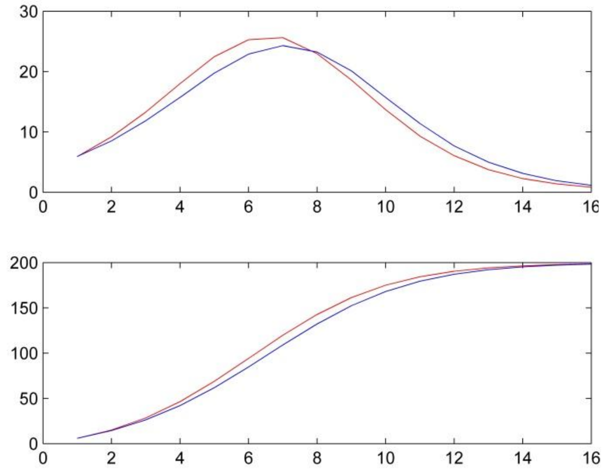
$\alpha_t = \overline{OI_t} - 1.5 \times \sigma_t$;

$n_1 = 0.15$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 34: Result – n_1 is considered

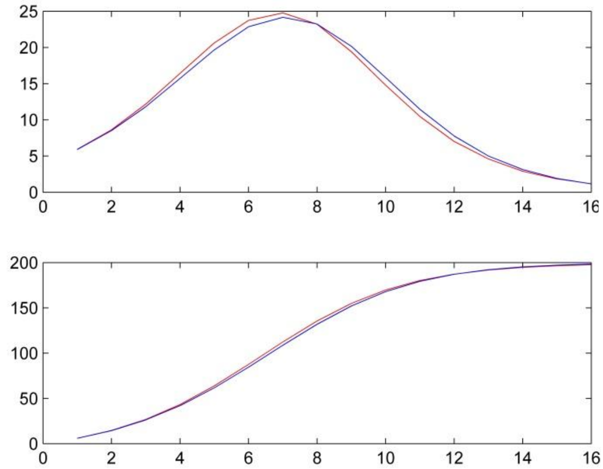


$\alpha_t = \overline{OI_t} + 1.5 \times \sigma_t$;

$n_2 = 0.15$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

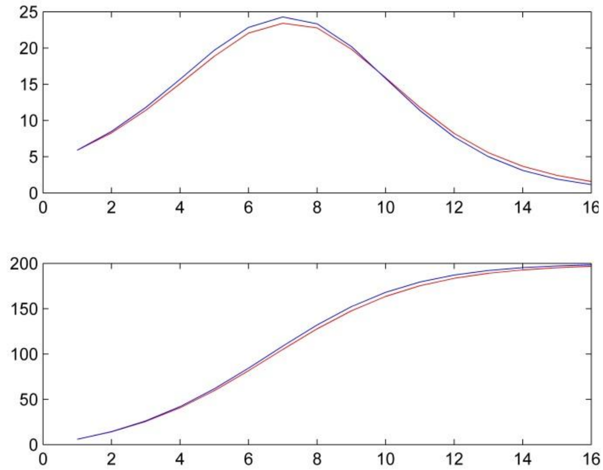


$\alpha_t = \overline{OI_t}$;

$n_2 = 0.15$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



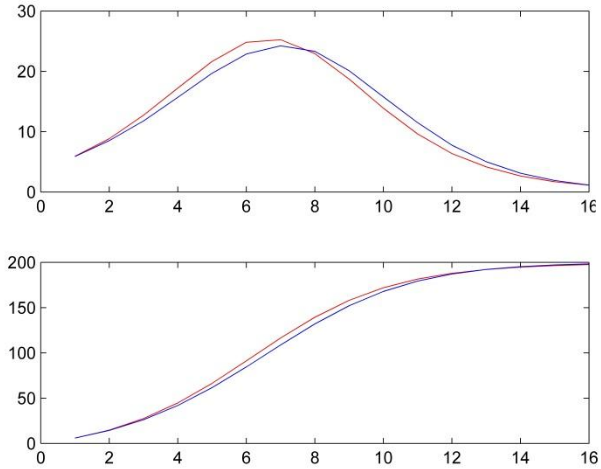
$\alpha_t = \overline{OI_t} - 1.5 \times \sigma_t$;

$n_2 = 0.15$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 35: Result – n_2 is considered



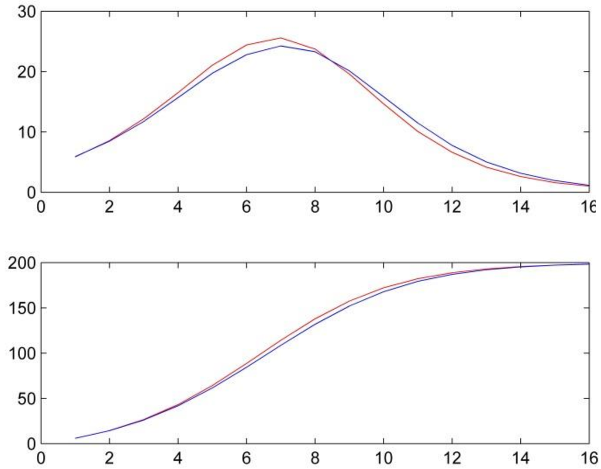
$\alpha_t = \overline{OI_t} + 1.5 \times \sigma_t$;

$n_1 = 0.15$;

$n_2 = 0.15$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



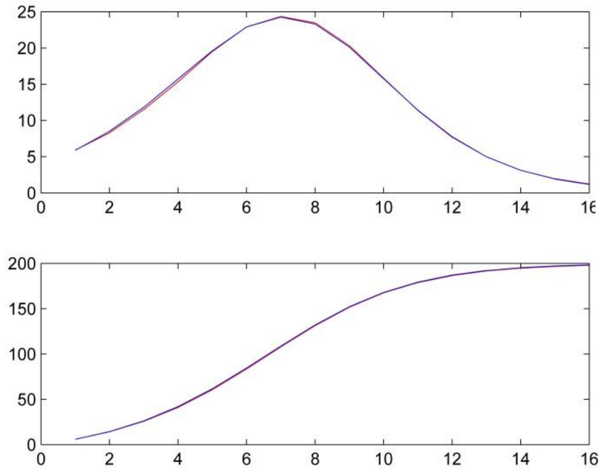
$\alpha_t = \overline{OI_t}$;

$\mathrm{n}_1 = 0.15$;

$\mathrm{n}_2 = 0.15$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



$\alpha_t = \overline{OI_t} - 1.5 \times \sigma_t$;

$\mathrm{n}_1 = 0.15$;

$\mathrm{n}_2 = 0.15$;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 36: Result – n_1 and n_2 are both considered

6.4.3 *Effect of Geographic Location*

As mentioned in Section 5.4.1, a multivariable normal distribution is introduced to generate the geographic location of organisations (with covariance equals $[10000\ 10; 10\ 10000]$). Three simulations are made here. First, locations are generated by one multivariable normal distribution with one centre point at $(0, 0)$, in which case all organisations are grouped in one area with the parameter of geographic location effect (a_{PD}) equaling 0.01 after calibration. Then the same multivariable normal distribution is used again to generate the input, but the value of the parameter a_{PD} is changed to 0.005. The result of the second simulation is compared with the first one in order to explore the role of a_{PD} in this diffusion model. Finally, locations are generated by four multivariable normal distributions with different centre points as $(0, 0)$, (300, 300), (200, 100), and $(500, 500)$, in which case four clusters exist ($a_{PD} = 0.01$) and each cluster has 50 organisations. The result is compared with the first simulation in order to test whether organisations that fall into multi clusters can make a change to the diffusion process. Figure 37 shows the probability density of organisations' locations in the first and third simulations.

In the first simulation, the result shows that the diffusion speed has a decrease compared with the curve of the modified Bass model. Compared with the first one, the second simulation indicates that the phenomenon observed above is weakened by the decreased value of the parameter a_{PD}, which means the increase of value a_{PD} will delay the diffusion speed. Compared with the result of the first simulation, the diffusion speed of the third simulation has a further decrease. Therefore, it is concluded that the statistical distribution of geographic locations has an influence on the overall diffusion process: to cluster organisations in one area increases the diffusion rate through changing the interactions between organisations, even if the average geographic location effect of all paired organisations in the system and the averaged inter-organisational influence (parameter q_t) do not change. (see Figure 38)

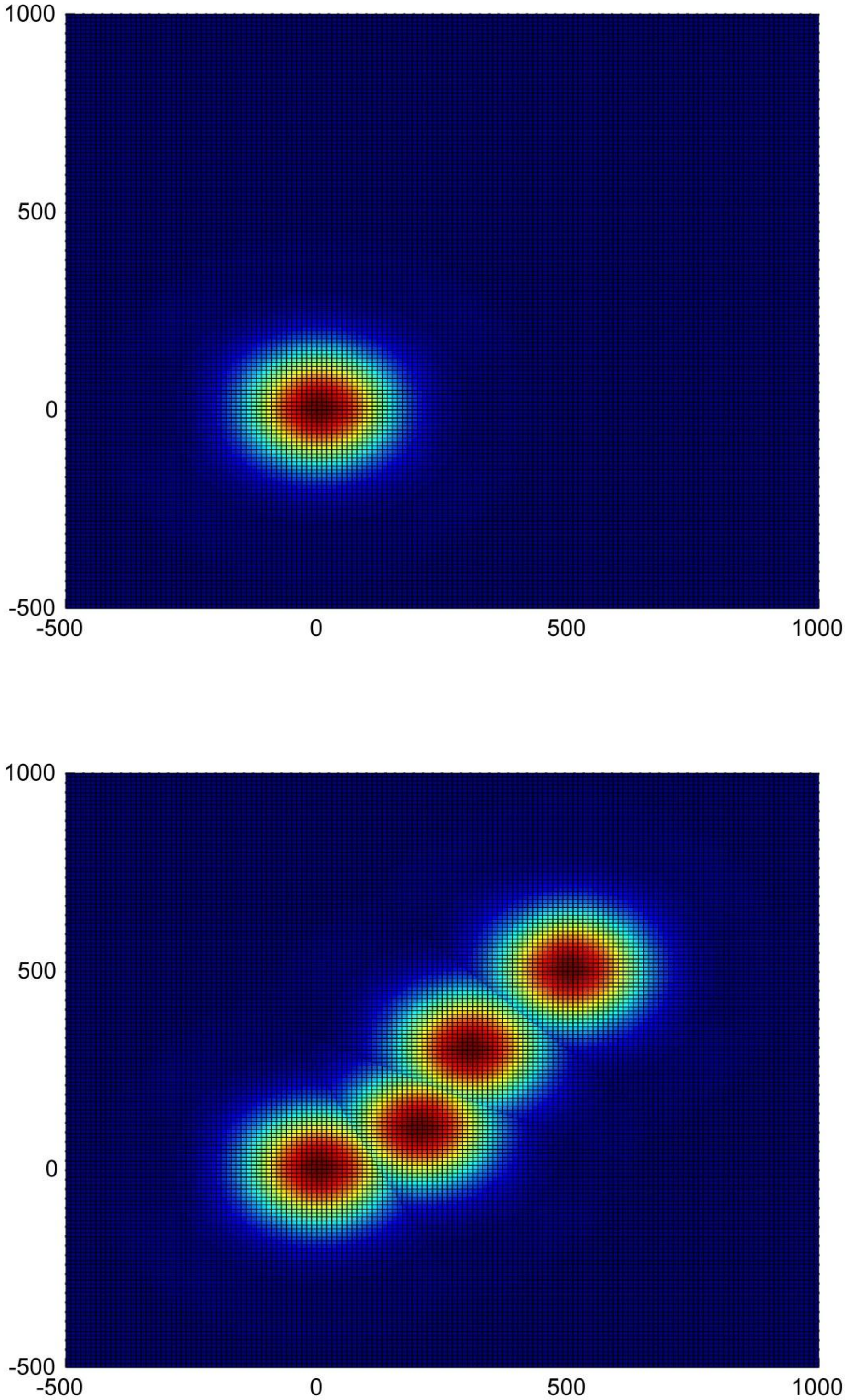
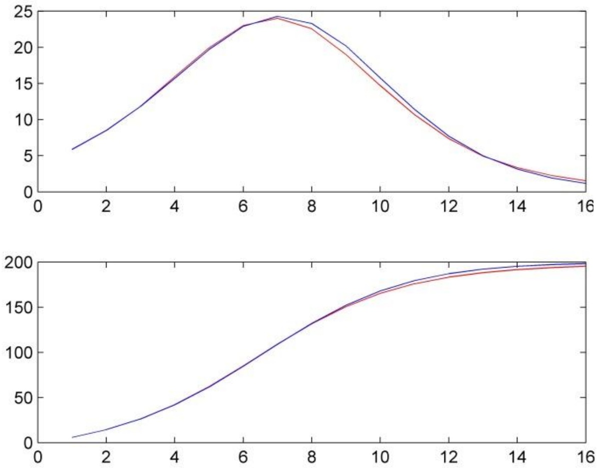


Figure 37: Probability Density of Organisations' Locations

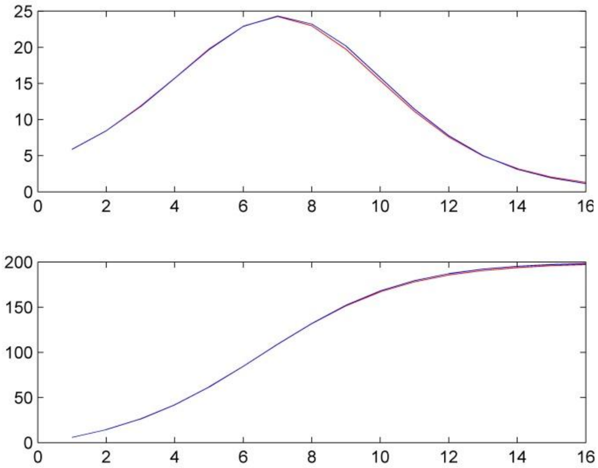


$a_{PD} = 0.01$;

One cluster;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

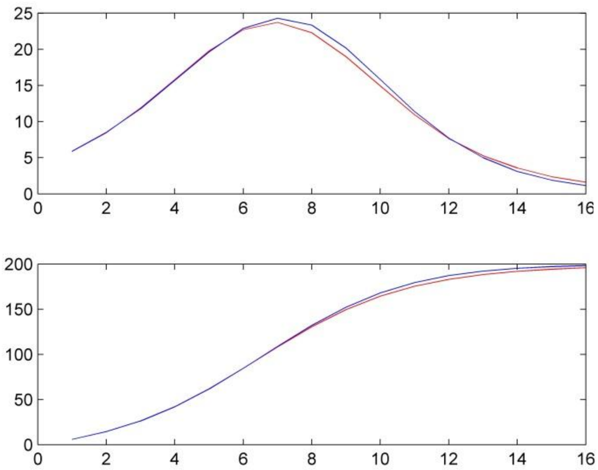


$a_{PD} = 0.005$;

One cluster;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters



$a_{PD} = 0.01$;

Four clusters;

Bell shape curves represent the number of new adopters;

S-shape curves represent the number of cumulative number of adopters

Figure 38: Result – Effect of Geographic Location

Input						Output			
Row	Effect of GL	Opinion leadership		OI Difference		SA	UA	SA2	UA2
		α_t	β_t	n_1	n_2				
1	$a_{PD}=0$	$\overline{OI_t}+1.5\times\sigma_t$	1	0	0	0.48632	13.94178	7.2004	90.80198
		$\overline{OI_t}$				0.00906	13.79596	0.12972	92.86662
		$\overline{OI_t}-1.5\times\sigma_t$				0.39218	13.86062	6.32582	96.1905
2	$a_{PD}=0$	$\overline{OI_t}+1.5\times\sigma_t$	0.9	0	0	0.64352	13.98988	9.33038	91.61186
		$\overline{OI_t}$				0.01078	13.96274	0.16442	94.9498
		$\overline{OI_t}-1.5\times\sigma_t$				0.53446	13.90232	8.79048	97.39746
	$a_{PD}=0$	$\overline{OI_t}+1.5\times\sigma_t$	1.1	0	0	0.38238	13.76782	5.61592	89.30624
		$\overline{OI_t}$				0.0082	13.6877	0.1223	91.29196
		$\overline{OI_t}-1.5\times\sigma_t$				0.21158	13.6109	3.43834	92.46596
3	$a_{PD}=0$	$\overline{OI_t}+1.5\times\sigma_t$	1	0.15	0	0.78018	12.89328	23.12138	85.5972
		$\overline{OI_t}$				0.11268	13.7851	3.68028	94.09498
		$\overline{OI_t}-1.5\times\sigma_t$				0.61926	14.0913	13.8813	102.4446
	$a_{PD}=0$	$\overline{OI_t}+1.5\times\sigma_t$	1	0	0.15	2.70538	14.50264	39.45484	94.02836
		$\overline{OI_t}$				0.26474	13.28160	4.99806	91.12466
		$\overline{OI_t}-1.5\times\sigma_t$				0.3588	13.3674	10.16402	90.14988
4	$a_{PD}=0$	$\overline{OI_t}+1.5\times\sigma_t$	1	0.15	0.15	1.49484	13.72716	15.3175	85.8963
		$\overline{OI_t}$				1.095	14.10844	12.53944	90.54506
		$\overline{OI_t}-1.5\times\sigma_t$				0.04162	13.90320	3.43668	93.04438
5	A*	Equal, no peak	1	0	0	0.34766	13.10252	6.08844	84.24298
	B*					0.0521	13.32764	0.77384	86.16594
	C*					0.35742	13.14128	8.03092	85.58814

A*: Geographic location of 200 organisations follow a multivariable normal distribution, $a_{PD}=0.01$
B*: Geographic location of 200 organisations follow a multivariable normal distributions $a_{PD}=0.005$
C*: Geographic location of 200 organisations follow four multivariable normal distributions $a_{PD}=0.01$

Table 22: Simulation Result (2)

6.5 Effect of Organisational Innovativeness and Geographic Location on Individual Level

As with the above simulations, each set of inputs is simulated 50,000 times at this stage of the experiment. However, different to before, only one organisation is targeted in order to investigate the effect of organisational innovativeness and geographic location on the individual level. The number of successful adoptions and the average adoption time of the targeted organisation are marked as indicators of the result. The result is listed in Table 23 (Page 170).

6.5.1 Effect of Innovativeness on Individual Adoption

In this section, the simulation is implemented within two contexts. Function $f_2(OI_{k,t}, OI_{k',t})$ is not triggered at first, since the first context is designed to focus on the effect of organisational innovativeness on the targeted organisation's uncertain perception of the innovation's performance under the environmental influence and thus its adoption behaviour. The second context considers the diversity of inter-organisational influence in order to see if it can further influence the organisation's adoption behaviour when organisational innovativeness is changed. Similar with most simulations in this chapter, here, the value of p_t and q_t are fixed as 0.03 and 0.0025; organisational innovativeness follows a normal distribution with mean= $\overline{OI_t}$ and standard deviation= $\frac{\overline{OI_t}}{3}$ in each simulation.

In the first context, the targeted organisation adopts the innovation 49,540 times in 50,000 simulations with an average adoption time of 7.218, when organisational innovativeness equals the average value of the system ($\overline{OI_t}$). When its organisational innovativeness increases to ($1.5 \times \overline{OI_t}$), the result shows an increased number of successful adoptions (49,630) and early adoption times (6.80784). It changes negatively when organisational innovativeness falls below the mean value ($0.5 \times \overline{OI_t}$). More interestingly, the average time of adoption shortens dramatically (4.88416) by increasing innovativeness five times ($5 \times \overline{OI_t}$), while it does not prolong significantly (7.99192) even when its innovativeness reduces to 10% of the average value ($0.1 \times \overline{OI_t}$). This finding means that increased innovativeness has a gradually increased influence on the adoption time of the targeted organisation. Therefore, it is concluded that high innovativeness is only essential for the innovators, and low innovativeness is not the key reason for the behaviour of late adoption.

