Blockbuster Products and Brand Value in High-Tech Industries

(Job Market Paper)

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June 29, 2009

Abstract: High-tech industries are characterized by a high frequency of product entry and exit, and the sporadic introduction of some extremely popular products — "blockbuster" products. How much blockbuster products contribute to a firm's brand value is of utmost importance to both business and academia. This 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. I find that the Razr series products contributed about one quarter of Motorola's brand value during the study period, and Razr's premium and halo effects dominate its cannibalization effect. The proposed method allows brand value and halo, cannibalization, and premium effects to be dynamic, suggests and justifies a sale-volume-weighted brand evaluation approach by taking product popularity into account, and provides lower bound "absolute" monetary value estimates for these effects. The estimated monetary brand values are benchmarked using the estimates published by two brand evaluation companies, Interbrand and MillwardBrown. From a methodology perspective, this paper also allows that the "deep," or latent, parameters that 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, the counterfactual estimates will be biased.

Keywords: Halo, Cannibalization, Premium effect, Brand Value, Blockbuster Products, Dynamic, Mobile Phones.

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"To become a blockbuster is to be something consumers want to buy — something that's not just different but also better than anything else in its category, better because it meets heretofore unmet consumer needs." Gary Grossman.[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. Such 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 the 2009 *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 mobile service operators that carry the iPhone, such as AT&T and Vodafone. Interbrand (2006) also highlights the Razr's contribution to Motorola's brand value in its *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 this contribution 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 rest of the firm's products. Both the iPod and iPhone are regarded as having had strong halo effects on Apple's other 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 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 by the two indirect halo and cannibalization effects on a firm's other products, and by the direct premium effect from the

[1] "Blockbuster Products: More Than Mere Functionality," Jun. 25, 2006.
Source: http://chiefmarketer.com/creative/blockbuster_products_06252006/

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 is useful information for managers when they evaluate their product portfolios. Information about these effects is also very valuable in determining the optimal timing for the release of new products, and retirement of existing products, in the portfolio. For example, would Motorola have gained more value if it had introduced the first Razr one 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 the introduction of the Razr a month later have cost? Alternatively, Motorola can utilize the information to check how profits would differ if it would have 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 as well as its 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, and applies 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. Literature 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 three of these. 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. One 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 in 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.

From a methodological perspective, this paper shows that the "deep," or latent, parameters that 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 happened yet, and 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. With the data only after the announcement available, 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. In addition, the proposed method allows brand value and halo, cannibalization, and premium effects to be dynamic, suggests and justifies a sale-volume-weighted brand evaluation approach by taking product popularity into account, i.e., computing the brand effect of a firm as the sales-volume-weighted product-level willingness-to-pay, and provides lower bound "absolute" monetary value estimates for these effects by assuming that any mobile phone model after controlling for product characteristics offers a utility greater than outside option. Finally, the estimated monetary brand values are benchmarked using the estimates published by two brand evaluation companies, Interbrand and MillwardBrown. I normalize the Italian monthly brand value estimates of this paper to match the global annual estimates of Interbrand and MillwardBrown by setting the brand value of the market leader, Nokia, at the same level. The benchmarking results show that the estimates generated using the proposed methodology are consistent with published estimates.

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.

2 Literature review

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).

Meanwhile, 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. There is also a large number of papers that study the halo effect from various perspectives (e.g., Wu and Petroshius 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.[2]

2.2 Cannibalization Effect

The cannibalization effect has been studied intensively in both 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

[2]For example, 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. May. 03, 2005.

(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 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, i.e., 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.

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. What percentage of people that have not used the blockbuster product but think the product is superior to the existing ones is sometimes used in practice as a measure of the premium effect.[3] 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.

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 needs for valuation arises often in mergers and acquisitions. For example, Lenovo bought the PC unit of IBM together with the Thinkpad brand in 2005. In the same year, SBC bought AT&T and later used this brand name to consolidate its other brands, including Cingular. Information about 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 very similar good.

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

[3] 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. May 25, 2007.

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) and Nevo (2000) further advance this approach. 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, brand effects and their corresponding monetary values are taken to be dynamic, that is, varying over time rather than constant. Unlike Aribarg and Arora (2008); Sriram, Chintagunta, and Neelamegham (2006); Sriram and Kalwani (2007a,b); Dubé and Manchanda (2005), who all model dynamic brand effects as an intermediary step in pursuing their research goals, estimating the monthly brand effects and the corresponding monetary values is one of research objectives of the present paper, and the brand values are estimated in terms of total profit equivalence rather than marginal effects. Second, 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. Third, 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).

3 Theoretical Framework

3.1 Utility/Demand Function and Brand Effects

The demand functions are modeled, based on the random-coefficients logit utility function. Among a pool of products, an individual chooses the product providing her with the highest utility. Since consumers make purchasing choices on 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.[4] Therefore, *market* and *time* are exchangeable, as are *brand* and *firm* in this paper. As is typical in this literature, I assume that the utility function for a product as follows:

$$u_{ijt} = \boldsymbol{x_{jt}}\boldsymbol{\theta_i} + \xi_{jt} + \zeta_t + \epsilon_{ijt} \tag{1}$$

where u_{ijt} indicates the utility of individual i who chooses product j at time t, $\boldsymbol{x_{jt}}$ 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, ξ_{jt} is the structural error representing the unobserved consumer's willingness-to-pay for product j at time t, ζ_t is a time fixed effect, and ϵ_{ijt} is an error containing all random shocks and distributed type I extreme value.

The parameters of an individual i's utility function are:

$$\boldsymbol{\theta_i} = \boldsymbol{\bar{\theta}} + \boldsymbol{\Sigma}\, \boldsymbol{\nu_i}, \quad \boldsymbol{\nu_i} \sim N(\boldsymbol{0}, \boldsymbol{I_K}), \tag{2}$$

where $\boldsymbol{\theta_i}$ is a $K \times 1$ vector of parameters, $\boldsymbol{\bar{\theta}}$ is a vector of parameter means, Σ is a $K \times K$ matrix with all non-diagonal elements restricted to zero, and ν_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

[4]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. As 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.

coefficients logit model using "summary variables." I will discuss this approach in Section 5.1.

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

$$u_0 = 0. \tag{3}$$

The parameters of the utility function can be recovered, based on the market level aggregate price and volume in the logit demand setup, and following the Berry et al. (1995) approach. I define the time- (i.e., market-) adjusted willingness-to-pay for product j at time t as the sum of time fixed effect and product specific willingness-to-pay at time t:

$$\lambda_{jt} = \zeta_t + \xi_{jt}. \tag{4}$$

This is reasonable because ζ_t represents the average utility deviation at time t from the average of all of the time fixed effects in the sample, while ξ_{jt} is the utility deviation for product j at time t from the mean willingness-to-pay for all products in the sample at time t. Summing up ζ_t and ξ_{jt} thus gives a measure of the willingness-to-pay deviation for product j at time t from the overall average across all products and time periods.

Under standard assumptions in this literature, conditional on ν_i and integrating out over ϵ_{ijt}, the conditional market share (i.e., the expected probability of individual i choosing product j at time t) is:

$$s_{ijt}(\boldsymbol{x_{jt}}, \boldsymbol{\delta_t}, N(\boldsymbol{0}, \boldsymbol{I_{k_2}}); \boldsymbol{\theta_2}) = \frac{e^{(\delta_{jt}+\mu_{ijt})}}{1 + \sum_{r=1}^{J_t} e^{(\delta_{rt}+\mu_{irt})}}, \tag{5}$$

where $\boldsymbol{\delta_t}$ is a vector of the mean utilities of all products at time t, δ_{jt} is the mean utility, i.e., the linear part of the utility function of product j at time t, including ξ_{jt} and ζ_t, μ_{ijt} is the non-linear part of the utility function, including $\nu_i \sim N(\boldsymbol{0}, \boldsymbol{I_{k_2}})$, $\boldsymbol{\theta_2}$, and part of, if not all of $\boldsymbol{x_{jt}}$, 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 $\boldsymbol{\theta_2}$.[5]

The ξ_{jt}'s, which are of particular interest here, are structural residuals. One challenge that arises in using structural residuals to evaluate brand effects is that every residual is a deviation

[5]See Nevo (2000) for details.

from a mean across all products. This mean is normalized to zero, and therefore, the estimates for brand effects are all relative. Thus, 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 cannot do 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 time-adjusted brand effects, i.e., the sum of the willingness-to-pay for all products including outside option and the time fixed effects, such that the time-adjusted brand effects for any product in any time period is greater than or equal to zero. This normalization is based on the assumption that any mobile phone model or outside good offers consumers positive utilities at any time after controlling for the observed product characteristics. Thus, the grand average of these unobserved utilities are strictly positive. In other words, the econometric model here implicitly normalizes this positive unobserved grand average to zero. I claim that the lower bound of this average can be known because, if we know a positive random variable is randomly moving around its mean, the mean must be greater than or equal to the absolute value of the smallest realization of the deviation.[6] Therefore, the minimum of the realizations of λ_{jt}'s in all markets tells us that the average brand effects should be at least as large as the absolute value of the minimum realization of λ_{jt}. In other words, I can define the lower bound of average time adjusted brand effects at time t as:

$$\underline{\lambda_{jt}} = |\min_{J}\{\lambda_{jt}\}| + \lambda_{jt}, \tag{6}$$

where J is the number of all products in all markets. Correspondingly, the willingness-to-pay for the outside good changes from 0 to $|\min_J\{\lambda_{jt}\}|$.

Adding a constant, in this case $|\min_J\{\lambda_{jt}\}|$, to the linear utility function does not affect the demand function, as the exponentials of the constant in the numerator and denominator cancel out.[7] This transformation keeps all the features of the original model while offering a series of non-negative lower bound values of willingness-to-pay for all products in the sample. From now on,

[6]For example, if we do not know the mean of human height, but know the deviation from this mean for a sample of people, and if we know the smallest realization of this deviation, say, that a baby's height is four feet below the mean, then we know that this mean must be at least four feet.

[7]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.

I work with the "absolute value"[8] of willingness-to-pay rather than the relative values with respect to the industrial average. Correspondingly, Equation (4) can be replaced by the following one:

$$\underline{\lambda_{jt}} = \zeta_t + \underline{\xi_{jt}}, \tag{7}$$

where underlined variables are of lower bound non-negative values.

