NBER WORKING PAPER SERIES

FROM SUPERMINIS TO SUPERCOMPUTERS: ESTIMATING SURPLUS IN THE COMPUTING MARKET

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Working Paper No. 4899

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 1994

Thanks to Steve Berry, Tim Bresnahan, Ken Brown, Erik Brynjolfsson, Ellen Dulberger, Zvi Griliches, Bronwyn Hall, Roger Koenker, Pablo Spiller, and Frank Wolak for useful discussion. Participants at the CRIW, NBER, the University of Illinois, West-Virginia, and Econometric Society meetings also provided many useful comments. Julie Lee and Jennifer Howitt entered data. Sandra Ospina and Ken Brown provided excellent research assistance. I gratefully acknowledge funding from the Center for Economic Policy Research at Stanford University and the Arnold O. Beckman Endowment at the University of Illinois. I also thank the Charles Babbage Institute for their help with assembling the data used herein. Only I am responsible for the errors contained in this paper. This paper is part of NBER's research program in Productivity. Any opinions expressed are those of the author and not those of the National Bureau of Economic Research.

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ABSTRACT

Innovation was rampant in the computer industry during the late 1960s and the 1970s. Did innovation vastly extend the capabilities of computers or simply reduce the costs of doing the same thing? This question goes to the heart of whether the rate of decline in "constant-quality" computing prices incorrectly identifies the sources of improvement and benefits from technological change. This paper argues that innovation freed computers of technical constraints to providing new services, manifesting many new capabilities in systems with larger capacity. Both anecdotal and quantitative evidence suggest that many buyers adopted new systems to get access to these new capabilities, not solely to take advantage of lower prices.

The analysis divides itself into several related questions. First, what innovations in this period are associated with extensions of capabilities? Second, do buyers adopt products that embody extensions of capabilities? Third, how does a measurement framework represent that action? Are extensions embodied only in increases in capacity or are they embodied in other measurable features of a computer system as well?

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I. Introduction

Innovation is rampant in adolescent industries. Old products die or evolve and new products replace them. Each new generation of products offers new features, extends the range of existing features, or lowers the cost of obtaining old features. Vendors imitate each other's products, so that what had been a novelty becomes a standard feature in all subsequent generations. Depending on the competitive environment and the type of innovation, prices may or may not reflect design changes.

The computer industry of the late 1960s and 1970s experienced remarkable growth and learning. At the start of the period several technological uncertainties defied easy resolution. Most knowledgeable observers could predict the direction of technical change, but not its rate. Vendors marketed hundreds of new product designs throughout the 1970s, and a fraction of those products became commercially successful. In time the industry took on a certain maturity and predictability. By the late 1970s, both buyers and sellers understood the technical trajectory of the industry's products. Even the least experienced users understood the capabilities and limits of the most popular commercial systems.

This paper attempts to measure the economic benefits that accrued to buyers from technological innovation in the computer industry. Its thesis is that many innovations that created economic value in this period are associated with extensions in computing capabilities, as distinguished from a decline in prices, which occurred at the same time as the extensions. This paper does not argue that price decreases were unimportant to buyers, but that price decreases alone tell an incomplete story about the welfare improvements realized by buyers.

This thesis goes to the heart of the relationship between rapid "constant quality" price declines and the inferred improvement in economic welfare. The open issue concerns whether constant quality price indices provide the same information about the experience of a buyer who continues to buy computer systems with a similar set of characteristics, as well as a buyer who takes advantage of the availability of characteristics that did not previously exist. There are reasons to think constant quality price indices do not provide the same information for both types of buyers. The correspondence between constant quality price indices and economic welfare will be weaker when product characteristics cannot be repackaged (e.g., see Trajtenberg [1990]). For example, one large computer system may provide more services to a buyer than two systems with exactly half the amount of measurable characteristics. The appropriate welfare issue concerns buyer satisfaction with the extension of product space -- i.e., extensions of the range of quality available. If a set of adopters of new products could be accurately surveyed, how much would they be willing to pay not to give up the new capability associated with extensions of computers? A large body of work on "cost of living" indices suggests that the "willingness to pay" for product extensions may have a nonlinear relationship to constant quality price decreases.[1]

The problem considered here does not lend itself to a single statistical test or experiment. To reach a convincing conclusion, it would be better to see if a variety of

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[1] It is well known that price indices have problems measuring the benefits associated with new goods. The same problem arises if "extensions of product space" (e.g., inventing a system with computer capacity twice as high as any previous system) are associated with new services. In either event, there is an important issue regarding the procedures for incorporating new goods into price indices. As Triplett [1989] argues, the central issue in developing appropriate procedures revolve around the goals of the index; whether it intends to reflect changes in the "costs of producing" or changes in the "costs of living." This paper focuses primarily on issues regarding the measurement of changes accruing to buyers.

information sources points in a similar direction. This paper addresses itself to several related questions. First, what innovations in this period are associated with extensions of capabilities? Second, do buyers adopt products that embody extensions of capabilities? Third, how could a measurement framework represent that action? Are extensions embodied only in increases in capacity or other measurable features of a computer system?

Many of these questions require an explicit supply and demand framework. The difficult issue concerns the fit of a framework to a differentiated product industry; inevitably, some features of reality are sacrificed to a model. This paper modifies a Bresnahan-Berry model of vertical quality differentiation, which differentiates products along only one dimension, here, computing power.[2] While simple, this specification captures much of the difference in demand for systems with different computing capacity, i.e., measurable changes in demand for systems with higher speed and more memory. The paper argues that changes in capacity provide information about the introduction of new capabilities and services. Thus, the model quantifies an important extension in product space over time and the contribution to surplus from these extensions. In addition, the model estimates the decline in the cost function of computer vendors over time, which serves a secondary goal, namely to estimate a fully specified model of the computing market in which changes to the costs of producing quality alters market outcomes. Finally, though the model predicts inter-system competitive outcomes with only limited success, it provides a rough measure of the importance of new

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[2] All previous research investigates automobile producer and buyer behavior (Bresnahan [1981], [1987b], Feenstra and Levinsohn [1989], Berry, Levinsohn and Pakes [1993]). Previous use of these methods required a complete census on the price, quantity and characteristics of every product in the market. The methods developed here can be used when a complete census of product characteristics is not known, which suits data typically available to a computer industry researcher.

product entry for buyer surplus.

II. Technological changes in computing, 1968-1981

This section briefly describes important features of technological change in the mainframe computing market from 1968 to 1981. This period witnessed a rapid decline in prices, a dramatic extension of capabilities, and a notable change in the quality of alternatives to mainframes. For some buyers the economic benefit associated with technological change to mainframes was associated with declines in prices, for others it was extensions of capabilities. Each is discussed in turn.

Over the long run, mainframe products underwent rapid decline in prices per measurable unit of computing, usually measured by CPU speed and memory capacity. The important open debate concerns the association of dramatic change in price per computing unit with the introduction of particular products and other market events.[3] For example, there is no agreement about the improvement over previous generations associated with the introduction of the IBM system 370. This disagreement is important for any calculation of economic welfare because the system 370 replaced the system 360, and each was the most popular system in the United States in its day. Second, and more generally, the prices of old and new generations of systems, which may be substitutes, do not follow a simple pattern.

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[3] Construction of constant quality price indices has received much attention because of its importance for GNP measurement. There is much disagreement about the proper methods to use and the proper data to employ to measure this phenomenon. See Gordon [1989], [1990], Dulberger [1989], Cole et al [1986], Triplett [1986, 1989], Berndt and Griliches [1990], Berndt, Showalter, and Woolridge [1991], and Oliner [1992]. Related research on the welfare benefits from technical change uses similar price indices to recover surplus generated from declines in the price of aggregate computing capital. Sometimes this approach also requires measurement of willingness to pay for new capabilities, which is often difficult to obtain (e.g., see Bresnahan [1986], Flamm [1987], Berndt and Morrison [1992], Brynolfsson [1993]).

Some observers argue that "disequilibrium" influenced the pricing of mainframes, though there is much disagreement about its root causes (Fisher et al. [1983], Dulberger [1989], Gordon [1989]). This debate influences the interpretation of the technical improvements embodied in new and old vintages. Both issues are discussed below.

This industry also experienced extensions in capabilities in many dimensions. Some improvements are reflected in the easily measurable features of a system, particularly those extensions associated with increases in computing capacity. Larger computing memory and faster CPU speeds permitted users to address increasingly more complex problems and regularly perform tasks that could not be previously accomplished, let alone attempted. Scientific and engineering users were the first to take advantage of faster computing speeds and larger memories. Internal and external storage capacity also expanded, and input/output speeds increased. These innovations made large databases easier to use and broadened their potential applicability. Hardware architecture and operating system software underwent many refinements associated with multi-user systems, a development crucial to all timesharing applications and applications that require many users to perform quick queries of centralized databases. Service bureaus, insurance and banking users, and many large organizations employed these developments in new inventory and reservation systems. Later refinements required quick access to large databases in real-time. These applications diffused widely in the 1960s and the refinements began diffusing in the mid 1970s (Fisher, McGowan, and McKie [1983], Flamm [1989]).

Other extensions were also very important, but are not so easily associated with measurable features of a processor. Solid-state circuitry, improved air-conditioning units, and more compact design also made systems more reliable and lowered servicing costs, which resulted in the expansion of computing into ever more essential enterprise functions. New and better programming languages also diffused across many systems. By the end of the 1970s a third-party software industry had begun to mushroom, further diffusing refined application software across many computing platforms. Other peripherals also improved and became embodied in printers, terminals, and countless other minor components. The relevant point is that these innovations and many others were important to buyers, but are not easy to measure.

