Order Number 9331036

Spatial location and industry market structure: An empirical analysis of the personal computer market

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Harvard University, 1993

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Spatial Location And Industry Market Structure:

An Empirical Analysis of the Personal Computer Market

A thesis presented

by

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to

The Department of Economics

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

in the subject of

Economics

Harvard University

Cambridge, Massachusetts

May, 1993

ABSTRACT

Although most industries are composed of multiproduct firms producing heterogeneous goods, economic literature tends to abstract from the reality by assuming single-product firms, each manufacturing an identical commodity. Quality differences are often ignored. In this dissertation, an empirical analysis of spatial location and demand elasticities is carried out for a premier multiproduct industry with differentiated products, the personal computer industry, using a panel data. The study presents new applications of hedonic methods in industrial organization. Using hedonic coefficients as weights on individual characteristics, the multidimensional vector of attributes of each personal computer model is projected onto a unidimensional quality scale, and hedonic residuals serve as a measure of over/underpricing.

The first part of the study concerns model entry and exit. Firm-level decisions regarding where to locate new models in the existing product space are empirically examined. Significant differences in the spatial location are found between incumbents and entrants. Both model overpricing and brand reputation effects are found to be significant in affecting model exit from the market.

Demand elasticities for individual computer models, taking into account each product's quality and its location in product space, are estimated in the second part of the dissertation. Differences among products are modeled as distances in the linear, vertically-differentiated quality space. Instead of restricting each model's competition to the two nearest products, the cross-elasticities are allowed to diminish with distance

in the quality space. We find that two-stage least squares estimates of demand elasticities are consistent with the observed changes in market structure over the 1976-88 period. Using the estimated elasticities, implied price-cost margins are obtained, and are found to have declined significantly as the industry became more competitive.

In the final chapter, the data for 1989-91 are incorporated, and most of the above findings are confirmed. Since both model and firm turnover increased greatly, hedonic residuals do not predict exit in the later part of the sample. Despite a higher number of products on the market, however, spatial location patterns between incumbents and entrants remained similar. Estimates of demand elasticities and price-cost margins follow previous trends, consistent with the changes in the market structure.

ACKNOWLEDGEMENTS

I would like to thank faculty members who provided me with comments and help at various stages of my research. My thanks go to my advisors, Zvi Griliches, Richard Caves, and Ernie Berndt, who gave me helpful suggestions and patiently listened to my numerous seminar presentations. Zvi Griliches has supplied me with guidance and has employed me as a Research Assistant since my first year of graduate school, providing generous financial support from the Alfred P. Sloan Foundation program on computers and pharmaceuticals. I thank others who read and commented on my papers, mainly Adam Jaffe, Steve Berry, and Manuel Trajtenberg.

I am grateful to Jonathan Cohen and Amy Kim for collecting the original data, and to Ernie Berndt and Zvi Griliches for letting me use it. The data for the last few years of my sample was purchased from the Datapro Corporation. The quantity data for all the years was purchased from the International Data Corporation, both with the funding provided by the Sloan Foundation.

I owe a lot to my fellow graduate students, whose support and companionship made the last five years much more pleasurable. Among them are Steve Schran, Amy Bertin, Karyn Model, and Oved Yosha. They shared my many moments of misery and happiness with equal involvement, and made my graduate school experience memorable. My colleagues at the NBER supplied me with their company and a sympathetic ear daily. They include Elizabeth Kremp, Sara Ellison, Judy Hellerstein, Josh Rosett, Randy Kroszner and Neal Rappaport.

I express my warm thanks to my parents. From thousands of miles away, they followed my progress at every stage with never-ending interest and support. I have always wished they were closer to me physically so that I could share day-to-day events with them. But I could not have asked for them to be any closer to me emotionally than they already are. I have always felt very fortunate to have their approval and company, even if only in spirit.

Finally, I would like to thank the two people who are dearest to my heart. My husband Rob has encouraged me to undertake this task for as long as I have known him. He has never ceased to believe in me, despite my constant doubts. He provided me with continuous emotional support and love. Without him, this project would have never even been started. I thank my son Daniel for greeting me with a smile and a hug whenever I need it. He made all my efforts rewarding, and all my failures unimportant.

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To Daniel

Chapter I

Introduction

Market behavior, be it that of firms or consumers, has always been the fundamental concern of microeconomics. The analysis of how firms interact and how markets respond to their pricing decisions, has given rise to a wide range of theories dealing with alternative market conditions -- from perfect competition to monopoly, and everything in between. Theoretical results depend critically on specific assumptions about the nature of the market as well as the product itself. Serious complications arise if firms are allowed to produce multiple products and if the products themselves are heterogeneous.

It is the difficulties presented by such deviations that lead most theoretical work in industrial organization to adopt the simplifying assumptions of single-product firms and homogeneous goods. A survey of the literature underscores the prevalence of such simplifications. Unfortunately, few markets, if any, satisfy these stringent assumptions of theory. If our aim is to observe reality and test hypotheses, we need to take into account more of the actual complexity that is out there.

My intention in undertaking this project is to show that relaxing some of the major simplifying assumptions does not prevent an empirical analysis from being carried out. Instead of ignoring the product heterogeneity and the variety of commodities offered by each firm, those market realities can be utilized in empirical tests. Although the theoretical literature on firm location in product space dates back to the Hotelling's

[1929] paper, very few studies provide empirical analyses of firm spatial location decisions. The few empirical studies estimating demand elasticities for differentiated products have dealt mainly with the automobile market, and all placed stringent assumptions on cross-elasticities.

This dissertation presents an empirical analysis of the personal computer industry. The focus was motivated both by the industry's evolution over time and by the primary importance of product heterogeneity in its development. Though only about twenty years old, the industry's market structure, long the fascination of industrial organization researchers, has evolved from a few small firms run out of home garages and basements, to a massive market with several hundred companies and over ten million units sold annually in the U.S. alone. Although the average nominal price of personal computers has not changed much over the past twenty years, quality has increased dramatically, causing quality-adjusted prices to drop steeply year after year.

Such ferment offers the prospect of solid answers to some interesting questions of industrial organization. Do multiproduct firms replace their existing goods with new ones or do they refrain from introducing close substitutes? Are there any differences in strategic behavior between existing and new firms? If goods are differentiated in several characteristics, can we still compare them in a single product space? When analyzing market responses to price changes, we cannot simply assume a downward sloping demand curve, as the quality of each model becomes as important as its price -- two goods with identical prices but varying quality could face different demands.

To answer these questions, however, a basis of comparison among heterogeneous products needs to be established. Throughout this study, hedonic estimation is the crucial underlying tool. Hedonic coefficients provide weights on individual characteristics of the personal computer models to facilitate comparison among products. Additionally, hedonic residuals supply a measure of each model's overpricing, used as a determinant of a model's exit from the market. Although hedonic methods have been widely used beyond their traditional application in estimating price indexes, this study presents a new example of their employment in issues addressed in industrial organization, where conventional techniques often fail.

My analysis of firm behavior in the personal computer industry has been divided into two stages. In stage one, firms decide whether to enter the market and select models to be produced. By choosing product characteristics, they place their models in an imaginary quality space. In stage two, firms choose prices for their products, after their models' location has been determined. Theoretical issues and empirical estimation associated with the first stage -- a model spatial location, as well as a model's exit -- are discussed in Chapter II, focusing on the differences between existing and new firms in their strategic behavior. Chapter III deals with the second stage, estimating price elasticities of demand for individual personal computer models, as well as their implied price-cost margins. Changes in the elasticities and profitability over time are evaluated in the context of developments in the industry's market structure. Chapter IV provides an extension of the analysis, utilizing data from the past three years. I examined changes in firms' behavior and the market's response to it. I also assessed whether the industry remained profitable, despite falling prices and cut-throat competition.

Chapter II

Model Entry And Exit in a Differentiated-Product Industry.

1. Introduction.

Although there exists an extensive literature on the economics of entry, and a more modest one on exit, most such analyses have focused on firm-level decisions of whether to enter or leave the market. The analysis becomes much more complicated, however, in the case of multiproduct firms. Firms do not simply face a decision of where to locate themselves in a space of other firms; rather, incumbents introducing new products have to decide whether to replace their old models with similar new ones ("cannibalize" their own products) or spread their models throughout the entire product space. Firms decide how to deter entry through their spatial location decisions. Industries with multiproduct firms allow for analysis of entry and exit of particular goods, separating model effects from those of their producers.

This chapter analyzes patterns of entry and exit of individual models in the personal computer (PC) industry.[1] In the case of entry, issues pertaining to location of models in quality space are addressed, focusing on asymmetries in location of new products between incumbents and entrants. Are entrants more likely to locate their models in "empty" market niches, or in areas already occupied by incumbents' models? Do incumbents preempt the market by segmenting it, i.e. locating all their models in a

[1] We define personal computers as all micro-computers.

single market segment, as in Schmalensee's [1978] breakfast cereal model, or do they disperse their models along the quality space? In the case of exit, a hypothesis that models with relatively high prices, controlling for quality, are more likely to leave the market is tested. The model effects are separated from firm effects to test whether firms' reputation or economies of scope make their models survive in the market longer.

The personal computer market is an example of a multiproduct firm industry, with vertically differentiated, heterogeneous products. The industry has been growing since January 1975, when the first microcomputer, the Altair 8800, was introduced. During its early development, the industry was dominated by a few small-scale, mainly hobbyist-run companies. Entry into the market was then determined by technological innovation and the availability of system-compatible software. Companies often designed their own software with little compatibility among the systems. IBM introduced its PC in 1981 and dominated the market for several years. The industry gradually evolved into a large-scale market with a few big players. Producers of software and hardware started separating, with a higher degree of specialization and compatibility among companies.

The past few years have brought a large number of smaller firms into the market, making the industry quite competitive. There is substantial product differentiation, with most firms offering several models. Although there are no technical barriers to entry (existing technology is usually widely available), firm entry into the market and new product introduction involve sunk entry costs, such as establishing retail channels and advertising.

Personal computer models are differentiated in many attributes. In order to analyze spatial location decisions, one needs to be able to make a comparison between various models. A method of comparison among the multidimensional products, based on hedonic price estimation, is introduced.[2] Each model is first reduced to a unidimensional quality measure by using hedonic marginal implicit prices of each attribute as weights. That allows us to create a linear quality space. By selecting a set of attributes for their new models, firms locate in the quality space. Residuals from the hedonic estimation are used as a measure of model overpricing/underpricing, controlling for their attributes. This method of comparing heterogeneous products can of course be applied in other industries with products differentiated in many attributes, such as the automobile, household appliance, or stereo components industry.

A brief description of the data is next. Section 3 describes the hedonic estimation used both for comparison among differentiated products' spatial location, and in measurement of the overpricing of individual PC models. In section 4, firms' decisions relating to the spatial location of new models are examined. Section 5 describes factors affecting model exit from the market and summarizes empirical findings of model and firm effects. Finally, section 6 summarizes the chapter and presents some conclusions.

2. Data.

The data set used here as well as in the next chapter includes annual prices and

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[2] Bresnahan [1981] and Feenstra and Levinsohn [1990] also use hedonic coefficients to compare multidimensionally differentiated products, though applying a different methodology.

technical attributes for new personal computers sold in the U.S. from 1976 to 1988.[3] The data set is an unbalanced panel. There are 1480 model-level observations over the 13-year period. Due to some missing data, 1436 were used in the hedonic estimation. For each observation, the sample includes a set of technical specifications, price, as well as each model's name and its producer. The list of major attributes, with descriptive statistics and correlation coefficients among them, is in Table 2.1.

A model is identified by its brand name. Although model names are fairly specific, the definition of a model changed over the span of the dataset. In the initial period, models did not carry discrete options for their memory, storage capacity, etc. -- a model had a fixed specification. Towards the end of the sample period, however, most models could be "custom-made" with several configurations of RAM, MHz, and hard disk capacity. There still remained, however, a strategic decision by the firms whether to introduce a new model or continue the old one with new specifications. Introduction of a new model carries a fixed cost of a new design, marketing, and dealer arrangements. We therefore used the same designation the producers did.

The pattern of entry and exit of models and firms, as well as their stocks for each year, is summarized in Table 2.2. Significant entry in 1983 and 1987 is related to the first year of mass production of 16-bit and 32-bit processor PCs, respectively. Several models have multiple observations in a given year, corresponding to different versions of the same model offered. Some models may appear with the same set of specifications

[3] The data were originally collected by Cohen [1988], and later updated by Kim [1989]. Sources include technical model reviews in June issues of *Byte*, *PC Magazine*, and *PC World* for list prices and attributes, as well as ads in the Business section of June issues of *The Sunday New York Times* for discount prices. In addition, the *Dataquest Personal Computer Guide* was used for 1987 data.

in the retail and discount markets in the same year. The retail data includes list prices of PC models based on their technical reviews, or models sold by their brand-name manufacturers (e.g. PC Limited models sold by PC Limited), while discount data covers models sold by other sources (e.g. PCs sold through discount mail order, such as 47th Street Photo). There are 330 distinct firm-years, and 472 distinct models.

3. Hedonic Estimation.

Personal computers are vertically, or quality differentiated products. Vertical differentiation denotes product ordering, where with equal prices all consumers would agree on their preferred product.[4] Other vertically differentiated, multi-attribute products include automobiles and stereo components.

Quality comparison between vertically differentiated products requires an adjustment for heterogeneity in several dimensions. Hedonic estimation -- regression of a product price on its attributes -- is commonly used to adjust for quality differences, either over time or across products (see Griliches [1971], [1988] for discussion). The attribute coefficients in the hedonic equation represent average marginal implicit prices for each attribute. Their interpretation is not straightforward, however, since the coefficients contain information about both technology (costs) and preferences

[4] Although vertical differentiation applies to individual dimensions in characteristic space (most consumers would prefer a faster computer or a larger hard disk), it does not necessarily apply to the quality measure we construct.

(demand).[5] All that can be observed are equilibrium points, where marginal utility equals marginal cost. Figure 2.1 shows a relationship between price and quality. The estimated relationship is shown with a straight line, and quality as a single dimension for simplicity. The upward bending curves represent isoprofit schemes for various technologies, with increasing marginal cost, while the downward bending curves represent indifference curves for various utility functions, with diminishing marginal utility. Only the tangency (equilibrium) points are used in the estimation, incorporating supply and demand simultaneously. Since those points represent marginal utility *and* marginal cost, hedonic coefficients seem to be the right choice for representing the value attached to each attribute by the market.

Hedonic coefficients are somewhat restrictive. The model relates a product's own price to its characteristics, therefore assuming that entry of other firms or models into the market does not affect marginal costs or marginal utility of attributes. Hedonic coefficients may thus be endogenous, themselves affected by entry and exit from the market.

A. Measures of Spatial Location.

Whether products are differentiated vertically or horizontally, they can be placed in a product space by using an imaginary line or circle.[6] That allows for an analysis of spatial location of products. Since PCs are differentiated in many attributes, one faces

[5] For a discussion of the identification problem in hedonics, see: Rosen [1974], Epple [1987] and Bartik [1987].

[6] The reference is to Hotelling's [1929] model of spatial location, and its many variations.

a problem of comparing products in multidimensional space. The following method reduces several attributes to a single-dimensional measure of quality, by projecting the multi-attribute structure onto a linear scale. Each product, or each PC model, is assigned a measure of quality. For example, the quality of model *m* (with each model represented by *J* attributes) is measured by the weighted sum of its specifications:[7]

$$q_m = \sum_{j=1}^{J} \beta_j \, z_{jm} \tag{2.1}$$

or, representing each model as a vector of attributes:

$$q_m = \bar{\beta}' \, \bar{z}_m \tag{2.2}$$

where: j = attributes (j = 1,...,J);

z_{jm} = value of j^{th} attribute for model m; and

β_j = weight of j^{th} attribute.

The weight β_j should represent the marginal value that consumers and producers place on the j^{th} attribute. Such values can be approximated by the estimated marginal implicit prices from the hedonic regression.

A hedonic regression of computer real prices (in 1982 dollars) as a function of major technical attributes, producer, and age of each model was performed. See Table 2.3 for the regression results and for the list of exogenous variables.[8] For each model

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[7] The index is a valid approximation of the correct quality if product characteristics are separable, i.e. quality is a function of characteristics only. See Triplett [1987] for details.

[8] Berndt and Griliches [1990] used a similar equation to estimate price indexes for personal computers.

m, produced by firm *i* in year *t*, here is the pooled hedonic regression:

$$\ln P_{mit} = \beta_0 + \beta_i + \beta_t + \beta_1 \ln(RAM_{mit}) + \ldots + \beta_J\, AGE + \ldots + \epsilon_{mit} \quad \textbf{(2.3)}$$

As technology improved over time, the marginal costs of computer attributes dropped. A pooling of cross-section and time series data, with different intercepts for each year, but common coefficients for each attribute, was tested against the unrestricted model of annual regressions, using the Chow test, and rejected at the 1% level. The restriction was rejected even when time interactions of major characteristics were included in the model. Since the sample changes in 1982,[9] estimating separate pre-1982 and post-1982 regressions was tested against annual estimation. Again, the restriction was rejected at the 1% level.[10] Instead, separate hedonic equations were estimated for each year, unlike in Berndt and Griliches [1990]. Thus the weights β_{jt} vary across years.[11]

Since model attributes in a hedonic regression represent costs of production as well as valuation to consumers, a residual in a hedonic equation can be interpreted as a mark-up of price over cost, thus measuring over- or underpricing of a model, or as some

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[9] IBM joined the market in 1982, changing the nature of the competition.

[10] One could assume that due to the market structure of a few dominating firms with several peripheral companies, individual firms could have varying marginal implicit prices of attributes. The restriction of common attribute slopes across firms was imposed, however, due to the presence of several single-model companies.

[11] Although β's may still be endogenous, allowing them to vary from year to year lessens the imposed restriction. Pooled hedonic coefficients were used for graphs and some of the tables for clarity.

unmeasured value of a model.[12] The hedonic residuals are used as a measure of relative overpricing of PC models in testing a hypothesis that overpriced models are more likely to exit the market.

4. Model Entry -- Spatial Location and Preemption.

A. Spatial Location by Incumbents And Entrants.

This section analyzes spatial location decisions made by both incumbents and entrants when introducing new models into the market. The focus is on strategic decisions made by the two kinds of firms. Since PC components are to a large degree produced by firms other than the ones who sell the complete systems, the technology can be assumed to be available to any firm at the same time. Spatial location is therefore a strategic, not a technological decision. Each firm chooses which models it is going to offer, constrained by the existing technology at the time.

In industries with single-product firms and uniformly distributed consumers, the optimal entry deterrence strategy is for firms to locate evenly spaced in the product space so not to leave space for new entrants.[13] In the case of multiproduct firms, an incumbent has to decide where to place his new models relative to the existing models,

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[12] Besides the technical model specifications included in the regression, there are, for example, some unmeasured firm effects related to the availability of service and software, advertising, management, etc., as indicated by significance of the included firm dummies. Fixed-effect hedonic estimation is impossible due to the presence of small companies producing a single model. The residuals include also unmeasured model effects, such as quality of individual components. Firm dummies control some of those effects.

[13] For example, Bonanno [1987], D'Aspremont, *et al* [1979], Hay [1976], and Schmalensee [1978].

taking into account not only the location of potential entrants' products but also possible effects on the market for his own existing products. Furthermore, relaxing the usual assumption made in the literature on spatial location that consumers are uniformly distributed along the product space, changes the optimal outcome.

Assuming the entry decision is made sequentially, at any point in time we can distinguish incumbents and potential entrants into the market (period 0). In period 1, when firms decide which models to introduce, incumbents face a choice:

(1) they can segment the market by locating their new models close to their existing ones, therefore utilizing "local" scope economies, but at the same time creating substitutes for their previous models (cannibalizing), or

(2) they can try to preempt the market by locating their new models further away in the product space, thus not creating competition for their old models and occupying empty market niches before new entrants or other competitors do.

The first scenario is more likely in an oligopoly, the second under competitive market conditions.

All firms maximize present discounted value of their stream of future profits. The existence of economies of scope is assumed -- fixed costs decrease with the number of models the firm had produced in the past, due to increasing returns to research and development (R&D), advertising, and retail agreements.[14] Model-specific fixed cost (due to new retail arrangements, box design, new advertising) creates economies of scale.

[14] The decrease in costs associated with cumulative output is consistent with Lieberman's [1984] result.

Due to the scale economies a discrete set of models, and not a continuous spectrum, is produced. Because of the diminishing model-specific fixed cost, incumbent's costs of model introduction are lower than entrant's costs.

The preemption literature concludes that if multiproduct firms are allowed, an incumbent will preempt the entire market, on the assumption that it has a lot to lose as a monopolist who would share the market with potential entrants.[15] That is true under the assumption of a fixed product space and a uniform distribution of consumers. Because of the changing technology in the PC market, the constraints on the location decision are shifting over time. It is reasonable to assume that there exists a segment of consumers who always buy the highest quality (i.e. the most advanced technology) available. Therefore the location of consumers changes with the changing technology. Although an incumbent locates where the consumers currently are in order to preempt the market, shifting tastes facilitate entry; positive model entry costs prevent the incumbent from preempting the entire product space.

In this model, the incumbent's mechanism for deterring entry is through optimal location in product space, not price competition. The incumbent preempts new market segments, benefiting from cost and reputation advantages. That forces an entrant to place its models in more crowded (but less risky) quality segments if it wants to enter the market.[16] We would therefore expect the incumbent to serve both market segments:

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[15] Prescott and Visscher [1977], Eaton and Lipsey [1979], Eaton and Kierzkowski [1985] among others.

[16] The result differs from Judd [1985], where an incumbent would not enter the market for a substitute product, because the resulting price war with an entrant would hurt his profits in the original market. He would leave the new (here: highest quality) market for an entrant to occupy. Judd's result does not hold here due to the cost asymmetry and strong reputation effects. An alternative outcome in the entry-

the low-quality segment he was already occupying, and the new, high-quality segment. Under the hypothesis of incumbent cost advantage, its models would be more dispersed in the quality space than the entrant's models. Spatial location of models by incumbents and entrants in a price-quality space can be seen in Figure 2.2. It seems that while the low-end of the market is occupied exclusively by incumbents each year, the highest-quality models also tend to be introduced by incumbents. Entrants, by contrast, tend to place their models in the middle.

