國立交通大學

經營管理研究所

博 士 論 文

No.146

以跨代空間映射觀點探討新產品的
有機成長與交叉存活競爭

New Products' Organic Growth and Cross-Competitive Survival Patterns: A Multi-Generation Spatial Mapping Perspective

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國 立 交 通 大 學

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博 士 論 文

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摘　　要

科技品短暫的存續期間，市場擴散可以生物物種演進的概念來詮釋，使產品為一系列不斷進步調整的群體。本研究從單一品類的角度，觀察品牌產品在不同的進化階段，市場上相同屬性但不同規格產品的價格競爭形勢。從行銷的觀點，以羅吉特形式市場佔有率模型，分析台灣某通路商實際的交易買賣資料，藉由價格競爭指數計算出價格交叉彈性，反映品牌產品的相對吸引力，探索誘餌產品是否引起消費者選擇時的妥協和極端趨避心態；進一步以空間時態的自我羅吉斯模式，整合產品吸引力之估算，概念地捕捉新產品交叉銷售之自我蠶食或內在增長的意涵。此外，從市場進入的觀點，以存活分析檢視產品的品類族群競爭，Cox 正比例涉險模式顯示價格因素並不顯著。研究結果驗證早期階段消費者的妥協選項，考量產品間的相依性至空間自我相關集合，比傳統的線性銷售預測有較優之配適。透過心理與物理的討論，本研究認為妥協效果並非科技軌跡的唯一決定因子，其可能是基於買賣雙方內在趨力和產品發展路徑的必然結果；以產品內和產品間的空間映射，檢視跨世代新產品的有機成長，除了推翻「新高科技商品一定能存活」的假設外，也對展望理論「消費者傾向妥協中間選項為最佳決策」的論述提出質疑。

關鍵詞：妥協效果、科技軌跡、跨代空間映射。

New Products' Organic Growth and Cross-Competitive Survival Patterns: A Multi-Generation Spatial Mapping Perspective

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ABSTRACT

The market diffusion of high-tech products with their short life cycle duration can be interpreted in terms of biological species evolution, that is, as a series of continuously progressing product groups. This study focuses on different evolutionary stages of the same property, which differs in product specifications competition, from the perspective of a single brand product category. The transactions data of a leading brand of an actual Taiwan MP3 music player was analyzed by logit-type market share models. Price competition index and cross-price elasticity were calculated to estimate alternative products' attractiveness, and, consequently, whether the decoys create consumer compromise and extremeness aversion mentality. The autologistic choice model for a spatial-temporal pattern was also demonstrated to incorporate attractiveness in formal choice models; these estimates enable the authors to conceptually capture the cross-selling patterns of a new product's cannibalism or intrinsic growth. Additionally, the market entry view is also adopted to consider product survival duration; the Cox proportional hazard model reveals price is non-significant factor. The results verify consumers' midway compromise and decoy options at earlier stage. Incorporating the interdependence of products by modeling a spatial autocorrelation choice set leads to superior fit compared with the traditional linear sales predictions. This study proposes that compromise effect is not the only determinant for product growth, but that it may inevitably result from the technology's trajectory and product development path based on a two-fold inner drive. Using intra- and inter-competition spatial mapping to survey the organic growth of new cross-generational products, the long-term survivability can be assessed. These assessments have cast doubts on consumer acceptance of a new product launch, and the discourse of an individual's best choice as in prospect theory has been questioned, as this choice seems more compromised intermediate.

Keywords: compromise effect, technology trajectory, spatial mapping.

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In his poem, “The Road not Taken,” Robert Frost wrote, “Two roads diverged in a wood, and I--I took the one less traveled by, and that has made all the difference.” This dissertation has been a challenge, but one I have enjoyed. I am happy to present it to my advisor, Dr. Ying-Chan Tang, who not only provided sound advice about relevant theory, but also encouraged me throughout my academic program to avoid the shackles of traditional thinking.

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Min-Hua Wu

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1. Introduction

1.1 Research Background

With the global industry moving swiftly toward the post-globalization era, the competitive environment has become complicated and unpredictable, and technological products are increasingly characterized by a short life cycle. Retrospecting on the ICT industry's evolutionary change of the last several decades, Apple Computer introduced iPod in 2001, iPhone in 2007, iPad Tablet PC in 2010, and possibly iTV; is a series of new products for several generations. Companies innovate and adjust their product direction to gain competitive advantage and meet the spontaneously growing demand. Many corporations strive for research and development (R&D) and production of more advanced products to satisfy diversified consumer needs, attempting to create another industry life-cycle peak. Nevertheless, new products are intrinsically associated with a high level of market uncertainty. Changes in market competitors, the uncertainty of new technology paradigms, and the variety of consumer trends are affecting performance. Innovation is not just about launching a thoroughly new concept of goods, but involves improving the existing product in the market to give consumers a new experience that is truly innovative.

As old products are continuously replaced in favor of new ones, product types and features grow increasingly complex, and product elimination through competition accelerates. Moreover, businesses not only face competition from other brands but also face fierce struggles among the product lines of their own brands. As homogeneous products multiply, if businesses wish to preempt their competitors in launching new products, they must first understand the existing state of product competition on the market. Product life cycle (PLC) has been widely used in product management, strategic planning, and marketing activities. However, its definition and application are highly controversial.

Previous research criticized PLC as not being a conscientiously rigorous model; in particular, its use in the development of marketing products seems overly simplified. It ignores those important variables affecting sales, and may even lead managers to mishandle the competition situation and miss the opportunities for product innovation, leading to tautologies in deterministic and sequential stages (Dhalla and Yuspeh, 1976; Hunt, 1976, 2010; Tellis and Crawford, 1981; Wind and Claycamp, 1976). Product evolution cycle (PEC) is the concept that products are continually changing and evolving. This concept draws on the biological viewpoint of evolution to explain the growth and expansion of products (Chandrasekaran and Tellis, 2007; Holak and Tang, 1990; Norton and Bass 1987; Tellis and Crawford, 1981). Product species are not just objects with fixed characteristics and specifications, but a series of continuously progressing and changing groups.

As product development is the transformation of a market opportunity into a product available for sale (Krishnan and Ulrich, 2001), it is an intrinsic process that involves not only sellers' niche or habitat metabolisms and new product diffusion epidemics but also interactive marketing that includes up-selling, down-selling, and cross-selling (Kamakura, Kossar, and Wedel, 2004; Li, Sun, and Wilcox, 2005). Well-designed product lines push corporations to grow instead of self-cannibalizing. In the development process, technological products are generally based on an original model, to which an increasing number of new functions or attributes are added. Consumers facing the multitude of choices resulting from product evolution will attempt to determine the best reason for selecting a specific product. The diffusion of innovation theory can be used to explain commodities spread (Rogers, 1995). When consumers perceive the innovative products as superior to other competing goods, the product has a comparative advantage and a higher likelihood of consumer adoption, leading to the diffusion effect (Agarwal and Prasad, 1997; McDade, Oliva, and Pirsch, 2002; Taylor and Todd, 1995). Even so, according to the prospect theory (Kahneman and Tversky, 1979), consumers will focus more on potential losses rather than potential benefits when they are unsure of their preferences; thus, they tend to prefer less extreme choices.

In addition, consumers are often influenced by their context effect (Huber, Payne, and Puto, 1982; Simonson and Tversky, 1992), and endeavor to determine the best reason for selecting one specific commodity. The choice behavior under uncertainty is more easily interpreted as compromise effect; in particular, compromise effect can systematically influence consumer choice in regard to the wide range of product sets and attributes (Kiverz, Netzer, and Srinivasan, 2004; Simonson, 1989). This makes a moderate, compromised choice the best option. When a specific brand's competitor adopts a price-cutting strategy, the ability of this brand to fight back against such price-reducing behavior (cross-elasticity) is reflected in the change of market share or sales and provides an opportunity for attracting consumers. This is called brand attraction power, reflecting the behavior result of a firm and its competitors (Francois and MacLachlan, 1994; Woodside and Walser, 2007). Precisely, cross-price elasticity is the sales changes of other products resulting from the price change of one product. It can be used to observe the influence of a competing brand's price change, analyze market competition structure, and position further competitive brands (Cooper, 1988; Day, 1979; González-Benito, Martínez-Ruiz, and Molla-Descals, 2009; Kamakura and Russell, 1989). From a brand management perspective, the importance lies in understanding the substitution consumers recognize, measuring the power of brands under price competition, and forecasting the volume of sales (Bucklin and Srinivasan, 1991; Shocker, Stewart, and Zahorik, 1990).

This study adopts the marketing view in the product development research community to consider product competition. A product is a bundle of attributes, and consumer utility is a function of these attributes. Typically, consumers' decisions rely on product attribute level and price while corporation's performance metrics are conceded in whether the product fits the market, gains market share, or upgrades customer utility. In addition, competitive products are developed not only across firms but within the same firm over time (Krishnan and Ulrich, 2001). From the perspective of a single brand, we observe the price competition among products at different stages of evolution that had the same market attributes but different mode specifications. The focus of this study is not on the influence of price on sales but rather investigates the alternative or complementary price relationships between different product modes, as well as using cross-price elasticity to measure the attraction power of brands in price competition. Whether adding a decoy product option to the choice set under consideration by a consumer would increase the possibility of a specific product being selected was also explored.

Specifically, past studies analyzed product sales as a function of price or related marketing activities as consumer choice variables and did not incorporate other contextual view to study such as cross-selling and product line cannibalism. The focus of this article is to demonstrate the spatial pattern such as Apple's i-series, which enables the practitioners to view the sequential patterns of a new product's growth process of a particular product specification in the light of other competitive ones. Our aim is to demonstrate the applications of spatial competition models and interpretation of the associated parameters.

1.2 Motivation

Technology trajectory is the developed path of technology in its life cycle overtime and this path may be the growth rate of performance improvement, product diffusion, or the direction of advance within a technological paradigm (Dosi, 1982; Schiling, 2010). Considering the marketing view that a product is a bundle of attributes, this study incorporates spatial mapping perspectives to understand the diffusion of multi-generation products. In addition, we hope to comprehend the spatial competition between products in a product class over different generations and how the market entries are adopted by considering product survival duration.

For industrial economics, market entry plays a central role. From the perspective of a single brand, the multi-generation product can be regarded as continuous product entry. The effectiveness of market entry involves with various product modes and marketing activities. Price is an important consideration for products appearing attractive; combining duration and the price attribute allows us to understand the nature of competition and the market evolution. This study attempts to determine the influence of price variable over various product generations and investigate the new product hazard rate information to facilitate our understanding about technology trajectory and life cycle paths.

1.3 Research Objective and Contribution

In keeping up with the above, the research objectives are (1) to analyze a national MP3 brand on how the product-price variants of a specific product class (or category) influences each others' product attractiveness over different evolution cycles; (2) to probe consumer's utility function on whether the aversion for losses is compromised in the considered product choice set; (3) to compare multi-generation products' chance of survival on the basis of lifetime survival gains.

Our contribution is threefold. First, we provide a structured process of intra-brand product development research with the implementation of spatial science. We hope that this approach encourages researchers to be flexible about incorporating critical factors, multiple points, and multiple generations into their models. Second, we present an evolution cycle approach to organizing the product price competition, using the marketing perspective of several product generations in examining the compromise effect. The product attributes and consumer behavioral interaction enable marketers to target their communications more effectively. Third, we identify the technology's trajectory and discuss possibilities for future product line design that would extend in productive directions. On the premised rationality of the individual's inner drive for selecting a preferred product and the vendors' inner drive to satisfy their growing demand by product joint space, we acknowledge the role of individual behavior and marketing in the effectiveness of product development processes. This interdisciplinary research can complement previous study on entry and technology marketing.

The rest of the dissertation is organized as follows. Section 2 gives a brief overview of PLC and PEC, compromise effect, brand attraction, cross-price elasticity and the brand competition-analyzing model and reviews spatial science, focusing especially on the study applied by marketing or consumer research. Section 3 outlines our proposed model, including a conceptual framework and mathematical calculations, and Section 4 deals with data and empirical application. In Section 5, we discuss compromise phenomenon and multi-generational spatial diffusion from the marketing perspective, and covers the market entry view with regard to a single brand to discuss the actual product survival considering life time duration. Section 6 contains managerial and theoretical implications including the expected effect of pricing strategy on product launch decisions. Conclusion and further research direction are suggested in Section 7.

2. Literature Review

2.1 Product Life Cycle and Evolution Cycle

PLC theory is used to explain the life of products in the market, that is to say the entire process from a new product's entrance into the market to its elimination through competition (Vernon, 1966). From the marketing perspective, Kotler (1991) defined PLC as the relationship of sales varying over time in the period during which the product comes in the market until it is removed. There are four main assumptions: (1) the product has a limited life; (2) the seller encounters different challenges, problems, and opportunities at different stages; (3) the variation direction of income is not identical in each cycle and may increase or decrease; and (4) relevant product strategy must consider the stage that the product is at.

Most products go through four stages: introduction, growth, maturity, and decline. This theory was widely discussed in the past; however, scholars have questioned its validity. Hunt (1976) argued that since the fixed four stages have a bell-shaped distribution, to define the stage of one product by its sales, and then to forecast sales by the defined stage, is neither conscientious nor careful but a tautology. Wind and Claycamp (1976) indicated that PLC neglects important variables affecting sales, such as firm's marketing activities competitive reactions, and other relevant environmental factors. Dhalla and Yuspeh (1976) proposed that managers may mistakenly believe that the product has entered an early decline when they are not satisfied with sales conditions, leading them to miss innovation opportunities; PLC, thus, is a very dangerous tool for managers.

Tellis and Crawford (1981) claimed that PLC describes the actual state of biology, that is, all organisms experience birth, growth, maturity, and decline over time, which is an already quelled process as time passes; however, it is an over-simplified model used in the development of marketing products. They further proposed PEC to interpret product growth and diffusion from a biological point of view, which expresses a dynamic continuous changing process. The term "product" does not have fixed characteristics and specifications, but is a series of continuously progressing and changing groups (Chandrasekaran and Tellis, 2007).

Product evolution mainly includes four changes. They are (1) cumulative change, which involves aggregated product evolution where the product progresses step by step on the basis of prior successful experiences; (2) motivated change, wherein three forces contribute to the products' continued evolution, namely, general power (managers' or entrepreneurs' creativity), selective power (the market composed of consumers and competitors that affect sales), and intermediary power (such as government or other agents); (3) directed change, which are the linear results of changing, so that products will be more efficient, complex, and progressive through evolution; and (4) patterned change in which product evolution models are developed from five radiation models in biology—cladogenesis, anagenesis, adaptive radiation, stasigenesis, and extinction. These models are divergence (new product is not entirely a new concept but a combination of existing products or technologies and departs from the existing product line), development (new products constantly revised to meet the consumers' needs with a rapid increase in sales), differentiation (successful products on the market will be adjusted to satisfy different consumers' needs), stabilization (only minor changes in products, including packaging and trading services), and demise (sales are down and the product cannot remain in the market when it does not meet consumer expectations), respectively.

The empirical study by Holak and Tang (1990) is the first to deal comprehensively with PEC. They studied the value of evolutionary cycles and assessed the influence of three evolutionary forces (general, selective, and intermediary force) on the relevant product. As discussed above, products in PLC show single and fixed characteristics while PEC assumes that products are continually evolving and generally based on an original model to which new functions or attributes are added. Product variant of the MP3 music player for example is purely different due to its capacity, color, and mode (or type); the actual launch time in the market did not show the clear patterns of introduction, growth, maturity, and decline stages.