As the computer industry matured, users came to expect change -- i.e., extensions of capabilities or entirely new products -- and plan for change. Buyers modified the memory and speed of their CPU, but kept other durable investments in software or peripherals. Or, buyers enhanced particular software programs or peripheral components, but not other parts of their systems. As buyers learned about their needs and discovered technological opportunities, as new products were introduced, and as old products became obsolete, buyers had to continually reevaluate their situations. A regular cycle began to emerge: peripheral and software upgrading induced bottlenecks in CPUs, which induced further CPU upgrading, which induced further peripheral and software enhancements. The introduction of timesharing and techniques for querying central databases further accelerated these regular cycles.

Three important points follow from this cycle: first, upgrading to larger CPU capacity became associated with taking advantage of technical improvements in other parts of the system. Thus, the invention of, and reduction in the price of, large computing capacity enabled many users to take advantage of technical change in complementary components. For many buyers, demand for greater computing capacity reflected demand for complementary peripherals and software. Second, the extension of capabilities in peripheral components, software, and CPUs interacted with enhancements in other parts of the system. The economic value created by the extension of computing capacity, while obviously important, does not relate in any linear fashion to the decline in prices in constant quality CPUs. Value creation must also relate to the prices and functions in other parts of the system.

Third, the rate of value creation to a buyer could be much different than the rate of price decline in computing capacity. It may be faster if declines in prices enabled a user to realize local economies of scale in the distribution of computing services and employment of computing capital investments. Localized economies could produce the repackaging problem in CPU product characteristics, i.e., buyers value the increase in computing capacity embodied in CPUs. Since researchers of centralized management of computing facilities (e.g., Inmon [1985], Friedman and Cornford [1992]) emphasize the replacement cycle, this factor was probably very important for many buyers. On the other hand, the rate of value creation to a buyer could be slower if the bottlenecks underlying the replacement cycle choked off the ability to realize much advance. Since researchers of centralized management of computing facilities also emphasize increasing buyer dissatisfaction with translating enterprise needs into feasible technical solutions, particularly by the early 1980s, then many buyers may not have realize localized economies of scale.

Notable changes to non-mainframes partially determined the relative value buyers placed on the changes to large systems. If some buyers do not have a repackaging problem, declines in prices may simply induce purchases of cheaper computing power, but not necessarily purchases of a bigger CPU. That is, the choice between a large or a small CPU depends on the relative price/per characteristic for small and large systems, as each is introduced. This is important because there were many changes in these choices over the period. Few general-purpose computing substitutes for mainframes were available in 1968, but over the 1970s minicomputer hardware along with general-purpose software was developed, so that users could perform some small tasks that previously required mainframes. These minicomputers were especially attractive for a decentralized computing environment. By 1981 minicomputer vendors were also beginning to offer users viable growth paths for their systems if the users' needs outgrew large superminis.[4] In principle, buyers could (and many did) break up their computing needs into smaller units, taking advantage of decentralized management. Most importantly for empirical purposes, the costs and capabilities of smaller systems shift over the period, and their purchase is outside the view provided by the data in this paper.

This brief history suggests that it may not make sense to conceive of technological change as equivalent to a simple fall in the price level. Price declines enabled many events that took place. Yet, important episodes of value creation were associated with specific inventions that extended buyer capabilities into new areas -- e.g., the invention of reliable real-time database query, the invention of multi-user computing without interruption. Value creation was not associated solely (or even primarily) with the decline in costs of the delivery of these services. The willingness to take advantage of new capabilities in any period became associated with a willingness to adopt computing capacity of higher and higher levels. The

[4] Note that personal computers were only beginning to diffuse by 1981 and were largely employed as sophisticated terminals. PCs were not viewed as substitutes for mainframes except for very small problems.

importance of the willingness to pay for new capabilities will ultimately be an empirical issue. Is there evidence of much adoption of systems with increases in capabilities?

III. The Model

A supply-side model and a demand-side model comprise this paper's measurement framework. The model focuses attention on the demand for computing capacity. The model is flexible enough to allow underlying demand preferences to vary over different capacities and sizes and to change over time. It also permits the costs of supplying computing capacity to decline over time. Finally, it provides a rough test of whether vendors compete solely in measurable features of computing capacity.

III.1. Demand-side considerations

Consider a market in a given year. As in Bresnahan's [1981], [1987a] model of the automobile market, this study makes five assumptions: (1) All users evaluate all mainframe computers in terms of the same (vertical) index of quality, i.e., computing power. (2) Users differ in their willingness to pay for computing power. (3) There are many "uses" for computer systems, each requiring one computer system. (4) Each potential user compares among N possible different models. The net benefit from each model j in use i is $U_{ij} = e_i d_j - P_j$. Here, e is the marginal utility of quality, which varies across users i, d is quality, and p is price of the product. (5) There is a composite good of "lower" quality, which is not part of the focus product group, but is a potential option for purchase by users. This will be good zero, the "outside good." It sells for price P_0 and has quality d_0. In this study, the outside good is equivalent to a small IBM mainframe or a general-purpose superminicomputer. Its price and quality change each year.

Equilibrium in the market concerns the demand for computing power. The system chosen satisfies $U_{ij} > U_{ik}$ for all j, $k \neq j$. Thus, an optimal choice implies that $e_i > b_{jk} = (P_j - P_k)/(d_j - d_k)$ for all j, $k \neq j$. In equilibrium, users will find that they can rank systems (see Bresnahan [1981] for elaboration) according to their computing power. All j models are ranked according to d_j or P_j; either is equivalent in equilibrium.[5] Some systems will provide considerable computer power but will be expensive, while others will provide little computing power but will be inexpensive. The data in this study appear consistent with this structural assumption for two reasons: (1) A spread exists between the capabilities (and prices) of the least and most powerful mainframe, and (2) most measures of computing performance and prices are highly correlated.

Let the willingness to pay for computing power, e_i, be distributed according to some function F(z). This function represents the cumulative distribution of purchasers with a marginal utility of purchase less than z. Let S_j measure the market share of product j. Model j = N is the highest quality available and b_j measures a choice between j and j-1. This implies $b_j = F^{-1}(1 - [\Sigma^N_{k=j} S_k])$, j = 1,...N, where $S_j = Q_j/M$, Q_j is the quantity sold for product j, and M is the total potential size of the number of uses. If M is a parameter to be estimated and Q is data, then by design $0 < \Sigma^N_{j=1} S_j \leq 1$, so $M > \Sigma^N_{j=1} Q_j$, since the outside good is not observed. That is, estimates of M, the total size of the market, must exceed the total number of

[5] In this model $d_j > d_{j-1}$ implies $P_j > P_{j-1}$ for all observed j systems, since a system violating this inequality would not be chosen at all. Thus, prices must rise faster than quality as quality improves. Increasing the marginal costs of quality can yield this outcome. See Bresnahan [1981, 1987] and Berry [1992] for further elaboration.

observed purchases.[6] As in Bresnahan [1981], [1987a], this paper also employs a uniform distribution, $b_j = (1 - [\Sigma^N_{k=j} S_k])$. Thus, estimating the density is essentially the same as estimating M.[7] This is illustrated in Figure 1. The above implies a relationship between market share and quality, i.e., $d_j = d_{j-1} + (P_j - P_{j-1})/b_j$, $j = 1,...N$. To adapt to an incomplete data set (explained below), take the definition for b and substitute recursively to get $d_j - d_0 = \Sigma_{k=1} \{(P_k - P_{k-1})/(1 - [\Sigma^N_{h=k} S_h])\}$.

[Insert Figure 1 approximately here]

The model has several noteworthy features. First, equivalent prices between model j and j+1 imply equivalent qualities. Second, the value of $d_j - d_0$ is the net quality of a system compared with an outside good. Without a measure of the quality of the outside good, it is only possible to directly compute an index of a system's quality compared with an (unobserved) outside good. This makes for careful interpretation because the price and quality of the outside good are changing over time. Third, computing $d_j - d_0$ does not require any data on system characteristics, only data on prices and quantities. It is entirely a function of the total estimated users and the data about the prices and market shares. This will suit available data well, where there is acceptable information on prices and quantities, but not on every system's characteristics.

III.2. Supply-side considerations

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[6] Previous authors have assumed that M was known, so estimating M is one novelty here (Berry [1992]).

[7] Berry [1992] suggests using distributions other than the uniform. With an exponential distribution we get $b_j = -\Theta ln(S_j + exp(-b_{j+1}/\Theta)) = -\Theta ln(\Sigma^N_{k=j} S_k)$, where Θ is the mean of the exponential distribution. This must be set to 1, since it is not identified. Preliminary research also used an exponential distribution and found no change in the essential results, so this paper will only show results for the uniform distribution. For the price and quantity data used in this paper, estimates of implied quality with the two distributions were highly correlated in every year of this sample (around .9).

There are many optional forms for describing supply-side behavior. The simplest is the case of independent pricing. This model assumes that the economic actor who prices a system only considers the effect of a system's price on the profitability of that system and does not internalize the effect of that system's price on the profitability of any other system. Marginal revenue equals $MR_j = P_j - S_j/\{([1-(\Sigma^N_{h=j} S_h)]/(P_j-P_{j-1}) + [1-(\Sigma^N_{h=j+1} S_h)]/(P_{j+1}-P_j))\}$, where this expression takes advantage of the definition of b_j in terms of prices and implied qualities.[8]

The independent pricing model easily generalizes to a conjectural variations model (Bresnahan [1989]), an approach widely used in empirical applications for testing behavioral assumptions.[9] The conjectural variation parameter tests the assumption of Bertrand pricing, which is roughly equivalent to testing whether some unobserved factor other than demand for computing capacity influences prices. Marginal revenue is $MR_j = P_j - \exp(\delta)Q_j/M[(d_j - d_{j-1})^{-1} + (d_{j+1} - d_j)^{-1}]$. It is easier to estimate $\exp(\delta)$ than v, because it prevents accidental division by zero in a maximum likelihood algorithm. Testing Bertrand behavior amounts to testing $H{:}\delta = 0$. If δ is large, then v is close to 1 and Bertrand pricing is rejected. The demand elasticity for system j is $e^j_{QP} = -P_j g(P,Q,M)/\exp(\delta)S_j$. Notice that M and $\exp(\delta)$ are the only estimated parameters in MR and e^j_{QP}, which means many factors influence the estimate of M. This is important because the bounds on the estimate of M. $M > \Sigma^N_{j=1}Q_j$ limits the elasticity. Since $\exp(\delta)$ acts in inverse relation to M, estimates of δ may offset limits associated with

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[8] Note that marginal revenue must be suitably adjusted when $P_j = P_{j-1}$, which is a rare event in this data. This paper adopts the convention that both systems compete against their nearest neighbors. Thus, the marginal benefit from changing a price is from cutting into that neighbor's market share.

