Dynamics of Market Structure in Rapidly Developing Technology Industries

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Abstract

Our primary objective in this research is to develop a methodology to explore the ***dynamic changes*** that occur in technology intensive industries. These industries are characterized by continuous product innovation within an existing technology standard resulting in a marketplace consisting of overlapping generations of products. Changes in the market structure are often rapid due to the technological innovations and competition across manufacturers. Consequently, relative brand positions and competition patterns are likely to change over time.

The new contributions of this research can be classified under three headings:

1. The development of a methodology to examine the changes in brand positions for firms operating in rapidly evolving technology markets over time.
2. The development of a methodology to capture the time-varying substitutability between different (e.g., branded and non-branded) manufacturers as a market evolves.
3. The development of a methodology to assess the changes in demand over time as newer technologies replacing existing ones.

Our research estimates the total market demand as function of the underlying market characteristics using a modeling approach that builds on previous approaches developed by Bresnahan, et al. (1997), Elrod (1988) and Elrod and Keane (1995). Since none of these approaches account for the *dynamic* changes occurring in rapidly evolving technology industries, we generalize these methodologies by employing a *dynamic factor analytic* approach to model time varying cross-price elasticity across brands. In doing so, we also generalize the methodology proposed in Berry, Levisohn and Pakes (BLP, 1995) to rapidly developing technology industries.

As an illustration of the applicability of our proposed methodology, we apply the methodology to study the evolving personal computer industry over the period 1983-1994, providing a number of substantive insights into the evolution of this industry. We note that, although we use PC industry data, the methodology proposed is broadly applicable to a wide variety of technology markets.

Keywords: *Branding, pricing, random coefficients, high technology markets.*

1. Introduction

Much of the recent empirical IO research in marketing has been conducted in the context of relatively mature, stable consumer packaged goods markets. In these mature, slow growth markets, competitive interaction among firms is often characterized by a relatively stable pattern of competitive interaction over time. In contrast, modeling and estimating demand can be challenging since both the drivers of consumer demand and competitive positions tend to be volatile. Thus, the interplay of demand-side influences and competitive interaction across firms occurs along multiple dimensions, giving rise to a number of important theoretical and methodological challenges.

A common characteristic of many high-tech industries is the introduction of successive generation of technologies within a sustaining technology standard (e.g., mobile phones, PDAs, personal computers, etc.). For a manufacturer, the introduction of a new product with new technology needs to simultaneously consider the consequences for the company's existing products with older technology as well as the competitor's range of offerings. Moreover, new technologies may shift consumer preference in favor of the technology providers, either downstream or upstream firms in the supply chain. In addition to these, the market positions of firms at the same level may also fluctuate depending upon how they compete against each other in providing better services, introducing additional product line offerings, and building up brand images. The main focus of the current paper is to develop a methodology to analyze the evolution of competitive positions of the brands over time and the competition among overlapping generations of products over time.

The paper makes methodological and substantive contributions that apply to many technology-based product markets. Methodologically, one contribution is the development of a framework that extends the approaches taken by Elrod and Keane (1995) and by Berry, Levisohn and Pakes (1995) to incorporate dynamic changes in the underlying market structure over time. By extending these approaches, our model explicitly allows the position of each brand to change over time in the choice map. Hence, the model can capture any changes in the substitution pattern among brands (e.g., "branded" versus "generic") over time. Second, our approach allows us to compare the relative change in utility weights for each brand and type of technology (e.g., "frontier" versus “non-frontier”) over time. The key substantive findings fall under three main points. First, we are able to estimate and trace the evolution of each brand’s position in the market over time. Second, we are able to estimate the dynamic evolution of preferences for new versus older technologies over time. Third, we are able to assess the changes in substitutability between brands and technologies over time.

The remainder of the paper proceeds as follows. Section 2 describes the challenges of modeling demand interrelationship relative to the extant literature. Section 3 describes the model and the proposed methodology. Section 4 discusses the data in detail and provides summary statistics. The empirical model applying to our data are discussed in detail in Section 5, while the estimation results are discussed in Section 6. Section 7 concludes the paper.

2. Modeling Demand in Dynamic High-Tech Markets

An appropriate methodology to study markets characterized by evolving technology requires the integration of both the dynamics of brand positions and technological preferences within a choice framework. A natural starting point is the work by Bresnahan et al. (1997), who used a GEV choice model to estimate market demand for personal computers using two main dimensions, “branded/non-branded” and “frontier/non-frontier” technologies. An advantage of this approach is that, by proposing the use of instrumental variables, it is more flexible than the previously introduced models such as the nested Logit model (for examples see Goldberg 1995). However, a limitation of the Bresnahan, *et al*. and Goldberg approaches is that they do not consider the *dynamic* changes that often occur in an industry. For example, technology product markets are characterized by significant changes in the relative brand positions of manufacturers and the relative importance of technological enhancements over time. It is difficult, if not impossible to incorporate such dynamic changes in the GEV or nested logit frameworks.

Since our focus here is on these dynamic changes, we can’t simply adapt the Bresnahan (1997) or Goldberg (1995) approaches. Accordingly, we turn our attention to another approach, one that explicitly models the unobserved brand positions in order to infer the substitutability across brands. Elrod (1988) and Elrod and Keane (1995) developed a choice map or a factor-analytic probit model to investigate the market structure in a succinct way by modeling the unobserved brand attributes and relative positions among brands in the market.[1] However, rapidly evolving technology industries are often characterized by intensive competition and technological innovation that can result in dynamic changes in the brand positions themselves over time. Accordingly, we differ from their work by generalizing their modeling approach to allow the substitution pattern among brands (and generic ones) to also change over time.[2] Thus, our *dynamic factor analytic* model explicitly allows positions of each brand to change over time in the choice map.

Before we move on to the model, data and estimation, we need to address one additional issue for applying our methodology in practice. Specifically, we need to address the potential endogeneity bias caused by the likely correlation between product attributes unobserved in the data and the observed prices. In the industries with a large number of models or brands and each one lasts only for a few periods, it is generally infeasible to estimate fixed brand effects as a solution (for examples see Goldberg (1995)). Berry, Levinsohn and Pakes (1995) – herein BLP – and Berry (1994) set out a general choice model that helps to solve the endogeneity problem by specifying competition patterns and "inverting" the market share functions. We adopt their methodology but use a more general instrumental variables method without specifying the equilibrium competition behavior, which we believe is more applicable to most industries. Moreover, the BLP methodology is more applicable to a relatively stable market (such as the automobile industry) but will be difficult to approximate the changes in substitution patterns across many products over time if the industry exhibits a rapid evolution. We believe that our *dynamic factor analytic* approach, by modeling the changes in unobserved brand positions in the market, provides a succinct way to handle

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[1] Some applications, such as Chintagunta, et al. (2001), extended the market structure analysis to logit choice models and accounted for endogeneity of prices, but did not consider the possibility of changes in brand positions over time.

[2] The dynamic modeling is closest in theory to Luan et al. (2004) who study the dynamically changing substitution patterns among different product forms by explicitly modeling the diffusion of a new product form in a consumer-durable market and Sudhir et al. (2004) who model price competition across firms by allowing competitive conduct parameters to change overtime. This modeling approach allows us to compare the relative change in utility weights for each "brand" and "technology" when there are technological innovations and changes in brand positions over time. Further, unlike the work by Sudhir, et al. (2004), we model the time varying competitive relations between brands by capturing the dynamic changes in brand positions.

this dynamic issue. In short, our model incorporates the BLP approach to addressing endogeneity within a dynamic extension of the Elrod (1988) and Elrod and Keane (1995) framework.

3. The Model

We frame our model in an industry with changing technology, where the demand will be affected by both consumers' preference for manufacturer brands and technological levels. Further, a dynamic demand system takes account of the time-varying brand preference and technological development.

a. The Utility Model

We allow for the fact that each manufacturer has a portfolio of differentiated products in the market at any one point in time. We begin by assuming that if consumer *i* buys product *j* from a manufacturer *m* at time *t*, her (indirect) utility level will be equal to:

$$U_{ijt} = \lambda_{imt} + \kappa_{ijt} + x_{jt}\beta_i + \alpha_i p_{jt} + \xi_j + \varepsilon_{ijt} \qquad (1)$$

where the term λ_{imt} denotes consumer *i*'s preference for manufacturer brand *m* at time *t*, κ_{ijt} the preference for the technology embedded in product j at time t. Note that these preferences are time varying. The term x_{jt} is a vector of other explanatory variables including observed product attributes, p_{jt} the price of product *j* at time *t*. Variables α_i and β_i are random coefficients in the utility function. Similar to the BLP (1995) specification, there are two components to the equation error structure: the time-invariant error term ξ_j captures the unobserved attributes of product *j*. It is important for us to include an error assumption around ξ_j because a number of product attributes that will affect consumers' utility and the pricing decisions of manufacturers are unobserved in the data. Since we address brand-specific differences in the term capturing the preference for brand names (λ_{imt}), we assume that ξ_j is not manufacturer-specific. Thus, the term λ_{imt} captures brand-specific differences, whereas ξ_j captures unobserved product differences not related to the individual brand. The final term, ε_{ijt}, are the idiosyncratic errors, assumed to be *i.i.d.* over *i*, *j*, and *t*. By standard assumption if the consumer does not buy in the category, the utility derived from the outside option is $U_{iot} = \varepsilon_{iot}$.

