

**BRAND VALUE AND NEW PRODUCT QUALITY —  
MEASUREMENT, THEORY, AND EVIDENCE**

by

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A dissertation submitted in partial fulfillment  
of the requirements for the degree of  
Doctor of Philosophy  
(Business Administration)  
in The University of Michigan  
2010

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To My Wife Sari and Parents

## Acknowledgements

I would like first to thank my advisors, Professors Francine Lafontaine and Fred Feinberg, for their great guidance for years. Professor Lafontaine molded me from a business practitioner into an economist and showed me the light on the other side of the tunnel through my Ph. D. journey. Professor Feinberg led me to the marketing arena and guided my way in applying quantitative methods to marketing. I also want to thank my committee members Professors Yoonseok Lee, Jagadeesh Sivadasan, and Srinivasaraghavan Sriram for their invaluable advice. I am very grateful to Professors Anocha Aribarg and Puneet Manchanda for their sharp and constructive instructions. Special thanks are also due to Professors Katherine Terrell (Deceased), Jan Svejnar, Thomas P. Lyon, Avi Goldfarb, and Ying Fan, and my schoolmates, Professors Zhixi Wan, Sijian Wang, Shanshan Hu, Man Yu, and Thales Teixeira. Finally, I thank the Ross School of Business for financing the data collection, and Guiling Wang and Jun Chen for their excellent research assistant work. All remaining errors are mine.

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## Abstract

The dissertation contains two papers that study the interactions between brand value and new product quality. The first paper develops a method to evaluate the effects of blockbuster products on a firm's brand value, and applies this method to evaluate the effects of the introduction of the Razr on Motorola's brand value, i.e., the Razr's halo, cannibalization, and premium effects in the Italian mobile phone market. It finds that the Razr series products contributed about 70% of Motorola's brand value in Italy during the study period, and Razr's premium and halo effects dominate its cannibalization effect.

The second paper examines how brand values affect new product quality decisions. It proposes a theory that reconciles different predictions of Ofek and Sarvary (2003) and Randall, Ulrich, and Reibstein (1998) by characterizing the mixed strategy Nash equilibrium for a static game. Four drivers for firms' optimal product quality strategies with respect to brand value are identified. Simulations of dynamic games confirm the theoretic results of the static game although firms that take their future into account tend to soften their strategies in the dynamic game. This paper develops a theoretic model and empirically tests the proposed theory using data from the mobile phone industry in the Italian market. The empirical results provide strong support for the theoretic model. The generated insights indicate that either the prediction of Ofek and Sarvary (2003) or of Randall et al. (1998) is correct in its own research context.

## Chapter 1

# Blockbuster Products and Brand Value in High-Tech Industries

### 1.1. Introduction

High-tech industries are known for the sporadic introduction of some extremely popular products — “blockbuster” products such as the iPod and the iPhone from Apple Inc., and the Razr mobile phone series from Motorola Inc. A blockbuster product is defined in this paper as a product of a firm that 1) generates more sales than most of the other products of the firm, and 2) exhibits a positive impact on the other products of the firm, and therefore, on the reputation and image of the firm. Blockbuster products are extremely valuable to their manufacturer not only because they are sold at a premium and yield high margins, but also because they highly contribute to a firm’s brand value. In *Brandz Top 100*, a ranking that identifies the world’s most valuable brands measured by their dollar value, MillwardBrown (2009) acknowledges the iPhone’s contribution to the brand value appreciation of Apple and the mobile service operators that carry the iPhone, such as AT&T and Vodafone. Interbrand (2006) highlights the Razr’s contribution to Motorola’s brand value in *Best Global Brands 2006*. However, academic and industry knowledge about the contribution of blockbuster products to a firm’s brand value mostly relies on qualitative analysis. How to quantify the contributions of blockbuster products remains an unaddressed but important research task.

In this paper, I decompose the effect of blockbuster products on brand value into

halo, cannibalization, and premium effects. The halo effect is the extent to which the perceived positive features of a particular product confer benefits to the firm's other products. Both the iPod and iPhone have had strong halo effects on other Apple products, such as the company's computers. The cannibalization effect is "the extent to which one product's sales are at the expense of other products offered by the same firm" (Mason and George, 1994; Copulsky, 1976). A blockbuster product also exhibits a certain uniqueness/superiority related to the average product quality of non-blockbuster products. This uniqueness/superiority is unobservable to researchers but observable to its manufacturers and consumers. In this paper it is defined as the premium effect. Thus, a blockbuster product contributes to brand value through the indirect halo and cannibalization effects on a firm's other products, and by the direct premium effect from the blockbuster product itself.

The importance of this research question is threefold. First, quantifying the effects of product quality on brand value helps firms more accurately measure and forecast brand value. A firm developing a sequence of blockbuster products not only gains immediate reputation but also sends a strong signal that its brand value will be boosted in the future. Second, measuring the separate contributions of the halo effect, cannibalization, and premium effects of a blockbuster product on brand value provides information for managers when they evaluate their product portfolios. Information about these effects is also very valuable in determining the optimal timing to release new products and retire existing products in the portfolio. For example, would Motorola have gained more value if it had introduced the first Razr a month earlier? If so, how much? The answers to these questions tell the firm how much more it might be able to spend on R&D to speed up the R&D and product launch process. Conversely, what would its introduction a month later have cost? Motorola also can utilize the information to check how profits would differ if it had removed the first model from the market when it introduced the subsequent new Razrs. Would

that have been a better portfolio approach? Third, the approach developed here can be used by R&D managers to evaluate the monetary value of the uniqueness of each blockbuster product to a firm. Because the method developed in this paper uses aggregate market-level data and is not limited to blockbuster products, each firm in a market can apply the method to evaluate its own products and competitors' to generate and utilize the insights from all the comparable products in the market.

This paper develops a method to evaluate the effects of blockbuster products on a firm's brand value, then employs the method to evaluate the effects of the introduction of the Razr on Motorola's brand value, and the Razr's halo, cannibalization, and premium effects in the 2002-2006 Italian mobile phone market. Research has measured either the halo effect (e.g., Ailawadi, Lehmann, and Neslin, 2003) or the cannibalization effect (e.g., Srinivasan, Ramakrishnan, and Grasman, 2005a) but not all three effects. One method commonly applied in both academia and industry is to measure the sales change of a firm's existing products before and after the launch of a blockbuster product; however, a drawback of this method is that it actually measures the net spillover effect of the halo and cannibalization effects, not each effect separately. Although the value of the premium effect of a blockbuster product is very helpful to firms' R&D and marketing decisions, separating the uniqueness of a blockbuster product from its observed product characteristics also poses challenges for researchers. The proposed method measures explicitly the monetary value of each of these three effects.

This paper also enriches the brand evaluation literature by proposing an approach to estimating dynamic brand values with a static framework such that the computation burden is much less than using a dynamic framework and it is easier for practitioners to apply the method. Additionally, it provides lower-bound monetary value estimates for these effects by assuming that consumers' willingness to pay for any mobile phone model, after controlling for product characteristics and the willingness

to pay for outside good are greater than or equal to zero.

From a methodological perspective, this paper shows that the “deep,” or latent, parameters, which are generally regarded as fixed under structural estimation, can be changed before and after a shock. Without identifying or controlling for this deep parameter change, counterfactual estimates will be biased. For example, if a merger between a high brand value firm and a low brand value firm has been announced but not yet completed, a researcher may want to evaluate the impact of the merger by removing the low brand value firm and conducting counterfactual simulations. However, the brand value of the low brand value firm has been boosted after the announcement of the merger. Using only post-announcement data, the merger benefits for the high brand value firm, or the loss for the low brand value firm, would be overestimated. In practice, the data before the shock is required to correct such a bias.

The rest of the paper is organized as follows. In the next section, I review the related literature. Section 3 describes the theoretical framework and the intuition behind it. In section 4, I describe the data and briefly introduce the mobile phone industry in Italy. Section 5 discusses the econometric model, while section 6 presents the empirical results and benchmark comparisons. Section 7 contains concluding remarks.

## **1.2. Literature review**

### **1.2.1 Halo Effect**

The halo effect was first defined in psychology (Thorndike, 1920) and later applied to many other arenas including marketing. A large body of marketing literature focuses on correcting for the halo effect or halo error that results in biased estimates (Bass and Wilkie, 1973; Beckwith and Lehmann, 1975; Johansson, MacLachlan, and Yalch, 1976; Holbrook, 1983) for consumers’ rating (attitude) on product attributes. This bias correction also has been extended to brand evaluation (Leuthesser, Kohli,

and Harich, 1995), consumer satisfaction (Wirtz and Bateson, 1995) and evaluating firms' financial performance (Brown and Perry, 1994). A variety of techniques are developed to remove the halo effect such as partialling-out (Harvey, 1982) and the double centering method (Dillon, Muulani, and Frederick, 1984).

Another stream of literature has focused on rationalizing the halo effect, identifying its drivers and impact, and measuring it. Boatwright, Kalra, and Zhang (2008), for instance, use a decision-theory framework to offer a rationale for the halo effect. A large number of papers also study the halo effect from various perspectives (e.g., Wu and Petroschius, 1987; Bagozzi, 1996; Sine, Shane, and Gregorio, 2003; Banerjee and Bandyopadhyay, 2003). "Approaches to measuring the halo effect have ranged from simple observance of the average inter-attribute correlations to factor analysis of the rating data coupled with statistical correction for halo" (Leuthesser et al., 1995), or estimating regression coefficients as the halo effect (Ailawadi et al., 2007). Firms also rely on survey data to assess the halo effect, for example, using the percentage of customers who have purchased a blockbuster product and now want to buy, or have bought, other products from the same manufacturer.<sup>1</sup>

### **1.2.2 Cannibalization Effect**

The cannibalization effect has been studied intensively in economics and marketing. It is an important factor in a firm's decisions on the timing of their product introductions (Moorthy and Png, 1992), pricing (Carpenter and Hanssens, 1994; Meredith and Maki, 2001), demand forecasting (Srinivasan et al., 2005b), product line extension/design (Lomax et al., 1996; Fruchter, Fligler, and Winer, 2006; Davis, 2006), and product development strategy (Kim and Chhajed, 2000). The research on the cannibalization effect covers a broad range of topics (e.g., Simon and Kadiyali,

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<sup>1</sup>In 2005, Morgan Stanley conducted a survey regarding the percentage of iPod owners who had bought a Mac computer and concluded that the iPod halo effect measured by this percentage was about 20%. Source: [http://www.appleinsider.com/articles/05/03/18/ipod\\_halo\\_effect\\_estimated\\_at\\_a\\_staggering\\_20.html](http://www.appleinsider.com/articles/05/03/18/ipod_halo_effect_estimated_at_a_staggering_20.html). May. 03, 2005.

2007; Rao, Narasimhan, and John, 2009; Seetharaman, Feinberg, and Chintagunta, 2003).

A variety of methods also have been developed for measuring the cannibalization effect. Lomax et al. (1996) examine three of them: the gain-loss analysis described further below, the duplication of purchase tables, and a method based on deviations from expected share movements. Van Heerde, Leeflang, and Wittink (2004) propose a unit-sales-based decomposition approach for store data. “However, quantitative measures that can be easily monitored and interpreted are not commonly available” (Srinivasan et al., 2005a, p.359). The most commonly applied methods are the gain-loss analysis (e.g., Bawa and Shoemaker, 2004), which measures the sales volume change before and after the new product launch, and regression analysis (e.g., Rao et al., 2009; Fink and Rork, 2003), which uses the estimated marginal effect of an independent variable such as price as the measure for the cannibalization effect. When new products are ordinary, that is, they exhibit no halo effect, the gain-loss analysis measures the cannibalization effect. However, when new products are blockbuster products, this method fails to isolate the halo effect. Regression analysis yields estimates of marginal effects measured at current values — they do not offer a measure of the total cannibalization effect. The method proposed in this paper does not suffer from these limitations.

### **1.2.3 Premium Effect**

The economics and marketing literature mainly use “price premium” (Rao and Bergen, 1992; Hutton, 1997; Merino and Álvaro, 2005; DelVecchio and Smith, 2005; Howard and Allen, 2008) as a measure for how much greater a product (including both the uniqueness/superiority and the observed product characteristics) is compared to an average product. This concept is different from the “premium effect,” however, as the latter refers to the value of the uniqueness/superiority of a (blockbuster) product after controlling for the observed (to researchers) product characteristics. The price

premium can be technically defined as the positive residual between the transaction price and the estimated value from an hedonic model (e.g., Ong, Neo, and Spieler, 2006), and a variety of definitions exist in different research streams (e.g., Rao and Bergen, 1992; Kong, 2004).

In industry, managers would like to be able to measure the premium effect. One measure used to identify the premium effect is the percentage of people who have not used the blockbuster product but think the product is superior to existing ones.<sup>2</sup> In this paper, the premium effect is measured as the difference between the willingness to pay for a blockbuster product and that of an average product of the same brand. The proposed method splits the premium effect from the observed product characteristics and therefore provides firms with insights on the value for a range of uniqueness/superiorities by which blockbuster products are characterized. Firms could then incorporate these insights in their product development strategies.

#### **1.2.4 Brand Value**

Measuring and forecasting brand value is of particular importance. When brands change hands, their valuation is crucial to firms for determining the transaction price. The need for valuation arises often in mergers and acquisitions: For example, when Lenovo bought the PC unit of IBM together with the Thinkpad brand in 2005 and SBC bought AT&T and later used this brand name to consolidate its other brands, including Cingular. Information about the monetary value of brands is also essential for firms to measure their return on marketing investment, such as advertising. Monetary brand values also can assist managers in determining a firm's R&D and marketing strategies. For instance, a high brand-value firm can charge a higher price than its low brand-value competitor for a similar good.

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<sup>2</sup>A study in 2007 from Strategy Analytics Inc. found that 90% of handset owners rated the iPhone as being superior to existing mobile phones despite the fact that the iPhone had not yet gone on sale at the time of the survey. Source: Riley, Duncan, "Study Finds 90% of Handset Owners Believe iPhone Hype." Source: [www.techcrunch.com](http://www.techcrunch.com). May 25, 2007.

There is a rich literature on brands and branding (see Keller and Lehmann, 2006, for an excellent review on these topics). Brand evaluation methodologies can be categorized as survey-based studies (Srinivasan, 1979; Rangaswamy, Burke, and Oliva, 1992; Park and Srinivasan, 1994), experiment-based analysis (Swait et al., 1993), financial-data-based approaches (Simon and Sullivan, 1993; Interbrand, 2007; MillwardBrown, 2007), and market-level-data-based methods (Kamakura and Russell, 1993; Ailawadi et al., 2003; Goldfarb, Lu, and Moorthy, 2009). From a measurement perspective, this literature can also be grouped into studies focusing on brand effect in consumer utility (Srinivasan, 1979; Rangaswamy et al., 1992; Kamakura and Russell, 1993; Swait et al., 1993; Park and Srinivasan, 1994) and studies that focus on assessing the monetary value of brands (Ailawadi et al., 2003; Interbrand, 2007; MillwardBrown, 2007).

In this paper, I use market-level data to study the brand effects on consumer utility and to measure the monetary values of these brand effects to firms. In other words, I define the *brand effect* as consumer's willingness to pay for a brand and *brand value* as the monetary value of a brand to a firm when this brand effect is translated into the corresponding portion of the firm's profit. The studies closest to this paper are Kamakura and Russell (1993), Berry (1994), Berry, Levinsohn, and Pakes (1995), Nevo (2000) and Goldfarb et al. (2009). Berry (1994) proves that iteratively minimizing the difference between theoretical product market shares and actual market shares allow researchers to find the implied mean levels of utility for each product and further identify the parameters of the demand function. Berry et al. (1995) develop an approach that estimates structural residuals on the basis of the estimated mean utilities for products and the generalized method of moments (GMM). Nevo (2000) first estimates structural residuals and then obtains the brand dummy coefficients using the generalized least square regression. Kamakura and Russell (1993) and Goldfarb et al. (2009) use residuals as a measure for brand effects.

Although following this stream of literature, the brand evaluation method in this paper differs from these papers in the following ways. First, I estimate dynamic brand effects by using a static framework such that the computation burden is dramatically reduced; it is much easier for practitioners to apply the proposed method than using a dynamic framework. Second, departing from Aribarg and Arora (2008), Sriram, Chintagunta, and Neelamegham (2006), Sriram and Kalwani (2007a,b), and Dubé and Manchanda (2005), who model dynamic brand effects as an intermediary step in pursuing their research goals, one of this paper's research objectives is to estimate the monthly brand effects and the corresponding monetary values. I estimate brand values in terms of total profit equivalence rather than marginal effects. Third, in estimating brand value at the firm level, the proposed method takes into account the weight of each product in a manufacturer's portfolio, allowing for differences in popularity. Using the average willingness to pay for a manufacturer's products to represent the overall brand effect is appropriate when the market shares of products in a market are distributed evenly or almost evenly. However, in high-tech industries, the market shares of products vary a great deal, and products frequently enter and exit a market. Therefore, the varying popularity of high-tech products is taken into account. Last, the estimates I obtain are lower-bound estimates of the monetary values of a manufacturer's brand, not indices, as in Kamakura and Russell (1993), nor relative values compared to industry averages, as in Goldfarb et al. (2009).

### **1.3. Theoretical Framework**

#### **1.3.1 Utility and Demand Function**

The demand functions are modeled based on the random-coefficients logit utility function. Within a pool of products, an individual chooses the product providing her with the highest utility. Since consumers make purchasing choices in the same physical market (i.e., Italy) in each period (i.e., month) given the choice set (i.e., the available products in a market-month pair) and there is only one physical market for

this study, every time period is a market. In addition, each firm corresponds to only one brand.<sup>3</sup> Therefore, *market* and *time* are interchangeable, as are *brand* and *firm* in this paper.

One distinct feature of the proposed utility function from the typical model in this stream of literature is a dynamic brand effect. Formally, the utility function for a product is assumed as follows:

$$u_{ijt} = \mathbf{x}_{jt}\boldsymbol{\theta}_i + \lambda_{ft} + \zeta_{dec} + \epsilon_{ijt} \quad (1.1)$$

where  $u_{ijt}$  indicates the utility of individual  $i$  who chooses product  $j$  at time  $t$ ,  $\mathbf{x}_{jt}$  is a row vector of product characteristics of product  $j$  at time  $t$ ,  $\boldsymbol{\theta}_i$  is a vector of coefficients, where the subscript  $i$  indicates that each individual  $i$  may have her own specific coefficients,  $\lambda_{ft}$  is a dynamic brand effect for firm (brand)  $f$  at time  $t$ ,  $\zeta_{dec}$  is a December time fixed effect, and  $\epsilon_{ijt}$  is an error containing all random shocks and distributed type I extreme value.

How to define and estimate the dynamic structural brand effect,  $\lambda_{ft}$ , is the focal point here. In an ideal world, I can use brand-time dummy variables to estimate the dynamic brand effects. For example, such a model for six firms and 60 time periods would require estimating 359 dummy variable coefficients. However, it is rare to have so rich a data set even among the high-tech industries characterized by frequent new product entries. To meet this challenge, I propose a method to estimate dynamic brand effects on the basis of a static framework.

The proposed approach is to first estimate a Berry et al. (1995) type of utility function:

$$u_{ijt} = \mathbf{x}_{jt}\boldsymbol{\theta}_i + \lambda_f + \xi_{jt} + \zeta_{dec} + \epsilon_{ijt} \quad (1.2)$$

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<sup>3</sup>Each mobile phone manufacturer generally has only one brand for all of its products, except that Nokia uses “Nokia” as a brand for more than 99% of its mobile phones, and “Vertu” as the brand for its luxury mobile phones. Because the market share of Vertu is extremely small, we study only those mobile phones branded as the names of their producers. Thus, a firm represents a brand.

where  $\lambda_f$  is the brand fixed effect, i.e., the coefficient for the brand dummy variable, which does not change over time, and  $\xi_{jt}$  is the product-time fixed effect that can be interpreted as “consumer-perceived quality” or consumers’ “willingness to pay” for product  $j$  at time  $t$ .<sup>4</sup>

Estimating Equation (1.2) in a static framework is a less burdensome computation than doing so in a dynamic framework. However, the approach does not measure directly  $\lambda_{ft}$ . I will explain how I define and compute the dynamic brand effect on the basis of parameters estimated above in the next subsection.

The random coefficients of  $\theta_i$  can be written as:

$$\boldsymbol{\theta}_i = \bar{\boldsymbol{\theta}} + \boldsymbol{\Sigma} \boldsymbol{\nu}_i, \quad \boldsymbol{\nu}_i \sim N(\mathbf{0}, \mathbf{I}_K), \quad (1.3)$$

where  $\boldsymbol{\theta}_i$  is a  $K \times 1$  vector of parameters,  $\bar{\boldsymbol{\theta}}$  is a vector of parameter means,  $\boldsymbol{\Sigma}$  is a  $K \times K$  matrix with all non-diagonal elements restricted to zero, and  $\boldsymbol{\nu}_i$  is a vector of individual-level random shocks that are assumed to follow a multivariate standard normal distribution. In practice, I limit the number of random coefficients  $\boldsymbol{\theta}_i$  to  $k_2 \subset K$ , and leave others as fixed. Therefore, all  $K$  dimensions in Equation (2) are reset to  $k_2$ . However, all the random coefficients of interest that are ruled out in the computation can be recovered because the innovation of this paper advances the random coefficients logit model using “summary variables.” I will discuss this approach in Section 1.5.1.

I normalize the utility function of the outside good for any individual at any time as:

$$u_0 = 0. \quad (1.4)$$

The parameters of the utility function can be recovered, based on the market

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<sup>4</sup>If  $\xi_{jt}$  is interpreted as “willingness to pay,” it is different from the definition that is broadly used in the literature (e.g., Park and MacLachlan, 2008) —  $\xi_{jt}$  here is measured in terms of utility rather than dollars.

level aggregate price and volume in the logit demand setup, and following the Berry et al. (1995) approach. In practice, under standard assumptions in this literature, conditional on  $\nu_i$  and integrating out over  $\epsilon_{ijt}$ , the conditional market share (i.e., the expected probability of individual  $i$  choosing product  $j$  at time  $t$ ) is:

$$s_{ijt}(\mathbf{x}_{jt}, \boldsymbol{\delta}_t, N(\mathbf{0}, \mathbf{I}_{k_2}); \boldsymbol{\theta}_2) = \frac{e^{(\delta_{jt} + \mu_{ijt})}}{1 + \sum_{r=1}^{J_t} e^{(\delta_{rt} + \mu_{irt})}}, \quad (1.5)$$

where  $\boldsymbol{\delta}_t$  is a vector of the mean utilities of all products at time  $t$ ,  $\delta_{jt}$  is the mean utility, i.e., the linear part of the utility function of product  $j$  at time  $t$ , including  $\xi_{jt}$  and  $\zeta_t$ ,  $\mu_{ijt}$  is the non-linear part of the utility function, including  $\nu_i \sim N(\mathbf{0}, \mathbf{I}_{k_2})$ ,  $\boldsymbol{\theta}_2$ , and part of, if not all of  $\mathbf{x}_{jt}$ , and  $J_t$  is the set of all products at time  $t$ . Correspondingly,  $\boldsymbol{\theta}$  is categorized into two groups:  $\boldsymbol{\theta}_1$  contains all linear parameters while  $\boldsymbol{\theta}_2$  contains the nonlinear ones, and further,  $\boldsymbol{\theta}_1$  can be written as a function of  $\boldsymbol{\theta}_2$ .<sup>5</sup>

Then aggregate market share is the average of  $s_{ijt}$  over all  $\eta$  simulated individuals:

$$s_{jt}(\mathbf{x}_{jt}, \boldsymbol{\delta}_t; \boldsymbol{\theta}_2) = \frac{1}{\eta} \sum_{i=1}^{\eta} s_{ijt}(\mathbf{x}_{jt}, \boldsymbol{\delta}_t, N(\mathbf{0}, \mathbf{I}_{k_2}); \boldsymbol{\theta}_2). \quad (1.6)$$

### 1.3.2 Dynamic Brand Effects

I define first the unadjusted brand effects for firm  $f$  at time  $t$ ,  $\tilde{\lambda}_{ft}$ 's, which are time specific due to, for example, some market dynamics, and therefore, are not comparable over time. They need to be standardized by setting the average brand effects in all periods to the same level such that the normalized brand effects,  $\lambda_{ft}$ 's, correctly indicate the dynamics of brand effects. Then the brand dummy coefficient  $\lambda_f$  and product-time willingness to pay  $\xi_{jt}$  in Equation (1.2) are replaced by  $\lambda_{ft}$ . As a result, Equation (1.1) can be estimated with these steps on the basis of a static framework.

The unadjusted brand effect for firm  $f$  at time  $t$ ,  $\tilde{\lambda}_{ft}$ , is defined as the sum of

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<sup>5</sup>See Appendix A.1 or Nevo (2000) for details.

brand dummy coefficient  $\lambda_f$  and a deviation  $\Delta\lambda_{ft}$  from this mean, which is measured as a portfolio-share-weighted average of unobserved product qualities. Formally,

$$\begin{aligned}\tilde{\lambda}_{ft} &= \lambda_f + \Delta\lambda_{ft} \\ &= \lambda_f + \sum_{r \in \mathfrak{S}_t} \omega_{rt} \xi_{rt},\end{aligned}\tag{1.7}$$

$$\omega_{rt} = \frac{q_{jt}}{\sum_{r \in \mathfrak{S}_t} q_{rt}}\tag{1.8}$$

where  $\omega_{rt}$  is the portfolio share of product  $r$  out of all products of firm  $f$  at time  $t$ ,  $\mathfrak{S}_t$ .