[9] See the discussion in Bresnahan [1987] and Tirole [1989] for more on this point.

estimating M.

This model of vendor behavior has several obvious drawbacks. Independent pricing violates the spirit of multi-product competition in the mainframe computer industry.[10] Moreover, the above specification is not ideal for modelling the pricing of older systems, where the used market constrains pricing (Oliner [1993]). Finally, the above specifications do not treat vendors asymmetrically, which violates industry folklore about IBM' s dominance. These are important issues for the estimation of vendor behavior, though not necessarily important for the estimation of buyer surplus, nor necessarily for quantifying extensions in product space. The discussion of results will highlight when these issues pertain to this study's analysis.

IV. Estimation

Berry [1991] compares the computed implied quality with measured quality and the implied marginal revenue with measured marginal cost, which is the strategy used here, with modifications to match available data. The measures of quality are the vector x_j for product j. Then $d_j - d_0 = \exp(x_j\beta + \varepsilon d_j)$ and $MR_j = \exp(x_j\alpha + \varepsilon s_j)$, where εd_j and εs_j are error terms. The multiplicative form for the quality index is for convenience. The multiplicative form for marginal cost, following previous research (e.g., Bresnahan [1981], [1987a]), assumes that marginal costs are convex in characteristics. It also guarantees positive estimated marginal costs. It is necessary to instrument for x_j since the cost of designing systems with x_j characteristics determines the observed characteristics and their prices (and quantities and

[10] This experiment cannot employ Bresnahan's [1981] approach to this issue because in this paper's data it is very uncommon for the same firm to market two "neighboring" products.

implied quality), leading to simultaneous equations bias.

Note that d_j is an implicit function of M and P_0. This analysis assumes M is unknown and P_0 is known, with one exception described below.[11] Let $M = TQ(1+r)$, where $TQ = \Sigma^N_{j=1}Q_j$ is the total number of observed purchases. This analysis assumes $r_t = r_{t+1}$ for all t, but otherwise there will be separate supply and demand equations for each year in the initial estimates.[12] As described below, the data are arranged to determine P_0 in each year. This benefits the simulations later and does not significantly change estimation results.[13]

When M and the other parameters are not known, they can be estimated using nonlinear three-stage least squares (Amemiya [1985]). Minimize $f = \varepsilon'(\sigma \otimes P_z)\varepsilon$, where $\varepsilon = Y - (X'P_zX)^{-1}X'P_zY$, and $P_z = Z(Z'Z)^{-1}Z$, and $\varepsilon = (\varepsilon d_j, \varepsilon s_j)$, $Y' = (d', MR')$, d and MR are vectors of the left-hand side variables, x is the matrix of regressors, X is a block diagonal matrix of regressors x, z is a matrix of the set of instruments for x, and Z is a block diagonal matrix of instruments z. The choice of x and z will be discussed below. Note, however, that this system can be estimated since there exists a complete set of data on prices and quantities. There is no need for x variables for every system's characteristics. σ is a 2x2 matrix of consistent estimates for the variance and covariance of ε. These estimates are found from the nonlinear two-stage least squares errors and are equal to $\sigma = \Sigma(\varepsilon'\varepsilon)/T$, where T is the

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[11] If M is known, then it is easy to estimate the independent pricing model. P_0 can be left unidentified within a constant term. Thus, one can estimate $\ln(d_j - d_0) - x_j\beta = \varepsilon d_j$ and $\ln(MR_j) - x_j\alpha = \varepsilon s_j$ using a standard minimum-distance estimator.

[12] Other parameterizations of the size of the market did not produce qualitatively different results, so this paper only presents the simplest specification.

[13] Without further economic modelling of the outside good and its quality, d_0, the structural form for P_0 will necessarily be ad hoc. Bresnahan [1981, 1987] deals with this issue by positing a hedonic relationship between the quality of the outside good and its price.

number of observations. Minimizing the above yields estimates for α, β, and M, which then yields estimates of d_j-d_0 and elasticities.[14]

There is a subtle tradeoff between guaranteeing positive estimates of marginal costs and guaranteeing plausible elasticity estimates for every product. If marginal costs are positive by design, marginal revenue may be negative for a few observations where parameters estimates are "far away" from their respective optimums. This is problematic because it destroys any maximum likelihood algorithm (i.e., ln(MR) does not exist for MR < 0). The more general point is that the functional form cannot guarantee that all product elasticities are less than negative one at non-optimized parameters. This is related, since $MR_j = [P_j(1+1/e_j)]$.

The approximation $\ln[P_j(1+1/e_j)] \approx \ln(P_j) + 1/e_j$ eliminates both problems and results in positive marginal costs everywhere. This works well with this paper's data because $1/e_j$ is much less than -1 for all but a few observations in the final estimates. The alternative solution to the above problems, which is not presented, is to not guarantee that marginal costs are positive. This alternative lets elasticities attain both plausible and implausible values without stopping the whole estimation, but it sometimes results in negative predicted marginal costs. Since a few implausible elasticities are inevitable under either specification, at least the approximation above guarantees positive marginal costs. As it turned out, all but a few elasticities were much smaller than -1 at optimized parameters, so the cost of using the

[14] In practice, minimizing f can be very time consuming. Effort is saved by recognizing that the optimized estimated β and α will be $[\alpha,\beta]' = [X'(\sigma \otimes P_z)X]^{-1}[X'(\sigma \otimes P_z)Y]$. Setting β and α equal to optimized values and substituting into f yields a concentrated function determined solely by the value of M and market power parameters. It is then straightforward to find the optimal α and β (as functions of the optimal d and MR). The final step is to find the standard errors for all the estimates by computing the variance-covariance matrix with all the (already optimized) parameters.

approximation was small.[15]

V. Surplus Measurement

The total buyer surplus net of outside good = $\Sigma^{N}_{j=1}([b_j+b_{j+1}][d_j-d_0]/2-[P_j-P_0])Q_j$. Since d_0 is not identified, d_j alone cannot be identified. The d_j - d_0 can come from two possible sources. If there is characteristic data for all systems, then it is possible to use the estimate of β and X_j. Since this paper does not have data for all systems, d_j - d_0 come directly from the estimate of M and the data on prices and quantities.

This method does not measure the benefits from buying a system in terms of its characteristics. Nor does it measure the average benefits from buying a system, or the total benefits to buyers from computerization. There are two reasons for this. First, this model of each year's competition presumes to measure the benefits associated with the last bit of computing power purchased, not the surplus associated with buying the first fractional unit of computer power. Second, the method does not anchor the estimates of the quality of a system over time. That is, the absolute level of quality of a particular model is not constrained to be similar over time. Thus, surplus estimates may change over time due to changing units of comparison. In particular, the outside good changes each year, altering the relative benefits of being in the mainframe market.

These limitations make the method well suited to two unit-free estimates of the

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[15] One other alternative is to use an error structure like the one found in Bresnahan [1981,1987]. He solves for the optimal price and quantity under the assumption that the model is correct and compares those computed numbers against the actual observed data. Bresnahan's alternative requires a complete data set, i.e., characteristics for all models. While this exists for new automobiles, such data do not exist for the historical computer market, rendering this alternative infeasible.

importance of new entry. One is to estimate the percentage of surplus in a given year attributable to systems with certain features, such as young age or large computing power. The main advantage of this measure is that the percentage of surplus is unit-free and easily compared over time. If extension of capabilities matters in this market, then it must at least hold in the single capability extended here, computing power. If the percentage of surplus associated with large systems falls over time, then we reject the view that this factor matters.

A second experiment involves removing systems with particular characteristics and comparing surplus generated with and without those systems. This comparison is in the spirit of welfare calculations that hold population and demand characteristics constant, but change the choice set available to consumers. As before, the percentage difference in surplus is unit-free and easily compared over time. If buyers adopt new systems because they embody unobservable, but valuable, extensions of capabilities, then removing new systems could result in large losses in surplus.

VI. The Data

This paper's data on computer prices, quantities, and vintages comes from industry censuses from International Data Corporation's (IDC) EDP Industry Reports (EDP/IR)[16]. IDC estimated the number of installations of each type of computer system and, until 1981,

[16] Patrick McGovern began compiling this census in 1962 in Computers and Automation magazine. It continued in modified form under IDC auspices from the mid 1960s onward. The archives of the Charles Babbage Institute at the University of Minnesota contains a collection. This paper also makes use of a set of EDP Industry Reports contained at the Library for the Graduate School of Business at Stanford University.

estimated the monthly rental at which an average type of system leased.[17] The data in this paper begins with the December 31, 1968 report and ends with the January 1, 1981 report. The first year in which IDC distinguished between the number of installations inside and outside the United States was 1968. Over the entire fourteen year period, this data concerns the installed base of over 350 different computer systems (see appendix of Greenstein [1994]). This is clearly the best data available on the size of installed base and rental prices.[18]

VI.1. The sample

Without modification, two biases arise from maintaining exclusive use of IDC's definition of a mainframe. First, the 1968 and 1969 definition of a mainframe is too broad. It includes some systems that IDC reclassified as "Digital Dedicated Application" in 1970. These systems are actually minicomputers, like the DEC PDP-8, not general-purpose systems. Second, more redefinition problems arise on a smaller scale once IDC establishes several on going databases for systems other than mainframes (i.e., minicomputers, small business systems, desktop). Its researchers occasionally move a system into the mainframe category that was not previously there. Its researchers also move a system out of the mainframe

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[17] Phister identifies several years in which IDC revised the reported number of installations in previous years, particular for IBM models in 1967-1972. In those cases, Phister's reported updates were used. This makes this paper's estimates comparable with Phister's [1979] and Flamm's [1987a,b] description of the diffusion of computing equipment, which used more aggregate IDC data. It also makes this paper's results comparable to Oliner's [1992] analysis of the retirement patterns among IBM mainframes, which uses similar IDC data for IBM systems.

