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Reference Quality-based Competitive Market Structure for Innovation Driven Markets[1]

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ABSTRACT

Innovation-driven durable goods markets see substantial changes in quality and available choice sets and subsequent changes of the reference quality in the market over time. Considering the multi-attribute characteristics of these goods, it is important for businesses to identify attribute-specific competitive landscapes and develop competitive innovation strategies at the product attribute level. Therefore, this paper proposes a reference-dependent choice model for product quality at the product attribute level that can capture the asymmetric effect of innovation shocks on product demand, *i.e., the innovation elasticity of demand*, as well as the competitive market structure in product innovation. Moreover, we confirm that there is a certain quality span for a product attribute where the values of products depreciate most significantly due to innovation shocks, which we refer to as the *innovation shadow zone*. We demonstrate the effectiveness of the proposed approach in developing attribute-specific product innovation strategies using U.S. mobile telephone market data.

Keywords: reference quality, innovation-driven durable goods, competitive market structure, product innovation, innovation elasticity

1. Introduction

Product innovation is important and rapid in high-tech durable goods markets, such as those for mobile telephones, laptop and desktop computers, and digital cameras, in which companies constantly introduce new, better-quality products and remove older versions. For example, in the electronic chip market, 'Hwang's Law,[2]' which states that the memory density of electronic chips doubles every year, replaced 'Moore's Law,[3]' which states that it doubles roughly every two years, in 2002.

Due to the nature of rapid innovations in high-tech markets, consumer choice sets in these markets change rapidly, and consumers constantly update their expectations of the standard quality of product attributes. For example, in the desktop computer market, standard CPUs are rapidly replaced by newer versions, e.g., Core Solo by Core Duo; Core 2 Duo; and Core i3, i5, and i7 on an almost annual basis, while the standard capacity of hard disk drives has also improved from 128G (gigabytes) to 256G, 500G, 1T (terabyte), and currently large SSDs (Solid State Drives)[4] over the past few years. Additionally, the speed of innovation differs across product attributes, generating heterogeneous consumer preferences for products and creating strategic opportunities for companies.

Therefore, due to the multi-attribute characteristics of these innovation-based durable products, it is important for businesses to identify attribute-specific competitive landscapes and develop competitive innovation strategies at the product attribute level. This effort is also advisable from the perspective of multi-attribute portfolio management because of the distinct impacts of product innovations across different product attributes. Moreover, previous literature suggests that consumers' choices are mainly influenced by only some key product attributes (Bettman and Park 1980, Nowlis et al. 2010, and Shi et al. 2013).

Therefore, in this study, we suggest a new approach to analyzing competitive market structure at the product attribute level using the concept of reference quality. The reference effects of product attributes have been found to have a significant impact on consumer choice (Lattin and Bucklin 1989, Winer 1986, Kalwani et al. 1990, Kalyanaram and Little 1989, Kahneman and Tversky 1991, Kalyanaram and Winer 1995, Rust et al. 1999, Mazumdar and Papatla 2000, Rust

[2] Samsung has doubled the memory density of its products every year since 2002. The company dubbed this phenomenon "Hwang's Law" that year after Hwang Chang-gyu, the former head of Samsung Electronics' semiconductor business (Richter 2014).

[3] Moore's Law was based on a 1965 observation by Intel co-founder Gordon Moore, who claimed that the computing power of chips doubles every 18 months.

[4] SSD uses electronic interfaces compatible with traditional blockinput/output (I/O) hard disk drives, thus permitting simple replacement in common applications. SSD differs from traditional electromechanical magnetic disks, such as hard disk drives (HDDs) or floppy disks, which contain spinning disks and movable read/write heads. Compared with electromechanical disks, SSDs are typically more resistant to physical shock, run silently, and have less access time.

and Oliver 2000). This finding has an important strategic implication for product innovation at the product attribute level, such as asymmetric gain and loss in consumer product values from quality improvement. Since Kahneman and Tversky (1991) introduced the importance of a reference point on consumer utility in their prospect theory framework, many succeeding studies have documented reference effects for both product attributes and price (Lattin and Bucklin 1989, Winer 1986, Kalwani et al. 1990, Kalyanaram and Little 1989, Hardie et al. 1993, Kalyanaram and Winer 1995, Rust et al. 1999, Rust and Oliver 2000). For example, Tversky and Simonson (1993) demonstrated that the reference-dependent evaluation of an attribute applies not only to price but also to all other product attributes, while Rust et al. (1999) and Rust and Oliver (2000) analytically validated the importance of reference quality to consumer choice. Experimental studies have also demonstrated (e.g., compromise effect) the contextual-reference concept in consumers' quality perception (Simonson 1989; Simonson and Tversky 1992; Tversky and Simonson 1993; Kivetz, Netzer, and Srinivasan 2004).

However, an attribute-specific analysis of competitive markets has not yet been fully explored due to the limitations of previous approaches in discrete choice models for differentiated product demand, such as BLP (Berry, Levinsohn, and Pakes 1995) type choice models and competitive market structure analysis. Standard BLP models do not reflect product attribute-level innovation shocks because each product's characteristics are fixed. In other words, these models cannot capture the relative changes in consumers' valuation of product quality that is driven by rapidly changing standards, especially in high-tech durable goods markets. Therefore, the estimated own- and cross-elasticity of quality for an attribute do not reflect attribute-specific innovation shocks in the corresponding market, and as a result, the preceding studies were only able to provide limited strategic implications specific to a product attribute.

These own- and cross-elasticity of product attributes have been extensively investigated in the literature on competitive market structure analyses due to their usefulness in assessing the impact of companies' and competitors' marketing actions on market shares (Bucklin et al. 1998). Previous studies have even suggested a perceptual map that explains how customers perceive existing brands and the corresponding substitutability/complementarity among brands using a few dimensions that underlie many attributes (DeSarbo and Rao 1986, Elrod 1991, DeSarbo, Manrai and Manrai 1993, Elrod et al. 2002). However, with this approach, the dimensions of the resulting map are unlabeled, and managerial judgment and subsequent analyses of consumer perceptions are needed to interpret the map (Elrod et al. 2002). Similarly, the competitive market map using competitive clout and vulnerability suggested by Cooper (1988) and Kamakura and Russell (1989) is restrictive in that it focuses only on the elasticity of price or other non-fixed variables, such as advertising (Kamakura and Russell 1989). Therefore, the existing models in competitive market structure analysis do not provide any information beyond the market structure specific to price competition.

Therefore, in this study, we propose a reference-dependent choice model for product quality that can capture the asymmetric effect of innovation shocks on product demand and competitive market structure at the product attribute level. Because the reference changes for each time period depending on the competitive market environments, the reference-adjusted product quality variables are not dependent on a fixed term and change relative to the varying market references that reflect attribute-specific innovation shocks in this estimation. Therefore, a distinctive feature of the proposed model is that the product attributes become strategic variables that researchers can examine from the perspective of product innovation. In other words, the model estimates the asymmetric elasticity of gain and loss for the reference quality separately, which generates different innovation insights for businesses depending on their strategic positions over the product quality span of an attribute relative to the reference point. It also provides important strategic implications regarding the management of product attribute portfolios, i.e., how to manage the innovation levels and the combinations of different product attributes from the perspective of new product development. It is also noted that in regard to the empirical model setup, this study uses a static model of competition in each time period. However, competitive outcomes change across time periods because the reference quality level changes, i.e. consumers' level of desired product quality constantly changes, due to a continuous introduction of new products that are generally higher in quality than the current conventional level.

The remainder of this paper is organized as follows. In the next section, we discuss the relevant literature. We then present the theoretical concept behind our model. Next, we specify our reference quality-dependent demand model, which takes into account the key theoretical concepts. The subsequent sections relate to our empirical results, and we conclude with limitations and suggestions for future studies.

2. Literature Review

Market Structure Analysis

The analysis of competitive market structure is an important area of marketing research due to its significance in explaining the nature and extent of competition among companies and their products (Elrod et al. 2002), including the identification of competitors, market segmentations, product positioning, and pricing (Elrod et al. 2002, Cooper 1988, Kamakura and Russell 1989).[5] From the demand-side perspective, market structure analyses explain the extent to which the products under consideration are substitutes for or complements to competing products in the market. Therefore, these analyses aid in understanding competition and are useful for companies in designing new products or altering existing ones. Additionally, because they are based on a multi-attribute utility model, market structure analyses provide useful information regarding customer perceptions and evaluations of existing products in terms of product attributes (Elord et al. 2002).

However, neither external nor internal market structure analyses[6] provide information about market structure and competition at the product attribute level (Bronnenberg, Mahajan, and Vanhonacker 2000, Elrod 1988, Elrod 1997, Elrod et al. 2002, Elrod and Keane 1995, Erdem and Keane 1996, Shocker, Bayus and Kim 2001, Wittenschlaeger and Fiedler 1997). Although both approaches use information on the attributes of existing products to construct the perceptual map at the brand level, the dimensions are abstracted and assumed without labels, and the specific attribute information cannot be considered when building attribute-specific product design strategies, i.e., product innovation strategies (Chintagunta, Dube and Singh 2002, DeSarbo, Manrai and Manrai 1993, DeSarbo and Rao 1986, Elrod 1991, Lenk 2001).

Competitive market structures can be examined using price elasticities, as in the case presented by Kamakura and Russell (1989). They proposed a model that can identify the underlying determinants of brand-switching probabilities and aggregate responses to price changes. Using the cross-price elasticity from the multi-attribute choice model, these authors obtained a representation of a market structure that simultaneously revealed the brand preferences of key consumer segments and enabled the prediction of the magnitude of aggregate own- and cross-price elasticities. In their analysis, cross-price elasticity was divided into two different methods of competitive clout and vulnerability depending on how a company's own price change will affect the market share of the competing brands and vice versa (Kamakura and Russell 1989).