Then the dynamic brand effect,  $\lambda_{ft}$ , for a firm can be normalized by removing the average brand effect of all firms in a given time period from the unadjusted  $\tilde{\lambda}_{ft}$ :

$$\lambda_{ft} = \tilde{\lambda}_{ft} - \bar{\tilde{\lambda}}_{ft},\tag{1.9}$$

$$\bar{\tilde{\lambda}}_{ft} = \frac{1}{B} \sum_{f=1}^B \tilde{\lambda}_{ft},\tag{1.10}$$

where  $B$  is the number of all brands/firms in the sample. By doing so, the brand effects,  $\lambda_{ft}$ 's are comparable over time and they can be substituted for  $\lambda_f$  and  $\xi_{jt}$  in Equation (1.2). As a result, Equation (1.1) is obtained with dynamic brand effects.

The discussion above outlines the key steps to estimate the structural dynamic brand effects. Next, I explicitly focus on the proposed approach to computing  $\tilde{\lambda}_{ft}$ . Similar to the Herfindahl-Hirschman Index, which weights firm sizes (market shares as proxies) by their market shares to obtain an index for industry concentration, the deviation part of the proposed method weights willingness to pay for a firm's products in a period by their portfolio shares. The contribution of firm size to industry concentration and the contribution of products to a firm's brand value share a lot

of similarities. Only a few firms impact the industry concentration<sup>6</sup> remarkably and only a few products are extremely important to a single firm. Also, a few large firms are more influential than many small firms, just as a few blockbuster products have greater impact on a single firm than its multitude of other products.

The brand dummy coefficient measures the mean brand effect for all products of a firm in the sample, while the weighted average of willingness to pay addresses the brand effect deviation in a particular time period. One advantage of this approach is that it creates a mixture between an estimate that assigns equal weight to all products of a firm over time and a deviation measure that gives a different weight to each product of the firm in a given time period such that it reflects the dynamics of brand effects. This approach makes a balance between an overweight (portfolio-share weighted average of product-time level willingness to pay) and underweight (brand dummy coefficients) of top-seller products.

The rationale of the portfolio-share-weighted average of unobserved product qualities can also be clearly demonstrated by decomposing  $\Delta\lambda_{jt}$  (Appendix A.2). As a result, Equation (1.7) can be rewritten as follows:

$$\tilde{\lambda}_{ft} = \lambda_f + \bar{\xi}_t + \sum_{r \in \mathfrak{S}_t} \left( \omega_{rt} - \frac{1}{n_{ft}} \right) \xi_{rt}, \quad (1.11)$$

where  $n_{ft}$  is the number of products of firm  $f$  at time  $t$  and  $1/n_{ft}$  can be interpreted as a theoretical average portfolio share, i.e., the average product portfolio share if all products of firm  $f$  at time  $t$  have equal shares.

This decomposition shows that the proposed brand effect measurement has meanings on three levels:  $\lambda_f$  is the traditional brand dummy variable approach that assigns equal weights to all products of a firm in the sample and addresses the part of the brand effect that remains constant over time;  $\bar{\xi}_t$  measures the average deviation of a firm in a particular time period due to the average contribution of the firm's products

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<sup>6</sup>For example, the  $C_4$  industry concentration index accounts only for the top four firms.

in this time period, and equal weights are assigned to all products in the product portfolio; and  $\sum_{r \in \mathfrak{S}_t} (\omega_{rt} - \frac{1}{n_{ft}}) \xi_{rt}$  is a mechanism that adds a positive adjustment to the brand effect if the relationship between the unobserved product quality and portfolio share of a product is as expected, but puts a negative fine-tune to the brand effect if the positive correction relationship does not hold for a product.

### 1.3.3 Marginal Cost Recovery

The marginal costs of products are latent variables, but they can be recovered under an equilibrium assumption. In particular, I assume the market outcomes are a result of an oligopolistic Bertrand Nash equilibrium.

Formally, firm  $f$  maximizes its profit over its product portfolio, i.e., over all of its products in a time period, by setting prices. The profit function of firm  $f$  at time  $t$  is:

$$\Pi_{ft} = \sum_{j \in J_{ft}} (p_{jt} - c_{jt}) M_t s_{jt}(\mathbf{x}_{2,t}, \boldsymbol{\delta}_t; \boldsymbol{\theta}_2), \quad (1.12)$$

where  $p_{jt}$  is the price for product  $j$  at time  $t$ ,  $c_{jt}$  is the marginal cost<sup>7</sup> for product  $j$  at time  $t$ ,  $M_t$  is the size at time  $t$ , and  $J_{ft}$  is the set of all products of firm  $f$  at time  $t$ . Note that market size varies over time, which is often the case for high-tech industries. For example, the mobile phone industry has grown worldwide since the first mobile phone was launched in 1980's. I will present more details on market size estimation in Section 1.5.3.

Under standard assumptions, a unique Nash equilibrium can be derived by solving the following first order conditions for all products in a market:

$$s_{jt}(\mathbf{x}_{2,t}, \boldsymbol{\delta}_t; \boldsymbol{\theta}_2) + \sum_{l \in J_{ft}} \frac{\partial s_{lt}(\mathbf{x}_{2,t}, \boldsymbol{\delta}_t; \boldsymbol{\theta}_2)}{\partial p_{jt}} (p_{lt} - c_{lt}) = 0. \quad (1.13)$$

The markup for product  $j$  at time  $t$ ,  $p_{jt} - c_{jt}$ , can be derived from this equation.

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<sup>7</sup>I assume the marginal cost is equal to the variable cost of a product and remains a constant in a given period.

The marginal cost is then recovered using price less markup.

### 1.3.4 Evaluating Brand and Blockbuster Products' Effects

#### Brand Value

After estimating the utility/demand functions and recovering marginal costs, I can simulate a counterfactual scenario, compute the profit of the manufacturer of interest when brand effects are removed from product-level willingness to pay, and calculate the profit differences between the actual and counterfactual scenarios to obtain the monthly brand value for each manufacturer.

However, one common challenge that arises in the counterfactual calculations is that brand effects are in relative terms and researchers do not know the intrinsic value of a brand. As a consequence, when comparing distinct brand value estimates using various methods even for the same company in the same market/period, researchers typically can do no more than “compare rank orders of brand values and brand value differences” (Goldfarb et al., 2009, p.79).

I address this issue by normalizing the dynamic brand effects,  $\lambda_{jt}$ 's, to be non-negative numbers by adding a constant, which is the absolute value of the sum of intercept and the minimum realization of  $\xi_{jt}$ . Formally,

$$\underline{\lambda}_{jt} = |\theta_{1,0} + \min_{j \in J} \{\hat{\xi}_{jt}\}| + \lambda_{jt}, \quad (1.14)$$

where  $\theta_{1,0}$  is the intercept,  $J$  is the number of all products in all markets,  $\hat{\xi}_{jt}$  is the estimated value of  $\xi_{jt}$ , and the lower bar, “-”, indicates a lower-bound value herein. Correspondingly, the willingness to pay for the outside good changes from 0 to  $|\theta_{1,0} + \min_J \{\lambda_{jt}\}|$ .

This normalization is based on the assumption that any mobile phone model or outside good offers consumers non-negative utilities at any time after removing all the

observed product characteristics. Adding a constant, in this case  $|\theta_{1,0} + \min_J \{\lambda_{jt}\}|$ , to the linear utility function does not affect the demand function, as the exponentials of the constant in the numerator and denominator cancel out.<sup>8</sup> However, this transformation defines the sum of intercept and the willingness to pay for the worst product, in all time periods in the sample as the lowest brand effect base — a level that the brand effects will be if firms lose their brand values. In the counterfactual calculations, that the non-negative brand effects are reset to zero indicates that the lower-bound brand effects are removed.

Therefore, I define the counterfactual lower-bound brand effects for product  $j$  of firm  $f$  at time  $t$ ,  $\lambda_{ft}^c$ , as zero. By calculating the profit difference for each brand's products in both scenarios, I obtain each brand's contribution to the manufacturer's profitability, that is, the lower-bound monetary value of each brand in every time period under study.

### **Evaluating the Halo and Cannibalization Effects**

I use Motorola's blockbuster products, the Razr series products, to illustrate the approach. In October 2004, the first Razr mobile phone, Razr v3, was released, and quickly became a blockbuster product, followed by the other Razr series products, such as Razr v3i and Razr v3x, which were launched in December 2005. These three Razr products are categorized as blockbuster products in this study. Two other Razr mobile phone models exist in the data; because they were released in December 2006, the last period of this study. Therefore, I treat them as Motorola's other products.

Three steps are needed to estimate the halo effect: (i) to calculate the net spillover effect, i.e., the sum of the halo (positive) and cannibalization (negative) effects, in the same spirit of the gain-loss analysis discussed earlier; (ii) to estimate the cannibalization effect by the actual and counterfactual simulations; and (iii) is to obtain

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<sup>8</sup>For example,  $s = \frac{e^u}{1+e^u} = \frac{e^{(u+c)}}{e^{(0+c)}+e^{(u+c)}}$ , where  $s$  is market share and  $c$  is a constant, shows that adding a constant to the utility function does not affect the demand function.

the pure halo effect by subtracting the cannibalization effect from the net spillover effect, i.e.,  $(halo + cannibalization) - cannibalization = halo$ .

I utilize the fact that some Motorola products exist before and after the release time of the first Razr, Razr v3. Because their physical product characteristics do not change over time, these products offer a natural experiment to compare what happened to Motorola's other products due to the Razr. The release time of Razr v3 breaks the lifespans of those products into two parts: pre- and post-Razr periods. I measure the difference of the average willingness to pay for Motorola's other products before and after Razr v3's release as the net spillover effect of the Razr. Formally,

$$\tilde{\xi}^{net} = \frac{\sum_{t_2=1}^{T_2} \tilde{\xi}_{t_2}}{n_2} - \frac{\sum_{t_1=1}^{T_1} \tilde{\xi}_{t_1}}{n_1}, \quad (1.15)$$

$$\tilde{\xi}_{t(\cdot)} = \sum_{r \in J_{mt}} \kappa_{rt} \hat{\xi}_{rt} - \bar{\lambda}_{ft}, \quad (1.16)$$

$$\kappa_{rt} = \frac{q_{rt}}{\sum_{l \in J_{mt}} q_{lt}}, \quad (1.17)$$

where subscript 1 (2) indicates that a period  $t$  is prior to (on and after) the launch of the first Razr product,  $T_1$  and  $T_2$  are the corresponding numbers of time periods;  $\tilde{\xi}^{net}$  is the net spillover effect;  $\tilde{\xi}_{t(\cdot)}$  is the time specific overall willingness to pay for the Motorola products that exist before and after the launch of the first Razr;  $\hat{\xi}_{rt}$  is the estimated value of  $\xi_{rt}$ , and  $\kappa_{rt}$  is the sales volume share among these selected Motorola products;  $\bar{\lambda}_{ft}$  is the time-specific average brand effect defined in Equation (1.10);  $q_{rt}$  is the sales volume of product  $r$  at time  $t$  and  $J_{mt}$  is the time specific set of these selected Motorola products. Similar to the role of  $\bar{\lambda}_{ft}$  to dynamic brand effects as in Equation (1.9), removing the time-specific average brand effect makes the willingness to pay for these Motorola products comparable over time. As a result, I can take two averages of  $\xi_{t(\cdot)}$  across time and measure the difference between these two means as the net spillover effect.

Two scenarios are involved for computing the monetary value of the net spillover

effect for firm  $f$  at time  $t$ :

$$\text{Scenario I:} \quad \pi_{ft}^{nR} = g(\boldsymbol{\xi}_t^R = \hat{\boldsymbol{\xi}}_t^R, \boldsymbol{\xi}_t^{nR} = \hat{\boldsymbol{\xi}}_t^{nR}; \mathbf{X}_t^R, \mathbf{X}_t^{nR}), \quad (1.18)$$

$$\text{Scenario II:} \quad \pi_{ft}^{nR} = g(\boldsymbol{\xi}_t^R = \hat{\boldsymbol{\xi}}_t^R, \boldsymbol{\xi}_t^{nR} = \hat{\boldsymbol{\xi}}_t^{nR} - \tilde{\boldsymbol{\xi}}^{net}; \mathbf{X}_t^R, \mathbf{X}_t^{nR}), \quad (1.19)$$

where  $g(\cdot)$  is the profit function defined in Equation (1.12) with the set of products adjusted to include only Razr or non-Razr phones of Motorola; superscripts  $R$  and  $nR$  indicate Razrs and non-Razrs, respectively;  $\hat{\boldsymbol{\xi}}_t^{(\cdot)}$  is a vector of the corresponding estimated value of  $\boldsymbol{\xi}_t^{(\cdot)}$ ;  $\tilde{\boldsymbol{\xi}}^{net}$  is a vector of the same size as  $\hat{\boldsymbol{\xi}}_t^{nR}$  and with each element equal to  $\tilde{\xi}^{net}$ ; and  $\mathbf{X}_t^{(\cdot)}$  is the corresponding matrix of product characteristics. In Scenario I (the actual scenario), all products keep their originally estimated value  $\xi_{jt}$ 's, while in Scenario II, the net spillover effect,  $\tilde{\xi}^{net}$ , is removed from all Motorola's non-Razr products in the market after the first Razr's launch. Motorola's monthly profit differences for non-Razr products between Scenarios I and II indicate the monetary values of the Razr's net spillover effect on Motorola's other products in each period.

The monetary value of the cannibalization effect can be measured as the profit difference for all Motorola's non-Razr products between Scenario I and Scenario III in which all three Razr products are removed and the net spillover effect for all Motorola's non-Razr phones are removed. Formally,

$$\text{Scenario III:} \quad \pi_{ft}^{nR} = g(\boldsymbol{\xi}_t^{nR} = \hat{\boldsymbol{\xi}}_t^{nR}; \mathbf{X}_t^{nR}). \quad (1.20)$$

Given the value estimates of the cannibalization and net spillover effects, I can obtain the monetary value for the pure halo effect:

$$V^{halo} = V^{net\ spillover} - V^{cannibalization}, \quad (1.21)$$

where  $V^{(\cdot)}$  is the corresponding monetary value.

## Evaluating the Premium Effect

Since the premium effect of the Razr is its uniqueness/superiority to the average quality of Motorola's other mobile phones after controlling for the observed product characteristics, the main challenge rests on calculating this average. For computing the premium effect, it is important first to remove the Razr's net spillover effect on Motorola's other products because, in the counterfactual scenario, there should not be any halo or cannibalization effects if the Razrs are simply average-quality products.

I first calculate the portfolio-share-weighted average willingness to pay for these products in each time period, and then take an average over time to obtain the average willingness to pay,  $\tilde{\xi}^a$ , for Motorola's non-Razrs given they were not subject to the net spillover effect:

$$\tilde{\xi}^a = \frac{1}{T_3} \sum_{t=1}^{T_3} \left( \sum_{lt \in J_{nr,t}} \omega_{lt} (\hat{\xi}_{lt} - \tilde{\xi}_{lt}^{net}) \right), \quad (1.22)$$

where  $T_3$  is the number of the periods the Razrs exist in the sample,  $J_{nr,t}$  is the set of all Motorola's non-Razr products at time  $t$ ,  $\omega_{lt}$  is the portfolio share of product  $l$  at time  $t$  as defined in Equation (1.8), and  $\hat{\xi}_{lt}$  is the estimated value of  $\xi_{lt}$ .

The premium effect of Razrs can be calculated as the difference between Razrs' weighted average of willingness to pay and  $\tilde{\xi}^a$ . Formally,

$$\tilde{\xi}^{prem} = \frac{1}{T_3} \sum_{t=1}^{T_3} \left( \sum_{rt \in J_{r,t}} \kappa_{rt} \hat{\xi}_{rt} - \tilde{\xi}^a \right), \quad (1.23)$$

where  $J_{r,t}$  is the set of Razrs at time  $t$ ,  $\kappa_{rt}$ , as defined in Equation (1.17), is a sales volume share only among Razrs at time  $t$ .

I assume that this premium effect is applied to all Motorola mobile phones after the launch of the first Razr, I can compute the monetary value of the premium effect for Razrs between Scenario II, where the net spillover effect is removed for non-Razrs,

and Scenario IV, where the premium effect is removed for Razrs and the net spillover effect is removed for non-Razrs. Formally,

$$\text{Scenario IV: } \pi_{ft}^{nR} = g(\boldsymbol{\xi}_t^R = \hat{\boldsymbol{\xi}}_t^R - \tilde{\boldsymbol{\xi}}^{prem}, \boldsymbol{\xi}_t^{nR} = \hat{\boldsymbol{\xi}}_t^{nR} - \tilde{\boldsymbol{\xi}}^{net}; \mathbf{X}^R, \mathbf{X}^{nR}), \quad (1.24)$$

where  $\tilde{\boldsymbol{\xi}}^{prem}$  is a vector of the same size as  $\hat{\boldsymbol{\xi}}_t^R$  with each element equal to  $\tilde{\xi}^{prem}$ .

## 1.4. Industry Setting and Data

### 1.4.1 Industry Setting

Since 1981, when the first fully automatic cellular network in the world was launched, the growth of the mobile phone industry accelerated. The number of mobile phone users worldwide grew to around 3.3 billion, more than half the world population, by November 2007. Meanwhile, mobile phones (cellular phones, or handsets) underwent numerous technological innovations. They are more user friendly, with better interfaces and handy applications, and are associated with more useful and powerful mobile services. From a luxury good they transformed into a must-have personal communications tool.

I select Italy as the empirical setting because it is a well-developed mobile phone market, and because consumers can purchase mobile phone handsets from any shop and purchase mobile services from any mobile service operator. This structure implies that I can access clear price and quantity data for the study. The mobile phone penetration rate in Italy was 122% in 2007, the third highest among European countries after Luxembourg (158%) and Lithuania (127%). In sales volume, Italy, with a population of more than 59 million, is the second largest mobile phone market in Europe. Italy's mobile service/network operators during the 2002 to 2006 period included Telecom Italia Mobile (TIM), Vodafone (and Omnitel), Wind, and Blu. Omnitel

was acquired by Vodafone in early 2000,<sup>9</sup> and Blu ceased operation in August 2002. Although many different mobile phone manufacturers sell their products in Italy, as in most of the world market, six major manufacturers dominate the Italian mobile phone market during the study period of 2002 to 2006: Nokia, Motorola, Samsung, Sony-Ericsson, Siemens,<sup>10</sup> and LG. Therefore, in this study, I concentrate on these major mobile phone manufacturers.

#### 1.4.2 Data

I obtained a five-year panel data set from January 2002 through December 2006 with monthly quantities and prices for handsets from the GFK Group, a leading marketing research company which closely monitors the market. There are a total of 61 brands and hundreds of handset models in the original data set. I remove all handset models that are not produced by the six major manufacturers because the market shares of the excluded handset models are marginal. I also remove handset models with less than 0.1% monthly market shares<sup>11</sup> defined by the GFK Group because the volume of those handsets is so small that they can be neglected. A total of six brands with 479 mobile phone models remain for further study. I define an observation as product-time, i.e., phone-month, and therefore, have a total of 6018 observations. Table 1.1 shows summary statistics for the Italian market-level data.

Table 1.1: Summary Statistics of Handset Sales in Italy 2002-2006

Variables	Obs.	Mean	Std. Dev.	Min	Max	Measurement
Price	6018	219.04	133.47	33	916	Eur.
Volume	6018	8367.31	17,321	393	248,637	mm
No. of products/month	60	129.97	21.07	91	167	Unit
No. of products/firm/month	360	21.66	11.34	1	52	Unit
No. of products/firm	6	79.8	29.25	44	120	Unit

<sup>9</sup>I treat those phones recorded in the dataset as sold by Omnitel as Vodafone's.

<sup>10</sup>Siemens mobile phone division was sold to BenQ. It became BenQ-Siemens, and later went bankrupt.

<sup>11</sup>The market share defined by the GFK Group is different from that in this study, because the company defines its market size as the sum of quantities of all handsets it monitors, while I include the outside option.

Product characteristics data are from Internet websites, including the official websites of the six manufacturers and some mobile phone specialized websites. The data contains information on phone size, weight, form (monoblock or folded, etc.), number of radio frequency bands, whether there is a camera, how many pixels if there is a camera, and whether it supports mobile Internet, for example. Table 1.2 presents summary statistics for the handset characteristics.

Table 1.2: Summary Statistics of Handset Characteristics and Consumer Ratings

Variables	Obs.	Mean	Std. Dev.	Min	Max	Measurement
Form	479	1.68	0.67	1	3	Index
Length	479	99.68	13.31	70	160	mm
Width	479	46.75	4.01	30	69.7	Index
Height	479	21.23	5.31	6.9	110	Index
Extra display/keyboard	479	0.37	0.49	0	2	Index
D_color display	479	0.77	0.42	0	1	Dummy
D_Internet	479	0.88	0.32	1	1	Dummy
D_camera	479	0.54	0.50	0	1	Dummy
Camera meegapixels	479	0.47	0.68	0	3.15	million pixel
Bands	479	2.9	1	1	8	Index
Battery talktime	479	4.64	2.33	1.3	25	Index
Weight	479	100.07	25.91	59	320	Gram
Age	479	16.09	9.51	0	68	Month
Display colors	479	1.66	1.08	0.00004	168	10,000 color
Total networks	479	2.07	0.98	0	6	Index
D_email	479	0.46	0.50	0	1	Dummy
Design rating	470	7.81	0.56	5.2	9	Index
Feature rating	470	7.53	0.66	4.9	8.6	Index

Consumer rating scores are from a mobile phone website ([www.gsmarena.com](http://www.gsmarena.com)) including rating scores of *design* and *feature* for a mobile phone model. These data are useful to keep the model parsimonious, as explained in the next section. I compare these scores with similar scores on other websites, and benchmark these scores against industry experts' judgement on various popular phone models. A large number of people (hundreds of thousands) rate each product and the ranking for those products according to the corresponding rating scores are in line with industry experts' judgement.

## 1.5. Econometric Issues

In this section, I discuss three major econometric issues that are particularly important for the empirical work: the use of rating scores as variables that summarize consumer evaluation of design and features, the instrumental variables that address the price endogeneity, and the measurement of market size in growing industries.

### 1.5.1 “Summary” Variables of Product Characteristics

As described earlier, consumer rating scores for mobile phone models help generate insights into consumers’ evaluations of mobile phones. I write each of the *design* and *feature* rating scores as a function of some exogenous mobile phone characteristics, then use their corresponding fitted values, which are continuous on  $[1, 10]$ , as “summary” variables. In other words, the fitted values, which are a weighted average of phone characteristics that best predict the scores given by consumers, are interacted with simulated individual-level shocks. This procedure saves many degrees of freedom in the estimation, as two summary variables replace 11 phone characteristics that would otherwise appear in the non-linear part of the utility functions. This procedure yields a continuous function, which makes maximization easier.

Formally, the design and feature rating scores can be written as functions of observed exogenous characteristics:

$$\mathbf{S}_d = \mathbf{X}_d\boldsymbol{\beta}_d + \mathbf{e}_d \tag{1.25}$$

$$\mathbf{S}_f = \mathbf{X}_f\boldsymbol{\beta}_f + \mathbf{e}_f \tag{1.26}$$

where  $\mathbf{S}_d$  and  $\mathbf{S}_f$  represent the design and feature rating scores, respectively, and  $\mathbf{e}_d$  and  $\mathbf{e}_f$  are the error vectors.  $\mathbf{X}_d$  is a matrix of product characteristics that are related to design, including *form*, *length*, *height*, *D\_color display*, *D\_camera*, and *D\_camera\*megapixels*;  $\mathbf{X}_f$  is a matrix of product characteristics that are related to feature, including *D\_Internet*, *D\_extra display & keyboard*, *width*, *bands*, and *battery*

*talktime*. How a phone looks (*form*), size (*length* and *height*), and whether a phone has a color display are self-descriptive regarding design. A camera (*D\_camera*) and its quality (*D\_camera\*megapixels*) have evolved from a feature on a phone into a must-have characteristic, and therefore, are categorized as variables related to design rather than feature. *Width* is related to feature since it indicates how large the main display is. The other variables in the feature function such as *extra display and keyboard* are more related to feature than design.

Table 1.3: Estimated Parameters of Design and Feature Functions

	Design		Feature	
	Coeff.	S.E.	Coeff.	S.E.
Constant	12.076***	1.136	1.653***	1.324
D_Internet			0.590***	0.087
Form	0.173***	0.045		
Extra display/keyboard			0.153***	0.057
Ln(length)	-0.798***	0.226		
Ln(width)			1.240***	0.352
Ln(height)	-0.331***	0.125		
Bands			0.142***	0.030
D_color display	0.030	0.071		
Battery talktime			0.027**	0.012
D_camera	0.086	0.069		
Extra display/keyboard	0.117***	0.046		
R-square	0.2076		0.2565	
Adjusted R-square	0.1973		0.2485	
F(6, 463)	20.21			
F(5, 464)			32.01	
No. of Obs.	470		470	

Note: The dependent variables are design and feature ratings. \*\*\* indicates p-value  $\leq 0.01$ , \*\* states p-value  $\leq 0.05$ , and \* shows p-value  $\leq 0.1$ .

