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2 Price Indexes for Microcomputers: An Exploratory Study

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In recent years, a considerable amount of research has focused on the construction and interpretation of price indexes for computers.[1] The computer market is a fascinating one, for technological change has been rapid, there has been a great deal of entry and exit of firms and models, and, particularly in the microcomputer market, models have been simultaneously sold at different prices by standard retail and discount vendors.

Because of the rapid technological change and turnover of models and firms, Fisher, McGowan, and Greenwood (1983) have characterized the mainframe computer market as typically being in "disequilibrium." One consequence of this is that price indexes have been used for two rather different purposes, one to deflate expenditures or purchases into constant dollars, and the other to trace out movements in a technological frontier, such as a price-performance ratio.

If quality-adjusted prices reacted instantaneously and fully to the introduction of new technology, then an index that traced out the technological frontier

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1. See, e.g., the classic study by Chow (1967) as well as more recent ones by Archibald and Reece (1978), Gordon (1989, 1990), Michaels (1979), Oliner (1986), and Triplett (1989a).

would be identical to one that covered all models sold in the marketplace. In periods of disequilibrium, however, the two quality-adjusted price indexes might differ, with consumers tolerating transactions at more than one quality-adjusted price. One reason for such multiple price transactions would be if the supply of some new models is initially limited and, in spite of this excess demand, manufacturers offered new models at lower prices to facilitate dissemination of information about the new low-price technology. Another reason would be if surviving models were of higher quality in some unobserved characteristics or benefited from the accumulation of specialized software and know-how. The extent of such price disequilibrium is of course an empirical issue; some recent evidence on this issue for the mainframe computer market is presented by Dulberger (1989).

Although the mainframe computer market has received considerable attention, to the best of our knowledge there has been little empirical work on the microcomputer (PC) market.[2] In this paper, we focus attention on the interpretation of implicit price indexes and coefficients from hedonic price equations using detailed data from the list and discount U.S. microcomputer markets.[3] We define a *discount price* as that advertised for a particular model sold by a vendor other than the manufacturer and a *list price* as that advertised by the brand-name manufacturer; for example, we classify the advertised price of an IBM personal computer sold by 47th St. Photo as being a discount price, while we categorize the price advertised by IBM for the same model as being a list price. Much of the discount market is mail order. Presumably, transactions in discount markets take place at advertised prices, whereas considerably fewer transactions occur at list prices. Unfortunately, data by transactions prices are not available to us.

Our work builds on the research of two of our students, Cohen (1988) and Kim (1989). Cohen originally gathered and assembled price and characteristics data covering the time period 1976–87; the data, which he updated to include 1988, were then examined further by Kim. On the basis of hedonic regression equations with pooled data, both Cohen and Kim generated implicit PC price indexes for list and discount markets. Before doing estimation, both Cohen and Kim divided nominal prices for each model by the consumer price index (hereafter we call this CPI-adjusted price index a *relative* price index). Representative findings from Cohen and Kim are presented in table 2.1, as are the PC price index computed by Gordon (1990) and the BEA "official" PC price index. Both Gordon's and BEA's price indexes employ

2. A very brief discussion of PCs is presented in Gordon (1989, 1990). See also Catron (1989) and Sinclair and Catron (1990).

3. Hedonic regression methods and their interpretation are discussed in, among others, Griliches (1961, 1971, 1988), Triplett (1986), and Berndt (1991). Theoretical foundations for interpreting hedonic price equations are found in, among others, Rosen (1974) and Epple (1987). For a historical discussion of the incorporation of hedonic regression methods into official price indexes, see Triplett (1990).

Table 2.1 Relative Price Indexes for Microcomputers Based on Hedonic Regressions and Matched-Model Procedures

	Hedonic Regressions						
	Cohen		Kim		Matched-Model Procedure		
Year	List Prices	Discount Prices	List Prices	Discount Prices	Gordon	BEA	CPI
1976	4.7709						0.5828
1977	2.7347						0.6262
1978	2.0878	1.4558					0.6727
1979	1.8015	1.3638					0.7471
1980	1.6923	1.4726					0.8535
1981	1.4189	1.2700			1.3441		0.9345
1982	1.0000	1.0000	1.0000	1.000	1.0000	1.000	1.0000
1983	0.7118	0.4613	0.687	0.464	0.7459	0.777	1.0306
1984	0.5926	0.6225	0.617	0.920	0.5576	0.568	1.0651
1985	0.3898	0.3798	0.409	0.595	0.3871	0.511	1.1076
1986	0.2581	0.2494	0.268	0.393	0.2916	0.369	1.1291
1987	0.1913	0.1680	0.194	0.259	0.2201	0.321	1.1715
1988			0.123	0.200			1.2176
Average annual growth rates (AAGRs), (%) 1982–87	−28.16	−30.01	−27.96	−23.68	−26.12	−20.33	3.22
Entire period covered by the study (%)	−25.36	−21.33	−29.48	−23.53	−26.03		

Note: All the computer price indexes are relative to the CPI: i.e., the nominal computer prices have been divided by the consumer price index. Data are taken from Cohen (1988, app. D, p. 70), renormalized to 1982 = 1.000; from Kim (1989, app. 22); and from Gordon (1990, table 6.13, p. 237), renormalized and divided by the CPI. The BEA index is from the November 1988 issue of the *Survey of Current Business*, table 1, p. 22 (divided by the CPI). For further discussion of the Gordon and BEA indexes, see n. 4 below.

"matched-model" procedures.[4] To facilitate comparison of indexes, in the bottom row of table 2.1 we present AAGRs (average annual growth rates) for all the price indexes over the same time interval, 1982–87.