The dispersion issue can also be treated as a timing decision. Although we cannot treat new model introduction as a technology racing question (since the technology is available to all the players, as it is embodied in components produced elsewhere) when a new innovation becomes available, each firm makes a timing decision as to when to introduce it. Applying concepts of the innovation literature, since the new PC technology "builds on" the old technology and does not introduce drastic innovation, incumbents have a greater incentive to be first to introduce it, in order to extend their market power over new products (Gilbert and Newbery [1980]). An established firm benefits from learning effects and reputation advantages and therefore is more likely to introduce the new technology when it first becomes available while continuing its production of older, lower-quality models. Such a strategy will create a high dispersion in quality among the firm's models. On the other hand, a new entrant, or a continuing firm with relatively little experience (i.e. small economies of scope advantage), is more likely to wait with

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deterrence literature, where an entrant is deterred from coming in at all by the fact that his expected post-entry profits are lower than the current incumbent's profits, does not hold due to a growing demand. The result is consistent with Hay's [1976] model of sequential entry and with Bonanno [1987].

the new product introduction, placing its models in a more established market segment.

B. Previous Research.

Beginning with Hotelling's [1929] model of spatial location, there have been several theoretical models of entry deterrence and preemption in a multifirm market. In Hotelling's model, identical duopolists locate next to each other on a line. The results change when at least one assumption is violated, and either heterogeneous firms, sequential entry, or multiproduct companies are present. Few papers deviate from all of the above assumptions. The following studies derive spatial location entry-deterring strategies by multiproduct incumbents. Firms either spread their models or gather them in a single market segment, depending on market condition assumptions.

Schmalensee [1978] discussed entry deterrence in a market with localized rivalry among brands and economies of scope. In the case he analyzed, the market was dominated by a small number of major colluding firms which localized their brands in order to deter entrants most effectively. In the case of a non-collusive industry with many firms, such as the PC industry, firms do not make agreements to segment the market as each maximizes its own profits; indeed, the outcome could be the opposite, with firms spreading their models, as each tries to establish a reputation in several market segments.

Bonanno [1987] showed that with no threat of entry, firms would locate as far away as possible from each other to maximize their revenue. Facing a threat of entry in a market with multiproduct firms, entry deterrence can be achieved by changing the location of products by incumbents towards a higher product dispersion, in order to create competition faced by a potential entrant in every market segment, and therefore make his entry unprofitable.

Spence [1976] developed a model where in a growing industry, a firm would not produce close substitutes for its own product, as that would lower demand for its existing commodity. The firm would opt for more distant substitutes instead. In Eaton and Lipsey's [1979] model, an incumbent monopolist in a growing industry introduces a substitute for his own product before an entrant does, in order to preempt the market. Brander and Eaton [1984], in one of the very few papers to have modeled games by multiproduct firms, demonstrated that under an assumption of no entry, a segmented market structure (i.e. a structure in which the market is divided, each firm producing only close substitutes) yields higher profits than an interlaced market structure (where each firm produces less closely related products). If there is a possibility of entry, however, the result is reversed. Each of the above results, of course, depends on the specific assumptions of the respective models. There have been no empirical papers measuring the degree of model dispersion by individual firms.

C. Entrants' Spatial Location.

New entrants make a location decision for the models they introduce after they observe that of incumbents' models. Since incumbents act as leaders, entrants may be forced to locate closer to the existing models than incumbents do. On the other hand, entrants would search for empty segments in the quality spectrum either to avoid price wars or to "leap-frog," where entrants introduce innovative models before incumbents did. The latter hypothesis is not confirmed by Figure 2.2, where the highest quality models are introduced by incumbents, not by entrants.

One hypothesis is that entrants opt for empty market segments in placing their models, relative to location of incumbents' new models. In order to test the above hypothesis, for each new model we constructed a measure of average distance from all previous year's models:[17]

$$\bar{d}_{mit} = \frac{\sum_{n=1}^{N_{t-1}} \sqrt{(q_{mit} - q_{n,t-1})^2}}{N_{t-1}} \qquad \textbf{(2.4)}$$

where: N_{t-1} = number of models in year t-1;

q_{mit} = quality of model m by firm i in year t; and

$q_{n,t-1}$ = quality of model n in year t-1.

The average distance measure was regressed on firm and model characteristics. The regression results are presented in Table 2.4. Model (3) is log-linear, with the number of models in year t-1 on the right-hand side.

The ENTRANT dummy is negative and significant, rejecting the hypothesis that an entrant is more likely to locate in empty areas, in favor of an alternative that an entrant places his models in more crowded market segments. The result also shows that

[17] Weitzman [1991] uses a measure of distance between any two "species" (here models), which he states could be approximated by a hedonic weighted sum of distances between individual characteristics, as in the measure above.

there is no evidence of technological "leap-frogging." We control for the most innovative, or pioneering models and firms: the PIONMODEL dummy indicates models which were first to incorporate a new technology.[18] The innovative models, by definition, locate far away from the pack. The equivalent dummy for a firm which introduced any of such models, PIONFIRM, has a negative coefficient, possibly picking up other firm effects. The number of firms on the market in year *t-1*, NUMFIRM_{t-1}, captures market structure when entry decisions are made, thus controlling for the effects of competition. The more firms existed in year *t-1*, the more competitive the market, and therefore the fewer empty market niches to be filled by entrants, and the less significant the strategic location decision. The coefficient is negative and significant, as expected. The regression was tested for heteroscedasticity due to varying number of models per year -- squared residuals were regressed on the number of models in year *t-1*. The coefficient was insignificant.

D. Model Dispersion.

We tested the hypothesis that incumbents spread their new models along the quality space to deter entry, while entrants concentrate their models in a single market segment. Under the hypothesis, the dispersion of new models is higher for incumbents than for entrants.

[18] The new technology includes: the first 16- or 32-bit processor, the highest existing value of RAM, the fastest speed (MHz), or the largest capacity hard disk. A model was "pioneering" if it was the first to incorporate any of the new technologies. In some cases, more than one model introduced the same technology simultaneously. All of them would be denoted pioneering. A firm was "pioneering" if any of the models it ever produced incorporated the new technology.

To help address the question, for each firm in each year we construct a measure of a within dispersion:[19]

$$\sigma_{it} = \frac{\sum_{m=1}^{M_{it}} (q_{mit} - \bar{q}_{it})^2}{M_{it}} \quad where \quad \bar{q}_{it} = \frac{\sum_{m=1}^{M_{it}} q_{mit}}{M_{it}} \tag{2.5}$$

In order to measure whether a firm's models are relatively dispersed or concentrated, we compare the within dispersion to the total dispersion in year t:

$$\sigma_{t} = \frac{\sum_{n=1}^{N_{t}} (q_{nt} - \bar{q}_{t})^2}{N_{t}} \quad where \quad \bar{q}_{t} = \frac{\sum_{n=1}^{N_{t}} q_{nt}}{N_{t}} \tag{2.6}$$

and the relative dispersion index is:[20]

$$R_{it} = \frac{\sigma_{it}}{\sigma_t} \tag{2.7}$$

where: M_{it} = number of models by firm i in year t; and

N_t = total number of models by all firms in year t ($N_t = \Sigma_i M_{it}$).

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[19] Feenstra and Levinsohn [1990] use a somewhat similar approach for the case of the automobile industry. They first define neighborhoods of models, however, and then measure distance between models within a neighborhood by using the squared distance of weighted attributes, using hedonic coefficients as weights. Such a division of the PC market into segments seems questionable, as it cannot be assumed that competition is strictly localized. We therefore treat the entire PC model space as continuous, with elasticities of substitution declining gradually along the line.

[20] The dispersion measures, as well as the distance measure, were computed using a quality index based on coefficients from annual hedonic regressions. Using pooled hedonic coefficients did not alter the coefficient signs, though it did make some of them insignificant.

Quality measures (q_{mit}, q_{nt}) are computed as in equations (2.1) and (2.2). The index R_{it} measures the degree to which a firm's models are concentrated in one area, as opposed to dispersed throughout the entire market, in year t.[21]

As can be seen from Table 2.5, incumbents have had a steadily higher within dispersion than new entrants, consistent with my hypothesis.[22] The dispersion also seems to increase with firm age. An econometric estimation can indicate whether the asymmetry is attributed to firm age, or whether there exists a discontinuity between entrants and incumbents; whether firm experience accumulates with years on the market, or with the number of models a firm has produced; whether innovative firms differ in their spatial location decisions, and whether market structure is significant in affecting firms strategic decisions.

The relative dispersion index R_{it} was regressed on factors which could explain firm decisions regarding the spatial location of their models in a given year. The specification used is:

$$R_{it} = \delta_0 + \delta_1 \text{ ENTRANT}_{it} + \delta_2 \text{ FIRMAGE}_{it} + \delta_3 \text{ PIONFIRM}_i + \delta_4 \text{ NMODCUM}_{i,t-1} + \delta_5 \text{ NUMFIRM}_{t-1} + \epsilon_{it} \qquad \textbf{(2.8)}$$

[21] One of the difficulties with dealing with the measure is the presence of zeros. If a firm introduced a single model in a given year, its model dispersion is zero, as is its ratio to the total model dispersion that year. Thus a firm may appear to gradually scatter its models more and more every year (as is the case for Atari and Commodore), until it has only a single model on the market. Omitting observations where the measure equals 0 did not alter the regression results, however.

[22] The measure does correct for the number of models each firm had on the market each year.

where: R_{it} = relative dispersion measure, σ_{it} / σ_t;

ENTRANT_{it} = 1 if firm i was an entrant in year t;

FIRMAGE_{it} = firm's age in year t;

PIONFIRM_i = dummy equal to 1 if firm i was pioneering;[23]

$\text{NMODCUM}_{i,t-1}$ = number of models firm introduced before year t;

NUMFIRM_{t-1} = number of firms in year $t-1$.

The results of the estimation are included in Table 2.6. The ENTRANT dummy was included in order to test for the asymmetry between incumbents and entrants. It turns out that although model dispersion increases with firm age, indicating possible cost advantages due to learning effects, there is no significant difference between incumbents and entrants when firm age is included. The longer a firm has been on the market, the stronger its cost and reputational advantages. Therefore a firm can preempt the market by serving all market segments, i.e. distributing its models along the product space. The effect on dispersion is positive. Economies of scope, as measured by the total number of models a firm had introduced before year t, NMODCUM, are also significant. The interpretation is that regardless of a firm's age, the more models it had marketed in the past, the more established its reputation and the higher its past investment in advertising and R&D.[24,25] PIONFIRM is insignificant, indicating that innovative firms do not

[23] See footnote 18.

[24] A measure of economies of scale (firms' market share or its cumulative output) was not included for two reasons: (1) quantity data exist for 1037 out of 1480 observations only, and therefore yield 209 (instead of 330) firm-years; and (2) a firm's market share can itself be affected by the firm's model dispersion, introducing endogeneity.

differ in their strategic model dispersion from other firms (although their *level* of quality is higher). NUMFIRM controls for market structure in year *t-1*, when firms make their spatial location decisions. The sign is positive, as the fewer firms are there on the market, i.e. the closer the market structure is to an oligopoly, and the more likely they are to segment the market (as in the case of Schmalensee's breakfast cereal industry).

There are several problems with the interpretation of the coefficients, however. First, a firm's cumulative number of models is only an approximation for economies of scope, and could be endogenous. Exogenous measures of economies of scale/scope would give a clearer picture. Second, we did not include any demand measures, and firms' location decisions cannot be fully explained by the supply side only. Market shares could be used as an approximation for demand, but the measure has problems as explained in footnote 24.

5. Model Exit.

Despite the industry's continuous growth since its beginnings in the 1970s, there has been substantial exit of models from the market. Such model exit can be driven by firm effects -- certain firms' models tend to stay in the market longer because of those firms' reputation and/or economies of scope due to learning effects. But model exit can

[25] The variable could be reflecting the fact that more models are associated with a higher model dispersion. To avoid the effect, we divided both within and total dispersion by the squared number of models instead (M_{it}^2 and N_t^2, respectively). The ENTRANT dummy remained insignificant in all the regressions, while FIRMAGE was still positive and significant. The NMODCUM variable became insignificant. Both "linear" and "squared" dispersion indexes are correlated with the number of models a firm had on the market in a given year.

also be due to model effects -- a model may exit the market because it is overpriced relative to other models with similar attributes, or it has not been marketed well enough to have gained a sufficient market share. The following section presents an empirical analysis separating the two effects.

A. Firm Effects.

Firm-specific reasons for model exit may be related to the firms' order of entry into the market. They include high switching costs, coming from what Schmalensee [1982] called "pioneering brands." He showed that in a multibrand industry with sequential entry there is an advantage to early brands, or brand loyalty: because of decreased uncertainty after the initial purchase, customers are more likely to continue buying the brand they know, even if an entrant introduces a cheaper version of the same product. If high switching costs among producers exist in the PC market, new entrants' models would tend to leave the market first. Brand loyalty is more likely to pertain to firms than to individual models, since with the fast advancing technology customers are unlikely to make repeat purchases of the same model.

Whether a firm was pioneering or not, its survival in the market for a long period of time (due to outstanding management, for example), gives it a learning-effect advantage. Previous investment in advertising and R&D, as well as established reputation, might make the firm's models less likely to exit the market than similar models by other firms. Firm effects also include the firm itself leaving the market. In order to isolate the two kinds of firm effects, we separately analyze models produced by continuing firms only.

B. Model Effects.

Model exit may be caused by individual model characteristics, as well as by a producer's reputation or high firm-switching costs. Relatively high-priced models could be forced out of the market, even if other models by the same firm remain. In such cases, high pricing may indicate high costs of the *model*, and not firm-level inefficiencies.[26]

Relative overpricing of models is measured by using residuals from the hedonic regression described above. Because of the dual interpretation of hedonic coefficients, the residuals can represent either additional cost of a particular model (i.e. overpricing), or additional value to consumers, not captured by the included attributes.[27] If the market structure was not competitive, high residuals could also indicate market power not captured by the firm dummies.

If the first interpretation of residuals is true and if consumers select a PC on the basis of its set of attributes, models with higher hedonic residuals should be more likely to exit the market. If, on the other hand, the second interpretation is correct and the residuals capture value not perfectly correlated with the included characteristics, the

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[26] As the prices of computers drop every year due to continuously decreasing production costs (see Berndt and Griliches [1990]), more advanced technology becomes more accessible and therefore more popular, while the demand for lower-end models (e.g. 8-bit processor models) decreases. It could be the case that lower-end models become relatively high priced, as their production costs could not fall below a certain level. The data, however, does not substantiate that.

[27] These are separate from manufacturer effects, as firm dummies for major brands were included in the hedonic regression.

overpriced models would not be any more likely to exit the market than the underpriced ones, since whatever makes them more expensive raises their value to consumers. If higher-priced models are more likely to exit the market, the hedonic regression residuals would be associated with an increased probability of a model's exit.

C. Market Segments.

Besides separating firm and model effects, we test for the existence of market segments. If market segments existed, cross-elasticities of demand and supply would be higher within segments than between them, and models' exit should not be randomly distributed across the quality space. When a new technology opens a segment of the market, old technologies become obsolete. Due to shifting demand and technology, entire market segments would be exiting the market. The hypothesis related to the existence of market segments was tested, using a formula for the dispersion among all the models exiting in a given year, relative to the total dispersion of all the models in the same year (similar to equation (2.7)):

$$R_{et} = \frac{\sigma_{et}}{\sigma_t} = \frac{\dfrac{\sum_{i=1}^{N_{et}} (q_{iet} - \bar{q}_{et})^2}{N_{et}}}{\dfrac{\sum_{i=1}^{N_t} (q_{it} - \bar{q}_t)^2}{N_t}} \qquad \textbf{(2.9)}$$

Under the market segmentation hypothesis, the relative dispersion is significantly less than one. The results do not confirm the hypothesis. There are no significant differences between the average quality of exiting models as compared to the average quality of all the models in any given year, and the ratio of the two dispersion measures is not significantly different from one. We conclude that there is no evidence that the PC market is segmented.

D. Descriptive Analysis.

In order to test whether models with higher prices, controlling for quality, are more likely to exit the market, we use residuals from the hedonic regressions described by equation 2.3. Positive residuals indicate models' relatively high prices, given their attributes, producer, year of production, and age. Average residuals by model's age for both exiting and continuing models are included in Table 2.7.[28] As the table indicates, models which exited the market (at any age) had higher average hedonic residuals than models that survived longer.

Firm-related reasons seem also important in exit determination, with incumbent firms having an advantage over new entrants: almost half of the observations on models leaving after one year were on models produced by new firms (i.e. the firms were themselves one-year old when the new models left the market). Over one-third of those who left after their first year were produced by firms which themselves lasted for one year only. The relationship does not explain the causality of events -- firms might have exited because of their poor management, high costs, etc., or might have left *because*

[28] Residuals from a joint hedonic regression were used in the table to allow for year-to-year comparison. The probability-of-exit estimation, however, uses residuals from annual hedonic regressions.

their models were inferior.

E. Econometric Analysis.

In order to isolate the residual (overpricing) effects, from switching-cost and brand-loyalty effects, we estimated a regression of the probability of a model's exit in a given year. we assume that the distribution of the residuals is Weibull, and therefore use logit estimation. The right-hand side variables include measures of overpricing of models, as well as firm and model characteristics:

$$\begin{aligned} \Pr(\text{EXIT}_{mit}) = \; & \beta_0 + \beta_1 \,\text{RESID}_{mit} + \beta_2 \,\text{RESSIGN}_{mit} + \beta_3 \,\text{FIRMAGE}_{it} \\ & + \beta_4 \,\text{ENTRANT}_{it} + \beta_5 \,\text{MODELAGE}_{mit} + \beta_6 \,\text{NMODCUM}_{i,t-1} \\ & + \beta_7 \,\text{PIONFIRM}_i + \beta_8 \,\text{PIONMODEL}_{mi} + \epsilon_{mit} \end{aligned} \qquad \textbf{(2.10)}$$

where: EXIT_{mit} = 1 if model exits in year *t*, 0 otherwise;

RESID_{mit} = residual from annual hedonic regression;

RESSIGN_{mit} = signed residual squared;

FIRMAGE_{it} = firm's age in year *t*;

ENTRANT_{it} = 1 if firm *i* was an entrant in year *t*;

MODELAGE_{mit} = model's age in year *t*;

$\text{NMODCUM}_{i,t-1}$ = number of models firm introduced before year *t*;

PIONFIRM_i = dummy equal to 1 if firm was pioneering;[29] and

PIONMODEL_{mi} = dummy equal to 1 if model was pioneering.

[29] See footnote 18.

The estimation results are in Table 2.8. The last column presents results for continuing firms only; that regression allows us to examine model effects for models which did not leave the market due to their producers' bankruptcy.

The coefficient on hedonic residuals is both positive and significant, indicating that the residuals capture model overpricing, and the overpriced models are indeed more likely to exit the market. Since the signed residuals squared coefficient is negative, the probability of exit diminishes with residuals.[30] Interestingly, when positive and negative squared residuals are allowed separate coefficients, the negative residuals' effect is even stronger -- indicating that the most underpriced models have a much lower probability of exiting.

Under the assumption of firm-appropriated learning effects, costs will drop over time, as explained above, and new firms or models will have higher marginal costs, thus being forced to exit the market due to their position high up on the learning curve. The hypothesis is not confirmed at the model level -- the positive coefficient on the MODELAGE variable indicates that the longer a model has been on the market, the more likely it is to exit.[31] The effect of changing technology outweighs any possible model loyalty or cost advantage effects. There is some evidence, however, for learning effects in the case of firms. The FIRMAGE coefficient is negative and significant,

[30] The squared effect does not, however, offset the total effect of residuals on the probability of exit, since, first of all, residuals are significantly lower than one in absolute value, and second, the absolute value of the squared residual coefficient is smaller than that of the linear residual coefficient.

[31] An equation with a separate dummy for new models, allowing for discontinuity at age 1 was estimated, but the dummy was insignificant.

indicating that the longer the *firm* existed, the less likely is the model to exit.[32] Furthermore, new entrants' models are more likely to exit the market, as exhibited by the positive and significant coefficient on the ENTRANT dummy.

The negative effect of a firm's age on its models' probability of exit has two possible explanations. Besides the learning effect, there are strong reputational effects. If consumers develop strong brand loyalty, they are more likely to buy another model by the same brand. That provides some evidence for advantage to older firms and to incumbents. Since residuals do not, on average, differ between newer and more experienced firms, the brand loyalty explanation for strong firm effects seems more plausible than the learning effect story.[33]

Schmalensee's pioneering-brand hypothesis was tested by including dummies for the pioneering firm and model. The importance of firm effects was confirmed -- the pioneering firm dummy was significant and negative, while the pioneering model dummy was insignificant. The result may demonstrate the existence of some unmeasured firm characteristics -- service availability, reputation, successful marketing, etc., not captured by the firm's duration on the market.

We also tested whether marketing overpriced models was likely to make a firm drop out of the competition.[34] We looked at the correlation between average residuals

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[32] Omitting either of the age variables does not alter the coefficient on the other; the result is not, therefore, caused by the correlation of the two regressors.

[33] The learning effect could, however, give older firms cost advantages without lower prices. A credible threat of lowering their prices in case of entry could allow them to maintain higher markups.

[34] For some firms, the effect is already captured by producer dummies in the quality measure, but only major producers were included in the analysis.

for a firm in year *t-1* and the number of new models it introduced in year *t*. The correlation coefficients are insignificant. That result confirms the existence of firm effects, such as brand loyalty, which allows firms to successfully compete in the market despite their overpriced models.