Table 1.3 shows that consumers generally regard a more complex form as positive, and a larger size in length and height as negative in design. But width, i.e., the larger display size is preferred. A color display (*D\_color display*) and a high quality camera (*D\_camera* and *D\_camera\*megapixels*) are positively related to *design* while *D\_Internet*, *Extra display and keyboard*, *Bands*, and *Battery talktime* positively contribute to the feature ranking.

### 1.5.2 Instrumental Variables

For demand estimation, price is a well-known endogeneity problem. Since competing manufacturers try to maximize their profits, they know at least part of the structural residuals,  $\xi_{jt}$ 's, which are unobserved product characteristics, and factor these into their pricing policies. Therefore, prices are correlated with  $\xi_{jt}$ 's, and  $\xi_{jt}$ 's are correlated with quantities. One solution is to use instrument variables that are correlated with prices but not correlated with  $\xi$ 's in the empirical estimation.

I follow Berry et al. (1995) by directly using the first order basis functions of exogenous product characteristics, which include both the demand and cost characteristics except for the endogenous price. In particular, I use two out of the three sets of Berry et al. (1995) instruments as they are sufficient to make the estimation. Formally,

$$z_{jk} \quad \text{and} \quad \sum_{r \neq j, r \in \mathfrak{F}_f} z_{rk}, \quad (1.27)$$

where  $z_{jk}$  is the  $k$ th characteristic of product  $j$  produced by firm  $f$ , and  $\mathfrak{F}_f$  represents the set of all products of firm  $f$  at time  $t$ . The first set is the exogenous product characteristics. The second set is some particular product characteristics (for example, the  $k$ th characteristic) of all other products produced by the same firm except product  $j$ .

The first set of instrumental variables contains 18 exogenous product characteristics, including all utility/demand function variables except *price*. I also include email (*D\_email*), the interactions of color display dummy variable and number of colors (*D\_display colors\*number of display colors*), total network connections (*total networks*)<sup>12</sup>, and minor improvement variable (*Minor*).<sup>13</sup> The second set of instru-

<sup>12</sup>*Total networks* is the total number of networks/data transmission standards including GSM, CDMA, GPRS, UMTS, etc. It is a cost-related variable because it indicates the number of chips needed.

<sup>13</sup>A few mobile phone models of a firm, although very few of them, share the identical physical characteristics that are observable to researchers. However, these models may have different names due to some minor improvement, such as a software update. The variable *Minor* differentiates these products.

mental variables are the corresponding values of the sum of a firm's all other products.

### 1.5.3 Estimation of Market Sizes

High-tech industries are typically characterized by a rapid growth in market size. When applying the discrete choice demand model, an outside good (i.e., no purchase) option must be included, otherwise a uniform price increase would not result in lower market sales. The key challenge lies in estimating this outside good volume in each period. I also must take into account the dynamics of market growth.

I define the market size in a given time period as the number of people who may want to buy a mobile phone at the beginning of that period, and assume that one person buys only one or no mobile phone. A common practice in the literature is to use the total population as a basis to formulate a well-reasoned market size. For example, Berry et al. (1995) uses the number of households in the U.S. for automobiles, and Nevo (2001) uses an average cereal consumption per person per day multiplied by the population in a market and by the number of days in a year. Because both automobile and cereal are traditional products, demand is stable and the definitions of market size in those papers are valid. However, the market size for many high-tech products is expanding rapidly. In other words, market sizes for these products vary over time.

The outside good volumes need to fulfill three requirements: First, the market size, obtained by adding an outside good volume to the total mobile phone sales in each period, should represent the mobile phone sales growth pattern over time. Second, the total mobile phone market shares should increase over time as more people purchase mobile phones (consistent with the diffusion path of Bass (1969)). Third, the estimated market sizes should correctly mirror the Italian mobile phone market over time.

The solution in this paper is to define the outside good volumes as a constant for all months. Obviously, it fulfills the first two requirements above. For the third requirement, the value of this constant should depend on the Italian market. I first

estimate the mobile phone potential users on the basis of Italian population and mobile phone replacement cycle, then calculate the value of this constant on the basis of the 2006 mobile phone sales. I take Italy's 2004 population of 58,175,310 as the base population for all years of the data set, because its population has been stable, with only minimal increases each year, and 2004 is the midpoint of the 2002 to 2006 data set. Following mobile phone industry practice, I also define the potential buyer population as those between ages 15 and 64. This definition provides 38,698,371 potential Italian buyers, or 66.52% of the total population. Assuming that potential Italian buyers replace their mobile phones every two years, I obtain 19,349,186 as the 2006 market size (half of the potential buyers), denoted by  $Q$ . Then I calculate the outside good volume in each month, denoted by  $q_0$ , as follows:

$$q_0 = \frac{Q - \sum_{t=49}^{60} q_t}{12}, \quad (1.28)$$

where  $q_t$  is the monthly total mobile phone sales for all the six brands in 2006. Thus, a rounded number, 200,000 is the outside good volume. This results in annual purchasing ratios of 0.2758, 0.3195, 0.415, 0.4843, and 0.5016 for years 2002 to 2006, respectively. The purchasing ratios and their increasing trend are in line with industry experts' expectations.

## 1.6. Empirical Results

### 1.6.1 Utility/Demand Estimation and Goodness of Fit

I estimate the parameters of the utility/demand functions using the efficient GMM estimation with 200 simulated individuals. The results for the utility function estimation in Table 1.4 are consistent with expectations: parameters for *price*, *length*, *weight*, and *age* have negative signs, while those of *width*, *height*, *form*, *extra display* & *keyboard*, *D\_color display*, *D\_Internet*, *D\_camera*, the interaction term between *D\_camera*

and *megapixels*, *Bands*, *Battery talktime* and *D\_dec* are positive.<sup>14</sup>

Table 1.4: Efficient GMM Estimation Results with and without Summary Variables

Variables	Without Summary Variables		With Summary Variables	
	1st stage Coeff.(S.E.)	2nd stage Coeff.(S.E.)	1st stage Coeff.(S.E.)	2nd stage Coeff.(S.E.)
Constant	-12.56*(7.12)	-12.56*(7.01)	-12.69**(6.46)	-12.69**(6.44)
Price	-0.70*** (0.04)	-0.70*** (0.04)	-0.87*** (0.05)	-0.87*** (0.08)
Ln(length)	-0.32(0.98)	-0.32(0.96)	-0.58(0.83)	-0.58(0.83)
Ln(width)	4.81*** (1.19)	4.81*** (1.16)	5.00*** (1.34)	5.00*** (1.33)
Ln(height)	0.20(0.34)	0.20(0.33)	0.04(0.33)	0.04(0.33)
Form	0.30*(0.12)	0.30*(0.12)	0.29*(0.12)	0.29*(0.12)
Extra display/keyboard	0.09(0.08)	0.09(0.08)	0.12*(0.06)	0.12*(0.06)
D_color display	0.90(0.10)	0.90(0.10)	0.18**(0.07)	0.18**(0.07)
D_Internet	0.13(0.32)	0.13(0.30)	0.00(0.19)	0.00(0.19)
D_camera	0.28*** (0.07)	0.28*** (0.07)	0.38*** (0.05)	0.38*** (0.05)
D_camera*megapixels	0.00(0.01)	0.00(0.01)	0.03** (0.01)	0.03** (0.01)
Bands	0.14*** (0.04)	0.14*** (0.04)	0.16** (0.07)	0.16** (0.07)
Battery talktime	0.15** (0.06)	0.15** (0.06)	0.14** (0.06)	0.14** (0.06)
Weight	-0.89(0.68)	-0.89(0.67)	-0.65(0.67)	-0.65(0.67)
Age	-0.58*** (0.09)	-0.58*** (0.09)	-0.42*** (0.07)	-0.41*** (0.07)
D_dec	0.06(0.43)	0.06(0.42)	0.77** (0.39)	0.77** (0.39)
D_LG	-0.40*** (0.13)	-0.40*** (0.13)	-0.37** (0.16)	-0.37** (0.16)
D_Motorola	0.48*** (0.11)	0.48*** (0.11)	0.39*** (0.11)	0.39*** (0.11)
D_Nokia	1.07*** (0.12)	1.07*** (0.11)	1.11*** (0.13)	1.11*** (0.13)
D_Samsung	0.16(0.12)	0.16(0.12)	0.22** (0.10)	0.22** (0.10)
D_Siemens	-0.16(0.10)	-0.16(0.10)	-0.20** (0.10)	-0.20** (0.10)
$\nu_{i,1}$ *Constant	-3.45(2.38)	-3.42(2.31)	0.23(5.91)	0.22(5.76)
$\nu_{i,2}$ *Price	-0.15(0.52)	-0.14(0.56)	0.25(0.24)	0.27(0.22)
$\nu_{i,3}$ *D_Internet	0.19(3.20)	0.20(3.21)		
$\nu_{i,4}$ *Weight	0.66(0.49)	0.63(0.50)		
$\nu_{i,5}$ * $\widehat{Design}$			-0.69*** (0.25)	-0.69*** (0.25)
$\nu_{i,6}$ * $\widehat{Feature}$			-0.09*** (1.23)	-0.09*** (1.22)
$\nu_{i,7}$ *Age	1.09*** (0.21)	1.08*** (0.21)	0.67*** (0.17)	0.67*** (0.17)

Note: The dependent variable is market share. The Efficient GMM method generally contains two stage estimations. An identity weighting matrix is applied in the 1st stage and a weighting matrix based on the 1st stage parameter estimates is used in the 2nd stage to reduce the variances of the estimated parameters. The default brand is Sony-Ericsson. \*\*\* indicates p-value  $\leq 0.01$ , \*\* states p-value  $\leq 0.05$ , and \* shows p-value  $\leq 0.1$ .

The linear price coefficient is  $-0.87$ , indicating that a typical consumer's utility decreases if price increases. The absolute value of the coefficient for the interaction term between individual price shock and price can be interpreted as the standard error

<sup>14</sup>The coefficients in Table 1.4 are the marginal utility for consumers while those from the summary variable regressions are marginal effects on consumers' rating scores for *design* and *feature*. The signs of the coefficients of the product characteristics in both estimations should be the same because the directions of their effects to both dependent variables should be the same, but their magnitudes should differ because they measure the marginal effect on different dependent variables.

of the random price coefficient distribution if I assume it is distributed asymptotically normal. In other words, the random price coefficient is distributed as  $N(-0.87, 0.27^2)$ . This gives different individuals corresponding price coefficients to reflect their differences in price sensitivity.

Interpretations are not so straightforward for the coefficients of the other two interaction terms, the fitted values of design (feature) score and some individual level shocks. Recall that the fitted values of design and feature scores are linear functions of some phone characteristics. Therefore, I can recover the coefficients of the interaction terms between the linear parameters and some random shocks. The results are presented in Table 1.5, and details of the recovering process are documented in Appendices A.3 and A.4. Similar to the role of the random price coefficient, the distribution of these random coefficients reflect the differences between various consumers in their individual-level preferences for mobile phone characteristics.

Table 1.5: Mean and S.E. of Random Coefficient Distributions

Variables	$\bar{\theta}$	$\sigma$
Constant	-12.69	69.49
Price	-0.87	0.27
Form	0.29	0.12
Extra display/keyboard	0.02	0.01
Ln(length)	-0.58	0.55
Ln(width)	5.00	0.11
Ln(height)	0.04	0.23
Bands	0.16	0.01
Battery talktime	0.14	0.00
D_Internet	0.00	0.05
D_color display	0.18	0.02
D_camera	0.38	0.06
D_camera*megapixels	0.03	0.08
Age	-0.41	0.68

Note:  $\sigma$  is the standard error (S.E.) of  $\bar{\theta}$ . Both  $\bar{\theta}$  and  $\sigma$  are the two parameters of an assumed normal distribution of consumers' marginal taste for a product characteristic.

For the goodness of fit, I first run the Hargan-Hansen J test for overidentifying restrictions. Because there are 36 instruments and a total of 26 parameters, the model is overidentified. The J test with an over-identifying statistic of 0.02 cannot reject

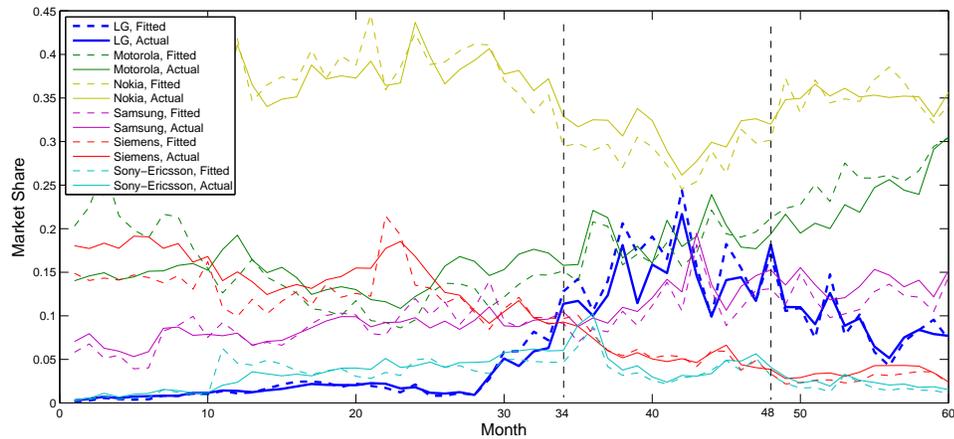
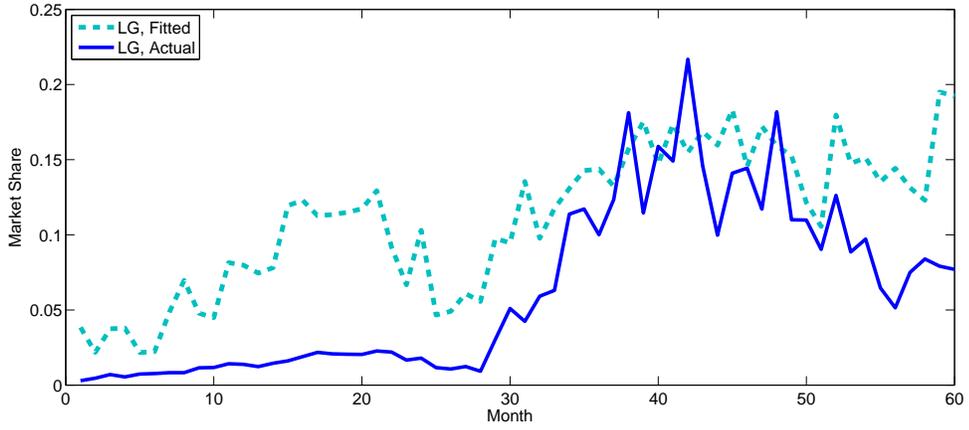
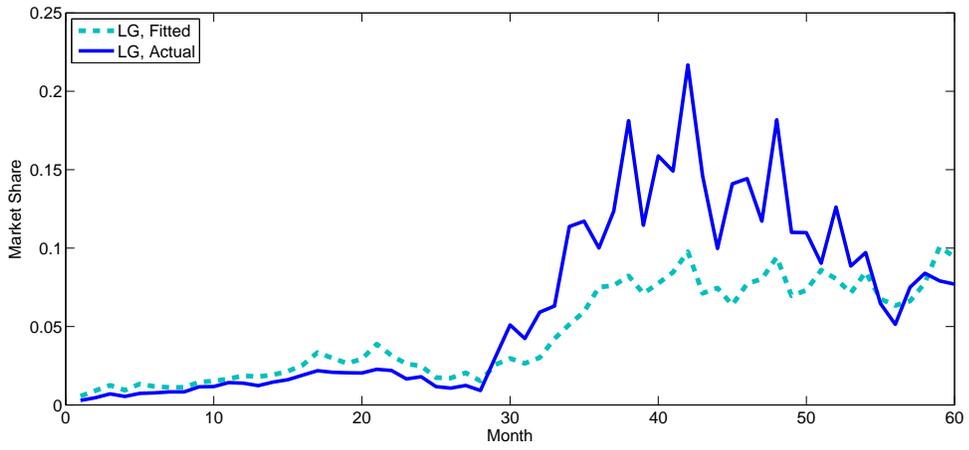


Figure 1.1: Market Share Fit for Six Firms Using Proposed Approach

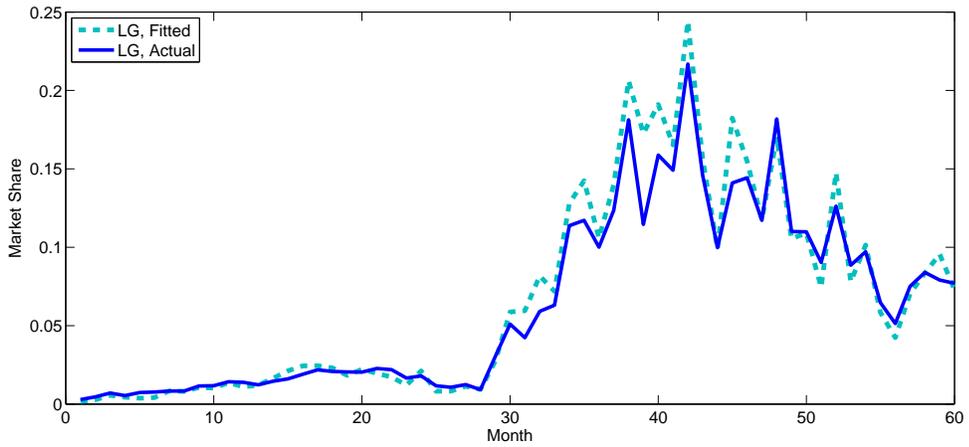
the null hypothesis that the 36 moment conditions are valid. In-sample predictions of the market shares are illustrated in Figure 1.1. It shows that the model fits well: The predicted in-sample market shares of all six brands fluctuate closely around the actual market shares. In addition, I compare the models by computing the mean square errors (MSE) of the proposed model ( $MSE = 1.3700 * 10^{-4}$ ), a random coefficient logit model ( $MSE = 1.4063 * 10^{-4}$ ) using a mixture of brand dummy coefficients and equally weighted product-time level willingness to pay to represent brand effects, and a random coefficient logit model ( $MSE = 1.4728 * 10^{-4}$ ) using only brand dummy coefficients. The MSE for the proposed model is the minimum of the three MSE's. The J test lends support to the proposed econometric model, and the model comparisons via the MSE indicate that the random coefficients logit model with the proposed brand evaluation method fits the data better than the other two random coefficients logit models using different approaches. Figure 1.2 visually shows the market share fit for LG using the three methods and indicates that the proposed method fits the best.



(a) Fitted Value Using Brand Dummy Approach



(b) Fitted Value Using Brand Dummy and Equal Weight of  $\xi_{jt}$



(c) Fitted Value Using Proposed Approach

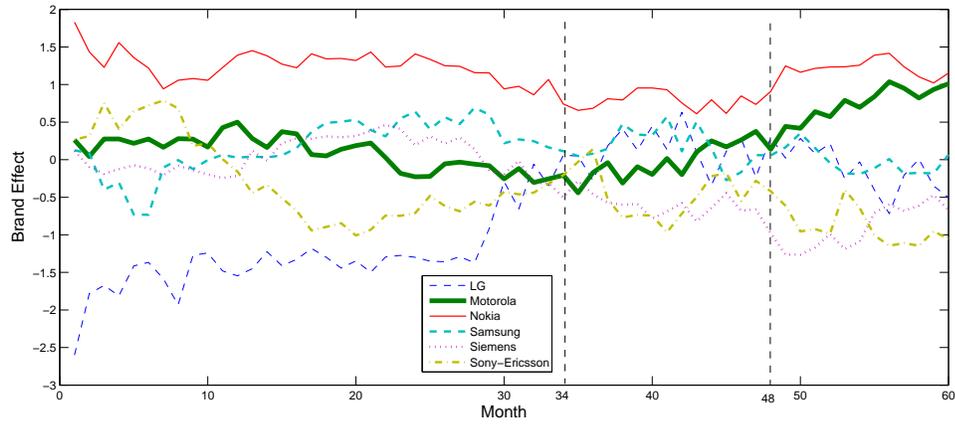
Figure 1.2: Goodness-of-Fit Comparisons among Three Approaches

### 1.6.2 Dynamic Brand Values and the Merits of the Proposed Method

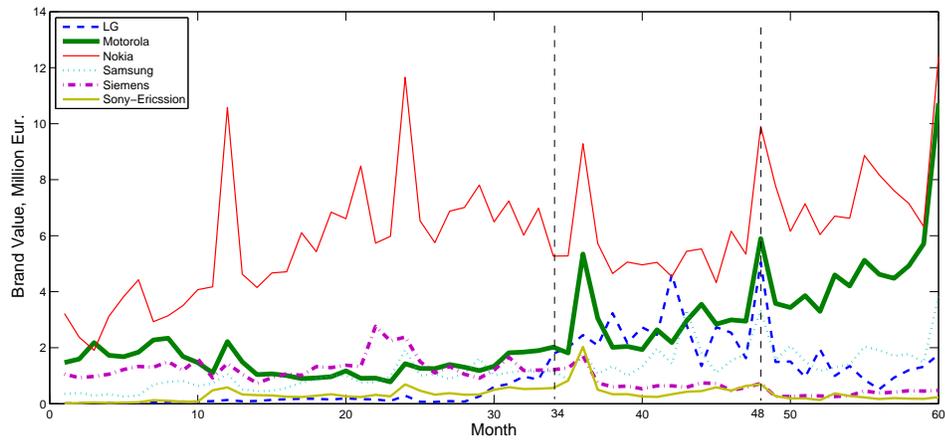
Dynamic brand effects are illustrated in Figure 1.3(a). The brand effect of Nokia is the highest across time periods although a downtrend presents around Period 34, when the first Razr is launched into the market, until Period 48, when the other two Razrs are released by Motorola. The brand effects of Motorola gradually fall towards Period 34 and then increase steadily through the end of the study period. The brand effects of LG start to jump higher around Period 30 when it launches some of its blockbuster products. Its brand effects maintain a high level for about two years until they fall a bit towards the end of the study period. The brand effects of Samsung are stable. Those of Sony-Ericsson and Siemens move around in the lower territory. The brand effects for Siemens, in particular, move all the way down especially after Siemens mobile phone division is sold to BenQ, around Period 48. All these findings lend support to observations in the industry, to date.

Because the brand effects are relative compared to the average brand effect, it is quite helpful for managers and researchers to know the monetary value of these brand effects, that is, brand values defined in this paper. By running a variety of counterfactual scenarios, I obtain the monetary brand value for each major mobile phone manufacturers. Figure 1.3(b) shows the dynamic lower-bound brand values for these six firms. In general, although the patterns are similar between Figures 1.3(a) and 1.3(b), distinctions are more clearly defined in Figure 1.3(b). The magnitudes of brand values are much more salient and clearer than those of relative brand effects. For example, the brand values of Nokia before Period 34 are much higher than those of the other firms. The brand value gap between Nokia and Motorola narrows after the launch of the Razr. The brand value of Samsung increases steadily toward the end of the study period – this trend is vague in Figure 1.3(a).

Table 5 presents the summary statistics for monthly brand values. During the 60-month period in Italy, the average monthly brand monetary value of Nokia is



(a) Monthly Brand Effects



(b) Monthly Brand Values

Figure 1.3: Brand Effects and Their Monetary Values for Six Firms

EUR 6.01 million, far higher than other mobile phone manufacturers, followed by Motorola, EUR 2.50 million, and Samsung, EUR 1.23 million. The fourth is LG, average monthly brand value of EUR 1.01 million, followed by Siemens with EUR 0.99 million. Sony-Ericsson's average monthly brand value is EUR 0.35 million.

One interesting point deserves our attention. In terms of the average monetary brand value over the 60-month period, LG ranks fourth, but it ranks sixth when brand effects are measured by the brand dummy coefficients, which assign an equal weight for all products of a firm during the same 60-month periods. Which rank

should managers adopt? I propose the former because the model using the proposed method is a better fit than the pure brand dummy approach as previously described. In addition, the performance of these six major mobile phone manufacturers to date lends support to the evaluation. Finally, and more important, the proposed method has advantages over the brand dummy approach, especially in regard to high-tech industries.

As indicated earlier, the brand dummy variable approach is the most commonly used in both economics and marketing. It is popular because the coefficients of brand dummies have a clear economic interpretation; the econometrics applied have existed for a long time and it is standard; and, most important, it measures the brand effects for traditional industries very well. However, this approach has two major disadvantages. All products are given equal weight in calculating brand effects and, by construction, brand effects are constant such that the dynamics of brand effects are not reflected. When estimating the high-tech industries characterized by introductions of sporadic blockbuster products, product entry and exit, and rapid market growth, this method becomes inadequate.

On the other hand, the proposed method obtains dynamic brand values using the same theoretical framework. It also offers a flexible measure to decide how many periods to use to measure the mid- or long-term brand value on the basis of industry traits and market dynamics. For example, both Interbrand and MillwardBrown use a five-year average return of a firm's intangible assets to estimate brand values for

Table 1.6: Monthly Brand Values in the Italian Market, Million Eur.