Then the result is re-simulated with inter-organisational influence being triggered. Similar to the simulation in the first context, the result indicates that a high innovativeness level is positively related to the behaviour of early adoption. However, one surprising finding here is that, for those innovators, their total number of successful adoptions is small, although their adoption time is early. For instance, when the innovativeness of the targeted organisation increases from $\overline{OI_t}$ to ($5 \times \overline{OI_t}$), its average adoption time changes from 6.68542 to 4.57984, but the number of successful adoptions decreases from 49,855 to 45,595, which shows a conflicted result with the result of the first context in this section. Therefore, it is believed that the effect of opinion leadership and innovativeness difference has a particular influence on the adoption behaviour of the targeted organisation. In order to further explore this issue, the author designed a function to calculate the average inter-organisational influence received by the targeted organisation when it adopts the innovation.[36] On the one hand, the result shows that innovative organisations are very unlikely to be influenced by others when they make decisions to adopt innovations. Their average inter-organisational influence is only 0.000863 when their innovativeness is around $5 \times \overline{OI_t}$, compared to the value of 0.25848 when their innovativeness level equals $\overline{OI_t}$. Therefore, although many of them may adopt the innovation very early, their adoption probability usually increases very slowly over time. On the other hand, laggards also do not receive much influence from others when they adopt innovations; the simulation study shows that the average inter-organisational influence is 0.19386 when $OI = 0.5 \times \overline{OI_t}$ and 0.12888 when $OI = 0.1 \times \overline{OI_t}$. Hence the author argues that those laggards' adoption behaviours are neither influenced very much by themselves or by others' opinions, but should be considered as 'unusual' or 'lucky'.

6.5.2 Effect of Geographic Location on Individual Adoption

Finally, function $f_3(GL_{k,k'})$ is triggered (one cluster with the central point at $(0, 0)$) and the location of this targeted organisation changes from coordinate (0, 0) (centre of the cluster) to (500, 500) in order to test the effect of geographic location on adoption behaviour. Here the function $f_2(OI_{k,t}, OI_{k',t})$ is set to be homogeneous. The innovativeness of this organisation is set as $\overline{OI_t}$, $1.5 \times \overline{OI_t}$, and $0.5 \times \overline{OI_t}$ separately. A negative effect is found in its successful adoptions and average adoption time, which indicates a close relationship between geographic location and individual adoption probability. Specifically, the average time of adoption is prolonged when the organisation moves from the centre

[36] The author does not calculate the value when $f_2(OI_{k,t}, OI_{k',t})$ is not triggered. The sum of inter-organisational influence of the targeted organisation in row 1 of Table 23 is mainly determined by the average time of adoption. If organisations adopt the innovation earlier, the value is low. If the adoption time is late, the value is big.

point to the edge of the cluster: 6.46076 vs. 7.98574, 6.1118 vs. 7.61378, and 6.73958 vs. 8.34334. At the same time, the number of successful adoptions decreases dramatically: from 49,940 to 19,535, from 49,945 to 25,825, and from 49,925 to 11,295, which means the organisation will lose contact to the early adopters if it leaves the cluster, and thus has fewer opportunities to adopt the innovation. Therefore, it is concluded that the location of the organisation has influence on the effect of inter-organisational influence, the organisation's adoption probability, and its adoption time.

Input				Output		
Row	***OI***	***GL***	$f_2(OI_{k,t}, OI_{k',t})$*	***Average time of adoption***	***Number of successful adoptions***	***Average Social Contagion Effect***
1	$\overline{OI_t}$	Not Considered	Not Considered	7.218	49540	Not measured
	$1.5 \times \overline{OI_t}$			6.80784	49630	
	$0.5 \times \overline{OI_t}$			7.60158	49460	
	$5 \times \overline{OI_t}$			4.88416	49935	
	$0.1 \times \overline{OI_t}$			7.99192	49340	
2	$\overline{OI_t}$		Considered*	6.68542	49855	0.25848
	$1.5 \times \overline{OI_t}$			6.53996	49745	0.22166
	$0.5 \times \overline{OI_t}$			8.18468	48140	0.19386
	$5 \times \overline{OI_t}$			4.57984	45595	0.000863
	$0.1 \times \overline{OI_t}$			9.68234	41200	0.12888
3	$\overline{OI_t}$	(0,0)	Not Considered	6.46076	49940	0.2872
		(500,500)		7.98574	19535	0.00128
	$1.5 \times \overline{OI_t}$	(0,0)		6.1118	49945	0.26868
		(500,500)		7.61378	25825	0.00128
	$0.5 \times \overline{OI_t}$	(0,0)		6.73958	49925	0.31104
		(500,500)		8.34334	11295	0.0013

*: Parameters are set as: $\alpha_t = \overline{OI_t} + 1.5 \times \sigma_t$, $\beta_t = 1$, $n_1 = n_2 = 0.15$

Table 23: Simulation Result (3)

6.6 Managerial Implications

It is expected that the result of simulating the agent-based diffusion model can link to real phenomena and thus provide meaningful implications. In this section, several implications are discussed from both the aggregated level and the individual level, which is likely to be helpful to industry policy makers and managers in the organisations, respectively.

6.6.1 Effect of Organisational Innovativeness

Organisational innovativeness has long been considered as having an important effect both on innovation adoption and innovation diffusion. However, the definition of organisational innovativeness is blurred and sometime even conflicted. In this study, information regarding innovation from the environment and from other members of the system is considered differently since the nature of the behaviours resulting from these are different: the former source of the information is from the environment and it contains risk, causing the need for organisations to use their own knowledge and attitude to make decisions based on the information; the latter is relatively validated information and the decisions made based on the information is more related to the conformity effect. Therefore, it is obvious that the higher innovativeness an organisation has, the more open and positive it is to innovation information from the environment, thus leading to early adoption and faster diffusion.

From an aggregated level, previous studies, especially epidemic diffusion models, normally emphasise the external factors (factors outside the agents) of diffusion such as price and advertising. The result of this study further suggests that the internal factors (organisational innovativeness) also have a similar effect on diffusion. The simulation results suggest that the system level of organisational innovativeness is positively related to diffusion. Therefore, to encourage all organisations to engage in innovative activities is significant for the spread of an innovation, thus generating economic benefit more quickly for the system. Furthermore, as suggested in the model, an increase in the system level of organisational innovativeness at the beginning of the diffusion process leads to a better performance than when it is undertaken later, since a significant number of early adopters will also enhance the inter-organisational influence and thus speed up the whole diffusion process. Also the statistical distribution of organisational innovativeness is closely related to the diffusion process and the model suggests that the systems in which members' innovativeness tend to be more equal is better for diffusion than the systems where only a few extremely high innovative organisations exist. For instance, a similar issue in the marketing field can be explained as follows: innovation diffuses faster in countries with low Gini coefficient (see Glossary) from a long term view, if the GDP (see Glossary) per capital of the countries are similar.

At an individual level, the model identifies a notable correlation between a high innovativeness and early adoption/high adoption rate. Basically, it is believed that organisations with high innovativeness are capable of adopting innovations relative to others. Additionally, the model indicates that organisational innovativeness is especially important to those organisations that are keen to be innovators, but it is not the main factor for those organisations who want to stay in the majority category, and it is not the main reason for those organisations to become laggards. Therefore, it is concluded that organisations should only emit an excessive focus on their own innovative activities, if they are or they want to be the innovation leaders of the system.

6.6.2 Effect of Opinion Leadership

Most previous studies only emphasise the important role of individual opinion leaders. Normally they do not consider the role of opinion leadership at a system level. Furthermore, although the importance of opinion leadership is well recognised, people still lack knowledge of how important it is and how it can influence the diffusion process with quantitative understandings.

From the system level, there are two points that may be interesting for people to consider. First, the average level of opinion leadership (it is also reflected in q_t) does have a positive relationship with the rate of diffusion. Although the change of average level of opinion leadership does not have an immediate effect when compared with organisational innovativeness, it does have a bigger influence when taking the long term view. For those innovations that contain high risk, the policy makers may want to have a slow take-off in order to create enough time for a complete trial of the innovation, and a faster growth spurt when the utility of the innovation has been confirmed. In this case, it would be more efficient to alter the structure of opinion leadership in the system than to try to change those factors relating to organisational innovativeness and the environment. Second, the shape of the opinion leadership curve is also important for the overall diffusion process: those innovative opinion leaders will adopt the innovations earlier, influence others for a longer time, and speed up the whole diffusion process from a long term view. Therefore, this finding is somehow consistent with the existing studies on the important role of opinion leaders: to target those opinion leaders and make them adopt the innovations earlier is important for diffusion. According to the study of Banerjee (1992), if innovators are high status individuals who can lead others to imitate them, the diffusion process will become particularly fast. Third, the concentration level of the opinion leadership curve can further enlarge the effect discussed in the second issue. This finding suggests policy makers are making imbalanced opinion leadership structures where only a few innovative organisations are particularly influential and others are satisfied with the role of 'followers' in order to speed up the diffusion. Although this approach may prohibit innovation creation activities in the system from an overall view (as most organisations will just wait for the innovations instead of creating them), it can promote diffusion of a given innovation as suggested by the model.

To sum up, three aspects of the overall diffusion curve can be changed by opinion leadership: the average level of opinion leadership; the 'location' of opinion leaders; the concentration level of opinion leadership. In general, the diffusion rate can be increased by either increasing the average level of opinion leadership in the system, or by increasing the reputation and trust of those potentially early adopters and thus pushing them to be opinion leaders. It is believed that to further combine the above findings with the studies of innovation policy making will provide a new means of managing the diffusion trend.

6.6.3 *Effect of Innovativeness Difference*

A number of factors define social status. In this study, the author simply uses innovativeness as the indicator of social status, as it is assumed that the organisation with high innovativeness normally also has high social status within a system.

In the proposed agent-based diffusion model, the average level of the innovativeness difference effect is also determined by the value of parameter q_t. Therefore, it is easy to conclude that if organisations have a better channel for information transfer, the inter-organisational influence effect will be increased, positively affecting diffusion speed.

Furthermore, it is easier for organisations with high innovativeness to influence those with low innovativeness than it is in reverse. In other words, the fluidity of the information from innovators to non-innovators and from non-innovators to innovators impacts the diffusion process differently. Specifically, the information transferred from organisations with higher innovativeness to organisations with lower innovativeness is more valuable than it is in reverse. From model simulation with a fixed value of q_t, the consideration of the innovativeness difference effect still results in diffusion curves with a faster increase, which can be further enhanced by the 'location' of opinion leaders.

6.6.4 *Effect of Geographic Location*

A simple understanding of the location theory is this: organisations choose locations that can maximise their profits and people choose locations that can maximise utility. The location strategy of organisations when targeted at innovation has long been studied, but with various, sometimes conflicted findings. There are many reasons for these conflicted findings: the type of research target, the measures of geographic location effect, and use of different methodologies. However, it is commonly agreed that the geographic proximity of organisations can increase the level of interaction for knowledge/information, so organisations tend to cluster naturally (Gibbons 2004). Also clustering can be explained by a few other factors such as external threats, shared culture and ethics, similar interests, and pre-existing familiarity with other organisations (Doz, Olk & Ring 2000). This agent-based model is based on the assumption that physical distance has a negative and non-linear effect on inter-organisational influence, thus impacting both individual adoption and diffusion.

From an aggregated level, the model simulation indicates that the average effect of physical distance between all paired organisations is related to the diffusion process. This is similar to when q_t is used to represent the average level of opinion leadership in the system. Therefore, it is better to cluster all organisations in order to promote the information/knowledge transfer between them and thus speed up the diffusion process. However, if the change of organisations' locations does not influence q_t, to locate organisations in one cluster is still better than to locate them in a few clusters to the overall diffusion speed. This finding can give policy makers implications, for instance, 'one big science park and a few smaller science parks, which one is better?'

From the individual level, organisations' location strategies are varied according to their own characteristics. First, those innovators who already hold the most information/knowledge about innovations cannot normally receive valuable information/knowledge from others in the system as expected. Therefore, their innovation performance is not dependent upon the physical closeness with other organisations. Instead, they tend to be close to places with high innovative activities such as universities and research centres. Second, for the organisations who are neither innovators or laggards, an inter-organisational network is the key channel for gaining appropriate information about innovation. Therefore, the organisations need to be gathered in one area for better information/knowledge transfer and sharing. In order to combine ideas from the two aspects, Bathelt et al. (2004) used to propose a Local Buzz and Global Pipeline model, which means organisations clustered in a particular region also seek access to knowledge outside the cluster as an essential complement of the knowledge they can access locally. Third, laggards are not eager to identify innovations, and thus do not have the preference to be close to others and imitate them.

6.6.5 A Roadmap Towards Innovation

The following paragraph aims to combine the individual innovativeness strategies and individual location strategies discussed above, and develop an innovation roadmap for organisations. In the first step, the author proposes a new adopter-category model (see Section 2.4.1). This model is developed via the Rogers model of adopter-category, but combines the middle three categories into one (Table 24). In the new model, organisations are classified into three categories (innovators, the majority, and laggards) on the basis of their innovativeness levels.

Rogers Model	Percentage	Percentage	Our Model
Innovators	2.5%	2.5%	Innovators
Early Adopters	13.5%		
Early Majority	34%	81.5%	Majority
Late Majority	34%		
Laggards	16%	16%	Laggards

Table 24: A New Model of Adopter-Category

Combining the simulation results from this study, it is considered that laggards neither rely on themselves or others in adopting innovations, their adoption decisions are normally made based on 'luck'; for the organisations who fall into the majority category, information from others plays a dominant role in their decision making process and thus location is a central issue for them to consider; for the innovators, innovation decisions are mostly decided by their own innovativeness.

Following on from this, a framework (Figure 39) is developed. Corresponding to the above discussions, the framework can be explained as follows: if organisations want to remain as laggards, the strategy is to do 'nothing': no need for any innovation activities and no need to care about any location problems; if organisations want to move from being laggards to being part of the majority, movement to a cluster is more efficient than putting much effort into their own innovation activities. This is because to imitate others is easier than innovating by themselves; if organisations want to maintain their majority category, what they need to do is simply maintain the network with other organisations. Therefore, location remains more important than innovativeness; if organisations start planning to become the innovation-leaders in this system, they have to start investing themselves. They may consider moving away from other organisations, because the information from others will gradually become invaluable, and also because they do not want to be imitated by others anymore. Meanwhile, they may also consider their new locations as close to high innovative activities such as universities and research centres.

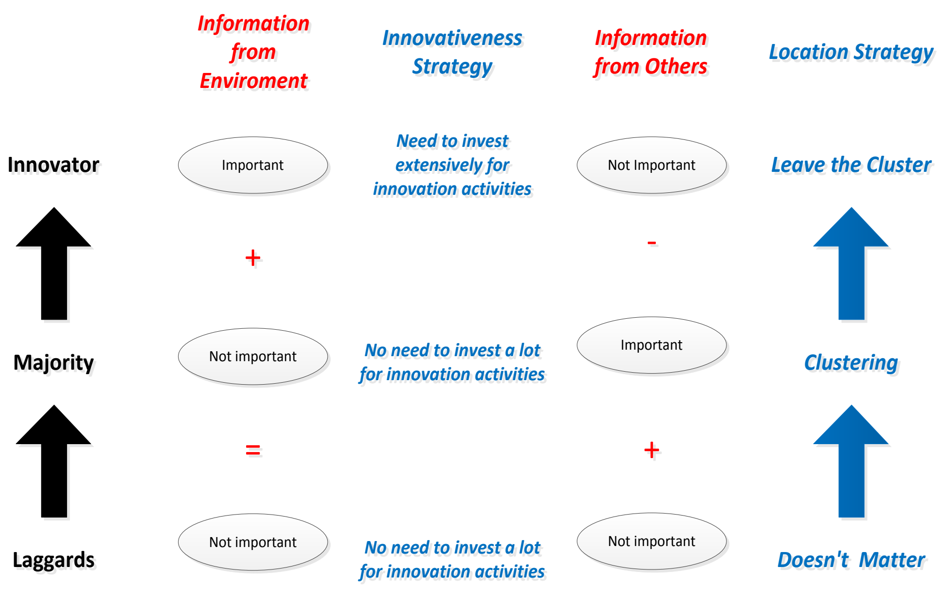


Figure 39: Innovativeness and Location Strategies

6.6.6 Quantitative Implications

It is clear that while many factors can contribute to diffusion speed, in most situations, only a few of these factors can be truly managed. This is due to various reasons such as ease of implementation and shortage of budget. Therefore, one challenging question for the decision makers is to decide the best strategy when limited recourses for innovative activities are available.

One merit of using mathematical equations is their ability to support further quantitative analysis. Through the proposed agent-based model and the following simulation study, we not only understand '*how each factor and its corresponding parameter(s) influence diffusion*', but also know '*how much each factor and its corresponding parameter(s) influence diffusion*'. Then by comparing the differences in diffusion caused by various factors and parameters, it is potentially beneficial for policy makers and organisation managers to make appropriate diffusion policies and organisation strategies.

6.7 Summary

This chapter analyses the agent-based diffusion model proposed in Chapter 4 under the simulation context designed in Chapter 5. It links the results of the simulation with real phenomena, and generates implications from both macro and micro levels.

The result from the NetLogo simulation shows a mimic view of the diffusion process. Additionally, it also tries to incorporate a few other factors such as multi-innovation diffusion, birth and death of organisations, cost of innovations, and organisational budgets. Although significant, some of these factors have rarely been considered in the existing diffusion model literature. This simulation may give implications for future modellers to further investigate the role these factors in diffusion actually play.

However, the NetLogo simulation only produces one single possible result from each simulation and it does not support further analysis for the model. Therefore, the proposed agent-based model is mostly simulated and analysed by using MatLab. Some results from the simulation are consistent with the findings in previous diffusion studies, while other results indicate findings that have not been proposed in the existing literature. A summary of the critical issues are presented as follows.

Findings that are consistent with the existing literature

Information regarding innovation from the environment exerts a positive influence throughout the diffusion process, while the information regarding innovation from other members in the system exerts a visible influence sometime after the start of diffusion. Therefore, the environmental effect contributes more to the take-off stage, while the inter-organisational influence plays an important role following the take-off stage;

The distribution of organisational innovativeness influences the overall diffusion process. Specifically, the diffusion speed changes positively when organisational innovativeness tends towards a left-skewed distribution, but negatively when it tends towards a right-skewed distribution. It does not change when it follows a normal distribution;

Organisational innovativeness has a positive effect on individual adoption decisions. The increased innovativeness level makes the organisation become more likely to adopt innovations;

Organisations that are far from others tend to suffer less influence from others, thus their adoption probability will decrease and their adoption time will delay.

Findings that have not been mentioned in the existing literature

The distribution of opinion leadership does have an impact on the overall diffusion process. Specifically, the diffusion speed increases when the curve of opinion leadership tends to be left-skewed; decreases when the curve of opinion leadership tends to be right-skewed; and it does not change when the curve of opinion leadership tends to be a normal distribution shape. Additionally, the effect caused by the shape of the opinion leadership curve will be further enlarged if the curve tends to be more concentrated. When the effect of innovativeness difference in the model is triggered (high-innovativeness organisations are more likely to influence low innovativeness organisations than it is in reverse), the diffusion speed increases, especially when the opinion leaders in the system tend to be early adopters.

Although the level of organisational innovativeness is positively related to organisations' adoption probability and average adoption time, this relationship is not a linear one. Specifically, organisational innovativeness is obviously vital for the innovators, while it does not visibly help the majorities and laggards.

The effect of geographic location proposed in this study also has a non-linear relationship with adoption probability and adoption time of each individual organisation. Specifically, although it does not influence the innovation performance of innovators and laggards significantly, it remains important for the majority.

Based on the above findings, this chapter further suggests a few implications that could benefit our understanding of the diffusion process: organisational innovativeness, opinion leadership, innovativeness difference, and geographic locations, from both the macro and micro level. Additionally, Section 6.6 proposes a roadmap to guide organisations who want to change their innovation strategies. Finally, a few quantitative implications are given with the aim of providing a means of quantifying these factors of diffusion in order to assist the creation of diffusion policy/strategy.

Chapter 7 Conclusions

"One of the greatest pains to human nature is the pain of a new idea"

Walter Bagehot (1826 - 1877)

There is extensive literature on the factors of diffusion and we discuss a few of them in this study through a modelling approach: the effect of organisational innovativeness on diffusion, the effect of opinion leadership on diffusion, the effect of geographic location on diffusion, the effect of self-conformity on diffusion, and the relationship between organisational innovativeness and opinion leadership. Furthermore, most of these studies tend to be independent. Therefore, this study raises a question that is, *'if the theories and empirical findings from those studies are combined, can we get anything more or anything different?'*.