Following Kamakura and Russell (1989), other scholars including Cooper and Inoue (1996), Heerde et al. (2004), and Rutz and Sonnier (2011), have used the concept to analyze various

[5] From the supply-side perspective, the economic literature contains an extensive and comprehensive discussion of industrial organization, while the demand-side market structure is predominantly covered by the marketing literature (Elrod et al. 2002).
[6] External analyses presume that the attributes that drive choice and the values of the brands with regard to these attributes are known to the researcher and use data about consumer perceptions of existing brands. A good example is conjoint analysis. In the case of internal analyses, conjoint analysis assumes that a few dimensions are enough to explain substitutability/complementarity among brands. However, the number of dimensions and the locations of the brands on these dimensions are determined solely from preference/choice data. However, the dimensions of the resulting map are unlabeled (Elrod et al. 2002).

marketing issues while considering the competitive market structure. However, these approaches do not provide a complete picture of the competitive market structure because they do not account for other product attributes except for price, such as product functions or features, because these product attributes are brand-specific and constant over product life cycles in contrast to price, which frequently changes over the course of a product's life cycle. Therefore, previous market structure analyses that use own- and cross-elasticities do not fully capture the nature of an attribute-specific competitive market structure that changes over time due to product innovation. Consequently, these models do not provide insights into product innovation strategies at the product attribute level.

Therefore, by incorporating the concept of reference quality in consumer choice, this study enables us to evaluate the asymmetric effect of innovation shocks on the competitiveness of product attributes. Additionally, incorporating reference quality also enables us to identify competitive market structure at the product attribute level, which has important implications for developing attribute-specific product design strategies, i.e., product innovation strategies.

Prospect Theory and Reference Quality

According to prospect theory (Kahneman and Tversky 1979), consumer utility for an outcome is a function of gains and losses with respect to a reference outcome rather than the final outcome. Since the development of prospect theory, consumers' reference formation behavior in their choice decisions has been broadly examined and documented in the economics, psychology and marketing literatures. In the case of behavioral experiments, previous studies have documented reference effects for both product attributes and price. However, the development of an empirical understanding of consumer choice based on the theory has been limited to reference-price formation (Lattin and Bucklin 1989, Winer 1986, Kalwani et al. 1990, Kalyanaram and Little 1989, Kalyanaram and Winer 1995, Mazumdar and Papatla 2000).

Therefore, empirical research has paid limited attention to the reference effects of product quality, and the important role of reference quality in competitive market structure analysis has not been well addressed. Notably, product quality is often used as a summary measure of a product's attractiveness exclusive of price, and the price-quality trade-off explains the competition between brands in different tiers of the market (Blattberg and Wisniewski 1989, Sivakumar 2007, Sivakumar 2011). The reference quality, similar to the reference price, focuses on the loss aversion behaviors of consumers regarding product quality. Compared with the literature on reference price, there is relatively limited literature on reference quality that investigates the phenomenon and the related strategic insights.

This lack of attention to the role of reference quality, especially in empirical settings for durable goods, may stem from the fact that empirical research in this area has been based on scanner data for non-durable goods for which prices change often due to promotion but for which quality levels and choice sets are very stable. If the consumer behavior literature that is related to expectation-satisfaction and services is excluded, Rust et al. (1999), Rust and Oliver (2000), and Hardie et al. (1993) previously examined this phenomenon. Rust et al. (1999) suggested a dynamic decision model for reference quality using Bayesian updating with an analytical model and two behavioral experiments. Together with Rust and Oliver (2000),[7] Rust et al. (1999) analytically validated the importance of reference quality in consumers' choice decision.

Hardie et al. (1993) suggested empirical evidence of reference quality effects in their examination of non-durable packaged goods. However, in their formulation, reference quality is the product quality of the last brand purchased by the consumer. Because the products and choice sets in their data are stable, there was no investigation of how changes in choice sets or product quality over time impact reference quality. After these studies, there has not been a follow-up study, and the reference quality concept has not yet been extended to product innovation.

However, reference quality provides an important foundation for the product design and innovation literature, especially in the technology-driven durable goods markets in which product quality is constantly changing because reference quality enables the effect of quality change, i.e., product innovation, on consumers' product choice to be captured considering idiosyncratic consumer behavior, e.g., loss aversion. Additionally, by using product quality as a changeable variable similar to price for a specific product depending on the changing reference quality of a market, the elasticity of the product attributes can be used to address strategic issues including product design and innovation. Therefore, by introducing reference quality in product attribute variables, the previous limitations of the market structure analyses can be overcome, particularly regarding the price elasticity-oriented model proposed by Cooper (1988) and Kamakura and Russell (1989).

Figure 1 below demonstrates the value function (Kahneman and Tversky 1979, Kahneman and Tversky 1996, Kivetz 2003, Thaler 1985, Tversky and Kahneman 1991) and its asymmetric structure with a concave curve for the gains and a convex curve for the losses. Here, the magnitude of the value reduction is determined by λ, the degree of loss aversion, and λ is greater than 1 due to consumers' loss-aversion behavior.

[7] In their paper, it was introduced as customer delight, which refers to a profoundly positive emotional state that generally results from having one's expectations exceeded to a surprising degree.

[Insert Figure 1 about here]

3. Innovation Elasticity and Innovation-driven Competitive Market Structure

3.1. Probabilistic Choice Model with Reference Quality

In this section, the proposed reference quality model that describes the asymmetric effect of innovation shocks on product demand at the product attribute level is explained in terms of consumers' innovation sensitivity, i.e., *the innovation elasticity of demand*. A unique feature of the proposed model is that it estimates the elasticity of gain and loss against the reference quality separately and provides strategic insights into attribute-level product competitiveness and the corresponding competitive market structure of a product attribute.

Whether determined through aggregate or individual data, the reference dependence is an important determinant of consumer brand choice (Mazumdar et al. 2005, Zhou 2011). In reference price studies using individual-level scanner data, researchers have modeled the formation of individual-level reference (Erdem et al. 2001, Kalyanaram and Little 1994, Mayhew and Winer 1992, Rajendran and Tellis 1994). However, the reference price can also be encoded at the product category level using the average price of different brands (Helson 1964, Mazumdar et al. 2005, Monroe 1973) or the price that is frequently charged in a product category (Mazumdar et al. 2005, Urbany and Dickson 1991). Encoding the reference price at the product level can be beneficial because retaining the price information for several brands with small differences in price and quality may create a cognitive burden for consumers (Mazumdar et al. 2005).

Additionally, previous studies have confirmed that product category-level references are more adaptive in nature, especially when a market is evolving rapidly (Anderson et al. 1994, Johnson et al. 1995, Anderson and Salisbury 2003, Zhou 2011). In particular, Anderson and Salisbury (2003) emphasized that market-level references (expectations) are rational and that their progress is significantly more adaptive in nature, suggesting that aggregate-level data are more appropriate for the analysis of the reference effect. Additionally, while it is better to use individual-level data for the analysis of the reference price, which is an internal price specific to a product, category-level aggregate data are more appropriate for the analysis of reference quality, which is an internal standard for an attribute of a product category, e.g., the display size of a laptop computer or battery life of a mobile telephone, because the product attributes for a specific product do not change over its product life cycle, unlike its price. Therefore, we modeled the reference quality at the product category level in our study. However, we consider consumer heterogeneity in how the differences in the reference points affect utility and consumer choice by using a random coefficient choice model.

Let *i* be the number of consumers (households) in the panel and *j* the number of products at time *t*. Consider a general model in which consumer i = 1, 2,…,*I* on any purchase occasion *t*=1,2,…,*T* chooses a single product *j* from a set of *j*=1,2,…, *J* distinct items in a product category. Assume that the (indirect) utility that this consumer derives from the purchase of this item is a function of preference, price, product attributes, and loss and gain relative to reference quality. This assumption yields indirect utility U_{ijt} that consumer i would derive from the purchase of product *j* on purchase occasion *t*:

$$U_{ijt} = \alpha_{ij} + \beta_{pi} p_{jt} + \sum_d \beta_{di} X_{jdt} + \sum_l \left(\beta^l_{G,i} G q^l_{jt} + \beta^l_{L,i} L q^l_{jt}\right) + \xi_{jt} + \varepsilon_{ijt}$$

$$for\ i = 1, \dots, I,\ \ j = 1, \dots, J_t, d = 1, \dots, D, l = 1, \dots, L, and\ t = 1, \dots, T \qquad (1)$$

where α_{ij} is a brand and consumer-specific constant; β_{pi} represents consumer *i*'s price sensitivity for consumer choice, β_{di} is a vector of individual-specific taste coefficients on observed product characteristics X_{jdt} that are *dichotomous* (i.e., 0 or 1) in their value, such as digital cameras, games, or MP3s, and $\beta^l_{G,i}$ and $\beta^l_{L,i}$ are consumer-specific random parameters for the gain and loss in quality for specific product attributes, q^l_{jt}, that have *continuous* values in their measures, enabling us to construct variables of gain and loss in quality, Gq^l_{jt} and Lq^l_{jt}. Note that it is not necessary to construct the variables for reference quality, Gq^l_{jt} and Lq^l_{jt}, for all of the continuous product attributes because the contribution of our approach is not on the exact reference point-formation process but rather to suggest managerial implications for businesses that produce high-tech durable goods in their strategic management of product attribute-level innovation. Therefore, we can construct reference quality variables that focus on one or a few specific product attributes that are strategically important for companies and therefore must be analyzed to identify their competitive market structures. In our empirical exploration in the next section, for demonstration purposes, we use only weight and talk time variables that are continuous. ξ_{jt} identifies the mean across consumers of unobserved (by the econometrician) product characteristics, and ε_{ijt} represents the distribution of consumer preferences around this mean. Notably, loss aversion for attribute *l* will be observed if λ_l in the following equation is greater than 1:

$$\beta_{L,i}^{l} = \beta_{G,i}^{l} \times \lambda_l \tag{2}$$

In this way, we can also compare the degree of loss aversion of multi-attributes. Gq_{jt}^{l} is the gain from the difference between the level of an attribute l (q_{jt}^{l}) and the reference point (RQ_t^l) of the attribute at time t, given that RQ_t^l is worse than q_{jt}^{l}. Lq_{jt}^{l} is the loss from the difference given that RQ_t^l is better than q_{jt}^{l} at time t.[8] In our model, following the previous literature, a subtractive form is assumed for the reference structure, where the gain or loss from an actual attribute level is based on its absolute distance from the reference point of the attribute. This subtractive form of reference formation is popular in the literature (Erdem et al. 2001, Kalyanaram and Little 1989, Kivetz et al. 2003, Mayhew and Winer 1992, Rajendran and Tellis 1994). Here, we define

$$Gq_{jt}^{l} = log\left(max\{q_{jt}^{l} - RQ_t^l, 0\} + 1\right) \tag{3}$$

$$Lq_{jt}^{l} = log\left(max\{RQ_t^l - q_{jt}^{l}, 0\} + 1\right) \tag{4}$$

Here, we can have different levels of reference points (RQ_t^l) in constructing reference quality variables. Based on the previous literature on reference price that used the category-level average price (Helson 1964, Monroe 1973, Mazumdar et al. 2005), we consider different types of the average quality of the category – the average level of attribute *l* for all the products in one month, the sales-weighted average level of attribute *l* for all the products in one month, the level of attribute *l* for the product with the highest sales in one month, and the sales-weighted average level of attribute *l* for all the products of a leading company with the greatest market share in one month – and select the best-performing reference point using a non-nested test for a random coefficient model.

We note that the endogeneity issue on the reference points of product attributes can be minimal in our model. First, the reference point is not necessarily the best product quality that competing companies want to achieve. Rather, it is the cognition-based level of quality that consumers have in mind considering the currently available choice sets in the market. Second, this study looks at the feature phone industry, which has already been saturated in terms of technological innovation, with most products in the market that have similar product attributes.

[8] In the case of an attribute *l* in which the consumer benefits increase with the decrease of absolute amount, such as the *weight* of a mobile phone, Gq_{jt}^{l} and Lq_{jt}^{l} are expressed as $Gq_{jt}^{l} = log\left(max\{RQ_t^l - q_{jt}^{l}, 0\} + 1\right)$ and $Lq_{jt}^{l} = log\left(max\{q_{jt}^{l} - RQ_t^l, 0\} + 1\right)$.

Moreover, each company's product portfolio consists of numerous products with a wide range of product attributes, and therefore, there are many alternatives available in the market. Hence, it is unlikely that a single company would greatly influence the reference point by introducing a product with the highest product quality for one specific attribute, unless the product dominates the entire market, which is not the case in our data. Finally, companies cannot change the product characteristics of their products within one month, which is the unit of time in our study.

3.2. Reference Quality and Innovation Elasticity

Given the probabilistic choice model with reference quality described above, the market share elasticity for gain and loss in product quality, referred to as the *quality elasticity of demand* or *innovation elasticity* when focusing on high-tech durable goods markets, is given as follows: for attribute *l*, if model *k*'s value of attribute *l* is greater than the reference point of attribute *l*, $\text{i. e.}, RQ_t^l$, then attribute *l*'s (own- and cross-) elasticities of the market shares (s_{jt}) are as follows:

$$\begin{aligned}\eta_{jkt}^{G,l} &= \frac{\partial s_{jt}}{\partial Gq_{kt}^l}\frac{Gq_{kt}^l}{s_{jt}} \\ &= \frac{Gq_{jt}^l}{s_{jt}}\int e^{-Gq_{jt}^l}\cdot\beta_{G,i}^l\cdot s_{ijt}\ \cdot\left(1-s_{ijt}\right)\ dP(\theta_i)\ if\ j=k \\ &= -\frac{Gq_{kt}^l}{s_{jt}}\int e^{-Gq_{kt}^l}\cdot\beta_{G,i}^l\cdot s_{ijt}\ \cdot s_{ikt}\ dP(\theta_i)\ if\ j\neq k \qquad (5)\end{aligned}$$

where s_{ijt} is the probability of consumer *i* choosing model *j*, and $P(\theta_i)$ represents the population distribution functions. In contrast, if model *k*'s value of attribute *l* is lower than the reference point of attribute *l*, $\text{i. e.}, RQ_t^l$, then attribute *l*'s (own- and cross-) elasticities are defined as follows:

$$\begin{aligned}\eta_{jkt}^{L,l} &= \frac{\partial s_{jt}}{\partial Lq_{kt}^l}\frac{Lq_{kt}^l}{s_{jt}} \\ &= -\frac{Lq_{jt}^l}{s_{jt}}\int e^{-Lq_{jt}^l}\cdot\beta_{L,i}^l\cdot s_{ijt}\ \cdot\left(1-s_{ijt}\right)\ dP(\theta_i)\ if\ j=k \\ &= \frac{Lq_{kt}^l}{s_{jt}}\int e^{-Lq_{kt}^l}\cdot\beta_{L,i}^l\cdot s_{ijt}\ \cdot s_{ikt}\ dP(\theta_i)\ if\ j\neq k \qquad (6)\end{aligned}$$

Based on Prospect Theory (Kahneman and Tversky 1996) and regarding the reference price (Kalwani et al. 1990, Kalyanaram and Little 1989, Kalyanaram and Winer 1995, Lattin and

Bucklin 1989, Mazumdar and Papatla 2000, Winer 1986), it is expected that the innovation elasticity for gain ($\eta_{jkt}^{G,l}$) and loss ($\eta_{jkt}^{L,l}$) are asymmetric and the absolute value of innovation elasticity for loss is greater than that for gain.

3.3. Innovation-driven Competitive Market Structure

Due to the asymmetric characteristics of the value function, a product is expected to have different degrees of demand changes against innovation shocks depending on the value position of its product attributes. While consumer preference on the products in the market will be influenced differently by an innovation shock depending on a product's attribute positions on the quality span, each product's market share can change differently depending on the relative degree of the value reduction of highly substitutable products in the market. Hence, it is necessary to evaluate how an innovation shock indirectly impacts each brand's market share via product preference changes on other competing products. To better understand the competitive market structure of a product attribute based on the value function of reference quality, we mathematically defined the summary measure of the innovation-driven attribute competition utilizing the summary measures suggested by Kamakura and Russell (1989) and Cooper (1988).

For market *t*, we define *the competitive innovation vulnerability* for attribute *l* of product *k* as follows:

$$Competitive\ Innovation\ Vulnerability_{k,t}^{l}$$
$$= \left[\sum_{j\neq k}\left(\eta_{jkt}^{G,l}\right)^2 \cdot 1\left\{model\ k's \text{ attribute } l \geq RQ_t^l\right\} + \sum_{j\neq k}\left(\eta_{jkt}^{L,l}\right)^2 \cdot\right.$$

1model k′s attribute *l< RQtl− j≠ kηkjtG, l2·1model j s attribute l≥*

RQtl+ηkjtL, l2·1model j s attribute l< RQtl

(7)

which represents the post-innovation vulnerability of product *k* reflecting consumer preference changes on both product *k* and competing products whose attributes *l* are in different gain or loss positions. Specifically, the first part of the right-hand side reflects consumers' substitution from product *k* to other products in the aftermath of innovation shock, and the second part reflects how much product *k* can benefit from the value reduction of highly substitutable products.

4. Data

4.1. Mobile Industry

The mobile communications industry is one of the largest industries in the U.S. In 2004, the total revenues of the U.S. mobile communications industry reached 145 billion dollars. This industry includes transport services, mobile telephones, capital expenditures and infrastructure equipment, including Wi-Fi equipment. In 2004, there were 163.1 million mobile telephone subscribers. However, there was a saturation in the growth of the mobile telephone market in 2001 and 2003. In 2001, mobile telephone shipments fell for the first time in the industry's history. During this period, new subscribers no longer drove the demand for mobile telephones. Instead, existing subscribers replaced their handsets for a variety of reasons – replacing lost, stolen or damaged handsets or acquiring a new handset design that was smaller, lighter or had a full-color display. Consequently, between 2001 and 2002, the overall growth rate of this market fell to 7.6 percent.[9]

The mobile telephone industry is highly concentrated. Table 1 reports U.S. mobile telephone sales from 2001 to 2004. Nokia is the indisputable industry leader, controlling more than one-third of the market. The three-firm concentration ratio is almost 70%. Nokia is a dominant firm across the board, offering a large variety of handsets that serve low- to high-end consumers. Samsung started to focus on the high-end segment to ensure higher margins and profitability from 2002 onwards and attained the second rank in unit share of the market. Motorola has maintained its third-ranked position in market share since 2002 by introducing the largest number of new handsets. Nevertheless, all of the leading manufacturers have extensive product varieties with comprehensive new features, such as cameras, SMS messaging systems, and color displays. These developments suggest that product differentiation plays an important role in the mobile telephone market.

[Insert Table 1 about here]

4.2. Data Description

The data set used in this paper comes primarily from NPD Techworld, a leading marketing research company in the consumer electronics, information technology and imaging markets. NPD Techworld collects both point-of-sale (POS) and consumer tracking information. The data set for the U.S. mobile telephone market has been collected by surveying consumers throughout

[9] J.D. Power and Associate Reports, Sept. 25, 2002.

the United States from January 2000 to April 2004 (40 monthly observations). Additionally, the data have been adjusted using demographic characteristics. The surveys were sent in a way that is proportional to the U.S. Census in terms of geography, gender, income level, household size and age.[10] The total units sold and revenue for each product in one month were calculated by projecting up from the actual respondents.[11] Therefore, the data are consistent with our empirical estimation of a random coefficient model because we use the total U.S. population from the U.S. Census Bureau for the potential size (M_t) of the market.