2.2 Compromise Effect

Huber et al. (1982) proposed that consumers' choices are influenced by the related characteristics of different program choices. These effects are called context effect. In consumers' considered choice set, the probability that a certain product will be optioned increases if a decoy product is introduced to this set. Simonson (1989) assumed that consumers will attempt to find the best reasons for selecting a specific product in different product option programs. Three results for the prediction of compromise effect and interpretation of attraction effect were obtained: (1) the market share of the alternative will increase while there exists a compromised alternative in the product choice set; (2) the influence of attraction and compromise will be greater when consumers want to rationalize their and other people's decision; and (3) the option of a dominant brand and a compromise brand is related to complex decisions.

Simonson and Tversky (1992) agreed that consumers' choices are influenced by their context effect (consumers' considered choice set). They addressed two hypotheses related to the choice set: (1) the tradeoff contrast: consumers compare certain product attributes when they proceed to make a selection in a particular set; different results will be generated under different comparison baselines; (2) extremeness aversion: consumers fear an extreme choice since they wish to avoid an extreme choice outcome when there is no explicit preference, causing them to select products with more moderate attributes. Kiverz et al. (2004) established a theoretical mechanism for the influence factor of compromise effect. They suggested investigating whether joining the compromise effect to previous consumers' choice models would yield better prediction ability. The advantage of this model is the use of a single reference point; this can be helpful for market analyzers in drafting a product launch strategy and in increasing the attraction of a specific product. In addition, the compromise effect can systematically influence consumers' choice under a larger product set. To generalize the concept of compromise, it has the same meaning as consumers' being loss averse and the concavity of their consideration set (they would prefer the middle commodity).

2.3 Brand Attraction

Previous studies presented the multi-dimensional view on the definition of brand attraction. Srivastava and Shocker (1991) indicated that the connotation of brand equity derives from a multi-dimensional concept of brand attraction and brand value; brand attraction is further denote performance-profitability, life-weaknesses, and scalability-growth potential. Francois and MacLachlan (1994) considered that brand attraction reflects firms' and competitors' actions taken previously and discussed the attraction by dividing them into internal (essential) and external (nonessential) points of view. Internal perspective includes consumers' long-term experience of a particular brand; external perspective is short-term stimulus, such as the ability of a specific brand to resist a competitor's price reduction behavior (cross-elasticity), which may involve the market share or sales reaction of a competitive firm implementing marketing tools. How both affect the brand health can be explored through internal and external perspectives.

Woodside and Walser (2007) provided a clear definition for brand attraction: a brand's relatively greater attraction for consumers in comparison with other brands or the product attributes of a given brand. This implies the intensity of competitive brands is an inconsistent and relative concept. With reference to methods for measuring brand attraction, MacLachlan and Mulhern (1991) suggested questionnaire measurement and conjoint analysis through survey questionnaires in accordance with the existing and potential customers. Farquhar and Ijiri (1993) used the internal records as measures of brand strength from a business perspective. Kamakura and Russell (1994) suggested beginning with the transaction data of the existing market, such as supermarket scanner data.

2.4 Price Elasticity and Brand Competition-Analyzing

Price elasticity refers to the way in which the changes in a product's market position (such as price or promotion) can be transformed to changes in sales or market share (Cooper, 1988). Cross-price elasticity means the sales change of another product resulting from the price changes of one product. Two products are substitutes if the cross elasticity is positive, whereas, they are complements if the cross elasticity is negative. Economists try to define consumer or market demand curves from the variation of price elasticity; marketing scholars also use it to study the market structure, and hence, extend its use to a variety of estimation methods.

Day, Shocker, and Srivastava (1979) analyzed the difference between data collected from subjective judgments and data obtained from real behavior: subjective judgments include cognition and preferences; purchasing behavior is the actual behavior (such as retail channel data). Research advocated measuring the brand transition probability and cross-price elasticity by actual behavioral data and observing the influence that the price change of a competing brand has on other flexible structures of a market-share attraction model. The competitive interaction model and multinomial-logit model were combined, focusing on the asymmetrical influence among brands in market share. The calculated cross-price elasticity could be used to position competing brands; it is a complete model for understanding the market structure through cross-price elasticity.

Kamakura and Russell (1989) proposed the market response model of consumer heterogeneity and analyzed the market structure by calculated elasticity statistics. Shocker et al. (1990) addressed the importance of cross-price elasticity based on brand management, for the following reasons: (1) the relative degree of cross-elasticity can provide insights into the market structure and knowledge of possible substitutes considered by consumers; (2) it can be applied to measure brand power in price competition. Bucklin and Srinivasan (1991) suggested that the cross-price elasticity can be used to predict changes in sales volume when a particular brand adopts a promotion strategy. Russell (1992) proposed a latent symmetric elasticity structure model; the elastic matrix is assumed to be decomposed into two parts: symmetric alternative indicators (illustrating the competition intensity among brands) and brand coefficient (measuring the overall impact of a brand on its competitors). Symmetric substitution elasticity is applied with the multidimensional scaling method.

Recently, DeSarbo, Grewal, and Wind (2006) employed a space method to express a competitive market structure chart that assumes a correlation between brand distance and the degree of substitution of price changes. González-Benito et al. (2009) divided the cross-price effect in the market response model into two elements: (1) price changes of a brand will have different effects on the prices of other brands; and (2) the price of each brand will affect the competition brand. The asymmetric matrix derived from cross-price elasticity can be portrayed as a positioning map.

According to the above literature, the relative market share or relative sales of brands can be applied to define the brand attraction. This study utilizes the actual product sales to reflect a specific product attraction. A distributor's transaction data is the basis for analysis; it belongs to existing market-related transaction information and can reflect consumers' actual purchasing behavior; the product level analysis and discussion are based on the data in this study.

2.5 Spatial Science

Spatial statistical methods involve the analysis of geo-referenced data, when the relative locations of observations are important; that is, the locations are explicitly taken into account, especially relative ones (Heikkinen, 2011). They often include a map projection of a geographic region onto a plane and can also be applied in abstract spaces spanned by covariates. Researchers have applied this concept to model intra-household behavioral interaction and market basket selection (Boztuğ and Hildebrandt, 2003; Russel and Petersen, 2000; Yang, Zhao, Erdem, and Zhao, 2010).

Boztuğ and Hildebrandt (2003) tested whether products chosen on a shopping trip in a supermarket are an indicator of the preference interdependencies between different products or brands. They regarded the bundle chosen as an indicator of a global utility function in which the function related to a product bundle is the result of the marketing mix of the underlying brands. A multivariate logistic model was adopted that estimated by methods of spatial statistics. Comparing cross-nation buying behavior, they found strong effects for the cross-category variables, but only non-significant ones for the base variables such as price and time effect of purchases. The existence of global utility implies a cross-category dependence of brand choice behavior. The non-significant factor may have underlying methodological reasons or may be the result of cultural differences.

Yang et al. (2010) argued that quantitative models in marketing typically focus on the household as the unit of analysis while ignoring the individual family members' behavior and the behavioral interactions among household members. The authors developed a model to capture multiple agents' simultaneous choice decisions over more than two choice alternatives in the context of family members' television viewing. They probed whether the television was on, what type of program was playing, and which family members were watching. In doing so, they estimated the individual's intrinsic preference and the extrinsic preference from a joint consumption with other members. Auto-logistic choice model and hierarchical Bayesian were utilized to test group decision-making heuristics; the results show the behavioral interaction family members may exhibit in joint consumption occasions.

For single region spacial study, this single region represents a time interval as in time series or survival analysis (Heikkinen, 2011). If we focus on one specific product category, it can be said that there is a single market for products to compete. In an industry, potential entrants may decide to join this market. Market equilibrium is thought to be brought about by a pool of potential entrants, ready to enter if incumbent firms earn excessive profits (Klepper and Simons, 2000). Few studies have considered the implications of a company increasing product modes in its product line in order to provide consumers alternatives and to increase the possibility of choices. Research has not shown whether this can be a deterrent for all the market entrants or analyzed how product attributes affect product attractiveness and survival over the product's evolution. We thus shed new light on the important aspects of market entry, and provide new insights on consumer behavior and marketing.

2.6 Competitive Entry

Barriers to market entry influence firms' profitability by preventing new competitors from entering markets. The magnitude of barriers in deterring entry of competitors into markets is expected to vary by industries and stage of PLC (Gotz, 2002; Karakaya and Kerlin, 2007; Karakaya and Stahl, 1989; Yang, 1998). Research conducted by Karakaya and Kerlin (2007) focused on the importance of barriers to entry and examined the impact of different industries (biotechnology, waste management, pharmaceutical preparations, tobacco, and alcohol) and PLC stages. They proposed that both industry and PLC stages should be utilized as contingency factors in market entry strategy formulation, including the mode and timing of entry. Additionally, finances required for capital expenditures and competitiveness are important determinants of market entry decisions for potential market entrants.

Game theory of microeconomics has been applied to marketing. According to Varoufakis (2001), game theory can be defined as the analysis of rational behavior under circumstances of strategic interdependence, when an individual's best strategy depends upon what his opponents are likely to do. Most firms produce more than one product. When a firm produces different products sold in different markets and the value of one product depends on the demand for the other, this type of dependence is referred to as cross-market network effect (Chen and Xie, 2007). It is widespread across many different industries in which firms provide multiple products to different sets of customers. Strauss (2000) asserted that a cross-market network effect affects the optimal prices of the two interdependent products in opposite directions: the stronger the cross-market network effect, the larger the difference in profit margins between the two products.

Cabral and Villas-Boas (2005) studied oligopoly price competition between multi-product firms whose products interact in their profit function. The main point of their research is that under certain conditions, inter-firm profit interactions lead to Bertrand supertraps. They proposed that the effect of price competition is so powerful that the strategic effect of competition on firms' profits by an economic force may dominate its direct effect on profit that applies to a monopoly firm. That stronger economy of scope may lead to lower profitability for firms in competition if their products interact in profit functions.

Chen and Xie (2007) examined the impact of a cross-market network effect on firms' competitive strategies. Their study paid special attention to the interaction between the cross-market network effect and asymmetry in customer loyalty. They considered two competing firms that differed in customer loyalty. Both firms sold two different but related products: a primary product and a secondary product. They extended their study to a two-period game under the interdependence of the two markets, whereby a profit in one market may be gained at the cost of the other and by the positive relationship between a larger loyalty segment and a higher opportunity cost of price competition in the product of the primary market. Results show that the entrant can outperform the incumbent if the incumbent's feasible loyalty level is at a mid-level and the entrant has a low entry cost. This suggests that asymmetry in customer loyalty can be a source of first-mover advantage or disadvantage. A first mover may be at a disadvantage to the entrant in both profit and market share if its advantage in loyalty is neither sufficiently small nor sufficiently large.

This study discusses a single brand with related product cross-generations as it related to the concept of interdependence between different products. In the initial stage, disruptive innovation may occur to capture customers who do not possess the product. After that, a maintenance strategy is implemented to launch a better product in the existing market. An individual's best choice depends upon what opponent alternatives he is likely to buy. Price competition in a product line also exists in the presence of the interdependence of products.

3. The Proposed Model

3.1 Conceptual Overview

This study probes the effect of the price of different product modes belonging to a single brand category on the relative attractiveness of other products. We discussed several evolutionary stages for determining the structure of market competition. In addition to consumers' choices among a product set, we also discuss innovation types in inter-generational products, attempt to determine the product evolution path, and then discuss the next generation development. The research concept is depicted in Figure 1.

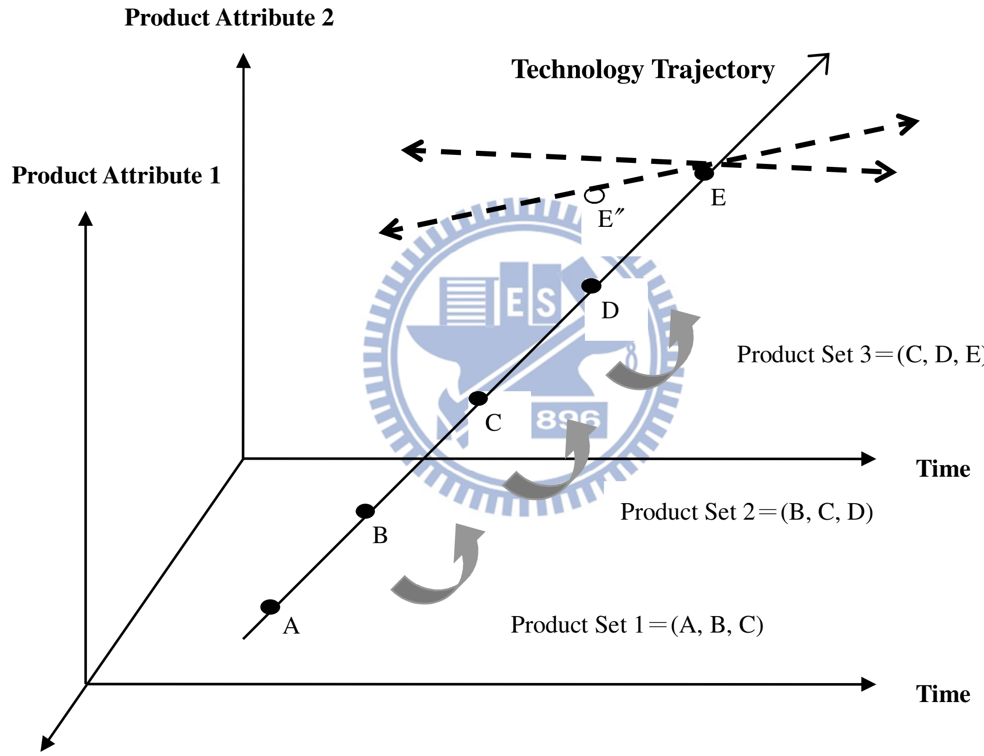


Figure 1. Research Concept Sketch

The focus is on the dynamic of new product's diffusion path. The general researches in diffusion usually use static viewpoint to investigate, few have discussed the dynamic complexity. We use multi-generation of intra-brand product with the implementation of spatial science to analyze the competition of products in each evolution cycle. Now let us assume that the considered set of chosen product choice is composed by product A, B, and C in the first generation. If consumer's aversion for losses is compromised, the probability of option B in product set {A, B, C} will be bigger than in set {B, C, D} of the second generation. Innovation, acceptance, and diffusion are related continuous processes; consumers' compromise effect denotes that brands gain share when the one selected is the intermediate rather than extreme option. Consequently, the interaction between new products were assessed in each generation. Whether a decoy creates consumer compromise and extremeness aversion mentality was also detected.

With time and technological advancement, new-generation products are introduced into the market and end up competing with previous-generation products. According to the diffusion model of high-tech products by Norton and Bass (1987), a new product may not immediately become a huge success, with the sales growth being a gradual diffusion process. New-generation products may expand the company's sales through better specifications, wider applications, and improved features, but may also cannibalize existing products' sales.

How the product's attribute influences each other's product attractiveness over various generations was analyzed. Then the process and interaction among multiple products and the characteristic of products' diffusion can be identified. The type of vertical or horizontal diffusion allows us to understand the path of technology's trajectory. Under different diffusion rates, product development may move toward E or E″ (i.e., consumer choice not going for the latest product immediately, but after some time buffer), and then proceed on new trajectories, indicative of the varying new product developments. Combining discussions of consumer psychology and product physical attribute allows us to understand the nature of competition and the market evolution.