b. Modeling the Brand Preference – A Dynamic Factor Analytic Approach

To model the time-varying preference for brands, we assume that consumers care about a number (K) of brand-specific unobserved attributes. For example, if "perceived quality" of brands and "services" provided by manufacturers are two perceived attributes that consumers care about (which are not in data), then $K = 2$. We model such a relationship through a ***factor-analytic*** model (Elrod and Keane 1995) where:

$$\lambda_{\text{imt}} = L_{mt}c_i + \eta_{imt} \tag{2}$$

the term c_i is a $K\times 1$ vector random variables distributed as standard normal $N(c, I_K)$, where I_K is an identity matrix with dimension K.[3] Preference weights c*'s* are assumed to be time-invariant.[4] The term L_{mt} is a $1\times K$ row vector, denoting the values that brand m have for K brand attributes. In general we can specify the function as the following:

$$L_{mt} = L(z_{mt}) \tag{3}$$

where $L(.)$ is a $1\times K$ vector of functions describing the time-varying brand attributes values, and z_{mt} is a vector of explanatory variables related to consumers' perceived brand attributes that helps to explain the change in brand positions. Possible candidates for z_{mt} include relative advertising expenditures, labor employed, and capital investment *etc.* that may explain the changes in brand attributes perceived by consumers. We interpret L_{mt} as brand positions (with K dimensions) in the market over time. This *dynamic factor analytic* model allows for the time-varying brand positions, which is a major difference from Elrod (1988) and Elrod and Keane (1995), where they assumed L*'s* to be fixed over time.

Assume that $K = 2$. In estimation, we need to place the following identification restrictions in (3):

[3] This assumption is useful for the model identification.

[4] It is possible that we model the time-varying preference c's; however, it will be difficult to identify the model from the data if both values of brand attributes and the consumer preferences are allowed to change.

(a) Brand attributes values for one brand, say, brand M, are zero, for all t, so that it is located at the origin of the map (*translational invariance*). In the market position map brand M is always at (0,0).

(b) Brand attributes values for one brand, say, brand *1*, is located along the horizontal axis. That is, $L_{m,t,2}$ for brand *1* is zero for all t (*rotational invariance*).

Finally, η's in (2) is a stochastic error term distributed as $N(0,\sigma_\eta^2)$.

This dynamic factor analytic model allows us to address two questions. First, what are the changes in brand preferences over time, particularly as compared with the change in different technologies that may be produced by upstream manufacturers? Second, what are the changes in relative brand positions for the branded manufacturers over time? For example, if the positions are declining in the attribute space, or if brands are converging to each other in market positions, we can expect more intensive competition in the industry as brands become more substitutable. On the other hand, if the brand positions are improving and diverging, substitutability among brands will decline and hence competition will be more localized.

c. Modeling Preferences for Evolving Technologies

To model the time-varying preferences for the technology embedded in product *j* at time *t*, κ_{ijt}, we assume a technology preference function as the following:

$$\kappa_{ijt} = \kappa^j(tech_j,\ tech\ status_j, t) \qquad (4)$$

where "$tech_j$" is the technology level used by product *j*, "$tech\ status_j$" the status of the technology ("*Frontier*" *vs.* "*Old*" technology), and "*t*" is the length since the new technology was introduced. "*Tech status*" is important to consumers who are frontier-technology loving (consumers who will pay a price premium for the new technology) or risk averse (consumers who will avoid the latest technology if there is not enough information). Over time this preference will change as more information about the technology is available. Including κ_{ijt} in the utility function will tell not only consumers' preference weight of each technology, but also how new technologies are diffusing and substituting older ones. It also implies a change in consumers' perception of the technology and hence substitutability with other technologies as a previously frontier technology is replaced by a newer one.

d. The Market Share Equation

Assuming that ε_{ijt} in (1) is Gumbel distributed, we have a multinomial logit demand model. Let s_{jt} be the market share of product j at t. Substituting in equations (1) and (2), we can specify the market share function, similar to BLP (1995), as the following:

$$E(s_{jt}) = \int \frac{\exp(\lambda_{imt} + \kappa_{ijt} + x_{jt}\beta_i + \alpha_i p_{jt} + \xi_j)}{1 + \sum_{\substack{k=1,\ldots,J; \\ l=1,\ldots,M}} \exp(\lambda_{ilt} + \kappa_{ikt} + x_{kt}\beta_i + \alpha_i p_{kt} + \xi_k)} dF(\alpha_i, \beta_i, c_i, \kappa_{it}', \eta_{it}) \qquad (5)$$

where *F(.)* is the distribution function of all stochastic parts in the utility function.

We assume that the introductions of new technologies and new models for each manufacturer in the industry are exogenous. This is important and will be used to find price instruments that are uncorrelated with the unobserved product attributes ξ_j (explained in more detail later). Although we believe that a full dynamic analysis of technological evolution and new product introduction is an important future project, it is beyond the scope of this paper, especially since we do not have cost data about R&D and product line expansion.

Finally, note that price endogeneity is a major concern in equation (5): the term ξ_j represents the unobserved product attributes that may very well be correlated with prices in many markets. For example, in the case of the personal computer data used in the empirical part of this study, prices will be affected by the speed or memory that is not observed in the data. Hence, we need an appropriate set of instrumental variables that is correlated with prices but uncorrelated with ξ_j. We will provide a detailed discussion of the instruments in the section of empirical estimation.

4. The Data: The Personal Computer Industry 1983-1994

In order to illustrate the potential for the methodology detailed above, we use data on the personal computer market. We note that our empirical application is intended to be an illustration of the potential applicability of the methodology, rather than an "industry study" of the PC market *per se*.

A personal computer can be defined as a general-purpose, single-user machine that is microprocessor based and can be programmed in a high-level language. Excellent historical reviews of the personal computer industry are given in Langlois (1992) and Steffens (1994). For our purposes, information was collected from International Data Corporation's (IDC) *Processor Installation Census* (PIC). IDC is the oldest among the various firms that tracks the American computer industry and is widely recognized as having a very accurate picture of the activity in this industry. Detailed information on the IDC data can be found in Bayus and Putsis (1999) and Putsis and Bayus (2001).

Our study population includes all firms that sold desktop personal computer in the United States during the period 1983-1994. Unlike the years before 1983, these twelve years were characterized by rapid expansion in sales – sales grew from under 1 million units to over 16 million units by 1994. In addition, the number of competing firms in the market increased from just over 100 in 1983 to well over 300 by 1994. Technology also changed substantially over this period. For example, the microprocessors used in the first generation personal computers (*e.g.*, Intel's 8080) were succeeded by the second generation (*e.g.*, Intel's 286), the third generation 386) and the fourth generation (*e.g.*, Intel's 486) and the fifth generation (*e.g*., Pentium) technology.

In terms of product market competition among PC manufacturers, many brands were created and grew significantly (e.g., Dell, Compaq etc.) during this period, while many declined significantly (e.g., Tandy) (see Figure 1). Compaq and Gateway entered the market in 1984, Dell in 1985, and Packard Bell (PB) in 1986. They started small, gained market share gradually, and all became important players in the market in the 1990s. For example, both Compaq and PB overtook IBM in market share in 1994. The personal computer industry experienced rapid evolution in the chip technology in 1983-1994. Every four to five years a new generation was introduced into the market aimed at replacing older generations. As a result, the product-life cycle of each generation of microprocessors had a span of about eight to ten years (see Figure 2). Also note that in general it took four to five years before the sales of a new technology to pass that of the older technology. For example, chip technology 486 was introduced in 1989 and its sales were lagged behind that of 386 until 1993.

[Insert Figures 1 and 2 about here.]

The data also demonstrate an interesting pattern of pricing competition between national and generic manufacturers. The early 1990s saw a drastic change in competition strategy among branded computer manufacturers: they became more aggressive in terms of pricing competition in both of the markets for frontier and older technologies (Figure 3). For example, the big price premiums for frontier and old technology products for national brands in the 1980s were virtually non-existent in the periods of 92-94. Because of this change, generic brands were losing market to branded manufacturers starting from the early 1990s (see Figure 4). The above phenomena illustrate the rapid evolution in the PC market structure. It is important to develop a methodology to analyze the dynamic changes in the market so that researchers can better understand the basic driving forces for the change in competition strategies of national manufacturers

[Insert Figures 3 and 4 about here.]

5. Model Estimation

We present the details of the demand model using some of the intuition obtained from the data as a guide to an appropriate specification in this market. We also discuss the estimation methodology embedded in the BLP framework.

a. An Estimation Model

We identify seven "national" brands in our model as IBM, Compaq, Dell, Gateway, Packard Bell (PB), Hewlett Packard (HP), and Tandy.[5] These seven brands altogether own about 40 percent of the PC market in 1994. Tandy was a brand with a large market

[5] Another major brand in our sample period is Apple. Considering that the consumer segment for Apple is very different from the other seven brands, which basically relied on the Wintel technology, we exclude Apple from the estimation model. The "outside" option in the demand model, hence, will include the options of non-purchase or buying computers from Apple.

share in the 1980s, though it declined starting from the late-80s. New entrants such as Compaq, PB, Dell and Gateway gained rapid growth in market share especially starting from the early 90s (see Fig.1). Note that the number of national brands in the model is flexible; one can change the number to check the model robustness.

