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ABSTRACT

Supply and demand functions are typically estimated using uniform prices and quantities across products, but where products are heterogeneous, it is important to consider quality differences explicitly. This paper demonstrates a new approach to doing this by employing hedonic coefficients to estimate price elasticities for differentiated products in the market for personal computers. Differences among products are modeled as distances in a linear quality space derived from a multi-dimensional attribute space. Heterogeneous quality allows for the estimation of varying demand elasticities among models, using models' relative positions as measures of market power. Instead of restricting market competition to the two nearest models, as is typically done in the differentiated-product literature, cross-elasticities of substitution are allowed to decline continuously with distance between models in quality space.

Using data on prices, technical attributes, and shipments of personal computers sold in the United States from 1977 to 1988, two-stage least squares estimates of demand elasticities are obtained. The estimated elasticities vary across models and over time, and are consistent with observed changes in market structure. Entrant firms, as well as new models, are found to face more elastic demand. The estimated elasticities are used to calculate price-cost markups and industry profit-revenue ratios. Both measures decline significantly, indicating a decrease in industry profitability over time, as the market became more competitive.

Estimating Demand Elasticities in a Differentiated Product Industry: The Personal Computer Market

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I. Introduction

Supply and demand functions are typically estimated using uniform prices and quantities across products, yielding a single industry-wide demand elasticity estimate. However, most industries are characterized by multiproduct firms producing differentiated rather than uniform goods. Each product is likely to face a different demand elasticity. It would be misleading, for example, to use a single estimate of demand elasticity for a Mercedes and a Ford Escort. Instead, individual products' attributes and their market position should be used in demand elasticity estimation.

Beginning with Rosen (1974), economists have employed various means of estimating demand and supply for differentiated products or individual attributes. 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), Berry (1992), Feenstra and Levinsohn (1995), and Berry, Levinsohn, and Pakes (1995). A large number of products forces the analysts to place strong restrictions on demand to avoid estimating thousands of elasticities. In most of the studies, models are assumed to compete only with their two nearest competitors. However, a sufficient drop in price could presumably make consumers move to a different market segment, making the assumption too stringent. Cross-elasticities are often estimated only after the market is aggregated to two general types of products (see Bresnahan (1989) for review).

This paper 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 (PCs), differences among products are modeled as distances in a linear quality space derived from a multi-dimensional attribute space using hedonic coefficients as weights. I design a supply and demand model that allows for variation in demand elasticities among differentiated products and over time. The relative positions of models in the quality space measure their market power. Instead of restricting market competition to the two nearest models, a new method allows cross-elasticities of substitution 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. 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, I compute two measures of industry-level profitability: the annual price-cost markups and the total profit-revenue ratio. Both measures indicate a significant decline in profitability with the increase in market competition over time.

The paper proceeds as follows. Sections II and III describe the theoretical models of demand and supply, respectively, leading to two estimable equations. Section IV describes the data, while section V provides estimation results. Section VI discusses industry profitability changes. Section VII concludes.

II. Demand

Personal computers are vertically differentiated products, where "more" of a given characteristic is considered "better."[1] 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 valuation of quality, δ_i. Utility functions vary subject to a random component ε_{im}, which includes consumers' brand preferences:

$$u_{im} = \delta_i z_m - \alpha P_m + \varepsilon_{im} \qquad \varepsilon \sim \text{iid} \tag{1}$$

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

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

Assuming that the willingness to pay for quality equals $\delta_i = \delta + \varphi_i$, so that $E(\delta_i) = \delta$:[2]

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

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

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

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

[2] Although tastes vary, in the case of vertically differentiated products consumers care mainly about quality, and higher prices indicate 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 difference). Therefore ignoring the heterogeneity in taste and income in demand for PCs is not as important as in the case of other commodities.

$$\Pr(\text{buy } m) = \Pr\left((\varepsilon_{im} - \varepsilon_{in} + \varphi_i (z_m - z_n)) \geq (\delta z_n - \alpha P_n) - (\delta z_m - \alpha P_m)\right) \quad \text{for all } n \qquad (2)$$

Market share of model *m* is determined by the proportion of consumers for whom the inequality in equation (2) is true.[3] Assuming that 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:[4]

$$s_m = \frac{e^{\delta z_m - \alpha P_m}}{\sum_{n=1}^{N} e^{\delta z_n - \alpha P_n}} \qquad (3)$$

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. I can

[3] I 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, relative market shares will be unchanged, while quantities would change.

[4] 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 I estimate robust standard errors.

therefore constrain $\delta = \alpha$. Market share is a function of quality-adjusted prices of PC models,[5] but I include firm effects in the equation separately to control for brand reputation effects.

Market share of model *m* produced by firm *i* in year *t* (s_{mit}), allowing for varying coefficients on all other models' prices, becomes:

$$\ln s_{mit} = \gamma_0 + \gamma_i + \gamma_1 (P_{mit} - q_{mit}) - \ln \sum_{n=1}^{N} e^{\gamma'_{2mn}(P_{nt} - q_{nt})} + \nu_{mit} \tag{4}$$

Own demand (market share) changes with own quality-adjusted price (the coefficient is proportional to own price elasticity of demand) and with quality-adjusted prices of substitutes (the coefficients represent cross-elasticities of demand).[6] Unlike Feenstra and Levinsohn (1995), I do not assume that two models with identical technical specifications are perfect substitutes. My model allows for brand effects, hence firm dummies in the demand equation.