3.2 Joint-Space Mapping

In order to investigate the interaction between new products released on the market by a multi-products brand at different points in time, this study uses the logit-type market share model (González-Benito et al., 2009) for calculating the price competition index of each product. The competition index serves to calculate the cross-price elasticity in order to determine the relationship between changes in the relative attractiveness of products caused by changes in product prices. This contributes to define the directions toward which the consumer's compromise tendency moves as technical progress. A technological trajectory can be represented by the movement of multi-products trade-offs cross over different generations, and the trajectory in the multi-generation space defined by these analyzed price and product attractiveness variables.

To take this one step further, we integrate the competitive interaction model of market sales and the autologistic model of spatial patterns to view the product's intrinsic growth. The autologistic model is a flexible model for predicting the presence or absence of disease in an agricultural field on the basis of soil variables (Gumpertz, Graham, and Ristaino, 1997). This research applies it to marketing to analyze whether a product possesses attractiveness or not by considering products' spatial correlation. As shown in Figure 2, the procedure involves three steps. In the first step, we construct a price competition index using the target product's actual purchase histories by all customers for different generations. This analysis includes prices and sales volumes of each product specification. In the second step, we build an attraction model based on the price competition outcome. As will be seen subsequently, this measure links the estimated purchase odds of the focal product to buying intent or aversion derived from the cross-price elasticity. In the final step, we use the predictive autologistic choice model to forecast the probability that each product specification has an effect as if a tugging action were applied.

Logit-Type Market Share Model

Transaction Data — Equation (1) (2)

Price Competition Index to Reveal Multi-Products Brand Interaction

↓

Attraction Measure

Price Competition Index Outcome — Equation (3) (4)

Cross-Price Elasticity to Determine the Relative Attractiveness Relationship

↓

Autologistic Choice Model for Constructing Joint-Space Map

Aggregated Data — Equation (5)

Products' Spatial Correlation to Determine the Product Growth Path

Figure 2. Conceptual Overview of Models

3.3 Mathematical Calculations

The logit-type market share model assumes that price is the determining factor in market share; the attractiveness of a particular product is the response variable. It splits the price cross-effects in the market response model into two elements: the first one is the changes in price of other products resulting from the changes in prices of a certain product; the second element is the interaction influence on all other competitive products caused by the price of each product. The subjects in this study are various products modes under a single brand from three generations, so as to transform the original relative attractiveness model among brands into products specially designated to a certain brand category. The analysis of the models is as follows:

$$\pi_t(j) = \frac{A_t(j)}{\sum_{j' \leftarrow J} A_t(j')} \tag{1}$$

$$A_t(j) = e^{(\alpha_j + \sum_{j' \neq j} {}_{j' \leftarrow J} \beta_{jj'} P_t(j'))} \tag{2}$$

where, $\pi_t(j)$ represents the relative attractiveness of product j in period t; $A_t(j)$ is the attraction of product j in period t; α_j is the interior attraction of product j independent of price effects; $\beta_{jj'}$ stands for the price competition index of product j and j'; and $P_{t(j')}$ is the price of product j' in period t.

The relative attractiveness of product j in period t can be calculated by formula (1), that is, the ratio of the attraction of product j in a certain time period to its competing products' attractiveness. The attraction of product j in a certain time period is computed by formula (2); the attraction is divided into two parts: attraction of product j itself without regard to prices and its attraction when influenced by prices. We focus on the latter that discusses the price competition index of product j when its attraction is caused by the prices of other existing products in the market.

The attraction model (2) used the logarithm and results in formula (3). The relationship of price and attractiveness can be found by regression estimates according to the products existing in the market at each stage. The price competition index from mutual influences of individual products was obtained, and then the cross-price elasticity from the price competition index was found using formula (4).

$$\ln A_t(j) = \alpha_j + \sum_{j' \neq j} {}_{j' \leftarrow J} \beta_{jj'} P_t(j') \tag{3}$$

$$\delta(j, j') = \left(\beta_{jj'} - \sum_{j' \neq j} {}_{j'' \leftarrow J} \beta_{j'' j'} \pi_t(j'') \right) p_t(j') \tag{4}$$

where $\delta_{(jj')}$ represents the cross elasticity in product j and j'; $\pi_t(j'')$ is a delegate of the relative attractiveness of product j''; and $\beta_{j''j'}$ presents the price competition index of product j' and j''. The cross elasticity of product j and j' is due to the influence of the price of product j' on the sales of product j, and subtracts the influence of the price of product j' on other products' attraction. Therefore, considering market competition into consideration, deriving the cross elasticity, and discussing these products enables one to identify substitutes or complementary relationships through the elasticity.

In the autologistic model, the log odds of attraction in a particular quadrat (here meaning product mode or specification) are modeled as a linear combination of high or low attraction in neighboring quadrats as well as the price and memory variables. Neighboring quadrats can be defined as adjacent quadrats within a generation, quadrats in adjacent generations, quadrats two generations away, and so on. There are three features of the autologistic model that make it well suited to the study of spatial patterns of attractiveness: (1) it applies specifically to binary response variables such as high or low attraction; (2) explanatory variables can be incorporated into the model; and (3) the probability of high attraction in a quadrat depends explicitly on whether the neighboring plots are attracted.

Traditionally, logistic regression is often used to model nonspatial binary data (Gumpertz et al., 1997). This research incorporates spatial correlation into logistic regression models by modeling the probability of high attraction in a given quadrat (product mode) as dependent on the attraction status of neighboring quadrats. This method was originally developed by physicists to model an electron spin at each site in a magnetic field (Cressie, 1991). It has also been extended to ordered categorical data, such as disease ratings on a scale of 1 to 4 (Strauss, 1992); similarly, we rated a categorical scale of product memory attributes as independent variables since the marketing communication mechanism lies in capacity attributes, especially in regard to technology goods.

For rectangular lattices, there are some standard systems of neighbors (Besag, 1972). We applied and modified it as a first-order system includes only the four adjacent quadrats in the set of neighbors—two within the generation and two in adjacent generations; a second-order system includes the four diagonal neighbors in addition to the quadrats of the first-order system; a third-order system includes quadrats two generations or columns away, shown in Figure 3.

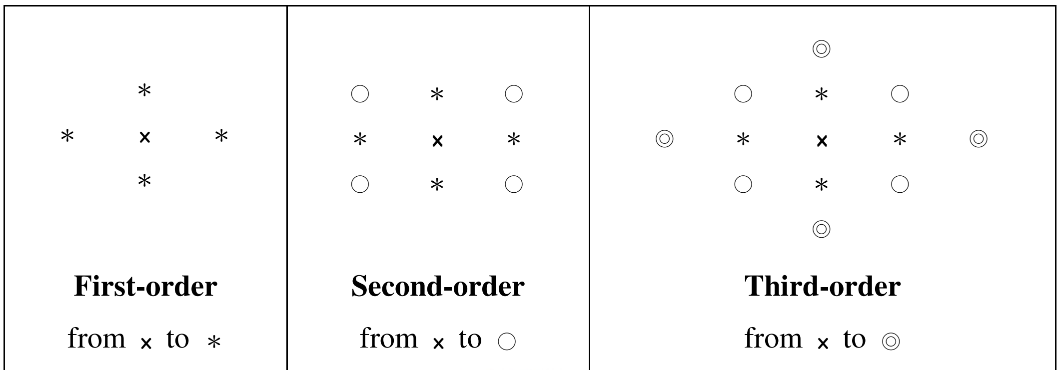


Figure 3. Modified Standard Systems of Spatial Mapping

A set of products can be defined for each quadrat in the lattice; if quadrat i is a neighbor of quadrat j, the converse is also true. For binary data, if the response at site i depends in a pairwise fashion on the observed number of neighbors with attraction presence and on covariates, then the conditional probability of a particular response, $y_i = 1$ (high attraction) or $y_i = 0$ (low attraction), is as follows:

$$\Pr(Y_i = y_i \left| x_i, y_j, j \in N_i \right.) = \frac{\exp\left\{\sum_{k=0}^{r} \beta_k x_{ik} y_i + \sum_{j \in N_i} \gamma_j y_i y_j\right\}}{1 + \exp\left\{\sum_{k=0}^{r} \beta_k x_{ik} + \sum_{j \in N_i} \gamma_j y_j\right\}}$$

where the set of products of the ith site is denoted as N_i. Since y_i takes the value 1 if the attraction is high, the log of the odds of attraction being present is expressed in formula (5).

$$\text{logit}(\Pr(Y_i = 1) \left| x_i, y_j, \textit{for } j \in N_i \right.) = \sum_{k=0}^{r} \beta_k x_{ik} + \sum_{j \in N_i} \gamma_j y_j \tag{5}$$

The first-order spatial dependence is when the spatial dependence is of the same magnitude down generations and across generations. $\sum_{j \in N_i} y_j$ is the sum of the number of high attractions in the four neighbors. The parameters β_k quantify the effects of the covariates given the attraction status of the neighbors. For instance, if price is a covariate, its parameter would measure the log of the increase in odds of high attraction that was due to increasing price, after accounting for the effect of attraction in any neighboring quadrats. This type of model has flexibility in that neighbors may be defined in any way that makes sense. If spatial correlation is present, the covariates alone are not sufficient to account for the observed spatial variability. In some settings, spatial correlations can be completely eliminated by regression on covariates. In the present application, however, attractiveness is actually spread or whittled away from one product to another, so it is likely that, even after considering the variables, the attractiveness status of the neighboring quadrats could be an important predictor of attractiveness presence.

3.4 Lifetime Distributions

As the study concerns the duration of product mode after market entry, and these products become competitive at different times, lifetime data analysis is proposed for attractive comparison. Assuming that T is a nonnegative lifetime random variable, functions of T are summarized as follows:

Probability density function: $f(t)$, $\forall t \geq 0$ (6)

Distribution function: $F(t) = \int_0^t f(x)dx$ (7)

Survival function: $S(t) = P(T > t) = 1 - F(t) = \int_t^\infty f(x)dx$ (8)

Hazard function: $h(t) = \lim_{\vartriangle t \to 0} \frac{P(t \leq T < t + \vartriangle t \mid T \geq t)}{\vartriangle t}$ (9)

Cumulative hazard function: $H(t) = \int_0^t h(x)dx$ (10)

Among these, survival function $S(t)$, which means the probability of a product surviving to time t, is decreases monotonically. Hazard function $h(t)$ specifies the failure probability during a very short interval of time, for example, from t to $t + \vartriangle t$, given that the product survives till time t. These functions can provide mathematically equivalent specifications of the distribution of T. This means that if any of them are known, the others are uniquely specified.

The lifetime of a product is said to be censored when its end-point of interests has not been observed, but is known to have occurred at certain interval. There are several types of censoring: (1) right censoring- the observed lifetime is less than or equal to the actual but unknown lifetime, in brief, not experiencing the event at the end or termination; (2) left censoring- the actual lifetime is less than that observed—this situation is encountered when experiencing the event before the start of study or when the only thing for sure is the event occurring at or before the observed time; (3) interval censoring- the event has occurred within an interval of time, but the exact time point is unknown.

Two methods can be employed to estimate the survival function. First, the life table method is a modification of the frequency table to deal with censored data and is a widely used method of portraying lifetime data. This method emphasizes estimation of the conditional probability of death in an interval given surviving to the start of that interval and the probability of surviving past the end of an interval. Assumptions for the life table method are as follows: (1) censored event times are independent of their real lifetimes; and (2) the censoring times and failure times are uniformly distributed with each interval. The second method is product limit estimate, also called Kaplan-Meier estimate. To obtain this estimate of survival, the lifetimes for those experiencing the specified event are first ranked in increasing order. If both censorings and failures occur at the same time, then the censorings are assumed to occur after the failure time. The Kaplan-Meier method assumes that all of the subjects with censored times were at risk at the time of the failures.

4. Empirical Application

4.1 Industry Property and Data Sources

The target industry is that of the MP3 (MPEG-1 AUDIO LYER3) music player, a market that has already entered the saturation phase in a majority of developed countries. Following the first purchase, product sales become dependent on the consumers' purchasing related, upgraded products or on discarding old products in favor of repurchase. Therefore, compared to PLC, using PEC can provide a more comprehensive perspective for understanding the interaction and competition among products in each evolutionary cycle. This understanding can provide a basis for determining the future development trends of products when formulating marketing strategies.

MP3 is a kind of digital audio encoding and destructive compression format developed by MPEG (Motion Picture Experts Group). It is designed to reduce the amount of audio data, filter out the voices that people cannot accept when listening to music. In applying psychological acoustics to determine whether the audio composition can be discarded, the MP3 format for music compression does not differ much from the CD format of music storage as far as the human ear is concerned. The first MP3 music player in the world was manufactured by Saehan Information Systems in Korea in 1998 and its subsequent product sales grew exponentially each year.

Currently, the globally competitive, major vendors in the market are Apple, Creative, Samsung, Sony, SanDisk, Microsoft, iRiver, etc. Industrial concentration is low. With the introduction of its iPod series products, Apple has achieved leadership; its global market share was 26.7% in 2007, and over 20% in 2009, whereas other manufacturers have less than 10% market share. In the US market alone, its market share was 70% in 2010 (Yoffie and Kim, 2010). Nevertheless, an analysis of the PLC of the global MP3 music player shows its introductory stage was from 1998 to 2001, at which time there were only a few R&D manufacturers; 2002 to 2006 saw the growth stage; in 2007, it matured, and since then, the growth rate has gradually declined and has become negative. Even with the economy's rebound in 2010, market growth is still limited. It is predicted that the product will enter a decline in the future because of market saturation.

In addition to the declining quantity of MP3 products delivered as a result of market saturation, there will be further decline due to MP3 music phones absorbing most of the original market. As with personal computers, consumers' first purchase will not be the main source of sales in the future; rather, product sales will depend on consumers purchasing related upgraded products or discarding old or damaged products in favor of repurchase. Firms must provide more powerful product features, for example, advanced wireless connectivity and high-end displays to attract consumers to buy the new products (iSuppli, 2008). At present, Apple, Samsung, Microsoft, and iRiver have adjusted their strategic direction to pursue the development of multimedia products; they no longer manufacture just the MP3 pure play music products but have introduced more polybasic PMP-related (portable multimedia player) products, using innovation to stimulate a market in which growth is limited.

The transaction data for Taiwan's market leader is analyzed. Following the leading brand, MSI, Creative, and Panasonic have the sequence market shares. The analysis can be extrapolated to analyze the music industry. This research endeavors to examine MP3 products among which the brand in Taiwan was the leader, in the context of the global MP3 player's industrial development, and then to explore the competition among various types of music players.

4.2 Database Description

This study probes the effect of the price of different product modes belonging to a single brand category on the relative attractiveness of other products. To measure the relative attractiveness of specific brand products, this study used existing data on market transactions. Using the database systems of certain distributors in Taiwan, 15 months of sales records on MP3 transaction data were collected: a total of 7,936 entries of observed data for 53,197 units sold. The authors analyzed the price competition among nine different product types launched on the Taiwan market by the leading brand. The influence of the prices of specific products on the sales of other products was used to reflect the relative attractiveness of this brand's products. This study discusses the brand in three stages from the PEC perspective, and uses the research results to determine the structure of market competition.

