Order Number 9512309

Estimating the economic benefits of advances in computer technology

Brown, Kenneth Hackman, Ph.D.

University of Illinois at Urbana-Champaign, 1994

U·M·I
300 N. Zeeb Rd.
Ann Arbor, MI 48106

ESTIMATING THE ECONOMIC BENEFITS OF ADVANCES IN COMPUTER TECHNOLOGY

BY

KENNETH HACKMAN BROWN

B.S., Saint Louis University, 1990
M.S., University of Illinois, 1992

THESIS

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Economics
in the Graduate College of the
University of Illinois at Urbana-Champaign, 1994

Urbana, Illinois

UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

THE GRADUATE COLLEGE

JULY 1994

WE HEREBY RECOMMEND THAT THE THESIS BY

KENNETH HACKMAN BROWN

ENTITLED ESTIMATING THE ECONOMIC BENEFITS OF ADVANCES IN COMPUTER TECHNOLOGY

BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF DOCTOR OF PHILOSOPHY

Director of Thesis Research

Head of Department

Committee on Final Examination†

Chairperson

† Required for doctor's degree but not for master's.

O-517

To the memory of my grandmother,

Irma "Honey" Hackman
1914–1989

ACKNOWLEDGMENTS

Throughout the course of my graduate school career I have had help and support from many people. I would especially like to thank Shane Greenstein for his guidance, comments and financial support through the process of writing my dissertation. I am very thankful to have met someone who shares my love for computers and new technology, and who allowed me to do research on a topic I have so much interest in. I would also like to thank Roger Koenker and Jan Brueckner. They have supported my work from the beginning, and have always left their doors open for me. They sparked my interest in applied econometrics and hedonic price functions, and for this I am most grateful.

I would like to thank Francisco Cribari-Neto for his help during the early years of graduate school. If I only had one-half of his desire to succeed I would surely have a long and successful career. And special thanks to Tom Nonnenmacher for helping me keep my sanity the last four years. Without him, I would not be finishing now.

I would like to thank Pat Welch, Muhammad Islam and Rick Chaney. They were strong influences during my undergraduate years and pushed me to do my best. While I can not say that I have always agreed with their advice to go to graduate school, now that this experience is coming to an end, I can only say thank you for having confidence in me. I hope that I can have as much positive influence on a student someday as these three have had on me.

I would especially like to thank my family. My Mom has always given me unconditional love and support regardless of my goals. She has always had confidence in me and encouraged me to be whatever I chose. None of my successes would have been possible without her. My wife Traci has put up with a great deal over the past few years. Thank you for not giving up on me and for pushing me to get this dissertation finished. Without you I would never have

completed it. Your love has been the best medicine for my graduate school blues. Finally, I would like to dedicate this work to my grandmother. She always knew what was best for me, and I only wish that she could be here to share this with me. No one would have been more proud.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1
INTRODUCTION

It has become common practice to compute hedonic price indexes to estimate the price changes for a product holding the product quality constant. Recently, a great deal of attention has been given to a number of factors surrounding these indexes such as the functional form to use when estimating the hedonic price function and the set of product characteristics to include in that function. In addition to these factors, a great deal of research has evolved around the procedure and necessary conditions for estimating demand and supply parameters from the estimated hedonic price function. However, little attention has been given to analyzing the implications of these indexes. In other words, while it is well known that hedonic indexes provide us with a good estimate of the price per quality change in a product over time, it is not well known what other information can be extracted from these indexes.

One question of interest is: How much do buyers benefit from improvements in product technology? Since the hedonic index tells us how much more quality a buyer can purchase holding price fixed, one might believe that the hedonic index provides us with an answer to our posed question. In some sense the hedonic index does provide us with an estimate of this benefit, except that it ignores important factors. First, the hedonic index implicitly assumes that all levels of product quality exist at all time periods. Thus, buyers cannot benefit from the introduction of previously unavailable product quality levels. Second, and related, since all quality levels are assumed to exist, buyers cannot benefit from the introduction of a greater variety of product quality levels. Buyers obviously benefit from these factors in addition to the buying power factor, and a price index, such as the hedonic index, which ignores them will be a biased estimate of the benefits received.

In this research we look at an alternative to the hedonic index for estimating the benefits buyers receive from improving product technology. As with the traditional hedonic method, this alternative begins by estimating a hedonic price function. However, the similarity ends there as we continue beyond this price function and estimate demand relationships for characteristics for individual buyers. With these demand curves we predict buyers' past and future product purchases assuming that their demands do not change over time. We predict these purchases by allowing buyers to optimize their individual bid curves subject to past and future hedonic price functions. In this fashion we are able to determine the benefits the buyer receives from both a lower price and higher quality. It is capturing this higher quality level which distinguishes our index from the hedonic index. After predicting past and future purchases, we compute a price equivalent utility index which measures the benefits a buyer receives from being able to move from one bid curve to another over time. We then aggregate the indexes of the individual buyers to compute a single benefit index for the product for a given time period. We apply our model to data on the mainframe computer market from 1985–1991 and compare the results with those obtained from the traditional hedonic index approach.

This research is important for a number of reasons. First, as Trajtenberg (1990) has pointed out, it is important to measure new technology or product innovation in terms of its benefits to buyers of that technology. The hedonic index merely estimates the change in price per quality over time and does not take into consideration what if any of the new technology is being purchased. As Greenstein (1994) has pointed out, the time between the introduction of a new mainframe computer and the time when that computer becomes the average computer purchased is between six and eight years. With this lag, we would expect that the hedonic index which does not account for actual purchases would be a biased estimate of the benefits to buyers. We expect this bias to be in the direction of overstating the benefits to buyers. Second, because the hedonic index does not account for actual product purchases, it is not sensitive to the distribution of buyers across the product space. Thus, a market where every purchaser buys the same product will have the same hedonic price index as a market where every purchaser buys a different product. This implicitly assumes that all buyers benefit by exactly the same amount as the hedonic price function shifts over time. Results from our benefit index indicate that this assumption is not valid, and, in fact, buyers at different locations in the product space receive different levels of benefits depending on the shape of their individual bid curves. This implies that the hedonic price index will be biased as an estimate of the benefits to buyers. Third, hedonic price indexes are used by the U.S. government to compute official price indexes. The biases pointed out here imply that these official indexes are inadequately measuring the benefits associated with quality-adjusted price changes.

In chapter 2, we examine the relationships between the hedonic price index and our utility index. We compare the indexes both geometrically and via four numerical examples. The geometric analysis shows that in general the hedonic index will decline at a faster rate than our utility index. This in turn implies that a hedonic index will overstate the benefits buyers receive from changes in the hedonic price function over time. We find that this result is mainly due to the assumption that buyers have a diminishing marginal utility for higher levels of product characteristics. We believe that this is a natural assumption, and it follows closely the model described by Rosen (1974). The numerical examples illustrate two main points. First, we find that the utility index is sensitive to the distribution of buyers across the product space. This implies that buyers at different portions of the product space receive different levels of benefits. The hedonic index does not allow for this and therefore biases it as an estimate of the benefits to buyers from new technology. Second, we find that the utility index is sensitive to the maximum available levels of characteristics. The hedonic index assumes that all levels of characteristics already exist and cannot account for the development of higher levels of quality. The results here indicate that these levels are important for determining the benefits to buyers, and imply that the hedonic index will provide a biased estimate of the benefits to buyers.

Now, given our findings in chapter 2, it is important to get an indication of the degree of bias that the hedonic index provides. Given that the hedonic index is quite simple to compute and the benefit index is quite difficult to compute, should the bias be small, we might still advocate the use of the hedonic price index as an estimate of the benefits to buyers from new technology.

In order to address the issue of the extent of bias, we apply our model to data on the mainframe computer industry from 1985–1991 in chapter 3. This data is quite detailed and is the main reason we are able to follow this line of research. Previous research had data on the set of available computers, their characteristics and prices. We not only have this data, but we also have data on the set of computers actually purchased as well as information pertaining to the actual buyers. This data allowed us to extend the traditional hedonic approach by estimating demand for characteristics for individual buyers and using those estimates to predict past and future computer purchases. Being able to predict these purchases allowed us to measure benefits not only in terms of lower price, as the hedonic index, but also in terms of higher quality levels purchased. The data which was available to previous researchers was insufficient to compute these demand estimates, and thus insufficient to predict past and future purchases. Without these predictions one could not compute a utility index of the type we have computed.

The results in chapter 3 indicate that the hedonic index overstates the benefits to buyers by as much as 50%. This bias was sensitive, though, to the set of buyers we used to compute the index, *i.e.* the index computed using the 1985 set of buyers as the base revealed a different level of benefits than the index computed using the 1991 set of buyers. This supports the finding in chapter 2 that the distribution of buyers is an important factor when computing the benefit index.

One of our concerns with the results obtained in chapter 3 was the sensitivity of the results to the functional form used to estimate the hedonic price function. This is an issue which has received much attention in the literature and we addressed it in chapter 4. We compared a number of alternative functional forms to the quadratic form we adopted in chapter 3. These alternatives included linear, log-linear, log-log, cubic and generalized additive models. In general we found that the quadratic model offered a good approximation to the alternatives. However, we found with the log-log and generalized additive model that they provided significantly better fits than the quadratic. Unfortunately, these models turned out to be quite difficult to use when attempting to compute the benefit index. Due to this factor, we advocate the quadratic model for now as an approximation and recommend pursuing this issue further in future research.

In addition to the difficulties encountered with regard to computing the benefit index using the alternative functional forms, we found that computing standard errors for the benefit index could be quite difficult. We believe that some delta-method approach or some bootstrap approach will be necessary to derive standard errors for the benefit index. Only with these standard errors in hand will we be able to completely investigate the importance of the choice of functional form on the benefit index.

CHAPTER 2

AN ANALYTICAL COMPARISON OF THE INDEXES

2.1 INTRODUCTION

One of the most common methods for measuring technological change is the hedonic price index. This method measures the average change in product price holding product quality constant. However, as Trajtenberg (1990) points out, this method does not account for "filling-in" or "extensions" in the product space, nor does it take into consideration the benefits buyers receive from product innovation. In this chapter we describe an alternative procedure based on Rosen (1974) that uses buyer's demand for product characteristics to measure how much buyers benefit from improvements in product technology.

We compare this method with the hedonic index method both geometrically and via a numerical example. We show that our benefit (or utility) index will in most cases decline at a slower rate than a hedonic index, implying that a hedonic index overstates the true benefits to buyers from improvements in product technology. We also show that our benefit index accounts for the distribution of buyers across the product space as well as extensions in the product space, whereas the hedonic index does not account for either factor.

These findings are important for a number of reasons. First, as Trajtenberg (1990) argues, product innovations must be measured in terms of their benefits to buyers. The slower rate of decline for the benefit index implies that hedonic indexes are not properly measuring the benefits to buyers from improvements in technology. Second, buyers purchasing low levels of quality do not receive the same benefits from advances in technology as buyers purchasing high levels of quality. Since the hedonic index does not account for individual buyers, it cannot account for this factor, whereas our benefit index does. Finally, a hedonic index disregards the effects of the introduction of higher levels of characteristics than were previously available. However, as will be demonstrated in our numerical example, buyer's benefits from new technology are sensitive to the level of the highest quality available. Each of these factors is important for the computation of the benefits from new technology. Unfortunately, the hedonic index is unable to account for these; thus, the computation of the benefits from product innovation requires some alternative procedure. In chapter 2 we will examine the extent of the bias of the hedonic index when computing the benefits to buyers from product innovation.

In the next section we will describe the methods for computing hedonic indexes and for computing our benefit index. In section 3 we will compare these methods geometrically, and in section 4 we will compare the methods via a numerical example. These two sections will illustrate the importance of various factors to the computation of these indexes. In the final section we will give concluding remarks.

2.2 COMPUTING THE INDEXES

2.2.1 The Hedonic Index

Hedonic methods have been used since Court (1939) to compute quality-adjusted price indexes for quality differentiated products. The methods have been applied to a variety of industries, most commonly automobiles and computers. In 1986 the methods were accepted by the Bureau of Economic Analysis for the computation of the official price index for computers. This section will describe basic hedonic theory and a method for deriving quality-adjusted price indexes from estimated hedonic surfaces.

The main idea behind the hedonic price index is that a quality differentiated product can be described by a (small) set of product characteristics. For example, computer speed and memory are typically chosen as characteristics. At a given time t, there are m_t products available and n_t products sold.[1] The goal of the hedonic is to estimate a relationship between

[1] If we assume that the m_t products only consist of products actually purchased, then $n_t \geq m_t$. However, if not all m_t products are purchased we could have $n_t < m_t$.

product price and product characteristics of the form

$$P_t = H(x_{1t}, \ldots, x_{kt}). \tag{2.2.1}$$

P_t is an n_t-vector of observations of product prices and x_j, $j = 1, \ldots, k$ are n_t-vectors of observations on k product characteristics. The variables are subscripted with t's because we assume that the surface shifts over time. In the computer literature, (2.2.1) is typically estimated as an OLS regression of the form (Triplett, 1989):

$$\log(P_t) = \beta_0 + \sum_{j=1}^{k} \beta_j \log(x_j) + \sum_{t=2}^{T} \gamma_t D_t + \varepsilon. \tag{2.2.2}$$

The D_t are time dummy variables, implying that the surfaces are separated only by a constant, γ_t.[2]

Having estimated (2.2.2), our goal is to derive a quality-adjusted price index. We choose $t = 1$ as our base year so that I_1, the price index at $t = 1$, equals 100.00.[3] We need to compute I_t, $t = 2, \ldots, T$. In (2.2.2), the estimates of γ_t represent the change in $\log(P_t)$ holding all other variables fixed. Thus, we can use the $\hat{\gamma}_t$'s to determine how much $\log(P_t)$ changed between $t = 1$ and $t = t$ holding quality constant. Then, since our interest is P_t and not $\log(P_t)$, we can estimate the change in price between $t = 1$ and $t = t$ by $\exp(\hat{\gamma}_t)$, $t = 2, \ldots, T$. Note that $\exp(\hat{\gamma}_t)$ is not an unbiased estimate of $\exp(\gamma_t)$. A standard method for correcting this bias is to add one-half the coefficients' variance to the estimated coefficient (Goldberger, 1968; Teekens & Koerts, 1972; Triplett, 1989).

Berndt (1991) describes a number of issues that surround the computation of these indexes. We will discuss two. First, (2.2.1) is commonly estimated as log-log. However, no theoretical justification exists for this choice. It is usually chosen based on some goodness-of-fit criterion. Triplett (1989) has argued that the log-log specification is incompatible with

[2] Actually, this is true only if we are interested in $\log(P_t)$. If our interest is P_t, then the difference is multiplicative in $\exp(\gamma_t)$.

[3] The choice to set the base to $t = 1$ is arbitrary. We did this because we set $\gamma_1 = 0$. Had we excluded some other year's dummy variable we would have set that year to the base year.

a priori knowledge of the computer industry and that other forms should be tried. To date, though, little research on computers has addressed this issue directly; see however Berndt, Showalter & Woolridge (1993).

Second, these quality-adjusted indexes answer the question: How much has the average price of a product fallen over time holding product quality constant? Another question one might ask is: How much have buyers benefited from improvements in quality? Answering the second question is important because it is important to measure technological change in terms of its benefits to buyers, rather than simply as a reduction in prices. Unfortunately, obtaining an answer to the second question is much more difficult. This requires data on individual buyers and estimates of demand for product characteristics, in addition to the hedonic surfaces estimates. This type of data is often not available. Previous work has had data on the prices and characteristics of individual computer systems and occasionally on the number of each system sold. However, these previous studies have not used any information regarding the buyers of these systems. In chapter 3 we will describe the data we will use to perform our empirical analysis. It includes data on the computer systems as well as information on the buyers. With this data we will estimate a benefit index for buyers, and we will compare its estimates with the hedonic index.

2.2.2 The Benefit Index

Rosen (1974) described the theory underlying a hedonic surface. He showed that the surface could be viewed as an envelope to buyers' bid curves and sellers' offer curves. A bid curve is a relationship which describes a buyer's willingness to trade-off price for product characteristics when making a purchase decision. An offer curve represents the same trade-off for making the selling decision. Buyers and sellers use these to choose the optimal product, and transactions occur where these bid and offer curves are tangent. The hedonic surface then maps out this set of transactions. This can be seen in Figure 2.2.1 for a product with a single characteristic dimension x. Here the buyer purchased a product with characteristic level x^0 for price P^0 at time t. H_t maps out the set of all transactions at time t, and H_{t+k} maps out the set of all transactions at time $t+k$.

The traditional hedonic method estimates the change in price for x^0 between time t and time $t+k$, or $P_t^0 - P^1$. Our interest is in determining how much the buyer benefits between time periods assuming the buyer maximizes his bid curve at both time periods. Notice that in Figure 2.2.1 the buyer optimally chooses $\hat{x}$ at time $t+k$ rather that x^0. This implies that the buyer benefits from both a reduction in prices and an increase in the level of characteristics purchased. The hedonic index on the other hand only accounts for the reduction in prices beteen the two time periods. Therefore, in general the benefit index will be different than the hedonic index. Our goal in this chapter is to gain some insight regarding the relationship between the two indexes. First, though, let us define the benefit index more formally.

We assume that each buyer solves

$$\max \quad u(x, P) \qquad s.t. \quad P = H_t(x) \tag{2.2.3}$$

where u represents the buyers utility from purchasing characteristics x for price P, H_t is the hedonic price function at time t, x is a vector of product characteristics and P is the product price.[4] H is assumed to be twice continuously differentiable with $dH/dx > 0$.[5] u is chosen such that $u_x > 0$, $u_{xx} < 0$ and $u_P < 0$. Finally, we assume that prices decline and higher levels of characteristics become available simultaneously over time. This mirrors actual observations in the computer industry. The first order condition for (2.2.3) is

$$\nabla u(x, H_t(x)) = 0. \tag{2.2.4}$$

Solving this implies an optimal choice for x at time t, which we will call x_t^0. We then define $P_t^0 = H_t(x_t^0)$ and $u^0 = u(x_t^0, P_t^0)$.

[4] We assume for simplicity that H_t is exogenous to buyers.

[5] This rules out the possibility of "filling-in" the product space. Thus, with our model, all technological innovation must come in the form of extensions in the product space.

Substituting H_{t+k} for H_t in (2.2.4), we can obtain an optimal solution for x at time $t+k$, which we will call $\hat{x}_{t+k}$. We then define $\hat{P}_{t+k} = H_{t+k}(\hat{x}_{t+k})$ and $\hat{u}_{t+k} = u(\hat{x}_{t+k}, \hat{P}_{t+k})$.

To compute our benefit index we need to compute the change in utility between time t and time $t+k$, given by $u^0 - \hat{u}_{t+k}$. Inverting u gives $P = F(x, v)$ where v is indirect utility. We can compute the utility change in price units by $F(\hat{x}_{t+k}, u^0) - F(\hat{x}_{t+k}, \hat{u}_{t+k})$. We define $F(\hat{x}_{t+k}, u^0)$ as P^*_{t+k}. $F(\hat{x}_{t+k}, \hat{u}_{t+k})$ is the same as $\hat{P}_{t+k}$ defined above. Thus, the utility change measured in price units is $P^*_{t+k} - \hat{P}_{t+k}$.

Given this we set the base year for our index to $t = t$, implying $I_t = 100$. We then compute $I_{i,t+k}$ as $\hat{P}_{i,t+k}/P^*_{i,t+k}$ for an individual buyer, or as

$$I_{t+k} = \frac{\sum_{i=1}^{n} w_i I_{i,t+k}}{\sum_{i=1}^{n} w_i} \tag{2.2.5}$$

for the entire market. w_i represents some weight typically chosen as P^0_{it} or $P^*_{i,t+k}$. In an analagous fashion we could compute $I_{t+k+1}, \ldots, I_T$.

The index computation that we have described may be sensitive to the initial set of buyers used. Therefore it is important to compute the index using different sets of buyers and to compare the outcomes.

The computation changes somewhat when we take buyers from time t and compute the index for time $t-k$ (instead of time $t+k$ as before). Figure 2.2.2 illustrates this situation. In the figure, μ_{t-k} represents the maximum level of characteristic which was available at time $t-k$. As shown, $\hat{x}_{t-k}$ is between zero and μ_{t-k}. However, the optimal choice for the buyer might have been $\hat{x}_{t-k} > \mu_{t-k}$ or $\hat{x}_{t-k} < 0$. If the optimal $\hat{x}_{t-k}$ is greater than μ_{t-k}, we assume the buyer would purchase μ_{t-k}, the next best thing available; if the optimal $\hat{x}_{t-k}$ is less than zero, we assume this buyer is better off in some alternative market. For example, with computers a buyer might purchase a minicomputer instead of a mainframe, and in this context those are considered different markets. In this case we compute the benefit from moving from $x = x^0_t$ to $x = 0$, the point where the buyer would be indifferent between the two markets.

In any case, we compute $P^{**}_{i,t-k}/P^0_{it}$ for an individual buyer, or for the entire market:

$$\frac{\sum_{i=1}^{n} w_i P^{**}_{i,t-k}/P^0_{it}}{\sum_{i=1}^{n} w_i} \tag{2.2.6}$$

where $w_i = P^0_{it}$.

The index that we have described here is a "cost-of-living" index because it tells us how much money we would have to give to or take from the buyer in order to make them indifferent between the two time periods. This is in contrast to the hedonic index which only estimates the average change in price for the product holding product characteristics constant. The next section compares the hedonic index and our "cost-of-living" index geometrically.

2.3 COMPARING THE INDEXES

The previous section described the methods for obtaining a hedonic price index and a price equivalent benefit index from a hedonic surface. In this section we will compare these two indexes geometrically to determine if one or the other price index should decline at a faster rate. It will be shown that in most cases the benefit index will decline at a slower rate than the hedonic index; thus the hedonic index overstates the benefits buyers receive from improvements in product technology. The "forward" index that we will discuss is the benefit index with buyers moving from time t to time $t+k$, and the "reverse" index is the benefit index with buyers moving from time t to time $t-k$. We assume that prices decline and higher levels of characteristics become available simultaneously over time.

2.3.1 Hedonic Index vs. Forward Index

Figure 2.3.1 illustrates the situation. We have a product with a single characteristic x. Our buyer purchases x^0_t in time t and based on demand we predict the buyer will purchase $\hat{x}_{t+k}$ at time $t+k$ (we call this the counterfactual x). We assume the form of H_t and H_{t+k} is of the form (2.2.2). Finally, we define $F^0 = F(x, u^0)$ and $\hat{F} = F(x, \hat{u})$ (to simplify notation we will often drop the utility level argument).

The hedonic index, I^H_{t+k}, is computed as $H_{t+k}(\tilde{x})/H_t(\tilde{x})$ where $\tilde{x}$ is any value of x. From (2.2.2), this is

$$I^H_{t+k} = \frac{\exp(\hat{\beta}_0 + \hat{\beta}_1 \log(\tilde{x}) + \hat{\gamma}_{t+k})}{\exp(\hat{\beta}_0 + \hat{\beta}_1 \log(\tilde{x}) + \gamma_t)}. \tag{2.3.1}$$

Now, assuming that $\gamma_t = 0$, (2.3.1) reduces to $\exp(\hat{\gamma}_{t+k})$. This result was derived in the previous section, but here we point out that this holds true for any x; in particular $\hat{x}_{t+k}$.

We focus on $\hat{x}_{t+k}$ because the forward index is computed as $I^B_{t+k} = \hat{F}(\hat{x}_{t+k})/F^0(\hat{x}_{t+k})$. Our concern is whether this value will be larger or smaller than I^H_{t+k}.

__**Proposition 2.3.1:**__*Assume the hedonic surfaces are convex for each t, the bid curves are concave for each t, $\hat{x}_{t+k} > x^0_t$, H_t and u^0 are tangent at x^0_t and H_{t+k} and $\hat{u}_{t+k}$ are tangent at $\hat{x}_{t+k}$, then the forward benefit index will decline at a slower rate than the hedonic index.*

We use the following lemma to illustrate this.

__**Lemma 2.3.1:**__*If $g(\cdot)$ is convex, $h(\cdot)$ is concave, $g(\cdot)$ and $h(\cdot)$ are twice continuously differentiable, $g(\cdot)$ and $h(\cdot)$ are tangent at x_0 and $x_1 \neq x_0$, then $g(x_1) > h(x_1)$.*

Proof: Since $g(\cdot)$ is convex, we know that $g(x_1)$ lies above the line tangent to $g(\cdot)$ at x_0. We also know that since $h(\cdot)$ is concave, $h(x_1)$ lies below the line tangent to $h(\cdot)$ at x_0. But $g(\cdot)$ and $h(\cdot)$ are tangent at x_0 and therefore have the same tangent line at x_0. Thus $g(x_1)$ must be greater than $h(x_1)$.

We know that $\hat{F}(\hat{x}_{t+k}) = H_{t+k}(\hat{x}_{t+k})$ and that $F^0(\hat{x}_{t+k}) \leq H_t(\hat{x}_{t+k})$ from Lemma 2.3.1. Thus we have

$$\frac{\hat{F}(\hat{x}_{t+k})}{H_t(\hat{x}_{t+k})} \leq \frac{\hat{F}(\hat{x}_{t+k})}{F^0(\hat{x}_{t+k})}. \tag{2.3.2}$$

This implies that

$$\frac{H_{t+k}(\hat{x}_{t+k})}{H_t(\hat{x}_{t+k})} \leq \frac{\hat{F}(\hat{x}_{t+k})}{F^0(\hat{x}_{t+k})} \tag{2.3.3}$$

$$I^H_{t+k} \leq I^B_{t+k}. \tag{2.3.4}$$

Equation (2.3.4) states that the benefit index will have a larger value than the hedonic index at time $t+k$, implying that the hedonic index will decline at a higher rate; how much faster is unclear from this exercise. Notice that this relationship was computed for a single buyer. The aggregate benefit index is a weighted average of I^B_{t+k} for all buyers. Since (2.3.4) holds for all x, when we weight the $I^B_{i,t+k}$, the final index will maintain the inequality.

2.3.2 Hedonic Index vs. Reverse Index

Figure 2.3.2 illustrates the situation. Again we have a product with a single characteristic x. The buyer purchases x^0_t in time t and then we predict what the buyer would have purchased at time $t-k$. This is given by $\hat{x}_{t-k}$. We show three different $\hat{x}_{t-k}$'s because there are three cases to examine: $\hat{x}_{1,t-k} > \mu_{t-k}$, $0 \leq \hat{x}_{2,t-k} \leq \mu_{t-k}$ and $\hat{x}_{3,t-k} < 0$. (Recall that μ_{t-k} is the maximum amount of x which could be purchased at time $t-k$).

For any $\tilde{x}$, the hedonic index is given by $I^H_{t-k} = H_{t-k}(\tilde{x})/H_t(\tilde{x})$. The "reverse" benefit index is given by $I^B_{t-k} = \hat{F}(x^0_t)/F^0(x^0_t)$. Our interest is whether I^H_{t-k} is larger or smaller than I^B_{t-k}.

<u>**Proposition 2.3.2:**</u>*Given the assumptions of Proposition 2.3.1, the reverse benefit index could decline at a higher or lower rate than the hedonic index.*

There are three cases which need to be examined in order to see this. In case 1, the buyer would optimally choose to purchase $\hat{x}_{1,t-k} > \mu_{t-k}$. However, the most x the buyer can purchase is μ_{t-k}. We assume that a buyer faced with this situation will purchase μ_{t-k}.

There are two possible outcomes. First, when the buyer purchases μ_{t-k} on $\hat{F}^*_{1,t-k}$, we could have $\hat{F}^*_{1,t-k}(x^0_t) > H_{t-k}(x^0_t)$. When this occurs we have $I^B_{t-k} > I^H_{t-k}$, which implies that the benefit index will have a higher growth rate. Second, when the buyer purchases μ_{t-k} on $\hat{F}^*_{1,t-k}$, we could have $\hat{F}^*_{1,t-k}(x^0_t) < H_{t-k}(x^0_t)$. When this occurs we have $I^B_{t-k} < I^H_{t-k}$ implying that the benefit index will have a lower growth rate.[6] Therefore, the number of buyers in each category will determine whether the benefit index ultimately has a higher or lower growth rate than the hedonic index.