In each market, the overall effect of brand b on consumers' willingness-to-pay, $\underline{\xi_{bt}}$ is defined as the sales-volume-weighted average of $\underline{\xi_{jt}}$ for all $j \in J_{bt}$, where J_{bt} is the set of all products sold under brand b at time t. Formally,

$$\underline{\xi_{bt}} = \sum_{j \in J_{bt}} \frac{q_{jt}}{\sum_{l \in J_{bt}} q_{lt}} \underline{\xi_{jt}}. \tag{8}$$

It is justified because $\xi_{jt}|(s_{jt}, \boldsymbol{x_j}, P_{jt})$[9], is obtained via the Berry et al. (1995) approach and ξ_{bt} is a function of ξ_{jt} for all $j \in J_{bt}$ conditional on the observed product characteristics $\boldsymbol{x_j}$ and price P_{jt}, i.e., $\xi_{bt} = f(\xi_{jt}|s_{jt}, \boldsymbol{x_j}, P_{jt}) = \sum_{j \in J_{bt}} \frac{s_{jt}}{\sum_{l \in J_{bt}} s_{lt}} f(\xi_{jt}|\boldsymbol{x_j}, P_{jt})$. In the simplest case, we can choose $f(\xi_{jt}|\boldsymbol{x_j}, P_{jt}) = \xi_{jt}$ and obtain Equation 8. This derivation shows that we should take the market share, or sales volumes, into consideration to estimate brand effects by factoring out the probabilistic term — market share. In contrast, the brand dummy approach is an approximation of the proposed method here by assuming an even market shares for all products of a brand in a time period.

Correspondingly, the adjusted brand effect on consumers' willingness-to-pay is:

$$\underline{\lambda_{bt}} = \sum_{j \in J_{bt}} \frac{q_{jt}}{\sum_{l \in J_{bt}} q_{lt}} \underline{\lambda_{jt}}. \tag{9}$$

$\underline{\lambda_{bt}}$ in this framework translates to a willingness-to-pay for brand b at time t. There are two immediate advantages of using $\underline{\lambda_{bt}}$. First, it varies period by period. Second, it assigns different weights to blockbuster products and unpopular products on the basis of their sales volumes, reflecting differential contributions various products make to the brand value of their manufacturer. This

[8]Strictly speaking, the normalized brand effects are still in relative terms. However, they exhibit "absolute value" because the value difference between the actual and counterfactual scenarios are absolute monetary values.

[9]For illustration purpose, I split the matrix of observed product characteristics into two parts: price, P_{jt}, which varies over time and other characteristics $\boldsymbol{x_j}$, which are time invariant. I use P_{jt} to highlight that ξ_{jt} and s_{jt} are not necessarily positively corrected because of the role of price.

is particularly important for the high-tech industries as the risk of developing successful products is high, and as a result, some products are extremely popular and others quickly fade.

In this subsection, I have discussed the modeling for the utility/demand functions, and introduced three key modeling concepts, namely, $\underline{\xi_{jt}}$, $\underline{\xi_{bt}}$ and $\underline{\lambda_{bt}}$: The first one corresponds to the lower bound willingness-to-pay for a product in a market; the second represents the sales-volume-weighted average of product-level willingness-to-pay capturing the corresponding brand-level willingness-to-pay; and the third suggests the sum of time fixed effect and brand-level willingness-to-pay as the time-specific brand effect of a mobile phone manufacturer.

3.2 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 b 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 b at time t is:

$$\Pi_{bt} = \sum_{j \in J_{bt}} (p_{jt} - c_{jt}) \, M_t \, s_{jt} \left(\boldsymbol{x_{2,t}}, \boldsymbol{\delta_t}, N(\boldsymbol{0}, \boldsymbol{I_{k_2}}); \boldsymbol{\theta_2} \right), \tag{10}$$

where p_{jt} is the price for product j at time t, c_{jt} is the marginal cost[10] for product j at time t, and M_t is the size 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 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:

$$s_{jt} \left(\boldsymbol{x_{2,t}}, \boldsymbol{\delta_t}, N(\boldsymbol{0}, \boldsymbol{I_{k_2}}); \boldsymbol{\theta_2} \right) + \sum_{l \in J_{bt}} \frac{\partial s_{lt} \left(\boldsymbol{x_{2,t}}, \boldsymbol{\delta_t}, N(\boldsymbol{0}, \boldsymbol{I_{k_2}}); \boldsymbol{\theta_2} \right)}{\partial p_{jt}} (p_{lt} - c_{lt}) = 0. \tag{11}$$

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

[10] I assume the marginal cost is equal to the variable cost of a product and remains a constant in a given period.

cost is then recovered using price less markup.

3.3 Evaluating Brand and Blockbuster Products' Effects

3.3.1 Brand Value

After estimating the utility/demand functions and recovering marginal costs, I can start to 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.

Formally, I define the counterfactual willingness-to-pay after removing brand effects for product j of brand b at time t as:

$$\underline{\lambda_{jt}^{c}} = \underline{\lambda_{jt}} - \underline{\lambda_{bt}}. \tag{12}$$

By calculating the profit difference for each brand's products in both scenarios, I obtain each brand's contribution to the manufacturer's profitability in each time period under study. These brand values vary period by period, and therefore reflect the dynamics of product quality and brand value. One point worth noticing in Equation (12) is that time fixed effects cancel out in the calculation of the counterfactual scenario. Not only does this reduce computational burden, but it also allows more degrees of freedom in the demand estimation by using demeaned market-level product characteristics rather than time dummy variables.

3.3.2 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 soon took off as 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; they were released in December 2006, the last period of this study. Therefore, I regard 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 the pure halo effect by summing both the net spillover effect and the absolute value of the cannibalization effect, i.e., $(halo - cannibalization) + cannibalization = halo$.

I utilize the fact that some other Motorola products whose lifespans overlap with the release time of the first Razr, Razr v3. Because their 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. Let T_1 denote the total number of pre-Razr periods and T_2 the number of post-Razr periods. I measure 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,

$$\underline{\xi}^{net} = \frac{\sum_{t_2 \in T_2} \underline{\xi_{t_2}}}{T_2} - \frac{\sum_{t_1 \in T_1} \underline{\xi_{t_1}}}{T_1}, \tag{13}$$

where $\xi_{t_{(\cdot)}}$ is the sales-volume-weighted average willingness-to-pay for Motorola's non-Razr phones whose lifespan overlaps the release time of Razr v3 at time $t_{(\cdot)}$.

In the counterfactual scenario, I remove the estimate of this net spillover effect, $\underline{\xi}^{net}$, from all other Motorola's products in the market after the Razr's launch. Motorola's monthly profit differences for non-Razr products between the actual and counterfactual scenarios indicate the monetary values of the Razr' net spillover effect on Motorola's other products in each period.

In another counterfactual simulation, the monetary value of the cannibalization effect can be measured as the profit difference for all Motorola's non-Razr products between the actual scenario and a counterfactual scenario in which all three Razr products are removed and the net spillover effect for all Motorola's non-Razr phones are removed. Given the value estimates of the cannibalization and net spillover effects, I can obtain the monetary value for the pure halo effect.

3.3.3 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 to first 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 effect if the Razrs are just average-quality products.

I calculate the sales-volume-weighted average willingness-to-pay for these products in each time period. Assume that the willingness-to-pay for all Razr products at time t without their premium effects is equal to this weighted average willingness-to-pay for Motorola's other products, $\underline{\xi_t^a}$. Thus, $\underline{\xi_t^a}$ can be calculated as:

$$\underline{\xi_t^a} \quad = \quad \frac{\sum_{lt \in F_t} \left(q_{lt} \, \underline{\xi_{lt}^c} \right)}{\sum_{lt \in F_t} (q_{lt})}, \tag{14}$$

where F_t is the set of all Motorola's non-Razr products at time t. $\underline{\xi_{lt}^c}$ is the counterfactual value of $\underline{\xi_{lt}}$ less the Razr's net spillover effect.

The premium effect for Razr r at time t is the difference between the willingness-to-pay for r and the average willingness-to-pay for Motorola's other products, i.e., $\underline{\xi_{rt}} - \underline{\xi_t^a}$. Given this premium effect measurement, I simulate a counterfactual scenario to calculate the monetary value of the Razr's premium effect as the profit difference for the Razr products between the actual scenario and a counterfactual scenario in which the Razr's premium effect is set to zero.

3.4 Estimation Strategies

There are two major estimation challenges for estimating the demand function. First, adding 59 time dummy variables to the utility function would result in lacking of enough moment conditions. To overcome this challenge, I demean all product characteristics in each time period, a practice that is equivalent to using time dummy variables for consistently estimating the coefficients of independent variables that linearly enter the utility function. Equation (1) then becomes

$$u_{ijt} = \boldsymbol{\tilde{x}_{jt} \theta_i} + \lambda_{jt} + \epsilon_{ijt},$$

where $E(\lambda_{jt}) = E(\xi_{jt} + \zeta_t) = 0$, $\tilde{x}_{jt}$ is the per-period demeaned product characteristics matrix corresponding to $\boldsymbol{x_{jt}}$, and E represents the expected value.

As shown in Equations (12) to (14), the time fixed effects do not affect the results of the brand value computation. To estimate the halo effect, however, the time fixed effects is needed to be removed because some computation is across time, for example, the estimate of the net spillover effect. One of the solutions is to assume that ζ_t as the average of all time-adjusted brand-level willingness-to-pay at time t. Formally,

$$\hat{\zeta}_t = \frac{1}{B_t} \sum_{r \in J_{B_t}} \hat{\lambda}_r, \tag{15}$$

where B_t is the total number of brands at time t, J_{Bt} is the set of all brands at time t, and $\hat{\lambda}_r$ is the estimated brand effect for firm r defined in Equation (8). I assume that the industry average of brand effects at time t is the time fixed effect. This approach can also be understood by normalizing all brand effects on the basis of their industry average in each time period. Then ξ_{jt} can be recovered by

$$\hat{\xi}_{jt} = \hat{\lambda}_{jt} - \hat{\zeta}_t. \tag{16}$$

The second challenge in estimating the demand function is the large number of random coefficients that need to be estimated, and some are discrete. I advance the random coefficients logit model by using some continuous "summary variables" to replace a number of the linear independent variables, which otherwise should be part of nonlinear independent variables in the utility function. Then all the random coefficients for the variables that were summarized can be recovered after the estimation. More details are discussed in Section 5.1 and Appendix.

4 Industry Setting and Data

4.1 Industry Setting

Since the first fully automatic cellular network in the world was launched in 1981, the growth of the mobile phone industry has been accelerating. 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) have undergone numerous technological innovations. They are more user friendly, with better interfaces and handy applications, and are associated with more useful and powerful mobile services. They have transformed from a luxury good 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 a consumer 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%). Italy, with a population of more than 59 million, is the second largest mobile phone market in Europe in sales volume. Its 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,[11] and Blu ceased operation in August 2002. More than 20 different mobile phone manufacturers sell their products in Italy. However, as in most of the world market, the Italian mobile phone market is dominated by six major manufacturers: Nokia, Motorola, Samsung, Sony-Ericsson, Siemens,[12] and LG during the study period of 2002 to 2006. Therefore, in this study, I concentrate on these major mobile phone manufacturers.