Information on the different product types selling in the observation period include product memory, mode, buyers' name, and purchasing time. Drafting the sales revenue and sales volume of all products with respect to selling time fails to show a simple-four cycle distribution of introduction, growth, maturity, and decline as expected in PLC. The survival time observed for each mode of product in the market is from 7 to 16 months; the shortest is for mode 720 (7 months from February 2005 to August 2005) and the longest is for modes 200 and 210 (both 16 months from December 2004 to February 2006). Meanwhile, although memory DRAM (dynamic random access memory) was expensive both before and after 2004, it can store more capacity, and the size of memory capacity, therefore, became the greatest force that pushed consumers to make purchases at that time (Yoffie and Kim, 2010). The follow-up products discussion is divided into three stages because makers of MP3 continue to introduce new products, as they have a short life cycle. To maintain the accuracy of the study estimates, the products are classified according to the PEC concept. The first phase of product specifications is 128/256MB, the second is 256MB products, and the third phase consists of 512MB, 1G, and 5G memory.

The average price and sales volume of each product specification according to PEC stages are displayed in Table 1. Firms adjusted the product price over time. Moreover, the total sales of existing products also change in the light of new product launches. Corporations use the product mode as their communication mechanism in advertising and promotion, while modes are prioritized according to memory capacity, and organized by their launch dates. Therefore, consumers' purchases also depend on the order of mode, apart from the memory capacity.

Table 1. Product Price and Sale in Each PEC (Price Unit: NT dollar)

PEC	Mode	110	120	150	102	180	130	200	210	720
First March to June 2004	Average Price	3327	4546	5348						
	Sales Volume	2674	3822	1384						
Second July to Oct 2004	Average Price	3155	4061	5180	2950	4715				
	Sales Volume	2345	3594	694	650	1365				
Third November 2004 to May 2005	Average Price			4407	2693	3700	3668	4835	3309	7578
	Sales Volume			321	360	415	2319	4366	10583	68

4.3 Joint-Space Reasoning

The first PEC includes the 128MB generation; the firm sold modes 110, 120, and 150. This research infers that the relationship between the sales volume of 110 and the average prices of 120 and 150 has significant relevance; likewise, the relationship between the sales of mode 120 and the average prices of 110 and 150; and that between the sales of mode 150 and the average prices of 110 and 120. The entire ratiocination proposes that there exists significant association between the sales of each product mode and the average prices of other modes in the first PEC stage. Similarly, firms lead in 256MB-generation sales in the second PEC phrase, with product specifications for 102, 110, 120, 150, and 180. A correlation may be inferred between the sales of 102 and the prices of 110, 120, 150, and 180. The rest may be deduced by analogy, resulting in a total of five relationships. The overall proposed ratiocination is that there exists significant association between the sales of each product mode and the average prices of other modes in the second PEC stage.

The third PEC is a complete product line generation, having product specifications for 102, 130, 150, 180, 200, 210, and 720. There is evidence of a correlation between the sales of 102 and the prices of 130, 150, 180, 200, 210, and 720. The rest may be deduced by analogy; a total of seven relationships ought to be significant and it is inferred that there exists significant association between the sales of each product mode and the average prices of other modes in the third PEC stage. We can then investigate the causation of compromise effect through price elasticity's influence on choice or attraction's influence on market share.

4.4 Product Price Competition

All the regression equations were derived using formula (3) for the relations between the sales of each product and the prices of other product modes targeted at each evolution stage. The results are summarized in Table 2, and most of the reasoning is supported. The indices in the first PEC stage all reach statistical significance. By observing the positive or negative sign, we can discern the intra-brand interaction. For example, for the sales attraction of mode 110, the price of mode 120 has a negative influence on the sales of mode 110, that is, mode 120 weakened the appeal of mode 110. On the other hand, the price of mode 150 has a positive influence on the sales of mode

110, that is, mode 150 increased the attractiveness of mode 110; the equation is as follows:

$$Q_{110} = e^{(0.84315 - 0.00005 P_{120} + 0.00006 P_{150})}$$

Compared to the first stage, another two product modes were promoted in the second PEC, namely, 102 and 180. Mode 102 is low-priced in the product set; the price of mode 180 is between 120 and 150. Observing the firm’s pricing adjustments, the average price of the existing products in the first phase (mode 110, 120, and 150) was seen to descend in the second stage. In the third PEC stage, two products dropped out (mode 110 and 120) and four new specifications entered the market (mode 130, 200, 210, and 720), so that a total of seven product specifications were sold in the market. Mode 210 and 130 mainly filled the price space left vacant with the departure of 110 and 120. Mode 200 and 720 entered the market at a high price. The average price of the existing products in the second phase (modes 102, 150, and 180) was seen to descend in the third stage. Regression analyses in connection with the seven products in the third stage were derived; all are statistically significant.

Table 2. Regression Outcome in Each PEC

PEC	DV	IV	Estimates	R-Square (%)	P-value
1	Q110	P120, 150	-0.00005; 0.00006	1.07	0.0161**
	Q120	P110, 150	-0.00014; 0.00012	5	<0.0001***
	Q150	P110, 120	0.77772; -0.4780	23.88	<0.0001***
2	Q102	P110, 120, 150, 180	0.33659; -0.13867; -1.35633; -0.04573	89.83	<0.0001***
	Q110	P102, 120, 150, 180	0.00014; -0.00018; 0.00007; 0.00024	9.53	0.0003***
	Q120	P102, 110, 150, 180	2.16041; 0.04307; -0.02023; -0.43080	72.14	<0.0001***
	Q150	P102, 110, 120, 180	2.73655; -0.58050; 0.10160; -0.43080	72.87	<0.0001***
	Q180	P102, 110, 120, 150	2.18442; -0.05692; -0.11222; -1.01460	91.41	0.1792
3	Q102	P130, 150, 180, 200, P210, 720	0.45214; -0.66950; -2.23780; 0.52590; -0.3028; 0.97222	67.21	<0.0001***
	Q130	P102, 150, 180, 200, P210, 720	-1.53180; -0.36898; -0.87832; 0.38006; -0.02166; 0.35683	33.76	<0.0001***
	Q150	P102, 130, 180, 200, P210, 720	0.89287; -0.02111; -2.01152; -0.01988; -0.10337; 0.22218	72.61	<0.0001***
	Q180	P102, 130, 150, 200, P210, 720	0.57991; -0.00667; -1.87467; 0.18420; -0.10844; 0.15413	84.24	<0.0001***

Table 2. Regression Outcome in Each PEC (Continued)

PEC	DV	IV	Estimates	R-Square (%)	P-value
3	Q200	P102, 130, 150, 180, P210, 720	-1.16882; -0.12895; -0.26180; 0.15157; -0.13491; 0.07178	9.89	0.0004***
	Q210	P102, 130, 150, 180, P200, 720	-0.00009; -0.00024; -0.00010; 0.00016; 0.00023; 0.00014	9.24	0.0008***
	Q720	P102, 130, 150, 180, P200, 210	-0.28239; -0.01415; -1.17912; 0.40590; -0.40393; 0.40980	78.63	<0.0001***

** is significant in level 0.05; *** is significant in level 0.01

Table 3 presents the price competition index among products. From the positive or negative sign, we know that with regard to the sales attraction of mode 120, the price of mode 110 weakens its appeal; contrarily, the price of mode 150 increases its appeal. With regard to the sales attraction of mode 150, the price of mode 110 increases its attractiveness, but the price of mode 120 weakens its attractiveness. On the basis of the above interaction, mode 110 and 120 are mutually competitive in price, whereas mode 110 and 150 are complementary in price. There is no clear competitive relationship between 120 and 150; the price of mode 120 weakens the attraction of 150; however, the price of mode 150 increases the attraction of 120.

Two products were launched in the second stage, of which 102 is the cheaper one in the product set. From the price competition index (only significant items are listed), the effect of this low-priced good can be summarized as that of its price generating a positive impact on modes 120, 150, and 180, respectively; thereby increasing other products' attraction. Another mode, 180, is a mid-priced good; it has a positive effect on the sales of mode 110 by increasing the attraction of mode 110; however, its price has a negative effect on the sales of 120 by decreasing its attraction. In the third PEC, four products enter the market: modes 210 and 130 were priced at the median, while modes 200 and 720 were priced higher. Some conclusions can be summarized from the significant product comparisons. The price of mode 720 has a positive influence on the sales of modes 150, 180, 200, and 210, increasing other products' attraction. Both high-priced products 200 and 720 have a positive influence on modes 130 and 180, showing that they add attraction to middle-priced products. Compared with these two high-priced products, the price of mode 200 reduces the attraction of mode 720; however, 720 increases the product attractiveness of mode 200.

Table 3. Price Competition Index and Cross Elasticity in Each PEC

PEC	Product interaction (j,j′)	Price competition index (βjj′)	Cross elasticity (δ)	Substitute or Complementary
Stage 1	(110,120)	-0.00005	462.79356	Substitute
	(110,150)	0.00006	-0.29132	Complementary
	(120,110)	-0.00014	-551.68616	Complementary
	(120,150)	0.00012	0.47394	Substitute
	(150,110)	0.77772	2587.70060	Substitute
	(150,120)	-0.47803	-2173.12590	Complementary
Stage 2	(120,102)	2.16041	4461.54300	Substitute
	(150,102)	2.73655	2333.18700	Substitute
	(180,102)	2.18442	1207.67800	Substitute
	(110,180)	0.00024	44.24539	Substitute
	(120,180)	-0.01286	-61.05280	Complementary
Stage 3	(102,130)	0.45214	1806.520	Substitute
	(200,130)	-0.12895	-504.868	Complementary
	(210,130)	-0.00024	112.9073	Substitute
	(102,200)	0.52590	2265.252	Substitute
	(130,200)	0.38006	1773.872	Substitute
	(180,200)	0.18420	582.791	Substitute
	(720,200)	-0.40393	-2288.910	Complementary
	(720,210)	0.40980	1356.162	Substitute
	(102,720)	0.37222	2204.424	Substitute
	(130,720)	0.35683	2420.770	Substitute
	(150,720)	0.22218	1041.131	Substitute
	(180,720)	0.15413	522.535	Substitute
	(200,720)	0.07178	40.44491	Substitute
	(210,720)	0.00014	-669.873	Complementary

Further, formula (4) is used to solve cross-price elasticity between products. The conclusions for PEC1 are that mode 120 is a substitute and mode 150 is a complement for mode 110; for mode 120, mode 110 is a complement and mode 150 is a substitute. In accordance with mode 150, mode 110 is a substitute, whereas 120 is a complement. To synthesize the competition in PEC2, it can be acknowledged that the low-priced mode 102 is a substitute for modes 120, 150, and 180. In PEC3, the median-priced mode 130 is a substitute for 102 and 210; however, it is a complement for mode 200; another median-priced mode, 210, is a substitute for 720. The higher-priced mode 200 is a substitute for modes 102 and 130; another higher-priced mode, 720, is substituted for modes 150, 180, and 200, but complements 210. Finally, modes 102 and 720; 180 and 200; 180 and 720 are mutually substitutes of each other. Table 4 is the relative attractiveness of products stratified on each PEC stage on the basis of the above results.

Table 4. The Relative Attractiveness of Products in Each PEC

PEC \ Mode	110	120	150	102	180	130	200	210	720
1	0.5136	0.9418	0.2131						
2	0.3720	0.7111	0.0873	0.0813	0.1874				
3			0.0177	0.0199	0.0230	0.1439	0.3104	1.3483	0.0037

4.5 Spatial Correlation

After investigating the interaction between products, this research integrates the findings in the spatial pattern. The autologistic model incorporates the spatial autocorrelation by conditioning the probability that a high or low attraction quadrat will be attractive in neighboring quadrats. The definition of neighboring quadrats is a set of products tailored to the particular situation under this study. Here, we established a categorical scale of product memory capacity, with a rating of 1 for 128MB, 2 for 256MB, 3 for 512MB, 4 for 1G, and 5 for 5G. Moreover, the derived critical values of attractiveness had an average of 0.37082, on the basis of which attraction could be considered high or low. The independent variables analyzed were price and memory; the dependent variable was the high/low relative attractiveness of products.

This research fits three models to the data. MODEL1 is a logistic regression model to probe the effects of price and memory on attractiveness, ignoring spatial correlation. This is a preliminary model used to check whether the covariates alone can explain the spatial patterns. If spatial correlation is still present in the residuals, the covariates alone are not sufficient to account for the observed spatial variability. As we have proved, attractiveness is actually spread or whittled away from one product to another, and the attractiveness status of the neighboring quadrats could be an important predictor of attractiveness. MODEL2 is a second-order autologistic model with product price and memory as covariates; it is constructed by adding terms for attraction in adjacent quadrats within the generation (W), in adjacent generations (A), and diagonally (D). MODEL3 is a pure autologistic model without covariates. These predictions are based solely on attractiveness in the neighboring quadrats and are used to check whether the covariates can be dropped from MODEL2. The three models are the following:

MODEL1: logit $(p_{ij}) = \beta_0 + \beta_1 P_{ij} + \beta_2 M_{ij}$ (11)

MODEL2: logit $(p_{ij}) = \beta_0 + \beta_1 P_{ij} + \beta_2 M_{ij} + \gamma_1 W_{ij} + \gamma_2 A_{ij} + \gamma_3 D_{ij1} + \gamma_4 D_{ij2}$ (12)

MODEL3: logit $(p_{ij}) = \beta_0 + \gamma_1 W_{ij} + \gamma_2 A_{ij} + \gamma_3 D_{ij1} + \gamma_4 D_{ij2}$ (13)

In the three models, P denotes product price, M is product memory capacity, and the subscripts i and j indicate generation and quadrat, respectively. The numbers of high-attraction neighbors are indicated by $W_{ij} = Y_{i,j-1} + Y_{i,j+1}$, meaning the number of highly attractive quadrats of the two adjacent quadrats within the same generation. A_{ij} is the number of highly attractive quadrats of the two adjacent quadrats in first-order neighboring generations; D_{ij1} is the number of highly attractive quadrats of the two diagonal quadrats in the (1,1) and (-1,-1) direction; and D_{ij2} is the number of highly attractive quadrats of the two diagonal quadrats in the (-1,1) and (1,-1) direction in second-order neighboring generations. The types of neighbors of site T_{ij} are diagrammed in Table 5.

Table 5. Types of Neighbors of Site T_{ij}

		Quadrat		
		$j+1$	j	$j-1$
	$i+1$	D_{ij1}	A_{ij}	D_{ij2}
Generation	i	W_{ij}	T_{ij}	W_{ij}
	$i-1$	D_{ij2}	A_{ij}	D_{ij1}

Including four separate terms for neighbors permits us to examine whether correlations across generations are as strong as those within generations and whether there are any diagonal gradients in product growth. If we thought that there was a gradient in a different direction, such as the (1, 2) direction, we could add terms to the model to capture the expected pattern. All models were fitted to the inner 3×9 lattice of 27 quadrats so that models involving adjacent quadrats and quadrats two spaces away could be accommodated. In each PEC, 9 quadrats had price and memory information, which memory value was from 1 to 5. The regression coefficients give estimates of the increase in odds of attraction if neighbors within a generation or in adjacent generations show attraction symptoms; thus, we obtain information about the degree of spread in different directions.