As is seen in table 2.1, all relative price indexes suggest rapid declines in the quality-adjusted price of microcomputers.[5] Cohen reports an AAGR of −25.36 percent in relative price of PCs over the time frame 1976–87 for list prices and a slightly lower −21.33 percent for discount prices. Kim finds an AAGR of −29.48 percent for list prices for 1976–88 and −23.53 percent for discount prices. Gordon's calculations suggest an AAGR of −26.12 per-

4. Gordon's index is based on data covering twenty-one PC model years for 1981–87, taken from advertisements in *Business Week* and *PC Magazine*. Precisely how the BEA PC price index is constructed is not clear. According to Cartwright and Smith (1988, 22), "For personal computers (PC's), a matched model index was introduced in 1987. It is now constructed using price changes of IBM PC's, judgmentally adjusted by BEA to reflect price changes for other models, for 1983 and price changes of models sold by IBM and three additional manufacturers for 1984–87."

cent for the shorter period 1982–87 (a mix of list and discount prices), while the BEA relative price index falls at a smaller AAGR of -20.33 percent for the same period.

The research results we report in this paper extend the work of Cohen, Kim, and Gordon in a number of related ways. First, we focus attention on the more general interpretive implications of the fact that the PC market is a changing one during the period 1982–88, involving shake outs of some models, successful innovations for others, and dramatic changes in product characteristics. The data sample that we observe is opportunistic in the sense that it represents new (not secondhand) models only and within that set only those that survived for one year or more. We examine whether surviving vintages are priced at a premium and how prices of surviving vintages adjust when new models are introduced incorporating technological advances.

Second, we examine several econometric implications of the fact that, owing to differential survival rates in the marketplace, our data are in the form of an unbalanced panel. In particular, we explore implications for estimation of how one implements empirically the identity that the year in which the model is observed is the sum of the year in which the model was first introduced and its age in years since introduction. A diagnostic test is discussed and implemented for checking our hedonic specification. Issues of sample selectivity are also addressed.

Finally, we construct and comment on a variety of price indexes that can potentially serve as deflators for microcomputer investment series or as measures that trace out a technological frontier in the PC market.

2.1 The Data

The data set available for this study includes price and technical attribute measures for new (not used) personal computers sold in the United States from 1976 to 1988. The 1976–87 data were originally collected and analyzed by Cohen (1988); these data have been updated by Cohen to 1988, have been employed by Kim (1989) in further analysis, and have undergone additional revisions by us. The primary source of technical data was the *Byte* magazine comprehensive technical reviews. Since both list and discount prices often varied within each calendar year, the June issues of *Byte*, *PC Magazine*, and *PC World* were employed for list price data, while ads in the "Science and Technology" and "Business" sections of a Sunday *New York Times* issue in early June of each year were employed to obtain discount prices.[6] Additional data sources included the *Dataquest Personal Computer Guide* and IBM pricing and technical data.

5. To convert the relative price indexes into nominal price indexes and thereby make entries in table 2.1 consistent with published numbers, simply multiply the relative price index by the appropriate CPI (given in the last column of table 2.1).

6. The first PC advertising appeared in the *New York Times* in 1981.

Characteristic and performance data collected by Cohen include RAM (the amount of random access memory standard on each PC model, measured in kilobytes [KB]), MHZ (the clock speed, measured in megahertz, or millions of cycles per second), HRDDSK (the amount of storage on the hard disk, if one exists, measured in megabytes [MB]), NUMFLP (the number of floppy disk drives standard on each model), SLOTS (the total number of eight-, sixteen-, and thirty-two-bit slots available for expansion boards), and AGE (the number of years the model has been sold on the market, where the model has an age of zero in its initial year).

As we noted earliei, an important feature of the PC market is that it is changing very rapidly. A model introduced in year 0 may survive with unchanged characteristics into year 1, year 2, or even longer, or, as is often the case, it may survive with differing characteristics into other years (we call this a changed *version* of the model). Other models may exit after being in the market only one year. Hence, the stock of models sold in any given year consists of new and incumbent models and, among the incumbent models, new and old versions.

To highlight the evolution of the PC market, in table 2.2 we present arithmetic means of characteristics for models newly introduced from 1982 through 1988. As is seen there, the mean nominal price decreased slightly, about 3 percent, from $3,617.61 in 1982 to $3,508.47 in 1988, while mean RAM increased more than tenfold from 94.92 to 1,069.39KB, MHZ clock speed jumped more than three times from 4.4046 to 14.8201, and the mean hard disk storage rose from 0 to 43.638MB.

In table 2.3, we summarize the mixed nature of the PC market from 1982 to 1988, including new and up to age 3 models, separately for the total, list, and discount markets. For the total market, 58 percent (722 of 1,265) are new models, 29 percent (372) are models that survived one year (perhaps with changed characteristics and reduced prices to meet the market competition

Table 2.2 Mean Values of Characteristics for New Models, 1982–88

Year	N	RAM	MHZ	HRDDSK	NUMFLP	SLOTS	Nominal Price
1982	13	94.92	4.4046	0.000	1.154	3.308	3,617.61
1983	59	122.78	4.6807	2.161	1.237	3.322	3,017.66
1984	80	204.00	5.1998	3.012	1.338	3.325	3,026.96
1985	61	326.69	5.9974	4.607	1.295	4.000	2,991.15
1986	123	539.25	7.6016	11.220	1.195	5.081	2,955.60
1987	245	773.09	10.1033	22.355	1.098	5.016	3,251.40
1988	141	1,069.39	14.8201	43.638	1.014	5.993	3,508.47

Note: N is the number of new models by year; RAM is kilobytes of random access memory standard on each model; MHZ is clock speed in megahertz; HRDDSK is the amount of storage on the hard disk, if one exists, in megabytes; NUMFLP is the number of floppy disk drives standard on each model; SLOTS is the total number of eight-, sixteen-, and thirty-two-bit slots available for expansion boards; and nominal price is the price in current (nominal) dollars.