This study models the diffusion phenomena with parameters/variables that represent the effect of organisational innovativeness, opinion leadership, innovativeness difference, and geographic location, respectively. Specifically, the model proposed in this study is based upon the theories and assumptions listed below:

Two Step Flow Theory (Katz & Lazarsfeld 1955) ***/the Bass model*** (Bass 1969):[37] this forms the basic structure of the proposed diffusion model in this work. Using the two step flow theory, diffusion influences are grouped into two streams: the environmental effect and the social contagion effect. Normally, the environmental effect is in the form of the mass media and the social contagion effect is explained by word of mouth. The Bass model is under the assumption that the environmental effect is equal to any member in the system and that the social contagion effect is linearly related to the number of existing adopters.

[37] Readers are referred to Chapter 3 of this thesis, where it shows that the Bass model is developed on the basis of two step flow theory.

The von Neumann-Morgenstern Framework (von Neumann & Morgenstern 1947): this framework is based on the assumption that potential adopters are risk averse towards an innovation. As with the Bass model, this framework has also been well praised for explaining the diffusion curve. There are mainly two reasons for introducing the ideas from this framework into the proposed model. One is to modify the simple linear relationship between the amount of information about the innovation and the adoption probability in the Bass model. The other is to convert the parameter region, so the modified model is capable of covering a greatly diverse individual range.

Opinion Leadership in Diffusion: the concept of opinion leadership was originally proposed in the two step flow theory but then studied excessively as an independent topic, due to its unique role in diffusion. Opinion leaders are those individuals who act as information spreaders in diffusion. Without opinion leaders, information would be hard to transfer between individual members. As a central topic in diffusion, its concept, significance, characteristics, measures, and relationship to innovativeness have been widely studied. However, the way of incorporating opinion leadership as a factor into diffusion models is a field that has not been fully explored. Specifically in this study, two findings about opinion leadership, taken from the current literature, are used to model opinion leadership. First and to generalise, opinion leadership is positively related to innovativeness. Second, opinion leadership does not always increase along with innovativeness. Instead, it decreases after reaching a peak point that is determined by the characteristics of the system.

Innovativeness Difference in Diffusion: beyond social contagion, self-conformity is another way of understanding the force of diffusion (Ansari, Fiss & Zajac 2010). Organisations are more likely to imitate others who have similar innovativeness levels, since they share similar characteristics and normally desire similar requirements from the innovation. This argument has been proposed and discussed in a number of works (Moore 1991; Riesman 1950; Homans 1960;

Bourdieu 1984; Van den Bulte & Joshi 2007). Following the ideas from the dual market diffusion models and global diffusion models, this study seeks to further explore the role of innovativeness difference in diffusion. Based on the above knowledge, the author makes two assumptions on this topic. First, the level of innovativeness difference is negatively and nonlinearly related to inter-organisational influence. Second, organisations with lower innovativeness levels are even more difficult to influence organisations with higher innovativeness.

Geographic Location in Diffusion: the geographic location of organisations, and more specifically in this study, the physical distance between organisations, is investigated as the final variable. The existing literature shows that the role of geographic location in diffusion is very much related to the research context. This work assumes that the inter-organisational influence between two organisations decreases exponentially with their physical distance.

To sum up, the model in this study is developed via theories and assumptions derived from the current literature. Then the model is analysed through a simulation approach so as to understand the role of each targeted interest.

7.1 Chapter Revisit

Chapter 1 is the introduction of this thesis that explains the research background, the research gaps, the research questions, potential contributions, and the thesis structure. Section 1.1 reveals that innovations are imperative for organisations. Then Section 1.2 further states that innovations need diffusion to attain their ultimate economic value. The research questions in this study are influenced by a desire to combine a number of concepts (organisational innovativeness, opinion leadership, innovativeness difference) into a diffusion model, in order to understand their respective roles in diffusion.

Chapter 2 reviews the existing knowledge on organisational innovativeness and diffusion models. The aim of reviewing the organisational innovativeness literature is to explain that organisational innovativeness is significant to an organisation's adoption behaviour, and that it is also measurable, so it should be a valuable variable in diffusion models. The literature review of diffusion models aims to give a historical understanding of the development of diffusion models in order to provide some inspiration on the development of the agent-based model in this study. Additionally, as the initial motivation of this work is to find a way of introducing organisational innovativeness into diffusion models, it is also valuable to explore the existing knowledge on the link between these two concepts. Therefore, the third section of the chapter tries to dig into this area by analysing models of adopter-category. The review does show a close link between organisational innovativeness and diffusion models: on the one hand, the adopter-category models normally use individual innovativeness levels to assign organisations into certain pre-defined categories; on the other, the adopter-category models can be a direct way to draw a diffusion curve.

The modified Bass model proposed in Chapter 3 was subsequently used as the basic structure for developing the agent-based diffusion model outlined in Chapter 4. This modified Bass model fills a few of the Bass model limitations, and it does this, by incorporating ideas from the von Neumann-Morgenstern framework. Additionally, the model can incorporate individual diversities with a greater range compared with the Bass model. The empirical study shows that the modified Bass model is a good fit to the real data.

Chapter 4 is at the core of this thesis, introducing an agent-based model to solve the research questions and fill in the research gaps. The attributes of the proposed model is summarised as follows: first, the agent-based model is an extension of the modified Bass model in Chapter 3, and thus it is also based on the assumption that potential adopters are, on average, risk averse. Second, organisational innovativeness is used to update the information flow between organisations and the environment. Third, opinion leadership is introduced into the model of inter-organisational influence and modelled by using innovativeness as a direct indicator; this is abstracted from a list of theories, propositions, and empirical findings in the existing literature. Fourth, organisational innovativeness is assumed to be an indicator of the social status of the organisation and thus the innovativeness difference between the two organisations is used to represent the social status difference between them. Fifth, the author focuses on physical distance as a supplement to the inter-organisational influence.

Chapter 5 explains the research methodology used in this work. The application of the proposed agent-based model only requires two inputs, organisational innovativeness and geographic location, which are both measureable. However, this work uses a simulation study in order to explore the diffusion phenomena from a generalised perspective. The simulation context defined in this study is a typical diffusion process of an innovation in a specific industry. The inputs of the proposed model (organisational innovativeness and geographic location) are generated through specific statistical distributions derived from the current literature, and the range of parameters is also defined from previous empirical works. However, it should be emphasised again that the context only represents a general diffusion process, and not specific cases. The end of this section gives an example of how to implement the proposed agent-based model in a real word case.

Following the simulation context defined in the previous chapter, Chapter 6 simulates the proposed agent-based diffusion model, analyses the findings, and tries to link these findings to real phenomena, in order to provide implications. The result of the simulation is analysed from both macro and micro levels with respective approaches and indicators and thus benefits both policy makers and organisation managers.

7.2 Summary of Major Findings

A modified Bass model is developed by combining the ideas from the Bass model and the von Neumann-Morgenstern framework. After gathering 12 sets of real diffusion data from previous diffusion studies, the author makes an empirical test on the performance of the modified Bass model through a NLLS + numerical analysis parameter estimation approach. The empirical analysis shows that the modified Bass model performs similarly to the Bass model and is even superior in a few circumstances. Also the result shows that different diffusion models may fit different diffusion data sets. Finally, and most importantly, this model can be used at the individual level and is able to incorporate factors of diffusion with great diversity.

The proposed agent-based diffusion model is developed based on the structure of the modified Bass model. It maintains all characteristics inherited from the modified Bass model, and it consists of a few additional factors: organisational innovativeness, opinion leadership, innovativeness difference, and geographic location. Results of the model simulation shows good fit with the findings in a few previous studies. Furthermore, it provides a way of quantifying these concepts for further analysis and suggests implications for both policy makers and mangers in organisations.

From an aggregated level, a few findings are summarised as follows. First, the mass media and word-of-mouth are both positively related to the diffusion process. The simulation result is also consistent with previous literature on the importance of the take-off stage in diffusion (Mahajan & Muller 1998). Second, the diffusion process can still be influenced by the distribution of organisational innovativeness when the average innovativeness level of the system is fixed. A few similar attempts in the marketing literature have used Gini coefficient and GDP per capital as a measure of the consumer tendency to adopt innovations (specifically, use Gini coefficient to explain the distribution of consumers' innovativeness) and thus to model the diffusion process (Van den Bulte & Stremersch 2004). The findings here further emphasise the importance of incorporating measures of organisational innovativeness in diffusion models. Third and more importantly, the model suggests that the distribution of opinion leadership also impacts upon diffusion: the diffusion rate will increase if opinion leaders tend to be innovators and will further speed up if opinion leadership is held intensively by only a few innovative organisations. Therefore, to target those key opinion leaders and shorten their adoption time is significant for diffusion. Furthermore, the model provides quantitative discussions on the effect of manipulating the 'location' of opinion leaders, which could implicate policy makers. For instance, as an alternative to increasing the average innovativeness of the system by 5%, policy makers can alter the 'location' of opinion leaders by moving them from the middle of the adopter-category model to the early-adopter category. Fourth, organisations tend to influence others with similar levels of innovativeness to themselves, and the information transferred from organisations with higher innovativeness to organisations with lower innovativeness is more valuable than it is in reverse. From model simulation, the consideration of the innovativeness difference effect results in diffusion curves with a faster increase, which can be further enhanced by the 'location' of opinion leaders. Finally, the distribution of organisational locations does affect the diffusion speed at a system level: to cluster organisations in one area is better for the diffusion of innovation, even if the average geographic location effect of all paired organisations in the system does not change.

The result of analysing organisational innovativeness and geographic location at an individual level can be summarised as follows: organisational innovativeness and geographic location are both related to the adoption behaviours of organisations, but at different degrees due to the characteristics of the organisations; organisations' self-effort is the only way for being innovators in diffusion, but is not important for those that are not very innovative; the inter-organisational influence including opinion leadership, innovativeness differences, and the geographic location effect is significant for the majority, but not for innovators or laggards.

Together, the above findings explain how the change of parameters and variables will influence the interested factors of diffusion (organisational innovativeness, opinion leadership, and geographic location), and thus influence individual adoption behaviours and the overall diffusion trend. Therefore, the research questions are answered.

7.3 Research Contributions

This study contributes to the existing body of knowledge from three perspectives, from that of: the academic literature; the methodology of diffusion models; and the theory of practice. These contributions are summarised below.

7.3.1 Contribution to Academic Theory

Through modelling and simulating the diffusion process with factors, this study correspondingly fills in the research gaps that are listed in Section 1.3.

The first research gap can be identified as occurring in work by Hauser (2006), where it points out the issue of incorporating measures of innovativeness into diffusion models. The current study covers this issue from two aspects. In the literature review chapter, the author reviews the measures of organisational innovativeness, which can be used as a guideline to assess organisational innovativeness. Then in the proposed agent-based diffusion model, organisational innovativeness is incorporated as a key factor. By combining the two aspects, this study shows that innovativeness is both measurable and modellable. However, this gap is not fully covered, as the author does not develop an explicit measure of organisational innovativeness and the proposed model is not validated by real data. This leaves opportunities for future studies in this field.

The second research gap listed in Section 1.3 is the role of opinion leadership in diffusion models. This work use innovativeness to model opinion leadership in order to emphasise the close link between them that has already been discussed. The result of the simulation shows a comprehensive view as to the role of opinion leadership in diffusion, something only partially discussed in the existing literature.

Location issues in diffusion models make up the third gap. Most location studies in the field of diffusion usually try to explore how the cluster phenomenon can influence diffusion speed and how the location of one organisation can benefit itself in innovation adoption. However, the author believes that two issues have been neglected in this field. First, how the distribution of organisations' locations can influence the diffusion from a system level has not been fully investigated. Second, the characteristics of organisations are different, so clustering may not be the answer for all of them. Under the assumption that the physical distance between organisations will weaken the inter-organisational influence, this work explores the location strategy from both macro and micro levels.

The fourth gap mentioned in Section 1.3 is the potential link between epidemic diffusion models and probit diffusion models. As a bridge between macro level diffusion models and micro level diffusion models, the agent-based diffusion models that focus on both individual characteristics and the interactions between them and the environment, have been increasingly popular in modelling diffusion phenomena. The proposed model in this study consists of the fundamental ideas of the epidemic diffusion model and probit diffusion model, showing that the two streams of modelling approaches can be combined together to create more meaningful models.

The final issue, the synthesised view of the social contagion effect and the self-conformity effect in diffusion, is partially answered by introducing the factor of innovativeness difference into the proposed diffusion model. On the one hand, most diffusion models, including the proposed model in this study, are developed based on the understanding of the social contagion effect. On the other, the concept of self-conformity has been inspired by a few models such as some dual-market diffusion models, which consider this effect from a multi-category level by grouping individuals or organisations into a number of categories due to social status. The proposed model in this study uses innovativeness difference as an indicator to explain how much a potential adopter wants to imitate each of the existing adopters.

7.3.2 Contribution to the Methodology of Diffusion Models

It is always good for models to be validated and analysed by the use of real world data. However, a simulation study is used in this work for the following reasons. First, simple models such as the Bass model have an analytical solution, which can benefit further analysis. While for other models, it is difficult to analyse in an analytical way due to their complex structure. Through a simulation study, parameters and variables can be controlled in order to test their effects, and thus an analytical solution becomes unnecessary. Second, the desired real world data could be very difficult to obtain. Through a simulation study, data can be generated through a logical means, that is, by way of computer, which will largely reduce the cost of model validation. Finally and most importantly, the results generated by the real world data are only the results for a few specific cases, and the data may contain different degrees of bias due to the various contexts. Through a simulation study, a wide range of possible inputs can be generated and thus the result can show a complete view of the phenomenon. To sum up, this study shows that a simulation study can be a good alternative to the traditional analytical and empirical methodologies, and is even superior in a few aspects.

Furthermore, the author developed a parameter estimation technique in Section 3.6, which can be applied to those models that do not have a closed form solution. An experiment shows that this technique is accurate and robust, also that it is simple to implement.

7.3.3 Contribution to Theory of Practice

With the proposed model and its simulation results, two practical questions can be raised here. First, as a policy maker, how to manipulate the diffusion process of an innovation through influencing innovativeness, opinion leaderships, and locations of the organisations? Second, as a manager of an organisation, how to make appropriate innovativeness and location strategies to match its innovation positioning? We provide some implications to these two questions as follows.

On the macro level, this study suggests a few ways that the policy makers can manipulate the diffusion process. First, innovativeness is a key factor needs to be considered in diffusion and diffusion models. This study further suggests that the shape of innovativeness distribution also has a direct impact on diffusion. The simulation result shows that more organisations with high innovativeness is more important to the diffusion rate than a few organisations that are very innovative. Second, the results of this study suggest that to push opinion leaders to become more innovative and to enhance those opinion leaders' influence is significant for the speed of diffusion. Third, if the information transfer from high-innovativeness organisations to low-innovativeness organisations is more fluency than it is in reverse, the diffusion rate will increase. Fourth, to cluster organisations in one area is always better for the diffusion rate, even if the average level of interactions between organisations is controlled.

On the micro level, this study also promotes thinking about organisations' innovation strategies. Innovative organisations should focus more on their own development, and to a certain degree they even need to limit their contact with others in order to protect their 'knowledge' of innovations. According to Alcácer and Chung (2007), innovative organisations choose only locations with high levels of academic activity (such as universities and research centres) and try to avoid locations with industrial activity so as to distance themselves from competitors. Also Pouder and Caron (1996) point out that clusters will gradually become a limitation for innovative organisations, as they may view the future from a cluster level, rather than an industry level. However, for the majority of companies that are not very innovative, these should pay more attention to their relationship with others for information/knowledge sharing in order to avoid becoming laggards. Therefore, organisations with lower innovativeness tend to be close to innovators (Alcácer & Chung 2007) and Alcácer (2006) have also found that less-capable organisations collocate more than the capable ones.

7.4 Research Limitations

Most importantly, the author has developed the model based on a combination of the theories, the abstract of the facts, and the assumptions that are deduced from the existing findings. Therefore, the phenomena represented by the proposed model cannot totally match the real world. In other words, the model and its result only show a generalised view of the problem, but may not match each individual case. Also during the model simulation, for instance, Normal distribution and Gamma distribution are used to generate organisational innovativeness for the simulation study, while in real world the distribution of organisational innovativeness is usually a complex phenomenon that cannot be explained by a simple and smooth curve. Furthermore, as the model is an extension of the modified Bass model outlined in Chapter 3, it operates under the assumption that the potential adopters are averagely risk averse. Although a number of empirical studies have shown that using risk averse to present the potential adopters' average risk attitude can provide a good fit with the real world data, this assumption could also be the limitation of this model because the potential adopters also could be risk neutral or even risk seeking on average. However, these limitations listed in this paragraph are all due to the nature of theoretical research. This is what theorisation should be and that is why the author cites Solow's (1956) argument on theorisation at the beginning of Chapter 4.

The proposed agent-based diffusion model is discussed only on the basis of theoretical analysis and computing simulation, so it lacks appropriate real data for further validation and analysis. For instance, although the current literature provides a wide range of measures for assessing organisational innovativeness, they are all limited in certain aspects such as ease of implementation, accuracy, recall problem, and so on; also the opinion leadership is modelled based on organisational innovativeness in this study, not first-hand data.

This model sacrifices a few attributes in order to introduce those factors of diffusion: due to its complex model structure, this model cannot provide a closed-form solution, which may limit the model value for further analysis to a certain degree; its ease of application may also be influenced.

7.5 Future Research

Future research can be made by either filling the research limitations listed in Section 7.4 or extending the current model to answer other questions. A few potential areas are listed as follows.

7.5.1 Empirical Support

To further validate the model, annual data from individual organisations is needed. The data includes an organisation's annual innovativeness data and geographical location data. In addition, it would be beneficial if the annual data for assessing an organisation's opinion leadership was available.

7.5.1.1 Organisational Innovativeness and Opinion Leadership

Measures of organisational innovativeness are usually influenced by not only the factors listed in Section 2.2.2, but also those commonly used moderators. In order to avoid biases from these moderators, the research context should be carefully defined. Damanpour (1991) lists four moderators that can potentially influence the results of organisational innovation studies: types of organisation, types of innovation, scope of innovation, and stages of innovation. Furthermore, size is also believed to have a certain effect on measure results (Damanpour 1992).

A few guidelines for the desired measure of organisational innovativeness are listed as follows. First, as the data is used to study the diffusion of an innovation in an industry, the effect of innovation type and cross-industry effect can be ignored. Second, different industries have different intensities toward innovation (Smith 2005). Generally, innovative industries have more innovations to study and organisations in these industries are more eager to engage in innovative activities. Therefore, data from high-tech industries is preferable. Third, it is expected that a measure can assess organisational innovativeness from an overall view in order to indicate the overall ability of organisations towards adopting innovations. Therefore, a mix of indicators would be preferred. Fourth, the data should be received on an annual basis.

To gain real opinion leadership data can be beneficial to the current study from two perspectives: it can validate the relationship between the organisational innovativeness and opinion leadership that is proposed in this study; it can validate the proposed diffusion model and thus also validate the relevant results that are derived from the model. As discussed in Section 4.7.1, the existing measures of opinion leadership are mainly made through surveys or observations. Similar to the desired measure of organisational innovativeness, the expected measure of opinion leadership should also be accurate and on a time serial basis.

7.5.1.2 Geographic Location

Compared with organisational innovativeness and opinion leadership, the physical distance between each paired organisation is relatively easy to obtain. However, to use physical distance as the indicator of geographic location effect has limitations, since the effect of physical distance on organisations' interactions is further influenced by other factors such as communication technology, ease of transportation, and so on. Therefore, alternative measures of geographic locations are desired in order to assess the model from other perspectives for potentially different implications. For instance, the concept of Voronoi Polygons has been used in marketing as a representation of geographic proximity (Hofstede, Wedel & Steenkamp 2002; Bronnenberg & Mela 2004; Bronnenberg & Mahajan 2001). This approach divides geographic space into mutually exclusive areas around certain centres. Also the physical distance can be modified into 'weighted distance' on the basis of other factors.

7.5.2 Network Effect in Diffusion

Network effect takes on an important role in diffusion, since within- and cross-segment communications within a network structure exert significant influence on the diffusion process (Bohlmann, Calantone & Zhao 2010). Network effect can be broadly defined as the circumstance whereby the action of one agent is influenced by the number of agents taking similar actions (Liebowitz & Margolis 1994). Network effect has great similarities with the social contagion effect, the concept used in diffusion and diffusion models.