The omnibus test of model coefficients is implemented on an overall hypothesis that tends to find general significance of at least one of the parameters involved, and is conducted on a rational quadratic statistic like Chi-square in logistic regression. Since significance is observed, the regression model containing the covariates has explanatory ability. Overall, MODEL1 is significant with Chi-square 7.793 (df = 2, P-value 0.020), Cox & Snell R-square 0.251 (pseudo-variance explained). MODEL2 is also significant with Chi-square 15.086 (df = 6, P-value 0.020), R-square 0.428. MODEL3 is not significant since it has Chi-square 7.600 (df = 4, P-value 0.107), R-square 0.245.

The Hosmer and Lemeshow test provides a formal statistical test for goodness-of-fit for logistic regression models. The test assesses whether the predicted probabilities for covariates match the observed probabilities, is used frequently in risk prediction models. The results show models fit by P-values are not less than 0.05, the observed event rates match expected event rates in subgroups of the model population (Hosmer and Lemeshow, 2000). Comparing these three models, the second one has better explanatory ability and less misclassification; we subsequently focused on MODEL2.

Table 6. Chi-square Statistic for Comparing Models

	Omnibus			Hosmer–Lemeshow			R-square	
Model	Chi-square	df	Sig.	Chi-square	df	Sig.	Cox & Snell	Nagelkerke
MODEL1	7.793	2	0.020	3.138	6	0.791	0.251	0.407
MODEL2	15.086	6	0.020	2.605	7	0.919	0.428	0.694
MODEL3	7.600	4	0.107	4.570	6	0.600	0.245	0.398

While significance is found in the omnibus test, the differences among the coefficients are not specified. The parameter estimates and percent of quadrats misclassified for each fitted model are shown in Table 7. Misclassification is the proportion of quadrats for which the predictions do not match the attraction status actually observed. Although no predictor variables in MODEL2 are statistically significant, this may be because of consumers' risk awareness when considering new-generation products, which then may overshadow the other existing differences (as discussed in the next section). The regression coefficients give estimates of the increase in odds of attraction if neighbors within a generation or in adjacent generations show attraction symptoms; thus, we obtain information about the degree of spread in different directions.

Table 7. Parameter Estimates and Proportion on Quadrats Misclassified

Model	Intercept	Price	Memory	Within-generation Selling	Across-generation Selling	Diagonal (1, 1)	Diagonal (-1, 1)	Missclass.
MODEL1	9.456	-0.001	-3.438*					14.8%
MODEL2	63.111	-0.001	-20.542	-0.314	-20.491	-0.014	0.053	7.4%
MODEL3	6.649			-1.291	-3.499	0.754	-0.697	14.8%

* is significant in level 0.1

The log odds of attractiveness presence in a particular quadrat, also called the logit, is modeled as a linear combination of price and memory capacity in the quadrat, and high attractiveness in neighboring quadrats. Under the logit of the autologistic model with covariates, if a variable increases by one unit while the other variables remain constant, the logit of the product that is attracted increases by β units. The odds ratio for an increase of one unit is taking an exponential index as its parameters. For every unit increase in price, the odds ratio 0.99 means that the odds of attractiveness decreases 1%. For memory rating, the odds ratio 0.00001, or nearly to zero, shows that memory may not be the determinant of consumers' choice. Since the odds ratio for across-generation-selling is also nearly zero, the multi-product seems not to have a vertical diffusion. Within-generation-selling demonstrates a product interaction characteristic since the odds ratio is 0.7305 for increasing product specifications with the odds of high attraction decreasing 26.95%. Comparing the diagonal effect, the odds ratio 0.986 means that the odds of attractiveness decreases 1.39% for every increase in (1,1), whereas the odds of attractiveness increases 1.0544 times for increases in (-1,1) neighboring quadrats.

4.6 Survival in a Competitive Market

The focus of this study is on one specific product category, a single market for products to compete represents a time interval as in time series or survival analysis. Research has not shown whether a company increasing product modes in its product line to provide consumers alternatives can be a deterrent for all the market entrants or analyzed how product attributes affect product attractiveness and survival over the product's evolution. Therefore, the market entry perspective is also adopted and explored how product attributes condition the attractiveness.

The research data is aforementioned MP3 music player sales records; this includes three modes in PEC1, five modes in PEC2, and seven modes in PEC3. In spatial science, there is a type of data that belongs to point patterns, which is typically the locations of all objects or events of interest within regions, and possibly attributes attached to them (marked point pattern) (Heikkinen, 2011). Back to look at the market flat, the appearance of products formed the point patterns and we examined the association between the prevalence of the mode, possible result of diffusion, and whether or not it was attractive.

Regarding the price attribute, in order to detect whether the subsequent generation was associated with higher diffusion efficacy under the interdependence of the product, the dependent variable was the anteriorly calculated attractive versus non-attractive. The independent variables were the duration of selling months and pricing. Data dealt with in lifetime analyses are time to event. The times to event vary depending on the types of events. They may be named lifetimes, survival times, failure times, etc. Similar data is also captured when measuring the time to complete a task. In general, time in medical research is measured as the time from diagnosis to death or failure; analogously, in this research we measure the time from a product's market entry to its withdrawal.

What is new in lifetime data analysis is that we may have to deal with partial information, that is, there may exist censored or truncated data. Also, the subjects may start at different times. Moreover, the distribution of time to event is usually far from normal distribution. These features mean that standard statistical methods are inappropriate (Lawless, 2003). Basic objectives of lifetime data analysis include specifying models to represent the distribution of times to event for understanding the patterns and the relations with other variables and making statistical inferences on the basis of the model.

To compare methods of estimating the survival function, life table methods are useful in summarizing large data sets of lifetime, even if lifetimes and censoring times are known exactly. However, if precise estimation of the underlying survival function is important, then the Kaplan-Meier estimate is preferred (Lawless, 2003). Both estimates of the survival function can be presented in either tabular or graphic form. This research adopted the Kaplan-Meier estimate to analyze the intra-brand product competition data. Specifically, it is of interest to determine whether samples have arisen from identical survivor functions. The hypotheses being tested in this research are as follows:

H_0 : *The survival curves for three product generations are the same.*

H_a : *The survival curves for three product generations are not the same.*

In this multiple product case, we used the Kaplan-Meier estimate to test whether the survival time distributions of the three generations products are equal (except for grasping the survival distribution of products in an entirety flat market). In other words, we tested homogeneity of survival curves for length over strata. This study first examined the lifetime distribution of different product modes in the market macrocosm. There are totally night modes in the MP3 transaction database, including price, sales, and sales duration. The model depicts duration of each mode. Time is defined in discrete month periods $t = 1, 2, \ldots$, where period 1 is the start of the competition. In each period, it is assumed that a new entrant may join the competition. Product attractiveness was analyzed for the data given in this research. If the product is non-attractive, it can be considered its death, and the residual mode can be regarded as right censored data that is attractive. The number of censored and uncensored values is 6 and 3; in total 33.33% of product mode became attractive during market battle and 66.67% failed. The Kaplan-Meier estimator and estimated variance is shown in Table 8.

Table 8. Kaplan-Meier Estimator and Its Estimated Variance

Time on Study (t)	$\hat{S}(t)$	Standard Error
$0 \leq t < 7$	1.0000	0.0000
$7 \leq t < 8$	0.8889	0.1048
$8 \leq t < 10$	0.7778	0.1386
$10 \leq t < 13$	0.6222	0.1779
$13 \leq t < 15$	0.4667	0.1896
$15 \leq t < 16$	0.3111	0.1792
$16 \leq t$	0.1556	0.1419

The survival curve is presented in Figure 4 to synthesize the above estimates. Survival function displays a decreasing form accompanied by time increases. The estimated mean survival time is 12.5556 months and its standard error is 1.3176.

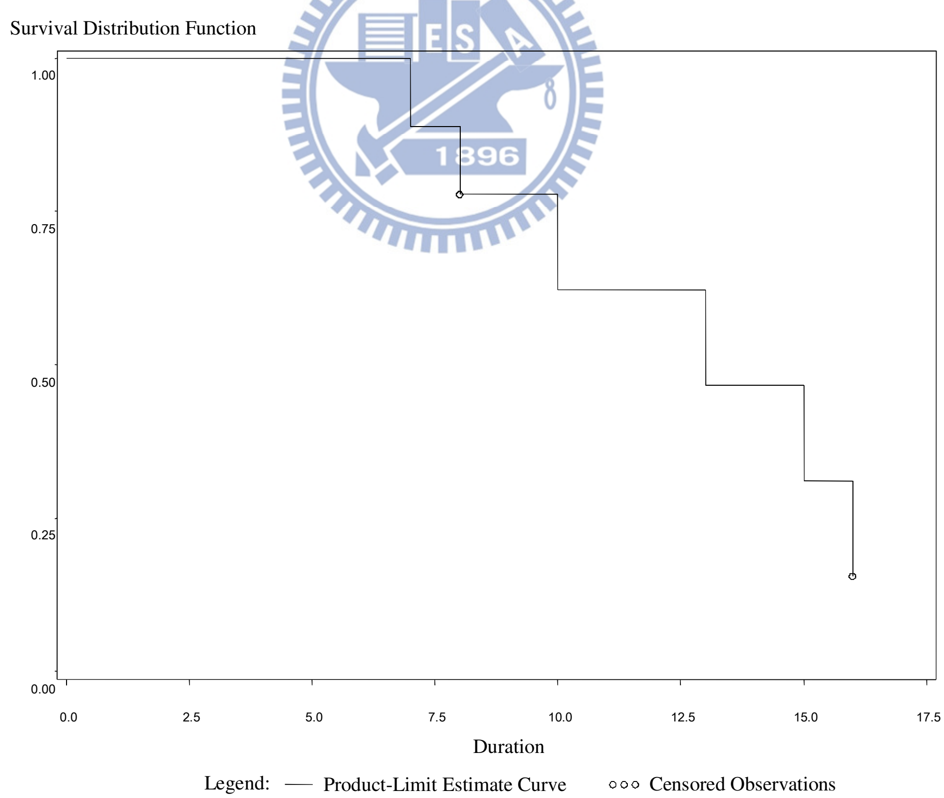


Figure 4. Survival Curves of MP3 Product

The following questions considered the generation effect (using results from Kaplan-Meier estimates), the estimated survivor function, the estimated mean survival time and its standard error (using the generalized Wilcoxon and log rank tests to test the hypothesis that the three generation survival time distributions are equal) and plot estimates of the survival functions for the three populations the form of the plot. Table 9 presents the rank statistics of three generations of products.

Table 9. Rank Statistics

MP3 Products	Log-Rank	Wilcoxon
Generation 1	-0.3786	-8.000
Generation 2	0.9524	6.000
Generation 3	-0.5738	2.000

The Wilcoxon and log rank tests are nonparametric methods for comparing groups of survival data. Gehan (1965) extended the Wilcoxon test to allow censoring; his generalized testing procedure involves combining samples and ranking them based on their lifetime. To construct the generation-rank statistics, the following procedure is used. The statistic is set to be 1 if the products of the considered generation are more successful than those of the compared generation; 0, if equally successful; and -1, if less. The end generation-rank statistic for a particular generation is obtained by the summing the statistics over all comparisons. The null hypothesis is tested on the basis of the value of this statistic; rejection was decided if it is too large or too small.

The main difference between the generalized Wilcoxon and log rank tests is in the weighing of the event. When the event is earlier in the time frame, the generalized Wilcoxon test is more appropriate since it gives greater weight to the earlier differences; the log rank test is better otherwise as it gives equal weight regardless of the time of occurrence. To define products generation for different strata, Table 10 presents the homogeneity testing of survival curves for length over strata, and tests the hypothesis that the effects of the products are the same in the three strata at $\alpha = 0.05$. Overall, there is not a significant difference in survival time distribution among these products.

Table 10. Testing Equality of Survival Curves for Duration over Strata

Test	Chi-Square	DF	P-value
Log-Rank	0.7669	2	0.6815
Wilcoxon	0.5933	2	0.7425
-2Log(LR)	0.5219	2	0.7703

Estimates of the survival curves of the three generations are presented in Figure 5. Because they are not significant difference, the curves cross. There are only three products modes in the first generation. Its curve line is steep, reflecting that the mean of estimated survival time is 13 months. The second generation seems to be a transitional generation. Its average estimated survival time is 10.8 months, which is shorter than two others. The third generation is a complete product line period. Its mean of estimated survival is 12.1429 months. All survival function displays decreasing forms accompanied by time increases. Among technological products, each generation has a short life span.

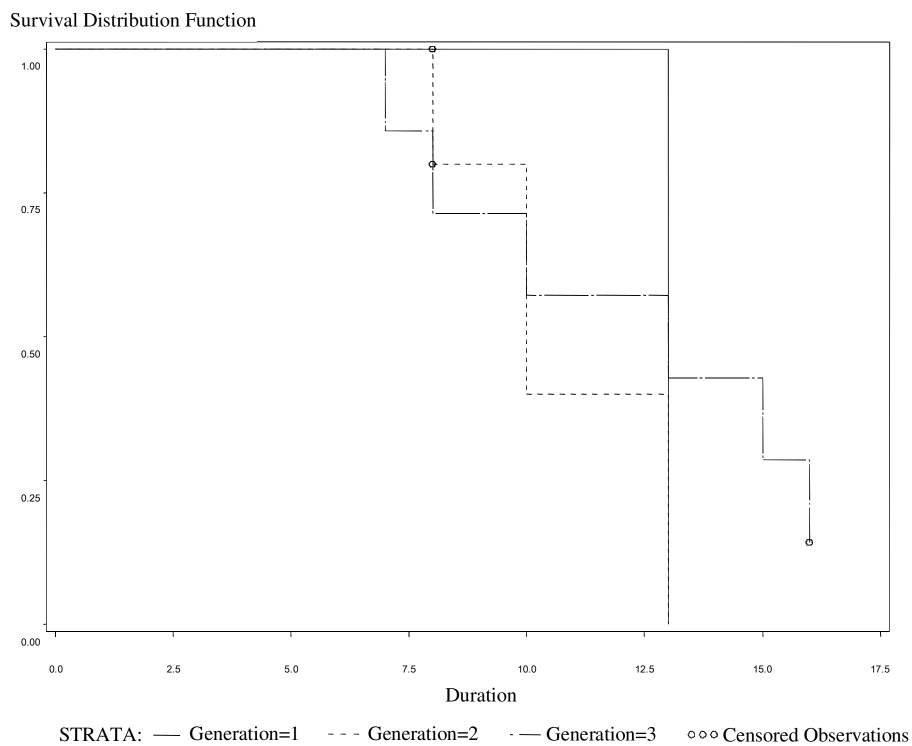


Figure 5. Survival Curves of Three Generations

4.7 Proportional Hazards

When it is necessary to understand and exploit the relationship between lifetime and certain covariates, we can model the effects of covariates on survival. Proportional hazards models are commonly used. Its hazard form is as follows:

$$h(t|x) = h_0(t)c(\beta' x) \tag{14}$$

where $h_0(t)$ is a baseline hazard rate without covariates and $c(\cdot)$ is a nonnegative function. A typical choice for $c(x'\beta)$ is $\exp(x'\beta)$. A proportional hazard is as follows:

$$\frac{h(t|x_1)}{h(t|x_2)} = \frac{c(\beta' x_1)}{c(\beta' x_2)} \tag{15}$$

Ratio of hazards does not depend on lifetime, and hazards for different covariates are proportional. Cox (1972) is the first scholar to propose a distribution-free approach to estimate β and $h_0(t)$. This kind of model is also called semi-parametric because $h_0(t)$ is nonparametric and the parametric part is introduced by covariates.