4.2 Data

I obtained a five-year panel data set from Jan. 2002 through Dec. 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 the handset models that are not produced by the six major manufacturers because the market shares of the excluded handset models are marginal. Also removed are the handset models with less than 0.1% monthly market shares[13] 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 are left for further study. I define an observation as product-time, i.e., phone-month, and therefore, have a total of 6018 observations.

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

[11] I treat those phones recorded in the dataset as sold by Omnitel as Vodafone's.

[12] Siemens mobile phone division was sold to BenQ. It became BenQ-Siemens, and later went bankrupt.

[13] 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.

there is a camera, how many pixels if there is a camera, whether the model supports GPRS technology, whether it supports mobile Internet (WAP), and whether it has email function, etc. Table 1 presents summary statistics for the handset characteristics. I believe these account for all the most important characteristics of handsets.

[Table 1 here]

Consumer rating scores are from a mobile phone website (www.gsmarena.com) including rating scores of *design* and *feature* for a mobile phone model. These data are useful for keeping 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' judgment on various popular phone models, I am convinced that the data is meaningful because of the large number of people who rate for each product (hundreds of thousands), and the ranking for those products according to the corresponding rating scores are in line with industry experts' judgement.

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.

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 [0, 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 I have two summary variables replacing the nine phone characteristics that would otherwise appear in the non-linear part of the utility functions. Second, this procedure yields a continuous function, which makes maximization much easier.

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

$$\boldsymbol{S_d} = \boldsymbol{X_d \beta_d} + \boldsymbol{e_d} \tag{17}$$

$$\boldsymbol{S_f} = \boldsymbol{X_f \beta_f} + \boldsymbol{e_f} \tag{18}$$

where $\boldsymbol{S_d}$ and $\boldsymbol{S_f}$ represent the design and feature rating scores, respectively, and $\boldsymbol{e_d}$ and $\boldsymbol{e_f}$ are the error vectors. $\boldsymbol{X_d}$ is a matrix of product characteristics that are related to design, including *form, length, height, Internet*, and *connectivity*; $\boldsymbol{X_f}$ is a matrix of product characteristics that are related to feature, including *extra display, width, email, Internet*, and *connectivity. Form* is an index variable describing whether a mobile phone is monoblock (also called candy bar), folded, for instance. *Length* and *height* are self-descriptive regarding design. *Width* is related to feature since it indicates how large the main display is, and *extra display* is also a feature. Whether there is *Internet* function and how many *connectivity* mechanisms affect a mobile phone's design a great deal, and are also features. *Email* is a feature rather than a design element as this functionality has little impact on how a mobile phone looks.

Table 2 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. Both *Internet* and *connectivity* are positively related to both the design and feature rating scores, while *email* and *extra display* are positively related to the feature rating scores.

[Table 2 here]

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 errors, ξ's, which, to econometricians, are unobserved product characteristics, and factor these into their pricing policies. Therefore, prices are correlated with ξ's, and ξ's are correlated with quantities. One solution is to use instrument variables that are correlated with prices but not correlated with ξ'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 only the exogenous product characteristics, which are the first set of the Berry et al. (1995) instruments, as they are sufficient to make the estimation.

The 18 instrumental variables contain all utility/demand function variables except *price* and *extra display*. The latter is replaced with *extra display keyboard*, which is the sum of two dummy variables *extra display* and *extra keyboard*. These two variables contain information related to marginal costs. I also include *standardized size* (cubic root of volume), number of radio frequency *bands*, number of *display colors*, *color display dummy*, *camera dummy*, *camera pixels* and *total networks*, which is the total number of networks/data transmission standards including GSM, CDMA, GPRS, UMTS, etc. It is a more cost-related variable because it indicates the number of chips needed. I also include two interaction terms: *camera dummy*camera pixels*, and *color display dummy*display colors*.

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 because, 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. Meanwhile, I also must take the dynamics of market growth into account.

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 of 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. Since 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 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, and 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 our data set, because its population has been stable, with only minimal increases each year, and 2004 is the midpoint of our 2002 to 2006 data set. Following the 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 the potential Italian buyers replace their mobile phones every two years, I obtain 19,349,186 as the 2006 market size (half of potential buyers), denoted by Q. Then I calculate the outside good volume in each month, denoted by q_0, as follows:

$$q_0 = \frac{Q - \sum_{t=49}^{60} q_t}{12}, \tag{19}$$

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 the industry experts' expectations.

6 Empirical Results

6.1 Utility/Demand Estimation and Goodness of Fit

I estimate the parameters of the utility/demand functions using the efficient GMM (Generalized Method of Moments) estimation with 200 simulated individuals. The results for the utility function estimation in Table 3 are consistent with expectations: parameters for *price*, *length*, and *height* (thinness) have negative signs, while those of *form*, *width*, *extra display*, *email*, *Internet*, and *connectivity* are positive.[14]

[Table 3 here]

The linear price coefficient is -0.9, 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 of the random price coefficient distribution if I assume it is distributed asymptotic normal. In other words, the random price coefficient is distributed as $N(-0.9, 0.36^2)$. 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 4, and details of the recovering process are documented in the Appendix. 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 4 here]

For the goodness of fit, I first run the Hargan-Hansen J test for overidentifying restrictions. Since there are 18 instruments and a total of 14 parameters, the model is overidentified. The J test with an over-identifying statistic of 0.074 cannot reject the null hypothesis that the 18 moment conditions are valid. In-sample predictions of the market shares are illustrated in Figure 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 also compare the models by computing the mean square errors (MSE) of the standard logit model without and with brand dummy variables

[14] The coefficients here are the marginal utility for consumers while those from the "summary variables" 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 their effects to both dependent variables should be the same, but their magnitudes should not be the same because they measure the marginal effect on different dependent variables.

and of random coefficients logit model. The MSE of $1.3866 * 10^{-4}$ for the proposed model is the minimum out of those of the three MSE's, less than $2.2568 * 10^{-4}$ and $2.1733 * 10^{-4}$ for the logit models without and with brand dummy variables, respectively. The J test lends support to the proposed econometric model, and the model comparisons via the MSE indicates that the proposed random coefficients logit model fits the data better than the other two logit models.

6.2 Dynamic Brand Values and their Impact on Other Firms' Profitability

The empirical results for brand effects (i.e., brand-level willingness-to-pay, ξ_{bt}) are based on the estimated product-level willingness-to-pay (i.e., ξ_{jt}'s) of all the products of a given brand from the demand estimation. Table 5 presents the results for the estimated monthly brand monetary values, computed as the profit difference between the actual and counterfactual scenarios, for all six mobile phone manufacturers. During the five-year period in Italy, the average monthly brand monetary value of Nokia is EUR 34.61 million, far ahead of that of the rest mobile phone manufacturers, followed by Samsung, EUR 16.03 million, and Motorola, EUR 15.5 million. The fourth is LG, with an average monthly brand value of EUR 8.1 million, followed by Siemens with EUR 6.27 million. Sony-Ericsson's average monthly brand value is EUR 3.61 million.

[Table 5 here]

[Table 6 here]

Table 6 exhibits the average effects of one manufacturer's loss in brand value on other firm's profitability in competition. Comparing the numbers across Table 6a to 6e, I can generate insights on the relative strength of firms' product portfolios in the competition by identifying which firm would benefit more from which firm's loss in brand value. I identify two interesting points: First, Samsung and Motorola are nearly symmetric in their brand values and responses to other firms' loss in brand value. For example, if Nokia lost brand value, Samsung and Motorola each would gain on average EUR 9.8 million and EUR 9.2 million per month, respectively. Second, concerning the competition between Samsung and Motorola, Samsung would gain EUR 4.27 million from Motorola's loss in brand value, while Motorola could only gain EUR 2.32 million from Samsung's loss in brand value. Actually, the market leader, Nokia, also gains much more from Motorola's loss in brand value than from Samsung's. One insight from this analysis is that Samsung's product portfolio is stronger than Motorola's. That a firm loses its brand value and others do not gain much from it indicates that the firm's product characteristics offers so much consumer utility that a loss in brand value does not disable much of the firm's competitiveness.

[Figure 2 here]

Since brand values change over time, I examine the dynamics of brand values, and their effects on other firms' profitability in competition. Figure 2 illustrates this dynamic for each of the six scenarios. Because the figures show the profit loss for the firm that loses its brand value, the negative profit loss curve (the thicker line in each sub-figure) represents a positive brand value for that firm; that is, a negative profit change from brand value loss represents a positive equivalent amount of worth of brand value. Nokia's brand value is the most stable. Motorola's brand value increases gradually from the period 34, when the Razr was first released, and maintains a growing trend at least until period 60. Samsung exhibits an increasing trend in its brand value over time. LG's brand value increases dramatically in 2006. Sony-Ericsson increases, then decreases in its brand value. Siemens reaches its highest brand value in 2004, and during the remaining years its brand value decreases dramatically. The lowest range during year 2006 represents the brand effect of BenQ-Siemens. All these findings lend support to observations in the industry, to date.

6.3 Comparing Two Brand Effect Estimation Methods

In this subsection, I highlight the advantage of the proposed method in reflecting the dynamics of brand values by comparing it to an approach that is theoretically identical to the brand dummy approach. The method 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 all firms and their estimated brand values are constants. Brand managers may want to examine their firm's brand value on a quarterly or semiannually basis; the brand evaluation method in this paper offers managers such flexibility. Moreover, in theory, methods that take product popularity into account should produce results much closer to reality than those that do not. For example, if a firm has n products with one blockbuster product sales volume in the millions while another product sales volumes are marginal, the brand value of this firm should be high, while a brand evaluation method that assigns equal weight to all n products would obtain a low brand value for the firm.

Next, I focus on a comparison of the proposed method — a sales-volume-weighted average of a brand's corresponding ξ_{jt}'s — to a "total average approach," averaging across all products of a brand across all periods. In theory, the total average approach is identical to the brand dummy variable approach, and in practice, is analogous to it.[15] Formally,

$$\xi_b = \frac{1}{n_b} \sum_{r \in J_b} \xi_r, \tag{20}$$

where J_b is the set for all products of brand b across all time periods in the sample, and n_b is the number of products in set J_b.

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 currently 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 fast market size growth, this method becomes inappropriate.

The difference between these two methods are shown in Figure 3a and 3b. The first figure shows the brand effects obtained using the total average/brand dummy approach. The second represents the results obtained via the sales-volume-weighted average approach. The figures exhibit a clear difference between a static Figure 3a and dynamic Figure 3b — the brand effects of Motorola and Samsung, for example, are almost identical in the Figure 3a, but differ in various periods in Figure 3b.