[18] No other comparable data source exists for this period. Remarkably, only a few studies of the computing market (e.g., Micheals [1979], Phister [1979], Flamm [1987a,b], Dulberger [1989], Oliner [1992], Khanna [1994]) have used parts of this data and none have ever exploited all facets of it (e.g., see Greenstein [1994] for an examination of diffusion) .

category that previously was there.[19]

The best solution to this problem defines the outside good consistently across different years of the sample. This paper's outside good is the smallest mainframe offered by IBM, a system 360/20 (introduced in September 1965). The system 360/20 has the virtue that it is very close to the smallest mainframe in IDC's census, but it provides a more consistent definition of the lower bound on this market over time than that used by IDC. Moreover, its price changes throughout the sample period, reflecting real changes in the quality and market price of systems performing small decentralized computing tasks. Finally, it eliminates only a few useful potential observations in each year.[20] Table 1 shows the results of this selection. Consistently defining the outside good does not impose a large loss. The systems used by more than 20,000 buyers typically are sampled. The greatest losses occur in the most recent years, when this procedure eliminates 12 of the 178 potential observations from IDC's census.

[Table1 approximately here]

Even with a consistently defined outside good, two potential problems remain. First, IDC revised its survey scope twice, once between 1969 and 1970, and once between 1976 and 1977. In both cases, IDC consolidated the number of models it covered.[21] Second, by the end of the sample, the difference between mainframes and some large general-purpose

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[19] The most important case is IDC's decision to include the IBM System 36 in the sample in 1976 (estimated installed base at 5000 units) and exclude it from mainframes after that (but include it in "small business systems"). Early experiments showed that this particular flip-flop makes 1976's estimates inconsistent with other years.

[20] Part of the reason is that there is less characteristic data available for the small systems. In addition, the vast majority of eliminated systems were commercial failures.

[21] For example, the number of models covered in 1969 was 176, while only 147 were covered in 1970. In 1976 there were 205 models covered, but only 188 in 1977. See Table 1.

minicomputers (a.k.a. "superminis") becomes blurred, which raises questions about the survey's completeness. The main issue is whether IDC included in the mainframe category all the super-minicomputer systems that were close substitutes for general-purpose mainframes. A reasonable case could be made that IDC included most relevant systems,[22] but a reasonable case could also be made that it did not.[23] Ending the sample in 1981 holds this problem to a minimum.

VI.2. Definition of market share and price

The paper uses the installed base of systems in a given year as a measure of quantity and market share. This is justified because most buyers leased their equipment in the late 1960s and 1970s. Moreover, many mainframe computers are not subject to frequent mechanical breakdowns, so the services delivered do not physically depreciate rapidly after sale, if at all (though its market value may depreciate due to technological obsolescence). This drawback is that this definition overstates the popularity of an old system (and the general competitiveness of the market) by showing that old and new systems are in competition.

While Phister [1979] clearly believes that IDC's estimates of installed base are the best

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[22] It is not clear whether the money spent on superminis ever amounted to more than a small fraction of the amount of money spent on mainframes. According to the 1983 IDC census for minicomputers and mainframes, the value of installed base associated with super-minicomputers came to roughly half the value of all minicomputers, or roughly 15 percent of the value of the installed base of mainframes. IDC's census differs from the other censuses, particularly CBEMA's, because IDC includes several systems as mainframes (i.e., those from IBM) which others classify as super-minicomputers. This makes IDC's census more "complete," which matters by the early 1980s. For example, according to the CBEMA [1992], in 1976 mainframe shipments reached over 5 billion dollars, while the total spent on all minicomputers was 1.8 billion. By 1982, CBEMA estimates that mainframe shipments reached 10.6 billion and minicomputer shipments reached 7.7 billion. CBEMA does not state what fraction went to super-minicomputers, but 7.7 billion clearly overstates the size of the competition between mainframe and minicomputers.

[23] The most questionable omissions in IDC's mainframe tables are those regarding the VAX models from DEC, and similar competitive models from other firms such as Wang, Prime, and Data General.

among the available alternatives, he nevertheless warns about several potential problems that could influence calculations using these data.[24] Dulberger also questions the accuracy of IDC's estimates of installed base, while conceding that they are the best publicly available.[25] Given these concerns, the data was tested for internal consistency, which it readily met.[26] In any event, no alternative is satisfactory. Sales data is not available, and it is not possible to estimate sales from the change in installed base from year to year, because it becomes an increasingly poor estimate of shipments of systems when systems become more than a few years old.

IDC estimated the price of a typical system configuration, which is the price used in this study. IDC's estimates are probably the right order of magnitude, but are also subject to measurement error. Phister uses these prices for estimates of the value of installed base. However, he believes that the prices for obsolete systems are too high, since IDC would use the last offered price for a system lacking any recent transaction, but that the bias in old prices influences only a few of the systems in the United States. Flamm reaches a similar conclusion before using Phister's estimates for a few calculations.[27] Thus, no strong

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[24] He states on pg. 250, "It is my opinion that IDC's staff, files, and data sources make that organization's published statistics the best available." Yet, due to occasional revisions of previous EDP/IR reports, Phister is not convinced that IDC's estimates of the size of installed base are precise. However, many of his uses of this data reveal his belief that IDC got the general order of magnitude correct. Where available, this paper uses Phister's corrections.

[25] One especially difficult problem is that IDC may underestimate the number of users who upgrade their systems (Dulberger, private communication).

[26] The history of each new system was examined. Did the development of its installed base follow a reasonable pattern of growth, i.e., several years of growth followed by several years of decline? The absence of such a pattern questions the plausibility of the data.

[27] In addition, using these prices is not without precedent in the hedonic literature. The prices for new systems used by Gordon (as well as many others) are very similar to those used here. Gordon's prices for his sample after 1977 were taken from Computerworld, which is published by IDC.

conclusions should rely exclusively on one price.

VI.3. System characteristics

The characteristics that make up x_j partially overlap those used in Gordon's [1989], [1990], Dulberger's [1989], and Oliner's [1992] analysis of computer system hedonic regressions (see Triplett for a complete summary of the relevant issues). MIPS, or millions of instructions per second, is an estimate of speed. The maximum memory included in a system is an estimate of memory size.[28]

MIPS and memory size data are not available for every system in every year. Computer Intelligence Corporation (CIC) provides information about the features of systems extant in 1991 and other important historical systems.[29] CIC's characteristic data covers roughly three quarters of the most important mainframe and super-minicomputer systems (used primarily in business applications) in 1981, or more than 90 percent of the installed base, which makes it more comprehensive than any other single data source. Table 1 shows that CIC characteristic data matches an increasing fraction of the total number of models IDC surveyed. The sample size begins at 59 for 1968 and grows to 178 by 1981.

IDC provides a measure of the technical generation of a system. Dulberger [1989]

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[28] Because minimum and maximum memory are highly correlated (between .6 and .7 in a year), only one could be used. Because there are many reasons to think that maximum memory is more relevant to buyers than minimum (Bresnahan and Greenstein [1992]), maximum memory is used throughout the estimation.

[29] The measures of these variables come from Computer Intelligence Corporation's (CIC) 1991 Computer System Report, which has many virtues relative to alternatives. The Computerworld data, which Professor Gordon has kindly lent out, begins in 1977. It covers too few systems up to 1981 to be useful. The Auerbach data, which Professor Michaels has lent out, covers the early part of the 1970s. Unfortunately, it also only covers a small number of years. While the Phister (1979) data covers a longer period, it generally only records the system characteristics for the most popular systems and not the whole market. In fact, Phister's data covers only about 20 percent to 30 percent of the system models surveyed by IDC. CIC's data covers the same systems, plus many more.

argues that hedonic techniques may be mismeasuring the factors deciding prices when the data is taken from a cross-section of systems in a market undergoing rapid technological "leap frogging" by successive new systems. Dulberger argues that this "disequilibrium" requires an explicit treatment in a hedonic framework. The simplest means for testing Dulberger's argument, as found in Berndt and Griliches [1990] and Oliner [1992], is a measure of the time that has elapsed since introduction. This variable is labeled "techage." Systems that had more experience in the marketplace should have more software and other complementary system enhancements, which increase the system's quality for the user.

IDC's censuses categorize every system by size, with size ranging from 2 to 7. This measure is of limited usefulness for a regressor because it is categorical, not continuous, and is highly correlated with MIPS and memory. However, it will be useful for the simulations, because it is available for all systems, and therefore it provides a means for testing important differences between entry behavior on the highest and lowest end of the computing-power spectrum.

Instruments (the z matrix) for each system are all of the characteristic data from the nearest lower and higher neighboring system (for which there is characteristic data). These characteristics are typically exogenous, since they are designed by another firm. Yet they are also correlated with the characteristics of the neighboring system, so they make for good instruments.[30]

Table 2 shows how the typical system in the sample changes over time. The average price of a system (deflated by a producer price index) and the average size of a system's

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[30] Thanks to Steve Berry and Frank Wolak for this suggestion.

installations included in the sample decline over most of the years of the sample. The typical system contains more memory (from 1099 to 5592 maximum memory on average) and performs more instructions per second (from .326 to 2.22). These statistics about MIPS and memory suggest that the product space was extended over the sample period, but they are insufficient for conclusions about the economic importance of the extension. The most dramatic changes in the average occur in the last three years of the sample upon the entry of some large supercomputers. Despite the addition of new systems to the sample, the average technical age grows (from 4.1 to 8.9); the inclusion of some very old systems in the sample of later years is to blame for this increase in the average.