Because the survival functions of different generations reveal homogeneity and the third stage has the complete product line and its whole sales duration reveals difference as well as the second generation is just a transitional generation. We use the third generation complete product line data to examine the association between price attribute and possible result of diffusion that is attractive or not. A proportional hazard model was designed to determine whether or not price influences attractiveness. The model fit statistic computed using proportional hazards with covariates is 17.050 in criterion -2 LOG L, AIC, and SBC. The entire model does not get significance from the statistic displayed in Table 11. The global null hypothesis tests whether beta is equal to zero or not. Even though we fitted a proportional hazard model stratified on three generations, the entire model is also not significant.

Table 11. Testing Global Null Hypothesis of Proportional Hazards Model

Test	Chi-Square	DF	P-value
Likelihood Ratio	1.5043	1	0.2200
Score	1.7377	1	0.1874
Wald	1.5069	1	0.2196

Maximum-likelihood estimates of the model computed setting price as a covariate are reported in Table 12; price has non-significant difference on product attractiveness at $\alpha = 0.05$. The censored percent in the third generation is 14.29% (one seventh). By rewriting maximum-likelihood estimates by setting three generations as strata, with price indicator included, the result is still similar. To interpret the value of hazard, for product becoming attractive at some particular time, with time measured in months; this means that if hazard stays at the value over a period of time, the danger that one product would expect to be failed is 1.001 times. However, this does not reach the statistical significance meaning.

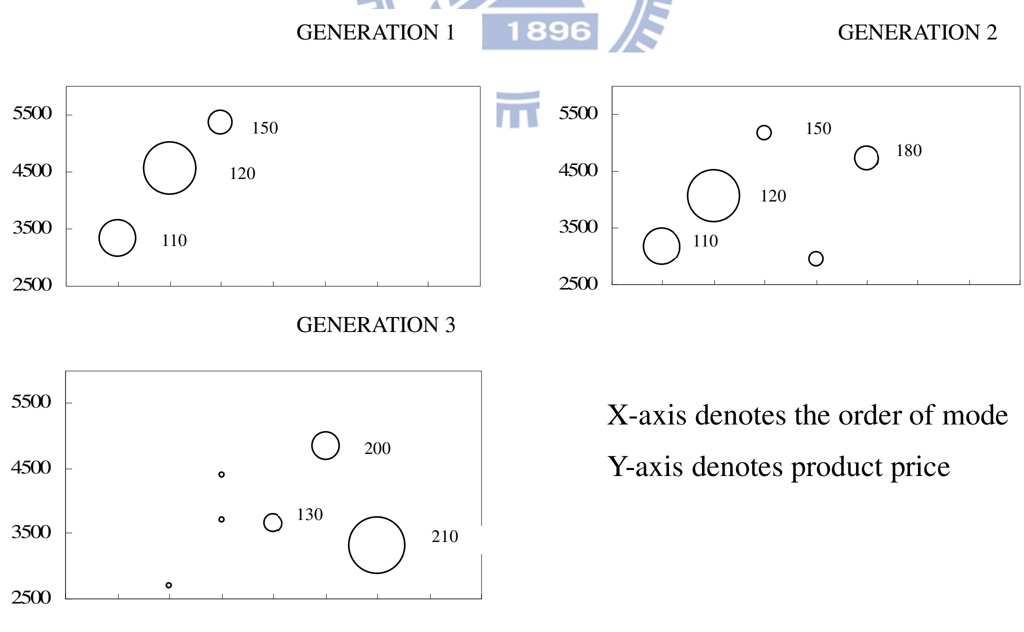
Table 12. Maximum Likelihood Estimates of Proportional Hazards Model

Variable	DF	Parameter Estimate	Standard Error	Chi-Square	P-value	Hazard Ratio
Price	1	0.0005263	0.0004287	1.5069	0.2196	1.001

5. Discussion

5.1 Compromise Phenomenon

Figure 6 draws the variation of consumers' compromise option by the relative attractiveness of each product mode when setting the attributes for axes. In the first PEC, mode 150 has the lowest relative attractiveness among the product set of the market, although it is the highest priced in this stage, but its existence generates positive attraction for the other product sales; in addition, prices between products segmented each other. Mode 120 is moderately priced in the product portfolio, but has the highest sales volume, reflecting the compromise effect. Consumers do not choose the extreme prices of goods but prefer middle attribute items. Therefore, corporations can set decoys to encourage consumers to buy the main product when introducing new products. On the other hand, they ought to explore the hidden meaning of the price competition index being negative with regard to the goods. For example, mode 120 makes other products less attractive, but that does not mean it should be excluded from the product set, because according to the value of relative attractiveness, it is the best item in the first phase of the market.



X-axis denotes the order of mode

Y-axis denotes product price

Figure 6. Product Attribute Position of Choice Set

Inspection of the low-priced mode 102 in PEC2 reveals that it has a positive price competition index for other products and substitutes for the other modes, which is confirmed by the extremeness aversion effect, since consumers will tend to the medium one. Although the relative attractiveness of 102 is not the greatest, it increases the attractiveness of others. This item not only segments the prices among products that complete the product line but also produces positive attraction for others due to this extreme price. To increase the sales of new core goods by a decoy is a worthwhile strategic direction. In PEC3, the price of the newly introduced modes 130 and 210 mainly have a negative relationship on others' sales attractiveness, which indicates that the synergy effect is not large for the whole product set. On the other hand, the price of mode 720 has a positive impact on the sales attractiveness of other modes; since it is the highest priced item in this stage, not only does it increase the sales appeal of the others but it also obviously contributes to product positioning since prices become more differentiated, so as to generate extremeness aversion because of consumers' compromise.

One phenomenon needs to be noted regarding the low-priced goods at this stage (mode 210), that is, its average price is much lower than the existing products, making it the number one seller. This is owing to its advantageous characteristics of price and memory capacity, so that consumers do not find it a difficult trade-off. It also allows cheap goods to enter the market mainstream, resulting in future product portfolio problems. In other words, an individual's best choice is found to be the intermediate and not extreme, as is deemed in prospect theory (Kahneman and Tversky, 1979), is not necessarily be supported. Since a product is a bundle of attributes, consumers compare product attributes when they proceed to make a selection in a particular set. Individuals are more concerned about their choice of product meeting a certain basic level of needs. Once an attribute level of an extreme option is beneficial and can upgrade their utility, consumers' preferences can be ascertained. This may undermine the premise that the option of a compromise product is related to complex decisions or there is no explicit preference on each attribute (Simonson, 1989; Simonson and Tversky, 1989). The probability that an advantageous new product will be chosen increases even when relevant decoy products are introduced. For compromise decisions, this logic is not that strong.

The main research findings are as follows. The direction of change in a price competition index is not necessarily positive, and the attraction of the prices of a specific product mode with regard to other products is not necessarily a positive or negative attraction. In the product portfolios, the lowest or highest priced products are the most likely to generate positive attraction, verifying the extremeness aversion of consumers. Products with extremely high prices produce more stable extremeness aversion effects on consumers. However, when prices are too low, consumers' choices move toward the low end. Consumers may even select extremely low-priced products, thereby negating the effects of midway compromise options and decoy options. This is caused from consumer' rational decision and corporations' marketing diffusion to satisfy the market needs by incremental innovation.

5.2 Multi-generational Spatial Diffusion

From the proposed analysis process and empirical result, we can derive a convergent thinking. As the odds ratio for across-generation-selling is nearly zero, within-generation-selling demonstrates that with product interaction leading to increasing product modes, the odds of high attraction increases; these multi-products reveal not vertical but horizontal diffusion. Comparing the diagonal effect, the attractive effect of the positive slope in Table 5 is greater than the negative diagonal slope. The negative diagonal slope (1,1) means that the product goes to the next generation and next mode, reflecting technology improvement and evolution; the positive diagonal slope (1,-1) means that the product goes to the next generation but decreases the mode choice. As innovation, acceptance, and diffusion are continuous processes and related to each other, we draft the purchase time and quantity according to each phase, merging the diffusion direction to show the product development path in Figure 7.

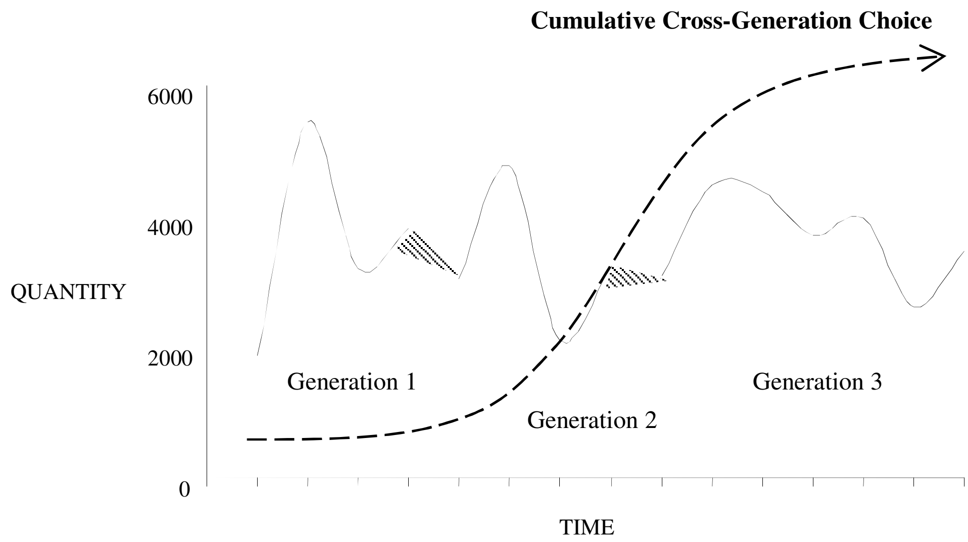


Figure 7. A Series of Technological Generations

The diffusion model of Rogers (1995) assumes that accepters of a new product are normally distributed. Mahajan, Muller, and Bass (1990) indicated that innovators exist throughout the spread of the period, and were not only distributed in the newly listed period; although the current purchaser number shows a bell-shaped curve, the overall cumulative accepter distribution is an S-shaped curve; this is the same as Rogers' model. In this study, the actual time and purchase volume create an approximate bell-shaped curve as time passes. Corporations introduced the next generation products while the curve was declining. According to Christensen (1997), situations can be divided into those requiring maintenance and those requiring disruptive innovation: maintenance innovation seeks to provide better performance and more expensive products to customers; disruptive innovation seeks to provide simpler and more convenient products. Destructive innovation is often an important strategy for market followers to beat the market leader.

In Figure 7, the dashed line represents product features to be used by customers, in line with customers' demand for product performance as time goes by. Customers' requirements for performance are increasing. Maintenance innovation refers to corporations' efforts to meet the requirements of the market; hence, there is continuous technology R&D to produce better products. The rate of technological progress is faster than the speed with which customers can absorb it, and, therefore, leads to companies often providing more than what customers demand. Since the so-called complements in this study are helpful for the sales of existing product lines after launching, substitutes are the substitution effect between the old and new products, rather than substitution between categories. Consumers' decisions rely on a trade-off between old and new products, specifications, and prices; product modes reflect the channel arrangement. The overlap area between generations is what we call substitution.

As mode 150 spans across three generations, it can be regarded as the core product to research horizontal and vertical diffusion influence. When the choice set increased modes 102 and 180, the core item 150 changes so that it has only a negative price competition index on the sales attraction of mode 110, although it originally had a totally positive impact on others in the first generation. That means that the interactions between the goods change unceasingly in accordance with the market product categories that increasingly or decreasingly change, so that real-time market information becomes more important. Especially, the core item has a diagonal neighboring effect on others, and this shows a negative impact and the fact that cannibalism occurred.

The essence of this phenomenon is that a joint probability distribution of the attractive occurrence of multiple-products can be derived when there is proper specification of the conditional probability of the event occurrence, conditional on the occurrence of other modes. The competitive interactions among products possess not merely substitution relationship but also complementary or competitive equilibrium. As the attractive effect of the positive diagonal slope is greater than the negative diagonal slope, that is, if the product goes to the next generation but decreases the mode choice will generate positive attraction for the other product sales. The results provide some cues that the analyzed product category has not reached the diffused market takeoff. To focus more on core item is a suggested rules for bringing innovations to market.

As for the predictor variables, price and memory are statistically non-significant; though the result is expected, this result may have been influenced by the fact that only new cross-generational products are being considered. New products may be risky in the consumers' profit calculation, which has subjective aspects. Risk-averse consumers will prefer tried-and-tested items even if the latest ones *seem better*, while tech-savvy ones will want the latest even if these are *potentially risky*. Thus it is very likely that new-generation products may perform worse than old-generation ones. This generates product attributes no longer be important; new technological products may not survive under the conditional probabilities of existing products.

Evolutionary adjustments result from cumulative change; consumers' utility function is expressed by the attraction function; and both sides' inner drive constructs the whole technology trajectory. Compromise is also caused by the scientific and technological trajectories, not only the price mechanism. Attractiveness is inferred to move from one generation to other, and thus the attractiveness of neighboring quadrats could be an important predictor. The higher the attractiveness of previous-generation products and the faster the development of new-generation products, the higher the negative impact on consumers' aversion. As the diffusion is mainly horizontal, if a product can not only increase the sales attractiveness of others but also contribute to product positioning, we call it "organic growth."

The concept of "organic words" was proposed by educators in the early 1950s, and entails teaching a child a group of *base* words, over which the child's vocabulary can later be expanded. This later learning happens as children hear the words spoken by their teachers, parents, and friends, and continues till sentience. In our study, products' organic growth is similar. We base growth on a previous- or existing-generation product and see how this growth increases as new-generation products are introduced.

5.3 Intra-Brand Competitive Survival

For technology companies, there is now a focus on how to create a unique competitive advantage in homogeneous products and earn customers' support. This research employed lifetime data analysis to compare multi-generation products to show diffusion quality. This framework hopes to complement previous research on entry and technology marketing. The analysis helps managers test the effectiveness of different generation products as well as communicate complex ideas to senior management.

The analyzed data is a multi-generational product category; the lifetime distribution shows that there is not a significant difference. This identifies that the generation demarcation we made is reasonable. In order to procure the accuracy of the study estimates, products are classified according to the PEC concept, embracing product mode, memory capacity, and the order of mode. The classification should have no bias. To go further, we account for the attribute efficacy of products. The model yields implications regarding firms' survival and entry. Results show that price is a non-significant factor in consideration of product attractiveness. Consequently, we can conclude that the consumer compromise effect is not the only determinant for technology trajectory.

Tang and Liou (2010) transformed the fixed and one-way determinism of "sustainable competitive advantage creates superior performance" of Porter (1985) to Bayesian probability inference: an organization with a sustainable competitive advantage is likely to achieve superior performance. That is, we cannot assert that all results must follow the same reason, or that past sustainable competitive advantage will inevitably lead to high performance. By virtue of the same argument, when we think about the prevalence of product, it is not only because the existence of the compromise effect that corporations add alternatives to force consumers to choose. Corporations themselves would like to supplement product joint space in order to satisfy their growing demand and consumers' variable demand. If the price is not well segmented and arranged, enterprises may misjudge the market demand as self-defeating, and hence cannot increase product attractiveness as doing right to do wrong.