In case 2, we have $0 \leq \hat{x}_{2,t-k} \leq \mu_{t-k}$. Since H_{t-k} is convex , $\hat{F}_{2,t-k}$ is concave, H_{t-k} and $\hat{F}_{2,t-k}$ are tangent at $\hat{x}_{2,t-k}$ and $\hat{x}_{2,t-k} < x^0_t$, we have $\hat{F}_{2,t-k}(x^0_t) \leq H_{t-k}(x^0_t)$ by Lemma 2.3.1. Therefore, we will have $I^B_{t-k} < I^H_{t-k}$ and the benefit index will have a lower growth rate than the hedonic index.

In the final case, we have $\hat{x}_{3,t-k} < 0$. Here we assume that buyers are in some other market and we compute the benefit level associated with being indifferent between this market and the other. This occurs at $x = 0$ on $\hat{F}^*_{3,t-k}$. Since $\hat{F}^*_{3,t-k}$ and H_{t-k} intersect at 0, H_{t-k} is convex, $\hat{F}^*_{3,t-k}$ is concave and $x^0_t > 0$, we have $\hat{F}^*_{3,t-k}(x^0_t) \leq H_{t-k}(x^0_t)$ by Lemma 2.3.1. This implies that $I^B_{t-k} \leq I^H_{t-k}$ and the benefit index will have a lower growth rate than the hedonic index.

Each of these possible outcomes was computed for a single buyer. Our main interest though is the aggregate index. In general, we will have buyers who fall into each of the four possible outcomes. Thus, it is unclear whether the aggregate benefit index will show a higher or lower growth rate than the hedonic index as Proposition 1.3.2 states. We will show in section 4 that the outcome depends in part on the distribution of buyers across the product space and in part on the location of μ_{t-k}.

2.3.3 Forward Index vs. Reverse Index

The two previous sections have compared the forward and reverse benefit indexes with

[6] This case is not shown in Figure 2.3.2. This would occur if $\hat{F}^*_{1,t-k}(x^0_t)$ was below $H_{t-k}(x^0_t)$ in the figure.

the hedonic index. There we saw that the forward index should decline at a slower rate than the hedonic index, and that the reverse index could decline at a faster or slower rate than the hedonic index depending on various factors. In this section we will compare the forward index with the reverse index.

With the forward index we observe buyers' purchases at time t, and based on demand we predict the purchases at time $t+k$. With the reverse index we observe buyers' purchases at time $t+k$, and based on demand we predict purchases at time t. If the set of purchases predicted from t to $t+k$ is equal to the set of observed purchases at time $t+k$, and the set of purchases predicted from $t+k$ to t is equal to the set of observed purchases at time t, then the forward and reverse indexes will have the same growth rate.

The conditions we need to satisfy this relationship, however, are unlikely to be found in any real data set. A more likely scenario would involve the distribution of buyers changing over time. In this case, there is little we can say about the relationship between these two indexes. We can say that if the distribution of buyers is such that the reverse index declines more rapidly than the hedonic index (as in case 1 above), then, since the forward index must decline more slowly than the hedonic index, the reverse index will decline faster than the forward index.

When these conditions are not met there is nothing we can say about the relationship between these indexes. This can be seen by examining Figure 2.3.3. There we have a product with a single characteristic x. We show a single buyer in time t who purchases $x^0_{F,t}$, and we predict they purchase $\hat{x}_{F,t+k}$ at time $t+k$. We also show a single buyer at time $t+k$ who purchases $x^0_{R,t+k}$, and we predict they purchase $\hat{x}_{R,t}$ at time t. Based on the shapes of the bid curves in the figure at time t, we see that the forward index will have a higher growth rate than the reverse index. This comes as a result of the bid curves having equal slopes at $x^0_{R,t+k}$, but different slopes at all other points (this explains the different choices at time t). To see that the reverse index could decline more rapidly than the forward index, simply interchange the F and R subscripts in the figure.

2.4 NUMERICAL EXAMPLES

The two previous sections have shown how to compute a hedonic index and our benefit index, as well as pointing out some of the relationships amongst them. Section 3 pointed out that the forward and reverse benefit indexes are sensitive to the distribution of buyers across the product space and the level of the maximum available characteristic, labeled μ_{t-k} in the previous section. In this section we provide four examples that illustrate these results. We show that as the distribution of buyers shifts toward higher levels of characteristics, the growth rate of our benefit index increases. This implies that buyers who purchase high levels of characteristics benefit more from extensions in the product space than buyers who purchase low levels of characteristics. We also show that as the level of the maximum available characteristic increases, so do the benefits to buyers. This occurs because when the level of the maximum available characteristic increases, buyers are less constrained when making purchase decisions and can choose characteristic levels optimally. The first two examples consider the effects of these factors on the forward index, and the last two examples examine the effects on the reverse index.

2.4.1 Forward Index

For this example we assume a product with a single characteristic x and we assume two time periods. We begin by specifying a hedonic surface for each time period given by

$$H_1: \quad \log(P) = a + b\log(x) \qquad (2.4.1A)$$

$$H_2: \quad \log(P) = a + b\log(x) + \gamma \qquad (2.4.1B)$$

where the surfaces are separated only by the constant term γ. This follows closely the computer literature where surfaces are typically estimated as log-log and are separated only by a constant term. Second, we specify a linear bid function for each buyer of the form

$$\text{Bid}_i: \quad P = (1-b)\exp(a + b\log(c_i)) + (\exp(a + b\log(c_i))\frac{b}{c_i})x \tag{2.4.2}$$

where a and b are the same as in (2.4.1A) and (2.4.1B) and c_i is a parameter which distinguishes each buyer's bid curve. Assuming buyers choose a level of x where (2.4.2) is tangent to (2.4.1A) at time 1, buyers purchase $x_{1i} = c_i$. This can be seen by setting $dH_1/dx = dP/dx$ and solving for x. Then, assuming the slope of the bid curve does not change over time, buyers purchase $x_{2i} = c_i \exp(\gamma/(1-b))$.

The specification of a linear bid curve in this example does not detract from our main points. We specify it in this fashion to allow for ease of computation. Since in general buyers' bid curves will be strictly concave, any growth rates we obtain for our benefit indexes using a linear bid curve will be higher than they would be normally.

Next we assume that μ_1 is the maximum available level of x at time 1 and μ_2 is the maximum available level of x at time 2. Given these definitions we define

$$c^* + \varepsilon = \{c_i \mid c_i + \varepsilon = \mu_1\} \tag{2.4.3A}$$

$$\tilde{c} = \{c_i \mid c_i \exp(\gamma/(1-b)) = \mu_2\}. \tag{2.4.3B}$$

We define these in this way so that the support of c is between ε and c^*. $c^* + \varepsilon$ represents the level of c where buyers choose μ_1 at time 1. $\tilde{c}$ represents the level of c at time 1 for a buyer who will choose μ_2 at time 2; buyers with $c > \tilde{c}$ will be constrained to also purchase μ_2 at time 2. We assume that all levels of x are purchased at time 1 and that no buyers exist with $c_i > c^* + \varepsilon$. We assume that at both time periods ε is the smallest level of x available for purchase. All buyers between ε and $\tilde{c}$ at time 1 are able to maximize their bid curve at time 2, while all buyers between $\tilde{c}$ and $c^* + \varepsilon$ are constrained to μ_2 at time 2. Thus, as μ_2 increases, $\tilde{c}$ increases and less buyers are constrained at time 2.

We assume a distribution over c_i for buyers at time 1. We assume

$$c \sim \text{Triangular}(\varepsilon, c^* + \varepsilon, m)$$

where ε is the lower bound of the support of the distribution, $c^* + \varepsilon$ is the upper bound of the support of the distribution and m represents the median. We choose this distribution for ease of computation. This distribution has a single peak at m and allows one to change the skewness of the distribution by simply increasing or decreasing m. This is beneficial for us since one of our goals is to determine the effect on the hedonic index and benefit index from changes in the skewness of the distribution of buyers. While it may be the case that no dataset follows a triangular distribution, it does have bounded support and a single peak which is probably a good first approximation to a typical dataset. This distribution has density

$$f(c) = \begin{cases} 2c/c^* m, & c < m; \\ 2(c^* - c)/c^*(c^* - m), & c \geq m. \end{cases} \tag{2.4.4}$$

For reference, see Johnson & Kotz (1970). Given this we can derive

$$P_i^0 = \exp(a + b\log(c_i)); \tag{2.4.5A}$$

$$\hat{P}_{Li} = \exp(a + b\log(c_i \exp(\gamma/(1-b))) + \gamma), \qquad c_i < \tilde{c}; \tag{2.4.5B}$$

$$\hat{P}_{Gi} = \exp(a + b\log(\tilde{c}\exp(\gamma/(1-b))) + \gamma), \qquad c_i \geq \tilde{c}; \tag{2.4.5C}$$

$$P_{Li}^* = \left(\frac{c_i - bc_i + bc_i \exp(\gamma/(1-b))}{c_i}\right)\exp(a + b\log(c_i)); \qquad c_i < \tilde{c}; \tag{2.4.5D}$$

$$P_{Gi}^* = \left(\frac{c_i - bc_i + b\tilde{c}\exp(\gamma/(1-b))}{c_i}\right)\exp(a + b\log(c_i)); \qquad c_i \geq \tilde{c}; \tag{2.4.5E}$$

where P^0, $\hat{P}$ and P^* have been defined previously. The L subscript represents buyers with $c_i < \tilde{c}$ and the G subscript represents buyers with $c_i \geq \tilde{c}$. Finally, we can specify our forward benefit index as

$$I^F = \int_{\varepsilon}^{\tilde{c}} \frac{\hat{P}_L}{P_L^*}\frac{2c}{c^*m}dc + \int_{\tilde{c}}^{m} \frac{\hat{P}_G}{P_G^*}\frac{2c}{c^*m}dc +$$

$$\int_{m}^{c^*+\varepsilon} \frac{\hat{P}_G}{P_G^*}\frac{2(c^*-c)}{c^*(c^*-m)}dc, \qquad \tilde{c} < m; \qquad (2.4.6A)$$

$$I^F = \int_{\varepsilon}^{m} \frac{\hat{P}_L}{P_L^*}\frac{2c}{c^*m}dc + \int_{m}^{\tilde{c}} \frac{\hat{P}_L}{P_L^*}\frac{2(c^*-c)}{c^*(c^*-m)}dc +$$

$$\int_{\tilde{c}}^{c^*+\varepsilon} \frac{\hat{P}_G}{P_G^*}\frac{2(c^*-c)}{c^*(c^*-m)}dc, \qquad \tilde{c} \geq m. \qquad (2.4.6B)$$

The prices P^0 and $\hat{P}$ are found by finding the point where the bid curve for each buyer is tangent to H_1 and H_2. We then determine P^* by substituting x_{2i} into the equation for the bid curve at time 1. The index is found by dividing the buyers into three separate groups; ε—$\tilde{c}$, $\tilde{c}$—m and m—$(c^* + \varepsilon)$. We then integrate over the various regions of c. The integrand is determined by substituting in the appropriate $\hat{P}$ and P^* (depending upon whether $c < \tilde{c}$ or $c \geq \tilde{c}$) and the appropriate density (depending upon whether $c < m$ or $c \geq m$). Given (2.4.5) and (2.4.6) we can determine the effects of changing m and μ_2. We do this in Examples 1 and 2.

__Example 1:__*Assume that $a = 1$, $b = 2$, $\gamma = -2$, $\mu_1 = 1$ and $\mu_2 = 4$. Given the setup just described, if m, the median of the distribution of buyers at time 1, increases, then the growth rate on the forward benefit index will increase and the average benefit to buyers will increase.*

We see in Table 2.4.1 that as m increases, implying a distribution that moves from skewed right to skewed left, the index at time 2 decreases. This in turn implies a higher growth rate and an increase in benefits, *i.e.* as the median buyer purchases a higher level of x, the average benefit to buyers increases. With μ_2 fixed, as m increases, a larger number of buyers necessarily get constrained at μ_2. However, at the same time that the average purchase at time 1 is getting larger, so is the average purchase at time 2. This implies that as m increases, more buyers take advantage of the extension in the product space (although for many buyers not as much as they would like). This result *in this example* implies that the benefits from taking advantage of extensions in the product space outweigh the constraints at μ_2.

The most important point to notice about Table 2.4.1 though is that the index at time 2 depends on the distribution of buyers at time 1. A hedonic index at time 2 would be $\exp(\gamma) = 13.53$ regardless of the distribution at time 1. Our benefit index thus clearly illustrates that all buyers do not benefit from improvements in product technology by the same amount and that a hedonic index misrepresents those benefits. In the case of our forward index we see that the bias of the hedonic index is to overstate the true benefits to buyers. The next chapter will provide an empirical example using data on the mainframe computer industry to see if this in fact holds true in that industry.

Example 2: *Assume that $a = 1$, $b = 2$, $\gamma = -2$ and $m = .5 + \varepsilon$ (which implies that buyers are distributed symmetrically over the product space). Given the setup previously described, if μ_2 increases, then the growth rate of the forward benefit index will decrease.*

Table 2.4.2 shows that as μ_2 increases I_2 increases, implying a lower growth rate and lower average benefits for buyers. This is counterintuitive to what we expected. μ_2 increasing has the effect of freeing up a constraint for buyers who would like to purchase more, thus allowing more benefit as a result of further extensions in the product space. This should result in a higher growth rate for the index. We get the opposite result. We fear that this result is a consequence of our definition of P^*. The way P^* is currently defined, as x_2 increases for an individual buyer, so does P^*. Since P^* is in the denominator for our index, this has the effect of changing the base for the index, *i.e.* while $P^* - \hat{P}$ may be increasing, since P^* is also increasing, it is not clear if the index will increase or decrease. A more appropriate definition of P^* would be the P that satisfies $\text{Bid}(x^0, P) = \hat{u}$ where $\hat{u}$ is the level of utility along Bid when Bid is tangent to H_2 at $\hat{x}$. The index would then be computed as $\frac{P^*}{P^0}$. Unfortunately, defining P^* in this way has the possibility of P^* being negative for some buyers.[7] We chose to avoid this problem by computing our index at $\hat{x}$ (which changes over time) rather than at x^0 (which remains fixed over time). It appears that this is a potential problem for the forward index. The reverse index that we will discuss later does not suffer from this problem and we feel it may be more appropriate. The important question for the forward index is: How close is the forward index to the reverse index? As an empirical matter this question is important because in practice the forward index is the easiest and most obvious to compute. In the next chapter we will consider this issue when comparing the forward index to the reverse index.

2.4.2 Reverse Index

Up to this point our example has focused on the forward index. Now we will assume we have a set of buyers at time 2 and we want to determine how much worse off they would have been had they faced H_1 instead of H_2. We will define

$$\tilde{c} = \{c \mid c\exp(\gamma/(b-1)) = \mu_1\}; \tag{2.4.7A}$$

$$c^0 = \{c \mid c\exp(\gamma/(b-1)) = \varepsilon\}; \tag{2.4.7B}$$

$$c^* = \{c \mid c = \mu_2\}. \tag{2.4.7C}$$

$\tilde{c}$ represents the level of c at time 2 for which buyers would choose to purchase μ_1 at time 1. c^0 represents the level of c at time 2 for which buyers would choose to purchase ε at time 1. c^* represents the maximum level of c at time 2. The bid curve will be given by

$$\text{Bid}_i: \qquad P = \delta_i + (\exp(a + b\log(c_i) + \gamma)\frac{b}{c_i})x \tag{2.4.8}$$

[7] Since the bid curve is concave it will lie below H_2 at x^0. Depending on how "low" H_2 is and the shape of the bid curve, we could have the bid curve falling below zero at x^0, implying a negative P^* and a negative index.

where δ_i is chosen so that the bid curve will be tangent to H_2 at time 2 and H_1 at time 1. This bid curve is chosen so that buyers will purchase $x_2 = c_i$. We again assume that all levels of x are purchased at time 2 and that the distribution of buyers over c is triangular. The prices are now defined as

$$P^0 = \exp(a + b\log(c_i) + \gamma), \qquad \varepsilon < c_i < c^* \qquad (2.4.9A)$$

$$\hat{P}_G = \exp(a + b\log(\tilde{c}\exp(\gamma/(b-1)))), \qquad \tilde{c} < c_i < c^* \qquad (2.4.9B)$$

$$\hat{P}_M = \exp(a + b\log(c_i\exp(\gamma/(b-1)))), \qquad c^0 < c_i < \tilde{c} \qquad (2.4.9C)$$

$$\hat{P}_L = \exp(a + b\log(c^0\exp(\gamma/(b-1)))), \qquad \varepsilon < c_i < c^0 \qquad (2.4.9D)$$

$$\begin{aligned} P_G^* = {} & \exp(a + b\log(\tilde{c}\exp(\gamma/(b-1)))) - \exp(a + b\log(c_i) + \gamma) * \\ & \frac{b}{c_i}\tilde{c}\exp(\gamma/(b-1)) + \exp(a + b\log(c_i) + \gamma)b, \qquad \tilde{c} < c_i < c^* \qquad (2.4.9E) \end{aligned}$$

$$\begin{aligned} P_M^* = {} & \exp(a + b\log(c_i\exp(\gamma/(b-1)))) - \exp(a + b\log(c_i) + \gamma) * \\ & \frac{b}{c_i}c_i\exp(\gamma/(b-1)) + \exp(a + b\log(c_i) + \gamma)b, \qquad c^0 < c_i < \tilde{c} \qquad (2.4.9F) \end{aligned}$$

$$\begin{aligned} P_L^* = {} & \exp(a + b\log(c^0\exp(\gamma/(b-1)))) - \exp(a + b\log(c_i) + \gamma) * \\ & \frac{b}{c_i}c^0\exp(\gamma/(b-1)) + \exp(a + b\log(c_i) + \gamma)b, \qquad \varepsilon < c_i < c^0 \qquad (2.4.9G) \end{aligned}$$

where P^0, $\hat{P}$ and P^* were defined previously. The G and L subscripts are as before and the M subscript represents buyers with $c^0 < c_i < \tilde{c}$. The index is defined as

$$\begin{aligned} I^R = {} & \int_{\varepsilon}^{c^0} \frac{P_L^*}{P^0}\frac{2c}{c^*m}dc + \int_{c^0}^{\tilde{c}} \frac{P_M^*}{P^0}\frac{2c}{c^*m}dc + \int_{\tilde{c}}^{m} \frac{P_G^*}{P^0}\frac{2c}{c^*m}dc + \\ & \int_{m}^{c^*+\varepsilon} \frac{P_G^*}{P^0}\frac{2(c^*-c)}{c^*(c^*-m)}dc, \qquad \tilde{c} < m \qquad (2.4.10A) \end{aligned}$$

$$\begin{aligned} I^R = {} & \int_{\varepsilon}^{c^0} \frac{P_L^*}{P^0}\frac{2c}{c^*m}dc + \int_{c^0}^{m} \frac{P_M^*}{P^0}\frac{2c}{c_m^*}dc + \int_{m}^{\tilde{c}} \frac{P_M^*}{P^0}\frac{2(c^*-c)}{c^*(c^*-m)}dc + \\ & \int_{\tilde{c}}^{c^*} \frac{P_G^*}{P^0}\frac{2(c^*-c)}{c^*(c^*-m)}dc. \qquad \tilde{c} > m \qquad (2.4.10B) \end{aligned}$$

The prices and index were found in the same fashion as we found the prices and index for the forward case. Examples 3 and 4 examine the effects of changing m and μ_1.

<u>Example 3:</u> *Assume that $a = 1$, $b = 4$, $\gamma = -2$, $\mu_1 = 1$, and $\mu_2 = 10$. Given the setup just described, if m increases, then the growth rate of the reverse benefit index will increase and buyers will be worse off at time 1.*

Table 2.4.3 shows that as the distribution of buyers becomes more skewed to the left, buyers on average will be worse off in the previous time period (as seen by a higher index number at time 1). This in turn implies a higher growth rate between time periods.

This result comes as a consequence of $\tilde{c}$ being fixed. With $\tilde{c}$ fixed, m increasing implies that more buyers will be constrained at μ_1 at time 1 (instead of being able to optimize at $x > \mu_1$ which was unavailable). This result is similar to what we saw with the forward index. In both instances, the changing distribution affected the number of buyers who were constrained and the number who could take advantage of extensions in the product space.

Hedonic indexes are unable to take into consideration this changing distribution. Tables 2.4.1 and 2.4.3 clearly show that changing this distribution affects the growth rate of the index and the average benefits buyers receive. Since a hedonic index does not account for this, it is likely that the hedonic index misrepresents the true benefits from improvements in product technology. However, the degree of misrepresentation is actually an empirical question and it must be investigated whether hedonic indexes come "close" to benefit indexes. The evidence from this example suggests that the bias would be for the hedonic index to overstate the true benefits to buyers from improvements in product technology, but the extent of the bias is unclear at this point. We will consider this issue in the next chapter when we look at the performance of various indexes in the mainframe computer industry.

<u>Example 4:</u> *Assume that $a = 1$, $b = 4$, $\gamma = -2$, $\mu_2 = 10$ and $m = 5$. Given the current setup, if μ_1 increases, then the reverse benefit index will have a lower growth rate and buyers* *will be better off at time 1.*

Table 2.4.4 shows that as μ_1 increases, the reverse index at time 1 takes on smaller values. This implies that buyers at time 1 are better off as μ_1 increases. While this point seems obvious, we found earlier that the forward index recorded less benefit when μ_2 increased. The result here implies that the reverse index may be more appropriate than the forward index for computing a benefit index. In theory, both indexes should be computable; however, as pointed out earlier, there may be a problem with computing P^*. So, while the forward index is the most obvious to compute, it may be quite far from the reverse index as a result of using a changing P^*. The important empirical question is: How close is the forward index to the reverse index? We will address this question in the next chapter.

The final point to note about these examples is that each benefit index computed shows a slower growth rate than the hedonic index. This is important because the hedonic is the index that is typically computed. The examples here show that the hedonic index will tend to overstate the true benefits to buyers from product innovation. This is in contrast to the results obtained by Trajtenberg (1990) who used data on computed tomography scanners. His results and discussion seem to imply that a benefit index should decline at a faster rate than a hedonic index. Our index is not directly comparable to his since he allows for "filling-in" the product space. However, the discrepancy between his results and ours can be described by looking at some simple features of the datasets. The CT scanner industry has the majority of buyers purchasing the highest level of characteristics available and the technology improving by a large degree, whereas we find exactly the opposite in computers with most buyers purchasing low levels of characteristics and only small increases in the levels of available characteristics. Since our index declines at a faster rate as buyers shift toward higher levels of characteristics, we would expect that moving all buyers to the highest level of characteristic and extending the product space by a large degree would result in our index declining at a higher rate than the hedonic index.

This section has compared a hedonic index with our forward and reverse benefit index. First, we found evidence to support the earlier claim that a benefit index will show a lower growth rate than a hedonic index. Second, we discovered a problem with our forward index which could lead it to provide incorrect results. Third, we found that the benefit index is sensitive to the distribution of buyers across the product space. We noted that this is a factor which the hedonic index cannot incorporate. Finally, we found that the benefit index is sensitive to extensions in the product space. Again, this is a factor which is not incorporated by a hedonic index.

2.5 CONCLUSION

This chapter has presented an analytical and numerical comparison of hedonic indexes and benefit indexes. We have shown that a benefit index which accounts for actual product purchases and extensions in the product space, as measured by previously unavailable product levels, will have a lower growth rate than a hedonic index in most cases. This is because buyers have a diminishing willingness to pay for higher product quality, *i.e.* as the level of product quality increases, buyers are willing to pay less for each unit of quality. This in turn implies that buyers benefit by less than a hedonic index would indicate.

We have also shown that in contrast to a hedonic index, our benefit index accounts for factors such as the distribution of buyers across the product space and extensions in the product space. These factors are important because buyers located in different portions of the product space do not benefit equally from improvements in product technology. The importance of these factors was demonstrated in section 2.4 in our numerical example.

Finally, we have shown that our 'forward' and 'reverse' benefit indexes may lead to quite different results regarding the benefits to buyers between two (or more) time periods. This occurs mainly because the forward index has a denominator which changes over time. If average product price per performance has fallen a great deal between time periods and/or the level of quality purchased at the initial time period is small, then the buyer may only be willing to pay a negative price. This price is obviously undefined and forced us to compute our forward index allowing our buyers base price to change over time. While we conclude that this is an obvious pitfall to our forward index, the important question concerns how close the forward index is to the (correct) reverse index. This question is an empirical one, and we will address it empirically in the next chapter using data on the mainframe computer industry from 1985–1991.