	Mean	S.E.	Min	Max
LG	1.01	1.17	0.01	5.04
Motorola	2.50	1.74	0.78	10.74
Nokia	6.01	2.11	1.91	12.39
Samsung	1.23	0.72	0.26	2.76
Siemens	0.99	0.53	0.26	2.76
Sony-Ericsson	0.35	0.29	0.01	2.03

Note: The number of observations is 60 (time periods) for every manufacturer.

all firms and their estimated brand values are constants, however, brand managers may need to examine their firm’s brand value on a quarterly or semiannually basis. The brand evaluation method in this paper offers managers that flexibility. In theory, methods that take product popularity into account should produce results much closer to reality than those that do not.

### 1.6.3 Values of the Razr’s Halo, Cannibalization, and Premium Effects

In the sample, lifespans of 20 Motorola products coincide with the release time of Razr v3. Two of the twenty were released simultaneously with the Razr v3, and therefore, are not included in the estimation because I cannot compare the pre- and post-Razr willingness to pay for those two products. I estimate the net spillover effect for the remaining 18 products analyzed, but the effects for Motorola products launched after the Razr v3 release remain unknown. Assuming the post-release Motorola products have the same net spillover effect as the 18 products, I obtain the value of the net spillover effect by calculating the profit difference between two scenarios. Similarly, the value of the cannibalization effect is computed as the profit difference between the actual scenario and a counterfactual scenario in which all three Razrs are removed. Then I recover the pure monetary value of the halo effect using the value of net spillover effect less that of the cannibalization effect.

Table 1.7: Measure of the Razr’s Premium and Net Spillover Effects, Index

	Mean	S.E.	Min	Max
Net Spillover Effect	1.01	1.17	0.01	5.04
Premium Effect	2.50	1.74	0.78	10.74

Note: The net spillover effect is computed as a difference between the mean of 27 periodic measures (from Period 34 to 60) and the average of 22 periodic measures (from Period 12 to 33). Among Motorola’s non-Razr phones that coincide with the first Razr’s launch, the first one was released in Period 12.

As shown in Table 1.7, two effects, the net spillover effect (1.03) and the premium effect (2.22) are estimated to compute the monetary values for the halo, cannibalization, and premium effects. The dynamics of the spillover effect and the corresponding

monetary value are illustrated in Figures 1.4(a) and 1.4(b); the dynamics of the premium effect and the corresponding monetary value are shown in Figures 1.5(a) and 1.5(b).

Table 1.8: Monthly Monetary Values of the Razr's Effects, Million Eur.

	Mean	S.E.	Min	Max
Net Spillover Effect	1.66	0.89	0.83	4.38
Premium Effect	1.02	0.17	0.01	3.85
Cannibalization Effect	-0.01	0.01	-0.00	-0.04
Halo Effect	1.67	0.15	0.83	4.42

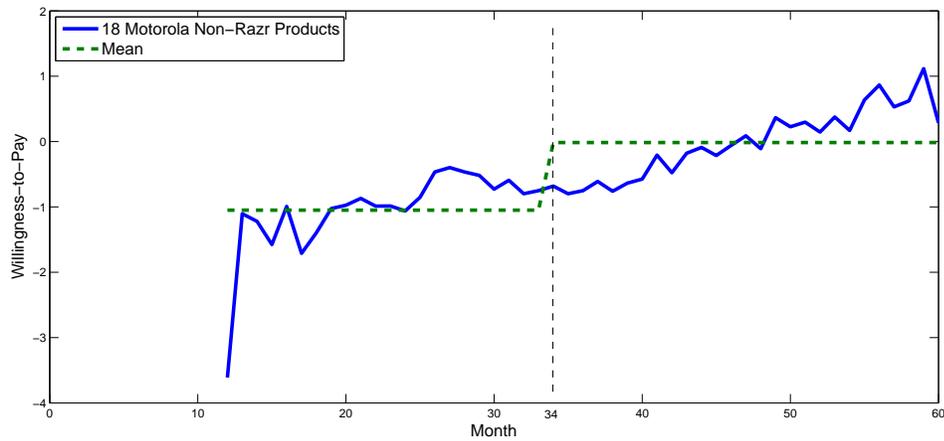
Note: The number of observations is 27 (from Period 34 to 60).

Table 1.9: Contribution of the Razr to Motorola's Brand Value

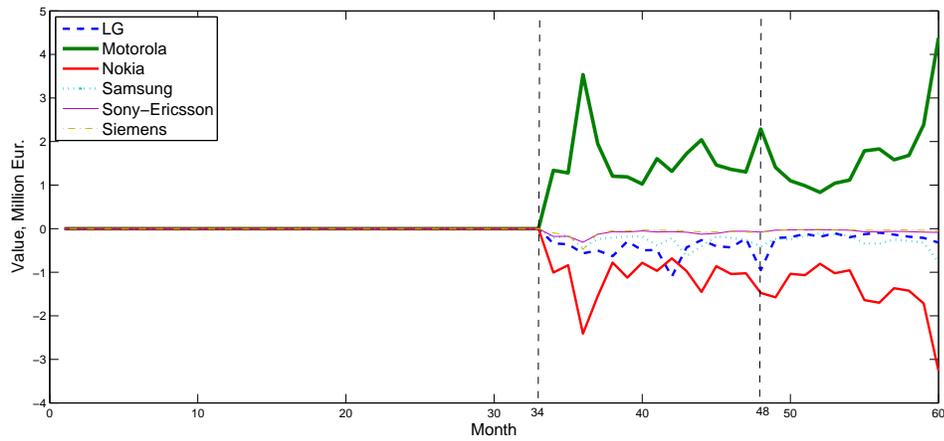
	Monthly Value, Million Eur.	Contribution to Brand Value
Value of Halo Effect	1.67	43.83%
Value of Premium Effect	1.02	26.77%
Value of Cannibalization Effect	-0.01	-0.26%

Note: The contribution is computed as a percentage of the average value of an effect over EUR 3.81 million (the average monthly brand value of Motorola during Periods 34-60).

The simulation results in Table 1.8 indicate that the average monetary value for Razr's net spillover effect is EUR 1.66 million with a standard error of EUR 0.89 million. The value for the cannibalization effect is EUR -0.01 million with a standard error of EUR 0.01 million. I sum the absolute monetary values of both effects in each period and compute the average of the sums across all corresponding periods to obtain the average value of the halo effect of EUR 1.67 with a standard error of EUR 0.15 million. The value of the premium effect is EUR 1.02 million, with a standard error of EUR 0.17 million. Table 1.9 summarizes the average contribution of each effect on Motorola's brand value. On average, the value of the halo effect accounts for the biggest contribution (43.83%) to the brand value of Motorola. The value of the premium effect is 26.77%, and the cannibalization effect accounts only for -0.26%. In other words, the cannibalization effect is strongly dominated by the halo and premium effects.



(a) Net Spillover Effect

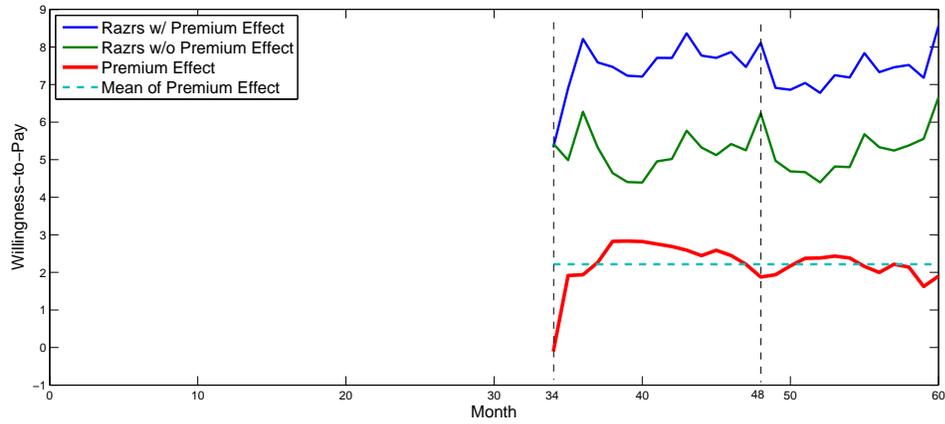


(b) Value of Net Spillover Effect

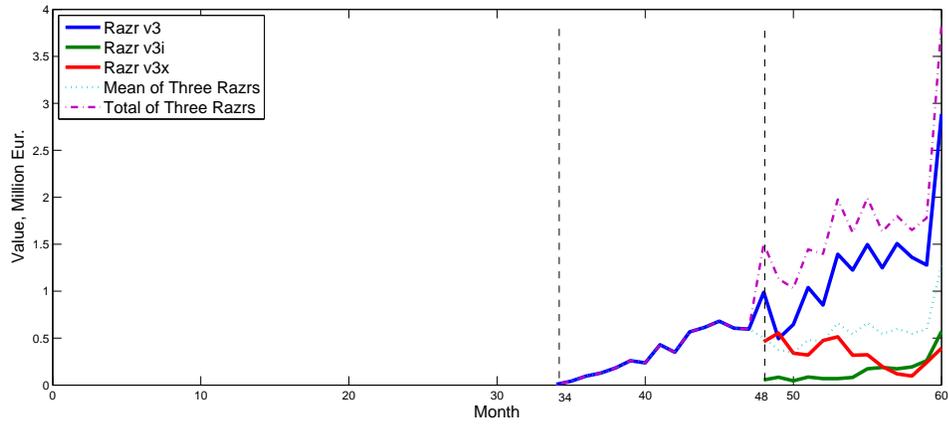
Figure 1.4: Net Spillover Effect and Value of Razrs on Motorola's Non-Razrs

To explore the proposed method and generate more managerial insights, I investigate the dynamics of these effects for the Razr products, because all three Razr products continue through the end of the study period. As stated earlier, the fourth and fifth Razrs were launched into the Italian market in December 2006, the last period of this study. At that time a total of five Razrs coexisted in the market. One empirical question, therefore, is how much the Razr product line can be extended. Is it a good strategy to develop and launch more Razrs into the series?

As illustrated in Figure 1.6, comparing the value of the halo effect before Period



(a) Premium Effect



(b) Value of Premium Effect for Each of Razrs

Figure 1.5: Premium Effect and Value of Razrs

48, when only the first Razr exists, to the value after Period 48, when the three Razrs coexist, I find that the value of the halo effect remains steady, neither increasing nor decreasing over time (except for the peaks during Christmas months). The number of products from the same theme does not seem to boost the value of the halo effect. This is intuitive because all Razr products share the same attractive features/themes that create the halo effect. The cannibalization effect is marginal because the Razrs are so distinctive from the other mobile phones. However, the total value of the premium effect, as shown in Figure 1.5(b), increases when there are three Razrs in the market. It appears that when more blockbuster products sharing similar features are

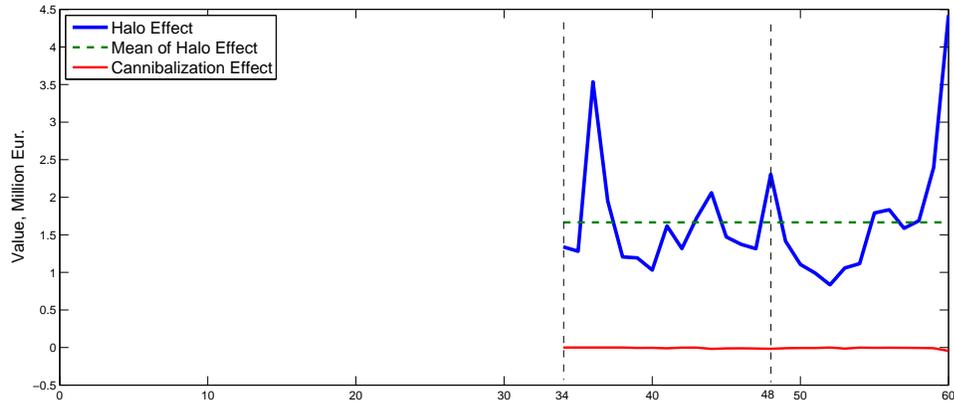


Figure 1.6: Value of Halo and Cannibalization Effects

developed and launched into a market, the total premium effect increases, although these newcomers contribute much less to the total value of the premium effect.

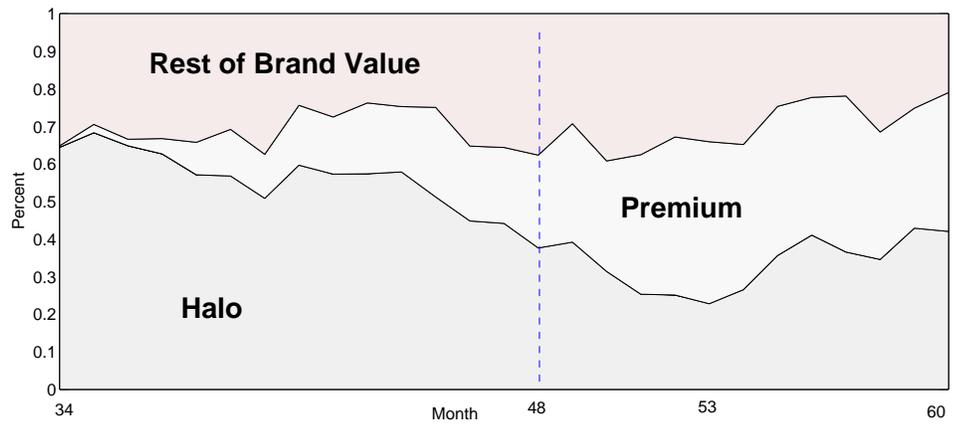


Figure 1.7: Contribution of Razrs to Motorola's Brand Value

How much Razrs contribute to Motorola's brand value over time is one of the key research questions of this paper. Figure 1.7 presents the empirical results of the values of halo and premium effects in terms of percentage of Motorola's brand value between Period 34 and 60. The negative contribution of the cannibalization effect is too marginal to be visible. Figure 1.7 illustrates some very interesting patterns with new insights, different from those generated from the comparisons of monetary values of halo and premium effects in Figure 1.6. The overall contribution of the three

Razrs to Motorola's brand value is fairly stable, around 70% regardless of whether there is only one Razr or three. However, the contribution of the Razr's halo effect to Motorola's brand value starts almost at its highest level (68.32% in Period 35) and gradually decreases to its lowest level (23.08%) in Period 53, five months after the two Razr latecomers are launched; then the contribution of the halo effect increases by the end of the study period, to a level (42.47%) that is close to the contribution level (44.62% in Period 47) before the two Razrs are released to the market. Meanwhile, the contribution of the Razr's premium effect increases dramatically from 0.4% in Period 34, when the first Razr is launched, to 43.14% in Period 53, when the contribution of the halo effect is at its lowest level. The contribution of the premium effect is stable after Period 53, ranging between 31.96% (in Period 59) and 41.55% (in Period 57).

This analysis provides several new insights. First, the contribution of the Razr's halo effect to Motorola's brand value decreases although the monetary value of the halo effect is relatively stable over time. Second, the contribution of the Razr's premium effect is stable after a long steadily increasing time range. These findings suggest that the contribution of the first blockbuster product of its own kind to a firm's brand value is the greatest compared to those sharing the same theme. In addition, the contribution of the premium effect increases over time to reach its peak level and, once there, it remains stable. These findings imply that managers should take the dynamics of the contribution of blockbuster products to a firm's brand value into consideration in deciding whether to develop a completely new kind of blockbuster product to increase the contribution of the halo effect to the firm's brand value, or a blockbuster product sharing the same theme to leverage the contribution of the premium effect, saving on product development costs.

## **1.7. Concluding Remarks**

This paper proposes a structural approach to estimate the monetary values of blockbuster products' halo, cannibalization, and premium effects, and advance the

“profit-difference” brand evaluation method. The proposed method clearly separates the halo effect from the cannibalization effect, and the premium effect from the net spillover effect, i.e., the sum of the halo and cannibalization effects. It is a general framework that can be applied to many products; it is not limited to blockbuster products, nor is it limited to high-tech industries. However, because it meets the needs of high-tech industries, the proposed method would work well when growth of market size, frequent product entry and exit, and the emergence of new features present challenges to methodological processes.

In the empirical study of the Razrs’ contribution to Motorola’s brand value, the results show that blockbuster products are indeed important to a manufacturer’s brand value. The Razr series contributes approximately 70% of Motorola’s brand value from October 2004 to December 2006. When Motorola extends its production line with the introduction of two more Razrs, the contribution of the Razr’s halo effect starts high and decreases steadily, because all Razrs share a similar design and features. However, the total monetary value of the premium effects increases when more similar blockbuster products enter the market. The value of the cannibalization effect is marginal mainly because blockbuster products are clearly differentiated from the other products. These findings show that blockbuster products are important to a firm’s brand value; the cannibalization effect is marginal if blockbuster products are distinctive from the other products of the firm. The dynamics of the contribution of blockbuster products to a firm’s brand value explicitly illustrates the tradeoffs between developing a completely new blockbuster product and producing one with the same or similar theme.

One important contribution of this paper is to provide an easier method for practitioners to estimate dynamic brand values using a static approach. It provides a useful tool for dynamic brand value estimation when the data are limited, for example, when only one observation for a brand in a certain market or a single time

period is available. The proposed approach enables investigation into how brand values change over time and how blockbuster products affect brand values; neither can be examined under the brand dummy variable approach. The method also considers the weight of market shares so that the popularity of various products is taken into account in arriving at final estimates of brand value. Among similar structural methods, this method is the first to obtain a lower-bound monetary brand value, rather than an index or a pure relative value compared to an industrial average. In addition, one of the innovations of this paper — the summary variable approach — permits estimating the random coefficients logit model in a more parsimonious manner with less computational burden.

From a methodology perspective, this paper also allows the deep, or latent, parameters that are generally regarded as fixed under structural estimation to be changed before and after a shock. Without identifying or controlling for this deep parameter change, the counterfactual estimates will be biased. From a managerial perspective, the results show that the cannibalization effect of the Razr is strongly dominated by its premium and halo effects. Providing measures of these effects is important as firms struggle to make wise decisions about R&D investment to develop more blockbuster products. These are critical decisions in high-tech industries like the mobile phone industry where there are many products in a large and rapidly changing market. The results indicate that increasing the number of blockbuster products sharing the same theme or similar key features does not increase the halo effect or average premium effect per product but does increase the *total* premium effect. Managers may want to develop new blockbuster products with different themes from the existing ones if the goal is to increase the halo effect.

The proposed method can be extended several ways in future work. First, since brand value is dynamic and can vary over a short period of time — for example, monthly, as in this paper — researchers can also ask whether brand values affect

firms' operational and strategic decisions, such as the quality of the new products they choose to market. Generally, people tend to think of brand value as static, or at least as something that changes slowly, and only in the long-run. High-tech industries are fast-moving and fiercely competitive. Therefore, these industries may provide enough variation for researchers to test this hypothesis. A further extension would include advertising in the framework. Do brand values and new product quality jointly affect firms' advertising decisions? If so, how do brand values, new product quality, and advertising interact with each other? If the reverse effects, i.e., the effects of brand value on new product quality and advertising do exist, researchers have neglected some important aspects of the relationships among these variables in both theory and empirical analysis, and as a result, existing empirical results describing the relationships among these factors may be biased.

## Chapter 2

# Brand Value and New Product Quality: Theory and Evidence

### 2.1. Introduction

Every year, large numbers of firms expand their R&D efforts to develop and bring to market a variety of new products. Despite some sporadic revolutionary breakthroughs in technology or design, new products often share most of the characteristics of existing products in a category. It is well-known that firms make decisions about their new product introduction on the basis of expected market demand, competition, and costs. However, it is less clear how a firm's brand value affects its new product quality decisions.

By quality, I mean a bundle of product characteristics that offer utility to consumers and adopt the definition of Abbott (1955, pp.126-127): "Differences in quality amount to differences in the quantity of some desired ingredient or attribute."<sup>1</sup> By assuming a positive price and quality correlation, *high(low)-quality* and *high(low)-end* are equivalent and exchangeable in this paper. For example, a 8-GB iPod is regarded as of higher quality (high-end) than a 4-GB iPod (low-end), *ceteris paribus*.

Common wisdom suggests that product quality affects the brand value of a firm. Moreover, some research concludes that product quality, especially high quality, is very important to the brand value of a firm (Randall, Ulrich, and Reibstein, 1998) and to the success of a product (Henard and Szymanski, 2001). Research interest on

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<sup>1</sup>For different quality definitions, see Garvin (1984) and Tellis and Johnson (2007).

this relation and data availability have led to many studies that concentrate on the impact of product quality on brand value (Sriram and Kalwani, 2007a; Aribarg and Arora, 2008).

In contrast, it is uncommon for people to think that the reverse effect exists, because the brand value is often regarded as fairly stable, at least in the short run. One notable exception is Ofek and Sarvary (2003) who study dynamic competition in markets characterized by the introduction of technologically advanced next-generation products. They conclude that the presence of reputation effects can encourage a technology leader to underinvest in R&D, leading to alternating leadership between a duopoly of firms. They imply analogously, although not strictly, that a high-brand-value firm (technology leader) tends to produce low-end product (underinvesting in R&D).

Empirical work on the effects of brand on firms' new product introduction decisions is even rarer. Randall et al. (1998) note this reverse causality when they study the relationship between product quality and brand value in the context of the U.S. mountain bicycle industry. They state that for their empirical "results to be derived by this reverse causality<sup>2</sup>, it would require that firms with high brand equity would be less likely to extend downward than firms with low brand equity" (Randall et al. 1998, p.374).

These two papers lead to contradictory predictions: a high-brand-value firm is more likely to produce low-end products than a low-brand-value firm according to Ofek and Sarvary (2003), but a high-brand-value firm is more likely to produce high-end products in Randall et al. (1998). Finally, Hörner (2002) implicitly suggests that brand value does not affect a firm's new product quality decisions because firms, under certain conditions, should always provide high quality.<sup>3</sup> How to reconcile these differ-

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<sup>2</sup>Randall et al. (1998) refer to the reverse effect as that brand equity causes product line extent.

<sup>3</sup>Hörner (2002) explains why competition helps preserve reputations. Without competition, a firm does not always work hard to provide a high quality product.

ent predictions has not been explored further in the theoretical literature. Moreover, there is no empirical work on this question.

Some real life evidence, however, suggests that firms' brand values indeed affect their new product quality decisions. For example, in spring 2009, Apple Inc. — a company that tops 2009 *BusinessWeek's* most innovative list<sup>4</sup> and ranked 24th in the 2008 world's most valuable brands by Interbrand (2008) — released its new iPod shuffle “Small Talk.” This was a low-end product priced at USD 79, slightly lower than some of the 4-GB-storage music players of competing brands such as Gateway. In other words, Apple launched a low-end product with a premium brand value at a competitive price. One explanation for this new product launch is that Apple tried to capitalize on its premium brand value. In contrast, Hyundai, an automobile manufacturer whose brand value falls behind most of its global competitors, launched its first luxury car, the Genesis, at USD 36,000 into the U.S. market in Summer 2008.<sup>5</sup> At least two possible interpretations are reasonable: Hyundai attempted to earn direct profit from the luxury car segment, and/or Hyundai wanted to improve its brand value.

This paper develops a static game theoretic model to characterize the conditions under which a high-brand-value firm is more likely to produce low-end (high-end) products than a low-brand-value firm. The model shows that three key factors determine a firm's mixed strategy Nash equilibrium regarding new product quality. These factors are (i) product development cost difference between high- and low-end products, (ii) the importance of brand value in competition, (iii) the role of brand across different market structures, and (iv) a relationship of market sizes for different market structures (represented by monopoly and duopoly profits and a linear function of these profits).

The static game is then extended to a dynamic Markov game. This allows the

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<sup>4</sup><http://mac.blorge.com/2009/04/10/apple-tops-businessweeks-most-innovative-list/>

<sup>5</sup>[http://www.usatoday.com/money/autos/2008-01-07-hyundai\\_N.htm](http://www.usatoday.com/money/autos/2008-01-07-hyundai_N.htm)

model to account not only for the effect of brand value on new product quality but also the impact of new product quality on future brand value. Though the dynamic model does not yield closed form solutions, simulations of the Markov Nash equilibrium with a variety of parameter values confirm the findings from the static model. In addition, the dynamic model generates new insights. Finally, the predictions of the model are tested in the context of mobile phone industry in Italy, a setting whose characteristics suggest that high-brand-value firms will choose to milk its brand. The data lend strong support to the predictions of the model. It is also the first to provide empirical evidence that brand value affects new product quality.

The rest of the paper is organized as follows. I review the related literature in the next section. In Section 3, I set up a static complete information game and derive the theoretical results. Section 4 describes the dynamic Markov game and presents the simulation results. Section 5 contains concluding remarks.

## **2.2. Literature**

Two streams of literature are most directly related to the research question of this paper: the vertical product differentiation and brand effects. In this section, I discuss the literature first and then outline the connections between the current paper and Ofek and Sarvary (2003).

Product differentiation is typically separated between horizontal differentiation (Hotelling, 1929; d'Aspremont, Gabszewicz, and Thisse, 1979; Lane, 1980; Hauser, 1988) and vertical differentiation (Gabszewicz and Thisse, 1979; Shaked and Sutton, 1982, 1983, 1984; Sutton, 1986; Moorthy, 1988; Wauthy, 1996), although some researchers (e.g., Shaked and Sutton, 1983; Champsaur and Rochet, 1989) find that the equilibrium results of both kinds of differentiation models are similar. In this paper, I focus on vertical differentiation, i.e., all consumers agree that more of a characteristic is always better, but they vary in their willingness to pay for this characteristic.