In the studies of Farrell and Saloner (1985) and Katz and Shapiro (1985), direct and indirect network externalities are distinguished. Direct network externalities are those that are generated through a direct physical effect of the number of adopters on the quality of the product, for instance, the quality of the communication tools (such as mobile phone, email, social networking website, and so on) depend very much on the number of existing users. Indirect network externalities also depends on the number of usages on the quality of the product, but the benefit does not go to the product itself, for instance, the more people have adopted a type of hardware, the more software based on the hardware users normally can get. These two types of network externalities are not distinguished in the current diffusion models.

7.5.3 Risk Attitude and Social Learning

As mentioned before, the proposed model is limited by the assumption that potential adopters are averagely risk averse. Therefore, one interesting opportunity here could be the introduction of a whole set of risk attitude factors, that either differentiate potential adopters into three categories (risk averse, risk neutral, and risk seeking) or use a variable to present the level of risk attitude. The result may give people more implications as to the effect of adopters' attitudes towards innovation and thus on the whole diffusion process.

Most diffusion models, especially the simple ones, tend to depict the aggregated trend of diffusion based upon an assumption that the innovation will finally be diffused successfully. They are incapable of explaining the uncertain nature of the take-off stage of diffusion. According to Delre et al. (2007), 90% of innovations proposed by R&D departments are not finally approved by other departments, 50% of innovations introduced into the market fail completely, and more than 70% of the rest do not reach their expected goals. To model these diffusion phenomena we may need to introduce ideas from social learning models. These social learning diffusion models propose that potential adopters evaluate the value of positive feedback from exiting adopters and make their adoption decisions. They might be a great supplement to the current diffusion models.

7.5.4 Optimisation Issues

Optimisation is one of the key fields in operational research. Optimisation problems refer to the selection of the best element from a set of alternatives in order to achieve the best performance. Based on the proposed model in this study, it is possible to explore a few more optimisation issues and a typical question here could be: '*When the costs of the following items are identical, how do you manage the diffusion efficiently with a limited budget?*'

Cost of changing the organisational innovativeness;

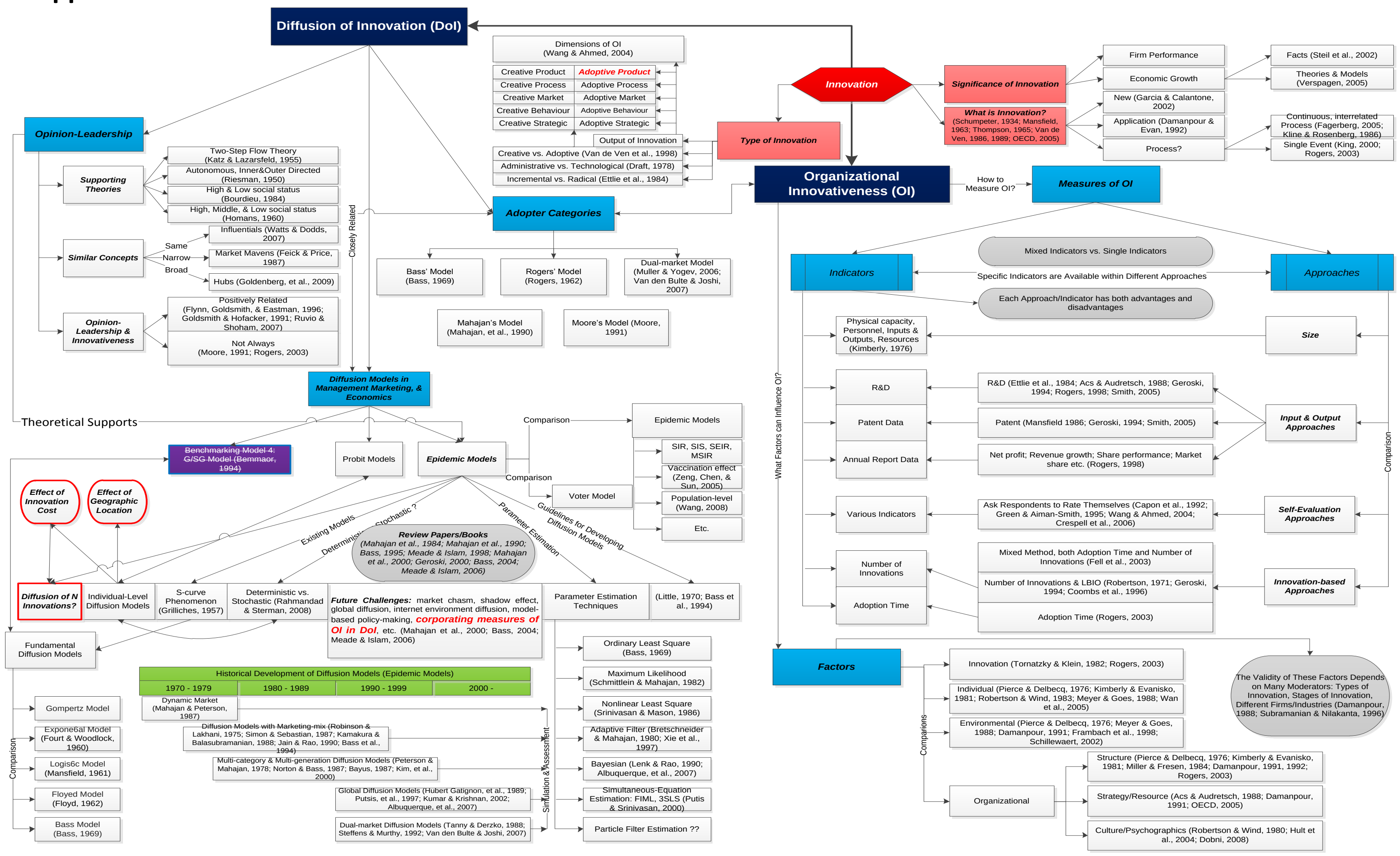
Cost of changing the opinion leadership;

Cost of changing the location of organisations;

Cost of changing other factors that are indicated by the corresponding parameters in the proposed diffusion model.

The answer to this question is potential to help developing better innovation strategies.

Appendix 1: Literature Review Framework



Appendix 2: Measuring Organisational Innovativeness – a trial analysis

Eleven world-leading pharmacy companies are studied and the data is collected through DataStream. Six organisational innovativeness indicators are used here including R&D/net sales, R&D/market Value, number of employees, net sales, R&D expenditure, market value, and net income. The data is analysed by using correlation and factor analysis. A few findings are listed as below:

- R&D/Net sales and R&D/Market value are not correlated with any of the other indicators except number of employees (-0.429 and 0.464 respectively);
- R&D/net sales and R&D/market value are negatively related and the correlation is not significant (-0.262);
- R&D expenditure, net sales, net income, market value, and are correlated significantly;
- The result of factor analysis is generally considerable (0.681);
- Six organisational innovativeness indicators finally reduce to two latent variables: the first has a good representation to R&D, net sales, number of employees, net income, and market value (all positive); the second one has a good representation to R&D/net sales and R&D/market value and also combines considerable parts of number of employees and market value. Therefore, the two latent variables might lead to organisational innovativeness capacity and organisational innovativeness intensity respectively.

	Mean	Std. Deviation	N
R&D/Net sales	.13593315813474	.047380051562006	165
R&D/Market Value	.07479029516173	.181868803669648	165
Number of Employees	59322.74	37553.799	165
Net sales	1.95E7	1.434E7	165
R&D	2539869.53	1.978E6	165
Net Income	3130822.87	2.892E6	165
Market Value	7.18E7	5.822E7	165

		R&D/Net sales	R&D/Market Value	Number of Employees	Net sales	R&D	Net Income	Market Value
R&D/Net sales	Pearson Correlation	1	-.262**	-.429**	-.160*	.169*	.098	.171*
	Sig. (2-tailed)		.001	.000	.039	.030	.211	.028
	Sum of Squares and Cross-products	.368	-.371	-1.251E5	-1.788E7	2.591E6	2.199E6	7.719E7
	Covariance	.002	-.002	-763.065	-1.090E5	15797.608	13408.145	470675.866
	N	165	165	165	165	165	165	165
R&D/Market Value	Pearson Correlation	-.262**	1	.464**	.184*	.001	-.098	-.269**
	Sig. (2-tailed)	.001		.000	.018	.986	.209	.000
	Sum of Squares and Cross-products	-.371	5.425	519501.927	7.881E7	80423.025	-8.484E6	-4.671E8
	Covariance	-.002	.033	3167.695	480559.172	490.384	-51734.755	-2.848E6
	N	165	165	165	165	165	165	165
Number of Employees	Pearson Correlation	-.429**	.464**	1	.850**	.643**	.493**	.445**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000
	Sum of Squares and Cross-products	-1.251E5	519501.927	2.313E11	7.504E13	7.827E12	8.789E12	1.595E14
	Covariance	-763.065	3167.695	1.410E9	4.575E11	4.772E10	5.359E10	9.728E11
	N	165	165	165	165	165	165	165
Net sales	Pearson Correlation	-.160*	.184*	.850**	1	.909**	.767**	.647**
	Sig. (2-tailed)	.039	.018	.000		.000	.000	.000
	Sum of Squares and Cross-products	-1.788E7	7.881E7	7.504E13	3.372E16	4.230E15	5.219E15	8.862E16
	Covariance	-1.090E5	480559.172	4.575E11	2.056E14	2.579E13	3.182E13	5.404E14
	N	165	165	165	165	165	165	165
R&D	Pearson Correlation	.169*	.001	.643**	.909**	1	.832**	.742**
	Sig. (2-tailed)	.030	.986	.000	.000		.000	.000
	Sum of Squares and Cross-products	2.591E6	80423.025	7.827E12	4.230E15	6.416E14	7.808E14	1.402E16
	Covariance	15797.608	490.384	4.772E10	2.579E13	3.912E12	4.761E12	8.549E13
	N	165	165	165	165	165	165	165
Net Income	Pearson Correlation	.098	-.098	.493**	.767**	.832**	1	.716**
	Sig. (2-tailed)	.211	.209	.000	.000	.000		.000
	Sum of Squares and Cross-products	2.199E6	-8.484E6	8.789E12	5.219E15	7.808E14	1.372E15	1.978E16
	Covariance	13408.145	-51734.755	5.359E10	3.182E13	4.761E12	8.364E12	1.206E14
	N	165	165	165	165	165	165	165
Market Value	Pearson Correlation	.171*	-.269**	.445**	.647**	.742**	.716**	1
	Sig. (2-tailed)	.028	.000	.000	.000	.000	.000	
	Sum of Squares and Cross-products	7.719E7	-4.671E8	1.595E14	8.862E16	1.402E16	1.978E16	5.559E17
	Covariance	470675.866	-2.848E6	9.728E11	5.404E14	8.549E13	1.206E14	3.390E15
	N	165	165	165	165	165	165	165

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.681
Bartlett's Test of Sphericity	Approx. Chi-Square	1190.559
	df	21
	Sig.	.000

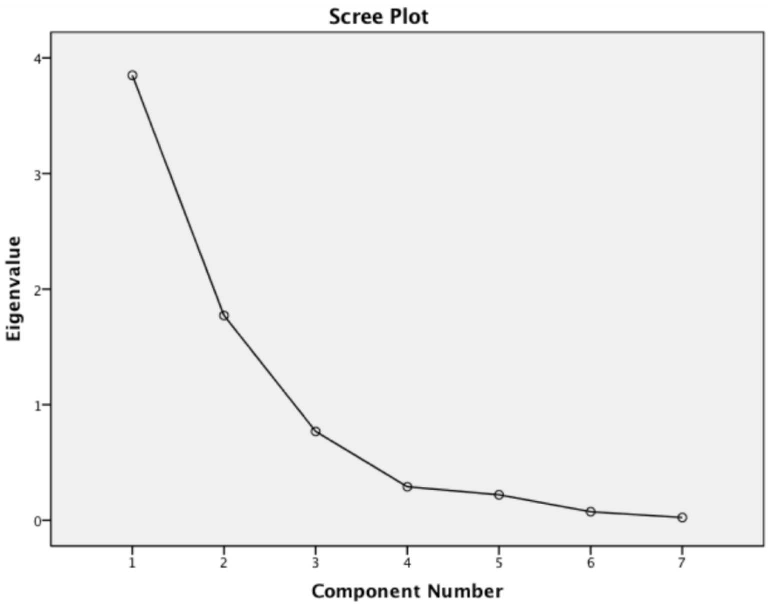
	Initial	Extraction
R&D/Net sales	1.000	.580
R&D/Market Value	1.000	.635
Net sales	1.000	.951
Number of Employees	1.000	.928
R&D	1.000	.923
Net Income	1.000	.815
Market Value	1.000	.790

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.849	54.993	54.993	3.849	54.993	54.993	3.792	54.175	54.175
2	1.772	25.309	80.301	1.772	25.309	80.301	1.829	26.126	80.301
3	.769	10.984	91.285						
4	.290	4.148	95.433						
5	.221	3.156	98.589						
6	.074	1.062	99.652						
7	.024	.348	100.000						

	Component	
	1	2
R&D/Net sales	-.049	.760
R&D/Market Value	.092	-.791
Net sales	.962	-.159
Number of Employees	.797	-.542
R&D	.945	.174
Net Income	.868	.248
Market Value	.796	.396

	Component	
	1	2
R&D/Net sales	.078	-.758
R&D/Market Value	-.041	.796
Net sales	.922	.317
Number of Employees	.696	.666
R&D	.960	-.015
Net Income	.897	-.100
Market Value	.850	-.258

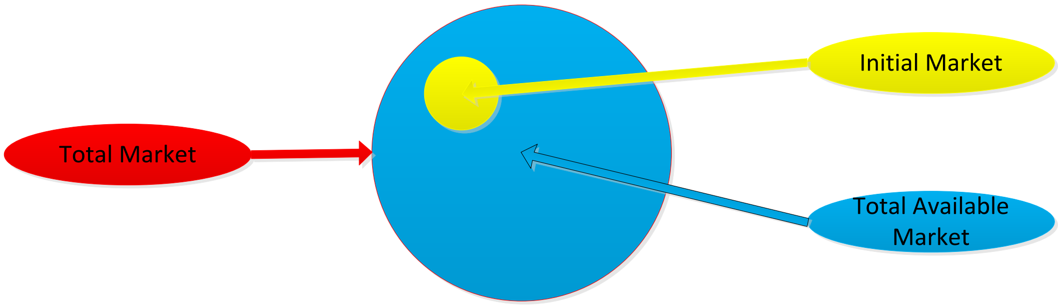
Component		1	2
	1	.986	.166
	2	.166	-.986



In this trial analysis, the author also uses inflation rate and log function to modify the data respectively. However, the performance does not improve. The reason might be that most of the indicators are currency-based figures (except number of employees). If they are modified and changed together following the same means, the overall performance is not influenced significantly.

Appendix 3: Re-Consideration of The G/SG Model

After setting the value of $t(0)$ and $F(0)$ in the Gompertz model, we consider the adopters before $t(0)$ as Initial Market M_I within the Total Market M_T and we want to predict the diffusion process in the left Total Available Market M_{TA}, which means $M_{TA} = M_T - M_I$ (see the figure below). Following Gompertz model $F(t) = M_{TA} \times e^{-\eta e^{-bt}}$.



Then we further assume that Total Available Market M_{TA} is dynamic, and specifically, the growth rate of new available market falls exponentially: $M'_{TA} = be^{-bt}$. Therefore, Gompertz model becomes: $F(t) = M_{TA}(1 - e^{-bt}) \times e^{-\eta e^{-bt}}$, which is G/SG model.

The reason why $(1 - e^{-bt})$ is used to represent the increasing market M_{TA} is because there is an underlying assumption here, 'change of an unit market is a Poisson process'. From another aspect, we can also understand this issue as: the change rate of M_{TA} is a constant ($\frac{M'_{TA}}{1-M_{TA}} = constant$)

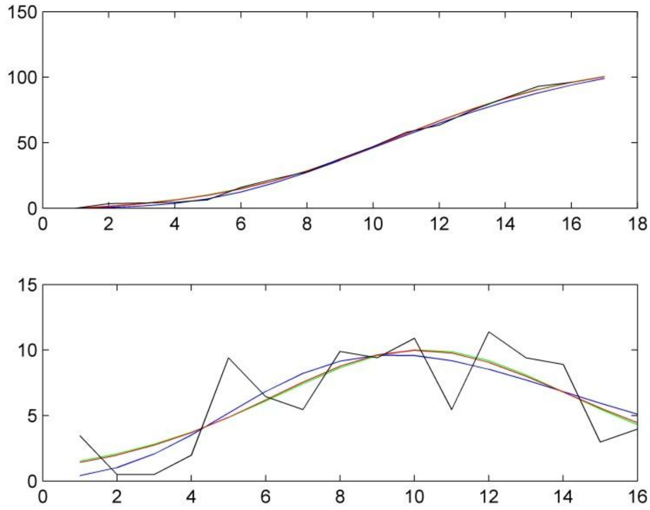
Back to the Gompertz Law, we can transform Shifted Gompertz Function into the following version: $K\frac{\left(F(t)/\left(1-e^{-bt}\right)\right)'}{F(t)/\left(1-e^{-bt}\right)} = \frac{1}{F(t)/\left(1-e^{-bt}\right)}$. So we can understand the G/SG model as: '*Relative growth rate falls exponentially with current relative size*'.

Appendix 4: Performance of Diffusion Models

This appendix shows the resulting figures from the comparison of the three diffusion models (the Bass model, the Gompertz Model, and the modified Bass model) in Chapter 3.

In these figures, the black curves represent the real data; the red curves represent the diffusion processes estimated by the modified Bass model; the blue curves represent the diffusion processes estimated by the Gompertz Model; and the green curves represent the diffusion processes estimated by the Bass model.