2.6 TABLES

2.4.1 Effect of Changing m on Forward Index	
m	I_2
0.10	51.29
0.20	50.99
0.30	50.62
0.40	50.11
0.50	49.41
0.60	48.38
0.70	47.11
0.80	45.77
0.90	44.46

Table 2.4.2 Effect of Changing μ_2 on Forward Index	
μ_2	I_2
2.00	34.09
3.00	43.52
4.00	49.41
5.00	52.28
6.00	53.39
7.00	53.62

Table 2.4.3 Effect of Changing m on Reverse Index	
m	I_1
1.00	288.37
2.00	293.67
3.00	300.09
4.00	306.44
5.00	312.12
6.00	317.09
7.00	321.42
8.00	325.23
9.00	328.61

Table 2.4.4 Effect of Changing μ_1 on Reverse Index	
μ_1	I_1
1.00	312.12
1.50	284.49
2.00	266.17
2.50	255.35
3.00	249.75
3.50	247.20
4.00	246.25
4.50	246.00
5.00	245.98

2.7 FIGURES

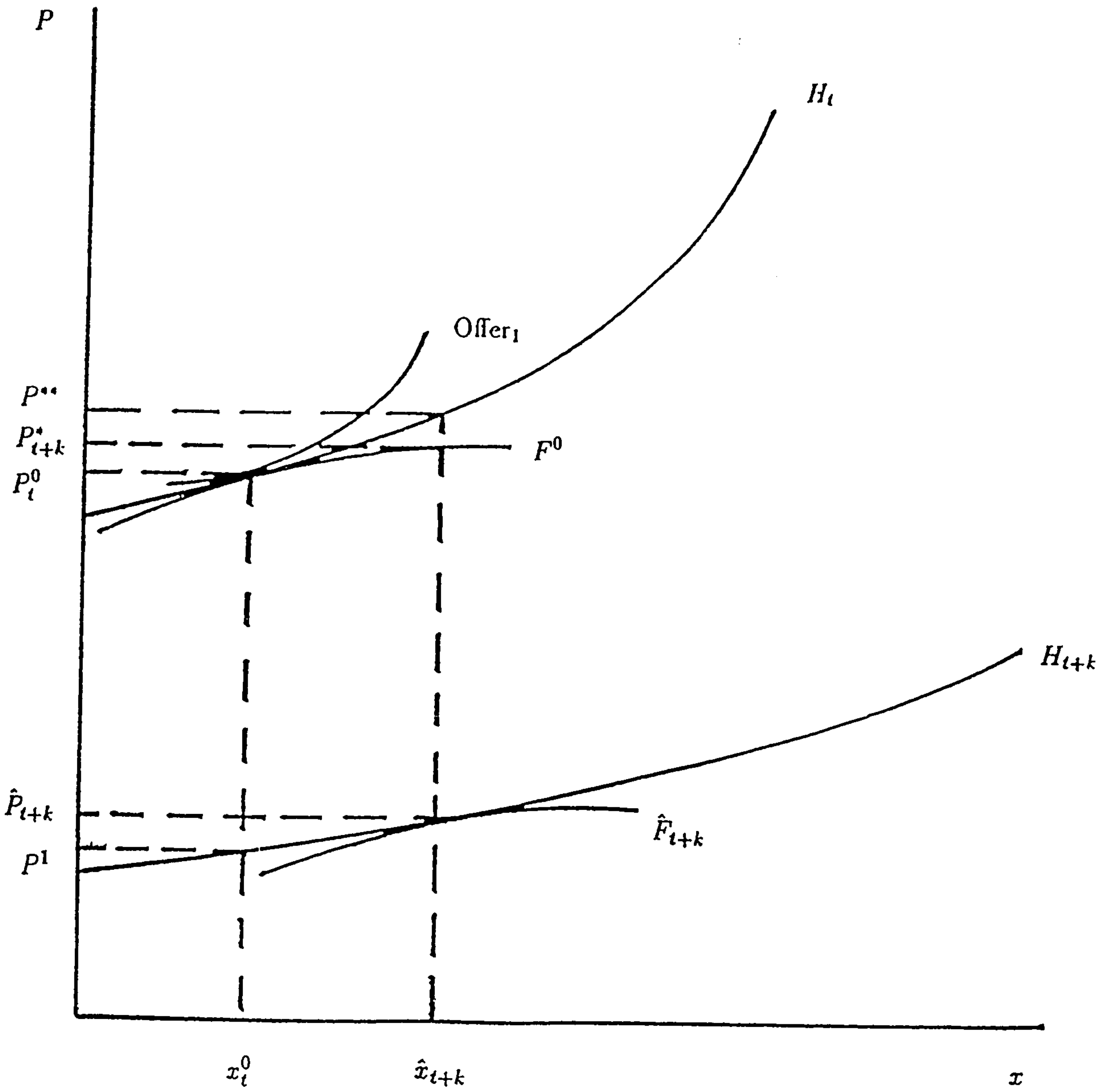


Figure 2.2.2

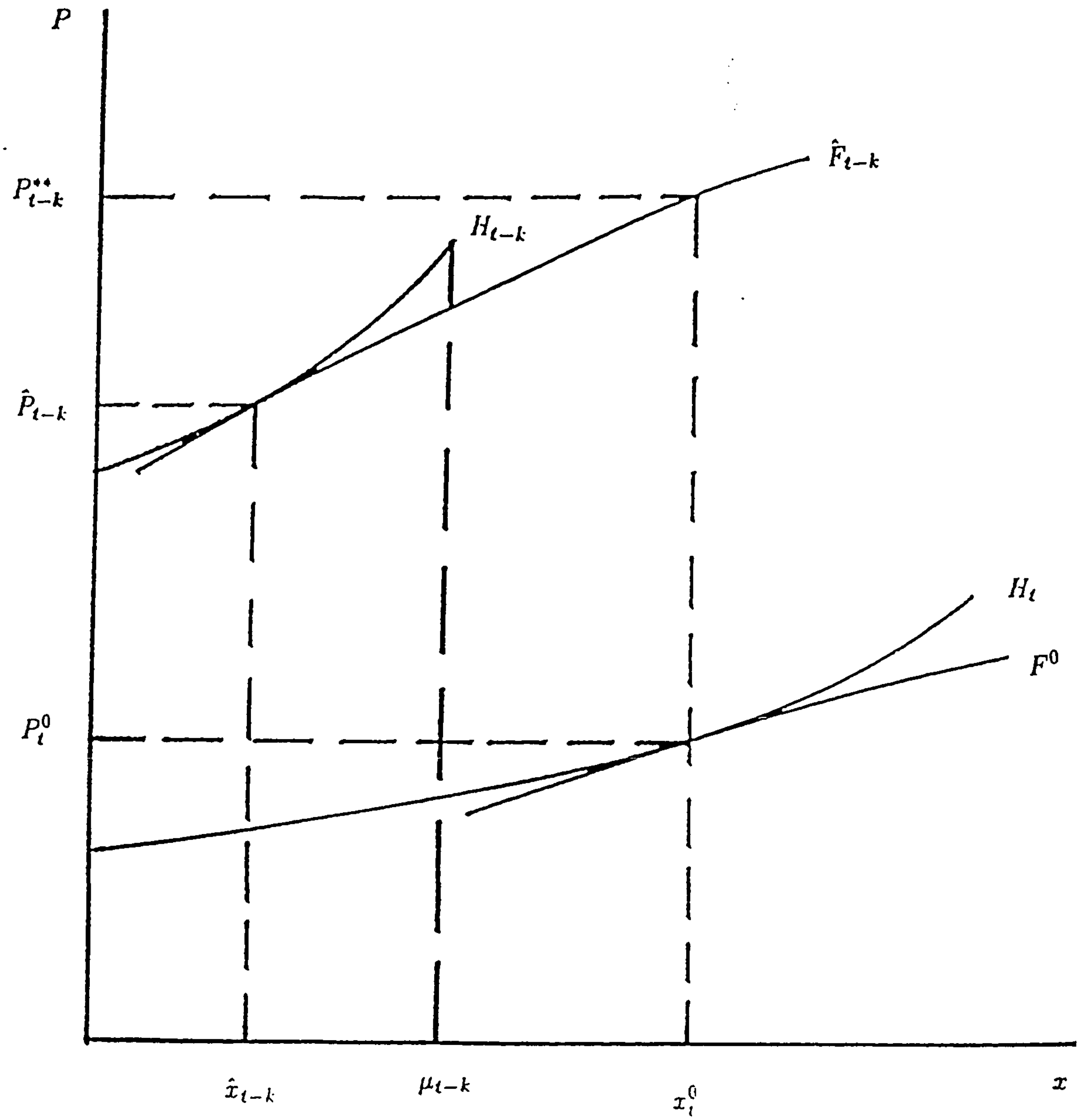


Figure 2.3.1

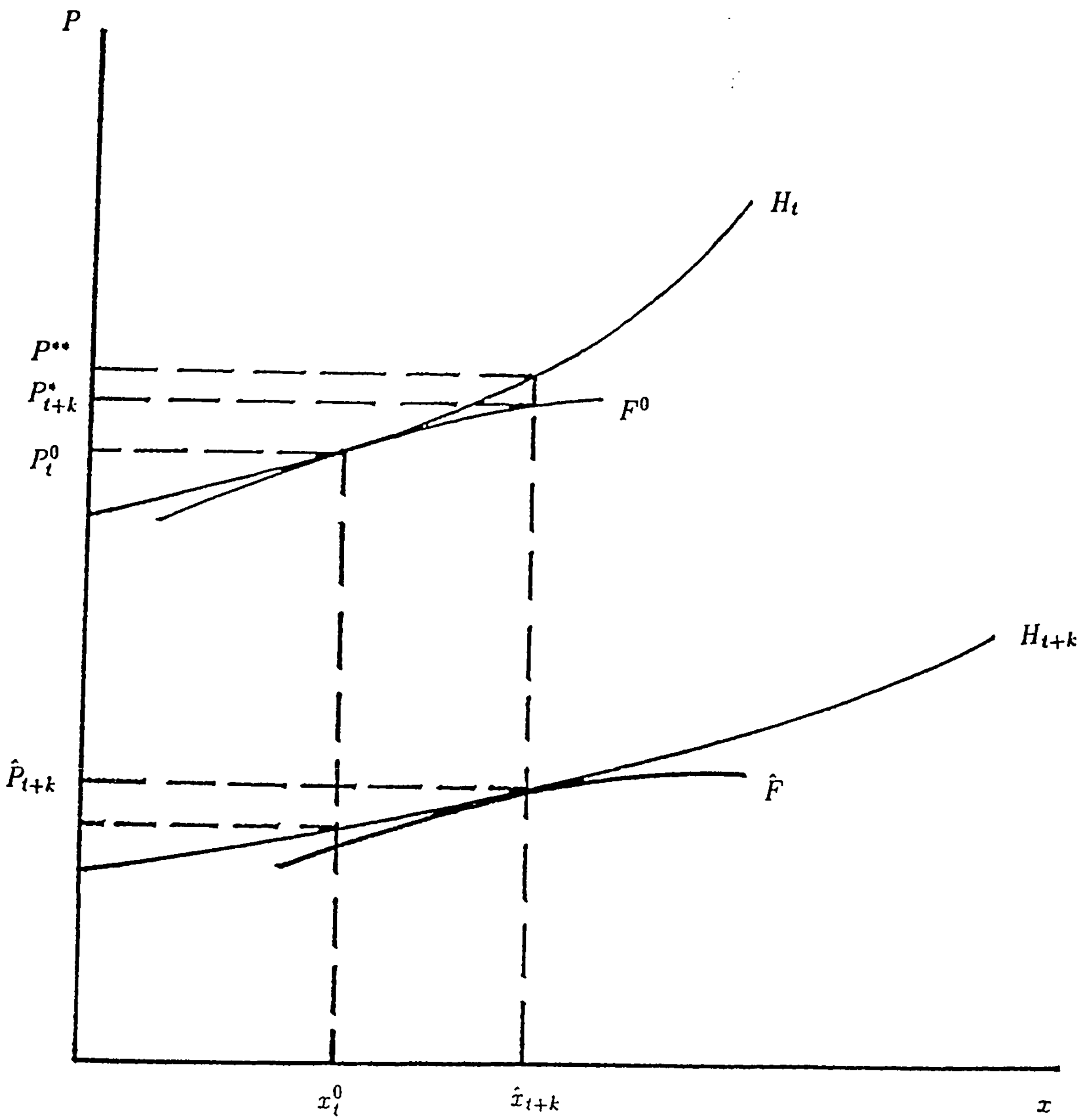


Figure 2.3.2

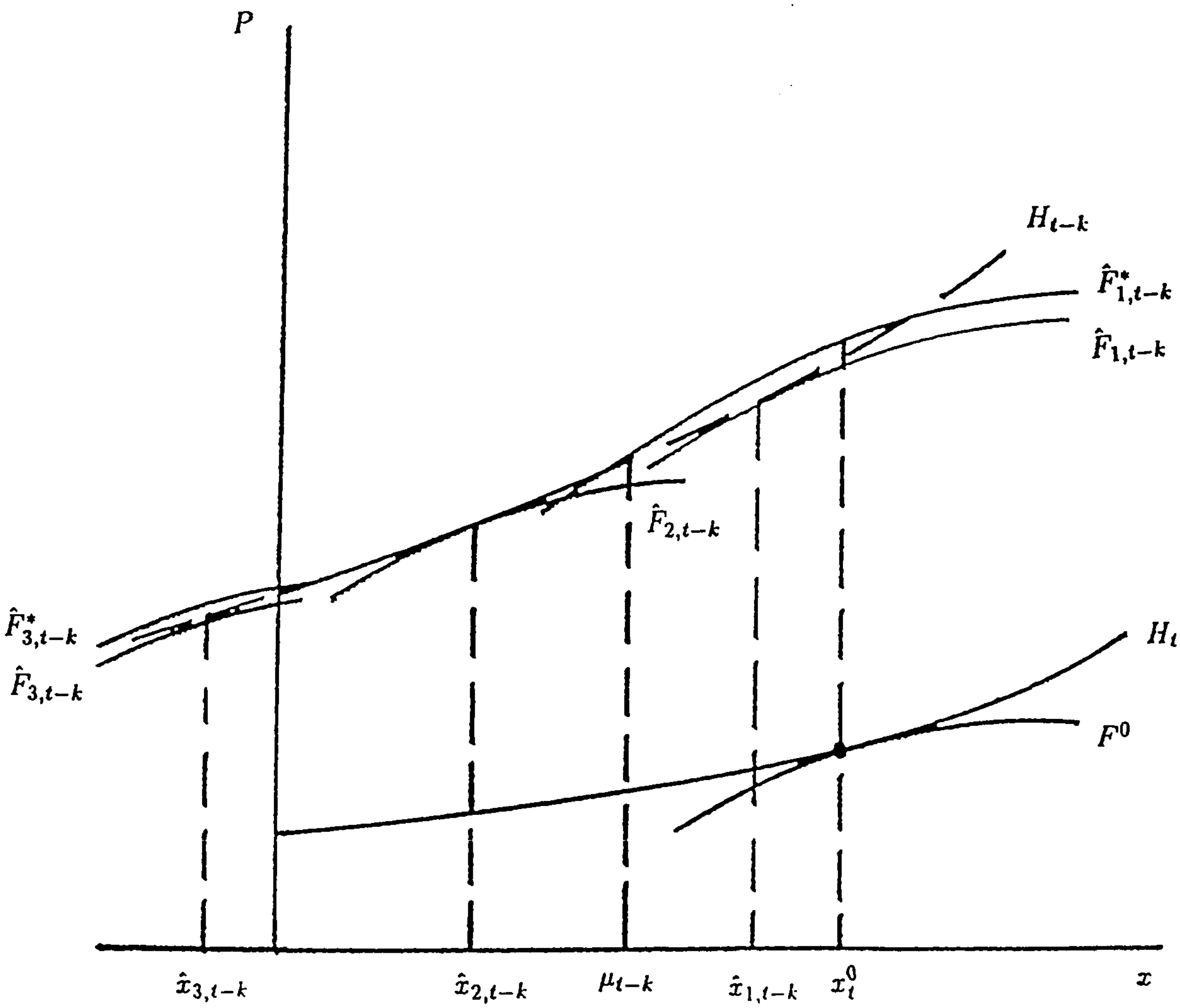
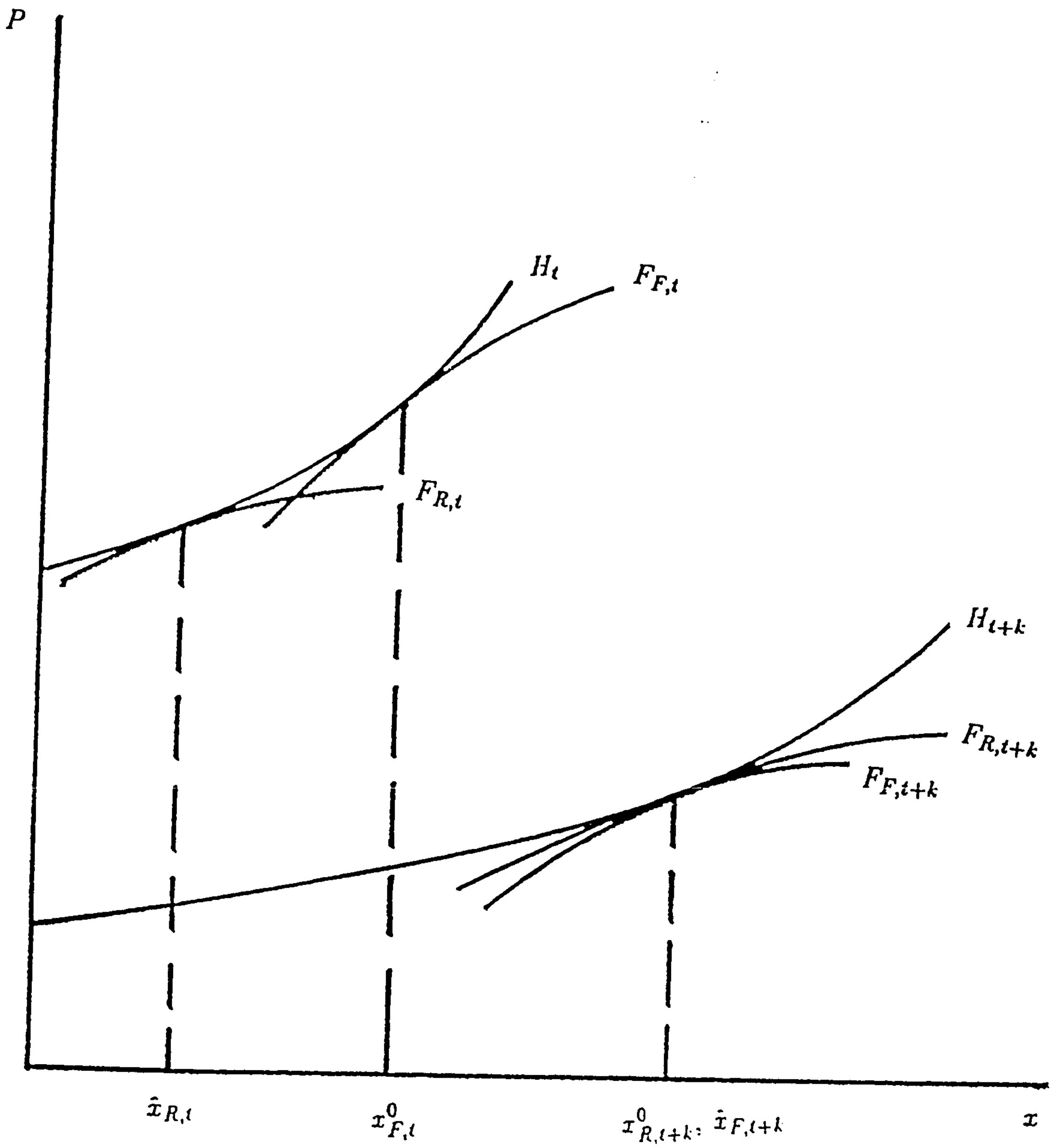

P
H_{t-k}
$\hat{F}^*_{1,t-k}$
$\hat{F}_{1,t-k}$
$\hat{F}_{2,t-k}$
$\hat{F}^*_{3,t-k}$
$\hat{F}_{3,t-k}$
H_t
F^0
$\hat{x}_{3,t-k}$
$\hat{x}_{2,t-k}$
μ_{t-k}
$\hat{x}_{1,t-k}$
x_t^0
x

Figure 2.3.3



CHAPTER 3

AN EMPIRICAL COMPARISON OF THE INDEXES

3.1 INTRODUCTION

Since the mid 1960s researchers have been computing hedonic price indexes to measure the quality-adjusted price changes that have been taking place in mainframe computers. This research shows that "price per performance" in mainframe computers has fallen rapidly over the past 30 years (Triplett 1989). The traditional method for computing hedonic indexes focuses on the average price change for mainframe computers holding product characteristics constant. These methods address the question: How much has price per unit of quality declined in mainframe computers over time? While the answer is of interest, a more interesting question is: How much do buyers *value* improvements in computer technology? In this chapter we propose a price index that accounts for the benefits to buyers from improvements in mainframe computer technology.

Such indexes are difficult to produce because buyers receive different benefits from technical change and an index must aggregate over these different experiences. Our index emphasizes two factors. First, we directly address the "repackaging" problem, *i.e.*, a single mainframe is not equivalent to, but superior to, two mainframe computers embodying one-half the characteristics. This permits us to explicitly account for "extensions in the product space" that result from technical change, thus we measure the benefits buyers receive from moving to previously infeasible portions of the product space. Second, we allow for diminishing marginal utility in product characteristics. While this is a natural assumption for an economic analysis, it contrasts sharply with approaches used previously, as explained below. We expect our index to differ from a hedonic because traditional hedonic methods because the latter do not incorporate these factors, measuring only the change in the intercept between different hedonic surfaces. The interesting empirical issue concerns whether our utility-based index differs from a traditional hedonic, and if so, by how much.

The data set that we use differs from data used in previous studies. We observe 21,268 acquisitions of mainframe computers from 1985 to 1991 as surveyed by the Computer Intelligence Corporation. We observe characteristics of the purchases being made and the characteristics of the firms making those purchases. Previous work only had data on the set of systems available for sale. Our more detailed data allows us to measure the benefits each buyer receives from technological change, rather than simply measuring the displacement of the hedonic price–quality relationship.

We show that our index declines at a much slower, although still quite fast, rate than the hedonic index, implying that hedonic methods overstate the true benefits buyers receive from improving technology in mainframe computers. The results have a number of implications. First, our results differ from those of Trajtenberg (1990). His work on CT-scanners implied that utility based indexes would account for more technological innovation than hedonic indexes and thus would decline at a faster rate. We find the opposite, and argue that this occurs because all buyers have a declining marginal bid for characteristics, which outweighs the benefits received bya few from extensions in the product space. Second, the rate of decline in the utility index depends on the set of buyers used to compute the index. Hedonic methods are unable to account for this distribution of buyers at all. We find that weighting by historically later sets of buyers tends to lead to faster rates of decline in our utility-based index. We explain why in the text. Third, these results imply that the U.S. Government indexes, computed using traditional hedonic methods, may be inadequately measuring the benefits associated with quality-adjusted price changes. This is because hedonic methods do not take into consideration how buyers value the set of computers actually being purchased, but instead only take into consideration the price per unit of characteristic of the set of computers available for sale.

The results in this chapter are obtained using a special functional form—one that allows easy computation. We are aware that our results may be sensitive to that choice. However, we do not fully explore this issue in this chapter since doing so detracts from our main point. We will pursue it in the next.

The next section of this chapter will describe the methodology we will follow to arrive at our estimated price index. In addition we will describe the procedure for computing a traditional hedonic index, and point out the differences between the two methods as we go along. The third section will describe the dataset to be used for this analysis. Our ability to employ our methodology is a result of the detailed dataset we have on the characteristics and behavior of buyers in the mainframe computer market. This type of data has not been analyzed for this purpose previously and allows us to move forward in new directions. The fourth section describes the specific models that we look at and gives the main results of the paper. It is here that we compute our utility-based, "cost-of-living" index along with a traditional hedonic index and point out the disparity between the two. In section 5 we give concluding remarks and directions for later research.

3.2 METHODOLOGY

3.2.1 Review

Beginning in 1967 with Chow's pioneering work on the growth in demand for computer services, many authors have looked at the question of how best to measure technological change in computers. Essentially all of this work has used hedonic methods to derive quality-adjusted price indexes for various computer components. These methods were accepted in 1986 by the U.S. Department of Commerce, Bureau of Economic Analysis, for determination of the official computer price index—an index that was previously assumed to be 100 over the entire 1953–1985 time period (Berndt,1991,p.123). The consensus from hedonic studies on improvements in the mainframe computer industry is that over the last 30 years, improvements in price per performance occurred at roughly 15 to 25 percent per year (Triplett 1989).

The most frequently employed method for obtaining these indexes is the dummy variable method. This method estimates

$$g(P_{it}) = \beta_0 + \sum_j \beta_j h(x_{ijt}) + \sum_{t=2}^{T} \beta_t D_{it} + \varepsilon_i \tag{3.2.1}$$

where i indexes the observations, j indexes the computer characteristics respresented by x, t indexes time and g and h are typically taken to be logarithmic functions; however, other choices have been employed.[8] The D_t are time dummy variables and the β_t coefficients estimate the change in price not accounted for by changes in the characteristics. Assuming we take g and h as natural logarithms, the index is computed by setting the index in the excluded year to 100 and exponentiating the estimated β_t coefficients.[9]

Trajtenberg (1990) argued that innovations should be measured in terms of their value to users, following a long literature of cost-of-living indexes and welfare economics of innovation. He outlined an approach based on hedonic price functions and discrete choice models. The main idea was to measure the benefits buyers received from facing alternative choice sets. This argument emphasized two factors—the difference between *buyer* location and *product* location in the product space, and extensions in the product space.

In estimating demand for characteristics he ran into the problem of upward sloping demand curves. He argued that this came as a result of a correlation between unobserved quality characteristics and price. In a logit setting, this problem has no solution without explicit modeling of the random error (See Berry, Levinsohn & Pakes (1993). We expect a similar scenario with mainframe computers as it has often been argued that there exist many unmeasureable characteristics.[10] For this reason, we chose not to follow the procedure described by Trajtenberg.

[8] In Triplett's (1989) survey of research on computers, 17 of the 23 papers discussed chose this log-log specification. Only 4 of these 17 papers tested this functional form against any others. Two papers chose a linear form and two chose a log-linear form.

[9] $\exp(\hat{\beta}_t)$ is a biased estimate of $\exp(\beta_t)$, implying that the index is also biased. One correction is to add one-half of the coefficient's variance to the estimated coefficient (Triplett 1989).

[10] See for example Berndt (1991)

We employ an alternative approach, estimating demand directly from the estimated hedonic price function as in Rosen (1974), and using those estimates to measure surplus changes associated with technological change. This methodology has the advantage that its strengths and weaknesses are well known (e.g. Brown and Rosen 1982, Diamond and Smith 1985, Bartik 1987 and Epple 1987). In addition, it is well suited for directly computing the effects of the distribution of demand on the differences between a traditional hedonic index and a utility based index. Therefore, we continue in the next section to review Rosen (1974) and to discuss the issues surrounding his proposed methodology.

3.2.2 Rosen (1974)

Rosen (1974) suggested an econometric methodology to identify the demand and supply parameters in a differentiated product market. Rosen observed that a hedonic price function represents a locus of equilibrium transactions between buyers and sellers. This surface represents an upper envelope of buyers' bid functions and a lower envelope of sellers' offer functions (see Figure 3.2.1). Transactions occur where these bid and offer curves are tangent. As a consequence, the marginal hedonic price function represents the locus of intersections between buyers' marginal bid and sellers' marginal offer curves (see Figure 3.2.2). The questions is: how can one identify these marginal bid and/or marginal offer curves econometrically? Rosen suggested estimating the following system of equations

$$p_j(x) = F^j(x_1, \ldots, x_n, Y_1) \qquad \text{Demand} \tag{3.2.2}$$

$$p_j(x) = G^j(x_1, \ldots, x_n, Y_2) \qquad \text{Supply.} \tag{3.2.3}$$

Here, p_j represents the estimated marginal price for characteristic j, defined as the first derivative of the hedonic function at the observed levels of characteristics, and x_j represents the observed levels of characteristics (the same ones used when estimating the hedonic surface in (3.2.1)). Because of the nonlinearity of the hedonic surface, seen in Figure 3.2.1, buyers and suppliers simultaneously choose both the levels of characteristics and the marginal prices for those characteristics (given by the slope of the hedonic surface). This implies that the system given by (3.2.2) and (3.2.3) has $2n$ equations and $2n$ endogenous variables (where n represents the number of characteristics). Y_1 and Y_2 represent exogenous demand and supply shift variables. These are simply characteristics of corresponding buyers and suppliers. Given this setup, Rosen suggested that this was a typical identification problem to be estimated by some simultaneous equations method.

Since this work, a great deal of discussion has refined the suggested methodology, including Brown & Rosen (1982), Diamond & Smith (1985), Bartik (1987) and Epple (1987), as well as others. Each has argued that this is not a typical identification problem, and each has suggested alternatives to the original methodology. In the next section, we develop the methodology we will follow to obtain estimates of demand, point out the identification problems these other papers have addressed and employ the solutions they have proposed.

3.2.3 Estimating Demand

Following the suggestions of Brown and Rosen (1982) and Diamond and Smith (1985) we make two initial assumptions. First, we assume that the demand parameters are the same for all buyers and do not change over time. Each buyer's demand is differentiated only by a set of buyer characteristics used to describe the heterogeneity among buyers. Second, we assume that supply is exogenous to buyers and that demand can be estimated without estimating supply. Diamond and Smith argued that this was reasonable since the source of simultaneity in this model does not arise between a buyer and a computer system. Instead, movements by buyers are to new systems rather than along the offer curve of the same system.[11] This implies buyers take the hedonic price function as exogenous and simply locate themselves on it.

We begin by estimating a hedonic price function for each year which is exogenous to each buyer. These functions take the form

[11] This follows from the typical assumption that each supplier produces only one product and each buyer purchases only one. We assume that there exists an offer curve for each system rather than each supplier.

$$g_t(P_{it}) = h_t(x_{1it}, \ldots, x_{nit}, \varepsilon_{it}) \quad t = 1, \ldots, T \tag{3.2.4}$$

where x_j represents the j^{th} computer characteristic and g and h are some functions which may change over time. ε represents the error term. We estimate (3.2.4) separately for each year.[12]

The next step is to differentiate (3.2.4) with respect to each of the x_j's to obtain n marginal price functions for each year. Each of these functions is a function of the n computer characteristics. Denote these functions by mp_{ijt}. With these mp_{ijt} functions we compute estimated marginal prices for the characteristics by evaluating the mp_{ijt} at the observed levels of characteristics to obtain $\widehat{mp_{ijt}}$. This yields n vectors of estimated marginal prices for each year. We combine these vectors to obtain a marginal price vector for each characteristic.