[Figure 3 here]

As illustrated, Motorola's brand effects (the thicker curve) in Figure 3b show a downward trend through about period 34, followed by an upward trend all the way to period 60. This trend

[15] In theory, if brand dummy variables are strictly independent of product characteristics, then the brand effects estimated by the brand dummy variable approach and the total average approach are the same. However, in practice, brand dummy variables are at least correlated with product characteristics to a certain extent, then with or without brand dummy variables in a model will affect the estimated values of the coefficients of product characteristics. In such cases, the total average approach is not identical to the brand dummy approach. Nevertheless, the estimated brand effects of both approaches share the same characteristics.

is consistent with our expectation because the first Razr was released in October 2004, which corresponds to period 34 in the graph. Since then, Motorola benefits greatly from both the Razr's halo and premium effects, and its brand value steadily increases through the end of 2006.

6.4 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, but effects for Motorola products launched after the Razr v3 release remain unknown. Assuming the post-release products have the same net spillover effect as the 18 products, I obtain the value of the cannibalization effect by computing 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 plus that of the cannibalization effect.

[Table 7 here]

Two effects, as shown in Table 7a, the net spillover effect (0.2656) and premium effect (1.2905) are estimated first, 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 Figure 4; the dynamics of the premium effect and the corresponding monetary value are shown in Figure 5.

The simulation results in Table 7b indicate that the average monetary value for Razr's net spillover effect is EUR 2.90 million with a standard error of EUR 1.20 million; the value for the cannibalization effect is EUR -0.27 million with a standard error of EUR 0.24 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 3.17 with a standard error of EUR 1.08 million. The value of the premium effect is EUR 1.16 million, with a standard error of EUR 0.54 million. Table 7c summarizes the average contribution of each effect on Motorola's brand value. Overall, the value of the halo effect accounts for the biggest contribution (20.45%) to the brand value of Motorola, the value of the premium effect is 7.47%, and the absolute value of the cannibalization effect accounts for only 1.76%. In other words, the cannibalization effect is clearly dominated by the halo and premium effects. This finding sheds lights on the puzzle of which effect is more dominant in the mobile phone industry. It also offers managerial clues on high-tech firms' product line design and marketing strategies in that the cannibalization effect of blockbuster products is marginal, especially when there are many products in a market.

[Figure 4 here]

[Figure 5 here]

To explore the proposed method and generate more managerial insights, I investigate the dynamics of these effects for the Razr products, since 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 have more and more Razr series that are developed and launched?

As illustrated in Figure 5c, comparing the the halo effect of the Razr before and after period 48, i.e., when only the first Razr exists and when the three Razrs coexist, I find that the halo effect does not increase or even slightly fall over time. In other words, the number of products from the same theme does not boost the halo effect. This is intuitive because all Razr products share the same attractive features/themes that create such a halo effect. However, the value of the cannibalization effect does increase dramatically when there are two more Razrs in the market. That means when more blockbuster products sharing the similar features are developed and launched to a market, the total cannibalization effect increases with the number of blockbuster products, while the halo effect remains the same or decays slightly over time regardless of the number of these products. To managers, this finding implies that product line extension to a blockbuster product should be controlled at an optimal level.

6.5 Benchmarking Long-term Brand Values

The six mobile phone manufacturers in this study are among the most valued brands in the world. One advantage of estimating their brand values is that, in addition to the econometric model comparison, it is possible to examine the validity of the method by benchmarking the estimates in this paper to some of the most commonly applied brand value estimates in the industry. I use the estimates from two brand evaluation companies, Interbrand and MillwardBrown. Since the data covers a period from 2002 to 2006, to estimate the brand values for the six mobile phone manufacturers in 2007, I compare the estimates of this paper with the 2007 brand values of the two evaluation companies.

To achieve this goal, I need to convert the Italian market-specific brand values to their corresponding brand values in the world markets, because the estimates of this paper are the brand values of the manufacturers in Italy, whereas those of Interbrand and MillwardBrown are the global brand values. An ideal approach is to calculate the weight of the Italian market in the world market, involve the exchange rate of different currencies in different periods, and address the strengths of the six mobile phone manufacturers presenting in different markets in the world. However, along each step, there would be more errors, or noise, built into the process and eventually the results may be far from reality, especially when the goal here is to benchmark the results, not to estimate the global brand values for these firms. Therefore, a straightforward approach is to normalize the estimates of this paper to match the brand value estimates of Interbrand and MillwardBrown by first obtaining a multiplier, calculated as the ratio of the long-term brand value estimates of Interbrand and MillwardBrown to the monthly average brand value estimates of this study, and then using this factor to multiply all the estimates to scale them on the Interbrand and MillwardBrown scale. By calculating this multiplier, I skip the brand evaluation processes of Interbrand and MillwardBrown and put the three sets of measurements on the same scale for benchmarking purposes.

I calculate this multiplier using Nokia's brand value estimates because it is the highest one among the six, and its measures from both Interbrand and MillwardBrown are the closest: Interbrand's USD 33,696 million vs. MillwardBrown's USD 31,670 million. I take an average of these two, divide this value of USD 32,683 million by our average monthly Nokia brand value estimate, EUR 33.32 million, to obtain a factor of 980.76.

[Table 8 here]

[Table 9 here]

Table 8 shows that most of the estimates in this paper are consistent with Interbrand and MillwardBrown. Since the Nokia brand value estimate in this paper is normalized to match the average of those by Interbrand and MillwardBrown, all three estimated Nokia brand values are close. The interesting comparison is for the other five firms. All long-term brand value estimates for

Samsung, Siemens, and Sony-Ericsson are similar: The Samsung brand value estimate of USD 15.35 billion is higher than MillwardBrown's USD 12.74 billion, but less than Interbrand's USD 16.85 billion; for Siemens, the estimate of USD 5.86 billion is not much less than Interbrand's USD 7.74 billion and MillwardBrown's USD 9.11 billion. Because Sony-Ericsson falls out of the list of the top 100 highest-brand-value firms of either Interbrand or MillwardBrown, their estimates are unknown. However, their value range is known by checking the brand values for the last, i.e., the 100th firm, in the lists of Interbrand and MillwardBrown. The information reveals that Interbrand's Sony-Ericsson brand value estimate is less than USD 3.03 billion, and that MillwardBrown's estimate is less than 5.39 billion. The estimate of USD 3.44 billion in this paper is slightly more than Interbrand's higher bound value, while in the range of MillwardBrown's, and all three brand value estimates are within reasonable range of each other.

The brand value estimates of LG and Motorola in this paper deviate farthest from the figures of Interbrand and MillwardBrown. For LG, the estimation results indicate that the LG brand effects shift dramatically upwards from mid-2004 onwards, and the data shows that there is a sudden increase in the number of LG mobile phones in Italy from June 2004. This abrupt brand value jump is due to one blockbuster product of LG. It may be another interesting story; however, I focus on the Razr products and Motorola in the empirical part of this paper.

The difference between the estimates here and those of Interbrand and MillwardBrown highlights the role of the Razr in Motorola's brand value. Recall that estimates in this paper are made under the assumption that blockbuster products continued to be blockbusters into year 2007. In reality, this assumption is false because the Razr faded around the end of 2006, and Motorola did not have similar blockbuster products to replace it. Therefore, I recalculate Motorola's average monthly brand value by subtracting the values of the Razr's net spillover effect and adding the absolute value of the cannibalization effect as the adjusted average monthly brand value, and apply the same multiplier as before to scale it to match the brand value estimates of Interbrand and MillwardBrown. Then I obtain the updated 2007 Motorola's brand value — USD 10.58 billion. This estimate is just slightly less than MillwardBrown's USD 10.79 billion. Therefore, in this particular case, the estimate in this paper lends more support to MillwardBrown's estimate than Interbrand's.

I want to conclude this section with one of the best descriptions of Razr's roles in Motorola: "In recent years, it (Motorola) has enjoyed success with one-off products, but has failed to develop a pipeline of exciting replacement products to maintain upward momentum. The Razr, for example, was highly successful at launch and significantly raised the profile of the brand. However, the company failed to launch any blockbuster handsets before the Razr approached the end of its lifecycle" (Interbrand 2007, p.38). While Interbrand descriptively states the importance of the Razr to Motorola's brand value, I pinpoint the monetary value of its importance and investigate its dynamics for its three effects.

7 Concluding Remarks

This paper proposes a structural approach to estimate the monetary values of blockbuster products' halo, cannibalization, and premium effects, and advance, especially for high-tech industries, 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. The brand value estimates are benchmarked against those of Interbrand and MillwardBrown, and the results are consistent with these expectations-based estimates. The empirical results show that blockbuster products are very important to a manufacturer's brand value. In the case of the Razr, this product series contributes approximately one quarter of Motorola's brand value from October 2004 to December 2006.

For advancing the "profit difference" brand evaluation methods of the literature, important differences between the proposed approach and current brand evaluation methods include the fact that the brand effects and the corresponding brand values are dynamic in the current paper rather than static. Thus the proposed approach enables investigation of how brand values change over time, and how blockbuster products affect brand values, neither of which are possible under the brand dummy variable approach. The proposed method also considers the weight of market shares in the modeling 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 an absolute (lower bound) monetary brand value, rather than an index or a relative value compared to an industrial average. Finally, one of the innovations of this paper — the "summary variable" approach — enables estimating the random coefficients logit model in a more parsimonious manner with less computational burden.

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 with decisions about how much they should spend to develop more blockbuster products, especially in a high-tech industry like the mobile phone industry where the number of products in a market is large. Second, the results indicate that increasing the number of blockbuster products sharing the same theme or similar key features does not increase the halo effect but does increase the cannibalization effect. This suggests important tradeoffs in developing the blockbuster product line. Third, the analysis of brand value reveals the quality of the firms' product portfolios. For example, the brand values of both Samsung and Motorola are close to one another. However, the results showed that Samsung would gain much more from Motorola's brand value loss than Motorola would gain from Samsung's brand value loss. This indicates that Samsung's overall product portfolio quality offered consumers more utility than Motorola's. Knowing this can help firms better understand the strengths and weaknesses of not only their brands but also product portfolio, and serve as an important input to their strategy and product portfolio management.

The proposed method can be extended, in future work, in several ways. First, since the brand value is dynamic and can vary over a short period of time — e.g. monthly as in this paper — we 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, we 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 with fierce competition. Therefore, these industries may provide enough variation for researchers to test this hypothesis. Second, 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, we have neglected some important aspects of the relationships among these variables in both theory and empirical analyses, and as a result, existing empirical results describing the relationships among these factors might be biased.