Table 2.3 Vintage Composition of Microcomputer Market, 1982–88

	No. of Price Observations				
Year	AGE = 0	AGE = 1	AGE = 2	AGE = 3	Total
1982:					
Total	13	7	12	9	41
List	10	5	4	5	24
Discount	3	2	8	4	17
1983:					
Total	59	9	5	6	79
List	53	5	3	1	62
Discount	6	4	2	5	17
1984:					
Total	80	44	3	0	127
List	63	25	2	0	90
Discount	17	19	1	0	37
1985:					
Total	61	39	12	2	114
List	59	18	5	0	82
Discount	2	21	7	2	32
1986:					
Total	123	35	23	6	187
List	106	26	13	2	147
Discount	17	9	10	4	40
1987:					
Total	245	92	42	11	390
List	217	63	30	9	319
Discount	28	29	12	2	71
1988:					
Total	141	146	32	8	327
List	129	59	5	0	193
Discount	12	87	27	8	134
Grand total	722	372	129	42	1,265
List total	637	201	62	17	917
Discount total	85	171	67	25	348

from frontier models), 10 percent (129) survived two years, and 3 percent (42) remained in the marketplace for three years.

Altogether, about 72 percent of our model observations are taken from the list market, while 28 percent represent discount quotations. However, as is also seen in table 2.3, the age composition of models varies considerably between the list and the discount markets. Specifically, discount markets tend to have a much smaller proportion of new models and much larger proportions of one-, two-, and three-year-old models. Finally, it is worth noting that, in our data set, some models are sold in both the list and the discount markets (e.g., IBM and Compaq) and are therefore "observed" twice, while others are only in the list market (e.g., PC Limited); however, no model is observed only in the discount market.

To focus attention on issues involved in interpreting coefficients with unbalanced panels, in this paper we adopt in essence the regressors and functional form employed by Cohen and Kim, in which the logarithm of the real price (LRPRICE) is regressed on the logarithm of several characteristics, including LRAM, LMHZ, LHRDDSK (log[HRDDSK] + 1]), LNUMFLP (log[NUMFLP + 1]), LSLOTS (log[SLOTS] + 1]), and a number of dummy variables.

The dummy variables for characteristics include PROC16 (= 1 if model has a sixteen-bit processor chip, otherwise 0), PROC32 = 1 if model has a thirty-two-bit processor chip), DBW (= 1 if system comes with a monochrome monitor), DCOLOR (= 1 if system comes with a color monitor), DPORT (= 1 if model is portable or convertible), DEXTRA (= 1 if model has a significant piece of additional hardware included, otherwise 0; examples of such extra hardware include modems, printers, or an extra monitor), and DDISC (= 1 if system price is discounted by the vendor).

The dummy variables for manufacturers are DIBM (= 1 if system is made by IBM), DAPPLE (Apple), DCOMMO (Commodore), DCMPQ (Compaq), DNEC (NEC), DRDIOSH (Radio Shack), DPCLIM (PC Limited), and DOTHER (made or sold by any other company than those noted above).

Finally, a number of time and vintage effect dummy variables are employed. For time effects, the dummy variables T82, T83, . . . , T88, take on the value of 1 if the PC model was sold in that year and otherwise equal 0. For vintage effects, the dummy variables V79, V80, . . . , V88 take on the value 1 if the model was originally introduced in that year and otherwise equal 0.

The above variables, as well as several other measures, were included as regressors in a number of specifications examined by Cohen and by Kim using data beginning in 1976. Since the PC market was very small from 1976 until the entry of IBM in late 1981 (only 156 models were introduced before 1982), in this paper we confine our attention to the period 1982–88 and the 1979–88 vintages, restricting our sample to PC models whose age is three years or less, and dividing the AGE variable into three dummy variables, AGE1, AGE2, and AGE3, with a new model having an implicit age of 0. The data used in our regression analysis are summarized in table 2.4, where we present sample means as well as minimum and maximum values of the various variables.

2.2 Econometric Issues

Our data set comes in the form of an unbalanced panel, in that the number of observations by age, and by vintage, varies by year. Let the vintage of model i (the year in which it was first introduced) be V, where $V = 79, 80, \ldots, 88$; let the year (time period) in which the model is observed be T, where $T = 82, 83, \ldots, 88$; and let the age of the model of vintage V observed in time period T, in years, be A, where A is either 0, 1, 2, or 3. This yields the identity that, for any model observation,

Table 2.4 **Summary of Microcomputer Data, 1982–88**

Variable	Mean	Minimum Value	Maximum Value
PRICE	2,846.96	40.00	13,995.00
RAM	560.73	1.00	4,096.00
MHZ	8.3474	1.00	25.00
HRDDSK	17.199	0.00	314.00
NUMFLP	1.1526	0.00	2.00
SLOTS	4.5644	0.00	21.00
AGE	0.5976	0.00	3.00
PROC16	0.5510	0.00	1.00
PROC32	0.1344	0.00	1.00
DBW	0.4213	0.00	1.00
DCOLOR	0.0285	0.00	1.00
DPORT	0.1747	0.00	1.00
DEXTRA	0.0206	0.00	1.00
DDISC	0.2751	0.00	1.00
DIBM	0.0988	0.00	1.00
DAPPLE	0.0427	0.00	1.00
DCMDRE	0.0285	0.00	1.00
DCMPQ	0.0648	0.00	1.00
DNEC	0.0427	0.00	1.00
DRDIOSH	0.0490	0.00	1.00
DPCLIM	0.0166	0.00	1.00
DOTHER	0.6569	0.00	1.00
T82	0.0324	0.00	1.00
T83	0.0635	0.00	1.00
T84	0.1004	0.00	1.00
T85	0.0901	0.00	1.00
T86	0.1478	0.00	1.00
T87	0.3083	0.00	1.00
T88	0.2585	0.00	1.00
		$N = 1{,}265$	