6. Summary and Conclusions.

This chapter utilized empirical analysis to answer questions dealing with model entry and exit in the personal computer industry. The industry is characterized by multi-product firms with products vertically differentiated in several attributes. A method reducing multidimensional models to a single quality measure was used to analyze spatial location of entering models, where "space" indicates a quality spectrum. Patterns of location of models by incumbents and entrants in the quality space were analyzed, using a measure of a relative spatial dispersion. The econometric results show that entrants tend to locate their models in relatively more crowded areas of the market, while older firms utilize their advantage due to reputation and economies of scope, and tend to preempt the market by dispersing their models along the quality space. The longer a firm has been on the market, and the more models it had produced in the past, the larger is its advantage, and the more likely it is to spread its models in the quality spectrum. There is no discontinuity, however, between incumbents and entrants.

Model and firm effects were distinguished in the case of exit of models from the market by using hedonic regression residuals to measure individual models' overpricing, controlling for their quality, brand, and age. Model exit seems to be caused by both model and firm effects. Again, evidence for strong reputational and learning effects was found: the older the firm, the less likely its models are to exit. Similarly, more innovative, or pioneering firms' models are less likely to leave the market, controlling for model characteristics. Both factors might be associated with firms' reputational advantage, as well as their cost advantage due to prior investment in advertising and R&D. We do not have sufficient data to isolate these two kinds of firm effects.

Chapter III deals with the second stage of the game played by the PC producers -- after the location in quality space is set, prices are determined. We analyze the market response to the price changes in the PC industry, taking the spatial location of models in the quality space as given. The location is used as a measure of market power for individual models.

TABLE 2.1: SUMMARY STATISTICS FOR MAJOR VARIABLES, 1976-1988

Variable	Mean	Std. Deviation	Min	Max
(1) Price	2726.3	2119.0	40.00	13995
(2) RAM	500.73	496.43	0.5	4096
(3) MHz	7.75	4.808	0.5	25
(4) Hard Disk	15.58	34.482	0	314
(5) # Floppy Drives	1.07	0.614	0	3
(6) # Slots	4.72	3.721	0	22
(7) 16-bit Proc.	0.480	0.500	0	1
(8) 32-bit Proc.	0.124	0.329	0	1
(9) B&W Monitor	0.408	0.492	0	1
(10) Color Monitor	0.028	0.166	0	1
(11) Portable	0.156	0.363	0	1
(12) Add'l Hardware	0.018	0.134	0	1
(13) Discount Price	0.278	0.448	0	1

Sample Correlation Coefficients:

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Price	1	0.36	0.42	0.54	0.06	0.25	-0.02	0.44	-0.07	0.05	-0.09	-0.02	-0.22
RAM		1	0.75	0.51	0.04	0.17	0.12	0.62	-0.14	0.04	-0.08	-0.06	-0.08
MHz			1	0.57	0.10	0.26	0.09	0.76	-0.16	0.07	-0.09	-0.07	-0.12
Hard Disk				1	-0.07	0.22	-0.04	0.55	-0.15	0.04	-0.11	-0.05	-0.03
# Floppy Drives					1	-0.03	0.14	-0.08	0.16	0.05	0.05	0.03	0.01
# Slots						1	0.14	0.18	-0.33	-0.01	-0.37	-0.12	-0.10
16-bit Proc.							1	-0.36	0.05	-0.04	-0.04	-0.02	-0.04
32-bit Proc.								1	-0.21	0.10	-0.09	-0.04	-0.09
B&W Monitor									1	-0.13	0.37	0.13	0.03
Color Monitor										1	-0.01	0.04	0.03
Portable											1	0.11	0.05
Add'l Hardware												1	-0.02
Discount Price													1

TABLE 2.2: ANNUAL ENTRY AND EXIT OF PC MODELS AND FIRMS

Total number of models: 472

	# of models			# of firms		
Year	Entry	Stock	Exit	Entry	Stock	Exit
1976	-- *	10	8	-- *	7	3
1977	12	14	7	6	9	3
1978	3	10	2	1	8	2
1979	6	14	2	3	9	1
1980	5	17	6	0	8	1
1981	6	16	2	3	10	1
1982	9	24	6	4	13	1
1983	39	57	27	13	24	4
1984	54	82	47	17	35	9
1985	53	86	39	20	44	15
1986	87	127	53	18	51	14
1987	122	204	118	20	55	23
1988	66	155	-- *	22	57	-- *

Overall Statistics:

	Mean	Min	Max
Total # models/firm	6.09	1	85
# models/firm in a year	2.47	1	20
# models/entrant	1.54	1	6
# models/exiting firm	1.58	1	6

* There is no information about entry in the first year of data, or exit in the last year.

FIGURE 2.1: HEDONIC ESTIMATION, PRICE vs. QUALITY

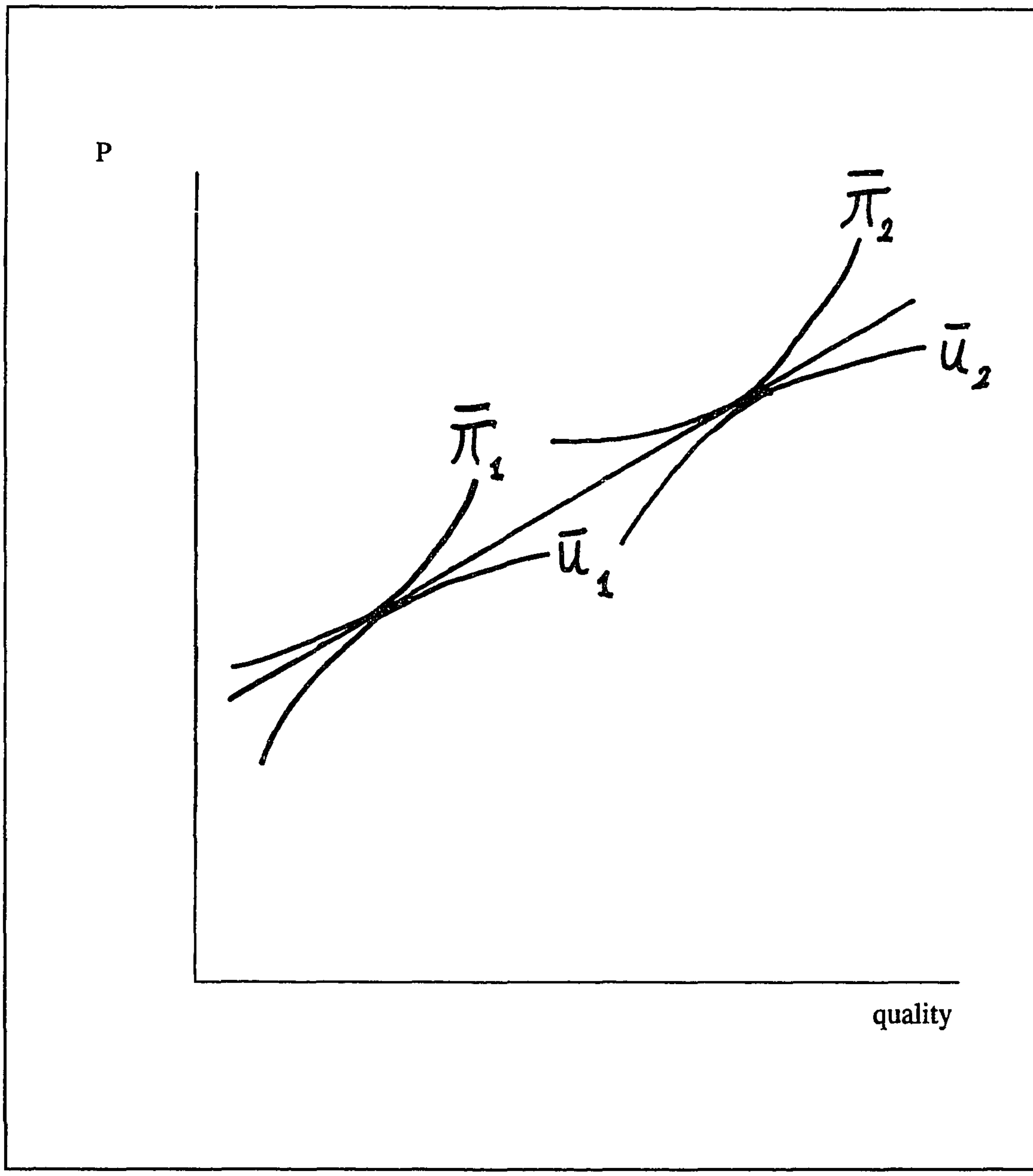

TABLE 2.3: HEDONIC REGRESSION, 1976-1988
DEPENDENT VARIABLE: log (Real Price) *

VARIABLE	COEFFICIENT	T-STATISTIC
LOG (HARD DISK)	0.164	19.64
LOG (RAM)	0.339	18.10
LOG (MHZ)	0.213	5.82
LOG (# FLOPPY DRIVES)	0.367	7.98
LOG (# SLOTS)	0.085	4.38
BLACK & WHITE MONITOR DUMMY	0.068	2.53
COLOR MONITOR DUMMY	0.134	1.93
DISCOUNT MARKET DUMMY	-0.274	-9.86
EXTRA EQUIPMENT DUMMY	0.224	2.68
PORTABLE DUMMY	0.218	5.66
16-bit PROCESSOR DUMMY	0.252	7.24
32-bit PROCESSOR DUMMY	0.587	9.59
AGE	0.055	3.95
APPLE DUMMY	0.157	2.67
ATARI DUMMY	-0.574	-7.66
COMMODORE DUMMY	-0.413	-6.23
COMPAQ DUMMY	0.339	6.51
IBM DUMMY	0.032	0.75
NEC DUMMY	0.137	2.25
RADIO SHACK DUMMY	-0.023	-0.45
ZENITH DUMMY	0.242	3.78
WYSE TECHNOLOGY	0.040	0.54
EPSON DUMMY	-0.119	-1.53
KAYPRO DUMMY	0.093	1.18
NCR DUMMY	0.318	4.04
NORTHGATE DUMMY	0.185	1.94
Intercept	6.167	66.78
$R^2 = 0.757$	$F = 117.6$	$N = 1436$

* Year dummy coefficients omitted for clarity

FIGURE 2.2: LOCATION IN PRODUCT SPACE, INCUMBENTS/ENTRANTS

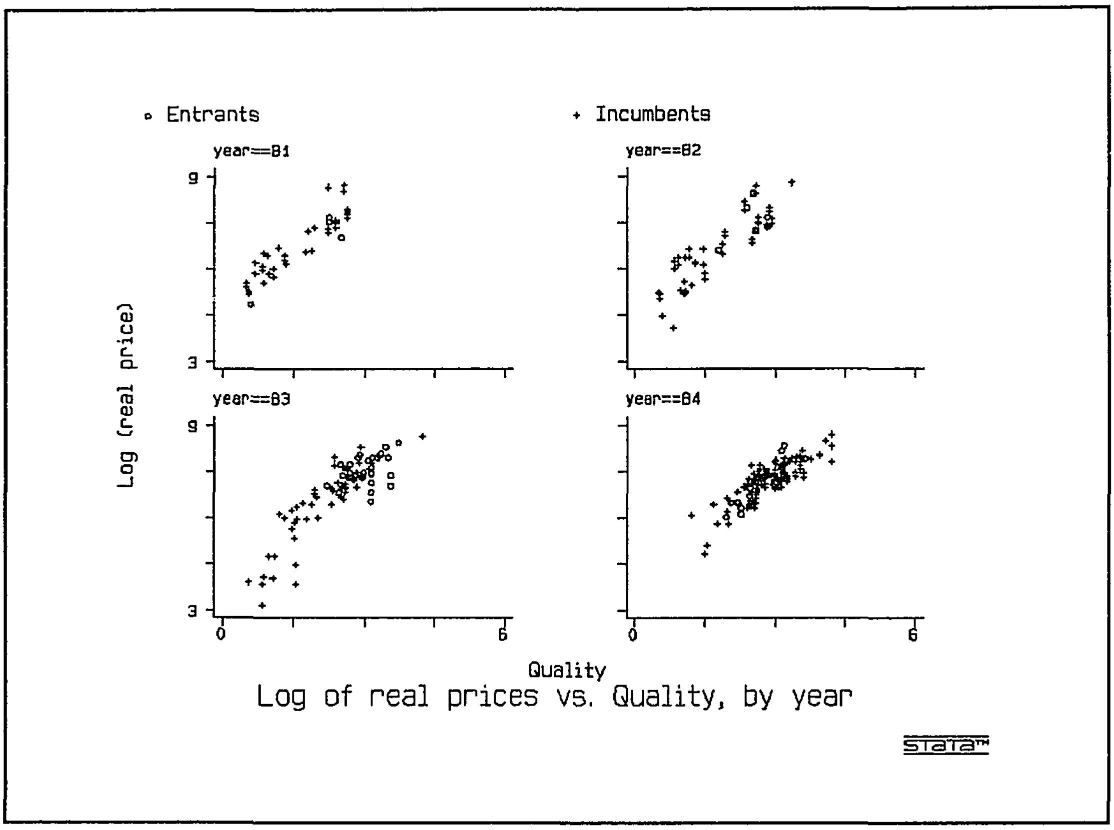

FIGURE 2.2, continued

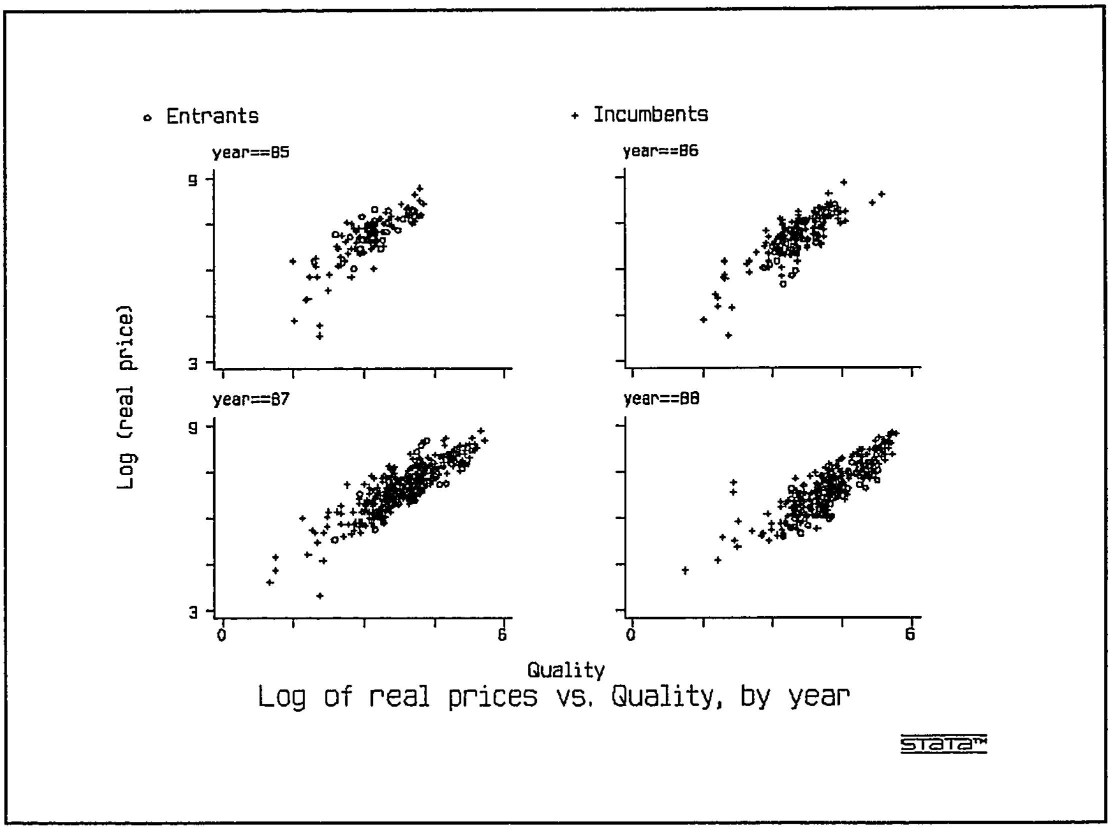

TABLE 2.4: NEW MODELS' SPATIAL LOCATION
(t-Statistics in Parenthesis)

Dependent variable: d_{mit} = average distance of a new model from all models in year *t-1*; equation (3) is in a log-linear form

	(1)	(2)	(3)
INTERCEPT	5.541 (17.92)	6.132 (19.23)	3.061 (19.97)
$ENTRANT_{it}$	-0.853 (-3.69)	-0.629 (-2.74)	-0.212 (-2.39)
$PIONFIRM_i$	-0.614 (-2.35)	-0.674 (-2.63)	-0.080 (-1.20)
$PIONMODEL_{mi}$	4.057 (9.33)	3.922 (9.21)	0.682 (6.17)
$NUMFIRM_{t-1}$	-0.104 (-18.03)	-0.168 (-13.69)	-2.319 (-15.01)
$FIRMAGE_{it}$	0.179 (3.62)	0.201 (4.13)	0.183 (2.99)
$NMODELS_{t-1}$		0.019 (5.87)	2.209 (18.62)
N	760	760	760
R^2	0.389	0.416	0.424
F statistic	96.03	89.33	92.54

$ENTRANT_{it}$ = dummy equal to 1 if firm *i* was an entrant in year *t*;
$PIONFIRM_i$ = dummy equal to 1 if firm was pioneering (see text);
$PIONMODEL_{mi}$ = dummy equal to 1 if model was pioneering (see text);
$NUMFIRM_{t-1}$ = number of firms in year *t-1*;
$FIRMAGE_{it}$ = firm's age in year *t*; and
$NMODELS_{t-1}$ = total number of models in year *t-1*.

TABLE 2.5: AVERAGE WITHIN DISPERSION IN MODEL QUALITY FOR INCUMBENTS (I) AND ENTRANTS (E), AND BY FIRM'S AGE

	R_{it}	
YEAR	INCUMBENTS	ENTRANTS
1977	0.131	0.058
1978	0.011	0.000
1979	0.037	0.008
1980	0.083	-
1981	0.054	0.000
1982	0.139	0.034
1983	0.279	0.013
1984	0.132	0.027
1985	0.089	0.034
1986	0.135	0.015
1987	0.242	0.065
1988	0.207	0.132
TOTAL	0.157	0.049

FIRM AGE	AVG DISPERSION
1	0.049
2	0.076
3	0.082
4	0.109
5	0.218
6	0.234
7	0.315
8	0.246
9	0.238
10	0.390
11	0.847

TABLE 2.6: RELATIVE MODEL DISPERSION
(t-Statistics in Parentheses)

Dependent variable: R_{it}, Relative dispersion index for firm *i* in year *t*

	(1)	(2)
INTERCEPT	-0.017 (-0.29)	0.011 (0.25)
$ENTRANT_{it}$	0.043 (0.90)	0.043 (0.93)
$FIRMAGE_{it}$	0.051 (4.23)	0.052 (4.32)
$PIONFIRM_{i}$	0.102 (1.88)	0.079 (1.64)
$NMODCUM_{i,t-1}$	0.019 (2.98)	0.021 (3.45)
$NUMFIRM_{t-1}$	0.001 (0.75)	
N	323	330
R^2	0.275	0.275
F	24.06	30.87

$ENTRANT_{it}$ = dummy equal to 1 if firm *i* was an entrant in year *t*;
$FIRMAGE_{it}$ = firm's age in year *t*;
$PIONFIRM_{i}$ = dummy equal to 1 if firm was pioneering (see text);
$NMODCUM_{i,t-1}$ = number of models firm has introduced before year *t*; and
$NUMFIRM_{t-1}$ = number of firms in year *t-1*.

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TABLE 2.7: AVERAGE RESIDUALS BY MODEL'S AGE *

Model's Age	Average Residual **		Standard Deviation	
	exiting	continuing	exiting	continuing
1	0.063	0.044	0.412	0.366
2	0.014	-0.027	0.454	0.434
3	0.074	-0.086	0.379	0.417
4	0.090	-0.153	0.655	0.427
5 +	0.026	-0.034	0.363	0.231

* Models existing through 1988 excluded
** Residuals from pooled hedonic regression

TABLE 2.8: LOGIT ESTIMATION RESULTS

(t-Statistics in Parentheses)

Dependent variable: Pr($EXIT_{mit}$), Probability of exit of model *m* by firm *i*, in year *t*
Last column: continuing (non-exiting) firms only

	(1)	(2)	(3)
INTERCEPT	-0.285 (-1.50)	-0.026 (-0.18)	-1.101 (-5.13)
$RESID_{mit}$	1.421 (3.56)	1.331 (3.36)	1.018 (2.27)
$RESSIGN_{mit}$	-1.142 (-2.23)	-1.068 (-2.09)	-0.860 (-1.51)
$FIRMAGE_{it}$	-0.115 (-2.91)	-0.152 (-4.19)	-0.075 (-1.90)
$ENTRANT_{it}$	0.440 (2.16)		0.586 (2.53)
$MODELAGE_{mit}$	0.211 (3.25)	0.182 (2.87)	0.247 (3.51)
$DISTANCE_{mit}$	0.001 (0.83)	0.001 (1.29)	
$NMODCUM_{i,t-1}$	0.095 (5.86)	0.089 (5.62)	0.105 (6.31)
$PIONFIRM_{i}$	-1.586 (-7.61)	-1.533 (-7.49)	-1.179 (-5.35)
$PIONMODEL_{mi}$	0.367 (1.15)	0.321 (1.02)	0.244 (0.72)
N	1092	1092	911
chi^2	133.04	128.34	71.73
log likelihood	-681.14	-683.49	-535.57

RESID = residual from annual hedonic regressions;
RESSIGN = signed residual squared (+ for positive, - for negative);
FIRMAGE = firm's age in year *t*;
MODELAGE = model's age in year *t*;
DISTANCE = for each model, avg distance from all previous year's models;
NMODCUM = number of models firms has introduced before year *t*.