More specifically, we found that the prices of future generations continue to decrease over time. From the retailer's point of view, price promotions are commonplace and have a significant effect on consumers' purchasing decisions (Blattberg, Eppen, and Lieberman, 1981; Guadagni and Little, 1983). The depth of promotions is developed by retailers for specific product price decreases. Previous research indicates that the higher depth increase quality-per-dollar equivalent of brands is then accompanied by a higher degree of acceleration purchase effect, which may change in consumers' brand loyalty by degrees (Bell, Chiang, and Padmanabhan, 1999; Raju, 1992). In recent years, as commodity scanner data has become easy to obtain, researchers have discussed the benefits of brands on sales profits by retailers' actual transactions. It has been proposed that national brands (manufacturer brands) with mid-price points are not appropriate to take too high-priced promotions (Tang, Wu, and Peng, 2009).

This research uses business-to-business (B2B) procurement to reflect the business-to-consumer (B2C) sales situation. We believe that for a domestic leading brand, because price does not have enough influence on product attractiveness (especially in a product saturation cycle), corporate focus on R&D to introduce new functions or new insights is more important. If a company makes many launches, these products are likely to cannibalize each other, and shorten their life spans. Life span is also affected by the rate of technological progress, which may lead to consumers trending toward newer products. This phenomenon should be studied further, especially by the design and engineering departments, which can then design products accordingly to increase their life spans.

6. Managerial and Theoretical Implications

6.1 New Product Development

Business growth and sustainable development is a long sought after goal of enterprises. The autologistic model was employed in analyzing a spatial-temporal pattern of new product development and its intrinsic growth. It is challenging to keep the reasoning of the research manageable when attempting to probe whether the compromise exists and why it really has a role, in the light of reviews of several different academic communities. Indeed, we argue for a synthesis of these paradigms into the decision perspective of product development. The actual transaction database is helpful for us in looking back to survey the compromise effect and further enables decision making or determination of the possibility for new product launches.

These results can be important information for managers to arrange their product line design and new-product launching strategy. As we have discussed, consumers' choices will move to the lower or even extremely low priced products, nullifying the compromise effect and benefits of decoys; corporations ought to notice product price segments. In this sample duration, the average price of a variety of products continues to decline, reflecting that firms in Taiwan use price reduction as the main strategy. Why does the reduction in price of a specific good not result in increasing the attraction of competitive items in the same brand? Some cross-price elasticity of products is larger than zero, when the price of a certain product reduces, it leads instead to the decrease in another product's attraction. This reveals that reduction promotion is not necessarily a good pricing strategy. If corporations would like to upgrade the attraction of a product set through the price mechanism, they should observe interaction between products to prepare the most appropriate reduction program.

In different evolutionary cycles, the effect of the price of some products on the sales of other modes is not consistently attractive; for example, the new mode 180 in the second phase has not increased the attractiveness of other commodities. In other words, even the introduction of more items does not necessarily increase the attractiveness of other products effectively, as illustrated in Figure 8. The space scatter plot is with product attractiveness, price, and generations based on the surveyed transaction MP3 data. Hence, price segmentation and positioning in the same brand is not enough. This study suggests relying on the positive price index as a strategic direction for product management, retaining those products that lead to positive price competition with other products for the entire portfolio.

In product growth, since the competitive strategy of MP3 player firms is price promotion, further decision-making formulation can include cross-elasticity in addition to the price competition index to understand the substituting or complementary relationship between specific products. It is noteworthy that as modes 180 and 200 are substitutes in the third stage, the decline of the price of mode 200 also results in mode 180 being attractively reduced. Corporations can capture the market in a continuous state of interaction through the cross-price elasticity, and attempt to reduce the degree of competition within the same brand. Although some products are not purely substitutes or complementary, the analysis still clearly indicates one item's decline affects others' attraction, hence serving as a reference for price promotion strategies utilizing the relevant market information.

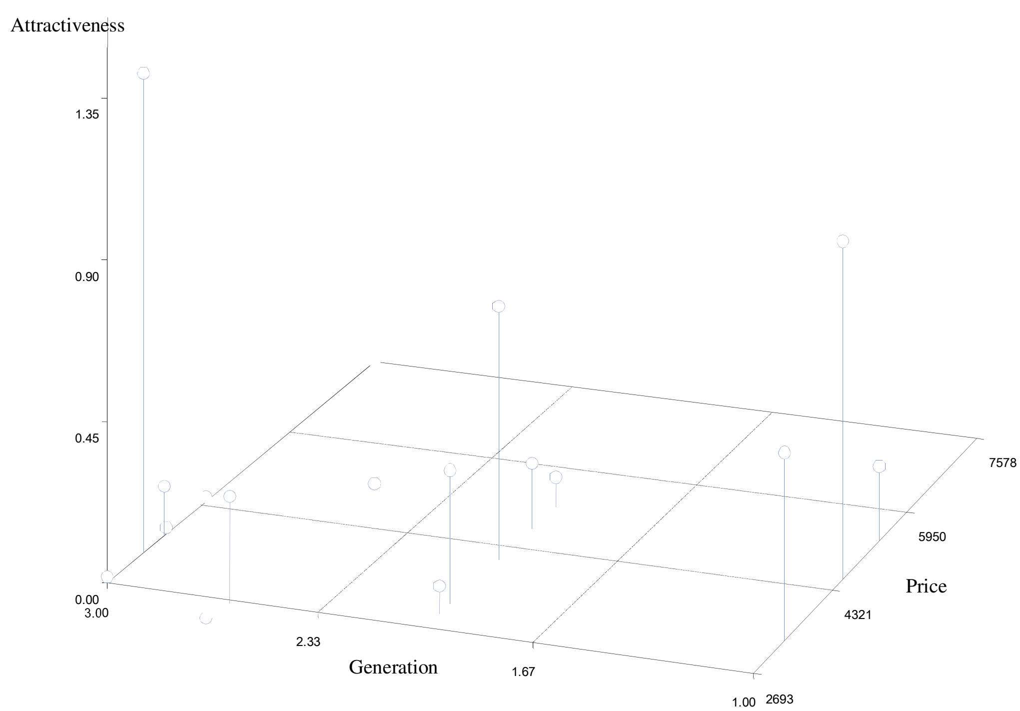


Figure 8. Three-dimensional Scatter Plot for Different Generations

The competitive advantage theory of Porter (1985) indicates that sustained advantage is based on long-term performance that is higher than the industry's level; the basic configuration is low-cost and differentiation. Organizations' important advantages and disadvantages can be summed up as goods that are relatively low cost or their differentiation. This research suggests that if brand differentiation is not apparent, not to mention the formation of competitive advantage, there is a difference and have a follow-up compromise. Finally, from the perspective of global competition, although the domestic brand of MP3 music players is a market leader in Taiwan, its emphasis has been on the fine-tuning of the existing product features and functions, such as changing colors and increasing memory capacity; it has not injected new features and has only adopted a follower strategy in development evolution. We expect that more global digital audio players like Apple will continuously inject new functions and features into their products, and that products will not be just the permutations and combinations of existing products but have a completely new life, to meet rapidly changing market needs and trends. That is back-to-basics, to meet consumers' desires, to exceed the consumers' imagination, as they are fundamental to marketing.

Apple's suppliers TPK are looking forward to the touch screen becoming the new technology trajectory, dominating the Smartphone and Tablet PC (e.g., Dosi, 1982; Levinthal, 1997, 1998). It has devoted resources to technology R&D and production capacity development and has therefore made excess profits. This study supports the concept of PEC, in which products are a series of progressive groups. In addition to Apple's launching different generation products, Microsoft continued to update the Windows operating system in 1984–2004 (Casadesus-Masanell and Mitchell, 2010). Does such activity have a role in attracting customers that are without a product, or do the companies want to expand into new markets to meet their demand for internal growth? Since Windows may be replaced by Linux, Google Android, or Apple iOS (Edelman and Eisenmann, 2011), will it be able to resist this possibility? An incumbent naturally wants to resist its resources diffusing to new market entrants by the creation of barriers. This study hopes to provide a basis for reflection on the connotation of product diffusion. Looking across the multiple academic perspectives helps us not only to integrate these perspectives but also to identify interdependencies among these phenomena.

6.2 Product Attractiveness Observation

Ideally, corporations can observe the interactions between products and then make an appropriate price mechanism to upgrade the attraction of a product set. Price competition index and cross-price elasticity can be calculated to figure out how the price variation of a specific product influences the relative attractiveness of others. However, if they want to quickly get an overview of a product line instead of rigorously and exactly calculating the attractive numericals and price competition index, the sales volume can be a simple object for observation. Figure 9 is a two-dimensional matrices with product attractiveness, price, and sales volume based on the surveyed transaction MP3 data. The positive relationship of attractiveness and sales can be found; this makes it possible to evaluate alternative products' attractiveness; in turn, through market visibility, firms can consider whether they need to modify their competitive strategy or launch new generations of products.

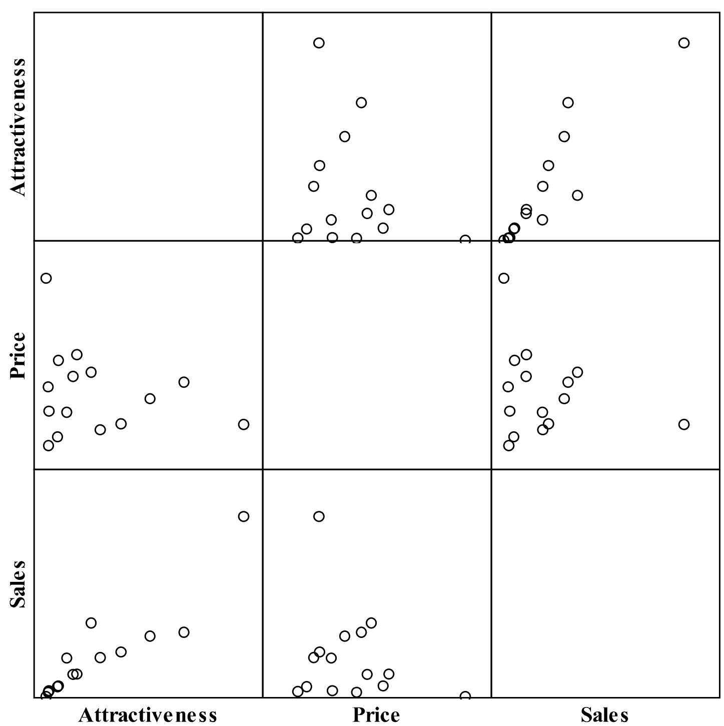


Figure 9. Scatter Plot of Product Information

Actual purchase history is a simple observation target, but purchase pre-history, which entails subjective and objective comparisons among various products of different generations and is thus vital, is difficult to find. Standard statistical methods with sales as a direct variable—such as testing raw sales (assumed to be normal) against the null hypothesis (right-skewed: 12.591, leptokurtic: 200.507; P-value of the Kolmogorov-Smirnov goodness-of-fit tests: ≤ 0.05)—are inappropriate. This research builds an attraction model, and then links the estimated purchase odds of the focal product to choice probability obtained using cross-price elasticity. The logit-type market share model connects prices and relative attractiveness. The focus is not on the influence of price on sales but rather on the alternative price relationships between products at different stages of evolution. In addition, the autologistic model with the data aggregating each product specification according to PEC stages (involving adjacent quadrats and quadrats two spaces away), supply the log odds of attraction in a given product mode as dependent on the attraction status of neighboring quadrats. The diverse knowledge sources and results are helpful to determine the structure of market competition.

6.3 Market Competition

This research intends to aim at the same brand entrant into a market with a dominant product item. We would like to address whether the price is effective in attractiveness, accompanied by the different product specifications, to understand the prediction of sales response and then consider an entrant strategy. We have used the MP3 music player generation as an example of effectiveness that contributes to the company's competitive advantage. In order to do so, we collected actual transaction data for statistical analysis to help identify the late entry product mode in attractiveness and methods to promote and enhance competitive advantage. We believe that this is a particularly interesting product category because consumer electronic products often have a leading brand dominating the industry, even though they appear to a minority of entrants. Moreover, the diffusion of technology products has drawn a lot of attention due to the sharp increase of technology improvement. So far, the popular Smartphone have latent market capacity. The analyzed MP3 music players ought to provide product path insight for new product categories.

Previous research on entry deterrence has suggested many strategic actions for an incumbent firm (Gruca and Sudharshan, 1995). Optimal strategies in the entry game suggest that responding with a price increase by the incumbent can be a defensive strategy when a new product enters the market (Chen and Xie, 2007; Davis et al., 2004;

Hauser and Shugan, 1983). However, although we stand on a single brand perspective, the results also can reveal that competition in the industry usually results in lower prices to go along with multi-generation development. This phenomenon supports prior research that price promotion is the outcome of competition (Narasimhan, 1988).

Lifetime data analysis for product generations is proposed. We began with the Kaplan-Meier estimate method to determine whether different generations of product attractiveness have arisen from identical survivor functions. This tests whether these survival times from multi-generation products have significant differences. Subsequently, when product pricing has been studied, the Cox proportional hazard model was applied to detect the pricing efficacy. The results can be employed to provide managers with insights about market behavior when launching new products. A manager was able to successfully argue why he thought the proposed launch strategy from senior management might not achieve the desired objectives.

When a firm introduces a new product, the time and money invested in product quality or product attractiveness and pricing are all critical management decisions that can dramatically affect a market entry strategy. If a product operates in many product modes in each generation, its resources become more thinly spread and thus may hamper the attractiveness of a core item. In contrast, a product segment ensures the necessary product difference to enter more product modes in the generations; hence, corporations can obtain performance from gaining market share or upgrading customer utility.

6.4 Continuation of Disruptive Innovation

This dissertation is an interdisciplinary research of marketing, statistics, strategy, and technology. The topics include the following: the interpretation of the market diffusion by evolution of biological species concept, consumer behavior and new product pricing, multi-products price competition in a single brand, consumer’s compromise and extreme aversion of mentality, and product survival rate and spatial-temporal correlation based on the statistical model. The purpose is to explore the implications of technology product’s cross-selling patterns on intrinsic growth through the integration of these theories. In the battle between consumer psychology and product physical attribute, we found an interesting results which different from the traditional disruptive innovation theory.

Figure 10 is a three-dimensional surface with product attractiveness, price, and sales volume based on the surveyed transaction MP3 data. Corporations reinforce their product line as times goes by, the relationship between product attribute and choice result is a surface, especially in the latter complete product line stage. Previous research explained disruptive innovation in a simple linear, ignoring the interdependency among commodities and multi-generation space. We propose that on the premised rationality of individuals, technological trajectory can be represented by the movement of multi-products trade-offs, consumers have the motivation to explore the environment and engage in selecting a preferred product. And the vendors devote to satisfy their growing demand by product joint space, thus, a technological trajectory is a cluster of possible technological directions whose outer boundaries are defined by the nature of the paradigm itself. We acknowledge the interaction of individual behavior and marketing in the effectiveness of product development processes.