A. Cross-Elasticities of Demand

The above equation presents an estimation problem. Even in a one-hundred product market there are 10,000 cross-elasticity coefficients to estimate, and the PC market has over 300 models in some years. Analysts have typically imposed stringent constraints on demand

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

[6] 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: $\ln (s_m/s_0) = (z_m - z_0)\,\delta - (P_m - P_0)\,\alpha$. The specification does not allow for cross-elasticity estimation, however.

structure: either each product competes with its two nearest neighbors only (e.g., Bresnahan (1981)), or all the products are summarized by two general types (e.g., Gelfand and Spiller (1987)). Even though I reduced the quality to a single dimension, I did not restrict market competition to the two nearest models—a sufficiently large price drop for a model located further away could make it a valid substitute.

A cross-elasticity between a pair of products depends on the degree of substitution between them. It is therefore reasonable to expect that the more similar are two models' attributes (i.e., the closer to each other they are located in the product space), the more customers would consider them to be substitutes. The cross-elasticity of demand between models *m* and *n* can therefore be assumed to be inversely proportional to the distance in quality space between them: $\gamma'_{2mn} = \frac{\gamma_2'}{d_{mn}}$. The specification allows each model to have a non-zero cross-elasticity with each of the other products on the market.

B. Own Price Elasticities of Demand

Own price and prices of substitutes are not the only factors that affect demand. Just as a monopolist faces more inelastic demand than does a competitive firm, a model with market power is likely to face more inelastic demand than a model with several substitutes. The market power 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. I measure the "crowding" with the average distance from other models. To account for each model's market power, I weigh own quality-adjusted prices by the average distance from each model's substitutes, $\overline{d}_{mn}$. The demand equation becomes:

$$\ln s_{mit} = \gamma_0 + \gamma_i + \gamma_1 \frac{P_{mit} - q_{mit}}{\bar{d}_{mn}} - \ln \sum_{n=1}^{N} e^{\gamma_2 / \frac{P_{nt} - q_{nt}}{d_{mn}}} + \nu_{mit} \tag{5}$$

A linear approximation to equation (5) is:[7]

$$\ln s_{mit} = \gamma_0 + \gamma_i + \gamma_1 \frac{P_{mit} - q_{mit}}{\bar{d}_{mn}} + \gamma_2 \ln \sum_{n=1}^{N} e^{\frac{P_{nt} - q_{nt}}{d_{mn}}} + \nu_{mit} \tag{6}$$

where: $\bar{d}_{mn} = \sum_{n=1}^{N} \frac{d_{mn}}{N}$ = average distance from model *m*'s substitutes;[8] 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 (1). Since a model's relative location (or quality) enters the consumers' utility function, each model's demand elasticity depends on its location in the quality space, not just on its quality-adjusted price. The assumption allows to distinguish between a model with a low price and low quality, and a model

[7] The linear approximation facilitated the inclusion of all the competitors in cross-elasticity of demand estimation. The nonlinear equation (5) was estimated including two nearest neighbors, then four, six, eight, and finally 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.

[8] Feenstra and Levinsohn (1995) 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.

with a high price and high quality. The two would face different demand elasticities, even if their quality-adjusted prices were identical.

III. Supply

Firms engage in a two-stage game: in stage one they enter or exit the market, and decide which models to produce; i.e., they compete in spatial location of models in the model quality space. I analyzed the first stage in Stavins (1995). Stage two is a Bertrand-Nash competition in prices: each firm chooses own models' prices to maximize its profit, taking other firms' prices and all the models' location as fixed.[9] Therefore, the attributes of models produced are predetermined in the second stage.

Each firm i chooses prices of all its models, P_{mit}, to maximize its profit in year t, π_{it}. The quantity sold of each model equals 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; the fixed cost is allowed to decrease with the number of models the firm has produced in the past, exhibiting economies of scope. Marginal cost does not change with the number of units produced,[10] although it does increase with the attributes embodied:

[9] Fixed costs of a new model can be assumed sufficiently large for the assumption to hold.

[10] 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.

$$\max_{P_{mit}} \pi_{it} = \sum_{m=1}^{M_{it}} [(P_{mit} - c_{mit}) Q_t \, s_{mit} - (F_{mit}(\sum_{\tau=0}^{t-1} M_{i\tau}))] \tag{7}$$

where M_{mit} is the number of models by firm i in year t, c_{mit} is the marginal cost of model m, F_{mit} is the fixed cost of model m, and $\sum_{\tau=0}^{t-1} M_{i\tau}$ is the cumulative number of models produced before t.

Differentiating equation (7) with respect to the model's price gives the following first order condition:

$$(P_{mit} - c_{mit}) Q_t \frac{\partial s_m}{\partial P_m} + Q_t \, s_{mit} + \sum_{\substack{m'=1 \\ m' \neq m}}^{M_{it}} (P_{m'it} - c_{m'it}) Q_t \frac{\partial s_{m'}}{\partial P_m} = 0 \tag{8}$$

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 (6):

$$P_{mit} = c_{mit} - \frac{1}{\gamma_1} \bar{d}_{mn} [1 + \gamma_2 \sum_{\substack{m'=1 \\ m' \neq m}}^{M_{it}} (P_{m'it} - c_{m'it}) \frac{1}{d_{mm'}}] \tag{9}$$

Equation (9) shows that price equals marginal cost (c_{mit}) plus price-cost margin (PCM). c_{mit} is a function of model attributes, while 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 (6)). In other words, the closer the model is located to other firms' models, the closer its price is to its marginal cost: as $\bar{d}_{mn} \rightarrow 0 \Rightarrow P_{mit} \rightarrow c_{mit}$. The model's market power is approximated by its relative position in the quality space. 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 on other models by the same firm are, reflecting firm effects (such as management and reputation advantages).