The next step is to estimate demand of the form

$$\widehat{mp_{ij}} = f(x_{1i}, \ldots, x_{ni}, B_i, \nu_i). \tag{3.2.5}$$

Because in general the x_{ij} in (3.2.5) are correlated with ν_i, we must provide instrumental variables for the estimation of (3.2.5) (Epple 1987, Bartik 1987). Plausible instruments, as described by Bartik (1987), should be correlated with the choice of computer characteristics but uncorrelated with unobserved tastes.

B represents buyer characteristics and describes the heterogeneity among buyers. While the shape of each individual demand curve is the same as any other, the B portion of (3.2.5) will shift the demand curves. The location of any demand curve is described completely by B.

At this point a number of issues arise. Recall that in the first step we estimated (3.2.4) separately for each year t. Brown and Rosen (1982) pointed out that if (3.2.4) were estimated as a pooled regression with all years included, estimation of (3.2.5) may not yield

[12] As stated earlier, g is usually taken to be logarithmic and h as the sum of the logarithms of the x_j's. However, we will not attempt to use this form in the computation of our utility index because of the computational difficulties that will arise in attempting to solve a system of nonlinear equations.

any new information since it is a function of the same n characteristics. For example, if (3.2.4) were quadratic and (3.2.5) linear, then the marginal price functions, mp_{ij}, would be linear functions of the x_j. Thus, since (3.2.5) is also linear and a function of the same n characteristics, there would be nothing to estimate. The coefficients in (3.2.5) could be determined directly from the coefficients in (3.2.4). Brown and Rosen suggested that one way around this without imposing any functional form restrictions would be to estimate (3.2.4) separately for each market (here distinguished by time). This would result in a different marginal price function for each year and, assuming the demand function was constant over time, a meaningful estimate in (3.2.5). Of course there needs to be a significant difference between the estimates in (3.2.4) for this to hold true. This suggestion was reiterated by Diamond and Smith (1985) and employed by Bartik (1987).

One of our main concerns at this point is the requirement that demand parameters remain constant over time for all buyers. While the assumption is being employed in order to identify demand parameters, it is not clear that this is really plausible for this industry. However, the time period we are looking at is during a mature stage of the mainframe computer industry. Thus, it could be argued that buyers are aware of the relative values of the characteristics throughout the entire time frame and that these values do not change. In other words, buyers know how important computing speed is relative to memory, and the relative valuation of the two does not vary during the period. We intend to investigate this assumption further in future work.

Another issue concerns estimating supply. We have said that we will assume supply is exogenous to buyers. However, this is an industry clearly dominated by a few large firms, and it is possible that they influence the shape and location of the hedonic surface. This would then imply that changes we see in a computed index are not solely attributable to technological change but instead to a combination of technological change and firm market power. Since our goal is to measure the benefits that accrue to buyers from facing different choice sets, and not the sources of those benefits, this fact should have little affect on our results. An additional point to make regarding this is that Diamond and Smith (1985) argue that either side of the market can be estimated without regard to the other side. This follows from the assumption that buyers do not move *along* a system's offer curve or systems *along* buyers' bid curves, but instead movements are along the market price function, which implies movements to *new* systems or *new* buyers. If we later incorporate supplier behavior, as we hope to do in the future, we will reconsider our specification.

Having pointed out these caveats, we proceed to estimate (3.2.5) separately for each characteristic using the estimated marginal prices as the regressor. This will yield n separate demand equations which can be used to compute a price index.

3.2.4 Computing a Price Index

Once we have estimated demand, we are ready to compute a utility-adjusted price index. Our procedure mirrors Trajtenberg's (1990) idea of measuring quality change by the "hypothetical price change that would have resulted in the same welfare effect" (p 31). First, let us summarize the entire procedure. The index is computed by taking the buyers in each year, t, and placing them into consecutive later years, $t+1, \ldots, T$, to determine what set of characteristics they would have purchased had they actually faced a later year's set of choices as represented by the hedonic price function. The new set of characteristics is computed by finding the point at which each buyer's demand curve intersects the marginal hedonic price functions for the later year. We then compute the price that this new set of characteristics would have cost in year $t+k$. Call this a "counterfactual price." We then compute the price that this set of characteristics would have cost in year t, while holding the buyer's utility constant at the level observed in year t. Call this a "constant-utility price." The ratio of these two prices, the constant-utility price and the counter-factual price, is the index for this buyer. We then compute a weighted average of all individual's indexes using either the expenditure observed in year t or the constant-utility price as the weights. This is depicted in Figure 3.2.3 for a single individual and a single computer characteristic.

We now describe this more formally. This model is similar to a consumer's utility maximization problem. Here we have a buyer solving the problem:

$$\max \quad u(x, P) \quad st. \quad P = H_t(x) \tag{3.2.6}$$

where u represents the buyer's utility from purchasing characteristics x for price P, H_t is the hedonic price function at time t, x is a vector of product characteristics and P is the product price. H is assumed to be twice continuously differentiable with $\mathrm{d}H/\mathrm{d}x > 0$. u is chosen such that $u_x > 0$, $u_{xx} < 0$ and $u_P < 0$. Solving this problem yields a solution (x_t^0, P_t^0). We assume that u is additively seperable in characteristcs, although this could be relaxed. The first order condition for (3.2.6),

$$\nabla u(x, H_t(x)) = 0, \tag{3.2.7}$$

implies an optimal choice for x at time t, which we will call x_t^0. Given this, we define $P_t^0 = H_t(x_t^0)$ and $\mathrm{u}^0 = u(x_t^0, P_t^0)$. Using (3.2.7), but substituting $H_{t+k}(x)$ for $H_t(x)$, we obtain an optimal solution for x at time $t + k$, which we call $\hat{x}_{t+k}$. We then define $\hat{P}_{t+k} = H_{t+k}(\hat{x}_{t+k})$ and $\hat{\mathrm{u}}_{t+k} = u(\hat{x}_{t+k}, \hat{P}_{t+k})$. Finally, we define P^*_{t+k} as the P that satisfies $u(\hat{x}_{t+k}, P) = u^0$.

In words, P_t^0 is the *observed* price the buyer paid for the observed set of characteristics at time t, $\hat{P}_{t+k}$ is the *counter-factual* price the buyer would pay for the counter-factual set of characteristics when facing the hedonic surface at time $t + k$ and P^*_{t+k} is the *constant-utility* price the buyer would pay to purchase the counter-factual set of characteristics while remaining at the level of utility observed at time t, u^0. u^0 is the level of utility the buyer achieved at time t, and $\hat{\mathrm{u}}$ is the level of utility the buyer would achieve at time $t+k$ assuming demand is constant over time.

To compute an index for a single buyer, we need to know the level of characteristics that would have been purchased had the buyer actually faced H_{t+k} rather than H_t as shown in Figure 3.2.3. This is given by $\hat{x}_{t+k}$ defined above. At time $t+k$ this bundle of characteristics will cost $\hat{P}_{t+k}$ and the buyer will achieve a level of u equal to $\hat{\mathrm{u}}_{t+k}$.

Next, we need to determine the price $\hat{x}_{t+k}$ would have cost the buyer had $\hat{x}_{t+k}$ been purchased instead of x_t^0 in year t holding the buyer on the same bid curve, u^0. The reason that we can hold $\hat{x}_{t+k}$ constant when moving from time $t+k$ back to time t is a consequence of our assumption that demand remains constant over time. We actually shift H_{t+k} vertically until it is tangent to u^0. Since demand does not change over time, when we shift H_{t+k} parallel, it will be tangent to u^0 at the same x that it was tangent to $\hat{u}_{t+k}$, namely $\hat{x}_{t+k}$. Thus we only need to find the price of $\hat{x}_{t+k}$ on the bid curve of the observed year, u^0. This is P^*_{t+k} defined above and shown in Figure 3.2.3.

Unfortunately, the bid curve u^0 is unobserved. All we know is the observed price, P_t^0. However, the demand curve (3.2.5) is actually an estimate of the slope of the marginal bid curve, $u^{0\prime}$. Therefore, if we integrate the demand function between x_t^0 and $\hat{x}_{t+k}$, this gives us the difference between P_t^0 and P^*_{t+k}. If we then add P_t^0 to this amount, this gives us the price we are looking for—P^*_{t+k}.

Now, we set the base year for our index to the year the buyer is observed. If t is the year we observe the buyer, then we compute

$$\frac{I_{t+k}}{I_t} = \frac{P^*_{it+k} - \hat{p}_{it+k}}{p^*_{it+k}} \tag{3.2.8}$$

where t represents the observation year and $t+k$ some later year. We compute this index for each buyer observed in year t.

The final step is to aggregate these individual indexes into a single index. We choose to create a weighted average of these individual indexes, using either P_t^0 or P^*_{t+k} as the weights. Thus, we compute both

$$1 - \frac{\sum_i P_{it}^0 \frac{P^*_{it+k} - \hat{P}_{it+k}}{P^*_{it+k}}}{\sum_i P_{it}^0}, \text{and} \tag{3.2.9A}$$

$$1 - \frac{\sum_i P^*_{it+k} \frac{P^*_{it+k} - \hat{P}_{it+k}}{P^*_{it+k}}}{\sum_i P^*_{it+k}} \tag{3.2.9B}$$

$$= \frac{\sum_i \hat{P}_{it+k}}{\sum_i P^*_{it+k}}. \qquad (3.2.9C)$$

These choices of weights allow the index to account for the distribution of buyers across the product space. Notice that they also represent a ratio of surplus to expenditure. It turns out that with our data, the difference between using P_t^0 and P_{t+k}^* as weights is minimal. We compute an index of this type for each year t from $t = 1$ through $t = T - 1$ with year T as 100 in each index. Doing this allows us to examine how the index changes as the distribution of buyers changes.[13]

Up to this point we have only considered the benefits received from buyers in year t when given the alternative choice set at time $t+k$. However, in an analagous fashion, we can measure the benefits received from buyers in year t when given the alternative choice set at time $t-k$. P_t^0 is still defined as the observed price for the observed set of characteristics, and $\hat{P}_{t-k}$ is still defined as the counter-factual price for the counter-factual set of characteristics. P_{t-k}^{**} will now be defined as the P that solves $u(x_t^0, P) = \hat{u}$, or the price that the buyer would pay to purchase the observed set of characteristics while remaining on the counter-factual bid curve. The index for an individual buyer, using P_t^0 as the weight, is computed as

$$1 + \frac{\sum_i P_{it}^0 \frac{P_{it-k}^{**} - P_{it}^0}{P_{it}^0}}{\sum_i P_{it}^0}, \qquad (3.2.10A)$$

$$= \frac{\sum_i P_{it-k}^{**}}{\sum_i P_{it}^0}. \qquad (3.2.10B)$$

We will call the index computed in this fashion the "reverse index."[14] Again notice that this is a ratio of surplus to expenditure.

There are two potential problems with computing our counter-factual levels of characteristics. First, it is possible that a buyer will choose a counter-factual set of characteristics

[13] Note that in computing this index we have compared utility levels at the counterfactual level of characteristics. Since our bid curve is concave, if we compared utility levels at the observed level of characteristics we might be confronted with a negative counterfactual price. We avoid this problem by restricting our attention to the counterfactual level of characteristics.

[14] We will call the index described earlier where buyers go from t to $t + k$ the "forward index."

which is larger than the largest system that was available at time $t-k$. When this occurs, we give the buyer the largest set of characteristics which was available at time $t-k$. We refer to this as "buyers hitting a corner." Second, depending on the slope and location of the demand curve, it is possible that a buyer will choose to purchase a negative set of characteristics. When this occurs, we assume the buyer would no longer be in this market, but would instead be in a market for some smaller computer, say a minicomputer. In this case, we compute the utility level which would leave the buyer indifferent between being in the mainframe market and some alternative market. This utility level occurs where H_{t-k} and $\hat{u}$ are tangent at zero.

The procedure described here yields an index which adjusts for quality changes and at the same time takes into account the buyer's demand for characteristics. In addition, the final index weights each buyer by either their observed level of expenditure or by a constant-utility level of expenditure which will then allow the index to account for the distribution of buyers in the product space. A hedonic index computed by the dummy variable method does not account for changes in the marginal utility of characteristics, nor does it account for the distribution of buyers. Instead it looks only at the rate at which the intercept of the hedonic surface is changing. Based on these differences it is not clear whether our index should have a higher or lower growth rate. We will compare indexes computed using both methods in our Results section.

3.2.5 Figures

Figure 3.2.1

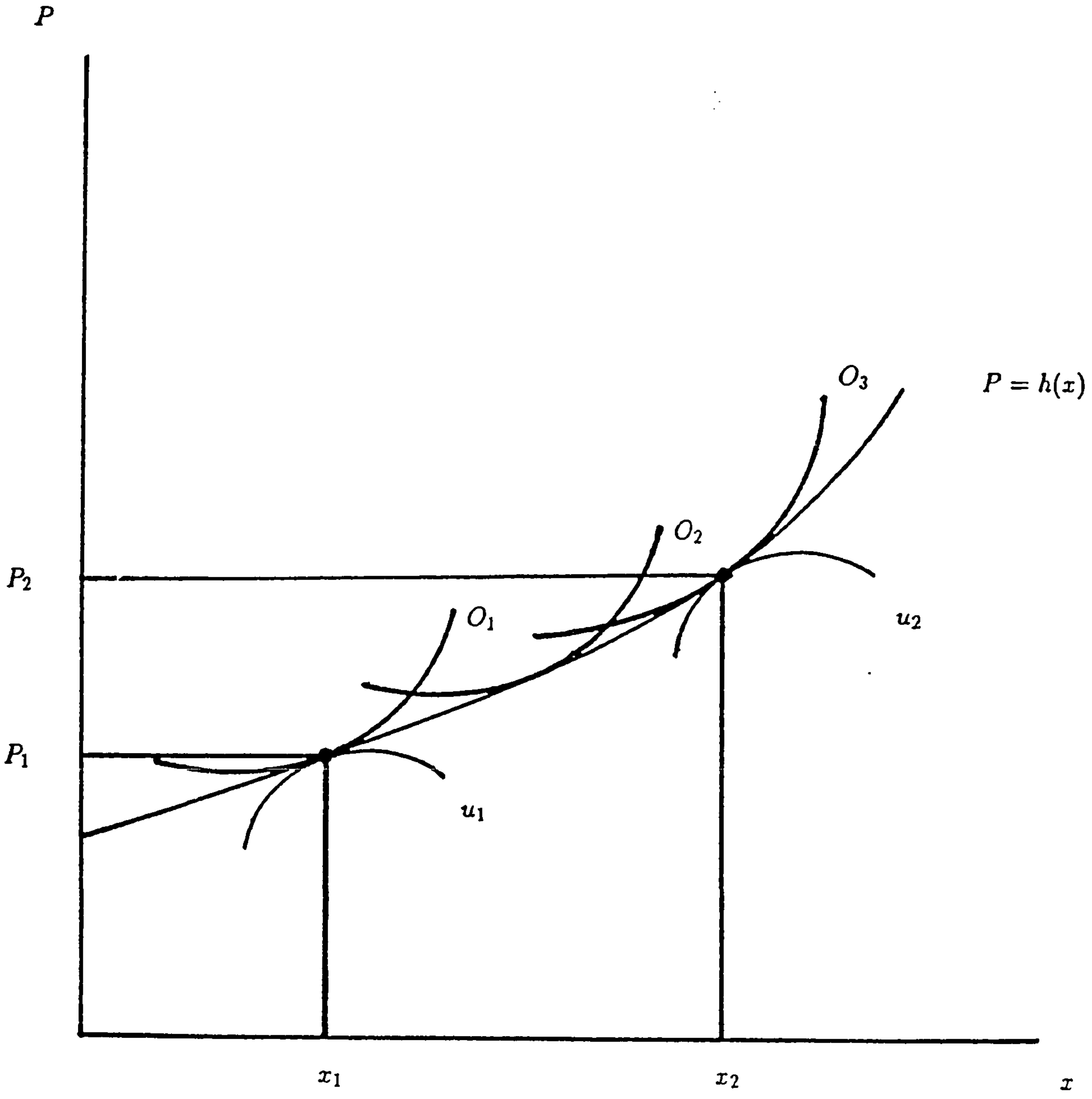


Figure 3.2.2

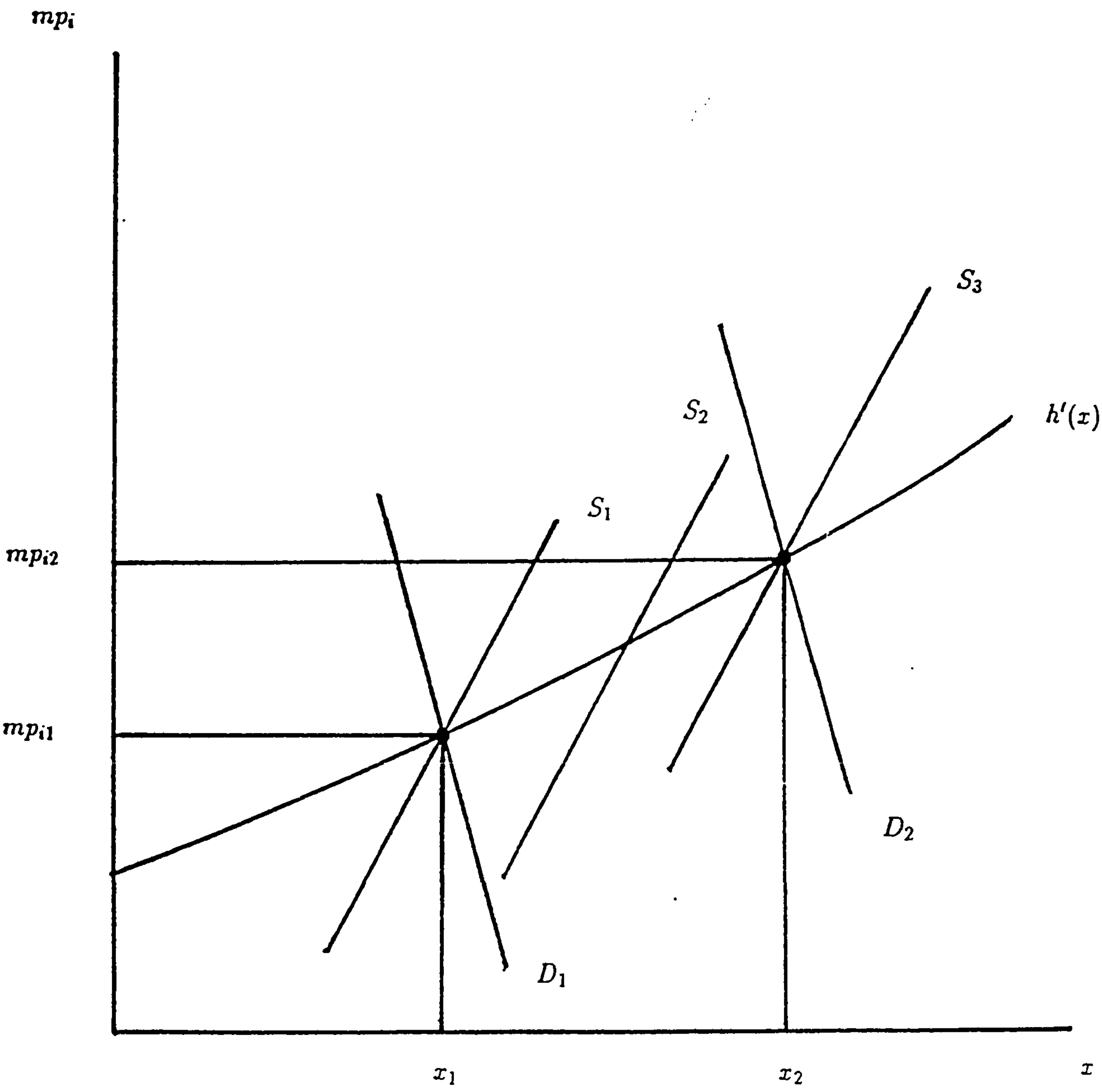
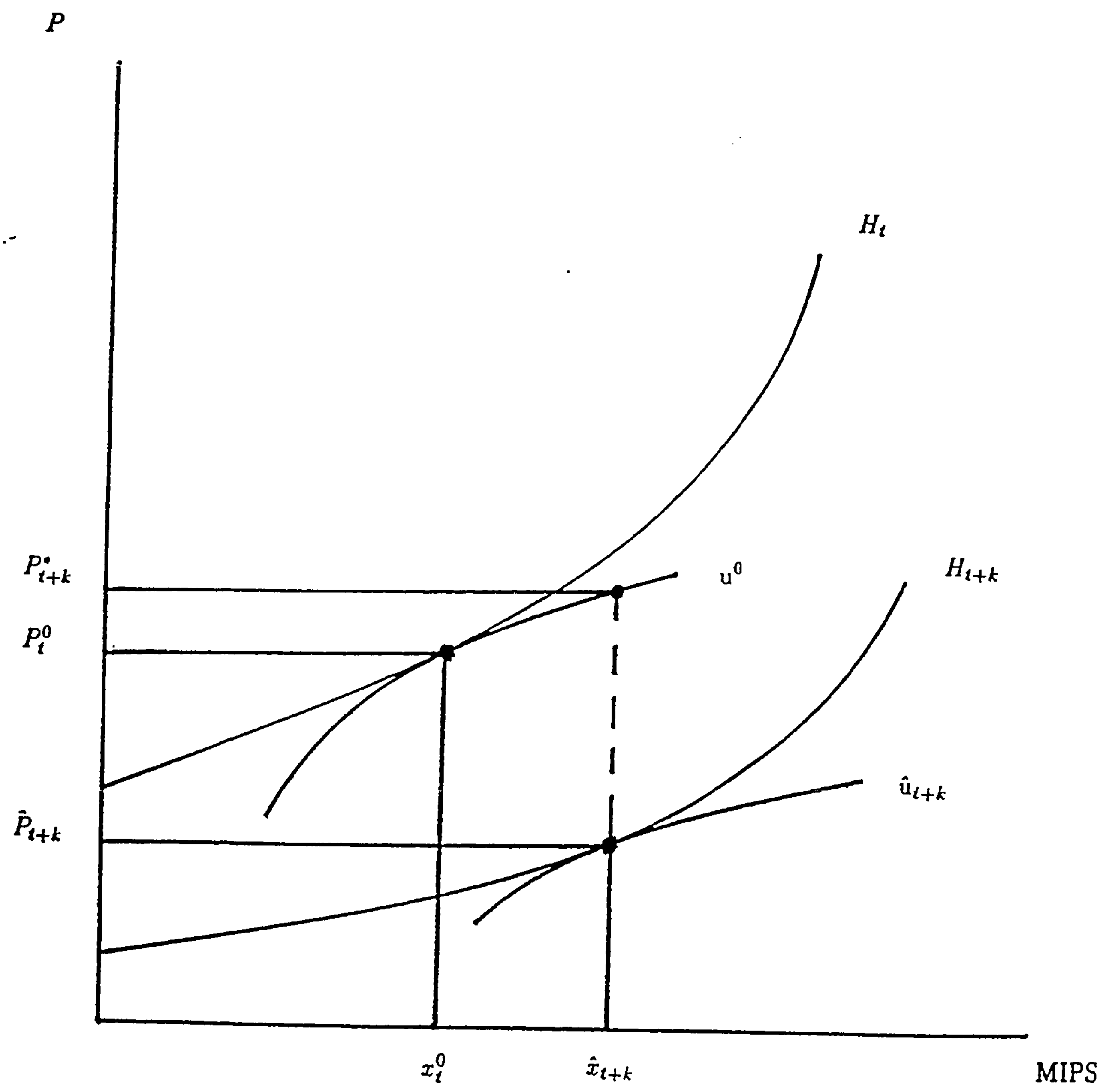


Figure 3.2.3



3.3 DATA

The data to be used for this analysis is a subset of the Computer Installation Data File kept by the Computer Intelligence Corporation (CIC). The installation file contains information on over 70,000 computer installations and 140,000 computer systems in the United States. All information on the file is collected directly from the users through mail surveys and telephone follow-ups and it is updated on a continuous basis.

Information on the file is categorized as being either site data or system data. Site data refers to those data elements concerning the company at which a computer system is located. "System" is used as a collective term rather than meaning a computer system itself. System data includes data on the mainframe, software and peripheral equipment at the computer installation. Each Computer Installation Data File record contains both site data and system data.

CIC prepared a database containing their complete records for every site in the United States with a medium to large general purpose computer system for every year from 1984 to 1991. This time period was selected because CIC could guarantee the data's historical accuracy and completeness.

This particular subset of CICs data files is extraordinarily rich in detail. CIC provides data on over 44,000 medium to large systems in 1984 and over 58,000 by 1991. Each year provides data on over 14,000 sites that use a medium to large computer system. Each of those 14,000 records includes the name and address of the private company (and parent) at which the system is located, as well as broad information about the company, such as the (four digit) SIC associated with the site, the number of employees and the amount of revenue. Unfortunately, some of the variables are not reported for the entire time period, making use of the entire data set a difficult task.

More importantly, though, the files contain detailed descriptions of every medium to large system and its use at the site. Specific information includes the system name and model, the amount of memory, the amount of peripheral equipment used, the primary language used, the likely market value of the system, the method by which the system was acquired and at what level such acquisition decisions are made. The file also provides information about the total MIPS and DASD, as well as the number of programmers at the site.

Since our interest here is the effect of new technology on price index computation, we look only at the acquisitions of new computer systems.[15] This is similar to the previous research done in this area where researchers typically use the set of systems available for sale to perform their analysis.

The acquisitions data set was generated from the site data. The site data included a variable for each system indicating whether it was a new acquisition or not. This encompassed 69,179 observations from 1984–1991. In order to perform our analysis we require data on the site from the previous year. Therefore, we removed all observations for which there was no site information the previous year. There were now 42,221 observations. Finally, we chose to restrict our attention to mainframes, so we excluded all observations which were not. This brought the dataset to 27,217 observations. The reason for choosing mainframes was simply because they have been the major focus of previous work.

The final set of data we needed for our analysis was system characteristics. CIC publishes a guide called the Computer Systems Report Users Guide which contains information on all systems known to them. The Guide contains the system name and a list of characteristics including MIPS, minimum memory, maximum memory, KVA (kilovolt-amperes[16]) ratings and others. To complete the acquisitions dataset we simply matched the system names with those in the Guide and merged the characteristics with the list of acquisitions. Due to name discrepancies and the inclusion of some non-mainframe acquisitions in the dataset, the size of the data was narrowed further to 21,268 observations. This is the dataset used in the analysis.

[15] Oliner (1992) examines the second-hand market for a sample of IBM systems.

[16] This is the electrical measurement used by the Uninteruptible Power Systems vendors to rate their system's capacity

In the remainder of this section we give definitions for the different variables used, as well as descriptive statistics. More detailed descriptive statistics can be found in the Appendix.

3.3.1 Price

The system price we use here is provided by CIC and is defined as the "estimated value of a 'typical' configuration if purchased today." The drawback to this is that all acquisitions of the same system will get the same price associated with them regardless of the true configuration which was purchased. "Typical" is defined by CIC as "an average size system with a normal compliment of peripherals and terminals." This is the same type of price that previous work has used. The computer characteristics to be described later are associated with systems in the same manner, so that all systems of the same type have the same price and the same characteristics during a given year. Fortunately, prices for the same system change over time, so there is variation in both the cross section and time series. While this is not the most desireable setup, it is consistent, and is virtually the same as what has been used in the hedonic literature.

We transformed the price data by adjusting for inflation using the Producer Price Index each year to get a real price. This was done so that we would be measuring technological change with inflation factored out rather than measuring the two simultaneously. Table 3.3.1 provides descriptive statistics for the transformed price data (measure in hundreds of dollars).

3.3.2 Computer Characteristics

The mainframe characteristics we choose to use are minimum memory, maximum memory and MIPS. Minimum and maximum memory are the minimum and maximum amounts of main storage supported on the system. MIPS is a measure of the speed of the mainframe measured in millions of instructions per second.