Corresponding to the dynamic factor-analytic model in equations (2) and (3), we assume that the number of unobserved brand attributes $K = 2$. In order to identify the model, we assume that the preference weights c_1 and c_2, corresponding to equation (2), are fixed over time. We assume that the brand attributes values of a generic PC are zero so it is always located at *(0,0)* in the position map. For estimation purpose we also choose to use HP as the brand that is located along the horizontal axis since it is a relatively mature brand in the data.

If we have data for z_{mt}, we may first obtain estimates $\hat{L}_{mt}$ for each m and t under the above identification restrictions. This algorithm works because each manufacturer produces a portfolio of products under same brand names in each year (there were about 350 different models in our data produced by the seven manufacturers from 1983 – 1994). Then we can regress $\hat{L}_{mt}$ against z_{mt}. Here we do not observe other data related to brand attributes except time dummies; hence, corresponding to equation (3), we use a linear function to approximate the time-varying brand positions:

$$L^t_{m,1} = L^0_{m,1} + L^1_{m,1} \times t_{83} \tag{6.1}$$
$$L^t_{m,2} = L^0_{m,2} + L^1_{m,2} \times t_{83} \tag{6.2}$$

Here t_{83} is the number of year after 1983 and, if a personal computer manufacturer operated after 1983, t is the number of years of its existence. Parameters ($L^0_{m,k}, L^1_{m,k}$), $k = 1, 2$, are estimated from the model.

Finally, η_t in equation (2) is assumed to be *i.i.d.* over products (j), consumers (i) and time (t), distributed as $N(0, \sigma_\eta^2 \cdot I_J)$, where I_J is a $J \times J$ identity matrix, and σ_η denotes the standard deviation that is assumed to be equal for all brands. As there are seven "national" brands in model, we need to estimate two parameters (the L_m's) for HP, and four parameters for other six brands, and a σ_η.

The microprocessor technology used by a model, which is observed in the data, is one important factor affecting consumers' preference for technology, since the microprocessor design directly determines the computer's overall power and performance. The most important chip manufacturer is Intel, which produced chips that were used widely by all top PC manufacturers except Apple.

Corresponding to equation (4), we specify the technology preference function as:

$$\kappa_{ijt} = \rho \cdot tech_j + \tau_{it} \cdot 1\{F\}_{jt} \qquad (7)$$

where $tech_j$ is a vector of binary variables for different generation/model of microprocessor technologies. In our data, there are 7 major generations including the following:

1. Z80 (introduced in 1973)
2. Proprietary (introduced in 1969)
3. 8080/8085/8086/8088 (introduced in about 1974)
4. Intel 286 (introduced in 1982)
5. Intel 386 (introduced in 1986)
6. Intel 486 (introduced in 1989)
7. Intel Pentium (introduced in 1993)

The term $\boldsymbol{1}\{F\}_{jt}$ is an indicator variable corresponds to *"tech status"* in equation (4), which is equal to 1 if the microprocessor contained in product *j* is a frontier technology at time t and 0 otherwise. We define a frontier technology as the leading technology in the market at time *t*. For example, the frontier technology was 386 from 1987 to 1989, and 486 from 1990 to 1992.[6] The variable τ_{it} denotes consumer *i*'s preference for frontier technology at time *t*. To allow the preference to be time-varying, we assume that:

$$\tau_{it} = \tau_{0,i} + \tau_1 \times t_{j,INTROD} + \tau_2 \times (t_{j,INTROD})^2 \qquad (8)$$

where $\tau_{0,i}$ is a random preference coefficient for the frontier technology (explained in more detail later), τ_1 and τ_2 capture the change in preference after the technology is introduced and $t_{j,INTROD}$ denotes the length of time (years) after the technology used by product *j* is introduced.

[6] 386 and 486 were introduced into the market late in the years 1986 and 1989, respectively. There were very few models incorporating these two technologies in their introduction years. Hence, 286 and 386 were still the frontier technology in years 1986 and 1989, respectively.

The term α_i in equation (1) is a random coefficient implying the stochastic disutility of cost of purchase of personal computer. Conceptually, consumers who prefer frontier technology may have different price sensitivity from those who are more risk-averse (followers). To model this relationship we assume that

$$(\alpha_i,\ \tau_{0,i})' = (\alpha_0, \tau_0)' + (\nu_\alpha,\ \nu_\tau)', \text{ and}$$

$$(\nu_\alpha,\ \nu_\tau)' \sim N(0, \Sigma_1)$$

In the model estimation we will estimate the mean preference coefficients (α_0, τ_0), and the matrix Σ_1 that includes variance-covariance parameters (var(price), cov(price-frontier), var(frontier)). If the off-diagonal elements in Σ_1 are positive (negative), then consumers who have a higher value for the frontier technology will be less (more) price-sensitive. A positive correlation will confirm the conventional belief that innovators care less about prices, while a negative correlation will imply that innovators probably are more knowledgeable and hence tend to search more for bargain deals when they purchase new computers.

The term x_{jt} in equation (1) includes a vector of explanatory variables observed in data. In our specific application, it includes the following variables: year since 1983, YR_{83}; and its square, YR_{83}^2; quarter of the year when the model is introduced (DFI quarterly, which adjusts for seasonal effects); country of origin of manufacturer (Foreign = 1); configuration (Tower = 1; non-tower configuration = 0); unemployment rate; GDP growth rate. For simplicity sake we assume homogeneity among consumers for β's, *i.e.*, $\beta_i = \beta$.

b. The Estimation Algorithm and Instruments

Combining equations (1) to (8) we obtain a market share equation of product *j* at *t* as

$$E(s_{jt}) = \int \frac{\exp(\delta_{jmt})\exp(\omega_{ijt}(\nu_{\alpha,i}, \nu_{\tau,i}, c_i, \eta_{it}'))}{1 + \sum_{\substack{k=1,\ldots,j;\\ l=1,\ldots,M}} \exp(\delta_{klt})\exp(\omega_{ikt}(\nu_{\alpha,i}, \nu_{\tau,i}, c_i, \eta_{it}'))} \times dF(\nu_{\alpha,i}, \nu_{\tau,i}, c_i, \eta_{it}') \qquad (9)$$

where $\delta_{jmt} = x_{jt}\beta + \alpha_0 p_{jt} + \rho \cdot tech_j + (\tau_0 + \tau_1 \times t_{j,INTROD} + \tau_2 \times (t_{j,INTROD})^2) \times 1\{F\}_{jt} + \xi_j$ is the mean utility (in Table 1 below, these variables and the related coefficients are listed as "Estimates in the Mean Utility"), and $\omega_{ijmt} = L_{mt}c_i + \eta_{imt} + \nu_{\alpha,i} \cdot p_{jt} + \nu_{\tau,i} \cdot 1\{F\}_{jt}$ is the stochastic part in utility function and will be simulated using distribution $F(\nu_{\alpha,i},\nu_{\tau,i},c_i,\eta_{it}{}')$ (in Table 1 below, these variables and the related coefficients are listed as "Estimates of Random Coefficients").

Given simulated random variables $(\nu_{\alpha,i},\nu_{\tau,i},c_i,\eta_{it}{}')$, we use a contraction mapping technique suggested in BLP (1995) to solve for δ's recursively. Now that p_{jt} is correlated to ξ_j. To estimate the mean utility coefficients in δ, we have to use instrumental variables. We use the following seven sets of IVs to form our moment condition:

i) x_{jt}, $tech_j$, and $1\{F\}_{jt}$;

ii) the number of other products produced by same manufacturer (see Bayus and Putsis 1999 for a discussion of the impact of product proliferation and of managing a broader portfolio of products under the same brand);

iii) the number of products produced by other manufacturers using the same technology (see Putsis and Bayus 2001 for a discussion of how a plethora of brands can preclude entry and lessen the competitive intensity in a market);

iv) the number of products produced by other manufacturers using different technology (see Putsis and Bayus 2001 for a discussion of how this impacts the likely cost structure of those firms competing in the market);

v) the number of products produced by the same manufacturer using the same generation of technology (as above, see Bayus and Putsis 1999 for a discussion of how this impacts the likely cost structure of those firms competing in the market),

vi) the number of years after the technology of the product has been developed; and

vii) the number of years before a new Intel technology (that is, 386 (87), 486 (90) and Pentium (93)) will be developed.

Our instruments ii) to v) are similar to the "PD-specific" instruments used in Bresnahan *et al* (1997). As suggested there, these instruments will pick up competitive interactions in the industry. They tell about the "group structure of product differentiation" in the industry (p.S33) and will affect pricing decisions. But they are uncorrelated with unobserved product characteristics ξ_j under our previously mentioned assumption that the product-specific entry process is exogenous. Since major technological innovation efforts in our sample period were made mostly by Intel and Microsoft, product entry decisions may be largely uncorrelated with the unobserved firm-specific demand shocks. Therefore, we believe that the exogenous product entry assumption makes sense in the personal computer industry. Bresnahan *et al.* argued that by using these IVs the model allows different types of non-cooperative games such as Bertrand and Cournot competition, therefore it is more general than the Bertrand pricing competition model as specified in BLP (1995).