12 sets of curves represent 12 diffusion processes respectively. There are two figures in each set of curves. Specifically, the bell shape curves are the results of the number of new adopters and the S-shape curves are the results of the cumulative number of adopters.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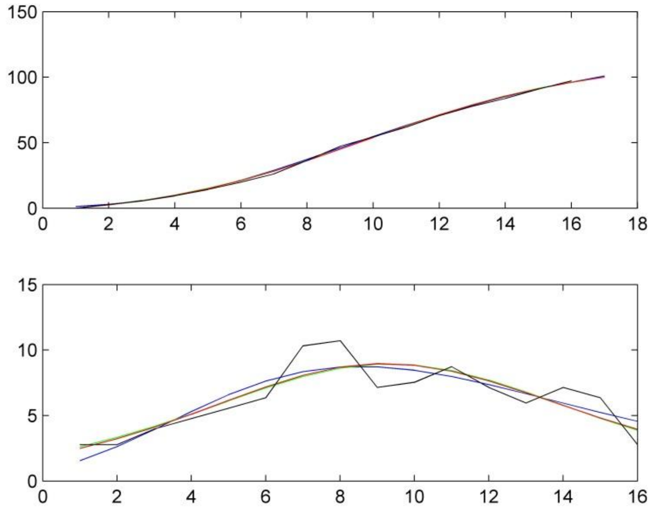
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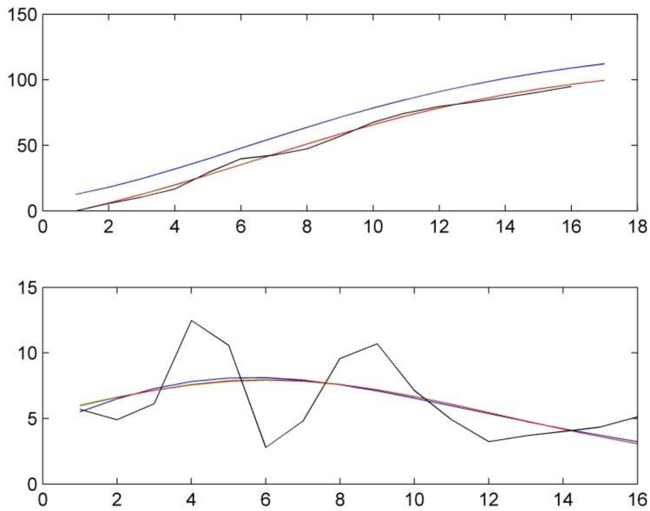
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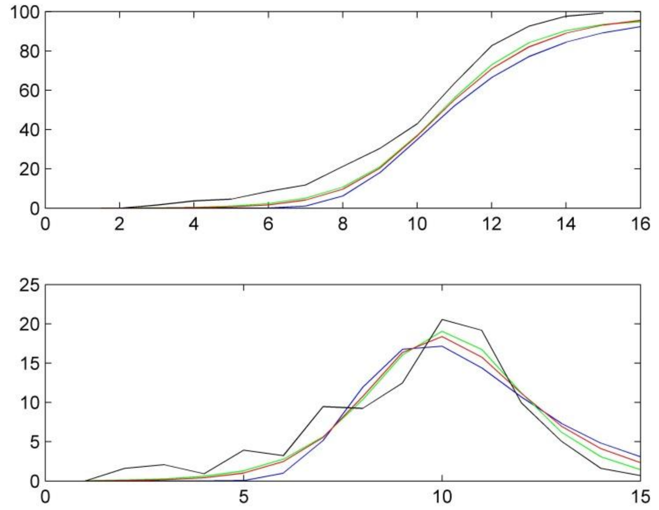
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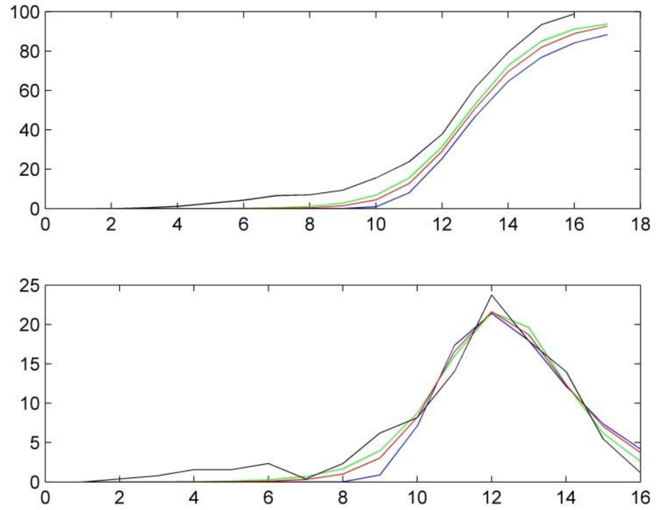
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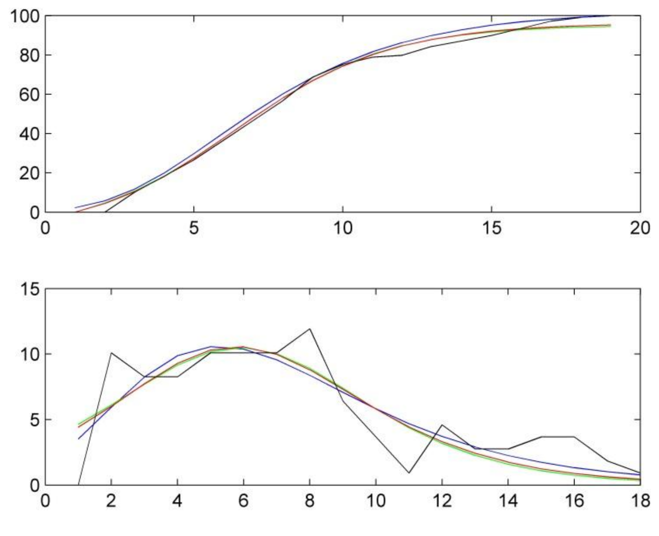
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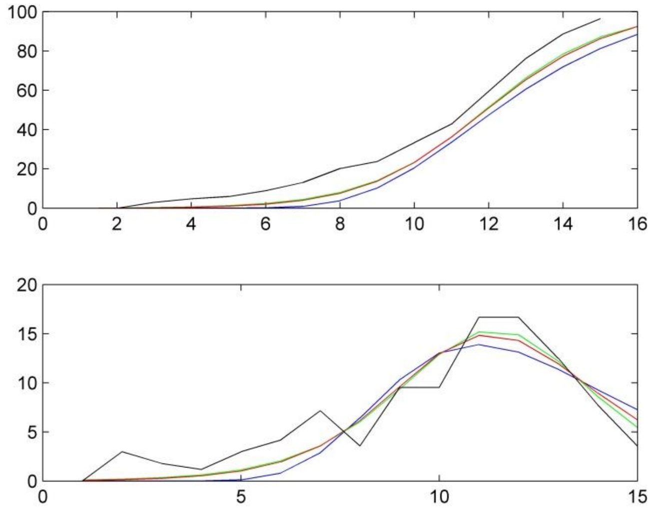
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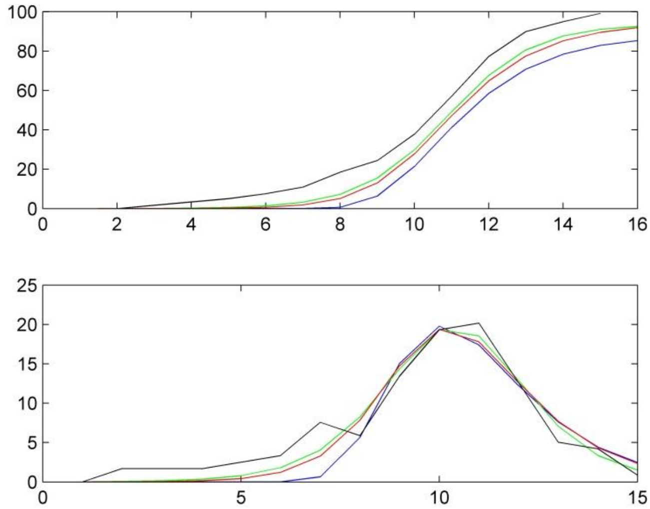
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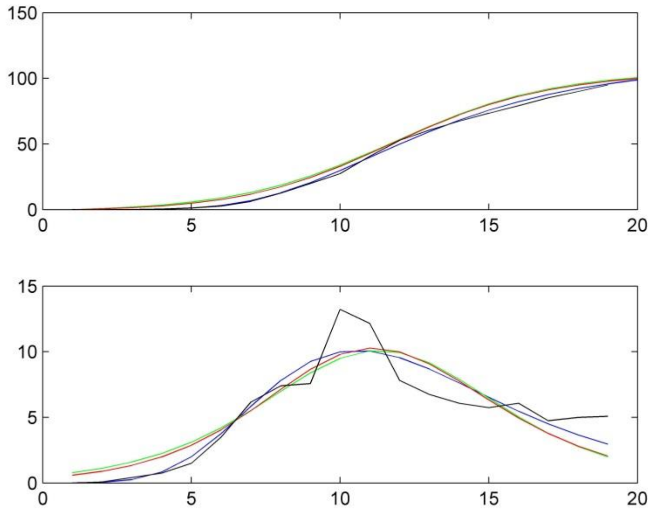
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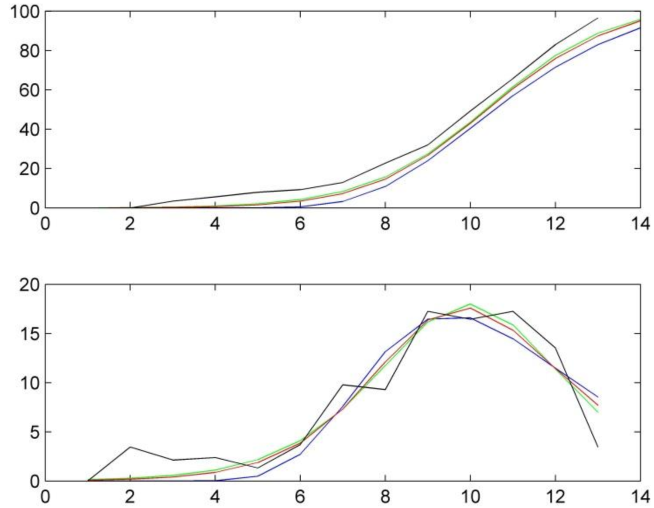
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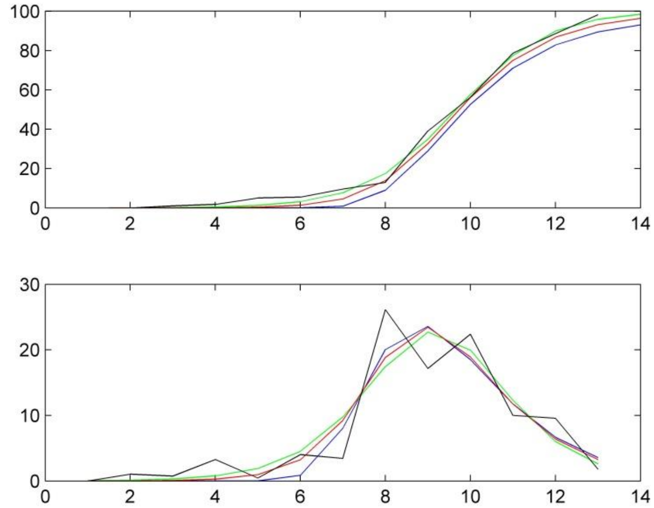
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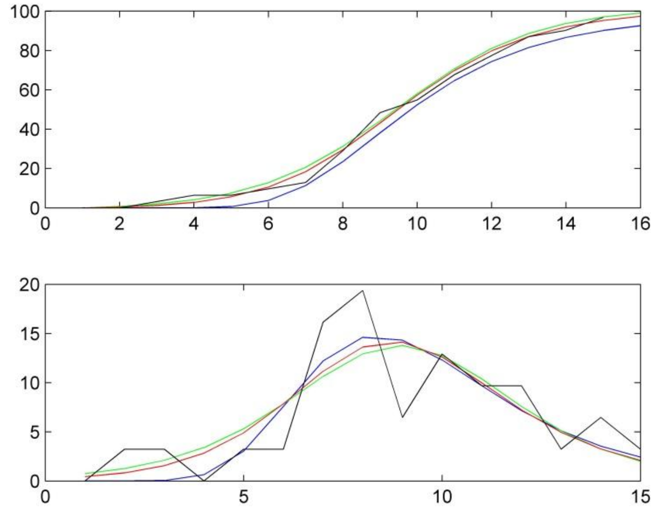
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Appendix 5: Simulation Result

	1st Simulation (10,000 times)				2nd Simulation (10,000 times)				3rd Simulation (10,000 times)				4th Simulation (10,000 times)				5th Simulation (10,000 times)			
	SA, NA	***UA, NA***	***SA, CA***	***UA, CA***	***SA, NA***	***UA, NA***	***SA, CA***	***UA, CA***	***SA, NA***	***UA, NA***	***SA, CA***	***UA, CA***	***SA, NA***	***UA, NA***	***SA, CA***	***UA, CA***	***SA, NA***	***UA, NA***	***SA, CA***	***UA, CA***
1	0.1375	13.3651	2.3527	84.9128	0.124	13.3042	2.2245	84.7009	0.1225	13.271	2.254	83.5298	0.1333	13.3788	2.4219	85.5202	0.1468	13.3383	2.6297	84.0852
2	0.4773	13.1273	8.6136	80.2789	0.5023	13.1288	9.3028	80.0537	0.5726	13.1053	10.5289	79.1875	0.4913	13.2346	9.026	82.4905	0.479	13.1656	8.8466	80.886
3	0.2902	13.5241	4.7163	85.4337	0.3473	13.7225	5.8141	88.2138	0.332	13.7667	5.7178	88.8472	0.3369	13.6436	5.8969	88.0593	0.3326	13.4875	5.4406	84.9747
4	1.3486	13.7259	21.5856	84.9297	1.4345	13.7336	22.8879	85.6974	1.3934	13.7138	22.5734	85.6142	1.3939	13.7625	22.557	86.1273	1.4363	13.8338	23.0081	86.4764
5	0.5469	13.0497	9.4121	76.0359	0.5036	13.0962	8.3612	78.3974	0.5043	13.1328	8.5134	76.8202	0.5379	13.9701	9.1021	75.0807	0.4763	13.1045	8.1406	77.1718
6	2.3085	12.8453	38.007	67.8068	2.4893	12.83	41.761	66.8993	2.0783	12.8786	35.3662	68.1227	2.2759	12.9025	37.4302	68.5123	2.3966	12.8091	40.5396	68.3637
7	0.0049	13.9101	0.0276	85.1736	0.0013	13.3985	0.013	86.7241	0.0012	13.3283	0.0053	86.1404	0.0024	13.38	0.0039	86.5704	0.004	13.4828	0.0189	88.9813
8	0.0062	13.389	0.1029	87.3147	0.0095	13.3394	0.1281	87.7247	0.014	13.3725	0.1773	86.2425	0.0019	13.3501	0.0055	0.1034	0.0097	13.5194	0.1034	88.4183
9	0.0026	13.5029	0.0249	87.9251	0.0029	13.2506	0.0249	85.1119	0.0032	13.4338	0.0259	87.3351	0.0019	13.3219	0.0102	86.4465	0.0071	13.3614	0.122	87.6663
10	0.2141	13.2573	4.0471	87.1892	0.1404	13.3547	2.4201	87.8804	0.112	13.2692	1.9355	86.8538	0.1507	13.2932	2.7018	87.0094	0.1148	13.3636	1.9972	88.8428
11	0.5083	13.8995	7.5005	90.1361	0.6288	13.9389	9.3872	90.4883	0.4452	13.8891	6.4628	90.0216	0.4338	14.0272	6.6031	91.3544	0.4155	13.9542	6.0484	92.0095
12	0.0025	13.7388	0.0071	92.6698	0.0194	13.8774	0.3333	93.8348	0.0097	13.704	0.1169	91.0199	0.0102	13.9605	0.1484	94.9752	0.0035	13.6991	0.0429	91.8334
13	0.3949	13.817	6.2629	95.9999	0.3339	13.7813	5.6839	95.6389	0.3711	13.8089	5.7944	94.0794	0.4269	13.9938	7.0065	98.3022	0.4341	13.9021	6.8814	96.9321
14	0.6174	13.9769	8.8926	92.4016	0.9301	13.9672	13.6586	90.0366	0.4776	13.9375	6.9444	90.3023	0.5717	13.9972	8.2616	92.5015	0.6208	14.0706	8.8947	92.8173
15	0.005	14.0592	0.0497	96.3555	0.0013	13.8153	0.0029	92.7554	0.0023	13.9694	0.0242	95.0141	0.0427	14.0104	0.7273	96.3513	0.0026	13.9594	0.018	94.2727
16	0.5181	13.8234	8.3983	96.2421	0.5642	13.9995	9.6188	99.5403	0.5689	14.0115	9.5067	99.3094	0.5199	13.8018	8.2691	95.4988	0.5012	13.8754	8.1595	96.3967
17	0.3321	13.8302	4.8323	89.3034	0.3952	13.5946	6.1333	86.0933	0.5009	13.8144	7.2616	91.298	0.3882	13.7672	5.6469	88.9268	0.2955	13.8327	4.2055	90.9097
18	0.0025	13.5938	0.0208	89.7421	0.0089	13.6841	0.1467	91.3345	0.0034	13.8039	0.0558	92.2163	0.0127	13.7054	0.2099	92.148	0.0135	13.6513	0.1783	91.0189
19	0.1822	13.3866	2.8334	89.2516	0.2541	13.5429	4.1646	91.0355	0.1554	13.6878	2.412	93.5725	0.2943	13.8592	4.8387	95.8066	0.1719	13.578	2.943	92.6636
20	0.7899	12.8446	22.3775	84.8894	0.8062	12.9404	23.4134	86.9351	0.5968	13.0083	18.0877	85.7498	0.7166	12.9001	21.0522	86.2068	0.9914	12.773	30.6761	84.2049
21	0.1619	13.7577	5.8404	94.0071	0.0879	13.8434	2.8825	94.0629	0.0805	13.8935	2.3095	95.5544	0.1082	13.7704	3.5637	94.057	0.1249	13.6605	3.8053	92.7935
22	0.6409	14.2292	13.5903	104.666	0.7885	13.9356	16.8905	101.4173	0.6884	13.9316	15.3448	99.9826	0.4517	14.3058	9.8021	104.4705	0.5268	14.0543	13.7788	101.6864
23	2.6025	14.3807	37.873	91.2956	2.6557	14.4217	37.9585	96.3035	3.1355	14.8025	47.5908	96.3035	2.7199	14.4833	38.8279	93.7512	2.4133	14.425	35.024	92.488

24	0.3412	13.8705	3.5167	90.5521	0.152	1.1951	14.0006	93.774	0.2676	13.8635	2.4969	90.2993	0.1773	13.8458	1.4823	90.3623	0.3856	13.8304	3.4938	90.6356
25	0.531	13.5011	13.9579	92.0272	0.2445	13.3634	7.7672	89.9651	0.3406	13.2576	9.9256	89.1391	0.3917	13.3962	10.4125	90.7728	0.2862	13.3187	8.7569	88.8452
26	1.8131	13.647	18.5402	83.8333	1.5124	13.605	15.3038	84.5444	1.3245	13.6161	13.1204	85.4879	1.3196	13.9271	13.8852	89.276	1.5046	13.8406	15.7379	86.3399
27	1.501	14.1838	16.234	90.8982	0.9493	13.9757	11.1897	89.7787	0.6595	14.232	8.2538	91.9289	1.5268	13.9663	17.1819	87.8696	0.8384	14.1844	9.8378	92.2499
28	0.0166	90.8855	13.7139	90.8855	0.0329	13.9022	0.2728	93.089	0.0503	13.8092	1.3691	93.012	0.083	13.7851	1.4058	92.4261	0.0253	13.9981	0.4218	95.8093
29	0.2647	13.1643	5.2736	85.1464	0.288	13.0946	4.8276	84.5052	0.4138	13.061	5.8709	82.8098	0.3559	13.1001	7.0062	84.4133	0.4159	13.0926	7.4639	84.3402
30	0.0472	13.2259	0.6286	84.2174	0.0399	13.3189	0.78	87.0095	0.0726	13.4242	0.9003	86.5912	0.0469	13.4177	0.7651	87.7454	0.0539	13.2515	0.7952	85.2662
31	0.3726	13.16	8.9734	85.037	0.2964	13.1207	6.1567	86.4737	0.4164	13.2261	9.3986	86.9048	0.2425	13.1188	5.2007	84.8457	0.4592	13.0808	10.4252	84.6795
	Adoption time	Number of adoptions	Inter-organisational influence		Adoption time	Number of adoptions	Inter-organisational influence		Adoption time	Number of adoptions	Inter-organisational influence		Adoption time	Number of adoptions	Inter-organisational influence		Adoption time	Number of adoptions	Inter-organisational influence	
32	7.1933	9905			7.1803	9919			7.268	9901			7.2414	9910			7.207	9903		
33	6.8527	9925			6.7645	9922			6.8108	9912			6.8284	9931			6.7828	9942		
34	7.6113	9905			7.5468	9880			7.626	9887			7.6119	9896			7.6119	9892		
35	4.8924	9985			4.8693	9989			4.903	9990			4.8861	9990			4.87	9981		
36	7.9816	9880			7.9724	9870			8.0017	9875			8.035	9859			7.9689	9857		
37	6.6638	9963	0.2581		6.7558	9965	0.2585		6.5836	9981	0.2645		6.7553	9966	0.2517		6.6686	9981	0.2596	
38	6.6332	9941	0.2165		6.4509	9960	0.2283		6.52	9960	0.2222		6.4412	9957	0.2275		6.6545	9929	0.2138	
39	8.2618	9552	0.1861		8.2366	9588	0.1923		8.026	9700	0.2023		8.1255	9707	0.1997		8.2735	9593	0.1889	
40	5.695	9039	0.000937		5.4828	9174	0.00083		5.655	9078	0.000887		5.5486	9105	0.000901		0.5178	9198	0.000761	
41	9.6255	8309	0.1302		9.6935	8218	0.1261		9.6813	8239	0.1291		9.7149	8154	0.1265		9.6965	8279	0.1325	
42	6.3927	9988	0.2869		6.4633	9988	0.2833		6.4356	9986	0.2871		6.4903	9984	0.2883		6.5219	9993	0.2904	
43	7.8105	3858	0.0012		8.0406	3767	0.0012		8.0643	4026	0.0015		8.0171	3918	0.0012		7.9962	3964	0.0013	
44	6.1534	9982	0.264		6.108	9991	0.2743		6.0732	9993	0.2607		6.0128	9991	0.2738		6.2116	9990	0.2706	
45	7.6165	5166	0.0011		7.6166	5075	0.0013		7.5987	5215	0.0015		7.7198	5157	0.0013		7.5173	5212	0.0012	
46	6.7009	9982	0.3133		6.8002	9986	0.3068		6.5612	9989	0.3175		6.8203	9984	0.3058		6.8153	9982	0.3118	
47	8.3096	2293	0.0012		8.3473	2246	0.0014		8.3246	2289	0.0012		8.3301	2354	0.0013		8.4051	2113	0.0014	

Appendix 6: A Paper: Multi-Generation Product Diffusion

Abstract

This paper offers a parsimonious and original model that captures the dynamics of multi-generational product diffusion (MGPD) in the current high-technology markets. The model seeks to explore and validate new understandings of the cross-generation effect, and consequently to interpret sales trends for multi-generational products. Although there are omitted variables from our analysis, the resultant model is capable of making generalizations. In the model estimation section, we demonstrate that the model fits real data for various high-technology products, with different diffusion patterns from different industries. Then in the numerical study section, we analyse the impact of the proposed cross-generation effect and provide some implications. This new approach can be understood and applied without specialized econometric expertise. We hope the insights offered by this research will benefit both academics and practisers in this area.