The original data sample included 338 mobile telephone models. Products with extremely low sales volumes and models that differed only in minor characteristics (e.g., telephone book capacity, number of ring tones) were aggregated. As a result, our final sample contains data on 202 models from eight manufacturers. Therefore, the panel is unbalanced, and we treat each month-model pair as a single observation. The total number of observations is 3,910.

We supplanted these panel data with product attribute information compiled from several sources, primarily from epinions (www.epinions.com), DealTime (www.dealtime.com), and manufacturers' online documentation. Product characteristics for which we have data include various product features, such as size, weight, type of display, battery time, digital camera, games, and MP3. However, dichotomous characteristics of feature phones, i.e., whether they have digital cameras and MP3 functions, cannot be properly modeled to reflect the continuous change in reference quality over time. Only size, weight, and talk time are the continuous variables in the data; however, size and weight are highly correlated. Moreover, weight and talk time were selected as the key drivers of mobile telephone choice by the trade press during the period of our data.[12]

Weight is the total weight of the mobile telephone in *grams* (*grm*) without attachable cameras or other additional equipment. The *Talk Time* is the length of time that a mobile telephone is engaged in transmission (telephone conversations, sending or receiving data) before it runs out of battery power. *Talk Time*, expressed in hours or minutes, is much shorter than standby time[13] because transmission requires more power. The *Talk Time* of mobile telephones

[10] Because surveys are not always returned in the same proportions, the data were adjusted accordingly.

[11] For example, let us say that the U.S. population is 250 million, and 25,000 respondents during a particular time period report. Of those 25,000, 1% or 250 respondents report that they purchased a new cellular telephone 'A.' By projecting up to the total population, we would say that during that time, 2.5 million 'A' cellular telephones were purchased. If a particular transaction involves the purchase of more than one telephone, it is adjusted accordingly.

[12] National Electronics Manufacturing Initiatives, Inc. (NEMI), a large industry-led international consortium (*Proceedings, SMTA (Surface Mount Technology Association) International Conference*, 2003).

[13] The maximum length of time that a mobile telephone or communicator is fully charged, turned on and ready to send and receive calls or data transmissions. Standby time is reduced by the amount of time that

has become an important factor in consumer choice because the inclusion of bigger, brighter screens, higher resolution, and still and video imaging capabilities and the addition of mobile technologies, such as Bluetooth and WiFi, comes at a price – more drain on the battery. One of the challenges for 3G mobile telephones is to ensure that those users' fundamental needs for mobile telephones are met, which includes acceptable standby and talk time. Customers quickly become dissatisfied if they find they cannot make a voice call because their talk time has been used up by the inclusion of peripheral features, such as a more sophisticated display, video camera, and Bluetooth.[14] Figures 2 and 3 below show the dynamics of the weight and talk time attributes with the sample periods showing a rapid decrease or increase in their values throughout the periods.

[Insert Figure 2 about here]

[Insert Figure 3 about here]

The sales-weighted averages of the prices and characteristics for each year in the sampled period (2001-2004) are listed in Table 2.

[Insert Table 2 about here]

As described in the previous section, total mobile telephone sales declined over our sample periods without category expansion. However, the sales-weighted average weight decreases over time, while talk time shows a consistent increasing trend. Throughout the sampled period, the sales-weighted average weight decreased approximately 9.3%, and the sales-weighted average talk time increased approximately 8.8%. During 2001 and 2002, these technological trends were more evident. The sales-weighted average weight decreased 17.1%, and the sales-weighted average talk time increased 22.1%. Considering the industry trends reported above, it seems natural that consumers' experience curve for mobile telephones and their expected level of quality play an important role in their choice of telephones.

5. Estimation and Results

5.1. Estimation and Reference Point Selection

the telephone is used for talking because talking on a telephone draws more energy from a battery than standby mode.

[14] Canalys research release (2004), "3G handsets on the rise."

Our econometric approach to the reference quality model is a random coefficient discrete choice model (e.g., McFadden 1984; Berry 1994; Berry, Levinsohn and Pakes 1995; Nevo 2001; Sudhir 2001).

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \sum \upsilon_i \qquad \upsilon_i \sim N(0, I_{W+1}) \tag{9}$$

where W is the dimension of the observed characteristics vector, and the matrix $\sum$ is a scaling matrix that captures the unobserved heterogeneity due to random shocks υ_i. In the econometric model, unobserved random consumer characteristics υ_i are assumed to be normally distributed. Let $\theta = (\theta_1, \theta_2)$ be a vector containing all of the parameters of the model. The vector $\theta_1 = (\alpha, \beta)$ contains the linear parameters, and the vector $\theta_2 = vec(\sum)$ contains the non-linear parameters. Therefore, the utility is represented with the mean utility δ_{jt} and a mean-zero heteroscedastic deviation from that mean, $\mu_{ijt} + \varepsilon_{ijt}$, which captures the effects of the random coefficients as shown below:

$$\begin{aligned} U_{ijt} &= \delta_{jt}(\alpha_j, Gq^l_{jt}, Lq^l_{jt}, p_{jt}, X_{jdt}, \xi_{jt}; \theta_1) \\ &\quad + \mu_{ijt}(\alpha_{ij}, Gq^l_{jt}, Lq^l_{jt}, X_{jdt}, \upsilon_i; \theta_2) + \varepsilon_{ijt} \end{aligned} \tag{10}$$

As is typical, the mean utility of the outside good, the consumer option to not purchase any of the brands, δ_{0t}, is normalized to be constant over time and equal to zero for identification purposes. The observed market share of product *j* is given by $s_j = S_j / M$, where S_j represents the units sold, and *M* is the market size, which is proportional to the total population.[15] We also make the usual assumption that consumers purchase one unit of the product that gives them the highest utility among all the possible products that are available in a certain month *t*.[16]

Because the error ξ_{jt} in the demand model is correlated with price, we use instrumental variable estimation techniques following the Generalized Method of Moments (GMM) estimation

[15] In this case, *M* is the total U.S. population because all the members of the population can purchase mobile telephones.
[16] This study does not explicitly account for upgrades or replacements. However, considering the average usage period for mobile telephones, this model could be viewed as a reasonable approximation of the true choice model for durable markets.

procedure in Berry (1994) and Berry, Levinsohn and Pakes (1995) and extended by Nevo (2001). As instruments, following Berry, Levinsohn and Pakes (1995), we consider companies' own and competitors' characteristics: (1) the product characteristics, (2) the average or sum of the product characteristics across all of the mobile telephones produced by the same company, and (3) the average or sum of the product characteristics across all mobile telephones not produced by the same company. Additionally, we include (4) the monthly average values of product characteristics as instruments. To confirm that the search leads to the global minimum of the objective function, we use different starting values and a non-derivative simplex search method (Nelder-Mead 1965) that is less vulnerable to local minima problems typical of gradient approaches. We use the minimum obtained as a starting value for a final gradient-based search (Nevo 2001).

To select the best-performing reference point in our estimation, we consider different types of category-level averages for an attribute *l*, i.e., (A) the average level of attribute *l* for all the products in the current market, (B) the sales-weighted average level of attribute *l* for all the products in the current market, (C) the level of attribute *l* for the product with the highest sales in the current market, and (D) the sales-weighted average level of attribute *l* for all the products of a leading company with the highest market share in the current market, as suggested by the previous literature discussed earlier. We perform the non-nested test for a random coefficient model proposed by Smith (1992)[17] because most of the models cannot be nested within each other as a result of the different types of reference quality variables in the models. There can be two particular cases of comparisons between each pair of competing models (Vuong 1989, Villas-Boas 2007): (1) two competing models are strictly non-nested, and (2) overlapping models have common explanatory variables and different additional explanatory variables. While the latter is our case, in both cases, we use the Cox-type non-nested test to examine the difference of GMM criterion functions for the two competing models under one of the competing hypotheses. We follow the two-step procedure proposed by Vuong (1989). There are two competing regression models H_g and H_h as follows:

$$H_g : y = X_g \beta + u_g \tag{9}$$
$$H_h : y = X_h \gamma + u_h$$

[17] Smith (1992) proposed a Cox-type non-nested test for competing models estimated by GMM. Non-nested linear regression models with heteroscedasticity and serial correlation of unknown form and differing instrumental validity assumptions are encompassed.

where X_g and X_h are matrices of variables including different types of reference quality variables, respectively. The β and γ are parameters to be estimated by simulated GMM. The Cox-type statistic is constructed by examining the behavior, under H_h, of the difference in the estimated GMM criterion functions for models H_g and H_h. A large positive Cox-type statistic in this one-sided goodness-of-fit test leads to a rejection of the model H_h against H_g (Villas-Boas 2007) with a weighted sum of the Chi-square distribution.

When testing non-nested models, it is important to note that they are sensitive to the variance-covariance estimator because the errors may have heterogeneity and temporal dependence of an unknown form. Therefore, we must construct test statistics using a heteroscedasticity and autocorrelation consistent (HAC) or robust covariance matrix. We use non-parametric kernel-based procedures to estimate a HAC covariance matrix, especially NW-PW, the kernel-based estimator of Newey and West (1994), because the Newey-West procedure is better able to detect the higher-order serial correlation (Den Haan and Levin, 1996).[18] The kernel-based procedure uses a weighted sum of the autocovariances to estimate the spectral density at a frequency zero, where the weights are determined by the kernel and the bandwidth parameter. In our estimation, we use the Barlett kernel to determine the data-dependent bandwidth parameter. However, we checked and confirmed the robustness of our NW-PW estimator with different bandwidth parameters for the Barlett kernel.