Since I do not have information about marginal costs of all other models, I now solve for marginal costs to eliminate them from the equation. In equation (9), price is a function of all other prices, marginal costs, and distances from other models. In a matrix form:

$$P = M_1 \, c + M_2 \, P + D_1$$

Yielding the marginal cost equation:

$$c = M_1^{-1} \, (I - M_2) \, P + D_2 \qquad \textbf{(10)}$$

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

$$c = \beta_c \, z + \omega \qquad \textbf{(11)}$$

Equating (10) and (11) and solving for P:

$$P = (I - M_2)^{-1} M_1 (\beta_c z + \omega) + D_3$$

or:

$$P = B_1 z + B_2 \bar{D}_{mn} + B_3 \bar{D}_{mm'} + \xi \quad \textbf{(12)}$$

Price is therefore a function of model attributes (z) and of the average distance from models by other firms ($\bar{D}_{mn}$), as well as the average distance from own models ($\bar{D}_{mm'}$). Both model attributes and model location in the product space are exogenous in the second stage of the market game.

IV. Data

The initial data set includes annual prices and technical attributes for new personal computers sold in the United States from 1976 to 1988.[11] The data set is an unbalanced panel. A model is identified by its brand name. 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 in the retail and discount markets in the same year. The retail data include list prices of PC models based on their technical reviews, or models sold by their brand-name manufacturers, while discount data are for models sold by other sources.

The data set was merged with a data set containing PC shipment quantities per year, obtained from International Data Corporation (IDC). The IDC data did not cover all of the PC models in my sample. Therefore only the overlap of the two data sets—972 observations, or two-thirds of the initial dataset, had quantity data. There are no quantity data for the year 1976.

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[11] 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.

The following table shows total shipment quantities in my sample as well as total quantities obtained from IDC and from Dataquest. The numbers do not correspond perfectly, but give an idea of the order of magnitude of the market. While my sample seems to be quite complete for the initial years, it covers only about half of the market in the last few years. I found no evidence of sample selection of models for which quantity data exists.

Year	My Sample Shipments [a] ('000)	Total Shipments [b] ('000)	Total Shipments [c] ('000)
1977	22.2	41.1	
1978	131.9	167.4	
1979	172.7	236.2	
1980	331.6	473.7	268.7
1981	471.9	778.3	486.1
1982	2000.4	3047.3	1655.5
1983	3316.6	5459.1	4931.4
1984	4223.1	6691.9	7490.7
1985	2593.8	5784.8	6369.6
1986	2997.7	6845.9	6941.4
1987	4375.3	8393.8	8618.3
1988	4006.2	9320.5	9959.8

[a] Source: International Data Corporation.
[b] Source: International Data Corporation. The numbers were reported as market total by IDC.
[c] Source: Dataquest. The numbers were reported as market total by Dataquest.

Some evidence of the changing market structure can be observed in Table 1. Both the

Herfindahl index and C(3)[12] decreased over time. Figure 1 shows changes in average model market shares for some leading firms as well as for the entire sample, where the average model market share decreased continuously since 1978.

V. Estimation

My goal is to estimate demand elasticities, as specified in equation (6). Prices may be endogenous, though. Since the supply equation is a reduced form regression of prices on exogenous variables, I begin with the supply equation estimation. I then use the estimated prices to obtain two-stage least squares estimates of the demand equation.

A. Supply

In scalar notation, equation (12) becomes:[13]

$$\ln P_{mit} = \lambda_0 + \lambda_t + \lambda_i + \sum_j \lambda_j z_{jmit} + \lambda_1 \sum_{n=1}^{N_t} \frac{d_{mn}}{N_t} + \lambda_2 \sum_{\substack{m'=1 \\ m' \neq m}}^{M_{it}} \frac{d_{mm'}}{M_{it}} + \xi_{mit} \qquad \textbf{(13)}$$

where z_{jmit} is attribute *j* of model *m* by firm *i* in year *t*, d_{mn} is the distance between model *m* and model *n* (produced by another firm), $d_{mm'}$ is the distance from model *m'* (produced by the same firm), n denotes other firms' models (n = 1, ... ,N_t), and m' denotes other models by the same

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[12] The Herfindahl index is the sum of each firm's market share squared, or $\sum_{n=1}^{N_t} s_{nt}^2$, while C(3) is the sum of market shares of the top three firms.

[13] Log-linear form was chosen based on the goodness of fit criteria.

firm ($m' = 1, \ldots, M_{it}$).

The above equation allows for a separate effect of the distance to other firms' models (accounting for the model's market power; expect an unambiguously positive effect) and the distance to own models. Concentration of own models in a single market segment indicates the firm's local market power,[14] but in Stavins (1995) I found that established firms disperse their models to preempt the market. The sign of the coefficient on own models' concentration is therefore ambiguous.

To obtain distance measures between models differentiated in several attributes, multidimensional models are reduced to a unidimensional quality measure.[15] Since models are vertically differentiated, hedonic regression coefficients provided marginal implicit prices of individual model characteristics. I start by estimating a hedonic equation of prices on model attributes and firm and year dummies.[16] Estimated marginal implicit prices serve as attribute weights in construction of a quality measure: $q_m = \sum_j \hat{\beta}_j z_{jm} = \hat{\beta}' z_m$. The quality measure q is a weighted sum of all the technical attributes, as well as firm dummies. The firm dummies serve as proxies for such firm attributes as service support. 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, $\bar{d}_{mn}$, is d_{mn} divided by the number of models. Its mean, by year, is shown in Figure 2. Descriptive statistics on the major variables are listed in Table 3.

The supply equation regresses price on model attributes and distances from other models.

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[14] The hypothesis is consistent with Feenstra and Levinsohn's (1995) finding.

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

[16] The results of that regression are in Table 2. A similar hedonic specification was used by Berndt and Griliches (1993) and Stavins (1995).