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Appendix

Derivation for "Summary" Variables

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

$$y_j = \boldsymbol{z_j \beta} + u_j, \tag{21}$$

where y_j is a summary variable, $\boldsymbol{z_j}$ is a $1 \times k$ row vector of product characteristics, $\boldsymbol{\beta}$ is a corresponding column vector of parameters, $(\beta^1_{1,z}\ \beta^2_{1,z} \ldots \beta^k_{1,z})$, and u_j is an error.

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

$$\ln(u_{ijt}) = [\boldsymbol{\tilde{w}_{jt}}\ \ \boldsymbol{\tilde{z}_{jt}}] \begin{bmatrix} \boldsymbol{\theta_{1,w}} \\ \boldsymbol{\theta_{1,z}} \end{bmatrix} + ([\boldsymbol{\tilde{w}_{jt}}\ \ \tilde{\hat{y}}_{jt}] \odot [\boldsymbol{\nu_{w,i}}\ \ \nu_{y,i}]) \begin{bmatrix} \boldsymbol{\theta_{2,w}} \\ \theta_{2,y} \end{bmatrix} + \lambda_{jt} + \epsilon_{ijt}, \tag{22}$$

where $\boldsymbol{\tilde{w}_{jt}}$ is a row vector of per-period demeaned product characteristics that enters both the linear and nonlinear parts of the utility function; $\boldsymbol{\tilde{z}_{jt}}$ is the per-period demeaned $\boldsymbol{z_j}$, i.e., $\tilde{z}_{jt} = [\tilde{z}^1_{jt}\ \tilde{z}^2_{jt} \ldots \tilde{z}^k_{jt}]$; $\boldsymbol{\theta_{1,w}}$ and $\boldsymbol{\theta_{1,z}}$ are the vectors of parameters for $\boldsymbol{\tilde{w}_{jt}}$ and $\boldsymbol{\tilde{z}_{jt}}$, 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 $\boldsymbol{\tilde{w}_{jt}}$; $\nu_{y,i}$ is the corresponding shock to $\tilde{\hat{y}}_{jt}$; $\theta_{2,y}$ is the parameter for $\nu_{y,i} * \tilde{\hat{y}}_{jt}$; and $\nu_{y,i}$, $\tilde{\hat{y}}_{jt}$, and $\theta_{2,y}$ are scalers.

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

$$f(\boldsymbol{\tilde{z}_{jt}}) = \boldsymbol{\tilde{z}_{jt}\theta_{1,z}} + (\tilde{\hat{y}}_{jt}\theta_{2,y})\nu_{y,i}, \tag{23}$$

and we know:

$$\tilde{\hat{y}}_{jt} = \boldsymbol{\tilde{z}_{jt}\beta}. \tag{24}$$

Therefore, we can input Equation (25) into (24) to obtain:

$$
\begin{aligned}
f(\tilde{\boldsymbol{z}}_{\boldsymbol{jt}}) &= (\tilde{z}^1_{jt}\theta^1_{1,z} + \tilde{z}^2_{jt}\theta^2_{1,z} + \ldots + \tilde{z}^k_{jt}\theta^k_{1,z}) + [(\tilde{z}^1_{jt}\beta^1_{1,z} + \tilde{z}^2_{jt}\beta^2_{1,z} + \ldots + \tilde{z}^k_{jt}\beta^k_{1,z})\theta_{2,y}]\nu_{y,i} \\
&= [\theta^1_{1,z} + (\beta^1_{1,z}\theta_{2,y})\nu_{y,i}]\tilde{z}^1_{jt} + [\theta^2_{1,z} + (\beta^2_{1,z}\theta_{2,y})\nu_{y,i}]\tilde{z}^2_{jt} + \ldots \\
&+ \ [\theta^k_{1,z} + (\beta^k_{1,z}\theta_{2,y})\nu^k_{y,i}]\tilde{z}^k_{jt}. \qquad (25)
\end{aligned}
$$

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

Recovering Σ from the Coefficients of $\widehat{S_d}$ and $\widehat{S_f}$

The coefficients of the fitted values of *design* and *feature*, i.e., 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 $price * \nu^p_i$ is clear — it represents the standard error of the random price coefficient of the utility function if we 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 (17) and (18), and the estimation in Section 5.1 (Table 2), we can obtain the following equations:

$$
\begin{aligned}
\widehat{S_d} &= 11.744 + 0.19 * form - 0.768 * ln(length) - 0.378 * ln(height) \\
&\quad +0.346 * Internet + 0.157 * connectivity, \qquad (26) \\
\widehat{S_f} &= 3.512 + 0.155 * extradisplay + 0.852 * ln(width) + 0.137 * email \\
&\quad +0.448 * Internet + 0.297 * connectivity. \qquad (27)
\end{aligned}
$$

By following Equation (2) in Section 3.1, and the estimation in Section 6.1 (Table 3), we input equations (27) and (28) above into (2) for $\widehat{S_d}$ and $\widehat{S_f}$:

$$\begin{aligned} 0.38 * \widehat{S_d} &= 0.38 * [11.744 + 0.19 * form - 0.768 * ln(length) - 0.378 * ln(height) \\ &\quad +0.346 * Internet + 0.157 * connectivity] \\ &= 4.463 + 0.072 * form - 0.292 * ln(length) - 0.144 * ln(height) \\ &\quad +0.131 * Internet + 0.060 * connectivity], \end{aligned} \tag{28}$$

$$\begin{aligned} 0.47 * \widehat{S_f} &= 0.47 * [3.512 + 0.155 * extradisplay + 0.852 * ln(width) \\ &\quad +0.137 * email + 0.448 * Internet + 0.297 * connectivity] \\ &= 1.651 + 0.073 * extradisplay + 0.400 * ln(width) \\ &\quad +0.064 * email + 0.211 * Internet + 0.140 * connectivity. \end{aligned} \tag{29}$$

Then we can obtain the equation for the nonlinear part of the utility function, μ_{ijt}:

$$\begin{aligned} \mu_{ijt} &= -1.76 * \nu_i + 0.36 * price * \nu_i^p + 0.38 * \widehat{S_d} * \nu_i^d + 0.47 * \widehat{S_f} * \nu_i^f \\ &= (-1.76 * \nu_i + 4.463 * \nu_i^d + 1.65 * \nu_i^f) + 0.36 * price * \nu_i^p + 0.072 * form * \nu_i^d \\ &\quad +0.073 * extradisplay * \nu_i^f - 0.292 * ln(length) * \nu_i^d + 0.400 * ln(width) * \nu_i^f \\ &\quad -0.144 * ln(height) * \nu_i^d + 0.064 * email * \nu_i^f + (0.131 * \nu_i^d + 0.211 * \nu_i^f) * Internet \\ &\quad +(0.060 * \nu_i^d + 0.140 * \nu_i^f) * connectivity, \end{aligned} \tag{30}$$

where ν_i^p, ν_i^d, and ν_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 (31) need further derivation for a clear interpretation. They are the coefficients for the intercept, *Internet*, and *connectivity* of the utility function. Let us denote them by α_1, α_2 and α_3, respectively. Their variances are

$$\begin{aligned} Var(\alpha_1) &= Var(-1.76 * \nu_i + 4.463 * \nu_i^p + 1.65 * \nu_i^f) \\ &= 3.098 + 19.918 + 2.723 = 25.738, \quad (31) \\ Var(\alpha_2) &= Var(0.131 * \nu_i^d + 0.211 * \nu_i^f) \\ &= 0.017 + 0.045 = 0.062, \quad (32) \\ Var(\alpha_3) &= Var(0.060 * \nu_i^d + 0.140 * \nu_i^f) \\ &= 0.0036 + 0.0196 = 0.023. \quad (33) \end{aligned}$$

Since we know that if the random coefficient of individual i for product characteristic k is $\theta_{ik} = \overline{\theta}_k + \alpha_{ik}$, where $\alpha_{ik} \sim N(0, \sigma^2)$, then $\theta_{ik} = \overline{\theta}_k + \sigma_{ik} * \tau_{ik}$, where $\tau_{ik} \sim N(0,1)$, i.e., the standard error of the random coefficient θ_{ik} is σ_{ik}. Therefore, we can take the square root of the three variances above and obtain the corresponding σ's, except for the coefficient of the *minor* dummy variable, which is not of interest to us and, therefore, not summarized earlier. The standard errors for the random intercept, $Internet$, and *connectivity* are 5.073, 0.248, and 0.152, respectively. Thus far, we have recovered all the σ's that are of interest[16] for the linear parameters of the utility function in Equation (1). Results are presented in Table 4.

[16] All non-diagonal elements were restricted to be zero. So is the σ for the *Minor* dummy variable.

Table 1a. Summary Statistics of Mobile Phone Characteristics

Variable	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	mm
Height	479	21.23	5.31	6.9	110	mm
Email	479	0.46	0.5	0	1	Dummy
Internet	479	0.88	0.32	0	1	Dummy
Connectivity	479	0.79	0.71	0	3	Index
Infred	479	0.41	0.49	0	1	Dummy
Bluetooth	479	0.37	0.48	0	1	Dummy
Wlan	479	0.01	0.11	0	1	Dummy
Extra display keyboard	479	0.37	0.49	0	2	Index
Extra display	479	0.34	0.47	0	1	Dummy
Full keyboard	479	0.03	0.16	0	1	Dummy
Size volume	479	0.99	0.34	0.39	0.56	100,000 cubic mm
Color display	479	0.77	0.42	0	1	Dummy
Display colors	479	1.66	1.08	0.00004	168	100,000 colors
Camera	479	0.54	0.5	0	1	Dummy
Camera pixels	479	0.47	0.68	0	3.15	million pixels
Bands	479	2.9	1	1	8	Index
Total networks	479	2.07	0.98	0	6	Index
Minor	479			0	1	Dummy
Table 1b. Summary Statistics of Design and Feature Scores						
Design score	470	7.81	0.56	5.2	9	Index
Feature score	470	7.53	0.66	4.9	8.6	Index
Table 1c. Summary Statistics of Mobile Phone Sales in Italy 2002-2006						
Price	6018	219.04	134.6	50	916	Euros
Volume	6018	8367.31	14348.19	393	248,637	Unit
No. of products of all firms in each time/market	60	129.97	21.07	91	167	Unit
No. of products of a firm in a time/market	360	21.66	11.34	1	52	Unit
Total No. of products of a firm	6	79.8	29.25	44	120	Unit

Table 2: Estimated Parameters of Design and Feature Score Functions

	Design		Feature	
	Coeff.	S.E.	Coeff.	S.E.
Constant	11.744	1.094	3.512	1.292
Form	0.19	0.042		
Extra display			0.155	0.055
Ln(length)	-0.768	0.216		
Ln(width)			0.852	0.337
Ln(height)	-0.378	0.115		
Email			0.137	0.062
Internet	0.346	0.075	0.448	0.085
Connectivity	0.157	0.034	0.297	0.044
R-squared	0.2697		0.3277	
Adj R-squared	0.2619		0.3205	
F(5, 464)	34.28		45.24	
No. of Obs.	470		470	

Note: All p-values are less than 0.01.