One of the major findings in the product differentiation literature (e.g., Shaked

and Sutton, 1982) is that firms try to vertically differentiate their products to mitigate the price competition in an oligopoly Bertrand game. Motta (1993) shows that firms always choose to offer distinct qualities in equilibrium. Some researchers conclude that firms try to differentiate but may not always want to maximize product differentiation. For example, Vandenbosch and Weinberg (1995) show that firms do not tend towards maximum differentiation, while Donnenfeld and Weber (1992) contend that dominant firms engage in maximal product differentiation and the later entrant always selects an intermediate quality. In the same spirit, vertical differentiation allows firms in the present paper to alleviate price competition. Contrary to Choi and Shin (1992), who do not require firms cover the market, I concentrate on firms that produce both high- and low-end products, i.e., firms cover the market by producing a full range of quality segments.

Some of the marketing literature on brands focuses on the effects of brands on consumers rather than firms. For example, authors have considered the effects of brands on consumers' product evaluation or perceived quality (Dodds, Monroe, and Grewal, 1991; Teas and Agarwal, 2000; Rao and Monroe, 1989), the impact of brand credibility on the variance of the stochastic component of utility (Swait and Erdem, 2007), the effects of brand value on consumer's perception of product similarity (Hui, 2004), or brands as signaling of quality to consumers (Erdem and Swait, 1998; Rao, Liu, and Ruekert, 1999; Brucks, Zeithaml, and Naylor, 2000). In contrast, this paper focuses on the effects of brand value on firms' strategic decisions.

The research closest to the current work is by Ofek and Sarvary (2003), who develop a theoretical framework in which the goal of competing firms is to ensure that their next generation technology product is a success, i.e., to be the industry leader. Their model can be viewed as a special case of the model presented here. These two papers also differ in many other respects. In this paper, the goal of firms is to maximize both their short- and long-run profits. In Ofek and Sarvary (2003), the

leader always has advanced products while the follower produces less-advanced goods, and a follower can take the leading position in a next-generation technology product. In the current paper, both high- and low-brand-value firms may choose, in any period, to produce either high-end or low-end products without ability constraints, and both firms can switch their brand value states in any period. Finally, in this paper, I use the model to derive predictions that are tested using data of the mobile phone industry in the Italian market, whereas there is no empirical component in Ofek and Sarvary (2003).

### 2.3. Model

I begin with the consumer utility function and the corresponding demand functions, and then set up the game in three steps: 1) I use a normal-form game with two quality levels for each of two firms to model the firms' product quality decisions; 2) I add asymmetry in brand values, i.e., one firm has a high brand value while the other has a low brand value; and 3) I incorporate product development costs into the model. There are two scenarios for the game when the brand values come into play. In Scenario I, brand value has a greater profit impact in the low-end segment than in the high-end segment. In Scenario II, the reverse is true.

#### 2.3.1 Utility and Demand Functions

I assume a representative consumer's utility from product  $j$  produced by firm  $f$  is:

$$u_{jf} = \kappa_j \beta - P_j \alpha + \lambda_f \gamma + \epsilon_{jf}, \quad (2.1)$$

where  $\beta$ ,  $\alpha$ , and  $\gamma$  are the coefficients for product  $j$ 's quality  $\kappa_j$ , price  $P_j$ , and brand  $\lambda_f$ , respectively, and  $\epsilon_{jf}$  is a shock that captures both demand- and firm-level shocks, and allows a type I extreme value distribution. The utility of the outside no purchase option is normalized to zero, and the market size is normalized to one. Thus, the demand functions are in the form of a logit model.

In a market where there would be only one firm with one product, the market share of the monopoly firm would be:

$$s_f^m = \frac{\exp(\kappa\beta - P^m\alpha + \lambda_f\gamma)}{1 + \exp(\kappa\beta - P^m\alpha + \lambda_f\gamma)}. \quad (2.2)$$

In a market where there are only two firms, each with different brand values, but only one product of equal quality to their competitor's, the demand function for the product of firm  $f$  is:

$$s_f^d = \frac{\exp(\kappa\beta - P^d\alpha + \lambda_f\gamma)}{1 + \exp(\kappa\beta - P^d\alpha + \lambda_f\gamma) + \exp(\kappa\beta - P^d\alpha + \lambda_{-f}\gamma)}, \quad (2.3)$$

In these equations,  $s$  is market share<sup>6</sup>,  $m$  and  $d$  refer to monopoly and duopoly, respectively,  $f$  is an index for a firm, and  $-f$  refers to the other firm.

These logit demand functions highlight some well-established key facts in the economics and marketing literature. First, even for a monopolist  $f$ , a higher brand value  $\lambda_f$  helps increase the total demand for its product. Second, in the duopoly case, the effect of firm  $f$ 's brand value on its demand is weaker than in the monopoly case. These insights are useful as I work through the derivations in the model below.

### 2.3.2 Normal-Form Static Game

Table 2.1: Normal-Form Game Setup

	H	L
H	$d_H,$ $d_H$	$m_H,$ $m_L$
L	$m_L,$ $m_H$	$d_L,$ $d_L$

Assume that there are two independent quality segments: high-end (H) and low-

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<sup>6</sup>Note that no purchase option counts as market share in the logit model. A monopoly's market share is a ratio of actual sales volume and the sum of the actual sales volume and potential sales volume. As a result, its market share is less than 1. This is different from the conventional definition of market share which does not include no purchase option.

end (L). The H and L products are differentiated to a certain extent such that the consumers in one segment will not shift to the other segment given that firms play optimally. I also assume that the overall quality of products in the same segment are identical even though they are produced by different firms.

Next consider a one-stage two-by-two game — a simple static game as in Table 2.1, where two identical firms, Firms 1 and 2, simultaneously choose one of two independent quality segments to enter by introducing a new product and then set the price. In any given period there are no existing products in any quality segment.

The only concern for a firm is what its competitor will do in the same period: If both firms have new products in the same quality segment, each will earn the duopoly profit  $d_H$  in the high-end segment, and  $d_L$  in the low-end segment. Otherwise, each will earn monopoly profit  $m_H$  or  $m_L$  depending on which segment it enters. I also assume that monopoly profit is always greater than duopoly profit for any firm no matter which segment it is in, i.e., the segment sizes are balanced such that the smallest monopoly profit among all firms is greater than the greatest duopoly profit. Formally,

$$m_f > d_{f'}, \quad \text{for } f, f' \in \{H, L\}. \quad (2.4)$$

These assumptions and game setup provide firms with new insights to help managers make optimal decisions when they face a hard problem and to help researchers reconcile the contradicting predictions. Thus, this paper focuses on the mixed strategy equilibrium and its drivers.

### 2.3.3 Game with Brand Value for Scenario I

Next, I add brand value as a state variable to the game (See Table 2). Because the brand values of firms at any time are likely to differ and one firm's brand value is almost always higher than the other, I assume brand value asymmetry. Refer the high-brand-value state as  $h$  and low-brand-value state as  $l$ . Since the present game

is static, I can arbitrarily assign the firms to the two states and name them Firms  $h$  and  $l$ . In this section, I also assume that a higher brand value has a greater effect on sales and profits in the low-end than the high-end segment (Scenario I)<sup>7</sup>.

Table 2.2: Game with Brand Value, Scenario I

		$l$ (low brand value)	
		H	L
$h$ (high brand value)	H	$d_H + b,$ $d_H - b$	$m_H + k_2b,$ $m_L - k_2b$
	L	$m_L + k_3b,$ $m_H - k_3b$	$d_L + k_1b,$ $d_L - k_1b$

In this setting, a product with a high brand value will offer consumers more utility than that with a low brand value. Therefore, the high-brand-value firm will earn more profit than the low-brand-value firm. Assume that total profit for both firms in each strategy combination, i.e., each cell in Table 2.2, remains the same as in Table 2.1.<sup>8</sup> The role of brand value can be modeled as a shift in profit from the low-brand-value firm to the high-brand-value firm.

Two factors, the impact of brand value and market structure, determine the size of the profit shift. Since there are two segments, brand value will affect the profit shift differently — stronger in one market and weaker in the other. In Scenario I, brand value has a larger effect on the low-quality segment. The profit shift is greater for the low-quality segment than for the high-quality segment. I denote the duopoly profit shift for the high-quality segment by  $b$ , and normalize other profit shifts as multiples of  $b$ . Thus, the duopoly profit shift for the low-quality market can be  $k_1b$ , and  $k_1 > 1$  by the assumption of Scenario I. I also denote the profit shift for the  $\{H^h, L^l\}$  case.

<sup>7</sup>See Appendix B.4 for Scenario II.

<sup>8</sup>Assume that firm  $h$ 's brand value is  $\xi$  and firm  $l$ 's is 0. Given the logit demand functions and the Bertrand game assumption, I can identify a solution for  $\xi$ , i.e.,  $\xi = \hat{\xi}$  such that the total profits with and without brand values are identical, i.e.,  $s^h(P^h(\xi), P^l(\xi), \xi)[P^h(\xi) - c] + s^l(P^l(\xi), P^h(\xi), 0)[P^h(\xi) - c] = 2s(P, P, 0)[P - c]$ , where  $s^{(\cdot)}$  and  $P^{(\cdot)}$  refer to, respectively, the optimal market share and price for firms  $h$  and  $l$  when they differ in brand value;  $c$  is constant marginal cost for both firms. Thus, this profit equivalence assumption implicitly suggests that the brand value difference between the two firms is  $\hat{\xi}$ .

The high-brand-value firm ( $h$ ) has a new product in high-quality segment ( $H$ ) while the low-brand-value firm ( $l$ ) has a new product in low-quality segment ( $L$ ), by  $k_2b$ ; and denote the profit shift for the  $\{L^h, H^l\}$  case by  $k_3b$ . In the  $\{H^h, L^l\}$  case, firm  $h$  has two advantages — Firm  $h$  has a high brand value, and its new product is in a segment where brand matters more; while in the  $\{L^h, H^l\}$  case, firm  $h$  still has a high-brand-value advantage but the impact of this high brand value is weakened. Therefore, the profit shift in  $\{H^h, L^l\}$  is greater than in  $\{L^h, H^l\}$ , i.e.,  $k_3b > k_2b$ .

The other factor that has an impact on the size of the profit shift is the market structure, monopoly or duopoly. The brand profit shift is greater for the monopoly profit than for the duopoly profit no matter which market it is, i.e.,  $k_2 > k_1$ . See proof of Lemma 1 in Appendix B.1. The intuition is straightforward: Because monopoly profits are much greater than duopoly profits, the corresponding profit shift, somewhat in proportion to these profits, should be in the same order. Thus, combining the profit-shift relationships derived earlier, I obtain the following inequality

$$k_3 > k_2 > k_1 > 1, \text{ and } b > 0, \quad (2.5)$$

where  $k_r$ ,  $r = 1, 2$ , and  $3$ , are the multipliers for the profit shifts in different cases, and  $b$  is the smallest profit shift among the four strategy combinations. In Scenario I, this is the duopoly profit shift due to brand value difference between the two firms in the high-quality market.<sup>9</sup> To simplify the problem, I also assume that this inequality has the same distance  $\Delta k$  between any two adjacent terms. Formally,

$$k_3 - k_2 = k_2 - k_1 = k_1 - 1 = \Delta k > 0. \quad (2.6)$$

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<sup>9</sup>In Scenario II,  $b$  is the duopoly profit shift in the low-quality market.

### 2.3.4 Game with Brand Value & Product Development Cost for Scenario I

One important element, the fixed cost of the new product development (including production setup cost), is embedded in the model in Table 2.3. Without this fixed cost, a firm would always adopt a strategy that leads to the highest variable profit.

Table 2.3: Game with Brand Value and Cost, Scenario I

		$l$ (low brand value)	
		H	L
$h$ (high brand value)	H	$d_H + b - c_H,$ $d_H - b - c_H$	$m_H + k_2b - c_H,$ $m_L - k_2b - c_L$
	L	$m_L + k_3b - c_L,$ $m_H - k_3b - c_H$	$d_L + k_1b - c_L,$ $d_L - k_1b - c_L$

Specifically, I assume that a firm incurs a fixed product development cost  $c_H$  if its product enters the high-end segment, and  $c_L$  for the low-end segment, and that the development cost for a high-end product is higher than that for a low-end product. Formally,

$$c_H > c_L, \quad \text{i.e.,} \quad c_H - c_L = \Delta c > 0. \quad (2.7)$$

### 2.3.5 Nash Equilibrium

In this subsection, I derive all Nash equilibria for this static game on the basis of the payoffs in Table 3 and the inequality relationships in Equations 2.4 to 2.7. However, the mixed strategy equilibrium in Proposition 2 is the focus here. Firms in many industries, such as computer, mobile phone, automobile, furniture, and fashion, produce a full range in a variety of qualities. Offering a portfolio is common optimal solution for firms and it is also confirmed in theory (Mussa and Rosen, 1978; Johnson and Myatt, 2003; Ishibashi and Matsushima, 2009). To characterize how these firms play a mixed strategy in their product quality decisions helps answer the research questions of this paper.

Propositions 1 and 2 are derived under the condition that the monopoly payoffs

dominate the duopoly payoffs after taking into account the brand value's profit-shift role and the fixed product development cost. Proposition 1 characterizes the Nash equilibria under such conditions, and Proposition 2 summarizes the conditions for the mixed strategy Nash equilibrium.

**Proposition 1** *If the monopoly payoffs dominate the duopoly payoffs, i.e.,  $m_j - d_{j'} > 0$  for  $j, j' \in \{H, L\}$ , and  $(m_L - d_H \geq 2b\Delta k - \Delta c) \cap (m_H - d_L \geq 2b\Delta k + \Delta c)$ , there are two Nash equilibria:  $\{L^h, H^l\}, \{H^h, L^l\}$ . (See Appendix B.2 for proofs.)*

Proposition 1 is the standard product differentiation result, namely, if the difference between the monopoly profit  $m_j$ ,  $j \in \{H, L\}$  and the duopoly profit  $d_{j'}$ ,  $j' \in \{H, L\}$  is large enough, both firms try to avoid each other in their product quality strategies.

**Proposition 2** *(i) Under the same conditions in Proposition 1, there is one mixed strategy equilibrium  $\{p_H^h, p_H^l\}$ , where  $p_H^h$  and  $p_H^l \in (0, 1)$  are the probabilities of Firms  $h$  and  $l$  choosing the high-end product strategy, respectively. Moreover,  $p_H^h \leq p_H^l$  only if  $\frac{5}{4}(m_H - d_L) - \frac{3}{4}(m_L - d_H) \leq b\Delta k + 2\Delta c$ . These conditions are sufficient conditions for  $p_H^h \leq p_H^l$ . If the last condition does not hold, while the conditions in Proposition 1 are true,  $p_H^h > p_H^l$ . (See Appendix B.2 for proofs.)*

The necessary condition,  $\frac{5}{4}(m_H - d_L) - \frac{3}{4}(m_L - d_H) \leq b\Delta k + 2\Delta c$ , implies that the low-brand-value firm is more likely to play a high-end product strategy with a higher probability than the high-brand-value firm if brand value matters more and is great the product development cost difference between high- and low-end products. This implies that, if both firms play mixed strategy Nash equilibrium, the effect of brand value and the new product development cost difference between the high- and low-end products will be related to the probabilities in the mixed strategies, namely, the greater a brand value's role and/or the greater the cost difference, the more likely  $p_H^h \leq p_H^l$ .

If the monopoly payoffs do not dominate the duopoly payoffs, one unique Nash equilibrium exists, either a pure strategy or mixed strategy. However, it is unlikely for firms to end up to any of the Nash equilibria characterized below because, in most industries and most of the time, monopoly payoffs dominate duopoly payoffs. Therefore, they are presented in Propositions 3 to 5 for the completeness of the characterization of the game.

**Proposition 3** (i) If  $(m_L - d_H < 2b\Delta k - \Delta c) \cap (m_H - d_L \geq 2b\Delta k + \Delta c)$ , the unique Nash equilibrium is  $\{L^h, H^l\}$ ; (ii) if  $(m_L - d_H \geq 2b\Delta k - \Delta c) \cap (\Delta c - b\Delta k \leq m_H - d_L < 2b\Delta k + \Delta c)$ , the unique Nash equilibrium is  $\{H^h, L^l\}$ . (See Appendix B.2 for proofs.)

**Proposition 4** If  $m_H - d_L < \Delta c - b\Delta k$ , the unique Nash equilibrium is  $\{L^h, L^l\}$ . (See Appendix B.2 for proofs.)

**Proposition 5** If  $(m_L - d_H < 2b\Delta k - \Delta c) \cap (\Delta c - b\Delta k \leq m_H - d_L < 2b\Delta k + \Delta c)$ , there exists no pure Nash equilibrium but a mixed strategy Nash equilibrium. (See Appendix B.2 for proofs.)

Proposition 3 describes conditions under which both firms try to avoid competing directly in the same segment. Proposition 4 indicates that, if the difference between the monopoly profit in the high-end segment and the duopoly profit in the low-end segment is small enough, less than the difference between cost difference and marginal brand value effects, both firms play a low-end product strategy. Proposition 5 states the conditions under which there is a mixed strategy Nash equilibrium.

In summary, if brand value has a greater role in the low-end segment than the high-end segment (Scenario I) and monopoly payoffs dominate duopoly payoffs (conditions for Propositions 1 and 2), two firms, if they play pure strategy Nash equilibrium, try to avoid each other in new product quality segments. Under the same conditions, if firms play a mixed strategy, the larger the effect of brand value and/or the greater

the product development cost difference between high-end and low-end products, the low-brand-value firm has a higher probability of entering the high-end segment than the high-brand-value firm.

## 2.4. Dynamic Markov Game

When firms take the future into account, they may not make the same choices as in the static game above because their actions in the current period can affect their future states. For example, their brand values may be high or low in the next period, partially depending on what they do today. Therefore, validating whether the key insights and conditions for the mixed strategy Nash equilibrium hold also in the dynamic setting is extremely important to identify the scope of the proposed theory. In addition, more interesting insights can be generated from a dynamic game. In this section, I study the mixed strategy Markov perfect equilibrium (MPE) in a dynamic setting for Scenario I.

### 2.4.1 Markov Game Setup

One key aspect that was not built into the static game is how the quality positioning of a product affects firms' future brand values. I take this aspect into consideration by allowing product quality positioning to affect firms' future brand values via transition probabilities from current state to the next-period state in a dynamic Markov game. I assume that a high-end product increases the probability of a firm's being high-brand-value in the next period than a low-end product.

Similar to the static game setup, I use  $h$  and  $l$  to refer to high- and low-brand-value states of a firm. Firms 1 and 2 can be either  $h$  or  $l$  in each period. If one firm's state is  $h$ , then the other's must be  $l$  because the probability for the brand values of two firms to be equal is zero. Let  $(l, h)$  or "0" indicate the state where firm 1's brand value is low while firm 2's brand value is high and  $(h, l)$  or "1" represent the other state. I show the assumptions concerning the transition probability matrix in Table

2.4. For example, the second row of Table 2.4 indicates that, if firm 1 is to have a high-end product and firm 2 is to produce a low-end product, the probability for both firms to fall into the same state in the next period is  $1 - \lambda_3$  and in the different state is  $\lambda_3$ .

Table 2.4: Transition Probability Matrix

$State_t$	$Action_t$ {Firm 1, Firm 2}	$State_{t+1}$	
		$(l, h)$	$(h, l)$
$(l, h)$	$\{H, H\}$	$1 - \lambda_2$	$\lambda_2$
$(l, h)$	$\{H, L\}$	$1 - \lambda_3$	$\lambda_3$
$(l, h)$	$\{L, H\}$	$1 - \lambda_1$	$\lambda_1$
$(l, h)$	$\{L, L\}$	$1 - \lambda_2$	$\lambda_2$
$(h, l)$	$\{H, H\}$	$\lambda_2$	$1 - \lambda_2$
$(h, l)$	$\{H, L\}$	$\lambda_1$	$1 - \lambda_1$
$(h, l)$	$\{L, H\}$	$\lambda_3$	$1 - \lambda_3$
$(h, l)$	$\{L, L\}$	$\lambda_2$	$1 - \lambda_2$

I make the following assumptions for the transition probabilities. If both firms produce the same quality-segment products, i.e.,  $\{H, H\}$ , or  $\{L, L\}$ , the probability for them to stay at the same state is  $1 - \lambda_2$ . If a low-brand-value firm produces high-end while high-brand-value firm produces low-end, the probability for them to shift from the current state to a different state next period is  $\lambda_3$ . Since the latter implies both firms try to do the reverse action relative to their state, the chance of switching state must be greater than if they took the same action, i.e.,  $\lambda_3 > \lambda_2$ . If the low-brand-value firm produces low-end while the high-brand-value firm produces high-end, the probability for them to shift from the current state to a different state in the next period is  $\lambda_1$ . Because both firms pursue actions that enhance their current state, the probability of switching state must be less than if they took the same strategies, i.e.,  $\lambda_2 > \lambda_1$ . Therefore, I have:

$$\lambda_3 > \lambda_2 > \lambda_1. \tag{2.8}$$

### 2.4.2 Simulation of the Mixed Strategy MPE

For the mixed strategy Markov perfect equilibrium, a system of six equations with six variables can be derived. Let  $V(a_f, a_{-f}|state)$  represent the expected value functions when Firm  $f$  takes the action  $a_f$  and its competitor Firm  $-f$  takes the action  $a_{-f}$  conditional on the brand value state. Four equations of the system, the expected value functions,  $V(H, p_H^h|0)$ ;  $V(L, p_H^h|0)$ ;  $V(H, p_H^l|1)$ ; and  $V(L, p_H^l|1)$ , are presented in Appendix B.3. Here, I use the same notations as in the static game to indicate, in a given period, the state of a high-brand-value firm as  $h$  and the state of a low-brand-value firm as  $l$ . For the mixed strategy, firm  $h$  mixes so that firm  $l$  is indifferent between its two strategies, i.e.,  $V(H, p_H^h|0) = V(L, p_H^h|0) \equiv V_1$ ; while firm  $l$  mixes to make firm  $h$  indifferent, i.e.,  $V(H, p_H^l|1) = V(L, p_H^l|1) \equiv V_3$ . These two equations together with the four value functions formulate the equation system. The reduced system of equations with four variables remain to be solved:  $p_H^h$ ,  $p_H^l$ ,  $V_1$ , and  $V_3$ .

While a closed-form solution cannot be derived from this system of equations, I can simulate this Markov game to verify the key findings from the static game. I do so by verifying that simulations converge to a unique solution when I vary the initial values for the search algorithm. I also examine how the values of the six outcome variables change as I modify values for the variables. The key interest is to verify that the greater  $b\Delta k$  and/or  $\Delta c$ , the more likely  $p_H^l > p_H^h$ .

Some criteria must be enforced to make sure the simulations yield valid results. First,  $p_H^h$  and  $p_H^l \in (0, 1)$  ensure that the solution is a mixed strategy rather than a pure strategy. Second,  $V(H, p_H^h|0)$ ,  $V(L, p_H^h|0)$ ,  $V(H, p_H^l|1)$ , and  $V(L, p_H^l|1) > 0$  ensures that firms do not take losses over the long-run.

For the simulation, I first fix  $\Delta k = 1$  and marginal cost  $c_L = 0$ . I then choose valid parameter values for  $m_H$ ,  $m_L$ ,  $d_H$ ,  $d_L$ ,  $b$ ,  $c_H$  that fulfill Equations 2.4 to 2.7, and for  $\lambda_1$ ,  $\lambda_2$ ,  $\lambda_3$  to meet the requirement of Equation 2.8. Finally, I choose a discount factor

$\delta \in (0, 1)$ . I draw 100 sets of random numbers, each with two uniformly distributed random numbers on  $(0, 1)$  as the different initial values for  $p_H^h$  and  $p_H^l$ , respectively, and two random numbers from a standard normal distribution as the initial values for  $V_1$  and  $V_3$ , respectively. The system of equations is then solved numerically 100 times with different initial values for each game. All 100 calculations lead to a unique solution. For the sensitivity analysis, I hold all else the same but change the values of brand effects on profit shift,  $b$ , or the values of the product development cost for high-end product,  $c_H$ , or both  $b$  and  $c_H$ .

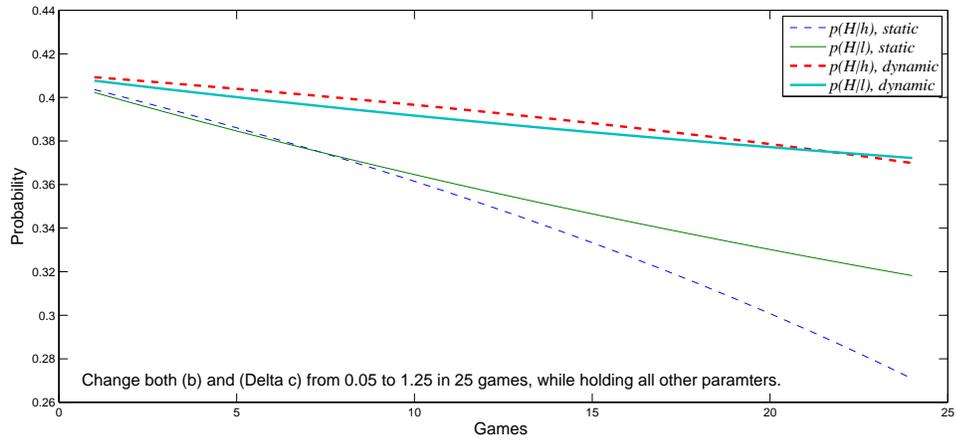
Let  $m_H = 14$ ,  $m_L = 16$ ,  $d_H = 6$ , and  $d_L = 7$ . I start from the case that both the effects of brand value,  $b$ , and the product development cost for high-end,  $c_H$ , increase gradually from 0.05 to 1.25 in 25 games. For example,  $c_H = 0.05$  and  $b = 0.05$  in the first game,  $c_H = 0.1$  and  $b = 0.1$  in the 2nd game and  $c_H = 1.25$  and  $b = 1.25$  in the 25th game. The MPE for the 25 games is illustrated in Figures 1 to 3.<sup>10</sup> The optimal mixed strategies follow closely the pattern of its corresponding strategies in the static game.