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Chapter III

Estimating Demand Elasticities in a Differentiated-Product Industry.

1. Introduction.

Supply and demand functions are typically estimated using uniform prices and quantities, but where products are heterogeneous, the quality dimension should be explicitly considered. This chapter provides a new application of hedonic coefficients in the estimation of price elasticities for differentiated-products. In the context of the market for personal computers, differences among products are modeled as distances in a linear quality spectrum derived from a multi-dimensional attribute space. Econometric estimation allows for tests of hypotheses regarding market structure, including reputation effects and changes in industry profitability over time.

Most industries are characterized by multiproduct firms producing differentiated rather than uniform goods. Therefore, in demand and supply estimation, products should not be treated uniformly. It would be misleading, for example, to use a single estimate of the demand elasticity for a Mercedes and a Toyota Tercel. Instead, varying product attributes can be utilized in demand elasticity estimation. We design a supply and demand model that allows for variations in the demand elasticities among differentiated products and apply it to an analysis of the personal computer industry.

The PC industry has been characterized by continuously changing market structure. The industry began as an oligopoly but evolved into monopolistic competition.

We would expect elasticities of demand for individual models to reflect those changes. Likewise, we would anticipate that the demand elasticities vary across market segments.

Beginning with Rosen [1974], economists have employed various means of estimating demand and supply for differentiated products or individual attributes. Although Griliches [1971] discussed the role of over- and underpricing, as measured by hedonic residuals, on differentiated goods' market shares, there is still no agreement as to the best way to estimate demand elasticities for products differentiated in several attributes. Recent studies include Bresnahan [1981], Levinsohn [1988], Trajtenberg [1990], Feenstra and Levinsohn [1990], Berry, Levinsohn, and Pakes [1992], and Berry [1991]. All of the above papers, with the exception of Trajtenberg's, focus on the automobile market. In most of the studies, strong restrictions are placed on demand: models are assumed to compete only with their two or few nearest competitors. However, a sufficient drop in price could presumably make consumers move to a different market segment, making the assumption too stringent.

This chapter presents a model of market demand based on consumers' utility maximization and market supply based on producers' profit maximization, in the context of the PC market. Estimated hedonic coefficients are employed as weights in modeling a multidimensional attribute space as a unidimensional, vertically differentiated quality scale. The relative position of models in the quality space measures their market power. Instead of restricting market competition to the two nearest models, cross-elasticities of substitution are allowed to decline continuously with distance in the quality spectrum. Two-stage least squares estimates of demand elasticities vary across models and over time and are consistent with observed changes in market structure. Reputation effects are tested by comparing demand elasticities for incumbents and entrants, and for new vs. older models. Entrants are found to face more elastic demand than incumbents, although the difference is not statistically significant. Similarly, new models were found to face more elastic demand than models which had been on the market for one or two years. Using the estimates of demand elasticities, we compute two measures of industry-level profitability: the annual price-cost margins and the total profit-revenue ratio. Both measures indicate a significant decline in profitability with the increase in market competitiveness over time.

The chapter proceeds as follows. Sections 2 and 3 describe the theoretical models of demand and supply, respectively, leading to two estimable equations. Section 4 describes the data, while section 5 provides estimation results. Section 6 discusses industry profitability changes. Section 7 concludes.

2. Demand.

Personal computers are vertically differentiated products, where "more" of a given characteristic is considered "better."[35] A computer model can be characterized by a set of its attributes and by its price. Each consumer i selects a computer model m to maximize his utility u_{im}, which increases with the quantity of embodied characteristics, z_m, and decreases with model price, P_m. Consumers are distributed according to their

[35] The only horizontal aspect of PC models is IBM-compatibility. The feature was controlled for by the inclusion of firm dummies.

valuation of quality, δ_i. Utility functions vary subject to a random component ϵ_{im}, which includes consumers' brand preferences:

$$u_{im} = \delta_i z_m - \alpha P_m + \varepsilon_{im} \; ; \quad \varepsilon \sim iid \tag{3.1}$$

Consumer selects model m if $u_{im} > u_{in}$ for all models n, or if:

$$\delta_i z_m - \alpha P_m + \varepsilon_{im} \ \geq \ \delta_i z_n - \alpha P_n + \varepsilon_{in} \quad \textit{for all } n$$

Assuming that the willingness to pay for quality equals $\delta_i = \delta + \varphi_i$, so that $E(\delta_i) = \delta$:[36]

$$\delta z_m - \alpha P_m + \varepsilon_{im} + \varphi_i z_m \ \geq \ \delta z_n - \alpha P_n + \varepsilon_{in} + \varphi_i z_n \quad \textit{for all } n$$

$$\Leftrightarrow \quad \varepsilon_{im} - \varepsilon_{in} + \varphi_i (z_m - z_n) \ \geq \ (\delta z_n - \alpha P_n) - (\delta z_m - \alpha P_m) \quad \textit{for all } n$$

we can specify the probability of buying model m by consumer i as:

$$Prob(buy\ m) = Prob((\varepsilon_{im} - \varepsilon_{in} + \varphi_i (z_m - z_n)) \geq (\delta z_n - \alpha P_n) - (\delta z_m - \alpha P_m)) \tag{3.2}$$

for all n.

[36] Although tastes vary, in the case of vertically differentiated products consumers care almost exclusively about quality, and a higher price indicates higher costs. In the case of horizontally differentiated goods, heterogeneity of tastes is much more important in demand determination (e.g. if a black refrigerator costs more than a white one, it is probably due to the distribution of taste rather than a cost differential). Therefore ignoring the heterogeneity in taste and income in demand for PCs is not as important as in the case of other commodities.

Market share of model m is determined by the proportion of consumers for whom the inequality in equation (3.2) is true.[37] If the residuals are distributed Weibull, the probability of selecting model m (i.e. model m's market share s_m) will have a multinomial logit distribution:[38]

$$s_m = \frac{e^{\delta z_m - \alpha P_m}}{\sum_{n=1}^{N} e^{\delta z_n - \alpha P_n}} \tag{3.3}$$

Taking logs of both sides:

$$\ln s_m = (\delta z_m - \alpha P_m) - \ln \sum_{n=1}^{N} e^{\delta z_n - \alpha P_n}$$

Since the model price is itself a function of attributes, including both prices and model attributes in the regression would create multicollinearity, making it difficult to interpret the results. Consumers care about prices and attributes simultaneously, and not independently. We can therefore constrain $\delta = \alpha$. Using hedonic coefficients as weights, the vector of attributes z_m is modeled as unidimensional quality q_m (derived as described in Chapter II). Market share becomes then a function of quality-adjusted prices of PC

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[37] We don't have any information on how many people did not buy a PC, and therefore cannot predict absolute levels of demand, only market shares of each model. In particular, when all the prices drop, quantities would change, but relative market shares would not.

[38] Since the variance of the residuals equals: $\sigma^2 = \sigma_\varepsilon^{\,2} + \sigma_\varphi^{\,2} z_m^2$, it may yield heteroscedastic coefficient estimates. Therefore we estimate robust standard errors.

models,[39] with firm effects in the equation to control for brand reputation effects.

Market share of model m produced by firm i in year t, including the residual, and allowing for varying coefficients on all other models' prices, becomes:

$$\ln s_{mit} = \gamma_0 + \gamma_i + \gamma_1 (P_{mit} - q_{mit}) - \ln \sum_{n=1}^{N} e^{\gamma_{2mn}'(P_{nt} - q_{nt})} + \nu_{mit} \tag{3.4}$$

Own demand (market share) changes with own quality-adjusted price (coefficient is proportional to own price elasticity of demand) and with quality-adjusted prices of substitutes (coefficients represent cross-elasticities of demand).[40] Unlike Feenstra and Levinsohn [1990], we do not assume that two models with identical technical specifications are perfect substitutes. Our model allows for brand effects, hence firm dummies in the demand equation.

The problem with the estimation of the above equation is that there are too many cross-elasticity coefficients to estimate. Since cross-elasticities depend on the degree of substitution between model m and each of its substitutes (models n), they can be assumed to be inversely proportional to the distance in quality space between model m and each model n: $\gamma_{2mn}' = \dfrac{\gamma_2'}{d_{mn}}$. We did not restrict the model competition to a neighborhood since

[39] Trajtenberg [1990] used hedonic residuals in his CT scanners analysis, a similar measure to quality-adjusted prices.

[40] An alternative method of market share estimation involves selecting one model as a base: $s_0 = \dfrac{e^{\delta z_0 - \alpha P_0}}{\sum_n e^{\delta z_n - \alpha P_n}}$, and estimating relative market shares: $\ln \dfrac{s_m}{s_0} = (z_m - z_0)\delta - (P_m - P_0)\alpha$. The specification does not allow for cross-elasticity estimation, however.

we did not find any evidence of market segmentation in Chapter II. Instead, we assumed that cross-elasticities diminish with distance from the model -- the further away a competitor is located, the lower we expect its cross-elasticity with the model to be.[41]

Besides its quality-adjusted price, each model's own demand elasticity is affected by its market power which can be measured by its relative position in the quality space. In particular, price elasticity of demand depends on how many substitutes the model has, just as an elasticity of demand faced by a monopolist is expected to differ from that faced by a competitive firm. That can be measured by whether the model is located in a "crowded" or an "empty" area in the quality space. If a model is located in a crowded area, its price increase will have a bigger effect on its market share than if there were no models around it. Therefore, the own price of each model is weighted by the average distance from its substitutes, $\bar{d}_{mn}$. The demand equation then becomes:

$$\ln s_{mit} = \gamma_0 + \gamma_i + \gamma_1 \frac{P_{mit} - q_{mit}}{\bar{d}_{mn}} - \ln \sum_{n=1}^{N} e^{\gamma_2' \frac{P_{nt} - q_{nt}}{d_{mn}}} + \nu_{mit} \qquad \textbf{(3.5)}$$

A linear approximation to equation (3.5) is:[42]

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[41] Bresnahan [1981] assumed that quality is linear, and thus each model competes with its two nearest neighbors only (one on each side on a linear scale). Even though we reduced the quality to a single dimension, we did not impose such strong restrictions on market competition -- a sufficiently large price drop for a model located further away could make it a valid substitute. Bresnahan's hypothesis was tested, however, and results are reported in section *5B*.

[42] The linear approximation was used in order to make estimation feasible. The nonlinear equation (3.5) was estimated including the two nearest neighbors, then four, six, eight, and finally the ten nearest neighboring models. In all the regressions, while the coefficient on the neighbors' prices was insignificant, the coefficient on own price remained *identical*. The linearization did not, therefore, bias the estimates and was used when all the competing models were included in the regression.

$$\ln s_{mit} = \gamma_0 + \gamma_i + \gamma_1 \frac{P_{mit} - q_{mit}}{\bar{d}_{mn}} + \gamma_2 \ln \sum_{n=1}^{N} e^{\frac{P_{nt} - q_{nt}}{d_{mn}}} + v_{mit} \tag{3.6}$$

where: $\bar{d}_{mn} = \sum_{n=1}^{N} \frac{d_{mn}}{N}$ = average distance from model m's substitutes;[43] and

d_{mn} = distance between models m and n.

The assumption that own demand elasticity and cross-elasticities depend on the distance from other models is motivated by the utility function in equation (3.1). Since a model's relative location (or quality) enters consumers' utility functions, each model's demand elasticity depends on its location in the quality space, not just on its quality-adjusted price. This assumption allows us to distinguish between a model with a low price and low quality, and a model with a high price and high quality. The two would face different demand elasticities, even if their quality-adjusted prices were identical.

The PC industry has been characterized by a changing market structure. The industry started as an oligopoly, gradually moving towards monopolistic competition. As such, if the above model correctly predicts demand elasticities, the estimated elasticities should increase in absolute value over time. We will also use the estimates of demand elasticities to test a hypothesis that incumbents' models face more inelastic demand than entrants' models, due to reputation effect. Using the Lerner index of monopoly power, we will evaluate changes in model price-cost margins over time.

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[43] Feenstra and Levinsohn [1990] used a harmonic mean of distances: $H = (\frac{1}{N} \sum_{n=1}^{N} \frac{1}{d_{mn}})^{-1}$. Using harmonic means generated higher standard errors and a lower explanatory power than arithmetic means. It also created a problem of division by 0.

3. Supply.

Despite the changes in the PC industry's market structure, it has always been characterized by imperfect competition with multiproduct firms. Players (producers) in the PC industry engage in a two-stage game: in stage one firms enter or exit the market, and decide which models to produce, i.e. they compete in locating their models in the model quality space. The first stage was analyzed in Chapter II. Stage two is a Bertrand-Nash competition in prices: each firm chooses own models' prices to maximize its profit, taking other firms' prices as fixed, and taking their own models' location as well as that of their competitors as fixed.[44] Therefore the attributes of models produced are predetermined in the second stage.

Each firm i chooses prices for all its models, P_{mit}, to maximize its profits in year t, π_{it}. The quantity sold of each model equals to its market share, s_{mit} (a function of prices) times the quantity of all PCs sold, Q_t. Model-specific fixed costs, such as retail agreements, advertising, and box design, give rise to economies of scale (as explained in Chapter II); the fixed cost is allowed to decrease with the number of models the firm has produced in the past, exhibiting economies of scope. Marginal costs do not change with the number of units produced,[45] although they do increase with the quantity of attributes embodied:

[44] The fixed costs of introducing a new model can be assumed to be sufficiently large for the assumption to hold.

[45] No individual producer is assumed to be large enough to create a monopsony effect on the marginal prices of PC components, largely manufactured by other firms.

$$\max_{P_{mit}} \ \pi_{it} = \sum_{m=1}^{M_{it}} [(P_{mit} - c_{mit}) Q_t \ s_{mit} - (F_{mit}(\sum_{\tau=0}^{t-1} M_{i\tau}))] \tag{3.7}$$

where: M_{mit} = number of models by firm i in year t;

c_{mit} = marginal cost of model m; $c_{mit} = f(z_{mit})$;

F_{mit} = fixed cost of model m;

$\sum_{\tau=0}^{t-1} M_{i\tau}$ = total number of models produced before year t;

Differentiating the above with respect to the model's price gives the following first order condition:

$$(P_{mit} - c_{mit}) Q_t \frac{\partial s_m}{\partial P_m} + Q_t \ s_{mit} + \sum_{\substack{m'=1 \\ m' \neq m}}^{M_{it}} (P_{m'it} - c_{m'it}) Q_t \frac{\partial s_{m'}}{\partial P_m} = 0 \tag{3.8}$$

or:

$$P_{mit} = c_{mit} - \frac{s_{mit}}{\partial s_m / \partial P_m} - \sum_{\substack{m'=1 \\ m' \neq m}}^{M_{it}} (P_{m'it} - c_{m'it}) \frac{\partial s_{m'} / \partial P_m}{\partial s_m / \partial P_m}$$

Substituting for all the partials from the market share equation (3.6), we get:

$$P_{mit} = c_{mit} - \frac{1}{\gamma_1} \bar{d}_{mn} [1 + \gamma_2 \sum_{\substack{m'=1 \\ m' \neq m}}^{M_{it}} (P_{m'it} - c_{m'it}) \frac{1}{d_{mm'}}] \tag{3.9}$$

Equation (3.9) shows that price equals marginal cost plus a price-cost margin: P = MC + PCM. The marginal cost, c_{mit}, is a function of model attributes, while the PCM increases with the model's market power, which is higher the larger is the model's distance from other firms' models ($-\frac{1}{\gamma_1} > 0$ from equation (3.6)). The model's market power can therefore be approximated by its relative position in the quality space. The closer the model is located to other firms' models, the closer its price is to its marginal cost: *as* $\bar{d}_{mn} \rightarrow 0 \Rightarrow P_{mit} \rightarrow c_{mit}$. If the industry were perfectly competitive, distance from other models should have no effect on price. The model's PCM is also higher the higher the markups are on the other models of the same firm, reflecting management and reputation advantages.

Since we do not have information about marginal costs of all other models, we now solve for marginal costs to eliminate them from the equation. In equation (3.9), price is a function of all other prices, marginal costs, and distances from other models. It can be written in matrix form as:

$$P = M_1 c + M_2 P + \bar{D}_1$$

yielding the marginal cost equation:

$$c = M_1^{-1} (I - M_2) P + \bar{D}_2 \tag{3.10}$$

Marginal cost can be also expressed as a linear function of model attributes:

$$c = \beta_c z + \omega \tag{3.11}$$

Equating (3.10) and (3.11) and solving for P:

$$P = (I - M_2)^{-1} M_1 (\beta_c z + \omega) + \overline{D}_3$$

or:

$$P = B_1 z + B_2 \overline{D}_{mn} + B_3 \overline{D}_{mm'} + \xi \tag{3.12}$$

Price is therefore a function of model attributes and of the average distance from models by other firms, as well as the average distance from own models. Both model attributes and its location in the product space are exogenous in the second stage of the market game.

4. Data.

The initial data set was described in Section 2 of the previous chapter. It includes annual prices and technical attributes of new personal computers sold in the U.S. from 1976 to 1988. The data set was merged with a dataset containing PC shipment quantities per year, obtained from International Data Corporation (IDC). Even though our initial dataset is not exhaustive, the IDC data did not cover all of the PC models in our sample. Therefore only the overlap of the two datasets -- 972 observations, or two-thirds of the initial dataset, had quantity data. There is no quantity data for the year 1976. The following table shows total shipment quantities in our sample as well as total quantities obtained from IDC. The numbers do not correspond perfectly, but give an idea of the order of magnitude of the market. While our sample seems to be quite complete for the initial years, it covers only about half of the market in the last few years. We found no evidence of sample selection for models for which quantity data exists:

Year	Our Sample Total Shipments ('000) [a]	IDC Total Shipments ('000) [b]
1977	22.2	41.1
1978	131.9	167.4
1979	172.7	236.2
1980	331.6	473.7
1981	471.9	778.3
1982	2000.4	3047.3
1983	3316.6	5459.1
1984	4223.1	6691.9
1985	2593.8	5784.8
1986	2997.7	6845.9
1987	4375.3	8393.8
1988	4006.2	9320.5

[a] Source: International Data Corporation.
[b] Source: International Data Corporation.

Some evidence of the changing market structure can be observed in Table 3.1. The Herfindahl index[46] decreased over time, while market shares of leading firms dropped. Figure 3.1 shows changes in average *model* market shares for some leading firms as well as for the entire sample. Note that the average market share decreased continuously since 1978.

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[46] The Herfindahl index is defined as $\sum_{n=1}^{N_t} s_{nt}^2$.

5. Estimation.

Our goal is to estimate demand elasticities, as specified in equation (3.6). However, prices may be correlated with unobservable to econometrician characteristics, and therefore endogenous. The supply equation is a reduced form, regressing prices on exogenous variables only. We therefore begin with the supply equation estimation, and use the estimated prices to obtain two-stage least squares estimates of the demand equation.

A. Supply.

In scalar notation, equation (3.12) becomes:[47]

$$\ln P_{mit} = \lambda_0 + \lambda_t + \lambda_i + \sum_j \lambda_j z_{jmit} + \lambda_1 \sum_{n=1}^{N_t} \frac{d_{mn}}{N_t} + \lambda_2 \sum_{\substack{m'=1 \\ m' \neq m}}^{M_{it}} \frac{d_{mm'}}{M_{it}} + \xi_{mit} \qquad \textbf{(3.13)}$$

where: z_{jmit} = attribute j, model m by firm i in year t;

d_{mn} = distance from model n by other firms;

$d_{mm'}$ = distance from model m' by the same firm;

n = other firms' models (n=1...N_t);

m' = other models by the same firm ($m'=1,\ldots,M_{it}-1$).

The above equation allows for a separate effect of the distance to other firms'

[47] Log-linear form was chosen based on the goodness of fit criterion.

models (accounting for the model's market power, where an unambiguously positive effect is expected) and the distance to own models. Concentration of own models in a single market segment indicates the *firm's* market power. The closer the other models by the same company are, the more local market power the firm has,[48] but in Chapter II we found that established firms disperse their models to preempt the market, thus strengthening their position in the entire product space. The sign of the effect of own models' concentration on price is therefore ambiguous.

In order to obtain distance measures between models differentiated in several attributes, multidimensional models are reduced to a unidimensional quality measure.[49] Since models are vertically differentiated, hedonic regression coefficients provided marginal implicit prices of individual model characteristics. We start by estimating a hedonic equation of prices on model attributes, firm and year dummies.[50] Estimated marginal implicit prices serve as attribute weights in constructing of a quality measure: $q_m = \sum_j \hat{\beta}_j z_{jm} = \hat{\beta}' z_m$, as was described in Chapter II. The quality measure q includes all the technical attributes, as well as the intercept and firm dummies. The firm dummies serve as proxies for such characteristics as service support, marketing and retail strategies. The measure was then used in the computation of the distance between models: $d_{mn} = \sqrt{(\beta' z_m - \beta' z_n)^2} = \sqrt{(q_m - q_n)^2}$. Average distance from all other models was calculated by dividing d_{mn} by the number of models. Its mean, by year, is shown

[48] The hypothesis is consistent with Feenstra and Levinsohn's [1990] finding.

[49] Including all of the competing models' attributes would more than exhaust the degrees of freedom.

[50] The results of that regression are repeated in Table 3.2.

in Figure 3.2. Descriptive statistics on the major variables created in this analysis are listed in Table 3.3.

The supply equation regresses price on model attributes and distances from other models. Since model selection was done in stage one of the game, model location in the quality space can be treated as exogenous in stage two.[51] The price equation was estimated using OLS. Because of possible heteroscedasticity, robust standard errors were estimated. The results are reported in Table 3.4. Including firm dummies (it is a reduced form equation) did not alter the distance coefficients -- spatial location effects cannot be explained by brand effects.

As expected, the average distance from other firms' models' has a positive effect on model price: models located in "empty" areas have a local monopoly power, which raises their price-cost margin. The average distance from own models coefficient is negative, but insignificant. It is possible that the market penetration effect and the own market segment strengthening effect counteract each other.