The sixth instrument is a proxy for change in chip prices. Because of "learning-by-doing" we expect costs of chip and hardware production will be lower the longer the years of introduction. The last instrument can be treated as a proxy for industry expectation about the coming technology innovation that will affect pricing decisions for all current models (e.g., chip prices may fall if a newer generation is expected to be coming soon). Since individual consumers are relatively uninformed, compared with manufacturers, about future technology innovation, and they may not be willing to postpone purchases for too long, the expectation of the coming technology innovation should not be an important factor in the unobserved demand shocks.

c. An Alternative Model

For model comparison purposes, we specify a simpler baseline model (the standard factor-analytic approach). In this base model, we assume that brand positions for brand *j* is fixed over time, *i.e.*, $L_{m,1}^{t} = L_{m,1}^{0}$ and $L_{m,2}^{t} = L_{m,2}^{0}$ for all t. All other parameters are the same as in the dynamic factor-analytic model. Note that this model incorporates the effect of technology changes while ignoring the potential dynamic changes in brand competitive positions. It is our expectation that the proposed model will do a better job explaining the data, but we include this base model in order to gauge the incremental value of modeling the dynamic changes in brand positions and hence the substitution patterns in the industry.

6. Results

a. General Estimation Results

We begin by presenting the general results in Table 1. Model "B" presents the results using the dynamic factor-analytic model, while Model "A" presents the results for the base model. A few general observations are in order. First, note that the coefficients for *(Year-83)* are significantly negative in both models. This implies that, *ceteris paribus*, the importance of personal computer hardware (in relation to innovations in chip technology and material prices) in the overall utility of consumers has declined over time. Second, the estimated coefficients for the variable "Origin" are positive suggesting that personal computers manufactured abroad result in a higher mean utility over the sample period. The estimated coefficient for the variable "Dimension" is positive in the proposed model (but negative in the base model), which suggests that a tower design is preferred on average. Third, note that the economic variables are all of the expected signs and statistically significant in our proposed model – the coefficient for the Unemployment Rate variable is negative and the coefficient for GDP Growth is positive.

[Insert Table 1 about here.]

The industry dynamics of the personal computer market are particularly interesting. For example, as one would expect, we find that the later the year of introduction of a technology, the higher the preference, especially for the x86 series. This implies improved chip technology replaced older ones over years, presumably complemented with software that is better able to tackle the tasks that personal computers were increasingly being used for over this period. However, compared with earlier innovations, estimation results seem to suggest that the introduction of the Pentium technology only increase consumers' utility marginally. This suggests that most of the changes in competition patterns in the early 90s that we discussed earlier (such as the convergence in pricing between national and generic brands) were generated mainly from market structure change instead of technological innovation. This, in our view, is a significant finding.

A new (or frontier) chip technology takes time to penetrate in the market before it is accepted by the general consumer. Accordingly, the coefficients for "Frontier" are negative (-3.24 in the proposed model B and –4.47 in the base model A). The coefficients for Frontier*Time (*i.e.*, t_{INTROD}) are negative (-0.53 and -0.34,), while that for Frontier*Time^2 are positive (0.14 and 0.15 respectively). Thus, it took about 6 years for the new technology to have positive mean preference in our proposed model. These somewhat surprising estimation results are quite reasonable when one considers (see Figure 2) that it took about 4 years before the sales of a new technology surpassed the old ones, and not before its status as "frontier" was taken over by another newer technology.[7] Note however, that there exists a great deal of heterogeneity in consumer preference for frontier technology. Table 2 shows that the variances of preference for "Frontier" are 45.25 in our proposed model B and 67.29 in the base model A. This implies that a significant proportion of consumers prefer new technology to older ones even in the first year of introduction. Once again, this is entirely consistent with expectations – overall, it takes time for a new technology to be accepted within the general population, but there is a significant proportion of consumers for whom the new technology will provide substantial utility.

[Insert Table 2 about here.]

One of the interesting results is that the covariance between "Price" and "Frontier" in Table 2 are negative (-0.24 and -0.006, respectively. See Table 2). This implies that consumers who prefer frontier technology are also *more* price-sensitive. Though inconsistent with the conventional wisdom that innovators prefer quality to low price, this result may make sense in the personal computer industry, especially in our sample period from mid-80s to mid-90s. A consumer who preferred frontier chip technology was most likely someone who possesses a great deal of knowledge about computers and likely has much more price information, as compared to average consumers. As a result, she may be more price-sensitive when deciding which computer to purchase. Note however, the result does not imply that manufacturers who are faster in

[7] For simplicity of model estimation we assume that this preference is time-invariant. However, it is possible that the preference for frontier technology is also changing over time. For example, it might take a longer period for 286 to be widely accepted in the early 80s than for Pentium in the early 90s, as consumers' knowledge about computers is growing over time, and the extent of technology innovation may be different among various generations of chip technology.

incorporating the newest technology should price at a lower profit margin for their new models. This is because it usually takes some years before their competitors are able to come out with new technology designs. For example see a discussion in Bresnahan *et al* (1997, p.S19) about the technical difficulties of designing and producing computers which can make effective use of the new chip technology. In this case, price discrimination at the beginning is still possible as early-adaptor manufacturers have a significant market power. Any ability to increase profit margins due to technological advantages will be enhanced or offset by gains or losses in brand equity over time. This is an important result, and we may use that as a starting point to investigate optimal dynamic pricing strategy of branded PC manufacturers.

b. Changes in Brand Positions

The random coefficients estimates from Table 1 above do not provide a clear sense of how brand positions have changed in our sample period. As discussed earlier, brand position changes will capture the changes in total brand preferences. In Figure 5, we plot these estimated changes over time, as implied by the time-varying brand coefficients, for the seven brands based on the estimation results (since we prefer the dynamic factor analytic model, we present only the brand equity results from this model here). We can see that starting from 1986, the year when all seven brands were in the market, Tandy and Gateway experienced declines in brand equity. The brand equity of other brands, on the other hand, experienced a growth. Compaq, PB and Dell, the three relatively new entrants in the industry (the earliest entrant was Compaq in 1984), were the top three with the highest equity in 1994. This is consistent with the observations in Fig. 1 that these three brands gained market share rapidly starting from the early 90s.

Note that these results are important – as noted earlier, if the positions are declining in the attribute space, or if brands are converging to each other in market positions, we can expect more intensive competition in the industry as brands become more substitutable. On the other hand, if the brand positions are improving and diverging, substitutability among brands will decline and hence competition will be more localized.

[Insert Figure 5 about here.]

As discussed earlier, the time-varying brand coefficients will also capture changes in each brand positions *relative* to each of the other brands. In Figure 6, we examine these changes in attributes space for each of the brands (the directions of changes are indicated by the arrows in the diagram – as a comparison, the shaded rectangles are the time-invariant brand positions estimated from the base model).

[Insert Figure 6 about here.]

We can see that IBM, HP, Compaq and PB grew along the dimension of attribute 1 (*c1*), while Dell and Gateway grew along the dimension of attribute 2 (*c2*). This is an interesting observation considering these two groups of manufacturers had different retailing strategies (the former relied on traditional retailers while the latter used a direct sales method to final individual consumers). It is also interesting to see that IBM and Dell led in *c1* and *c2* respectively in 1994, the last year of our sample. Tandy was the only brand showing significant decline in both dimensions. In general, brands did not converge over time in the attribute space, suggesting that consumers might not perceive the national brands as more and more alike each other. Yet, roughly speaking, HP, Compaq and PB are getting closer along *c1*, while Dell, Gateway and Compaq are getting closer along *c2*, in the later periods of our sample. This suggests that we have to examine the own- and cross-price elasticities, based on the estimation results, across products in order to better understand the changes in substitution and hence in competition patterns in the industry. We will study this issue in the next section.

c. Changes in Price Elasticities

In order to investigate the change in substitutability across brands and technologies over time, we calculated the relevant elasticities over time based on the estimation results. We first estimated the own- and cross-price elasticities among the seven national brands, and between national and generic brands. From years 1987 to 1994,[8] we increased and decreased the observed prices of all models of each national brand by 1 percent, then use the estimated changes in market share of the specific brand, of all other six national brands, and of all other generic brands, to compute the estimated

[8] We start from 1987 because the last national brand PB entered the industry in 1986. Also, 1987 was the year when a new chip technology 386 entered the market.

price elasticities in market share. Finally, we computed an industry aggregate measures by calculating the average own- and cross-price elasticities weighted by the market share of each national brand in each year based on the above estimated elasticities for individual brands. The results are reported in columns 2 – 4 in Table 3 using our proposed model.

[Insert Table 3 about here.]