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.[17] The price equation was estimated using OLS. Because of possible heteroscedasticity, robust standard errors were estimated. The results are reported in Table 4. Including firm dummies 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 coefficient on the average distance from own models is negative, but insignificant. It is possible that the market penetration effect and the own market segment strengthening effect counteract each other.

I compared the results to the hedonic regression results. The difference between the two models is the inclusion of the distance measures in the price regression. I reject the hypothesis that the distance measures' coefficients are jointly equal to 0 at the 1% level, even though I cannot reject the hypothesis that coefficients remained unchanged between the two models.

The above result has an important implication—since all the quality coefficients remained unchanged, the quality measure based on the hedonic regression is equal to 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 the estimation is done in a single step.

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

B. Demand

I next estimate the market share equation (6). Quality-adjusted prices used in the market share equation were computed using the unidimensional quality measure, i.e., applying hedonic marginal implicit prices as attribute weights.[18]

I used two-stage least squares (2SLS) estimation using the predicted prices obtained in the supply estimation. I also estimated three-stage least squares (3SLS) to test for possible residual correlation between the two equations. The results of the two methods are in Table 5.[19]

(1) *Own price elasticity of demand.*

The coefficients on own quality-adjusted prices are negative and significant in both specifications. Deriving from equation (6), demand elasticity equals:

$$\eta = \frac{\partial s}{\partial P}\frac{P_{mit}}{s_{mit}} = \frac{\partial \ln s}{\partial P} P_{mit} = \gamma_1 \frac{P_{mit}}{\overline{d}_{mn}} \qquad \textbf{(14)}$$

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

The 2SLS price coefficient yields an average estimated elasticity of demand of 6.3

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[18] Since I am interested mainly in demand effects, a better set of attribute weights would have been marginal utilities of the characteristics (instead of marginal costs), but they are not available.

[19] I did not estimate the market share equation using logit, because of logit's independence of irrelevant alternatives property. In the case of choosing among the PC models, consumers' utility would most likely increase with a larger choice of PCs. Furthermore, I have no information about the consumers purchasing individual models.

(applying the formula above), ranging from 2.9 in 1977 to 7.2 in 1988.[20] The estimates are consistent with the imperfectly competitive market structure of the PC industry. As Figure 3 shows, the estimated average demand elasticity increased over time (in absolute value), as the industry became more competitive. There is a significant difference between the initial few years and the post-1982 period, when several PC clones entered the market.

(2) Cross-elasticity of demand.

The cross-elasticity coefficient on prices of substitutes was insignificant in all the specifications.[21] I 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. The own price elasticity result is thus robust—regardless of how many "neighbors" the model is allowed to compete with, the effect of its own price on its market share 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.

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[20] The 3SLS estimates of price elasticities of demand average 10.8, ranging from 5.0 in 1977 to 12.4 in 1988.

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

(3) Firm effects.

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 that of the omitted firms' models, controlling for quality-adjusted prices of models. Negative coefficients on year dummies indicate the decrease over time in market shares of individual models. It is worth noting that when firm and year dummies were omitted from the market share regression, price coefficients remained unchanged, which confirmed the robustness of the estimated elasticities.

As the market became more competitive, I expected the leading firms' advantage to diminish. To test whether the firm effects declined over time, I included firm-year interaction dummies for all major companies. Almost all of the interaction terms were negative, indicating a decline in firm effects over time. The coefficients are in Table 6. The estimated brand effect decline ranged from 26% for IBM to 99% for Radio Shack over the 13-year period.

(4) Established brands.

Finally, I tested Schmalensee's (1982) advantage of established brands hypothesis by comparing demand elasticities for incumbents' vs. entrants' models, as well as for new vs. older models. If Schmalensee (1982) is correct, established firms' models should have lower demand elasticities, due to their reputation. 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 have a significantly lower market *share* than incumbents' models (the entrant dummy coefficient was negative and significant). However, although the interaction of the own price term with an entrant dummy was negative, indicating more elastic demand for entrants' models, the coefficient was not statistically significant.[22]

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 7). Models' age did not appear significant when treated continuously, but when the 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 8). The results show that a model that has been on the market for one or two years faces more inelastic demand than a completely new brand just entering the market, because of reputation and marketing of 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 4. Incumbents faced more inelastic demand in most years, although the difference was not statistically significant.

VI. Profitability

The increased competitiveness was likely reflected in the industry's profitability. With

[22] 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 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 markups should drop. Applying the Lerner index of monopoly power:

$$\frac{P_i - c_i}{P_i} = -\frac{1}{\eta_i}$$

where P_i is the price of model i, c_i indicates model i's marginal cost, and η_i denotes the price elasticity of demand faced by model i.

I 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 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[23]:

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

The ratio of the Herfindahl index to the elasticity of demand (equal to the profit-revenue ratio) over time is plotted in Figure 6. The industry profit-revenue ratio declined on average by 12.5% per year. Although for differentiated products price-cost margin computation is more complex,[24]

[23] 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 concentration/demand elasticities intra-industry over time. See Schmalensee (1989) for a survey.

[24] See Waterson (1984), chapter 2 for details.

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 are not 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.

VII. Summary and Conclusions

The paper 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, I estimate demand elasticities. The elasticities vary across computer models according to their market power, as measured by distances between models in a quality space. The estimates are consistent with the increasingly competitive structure of the industry—the demand elasticities increase over time, while the brand effect on model market share declines. I find that incumbent firms and older models face more inelastic demand, because of brand reputation and marketing effects.