The regression results were compared to the original hedonic regression results. The difference between the two models is the inclusion of the distance measures in the price regression. Although we reject the hypothesis that the distance measures' coefficients are jointly equal to 0 at the 1% level, all of the coefficients from the hedonic equation fall into the 95% confidence interval for the respective coefficient estimates in the price equation. We cannot reject the hypothesis that coefficients remained unchanged between the two models. When we re-calculated the distance measures using the new

[51] Potential estimation problems associated with that assumption are discussed in the Appendix.

marginal implicit prices of attributes from the price regression above, their correlation coefficients with the original distance measures equaled about 98%.

The above result has an important implication -- since all the quality coefficients remained unchanged, the quality measure based on the hedonic regression equals the quality measure based on the price regression. Therefore the estimated price will be the same whether quality is computed first and used in the distance computation (as above) or whether the estimation is done in a single step.

B. Demand.

We next estimate the market share equation (3.6). Quality-adjusted prices used in the market share equation were computed using the unidimensional quality measure discussed in the previous section, i.e. by applying hedonic marginal implicit prices as attribute weights.[52]

The market share equation was not estimated using logit estimation because of the independence of irrelevant alternatives (IIA) property of logit, namely that the ratio of probabilities between any two choices is unaffected by the availability of a third choice. In the case of choosing among the PC models, the above assumption would not hold. In particular, consumers' utility would most likely increase with a larger choice of PCs. Furthermore, we have no information about consumers purchasing individual models.

Instead, three methods of estimation were used for comparison: ordinary least squares (OLS), two-stage least squares (2SLS) using the predicted prices obtained in the

[52] Since we are interested in the demand side, a better set of attribute weights would have been provided by marginal utility of each characteristic (instead of marginal cost), but they are not available.

supply estimation, and three-stage least squares (3SLS) jointly with the price equation. OLS assumes exogeneity of prices. Although prices are set before consumers decide to buy a PC model, observations are annual. This allows firms to react to demand, thus making prices endogenous. In that case the 2SLS estimation is appropriate. On the other hand, market share is a function of quality-adjusted prices, which are not necessarily correlated with prices, in which case OLS estimates are unbiased. The 3SLS estimation was performed to test for possible residual correlation between the two equations. The results of all three methods are shown in Table 3.5.

Own quality-adjusted price coefficients are negative and significant in all the specifications. Deriving from equation (3.6), demand elasticity equals:

$$\eta = \frac{\partial s}{\partial P}\,\frac{P_{mit}}{s_{mit}} = \frac{\partial \ln s}{\partial P} P_{mit} = \gamma_1 \frac{P_{mit}}{\bar{d}_{mn}} \tag{3.14}$$

The specification allows for different elasticities for each model, depending on each model's relative location in the quality space.

The two-stage least squares estimation seems most convincing on theoretical grounds. The estimates of demand elasticities based on the 2SLS price coefficient are also consistent with the imperfectly-competitive market structure of the PC industry. As Figure 3.3 shows, the estimated average demand elasticity increased over time (in absolute value), as the industry became more competitive, ranging from 2.9 in 1977 to 7.2 in 1988. There is a significant difference between the initial few years and the post-1982 period, when several PC clones entered the market.

The cross-elasticity coefficient (on prices of substitutes) was insignificant in all the specifications.[53] We tested Bresnahan's [1981] hypothesis that a model competes only with its two nearest neighbors in a linear quality space. Only the two nearest models were entered into the market share equation. The cross-price coefficient was still insignificant. The equation was re-estimated several times, by adding two more neighbors in each subsequent run. Each time the cross-price coefficient remained insignificant, while the own quality-adjusted price coefficient did not change at all. Own price elasticity result is thus robust -- regardless of how many neighbors is the model allowed to compete with, the effect of own price does not change. The insignificant effect of other models' prices could be the result of simultaneous price changes of PC models due to the competitive structure of the industry. The average distance was included in the estimation to allow for a separate effect of spatial location on the model's market share.

Positive coefficients on major firm dummies indicate that those firms had a higher market share than predicted by the quality-adjusted prices of their models. The brand effect on model market share equals e^{β}. For example, the 2SLS coefficient on the IBM dummy of 2.021 indicates that, on average, IBM models' market share was over seven times higher than the omitted firms' models, controlling for quality-adjusted prices of models. Negative coefficients on year dummies indicate decreasing market shares of individual models over time. It is worth noting that when firm and year dummies were omitted from the market share regression, price coefficients remained unchanged, implying that the estimated elasticities result is robust.

[53] Other specifications included an average quality-adjusted price of substitutes, as well as residuals from the hedonic regression. The coefficient was always statistically insignificant.

Simultaneous with the increase in demand elasticities, one might expect the leading firms' advantage to diminish over time. In order to test whether the firm effects declined over time due to the increased market competitiveness, firm-year interaction dummies for all major companies were included in the market share regression. Most of the interaction terms were negative, indicating a decline in firm effects over time. The coefficients are in Table 3.6. The changes in firm effects varied -- brand effect decline ranged from almost no change in IBM's brand effect to a 99% decline in Radio Shack's brand effect over the 13-year period.

Finally, the advantage of established brands hypothesis was tested by comparing demand elasticities for incumbents' vs. entrants' models, as well as for new vs. older models. We expect the established firms' models to have higher than average *levels* of market share, but lower demand elasticities, due to their successful selling strategies, as well as their reputation. In order to test the hypothesis that entrants face higher demand elasticity for their models, both an entrant dummy and an interaction of the price terms with an entrant dummy were included in the second-stage market share regression. Similarly, model age and its interaction with price were included.

Entrants' models were found to have a significantly lower market share than incumbents' models (entrant dummy coefficient was negative and significant). However, although the interaction of own price term with an entrant dummy was negative, indicating a more elastic demand for entrants' models, the coefficient was not statistically significant.[54]

While the difference in price elasticities between incumbents and entrants is small, the average elasticity does seem to decrease with a model's age (Table 3.7). The models' age did not appear significant when treated continuously, but when an own price term was included separately for each age cohort, the price elasticity coefficients did decrease in absolute value for each of the initial few years (see Table 3.8). The results show that a model which had been on the market for one or two years faces a more inelastic demand than a completely new product just entering the market, due to reputation and marketing effects for individual models. The difference disappears after the initial couple of years on the market when a model becomes obsolete. The average price elasticities for incumbents and entrants over time are plotted in Figure 3.4. Incumbents faced more inelastic demand in most years, although the difference was not statistically significant.

6. Profitability.

Increasing demand elasticities could be expected to be reflected in industry profitability. With the development of technology and increased market competition, private rates of return to investment in technology and to innovation declined over time. As the price elasticity of demand increases, price-cost margins should drop.

---

[54] Entrants do, however, face significantly higher cross-elasticities of demand than incumbents do. Pooling of the two groups was tested using the Chow test. Joint regression was rejected at the 5% level but could not be rejected when the interaction terms were included.

The Lerner index of monopoly power is:

$$\frac{P_i - C_i'}{P_i} = -\frac{1}{\eta_i}$$

where P_i is the price of model i, C_i indicates model i's marginal cost, and η_i denotes price elasticity of demand faced by model i. We calculated implied average annual price-cost margins for individual computer models using the 2SLS estimates of demand elasticities, according to the Lerner index above. As Figure 3.5 shows, the implied average profit margins for individual models in the PC industry declined over time, from 35% at the beginning of the sample, to less than 15% at the end.

Another way of assessing the implied changes in industry profitability is by utilizing a measure of industry concentration (the Herfindahl index), as well as the total demand elasticity, and implementing the Lerner index[55]:

$$\frac{\Pi}{TR} = -\frac{Herf}{\eta}$$

The ratio of industry profit (plus fixed cost) to total revenue is proportional to the Herfindahl index, and inversely proportional to industry demand elasticity. The ratio of the Herfindahl index to the elasticity of demand over time is plotted in Figure 3.6. The industry profit-revenue ratio thus calculated declined on average by 12.5% per year. Although in the case of differentiated products the price-cost margin computation is more

[55] From Cowling and Waterson [1976]. Their results, as well as other studies, suggest that while cross-sectional or inter-industry studies linking markups with concentration and elasticity measures are questionable, there is a clearer link between *changes* in profitability and in intra-industry concentration/demand elasticities over time. See Schmalensee [1989] for a survey.

complex,[56] it is still proportional to a measure of market structure, and inversely proportional to elasticity of demand.

There is much controversy about the price-cost margin measurement, mainly because of problems associated with the measurement of marginal cost. Although the margins obtained by inverting demand elasticities may not be precise, they indicate the declining trend in profit margins, and they enable us to avoid the tedious marginal cost measurements that would otherwise be required.

7. Summary and Conclusions.

The chapter presents a model of market demand based on utility maximization and market supply based on profit maximization for goods differentiated in several attributes. Using data on personal computers and applying two-stage least squares, demand elasticities are estimated. The estimated elasticities vary across computer models, according to their market power, as measured by distances between models in quality space. The estimates are consistent with the increasingly competitive structure of the industry -- the estimated demand elasticities increase over time, while the brand effect on model market share declines. We find that incumbent firms and older models face a more inelastic demand, most likely due to brand reputation and marketing effects.

Based on the demand elasticity estimates, we use two methods of assessing changes in industry profitability over time: we apply the Lerner index of monopoly

[56] See Waterson [1984], chapter 2, for details.

power to calculate price-cost margins on individual models and use a ratio of the Herfindahl index to the elasticities of demand to obtain the total industry profit-revenue ratio. We find a significant decline in the industry profitability over time with both measures. As the industry became more competitive and demand elasticities increased, rates of return declined.

The chapter builds on the relatively small set of empirical studies analyzing demand and supply for differentiated goods. Although the distance measure is fairly simple, it makes the model flexible by allowing for heterogeneous estimates of demand elasticities without imposing arbitrary cross-elasticity constraints. The chapter utilizes hedonic regression methods in a new way. The approach taken could be used to help predict demand effects of price changes in various segments of a market, as well as the effects of changes in an industry's market structure over time. In the case of industries with relatively low model turnover, effects on the *change* in market shares over time could be estimated, instead of levels. In the PC industry, however, few models survive beyond their first year.

The accuracy of the estimation could be improved if better demand and supply instruments were available. Future empirical studies should focus on individual taste distribution, with endogeneity of taste in a market with continuously evolving technology possibly being incorporated. On the supply side, a firm-level cost measure could provide a good instrument. As is usually the case, availability of more data would expand empirical possibilities.

TABLE 3.1: MARKET SHARE OF LEADING FIRMS, BY YEAR

YEAR	HERFINDAHL INDEX	COMPANY	MARKET SHARE
1977	0.5177	Commodore Radio Shack Apple	0.6772 0.2257 0.0903
1978	0.5819	Radio Shack Commodore Apple	0.7433 0.1441 0.0910
1979	0.4328	Radio Shack Apple Atari	0.6833 0.1853 0.0579
1980	0.2137	Radio Shack Apple Atari	0.5489 0.2397 0.0905
1981	0.1614	Radio Shack Apple Commodore	0.5128 0.2447 0.1271
1982	0.1219	Commodore Sinclair Radio Shack	0.2999 0.1999 0.1800
1983	0.1071	Commodore Radio Shack TI	0.3905 0.1450 0.1168
1984	0.1278	Commodore IBM Apple	0.3315 0.2884 0.1636
1985	0.0872	Commodore Apple IBM	0.2487 0.2460 0.2450
1986	0.0393	IBM Apple Commodore	0.3072 0.2167 0.0867
1987	0.0338	IBM Apple Radio Shack	0.2674 0.2207 0.0949
1988	0.0210	IBM Apple Commodore	0.1851 0.1756 0.1195

FIGURE 3.1: ANNUAL CHANGES IN MODEL MARKET SHARES

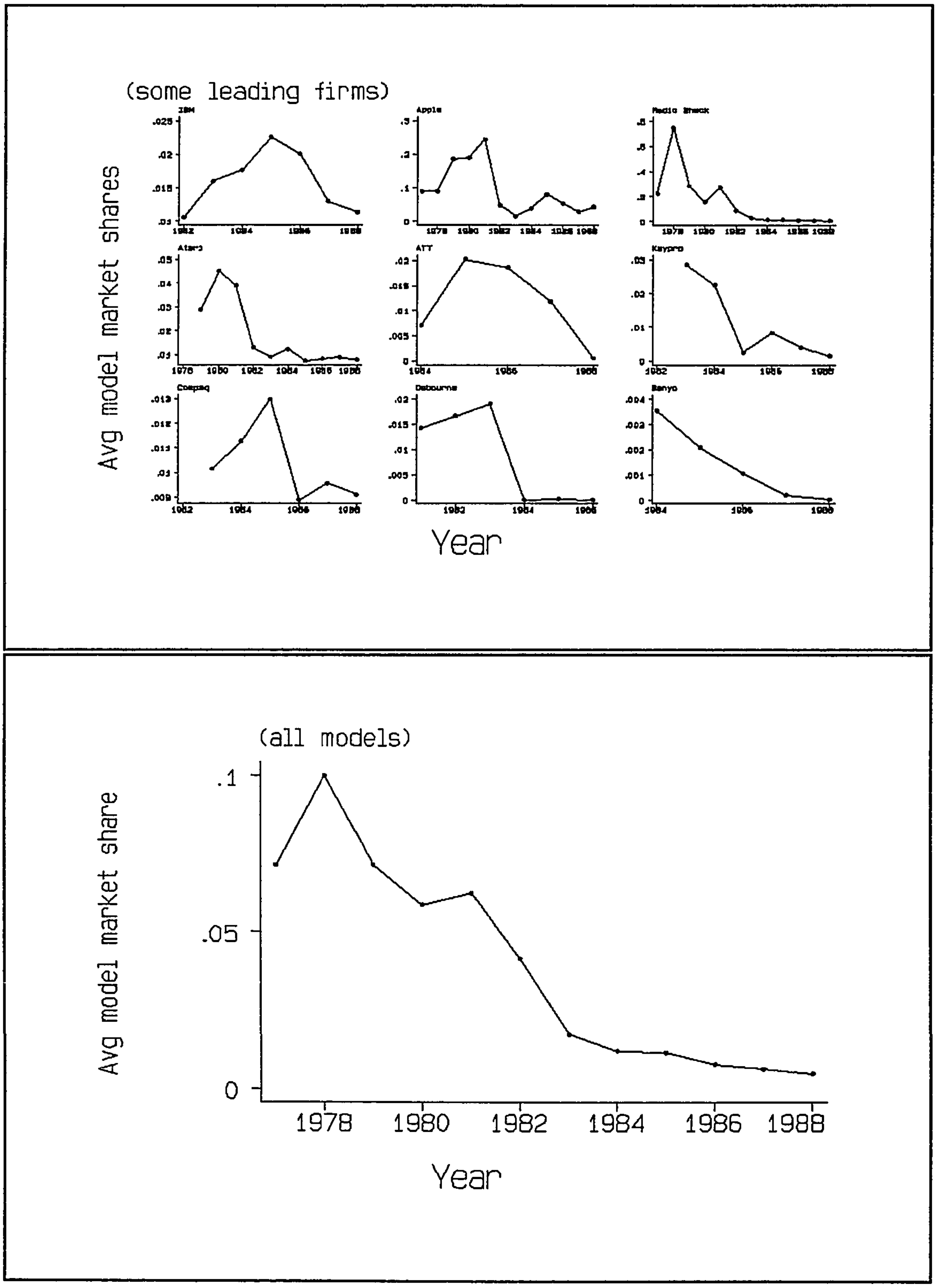


TABLE 3.2: HEDONIC REGRESSION, 1976-1988
DEPENDENT VARIABLE: log (Real Price) *

VARIABLE	COEFFICIENT	T-STATISTIC
LOG (HARD DISK)	0.164	19.64
LOG (RAM)	0.339	18.10
LOG (MHZ)	0.213	5.82
LOG (# FLOPPY DRIVES)	0.367	7.98
LOG (# SLOTS)	0.085	4.38
BLACK & WHITE MONITOR DUMMY	0.068	2.53
COLOR MONITOR DUMMY	0.134	1.93
DISCOUNT MARKET DUMMY	-0.274	-9.86
EXTRA EQUIPMENT DUMMY	0.224	2.68
PORTABLE DUMMY	0.218	5.66
16-bit PROCESSOR DUMMY	0.252	7.24
32-bit PROCESSOR DUMMY	0.587	9.59
AGE	0.055	3.95
APPLE DUMMY	0.157	2.67
ATARI DUMMY	-0.574	-7.66
COMMODORE DUMMY	-0.413	-6.23
COMPAQ DUMMY	0.339	6.51
IBM DUMMY	0.032	0.75
NEC DUMMY	0.137	2.25
RADIO SHACK DUMMY	-0.023	-0.45
ZENITH DUMMY	0.242	3.78
WYSE TECHNOLOGY	0.040	0.54
EPSON DUMMY	-0.119	-1.53
KAYPRO DUMMY	0.093	1.18
NCR DUMMY	0.318	4.04
NORTHGATE DUMMY	0.185	1.94
Intercept	6.167	66.78
$R^2 = 0.757$	F = 117.6	N = 1436

* Year dummy coefficients omitted for clarity (see Table 4 for similar results)

FIGURE 3.2: MEAN DISTANCE FROM OTHER MODELS, BY YEAR

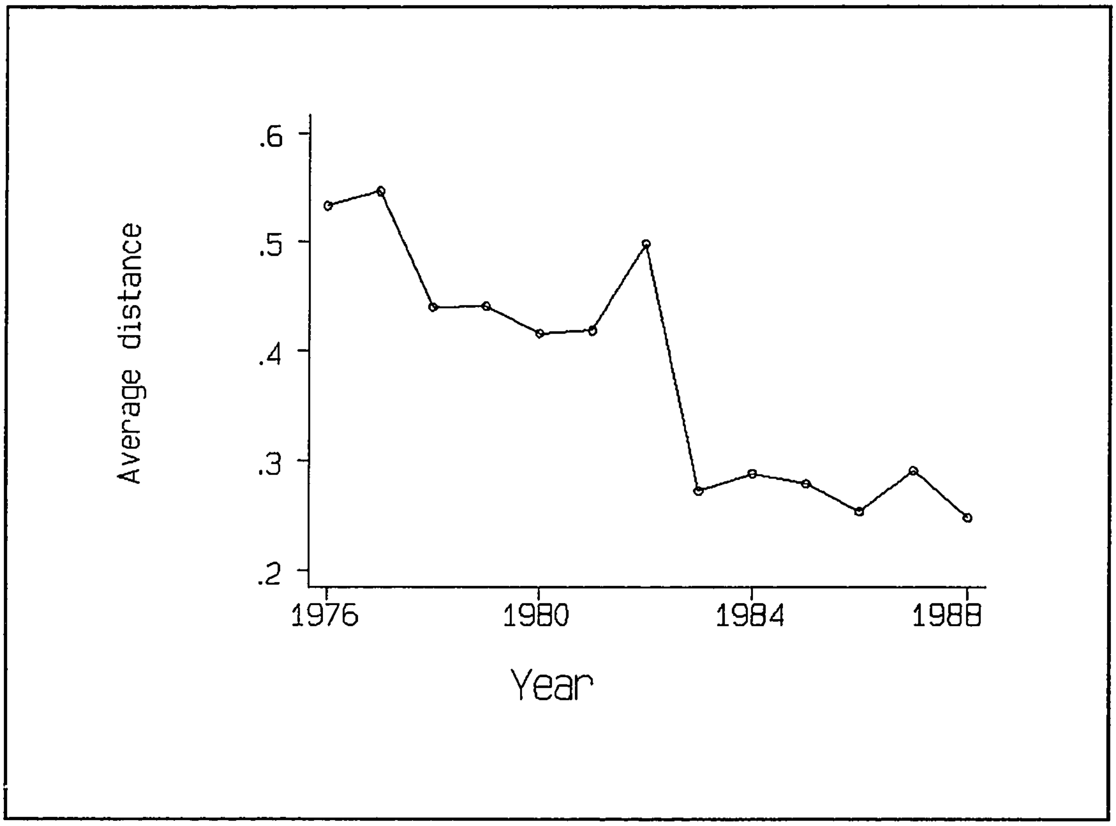


TABLE 3.3: DESCRIPTIVE STATISTICS ON MAJOR VARIABLES

$$\textit{quality is from}: \ \ln P = \hat{\beta}_0 + \hat{\beta}_t + \hat{\beta}_i + \hat{\beta}' z + \hat{u}$$
$$\ln q = \hat{\beta}_0 + \hat{\beta}_i + \hat{\beta}' z$$

Variable	Mean	Std. Deviation	Min	Max
Real price	1430.1	1102.2	22.7	7801.8
ln (Real price)	6.9743	0.825	3.123	8.962
Quality	767.70	791.01	45.5	5048.0
Avg distance from other models	0.2959	0.138	0.068	1.271
Estimated Real Price	1349.3	937.40	48.2	7076.1
Residual -- price equation	0	0.406	-2.22	2.10
Price - Quality	662.35	939.49	-1889.0	7517.2
Est. Price - Quality	581.57	728.30	-1620.1	4944.9
(Price - Quality) / avg distance	2320.6	3115.8	-6235.3	20558.5
(Estimated Price - Quality) / average distance	2025.9	2337.5	-4079.8	10793.2

TABLE 3.4: PRICE ESTIMATION, OLS
DEPENDENT VARIABLE: log (real price) *

VARIABLE	COEFFICIENT	T-STATISTICS **
Avg distance from other firms' models	0.152	1.92
Avg distance from own models	-0.048	-0.93
Single-model firm dummy	-0.100	-1.75
LOG (HARD DISK)	0.164	18.21
LOG (RAM)	0.338	7.38
LOG (MHZ)	0.212	4.22
LOG (# FLOPPY DRIVES)	0.368	6.09
LOG (# SLOTS)	0.085	4.02
BLACK & WHITE MONITOR DUMMY	0.071	2.52
COLOR MONITOR DUMMY	0.142	2.36
DISCOUNT MARKET DUMMY	-0.277	-10.48
EXTRA EQUIPMENT DUMMY	0.228	3.38
PORTABLE DUMMY	0.219	5.52
16-bit PROCESSOR DUMMY	0.260	7.34
32-bit PROCESSOR DUMMY	0.586	9.19
AGE	0.053	3.28
YEAR 1978 DUMMY	-0.449	-2.90
YEAR 1979 DUMMY	-0.575	-4.21
YEAR 1980 DUMMY	-0.635	-4.71
YEAR 1981 DUMMY	-0.854	-6.16
YEAR 1982 DUMMY	-1.119	-6.93
YEAR 1983 DUMMY	-1.507	-9.23
YEAR 1984 DUMMY	-1.554	-10.25
YEAR 1985 DUMMY	-1.970	-11.57
YEAR 1986 DUMMY	-2.388	-13.11
YEAR 1987 DUMMY	-2.725	-14.57
YEAR 1988 DUMMY	-3.109	-15.73
Intercept	6.131	42.22
$R^2 = 0.758$	$F = 109.05$	$N = 1436$

* Firm dummy coefficients omitted for clarity (see Table 3.2 for similar results)
** t-statistics are based on robust standard errors.