Several interesting results are observed from the table: the own-price elasticities do not change much over the years of our sample, but the cross-price elasticities among national brands, and especially between national and generic brands, jump up significantly in the years 1992 – 1994. These results are consistent with the industry belief that personal computers were "commoditized" starting from early 90s (possibly due to the "Intel Inside" and other marketing campaigns from upstream manufacturers such as Intel and Microsoft); hence, competition between national and generic manufacturers was much intensified (see Putsis and Dhar 1999).[9] The results also coincide with the convergence of prices between national and generic brands from 1992 – 1994 (see Fig. 3). All these provide strong evidence that the change in pricing competition pattern in the 90s is due to the increasing substitutability between national and generic brands, and also among national brands.

d. Assessing the Value of the Proposed Dynamic Factor-Analytic Model.

In order to demonstrate the value of our proposed dynamic factor-analytic model, we also compare the results with the estimated price elasticities computed from the base model (columns 8 – 10 in Table 3). By doing so, we will be able to know if the proposed methodology provides any additional power in explaining the underlying changes in market structure in the rapidly evolving industry, which are hidden from conventional static models.

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[9] For example, Bresnahan and Greenstein (1997) discussed the "competitive crashing" in the computer market in the early 1990s that firms previously targeted different segments now competed for the same customers; hence, more aggressive competition was observed among PC manufacturers, and the channel power has shifted toward the "Wintel platform".

Results are reported in columns 8 – 10 in Table 3. First, it is clear that the own-price elasticities in the base model over years (column 8) are all higher than that in our proposed model (column 2). However, cross-price elasticities among national brands (column 9), and between national and generic brands (last column), are much lower close to zero, which implies that the base model predicts a more localized market for each national brand. We also do not observe any increase in substitutability across brands in the 90s. One of the implications from the base model is that the sales growth due to price cuts comes mainly from growing market size, which implies low competitive relations in the industry. This does not explain the convergence of prices between national and generic brands from 1992 – 1994.[10] In contrast, results from our proposed model provides a story that the increasing substitutability among brands may generate such an outcome, especially when the technology improvements in the industry gradually stabilize during the period (our estimation results show that the utility increase for Pentium is marginal compared with the earlier -86 series innovations), which is consistent with the industry knowledge. This comparison demonstrates the importance of allowing dynamic changes in brand positions as in our proposed model.

e. A Robustness Check

Though our results show significant changes in the underlying industry structure, we are concerned that they may be due to other forces, especially technology innovation and the resulted changes in product line portfolio within firms, as new models are introduced and old ones are taken out in every year. Therefore, we are also interested to answer the following counter-factual question: What if the brand positions were maintained at the level of year 1987? We assume that brand attributes L_{mt}, for all national brands m and year t, are equal to $L_{m,87}$, i.e., the brand attributes level in 1987, and compute the price elasticities again as described above. By doing so, we are able to better understand how much of the change in substitutability came from changes in brand positions *vs*. from technological innovations (as new chip technologies were introduced in different periods) or from product line changes within national manufacturers (as new

[10] We believe that the cost side story (e.g., national manufacturers had higher production costs in the 80s, but had greatly improved the production efficiency starting from the 90s) is not very appealing as the only explanation for the observed changes in the PC industry.

models enter and old models exit in every year). The results are reported in columns 5 – 7 in Table 3 using our proposed model with brand positions fixed at the 1987 level.

In general, the own-price elasticity increases over time as shown in column 5. Note that new chip technologies 386, 486, and Pentium were introduced in years 1987, 1990, and 1993, respectively. Cross-price elasticities among national brands, and with generic brands, increase following the number of years a frontier technology is in the market. For example, the cross-price elasticity with other national brands in column 6 increases from .185 in 1993 (when Pentium was the frontier) to .201 in 1994, while the cross-price elasticity with generic brands in column 7 increases from .018 in 1993 to .055 in 1994. These are probably due to the fact that manufacturers are able to gradually increase the number of models incorporating the new chip technology. Comparing with the earlier results (Table 3, columns 2 – 4), the biggest difference, however, is that the cross-price elasticities between national and generic brands are much lower when brand positions are fixed at the level of 1987. Hence, it shows that the result of "commoditization" in the PC industry is mainly due to the changes in brand positions.

f. A Counter-Factual Pricing Experiment

As it is well-known that, for a general market share function, own- and cross-price elasticities are not constant over self and competitors' prices, we are concerned that the causality between increase in substitutability and changes in pricing competition may be reversed: Is it possible that the increase in substitutability is due to changes in the pricing strategies of national manufacturers? To answer this question, we performed a counter-factual pricing experiment. Let r_t^F and r_t^O be the average price ratios between national and generic brands for frontier and older technologies in period *t*, respectively (see Fig. 3). We multiplied the price of each product of each national brand in each year by the ratio of r_{87}^l / r_t^l, $t \geq 87$, and $l = F$ or O. As a result, the average price ratios in later years will be fixed at the same levels as in 1987. Then we estimate the own- and cross-price elasticities again as described previously. Table 4 below reports all the results.

[Insert Table 4 about here.]

Compared the results in Table 4 with that in Table 3, the values of elasticities are different. For example, the own-price elasticity in our proposed model (column 2) in 1994 is higher when the price ratios are fixed at the level of 1987, i.e., the higher the price level, the higher the own-price elasticity. Also, the cross-price elasticities among national brands and between national and generic brands in the proposed model (columns 3 and 4) are lower. However, the basic patterns remain the same. For example, the substitutability among national brands and especially between national and generic brands jumped up a lot from 1992 – 1994. This result implies that the drastic change in substitutability is not caused from the changes in pricing strategies of national manufacturers in the 90s. Comparisons with other models in other columns are all similar to previously discussed. In summary, our results suggest that the change in pricing strategies among national manufacturers in the 90s was due to the increase in substitutability among national brands, and especially between national and generic brands.

g. Substitutability between Frontier and Old Technologies

Finally, we investigated the changes in substitutability between frontier and old technologies over time as the former is gradually accepted in the market. To do so, we increased and decreased the prices of all products with the frontier technology (either -86 series or Pentium) in different years by 1 percent, and calculate the corresponding changes in market share using our proposed model. Table 5 below reports the estimated market share of frontier vs. old technology products as well as the calculated price elasticities.

[Insert Table 5 about here.]

We first examine the evolution of the market share of frontier technology relative to old ones. As the frontier technology is gradually accepted among general consumers, it gained market share rapidly. However, price is a major factor for the rate of adoption. For example, the price ratio for Pentium technology (relative to older technologies) was higher than that of previous generations.[11] Together with the fact that Pentium was only marginally better than 486 in terms of technology development, most consumers did not see the need to shift to buy Pentium computers at higher prices; hence, the market share of Pentium was small in 1993.

When we examine the own-price elasticities, those for frontier technology (column 4 in Table 5) declines over time, while for older technologies (column 6 in Table 5), they are increasing over the years after the technology was introduced. This is due to that, as previously discussed, early technology adaptors (innovators) are more price-sensitive. Another interesting result is that the cross-price elasticity between frontier and older technologies (column 5 in Table 5) is increasing. To upstream chip manufacturers such as Intel, there existed an opportunity to price discriminate by pricing higher when its new chip was introduced, as our estimation results show that a significant segment of innovators are willing to pay a high price premium for the frontier status. However, the opportunity might not exist for national computer manufacturers when their products have become more substitutable to generic products, as previously discussed, and when technology developments have become stabilized so that it was faster for manufacturers to introduce new models incorporating the frontier technology (such as the succession of Pentium for -86 series). Combining the above two factors, competition in the frontier technology market might have become more intensive in the 90s. Though we are unable to provide a more rigorous analysis due to data restriction, our results provide an intuitive explanation for why, starting from early 90s, the brand price premium for frontier computers diminished much faster and larger than other markets (see Fig. 3).

h. Results – Conclusion

In conclusion, by extending previous research to include dynamic changes in key factors that affect a market's evolution over time, our approach lends itself to insights that would not have been possible using previous methodological approaches. Our empirical application, which uses personal computer data as an illustration of a rapidly

[11] The ratio was about 2.6 in 1993, compared with, say, the ratio 1.8 for 486 when it was first introduced in 1989. As we can see from Fig. 3 that there was virtually no price premium for national brands for Pentium computers, and it did not seem very difficult for PC manufacturers to produce computers making use of Pentium (as opposed to the situation when 386 technology was introduced in the late 1980s), the premium price decision for Pentium was probably made by Intel.

evolving technology market, empirically tests the increasing competitive environment in the hardware market by understanding the *changes* in brand positions and the relative substitution relationships among PC manufacturers over this time period. We also test the changes in competition among different technology generations over time as technology develops. None of the substantive insights gained from this type of analysis would have been possible using any of the static frameworks discussed above.

5. Conclusions and Some Extended Research Questions

In this research we develop a methodology to explore the *dynamic changes* that occur in technology intensive industries, where changes in the market structure are often rapid due to the technological innovations and competition across manufacturers. Consequently, market response to price and relative brand positions are likely to change over time. We use a modeling approach that builds on previous approaches developed by Bresnahan, et al. (1997), Elrod (1988) and Elrod and Keane (1995). To account for the *dynamic* changes occurring in rapidly evolving technology industries, we generalize their methodologies by employing a *dynamic factor analytic* approach to model the time-varying market structure. The new contributions in this paper include:

1. The development of a methodology to examine the changes in brand positions for firms operating in rapidly evolving technology markets over time.
2. The development of a methodology to capture the degree of substitutability between different (e.g., branded and non-branded) manufacturers as a market evolves.
3. The development of a methodology to assess the changes in demand over time as newer technologies replacing existing ones.