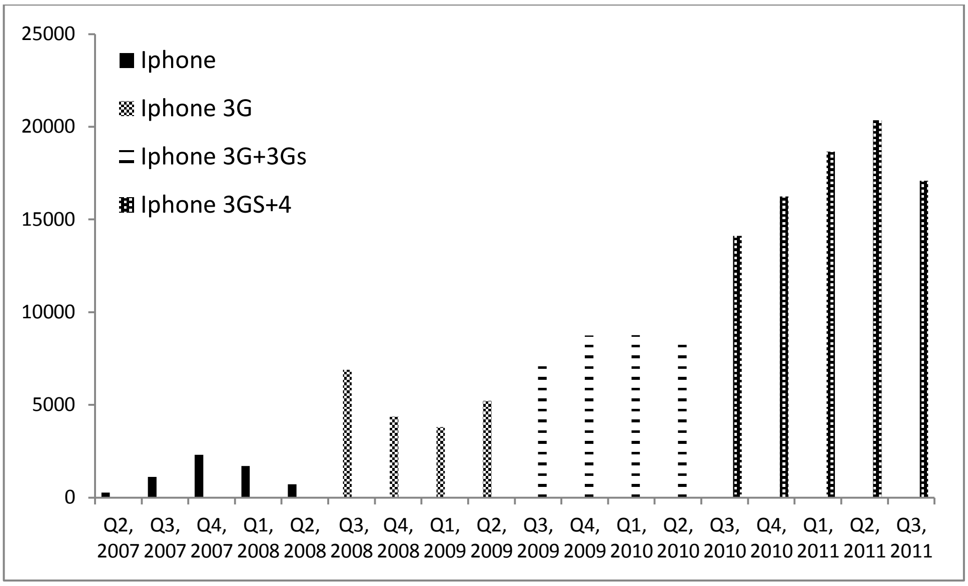
1. Introduction

One important field of the study of diffusion phenomena is to understand and predict the purchase demand of new products utilizing diffusion models. At an aggregated level, the purchase behaviour of first-purchase demand usually follows a bell-shape curve that will finally decay due to the saturation of market potential (Griliches 1957; Bass 1969; Meade & Islam 1998), that is, the sales curve reaches a peak and decline is expected thereafter. Following the benchmark work of Bass (1969), a number of models have been proposed. Some simply introduce new variables such as marketing-mix variables– price, promotion, etc.; some apply the model to more complicated contexts such as multi-generation, multi-category, and global diffusion; and a few others use the model to understand specific phenomena such as the saddle effect (Mahajan, Muller & Bass 1990; Bass 2004; Meade & Islam 2006; Geroski 2000; Mahajan, Muller & Wind 2000a; Baldridge & Burnham 1975; Peres, Muller & Mahajan 2010).

However, successful products in the market are normally substituted by newer generations with advanced attributes that can create new markets, update existing users, and thus repeatedly boost customers' demand. Therefore, one of the key demanding issue for both academics and practitioners is to understand and predict the sales behaviour of a multi-generational product (Mahajan, Muller & Wind 2000a; Bass 2004; Meade & Islam 2006; Peres, Muller & Mahajan 2010). Especially in recent years, the product growth pattern may have changed due to changes in the competitive environment and advances in firm level marketing strategy. Consider Apple's iPhone, it is one of the most widely proliferated smartphones in today's market and spans multiple successive generations. Figure 1 shows that sales of the iPhone have been increasing since the product was first released in 2007. However, the pattern of its sales trend changes after each new generation is released to market, this results in a different diffusion curve to classic bell-shaped curves that have emerged in previous MGPD studies. The iPhone is just one of several high-technology products that follow an unexpected growth pattern in today's market. Reflecting the importance of this issue, we attempt to reconsider and model the diffusion process of multi-generational high-technology products.

Most existing MGPD models are homogeneous models. They naturally do not consider the heterogeneity effect in diffusion, but are good in depicting the product growth trends by capturing the key diffusion drivers and thus explain the phenomena in a simple and accurate manner. Furthermore, simply using sales data as inputs, the homogeneous diffusion models are superior in terms of easy implementation than the heterogeneous ones that require extra data and more advanced estimation techniques. Beside heterogeneity effect, Decker and Gnibba-Yukawa (1984) summarise four sales affecting factors in the high-technology markets as interpersonal communication, democratization of innovation, network effect, and forward-looking behaviour. Specifically, interpersonal communication and network effect are embedded in most homogeneous diffusion models as the key diffusion drivers; democratization of innovation normally impacts the diffusion through the decrease of product price, and the work of Bass et al. (1994) has provided the homogeneous diffusion models a valid solution to this problem; forward-looking effect has been used extensively in understanding high-technology product growth, but is rarely adopted in a generalised MGPD setting. Therefore, this paper seeks to extend the cross-generation effect in existing homogeneous MGPD models by incorporating the forward-looking effect, and consequently to interpret sales trends for multi-generational products. We aim to provide a parsimonious and original model that captures the dynamics of MGPD in the current high-technology markets, and thus benefits both academics and practisers who are keen to understand the phenomena.

The remainder of the paper is structured as follows. The next section reviews existing approaches for understanding and modelling MGPD. Then a new approach is introduced consequently with a modified cross-generation effect that combines forward looking effect, after which the empirical validation of the proposed model is presented by using sales data of eleven products with diffusion patterns from different industries. In a numerical study, we examine how the proposed cross-generation effect influences the sales of multi-generational products, and subsequently evaluate the implications of the phenomena. Finally, conclusions are provided.



(Appendix 6, Figure 1) Figure 40: Sales of iPhone

2. Related Literature

Homogeneous and heterogeneous models are both used in the existing literature to understand the diffusion process. Homogeneous diffusion models usually operate through the understanding that potential customers decide to purchase a product due to their inner intention to purchase and other customers' influence. Heterogeneous diffusion models explain customers' purchase behaviour from the utility-theoretic point of view, that is, a customer adopts the product when her requirements for adoption are satisfied and the threshold for adoption is triggered. We review the existing works that are related to the current study from the two perspectives.

2.1. Homogeneous Models

The phenomena of MGPD are mostly modelled and explained through homogeneous models. The basic concept behind these models is that, the customer base of each product generation changes due to the introduction of new generations.

Although early attempts in this field may have started from Fisher and Pry (2006), the pioneering work is usually credited to Norton and Bass (NB) (1987). The NB model is suitable to describe the sales potential of a frequently purchased good. In the NB model, sales of each generation is derived by multiplying two variables: the probability of purchase following the Bass model (1969), and the dynamic customer base. The key concept embedded in the NB model is that, the later generation plunders the customer base of its earlier generation when they exist in the market simultaneously. Another important contribution in this field is the model proposed by Mahajan and Muller (MM) (1996), developed to describe sales of a durable good. Similar with the NB model, the primary focus of the MM model is the dynamic potential customers of each generation. In contrast, the MM model suggests a customer after purchasing one generation of the product will immediately become a potential customer of the following generation through upgrading, or leapfrogging. In others words, each generation plunders potential customers from its early generation in the NB model; each generation absorb product users from its previous generations as its potential customers in the MM model. Later works such as Speece and Maclachlan (2009), Islam and Meade (2008), Kim et al. (2000), Chanda and Bardhan (1988), and Stremersch et al. (2010) are more or less extended on the basis of the NB model or the MM model.

2.2. Heterogeneous Models

In general, product price decreases through time or product quality increases with the same price, and thus customers actually have many purchase options towards a product. In a simple case, Latin and Robert (2008) and Kim and Srinivasan (1995) propose their models, in which customers decide to buy a newer version of the product if the expected utility of the new generation is greater than the utility of their current one. In a more complicated setting where multi generations of a product exist in the market at the same time, customers evaluate the utility obtained by adopting each generation and the non-purchase utility, and then choose the option that results in the highest utility. Following this understanding, Jun and Park (2003) and Jun et al. (2011) integrate the diffusion effects and choice effects to explain customers' purchase behaviour regarding successive generations of a durable technology.

Perhaps one of the important sales affecting factors that are omitted by the homogeneous diffusion models but can be found in the heterogeneous ones is the effect of customers' forward-looking behaviour. Customers are likely to form expectations regarding future generations and thus to use these expectations in their current decision making (Takeyama 1994). Combining the understanding of heterogeneity and forward-looking effects, a number of utility-based approaches (Novos & Waldman 1984; Kiho 2002; Holsapple et al. 2008; Xie & Sirbu 1995; Sun, Xie & Cao 2004) have been proposed to understand the process of new product growth. However, all these models are not specifically designed to understand the MGPD problem. Specifically, the models of Melnikov (2002), Song and Chintagunta (2008), and Decker and Gnibba-Yukawa (1984) are for one-time purchase products; the model proposed by Erdem et al. (1995) is to understand the phenomena where different products compete with each other; and Prince's (2004) work is to model repeat purchase. One exception here is the study of Kim et al. (1991), in which the authors model customers' purchase behaviour towards successive generations of PCs with considerations of product quality of each generation, network externality, customer heterogeneity, and forward-looking effect. However, the model is tailored to understand the *small-office / home-office* PC market and thus does not provide a valid generalisation. For instance, the model considers effect of business disposition toward incertitude, which is not suitable in other product categories.

2.3. Motivation for the Current Research

The current research differs from existing MGPD studies by two points. First, the data applied in previous studies represent the diffusion phenomena from decades ago. The models that are validated based on these data may not reflect the characteristics of today's high-technology product markets. This is the main motivation of this study. As a result we attempt to bridge this gap in knowledge through the introduction of a new model and new sales data in order to reflect today's diffusion pattern. Second, the forward-looking effect is a key sales affecting factor in high-technology product diffusion (Novos & Waldman 1984). However, most existing models, both homogeneous ones and heterogeneous ones, do not incorporate the forward-looking effect to explain MGPD. Therefore, we extend the cross-generation effect used in previous homogeneous MGPD models to include the period for customers' forward-looking behaviour.

3. Model development

3.1. Theory of the Model

We employ two concepts of thinking in this study. First, a customer's purchase behaviour is influenced by the customer's inner intention to purchase and others' influence. This concept can be tracked back to two step-flow theory (Katz & Lazarsfeld 1955), and has been followed by most studies in the diffusion literature. According to the Bass model (1969) that is consistent with this stream of thinking, if $f_1(t)$ is defined as the number of adopters who buy the product at time t and $F_1(t)$ is the cumulative number of buyer at time t, the product diffusion process within M potential buyers can be modelled in Equation 1, where p and q are the parameters of innovation (customers decide to purchase the product based on their inner intention) and imitation (customers decide the purchase the product based on others' influence) respectively. This concept is applied in many influential models to study MGPD (the NB model, the MM model, and their extensions), that is, the Bass model is used to outline the initial purchase behaviour of each generation and then cross-generation effect will be added. Our model follows this approach, and thus we formulate the following assumptions:

- ***Assumption (1):*** *each generation of the product has a number of potential customers;*
- ***Assumption (2):*** *those potential customers initialise their purchase decision due to their inner intention to purchase and others' influence, which can be explain by the Bass model.*

(1) $$f(t) = \left(p + \frac{qF(t)}{M} \right) \left(M - F(t) \right)$$

Second, a customer's perception of the product's performance (x) can results in a change on her relative satisfaction to the product ($u(x)$) and thus purchase behaviour. Following the concept of von Neumann and Morgenstern utility theorem (1947), Chatterjee and Eliashberg (1990) model the above relationship in Equation 2, where η is a parameter.

(2) $$u(x) = 1 - \exp\left(-\eta x \right)$$

In applying this concept in the context of MGPD, we formulate another two assumptions following Assumption (1) and (2):

- ***Assumption (3):*** *potential customers' initial purchase decision may become uncertain due to the later generation with more advanced functions, and thus some* *of them may decide to prolong their purchase decision as they want to further evaluate the advanced one;*

- ***Assumption (4):*** *we choose time as the indicator for the possibility of the potential customers' decision-prolong behaviour, as the longer the current generation has emerged in the market, the higher perception that the current generation is becoming old and low quality they will have.*

Therefore, we can introduce the model structure of Equation 2 to explain the possibility $(1-\exp(-\eta t)$. Importantly, as a complementary to assumption (3), we have that:

- ***Assumption (5):*** *customers normally start to know a new generation even before it is officially released to market, and thus they may have started to be influenced by the later generation since then (**forward-looking effect**).*
- ***Assumption (6):*** *as companies normally release new generations of their products with an expected time interval, customers may start to expect the forthcoming generation soon after the current one is released.*

Next, the assumptions of the theories will be formulated in terms of a MGPD model.

3.2. The Model

We consider a product that has N successive generations and each generation has better performance than the previous one; we consider that the customers of each generation do not revert back to early generations.

For each generation i of the product that is released at time τ_i, we let p_i and q_i be the respective parameters to explain customers who decide to purchase the product through innovation and imitation channels, $f_i(t)$ and $F_i(t)$ are the number and cumulative number of customers who have initialised their purchase decision under the influence of the current generation, M_i be the potential market newly created by the official release of the current generation. Then following Assumption (1) and

(2), we explain how customers are influenced by the current generation as written in Equation 3.

(3) $$f_i(t)=\left(p_i+\frac{q_iF_i(t)}{M_i}\right)\left(M_i-F_i(t)+\sum_{t'=0}^{t}w_{i-1,i}(t')\right)$$

Here $\sum_{t'=0}^{t}w_{i-1,i}(t')$ are the cumulative potential customers who move from previous generation to generation i, due to the cross-generation effect proposed in this study. Considering our previous assumptions (3) and (4): the potential customers who have initialised their purchase decision under the influence of the ith generation ($f_i(t)$) may decide to prolong their purchase decision and further evaluate generation i+1 for more advanced functions; also the possibility will increase through time as can be explained by a similar model structure of Equation 2. Under this setting, there will be a continuous flow of potential customers from generation i to generation i+1 ($w_{i,i+1}(t)$), as proposed in Equation 4. Correspondingly, the number of actual purchasers of the ith generation ($s_i(t)$) can be calculated by Equation 5. Note that $f_i(t)=s_i(t)=w_{i,i+1}(t)=0$, when the generation i is not officially released; $s_i(t)=0, w_{i,i+1}(t)=f_i(t)$, if the generation i is no longer sold in the market.

(4) $$w_{i,i+1}(t)=f_i(t)\left(1-\exp(-\eta_i(t-t^*))\right)$$

(5) $$s_i(t)=f_i(t)-w_{i,i+1}(t)$$

In Equation 4, parameter η ($\eta\in[0,+\infty)$) is the decision prolong parameter. It is used to explain how likely the customers tend to delay their purchase decision due to the subsequent more advanced generation. t^* is the time point when customers start to be influenced by the later generation in prolonging their current purchase decision. In this study, we consider that customers start to know the forthcoming generation soon after the current one is released as proposed in Assumption (5) and (6), and therefore $t^* = \tau_i$.

In the model, parameter M_i is loosely defined as the new potential customers who are created by the official introduction of generation i. It represents a combination of the two types of potential customers: the potential customers who first know the product and the potential upgraders. Unlike the NB model and the MM model, the current model does not specifically state that previous products users will become potential customers of later generations. Under this setting, previous product users can become part of M_i if they are willing to, but also can leave the customer base as they are not necessarily loyal to the product. Furthermore, potential customers are allowed to leapfrog to advanced versions, for instance, potential customers of the first generation can wait and become a potential customer of the second generation, then further wait to become a potential customer of the third generation, and so on.

3.3. Constant Diffusion Parameters across Generations

One key difficulty in implementing this model to fit with real data is the large number of parameters. The model desires the values of four parameters p_i, q_i, and η_i, and M_i for each generation, and thus the total number of parameters to be estimated will be $4i$. The existing literature shows contradicting views as to whether diffusion rates, specifically, the values of parameters p and q in the Bass model, change across different generations. Some argue that the acceleration rate of diffusion processes across generations should be minimal or non-existent over time. Others ascertain that each generation of the product should be considered as an independent item, and thus have its own diffusion pattern. In a recent survey, Stremersch et al. (2010, p. 104) conclude that "*time is a factor that accelerates early growth, but generational shifts do not*". We adopt the view that parameters p_i and q_i in the model do not change across generations in this study. Furthermore, we assume that, the parameter η_i also does not change across generations, particularly if the company has a consistent marketing strategy for each product generation.

Therefore, the number of parameters reduces significantly from $4i$ to $i+3$. We believe that the above assumption can be easily proved on the basis of model fit, since it will be difficult for the simplified model to fit with real world data, if the values of p, q, and η actually differ across different generations of the same product.

4. The data

Most data used in previous MGPD studies utilise multiple technological generations, and most of them follow a classical diffusion pattern for each generation. We believe models that can produce a set of successive bell-shape curves were able to explain such data with varying levels of performance from case to case. However, decades have passed since such analyses were carried out and the data used may not truly reflect the diffusion patterns that are observed in today's markets. Therefore, we first fit the model with two most commonly used data sets in previous studies (IBM mainframe and DRAM) as case 1, and then introduce a few new data sets to further test the model.

The new data sets employed in this study are from five companies. These companies represent the relevant high achievement from both technology and market success, and have established a unique reputation in their specialised fields. We divide these products into three cases. The first case includes one company (Apple Inc.). The company is widely considered as a pioneer in leading the future direction of product development in the consumer electronics industry, and thus its products usually receive high anticipations from customers. The company's best known hardware products include its personal computer (iMac), laptop (MacBook, etc.), tablet computer (iPad), portable media player (iPod), and smartphone (iPhone). We exclude laptop in this analysis because the laptop has a few sub-product lines which make it difficult to categorise generations. The second case has three companies (Nintendo, Sony, and Microsoft), which together dominate the video game consoles industry. Nintendo and Sony are involved in both handheld console and home console market, while Microsoft only produces home consoles. However, we exclude the Nintendo home console, because the two previous generations were not successful in the market compared with Nintendo's Wii, and the inconsistent market performance between these three generations will result in a curve that is only likely to be explained by different diffusion parameters across generations. The final case has one company (Samsung Electronics), and the product we choose from this company is its smartphone. The company's smartphone had a relatively late start than the industry leaders such as Nokia, RIM, and Apple, however dramatic sales growth in the last two years has made Samsung world's largest smartphone producer. For these new data sets, some products' life cycle continue until demand ceases such as Sony's home console, while some products are discontinued before demand ceases such as Microsoft's home console. Such information is easily accessible from companies' public documents. Further details of these data sets can be found in Table I.