Main memory is valued for its storage use to allow for quicker access to software and data. Its measurement in bytes is standard in the industry so that different systems' memory may be compared in a straightforward manner. Most previous studies have often used both the minimum and maximum memory. This was done either to account for the lack of information as to which size of memory went with the recorded price, or to avoid the influence of different pricing schemes for the low-end models when different prices are available for different memory sizes (see Triplett (1989) and Dulberger (1989)). For a description of the 'pricing schemes' see Phister (1979). We use both minimum and maximum memory because we do not possess a price for different memory configurations for each system. Tables 3.3.2 and 3.3.3 give descriptive statistics for minimun and maximum memory measured in kilobytes.

While "speed" is a characteristic which can directly measure the effectiveness of a system, the measurement of speed is not nearly as straightforward as the measurement of memory. No less than five measures of speed, including addition time, multiplication time, memory cycle time, MIPS and KOPS (thousands of instructions per second) have been introduced as independent variables in the specification of the hedonic function. For definitions of these measures and others see Triplett (1989). The most recent studies prefer to use MIPS because it combines the speeds of many instructions and weights each instruction by the relative frequency of that instruction in the job. If the job is representative of the jobs which will be performed by the system, then this weighted measure computes some sort of "expected" speed. However, since typical jobs vary widely across processors, comparability across processors is difficult (see Triplett). For this reason, Dulberger (1989) chose to exclude all data except IBM and plug-compatible processors for which equivalent MIPS measures were available. Triplett's reply to this choice is that "... a non-comparability that may be disastrous for machine selection purposes may yet be acceptable for an economic measurement, in that the measurement error may be randomly distributed around the true hedonic regression line" (Triplett p.149). We choose to include all acquisitions, not discriminating on the basis of comparable MIPS. Later, for comparison purposes, we will perform the same exercise using only IBM and PCM processors. Table 3.3.4 provides descriptive statistics for MIPS.

Another variable we feel is important is reliability. Unfortunately, it is not clear how one would go about measuring this. However, in this era, the technology is more mature than in previous eras and reliability is probably not changing much over time or across systems. This would not necessarily be the case if we were comparing 1970 systems with 1990 systems. Berndt (1991) discusses the use of reliability as a computer characteristic and the problem of omitted variables in hedonic estimates. For a list of variables used in previous research see Triplett (1989).

3.3.3 Buyer Characteristics

The buyer characteristics are the variables used in the estimation of the demand functions which describe the heterogeneity among buyers. We chose seven categories of variables which were either available, or could be generated, from the CIC data. Each of the variables is lagged one period from the date of observation to avoid problems with these variables being endogenous to the choice of purchasing a new mainframe computer system. These variables include dummy variables for various SIC groupings, a dummy variable for whether or not the site owned an IBM system, the estimated purchase value of installed systems at the site, the MIPS rating of the system at the site with the largest MIPS rating, the total MIPS for all installed systems at the site, the total KVA rating for all installed systems at the site and the technical age of the youngest system owned during the previous year. Tables 3.3.5 and 3.3.6–3.3.12 give definitions and descriptive statistics for the buyer characteristics.

3.3.4 Instrumental Variables

Because in general the x's in the demand estimation are correlated with the error term in that equation (Bartik 1987, Epple 1987), we need to estimate that equation by instrumental variables. Bartik (1987) performs a similar exercise using housing data. The instruments should be variables which affect the choice of characteristics but do not affect unobserved tastes. The variables we use are time dummy variables, region dummy variables, an SMSA dummy variable and characteristics of the closest systems in characteristics space as measured by the Mahalanobis distance between systems. This distance is defined as

$$(x_0 - x_i)^T \Sigma^{-1} (x_0 - x_i)$$

where x_0 represents the characteristics of the system, x_i represents the characteristics of all systems except x_0 and Σ represents the covariance matrix of the variables minimum memory, maximum memory and MIPS.[17] Each of these variables affects the marginal prices paid for computer characteristics. However, assuming that tastes do not change over time or across regions and that tastes are unaffected by whether or not the buyer resides in an SMSA, these variables are uncorrelated with buyers' tastes, making them appropriate instruments. Definitions of these variables are given in Table 3.3.13.

The type of data used here is different than the type of data used in previous analyses. This data is at the buyer[18] level and describes the acquisitions as well as information about the buyers making the acquisitions. Previous work had data on the available systems, their characteristics and their prices. Because of the differences in the data, we are able to address the question of the amount of technological change taking place in a different manner. We could still perform the analysis as it has been done in the past, and we do so for comparison purposes, but it is important to see that there is a fundamental difference. The analysis here computes a utility based hedonic index because it takes into account the location of the buyers on the hedonic surface and what their demand for characteristics might look like. This method looks not only at technological change, but also the valuation of that change to buyers. Improvements which might make a regular hedonic index decline quickly may not be valued by buyers and may make a utility based index fall more slowly, or vice versa.

---

[17] The idea is that neighboring systems provide information about the costs of production without saying much about buyer demand.

[18] The buyers are private firms, educational institutions and government organizations

3.3.5 Tables

Table 3.3.1
Descriptive Statistics for Price

Year	Minimum	Median	Mean	Maximum	Std. Dev.
1985	0.00	390.70	1033.00	9200.00	1491.11
1986	0.00	656.30	1833.00	23910.00	2983.82
1987	0.00	608.80	1808.00	31740.00	3050.31
1988	0.00	734.90	2284.00	43990.00	3828.61
1989	0.00	707.10	2476.00	44790.00	4177.20
1990	0.00	821.80	3039.00	40680.00	5158.61
1991	0.00	777.40	2925.00	34740.00	5092.07
Total	0.00	638.70	2104.00	44790.00	3716.81

Table 3.3.2
Descriptive Statistics for Minimum Memory

Year	Minimum	Median	Mean	Maximum	Std. Dev.
1985	0.032	4.096	6.767	32.77	7.50
1986	0.032	4.096	14.320	65.54	19.92
1987	0.032	8.192	18.290	131.10	26.59
1988	0.060	16.380	29.890	131.10	37.42
1989	0.008	16.380	37.880	165.50	44.32
1990	0.032	24.580	46.710	262.10	47.07
1991	0.100	32.770	53.360	262.10	49.15
Total	0.008	10.240	26.450	262.10	36.84

Table 3.3.3 Descriptive Statistics for Maximum Memory					
Year	Minimum	Median	Mean	Maximum	Std. Dev.
1985	0.256	24.58	33.50	262.10	31.22
1986	0.256	32.77	65.54	262.10	80.36
1987	0.256	32.77	75.97	524.30	110.03
1988	0.512	40.96	279.00	2097.00	559.75
1989	0.032	65.54	374.40	3146.00	686.35
1990	0.064	81.92	732.70	4194.00	1227.92
1991	0.512	262.10	1102.00	4719.00	1456.48
Total	0.032	32.77	277.10	4719.00	697.95

Table 3.3.4 Descriptive Statistics for MIPS					
Year	Minimum	Median	Mean	Maximum	Std. Dev.
1985	0.10	2.70	5.21	28.00	6.39
1986	0.20	3.40	8.15	33.50	9.03
1987	0.10	4.20	9.31	49.00	11.21
1988	0.20	6.50	15.55	75.00	19.05
1989	0.10	7.90	21.24	114.00	26.61
1990	0.20	14.00	29.56	114.40	33.64
1991	0.40	21.60	35.36	114.40	36.58
Total	0.10	5.70	15.28	114.40	22.35

Table 3.3.5 Definitions of the Buyer Characteristics	
Variable	Definition
SIC	The standard industrial classification code of the site. These SICs are grouped into 24 two-digit groups. They are: 1–18, 20–26 & 29, 27, 28, 30–34 & 38 &39, 35, 36, 37, 40–47, 48, 49, 50, 51– 59, 62 &64–69, 60, 61, 63, 70–79, 81 & 83–89, 80, 82, 90 & 92–96 & 98 & 99, 91, 97. These are dummy variables which take the value 1 if the site is in the SIC grouping and 0 otherwise.
IBM	A dummy variable which takes the value 1 if the site had any IBM medium to large system and 0 otherwise.
Site Value	The estimated purchase value of the site in 1,000s of dollars. This amount was turned into real dollars by adjusting for the Producer Price Index.
Maximum MIPS	The number of MIPS on the system at the site with the largest MIPS rating.
Total MIPS	The sum total MIPS of all systems at the site.
Total KVA	The sum total of the KVA ratings of all systems at the site.
Age Young	The technical age (year of observation minus the vintage of the system) of the youngest system at the site.

Table 3.3.6
Number of 1's for SIC Dummy Variable

Group	1985	1986	1987	1988	1989	1990	1991
2	154	165	255	162	177	122	25
3	60	77	99	65	76	70	7
4	55	67	111	82	84	62	16
5	184	189	234	160	178	96	25
6	112	150	151	137	157	115	24
7	137	134	171	176	116	81	17
8	90	96	99	105	104	63	18
9	77	90	112	88	85	87	18
10	42	98	88	132	96	81	21
11	81	95	115	108	89	100	20
12	132	113	138	108	97	57	13
13	174	174	249	212	277	185	48
14	57	80	106	107	73	65	23
15	194	247	307	247	311	207	51
16	68	96	104	111	48	29	9
17	192	210	287	255	237	202	65
18	360	361	525	495	486	457	115
19	60	61	70	64	84	75	35
20	141	108	177	157	174	146	35
21	170	162	225	174	173	173	39
22	130	165	230	191	237	139	50
23	140	132	153	153	156	115	19
24	74	104	123	105	76	76	18

Table 3.3.7
Descriptive Statistics for Site Value

Year	Minimum	Median	Mean	Maximum	Std. Dev.
1985	372.10	7442.00	14880.00	62140.00	15836.80
1986	364.60	7657.00	21900.00	68370.00	22590.74
1987	179.10	9311.00	19510.00	106500.00	23889.48
1988	175.00	10850.00	28540.00	140000.00	36429.42
1989	33.67	11200.00	28880.00	138900.00	37127.44
1990	65.09	10580.00	26810.00	113900.00	32140.17
1991	39.46	11050.00	21570.00	94710.00	26235.58
Total	33.67	9311.00	23450.00	140000.00	29611.84

Table 3.3.8
Descriptive Statistics for Maximum MIPS

Year	Minimum	Median	Mean	Maximum	Std. Dev.
1985	0.10	1.40	3.92	99.00	6.12
1986	0.10	2.70	6.07	80.00	8.15
1987	0.10	2.70	6.81	99.00	10.30
1988	0.10	5.00	11.80	99.00	15.51
1989	0.00	6.40	14.87	104.00	19.47
1990	0.10	9.50	22.21	114.40	27.74
1991	0.10	13.00	29.35	114.40	35.52
Total	0.00	4.00	11.36	114.40	18.25

Table 3.3.9 Descriptive Statistics for Total MIPS					
Year	Minimum	Median	Mean	Maximum	Std. Dev.
1985	0.10	2.20	7.47	181.00	14.95
1986	0.10	3.80	13.39	205.10	24.64
1987	0.10	3.80	14.08	325.00	27.38
1988	0.10	6.90	22.26	392.00	39.06
1989	0.00	8.00	28.00	482.50	48.83
1990	0.10	13.00	44.13	644.60	78.74
1991	0.10	16.00	61.77	953.60	114.11
Total	0.00	5.40	22.49	953.60	48.89

Table 3.3.10 Descriptive Statistics for Total KVA					
Year	Minimum	Median	Mean	Maximum	Std. Dev.
1985	0.00	14.00	40.01	570.00	58.01
1986	0.00	21.20	52.77	476.40	71.88
1987	0.00	13.10	45.01	566.70	72.03
1988	0.00	23.30	50.68	632.00	72.19
1989	0.00	23.10	54.61	805.40	83.23
1990	0.00	29.60	71.23	905.70	115.96
1991	0.00	35.60	79.90	1063.00	128.98
Total	0.00	21.00	52.81	1063.00	82.65

Table 3.3.11
Descriptive Statistics for Age Young

Year	Minimum	Median	Mean	Maximum	Std. Dev.
1985	0.00	3.00	3.62	21.00	2.91
1986	0.00	3.00	3.79	21.00	3.04
1987	0.00	3.00	3.62	21.00	2.82
1988	0.00	3.00	3.35	23.00	2.72
1989	0.00	3.00	3.43	28.00	2.70
1990	0.00	3.00	3.59	26.00	2.57
1991	0.00	3.00	4.03	18.00	2.66
Total	0.00	3.00	3.58	28.00	2.80

Table 3.3.12
Number of 0's and 1's in IBM Dummy Variable

Year	0	1
1985	547	2392
1986	696	2538
1987	829	3380
1988	1254	2421
1989	1353	2296
1990	918	1923
1991	348	373

Table 3.3.13
Definitions of the Instrumental Variables

Variable	Definition
Time	A dummy variable for the time period of observation. The variable takes a 1 if the observation falls in the year, 0 otherwise.
Region	Dummy variables for the region of the country in which the site resides. There are 9 regions: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain and Pacific.
SMSA	This is a dummy variable that takes the value 1 if the site resides inside an SMSA and a 0 otherwise. This variable is provided by CIC.
Neighbors	These are characteristics (minimum memory, maximum memory and MIPS) of the closest neighbors to the system in characteristics space. The distance measure used is Mahalanobis distance defined as $$(x_0 - x_i)^T \Sigma^{-1} (x_0 - x_i)$$ where x_0 are the characteristics of the system, x_i represents the characteristics of all systems except x_0 and Σ represents the covariance matrix of the variables minimum memory, maximum memory and MIPS.

3.4 RESULTS

In this section we will compute a variety of price indexes based on both traditional hedonic methods and on methods we have proposed in the previous sections. Two main themes will emerge. First, it will be shown that traditional hedonic methods overstate the true benefits buyers receive from improvements in technology. This will be seen by the fact that our utility index, which assumes a declining marginal utility for characteristics, has a lower growth rate than the hedonic index. Second, while the utility index does decline at a slower rate than the hedonic index, it will be shown that this slower rate is sensitive to the distribution of buyers across the product space. However, even though the utility index is sensitive to this distribution, it will be pointed out that hedonic methods are unable to account for this distribution at all. We view both of these issues as significant drawbacks to hedonic methods, which should be added to Trajtenberg's (1990) criticism of these methods.

3.4.1 One Characteristic Model

We begin by looking at a model with one characteristic. This is a variation of a model used by Witte, Sumka and Erekson (1979) and analyzed by Epple (1987). We choose this model because of its ease of computation, and because it establishes some basic intuition for the multivariate case.

We first estimate a hedonic surface for each year of the form

$$P_{it} = \beta_{0t} + \beta_{1t} MIPS_{it} + \beta_{2t} MIPS_{it}^2 + u_{it} \tag{3.4.1}$$

where P is the price of the system and $MIPS$ represents the MIPS rating of the system.[19] Table 3.4.1 gives the estimation results and Figure 3.4.1 show the graphs of these hedonic surfaces. From the figure we notice that the shapes of the surfaces are not constant over time and that the 1986 surface crosses the 1985 surface. This implies a technological retrogression

[19] We choose this functional form as opposed to the traditonal log-log because it simplifies the computation of the $\hat{x}_{t+k}$'s. The next chapter will investigate the sensitivity of our index to this choice.

(in terms of price per performance) from 1985 to 1986 for part of the product space. This retrogression is important because it implies that an index may rise between 1985 and 1986 before beginning to decline through the end of the sample. Our estimation results show that all coefficients are significant except the intercept terms in 1986 and 1991 and that the parameter estimates vary widely over time. This variation is important because it implies that a flexible functional form is more appropriate than estimating a hedonic surface which only allows the intercept to change, as has been done in the past.[20]

The next step is to differentiate (3.4.1) with respect to $MIPS$ to obtain the marginal hedonic surface. This is given by

$$mp_{mips,it} = \hat{\beta}_{1t} + 2\hat{\beta}_{2t} MIPS_{it}. \tag{3.4.2}$$

We evaluate (3.4.2) at the observed levels of $MIPS_{it}$to obtain a vector of estimated marginal prices for $MIPS$ for each year. We then pool these vectors of marginal prices together to get $\widehat{mp}_{mips}$. We then estimate demand by estimating

$$\widehat{mp}_{mips,i} = \alpha_0 + \alpha_1 MIPS_i + B_i \Omega + \eta_i \tag{3.4.3}$$

by two-stage least squares using the instrumental variables described in the previous section.[21] Here B represents the matrix of buyer characteristics. For the instrumental variable "neighbors", we chose to include the nine closest systems in characteristics space as measured by Mahalanobis distance.[22] The results of the estimation of (3.4.3) are given in Table 3.4.2.

Table 3.4.2 shows that the coefficient on $MIPS$ is negative and significant implying downward sloping demand. The results also show that none of the SIC group coefficients

[20] Berndt, Showalter and Woolridge (1990) examine the sensitivity of hedonic price indexes for computers to the choice of functional form on the hedonic surface.

[21] This demand curve is derived from a bid curve of the form $P_i = \gamma_0 MIPS_i + \gamma_1 MIPS_i^2$ where $\gamma_0 = \alpha_0 + B_i\Omega$ and $\gamma_1 = \alpha_1/2$.

[22] We chose nine systems because all of their coefficients were significant in the first stage regression and this was the most we could include due to computing constraints.

are significantly different from zero using a 5% level of significance. However, it is also important to test whether they are different from each other. Unfortunately, the coefficients are significantly different from each other in only a few instances. All of the other buyer characteristics, except Age of the Youngest System, are significant.

Based on the estimate of (3.4.3) along with the estimates of (3.4.1) we proceed to compute the forward index for each year as described in the Methodology. The results of this computation are given in Tables 3.4.3A and 3.4.3B.

The first thing to notice when looking at these two tables is that it appears to make little difference whether we use P^* or P^0 as our weight. Second, looking at the 1985 column (which is the index computed using the 1985 buyers) we see that the index has an average annual growth rate (shown in the last row) which is slower than that found in previous studies. However, we are looking at a different time period than other studies, so we will need to compare these results with a price index computed in the traditonal fashion. We will do this below. Finally, we note the rise in the index between 1985 and 1986 when using the 1985 buyers. Recall that after examining Figure 3.4.1 we believed this might occur. The economic interpretation of this is that the price per performance in 1985 was lower than that in 1986 for a portion of the product space, and as a consequence buyers could achieve a higher utility level in 1985. However, we do note that the surfaces cross at two levels of MIPS—approximately 0.8 and 16.5. The 1985 surface lies above the 1986 surface between these two points. This implies that not all buyers were better off in 1985 than 1986. The computed price indexes say that on average, though, buyers were better off in 1985 than 1986.

As stated above, we need to compare our index with a traditional hedonic index. We compute two traditional hedonic indexes, shown in Table 3.4.4. In the first column we compute the index using a log-log functional form, and in the second column we compute the index using a log-linear functional form.

Both of these hedonic indexes have an average annual growth rate more than two times higher than those shown in the 1985 columns of Tables 3.4.3A and 3.4.3B. The log-linear hedonic index rises between 1985 and 1986, whereas the log-log index does not. This is very interesting because as stated earlier, almost all previous studies have employed a log-log form and have rarely tested it against any other forms. Here we see that while both the log-log and log-linear indexes overstate the benefits to buyers resulting from the shifts in the hedonic surface, the log-linear index does pick up the retrogression from 1985 to 1986. This is evidence that the choice of functional form is important when computng these indexes.

Returning to Tables 3.4.3A and 3.4.3B, we see that as we move across the tables the growth rates increase. This implies that the index computation is sensitive to the set of buyers we use as weights. In order to get a better understanding of this, we produced a boxplot showing the distribution of buyers across MIPS over time. This is shown in Figure 3.4.2. The shaded regions in the boxplot represent the interquartile range and the white line in the shaded region represents the median.

It is clear from the figure that the distribution of observed purchases is changing drastically over time. In fact, the maximum observed purchase in 1985 is nearly the median purchase by 1991. If all buyers benefit by exactly the same amount from improvements in technology, then this fact will not matter. However, Tables 3.4.3A and 3.4.3B clearly show that buyers do not benefit by the same amount as shown by the changing growth rates of the indexes over time. This observation is masked by the traditional hedonic index which assumes all buyers benefit by exactly the same amount.

One way to attempt to incorporate the changing distribution into a single index would be to "link" the adjacent indexes together. Assuming that we are better at predicting what a buyer would purchase in the next period rather than two or more periods ahead, we can place the 1985 buyers into 1986, the 1986 buyers into 1987, etc., choose some year as our base and then link these indexes together. We do this in Table 3.4.5 using both P^* and P^0 as our weights.

We see that these indexes have growth rates lower than the traditional hedonic and still pick up the increase from 1985 to 1986. These indexes decline more rapidly, though, than the utility indexes of Tables 3.4.3A and 3.4.3B using the 1985 buyers. This is because more weight is being given to buyers at higher levels of MIPS who benefit more from improvements in technology than those at lower levels

We next compute our "reverse" index. This is shown in Table 3.4.6. Again, we see rates of growth lower than the traditional hedonic and we see changing rates of growth depending on the set of buyers we use as weights. This index also rises between 1985 and 1986 except when we weight by the 1986 buyers. This is because, on average, more 1986 buyers were better off in 1986 than 1985. This is the opposite of what happened when we computed the forward index and weighted by 1985 buyers. This is further evidence that the distribution of buyers one uses as weights is important.

Table 3.4.7 shows the reverse linked index. The growth rate is lower than the traditional hedonic yet faster than the reverse index using the 1991 buyers as weights.

As a final step with this one characteristic model, we recompute all of the indexes using only the IBM and plug-compatible acquisitions as suggested by Dulberger (1989). She suggested this because of the noncomparability of MIPS ratings between IBM and plug-compatible systems with others. These indexes are given in Tables 3.4.8A–3.4.12.

All of the indexes are virtually identical to their counterparts using the entire data set. This is not surprising since approximately 80% of the acquisitions over this time period are IBM or IBM compatible. Figure 3.4.3 shows a boxplot of the distribution of MIPS using only the IBM and plug-compatible data. Comparing this with Figure 3.4.2 we see that the distributions are also almost identical. These results imply that at least for econometric purposes, the distinction between these two sets of data may be unnecessary.[23]

Trajtenberg (1990) argued that hedonic indexes were inadequate for two reasons. He described situations where hedonic methods would fail to account for technological change. The first was the introduction of new systems on the existing hedonic surface which "filled-in"

[23] While the distinction may be unnecessary for econometric purposes, it is necessary for purchase decisions; see Triplett (1989)

the product space. Because the new systems, by design, lie on the already existing hedonic surface, a hedonic index would not register any innovation. A second type of innovation which a hedonic index may not account for is an innovation which extends the range of the product space. If the new, previously infeasible, system is priced similar to systems on the existing hedonic surface, this too will fail to show up in the hedonic index (for a more complete description of these two cases see Trajtenberg (1990)). Our results to this point suggest two more inadequacies of hedonic indexes: they do not account for the distribution of buyers, nor the distribution of benefits associated with different parts of the characteristics spectrum.

Finally, as shown in the previous chapter, the utility index has a lower growth rate than the traditional hedonic index. This is a consequence of the concavity of the bid curve, or equivalently, the downward sloping demand. The results in this section lend empirical support to this analytical result.

This section has focused on comparing our utility index with a traditional hedonic index using a single characteristic. We could extend this model in two ways. First, we could add more computer characteristics to provide a more complete description of the product. Second, we could examine the sensitivity of the utility index to the choice of functional form on the hedonic surfaces. In the next section we will consider the former and in the next chapter we will consider the latter.

3.4.2 Three Characteristic Model

We now extend our description of a mainframe computer by adding minimum and maximum memory as characteristics. We choose this description because it closely resembles the descriptions used in previous research.[24] While we are choosing this set of characteristics, we do not believe that this is a complete description of a mainframe computer as stated by Dulberger (1989). Unfortunately, there are little, if any, other measured characteristics

[24] See Triplett (1989) for a list of studies and their choice of characteristics.

available to researchers. One variable which has often been discussed is reliability. Berndt (1991) points out that if reliability is correlated with the producer, then a producer dummy variable might be appropriate. While this may be true, there may be other unobservable characteristics which may be correlated with the producing firm which are not valued by buyers, but which in fact would affect our index. For this reason we chose not to include firm dummy variables. Future work could look into a better characterization of the computer system.

As in the one characteristic case, we begin by estimating a hedonic surface for each year of the form

$$P_{it} = \beta_{0t} + \beta_{1t}MIN.MEM + \beta_{2t}MIPS + \beta_{3t}MAX.MEM$$
$$+ \beta_{4t}MIN.MEM^2 + \beta_{5t}MIPS^2 + \beta_{6t}MAX.MEM^2 + u_{it}. \qquad (3.4.4)$$

At this point we do not include interactions among the variables in the specification of (3.4.4). We will consider this issue below. The estimation results are given in Table 3.4.13.

The results show that for the most part the coefficients are significant. In addition, all R^2 values are above 0.92. Three coefficients, $MAX.MEM$ in 1985, $MIN.MEM$ in 1986 and $MAX.MEM$ in 1990, are the wrong sign ($MAX.MEM$ in 1990 is not significantly different from zero). This is possibly due to a high correlation between $MIN.MEM$ and $MAX.MEM$. This correlation is 0.76. However, believing this to be a more correct set of characteristics than a $MIPS - MIN.MEM$ or $MIPS - MAX.MEM$ specification, we choose to maintain it.

We next compute the predicted marginal prices and estimate the following demand equations:

$$mp_{min,i} = \alpha_{10} + \alpha_{11}MIN.MEM + B_i\Omega_1 + \eta_{1i}, \qquad (3.4.5A)$$

$$mp_{mips,i} = \alpha_{20} + \alpha_{21}MIPS + B_i\Omega_2 + \eta_{2i}, \qquad (3.4.5B)$$

$$mp_{max,i} = \alpha_{30} + \alpha_{31} MAX.MEM + B_i \Omega_3 + \eta_{3i}. \qquad (3.4.5C)$$

We estimate each equation in (3.4.5) separately using two-stage least squares with the instruments described in Section 3.3.4. We decided not to include all three characteristics on the right hand side of each equation because the high correlation among them resulted in upward sloping demand curves. The above specification produced reasonable results. Table 3.4.14 gives the correlation matrix of the computer characteristics. Tables 3.4.15–3.4.17 give the demand estimation results.

Each of the demand equations is downward sloping. The SIC dummy variables are again rarely significantly different from the excluded group or each other. The remaining buyer characteristics, except Total KVA and the IBM dummyy in minimum memory demand and Age Young in maximum memory demand, are significant.

With these results, we proceeded to compute our forward index, shown in Tables 3.4.18A and 3.4.18B. The traditional hedonic indexes are given in Table 3.4.19.

The indexes shown in Tables 3.4.18A and 3.4.18B closely resemble those of the one characteristic model. The significant difference is that the three characteristic index has a higher growth rate than the one characteristic index. This should be expected since we are now allowing innovation to take place in different characteristic dimensions. Allowing this innovation permits buyers to obtain benefits they could not obtain in the one characteristic case.

As seen in the one characteristic case, the growth rates increase as we weight by later sets of buyers. Figures 3.4.4 and 3.4.5 show boxplots for the distributions of minimum and maximum memory. Again we see that the maximum purchase in 1985 is nearly the median purchase by 1991. The changes in these distributions along with the changes in the MIPS distribution significantly affect the growth rates we see as we weight by later sets of buyers. This continues to support the claim made in section 3.4.1 that the distribution of buyers is an important factor when computing the utility index. This factor is not taken into account in the computation of the traditional hedonic index.

Finally, we again see that these indexes rise between 1985 and 1986 when we weight by the 1985 buyers. However, it is not clear if this is due to technological retrogression in all characteristic dimensions or some subset of the dimensions, since we cannot draw the picture. Suffice it to say that, on average, the 1985 buyers were better off in 1985 than 1986 given their demand curves.

The hedonic indexes shown in Table 3.4.19 also look similar to the hedonic indexes computed for the one characteristic case. They both overstate the benefits of innovation to buyers and again, the log-linear model is the only one to detect the retrogression from 1985 to 1986. This further supports the earlier claim that the choice of functional form for the hedonic surface is a key aspect in computing a hedonic or utility index.