TABLE 3.5: MARKET SHARE ESTIMATION, OLS, 2SLS, and 3SLS
DEPENDENT VARIABLE: log (market share)

VARIABLE	OLS		2SLS		3SLS	
	COEFF	T-STAT *	COEFF	T-STAT *	COEFF	T-STAT
(P - q) / avg distance	-0.00066	-2.69	-0.00118	-3.72	-0.00295	-4.67
Avg distance from other models	-1.547	-3.98	-1.563	-4.14	-1.586	-1.12
ln $(\Sigma\, e^{(P-q)/\text{distance}})$	-0.003	-0.77	-0.003	-0.69	0.075	1.92
APPLE DUMMY	2.900	18.12	2.894	18.95	2.307	6.79
ATARI DUMMY	1.306	7.65	1.199	6.62	0.461	1.18
COMMODORE DUMMY	2.695	10.93	2.602	10.47	2.270	5.62
COMPAQ DUMMY	1.924	13.28	1.946	13.53	1.833	6.41
IBM DUMMY	2.060	12.67	2.021	13.00	1.946	10.14
NEC DUMMY	0.596	3.47	0.608	3.79	0.270	0.89
RADIO SHACK DUMMY	1.910	11.15	1.839	10.86	1.709	6.48
ZENITH DUMMY	1.309	7.26	1.359	7.61	1.382	4.44
WYSE TECHNOLOGY	1.013	6.54	0.964	6.74	1.019	2.59
EPSON DUMMY	1.512	8.47	1.494	8.48	1.538	3.99
KAYPRO DUMMY	0.873	3.10	0.869	3.18	0.885	2.36
NCR DUMMY	0.297	0.96	0.466	1.76	0.903	2.43
NORTHGATE DUMMY	-0.044	-0.14	0.195	0.74	0.632	1.41
YEAR 1978 DUMMY	-0.069	-0.11	-0.191	-0.33	-0.222	-0.24
YEAR 1979 DUMMY	0.124	0.25	0.082	0.14	0.765	0.89
YEAR 1980 DUMMY	0.086	0.19	0.057	0.10	0.263	0.36
YEAR 1981 DUMMY	0.110	0.24	0.059	0.10	0.328	0.45
YEAR 1982 DUMMY	-0.896	-1.90	-0.947	-2.07	-0.210	-0.26
YEAR 1983 DUMMY	-1.438	-3.09	-1.483	-3.23	-0.310	-0.33
YEAR 1984 DUMMY	-2.065	-4.69	-2.030	-4.64	-1.567	-2.11
YEAR 1985 DUMMY	-2.033	-4.59	-2.066	-4.73	-1.187	-1.38
YEAR 1986 DUMMY	-2.156	-4.88	-2.241	-5.15	-1.763	-2.30
YEAR 1987 DUMMY	-2.713	-6.31	-2.830	-6.67	-2.950	-4.28
YEAR 1988 DUMMY	-2.379	-5.43	-2.631	-5.83	-3.076	-4.53
Intercept	-3.643	-7.73	-3.448	-7.15	-4.020	-3.09
	R^2 = 0.508 resid correlation = -0.045 N = 972		R^2 = 0.511 resid correlation = -0.114 N = 972		R^2 = 0.324 resid correlation = 0.053 N = 972	

* t-statistics are based on robust standard errors.

FIGURE 3.3: AVERAGE DEMAND ELASTICITY BY YEAR -- 2SLS

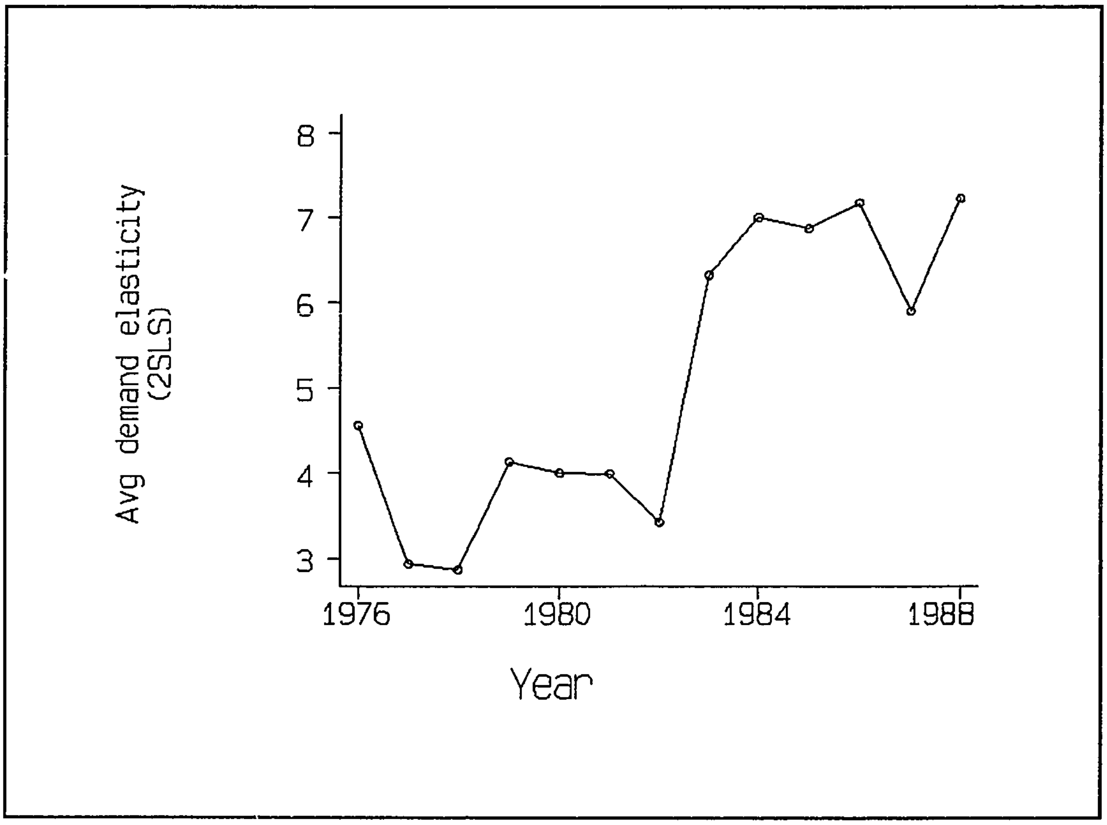


TABLE 3.6: BRAND EFFECT DECLINE ON MARKET SHARE (2SLS)
DEPENDENT VARIABLE: log (market share) *

VARIABLE	COEFFICIENT	T-STATISTIC
(Est. price-quality) / avg distance	-0.00095	-2.98
Avg distance from other models	-1.501	-3.57
Ln ($\Sigma\ e^{(\hat{p}-q)/distance}$)	-0.001	-0.41
APPLE DUMMY	4.012	7.62
ATARI DUMMY	3.297	4.40
COMMODORE DUMMY	4.807	8.33
COMPAQ DUMMY	1.928	1.45
IBM DUMMY	2.058	2.40
NEC DUMMY	-0.769	-0.61
RADIO SHACK DUMMY	6.278	13.04
ZENITH DUMMY	3.968	1.67
WYSE TECHNOLOGY	-6.824	-1.39
EPSON DUMMY	2.574	0.59
KAYPRO DUMMY	7.142	3.03
NCR DUMMY	3.696	0.89
NORTHGATE DUMMY	4.964	4.51
APPLE * YEAR	-0.088	-1.66
ATARI * YEAR	-0.178	-2.25
COMMODORE * YEAR	-0.217	-3.41
COMPAQ * YEAR	-0.013	-0.11
IBM * YEAR	0.013	0.17
NEC * YEAR	0.131	1.20
RADIO SHACK * YEAR	-0.425	-8.51
ZENITH * YEAR	-0.209	-1.05
WYSE TECHNOLOGY * YEAR	0.649	1.63
EPSON * YEAR	-0.104	-0.29
KAYPRO * YEAR	-0.557	-2.65
NCR * YEAR	-0.299	-0.83
NORTHGATE * YEAR	-0.622	-3.21
Intercept	-5.997	-47.84
$R^2 = 0.492$	$F = 32.65$	$N = 972$

TABLE 3.7: MEAN ELASTICITY BY MODEL AGE AND FIRM'S STATUS

Firm's Status	
Incumbents	6.202
Entrants	6.578
Model's Age	
0	6.975
1	6.102
2	5.226
3	3.518
4	3.143
5	2.948

TABLE 8: MARKET SHARE, PRICE TERM FOR EACH AGE COHORT

Variable	Coefficient	T - statistic
(P - Q) / distance [PRICE]	-0.00143	-4.09
PRICE if age=1	0.00117	2.72
PRICE if age=2	0.00205	2.99
PRICE if age=3	0.00015	0.12
PRICE if age=4	-0.00027	-0.21
PRICE if age=5	-0.00513	-2.95
PRICE if age> =6	-0.00655	-3.16

FIGURE 3.4: AVERAGE ELASTICITY: INCUMBENTS vs.ENTRANTS

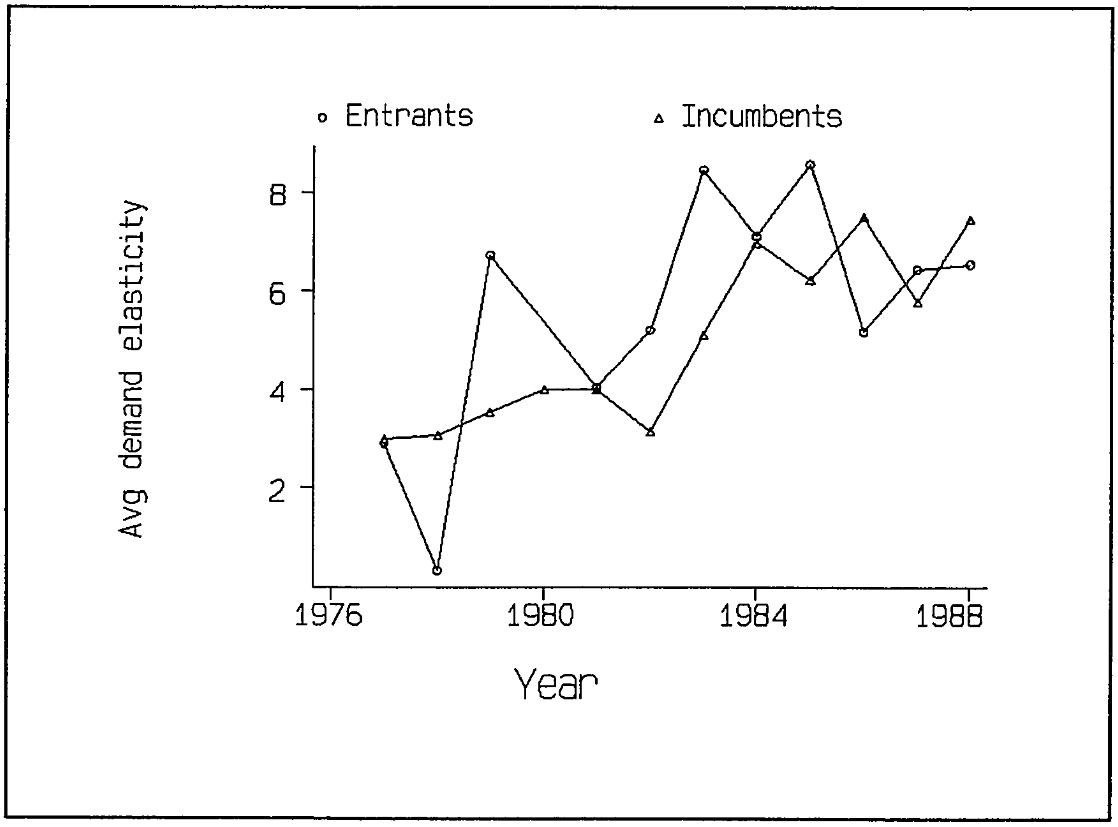


FIGURE 3.5: AVERAGE IMPLIED MODEL PRICE-COST MARGIN

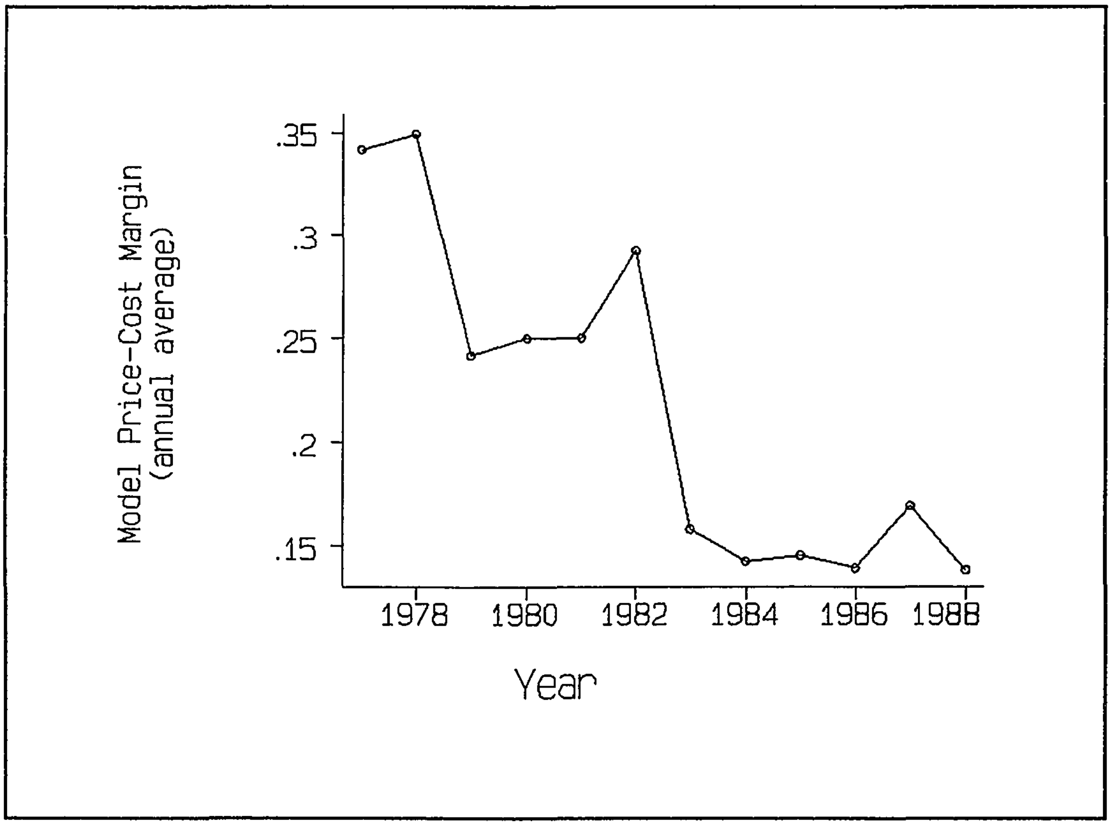
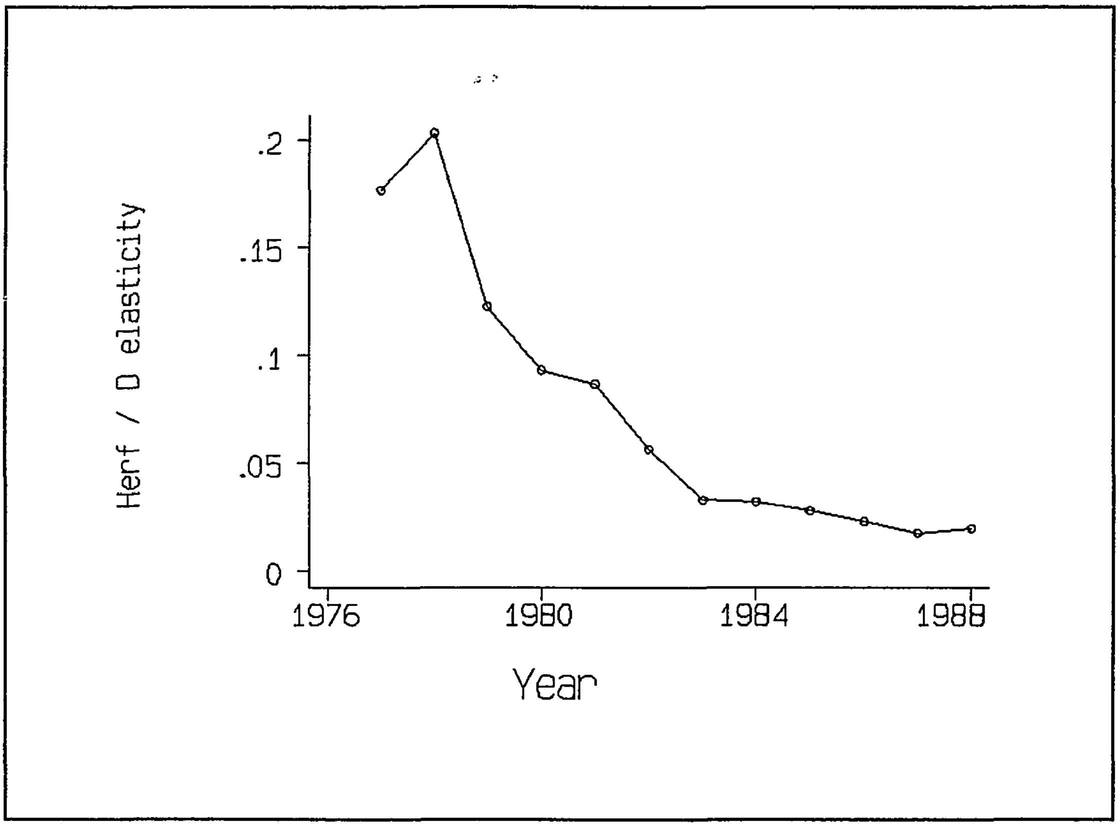


FIGURE 3.6: INDUSTRY PROFIT / REVENUE RATIO



Appendix

Although we assumed that firms choose their models' location (and thus distance between models) in the first stage of the game, while prices are set in the second stage, one can suspect that in locating a new model, a firm will take into account previous period prices. Representing model price as a function of its distance from other models (omitting its attributes for simplicity):

$$\begin{aligned} P_t &= \beta d_t + \varepsilon_t \\ P_{t+1} &= \beta d_{t+1} + \varepsilon_{t+1} \end{aligned} \qquad \textbf{(A1)}$$

but:

$$d_{t+1} = \gamma P_t + \eta_{t+1} \qquad \textbf{(A2)}$$

therefore:

$$P_{t+1} = \beta \gamma P_t + \beta \eta_{t+1} + \varepsilon_{t+1}$$

Even though lagged prices do not directly enter the equation, it is as if lagged dependent variables appeared on the right-hand side of the equation. It is well known that if there exists serial correlation, for example $\varepsilon_{t+1} = \rho \varepsilon_t + \nu_{t+1}$, the distance coefficient β in (A1) is going to be biased as follows:

$$\hat{\beta} = \beta + \frac{cov(d_{t+1}, \varepsilon_{t+1})}{var(d_{t+1})} = \beta + \frac{\gamma \rho \sigma_\varepsilon^2}{var(d_{t+1})} > \beta$$

Since the stock of models changes every year, one has to consider two groups of models separately: models entering in period $t+1$, and models surviving from t to $t+1$. For the new models the location is determined in $t+1$, and can depend on past prices. But the new models have no past, and thus for them $\rho=0$ (i.e. there is no serial correlation). Therefore we have to be concerned with the surviving models only. But the location of the surviving models is determined in period t, and is therefore exogenous in period $t+1$, and thus $\gamma=0$ in equation (A2).

In order to test whether the distance coefficient is biased because of the presence of serial correlation for the surviving models in the sample, we ran separate price regressions for the new models (sample of 770) and for the models surviving from the previous period (sample of 666). The estimated coefficients for the new models are almost identical to the pooled coefficients. The coefficient on the average distance from other firms' models for the surviving sample is indeed biased upwards: 0.494 vs. 0.152

for the pooled sample, but the own models' distance coefficient is even *lower* than the pooled sample coefficient: -0.165 vs. -0.048. We tested whether the two groups could be pooled, and could not reject pooling at the 1% level. Therefore estimated prices were based on pooled estimates, even though the estimates might be inefficient.

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Chapter IV

New Developments in the Personal Computer Market: 1989-1991

1. Introduction.

The two previous chapters showed strategic spatial location patterns persisting in the personal computer market during the late 1970s and most of the 1980s, as well as changes in the market structure leading to increasing demand elasticities and decreasing price-cost margins on individual PC models. In this chapter, we follow the previous analysis and test whether the incumbent-entrant differences persisted until the early 1990s, and whether price-cost margins continued to decline. The primary dataset was purchased from Datapro, and includes prices and attributes for new personal computers sold in the U.S. in the period of 1989-91. The data include list prices only, with no information on the actual transaction prices; therefore merging it with the 1976-88 data is problematic. The dataset was merged with a quantity of shipments dataset for the same period, purchased from the IDC Corporation.