[Table 2 approximately here]

Figure 2 provides an illustration of the diffusion of large systems and foreshadows results from the estimation. Figure 2 shows a box-plot of the distribution of MIPS in the computer systems used in each year.[31] The dark areas provide the range between the first and third quartile, while the white line shows the median. Every line above it represents a particular system until the maximum. While this is a coarse measure of computing capacity, the figure shows a gradual extension of the product space. It also shows a gradual buyer adoption of those extensions, and gradual shifting of revenues to systems with higher computing capacity. For example, the MIPS of the 95th percentile of 1968 is the median of the MIPS of systems in use by 1981. In addition, the product space between the maximum and the 95th percentile becomes progressively filled in over time with new products, even as

[31] The figure only shows the MIPS ratings for the systems that were used in the estimation. While this is an incomplete sample of the systems in use, the coverage tends to be almost complete for the largest systems and the most popular systems. Hence, this provides a pretty accurate reflection of changes for the larger systems.

these points vary. Yet many years must pass before the extensions of product space are widely adopted. The 95th percentile stays roughly the same between 1968 to 1973 and between 1974 and 1976, and only begins to grow after 1977.

[Figure 2 approximately here]

VII. Results

This section presents estimates of the model and various tests of those estimates. The discussion also presents calculations of buyer surplus and the rate of decline in the cost function. These estimates and calculations quantify the dramatic changes in the computer industry that took place over this period.

VII.1 The estimates

Table 3 presents estimates of the conjectural variations model. With a few exceptions, most of the estimates of α and β are of the predicted sign and are significant. Systems with more computing power possess higher quality and have higher marginal cost. More memory contributes to the perceived quality of a product and to its increasing cost in all but the 1968 sample. Faster systems have higher quality and higher marginal costs in all of the estimates except the 1972, 1973, and 1980 samples, when the coefficients are not significant. Older systems usually possess higher quality and have higher marginal cost, but the coefficient is insignificant half the time on the supply side. Estimates for the size of the potential market are small, estimated at 1 percent. For unapparent reasons, the model appears to fit badly in 1968, 1974, and 1980.

[Table 3 approximately here]

The variables measuring computing power are often quantitatively important on both the demand and the supply sides. These results are consistent with the basic assumption of this model, that computing power alone explains most of the cross-section variation in demand for computing. The varying size of the technical age variable does not support the view that disequilibrium pricing matters much for the model and data, which is also consistent with the methodological approach of this paper.

A curiosity of these first estimates is that coefficients on the supply side do not seem to show a large reduction in the costs of supplying characteristics over time. At most, there is a small (and erratic) downward shift in the costs of characteristics. This seems at odds with well-known declines in the costs of memory and processors. Later estimates showed that this pattern was an artifact of too much econometric freedom. A more constrained cost-function specification, more typical of the literature, will measure some anticipated decline below.

One other feature of these estimates has to do with the model's econometrics. The estimate of the implied quality of a system in one year has almost no econometric relationship to that estimate in another year. The model in each year requires that systems "price discriminate" between users with different willingness to pay for computing power, but it does not require similar quality estimates for a given system from year to year. Thus, nothing inherently ties down the estimates of the implied quality of a system from year to year and the estimates of surplus generated from those estimates of implied quality. Given this econometric freedom, it is remarkable that the coefficient estimates do tend to have the same sign and roughly same order of magnitude from year to year and roughly make sense. At the same time, the demand parameters are not close to constant across all years. These changes support the view that there are frequent changes to the basic relationship between the underlying valuation of computing capacity and the measurable features of computing capacity.

VII.2. Testing the model

The null hypothesis is that the conjecture parameter is zero, which is rejected. The value of the conjectural parameter rejects Bertrand pricing. The benefit to undercutting rivals is small, i.e., price increases are closely matched. All specifications and experiments with this data, many not shown here, could not eliminate this result.

There are two fundamental reasons for this estimate. First, many products are priced close together, especially at the low end where many older systems are found.[32] The model must interpret these systems as close substitutes, especially when each system has such low market share. While this is probably the right inference for most systems with small market share, it underemphasizes the importance of systems that have significantly higher market shares. Second, there is not enough flexibility in the marginal revenue equation to adapt to the wide dispersion of market shares in this data. The only free parameter is M, but M is constrained to be greater than the number of systems sold. While the model does attribute less competitive elasticities to the high-market share systems, it may scale all the elasticity estimates incorrectly. M would have to become much smaller to generate elasticity estimates that are sensible for the high-market share systems. The conjectural variations parameter provides more flexibility because it rescales the elasticities, while retaining more inelastic elasticities for systems with higher market share. Systems with large market shares display

[32] The difference between neighboring systems averages around 3 percent of the price of the lower priced system, but grows for the higher priced systems.

elasticities consistent with large differences between marginal cost and price, and high markups over marginal cost.[33]

This result suggests one of two things: First, if the model correctly models product differentiation, then the firms behave quite differently from Bertrand pricing (i.e., they are much less aggressive). Second, using a hypothesis that is more plausible, the parameter may show that some factors outside the model -- i.e., factors other than the pricing and product differentiation modeled here -- largely decide competition between vendors. This is plausible if vendors are competing by embodying unmeasured new features in each generation of their products. This possibility raises the same fundamental issues with which this paper began -- i.e., about the proper means for modeling product differentiation and behavior in this industry.

VII.3. Buyer's surplus

Table 4 summarizes the simulation of the consumer surplus for each year for the conjectural variations model. The estimates of net total surplus are large, roughly one to two billion dollars a month (these are net of the potential benefits of purchasing the outside good).[34] However, the estimates are also erratic, moving around by more than 50 percent from one period to the next. The average surplus per system, which controls for the changes in the number of systems in use in a year, makes more sense. These estimates also fluctuate,

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[33] Only a subset of the total number of systems available display high markups over cost, which seems plausible. Inspection of the data reveals that these systems are almost always the systems with large market shares and they almost always come from IBM. There is also a slight tendency for more expensive systems to have larger (absolute value) markups, but smaller markups as a percentage of price. This is because these systems are not as closely priced (in absolute value terms) to their neighbors as the lower priced systems and also have lower market shares.

[34] Strictly speaking, this restriction makes these estimates of surplus incomparable with previous surplus estimates in this market (e.g., Bresnahan [1987], Flamm [1989], Brynolfsson [1993]).

but less than those that estimate the amount of total surplus. These estimates show an irregular but steady decline in the consumer surplus per system after 1971. Table 4 also shows the net total surplus per net dollar expenditure (net of potential expenditure on the outside good). This too shows a slow but steady decline after 1971.

[Table 4 approximately here]

There are several possible explanations for the decline in net surplus per system and surplus per dollar. First, the model may increasingly fail to properly explain buyer exit from the mainframe market in the late 1970s. The availability of super-minicomputers, which shows up as a devalued mainframe computer in this model, could lie behind the trend. This notion is possible, but only partially successful. The rise in the net expenditure after 1977 is due to a large discreet change in the nominal price of the outside good (from 3675 to 2800) and inflation in the late 1970s, which produces the decline in the surplus per expenditure after 1977. Yet no such simple explanation can account for trends between 1971 and 1976. The decline in net surplus per system is the result of the increase in the number of systems but not the increase in net surplus. The lack of increase in net surplus is still the mystery.

A second possibility, the most plausible one, is that the reduction of product differentiation to one dimension oversimplifies substitution possibilities. The model implausibly shows a crowded product space as new systems enter, as if all new entry occurs on intensive margins. In practice, many new systems may enter on extensive margins that this model cannot measure. This new entry generates gains in true, yet unmeasured, consumer surplus. Therefore, the estimate in Table 4 is too low, particularly in later years as systems get many new capabilities. This explanation suggests that, at best, these estimates can only do a good job of estimating surplus generated at the extensive margin (more computing capacity).

VII.4. The importance of entry on extensive margins

Table 5 displays estimates of entry on the only extensive margin in this model, more computing capacity. The table shows the amount of surplus attributable to systems in IDC's size 5, 6, and 7 categories, the top three categories in its ordinal ranking of system size. The percentage of surplus attributable to systems with high capacities grows over time. Roughly 21 percent of total surplus in 1968 is attributable to systems of size 5, 6, and 7, and only 8 percent to systems of size 6 and 7. This grows to as much as 54 percent for all, and 23 and 14 for size 6 and 7, respectively, in 1981. Much of the growth in size 6 comes before 1976, while growth occurs almost every year for size 7 systems. This reflects a general trend and is not an artifact of any arbitrary data definition of size by IDC.[35]

[Table 5 approximately here]

The table highlights two other factors about growth on the extensive margin. First, the fraction of the installed base of systems attributable to the high-capacity systems is small, never amounting to more than 10 percent of the total number of systems in 1968 and 25 percent in 1981. Yet this small fraction of systems accounts for a disproportionate amount of consumer surplus -- 21 percent in 1968 and 54 in 1981. Part of this occurs because larger systems cost more to the customer. Even though there are fewer of them, the expenditure per system is great. Extending the product space a bit results in a huge increase of expenditure,

[35] For example, IDC's censuses show a perceptible decline in the entry of size 2 systems after 1976 (Greenstein [1993]). Yet this bias does not explain the time trend in table 6 because most size 2 systems were not included in this sample as a result of adopting a consistent definition for the outside good.

though not nearly as many new units. This estimate supports the argument that growth on the extensive margin may have large influences on buyer surplus.