As an illustration of the applicability of our proposed methodology, we apply the methodology to study the evolving personal computer industry structure over the period 1983-1994, providing a number of substantive insights into the evolution of this industry. We note that, although we use PC industry data, the methodology proposed is broadly applicable to a variety of rapidly evolving technology markets.

The research methodology used here and applied to the personal computer industry provides a great deal of insight into what has transpired over the period of the early 1980s until the mid-1990s. However, there are a number of questions that remain unanswered that we leave for future research. For example:

- We find that there is evidence of increasing substitutability among national brands and between national and generic brands that explains the convergence in prices between branded and generic personal computers starting from 90s. What does this imply changes in channel power between, say, national manufacturers and upstream chip suppliers? What does it imply about the optimal pricing policies used by branded manufacturers and upstream chip suppliers as technology develops?
- The fact that a significant segment of consumers who are willing to pay a high price premium for the frontier technology creates the possibility of price discrimination. However, as they lost market power, branded manufacturers were also losing the power of price discrimination. What will be the implication for optimal dynamic pricing strategy for frontier PCs?
- What are the key factors that generate the changes in brand competitive positions? In the personal computer industry, was it because of the advertising efforts from upstream manufacturers such as Intel and Microsoft? Or was it because of more intensive R&D efforts and hence faster technological innovations from those firms? What can a PC manufacturer do in order to improve its positions?

We leave these and other interesting research questions to future research. We believe that the methodology set out here will be extremely useful in answering question about the dynamics of this and other rapidly evolving technology markets. We encourage future research in this area.

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Estimates in the Mean Utility	Model A	s.e.	Model B	s.e.
TIME = Year – 1983	-0.571	0.153	-0.977	0.132
(TIME)2 = (Year – 1983)^2	0.016	0.009	0.025	0.008
DFI Quarterly	-0.646	0.016	-0.687	0.014
Origin	1.368	0.014	1.317	0.014
Dimension	-0.180	0.055	0.505	0.047
Unemployment Rate	-0.336	0.061	-0.257	0.063
GDP Growth	0.021	0.039	0.093	0.035
PROPRIETARY	-5.167	0.303	-4.762	0.227
Z80	-2.775	0.302	-4.248	0.229
8080/8085/8086/8088	-1.917	0.326	-3.375	0.248
286	-0.267	0.267	-1.588	0.205
386	0.670	0.209	-0.037	0.152
486	1.821	0.204	1.163	0.137
Pentium	2.079	0.340	1.186	0.300
Frontier	-4.662	0.230	-3.237	0.254
Frontier * Time	-0.344	0.186	-0.525	0.160
Frontier * Time^2	0.148	0.021	0.141	0.019
Mean Utility C1	1.993	0.029	1.760	0.027
Mean Utility C2	9.705	0.151	4.607	0.051
Price	-1.508	0.107	-1.975	0.099
Estimates of Random Coefficients				
C1: IBM	10.257	0.010	8.665	1.014
C1: IBM * TIME			1.381	0.065
C2: IBM	-1.737	0.003	-12.006	0.858
C2: IBM * TIME			-0.168	0.021
C1: Compaq	-7.134	0.079	-10.732	0.300
C1: Compaq * TIME			0.930	0.017
C2: Compaq	-0.187	0.002	1.764	0.011
C2: Compaq * TIME			0.031	0.006
C1: Dell	2.265	0.015	-3.785	0.887
C1: Dell * TIME			-0.358	0.094
C2: Dell	0.118	1.53E-04	-1.697	0.084
C2: Dell * TIME			0.562	0.015
C1: GATEWAY	-0.598	0.001	-11.093	0.078
C1: GATEWAY * TIME			-2.901	0.212
C2: GATEWAY	-1.642	0.007	-3.714	0.158
C2: GATEWAY * TIME			0.524	0.016
C1: P-B	2.266	0.029	4.899	0.374
C1: P-B * TIME			-0.663	0.108
C2: P-B	-0.756	0.001	-3.176	0.108
C2: P-B * TIME			0.600	0.020
C1: TANDY	-12.425	0.059	-8.900	0.562
C1: TANDY * TIME			-0.905	0.022
C2: TANDY	1.050	0.001	2.348	0.067
C2: TANDY * TIME			-0.142	0.014
C1: H-P	-38.653	0.091	-39.410	1.348
C1: H-P * TIME			3.597	0.214

Table 1. Model Estimation Results

Model A	Price	Frontier
Price	4.90E-05	-0.006
Frontier	-0.006	67.29

Model B	Price	Frontier
Price	0.12	-0.24
Frontier	-0.24	45.25

Table 2. Variance-Covariance between Price Coefficient and Preference for Frontier

	Proposed Model: Dynamic Changing Brand Positions			Proposed Model: Brand Positions Fixed at the Level of 1987			Base Model: Static Brand Positions		
Year	Own-Price Elasticity	Cross-Price Elasticity with Other National Brands	Cross-Price Elasticities with Generic Brands	Own-Price Elasticity	Cross-Price Elasticity with Other National Brands	Cross-Price Elasticities with Generic Brands	Own-Price Elasticity	Cross-Price Elasticity with Other National Brands	Cross-Price Elasticities with Generic Brands
1987	-1.812	0.085	0.010	-1.812	0.085	0.010	-4.085	0.023	0.004
1988	-2.042	0.095	0.013	-1.816	0.088	0.009	-4.950	1.91E-04	4.59E-04
1989	-2.423	0.097	0.033	-2.882	0.213	0.017	-4.411	2.00E-04	0.001
1990	-2.171	0.066	0.024	-2.210	0.150	0.010	-2.553	1.92E-04	0.002
1991	-2.210	0.039	0.036	-3.440	0.110	0.012	-3.161	1.89E-04	0.002
1992	-2.759	0.162	0.236	-3.691	0.204	0.033	-5.731	0.003	0.007
1993	-2.272	0.153	0.246	-3.672	0.185	0.018	-3.331	0.001	0.002
1994	-2.201	0.378	0.771	-3.444	0.201	0.055	-7.024	0.003	0.017

Table 3. Weighted Average Own- and Cross-Price Elasticities among National Brands and with Generic Brands

Year	Proposed Model: Dynamic Changing Brand Positions			Proposed Model: Brand Positions Fixed at the Level of 1987			Proposed Model: Dynamic Changing Brand Positions		
	Own-Price Elasticity	Cross-Price Elasticity with Other National Brands	Cross-Price Elasticities with Generic Brands	Own-Price Elasticity	Cross-Price Elasticity with Other National Brands	Cross-Price Elasticities with Generic Brands	Own-Price Elasticity	Cross-Price Elasticity with Other National Brands	Cross-Price Elasticities with Generic Brands
1987	-1.812	0.085	0.010	-1.812	0.085	0.010	-4.085	0.023	0.004
1988	-1.777	0.084	0.013	-1.700	0.094	0.007	-4.793	1.86E-04	3.91E-04
1989	-2.151	0.072	0.025	-2.713	0.163	0.015	-4.344	1.49E-04	0.001
1990	-2.247	0.065	0.024	-2.380	0.141	0.011	-2.440	1.82E-04	0.002
1991	-2.178	0.037	0.032	-3.155	0.106	0.009	-3.078	3.13E-05	0.001
1992	-2.672	0.105	0.118	-3.437	0.176	0.020	-5.745	0.001	0.005
1993	-2.452	0.141	0.154	-3.880	0.194	0.015	-3.511	0.001	0.001
1994	-3.071	0.322	0.502	-3.315	0.168	0.016	-3.388	4.89E-04	0.002

Table 4. Weighted Average Own- and Cross-Price Elasticities among National Brands and with Generic Brands, at Price Ratios 1987

Year		Market Share of Frontier	Market Share of Old	Own-Price Elasticity of Frontier	Cross-Price Elasticity between Frontier and Old	Own-Price Elasticity of Old
Frontier = "286"	84	0.129	0.871	-4.917	0.198	-0.715
	85	0.633	0.367	-0.494	0.194	-0.640
	86	0.728	0.272	-0.675	0.354	-0.614
Frontier = "386"	87	0.308	0.692	-1.266	0.054	-0.828
	88	0.389	0.611	-1.258	0.080	-0.933
	89	0.428	0.572	-1.380	0.142	-0.891
Frontier = "486"	90	0.205	0.795	-1.867	0.047	-1.051
	91	0.301	0.699	-1.627	0.076	-0.788
	92	0.441	0.559	-1.256	0.245	-0.775
Frontier = "Pentium"	93	0.056	0.944	-3.228	0.083	-0.706
	94	0.169	0.831	-1.460	0.175	-0.551