The test results show that the model (D) with *the sales-weighted average of attribute l for all of the products of a leading company with the greatest market share* in the current market as the reference quality (RQ_t^l) for each time period performs best in our estimation. When we assume the model (D) as H_g and other models, i.e., (A), (B), and (C), as H_h, we have large numbers of Cox-type test statistics that reject the model H_h against H_g: 113191.11 for model (A), 5984136.50 for model (B), and 1719.69.[19] This result is also consistent with the previous literature suggested by Anderson and Salisbury (2003) and Zhou (2011), which noted that the quality or functional level of the dominant brands of a leading company in the market generally has an important role as a reference point within the product category in the consumer decision-making process

[18] The kernel-based procedure uses a weighted sum of the autocovariances to estimate the spectral density at a frequency zero, where the weights are determined by the kernel and the bandwidth parameter. In our estimation, we use the Barlett kernel to determine the data-dependent bandwidth parameter.

[19] The critical value at the 95% significance level based on a weighted sum of Chi-square distribution is 2.85.

because it is often featured in advertisements with higher marketing budgets or is displayed prominently in stores and is hence more memorable.

5.2. Estimation Results

In Table 3, the structural parameter estimates are provided with their t-values. It is noteworthy that both wireless service providers and mobile handset manufacturers are controlled in the model because both sides have tie-ups with each other regarding some handset devices and because consumers are typically locked into long-term contracts with their service providers, which can partly explain why price sensitivity is not statistically significant. Additionally, as expected, we observe significantly positive signs on the mean preferences for color display and camera features. Although we detect negative signs on the mean preferences for MP3 players and games, the large standard deviations of random coefficients for these two dichotomous characteristics indicate the existence of considerable unobserved heterogeneity in consumer preferences.

[Insert Table 3 about here]

The estimated results focus on the coefficients for the two key attributes of weight and talk time to examine the effect of reference quality on product choices. As shown in Table 3, it was found that the coefficients of gain were greater than those of loss in both cases in which the gain and loss parameters were statistically significant. These results confirm that loss aversion exists on both key product attributes as consumers respond more to loss than to gain, i.e., $\lambda > 1$. Regarding the degree of loss aversion, heterogeneity was found across multiple product attributes, i.e., loss aversion for weight was higher than that for talk time: λ_{weight}= 2.38 and $\lambda_{talk\ time}$ = 1.55.

To further discuss the reference quality effect in the high-tech durable goods markets, including smartphones, computers, and tablets, we can consider shifts of the value function. We note that the introduction of new products with higher quality than the current conventional quality level will lead to a shift in reference quality (innovation shock) by constantly changing consumers' level of desired product quality and thereby shift the value function to the right. If the value function shifts to the right, as shown in Figure 4 below ($V \rightarrow V'$), then the values of the existing products, which are located in the previous value function (V), will depreciate suddenly and decrease to new value points on the new value function (V').

[Insert Figure 4 about here]

In particular, the values of products with quality between *RQ* and *RQ'* on the quality span depreciate most significantly due to the shift in the reference quality. Prior to this innovation shock, these products have been competitive in the market with positive value in the value function. However, because the product quality is not sufficiently better than *RQ'*, consumers experience a significant value loss after innovation shocks. Therefore, the region between the original reference quality (*RQ*) and the new reference quality (*RQ'*), *Region 2* in Figure 4, is termed *the Innovation Shadow Zone*. Because the magnitude of the value reduction is determined by λ, as λ becomes greater, the effect due to innovation shock becomes more severe. Therefore, it is important to measure λ for each product attribute. From the perspective of product innovation strategy, given the multiple product attributes, it is also crucial to compare how the degree of loss aversion differs across attributes. Hence, our findings on the degree of loss aversion for weight, $\lambda_{\text{weight}} = 2.38$, and for talk time, $\lambda_{talk\ time} = 1.55$, have a strategic implication that the innovation shock is more severe for talk time than weight.

The question that may arise is whether the results of our model are consistent with the depicted value function, which has an asymmetric structure with a concave curve for the gains and a convex curve for the losses. Hence, we computed the elasticities of demand with respect to each of the two product attributes at the product level and found that the results empirically support Figure 2. For illustrative purposes, we calculated the talk time and weight elasticities of several mobile telephones in March 2004 as shown in Table 4. In March 2004, Samsung had the highest market share, and we used the sales-weighted attribute quality of the company as the reference points for both talk time and weight.

[Insert Table 4 about here]

Centering on the reference quality, the products in the upper rows had higher product quality than the reference quality, while those in the lower rows had lower product quality than the reference quality. In Table 4(a), while all LG and Audiovox products' talk times can only be seen in the rows below the reference, Motorola, Nokia, and Sanyo had a wider range of product portfolios that had both shorter and longer talk times distributed in both the upper and lower rows in the table. Because diminishing sensitivities are detected when the distance from the reference point increases in both directions, the value function has a concave curve for the gain and a convex curve for the loss.

Consumer loss aversion behavior for talk time can be seen more clearly from pair-wise comparisons between models below and above the reference point. For example, the Motorola V120T had 128 more minutes of talk time than the reference point, while the Audiovox CDM9500 had 127 fewer minutes of talk time than the reference point. Although the degree of the difference was almost identical, the own talk time elasticity of the Audiovox CDM9500 was approximately 1.62 times greater than that of the Motorola V120T. Furthermore, in the other pair-wise cases, the elasticities of the products with loss were greater than those with gain. This supports the existence of consumer loss aversion. Similarly, Table 4(b) shows that the asymmetric S-shaped value function holds for another attribute (weight). Considering that the degree of loss aversion on weight is greater and the impact from innovation shocks is different accordingly, understanding the multi-attribute reference effects can be beneficial for product innovation strategies of companies with different product portfolios and combinations of product attributes.

Moreover, we also examine whether the value function shifts due to innovation shocks in Figure 2. To do so, we compared the changes in the estimated innovation elasticities of those products of which the attribute level is near RQ with those near RQ' for each product attribute before and after innovation shocks, i.e., the shift of the reference point, for all the observations in the data because by the shift of the value function, the largest changes in the diminishing rate of the value function (the slope of the value function) occur when the level of attribute is at RQ or RQ' (the diminishing rate of the value function V at RQ and that of V' at RQ' is infinite). Table 5 shows the average changes in innovation elasticity for those products of which the attribute level is near RQ and RQ' before and after the shift in the value function. As expected, the average elasticity decreases, yielding a negative value at RQ, while it increases at RQ' (from a low value to a high value), confirming the shift in the value function that corresponds to innovation shocks and the existence of innovation shadow.

[Insert Table 5 about here]

To check the robustness of our results, we also examine the innovation elasticity changes in each region in Figure 2 before and after the shift of the reference point. Regardless of the functional form of the value function, we expect the absolute changes in the diminishing rate of the value function before and after the value function's shift to be higher in region 2 than in the other regions. Therefore, we computed the average elasticity changes according to the shifts of the reference point for each region with respect to each attribute, as shown in Table 6. Regardless of the attributes, we find that the average change in innovation elasticity is the highest for region 2 among all of the regions with statistical significance. In other words, region 2 experiences the most substantial impact of innovation shock, and its innovation elasticity drops significantly after the shock. Therefore, both attributes confirm the existence of an innovation shadow.

[Insert Table 6 about here]

So far, we have discussed how a change in the reference point of a product attribute by innovation shock affects consumers' valuation of products with different quality positions. While useful for understanding why and the extent to which a consumer experiences a value loss for an attribute after innovation shocks, the value function itself is confined to the attributes of a single product without delivering the managerial implications of competition among products in the market. However, an innovation shock will differently affect consumer preference on the products depending on their attribute positions on the quality span, and therefore, each product's market share may change differently depending on the relative degree of value reduction of highly substitutable products in the market. Therefore, we must further evaluate how an innovation shock indirectly impacts each brand's market share via product preference changes on other competing products.

We discuss competition among products in the aftermath of product attribute-level innovation using innovation vulnerability in Equation (7). Using the structural parameter estimates for illustrative purposes, we computed competitive innovation vulnerability for both talk time and weight on mobile telephones with a wide range of product qualities and with relatively large market shares in March 2004. Along with other relevant measures for each product, we present the results in Table 7.

[Insert Table 7 about here]

As observed in Table 7, each mobile handset manufacturer provided multiple products, and each product was also characterized by different values over multiple product attributes. When a company was faced with innovation shock on multiple attributes, some attributes might be in a loss position, while others might be in a gain position within each company's own attribute-based product portfolio. Therefore, in these cases, the competitive innovation map that reflects the attribute-specific innovation vulnerability of companies' own products will be beneficial to the companies' product portfolio management. In Figure 5, we present the *competitive innovation* *map* after normalizing the competitive innovation vulnerabilities for the two product attributes in Table 7.

[Insert Figure 5 about here]

Notably, the suggested competitive innovation map is an illustrative example for multi-attribute high-tech durable goods and can be extended to *n* different strategic attributes that a company can identify and better prepare for consumer preference changes due to potential innovation shocks. The competitive innovation map can be used with the information provided in Table 7; for example, Kyocera's KE433C and Samsung's SPHA620 observed in the northeastern area are highly susceptible to innovation shocks in both attributes, and both companies noticeably rely heavily on these products, which account for approximately 63% and 26% of their total sales, respectively. Nokia's 3586 and Sanyo's SCP8100 in the southeastern area are vulnerable to reference point changes in weight but not talk time. The fact that Sanyo's SCP8100 accounts for 39% of its total sales indicates that Sanyo should prepare more thoroughly for a potential shift in the reference weight. The products of minor players such as Audiovox, Sony Ericsson, and LG are quite dissimilar from each other in both talk time and weight; however, all are positioned in the southwestern area and are therefore relatively less vulnerable to innovation shocks in both attributes. From the perspective of attribute-level product portfolio management, both Motorola and Nokia have a broad spectrum of products over wider ranges of attributes, and interestingly, all of their products except for Nokia's 3586 appear invulnerable to potential preference shifts after innovation. At the company level, however, Nokia is not quite invulnerable due to its high dependence on the 3586, which accounts for 25% of its total sales, while Motorola appears well-protected from innovation shocks, with its products with relatively large market shares located in the southwestern area. Under these circumstances, each company can use different product innovation strategies depending on the configuration of its attribute-based product portfolio to defend its market share more efficiently against the existing competing products. For example, companies can introduce new products with different combinations of product attributes by placing priority on improving vulnerable attributes.