However, the same estimates quantify a new aspect to extensive margin growth. Note how long it took for this market to register much growth on the extensive margin. Surplus in size 7 undergoes steady, but slow growth. Surplus in size 6 grows rapidly in the first half of the sample and slowly, but unevenly, from there on out. A close examination of the data illustrates why. The most popular size 6 system, IBM 360/65, was first installed in late 1965. By 1968 users installed over three hundred 360/65 models and over five hundred other more expensive systems. The IBM 37/155 then supplants the 360/65 as the most popular system of size 6 in the early 1970s, but the diffusion takes several years to reach its peak. By the late 1970s, however, no single system dominates the large system size category any longer. There is only gradual change on the extensive margin in the mid to late 1970s as new systems only slowly become widely used. The slow but steady entry of many different new systems accounts for most of the growth in the late 1970s.

Table 5 also presents estimates of the percentage of surplus in each year attributable to systems of different vintages, principally those less than or equal to 4 and 6 years old. This partially addresses the concern that new products not only are cheaper, but embody new unmeasured features not reflected in the price. First, as expected, young vintages tend to generate the most surplus, averaging 22 to 47 percent of surplus, depending on the measure. This result, combined with the inability of techage to predict system demand, suggests that buyers purchase systems for more than just capacity, but this quality is not measurable in a simple manner. Second, the importance of young vintages differs dramatically from year to year. A few specific vintages influence surplus estimates. The technical vintage introduced in 1965-66 dominates the surplus calculations until the mid 1970s, which unquestionably reflects the popularity of the IBM system 360. The next major wave of surplus is associated with the IBM system 370 (mostly vintage = 1971 and 1973). These two vintage effects do not work themselves out until virtually the end of the sample, when the entry of many new systems begins to influence the surplus simulations.

No other family of systems generates so much surplus as the system 360 and 370 because no other family of systems has such a large market share. While this qualitative result is not surprising (see Greenstein [1994]), it raises important issues. First, it suggests that estimates of the benefits from technical change in the early years of computing are determined by estimates of the benefits associated with the technical improvements in a few of the dominant systems of that era. Only in the later years are the benefits spread across more models. Second, it highlights the importance of properly measuring the benefits associated with the system 360/370. In any quantity-weighted measurement exercise, such as the above, small changes in estimates of the benefits associated with the system 360 and 370 lead to large changes in estimates of the benefits to society from technical changes in computing. This observation adds importance to the debate about the (measured) economic benefits associated with the system 370 (e.g., see Dulberger [1989], Gordon [1989], and Triplett [1989]) and whether most of the benefits from technical change accrued to buyers. Finally, these results again raise the unresolved question about the proper method for weighting a popular system relative to less commercially successful systems in a hedonic regression.

Table 6 puts the pattern of entry into final perspective. It computes the counterfactual surplus generated if all new systems were absent (those less than 4 and 6 years old). It displays this counterfactual surplus as a fraction of buyer surplus measured with all the systems. This is in the spirit of welfare calculations that keep the demand characteristics fixed, but alter the choices available to buyers. Removing young systems simulates demand in the absence of any technical change.[36] Not surprisingly, surplus declines without new systems. However, in any given year it does not decline by more than a few percentage points. The largest declines are associated with the counterfactual elimination of the system 360 in the early years of the sample. In the mid 1970s the decline is less than 1 percent and less than 3 percent by the late 1970s, especially for young systems.

[Table 6 approximately here]

Table 6 displays a well-known characteristic of counterfactual welfare measures of technical change: a new technology is only as good as the alternatives to it are bad. Even if no new systems were invented, buyers would continue to use old technology. In this model, old systems are very close substitutes, and switching between substitutes is assumed to be costless. The product space is "crowded" as a result, so that the absence of a new technology sends buyers to a worse, but lower priced, system. Since entry on the intensive margins can only generate large gains when the product space is not crowded, the biggest gains to such entry in this model are recorded early in the sample, when the industry is still young. Since this crowding is probably an artifact of not measuring all the dimensions that buyers value,

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[36] It seems less plausible to estimate the counterfactual surplus in the absence of a system of a particular size. In that counterfactual world, there would be a large supplier response in shortrun pricing behavior and longrun design behavior. Simulating that counterfactual behavior does not make any point that cannot already be made with the results in table 7.

and Table 5 shows that a substantial number of buyers continue to purchase young systems, Table 6 represents a (potentially severe) underestimate of the true surplus losses.

Table 6 echoes the observation that innovation takes a long time to achieve its full effect (only here it is about the entry of new systems). Though the net benefit from new systems is small in any given year, the cumulative effect over many years is quite large. That is, if all technical change had ceased in 1968, by 1981 the cumulative losses in each year would have been enormous. However, not to belabor the point, but the long-run estimate of loss is surely an underestimate. Much evidence suggests that important product characteristics are not being measured here. The amount of mismeasurement must increase as the time periods in comparison become further apart.

Tables 5 and 6 embody both the strengths and weaknesses of the approach taken in this paper. On the one hand, standard hedonic methods could not lead to these tables or the conclusions reached from them. Table 6 quantifies the benefits from new technology in use, while hedonic price methods stop at estimating improvements in what is available. Though this paper's conclusions require structural assumptions about the nature of demand, this is par for the course in using data on both quantities and prices. Any other structural model that incorporates more dimensions will necessarily show the same effects highlighted in this paper and possibly more. On the downside, Tables 5 and 6 are only as good as the structural assumptions that generated them. Parts of this paper (and other analyses of this market, Bresnahan and Greenstein [1992]) suggest that product differentiation is incompletely modeled here and potentially correlated with age. Entry probably also occurred on more extensive margins than are modeled. If that is so, Tables 5 and 6 provide a lower bound on the welfare losses from the absence of innovation.

VII.6. Cost function decline

Table 7 estimates cost functions on exactly the same data as was used in Table 3. The two equations use something akin to standard hedonic specifications but supplement it with a market power correction, as found in a vertical model with conjectural variations. Equation two takes the form $\ln(P_j) = [\Gamma Q_j]/[P_j Mg(P,Q,M)] + x_j\alpha + e_j$. The second equation is similar, but specifies a different Γ over time. The market size, M, is assumed to be about 1 percent larger than the observed market, taken from the previous conjectural variation estimates in Table 3.[37] All the data is pooled such that α has one coefficient for MIPS, memory, and age, but different year dummy coefficients, which captures the change in the level of the cost function of firms.[38] This specification assumes that all firms draw from the same cost function in a given year. Rather than explicitly model the demand side, which has little interest here, the estimates employ a reduced form for demand. Demand is a function of the same set of regressors and instruments as used previously, plus time dummies. This treats MIPS, memory, age, and market power as endogenous and the time dummies as exogenous.

[Table 7 approximately here]

The cost function estimates have the following three features: First, coefficients for memory, MIPS, and age all have the correct sign. Second, none of the estimates show a

[37] The above results suggest that little is lost by estimating a conjectural variations model as if M is known (even when it is not). In any event, in a conjectural variations model, the conjectural parameter would scale any estimate, effectively acting in the opposite direction of any estimate of the market size. Hence, it is much easier, and no less insightful, to simply assume a given size of a market, compute the implied product elasticities, and then estimate a conjecture parameter to scale the elasticity estimates properly.

[38] Though the dummy coefficients are unbiased estimates, the index will not be. It is a nonlinear function of an unbiased estimate. To correct for this bias, the estimated standard errors use an approximation suggested by Triplett [1989]. This involves adding one half of the standard error to the coefficient before computing the index.

monotonically declining rate of technical change. The most problematic of all the estimates are 1968 through 1970, which may be due to changes in IDC's sampling frame in those years. This problem does not seem to be a manifestation of the movement from the IBM 360 to the IBM 370, which was first introduced in 1971. Third, all the estimates measure rapid rates of technical change over the long run. Equation 1, which estimates only one conjecture parameter for the entire sample, finds a decline in the cost function of 20.0 percent over 14 years and 30.3 percent from 1971 to 1981. The second equation, which estimates a different conjecture parameter for each of the three IDC sampling periods, estimates declines of 11.7 percent over 14 years and 25.5 percent from 1971 to 1981.[39] The differences in the estimates suggest that functional form influences the precise estimate of change in market power and the change in the cost function. In both cases, decreases in the prices to consumers were due partly to changes in market power and partly to declines in the cost function.[40]

VIII. Conclusion

This paper measures the economic benefits that accrued to buyers from technical innovation in mainframe computers. The thesis is that many innovations that created economic value in this period are associated with extensions in computing capabilities. Answers to the questions raised in the introduction provide a suitable summary of this

[39] Interacting a time trend with the conjecture parameter did not result in qualitatively different conclusions. Equation two is presented because it is easier to interpret and read.

[40] Finally, it is not correct to infer that market power increased over time just because the Γ increased. Instead, one must examine changes in the distribution of product specific elasticities. Close examination of these elasticities, not shown here, reveals a more competitive market over time -- in the sense that the median product specific elasticity is more elastic, as are every other order statistic of the elasticity. This is not surprising in this model since the product space becomes increasingly crowded over time.

analysis.

What valuable innovations in this period are associated with extensions of capabilities? It was argued that technical change in the computing market involved much more than rapid declines in the price of existing capabilities. While price declines enabled many of the events that took place, important episodes of value creation were associated with specific inventions that extended buyer capabilities into new areas -- e.g., the invention of reliable real-time database query, the invention of multi-user computing without interruption. Value creation was not associated solely with the decline in costs of the delivery of these services.

Do buyers adopt products that embody extensions of capabilities? The economic history and the econometric results show that adoption decisions were not solely the result of buyers taking advantage of lower prices for existing capabilities. The data and estimates show that many buyers purchased larger computing capacity embodied in products that came into existence in the 1970s.

How does a measurement framework represent that action? This study argued that some fraction of the new capabilities associated with new systems is not measurable, but is complementary with increases in computing capacity. Therefore, a model of the supply and demand for products with different computing capacity will capture some demand for new capabilities. Such a model has several interesting features: 1. Buyers slowly adopt higher capacity systems, suggesting that greater attention needs to be paid to the diffusion of new technology in this market (Greenstein [1994]); 2. Decreases in prices to consumers were due partly to changes in market power and partly to declines in cost. All the estimates measure rapid rates of decline in the costs of providing computer capacity over the long run.