$$T \equiv V + A. \tag{1}$$

If T, V, and A were treated as continuous variables, one could not simultaneously introduce all three as regressors in a linear equation to be estimated by least squares, for exact collinearity would result. To avoid such collinearity, only two of the three could be included directly, and estimates for the third could be computed indirectly using (1). Alternatively, as has been discussed by Fienberg and Mason (1985), one could specify instead a model with nonlinear transformations of all three variables, such as their squared values.[7]

7. However, one cannot identify parameters in a full quadratic expansion of the three variables owing to the identity in (1). For discussions in the context of age, period, and cohort models, see Fienberg and Mason (1985) and Wilmoth (1989).

To begin with, suppose that one specified the regression equation

$$\ln P_{ivat} = \delta + \delta_v V + \delta_a A + X'\delta_x + \varepsilon_{ivat}, \tag{2}$$

where V and A are continuous variables, and X is a vector of model i–specific characteristics variables. This regression equation is equivalent to one with the $A = T - V$ identity from (1) substituted into (2); that is, it is equivalent to a regression equation with V, T, and X as regressors rather than V, A, and X:

$$\begin{aligned} \ln P_{ivat} &= \delta + \delta_v V + \delta_a(T - V) + X'\delta_x + \varepsilon_{ivat} \\ &= \delta + (\delta_v - \delta_a)V + \delta_a T + X'\delta_x + \varepsilon_{ivat} \\ &= \delta + \delta_v' V + \delta_a A + X'\delta_x + \varepsilon_{ivat} \end{aligned} \tag{3}$$

where $\delta_v' \equiv \delta_v - \delta_a$. In particular, direct and implicit least squares estimates of the δ, δ_v, δ_a, and δ_x coefficients in (2) and (3) are numerically equivalent, as are the equation R^2 values. Similarly, one could substitute $V \equiv T - A$ from the identity in (1) into (2) and obtain a regression equation with T, A, and X as regressors rather than V, T, and X as in (2) or V, A, and X as in (3):

$$\begin{aligned} \ln P_{ivat} &= \delta + \delta_v(T - A) + \delta_a A + X'\delta_x + \varepsilon_{ivat} \\ &= \delta + \delta_v T + (\delta_a - \delta_v) A + X'\delta_x + \varepsilon_{ivat} \\ &= \delta + \delta_v T + \delta_a' A + X'\delta_x + \varepsilon_{ivat} \end{aligned} \tag{4}$$

where $\delta_a' \equiv \delta_a - \delta_v$. Given the algebra of least squares, direct and implicit estimates of the δ, δ_v, δ_a, and δ_x parameters in (2), (3), and (4) are identical, as are the equation R^2 measures.

However, as we show below, when T, V, and A are discrete dummy variables rather than continuous, and if the coefficients of these variables are to be held constant over time and/or vintage, then by construction the simple adding-up conditions implied by (1) no longer hold, and least squares direct and implicit estimates of the parameters depend on the equation fitted. This raises a number of issues involving the interpretation of dummy variable coefficients and the maximal parameterization possible that avoids exact collinearity.[8]

In terms of interpretation, consider the following equation, analogous to (4), where T and A are vectors of dummy variables with T82 and A0 deleted, and the vintage dummy variables in V are all deleted:

$$\ln P_{ivat} = \alpha + T'\alpha_t + A'\alpha_a + X'\beta + u_{ivat}. \tag{5}$$

In this case, one might interpret estimates of the α_t as changes in the quality-adjusted price index relative to 1982, holding age fixed. Similarly, estimates of the α_a can be interpreted as the effects of age (relative to a new model of age 0) on price, holding time fixed. Intuitively, the α_t parameters in this T-A specification represent the general movement in average PC prices, given the average rate at which selectivity occurs in the sample.

8. A related discussion of this issue in the context of age, period, and cohort effects in earnings equations is presented by Heckman and Robb (1985).

While cumulated evidence from the mainframe market suggests that the α_t should decline with time (see, e.g., Cartwright 1986; Cole et al. 1986; Gordon 1989; and Triplett 1989a), it is not clear what one should expect for signs of the estimated α_a, which represent the effects of quality differentials on models of different ages sold contemporaneously, holding time fixed. According to one line of thinking, new models of superior quality should command a premium price, and, if market competition forced the valuations of all characteristics of incumbent models to obsolescence at the same rate, prices of surviving vintages would decline appropriately. Thus, since the time dummy captures the full price effect, one might expect estimates of α_1, α_2, and α_3 to be approximately zero. On the other hand, selectivity in the marketplace reveals survival of the fittest, and, if there are unmeasured characteristics (e.g., compatible software or hardware, differential service policies and warranties), then the age coefficients may to some extent be providing an estimate of the unobserved positive quality differentials among the survivors as vintages progress. To unscramble the obsolescence and selectivity components of the estimated age coefficients, one would need to assume that all the quality differences among vintages were already captured in the changing computer characteristics and their associated coefficients, assuring thereby that age coefficients reflected selectivity alone.