To deliver additional managerial implications at the product attribute level, in Table 8, we present pairwise product comparisons with a focus on how the preference change on the individual competing products will impact each product's market share when the reference point in talk time and weight shifts. To make the simulated results more interpretable, we consider an innovation shock on each of the two attributes by 1 unit, i.e., a 1-minute increase in the reference talk time and a 1-gram reduction in the reference weight. Thus, the value in the *i*th row and *j*th column represents the percentage point change in the market share of product *i* via the preference change on product *j* after a 1-unit innovation shock.

[Insert Table 8 about here]

Because the competitive innovation map in Figure 5 barely explains pairwise inter-product competition, Figure 5 can be better interpreted with the results presented in Table 8. In the case of LG's VX6000, which appears less susceptible to innovation shocks in both attributes in Figure 5, post-innovation consumer preference changes in the talk time attribute of Kyocera's KE433C will be most beneficial to VX6000's market share by 0.0076 percentage points, whereas Samsung's SPHA620, which is faced with a reduction in the reference weight, is expected to be most helpful to VX6000 by 0.0085 percentage points. Interestingly, Motorola's V300 and Sony Ericsson's T616 are expected to become more influential over competing products only when the reference weight reduction occurs. If we restrict inter-product competition to the 16 products listed in the table, Sony Ericsson's T616 benefits the most from the other 15 products, with a 0.9735 percent increase in market share when the reference talk time jumps; however, T616's value reduction by consumers does not result in an increase in the market share of these 15 products. In response to the reference weight reduction, Audiovox's CDM8900, with a 1.6436 percent increase in its market share, appears to benefit from consumers' product substitution across the listed products. In contrast, Kyocera's KE433C and Samsung's SPHA620 are expected to be most susceptible to post-innovation product substitutions by resulting in the largest proportions of share increase in most of the other products but earning only a 0.6820 percent increase in market share on talk time and a 1.3240 percent increase in market share on weight. This result is also consistent with Figure 5, in which Kyocera's KE433C is less vulnerable than Samsung's SPHA620 on weight, while both are highly vulnerable to post-innovation competition in both attributes.

6. Conclusion and Future Research

This study suggests a reference-dependent choice model for product quality that can capture the asymmetric effect of innovation shocks on product demand and competitive market structure at the product attribute level. The proposed model enables companies to build attribute-specific product innovation strategies in response to idiosyncratic innovation shocks. Additionally, the proposed model provides a strategy for managing an attribute-level product portfolio. By considering the loss-aversion behavior of consumers, different innovation opportunities were also identified depending on the different levels of product attributes that center on the market reference point. That is, the asymmetric effect of the product innovation elucidated the *innovation shadow zone*, a certain quality span for a product attribute in which the values of products depreciate most significantly due to innovation shocks of a market.

Additionally, the proposed model can overcome the limitations of the existing competitive market analysis by identifying innovation vulnerability at the product attribute level. The existing competitive market analysis is limited in extracting specific insights regarding product attributes because it provides a product's competitive market position only through abstracted attribute dimensions from consumers' underlying preferences; it does not provide attribute-specific information regarding the competitive market structure. Therefore, the usefulness of the competitive market analysis is inherently limited. Therefore, it does not provide information beyond the market structure that is specific to price competition. In contrast, the proposed model expands the scope of the competitive market analysis into the functional and form-related product attributes, which enables us to construct attribute-specific product innovation strategies.

From a managerial perspective, attribute-specific innovation often determines the success of a product in many markets (Krishnan and Ulrich 2001, Luchs and Swan 2011). The proposed model can help companies identify the weaknesses and strengths of each product attribute against competing products and select the most effective attributes for expanding or defending market share in general. Doing so is important for a company with limited resources because it must efficiently and effectively invest its limited resources to increase its market share and revenue. Moreover, the effect of the innovation shadow on the results emphasizes the importance of leading the market reference to escape significant disadvantages when an attribute's quality level is located between the previous and existing reference quality. Leading the reference at the attribute level can be achieved through continuous product innovation; however, it can also be achieved through other marketing methods such as pre-announcement and advertising that emphasize a specific attribute that is critical to the product's success.

A limitation of this study is that our static model did not fully incorporate the dynamics that arise from innovation and new products, which we leave for future research. More specifically, an area for future research may be to consider the effect of category expansion and to develop a dynamic model that can fully resolve companies' strategic actions given a forward-looking consumer's formation of reference quality. The effect of category expansion is especially important in markets where new products are constantly introduced and thereby new customers enter the market and people replace their current products. Hence, modeling a product category where the category demand is not fixed will make the model of reference quality more realistic and practical, enriching the innovation-strategic implications for companies. Additionally, developing the fully dynamic model that incorporates reference quality formation by forward-looking consumers would also be an important methodological contribution to the literature on new empirical industrial organization (NEIO). Future research will overcome the limitations of the proposed model and further generalize its applications.

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List of Abbreviations

BLP	Berry, Levinsohn, and Pakes (1995)
HAC	Heteroscedasticity and Autocorrelation Consistent
NW-PW	The Kernel-based Estimator of Newey and West (1994)
GMM	Generalized Method of Moments

Table 1. U.S. Sales of Mobile Phones to End Users, 2001 - 2004

Manufacturer	Market Share (%)				
	2001	2002	2003	2004	2001-04
Nokia	43.81	30.49	25.70	20.99	33.17
Samsung	13.28	21.02	20.01	26.26	18.40
Motorola	17.56	16.88	18.32	15.07	17.36
Kyocera	5.21	9.97	10.75	8.87	8.36
Sanyo	5.80	5.38	10.58	13.74	7.69
LG Electronics	2.67	12.22	8.09	7.76	7.23
Sony Ericsson	3.64	1.91	1.11	0.58	2.20
Audiovox	1.73	0.94	3.22	4.32	2.15
Others	6.30	1.19	2.22	2.41	3.44

Table 2. Dynamics of Prices and Technological Trends

	2001	2002	2003	2004[a]
Number of Products	165	192	208	173
Total Unit Sales (million)	182.62	142.09	146.79	47.91
Average Prices[b] ($)	96.83	114.77	112.72	124.68
Average Weight[c] (gram)	154.12	139.26	124.69	116.64
Average Talk Time[d] (min)	182.21	197.20	216.63	229.85

a. From January to April.
c.d. Sales-weighted average values.

Table 3. Estimated results of the model

	Reference Quality-Dependent Model			
	Means *t-value*	*S.D.* *t-value*		*Beta* *t-value*
Constant	-10.3032	0.0035	***Brand***	
	-34.4945	0.0015	Audiovox	0.8751
				2.1869
Price			Kyosera	1.2466
Price	0.3095	0.1064		2.6264
	1.6920	0.0773	LG	1.5783
				4.3790
Quality			Motorola	1.6273
Weight Gain	9.1091	0.0969		5.2765
	2.1350	0.1344	Nokia	2.0922
Weight Loss	-21.6981	0.0038		5.6398
	-6.8438	0.0031	Samsung	1.0961
Talk Time Gain	34.8995	0.0002		2.8938
	2.7308	0.0004	Sanyo	0.8022
Talk Time Loss	-54.0779	0.0368		1.8685
	-2.0866	0.0376	***Service Provider***	
Color Display	1.0208	0.2800	AT&T	-0.1630
	2.8915	0.0333		-0.8881
Camera	0.8552	0.0134	Sprint	0.3225
	2.3736	0.0033		2.1227
MP3 Player	-0.7723	0.7361	Verizon	1.2736
	-1.2558	0.0498		7.3536
Game	-4.5799	7.0656	Telus	-0.8889
	-6.5075	3.9859		-4.1091

Note: Sony-Ericsson is a base brand.

Table 4. Reference quality and product elasticities

(a) Talk time

Manufacturer	Model name	Quality zone	Talk time difference relative to reference point (minutes)	Elasticity
Motorola	V120T	Higher quality (i.e., longer)	128	1.2686
Nokia	5185		108	1.4980
Kyocera	QCP6035		78	1.9272
Sanyo	SCP4900		48	2.7638
Reference point = 221.89 minutes				
Sanyo	SCP5300	Lower quality (i.e., shorter)	-62	3.5129
LG	G4010		-72	3.1857
Nokia	5160		-102	2.3992
Motorola	V2397		-122	2.1187
Audiovox	CDM9500		-127	2.0544

* Regarding talk time, all LG and Audiovox products were below the reference point.

(b) Weight

Manufacturer	Model name	Quality zone	Weight difference relative to reference point(gram)	Elasticity
Samsung	SGHS307	Higher quality (i.e., lighter)	33	0.9404
Motorola	V66		24	1.1688
Audiovox	CDM8600		13	1.7197
Kyocera	KE433C		3	3.0166
Reference point = 102.76 grams				
Sanyo	SCP5400	Lower quality (i.e., heavier)	2	7.7474
Nokia	3589I		13	4.0147
Motorola	V120E		25	2.6949
Nokia	3285		36	2.1066
Sanyo	SCP7200		49	1.7390

Table 5. Average Changes of Innovation Elasticity at RQ and RQ'[20]

	Average elasticity changes at RQ	Average elasticity changes at RQ'
Talk Time	-0.037	0.716
Weight	-0.231	0.055

[20] The range of attribute levels that we consider in this estimation is RQ ± (RQ'- RQ)/2 for those products around RQ and RQ' ± (RQ'- RQ)/2 for those around RQ', while smaller ranges, i.e., stricter criteria, strengthen our results.