The patterns confirm the findings generated from the static game: *ceteris paribus*, when both  $b$  and  $c_H$  increase to a certain level, the relationship between  $p_H^h$  and  $p_H^l$  flips from  $p_H^l < p_H^h$  to  $p_H^l > p_H^h$ . However, the flipping point for the dynamic MPE curve occurs when both  $b$  and  $c_H$  are greater than those for the static Nash equilibrium curve. In addition, for both high- and low-brand-value firms, the probabilities to play high-end strategies drop much slower in the dynamic game than in the static game. These differences reflect the fact that firms consider the impact of their current actions on their future states, and their strategies in the dynamic game are “softer” than those in the static game.

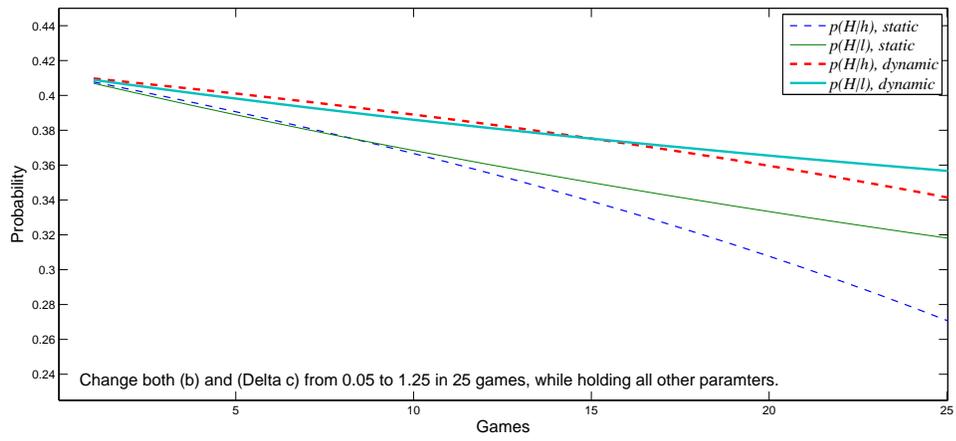
Since the discount factor, denoted by  $\delta$ , determines how important the future payoffs are, I also compare Figure 2.1(a) ( $\delta = 0.95$ ) with Figures 2.1(b) ( $\delta = 0.75$ )

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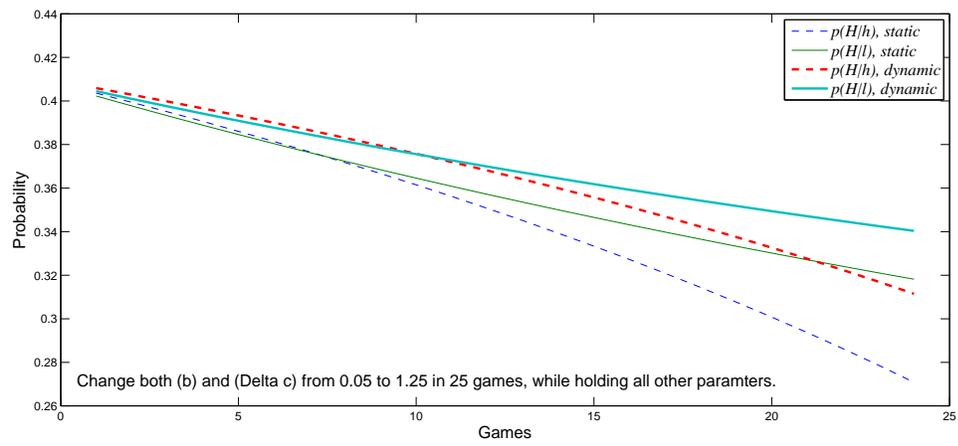
<sup>10</sup>The figures represented by these 25 games are sufficient to show that the inequality relationship between  $p_H^l$  and  $p_H^h$  switches.



(a)  $\delta = 0.95$



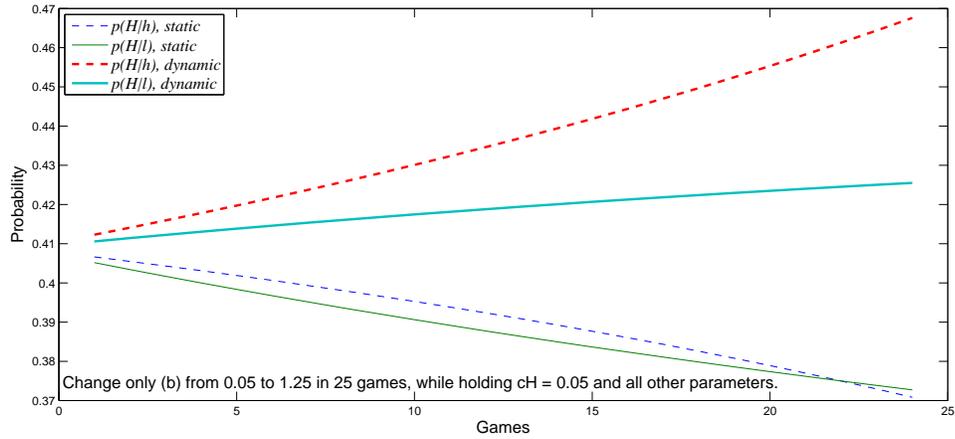
(b)  $\delta = 0.75$



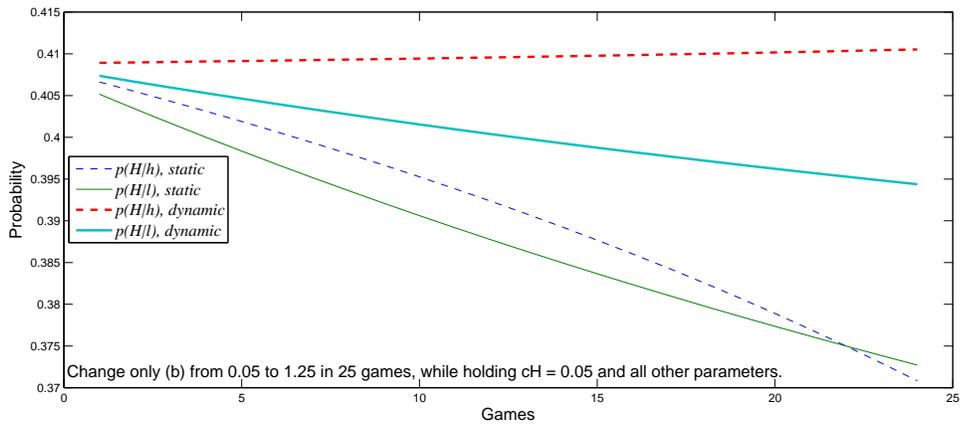
(c)  $\delta = 0.5$

Figure 2.1: Nash and Markov Perfect Equilibria for 25 Games (Both  $b$  and  $\Delta c$  Change)

and 2.1(c) ( $\delta = 0.5$ ), *ceteris paribus*. The flipping points for the static game are at the 9th game; while those for the dynamic games are at the 23rd, 16th, and 12th game in Figures 2.1(a), 2.1(b), and 2.1(c), respectively. This implies that the dynamic game changes towards the static game as the future becomes more heavily discounted.



(a)  $\delta = 0.95$

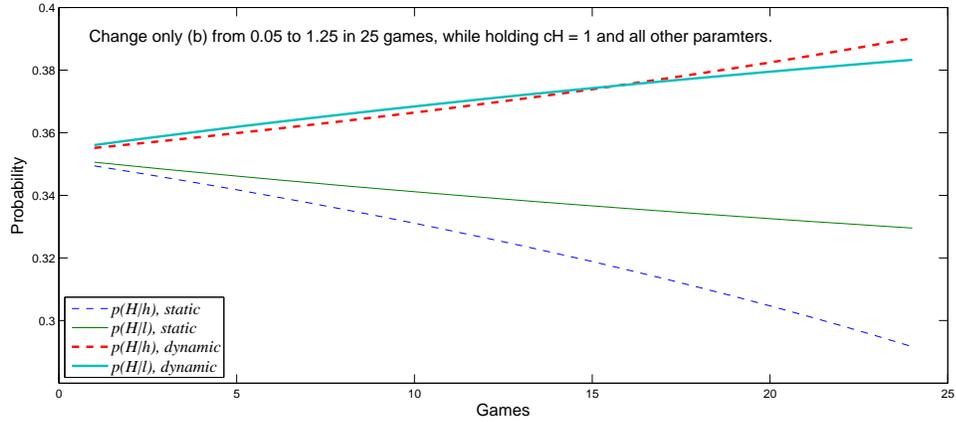


(b)  $\delta = 0.5$

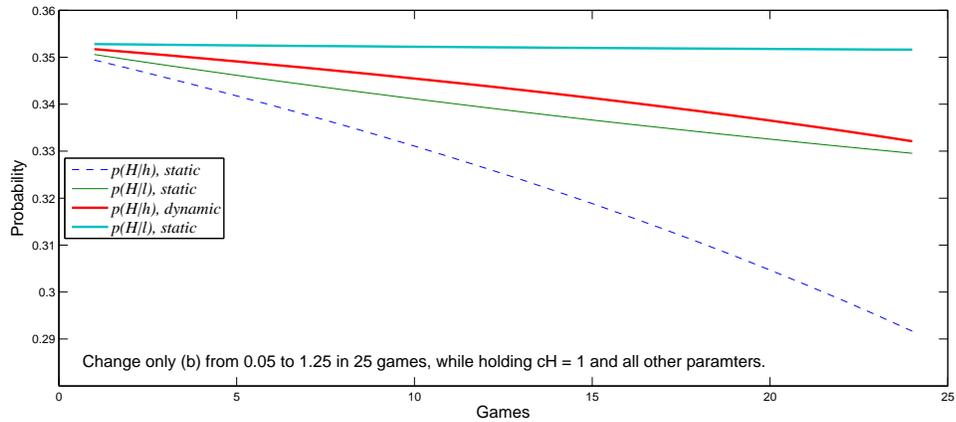
Figure 2.2: Nash and Markov Perfect Equilibria for 25 Games (Only  $b$  Changes while  $c_H = 0.05$ )

I obtain similar simulation results when only  $c_H$  varies. I expect the simulation results for dynamic and static games are very close because  $c_H$  only linearly enters the probability functions in both static and dynamic games. As anticipated, simulation results illustrate the same patterns for both static and dynamic games, and reaffirm

that when the future is discounted heavily, the flipping point for dynamic games is much closer to that for static games than when the future is more important.



(a)  $\delta = 0.95$



(b)  $\delta = 0.5$

Figure 2.3: Nash and Markov Perfect Equilibria for 25 Games (Only  $b$  Changes While  $c_H = 1$ )

Simulations show that, when both  $c_H$  and  $b$  or only  $c_H$  change, the dynamic games confirms same findings of the static games. However, some interesting patterns can happen when only  $b$  varies. For example, Figures 2.2(a) and 2.2(b) illustrate how the same sequences of games ( $m_H = 14$ ,  $m_L = 16$ ,  $d_H = 6$ ,  $d_L = 7$ ,  $c_H = 0.05$ , and  $b = 0.05, 0.1, \dots, 1.25$ ) will differ under two different discount factors. If  $\delta = 0.95$ , both firms have increasing probabilities of playing high-end while the high-brand-

value firm's probability increases much faster than the low-brand-value firm as shown in Figure 2.2(a). If  $\delta = 0.5$ , the low-brand-value firm has a decreasing probability of playing high-end while the high-brand-value firm keeps an increasing probability of playing high-end as indicated in Figure 2.2(b).

What will happen if  $c_H$  is high, say,  $c_H = 1$ , and I repeat the simulations as in Figures 2.2(a) and 2.2(a)? Figure 2.3(a) ( $\delta = 0.95$ , and  $c_H = 1$ ) shows that both firms in the dynamic game have increasing probabilities of playing high-end. The interesting point here is that the high-brand-value firm has a smaller probability of playing high-end than the low-brand-value firm when the role of brand value  $b$  is small. Figure 2.3(b) ( $\delta = 0.5$ , and  $c_H = 1$ ) indicates that when the future payoffs are less important, the patterns in the dynamic games are very similar to those in the static games.

In summary, simulations of dynamic Markov perfect equilibrium confirm the findings generated from the static game when both  $b$  and  $c_H$  increase simultaneously at the similar scales, only  $c_H$  increases, and/or only  $b$  increases. Some interesting findings evolve in some extreme cases: Both high- and low-brand-value firms tend to play a high-end strategy if the importance of brand value is high, if the future is very important, or if the current product quality positioning highly affects future brand value. This result is not unexpected if these three conditions go to extreme levels. However, in most situations, the three conditions are rarely so extreme as to lead to such a result. Rather, in most cases, firms play the mixed strategy Markov perfect equilibrium as predicted in the static game.

## 2.5. Testing the Theory

I use the mobile phone industry in the Italian market between 2002 and 2006 as an empirical context to test the proposed theory. During this period, six mobile phone manufacturers are major players: LG, Nokia, Motorola, Samsung, Sony-Ericsson, and Siemens. All produce a broad range of qualities and play a mixed strategy in their

new product quality decisions.

One potential concern about the empirical setting is that brand value estimates are Italy-specific while the new product decisions of the multinationals are based on a much broader perspective than Italy alone. However, the importance of the Italian market, the second largest in Europe and one of the largest in the world, makes Italian brand value estimates good proxies for the corresponding global brand values. The market structure — no bundling between handsets and service contracts so that manufacturers can bypass mobile service operators to distribute handsets directly to consumers — also ensures that manufacturers can introduce any products into the Italian market without incurring an abnormal cost. As a result, all major products are launched in the Italian market<sup>11</sup> and the corresponding data provide a valid empirical context for testing the proposed theory.

### **2.5.1 Industry Briefing and Hypothesis Formulation**

It is rare to see as many highly differentiated new products as in the mobile phone industry. Since the first fully automatic cellular network in the world was launched in 1981, the industry has grown tremendously and evolved constantly into new stages by merging with other industry's technology, product features, design, and ideas. Fierce competition also drives mobile phone manufacturers to develop and launch new products at an increasing pace.

The mobile phone industry is a high-tech industry, or a “technology-intensive” (John, Weiss, and Dutta, 1999) industry. Mobile phone design/development follows a strategy of “platform-based product development” (Krishnan and Gupta, 2001). This strategy is best described by some comments about the mobile phone leader Nokia, “The N96 is the lead product in the N series line up. All others have similar, but lesser capabilities — less memory, a lower quality camera, fewer video codecs, and

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<sup>11</sup>For example, I compare the handset models in Italy with those in Germany, the latter with a bundling between handsets and service contracts. The handset models in Germany are a subset of Italy's.

so on,” wrote Alec Saunders in *Nokia’s Evolving Product Strategy*.<sup>12</sup> This industry-wide product strategy implies that product development costs are much higher for the high-quality products than the low-quality products.

In addition, the brand value in the mobile phone industry also plays a crucial role in the success of the firms. Market share leaders are also brand value leaders in the mobile phone industry. The brand values of all mobile phone manufacturers<sup>13</sup> are among the top 100 most valuable brands in the world.

Last, the high-quality segment is more product-driven because high-quality products are greatly differentiated, while the low-quality segment is more brand-driven because they are fairly standard in design and used primarily for communication purposes. New entries to the high-end segment of the mobile phone industry provide a great example that products matter more than brands in the high-end segment. Both Apple Inc. and Google Inc. possess excellent brands in fields other than mobile phones before they enter the market, but Apple gains much greater success than Google mainly because of its product, the iPhone, rather than its brand.

According to the analysis above and the proposed theory, the mobile phone manufacturers’ mixed strategies can be predicted in the following hypothesis:

*If a mobile phone manufacturer’s relative brand value increases, its odds ratio of playing a high-end to a low-end product quality strategy decreases, while its relative brand value decreases, this odds ratio increases.*

### **2.5.2 Data**

The dataset contains three subsets. The first subset is a panel of monthly mobile phone sales volume and price in Italy between January 2002 and December 2006 from the six mobile phone manufacturers. There are a total of 479 products, of which 429

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<sup>12</sup><http://saunderslog.com/2008/02/17/nokias-evolving-product-strategy/>

<sup>13</sup>Sony-Ericsson is not among the top 100 brands ranked by Interbrand (2008) but its parent companies Sony and Ericsson are.

are new, and 60 periods, of which 59 are related to new products.<sup>14</sup> The summary statistics of the total numbers of mobile phones and new mobile phones are presented in Table 2.5.

Table 2.5: Total Number of Products over 60 Months

Firms	LG	Motorola	Nokia	Samsung	Siemens	Sony-Ericsson
No. of Products	65	87	105	120	58	44
No. of New Products	62	71	97	113	43	43

The second subset is the brand values from Huang (2010), who uses the same data as the first subset to estimate monthly brand value estimates. Because brand values vary over time, I can compute the corresponding brand value at the time when a product’s quality decision was made. The last subset contains the data collected from those manufacturers’ quarterly financial reports, including their global R&D investment, sales, and R&D investment as a percentage of global sales. Table 2.6 presents the global R&D investment as a percentage of global sales for the six major mobile phone producers.

Table 2.6: Global R&D Investment as a Percentage of the Global Sales

R&D as % of Sales	Mean	S. E.	Min.	Max.
LG	4.65	0.80	3.30	6.50
Motorola	11.45	2.22	9.23	15.67
Nokia	11.34	1.79	8.96	16.3
Samsung	8.31	1.11	6.41	10.09
Siemens	6.90	0.14	6.6	7.2
Sony-Ericsson	8.98	0.68	6.77	10.14

The dataset exhibits some special features. First, if each new product is an observation, the price and sales volume data seem to be in a panel format, however they are not because each new product is released only once. Second, the data can be a panel if I aggregate all products of a firm in a period into one observation. However, the number of observations would drop dramatically and a great deal of information

<sup>14</sup>I regard all mobile phones presented in the first period of the dataset as existing because I cannot differentiate the products launched prior to and in the first period.

would be lost. Third, the coexistence of old and new products provides a more realistic and richer circumstance for the study — when a new product is released, most of the old products are still present in the market.

### 2.5.3 Estimation Strategy

#### Empirical Setup

To test the hypothesis, I pool all 425 new products into one cross-section according to their launch times and denote the launch time for each new product as  $t$ . I run both logit and probit models to test the hypothesis. The dependent variable is discrete product quality: high-end or low-end. Following practices in the mobile phone industry, I use initial prices<sup>15</sup> of new products and a cut off price point to split new products into two segments. For example, a product is high-end if its initial price  $\geq$  EUR 450 and low-end if its initial price  $<$  EUR 450. I use a variety of price cut off points to ensure that the empirical results are robust.

The focal independent variable is a manufacturer’s brand value when a new product is launched. It involves two issues: the timing when a firm makes a product quality decision and the measurement for brand value. According to mobile phone industry experts, a mobile phone’s R&D cycle ranges from six months to two years. Although the average product development cycle becomes shorter over time due to fierce competition, the minimum time for fixing a product’s specifications shows little change — at least half a year prior to its launch for the sake of system integration, testing, production, and distribution. Thus, I adopt a six-month period as the time lag, i.e., the product quality decision is made based on the information available at  $t-6$ .<sup>16</sup> At  $t-6$ , firms make their product quality decisions on the basis of their brand values over a period of time — one or two quarters. We, therefore, use a six-month

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<sup>15</sup>Initial price is defined as the average monthly price when a product is launched. Since the price for almost all products gradually decrease over time, initial prices best reflect the manufacturer’s quality positioning for their new products.

<sup>16</sup>I also use data at  $t-5$  and  $t-7$  in the robustness check and empirical results are consistent.

average of the monthly brand values between  $t - 7$  and  $t - 12$  as the corresponding brand value measure at  $t - 6$  for a product.<sup>17</sup> As a consequence, the data are reduced to a 48-month period between March 2003 to December 2006 and the corresponding total number of new products becomes 382.

I use logit and probit models to test the hypothesis. Formally,

$$\ln\left(\frac{p_H}{p_L}\right) = \theta_0 + \theta_1 B_{t-6} + \sum_{r=2}^R \theta_r x_{r,t-6} + e, \quad (2.9)$$

$$\Phi^{-1}(p_H) = \rho_0 + \rho_1 B_{t-6} + \sum_{r=2}^R \rho_r x_{r,t-6} + \varepsilon. \quad (2.10)$$

where  $p_H$  and  $p_L$  are the probabilities of a new product (launched at time  $t$ ) being high-end and low-end, respectively;  $B_{t-6}$  is the corresponding brand value for the new product at time  $t - 6$ ;  $\theta_{(\cdot)}$  and  $\rho_{(\cdot)}$  are parameters, and  $x_{(\cdot),t-6}$  are independent variables;  $e$  is an error term distributed Type I extreme value; and  $\varepsilon$  is an error term distributed  $N(0,1)$ . In addition to brand value, the independent variables include (i) the number of competitors' existing products, (ii) the corresponding revenue in each quality segment, (iii) a firm's own global R&D investment, and (iv) firm dummy variables.

$\theta_1$  and  $\rho_1$  are the focus point because a negative and statistically significant value indicates that when brand value increases (decreases), the probability of being high-end with respect to the probability of being low-end decreases (increases). If so, the empirical evidence rejects the null hypothesis that brand value does not play a role ( $\theta_1 = 0$  and  $\rho_1 = 0$ ) and lends support to the alternative hypothesis, and therefore, to the proposed theory.

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<sup>17</sup>Three-month and nine-month averages of monthly brand values are included in the robustness check and empirical results are consistent.

## Addressing the Endogeneity

The endogeneity problem for brand value may be generated from three potential sources. First, brand value and new product decisions are causal to each other over time. New product launches affect a firm's current and future brand values; the affected brand value then influences the firm's decisions on future new product quality decisions. However, this is not an issue with the measurements I adopted for the quality and the brand value. Recall that high-end and low-end products are split based on their prices. The monthly brand value is measured as a weighted average of structural errors after controlling for the same product characteristics including price. Therefore, the brand value measurement does not contain product quality factors. In other words, by the setup of this measurement, brand value will affect product quality but the reverse is not true.

The second potential endogeneity problem can be caused by firms' predetermined new product strategies. For example, Nokia may decide to produce predominantly high-quality products as its strategy, i.e, it endogenously fixes a high  $p_H$  regardless of its brand value. In such a case, the empirical results may not be valid if I find a positive effect of Nokia's brand value on its odds ratio of  $p_H$  to  $p_L$  because these results can be caused solely by its endogenously fixed strategy rather than the effects of its brand value. To control such endogeneity, I use firm dummy variables in the regression to control firms' fixed product quality strategies and other time-invariant effects.

Another potential endogeneity problem is that firms' quality decisions may affect their R&D investment decisions. However, it should not be an issue for two reasons. Since the number of new products by any phone producer is large and these products cover both quality segments, the impact of one particular product's quality segment on R&D investment would be minimal. Moreover, mobile phone manufacturers typically manage its R&D investment fluctuating around a fixed percentage of sales. For

example, Siemens' quarterly R&D investment hovers closely around 7% of its revenue over the period of this study.

### 2.5.4 Empirical Results

This subsection presents two sets of empirical evidence. First, I show the relationship between relative brand values and the quality segments in a summary statistics format. It offers an intuitive illustration about the empirical patterns. Then, I present the empirical results of the logit and probit regression models.

Table 2.7: New Product Quality Changes w.r.t. Brand Value Changes

(a) C.P. = Eur 500, $B$ Changes					(b) C.P. = Eur 450, $B$ Changes			
	Down	Flat	Up	Total	Down	Flat	Up	Total
No. of High.	16	9	9	34	20	18	16	54
No. of Low.	125	89	134	348	121	80	127	328
Total	141	98	143	382	141	98	143	382
% of High.	11.35	9.18	6.29	-	14.18	18.37	11.19	-
% of Low.	88.65	90.82	93.71	-	85.82	81.63	88.81	-
% Total	100	100	100	-	100	100	100	-
(c) C.P. = Eur 400, $B$ Changes					(d) C.P. = Eur 350, $B$ Changes			
	Down	Flat	Up	Total	Down	Flat	Up	Total
No. of High.	29	27	21	77	42	33	36	111
No. of Low.	112	71	122	305	99	65	107	271
Total	141	98	143	382	141	98	143	382
% of High.	20.57	27.55	14.69	-	29.79	33.67	25.17	-
% of Low.	79.43	72.45	85.31	-	70.21	66.33	74.83	-
% Total	100	100	100	-	100	100	100	-

Note: The relative brand value change is made by comparing a six-month average brand value,  $B_{t-6} = \frac{1}{6} \sum_{r=t-7}^{t-12} B_r$ , with a three-month average brand value,  $B_{t-10}^* = \frac{1}{3} \sum_{r=t-11}^{t-13} B_r$ . (In a special case, when  $t = 13$ ,  $B_{t-10}^* = \frac{1}{2} \sum_{r=t-11}^{t-12} B_r$ .) The relative brand value is defined as flat, i.e., no change if the relative brand value change is in a small range, i.e.,  $-0.05 < B_{t-6} - B_{t-10}^* < 0.05$ . Last, C.P. refers to cutoff point.