(Appendix 6, Table I) Table 25: Data for Model Fitting

Company	Product	Data Type	Generations Used in the Estimation	
IBM	*Mainframe*	Yearly data; 24 data points	**1st Generation** | **2nd Generation** | **360 family** | **370 family**	• *Note that this data set is the number of products in use, not shipments. Therefore, this data sets is actually more suitable to study the substitution issue in diffusion;*
All DRAM Producers	*DRAM*	Yearly data, 21 data points	**64K** | **256K** | **1M** | **4M** | **16M**	• *The DRAM shipment data we choose here is between1978 – 1998, including 5 generations;*
Apple	*Smartphone*	Quarterly data; unit in thousands; 18 data points	**iPhone** | **iPhone 3G** | **iPhone 3GS** | **iPhone 4**	• *We exclude the data of iPhone 4s in the analysis, since its data is too little to consider;* • *iPhone is the first generation of this product line; iPhone 3G was first pre-announced in June 2008;*
	PC	Quarterly data; unit in thousands; 53 data points	**iMac G3** | **iMac G4** | **iMac G5** | **iMac (Intel Plastic)** | **iMac (Aluminium)** | **iMac (Aluminium Unibody)**	• *The sales data of iMac we use in the analysis is from 1999, that include six generations;* • *The generations of iMac are mainly characterized by the majors change on its design, but not hardware updates;*
	Portable Media Player	Quarterly data; unit in thousands; 23 data points (used)	**iPod Classic 5G** | **iPod Shuffle 2G, iPod Nano 2G** | **iPod Classic 6G, iPod Nano 3G, iPod Touch 1G** | **iPod Nano 4G, iPod Touch 2G** | **iPod Nano 5G, iPod Touch 3G** | **iPod Shuffle 4G, iPod Nano 6G, iPod Touch 4G**	• *We exclude the data before 2005 in the analysis, since (1) the product was in the take-off stage during the period of 2002 –2004; (2) the company release a new model of iPod every quarter in 2005, resulting too many generations to consider.* • *iPod has many lines of products and each of them has a few generations. After 2005, the company starts to release a new version of each product line at the same time, which makes it easier to define generations of iPod;*
	Tablet Computer	Quarterly data, unit in thousands; 6 data points	**iPad** | **iPad 2**	• *iPad is the first generation of this product line; iPad 2 was first pre-announced in March 2011;*
Nintendo	*Handheld Console*	Yearly data (fiscal year); unit in thousands; 15 data points	**Gameboy Colour** | **Nintendo DS**	• *We only have the data of recent ten years that covers three generations of Nintendo's Hand consoles; among these three generations, Nintendo 3D was released only a few months ago, and thus its data are too little to consider;*
Sony	*Home Con-sole*	Yearly data (fiscal year); unit in thousands; 17 data points	**PlayStation** | **PlayStation 2** | **PlayStation 3**	• *We consider the all three generations of Sony's PlayStation;* • *PlayStation is the first generation of this product line; PlayStation 2 was first pre-announced in 1999;*
	Handheld Console	Yearly data; unit in thousands; 6 data points	**PSP**	• *We consider the first generation of Sony's handheld console product line; PSP is the first generation; PSP vita was first announced in July 2009, and was released in December, 2011;*
Microsoft	*Home Con-sole*	Yearly data (fiscal year); unit in thousands; 11 data points	**Xbox** | **Xbox 360**	• *We consider the all two generations of Microsoft's Xbox product line;* • *Xbox is the first generation of this product line; Xbox 360 was first pre-announced in 2003;*
Samsung	*Smartphone*	Quarterly data; unit in thousands; 11 data points	**Pre Galaxy S era** | **Galaxy S era** | **Galaxy S II era**	• *We consider the last three year's sales data of Samsung smartphone products;* • *We divide the Samsung smartphone products into three eras, based on its two most important products: Galaxy S and Galaxy S II.* • *We consider the Pre Galaxy S era is the first generation of this product line; Galaxy S was first announced in March 2010;*

- *Data of IBM mainframe are from Mahajan and Muller (1996); data of DRAM are from http:phe.rockefeller.edu/LogletLab/DRAM; data of Samsung smartphone adopted from Strategy Analytics; other data sets are from companies' Investor Relations documents.*

5. Estimation and fitting

Under the assumption of constant diffusion parameters p, q, and η for all generations of a product, we fit the proposed model with the actual data in the following ways. For the data sets of IBM mainframe, DRAM, and those products from video game industry, we estimate the parameters of the proposed model by minimizing the function of $\sum_{t=T_0}^{T}\left(\sum_{i=1,2,\ldots}\left(E(s_i(t))-s_i(t)\right)^2\right)$ through generic algorithm estimation (Venkatesan, Krishnan & Kumar 2004), where $s_i(t)$ is the actual sales data of the ith generation of the product and $E(s_i(t))$ is the data predicted by the model. For the data sets of Apple's products and Samsung's smartphone, we estimate the parameters of the proposed model by minimizing the function of $\sum_{t=T_0.}^{T}\left(\sum_{i=1,2,\ldots}E(s_i(t))-s(t)\right)^2$ (where $s(t)$ is the actual aggregated sales data of the product) through generic algorithm estimation, as we only have the aggregated sales data of these products, but not the sales data of each individual generation.

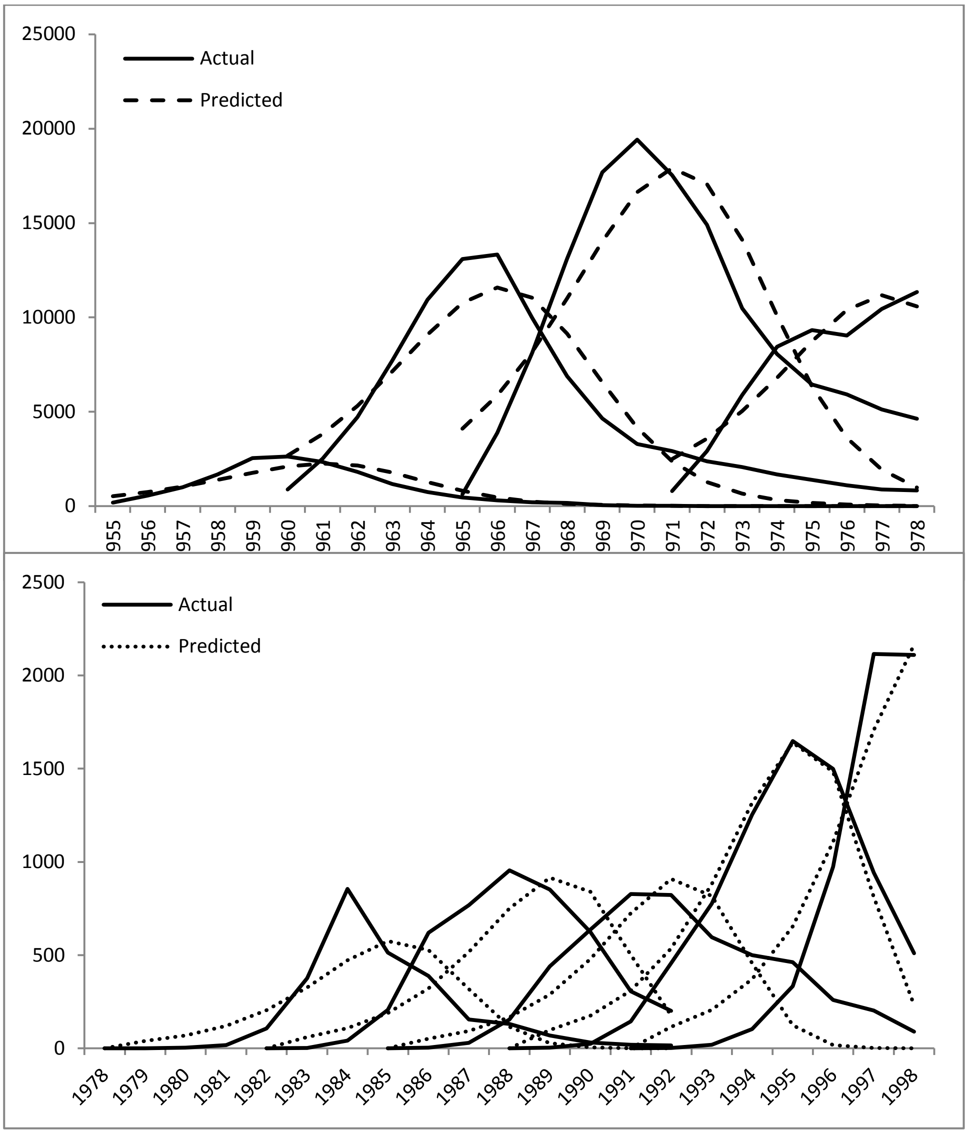
5.1. Result – Case 1

The data of the two products, IBM mainframe and DRAM shipments, have been frequently used in previous MGPD studies. It should be emphasized that the model in this study is not specifically designed to study the problem that are represented by these two data sets (especially see the description of the IBM data in Table I). However, due to their frequent uses in the literature, it would be interesting to see whether the proposed model can explain them. We assume that customers started to know a new generation of the product when it was officially released at that time, due to the poorer information transfer compared with today. Therefore, we use $t^* = \tau_{i+1}$ in Equation 4 in the estimation.

The estimation result is shown in Figure 2 and Table II. In generation, the model is capable to capture the growth trends of these two products as expected. Also the result shows a low value of parameter η, which indicates that customers did not tend to delay their purchase decisions due to the influence of following generations at that time.

(Appendix 6, Table II) Table 26: Estimation Result – Case 1

	p	q	η	M_1	M_2	M_3	M_4	M_5	R^2
IBM Main-frame	0.0310	0.4732	0.0015	17002	87679	135468	82360		0.8898 0.8907 0.8062 0.9012
DRAM	0.0139	0.8001	0.0146	3063	5012	4452	8770	10669	0.7395 0.7758 0.7913 0.9544 0.9544



(Appendix 6, Figure 2) Figure 41: Estimation Result – IBM mainframe and DRAM

5.2. Result - Case 2

The sales data of Apple's smartphone and tablet computer used in this study start from their first generation. As potential customers of the first generations might not know the time interval that the company would release new product generations (they even might not know whether the company would have a new generation or not at then), so they started to anticipate the second generations when the company first pre-announced them. This also applies to the cases of

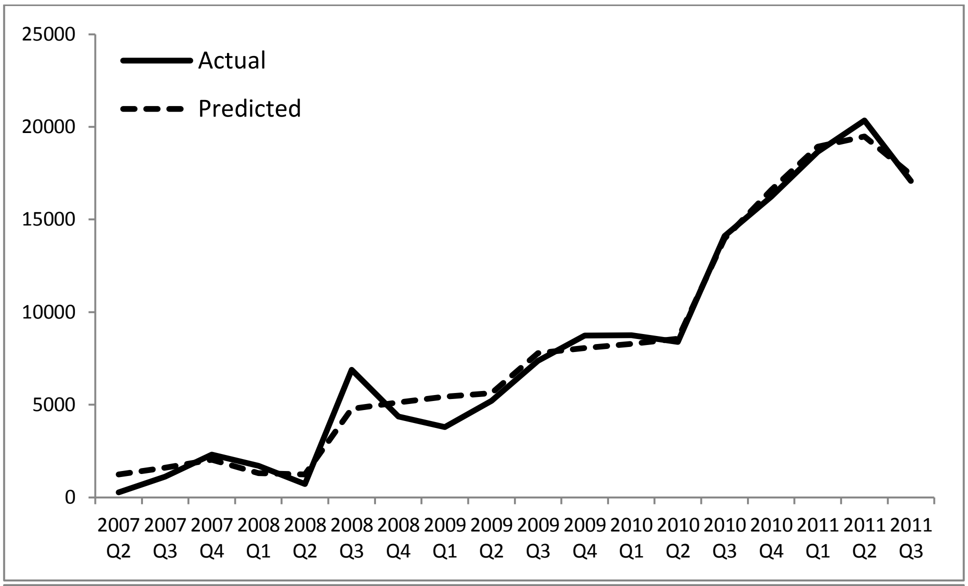
Sony's home console, Sony's handheld console, Microsoft's home console, and Samsung's smartphone.

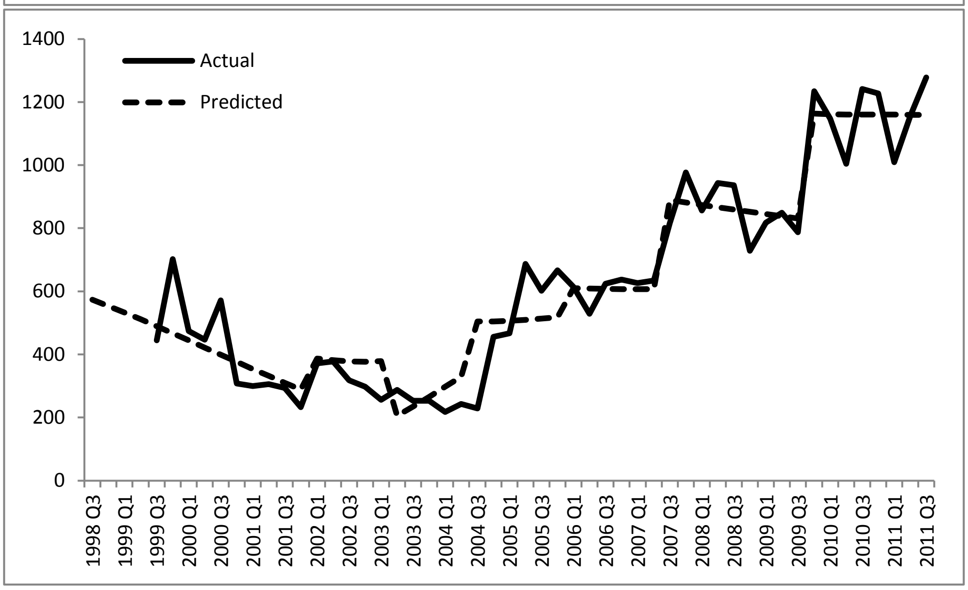
A graphical representation of the model's fit with the actual data is provided in Figure 3. For all Apple's products, the actual and predicted data are both overall sales of the products, as we do not have the sales data for individual generations. Remembering: (1) we define the generations of iMac based on the major changes of its design, while in each generation of iMac the company also provides a number of hardware updates, this results those slight fluctuations that are not captured by the model; (2) the announcement date of each new generation of iPod is actually in the last month of the third quarter, not the beginning of the fourth quarter as used in the model, this results in actual sales higher than the model predicts; (3) iPod's sales may be influenced by the seasonality effect, which is not considered in the proposed model. Therefore, the sales of fourth quarterly would be higher than the model predicts. Even including these expected errors, the predicted diffusion curve captures the actual trends very well.

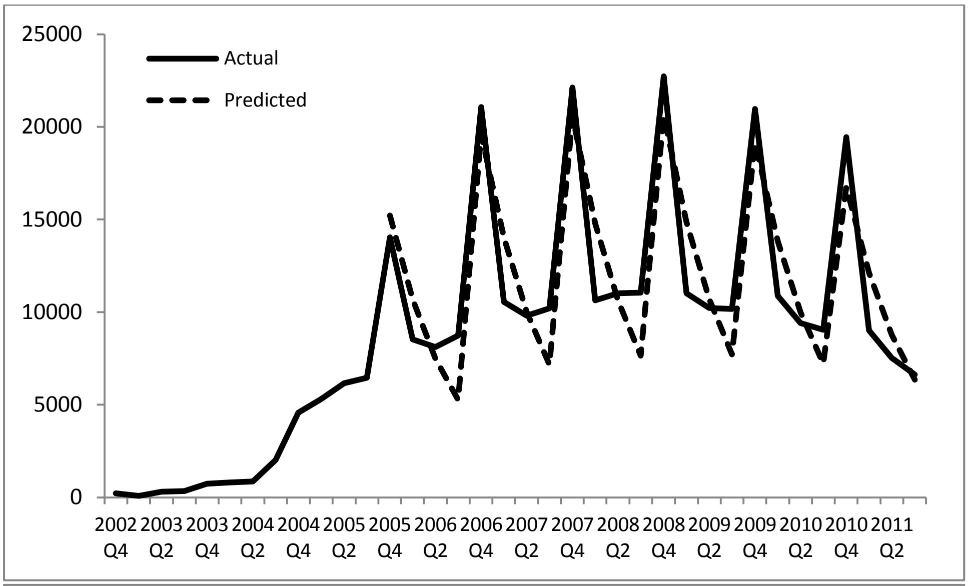
Table III shows the statistical results: the coefficients of determination values (R^2) are remarkably high, as 0.985, 0.916, 0.773, and 0.974. The values of p and q for iPhone and iPad are both high, which indicates a high influence of the products in the market. The q values for iMac and iPod are both low, meaning the sales growth of the two products are mainly boosted by customers' inner intention to purchase,. Finally, the result shows a clear existence of the proposed cross-generation effect in all four products. It is consistent with the fact that Apple's new products are usually anticipated by customers, and thus have strong influence to customers current purchase decisions. For certain generations of Apple's products, like in the cases of iMac and iPod, their sales start to drop own soon after they are released. This phenomenon can be hardly explained by previous homogeneous MGPD models, but can be easily explained by the forward-looking effect proposed in the current model, that is, customers prefer to purchase the products when they are new to the market, otherwise they will wait until the next new generation is released.

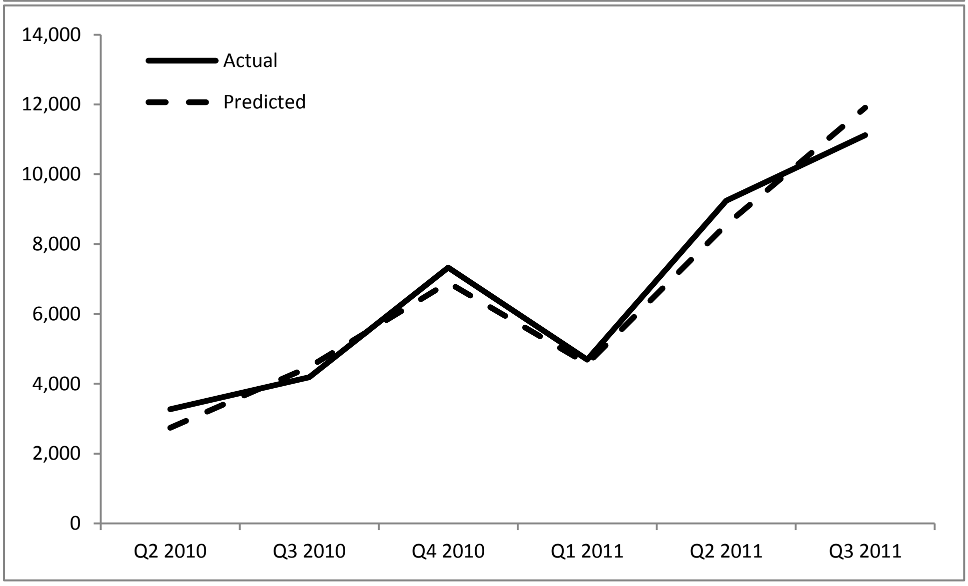
(Appendix 6, Table III) Table 27: Estimation Result – Case 2

	p	q	η	M_1	M_2	M_3	M_4	M_5	M_6	R^2
iPhone	0.0344	0.3406	0.2189	32427	122637	47211	204149			0.985
iMac	0.0258	0.0523	0.0603	22188	1897	18666	23094	33826	42839	0.916
iPod	0.0260	0	0.3273	584134	732554	762420	707067	616314		0.773
iPad	0.0745	0.7427	0.2027	57210	163696					0.974









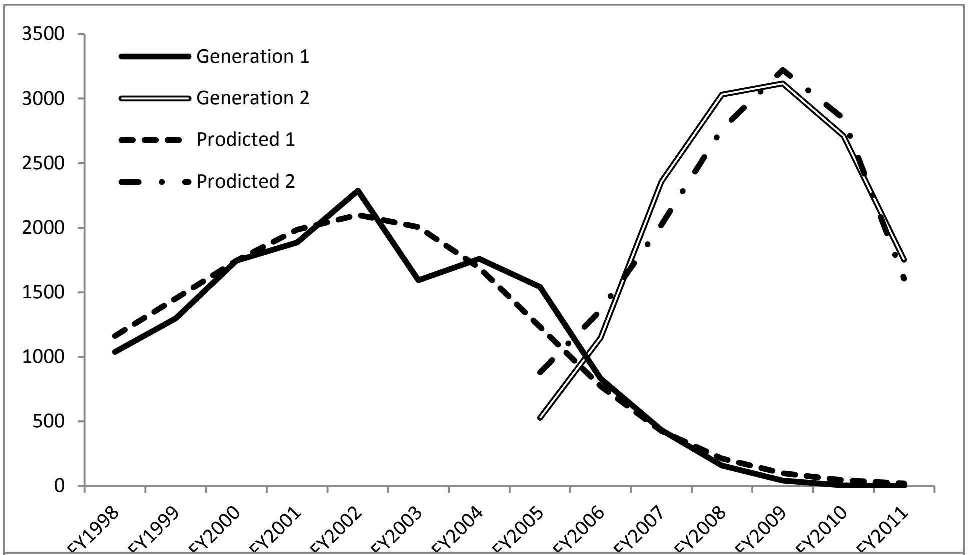
(Appendix 6, Figure 3) Figure 42: Estimation Result – iPhone, iMac, iPad, iPod (from top to bottom)