Are most extensions only embodied in capacity or other features of the products? Competition in computing is partially represented by extensions in computing capacity and partially by the technological age of systems, but not entirely. The conjectural variation estimates and the demand parameter estimates suggest there was not a stable relationship over time between measurable features of products and revealed buyer choice. This is not surprising because of the well-known changing value of outside goods. It is also not surprising because of the likely changing valuation of computing capacity that resulted from innovation of complementary components. Therefore, constant quality indices of price decline potentially omit the factors that influence changes to economic welfare for many buyers.

In sum, much significant innovation in this industry was associated with extending capabilities to new levels. This is not an argument that price decreases were unimportant to buyers, only that price decreases do not tell nearly the whole story about the welfare improvements realized by buyers -- perhaps they even tell a deceptive story. There are many implications from this conclusion for understanding competition and value creation in this industry (e.g., see Bresnahan and Greenstein [1992]). This study focuses on whether constant quality price indices provide good information about welfare benefits from technological change. It will for the buyers who continue to buy products with similar sets of characteristics, but not necessarily for the buyers who take advantage of the availability of characteristics that did not previously exist. Many buyers fall into this latter camp. It is time that these observations about extension of capabilities became a central part of the discussion about the creation of economic benefits from technological change in computing.

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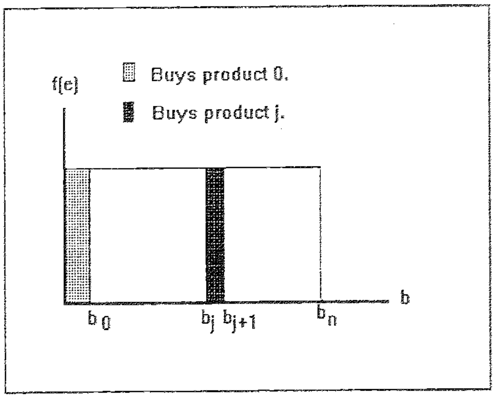
Figure 1

The determination of market share in a vertical model



Distribution of MIPS in Use
1968 - 1981

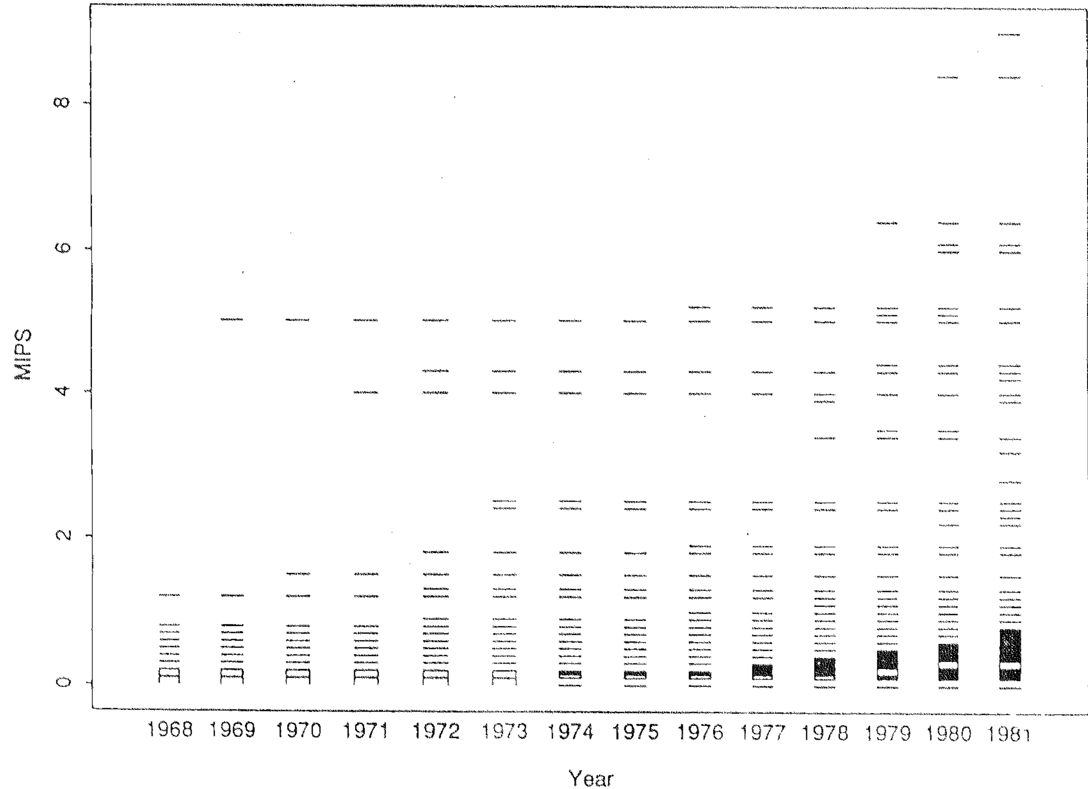


Table 1

Matching Industry Data with Characteristic Data

Year	Sample Installed Base	Orginal Number of Models	Models with Characteristic Data	
			All	Included in sample
1968	19361	166	59	53
1969	21470	176	66	60
1970	25233	147	72	64
1971	19008	154	81	67
1972	21909	171	95	77
1973	21541	173	103	88
1974	22253	181	113	96
1975	23351	189	119	101
1976	23673	205	133	113
1977	23436	188	134	122
1978	25124	205	148	136
1979	25261	218	150	138
1980	24723	244	167	155
1981	28116	257	178	166

Table 2

Sample Statistics

Maximum Memory

Year	Mean	Std Dev	Variance	Minimum	Maximum	Sample Size
1968	1.0993	1.7273	2.9836	0.0080	9.9200	53
1969	1.0962	1.7267	2.9816	0.0080	9.9200	60
1970	1.1426	1.7301	2.9933	0.0080	9.9200	64
1971	1.3489	1.8013	3.2445	0.0080	9.9200	67
1972	1.3197	1.5546	2.4168	0.0160	8.1920	77
1973	1.3984	1.6770	2.8123	0.0080	8.1920	88
1974	1.4783	1.8317	3.3550	0.0080	8.1920	96
1975	1.4520	1.7939	3.2182	0.0080	8.1920	101
1976	1.7331	2.3720	5.6264	0.0080	16.3840	113
1977	1.7934	2.5271	6.3861	0.0080	16.3840	122
1978	2.2391	3.9123	15.3063	0.0080	32.7680	136
1979	3.3615	6.1622	37.9726	0.0080	32.7680	138
1980	3.7290	6.4303	41.3483	0.0080	32.7680	155
1981	5.5925	11.7506	138.0776	0.0080	65.5360	166

Mips

Year	Mean	Std Dev	Variance	Minimum	Maximum	Sample Size
1968	0.3264	0.2654	0.0704	0.1000	1.2000	53
1969	0.3983	0.6560	0.4303	0.1000	5.0000	60
1970	0.4203	0.6626	0.4391	0.1000	5.0000	64
1971	0.5060	0.7800	0.6084	0.1000	5.0000	67
1972	0.5636	0.8637	0.7460	0.1000	5.0000	77
1973	0.5886	0.8647	0.7477	0.1000	5.0000	88
1974	0.5865	0.8571	0.7347	0.1000	5.0000	96
1975	0.5644	0.8413	0.7077	0.1000	5.0000	101
1976	0.6434	0.9436	0.8903	0.1000	5.2000	113
1977	0.6311	0.9163	0.8395	0.1000	5.2000	122
1978	0.6816	0.9593	0.9202	0.1000	5.2000	136
1979	0.9942	1.7482	3.0563	0.1000	15.0000	138
1980	1.0903	1.8502	3.4231	0.1000	15.0000	155
1981	2.2235	9.9076	98.1608	0.1000	99.0000	166

Table 2 (continued)

Sample Statistics

Monthly Rental Price (1982 Millions of Dollars)						
Year	Mean	Std Dev	Variance	Minimum	Maximum	Sample Size
1968	0.0801	0.0828	0.0069	0.0074	0.3844	53
1969	0.0840	0.1050	0.0110	0.0097	0.6434	60
1970	0.0939	0.1083	0.0117	0.0078	0.6210	64
1971	0.1134	0.1137	0.0129	0.0128	0.5815	67
1972	0.1104	0.1047	0.0110	0.0109	0.5103	77
1973	0.0987	0.0926	0.0086	0.0092	0.4302	88
1974	0.0859	0.0824	0.0068	0.0075	0.3963	96
1975	0.0767	0.0746	0.0056	0.0068	0.3583	101
1976	0.0694	0.0676	0.0046	0.0063	0.3336	113
1977	0.0720	0.0763	0.0058	0.0049	0.4143	122
1978	0.0687	0.0720	0.0052	0.0048	0.4089	136
1979	0.0731	0.0750	0.0056	0.0045	0.3731	138
1980	0.0638	0.0671	0.0045	0.0040	0.3575	155
1981	0.0584	0.0617	0.0038	0.0037	0.3379	166

Number of Installations Per System						
Year	Mean	Std Dev	Variance	Minimum	Maximum	Sample Size
1968	362.3019	874.8564	765373.6763	2.0000	4550.0000	53
1969	357.8333	920.8783	848016.8531	1.0000	6000.0000	60
1970	394.2656	1124.194	81263813.9442	3.0000	8200.0000	64
1971	283.7015	908.7735	825869.2429	1.0000	6700.0000	67
1972	284.5325	798.1648	637067.0154	1.0000	5720.0000	77
1973	244.7841	603.0341	363650.1482	1.0000	4360.0000	88
1974	231.8021	489.3544	239467.7604	1.0000	3104.0000	96
1975	231.1980	485.6864	235891.2604	2.0000	2750.0000	101
1976	209.4956	457.7657	209549.4129	2.0000	2685.0000	113
1977	192.0984	399.0211	159217.8580	1.0000	2460.0000	122
1978	184.7353	354.0059	125320.1516	1.0000	1820.0000	136
1979	183.0507	352.5604	124298.8368	1.0000	1910.0000	138
1980	159.5032	306.8748	94172.1477	1.0000	1930.0000	155
1981	169.3735	391.1079	152965.3991	1.0000	3600.0000	166