Based on the demand elasticity estimates, I use two methods of assessing changes in industry profitability over time: I apply the Lerner index of monopoly power to calculate price-cost markups on individual models, and use a ratio of the Herfindahl index to the elasticities of demand to obtain the total industry profit-revenue ratio. I find a significant decline in industry profitability over time with both measures. As the industry became more competitive and demand elasticities increased, rates of return to investment in technology declined over time.

The paper builds on the relatively small set of empirical studies analyzing demand and supply for differentiated goods. The distance measure makes the model flexible by allowing for heterogeneous estimates of demand elasticities without imposing arbitrary cross-elasticity constraints. The paper utilizes hedonic regression methods in a new way. The results could help predict demand effects of price changes in various segments of a market, as well as 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, since endogeneity of taste in a market with continuously evolving technology could be 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 1: MARKET SHARE OF LEADING FIRMS, BY YEAR

YEAR	HERFINDAHL INDEX	TOP 3 COMPANIES	C(3)
1977	0.5177	Commodore Radio Shack Apple	0.9932
1978	0.5819	Radio Shack Commodore Apple	0.9784
1979	0.4328	Radio Shack Apple Atari	0.9265
1980	0.2137	Radio Shack Apple Atari	0.8791
1981	0.1614	Radio Shack Apple Commodore	0.8846
1982	0.1219	Commodore Sinclair Radio Shack	0.6798
1983	0.1071	Commodore Radio Shack TI	0.6523
1984	0.1278	Commodore IBM Apple	0.7835
1985	0.0872	Commodore Apple IBM	0.7397
1986	0.0393	IBM Apple Commodore	0.6106
1987	0.0338	IBM Apple Radio Shack	0.5830
1988	0.0210	IBM Apple Commodore	0.4802

TABLE 2: HEDONIC REGRESSION
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).

TABLE 3: DESCRIPTIVE STATISTICS ON MAJOR VARIABLES

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

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 all 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
(Est. Price - Quality) / avg distance	2025.9	2337.5	-4079.8	10793.2

TABLE 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 2 for similar results).
** t-statistics are based on robust standard errors.

TABLE 5: MARKET SHARE ESTIMATION, 2SLS and 3SLS DEPENDENT VARIABLE: log (market share)

VARIABLE	2SLS		3SLS	
	COEFF	T-STAT *	COEFF	T-STAT
(P - q) / avg distance	-0.00118	-3.72	-0.00295	-4.67
Avg distance from other models	-1.563	-4.14	-1.586	-1.12
ln (Σ e $^{(P-q)/distance}$)	-0.003	-0.69	0.075	1.92
APPLE DUMMY	2.894	18.95	2.307	6.79
ATARI DUMMY	1.199	6.62	0.461	1.18
COMMODORE DUMMY	2.602	10.47	2.270	5.62
COMPAQ DUMMY	1.946	13.53	1.833	6.41
IBM DUMMY	2.021	13.00	1.946	10.14
NEC DUMMY	0.608	3.79	0.270	0.89
RADIO SHACK DUMMY	1.839	10.86	1.709	6.48
ZENITH DUMMY	1.359	7.61	1.382	4.44
WYSE TECHNOLOGY	0.964	6.74	1.019	2.59
EPSON DUMMY	1.494	8.48	1.538	3.99
KAYPRO DUMMY	0.869	3.18	0.885	2.36
NCR DUMMY	0.466	1.76	0.903	2.43
NORTHGATE DUMMY	0.195	0.74	0.632	1.41
YEAR 1978 DUMMY	-0.191	-0.33	-0.222	-0.24
YEAR 1979 DUMMY	0.082	0.14	0.765	0.89
YEAR 1980 DUMMY	0.057	0.10	0.263	0.36
YEAR 1981 DUMMY	0.059	0.10	0.328	0.45
YEAR 1982 DUMMY	-0.947	-2.07	-0.210	-0.26
YEAR 1983 DUMMY	-1.483	-3.23	-0.310	-0.33
YEAR 1984 DUMMY	-2.030	-4.64	-1.567	-2.11
YEAR 1985 DUMMY	-2.066	-4.73	-1.187	-1.38
YEAR 1986 DUMMY	-2.241	-5.15	-1.763	-2.30
YEAR 1987 DUMMY	-2.830	-6.67	-2.950	-4.28
YEAR 1988 DUMMY	-2.631	-5.83	-3.076	-4.53
Intercept	-3.448	-7.15	-4.020	-3.09
	$R^2 = 0.511$ resid correlation = -0.114 N = 972		$R^2 = 0.324$ resid correlation = 0.053 N = 972	

* t-statistics are based on robust standard errors.

TABLE 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 (Σ $e^{(\hat{p}-q)/distance}$)	-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
$R^2 = 0.492$	$F = 32.65$	$N = 972$