Alternatively, one might specify a regression equation using the vintage V and age A dummy variables rather than the T and A as in (5):

$$\ln P_{ivat} = \alpha + V'\alpha_v + A'\alpha_a + X'\beta + u_{ivat}, \tag{6}$$

where, say, the V82 vintage dummy variable was omitted. In terms of interpretation, note that, if the technical characteristics variables captured virtually all the quality changes embodied in models, then the vintage coefficients would essentially be capturing the decline in prices by vintage (i.e., by date of introduction), which in turn is some average of the difference between A and the implicit T over ages. Similarly, given that the specification (6) conditions on vintages, one can interpret the α_a age coefficients as representing the average price decline of surviving models over the sample years, reflecting the identity (1), $A \equiv T - V$ for all vintages. In a sense, it is another measure of the average rate of improvement in the quality of new computers, which forces the price of incumbent models to decline.

In spite of its apparent similarity with (5) given the identity (1), the specification in (6) is in fact quite different, except for the special case when models of only one age are considered (e.g., only AGE = 0 models). There are at least two reasons for this. First, the number of dummy variable coefficients is greater in (6) than in (5), for in (5) there are six time (T83–T88) and three age (A1–A3) coefficients, while in (6) there are nine vintage (V79–V88, V82 omitted) and three age (A1–A3) parameters. Thus, in general, one should not expect least squares estimates of α_a and β to be to same in the two specifications.

Second, while the age coefficients condition on time in (5), in (6) the conditioning is on vintage. In particular, in (6) the α_a age coefficients are interpreted as the effect on price of age (relative to a new model), holding vintage V (not time T) fixed. Since the conditioning changes, least squares estimates should also be expected to differ in (5) and (6).

To understand this better, consider a *V-A* specification such as (6). An implicit time coefficient such as that for, say, T88 could be computed in four different ways:

$$\begin{aligned} (7) \qquad & \alpha_{t,88} = \alpha_{v,88} + \alpha_{a,0}, \quad \alpha_{t,88} = \alpha_{v,87} + \alpha_{a,1}, \\ & \alpha_{t,88} = \alpha_{v,86} + \alpha_{a,2}, \quad \text{and/or } \alpha_{t,88} = \alpha_{v,85} + \alpha_{a,3}. \end{aligned}$$

Similarly, with *T-A* specifications as in (5), the implicit vintage coefficient for, say, V85 could be computed alternatively as

$$\begin{aligned} (8) \qquad & \alpha_{v,85} = \alpha_{t,85} - \alpha_{a,0}, \quad \alpha_{v,85} = \alpha_{t,86} - \alpha_{a,1}, \\ & \alpha_{v,85} = \alpha_{t,87} - \alpha_{a,2}, \quad \text{and/or } \alpha_{v,85} = \alpha_{t,88} - \alpha_{a,3}. \end{aligned}$$

Least squares estimation of the *V-A* and *T-A* specification implicitly weight and average over these four possibilities in different ways, and thus there is no reason to expect implicit and direct estimates of the α_v, α_a, and/or α_t coefficients to be numerically equivalent in the *T-A* and *V-A* models, unless the rates of vintage improvement, time inflation, and age depreciation are all constant functions of elapsed time. In this special case, identity (1) also holds for all the relevant dummy variable coefficients.

But, if the *V-A* and *T-A* specifications yield varying estimates because of their distinct conditioning and use of differing information, how is one to choose among them? For purposes of computing quality-adjusted price indexes, the directly estimated time coefficients based on (5) have a clear interpretation, and, for that reason, specification (5) has formed the basis of almost all hedonic price index studies. But is it necessary to delete the V variables completely? Can one not employ a specification that efficiently uses information simultaneously from the *T, A, and V* dummy variables yet avoids exact collinearity?

This issue has been addressed by Hall (1971), whose context involved use of a balanced panel data set for secondhand trucks. In our context, the maximal parameterization consistent with avoiding exact collinearity among the *T, V,* and *A* dummy variables turns out to be one in which eight of the original ten vintage dummy variables are added to the *T-A* specification (5); that is, two (not one) of the vintage dummies are deleted from the original set of ten (V79–V88) (see especially Hall 1971, 248).[9] We can write such a specification as

9. There is intuitive appeal to this additional normalization. Hall defined the price index as the product of vintage effects (embodied technical progress), depreciation, and time (disembodied technical progress). Thus, the logarithm of the price index is the sum of these three effects, each

$$\ln P_{ivat} = \alpha + T'\alpha_t + A'\alpha_a + V'\alpha_v + X'\beta + u_{ivat}, \tag{9}$$

where the vector of dummy variables in V consists of eight elements. As Hall noted, coefficients on the α_v should be interpreted as *differences* from the average rate of growth of technical progress embodied but unobserved in pairwise comparisons of vintages. For example, if one omitted the V82 and V83 dummy variables, the α_v coefficient estimates should then be interpreted as a contrast; for example, the coefficient on the V88 dummy variable should then be interpreted as the *difference* between the average 1988 vintage effect and the mean of the average vintage effects for 1982 and 1983. Alternatively, one can think of these as contrasts, deleting the middle vintages and interpreting the remaining coefficients as measuring period (acceleration) from the average rate of technological change. We suggest that a necessary condition for a hedonic price equation to be satisfactory is that the portion of quality change not captured by the characteristics variables should be unrelated to vintages; that is, in a desirable specification, the α_v should be approximately zero.[10]

It follows that, since the α_v coefficients represent contrasts in average rates of growth due to unobserved quality change, one can interpret a test that the $\alpha_v = 0$ as corresponding to a test that changes in characteristics among models and over time adequately capture quality changes between vintages and that average unobserved vintage effects are not systematically different in pairwise comparisons across vintages. Further, if it were found that the α_v are simultaneously different from zero, then one might interpret that result as suggesting model misspecification, reflecting either the effect of omitted characteristic variables or invalid stability constraints on the characteristics parameters over time. Hence, as noted above, a desirable specification would yield nonrejection of the null hypothesis that the α_v simultaneously equal zero, in which case (5) would be empirically supported as a special case of (9).[11]