The summary statistics are presented in Table 2.7. In order to test the robustness of the product quality positioning, I use a variety of price cut off points: EUR 350, 400, 450, and 500. All four subtables show a consistent pattern — the probability of high-end when the relative brand value increases is less than when it decreases. These summary statistics lend preliminary support to the proposed theory. Tables 2.8 and 2.9 show that the regression results for the different price cut off points consistently support the proposed theory. In addition, they show as similar pattern as that in

Table 2.8: Empirical Results of Logit/Probit Regressions with Different cut off Points, Part 1

C.P. = Eur 500				
	Logit		Probit	
	(1)	(2)	(1)	(2)
<i>B</i>	-3.249(1.081)***	-3.575(1.036)***	-2.310(0.760)***	-2.484(0.727)***
NoP_rival_L	-0.044(0.022)**	-0.065(0.015)***	-0.030(0.016)*	-0.047(0.011)***
NoP_rival_H	0.053(0.101)	0.041(0.082)	0.034(0.070)	0.032(0.058)
Rev_rival_L	-0.006(0.016)	-	-0.007(0.012)	-
Rev_rival_H	-0.031(0.036)	-	-0.018(0.028)	-
<i>D<sub>LG</sub></i>	-5.364(2.015)***	-5.854(1.474)***	-3.916(1.434)***	-4.304(1.055)***
<i>D<sub>Motorola</sub></i>	1.623(2.242)	0.040(0.987)	1.191(1.590)	-0.208(0.686)
<i>D<sub>Nokia</sub></i>	7.429(2.907)**	5.695(1.992)***	5.409(2.053)***	3.843(1.353)***
<i>D<sub>Samsung</sub></i>	2.655(3.015)	0.702(1.024)	2.027(2.163)	0.342(0.727)
<i>D<sub>Siemens</sub></i>	-1.396(1.323)	-1.485(1.234)	-0.980(0.903)	-1.114(0.786)
W_rev	-0.787(1.206)	-	-0.644(0.829)	-
W_rd_per	-0.407(0.625)	-	-0.302(0.438)	-
Constant	2.548(2.623)	0.610(1.397)	2.016(2.086)	0.462(1.028)
LR $\chi^2$	55.05( <i>d.f.</i> = 12)	52.99( <i>d.f.</i> = 8)	-	-
Pseudo <i>R</i> <sup>2</sup>	0.2400	0.2310	-	-
Log Likelihood	-	-	-87.15	-88.22
Wald $\chi^2$	-	-	35.25( <i>d.f.</i> = 12)	35.75( <i>d.f.</i> = 8)
C.P. = Eur 450				
	Logit		Probit	
	(1)	(2)	(1)	(2)
<i>B</i>	-2.739(0.856)***	-2.316(0.714)***	-2.159(0.653)***	-1.775(0.558)***
NoP_rival_L	-0.035(0.020)*	-0.056(0.011)***	-0.024(0.015)	-0.043(0.008)***
NoP_rival_H	0.010(0.061)	0.018(0.038)	-0.017(0.045)	0.011(0.029)
Rev_rival_L	-0.026(0.018)	-	-0.023(0.014)*	-
Rev_rival_H	0.023(0.033)	-	0.022(0.025)	-
<i>D<sub>LG</sub></i>	-4.076(1.461)***	-3.466(0.961)***	-3.175(1.138)***	-2.688(0.762)***
<i>D<sub>Motorola</sub></i>	-0.434(1.582)	-0.700(0.790)	-0.455(1.200)	-0.599(0.593)
<i>D<sub>Nokia</sub></i>	4.201(1.985)	3.562(1.328)***	3.150(1.513)**	2.664(1.011)***
<i>D<sub>Samsung</sub></i>	0.750(2.183)	0.815(0.763)	0.536(1.691)	0.609(0.587)
<i>D<sub>Siemens</sub></i>	-0.665(1.005)	-0.994(0.824)	-0.553(0.790)	-0.847(0.622)
W_rev	0.193(0.816)	-	0.173(0.593)	-
W_rd_per	-0.133(0.476)	-	-0.067(0.360)	-
Constant	1.966(2.334)	0.892(1.088)	1.469(1.869)	0.648(0.846)
LR $\chi^2$	57.86( <i>d.f.</i> = 12)	55.43( <i>d.f.</i> = 8)	-	-
Pseudo <i>R</i> <sup>2</sup>	0.1859	0.1781	-	-
Log Likelihood	-	-	-126.63	-128.22
Wald $\chi^2$	-	-	40.76( <i>d.f.</i> = 12)	39.51( <i>d.f.</i> = 8)

Note: Since all independent variables are the data at  $t-6$ , this time subscript is omitted for all. The six-month-average rule is applied to the number of competitors' existing products in the low-end and high-end segments at time  $t-6$ , denoted by *NoP\_rival\_L* and *NoP\_rival\_H*, respectively. The corresponding rivals' revenues are denoted by *Rev\_rival\_L* and *Rev\_rival\_H*, respectively. The R&D investment as a percentage of global sales, denoted by *W\_rd\_per*, is quarterly rather than monthly and is calculated as the monthly average of two-quarter corresponding data. The global sales of a mobile phone manufacturer is denoted by *W\_rev*, and the firm dummy variables for firm  $f$  is denoted by  $D_f$ .

Table 2.9: Empirical Results of Logit/Probit Regressions with Different cut off Points, Part 2

C.P. = Eur 400				
	Logit		Probit	
	(1)	(2)	(1)	(2)
<i>B</i>	-0.893(0.529)*	-0.848(0.522)	-0.706(0.427)*	-0.648(0.426)
NoP_rival_L	-0.030(0.021)	-0.043(0.010)***	-0.023(0.017)	-0.034(0.008)***
NoP_rival_H	-0.001(0.039)	0.002(0.032)	-0.003(0.031)	0.001(0.025)
Rev_rival_L	-0.006(0.017)	-	-0.004(0.014)	-
Rev_rival_H	-0.014(0.023)	-	-0.011(0.019)	-
<i>D<sub>LG</sub></i>	-1.643(1.152)	-2.296(0.796)***	-1.217(0.921)	-1.822(0.621)***
<i>D<sub>Motorola</sub></i>	-0.544(1.379)	-1.416(0.661)**	-0.340(1.107)	-1.173(0.515)**
<i>D<sub>Nokia</sub></i>	2.662(1.562)*	1.534(0.970)	2.232(1.286)*	1.149(0.795)
<i>D<sub>Samsung</sub></i>	1.928(1.893)	0.356(0.585)	1.744(1.576)	0.241(0.480)
<i>D<sub>Siemens</sub></i>	-0.903(0.829)	-1.369(0.693)**	-0.706(0.676)	-1.147(0.546)**
W_rev	-0.509(0.665)	-	-0.479(0.537)	-
W_rd_per	0.111(0.404)	-	0.106(0.327)	-
Constant	1.759(2.037)	1.156(0.926)	1.230(1.702)	0.931(0.770)
LR $\chi^2$	55.51( <i>d.f.</i> = 12)	52.99( <i>d.f.</i> = 8)	-	-
Pseudo <i>R</i> <sup>2</sup>	0.1446	0.1380	-	-
Log Likelihood	-	-	-164.08	-165.45
Wald $\chi^2$	-	-	44.03( <i>d.f.</i> = 12)	40.65( <i>d.f.</i> = 8)
C.P. = Eur 350				
	Logit		Probit	
	(1)	(2)	(1)	(2)
<i>B</i>	-0.331(0.413)	-0.303(0.411)	-0.206(0.327)	-0.167(0.322)
NoP_rival_L	-0.062(0.038)	-0.042(0.008)***	-0.049(0.030)	-0.034(0.006)***
NoP_rival_H	0.012(0.046)	-0.020(0.022)	0.007(0.038)	-0.019(0.018)
Rev_rival_L	0.014(0.027)	-	0.010(0.022)	-
Rev_rival_H	-0.030(0.028)	-	-0.024(0.023)	-
<i>D<sub>LG</sub></i>	-0.609(0.930)	-1.088(0.606)*	-0.531(0.752)	-0.853(0.467)*
<i>D<sub>Motorola</sub></i>	-0.717(1.120)	-0.963(0.558)*	-0.547(0.992)	-0.843(0.453)*
<i>D<sub>Nokia</sub></i>	1.426(1.419)	0.734(0.804)	1.107(1.191)	0.444(0.652)
<i>D<sub>Samsung</sub></i>	1.633(1.761)	0.583(0.534)	1.312(1.476)	0.399(0.438)
<i>D<sub>Siemens</sub></i>	-0.825(0.749)	-0.999(0.602)*	-0.768(0.634)	-0.908(0.498)*
W_rev	-0.299(0.596)	-	-0.264(0.490)	-
W_rd_per	0.151(0.350)	-	0.088(0.291)	-
Constant	2.251(1.830)	1.800(0.908)**	2.083(1.561)	1.578(0.778)**
LR $\chi^2$	57.83( <i>d.f.</i> = 12)	55.71( <i>d.f.</i> = 8)	-	-
Pseudo <i>R</i> <sup>2</sup>	0.1256	0.1210	-	-
Log Likelihood	-	-	-201.58	-202.59
Wald $\chi^2$	-	-	49.71( <i>d.f.</i> = 12)	47.41( <i>d.f.</i> = 8)

Note: Standard errors are in parentheses. \*\*\*, \*\*, and \* indicate that the p-value is less than 0.01, 0.05, and 0.1, respectively. d.f. refers to degrees of freedom. The number of observations is 382 for all regressions in Table 2.8 and 2.9.

Table 2.7 — the more significant the empirical result the higher the cut off point.

When a cut off point is of a greater value (for example, EUR 500 or 450 as in Table 2.8), the coefficient for brand value is negative and statistically significant, indicating that when a mobile phone manufacturer's brand value increases, the odds ratio of a new product's being high-end to being low-end decreases. For example, in the case of EUR-450-cut off-point (Logit (2)), the odds ratio of high-end to low-end decreases 2.3 if the relative brand value at  $t - 6$  increases one unit. When a cut off point gradually decreases (for example, EUR 400 and 350 as in Table 2.9), the coefficients of the brand value are still negative although they are not statistically significant.

Comparing any results of logit and probit regressions for the quality segments split by the same cut off point, the absolute value of the brand value coefficient in the probit model is consistently smaller than in the logit model. The results of the probit model are preferred to those of the logit model because the probit model allows the correlation among different products. Mobile phone characteristics are actually correlated, especially among products from the same manufacturer. Moreover, a smaller coefficient value provides a more conservative hypothesis testing.

I generate two more insights through these regressions. The rivals' revenue in each segment, mobile phone manufacturers' global revenue, and R&D investment as a percentage of the world revenue do not seem to affect mobile phone manufacturers' new product quality decisions. In all regressions presented in Tables 2.8 and 2.9, none of the corresponding coefficients are statistically significant. One explanation may be that mobile phone manufacturers monitor rivals' number of products in the market, as a major decision criterion, rather than other market measures such as revenue. The R&D investment for a product is much smaller than a firm's global revenue or R&D investment. Therefore, the quality decision for a particular product is not affected much, if any, by these global firms' sizes and R&D budget.

The second insight is that the market leader Nokia has a higher probability of

introducing high-end products, while LG has a lower probability, than Sony-Ericsson, *ceteris paribus*. For example, in the case of EUR-450-cut off-point (Logit (2)), Nokia's odds ratio of producing high-end to low-end is 3.6 higher than that of Sony-Ericsson, while LG's odds ratio is 3.5 lower than that of Sony-Ericsson. These findings suggest that brand values affect firms' new product quality decisions, as predicted by the proposed theory, even though firms may have their own predetermined product quality strategies.

## 2.6. Concluding Remarks

This paper examines how brand values affect new product quality decisions. It proposes a theory that reconciles different predictions of Ofek and Sarvary (2003) and Randall et al. (1998) by characterizing the mixed strategy Nash equilibrium for a static game. Simulations of dynamic games confirm the theoretic results of the static game although firms that take their future into account tend to soften their strategies in the dynamic game compared with those in the static game. Not only does this paper develop a theoretic model, but it also empirically tests the proposed theory using data from the mobile phone industry in the Italian market. The empirical results provide strong support for the theoretic model. The generated insights indicate that either the prediction of Ofek and Sarvary (2003) or Randall et al. (1998) is correct in their own research context.

Four drivers for firms' optimal product quality strategies with respect to brand value are identified in the static game: (i) product development cost difference between high- and low-end products ( $\Delta c$ ), (ii) the importance of brand value in competition ( $b$ ), (iii) the role of brand across different market structures ( $\Delta k$ ), and (iv) a relationship of market sizes for different market structures (represented by  $m_{(\cdot)}$ ,  $d_{(\cdot)}$  and their relation). However, most insights rest on the first two key drivers because, in practice, it is relatively easier to identify the first two than the last two.

Similar to the mobile phone industry, the computer industry (Ofek and Sarvary,

2003) falls into Scenario I because brand value plays a greater role in the low-end segment than in the high-end segment. (Low-end products are more homogenous while high-end products are more differentiated.) Brand value plays a crucial role in competition ( $b$ ) and product development cost difference is high between high- and low-end products ( $\Delta c$ ). On the basis of the proposed theory, I predict that high-brand-value firms have a greater probability of producing low-end products than low-brand-value firms. However, the mountain bicycle industry (Randall et al., 1998) is different, although it belongs to Scenario I. The product development cost difference between a high-end and low-end product is small. The importance of brand value is not as much as in the computer or mobile phone industry. These two characteristics, on the basis of the proposed theory, suggest that high-brand-value firms have a greater probability of producing high-end products than low-brand-value firms.

The paper generates implications for marketing and business managers of firms who play mixed strategies in their new product quality decisions. Managers can determine which scenario applies to their industry according to the industry characteristics. By following the theoretical insights of this paper, managers can adopt systematically the optimal strategy to maximize profit in both the short and long run. It also contributes to the literature by reconciling the seemingly contrasting predictions and by providing empirical evidence on the effects of brand value on firms' product quality decisions.

# Appendices

## A. Appendices for Chapter 1

### Appendix A.1. Details of the Theoretical Framework

All linear parameters of the utility function can be categorized as  $\boldsymbol{\theta}_1$ , a  $k_1 \times 1$  vector, and non-linear parameters fall into  $\boldsymbol{\theta}_2$ , a  $k_2 \times 1$  vector with all not-restricted-to-zero elements of  $\boldsymbol{\Sigma}$ . The linear utility function (1.1) can be rewritten as:

$$\begin{aligned} u_{ijt} &= \delta_{jt}(\mathbf{x}_{1,jt}, \xi_{jt}, \lambda_{ft}, \zeta_{dec}; \boldsymbol{\theta}_1) + \mu_{ijt}(\mathbf{x}_{2,jt}, \boldsymbol{\nu}_i; \boldsymbol{\theta}_2) + \epsilon_{ijt}, & (\text{A-1}) \\ \delta_{jt} &= \mathbf{x}_{1,jt}\boldsymbol{\theta}_1 + \lambda_{ft} + \xi_{jt} + \zeta_{dec}, \\ \mu_{ijt} &= (\mathbf{x}_{2,jt} \odot \boldsymbol{\nu}_i)\boldsymbol{\theta}_2, \end{aligned}$$

where  $\mathbf{x}_{1,jt}$  is a  $1 \times k_1$  row vector of product characteristics,  $\mathbf{x}_{2,jt}$  is a  $1 \times k_2$  row vector of product characteristics that are assumed to have random coefficients,  $\boldsymbol{\nu}_i$  is a  $1 \times k_2$  row vector of individual-level random shocks, and  $\odot$  represents a Hadamard product (element-by-element multiplication). I name the vector that contains  $\mathbf{x}_{1,jt}$ ,  $\lambda_{ft}$ , and  $\zeta_{dec}$  as  $\mathbf{X}_1$ .

In practice, the optimization problem can be limited only to searching for the nonlinear parameters  $\boldsymbol{\theta}_2$  because, deriving from the first order condition with respect to  $\boldsymbol{\theta}_1$  for minimizing the GMM objective function and from  $\xi_{jt} = \delta_{jt} - \mathbf{x}_{1,jt}\boldsymbol{\theta}_1 - \lambda_{ft} - \zeta_{dec}$ ,  $\boldsymbol{\theta}_1$  can be written as a function of  $\boldsymbol{\theta}_2$ :

$$\boldsymbol{\theta}_1(\boldsymbol{\theta}_2) = (\mathbf{X}'_1 \mathbf{Z} \mathbf{W}_n \mathbf{Z}' \mathbf{X}_1)^{-1} \mathbf{X}'_1 \mathbf{Z} \mathbf{W}_n \mathbf{Z}' \boldsymbol{\delta}(\boldsymbol{\theta}_2), \quad (\text{A-2})$$

where  $\mathbf{Z}$  is a matrix of instrumental variables and  $\mathbf{W}_n$  is a GMM-weighting matrix.

For the efficient GMM, the first stage GMM is to use an identity matrix as the weighting matrix. After estimating the parameters, a variance-covariance matrix of the parameters is obtained. The inverse of this variance-covariance matrix is then used as the GMM-weighting matrix to re-estimate the parameters, which have smaller variances than those estimated from the first stage GMM. This second-round estimation is called the second stage GMM.

## Appendix A.2. Decomposition of Brand Effects

Recall the following relation from Equation (1.7):

$$\Delta\lambda_{ft} = \sum_{r \in \mathfrak{S}_t} \omega_{rt} \xi_{rt}.$$

It can be rewritten as:

$$\Delta\lambda_{ft} = \sum_{r \in \mathfrak{S}_t} \left( \omega_{rt} - \frac{1}{n_{ft}} + \frac{1}{n_{ft}} \right) \xi_{rt}, \quad (\text{A-3})$$

where  $n_{ft}$  is the number of products of firm  $f$  at time  $t$  and  $1/n_{ft}$  can be interpreted as a theoretical average portfolio share, i.e., the average product portfolio share if all products of firm  $f$  at time  $t$  have equal shares.

If product portfolio share  $\omega_{jt}$  is greater (less) than the theoretical average portfolio share  $1/n_{ft}$ , product  $j$  is generally better (worse) than a theoretical average product for its manufacturer. Since  $E[\xi_{jt}] = 0$ , the product-level willingness to pay is estimated around the grand mean, zero, i.e.,  $\xi_{jt} > 0$  ( $\xi_{jt} < 0$ ) if this willingness to pay is greater (less) than average unobserved quality of all products in the sample.

Both willingness to pay and market share of a product are expected to be positively corrected. Intuitively, a higher than average willingness to pay increases a consumer's

utility of choosing this product and, therefore, results in an increase in sales and a larger than average portfolio share. Similarly, a lower  $\xi_{jt}$  should lead to a lower than average portfolio share. Theoretically, the empirical method that estimates  $\xi_{jt}$  as a function of market share  $s_{jt}$  ensures that this positive correction between  $\xi_{jt}$  and portfolio share  $\xi_{jt}$  holds.

If this relationship holds for a product, the firm is assumed to have taken correct marketing actions, such as right pricing for the product in a given time period, and, correspondingly, the proposed brand evaluation method awards the firm in the contribution of the product to the brand effect. Otherwise, the firm is assumed to have taken poor marketing decisions and the method punishes the firm by assigning a negative deviation from the mean brand value. For example, if a high-quality product is sold at a smaller portfolio share than a theoretical average product, one potential reason is that the price is too high even though its willingness to pay may be high. The brand evaluation method punishes the firm by assigning a negative contribution of the product to the brand effect. In contrast, if the same product outsells an average product and the willingness to pay is high as well, the proposed method awards the firm by counting a positive contribution of the product to the brand effect. More important, the logic applies to the low willingness to pay product as well. If a product is sold at below-average volume and its willingness to pay is low, everything is as expected: the contribution of the product to brand effect is positive. However, if the same quality product is sold at high-volume, most likely because of a promotion, the proposed method will assign a negative value to the brand effect. The table below shows how these relationships lead to different contributions of a product to the brand effect.

Based on the analysis above, Equation (1.7) can be interpreted as follows:

$$\tilde{\lambda}_{ft} = \lambda_f + \bar{\xi}_t + \sum_{r \in \mathfrak{S}_t} \left( \omega_{rt} - \frac{1}{n_{ft}} \right) \xi_{rt},$$

If $\omega_{rt} - \frac{1}{n_{ft}} > 0$ and $\xi_{jt} > 0$ , then $(\omega_{rt} - \frac{1}{n_{ft}}) \xi_{rt} > 0$ ;
If $\omega_{rt} - \frac{1}{n_{ft}} < 0$ and $\xi_{jt} < 0$ , then $(\omega_{rt} - \frac{1}{n_{ft}}) \xi_{rt} > 0$ ;
If $\omega_{rt} - \frac{1}{n_{ft}} > 0$ and $\xi_{jt} < 0$ , then $(\omega_{rt} - \frac{1}{n_{ft}}) \xi_{rt} < 0$ ;
If $\omega_{rt} - \frac{1}{n_{ft}} < 0$ and $\xi_{jt} > 0$ , then $(\omega_{rt} - \frac{1}{n_{ft}}) \xi_{rt} < 0$ .

which is Equation (1.11).

### Appendix A.3. Derivation for Summary Variables

I will use one summary variable to show the summary variable approach, and certainly more summary variables can be applied in a similar way. The empirical work provides an example, and the details are documented in the next section. Formally,

$$y_j = \mathbf{z}_j \boldsymbol{\beta} + e_j, \quad (\text{A-4})$$

where  $y_j$  is a summary variable,  $\mathbf{z}_j$  is a  $1 \times k$  row vector of product characteristics,  $\boldsymbol{\beta}$  is a corresponding column vector of parameters,  $(\beta_{1,z}^1 \beta_{1,z}^2 \dots \beta_{1,z}^k)$ , and  $e_j$  is an error.

Next, I can compute the fitted value of  $y_j$  as  $\hat{y}_j = \mathbf{z}_j \hat{\boldsymbol{\beta}}$ , demean  $\hat{y}_j$  for each time period to obtain  $\tilde{y}_{jt}$ , and use  $\tilde{y}_{jt}$  to interact with a random individual-level shock in the utility function. The utility function becomes

$$\ln(u_{ijt}) = [\tilde{\mathbf{w}}_{jt} \quad \tilde{\mathbf{z}}_{jt}] \begin{bmatrix} \boldsymbol{\theta}_{1,w} \\ \boldsymbol{\theta}_{1,z} \end{bmatrix} + ([\tilde{\mathbf{w}}_{jt} \quad \tilde{y}_{jt}] \odot [\boldsymbol{\nu}_{w,i} \quad \nu_{y,i}]) \begin{bmatrix} \boldsymbol{\theta}_{2,w} \\ \theta_{2,y} \end{bmatrix} + \lambda_{jt} + \epsilon_{ijt}, \quad (\text{A-5})$$

where  $\tilde{\mathbf{w}}_{jt}$  is a row vector of per-period demeaned product characteristics that enters both the linear and nonlinear parts of the utility function;  $\tilde{\mathbf{z}}_{jt}$  is the per-period demeaned  $\mathbf{z}_j$ , i.e.,  $\tilde{\mathbf{z}}_{jt} = [\tilde{z}_{jt}^1 \quad \tilde{z}_{jt}^2 \dots \tilde{z}_{jt}^k]$ ;  $\boldsymbol{\theta}_{1,w}$  and  $\boldsymbol{\theta}_{1,z}$  are the vectors of parameters for  $\tilde{\mathbf{w}}_{jt}$  and  $\tilde{\mathbf{z}}_{jt}$ , respectively;  $\odot$  represents a Hadamard product (element-by-element

multiplication);  $\boldsymbol{\nu}_{w,i}$  is a row vector of individual-level random shocks corresponding to  $\tilde{\boldsymbol{w}}_{jt}$ ;  $\nu_{y,i}$  is the corresponding shock to  $\tilde{y}_{jt}$ ;  $\theta_{2,y}$  is the parameter for  $\nu_{y,i} * \tilde{y}_{jt}$ ; and  $\nu_{y,i}$ ,  $\tilde{y}_{jt}$ , and  $\theta_{2,y}$  are scalars.