We did not find a reversal of the market share trend which persisted through the 1976-88 period. Although the rate of model turnover increased drastically (few models survive beyond their year of introduction) there was no decline in the number of models on the market.[57] Throughout the 1989-91 period, the Herfindahl index continued to drop, demand elasticities increased on average, and price-cost margins declined further,

[57] However, the number of firms declined slightly for the first time in 1991.

though remaining positive on average.

We tested a hypothesis that a decline in the marginal implicit prices of attributes of PCs can be explained by "crowding" in the quality space, and not by a decline in marginal cost of the components. The hypothesis was rejected -- even when the crowding is taken into account, marginal prices of most of the attributes are lower than in the previous sample.

Section 2 describes market changes that took place in the recent past. Section 3 compares hedonic estimation for the 1989-91 period with the previous sample and tests whether changes in hedonic coefficients can be explained by product space developments. Section 4 details spatial location issues, both in the case of new entry and in the case of model exit. Section 5 re-estimates demand elasticities and price-cost margins to find out whether previous trends in the PC industry market structure persisted. Section 6 concludes.

2. Market Changes.

Almost every recent study of the personal computer industry discusses a new revolution in the PC market. Prices and profit margins have been cut while the less successful companies have exited. A recent study by Berndt, *et al.* [1993] found that PC prices have declined by about 20 percent annually during the 1989-92 period. Our sample covering the 1989-91 period includes over a hundred companies and almost five hundred different models per year, up from about fifty companies and one hundred models at the end of the 1980s. The Herfindahl index has declined continuously, reflecting the declining trend in market concentration.[58] The market share of an average *model* in our sample has declined as well (see Figure 4.1).

The trend in market concentration changes has reversed recently. Several industry studies predict that 1993 is going to be the first year of higher market concentration, e.g.: "I would guess that 80 percent of the total PC market will be held by the 10 largest suppliers in five years, up from 58 percent last year."[59] The year 1991 was the first year with a decline in the number of firms in our sample, and the rate of turnover has increased as compared to the 1980s. As Table 4.1 indicates, a vast majority of firms and models each year are new entrants. Fewer than one-third of the models survive longer than one year.

Since the mid-1970s, the PC market has evolved from an oligopoly to a competitive one. It is monopolistic competition, however, and not perfect competition, as each company tries to find its own market niche in the more and more crowded product space. Here are some examples of market strategies pursued by individual firms:[60] ALR -- upgradability; Apple -- graphics, user friendliness; Compaq -- high-quality portables; Dell -- high-quality desktops, service support and warranties; GRiD -- pen-based portables; IBM -- targets mid-to-large businesses; NEC -- wide variety of

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[58] The Herfindahl index based on our sample for 1989, 1990, and 1991 was 0.02096, 0.01788, and 0.01732, respectively.

[59] *The New York Times*, March 18, 1993. See also *PC Week Special Report*, November 16, 1992, for an extensive industry analysis.

[60] Based on a market analysis by Datapro [1992].

peripherals; NeXT -- user-interface design; Toshiba -- lightweight portables with long battery power, color matrix active displays; Zenith -- 48-hour delivery, 30-day money-back guarantee. As compatibility between systems and the rate of technology diffusion increased, it became more and more difficult to find an empty niche in the current PC market. As a result, the dispersion between firms in the product space has declined, i.e. firms got closer to each other over time.

Besides changes in the market structure and the nature of the competition, the technology used in personal computers has also been evolving. While PCs became faster with more memory and storage, the marginal cost of the components declined. In the next section, we analyze the changes in the marginal price of PC attributes, trying to separate the cost decline factor from the product space crowding factor.

3. New Hedonic Estimation.

The quality of PCs has increased rapidly in recent years. Table 4.2 shows descriptive statistics on major PC attributes for the period 1989-91. As compared to Table 2.1, it is clear that PCs have become faster with more memory and storage than in the past.

We compared the results of hedonic estimation for the two periods: 1976-88 and 1989-91, using the same specification (Tables 3.2 and 4.3). Several things are worth noting. While the quantity of included characteristics increased, some marginal implicit prices declined. The marginal implicit price of a unit of RAM dropped from 0.339 to

0.222, while the marginal implicit price of a unit of hard disk storage dropped from 0.164 to 0.089. Similarly, the marginal implicit price for the number of floppy drives (which even became negative, due to a presence of low-quality models with two floppy drives), the number of slots, a display dummy, an extra equipment dummy, and a 16-bit processor dummy, all decreased when compared to the initial sample period. In contrast, the marginal implicit price of MHz and portability increased. Since these are hedonic coefficients, they can be interpreted as marginal cost or marginal valuation by consumers of a particular characteristic (see Rosen [1974]). These changes indicate a shift in the marginal cost of the components, and/or changes in consumers' preferences. In particular, portability became more important to consumers as PCs began replacing pads of paper and calculators, but not necessarily more expensive to producers. Each additional unit of RAM, on the other hand, became cheaper for manufacturers to add on.

Using a Chow test, we tested whether the entire dataset (1976-88 and 1989-91) could be pooled in the hedonic estimation. Pooling was rejected at the 1% level. Since the new dataset includes list prices only, we tried pooling the list market subset for 1976-88 with the new sample. The data still rejected it. Pooling was rejected even when time-attribute interactions were included. The changes in marginal prices of characteristics were too drastic for the pooling to be accepted.

Besides the changes in attribute coefficients, we can observe a deteriorating fit in the hedonic regression. The R^2 for the new sample regression is 0.71 vs. 0.76 for the previous sample, and 0.90 for the 1976-81 period. The reason for the decline is the changing nature of the product. While it was relatively easy to summarize a PC when the vector of attributes had few elements, new characteristics have emerged which are important to consumers, but less easily measured. For example, characteristics of portable computers, such as weight, battery time, and the quality of the screen, are not captured by the portable dummy (the only variable available). Additionally, several attributes are firm-specific (such as service support, warranties, delivery time, or the quality of the screen). Therefore, more information is now captured by the brand dummies, what makes brand coefficients larger. For example, the Compaq dummy increased from 0.34 for the 1976-88 sample to 0.54 for the 1989-91 period, the Apple dummy from 0.16 to 0.31, the IBM dummy from 0.03 to 0.43, and the Zenith dummy from 0.24 to 0.32. It is difficult to determine whether these companies charged higher margins on their PCs than before or whether (more likely) they offered something we could not capture with just a few characteristics.

We calculated a quality of each PC model, using marginal implicit prices of attributes from annual hedonic regressions as weights, as described in Chapter II: $q_{mt} = \hat{\beta}'_t z_{mt}$. The vector z_{mt} includes technical attributes, as well as firm dummies, which capture such quality components as service support, warranties and distribution channels. Two counteracting effects influenced changes in the quality measure over time: on the one hand, the quantity of embodied characteristics increased, but on the other, the weights (i.e. the marginal implicit prices) declined as it became cheaper to add a megabyte of RAM or of hard disk storage. As Table 4.4 shows, the quality increased drastically over the period our sample covers -- by over 2000% from 1976 to 1991, and by 27% from 1988 to 1991. The former effect was much stronger than the latter.

Although we can observe a decline in marginal *prices* of PC attributes, we cannot say whether the decrease can be entirely attributed to a change in marginal *cost*. An interesting question is whether the change in marginal prices was due to a change in the marginal cost of components resulting from technological progress, or due to the increased competition in the product market and therefore declining markups on PC components. In order to test a hypothesis that the marginal price decline can be entirely attributed to a more crowded product space, we constructed a measure of "crowding" and included it in the hedonic regression. Under the null hypothesis, the hedonic coefficients should remain unchanged between the two samples.

For each PC model, we measured an average distance from all the other models in the product space. As described in Chapter III, for each model m, the average distance from other models is constructed as follows: $\bar{d}_{mn}=\sum_{n=1}^{N}\frac{d_{mn}}{N}$ where $d_{mn}=\sqrt{(q_{mt}-q_{nt})^2}$ and $n=1,..,N$; N is the total number of models in the market in a given year. The redone version of the hedonic regression is shown in Table 4.5. As the results indicate, locating far away from other models increases a model's price, controlling for quality. The marginal prices of attributes increased slightly and became closer to the coefficients for the 1976-88 sample. The coefficients on hard disk storage, RAM, portability, and 32-bit processor all increased, but by insignificant amounts. Most of the competitive (or crowding) effect is captured already by the year dummies, as it varies over time rather than across models. The rest of the decline in marginal prices of PC characteristics should be attributed to the decline in their marginal cost.

4. Spatial Location.

A. New Models' Entry.

As was shown in Table 4.1, most PC models sold during the 1989-91 period were new. The turnover of both firms and models was extremely high. We analyzed the patterns of entry of new models during the last few years, focusing on differences in models' spatial location between incumbents and entrants. In particular, we tested the results found in Chapter II for the earlier period.

We tested the hypothesis of technological "leap-frogging," where new entrants introduce the most innovative products, later copied by less flexible, established firms. The phenomenon is found in some other high-technology industries. Eaton and Lipsey [1979], Salop [1979], and Ghemawat [1986] found that if an incumbent has sunk costs and some market power, he will introduce the new innovation to deter an entrant from entering the market and to avoid cannibalizing his own products. Their findings were confirmed for the period of 1976-88 -- we found no evidence of the leap-frogging in the PC industry. It is the older, more established firms who introduce the most technologically-advanced models, whereas entrants place their models in previously occupied market segments (i.e. entrants act as followers, while incumbents act as leaders).

If the results found in Chapter II remain valid, entrants should locate their models closer to existing models than do incumbents. In order to test that hypothesis, for every new model in year *t*, we measured the average distance from all models observed prior to the location decision (in year *t-1*). Every year, the average distance is higher for incumbents than it is for entrants. We further tested the hypothesis in a regression of the average distance on the entrant dummy, controlling for the number of models and number of firms in the market, as well as for each firm's age:

$$\bar{d}_{mit} = \alpha_0 + \alpha_1 ENTRANT_{it} + \alpha_2 NFIRMS_{t-1} + \alpha_3 NMODELS_{t-1} + \alpha_4 FIRMAGE_{it} + \varepsilon_{mit}$$

The results (Table 4.6) confirm the difference between incumbents and entrants. The older the firm is, the further away it locates its models from its competitors, indicating that the distance effect extends beyond the first year on the market. The results are consistent with our findings for the earlier sample.

When analyzing the patterns of new models' location in product space, it becomes evident that entrants consistently place their models in the low-to-medium quality segment, whereas incumbents place their models in the medium-to-high market segment. Since we previously found strong evidence of reputation and learning effects, the suspicion is that this pattern is caused by the fact that established firms have lower costs and/or reputation advantages and can therefore better afford the risk of marketing products which embody new technology. The location of new models by incumbents and entrants is shown in Figure 4.2. We can see that all the new models at the high-end of the quality spectrum are marketed by the established firms, while entrants place their models at the low or medium segment of the market.

B. Model Dispersion.

In a monopolistically competitive industry with no collusion and a threat of entry, we would expect incumbents to choose market interlacing as opposed to market segmentation. Under this scenario, incumbents disperse their models along the quality spectrum to deter entry as well as to avoid cannibalization of own products (e.g. Prescott and Visscher [1977]). We tested this hypothesis against an alternative that the incumbents' cost advantage, which leads them to introduce high-quality products while still marketing the low-quality ones, comes from learning effects and from economies of scope, and can therefore be fully explained by a firm's age and the number of models it had produced prior to year t, without any entrant/incumbent discontinuity.

As we did for the earlier sample, for each firm in each year, we construct a within dispersion σ_{it}:

$$\sigma_{it} = \frac{\sum_{m=1}^{M_{it}} (q_{mit} - \bar{q}_{it})^2}{M_{it}} \quad where \quad \bar{q}_{it} = \frac{\sum_{m=1}^{M_{it}} q_{mit}}{M_{it}}$$

We compare the within dispersion to the total dispersion σ_t:

$$\sigma_t = \frac{\sum_{n=1}^{N_t} (q_{nt} - \bar{q}_t)^2}{N_t} \quad where \quad \bar{q}_t = \frac{\sum_{n=1}^{N_t} q_{nt}}{N_t}$$

where: M_{it} = number of models by firm i in year t; and

N_t = total number of models by all firms in year t ($N_t = \Sigma_i M_{it}$).

to create the relative dispersion index: $R_{it} = \frac{\sigma_{it}}{\sigma_t}$.

The index R_{it} measures the degree to which a firm's models are concentrated in one area, as opposed to dispersed throughout the entire market, in year t. We tested the entrant/incumbent dispersion differences in a regression:

$$R_{it} = \beta_0 + \beta_1 ENTRANT_{it} + \beta_2 FIRMAGE_{it} + \beta_3 NMODCUM_{i,t-1} + \beta_4 NMODELS_{t-1} + v_{it}$$

Although there is strong evidence for learning effects and economies of scope -- the older the firm and the more models it had produced in the past, the higher its model dispersion (Table 4.7) -- there is also a discontinuity between incumbents and entrants. It seems that a firm establishes its reputation after just one year in the market. This result was not found for the 1976-88 sample.

C. Model Exit.

In Chapter II, we found that while overpriced models were more likely to exit the market, there were also strong brand effects allowing older firms' models to survive despite their relative overpricing. As a measure of overpricing we used hedonic residuals, i.e. the excess price controlling for quality characteristics. In a logit regression, positive residuals raised the probability of exit. A similar test was performed for the recent years.

As can be seen in Table 4.1, fewer than one-third of the models survive beyond the first year in the recent sample. All models are likely to exit the market in their first year. Therefore our logit regression of probability of exit yielded a positive, but insignificant coefficient on residuals (Table 4.8). Overpricing (and thus hedonic residuals) cannot predict the probability of exit. We cannot determine whether the hedonic residuals capture overpricing, but the overpriced models are not destined to exit, or whether they capture some additional value to consumers, uncorrelated with the included regressors.

Our other findings are not different from the analysis of the previous sample: a model is less likely to survive the longer it had already been on the market (obsolescence effect), and the fewer models its producer marketed in the past (economies of scope effect). Furthermore, the models of innovative firms have a higher chance of survival.

5. Elasticities of Demand and Price-Cost Margins.

In Chapter III, we estimated demand elasticities using two-stage least squares estimation of a market share equation:

$$\ln s_{mit} = \gamma_0 + \gamma_t + \gamma_i + \gamma_1 \frac{P_{mit} - q_{mit}}{\bar{d}_{mn}} + \gamma_2 \ln \sum_{n=1}^{N} e^{\frac{P_{nt} - q_{nt}}{d_{mn}}} + \nu_{mit}$$

The equation was estimated using predicted prices from the equation of prices on average distances, model attributes, firm and year dummies. Standard errors were adjusted to correct for the two-stage least squares process. The estimation was carried out for the 1989-91 period. The results of the market share equation are reported in Table 4.9. As in the previous sample, own quality-adjusted prices, scaled by the average distance from other models (a measure of model's market power), is negative and significant, indicating the sensitivity of market shares to own price changes. The cross-elasticity effect, i.e. the effect of quality-adjusted prices of other models, again turned out to be insignificant.

In order to evaluate the magnitude of own-price elasticities of demand, we calculated the elasticities using the formula:

$$\eta = \frac{\partial s}{\partial P}\frac{P_{mit}}{s_{mit}} = \frac{\partial \ln s}{\partial P}P_{mit} = \gamma_1\frac{P_{mit}}{\bar{d}_{mn}}$$

The top part of Figure 4.3 shows the changes in estimated average demand elasticities for the period 1989-91. As the PC market continued to become more competitive, the mean demand elasticities continued to rise. In order to put these numbers in perspective, we compared them to the previous sample results. The bottom panel of Figure 4.3 exhibits changes in average elasticities of demand for the entire 1977-91 period. The average elasticities increased to over 10 at the individual model level. Using the Lerner index of monopoly power: $\frac{P_i - c_i}{P_i} = \frac{1}{\eta_i}$, we calculated price-cost margins for individual models. As the top panel of Figure 4.4 shows, the price-cost margins continued to decline, and dropped to an average of less than 10 percent. Again, the bottom panel shows the complete trend from 1977 to 1991.

During the last couple of years, several industry studies have been predicting a reversal in the declining market concentration trend -- analysts have been speculating that prices could not possibly drop any further and that no more entry into the market would occur.[61] These predictions are not firmly based on recent evidence, at least as of the end of 1991. Although the rate of firm exit due to bankruptcy has increased during the last few years, there has been a net increase in the number of firms and the number of models until 1991. The markups on PC components have been declining over time as

[61] For example, *Workgroup Computing Series: Systems* by Datapro; *PC Week Special Report*, November 16,1992; *The Economist*, March 6, 1993.

the market becomes more competitive. The competitive effect, coupled with the drop in marginal cost of components, lead to a drastic decline in PC prices. Our estimates of price-cost margins are higher than what some industry analysts claim. The discrepancy is caused by two factors: first, the above estimates say by how much price exceeds marginal cost, and not what the profit rate is (the latter takes into account fixed costs); second, our sample does not cover the entire market, and some smaller, less profitable firms might have been excluded.

6. Summary and Conclusions.

The main purpose of this chapter was a descriptive analysis of the PC market during the 1989-91 period. We tested some of the findings from the earlier sample, and found the previous trends to continue for the most part. Although the profit rates in the industry declined significantly, the rate of turnover in the industry accelerated, and more firms have been exiting the market, we have not observed a reversal in the previously noted changes in market structure.

We tested a hypothesis that the decline in marginal prices of PC components was caused partly by the wiping out of markups on those components, and not purely by the technological progress. We found very weak evidence of that, since the market structure effect is correlated with the year dummies. A small part of the marginal price decline was caused by a more crowded product space. Lower market concentration lead to higher elasticities of demand, resulting in a decline in price-cost margins. Even though we have not found any evidence of zero profit rates, as predicted by some industry analysts, it is possible that in the next couple of years the competition will become severe enough to force more firms to exit the market and reverse the trend in market structure changes.

FIGURE 4.1: AVERAGE MODEL MARKET SHARE, BY YEAR

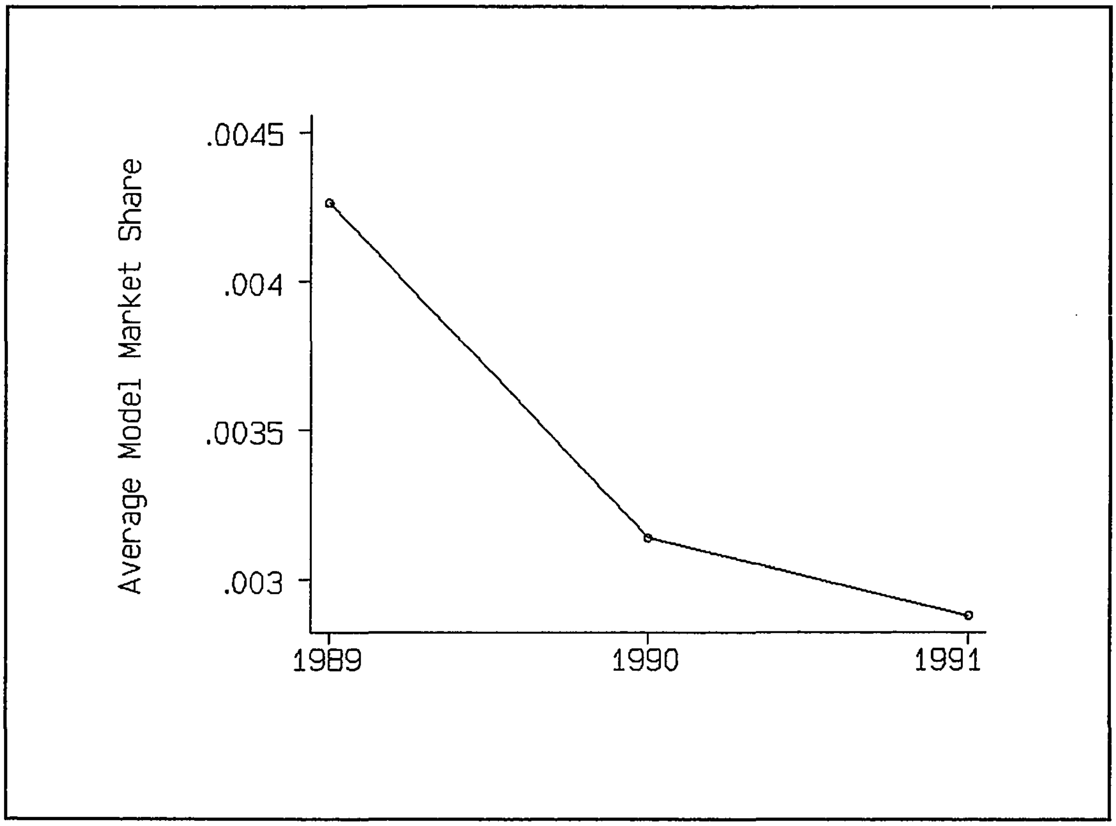


TABLE 4.1: MARKET CHANGES -- BY YEAR AND MODEL'S AGE

Year	Number of models			Number of firms		
	entering	stock	exiting	entering	stock	exiting
1989	292	353	230	80	107	43
1990	417	485	192	53	115	37
1991	290	497	-	22	102	-

Model's age	Number of observations (1989-91)
0	1541 (68.6%)
1	356 (15.9%)
2	170 (7.6%)
3	76 (3.4%)
4	79 (3.5%)
5	15 (0.7%)
6	5 (0.2%)
7	3 (0.1%)

TABLE 4.2: SUMMARY STATISTICS FOR PC ATTRIBUTES, 1989-1991

Variable	Mean	St. Dev.	Min	Max
Price	4259	3294	199	25000
RAM (K)	1604	1314	120	8000
MHz	18	7.3	3.6	40
Hard disk (MB)	50	75	0	800
Number floppy drives	1.4	0.8	0	4
Number of slots	5.8	2.9	0	24
16-bit processor	0.49	0.5	0	1
32-bit processor	0.43	0.5	0	1
Display dummy	0.46	0.5	0	1
Portable dummy	0.21	0.4	0	1
Extra equipment dummy	0.96	0.2	0	1