Hypotheses concerning parameter restrictions can of course be tested using the standard F-test methodology. As has been emphasized by, among others, Arrow (1960) and Ohta and Griliches (1976), when samples are large and

in rates of growth. To normalize the level of the price index, one normalizes levels of each of the three effects; i.e., one deletes one variable from each of the T, V, and A dummy variable sets and normalizes relative to that variable. But, in addition, one must normalize at least one of the growth rates since the product of the three effects implies that components are unidentified. This additional normalization is accomplished by deleting an additional vintage variable, thereby yielding a contrast in levels of the logarithmic regression, which is equivalent to a normalization in growth rates of one of the three components. For additional discussion, see Hall (1971).

10. Implicit in this test is the assumption that the different characteristics contained in the various vintages appreciate (owing to inflation) and depreciate (owing to technological change) at the same rate.

11. It is worth noting here that the choice of which two dummy variables to delete from the V vector is arbitrary in the sense that goodness of fit and numerical values of least squares estimates of α and the β's will be unaffected. However, the interpretation and numerical values of the least squares estimates of the α_t, α_a, and α_v will depend on this choice.

standard test procedures are employed, one is likely to reject most simplifying parameter restrictions on purely statistical grounds, even though they may still serve as adequate approximations for the purpose at hand. There are several ways one can deal with this problem.

First, to accommodate the larger sample size, we can compensate by choosing very tight significance levels for the standard F-tests. In this paper, we do that by choosing .01 significance levels. Second, one could adopt the more agnostic and conservative criterion that the null hypothesis holds only approximately rather than exactly in the sample. In such a case, as Leamer (1978) has shown, one could employ a Bayes procedure that, in essence, decreases the significance level as the sample size n increases. Although we investigated use of the Leamer-Bayes procedure, we do not report results based on it here in detail since, for every hypothesis we tested, the test statistic was less than the critical value and thus in each case the null hypothesis was not rejected.[12]

Finally, since in our hedonic regressions the dependent variable is LRPRICE, the root mean squared errors (RMSE) measure the unexplained variation in prices in, roughly, percentage units. A reasonable criterion is to use the difference in the RMSE of the constrained and unconstrained regressions as a relevant measure of the price-explanatory power of a particular model. As our alternative test criterion, we will therefore reject the null hypothesis when the RMSE under the alternative results in a reduction of more than 5 percent in the RMSE (the standard deviation of the unexplained variation in log prices). With an average RMSE of around 0.40, this RMSE criterion implies that we are looking for a movement of at least about 0.02, say, from 0.40 to 0.38, before we will "give up" on the more parsimonious parameterization implied by the null hypothesis.

2.3 Initial Results

We begin with results from a T-A model in which the time and age dummy variables are included but the vintage dummies omitted, as in (5). Results are presented in table 2.5 for three regressions—a pooled sample, list price observations, and discount price observations. In each case, the dependent variable is the logarithm of the real price (LRPRICE), and the variables are essentially those as in Cohen and Kim. Recall that, in many cases, a particular model appears in both the list and the discount markets. Given the specification of dummy variables, in each regression the estimated intercept term cor-

12. Specifically, we computed the Bayes factor asymptotic approximation developed by Leamer (1978, 108–14), translated from the condition that it exceeds one into an F-value expression that Leamer has shown to be equal to $(n - k) \cdot (n^{q/n} - 1)/q$, where n is sample size, k is the number of free parameters estimated in the unconstrained regression, and q is the number of parameter restrictions. For an application of Leamer's adjustment to the standard F-test procedure in the context of large samples, see Ohta and Griliches (1976).

Table 2.5 **Parameter Estimates for Specifications with Time and Age Dummy Variables Included—Pooled, List, and Discount Samples for 1982–88**

	Pooled Sample		List Price Sample		Discount Price Sample	
Variable	Estimated Parameter	t-Statistic	Estimated Parameter	t-Statistic	Estimated Parameter	t-Statistic
Intercept	4.8101	41.934	4.7316	33.152	4.4924	23.823
LRAM	0.3140	14.804	0.3313	12.746	.2721	7.875
LMHZ	0.3157	7.668	0.2197	4.409	.5482	7.620
LHRDDSK	0.1688	19.876	0.1716	17.710	.1543	9.005
LNUMFLP	0.4304	8.588	0.4753	7.869	.2913	3.365
LSLOTS	0.1721	8.483	0.1502	5.921	.2396	7.211
AGE1	0.1193	3.911	0.1296	3.531	.0414	0.735
AGE2	0.1542	3.448	0.2352	3.984	.0192	0.268
AGE3	0.2984	4.034	0.5333	4.748	.1469	1.454
PROC16	0.2087	5.817	0.2501	5.894	.1319	2.037
PROC32	0.5193	8.101	0.6560	8.829	.1926	1.500
DBW	0.0261	0.844	0.0222	0.633	−.0511	−0.944
DCOLOR	0.0315	0.423	0.0463	0.491	−.0129	−0.110
DPORT	0.3565	8.943	0.3400	6.763	.4703	7.273
DEXTRA	0.2756	3.242	0.2698	2.733	.4609	2.706
DDISC	−0.2903	−9.460				
DAPPLE	0.2729	3.627	0.1982	1.999	.4470	3.938
DCMDRE	−0.3291	−3.776	−0.3763	−3.089	−.1226	−0.981
DCMPQ	0.2678	4.176	0.3598	4.045	0.2266	2.394
DNEC	0.1114	1.548	0.2369	2.399	−0.0265	−0.251
DRDIOSH	0.0618	0.891	0.0162	0.205	0.4644	3.127
DPCLIM	−0.5047	−4.927	−0.4707	−4.402		
DOTHER	0.0062	0.141	0.0430	0.823	0.0027	0.034
T83	−0.3974	−4.768	−0.2193	−2.081	−0.8034	−5.889
T84	−0.4085	−5.017	−0.3494	−3.350	−0.2933	−2.298
T85	−0.8567	−10.110	−0.7645	−7.039	−0.7820	−5.845
T86	−1.2755	−14.937	−1.1804	−10.770	−1.2660	−9.402
T87	−1.6121	−18.728	−1.5201	−13.805	−1.6758	−12.368
T88	−2.0331	−22.412	−1.9813	−16.876	−1.9611	−14.177
R^2		0.7416		0.7003		0.8220
N		1,265		917		348
Root MSE		0.4166		0.4181		0.3796