Table 6. The average changes of innovation elasticity by the value function shift

	Region 1	Region 2 (Innovation Shadow Zone)	Region 3
Talk Time	0.318**	0.798**	0.238**
Weight	0.119**	0.131**	0.030**

* All values are significant at 95% significance level with a *t*-test.

Table 7. Illustration of results for competitive innovation vulnerability: March 2004

Manufacturer	Model	Talk Time(%) relative to reference*	Weight(%) relative to reference*	Market share**	Sales proportion (%) (Manufacturer)	Competitive innovation vulnerability for talk time	Competitive innovation vulnerability for weight
Audiovox	CDM8900	-12.980	-9.496	0.5543	12.274	-1.2634	-0.4725
Kyocera	2345	2.801	19.699	2.3887	26.356	3.4447	0.0921
Kyocera	KE433C	-5.315	-2.684	5.7052	62.949	33.5259	2.6193
LG	VX6000	-32.368	9.967	2.7696	44.507	-0.6429	1.1002
Motorola	V120T	57.808	24.565	3.5103	19.259	-1.0786	0.4054
Motorola	T730	-25.605	9.967	2.0602	11.303	-0.8000	0.4007
Motorola	V300	75.843	-2.684	0.4854	3.240	-1.1647	-0.3725
Nokia	5180	-45.894	65.437	2.2649	11.288	-1.0422	-0.3501
Nokia	3590	75.843	8.021	1.0789	5.377	-1.2667	-0.1221
Nokia	3586	-21.547	13.860	5.1147	25.491	3.2309	3.2486
Nokia	6340IG	62.317	79.062	2.0393	10.164	-1.2254	-0.3609
Samsung	SGHR225	12.720	-6.577	0.7520	2.194	-1.1997	-0.3825
Samsung	SPHA620	8.211	23.592	8.8080	25.680	19.0341	4.9808
Samsung	SGH-X427	35.264	-23.120	1.5464	4.509	-1.2652	-0.4310
Sanyo	SCP8100	-23.350	7.048	3.9619	38.819	1.0603	4.0559
Sony Eric	T616	35.264	-1.711	0.3162	47.471	-1.3371	-0.4504

* RQ(tt) =221.89, RQ(weight) = 102.76 grams

** The shares were computed among 120 products available in March 2004.

Table 8. Cross-sensitivities across products after innovation

(a) Percentage point change in market share if RQ for talk time increases by 1 minute

Talk time	Audiovox	Kyocera	Kyocera	LG	Motorola	Motorola	Motorola	Nokia	Nokia	Nokia	Nokia	Samsung	Samsung	Samsung	Sanyo	Sony Eric
	CDM8900	2345	KE433C	VX6000	V120T	T730	V300	5180	3590	3586	6340IG	SGHR225	SPHA620	SGH-X427	SCP8100	T616
CDM8900		0.0005	0.0015	0.0003	0.0001	0.0003	6E-06	0.0002	1E-05	0.0007	3E-05	0.0001	0.0011	2E-06	0.0005	1E-05
2345	0.0004		0.0067	0.0013	0.0003	0.0010	3E-05	0.0011	0.0001	0.0027	0.0002	0.0003	0.0043	9E-06	0.0020	4E-05
KE433C	0.0009	0.0055		0.0031	0.0007	0.0025	7E-05	0.0026	0.0002	0.0068	0.0004	0.0007	0.0103	2E-05	0.0050	0.0001
VX6000	0.0005	0.0025	0.0076		0.0003	0.0014	3E-05	0.0012	0.0001	0.0036	0.0002	0.0003	0.0054	9E-06	0.0027	6E-05
V120T	0.0006	0.0034	0.0099	0.0019		0.0015	4E-05	0.0016	0.0001	0.0040	0.0002	0.0004	0.0063	1E-05	0.0030	7E-05
T730	0.0004	0.0019	0.0057	0.0012	0.0002		2E-05	0.0009	0.0001	0.0027	0.0001	0.0002	0.0040	7E-06	0.0020	4E-05
V300	0.0001	0.0004	0.0012	0.0003	0.0001	0.0002		0.0002	1E-05	0.0005	3E-05	0.0001	0.0009	2E-06	0.0004	9E-06
5180	0.0004	0.0022	0.0065	0.0013	0.0003	0.0010	3E-05		0.0001	0.0027	0.0002	0.0003	0.0042	8E-06	0.0020	4E-05
3590	0.0002	0.0011	0.0031	0.0006	0.0001	0.0005	1E-05	0.0005		0.0012	0.0001	0.0001	0.0019	4E-06	0.0009	2E-05
3586	0.0009	0.0047	0.0140	0.0031	0.0006	0.0025	6E-05	0.0022	0.0001		0.0003	0.0006	0.0099	2E-05	0.0050	0.0001
6340IG	0.0003	0.0020	0.0058	0.0011	0.0003	0.0009	2E-05	0.0009	0.0001	0.0024		0.0002	0.0036	7E-06	0.0017	4E-05
SGHR225	0.0001	0.0007	0.0021	0.0004	0.0001	0.0003	9E-06	0.0003	2E-05	0.0009	0.0001		0.0013	3E-06	0.0006	1E-05
SPHA620	0.0015	0.0080	0.0237	0.0051	0.0011	0.0041	0.0001	0.0038	0.0002	0.0110	0.0006	0.0010		3E-05	0.0083	0.0002
SGH-X427	0.0002	0.0015	0.0044	0.0008	0.0002	0.0007	2E-05	0.0007	4E-05	0.0018	0.0001	0.0002	0.0028		0.0013	3E-05
SCP8100	0.0007	0.0036	0.0108	0.0024	0.0005	0.0019	5E-05	0.0017	0.0001	0.0052	0.0002	0.0004	0.0077	1E-05		8E-05
T616	0.0001	0.0003	0.0009	0.0002	0.0000	0.0001	4E-06	0.0001	9E-06	0.0004	2E-05	4E-05	0.0006	1E-06	0.0003	

Note: The value in *i*th row and *j*th column indicates the percentage point change in market share of product *i* via the preference change on product *j* after a 1-unit innovation shock, i.e., 1-minute increase of reference talk time.

(b) Percentage point change in market share if RQ for weight decreases by 1 gram

Weight	Audiovox	Kyocera	Kyocera	LG	Motorola	Motorola	Motorola	Nokia	Nokia	Nokia	Nokia	Samsung	Samsung	Samsung	Sanyo	Sony Eric
	CDM8900	2345	KE433C	VX6000	V120T	T730	V300	5180	3590	3586	6340IG	SGHR225	SPHA620	SGH-X427	SCP8100	T616
CDM8900		0.0004	0.0009	0.0008	0.0006	0.0006	0.0001	0.0004	0.0003	0.0013	0.0005	0.0001	0.0017	2E-06	0.0013	0.0001
2345	0.0002		0.0040	0.0030	0.0028	0.0023	0.0003	0.0020	0.0014	0.0049	0.0026	0.0004	0.0068	7E-06	0.0050	0.0002
KE433C	0.0005	0.0050		0.0074	0.0067	0.0056	0.0007	0.0048	0.0033	0.0120	0.0061	0.0009	0.0163	2E-05	0.0122	0.0005
VX6000	0.0003	0.0023	0.0045		0.0031	0.0030	0.0004	0.0023	0.0015	0.0064	0.0028	0.0004	0.0085	8E-06	0.0066	0.0003
V120T	0.0003	0.0031	0.0058	0.0044		0.0033	0.0005	0.0029	0.0021	0.0072	0.0038	0.0006	0.0099	1E-05	0.0073	0.0003
T730	0.0002	0.0017	0.0033	0.0030	0.0023		0.0003	0.0017	0.0011	0.0047	0.0021	0.0003	0.0063	6E-06	0.0049	0.0002
V300	0.0000	0.0004	0.0007	0.0006	0.0005	0.0005		0.0004	0.0003	0.0010	0.0005	0.0001	0.0014	1E-06	0.0010	5E-05
5180	0.0002	0.0020	0.0038	0.0030	0.0027	0.0023	0.0003		0.0013	0.0048	0.0024	0.0004	0.0066	7E-06	0.0049	0.0002
3590	0.0001	0.0010	0.0018	0.0014	0.0013	0.0010	0.0001	0.0009		0.0022	0.0012	0.0002	0.0030	3E-06	0.0022	0.0001
3586	0.0005	0.0042	0.0083	0.0074	0.0057	0.0055	0.0007	0.0042	0.0028		0.0051	0.0008	0.0157	1E-05	0.0121	0.0005
6340IG	0.0002	0.0018	0.0034	0.0026	0.0025	0.0019	0.0003	0.0017	0.0012	0.0042		0.0003	0.0058	6E-06	0.0042	0.0002
SGHR225	0.0001	0.0007	0.0013	0.0010	0.0009	0.0007	0.0001	0.0006	0.0004	0.0015	0.0008		0.0021	2E-06	0.0016	0.0001
SPHA620	0.0009	0.0072	0.0140	0.0122	0.0098	0.0090	0.0012	0.0070	0.0048	0.0195	0.0088	0.0013		3E-05	0.0201	0.0009
SGH-X427	0.0001	0.0014	0.0026	0.0020	0.0019	0.0015	0.0002	0.0013	0.0009	0.0032	0.0017	0.0003	0.0044		0.0032	0.0001
SCP8100	0.0004	0.0032	0.0063	0.0057	0.0044	0.0042	0.0005	0.0032	0.0021	0.0091	0.0039	0.0006	0.0122	1E-05		0.0004
T616	0.0000	0.0003	0.0005	0.0004	0.0004	0.0003	0.0000	0.0003	0.0002	0.0007	0.0003	0.0000	0.0009	9E-07	0.0007	

Note: The value in ith row and jth column indicates the percentage point change in market share of product i via the preference change on product j after 1 unit innovation shock, i.e., 1-gram reduction of reference weight.