Table 2 (continued)

Sample Statistics

Technical Age						
Year	Mean	Std Dev	Variance	Minimum	Maximum	Sample Size
1968	4.0758	1.9413	3.7686	0.3340	8.8340	53
1969	4.6989	2.1969	4.8262	1.0000	9.8340	60
1970	5.1931	2.5382	6.4426	0.9170	10.8340	64
1971	5.4792	2.9625	8.7765	0.2500	11.8340	67
1972	5.3781	3.2988	10.8823	0.8340	12.8340	77
1973	5.8166	3.4082	11.6161	0.4170	13.8340	88
1974	6.5785	3.7091	13.7573	1.1670	14.8340	96
1975	7.2281	3.8218	14.6060	1.1670	15.8340	101
1976	7.1648	4.2318	17.9084	1.3340	16.8340	113
1977	7.8173	4.2723	18.2525	1.1670	17.8340	122
1978	8.2595	4.6783	21.8868	1.1670	19.0000	136
1979	8.6930	5.0657	25.6615	1.0840	20.0000	138
1980	8.8090	5.4082	29.2483	1.0840	21.0000	155
1981	8.9833	5.7038	32.5337	1.1670	22.0000	166

Table 3

Parameter Estimates

Conjectural Variations														
Demand	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981
Const	-2.54*	-2.41*	-2.56*	-1.46*	-2.02*	-0.59	-4.13*	-3.61*	-3.82*	-2.85*	-2.66*	-2.14*	-6.14*	-3.43*
Mem	-0.26	0.31*	0.25*	0.10*	0.33*	1.21	0.37*	0.41*	0.16*	0.05*	0.12*	0.07*	0.30	0.07*
Mips	3.33*	0.08	0.21*	0.25*	-0.03	-0.94	0.18*	0.08	0.47*	0.58*	0.28*	0.18*	-0.20	0.08*
Age	0.04*	0.11*	0.13*	0.01	0.06*	-0.39	0.21*	0.11*	0.13*	0.05*	0.02	-0.03	0.32	0.04
Supply	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981
Const	-5.20*	-5.58*	-5.39*	-3.54*	-5.05*	-0.56	-6.73*	-5.96*	-5.39*	-5.30*	-4.26*	-3.90*	-9.02	-4.76*
Mem	-1.17*	0.75*	0.59*	0.50*	1.08*	3.36	0.59*	0.66*	0.27*	0.22*	0.27*	0.15*	0.46	0.11*
Mips	12.4*	0.15	0.38*	0.35*	-0.37*	-2.90	0.33*	0.16	0.71*	0.97*	0.49*	0.38*	-0.32	0.13*
Age	-0.15*	0.36*	0.34*	0.01	0.218*	-1.19	0.41*	0.24*	0.18*	0.13*	0.01	-0.01	0.50	0.05
exp(r)	0.015*													
exp(k)	90.04													
wsse	32.41													

Table 4

Estimated Surplus

Year	Net Surplus Per System*	Net Expenditure Less O.G.*	Total Installed Base	Net Surplus Per $ Net Expenditure*	Total Net Surplus*
1968	0.0701	649.53	25641	2.76	1796.84
1969	0.0742	783.69	27386	2.59	2033.79
1970	0.0694	892.01	29283	2.28	2033.82
1971	0.1153	859.85	24603	3.29	2837.05
1972	0.0938	923.13	26920	2.73	2525.84
1973	0.0553	889.75	27301	1.69	1511.44
1974	0.0334	864.14	27787	1.07	929.47
1975	0.0346	880.13	29510	1.16	1022.11
1976	0.0287	866.50	31583	1.04	909.08
1977	0.0417	1070.93	33201	1.29	1385.83
1978	0.0388	1163.21	36209	1.20	1407.28
1979	0.0380	1267.32	38386	1.15	1461.10
1980	0.0187	1337.63	43798	0.61	820.33
1981	0.0219	1457.85	49538	0.74	1086.45

*Net surplus measures the surplus generated net of the outside good. Net expenditure less O.G. represents the expenditure on systems in the sample ($\Sigma P_j Q_j$) less the expenditure on the outside good ($\Sigma P_0 Q_j$).

Table 5

Percentage Surplus Associated with Different Vintages and Sizes

Year	Techage ≤ 4 years		Techage ≤ 6 years		"Medium" Size = 5		"Large" Size = 6		"Very Large" Size = 7	
	A	B	A	B	A	B	A	B	A	B
1968	0.48	0.37	0.70	0.62	0.13	0.06	0.07	0.03	0.01	0.01
1969	0.08	0.11	0.73	0.63	0.15	0.08	0.08	0.03	0.02	0.01
1970	0.10	0.14	0.82	0.71	0.16	0.08	0.09	0.04	0.03	0.01
1971	0.06	0.10	0.16	0.22	0.19	0.10	0.11	0.05	0.03	0.01
1972	0.15	0.15	0.25	0.29	0.20	0.11	0.15	0.07	0.04	0.02
1973	0.29	0.24	0.36	0.36	0.23	0.12	0.17	0.08	0.05	0.02
1974	0.44	0.32	0.49	0.41	0.24	0.13	0.21	0.09	0.06	0.02
1975	0.27	0.30	0.53	0.48	0.25	0.13	0.19	0.08	0.06	0.02
1976	0.20	0.29	0.58	0.53	0.24	0.13	0.20	0.08	0.07	0.02
1977	0.10	0.24	0.44	0.52	0.21	0.12	0.20	0.09	0.08	0.03
1978	0.14	0.23	0.41	0.50	0.22	0.13	0.20	0.09	0.09	0.03
1979	0.23	0.28	0.35	0.46	0.22	0.14	0.21	0.10	0.11	0.04
1980	0.23	0.15	0.38	0.34	0.19	0.11	0.25	0.10	0.14	0.04
1981	0.31	0.27	0.49	0.47	0.17	0.10	0.23	0.10	0.14	0.05

A: Surplus associated with types of systems as percentage of total surplus.
B: Percentage of installed base associated with same type of system.

Table 6

Size of Counter Factual Surplus as a Percentage of Observed Surplus

Year	Techage ≤ 4 Years Old Removed	Techage ≤ 6 Years Old Removed
1968	0.961	0.938
1969	0.997	0.919
1970	0.994	0.875
1971	0.991	0.990
1972	0.994	0.982
1973	0.986	0.979
1974	0.973	0.970
1975	0.977	0.963
1976	0.982	0.958
1977	0.986	0.965
1978	0.985	0.965
1979	0.982	0.972
1980	0.990	0.980
1981	0.984	0.975

Table 7

Cost Function Estimates

Sample Statistics

Variable	Mean	Std Dev	Variance	Minimum	Maximum
Year	1975.8816	3.8561	14.8696	1968	1981
Mem	2.4305	5.4442	29.6394	0.0080	65.5360
Mips	0.8553	3.5653	12.7110	0.1000	99.0000
Age	7.2617	4.5623	20.8143	0.2500	22.0000
ln(price)	-3.0553	1.0447	1.0913	-5.6011	-0.4409

Correlation of Variables

	Mem	Mips	Age
Mips	0.24271562		
Age	-0.25643255	-0.12986814	
Ln(price)	0.26571416	0.22847909	-0.14177210

Table 7 (continued)

Cost Function Estimates

Equation 1

Valid cases:	1436	Dependent variable:	Log of price
R-squared:	0.218	Rbar-squared:	0.209
Residual SS:	4315.12	Std error of est:	1.744

Variable	Estimate	Standard Error	Real Cost Index
mem	0.276	0.0471**	
mips	0.166	0.0763*	
age	0.155	0.0771*	
Γ, CV param	-655.9	128.8**	
d68	-3.602	0.41**	100.0
d69	-3.678	0.45**	94.6
d70	-3.435	0.49**	123.1
d71	-3.457	0.50**	121.6
d72	-3.426	0.49**	124.2
d73	-3.771	0.51**	88.8
d74	-4.013	0.57**	71.8
d75	-4.425	0.61**	48.5
d76	-4.693	0.60**	37.1
d77	-4.658	0.65**	39.2
d78	-5.061	0.69**	26.7
d79	-5.448	0.74**	18.4
d80	-5.806	0.75**	13.1
d81	-6.615	0.81**	6.0

*T-value exceeds 1.96
**T-value exceeds 2.56

Table 7 (continued)

Cost Function Estimates

Equation 2

Valid cases:	1436	Dependent variable:	Log of price
R-squared:	0.193	Rbar-squared:	0.182
Residual SS:	6367.5	Std error of est:	2.120

Variable	Estimate	Standard Error	Real Cost Index
mem	0.234	0.0707**	
mips	0.127	0.106	
age	0.066	0.120	
Γ, 68-69	-132.7	252.3	
Γ, 70-76	-983.5	204.6**	
Γ, 77-81	-1470.3	603.0*	
d68	-3.479	0.52**	100.0
d69	-3.511	0.56**	98.8
d70	-2.586	0.67**	261.9
d71	-2.668	0.68**	243.7
d72	-2.635	0.67**	249.4
d73	-3.000	0.69**	174.9
d74	-3.141	0.77**	158.1
d75	-3.598	0.81**	102.1
d76	-3.897	0.80**	75.7
d77	-3.470	0.99**	127.0
d78	-4.023	0.96**	72.3
d79	-4.313	1.04**	56.3
d80	-4.751	1.02**	36.0
d81	-5.419	1.12**	19.4

*T-value exceeds 1.96
**T-value exceeds 2.56