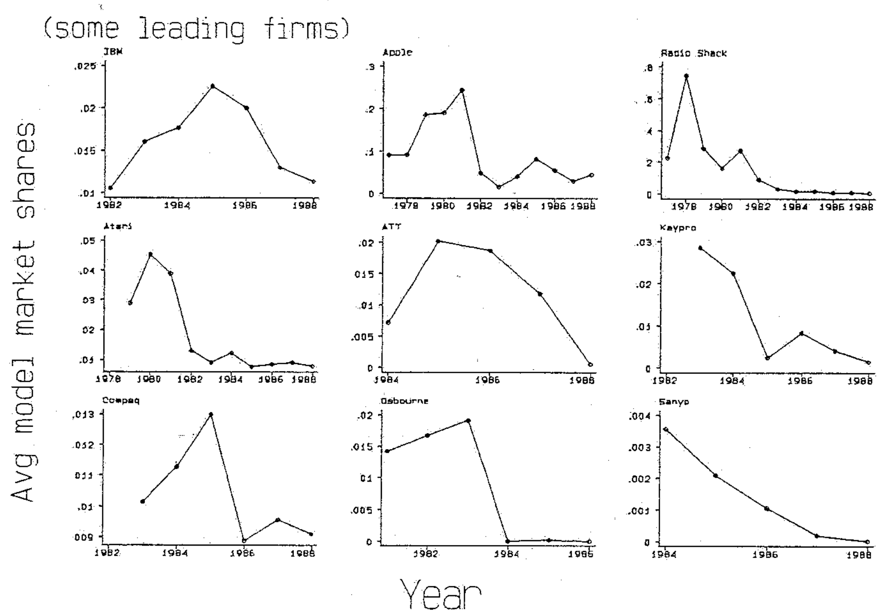
TABLE 7: MEAN DEMAND ELASTICITY BY MODEL AGE AND FIRM'S STATUS

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: MKT SHARE REGRESSION, 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 1: ANNUAL CHANGES IN MODEL MARKET SHARES