Tables 3.4.20–3.4.22 present the forward linked, reverse and reverse linked indexes. They convey much of the same information provided by their one variable counterparts. The interesting feature of these is the growth rates of the linked indexes. Each has a rate higher than the log-linear hedonic rate, but lower than the log-log hedonic rate. While we have been arguing that the utility index is superior to the hedonic index in measuring the benefits of innovation to buyers, we also realize that the results obtained from a utility index are sensitive to the set of buyers we use as weights. For example, the forward linked index using P^* as the weight has a growth rate of -30.38% from 1985–1991. If we exclude 1991, the growth rate is -16.38%. In order to try to overcome this sensitivity, we have proposed that a linked index may be appropriate since the final index is not dependent on a single set of buyers. In this three characteristic case, both our linked index and the hedonic index perform about the same in the long run. However, there is considerable variation in the short run.

The faster rate of decline in the linked index for the three characteristic case is a result of the enormous rate of growth for the 1990 buyers facing the 1991 hedonic surface. For example, the growth rate using P^* as a weight is over 100 percent between 1990 and 1991 using the 1990 buyers. That growth rate is never more than 54 percent using the other sets of buyers. This suggests that one might average the growth rates over all sets of buyers to get a linked index. We compute this for the forward index using P^* as a weight. This yields the index given in Table 3.4.23. Notice that now the growth rate is 21.44%, which is well below the P^* linked index growth rate given in Table 3.4.20 and well below the growth rates of the hedonic indexes. While the linked index computed previously was less dependent on the set of buyers than the utility index using a single set of buyers, computing the index in this fashion (averaging the growth rates over all sets of buyers) is even less dependent on the sets of buyers. While this is a nice feature of this index, it also has drawbacks. The main drawback is that it gives weight to buyers who are being projected far into the future. The farther we project into the future, the greater possiblity of hitting a margin. Buyers who hit the margin do not receive as much benefit as they would have had they purchased what was optimal. This implies that we should concentrate on projecting only a short time into the future.

Tables 3.4.24A–3.4.29 recompute all of the indexes of the three characteristic model using only the IBM and plug-compatible acquisitions. The utility and hedonic indexes change very little from their counterparts using all of the acquisitions. The most notable feature is that they all have higher growth rates than the "all data" indexes.[25] This implies that price per performance in IBM systems fell faster over the time period than the overall rate. Since the distributions of characteristics purchased do not seem to be drastically different between IBM and the entire data set, it must either be the case that IBM was lowering its prices at a faster rate than the overall rate, or that there is some unmeasured characteristic which is causing IBM's price per performance to fall relative to the other systems in the sample. This is interesting and needs to be investigated further by attempting to expand the set of measured characteristics.

[25] Note that these indexes are plagued by the 1991 problem described earlier. Removing 1991 results in a significantly lower growth rate.

3.4.3 Summary

In this section we have computed a large number of indexes providing a variety of interesting results. However, we believe that there are two main points made by the results. First, hedonic indexes overstate the true benefits received by buyers as measured by a price equivalent utility index, because hedonic indexes do not account for declining marginal utility of characteristics; and second, the traditional hedonic index fails to account for the distribution of buyers across the product space.

The traditional hedonic methods focus their attention on the average price change of the product holding product characteristics constant. This index says nothing about the benefits, measured by changes in utility, that buyers actually receive from the shifting hedonc surface. On the other hand, the utility index that we have proposed here does measure the benefits buyers receive from one period to the next following the suggestions of Trajtenberg (1990). Our utility index shows that, in mainframe computers, the traditional hedonic index overstates these benefits by a significant margin. If innovation must be measured in terms of its value to buyers, then based on the results presented here, one must be skeptical of the inferences drawn from the traditional hedonic index regarding changes to economic welfare.

The second point concerns the distribution of buyers across the product space. If buyers were uniformly distributed across the product space, and buyers' demand was such that they moved to new hedonic surfaces in a uniform fashion, then the traditional hedonic index would probably perform well. However, in the case that we have examined, the distribution of buyers is skewed so that a large proportion of buyers buy small mainframe systems. An index which assumes benefits to buyers in this scenario are the same as in the uniformly distributed case, while possibly giving some insight, will miss the true benefits buyers receive from improving technology. For this reason, we believe that, given appropriate data, the method of measuring innovation in this paper is superior to the traditional hedonic index.

3.4.4 Tables

Table 3.4.1 One Characteristic Model Hedonic Surface Estimates				
Year	Coefficient	Value	Std. Error	t value
1985	β_0	-265.53	69.42	-3.82
	β_1	3503.73	20.59	170.19
	β_2	-45.87	0.83	-54.96
1986	β_0	-4.35	106.83	-0.04
	β_1	3163.35	28.15	112.37
	β_2	-26.15	1.03	-25.44
1987	β_0	1373.90	155.29	8.85
	β_1	1809.72	24.67	73.36
	β_2	6.06	0.56	10.73
1988	β_0	673.00	194.72	3.46
	β_1	1667.63	20.25	82.37
	β_2	3.21	0.30	10.61
1989	β_0	-2440.01	176.70	-13.81
	β_1	1651.60	13.33	123.88
	β_2	-3.24	0.14	-22.46
1990	β_0	-1597.96	200.87	-7.96
	β_1	1008.34	12.42	81.20
	β_2	-0.70	0.12	-6.08
1991	β_0	-775.02	463.96	-1.67
	β_1	513.83	25.82	19.90
	β_2	1.61	0.23	7.06

Table 3.4.2 One Characteristic Model MIPS Demand Estimate			
Variable	Valuee	Std. Error	t value
α_0	1971.65	60.89	32.38
α_1	-12.82	0.49	-26.28
SIC-2	29.22	67.17	0.43
SIC-3	-27.61	77.34	-0.36
SIC-4	-73.95	78.44	-0.94
SIC-5	62.68	66.27	0.95
SIC-6	24.81	68.90	0.36
SIC-7	78.31	69.95	1.12
SIC-8	29.94	74.96	0.40
SIC-9	-43.34	75.06	-0.58
SIC-10	47.52	75.07	0.63
SIC-11	-25.29	73.24	-0.35
SIC-12	103.37	72.14	1.43
SIC-13	-26.30	65.40	-0.40
SIC-14	61.05	75.32	0.81
SIC-15	21.80	63.96	0.34
SIC-16	144.10	76.80	1.88
SIC-17	57.23	64.40	0.89
SIC-18	-30.31	60.96	-0.50
SIC-19	45.24	80.11	0.56
SIC-20	-20.69	67.88	-0.30
SIC-21	4.27	66.79	0.06
SIC-22	-30.55	67.07	-0.46
SIC-23	46.63	68.57	0.68
SIC-24	7.84	75.74	0.10
Site Value	0.05	0.00	11.23
Max Mips	-9.34	0.82	-11.37
Total Mips	-2.69	0.47	-5.75
Total KVA	0.75	0.20	3.73
Age Young	3.27	3.07	1.06
IBM	200.26	18.12	11.05

Table 3.4.3A One Characteristic Model Utility-Based Price Index–P^* as Weight						
	1985	1986	1987	1988	1989	1990
1985	231.38					
1986	267.69	234.22				
1987	196.32	193.97	226.93			
1988	190.36	189.47	198.62	221.20		
1989	182.88	182.52	183.32	183.27	208.17	
1990	135.47	135.36	135.58	136.17	136.79	187.32
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-13.98	-17.02	-20.49	-26.46	-36.66	-62.76

Table 3.4.3B One Characteristic Model Utility-Based Price Index–P^0 as Weight						
	1985	1986	1987	1988	1989	1990
1985	236.13					
1986	259.12	241.54				
1987	188.39	184.15	231.06			
1988	186.53	184.95	197.74	226.75		
1989	182.42	182.27	182.61	179.70	201.04	
1990	135.14	134.99	135.23	135.56	136.76	161.50
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-14.32	-17.64	-20.94	-27.29	-34.92	-47.93

Table 3.4.4 One Characteristic Model Traditional Hedonic Indexes		
Year	Log-Log	Log-Linear
1985	706.29	571.66
1986	666.91	651.22
1987	465.21	513.50
1988	383.74	455.22
1989	266.21	307.81
1990	179.84	195.30
1991	100.00	100.00
AAGR	-32.58	-29.06

Table 3.4.5 One Characteristic Model Linked Indexes		
Year	P^* as Weight	P^0 as Weight
1985	410.29	418.40
1986	474.68	459.14
1987	393.11	350.05
1988	344.07	299.57
1989	285.07	237.41
1990	187.32	161.50
1991	100.00	100.00
AAGR	-23.53	-23.85

Table 3.4.6 One Characteristic Model Reverse Index						
	1986	1987	1988	1989	1990	1991
1985	100.00	100.00	100.00	100.00	100.00	100.00
1986	78.15	104.61	104.81	104.45	104.89	106.79
1987		64.30	68.75	75.02	76.83	73.75
1988			67.81	68.11	71.47	69.82
1989				59.78	57.31	57.65
1990					45.33	38.00
1991						34.63
AAGR	-24.65	-22.08	-12.95	-12.86	-15.82	-17.67

Table 3.4.7 One Characteristic Model Reverse Linked Index	
Year	P^0 as Weight
1985	100.00
1986	78.15
1987	48.04
1988	47.38
1989	41.59
1990	32.90
1991	29.98
AAGR	-20.08

Table 3.4.8A One Characteristic Model Utility-Based Index–P^*–IBM Only						
	1985	1986	1987	1988	1989	1990
1985	233.29					
1986	266.68	236.75				
1987	195.09	192.37	227.82			
1988	190.65	189.68	199.31	221.70		
1989	183.58	183.49	184.08	183.72	207.76	
1990	134.04	133.96	134.26	134.93	135.59	184.59
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-14.12	-17.24	-20.59	-26.54	-36.56	-61.30

Table 3.4.8A One Characteristic Model Utility-Based Index–P^0–IBM Only						
	1985	1986	1987	1988	1989	1990
1985	238.26					
1986	259.91	243.86				
1987	185.88	181.25	232.35			
1988	187.35	185.23	198.15	227.27		
1989	183.03	182.93	183.35	177.83	200.77	
1990	133.84	133.77	134.11	134.60	135.78	158.70
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-14.47	-17.83	-21.08	-27.37	-34.85	-46.19

Table 3.4.9 One Characteristic Model Traditional Hedonic Indexes–IBM Only		
Year	Log-Log	Log-Linear
1985	735.16	552.83
1986	682.01	664.28
1987	453.40	487.97
1988	389.19	448.92
1989	270.50	308.01
1990	177.69	191.04
1991	100.00	100.00
AAGR	-33.25	-28.50

Table 3.4.10 One Characteristic Model Linked Indexes–IBM Only		
Year	P^* as Weight	P^0 as Weight
1985	420.01	433.73
1986	480.13	473.14
1987	390.13	351.66
1988	341.31	299.90
1989	282.84	234.66
1990	184.59	158.70
1991	100.00	100.00
AAGR	-23.92	-24.45

Table 3.4.11
One Characteristic Model
Reverse Index–IBM Only

	1986	1987	1988	1989	1990	1991
1985	100.00	100.00	100.00	100.00	100.00	100.00
1986	81.92	106.29	106.99	106.59	106.75	109.26
1987		65.18	69.84	75.93	78.05	74.86
1988			69.02	69.44	73.05	71.52
1989				60.90	58.97	60.02
1990					45.41	39.55
1991						35.25
AAGR	-19.94	-21.40	-12.36	-12.40	-15.79	-17.38

Table 3.4.12
One Characteristic Model
Reverse Linked Index–IBM Only

Year	P^0 as Weight
1985	100.00
1986	81.92
1987	50.24
1988	49.65
1989	43.54
1990	33.53
1991	29.88
AAGR	-20.13

Table 3.4.13
Three Characteristic Model
Hedonic Surface Estimates

Year	Coefficient	Value	Std. Error	t value
1985	β_0	-354.39	91.53	-3.87
	β_1	378.22	43.34	8.73
	β_2	3158.82	54.46	58.00
	β_3	-18.49	5.50	-3.36
	β_4	-6.68	1.46	-4.57
	β_5	-35.89	2.38	-15.11
	β_6	-0.02	0.02	-0.98
1986	β_0	-363.90	96.53	-3.77
	β_1	-23.91	26.47	-0.90
	β_2	3418.26	34.14	100.12
	β_3	0.74	5.68	0.13
	β_4	3.91	0.35	11.11
	β_5	-49.46	0.99	-49.73
	β_6	-0.03	0.02	-1.58
1987	β_0	-503.91	92.97	-5.42
	β_1	406.79	19.15	21.24
	β_2	618.03	31.39	19.69
	β_3	116.49	5.00	23.29
	β_4	-0.89	0.25	-3.63
	β_5	6.00	0.82	7.36
	β_6	-0.13	0.01	-8.97
1988	β_0	-295.86	179.06	-1.65
	β_1	466.20	19.51	23.89
	β_2	882.19	31.24	28.24
	β_3	2.35	1.13	2.08
	β_4	-0.91	0.13	-7.26
	β_5	4.54	0.40	11.25
	β_6	0.00	0.00	-0.65

Table 3.4.13 (cont.) Three Characteristic Model Hedonic Surface Estimates				
Year	Coefficient	Value	Std. Error	t value
1989	β_0	-2688.73	192.69	-13.95
	β_1	300.19	20.16	14.89
	β_2	902.15	27.41	32.91
	β_3	14.02	1.00	13.95
	β_4	-0.82	0.10	-8.24
	β_5	2.06	0.24	8.61
	β_6	-0.01	0.00	-14.67
1990	β_0	-2737.45	231.89	-11.80
	β_1	210.36	20.16	10.43
	β_2	768.65	28.03	27.42
	β_3	-0.29	0.51	-0.56
	β_4	-0.93	0.10	-9.32
	β_5	0.08	0.20	0.41
	β_6	0.00	0.00	4.58
1991	β_0	-1204.85	509.82	-2.36
	β_1	60.22	38.54	1.56
	β_2	456.06	55.55	8.21
	β_3	0.33	0.87	0.37
	β_4	-0.33	0.17	-1.98
	β_5	1.25	0.37	3.39
	β_6	0.00	0.00	2.50

Table 3.4.14 Correlation Matrix for Computer Characteristics			
	Min	Mips	Max
Min	1.00	0.92	0.76
Mips	0.92	1.00	0.86
Max	0.76	0.86	1.00

Table 3.4.15
Three Characteristic Model
Minimum Memory Demand

Variable	Value	Std. Error	t value
α_{10}	346.25	13.54	25.58
α_{11}	-1.35	0.06	-21.64
SIC-2	-34.95	14.66	-2.38
SIC-3	-48.38	17.23	-2.81
SIC-4	-27.29	17.02	-1.60
SIC-5	-32.43	14.88	-2.18
SIC-6	-38.58	15.38	-2.51
SIC-7	-28.82	15.16	-1.90
SIC-8	-13.84	16.70	-0.83
SIC-9	-24.28	16.54	-1.47
SIC-10	-16.20	16.73	-0.97
SIC-11	-39.42	16.40	-2.40
SIC-12	-34.21	16.18	-2.11
SIC-13	-34.39	14.38	-2.39
SIC-14	-28.12	16.42	-1.71
SIC-15	-38.28	14.17	-2.70
SIC-16	-22.55	17.32	-1.30
SIC-17	-22.50	14.21	-1.58
SIC-18	-21.07	13.44	-1.57
SIC-19	-48.66	17.20	-2.83
SIC-20	-27.43	14.94	-1.84
SIC-21	-37.30	14.55	-2.56
SIC-22	-21.39	14.59	-1.47
SIC-23	-34.09	15.07	-2.26
SIC-24	-31.56	16.34	-1.93
Site Value	0.00	0.00	3.96
Max MIPS	-0.73	0.19	-3.86
Total MIPS	-0.39	0.11	-3.55
Total KVA	0.04	0.04	1.01
Age Young	-4.37	0.67	-6.48
IBM	-3.24	3.94	-0.82

Table 3.4.16 Three Characteristic Model MIPS Demand			
Variable	Value	Std. Error	t value
α_{20}	1196.10	84.09	14.22
α_{21}	-7.63	0.67	-11.38
SIC-2	187.77	91.11	2.06
SIC-3	120.53	107.11	1.13
SIC-4	120.27	105.84	1.14
SIC-5	263.45	92.49	2.85
SIC-6	133.22	95.61	1.39
SIC-7	218.16	94.26	2.31
SIC-8	64.77	103.85	0.62
SIC-9	38.17	102.79	0.37
SIC-10	168.00	103.99	1.62
SIC-11	114.44	101.95	1.12
SIC-12	307.18	100.57	3.05
SIC-13	108.04	89.40	1.21
SIC-14	147.70	102.06	1.45
SIC-15	157.17	88.07	1.78
SIC-16	163.37	107.66	1.52
SIC-17	194.33	88.35	2.20
SIC-18	96.90	83.58	1.16
SIC-19	62.72	106.91	0.59
SIC-20	82.09	92.90	0.88
SIC-21	182.94	90.42	2.02
SIC-22	15.17	90.73	0.17
SIC-23	188.71	93.69	2.01
SIC-24	139.46	101.55	1.37
Site Value	0.03	0.01	4.54
Max MIPS	-7.79	1.20	-6.49
Total MIPS	-1.76	0.69	-2.56
Total KVA	0.95	0.27	3.50
Age Young	13.34	4.20	3.18
IBM	188.26	24.49	7.69

Table 3.4.17 Three Characteristic Model Maximum Memory Demand			
Variable	Value	Std. Error	t value
α_{20}	19.47	3.91	4.98
α_{21}	-0.01	0.00	-7.52
SIC-2	3.42	4.23	0.81
SIC-3	3.03	4.98	0.61
SIC-4	5.69	4.92	1.16
SIC-5	-0.07	4.30	-0.02
SIC-6	-2.56	4.44	-0.58
SIC-7	-2.88	4.38	-0.66
SIC-8	-3.79	4.83	-0.79
SIC-9	2.07	4.78	0.43
SIC-10	-2.22	4.83	-0.46
SIC-11	-2.23	4.74	-0.47
SIC-12	-0.64	4.67	-0.14
SIC-13	0.91	4.16	0.22
SIC-14	-0.12	4.75	-0.03
SIC-15	-0.20	4.09	-0.05
SIC-16	4.14	5.00	0.83
SIC-17	0.07	4.11	0.02
SIC-18	0.78	3.88	0.20
SIC-19	-0.71	4.97	-0.14
SIC-20	0.88	4.32	0.20
SIC-21	1.36	4.20	0.32
SIC-22	3.17	4.22	0.75
SIC-23	-3.72	4.35	-0.85
SIC-24	1.66	4.72	0.35
Site Value	0.00	0.00	0.83
Max MIPS	-0.24	0.05	-4.38
Total MIPS	0.09	0.03	2.93
Total KVA	-0.06	0.01	-4.47
Age Young	0.00	0.20	0.01
IBM	4.55	1.14	4.00

Table 3.4.18A Three Characteristic Model Utility-Based Price Index–P^* as Weight						
	1985	1986	1987	1988	1989	1990
1985	326.20					
1986	389.39	325.63				
1987	326.22	325.50	321.46			
1988	252.06	253.80	259.36	310.94		
1989	228.80	228.35	239.50	247.74	297.24	
1990	163.17	163.51	165.41	168.20	170.86	272.94
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-19.71	-23.61	-29.19	-37.81	-54.47	-100.41

Table 3.4.18B Three Characteristic Model Utility-Based Price Index–P^0 as Weight						
	1985	1986	1987	1988	1989	1990
1985	329.80					
1986	362.52	328.73				
1987	318.82	318.47	323.84			
1988	253.60	255.44	268.21	306.48		
1989	218.95	219.70	236.62	249.78	280.36	
1990	164.87	165.30	169.71	170.74	177.73	237.34
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-19.89	-23.80	-29.38	-37.33	-51.55	-86.43

Table 3.4.19 Three Characteristic Model Traditional Hedonic Indexes		
Year	Log-Log	Log-Linear
1985	863.50	484.86
1986	790.98	513.64
1987	532.31	388.36
1988	416.19	343.03
1989	284.22	225.12
1990	189.24	164.45
1991	100.00	100.00
AAGR	-35.93	-26.31

Table 3.4.20 Three Characteristic Model Linked Index		
Year	P^* as Weight	P^0 as Weight
1985	619.03	520.86
1986	738.95	572.53
1987	738.65	554.66
1988	595.96	459.38
1989	474.83	374.39
1990	272.94	237.34
1991	100.00	100.00
AAGR	-30.38	-27.51

Table 3.4.21 Three Characteristic Model Reverse Index						
	1986	1987	1988	1989	1990	1991
1985	100.00	100.00	100.00	100.00	100.00	100.00
1986	59.35	82.53	86.52	88.70	90.02	90.53
1987		49.03	74.77	81.00	85.51	88.60
1988			53.14	53.68	59.30	62.65
1989				48.78	53.94	57.07
1990					38.88	30.68
1991						29.01
AAGR	-52.18	-35.63	-21.07	-17.95	-18.90	-20.62

Table 3.4.22 Three Characteristic Model Reverse Linked Index	
Year	P^0 as Weight
1985	100.00
1986	59.35
1987	35.26
1988	25.06
1989	22.77
1990	16.41
1991	15.52
AAGR	-31.05

Table 3.4.23 Three Characteristic Model Linked Index–Average All Growth Rates	
Year	P^* as Weight
1985	362.06
1986	432.21
1987	395.52
1988	310.97
1989	273.77
1990	184.14
1991	100.00
AAGR	-21.44

Table 3.4.24A
Three Characteristic Model
Utility-Based Price Index–P^*–IBM Only

	1985	1986	1987	1988	1989	1990
1985	679.27					
1986	721.05	674.56				
1987	722.03	706.41	670.03			
1988	647.19	633.42	671.20	792.41		
1989	541.55	529.78	553.00	674.84	830.92	
1990	302.42	297.81	307.65	363.71	404.07	812.54
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-31.93	-38.18	-47.55	-69.00	-105.87	-209.50

Table 3.4.24A Three Characteristic Model Utility-Based Price Index–P^0–IBM Only						
	1985	1986	1987	1988	1989	1990
1985	715.29					
1986	707.64	704.08				
1987	727.45	707.00	702.53			
1988	652.46	634.63	681.98	834.36		
1989	547.65	538.72	570.85	687.23	900.56	
1990	306.00	299.67	312.18	365.76	434.23	1082.36
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-32.79	-39.03	-48.74	-70.72	-109.89	-238.17

Table 3.4.25 Three Characteristic Model Traditional Hedonic Indexes–IBM Only		
Year	Log-Log	Log-Linear
1985	886.58	450.60
1986	802.46	497.35
1987	507.14	350.64
1988	409.48	319.71
1989	283.20	213.66
1990	185.19	156.10
1991	100.00	100.00
AAGR	-36.37	-25.09

Table 3.4.26 Three Characteristic Model Linked Index–IBM Only		
Year	P^* as Weight	P^0 as Weight
1985	1761.89	2826.07
1986	1870.26	2795.84
1987	1958.57	2807.43
1988	1961.99	2725.31
1989	1670.89	2244.73
1990	812.54	1082.36
1991	100.00	100.00
AAGR	-47.82	-55.69

Table 3.4.27 Three Characteristic Model Reverse Index–IBM Only						
	1986	1987	1988	1989	1990	1991
1985	100.0	100.00	100.00	100.00	100.00	100.00
1986	79.3	87.79	91.50	93.50	95.07	95.92
1987		62.29	97.23	98.95	100.71	102.49
1988			65.55	80.29	83.42	84.88
1989				58.08	62.79	64.17
1990					43.89	26.94
1991						33.35
AAGR	-23.2	-23.67	-14.08	-13.58	-16.47	-18.30

Table 3.4.28 Three Characteristic Model Reverse Linked Index–IBM Only	
Year	P^0 as Weight
1985	100.00
1986	79.30
1987	56.27
1988	37.94
1989	27.44
1990	19.18
1991	23.74
AAGR	-23.97

Table 3.4.29 Three Characteristic Model Linked Index–Average All Growth Rates–IBM Only	
Year	P^* as Weight
1985	844.93
1986	896.91
1987	918.51
1988	854.45
1989	715.27
1990	386.01
1991	100.00
AAGR	-35.57