TABLE 4.3: HEDONIC REGRESSION, 1989-1991
DEPENDENT VARIABLE: log (Real Price)

VARIABLE	COEFFICIENT	T-STATISTIC
LOG (HARD DISK)	0.089	14.54
LOG (RAM)	0.222	12.61
LOG (MHZ)	0.466	10.11
LOG (# FLOPPY DRIVES)	-0.396	-10.07
LOG (# SLOTS)	0.050	1.81
DISPLAY DUMMY	-0.118	-4.28
EXTRA EQUIPMENT DUMMY	-0.124	-1.83
PORTABLE DUMMY	0.573	12.78
16-bit PROCESSOR DUMMY	0.243	4.42
32-bit PROCESSOR DUMMY	0.641	9.59
AGE	0.030	2.86
APPLE DUMMY	0.309	3.74
AST DUMMY	0.314	5.01
COMPAQ DUMMY	0.541	10.88
DELL DUMMY	0.279	6.76
HEWLETT-PACKARD DUMMY	0.399	7.83
IBM DUMMY	0.431	8.82
NEC DUMMY	0.270	4.24
RADIO SHACK DUMMY	0.083	1.08
ZENITH DUMMY	0.317	5.32
TOSHIBA DUMMY	0.193	2.54
YEAR=1990	-0.304	-9.48
YEAR=1991	-0.441	-13.06
Intercept	4.169	26.40
$R^2 = 0.709$	F = 166.2	N = 1597

TABLE 4.4: AVERAGE QUALITY OF PCs -- CHANGES OVER TIME

$$q_{it} = \sum_k \hat{\beta}_{kt} z_{kit}$$

Year	Mean	St. Deviation
1976	77.8	30.3
1977	113.8	49.5
1978	115.3	38.4
1979	127.3	50.1
1980	132.2	52.5
1981	143.7	51.9
1982	190.5	128.2
1983	280.3	141.5
1984	374.9	185.8
1985	451.7	231.3
1986	634.9	399.7
1987	929.7	746.4
1988	1388.2	1048.4
1989	1690.6	1046.2
1990	1701.6	1079.1
1991	1764.5	1232.3

TABLE 4.5: HEDONIC REGRESSION W/ DISTANCE MEASURE, 1989-1991
DEPENDENT VARIABLE: log (Real Price)

VARIABLE	COEFFICIENT	T-STATISTIC
LOG (AVG DISTANCE$_{nit}$)	0.033	2.94
LOG (HARD DISK)	0.098	14.33
LOG (RAM)	0.231	12.34
LOG (MHZ)	0.466	10.15
LOG (# FLOPPY DRIVES)	-0.398	-9.98
LOG (# SLOTS)	0.051	1.83
DISPLAY DUMMY	-0.113	-4.09
EXTRA EQUIPMENT DUMMY	-0.131	-1.93
PORTABLE DUMMY	0.541	12.85
16-bit PROCESSOR DUMMY	0.242	4.40
32-bit PROCESSOR DUMMY	0.616	9.50
AGE	0.028	2.70
APPLE DUMMY	0.286	3.43
AST DUMMY	0.309	4.88
COMPAQ DUMMY	0.482	10.50
DELL DUMMY	0.276	6.66
HEWLETT-PACKARD DUMMY	0.315	7.96
IBM DUMMY	0.426	8.68
NEC DUMMY	0.264	4.44
RADIO SHACK DUMMY	0.096	1.24
ZENITH DUMMY	0.312	5.22
TOSHIBA DUMMY	0.179	2.35
YEAR=1990	-0.284	-6.93
YEAR=1991	-0.428	-12.83
Intercept	4.140	26.11
$R^2 = 0.715$	$F = 148.8$	$N = 1597$

AVG DISTANCE$_{nit}$ = average distance from other models.

TABLE 4.6: NEW MODELS' SPATIAL LOCATION

Dependent variable: d_{mit}, average distance of a new model from all existing models

Variable	Coefficient	t-statistic *
ENTRANT	-0.441	-2.49
# OF FIRMS$_{t-1}$	-0.031	-3.55
# OF MODELS$_{t-1}$ **	-0.008	-4.92
FIRM'S AGE	0.115	5.54
Intercept	9.092	21.53
R^2 = 0.267	F = 152.0	N = 1789

* t-statistics based on robust standard errors

** the variable becomes insignificant when the dependent variable is divided by the lagged number of models

ENTRANT = 1 if firm was an entrant in year t;
# OF FIRMS$_{t-1}$ = number of existing firms when entry occurs;
# OF MODELS$_{t-1}$ = number of existing models when entry occurs; and
FIRM'S AGE = number of years firms has existed.

FIGURE 4.2: LOCATION IN PRODUCT SPACE: INCUMBENTS/ENTRANTS
(new models only)

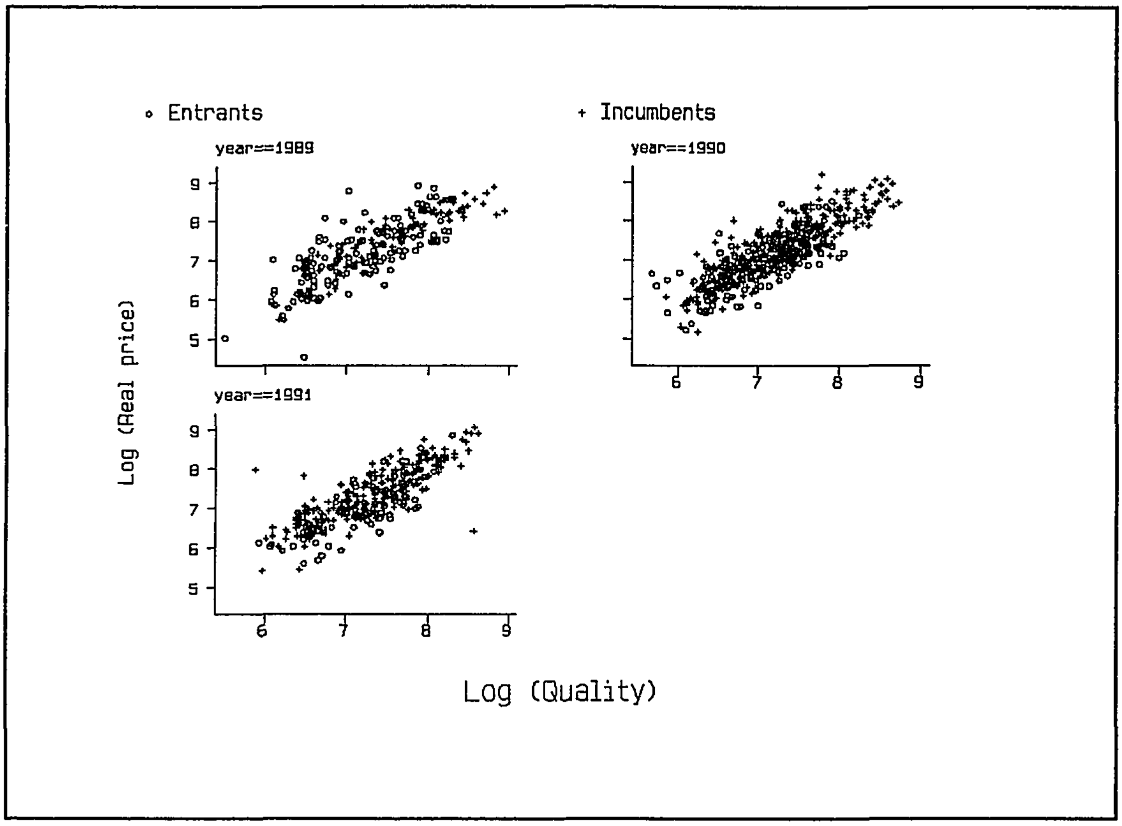


TABLE 4.7: ESTIMATION OF RELATIVE MODEL DISPERSION

Dependent variable: R_{it}, relative model dispersion for firm i in year t.

Variable	Coefficient	t-statistic
ENTRANT	-0.209	-6.03
FIRM'S AGE	0.027	4.68
$NMODCUM_{i,t-1}$	0.029	16.68
# OF $MODELS_{t-1}$	-0.001	-9.51
Intercept	0.694	13.58
R^2 = 0.401	F = 343.2	N = 2053

ENTRANT = 1 if firm is an entrant in year t;
FIRM'S AGE = number of years firm has existed;
NMODCUM = number of models firm has marketed prior to year t; and
# OF $MODELS_{t-1}$ = number of existing models in year t-1.

TABLE 4.8: PROBABILITY OF MODEL'S EXIT, LOGIT ESTIMATION (1991 excluded)

Dependent variable: $Pr(EXIT_{mit})$, probability of exit for model m, firm i, year t

Variable	Coefficient	t-statistic
RESID	0.839	0.81
RESSIGN	-2.373	-1.11
FIRM'S AGE	0.071	1.18
MODEL'S AGE	0.354	4.06
DISTANCE	0.018	1.31
NMODCUM	-0.101	-4.24
PIONFIRM	-1.217	-3.76
Intercept	-0.125	-0.51
log likelihood = -279.3	χ^2 = 106.25	N = 526

RESID = residual from pooled hedonic regression;
RESSIGN = signed residual squared (+ for positive residuals, - for negative);
FIRM'S AGE = number of years firm has existed;
MODEL'S AGE = number of years model has existed;
DISTANCE = average distance from existing models;
NMODCUM = number of models firm has marketed prior to year t; and
PIONFIRM = 1 if firm was first to introduce new technology.

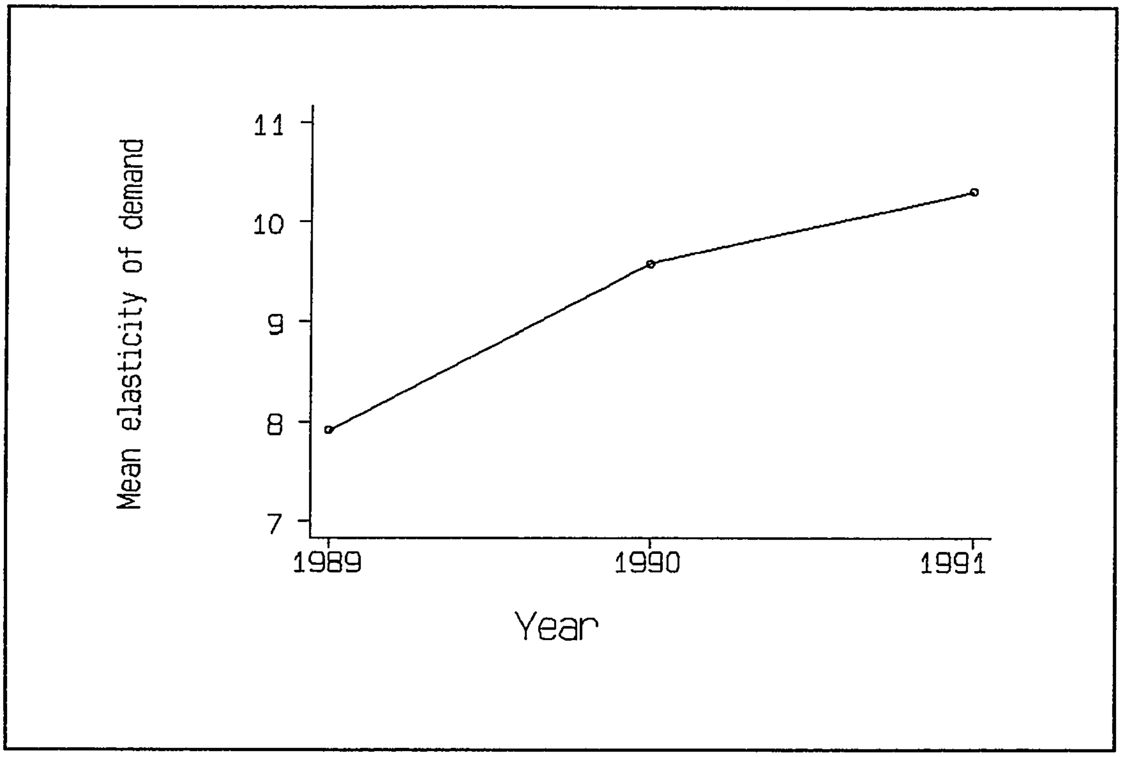
TABLE 4.9: MARKET SHARE ESTIMATION, 2SLS

Dependent variable: log(market share) in year t

Variable	Coefficient	t-statistic
$PRICE\_Q_{mt}$	-0.0227	-2.64
$LPRICE\_Q_{nt}$	0.0015	0.46
APPLE DUMMY	2.643	13.43
AST DUMMY	-0.411	-1.18
COMPAQ DUMMY	2.017	12.21
DELL DUMMY	1.189	9.41
HEWLETT-PACKARD DUMMY	1.081	6.40
IBM DUMMY	3.575	24.48
NEC DUMMY	1.826	9.29
RADIO SHACK DUMMY	1.201	4.42
ZENITH DUMMY	1.963	11.06
TOSHIBA DUMMY	1.111	4.74
YEAR=1990	-0.125	-1.93
YEAR=1991	-0.267	-2.13
Intercept	-7.471	-64.69
$R^2 = 0.482$	F = 66.1	N = 1009

$PRICE\_Q_{mt}$ = own quality-adjusted price, divided by avg. distance from other models;
$LPRICE\_Q_{nt}$ = $\ln(\Sigma \exp((P-q)/distance))$, for all other models n in year t.

FIGURE 4.3: AVERAGE DEMAND ELASTICITIES (1989-91 and 1977-91)



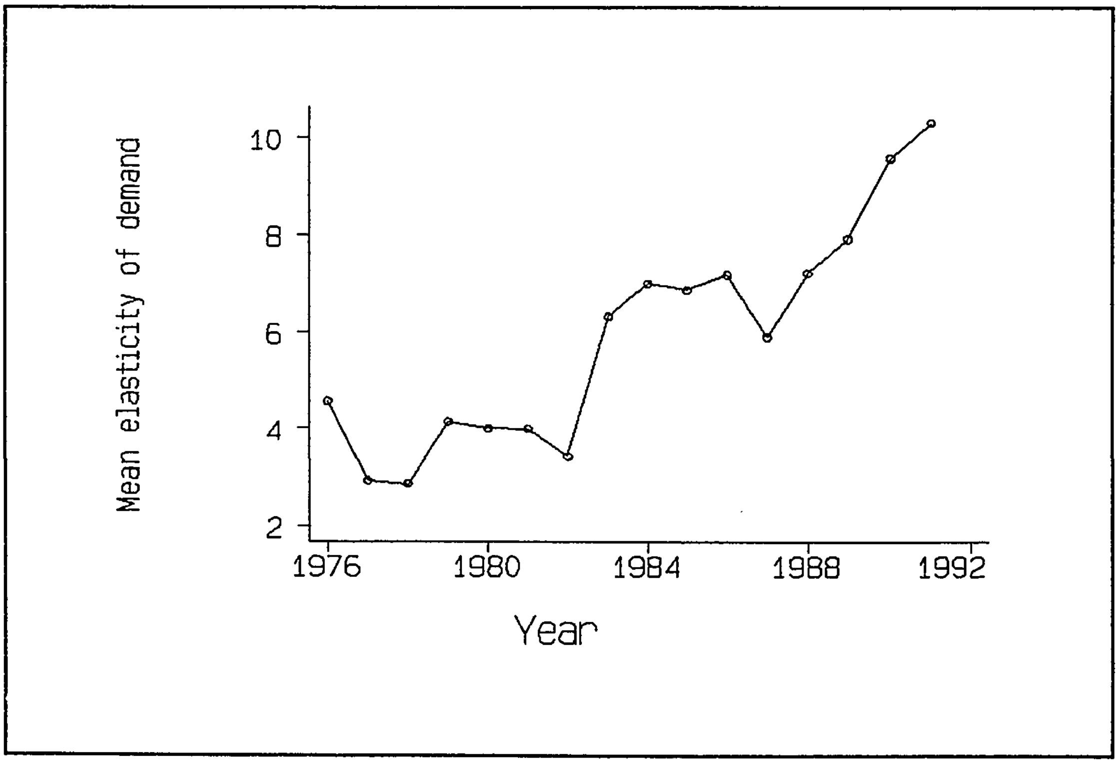
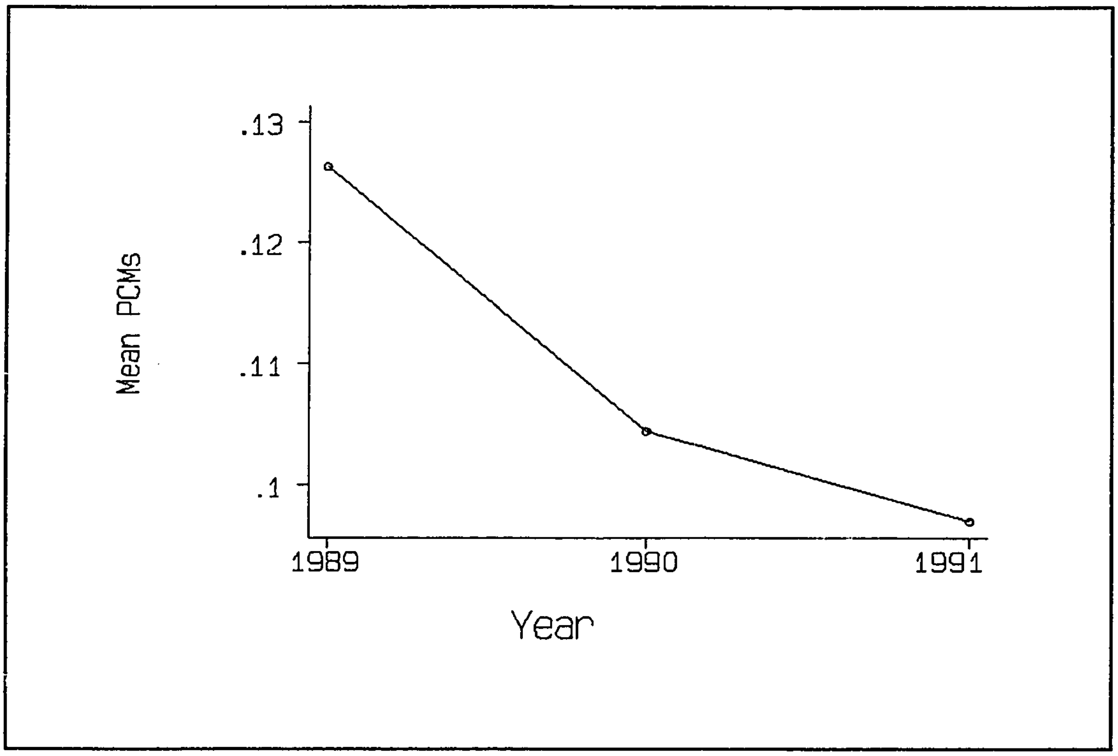
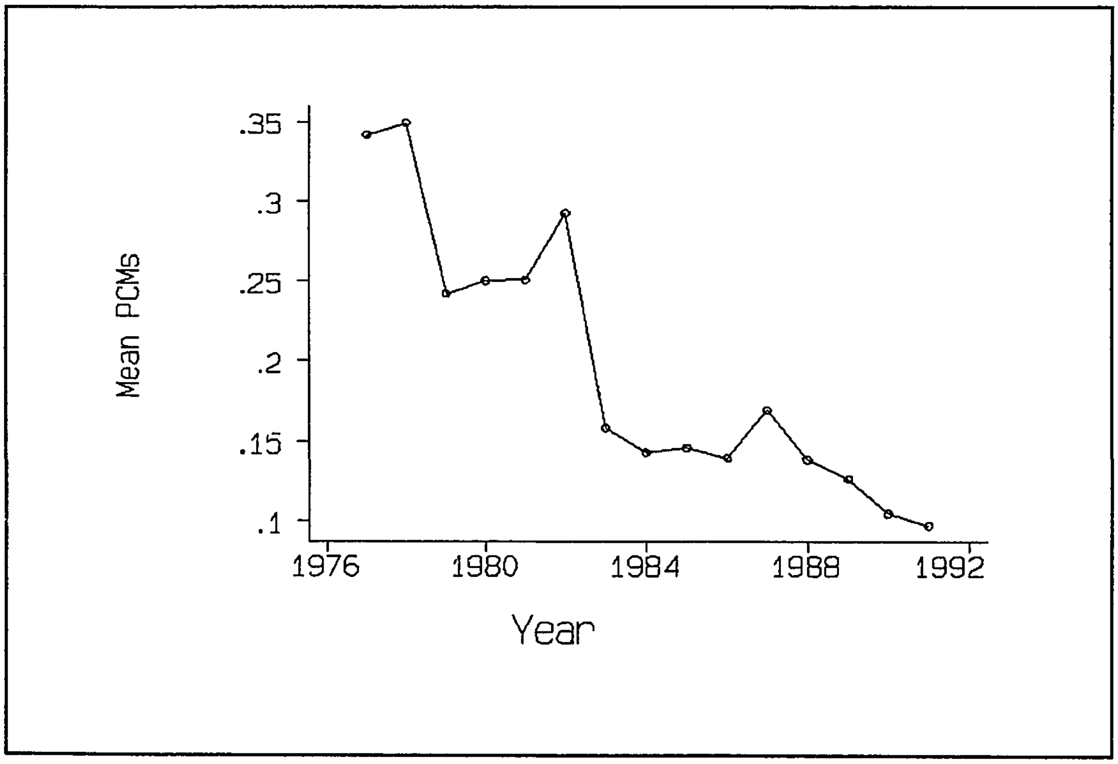


FIGURE 4.4: IMPLIED PRICE-COST MARGINS (1989-91 and 1976-91)





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