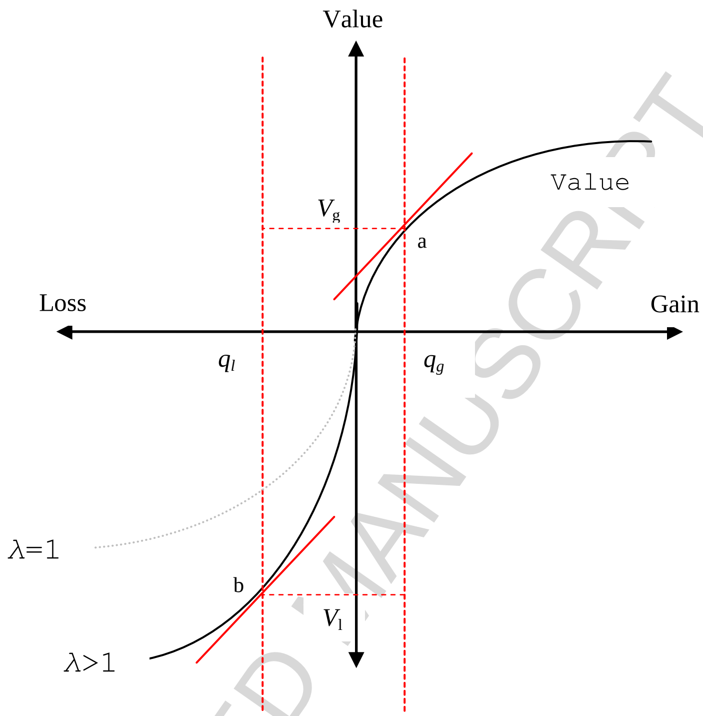


Figure 1. Value function for reference quality

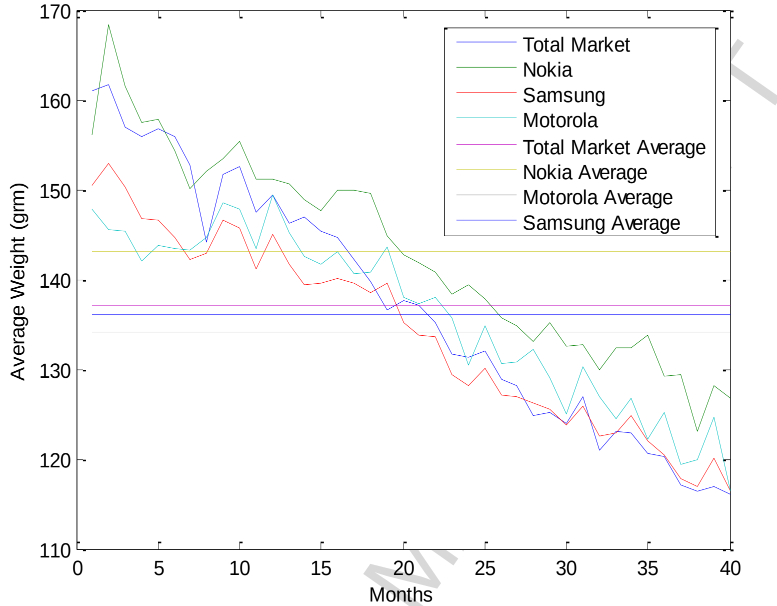


Figure 2. Dynamics of the average weight of mobile phones

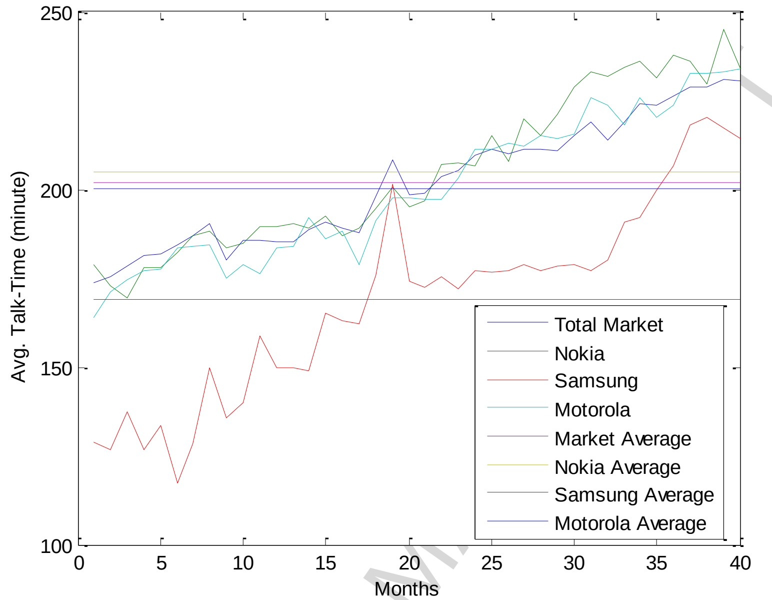


Figure 3. Dynamics of the talk time of mobile phones

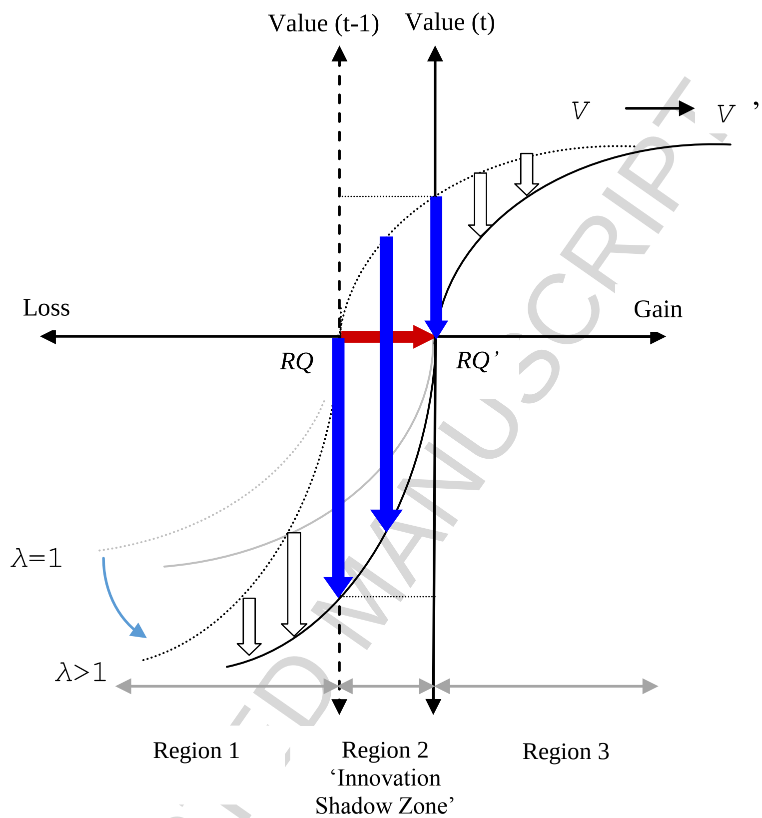
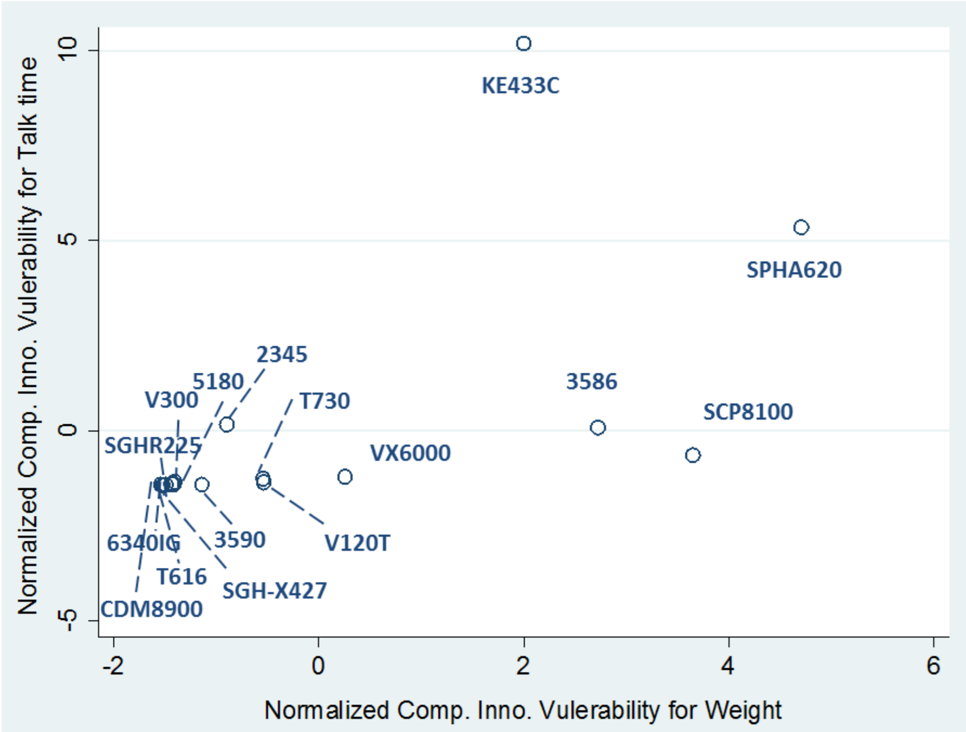


Figure 4. Shift of reference quality and Innovation Shadow Zone



Note: Values are normalized using the average competitive innovation vulnerability in Table 7 (Talk time: 3.2898, Weight: 0.8726).

Figure 5. Illustration of competitive innovation map for two product attributes