After the estimation, all terms in the utility function that are related to  $\tilde{\boldsymbol{z}}_{jt}$  can be written as:

$$f(\tilde{\boldsymbol{z}}_{jt}) = \tilde{\boldsymbol{z}}_{jt}\boldsymbol{\theta}_{1,z} + (\tilde{y}_{jt}\theta_{2,y})\nu_{y,i}, \quad (\text{A-6})$$

and I know:

$$\tilde{y}_{jt} = \tilde{\boldsymbol{z}}_{jt}\boldsymbol{\beta}. \quad (\text{A-7})$$

Therefore, I can input Equation A-7 into A-6 to obtain:

$$\begin{aligned} f(\tilde{\boldsymbol{z}}_{jt}) &= (\tilde{z}_{jt}^1\theta_{1,z}^1 + \tilde{z}_{jt}^2\theta_{1,z}^2 + \dots + \tilde{z}_{jt}^k\theta_{1,z}^k) + [(\tilde{z}_{jt}^1\beta_{1,z}^1 + \tilde{z}_{jt}^2\beta_{1,z}^2 + \dots + \tilde{z}_{jt}^k\beta_{1,z}^k)\theta_{2,y}]\nu_{y,i} \\ &= [\theta_{1,z}^1 + (\beta_{1,z}^1\theta_{2,y})\nu_{y,i}]\tilde{z}_{jt}^1 + [\theta_{1,z}^2 + (\beta_{1,z}^2\theta_{2,y})\nu_{y,i}]\tilde{z}_{jt}^2 + \dots \\ &\quad + [\theta_{1,z}^k + (\beta_{1,z}^k\theta_{2,y})\nu_{y,i}]\tilde{z}_{jt}^k. \end{aligned} \quad (\text{A-8})$$

Since  $\nu_{y,i} \sim N(0,1)$ , and if I assume that the distribution of the coefficients of  $\tilde{\boldsymbol{z}}_{jt}$  is asymptotically normal, I can identify the mean and standard error for each marginal effect for  $\tilde{z}_{jt}^\iota$  as  $\theta_{1,z}^\iota$  and  $\beta_{1,z}^\iota\theta_{2,y}$  for all  $\iota = 1, 2 \dots k$ , respectively.

#### Appendix A.4. Recovering $\Sigma$ from the Coefficients of $\widehat{S}_d$ and $\widehat{S}_f$

The coefficients of the fitted values of *design* and *feature*, denoted by  $\widehat{S}_d$  and  $\widehat{S}_f$ , in the utility function imply that an individual has her marginal utility from all product characteristics except price. The interpretation of the coefficient for the interaction term between price and individual-level price-specific random shock  $price * \nu_i^p$  is clear — it represents the standard error of the random price coefficient of the utility function if I assume that the distribution of the price coefficient is asymptotically

normal. The coefficients of  $\widehat{S}_d$  and  $\widehat{S}_f$  enable us to recover the coefficients for the unestimated interaction terms of random variables and the product characteristics.

Using Equations (1.25) and (1.26) and the estimates in Table 1.3, I can obtain the following equations:

$$\begin{aligned}\widehat{S}_d &= 12.076 + 0.173 * form - 0.798 * Ln(length) - 0.331 * Ln(height) \\ &\quad + 0.030 * D\_color\ display + 0.086 * D\_camera \\ &\quad + 0.117 * D\_camera * megapixels,\end{aligned}\tag{A-9}$$

$$\begin{aligned}\widehat{S}_f &= 1.653 + 0.590 * Internet + 0.153 * Extra\ display\ \&\ keyboard + 1.240 * Ln(width) \\ &\quad + 0.142 * Bands + 0.027 * Battery\ talktime.\end{aligned}\tag{A-10}$$

I use estimated coefficients in Table 1.4 and Equations (A-9) and (A-10) to compute the multiplies of  $\widehat{S}_d$  and  $\widehat{S}_f$ :

$$\begin{aligned}-0.69 * \widehat{S}_d &= -0.69 * [12.076 + 0.173 * form - 0.798 * Ln(length) - 0.331 * Ln(height) \\ &\quad + 0.030 * D\_color\ display + 0.086 * D\_camera \\ &\quad + 0.117 * D\_camera * megapixels] \\ &= -8.332 - 0.119 * form + 0.551 * Ln(length) + 0.228 * Ln(height) \\ &\quad - 0.021 * D\_color\ display - 0.059 * D\_camera \\ &\quad - 0.081 * D\_camera * megapixels,\end{aligned}\tag{A-11}$$

$$\begin{aligned}-0.09 * \widehat{S}_f &= -0.09 * [1.653 + 0.590 * D\_Internet + 0.153 * Extra\ display\ \&\ keyboard \\ &\quad + 1.240 * Ln(width) + 0.142 * Bands + 0.027 * Battery\ talktime] \\ &= -0.149 - 0.053 * D\_Internet - 0.014 * Extra\ display\ \&\ keyboard \\ &\quad - 0.112 * Ln(width) - 0.013 * Bands - 0.002 * Battery\ talktime.\end{aligned}\tag{A-12}$$

Then I can obtain the equation for the nonlinear part of the utility function,  $\mu_{ijt}$ :

$$\begin{aligned}
\mu_{ijt} &= 0.22 * \nu_i + 0.27 * price * \nu_i^p - 0.69 * \widehat{S}_d * \nu_i^d - 0.09 * \widehat{S}_f * \nu_i^f + 0.68 * Age \\
&= (0.22 * \nu_i - 8.332 * \nu_i^d - 0.149 * \nu_i^f) + 0.27 * price * \nu_i^p - 0.119 * form * \nu_i^d \\
&\quad - 0.014 * Extra\ display\ \&\ keyboard * \nu_i^f + 0.551 * ln(length) * \nu_i^d \\
&\quad - 0.112 * ln(width) * \nu_i^f + 0.228 * ln(height) * \nu_i^d - 0.013 * Bands * \nu_i^f \\
&\quad - 0.002 * Battery\ talktime * \nu_i^f - 0.053 * D\_Internet * \nu_i^f \\
&\quad - 0.021 * D\_color\ display * \nu_i^d - 0.059 * D\_camera * \nu_i^d \\
&\quad - 0.081 * D\_camera * megapixels * \nu_i^d + 0.68 * Age,
\end{aligned} \tag{A-13}$$

where  $\nu_i^p$ ,  $\nu_i^d$ , and  $\nu_i^f$  are the individual shocks that are specific to *price*, *design*, and *feature*, respectively, and they are independent and identically distributed (iid) random variables  $\sim N(0, 1)$ .

The three terms in the parentheses in Equation (A-13) need further derivation for a clear interpretation. They are comprised of the coefficient for the intercept of the utility function. Let us denote it by  $\alpha$ . The variance is

$$\begin{aligned}
Var(\alpha) &= Var(0.22 * \nu_i - 8.332 * \nu_i^d - 0.149 * \nu_i^f) \\
&= 0.048 + 69.422 + 0.022 = 69.493.
\end{aligned} \tag{A-14}$$

Since I know that if the random coefficient of individual  $i$  for product characteristic  $k$  is  $\theta_{ik} = \bar{\theta}_k + \alpha_{ik}$ , where  $\alpha_{ik} \sim N(0, \sigma^2)$ , then  $\theta_{ik} = \bar{\theta}_k + \sigma_{ik} * \tau_{ik}$ , where  $\tau_{ik} \sim N(0, 1)$ , i.e., the standard error of the random coefficient  $\theta_{ik}$  is  $\sigma_{ik}$ . Therefore, I can take the square root of the variance above and obtain the corresponding  $\sigma$ 's. The standard error for the random intercept is 69.493. Thus far, I have recovered all the  $\sigma$ 's that are of interest for the linear parameters of the utility function in Equation (1.2). Results are presented in Table 1.5.

## B. Appendices for Chapter 2

### Appendix B.1. Proof of Lemma 1

**Lemma 1** *The effect of brand value for a monopoly firm is greater than that for a duopoly firm, i.e.,  $k_2 > k_1$  or  $\frac{\partial \pi^m}{\partial \lambda^m} > \frac{\partial \pi^d}{\partial \lambda^d}$ , if  $0.5 > s^m > s^d > 0$ ,  $P^m > P^d > 0$ , and  $\gamma_i > 0$ .*

**Proof.**

A firm maximizes its profit in each period by setting its optimal price. In monopoly situation,

$$\max_{P_{jf}^m} \pi_{jf}^m = s_{jf}^m (P_{jf}^m - c_j), \quad (\text{B-1})$$

and in duopoly situation,

$$\max_{P_{jf}^d} \pi_{jf}^d = s_{jf}^d (P_{jf}^d - c_j), \quad (\text{B-2})$$

where  $m$  and  $d$  indicate a monopoly and duopoly situation, respectively;  $j$  refers to a high or low quality product strategy, and  $f$  refers to a high or low brand value firm. For parsimony, both  $j$  and  $f$  are omitted if not needed henceforth.

The corresponding first order conditions are:

$$\frac{\partial s^m}{\partial P^m} (P^m - c_j) + s^m = 0, \quad (\text{B-3})$$

$$\frac{\partial s^d}{\partial P^d} (P^d - c_j) + s^d = 0. \quad (\text{B-4})$$

The optimal pricing functions can be derived as:

$$P^m = c_j - \frac{1}{\alpha s^m (1 - s^m)}, \quad (\text{B-5})$$

$$P^d = c_j - \frac{1}{\alpha s^d (1 - s^d)}. \quad (\text{B-6})$$

In order to derive the impact of brand value on profit, I also need to derive the partial derivatives of optimal pricing function with respect to its corresponding market share:

$$\frac{\partial P^m}{\partial s_j^m} = -\frac{1}{\alpha (1 - s^m)^2}, \quad (\text{B-7})$$

$$\frac{\partial P^d}{\partial s_j^d} = -\frac{1}{\alpha (1 - s^d)^2}; \quad (\text{B-8})$$

and the partial derivatives of market share with respect to brand value:

$$\frac{\partial s^m}{\partial \lambda^m} = \gamma s_j^m (1 - s^m), \quad (\text{B-9})$$

$$\frac{\partial s^d}{\partial \lambda^d} = \gamma s_j^d (1 - s^d). \quad (\text{B-10})$$

Thus, the marginal effects of brand value on optimal profit in monopoly and duopoly situations can be derived as

$$\begin{aligned} \frac{\partial \pi^m}{\partial \lambda^m} &= \frac{\partial s^m}{\partial \lambda^m} (P^m - c_j) + s^m \frac{\partial P^m}{\partial s^m} \frac{\partial s^m}{\partial \lambda^m}, \\ &= \gamma \left[ s^m (1 - s^m) (P^m - c_j) - \frac{\gamma (s^m)^2}{\alpha (1 - s^m)} \right], \end{aligned} \quad (\text{B-11})$$

$$\begin{aligned} \frac{\partial \pi^d}{\partial \lambda^d} &= \frac{\partial s^d}{\partial \lambda^d} (P^d - c_j) + s^d \frac{\partial P^d}{\partial s^d} \frac{\partial s^d}{\partial \lambda^d}, \\ &= \gamma \left[ s^d (1 - s^d) (P^d - c_j) - \frac{\gamma (s^d)^2}{\alpha (1 - s^d)} \right]. \end{aligned} \quad (\text{B-12})$$

I assume that the total duopoly profit is less than a monopoly profit if the two firms compete; and that if they compete in a Bertrand game, the monopoly price is

higher than the duopoly price, i.e.,  $P^m > P^d > 0$ , and the monopoly quantity of a firm is greater than the duopoly quantity of any of the two firms, i.e.,  $s^m > s^d > 0$ , while the total quantity in a monopoly is less than that in a duopoly. In addition, I also assume the market size is large enough such that  $s^m \in (0, 0.5)$ .

Because  $y = s(1 - s)$  is an increasing function for  $s \in (0, 0.5)$  and  $s^m > s^d$ ,  $s^m(1 - s^m) > s^d(1 - s^d)$ . Since  $P^m > P^d$  and  $s^m(1 - s^m) > s^d(1 - s^d) > 0$ ,  $s^m(1 - s^m)(P^m - c_j) > s^d(1 - s^d)(P^d - c_j)$ . As  $\alpha < 0$  and  $\gamma > 0$ ,  $-\frac{\gamma(s^m)^2}{\alpha(1-s^m)}$  and  $-\frac{\gamma(s^d)^2}{\alpha(1-s^d)}$  are positive numbers, and  $-\frac{\gamma(s^m)^2}{\alpha(1-s^m)} > -\frac{\gamma(s^d)^2}{\alpha(1-s^d)}$ . Therefore, the sum of two larger positive numbers is greater than that of two smaller positive numbers, i.e.,  $s^m(1 - s^m)(P^m - c_j) - \frac{\gamma(s^m)^2}{\alpha(1-s^m)} > s^d(1 - s^d)(P^d - c_j) - \frac{\gamma(s^d)^2}{\alpha(1-s^d)}$ . Since  $\gamma > 0$ ,  $\frac{\partial \pi^m}{\partial \lambda^m} > \frac{\partial \pi^d}{\partial \lambda^d} \implies k_2 > k_1$ . ■

## Appendix B.2. Proof of Propositions 1 to 5

**Proof.** I derive the Nash equilibria, for the game presented in Table 3, under conditions that the monopoly payoffs dominate the duopoly payoffs. Formally, there are four conditions for firms  $h$  and  $l$ . Condition 1 (for Firm  $h$ ) always holds:

$$\begin{aligned} m_L + k_3b - c_L &\geq d_H + b - c_H \\ \implies m_L - d_H &\geq -(2b\Delta k + \Delta c); \end{aligned} \tag{B-13}$$

Condition 2 (for firm  $h$ ) holds true iff

$$\begin{aligned} m_H + k_2b - c_H &\geq d_L + k_1b - c_L \\ \implies m_H - d_L &\geq \Delta c - b\Delta k; \end{aligned} \tag{B-14}$$

Condition 3 (for firm  $l$ ) is valid iff

$$\begin{aligned} m_L - k_2b - c_L &\geq d_H - b - c_H \\ \implies m_L - d_H &\geq 2b\Delta k - \Delta c; \end{aligned} \tag{B-15}$$

and, Condition 4 (for firm  $l$ ) is fulfilled iff

$$\begin{aligned} m_H - k_3b - c_H &\geq d_L - k_1b - c_L \\ \implies m_H - d_L &\geq 2b\Delta k + \Delta c. \end{aligned} \tag{B-16}$$

For this set of equilibria, Condition 1 can be eliminated, because it always holds under the assumption in Equation (2.4). Condition 2 also can be eliminated because it is dominated by Condition 4.<sup>18</sup> Therefore, the game remains a coordinate game as long as Conditions 3 and 4 are true, and they are the conditions for the two pure and one mixed Nash equilibria in **Proposition 1**.

Regarding the mixed strategy, I derive the conditions for the low-brand-value firm to play a greater probability of high-quality strategy than the high-brand-value firm at a Nash equilibrium,  $p_H^l \geq p_H^h$ .

Firm  $h$  mixes between high- and low-end strategies to make firm  $l$  indifferent:

$$\begin{aligned} &p_H^h(d_H - b - c_H) + (1 - p_H^h)(m_H - k_3b - c_H) \\ = &p_H^h(m_L - k_2b - c_L) + (1 - p_H^h)(d_L - k_1b - c_L) \end{aligned} \tag{B-17}$$

↓

---

<sup>18</sup> $2b\Delta k + \Delta c - (\Delta c - b\Delta k) = 3b\Delta k > 0$

$$\begin{aligned}
p_H^h &= \frac{(m_H - d_L) - b(k_3 - k_1) - \Delta c}{\Delta\pi_H + \Delta\pi_L - a[(k_3 - k_1) + (k_2 - 1)]}, \\
&= \frac{\Delta\tilde{\pi} - 2b\Delta k - \Delta c}{\Delta\pi_H + \Delta\pi_L - 4b\Delta k},
\end{aligned} \tag{B-18}$$

where  $\Delta\pi_H = m_H - d_H$ ,  $\Delta\pi_L = m_L - d_L$ , and  $\Delta\tilde{\pi} = m_H - d_L$ .

Firm  $l$  selects a probability of playing high-end strategy to let firm  $h$  be indifferent:

$$\begin{aligned}
&p_H^l(d_H + b - c_H) + (1 - p_H^l)(m_H + k_2b - c_H) \\
&= p_H^l(m_L + k_3b - c_L) + (1 - p_H^l)(d_L + k_1b - c_L)
\end{aligned} \tag{B-19}$$

↓

$$\begin{aligned}
p_H^l &= \frac{(m_H - d_L) + b(k_2 - k_1) - \Delta c}{\Delta\pi_H + \Delta\pi_L + b[(k_3 - k_1) + (k_2 - 1)]}, \\
&= \frac{\Delta\tilde{\pi} + b\Delta k - \Delta c}{\Delta\pi_H + \Delta\pi_L + 4b\Delta k}.
\end{aligned} \tag{B-20}$$

Thus,  $p_H^l \geq p_H^h$  iff

$$\begin{aligned}
[(\Delta\tilde{\pi} - \Delta c) + b\Delta k](\Delta\pi_H + \Delta\pi_L - 4b\Delta k) &\geq [(\Delta\tilde{\pi} - \Delta c) - 2b\Delta k](\Delta\pi_H + \Delta\pi_L + 4b\Delta k), \\
b\Delta k &\geq 2(\Delta\tilde{\pi} - \Delta c) - \frac{3}{4}(\Delta\pi_H + \Delta\pi_L), \\
\implies \frac{5}{4}(m_H - d_L) - \frac{3}{4}(m_L - d_H) &\leq b\Delta k + 2\Delta c.
\end{aligned} \tag{B-21}$$

Thus, **Proposition 2** is approved.

Next, I derive the Nash equilibria for the situations when some or all monopoly payoffs do not dominate the duopoly payoffs. Since Condition 1 always holds given my assumption in Equation (2.4), I concentrate on the situations when some or all of the other three conditions are violated.

If Condition 3 is violated, while Condition 4 holds, (which implies Condition 2

holds as well,) there is only one Nash equilibrium,  $\{L^h, H^l\}$  (The 1st part of **Proposition 3**); if only Condition 4 is violated, while Conditions 2 and 3 hold, then  $\{H^h, L^l\}$  is the only Nash equilibrium (The 2nd part of **Proposition 3**); if both Conditions 2 and 4 are violated, i.e., Condition 2 is violated,<sup>19</sup> and no matter Condition 3 still holds or not,  $\{L^h, L^l\}$  becomes the unique Nash Equilibrium (**Proposition 4**); and, if both Conditions 3 and 4 are violated, there is no Nash Equilibrium and there is a mixed strategy Nash equilibrium (**Proposition 5**). ■

### Appendix B.3. Expected Value Functions for the Mixed Strategy MPE

Table b-1: Renamed Payoffs for Game with Brand Value & Cost, Scenario I

		$l$ (low brand value)	
		H	L
$h$ (high brand value)	H	$X_1 \equiv d_H + b - c_H,$ $Y_1 \equiv d_H - b - c_H$	$X_2 \equiv m_H + k_2b - c_H,$ $Y_2 \equiv m_L - k_2b - c_L$
	L	$X_3 \equiv m_L + k_3b - c_L,$ $Y_3 \equiv m_H - k_3b - c_H$	$X_4 \equiv d_L + k_1b - c_L,$ $Y_4 \equiv d_L - k_1b - c_L$

For parsimonious purposes, I rename the payoffs of Table 2.3 as in Table b-1. The four continuous expected functions are:

$$\begin{aligned}
V(H, p_H^h|0) &= Z + \delta [q(0|0, H, H)p_H^h + q(0|0, H, L)(1 - p_H^h)] \\
&\quad \{p_H^l [Z + \delta V(H, p_H^h|0)] + (1 - p_H^l) [W + \delta V(L, p_H^h|0)]\} + \\
&\quad \delta [q(1|0, H, H)p_H^h + q(1|0, H, L)(1 - p_H^h)] \\
&\quad \{p_H^h [M + \delta V(H, p_H^l|1)] + (1 - p_H^h) [Q + \delta V(L, p_H^l|1)]\} \\
&= Z + \delta(1 - \mu_1) \{p_H^l [Z + \delta V(H, p_H^h|0)] + (1 - p_H^l) [W + \delta V(L, p_H^h|0)]\} + \\
&\quad \delta\mu_1 \{p_H^h [M + \delta V(H, p_H^l|1)] + (1 - p_H^h) [Q + \delta V(L, p_H^l|1)]\} \quad (\text{B-22})
\end{aligned}$$

<sup>19</sup>Condition 2 is violated implies both Conditions 2 and 4 are violated, as it dominates Condition 4.

where

$$\begin{aligned}
Z &= Y_1 p_H^h + Y_3 (1 - p_H^A), \\
W &= Y_2 p_H^h + Y_4 (1 - p_H^A), \\
M &= X_1 p_H^l + X_2 (1 - p_H^B), \\
Q &= X_3 p_H^l + X_4 (1 - p_H^B), \\
\mu_1 &= \lambda_2 p_H^A + \lambda_3 (1 - p_H^A).
\end{aligned}$$

$$\begin{aligned}
V(L, p_H^h | 0) &= W + \delta [q(0|0, L, H) p_H^h + q(0|0, L, L) (1 - p_H^h)] \\
&\quad \{p_H^l [Z + \delta V(H, p_H^h | 0)] + (1 - p_H^l) [W + \delta V(L, p_H^h | 0)]\} + \\
&\quad \delta [q(1|0, L, H) p_H^h + q(1|0, L, L) (1 - p_H^h)] \\
&\quad \{p_H^h [M + \delta V(H, p_H^l | 1)] + (1 - p_H^h) [Q + \delta V(L, p_H^l | 1)]\} \\
&= W + \delta (1 - \mu_2) \{p_H^l [Z + \delta V(H, p_H^h | 0)] + (1 - p_H^l) [W + \delta V(L, p_H^h | 0)]\} + \\
&\quad \delta \mu_2 \{p_H^h [M + \delta V(H, p_H^l | 1)] + (1 - p_H^h) [Q + \delta V(L, p_H^l | 1)]\}, \quad (\text{B-23})
\end{aligned}$$

where

$$\mu_2 = \lambda_1 p_H^h + \lambda_2 (1 - p_H^h).$$

$$\begin{aligned}
V(H, p_H^l|1) &= M + \delta [q(0|1, H, H)p_H^l + q(0|1, H, L)(1 - p_H^l)] \\
&\quad \{p_H^h [Z + \delta V(H, p_H^h|0)] + (1 - p_H^l) [W + \delta V(L, p_H^h|0)]\} + \\
&\quad \delta [q(1|1, H, H)p_H^l + q(1|1, H, L)(1 - p_H^l)] \\
&\quad \{p_H^h [M + \delta V(H, p_H^l|1)] + (1 - p_H^h) [Q + \delta V(L, p_H^l|1)]\} \\
&= M + \delta \mu_3 \{p_H^l [Z + \delta V(H, p_H^h|0)] + (1 - p_H^l) [W + \delta V(L, p_H^h|0)]\} + \\
&\quad \delta(1 - \mu_3) \\
&\quad \{p_H^h [M + \delta V(H, p_H^l|1)] + (1 - p_H^h) [Q + \delta V(L, p_H^l|1)]\}, \quad (\text{B-24})
\end{aligned}$$

where

$$\mu_3 = \lambda_2 p_H^l + \lambda_1 (1 - p_H^l).$$

$$\begin{aligned}
V(L, p_H^l|1) &= Q + \delta [q(0|1, L, H)p_H^l + q(0|1, L, L)(1 - p_H^l)] \\
&\quad \{p_H^l [Z + \delta V(H, p_H^h|0)] + (1 - p_H^l) [W + \delta V(L, p_H^h|0)]\} + \\
&\quad \delta [q(1|1, L, H)p_H^h + q(1|1, L, L)(1 - p_H^h)] \\
&\quad \{p_H^h [M + \delta V(H, p_H^l|1)] + (1 - p_H^h) [Q + \delta V(L, p_H^l|1)]\} \\
&= Q + \delta \mu_4 \{p_H^l [Z + \delta V(H, p_H^h|0)] + (1 - p_H^l) [W + \delta V(L, p_H^h|0)]\} + \\
&\quad \delta(1 - \mu_4) \\
&\quad \{p_H^h [M + \delta V(H, p_H^l|1)] + (1 - p_H^h) [Q + \delta V(L, p_H^l|1)]\}, \quad (\text{B-25})
\end{aligned}$$

where

$$\mu_4 = \lambda_3 p_H^l + \lambda_2 (1 - p_H^l).$$

## Appendix B.4. Nash Equilibrium Characterization for Scenario II

Table b-2: Game with Brand Value & Cost, Scenario II

		$l$ (low brand value)	
		L	H
$h$ (high brand value)	L	$d_L + b - c_L,$ $d_L - b - c_L$	$m_L + k_2b - c_L,$ $m_H - k_2b - c_H$
	H	$m_H + k_3b - c_H,$ $m_L - k_3b - c_L$	$d_H + k_1b - c_H,$ $d_H - k_1b - c_H$

In scenario II, I assume that brand value has a greater impact on a high-end market than a low-end market. Thus, following the same steps, and switching the positions of  $H$  and  $L$  while making the corresponding changes for the payoff matrix. Table b-2 shows the normal-form game for Scenario II.

Note that all the inequality relations in Equations (2.4) to (2.7) still hold. Therefore, all five corresponding propositions can be derived similarly, and the results are just as switching all  $H$  and  $L$  product qualities, and switching the sign of  $\Delta c$  in both the statements and conditions of Propositions 1 to 5. Therefore, those propositions are not stated here. The key insights are as follows: When the monopoly payoffs dominate the duopoly payoffs in both segments, firms try to avoid each other. When firms employ mixed strategies, the greater the effects of brand value on profit shift and/or the smaller the fixed development cost difference between high-end and low-end products, the more likely the low-brand-value firm will play a low-quality strategy with greater probability than the high-brand-value firm. The intuition is that when the high-brand-value firm can go to high-end market with multiple advantages, i.e., the brand value's greater effect on the high-end-market profit than on the low-end-market profit, and product development cost is not much higher than for the low-end market, it is more likely to go to the high-end market, and the low-brand-value firm response by being more likely to go to the low-end market.

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