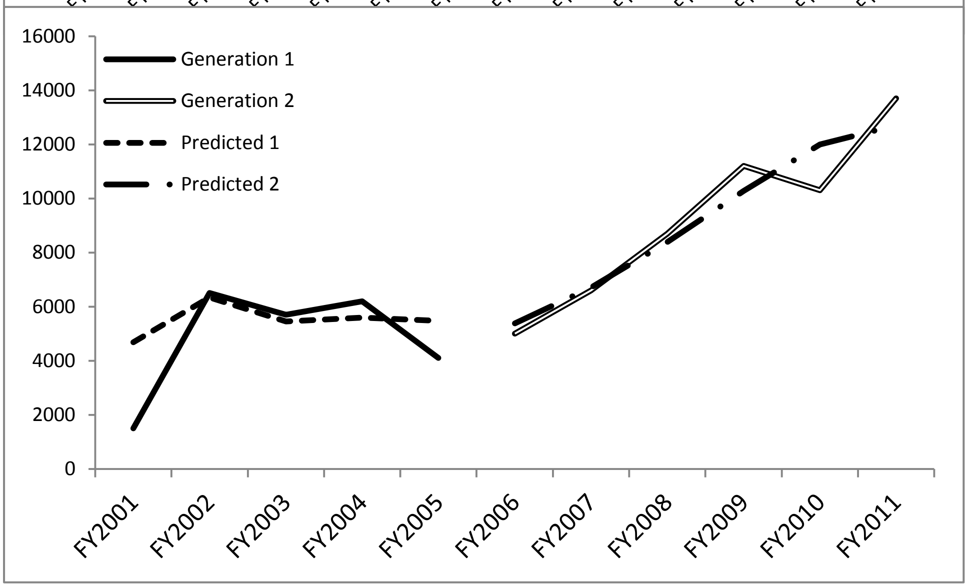
5.3. Result - Case 3

Figure 4 and Table IV show the fit of the model with the data of the four products from the video game industry. Again, there is close correspondence between the model and the data, especially Nintendo and Sony's handheld consoles (Gameboy and PSP). However, the model does not predict the sales of PlayStation well, specifically its second generation. We provide two possible reasons for this. First, the model clearly over-estimates the sales on the time points when a new generation is released, because the new generations are sometimes released at the end of the year and thus the actual data do not represent the whole year's sales. This issue also can be found in the model fit of Xbox. Second, note that we exclude the Nintendo's home console in this study due to the relative failure of the previous two generations (see Table I for more explanations). These two generations (1997 - 2007) are sold in the market at the same time with PlayStation 2. Therefore, some of Nintendo's potential customers might have gradually moved to Sony during this time period. Those potential customers may have changed the diffusion pattern of PlayStation, and thus made the second generation of PlayStation resulting in unexpected curves from the model. As can be seen in Figure 4, PlayStation 2 has long-term and stable sales after the peak point, which cannot be explained by the model but can be explained by the gradually plundered customer base from Nintendo.

(Appendix 6, Table IV) Table 28: Estimation Result – Case 3

	p	q	η	M_1	M_2	M_3	R^2
Gameboy	0.0459	0.4675	0.1154	25350	13249		0.957
							0.939
Xbox	0.0368	0.4048	0.2135	127151	130744		0.878
PlayStation	0.0524	0.3968	0.0495	137669	172229	69233	0.803
							0.657
							0.897
PSP	0.0923	0.5601	0.1696	91269			0.994


Generation 1
Generation 2
Prodicted 1
Prodicted 2
3500
3000
2500
2000
1500
1000
500
0
FY1998
FY1999
FY2000
FY2001
FY2002
FY2003
FY2004
FY2005
FY2006
FY2007
FY2008
FY2009
FY2010
FY2011


Generation 1
Generation 2
Predicted 1
Predicted 2
16000
14000
12000
10000
8000
6000
4000
2000
0
FY2001
FY2002
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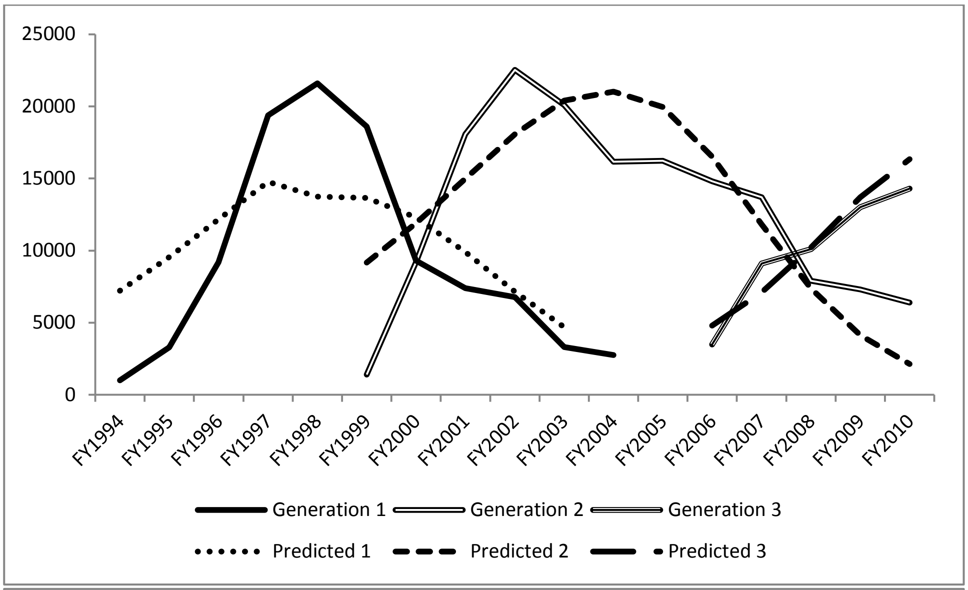
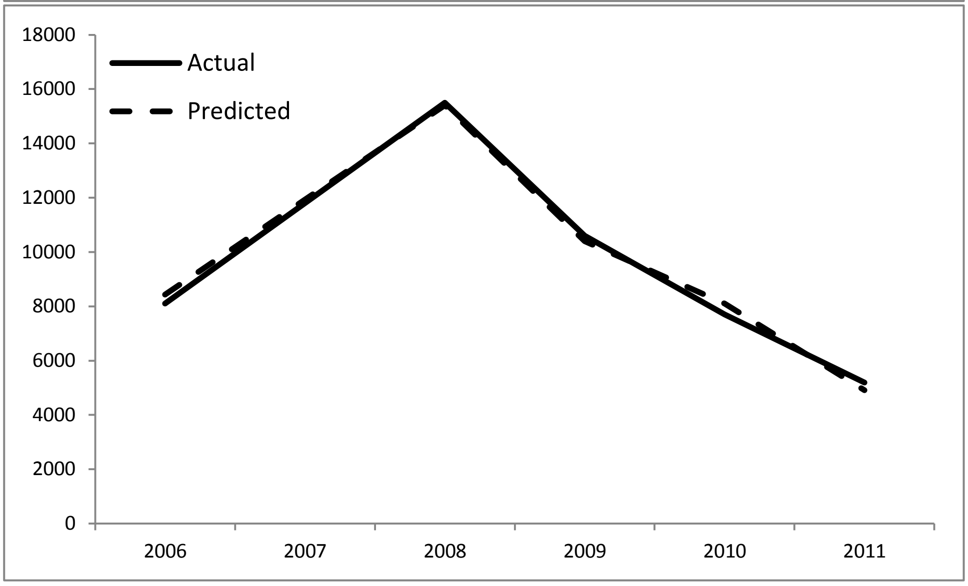
FY2008
FY2009
FY2010
FY2011





(Appendix 6, Figure 4) Figure 43: Estimation Result – Gameboy, Xbox, PlayStation, PSP (from top to bottom)

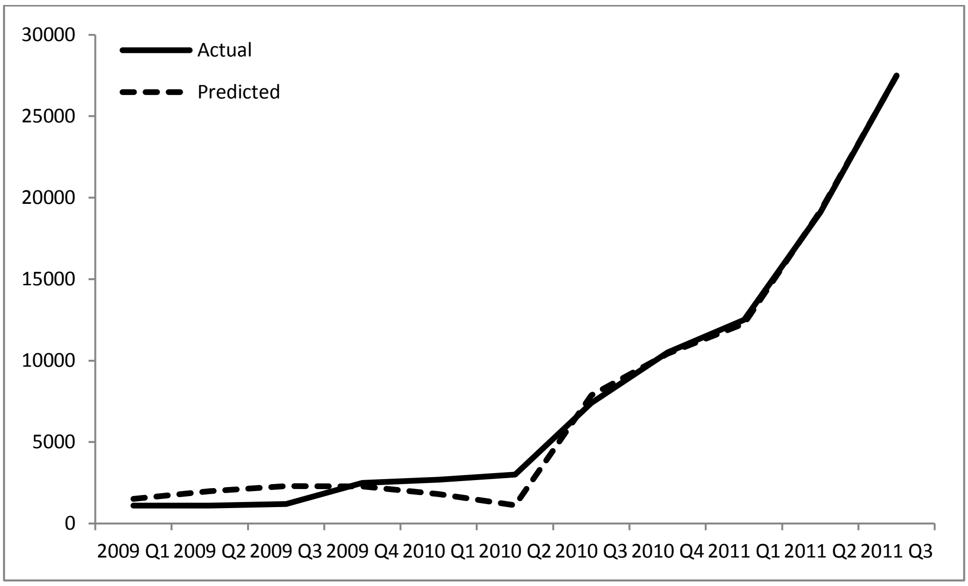
5.4. Result - Case 4

The model fits the data of Samsung smartphone remarkably well (see Figure 5 and Table V) with R^2 equals 0.991. While different with the previous two, the result in Case 4 does not support an obvious existence of parameter η, which indicates that customers of this product do not tend to delay their purchase decision due to the forthcoming generation. We give two potential reasons to explain this. First, the company does not tend to pre-announce their new product early: the company announced Galaxy S and Galaxy S II only one quarter before the official release date. Therefore, customers received relatively less information about the new generation, and thus did not prolong their purchase decision. Second, customers initially might not have great anticipation to the company's smartphones, as the smartphone market was dominated by Nokia, RIM, and Apple at that time. Figure 5 clearly shows that the sales of Samsung's smartphone are very low before the release of Galaxy S.

Considering the notable value of parameters p and q, Samsung's smartphone is enjoying a dramatic sales increase, and therefore it is not surprising that it has surpassed the sales of iPhone and become the biggest smartphone producer. Furthermore, due to the high popularity of its products, customers would start to have more anticipation for the company's future products, and thus the value of η and consequently the diffusion pattern could change in the following generations.

(Appendix 6, Table V) Table 29: Estimation Result – Case 4

	p	q	η	M_1	M_2	M_3	R^2
Samsung Smartphone	0.1137	0.6468	0.0006	10858	42671	103932	0.991



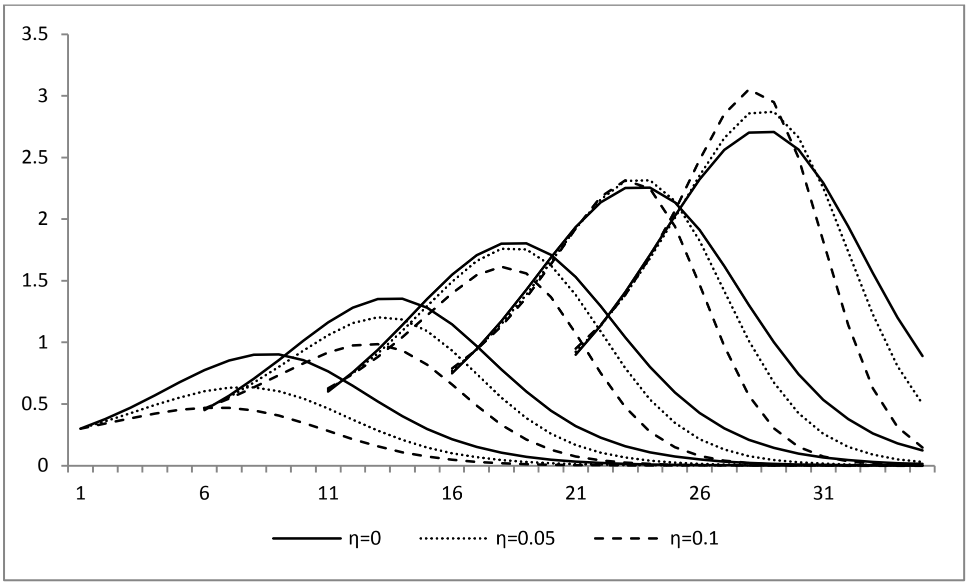
(Appendix 6, Figure 5) Figure 44: Estimation Result – Samsung Smartphone

6. Numerical Computations and Implications

The theory of the model roots in the contributions of Bass (1969) and von Neumann and Morgenstern (1947). The model fits with real data of various products with different diffusion patterns and from different industries, which reveals its empirical validity. The model suggests a new understanding of the cross-generation effect in MGPD as explained by parameter η, which we are able to affirm empirically in this study. Below we present computational results for the model in order to further investigate the impact of η on the sales of different generations of a product.

We consider a product that has five generations with their release time at $\tau_1 = 1$, $\tau_1 = 6$, $\tau_1 = 11$, $\tau_1 = 16$, and $\tau_1 = 21$. We set $p = 0.03$ and $q = 0.3$, as in a common range of diffusion models in the literature (Sultan, Farley & Lehmann 1990). In this experiment we consider the potential market of each generation increases gradually, thus: $M_1 = 10$, $M_2 = 15$, $M_3 = 20$, $M_4 = 25$, and $M_5 = 30$. Then we simulate the model (Equation 3, 4, and 5) three times with different values of η, the graphical representation of the result is shown in Figure 6. In the Figure, when parameter η increases, the sales of initial generations decrease, as more potential customers choose to wait for the newer generation; while interestingly, the model with bigger value of η will have a higher sales peak in the later generations. This is because the cross-generation effect in this study will gradually 'reserve' potential customers for the later generations, and thus increase the size of the initial potential markets for later generations.

As the cross-generation effect can reverse potential customers for later generations, the market potential of one generation starts to form before its official release date and is constantly changing, due to the flow of potential customers moving from its previous generation and the flow of potential customers going into its successive generation. It implies organizations must truly appreciate the market potential of their products.

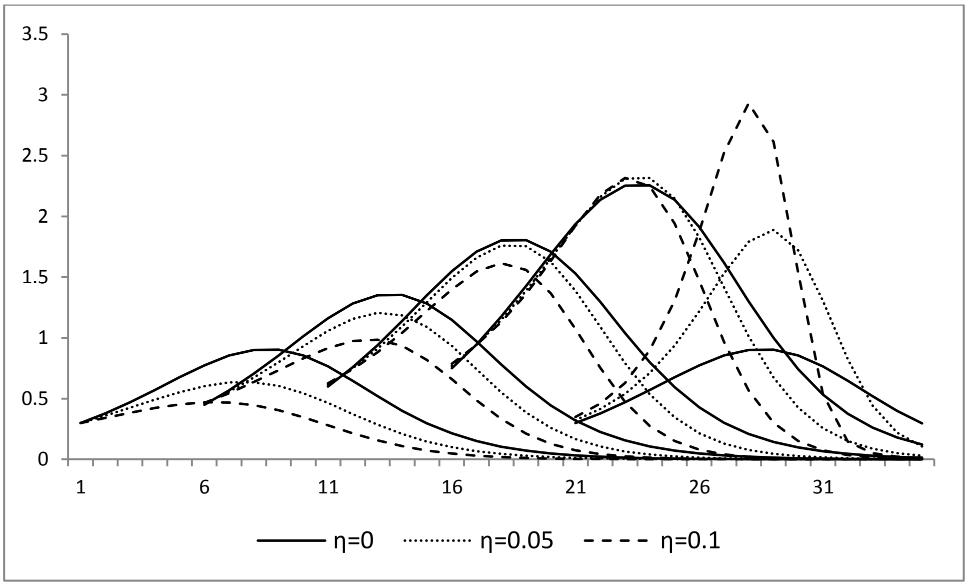


(Appendix 6, Figure 6) Figure 45: Simulation (1)

Each newer generation creates a larger customer base in the above simulation, and thus the benefit of the reserved market potential is not obvious. While in real word, it is common that although a new generation performs better than its former, it does not create a large size of new potential customers in the market (for instance, as indicated in the estimation result in previous section, iPhone 3GS did not create a large size of new potential customers compared with its predecessor and successor). Therefore, we introduce another simulation to demonstrate this issue. We use the same value for all the parameters in the first simulation, except letting $M_5 = 15$, that is, the fifth generation of the product does not create a significant number of new potential customers due to certain reasons. Figure 7 shows the result of the simulation: as expected, the sales of early generations decrease when the cross-generation effect is enlarged, because more potential customers are reserved for the later generations; also clearly, the sales of the fifth generation do not drop down visibly if the cross-generation effect is enlarged, because it receives more potential customers from its previous generation.

The above simulation is suitable for the case of monopoly, as it considers that the competition does not exist and the reserved potential customers are 100%

loyal to the company. In a market where competition exists, even if some of the reserved potential customers will change to purchase alternative products, the left part still has a good probability to help the company maintain a basic sales level.



(Appendix 6, Figure 7) Figure 46: Simulation (2)

7. Conclusion

This paper offers a simple, plausible, and original model that captures the dynamics of successive product growth. We view this study as an important step in understanding MGPD. The unique contribution of the model is to suggest and validate a new understanding of the cross-generation effect, and thus to explain MGPD in an accurate manner reflecting today's high-technology market. The model is derived from previous works in the area of diffusion, building upon the contributions of these studies. Although there are omitted variables (such as the effect of product price), the model is capable to explain generalizations, as shown empirically in the model fit section. The model's good fit with real data demonstrates that the proposed forward-looking effect is an important, and probably the most important, sales affecting factor that is missing in previous MGPD models in explaining today's high-technology market.

Through computational experiments, we demonstrate that the proposed cross-generation effect hinders the sales of each generation, but reserves these hindered sales for its later generations. This finding could imply companies from at least two perspectives. First, companies must truly appreciate the potential customers created by each generation of the products. Second, companies should link this finding to their marketing strategies carefully. On the one hand, not allowing the reserved potential customers will make the company vulnerable to the potentially failed new generations in the future. On the other, it may result in an Osborne effect that also harms the company, if customers are too much attracted by the companies' forthcoming products.

The products we applied to test the model are from: computing industry (personal computers and laptops); the mobile phone industry (smartphone); the home entertainment industry (video game console); and audio industry (portable media player). Except from the cases we used in this study, we believe the model has extensive application possibilities to other products in these industries, and potentially products in other high-tech industries. This new approach can be understood and applied without specialized econometric expertise. We hope the insights offered by this research will stimulate further work in this area.

Glossary

3SLS: Three-Stage Least Squares

ABM: Agent-based Model

FIML: Full Information Maximum Likelihood

FOMA: Freedom of Mobile Multimedia Access

GA: Generic Algorithm

Gini: The Gini coefficient is a measure of statistical dispersion developed by the Italian statistician and sociologist Corrado Gini

GDP: Gross Domestic Product

G/SG: Gamma Distribution / Shifted Gompertz Distribution

IOR: Inter-Organisational Relations

MLE: Maximum Likelihood Estimation

MSIR: Maternally-derived Immunity, Susceptibles, Infectives, Recovered with Immunity

NLLS: Nonlinear Least Square

OECD: Organisation for Economic Co-operation and Development

OLS: Ordinary Least Square

SA: Sensitivity Analysis

SEIR: Susceptibles, Exposed Individual in the Latent Period, Infectives, Recovered with Immunity

SIR: Susceptibles, Infectives, Recovered with Immunity

SIS: Susceptibles, Infectives, Susceptibles

STD: Sexually Transmitted Disease

UA: Uncertainty Analysis

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