Table 3. GMM Estimation Results with Various Outside Good Volumes

	1st Stage GMM		2nd Stage GMM	
	Coeff.	S. E.	Coeff.	S. E.
Price			-0.90	0.0821***
Form			0.06	0.0680
Extra display			0.04	0.0584
Ln(length)			-1.90	0.2572***
Ln(width)			3.21	0.2961***
Ln(height)			-0.71	0.1147***
Email			0.45	0.0456***
Internet			0.06	0.1728
Connectivity			0.21	0.0770***
Minor Dummy			-0.36	0.0521***
v	-1.80	0.0705	-1.76	5.0977
price $*v^p$	0.45	0.0017	0.36	0.1167***
design_hat* v^d	0.40	0.0043	0.38	0.2937
feature_hat*v^f	0.47	0.0031	0.47	0.2219**
GMM Objective	1,130.53		690.02	

Note: ***, **, and * indicate that the p-value is less than 0.01, 0.05, and 0.10, respectively.

Table 4. The Means and Standard Errors of Random Coefficient Distributions

	Mean	S. E.
Intercept	0	5.073
Price	-0.90	0.360
Form	0.06	0.072
Extra display	0.04	0.073
Ln(length)	-1.90	0.292
Ln(width)	3.21	0.400
Ln(height)	-0.71	0.144
Email	0.45	0.064
Internet	0.06	0.248
Connectivity	0.21	0.152

Note: The measurement unit is the same as in Table 1.

Table 5. The Monthly Brand Values for All Six Manufacturers in the Italian Market, Million EUR

	Mean	S. E.	Min.	Max.
LG	7.69	7.84	0.20	33.31
Motorola	14.85	5.77	6.12	36.01
Nokia	33.32	8.56	20.14	65.55
Samsung	15.35	6.59	4.57	38.95
Siemens	5.97	3.92	0.69	17.89
Sony-Ericsson	3.44	2.47	0.22	16.49

Note: The observation number is 60 (time periods) for each manufacturer.

Table 6a. The Monthly Profit Changes When LG's Brand Value Is Removed (Million EUR)

	Mean	S. E.	Min.	Max.
LG				
Motorola	1.89	2.24	0.03	9.85
Nokia	3.67	3.79	0.06	15.42
Samsung	1.98	2.33	0.02	9.92
Siemens	0.43	0.53	0.02	2.29
Sony-Ericsson	0.46	0.65	0.00	2.94

Table 6b. The Monthly Profit Changes When Motorola's Brand Value Is Removed (Million EUR)

	Mean	S. E.	Min.	Max.
LG	2.00	2.03	0.07	10.09
Motorola				
Nokia	8.76	3.76	4.10	27.47
Samsung	4.04	2.33	1.53	14.29
Siemens	1.47	1.01	0.24	4.09
Sony-Ericsson	0.85	0.65	0.07	5.02

Table 6c. The Monthly Profit Changes When Nokia's Brand Value Is Removed (Million EUR)

	Mean	S. E.	Min.	Max.
LG	4.03	3.45	0.15	14.17
Motorola	8.73	3.11	4.37	17.15
Nokia				
Samsung	9.29	3.92	1.96	21.06
Siemens	3.80	2.93	0.38	14.18
Sony-Ericsson	2.12	1.32	0.18	7.06

Table 6d. The Monthly Profit Changes When Samsung's Brand Value Is Removed (Million EUR)

	Mean	S. E.	Min.	Max.
LG	1.15	1.21	0.02	6.48
Motorola	2.21	1.08	0.81	5.73
Nokia	5.32	2.35	1.50	12.79
Samsung				
Siemens	0.88	0.69	0.09	3.56
Sony-Ericsson	0.54	0.33	0.03	1.74

Table 6e. The Monthly Profit Changes When Sony-Ericsson's Brand Value Is Removed (Million EUR)

	Mean	S. E.	Min.	Max.
LG	0.60	0.61	0.05	2.91
Motorola	1.74	1.22	0.42	5.01
Nokia	4.11	2.77	0.62	10.80
Samsung	1.66	1.00	0.34	4.35
Siemens				
Sony-Ericsson	0.41	0.34	0.04	1.43

Table 6f. The Monthly Profit Changes When Siemens' Brand Value Is Removed (Million EUR)

	Mean	S. E.	Min.	Max.
LG	0.35	0.57	0.00	3.68
Motorola	0.54	0.51	0.02	3.92
Nokia	1.27	0.84	0.06	5.40
Samsung	0.58	0.42	0.02	2.65
Siemens	0.24	0.24	0.01	1.10
Sony-Ericsson				

Note: The observation number is 60 (time periods) for each manufacturer.

Table 7a. The Measure of the Razr's Halo, Premium, and Cannibalization Effects

	Mean	S. E.	Min.	Max
Net Spillover Effect	0.2656			
Premium Effect	1.2905	0.6716	-1.4098	1.8422

Note: The Net Spillover Effect is calculated as a difference between a mean of 27 observations (period 34 to 60) and a mean of 22 observations (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.

Table 7b. The Values of the Razr's Halo, Premium, and Cannibalization Effects, Million Euro

	Mean	S. E.	Min.	Max
Value of Net Spillover Effect	2.8964	1.2048	1.4437	6.7350
Value of Premium Effect	1.1582	0.5443	0.2958	2.2399
Value of Cannibalization Effect	-0.2732	0.2440	-0.9160	-0.0175
Value of Halo Effect	3.1696	1.0846	1.7070	6.8018

Note: The observation number is 27, from period 34 to 60.

Table 7c. The Contribution of the Razr's Effects to Motorola's Brand Value

	Monthly Monetary Value in Italy, Million EUR	Contribution to Motorola's Unadjusted Brand Value
Value of Halo	3.1696	20.45%
Value of Premium	1.1582	7.47%
Value of Cannibalization	-0.2732	-1.76%

Note: The contribution is calculated as a percentage of the effect value over brand value.

Table 8. Long-Term Brand Evaluation Results and Comparison among Different Approaches

Estimates of This Paper			**Benchmarking Estimates**	
Firms	Monthly Brand Value in Italy, Million EUR	Global Brand Value (GBV), Million USD	Interbrand's Global Brand Value (GBV), Million USD	MillwardBrown's Global Brand Value (GBV), Million USD
LG	7.694	7,546	3,100	<5,387
Motorola (unadjusted)	14.847	14,561	4,149	10,787
Motorola (adjusted)	10.79	10,584	4,149	10,787
Nokia	33.324	32,683	33,696	31,670
Samsung	15.348	15,052	16,853	12,742
Siemens	5.973	5,858	7,737	9,111
Sony-Ericsson	3.444	3,378	<3,026	<5,387

Note: 1) Interbrand's 100th brand is Hertz with a brand value of USD 3,026 million, while MillwardBrown' 100th brand is Rolex with a brand value of USD 5,387 million.
2) For Motorola, "unadjusted" refers to the brand value estimates of this paper that are unadjusted for the Razr fade out at the end of 2006, and "adjusted" refers to those adjusted for this fact.
3) The multiplier is 980.76.