Table 5. Market Evolutions of Frontier and Old Technologies

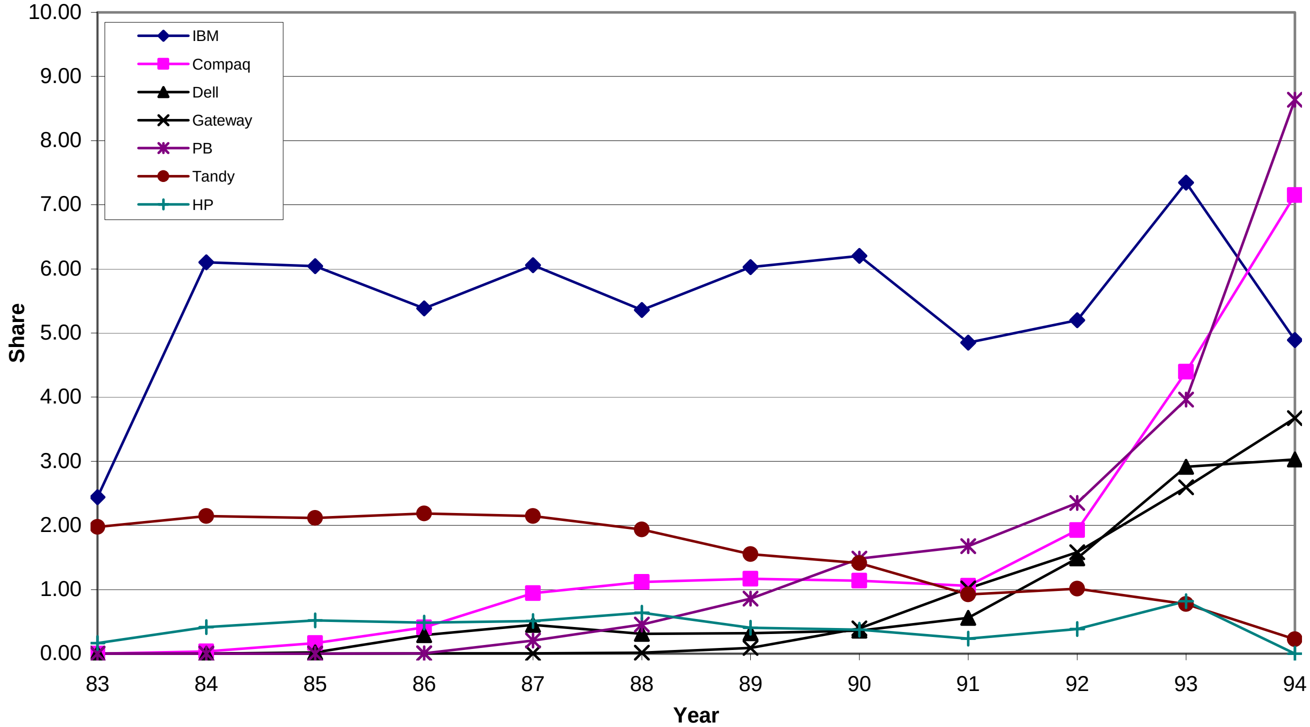

Fig. 1: Market Share of National Brands

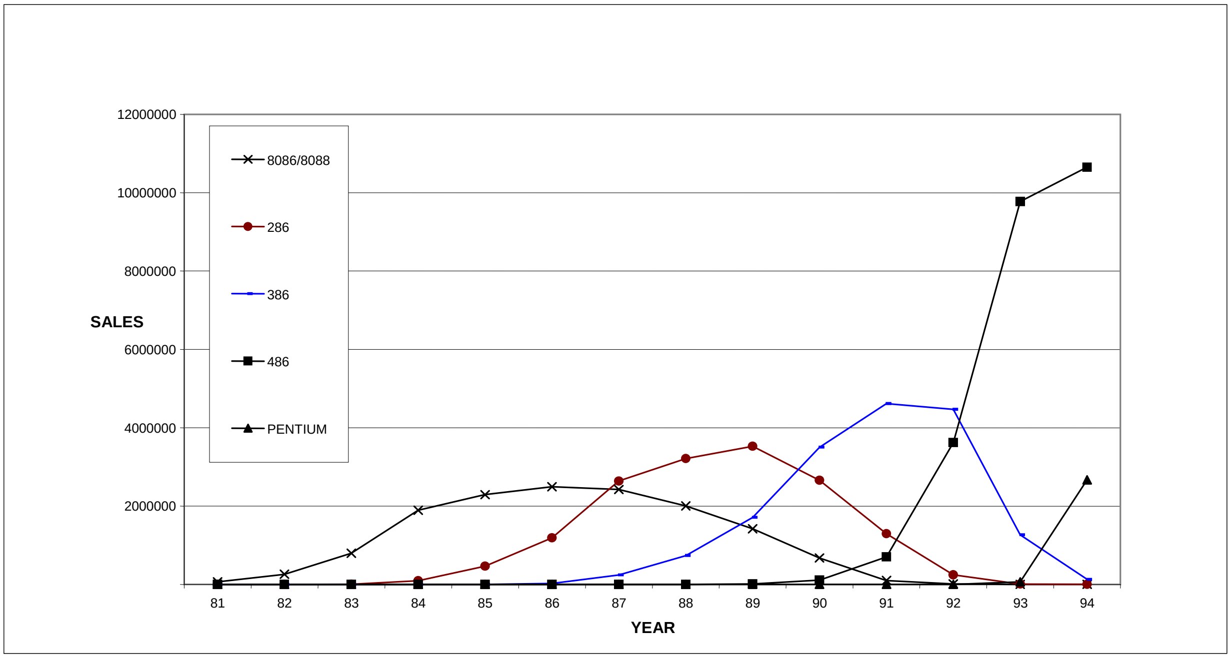

Fig. 2: PC Sales of Different Technologies

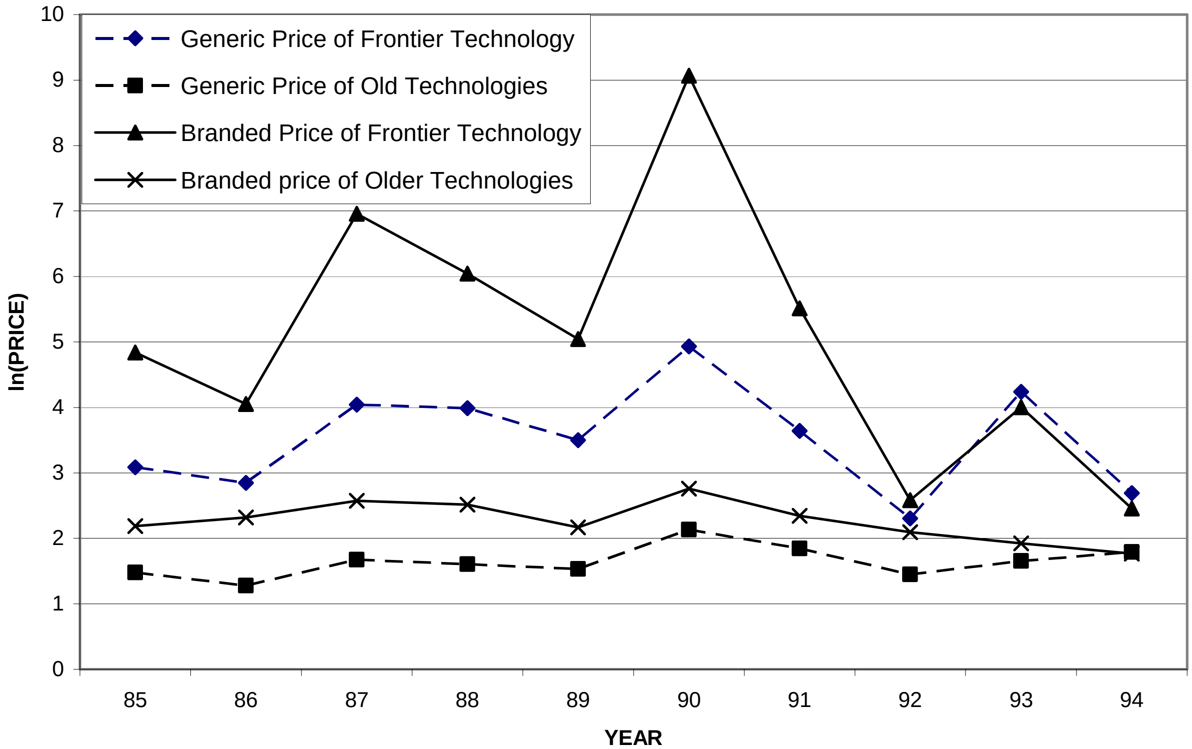

Fig. 3: Convergence of Branded and Generic Prices