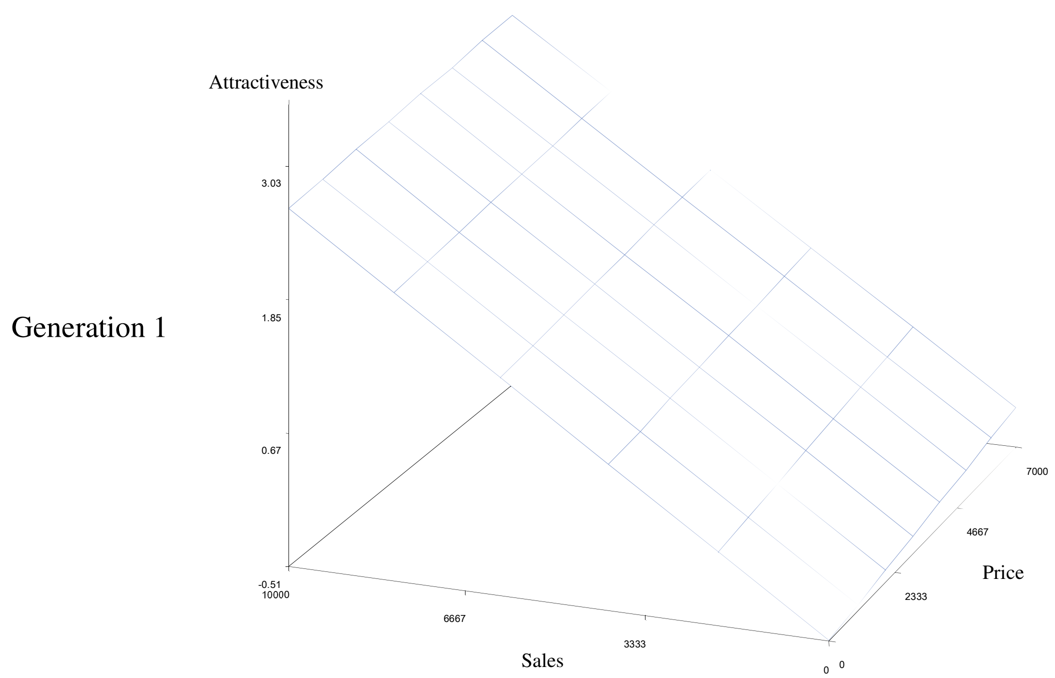
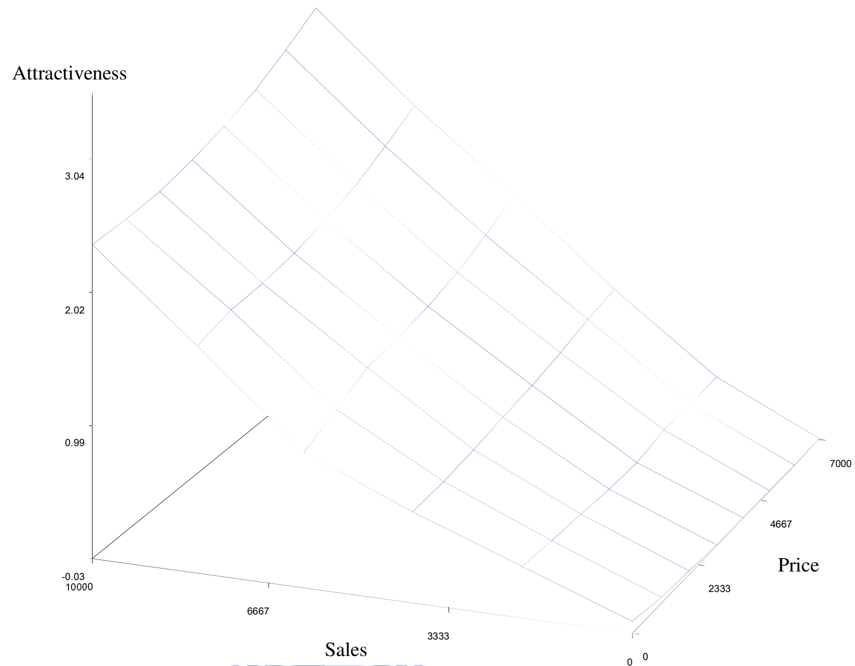


Figure 10. Three-Dimensional Surface for Different Generations

Generation 2



Generation 3

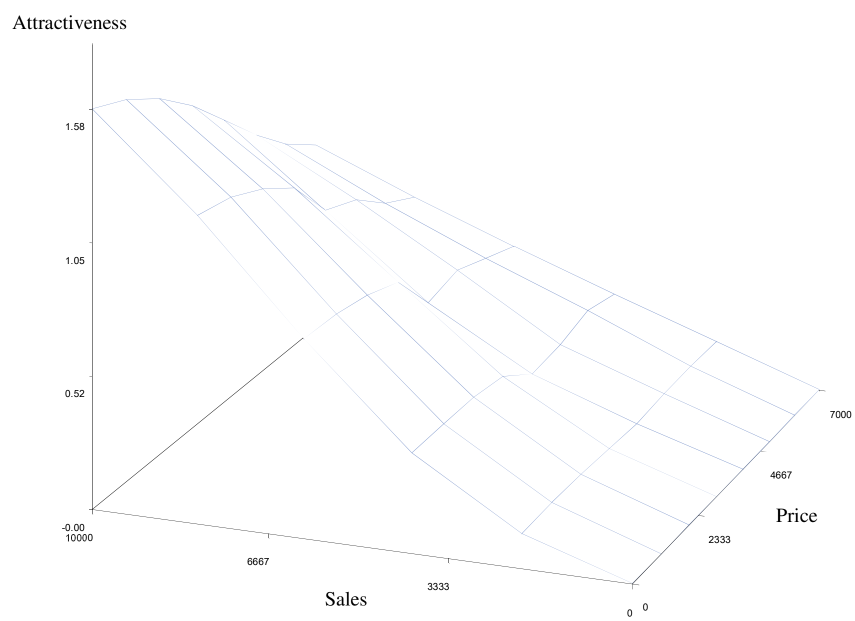


Figure 10. Three-Dimensional Surface for Different Generations (Continued)

In the product diffusion process, the results show that even the introduction of more items in different evolutionary cycles does not necessarily increase the attractiveness of other products effectively. We suggests relying on the positive price index as a strategic direction for product management, the concrete method is to enhance the organizational capacity. Recent studies have proposed organizational ambidexterity; empirical research supports the balance of organizational dynamic management capabilities (exploration and exploitation) was positively correlated to performance (Gibson and Birkinshaw, 2004; He and Wong, 2004; Lubatkin, Simsek, Ling, and Veiga, 2006; Raisch, 2008).

Exploration contains the activities to find new technologies, new business, new processes, and new production methods. Therefore, the activities are focused on exploring new opportunities. Exploitation involves in efficiency, selection, or implementation which emphasize on developing the existing determined resources (March, 1991). This research suggests to properly striking a balance between these two capabilities, and then the corporations identify the real market needs. In the procedure of enterprise dynamic growth, new-market disruptive innovation is encouraged. In creating critical relatively product attraction or with more powerful attraction it will be the efficient way.

7. Conclusion

7.1 Concluding Remarks

This research illustrated a process of building a model to help conceptualize the launch of an innovative product. It considers if it is likely that a consumer will select products with more moderate attributes, the percentage of product pricing hazard, and the market survival of the new product over time. For a product with a bundle of attributes, the compromise effect exists within a specific generation product set. Consumers' decision variables occur at the product attribute level and price. However, through the spatial mapping on intra-and inter-competition of a single brand across generations, we found that the surveyed product category only reveals horizontal diffusion.

Further, the price mechanism in autologistic and lifetime data analysis both shows non-significant; we propose that compromise is not the only determinant factor in a long-time technology trajectory. Although corporations increase alternatives for consumers to select as a market entry strategy, sometimes it can only be a transitive policy. This study addresses a struggle between psychology and physics among consumers; only a brand that can meet rapidly changing market needs and trends, continuously inject new functions into their products to have new life, and provide brand differentiation can gain competitive advantage. Moreover, through product interdependence among a product line, a product can not only increase the sales attractiveness of others but also contribute to product positioning to achieve organic growth.

7.2 Limitations

This study has some limitations. Consumers' purchase decision is the trade-off between old and new products and other attributes. Product modes reflect the channel arrangement. As some retailers' purchases were zero (especially in the final stage), this led to a large variation in cross-price elasticity. Additionally, this study is limited by the contents of the database and thus focuses only on the effect price has on products' attractiveness. The conclusions aim to identify the product competitive relationship between price and variation. The marketing idea was adopted that a product is a bundle of attributes and the performance metrics must fit with the market, yet the attractiveness may vary due to other attributes. Future research can analyze the actual influence of other attributes on price segment. Moreover, the use of economic game theory to try to find a compromise solution and an appropriate number of specifications are possible directions.

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APPENDIX

Censoring

This study concerns the duration of product mode after market entry, and these products become competitive at different times, lifetime data analysis is proposed for attractive comparison. We measure the times to event as varying from a product's market entry to its withdrawal. There are totally night modes in the MP3 transaction database, if the product is non-attractive, it can be considered its death, and the residual mode can be regarded as right censored data that is attractive; as shown in the following figure.

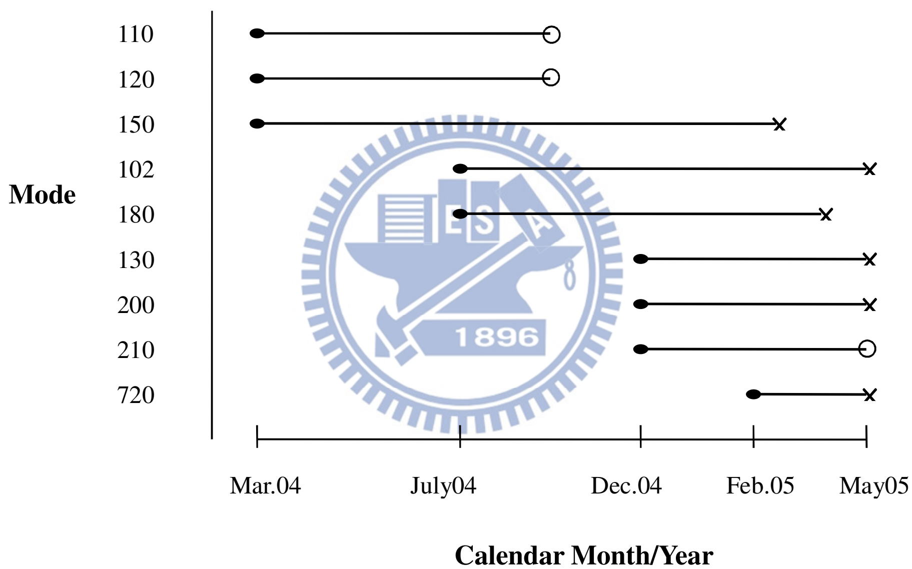

Figure 11. Product Incidence and Prevalence: • initial follow-up, × death, ○ alive.

Likelihood Function for Right censoring

Let $T_1, T_2, ..., T_n$ be lifetime random variables for n individual, and $t_1, t_2, ..., t_n$ be their observed times, either lifetimes or censoring times. Define $\delta_i = 1$, if $T_i = t_i$; $\delta_i = 0$, if $T_i > t_i$, then δ_i is a status indicator for t_i. Thus, the observed data is in the form of (t_i, δ_i), $i = 1, 2, ..., n$, and the likelihood function for this data set is of the form:

$$\prod_{i=1}^{n} f(t_i)^{\delta_i} S(t_i)^{1-\delta_i}$$

Regression Models for Lifetime Data

Assume there are k distinct failure times. Define $R(t)$ to be the risk set at t^-, and R_i to be the risk set at the time just prior to the i th failure. Then, $R_1 \supset R_2 \supset \ldots \supset R_k$. Define $X_{(i)}$ to be the covariate for the product failed at the ith failure time. The likelihood is as follows:

$$L(\beta, h_0) = \prod_{j=1}^{n} f(t_j | x_j)^{\delta_j} S(t_j | x_j)^{1-\delta_j}$$

$$= \prod_{j=1}^{n} h(t_j | x_j)^{\delta_j} S(t_j | x_j)$$

$$= \prod_{j=1}^{n} \left[h_0(t_j) \exp(x_j{}'\beta) \right]^{\delta_j} \exp\left[-\exp(x_j{}'\beta) H_0(t_j) \right]$$

The likelihood is a function of data, β, and $h_0(\cdot)$. Assuming that there are k failure times and $t_1 < t_2 < \ldots < t_k$, rewrite as follows:

$$= \prod_{j=1}^{k} \exp(x_{(i)}{}'\beta) h_0(t_i) \prod_{j=1}^{n} \exp\left[-\exp(x_j{}'\beta) H_0(t_j) \right]$$

$$= \prod_{j=1}^{k} \frac{\exp(x_{(i)}{}'\beta)}{\sum_{l \in R_i} \exp(x_l{}'\beta)} \prod_{j=1}^{k} h_0(t_i) \sum_{l \in R_i} \exp(x_{(i)}{}'\beta) \prod_{j=1}^{n} \exp\left[-\exp(x_j{}'\beta) H_0(t_j) \right]$$

Hence, $L_1(\beta) = \prod_{j=1}^{k} \dfrac{\exp(x_{(i)}{}'\beta)}{\sum_{l \in R_i} \exp(x_l{}'\beta)}$

$$L_2(\beta, h_0) = \prod_{j=1}^{k} h_0(t_i) \sum_{l \in R_i} \exp(x_{(i)}{}'\beta) \prod_{j=1}^{n} \exp\left[-\exp(x_j{}'\beta) H_0(t_j) \right]$$

$L_1(\beta)$ is not in general the probability density function or probability mass function of a subset of the data; hence it is called a partial likelihood. The estimate for β is derived by maximizing the partial likelihood and is therefore called PMLE of β. Since there is some information about β in the discard proportion of the entire likelihood, the resulting estimates are not fully efficient. However, the loss of efficiency is quite small. The properties of PMLE of β are consistent, asymptotically normal, and depend only on the ranks of the event times not their numerical values.

CURRICULUM VITAE

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Education

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Research Stream

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- Price Mechanism in Competitive Brand
- Bayesian Statistics in Consumer Choice and Decision

Published Journal Articles

1. 吳敏華、唐瓔璋、戴君芸、周春媛，「供應鏈採購決策因素與電子業赴大陸投資意願之關係」，企業管理學報，第 90 期，1-24 頁，民國 100 年。(國立臺北大學企業管理學系主辦及發行)
2. 唐瓔璋、吳敏華、林筱茹，「以單一品類的品牌產品競爭探討消費者選擇之妥協效果」，行銷科學學報，第 7 卷，第 1 期，21-50 頁，民國 100 年。(台灣行銷科學學會編輯，前程文化出版社發行)
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2. 唐璎璋、吳敏華、黃悅慈，「利用BG/NBD模型提升顧客流失管理效率」，國際ERP學術及實務研討會，國立中央大學，民國101年1月16日。

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Awarded Research Grants

1. Best Paper of the 2012TOPCO Thesis Award for the Doctoral Thesis. (NT$100,000)
2. International Conference Presentation Travel Grant Awarded by the National Science Council (NSC): Direct/Interactive Marketing Research Summit (D/IMRS). San Francisco, California, USA. NSC-99-2922-I-009-176. 09-10 Oct. 2010. (NT$55,000)

Certification and License

1. TIMS 行銷專業能力認證：初階行銷企劃證照，台灣行銷科學學會。
2. Advance Research Methodology Workshop: Bayesian Statistics and Marketing, Taiwan Institute of Marketing Science.

3. Proficiency Test for Financial Planning Personnel, Taiwan Academy of Banking and Finance.
4. 2008 International Logistics Academic Seed Trainers Camp (CILT Level II — International Certificate in Logistics and Transport), Taiwan Association of Logistics Management & The Chartered Institute and Transportation in Taiwan.
5. 博士班學生英語訓練課程：推廣教育科技英文寫作學分班，交通大學語言教學與研究中心。