Figure 1. The Actual and In-Sample Fitted Market Shares for All Six Brands

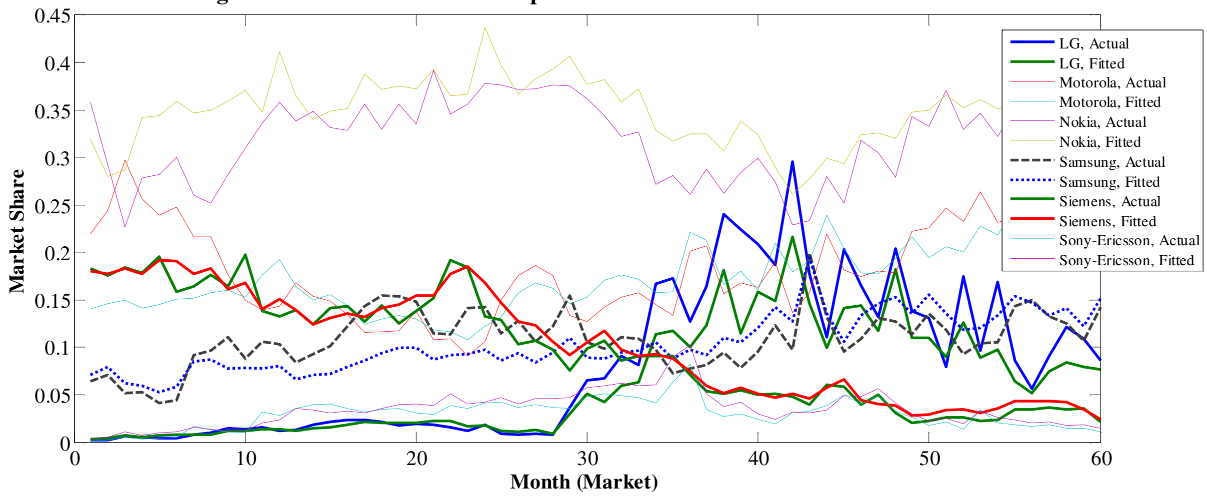

Figure 2a. Profit Changes of All Brands When LG Brand Effects Are Removed

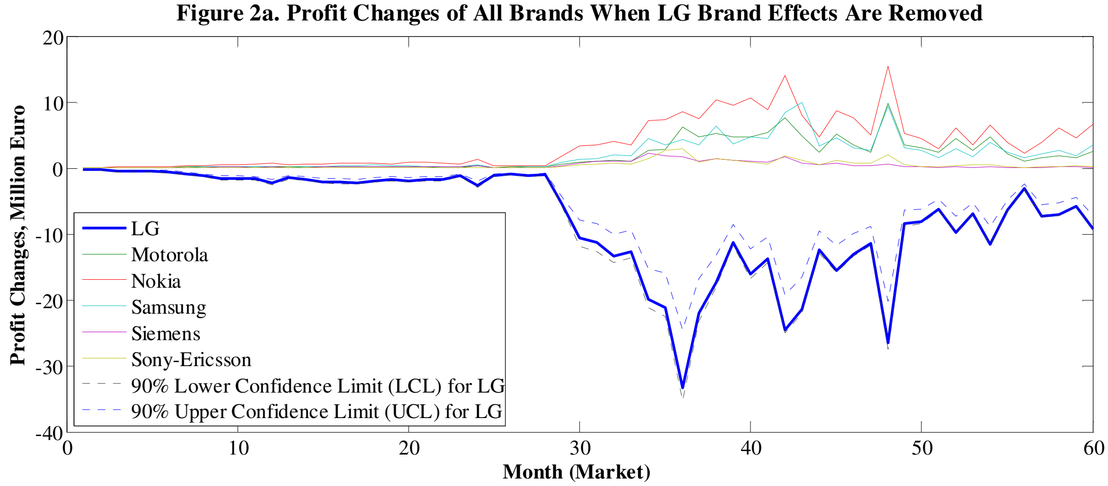

Figure 2b. Profit Changes of All Brands When Motorola Brand Effects Are Removed

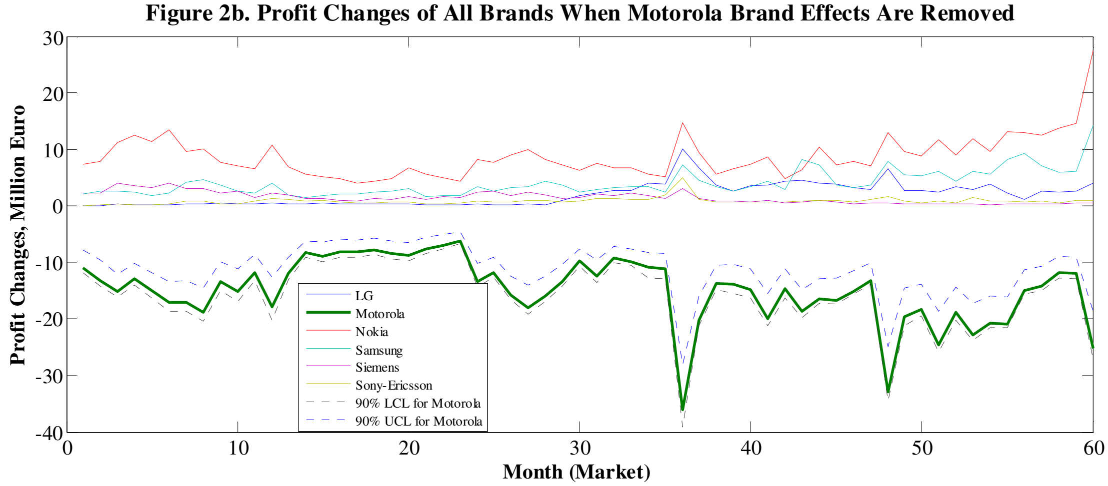

Figure 2c. Profit Changes of All Brands When Nokia Brand Effects Are Removed

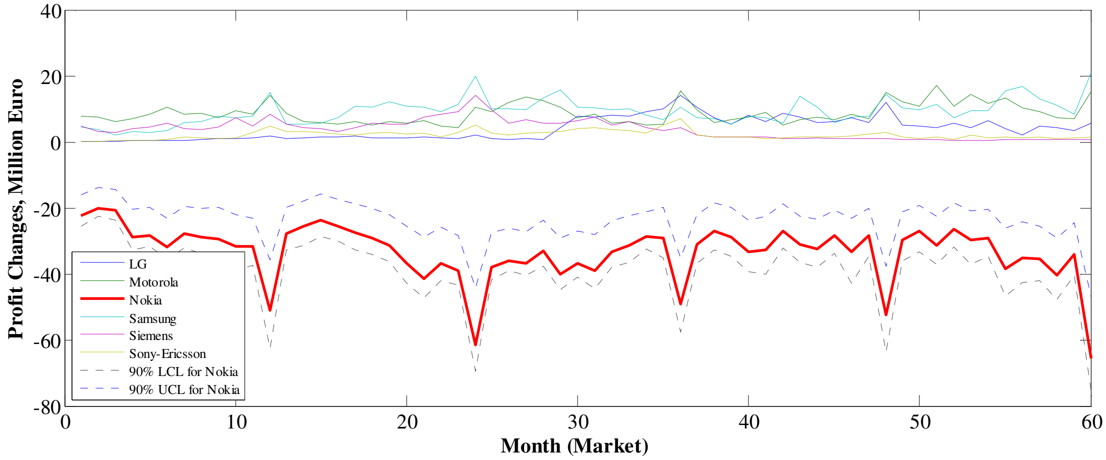

Figure 2d. Profit Changes of All Brands When Samsung Brand Effects Are Removed

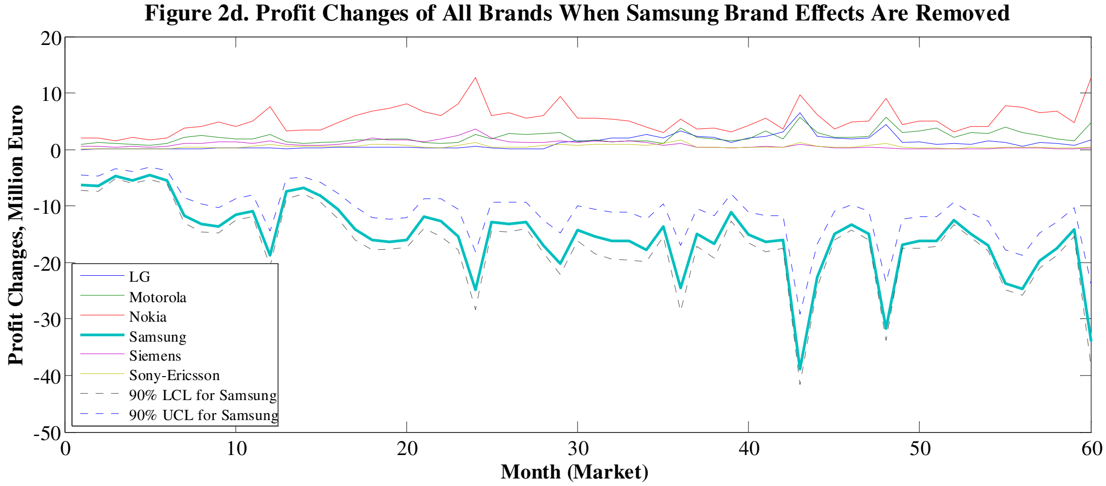

Figure 2e. Profit Changes of All Brands When Siemens Brand Effects Are Removed

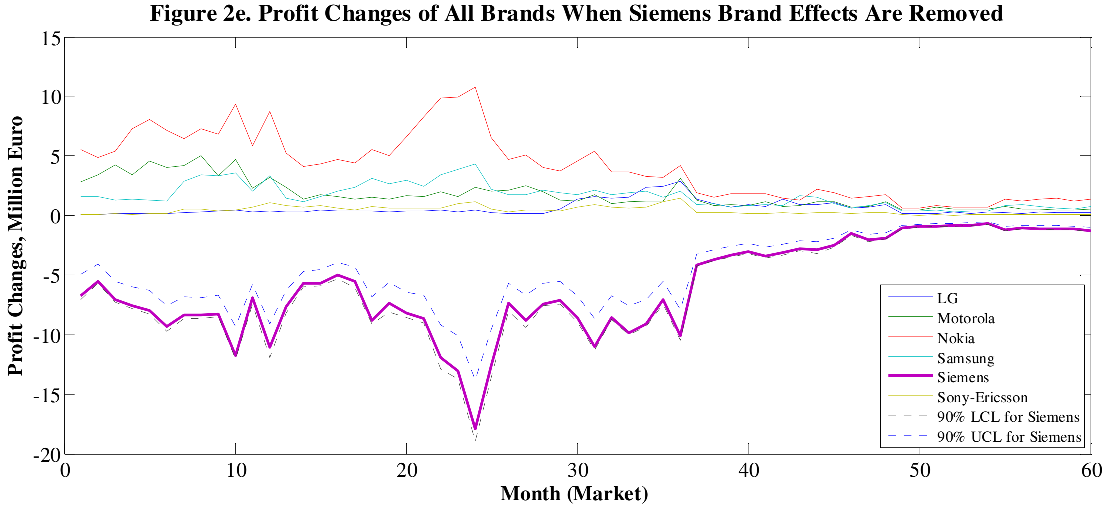

Figure 2f. Profit Changes of All Brands When Sony-Ericsson Brand Effects Are Removed

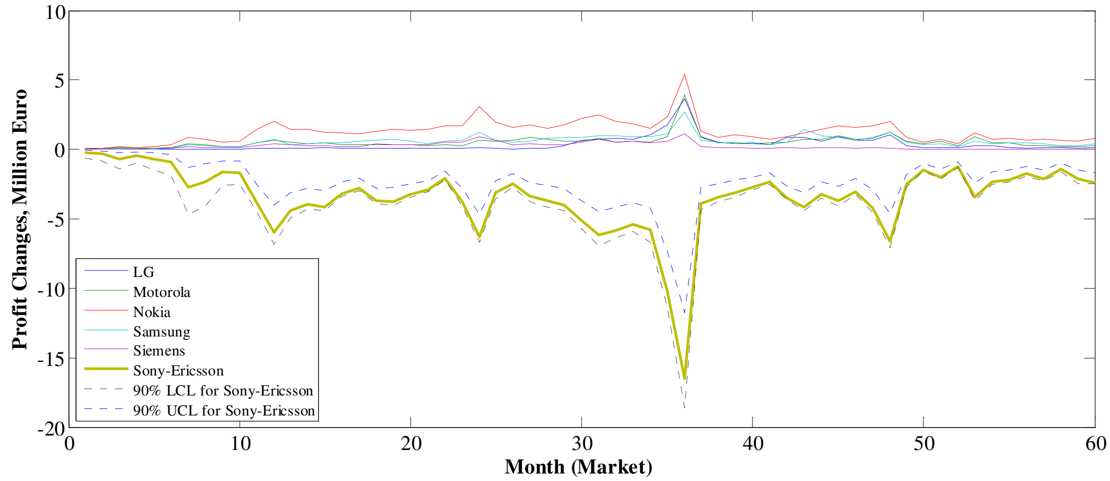

Figure 3a. The "Total Average Approach" / Brand Dummy Approach

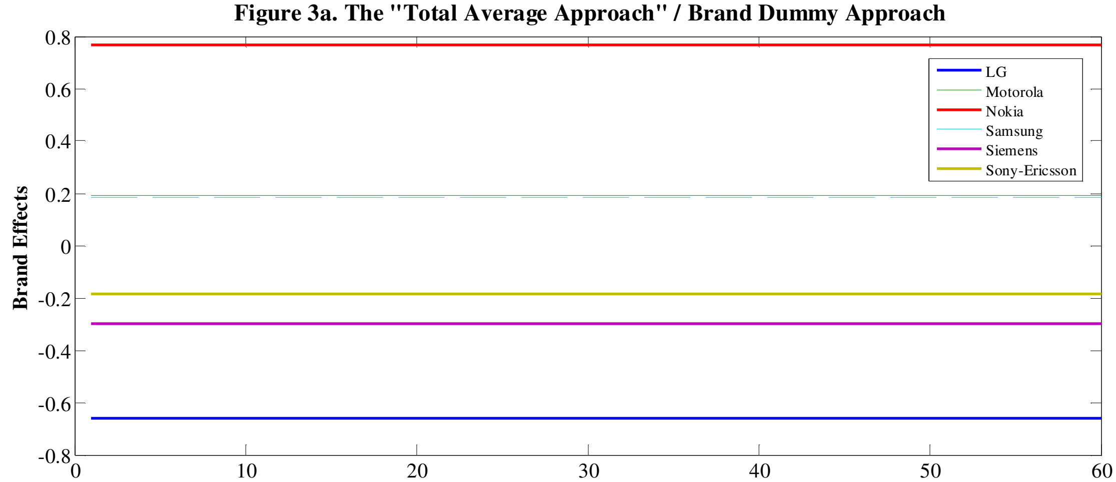

Figure 3b. The "Weighted Average Approach"