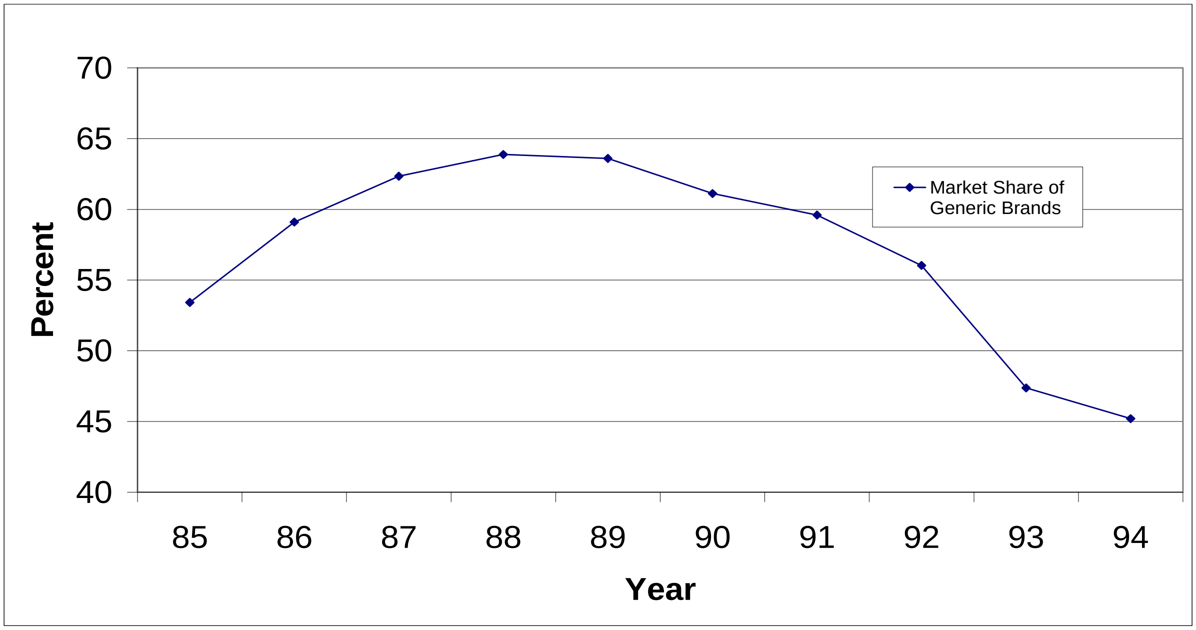

Fig. 4: Market Share of Generic Brands

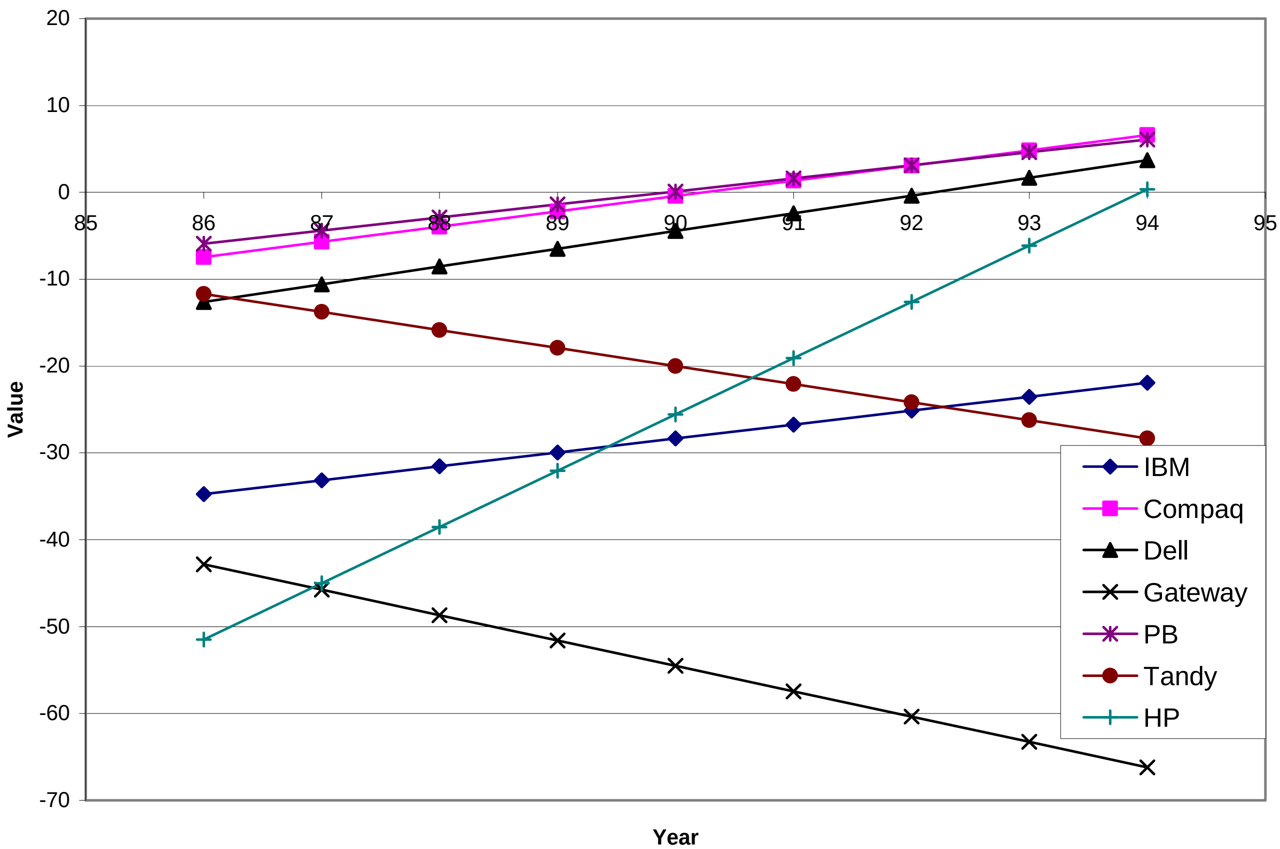

Figure 5: Estimated Changes in Brand Equity 1986 - 1994

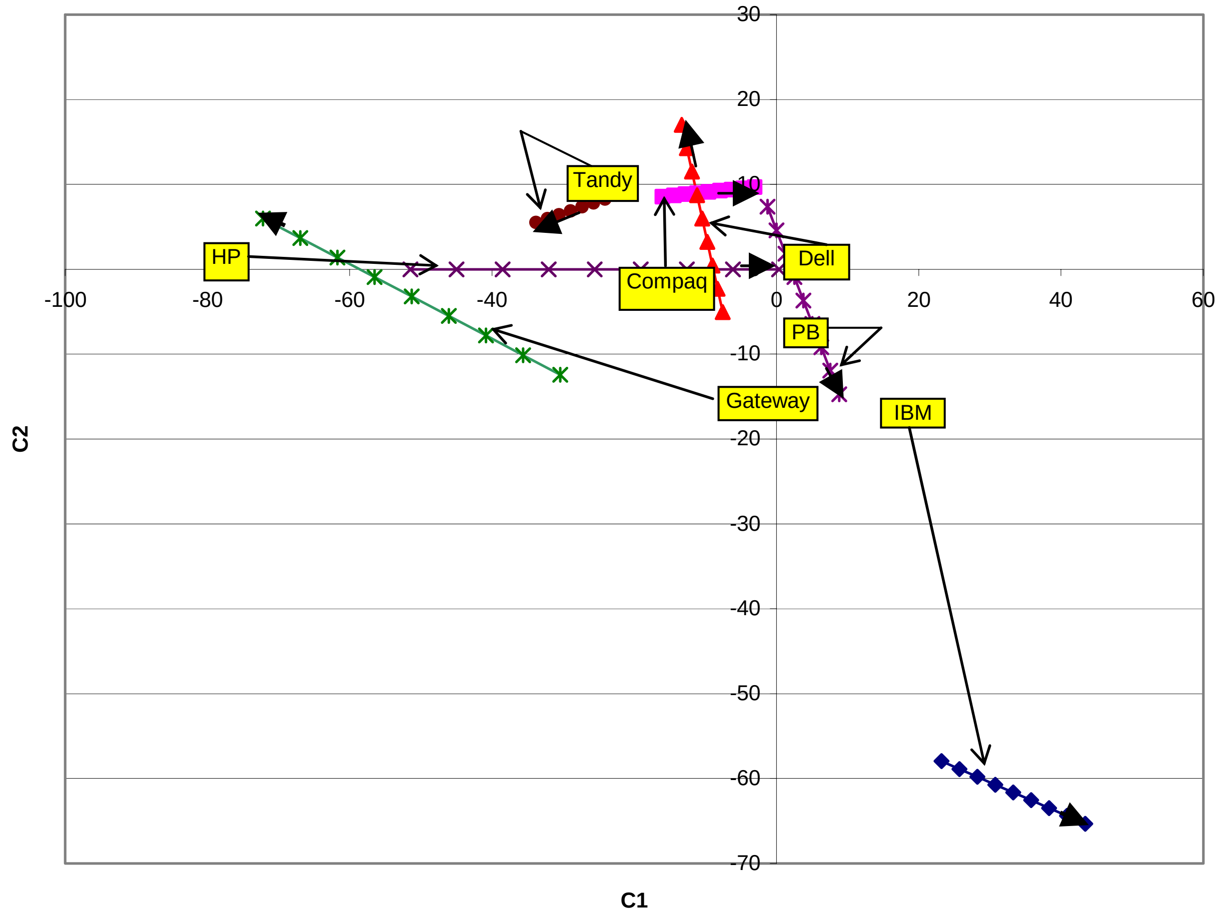

Figure 6: Estimated Changes in Brand Positions: 1986 - 1994