responds to that for a model of age 0 in 1982 that has an eight-bit processor, no monitor, and no extras, is not portable, is not in the discount market, and is made by IBM.

A number of results are worth noting. First, the coefficient on LMHZ is positive and significant in all three regressions but is largest in the discount market; coefficients on the LSLOTS variable follow a similar pattern. Coefficients on LRAM and LNUMFLP are also positive and significant but, in contrast, are larger in the list than in the discount market.

Second, in all three regressions, the coefficients on the age variables are positive, holding time fixed, suggesting that the age effects of selectivity are substantial. Interestingly, the effect of age is largest in the list market, where the age premium is statistically significant and increases with age, implying that list prices of surviving computers do not drop "fast enough." In the discount market, however, the age coefficients are statistically insignificant and follow no pattern. This suggests that some type of selectivity is occurring in the transition from list to discount markets and that, conditional on having entered the discount market, there is little age selectivity remaining.

Third, in terms of other dummy variable coefficients, estimates of PROC16 and PROC32 are positive, statistically significant, and larger in the list than discount market, and the positive DPORT parameter estimate is larger in the discount market. Although the general patterns of the time coefficient estimates are similar in the list and discount markets—revealing declines in quality-adjusted prices since 1982—in the discount market the pattern of estimates between T83, T84, and T85 is not monotonic, suggesting that the discount market is more volatile or that the discount sample is too small in these years to generate reliable parameter estimates.

Fourth, notice also that the DDISC coefficient in the pooled regression is negative ($-.2903$) and significant, as expected. We tested the null hypothesis that, aside from a parallel shift due to being in the discount market, all coefficients are identical in the list and discount markets. The F-test statistic corresponding to this null hypothesis is 2.77, while the .01 critical value is 1.73. Hence, on the basis of the F-test criterion, the null hypothesis of parameter equality in discount and list markets is rejected.[13] However, in terms of RMSE, the improvement under the alternative hypothesis is only 1.94 percent. Overall, we interpret these results as suggesting modest support for the null hypothesis of parameter equality in the two markets (aside from a parallel shift).

We also applied two other Chow-type tests to check for parameter equality over different subsets of the data. First, we ran separate regressions for the age equals zero-, one-, two-, and three-years-old subsamples and compared the residual sums of squares with those from the pooled model reported in column 1 of table 2.5. The calculated F-test statistic is 2.66, while the .01 traditional critical value is 1.44; however, the improvement in RMSE under the alternative hypothesis is 4.52 percent. Hence, although a tight criterion suggests rejection of the null, the RMSE approach lends marginal support in favor of the null hypothesis.[14]

Second, we ran seven yearly regressions, one for each year from 1982 to 1988, and then compared the residual sums of squares from these regressions

13. The Bayes-Leamer critical value is 7.39, considerably greater than the computed F-statistic of 2.77.

14. This F-test statistic value of 2.66 is also much smaller than the Bayes-Leamer large sample–adjusted critical value of 8.11.

with those from the pooled model reported in column 1 of table 2.5. With this test, we found more support for the notion of parameter instability. In particular, the F-test statistic for the null hypothesis of parameter equality is 5.18, much larger than the .01 critical value of 1.32.[15] Moreover, the improvement in RMSE under the alternative hypothesis is substantial—15.76 percent. Thus, parameters do not appear to be stable. We will return to a discussion of parameter instability over time later in this paper.

2.4 Further Results

To this point, our analysis has involved use of a traditional hedonic equation with time and age dummies. As discussed earlier, however, an alternative specification involves including vintage and age dummies—see equation (6)—instead of the time and age dummies as in (5). Recall that regression results (including R^2, parameter estimates, and standard errors) will vary somewhat when using the V-A specification rather than the T-A representation and that this should not be surprising, for, in (5), the total number of T-A dummy variable coefficients estimated directly is nine, while in (6) it is twelve. The R^2 and RMSE values given at the bottom of table 2.6 illustrate such variation among the various T-A and V-A specifications.[16]

One result of particular interest concerns the age coefficients. As is seen in table 2.6, with the V-A specification the age coefficients are negative and statistically significant and increase in absolute value with age. We interpret these age coefficients, conditioning on vintage, as capturing the average decline in prices of surviving computer models given steady improvements in new computers entering the market, that is, as the average difference between the time and the vintage effects. In a somewhat vague sense, therefore, these age coefficients capture the average effect of technical progress–induced obsolescence in our sample.