3.4.5 Figures

Figure 2.4.1
Graph of One Variable Hedonic Surfaces

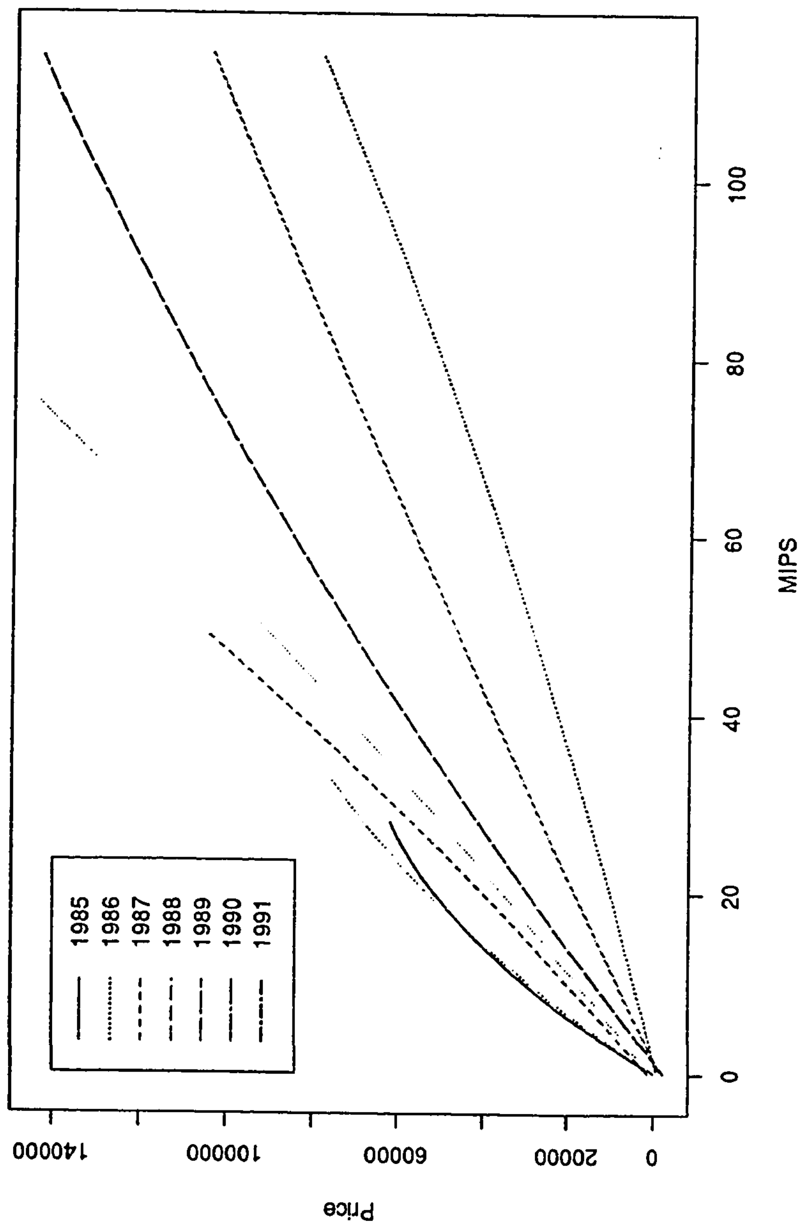


Figure 2.4.2
Box-Plot of MIPS–All Data

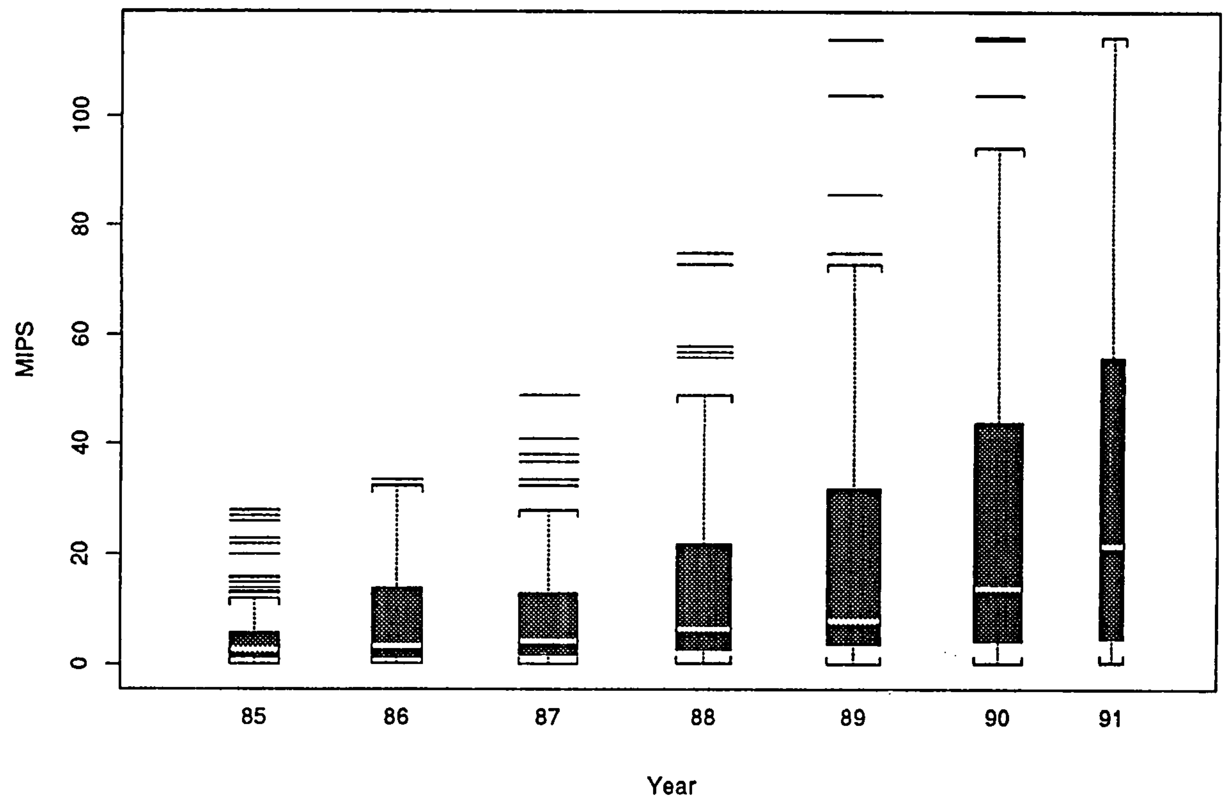


Figure 2.4.3
Box-Plot of MIPS-IBM Data

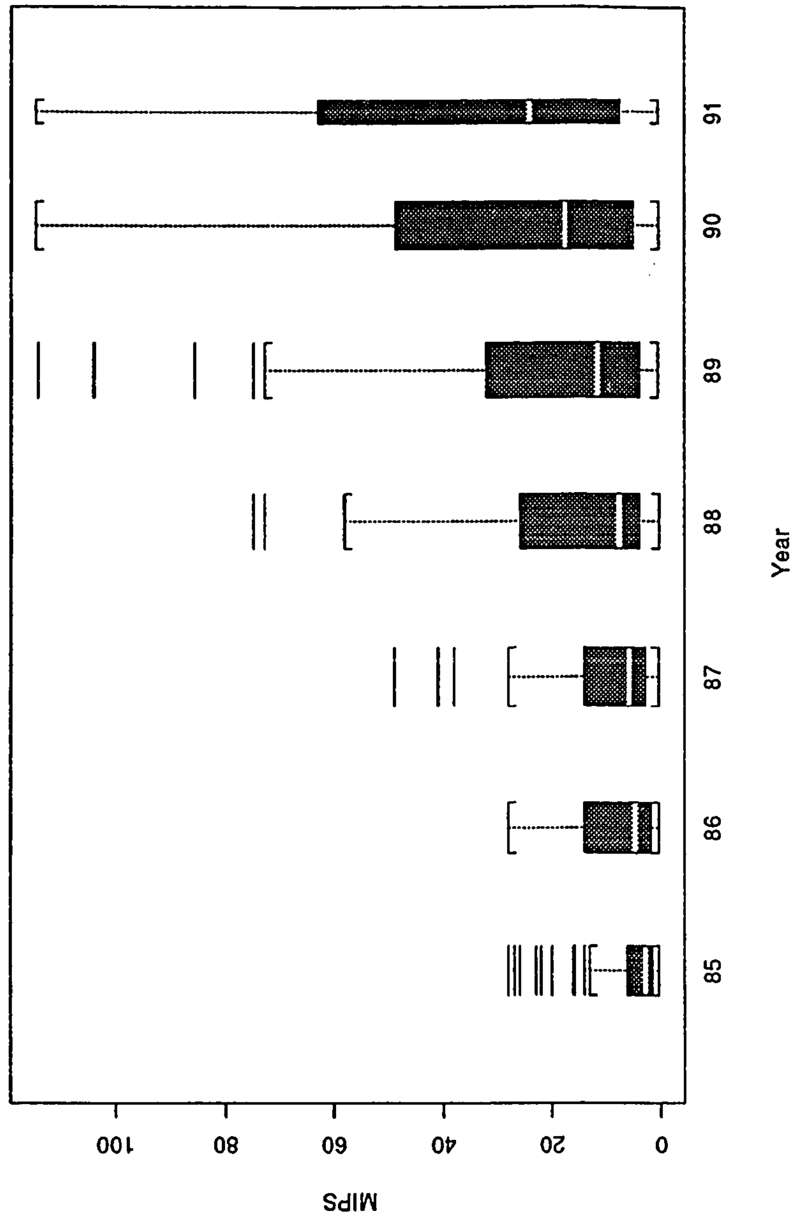


Figure 2.4.4

Box-Plot of Minimum Memory–All Data

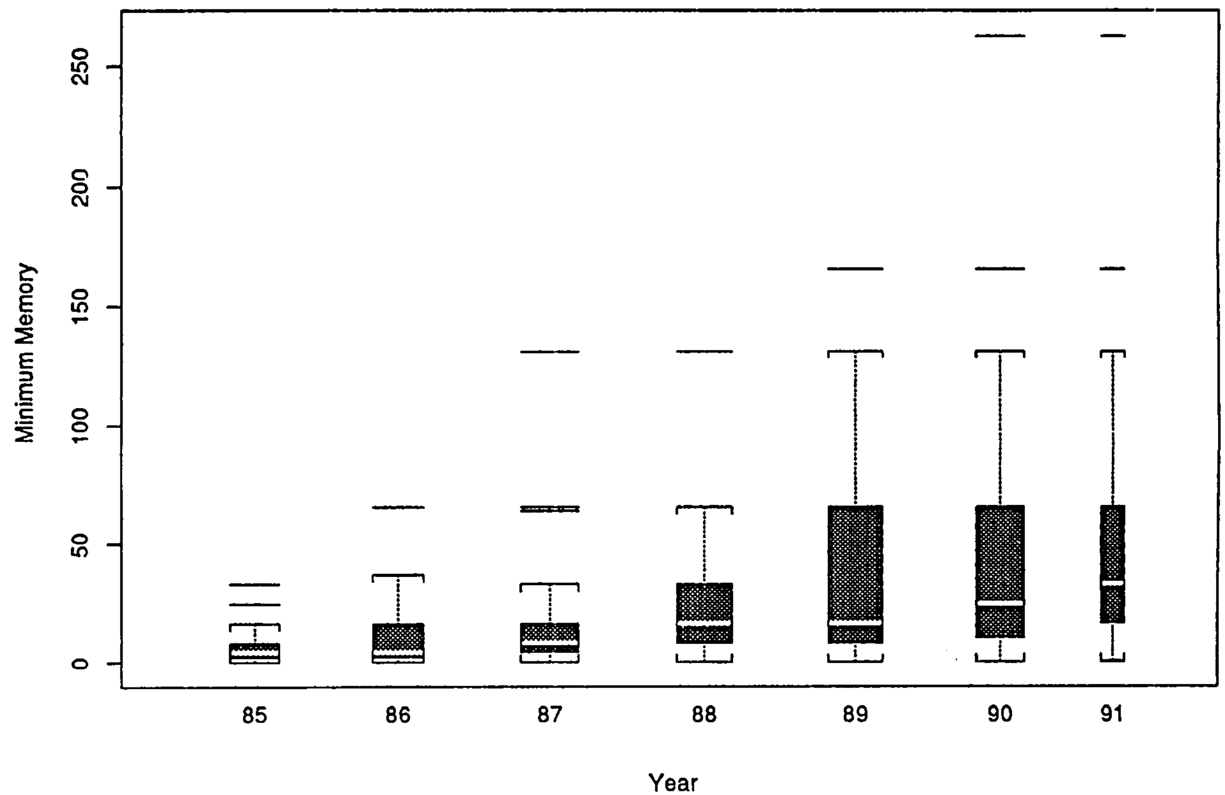
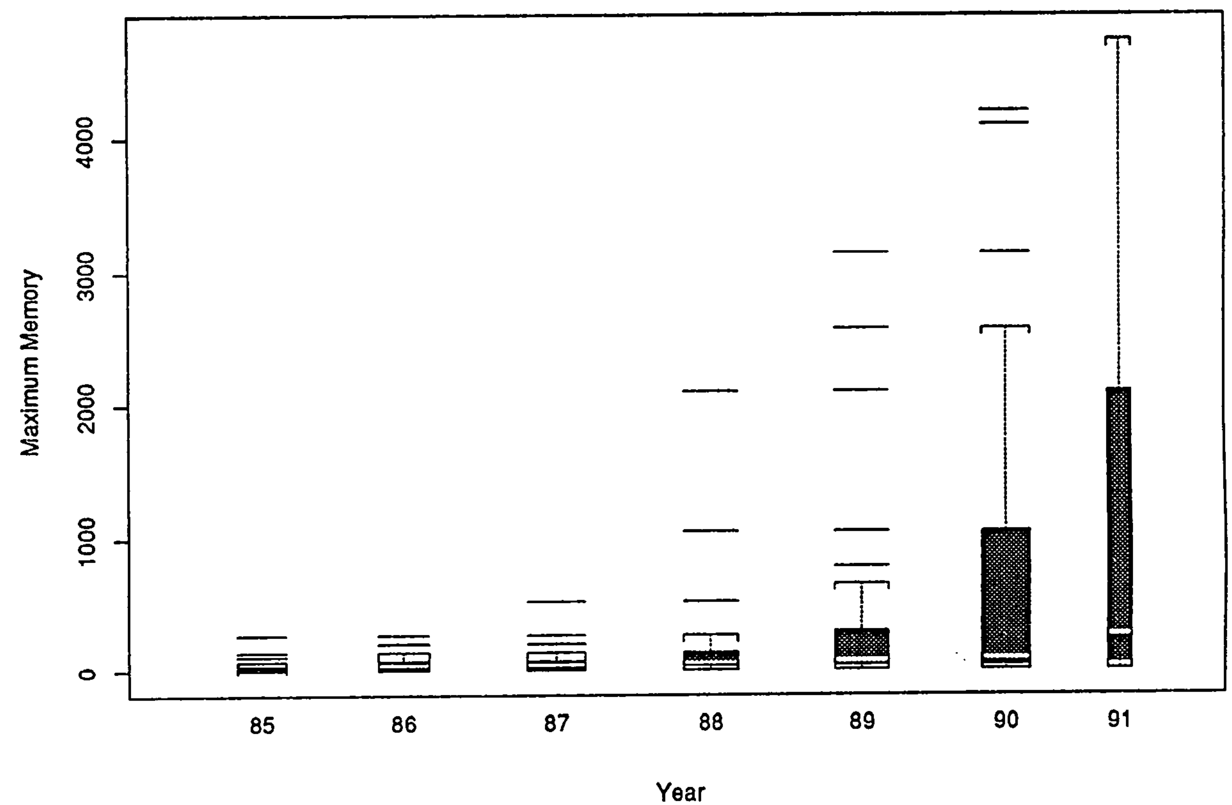


Figure 2.4.5
Box-Plot of Maximum Memory–All Data



3.5 CONCLUSION

In this chapter we have employed an extensive micro-dataset on the mainframe computer market from 1984–1991 in order to investigate the adequacy of traditional hedonic based quality-adjusted price indexes. We describe an alternative procedure based on Rosen (1974), Bartik (1987), Epple (1987) and Trajtenberg (1990). Using this method we have shown that an index which accounts for the benefits buyers receive from improvements in new technology declines at a slower rate than a traditional hedonic price index. This supports the claim made in Chapter 2 that a utility based index, with buyers having a diminishing marginal utility for characteristics, should fall slower than a hedonic index.

It was shown that while the utility index declined at a slower rate than the hedonic index, the rate of decline of the utility index was sensitive to the choice of buyers used to compute the index. However, it was also pointed out that hedonic indexes are unable to account for this distribution at all. We conclude that this failure to account for the distribution of buyers is an additional drawback of hedonic methods to be added to drawbacks described by Trajtenberg (1990).

We noted throughout the problems with using MIPS as a system characteristic and using acquisitions from both IBM and non-IBM vendors. We compared results using both sets of data, and for the most part there was little difference. If anything, we noted that the IBM-only indexes declined at a faster rate than the overall rate. This could have occurred for a number of reasons. First, it could be that IBM lowered its prices at a faster rate than the overall rate. Second, and more likely, there may be some unobserved characteristic, like reliability, which is keeping non-IBM systems' prices higher or allowing IBM prices to fall lower. In any event, we believe this warrants a search for even better data which will allow for a better description of a mainframe computer.

Finally, the results were obtained while maintaining a specific functional form for the hedonic surfaces in the first step of the computation of our index. In the next chapter we will investigate the robustness of our results to that choice by looking at various alternative functional forms.

CHAPTER 4
A LOOK AT FUNCTIONAL FORM

4.1 INTRODUCTION

In the previous chapter we adopted the use of the quadratic functional form on the basis of ease of computation. Our interest in this chapter is in determining the sensitivity of the computed benefit index to this choice. We find that there is a tradeoff between the precision of the hedonic price function estimates and the ease of use of those estimates for computing the benefit index. Our analysis shows, though, that the gains from alternative functional forms are small relative to the difficulties in computation that arise. These difficulties arise at the stage where we compute our predicted (or counterfactual) levels of characteristics. When we move away from the quadratic form (which has a linear marginal price surface) we are forced to solve a nonlinear system of equations. In the cases that we examine, this system of equations has a solution which is either difficult to obtain or which is not unique. For this reason we end up favoring the quadratic form.

Even though we find it difficult to depart from the quadratic form, we are still interested in the goodness-of-fit of the estimated hedonic surfaces. Having some idea of the goodness-of-fit relative to alternative forms should give us some indication of the sensitivity of the benefit index to the choice of functional form. The R^2 values obtained using the quadratic form are very high, and while we do find that a goodness-of-fit criterion would force us to choose an alternative form, we argue that making this change will not lead us to significantly different results. We offer support for this argument by computing approximate indexes that lead us to similar results.

One of the main issues surrounding the literature on hedonic regression and hedonic price indexes is the choice of functional form for the surface(s) to be estimated. It has been shown that hedonic price indexes can be quite sensitive to this choice. Various specifications have been suggested and used, such as linear, log-linear, log-log, Box-Cox and quadratic as well as a number of nonparametric forms. Little if an theory has been offered for the choice of functional form and usually one specification is chosen based on some goodness-of-fit criterion.

Notable exceptions to this are Triplett (1989) and Arguea & Hsiao (1993). Triplett has suggested that a form such as the semilog exponential form:

$$\log(P) = \beta_0 + \beta_1 x_1^r + \beta_2 x_2^s + \dots \tag{4.1.1}$$

should be tried. Unfortunately, to date, this form has not been attempted. Arguea & Hsiao, on the other hand, have shown that a particular model of buyer choice suggests that the form should be linear. We will describe and discuss their argument in a subsequent section.

In section 2 we examine the possible use of the log-linear or log-log forms. Section 3 describes and discusses Arguea & Hsiao's (1993) argument for the use of a linear functional form. Section 4 looks at the use of a higher order polynomial form and section 5 looks at the possibility of specifying the hedonic surface as a generalized additive model. Section 6 gives concluding remarks.

4.2 LOG-LINEAR OR LOG-LOG

As stated in the previous chapter, the most common functional forms used in the computer literature on hedonic price functions are log-log and log-linear. These have usually been chosen *a priori* or based on some goodness-of-fit test. Because of this, these seem the most obvious forms to use when estimating our benefit index. However, we quickly run into difficulty. Suppose we begin by estimating a surface of the form

$$\log(P_{it}) = \beta_{0t} + \beta_{1t} MIPS_{it} + u_{it} \tag{4.2.1}$$

assuming a characteristic space with a single dimension $MIPS$. As in the previous chapter we estimate a surface for each year t. Suppose also that we compute marginal prices and estimate demand of the form

$$\hat{mp}_i = \alpha_0 + \alpha_1 MIPS + B_i\Omega + \eta_i \tag{4.2.2}$$

Now, suppose we take a buyer from year t and we attempt to predict the level of $MIPS$ they would purchase if faced with the hedonic surface at time $t+1$. To compute this, we must find the point where the marginal hedonic surface for time $t+1$ intersects the demand surface. The marginal hedonic surface at time $t+1$ is given by

$$\frac{dP}{dMIPS} = \exp(\hat{\beta}_{0,t+1} + \hat{\beta}_{1,t+1}MIPS)\hat{\beta}_{1,t+1}. \tag{4.2.3}$$

We then need to solve

$$\exp(\hat{\beta}_{0,t+1} + \hat{\beta}_{1,t+1}MIPS)\hat{\beta}_{1,t+1} = \hat{\alpha}_0 + \hat{\alpha}_1 MIPS + B_I\hat{\Omega}_i. \tag{4.2.4}$$

Any solution to this equation will be difficult to obtain and work with. In addition, when we move to the more realistic situation of a multiple characteristic model, we will be faced with solving a simultaneous system of these equations and similar difficulty. One possible solution would be to approximate the left hand side of (4.2.4) with a Taylor series expansion. However, this seems to defeat the purpose of obtaining more precise estimates. We face similar difficulty when we use a log-log specification instead of log-linear as in (4.2.1). The important question to answer is: Will the estimated benefit index computed using (4.2.1) be significantly different from a benefit index computed using (3.4.1)?

To address this question we computed hedonic surfaces using the data described in the previous chapter for (4.2.1), a log-log specification and (3.4.1). We then computed Akaike's Information Criterion (AIC) for each surface. Those results are given in Tables 4.2.1 and 4.2.2.

Using the rule that we choose the model that minimizes AIC, we see in each table that the quadratic model would be accepted over the log-linear model in each year except 1991, and that the log-log model would be chosen over both the log-linear and quadratic in every year. However, we also see that within a given year all of the AIC values are fairly close, implying similar fits.

At this point we are faced with comparing the benefits from choosing a log-log form and achieving a better fit, and facing the difficulties associated with making that choice (in terms of further computation toward the benefit index). We feel that the quadratic fit is quite similar to the log-log fit (it is at least a good approximation) and that the difficulties associated with the log-log model outweigh the benefits from the better fit. We therefore stay with the quadratic model for now, and leave open the possibility of employing the log-log model in the future. This future work will obviously require a solution to the problem of obtaining counterfactual levels of characteristics.

4.3 ARGUEA & HSIAO (1993): LINEAR FUNCTIONAL FORM

Arguea & Hsiao (1993) examine a number of econometric issues related to estimating hedonic price functions. One of these is choice of functional form. They argue that, given certain assumptions, the theoretical model implies a linear functional form. They go on to use this model in an analysis of the automobile industry. In this section we review their argument, and using a linear form for the hedonic surface, proceed to compute our benefit index.

The argument makes a number of initial assumptions. First, they assume that products are divisible and, moreover, that the consumption technology is linear. In other words, buyers can obtain a level of characteristic z by choosing various linear combinations of products to get the desired level of z. For example, with computers, a buyer who desires 10 MIPS could purchase 1/2 of a computer with 10 MIPS and 1/6 of a computer with 30 MIPS. More formally, they assume the relationship

$$z = Bx \tag{4.3.1}$$

where z is the level of characteristics, x represents the quantities of the products and B is the consumption technology matrix. For the example just described,

$$z = [10] \qquad B = [1030] \qquad \text{and} \quad x = [\begin{smallmatrix}1/2\\1/6\end{smallmatrix}]. \tag{4.3.2}$$

For two characteristics, Figure 4.3.1 illustrates the situation (we assume 4 available products). When goods are mapped into this characteristics space, the location depends on the product price, the level of product characteristics, the consumption technology and the consumer's budget constraint.

Given a level of income for a consumer, the points A, B, C and D in Figure 4.3.1 are found by setting $x = e_i = (0,0,0,\ldots,m/P_i,\ldots,0,0,0)$, where m is income, P is product price and m/P_i occurs in the ith position, and then computing $z = Be_i$. This computation finds the levels of z that can be purchased if all of the income is spent on a single product. The area inside $0AD$ in Figure 4.3.1 is then the set of all convex combinations of 0, A, B, C and D. It represents the set of all feasible pairs (z_1, z_2).

Given some preference structure for the consumer, buyers optimize over this set. Assuming buyers spend all of their income, this solution will occur on the frontier $ABCD$. Without loss of generality, let us assume that product 1 maps to point A, product 2 maps to point B, product 3 maps to point C and product 4 maps to point D. Then let us suppose that the buyer's optimum occurs at point E. In this case, buyers are purchasing a combination of products 2 and 3 and none of products 1 and 4.

If we assume a representative consumer as Arguea and Hsiao, products 1 and 4 will never be purchased at their current prices. However, in a competitive equilibrium we would expect positive amounts of all goods to be consumed. Therefore, assuming a representative consumer and perfect competition the prices of products 1 and 4 must fall until $ABCD$ is a straight line as in Figure 4.3.2. Assuming ϕ is a vector of shadow prices for the characteristics z, the line $ABCD$ can be represented by

$$P = \phi z \tag{4.3.3}$$

Then given data on P and z, the surface can be estimated as a linear regression.

This result relies heavily on two main assumptions: (1) a representative consumer and (2) a linear relationship between goods and characteristics. We will discuss each of these assumptions in the context of mainframe computers in turn.

The assumption of a representative consumer may be acceptable in an analysis of the automobile industry as Arguea & Hsiao argue. However, our model is concerned with accounting for the different experiences each individual buyer encounters. If we were to assume a representative consumer, we would essentially be saying that all buyers benefit by exactly the same amount. In fact, one of the main points which our analysis makes is that the benefits to buyers differ across the product space. Making this assumption would mask this point.

The assumption of divisibility and additivity of computer characteristics has been discussed by Bresnahan & Greenstein (1994). They define the biggest job a computer can execute as the maximum feasible task (MFT). Consider the speed of a computer. The assumption of a linear relationship between goods and characteristics implies that two 1 MIPS systems are equivalent to one 2 MIPS system. However, this linear assumption ignores the MFT and the fact that the one system can perform some tasks which the two systems cannot perform. In this sense, the 2 MIPS system should be valued higher than the two 1 MIPS systems. This then implies that the relationship between goods and characteristics with computers is nonlinear.

The violation of these two assumptions in computers leads us to believe that the linear relationship specified by (4.3.3) is incorrect in our situation. Nevertheless, we do estimate the linear surfaces and compute the benefit index and compare the results with those obtained in chapter 3.

Table 4.3.1 provides AIC values for both the one variable and three variable hedonic surfaces. The values in this table can be compared with those in Tables 4.2.1 and 4.2.2 to compare the linear and quadratic specifications.

We see from these tables that for each year the quadratic model has a lower AIC value than the linear model. This in turn would lead us to accept the quadratic model over the linear model. This acceptance is further supported by noting that the quadratic terms in both the one variable and three variable surfaces were statistically significant except in a few instances. These results were given previously in Tables 3.4.1 and 3.4.13. We do not show the results here, but an F-test of the quadratic model vs. the linear model was able to reject the linear model.

Now, even though we do not believe the assumptions of Arguea & Hsiao are reasonable in our situation, and we have an abundance of evidence for choosing the quadratic model over the linear model based on goodness-of-fit, we still compute our benefit index using linear hedonic surfaces. The indexes for the one variable and three variable cases are given in Tables 4.3.2A–4.3.4.

The indexes for the one characteristic model shown in Tables 4.3.2A–B and 4.3.4 seem reasonable. The growth rates are similar to those obtained using the quadratic model, but the movements within each forward index more more erratic. The movement is an initial decline followed by a period of increase and an eventual decline. This is in contrast to the quadratic model where we saw an initial increase followed by decline through the end of the time period. This more erratic movement is most likely being caused by the linear hedonic surfaces crossing each other.

The forward indexes for the three characteristic model shown in Tables 4.3.3A–B make little if any sense, and the reverse index, which we do not show, consists entirely of negative values. This came as a result of upward sloping demand estimates and crossing hedonic surfaces. However, because of the evidence we have against using the linear model, we do not concern ourselves with these results.

Arguea & Hsiao (1993) claim that, given certain assumptions, the correct functional form specification for a hedonic surface is linear. We believe that these assumptions cannot be met with mainframe computers, and that the linear form is in fact incorrect. We support this claim with evidence that the quadratic model provides a superior fit, and evidence that indexes computed using the linear specification make little sense. We therefore choose the quadratic model over the linear model, and ignore the linear model in the remainder of our analysis.

4.4 HIGHER ORDER TERMS

In chapter 3 we used a quadratic functional form in estimating our hedonic surfaces. We chose this form at that time for its ease of computation. However, it is possible that a higher order polynomial might achieve a better fit at the expense of parsimony.

In this section we look at the effects of adding higher order terms. We show that using AIC as a selection criterion would force us to include these higher order terms. However, we argue that including these terms makes further computation difficult. For instance, including characteristics to the third power implies a quadratic marginal hedonic price function. Assuming linear demand, computing the counterfactual levels of characteristics results in non-unique solutions. In this case we are left with the difficult task of choosing among alternative solutions. We show that the quadratic model and cubic models have similar fits, and thus argue that the difficulties associated with adopting the cubic model outweigh the benefits from improved fit.

Table 4.4.1 gives AIC values for the quadratic and cubic fits (for a one characteristic model) for each surface from 1985–1991. We see that in every instance except 1985 the AIC value would recommend we choose the cubic form. Attempting to continue with this form causes difficulties. We can write the cubic form as

$$P = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \gamma_j x_j^2 + \sum_{j=1}^{k} \delta_j x_j^3 + u. \tag{4.4.1}$$

Assume we estimate (4.4.1) for each year and then try to compute the counterfactual level of characteristics for a time t buyer at time $t+1$. The marginal hedonic price function is given by

$$\frac{dP}{dx_j} = \beta_j + 2\gamma_j x_j + 3\delta_j x_j^2 \tag{4.4.2}$$

and demand is given by (4.2.2). To compute counterfactual characteristics we must solve

$$\hat{\beta}_j + 2\hat{\gamma}_j x_j + 3\hat{\delta}_j x_j^2 = \hat{\alpha}_0 + \hat{\alpha}_1 x_j + B_i \hat{\Omega} \tag{4.4.3}$$

for each x_j. Because (4.4.3) involves the square of x_j, there are obviously two potential solutions for each x_j. This then implies that there are 2^k potential configurations for each buyer for each year. The obvious solution to this problem is to choose the configuration which sets the buyer at the highest level of utility, and while this solution is obvious, the computation would be cumbersome.

In order to get an idea of the effect of including the cubic term on the benefit index, we compute an approximate index for both the quadratic and cubic specifications. The approximate index is defined as

$$\frac{I_{t+k}^A = \sum_{i=1}^{n} \left(\frac{H_{t+k}(x_{it})}{H_t(x_{it})} \right)}{n} \tag{4.4.4}$$

where $H_{(\cdot)}$ is the hedonic surface at time $(\cdot)$, and x_{it} represents the observed levels of characteristics at time t. This is essentially a hedonic index weighted by the levels of observed characteristics in the sense that buyers only benefit in terms of price reductions and not in terms of higher levels of quality.