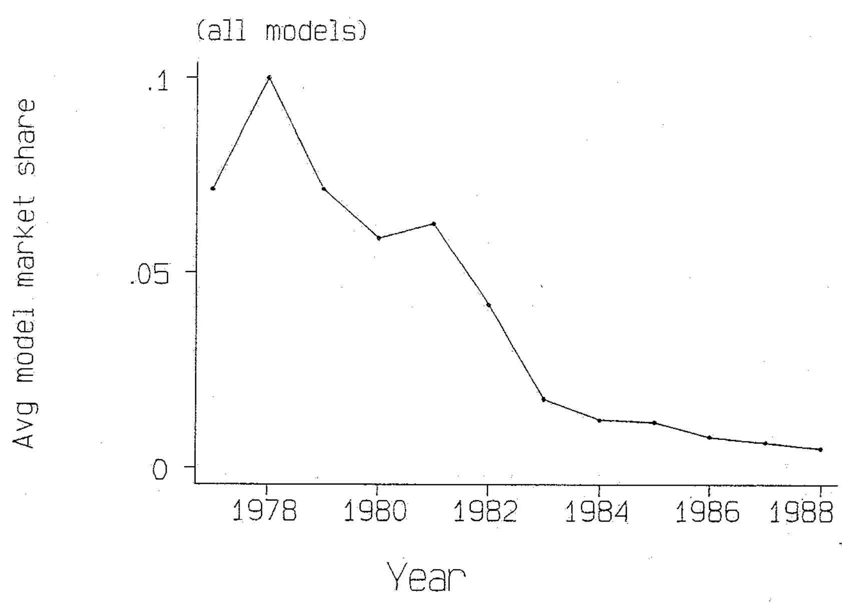


FIGURE 2: MEAN DISTANCE FROM OTHER MODELS, BY YEAR

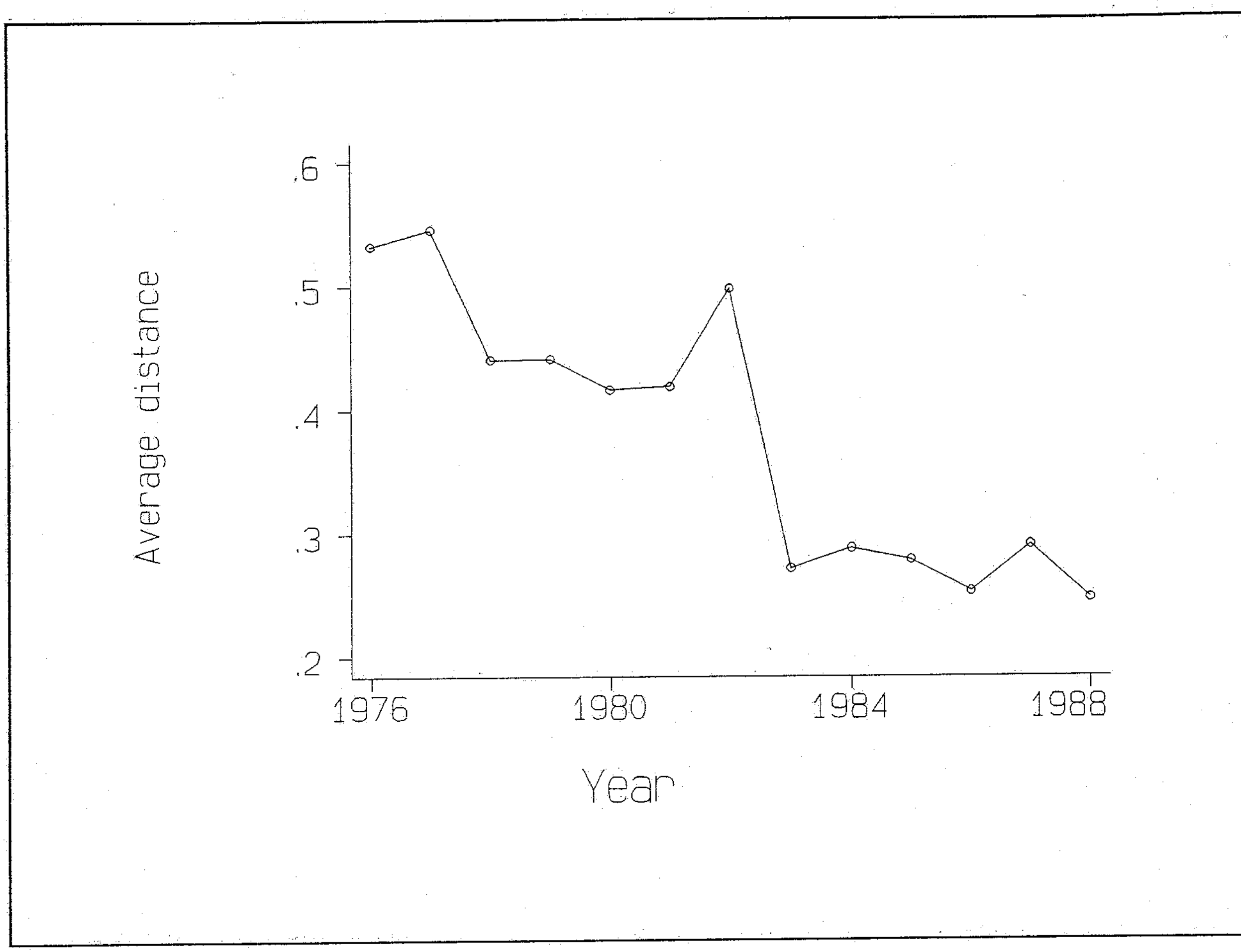


FIGURE 3: AVERAGE DEMAND ELASTICITY BY YEAR: 2SLS

FIGURE 4: AVERAGE ELASTICITY: INCUMBENT/ENTRANT BREAKDOWN

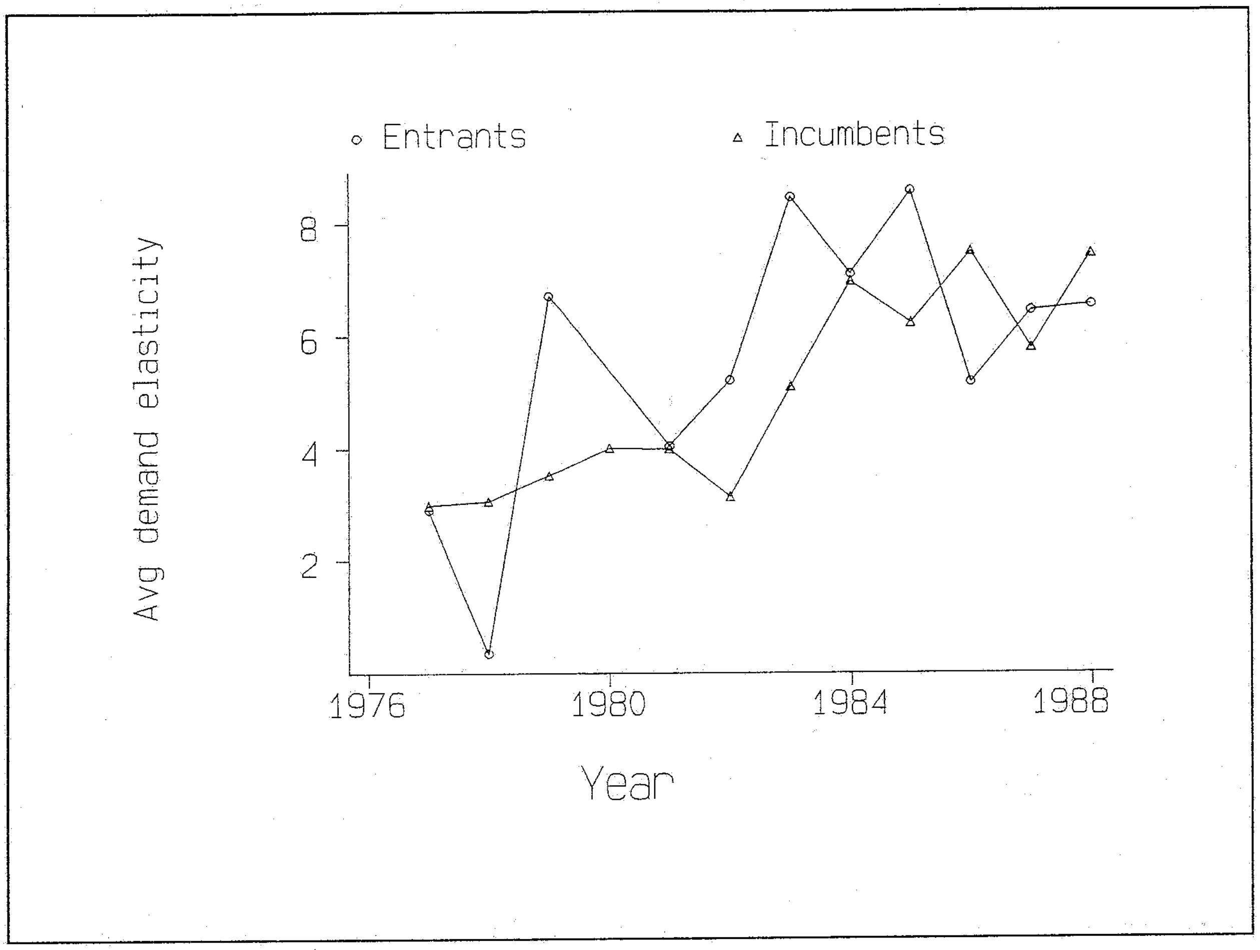


FIGURE 5: AVERAGE MODEL PRICE-COST MARGIN, BY YEAR

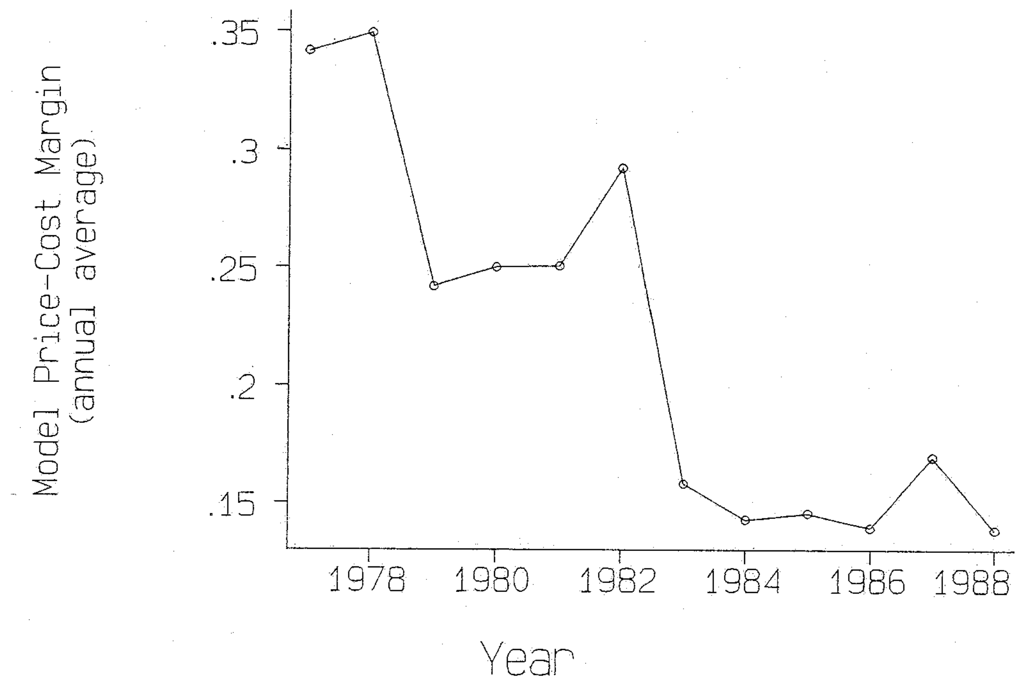
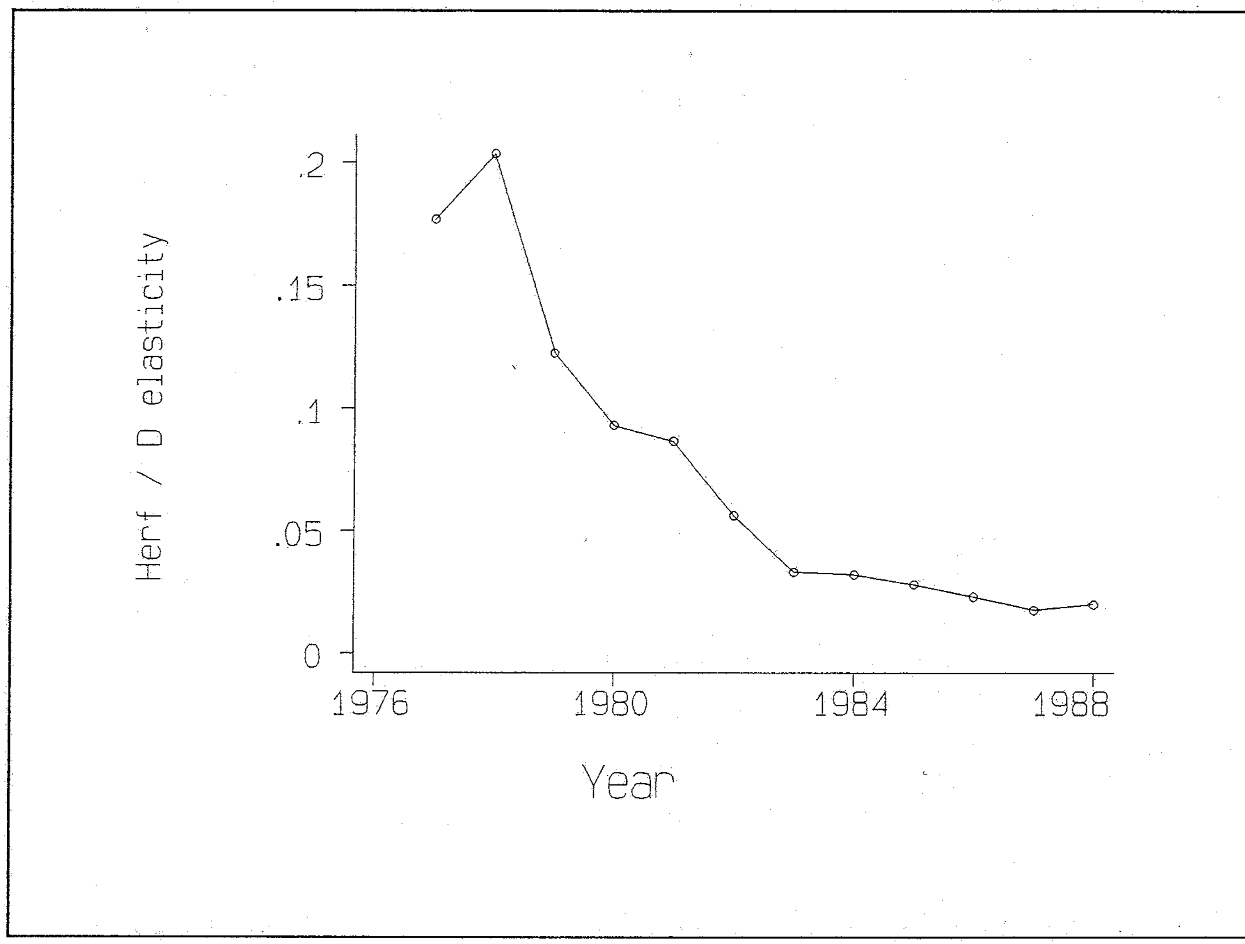


FIGURE 6: INDUSTRY PROFIT / REVENUE RATIO



Appendix

Although I 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):

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

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:

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

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 I 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 $\tau=0$ 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, I 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 average distance from the other firms' models coefficient 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. I 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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