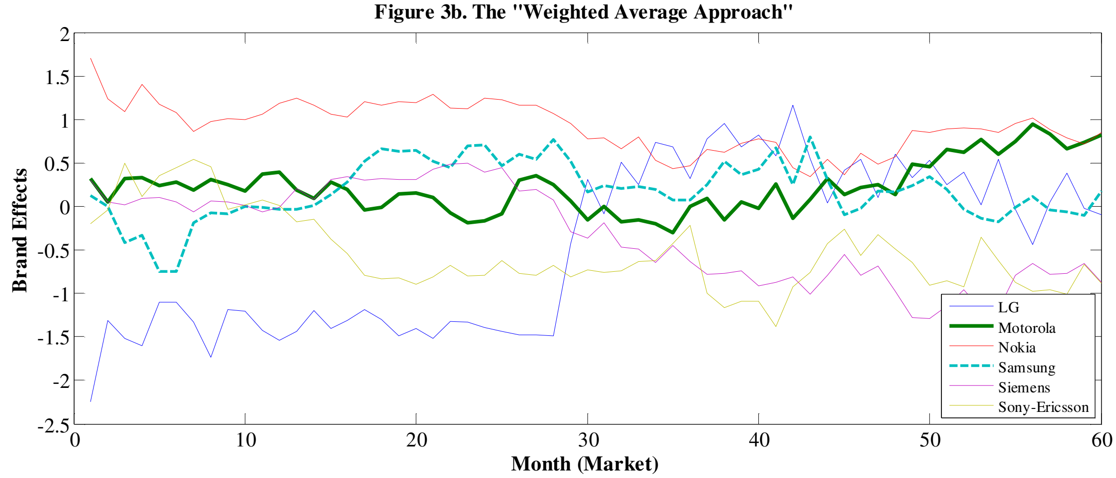

Figure 4a. The Willingness-To-Pay (WTP) for Motorola's Non-Razr Phones before and after the Razr Launch

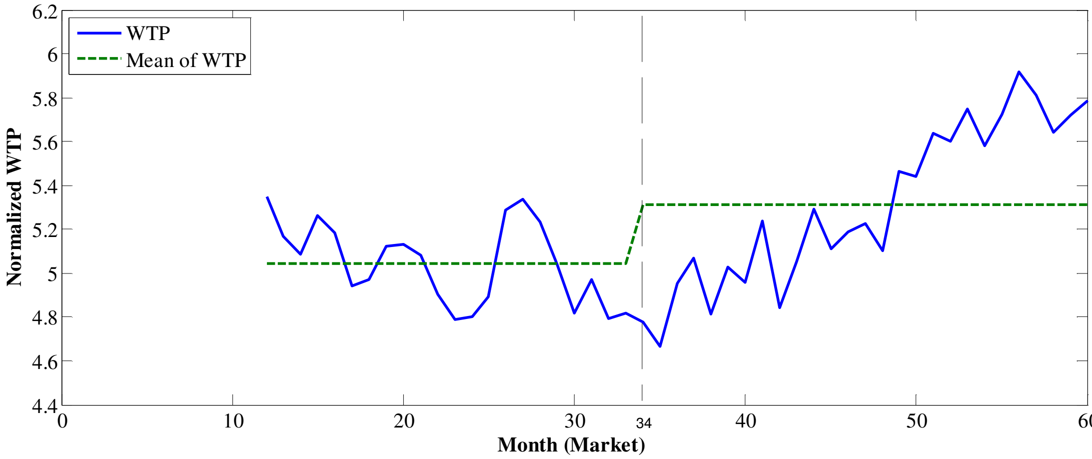

Figure 4b. The Monthly Monetary Value of the Razr's Net Spillover Effect

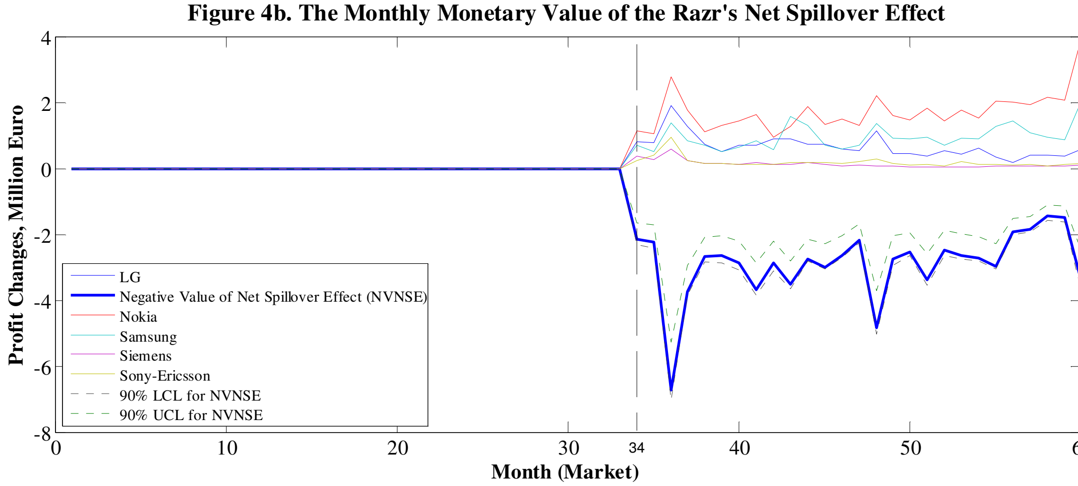

Figure 5a. The Razr's Premium Effect as a WTP Difference between W/ and W/O the Razr

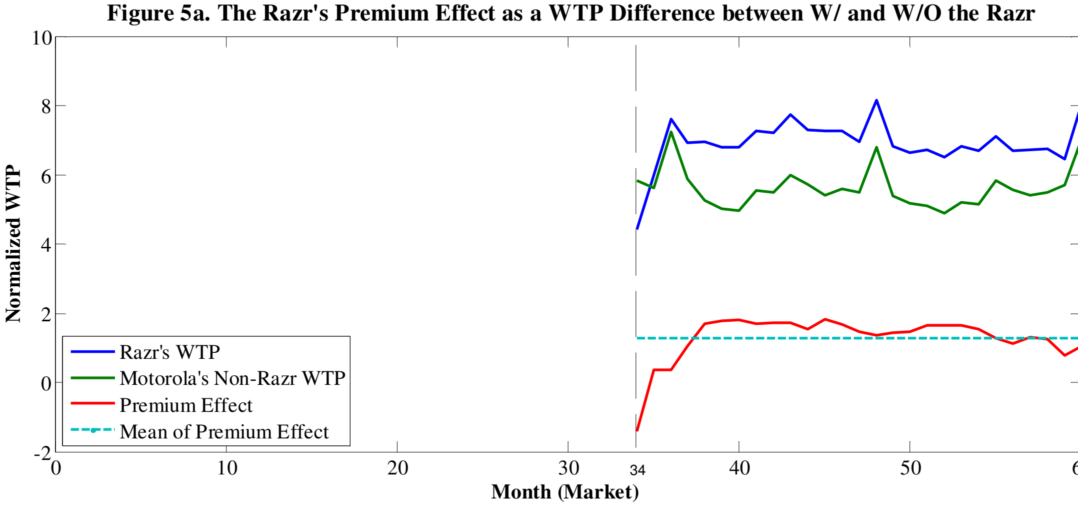

Figure 5b. The Value of the Razr's Premium Effect

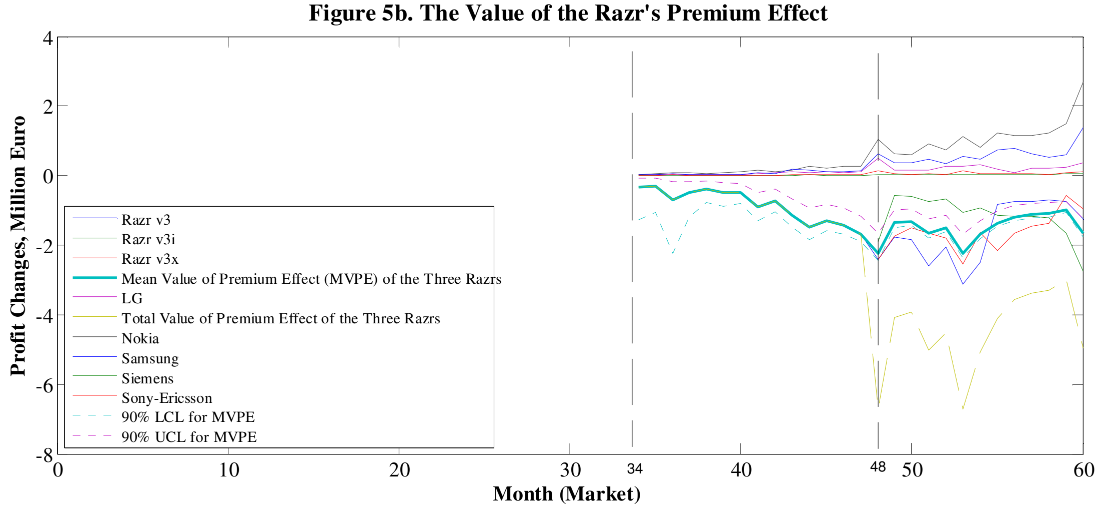

Figure 5c. The Value of the Razr's Halo and Cannibalization Effects