This is a crude estimate of the benefit index and in fact turns out to perform much like the traditional hedonic index. However, it should be useful for comparisons of models. If the approximate indexes are roughly the same, then the argument goes that the models provide roughly the same fit and that buyers will benefit roughly the same under either scenario. We compute this index for the one characteristic case for both the quadratic and cubic models.

These indexes are shown in Table 4.4.2. Except for the movement from 1987–1988, the movements in each index are nearly the same in percentage terms. This evidence along with the similarity in the fits implies that a benefit index computed with either model would probably be "close."

Again, as in the log-log case, we do not have firm evidence that the benefit indexes computed with quadratic hedonic surfaces are similar to benefit indexes computed using cubic hedonic surfaces. Unfortunately, the only firm evidence would be the indexes themselves, and at this point we are not prepared to move in this direction when the benefits from doing so may be small. For now, we rely on the evidence that we have shown and conclude that the difficulties associated with adding higher order terms outweigh the benefits associated with an improved fit. We therefore stay with the quadratic specification.

4.5 GAM: A FURTHER POSSIBILITY?

The previous sections in this chapter have described some alternatives to the quadratic form used in the previous chapter. Each of those forms is parametric. In this section we would like to discuss the possible use of generalized additive models (GAM); Hastie & Tibshirani (1990). These models are semi-parametric in nature and employ smoothers to fit a surface to the data. We will provide a brief description of these models, as well as comparing the hedonic surface fit with a GAM and the hedonic surface fit with a quadratic form. The results of this comparison will show that the GAM provides a much better fit than the quadratic. We believe therefore that GAM should be given serious consideration when estimating hedonic surfaces. However, we will show that these models, like the others discussed in the chapter, are difficult to use when computing counterfactual characteristics.

Additive models are defined by

$$Y = \alpha + \sum_{j=1}^{k} f_j(x_j) + \varepsilon \tag{4.5.1}$$

where x_j and ε are independent, $E(\varepsilon) = 0$ and $\text{var}(\varepsilon) = \sigma^2$. x_j could be a single predictor variable or could have multiple dimensions. The f_j are unknown functions, or data transformation, which the researcher wishes to estimate.

Hastie & Tibshirani (1990) discuss the method for fitting (4.5.1). This method is based on smoothers. There are a number of issues surrounding the use of smoothers including which smoother to use and how big to make the neighborhoods around the target value. A complete description of these issues is beyond the scope of this work. However, to get an idea of the method, we will describe a smoother and how we chose the neighborhood size, and then we will apply this to the data used in chapter 3 to estimate a hedonic surface. We will then compare this with the quadratic hedonic surface based on fit and usefulness.

The smoother that we choose to use is a smoothing spline. The smoothing spline finds the function f, among all functions f with two continuous derivatives, that minimizes the penalized residual sum of squares

$$\sum_{i=1}^{n}(y_i - f(x_i))^2 + \lambda \int_a^b (f''(t))^2 dt \tag{4.5.2}$$

where λ is a fixed constant and $a \leq x_1 \leq \ldots \leq x_n \leq b$. The first term in (4.5.2) measures the residual sum of squares and the second term measures the curvature of f. As $\lambda \to \infty$, the curvature penalty dominates and (4.5.2) will approach a linear regression, whereas when $\lambda \to 0$, there is essentially no penalty for curvature and the function f will be a twice continuously differentiable function that interpolates the data.

It can be shown (Hastie & Tibshirani (1990)) that (4.5.2) has a unique solution for f. This solution is the natural cubic spline. The natural cubic spline fits a cubic polynomial between the unique values of x and "connect" these polynomials so that the second derivatives are continuous. The natural cubic spline is linear beyond the boundaries of the data.

Since the natural cubic smoothing spline fits a polynomial between each of the unique values of x, it is not necessary to choose the neighborhood size. However, we still need to choose λ. We choose to use a data driven approach for picking λ known as cross-validation. Cross-validation works by leaving out data observations one at a time and computing the smooth at the missing point using the remaining data points. One then computes

$$CV(\lambda) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{f}_\lambda^{-i}(x_i))^2 \tag{4.5.3}$$

where $\hat{f}_\lambda^{-i}$ represents the fit at x_i leaving out the i^th data point. The parameter λ is chosen by computing (4.5.3) for a range of possible λ's, and the λ that minimizes (4.5.3) is chosen as $\hat{\lambda}$.

Given this smoother, we estimate a GAM of the form

$$P = \sum_{j=1}^{k} s(x_j) \tag{4.5.4}$$

where $s(\cdot)$ implies that the smoother described above is used in the estimation. After estimating (4.5.4) for both the one characteristic and three characteristic cases for each year, we compared the computed fits with the corresponding quadratic fits via an F-test. Without exception, the GAM fit was significantly different and superior to the quadratic fit. In fact, in every instance the GAM fit reduced the residual sum of squares by at least ten percent. However, we should expect this type of improvement since the GAM has much more freedom in fitting.

The drawback to the GAM model, as with the other models discussed in this chapter is its usefulness. There do exist numerical methods for obtaining derivatives of the fitted surface at specific characteristic levels. This would allow us to compute marginal prices and to estimate demand. Unfortunately, one cannot write down a specific form for the marginal price function. This renders the computation of counterfactual characteristics difficult. Numerical methods could be employed, but would be quite expensive computationally. The reason is that one would be required to solve an optimization problem for each buyer and each characteristic. With three characteristics and more than 20,000 observations in our data set, this would obviously be quite tedious. Without a means for lowering the dimension of the problem, we chose to pass over this possibility.

Generalized additive models do provide a much better fit than the other models discussed in this chapter, but their potential usefulness for computing benefit indexes is limited. Here we have simply provided evidence that GAM yields a superior fit to any of the other models examined with our data set. We leave open the possibility that with appropriate numerical methods and computing power the GAM could be a useful tool for estimating hedonic surfaces, hedonic indexes and benefit indexes.

4.6 CONCLUSION

In this chapter we have attempted to address the issue of functional form for a hedonic surface. Our goal was to determine the sensitivity of our benefit index to this choice. We looked at a number of alternative functional form specifications including log-linear, log-log, linear, cubic and GAM. In general, our results showed that while some of these specifications provided significantly better fits than the quadratic fit we adopted in chapter 3, the difficulties associated with these alternative models rendered them difficult to use. A Taylor series approximation is feasible, but this seems to defeat the purpose of obtaining a more precise fit.

The difficulties arose mainly at the stage where we needed to compute counterfactual characteristics. The forms listed above all have nonlinear marginal price functions associated with them. Thus when we attempt to compute the predicted levels of characteristics by finding the point where the characteristic demand intersects the marginal hedonic price function, we are faced with solving a nonlinear system of equations. Finding this solution is difficult and in most cases is not unique. We do not run into these same problems when we use the quadratic form. Therefore, we are faced with the tradeoff that these alternative forms may provide better fits but at the same time are difficult to work with.

We believe this tradeoff favors the quadratic form, because it is quite simple to use and provides a fit similar to, although worse than, the alternatives described. We support this by providing evidence in the form of AIC values and approximate indexes. The evidence leads us to believe that choosing an alternative form will probably have little affect on the final benefit index. Unfortunately, we cannot support this with the actual benefit indexes, which would be preferred, because of the difficulties in computing them. We rely instead on the available information to support our claim. In the future we hope to overcome the problems associated with these alternative models and to provide a more in-depth analysis of the sensitivity of the benefit index to the choice of functional form on the hedonic surface.

4.6 TABLES

Table 4.2.1 One Characteristic Model AIC Values for Various Fits			
Year	Log-Linear	Log-Log	Quadratic
1985	72708.30	68424.72	68739.48
1986	82182.64	77601.42	78679.03
1987	109843.20	105303.40	108476.20
1988	97854.82	92634.83	95605.66
1989	96513.47	91578.89	94377.92
1990	73841.82	69995.32	72410.83
1991	17430.81	16766.25	17522.77

Table 4.2.2 Three Characteristic Model AIC Values for Various Fits			
Year	Log-Linear	Log-Log	Quadratic
1985	72689.70	68226.19	68590.41
1986	81954.46	77485.07	76696.10
1987	109827.00	104131.20	103563.10
1988	97513.97	92114.56	94154.19
1989	96044.58	90441.50	93428.74
1990	73273.02	68956.65	72220.31
1991	17356.83	16344.74	17492.54

Table 4.3.1 One and Three Characteristic Model Linear Functional Form		
Year	One Char.	Three Char.
1985	70816.72	70273.28
1986	79267.45	78670.11
1987	108587.90	104925.20
1988	95714.57	94275.78
1989	94848.72	93972.58
1990	72445.60	72340.85
1991	17569.19	17520.83

Table 4.3.2A One Characteristic Model–Linear Hedonic Utility-Based Price Index–P^* as Weight						
Year	1985	1986	1987	1988	1989	1990
1985	229.30					
1986	105.35	233.12				
1987	157.79	161.78	224.29			
1988	188.29	186.56	198.92	214.44		
1989	176.24	176.12	176.72	173.51	198.80	
1990	136.76	136.58	136.61	134.59	133.67	178.56
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-13.83	-16.93	-20.19	-25.43	-34.36	-57.97

Table 4.3.2B One Characteristic Model–Linear Hedonic Utility-Based Price Index–P^0 as Weight						
Year	1985	1986	1987	1988	1989	1990
1985	240.28					
1986	90.67	247.72				
1987	109.02	110.16	235.62			
1988	173.36	172.65	180.50	226.77		
1989	180.08	180.65	180.68	176.48	195.14	
1990	137.81	137.98	137.75	135.96	134.30	157.17
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-14.61	-18.14	-21.43	-27.29	-33.43	-45.21

Table 4.3.3A Three Characteristic Model–Linear Hedonic Utility-Based Price Index–P^* as Weight						
Year	1985	1986	1987	1988	1989	1990
1985	311.86					
1986	21.33	315.76				
1987	246.56	246.34	302.70			
1988	238.13	236.80	240.61	294.53		
1989	222.86	221.55	220.28	217.63	278.22	
1990	169.95	169.25	168.01	166.61	166.38	257.01
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	-18.96	-23.00	-27.69	-36.01	-51.16	-94.39

Table 4.3.3B Three Characteristic Model–Linear Hedonic Utility-Based Price Index–P^0 as Weight						
Year	1985	1986	1987	1988	1989	1990
1985	-58.95					
1986	114.62	-58.17				
1987	74.51	75.97	-58.93			
1988	75.78	76.95	74.28	-59.33		
1989	78.62	79.64	78.59	77.28	-61.02	
1990	87.74	88.26	87.77	87.57	85.07	-64.18
1991	100.00	100.00	100.00	100.00	100.00	100.00
AAGR	NA	NA	NA	NA	NA	NA

Table 4.3.4 One Characteristic Model–Linear Hedonic Reverse Index						
Year	1985	1986	1987	1988	1989	1990
1985	100.00	100.00	100.00	100.00	100.00	100.00
1986	115.89	98.03	98.65	98.91	99.19	99.26
1987		93.62	92.67	94.49	95.64	96.52
1988			91.46	89.82	92.23	94.23
1989				74.95	72.26	78.66
1990					56.94	50.75
1991						48.81
AAGR	14.75	-3.30	-2.97	-7.21	-11.26	-11.95

Table 4.4.1
One Characteristic Model
AIC Values for Quadratic and Cubic Models

Year	Quadratic	Cubic
1985	68739.48	68741.21
1986	78679.03	78547.67
1987	108476.20	108435.00
1988	95605.66	95409.94
1989	94377.92	93715.62
1990	72410.83	72365.06
1991	17522.77	17519.48

Table 4.4.2
One Characteristic Model
Approximate Index for Quadratic and Cubic

1985	100.00	100.00
1986	97.97	97.02
1987	77.41	75.74
1988	64.44	74.22
1989	29.82	44.85
1990	17.53	22.18
1991	10.02	14.26
AAGR	-38.34	-32.46

4.7 FIGURES

Figure 4.2.1

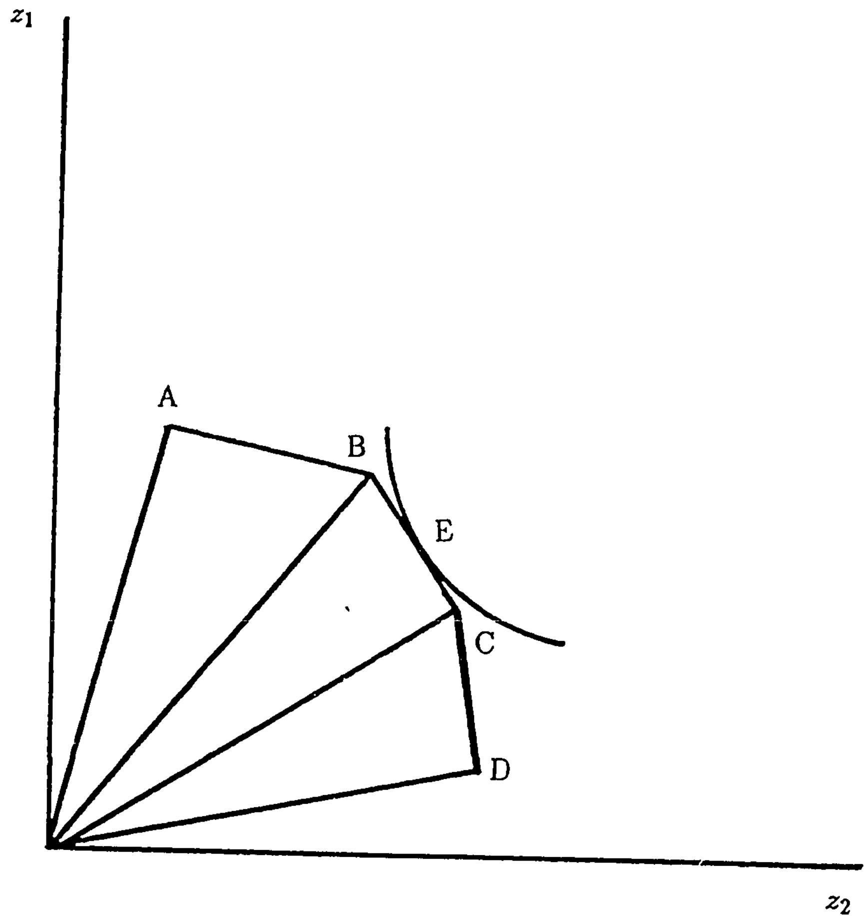
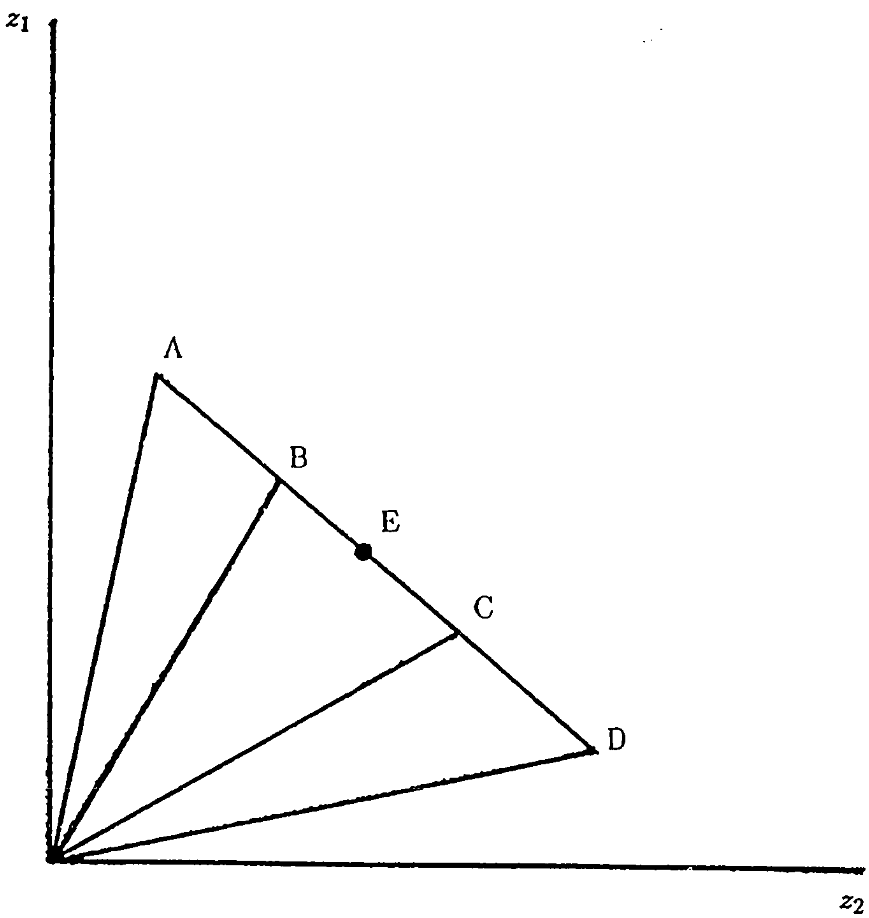


Figure 4.2.2



CHAPTER 5
CONCLUSION

Until recently, hedonic price indexes were the predominant method for measuring the improvements in price per performance for mainframe computers. These indexes showed that price per performance improved at roughly 20–25% over the past 30 years. However, little attention has been given to how well these indexes measure the benefits buyers receive from improvements in computer technology. Trajtenberg (1990) proposed a method for measuring the benefits from product innovation and applied his procedure to the computed tomography scanner industry. His results show that hedonic indexes understate the true benefits from improvements in technology in that industry. In this work we have proposed an alternative procedure which also measures the benefits which acrue to buyers from improving product technology. We find, in contrast to the results of Trajtenberg, that the hedonic index overstates the true benefits to buyers from product innovation in the mainframe computer industry.

In chapter 2 we compared our benefit index with the hedonic index both geometrically and via a numerical example. Our findings show that the benefit index will decline at a slower rate than the hedonic index under most circumstances. This result implies that the hedonic index will most likely overstate the true benefits buyers receive from improving product technology. This result comes as a consequence of our assumption of diminishing marginal utility for product characteristics, i.e. buyers have a lower willingness to pay for higher levels of characteristics on a per unit of characteristic basis. This assumption is a consequence of a concave bid curve and downward sloping demand.

In addition to the main result that the benefit index will most likely decline at a slower rate than the hedonic index, we found that the benefit index is sensitive to the distribution of buyers across the product space and to the level of the highest available quality. With regard to the distribution of buyers, we found that as the distribution of buyers shifted toward higher levels of quality, the benefit index declined at a faster rate. This implies that buyers purchasing high levels of quality must benefit more from price reductions and extensions in the product space than buyers purchasing low levels of quality. Therefore, industries in which most buyers are purchasing the highest level of quality available have buyers who benefit more from improving technology than industries where most buyers are purchasing low levels of quality. With regard to the level of the highest available quality, we found that as that level increased, the benefit index declined at a faster rate. This occurred because increasing this level effectively frees up a constraint for buyers and allows them to optimize when making a purchase decision. Thus, industries which see fast rates of growth in available quality levels have buyers who benefit more than industries where there is little or no growth in the highest available quality.

Both of these results are intuitively appealing, but unfortunately the hedonic index does not incorporate either factor. Changing the distribution of buyers or the highest available quality level has no effect on the hedonic index. We therefore argue that the hedonic index is a biased measure of the benefits to buyers. The evidence we obtained in chapter 2 indicated that the hedonic index overstates the benefits to buyers, but Trajtenberg's results indicate the opposite. We took up this bias issue as an empirical one in chapter 3 and investigated the performance of both our benefit index and the hedonic index with data on the mainframe computer industry from 1984–1991.

In chapter 3 we employed a new dataset on the mainframe computer industry from 1984–1991. This dataset was unique for this industry because it was at the buyer level. The data described the purchases by individual buyers as well as characteristics of those buyers. This detailed data allowed us to move in directions previously unavailable to researchers. With this data we proceeded to follow a procedure initially suggested by Rosen (1974) for estimating demand for product characteristics. As with previous research, we focused on speed and memory as our characteristics. Then given estimates of demand, we estimated our benefit index.

The results for our benefit index in the mainframe computer industry showed that the benefits to buyers from improving computer technology are roughly one-half those that the hedonic index would indicate This result was initially quite suprising because it is the opposite of what we expected given Trajtenberg's results. However, we were able to reconcile the differences by looking at the differences in the data used. The computed tomography scanner industry which Trajtenberg analyzed is characterized by buyers who purchase the highest levels of quality available and by technology which changes dramatically over time. In contrast, the mainframe computer industry during the time period which we investigate is characterized by buyers who purchase predominantly low levels of quality and by technology which changes very little over time. In addition to the differences in the data, Trajtenberg's model accounts for the greater variety of products which become available over time in addition to the introduction of previously infeasible levels of quality. The incorporation of this product innovation would cause Trajtenberg's index to decline at a faster rate than ours and thus account for more benefits. Based on our results in chapter 2 which showed that the benefit index would decline at a faster rate given buyers at higher levels of quality and technology which changes a great deal over time, we argue that these factors, data differences and model differences, explain the discrepancy between the indexes.

Finally, in chapter 4 we looked at the sensitivity of the benefit index computed in chapter 3 to the choice of functional form for the hedonic surface. In general, we found that the quadratic form which we used in chapter 3 provided a similar fit to the alternatives we investigated, namely log-linear, log-log, linear, cubic and a generalized additive model. Unfortunately, each of these alternative forms turned out to be excessively difficult to use when attempting to compute the benefit index. Therefore we were unable to directly compare results from different specifications. However, since the quadratic form was simple to use and provided a similar fit, we argued that the quadratic form was a good approximation and could be chosen on the basis of ease of use. We left a complete analysis of this issue to future work.

While this work has moved in a new direction for research into the benefits from product technology, there are a number of issues which need to be addressed. First, and most importantly, a method for obtaining standard errors for the benefit index is missing from this analysis. Thus while we have obtained a benefit index which declines at roughly one-half the rate of the hedonic index, we have not performed any statistical tests for the difference between the rates of change. Obtaining standard errors will not be trivial due to the complexity of the procedure for obtaining the benefit index. We believe that an approach based on the delta-method is one possibile strategy, and that estimating the standard errors via some bootstrap method is another possibility. We hope to address this issue soon in future research. A second issue concerns the choice of functional form. While we attempted to address this issue in chapter 4, we were for the most part thwarted in our efforts, because the alternative forms which we investigated proved to be difficult to use when estimating the benefit index. In order to effectively address this issue, one needs to first solve the standard error issue in order to be able to test amongst competing specifications, and second one must solve the problem of computing the benefit index when using these alternative forms. A third issue which needs to be addressed is the assumption of additive separability. We employed this assumption in order ease the computation of the benefit index. We then ran into difficulties when we attempted to relax it by obtaining upward sloping demand curves. This is most likely an anamoly of our data and not a result directly connected to our model. This model should be applied to other datasets in order to investigate this specification issue.

BIBLIOGRAPHY

Arguea, N. M. & Hsiao, C. (1993). Econometric issues of estimating hedonic price functions. *Journal of Econometrics*, 56, 243–267.

Bartik, T. J. (1987). The estimation of demand parameters in hedonic price models. *Journal of Political Economy*, 95(1), 81–88.

Berndt, E. R. (1991). *The practice of econometrics: Classic and contemporary.* Reading, MA: Addison-Wesley.

Berndt, E. R. & Griliches, Z. (1990). Price indexes for microcomputers: An exploratory study. National Bureau of Economic Research Working Paper No. 3378.

Berndt, E. R., Showalter, M. H. & Woolridge, J. M. (1990). On the sensitivity of hedonic price indexes for computers to the choice of functional form. Manuscript from the Massachusetts Institute of Technology.

Berry, S., Levinsohn, J. & Pakes, A. (1993). Automobile prices in market equilibrium: Part I and II. National Bureau of Economic Research Working Paper No. 4264.

Bresnahan, T. & Greenstein, S. M. (1994). Technological competition and the structure of the computer industry. Mimeo, Department of economics, University of Illinois.

Brown, J. N. & Rosen, H. S. (1982). On the estimation of structural hedonic price models. *Econometrica*, 50(3), 765–768.

Chow, G. C. (1967). Technological change and the demand for computers. *American Economic Review*, 57(December), 1117–1130.

Court, A. T. (1939). Hedonic price indexes with automobile examples. In *The Dynamics of Automobile Demand.* New York: The General Motors Corporation, 99–117.

Diamond, D. B., Jr. & Smith, B. A. (1985). Simultaneity in the market for housing characteristics. *Journal of Urban Economics*, 17, 280–292.

Dulberger, E. R. (1989). The application of a hedonic model to a quality-adjusted price index for computer processors. In D. W. Jorgenson & R. Landau (eds.), *Technology and capital formation.* Cambridge, MA: The MIT Press.

Epple, D. (1987). Hedonic prices and implicit markets: Estimating demand and supply functions for differentiated products. *Journal of Political Economy*, 95(1), 59–80.

Flamm, K. (1987). *Targeting the computer.* Washington, D.C.: The Brookings Institution.

Goldberger, A. S. (1968). The interpretation and estimation of cobb-douglas functions. *Econometrica*, 35(September), 464–472.

Greenstein, S. M. (1994). Did computer technology diffuse quickly?: Best and average practice in mainframe computers 1968–1983. National Bureau of Economic Research Working Paper No. 4647.

Hastie, T. J. & Tibshirani, R. J. (1990). *Generalized additive models.* Vol. 43 of *Monographs on Statistics and Applied Probability.* New York: Chapman and Hall.

Johnson, N. L. & Kotz, S. (1970). *Continuous univariate distributions–1.* Boston, MA: Houghton-Mifflin.

Johnson, N. L. & Kotz, S. (1970). *Continuous univariate distributions-2.* Boston, MA: Houghton-Mifflin.

Oliner, Stephen (1992). Constant-quality price change, depreciation, and retirement of mainframe computers. Manuscript from the Board of Governors of the Federal Reserve System, Division of Research and Statistics.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, 82, 34–49.

Teekens, R. & Koerts, J. (1972). Some implications of the log transformation of multiplicative models. *Econometrica*, 40(September), 793–819.

Trajtenberg, M. (1990). *Economic analysis of product innovation.* Cambridge, MA: Harvard University Press.

Triplett, Jack E. (1989). Price and technological change in a capital good: A survey of research on computers. In D. W. Jorgenson & R. Landau (eds.), *Technology and capital formation.* Cambridge, MA: The MIT Press.

Witte, A. D., Sumka, H. J. & Erekson, H. (1979). An estimate of a structural hedonic price model of the housing market: An application of Rosen's theory of implicit markets. *Econometrica*, 47(5), 1151–1173.

VITA

KENNETH HACKMAN BROWN

Education

August, 1990 to Present	University of Illinois Champaign, IL Degree: M.S. in Economics
September, 1986 to May, 1990	Saint Louis University St. Louis, MO Degree: B.S. in Business Administration

Job Experience

June, 1992 to Present	University of Illinois Research Assistant to Professor Shane Greenstein
September, 1991 to May, 1992	University of Illinois Teaching Assistant Economics 172: Economic statistics
May, 1989 to August, 1990	Southwestern Bell Corporation St. Louis, MO Student Manager of Economic Analysis
January, 1989 to May, 1989	Southwestern Bell Corporation St. Louis, MO Internship in Economic Analysis

Academic Honors

Recipient of the Robert Harbeson Memorial Dissertation Fellowship, University of Illinois

Twice named to the *Incomplete List of Teachers rated as Excellent by their Students*—University of Illinois

Recipient of the Illinois Power Fellowship—University of Illinois

Graduated *magna cum laude*—Saint Louis University

Who's Who Among America's College Students—Saint Louis University

Midwest Collegiate Conference Academic Honor Roll–Golf—Saint Louis University

Saint Louis University Scholar Athlete Award

Publication

"On hypothesis testing: A selective look at the lagrange multiplier, likelihood ratio and wald tests." *Revista de Econometria*, 12(2), 1992, (with Francisco Cribari-Neto).