Since the interpretations and results from the T-A and V-A specifications differ considerably, and although our purpose of computing price indexes lends a priori support to use of the T-A model specification in table 2.5, one might still question whether using information from vintages in addition to that contained in the T-A model significantly improves model fit. In the previous section, we noted that a fuller T-A-V specification is possible, provided that two variables are deleted from the V vector. Moreover, in our context, a test for the null hypothesis that the α_v coefficients are simultaneously equal to zero can be interpreted as a specification test, providing information on

15. The corresponding Bayes-Leamer critical value is larger at 9.03.

16. While not reported here for reasons of space, it is worth noting that the slope coefficient estimates differ between the T-A and the V-A specifications, although in many cases the differences are not large.

Table 2.6 Selected Parameter Estimates with Time and Age and Vintage and Age Dummy Variable Specifications for Pooled, List, and Discount Samples, 1982–88 (absolute values of *t*-statistics in parentheses)

AGE1	0.1193	0.1296	0.0414	−0.2535	−0.2523	−0.2513
	(3.911)	(3.531)	(0.74)	(8.450)	(7.008)	(4.409)
AGE2	0.1542	0.2352	0.0192	−0.5846	−0.5026	−0.6707
	(3.448)	(3.984)	(0.27)	(12.44)	(7.978)	(8.943)
AGE3	0.2984	0.5333	0.1469	−0.8577	−0.5666	−1.0561
	(4.034)	(4.748)	(1.454)	(10.72)	(4.427)	(9.429)
T83	−0.3974	−0.2193	−0.8034			
	(4.768)	(2.081)	(5.889)			
T84	−0.4085	−0.3494	−0.2933			
	(5.017)	(3.350)	(2.298)			
T85	−0.8567	−0.7645	−0.7820			
	(10.11)	(7.039)	(5.845)			
T86	−1.2755	−1.1804	−1.2660			
	(14.94)	(10.77)	(9.402)			
T87	−1.6121	−1.5201	−1.6758			
	(18.73)	(13.80)	(12.37)			
T88	−2.0331	−1.9813	−1.9611			
	(22.41)	(16.88)	(14.18)			
V79				1.5830	1.2007	1.9415
				(8.650)	(4.727)	(7.164)
V80				1.0504	0.9474	1.1670
				(7.450)	(4.174)	(5.693)
V81				0.4454	0.5003	0.3439
				(3.095)	(2.690)	(1.415)
V83				0.1646	0.0942	0.3536
				(1.770)	(0.819)	(2.267)
V84				−0.1888	−0.2287	−0.0707
				(2.030)	(1.972)	(0.450)
V85				−0.5502	−0.5869	−0.4144
				(5.731)	(4.890)	(2.527)
V86				−0.9763	−1.0051	−0.8583
				(10.06)	(8.172)	(5.298)
V87				−1.2928	−1.3289	−1.2157
				(13.19)	(10.72)	(7.551)
V88				−1.8130	−1.8808	−1.3605
				(16.94)	(14.36)	(6.637)
R^2	0.7416	0.7003	0.8220	0.7455	0.7059	0.8112
N	1,265	917	348	1,265	917	348
Root MSE	0.4166	0.4181	0.3796	0.4140	0.4149	0.3927

whether the effects of unobserved and omitted characteristic variables are systematic among vintage comparisons and/or whether equality constraints on characteristics parameters are invalid over vintages.

We therefore ran an additional regression in which eight vintage dummy variables were added to the model reported in column 1 of table 2.5 and V82 and V83 were deleted. The F-test statistic for the null hypothesis that $\alpha_v = 0$ is 5.94, the traditional .01 F-critical value is 2.51, and the improvement in RMSE is almost up to our 5 percent threshold.[17] Hence, although the evidence is not clear cut, we interpret these results as providing some support for the alternative hypothesis, suggesting a reassessment of the *T-A* specification in column 1 of table 2.5, looking in particular for the parameter restrictions that might be contributing to the rejection of the null hypothesis.

This led us to reexamine our earlier year-by-year regressions and to look for patterns of parameter inequality over time. Inspection revealed that, although coefficients on a number of variables trended over time, the most marked trends were for coefficients on the LRAM, LMHZ, LHRDDSK, and DOTHER variables. We then specified and estimated two additional models using pooled data, one with overlapping samples in which three separate regressions were run for the overlapping periods 1982–84, 1984–86, and 1986–88, and the other for the entire period 1982–88 with several time-interaction variables added, LRAM * TC, LMHZ * TC, LHRDDSK * TC, and DOTHER * TC, where TC is a time counter increasing annually from zero in 1982 to six in 1988. Results from these *overlapping* and *time-interaction* regressions are presented in table 2.7.

The results presented in table 2.7 represent an improvement in the model specification, accounting somewhat for the considerable variation among parameter estimates over time. For example, in the 1982–84, 1984–86, and 1986–88 regressions, coefficient estimates on LRAM, LHRDDSK, LNUMFLP, and DOTHER fall continuously, while that on LMHZ increases. Trends are also apparent in several other coefficients. Moreover, when the pooled 1982–88 regression model with time interactions is estimated, negative and statistically significant estimates are obtained for LRAM * TC, LHRDDSK * TC, and DOTHER * TC, while that on LHMZ * TC is positive and significant. Hence, both these more general specifications appear to provide improved estimates.

To check further on the validity of these two specifications, we added to each regression the set of eight dummy vintage variables and then tested the null hypothesis that $\alpha_v = 0$. Our results are more satisfying and lend qualified support for the models reported in table 2.7. In particular, as shown in table 2.8, for 1982–84 and 1984–86 the calculated F-statistics are less than the .01 critical values, for 1986–88 the calculated F-statistic is larger, but in all three cases the improvement in RMSE with vintage variables included is less than 1.5 percent.[18] Hence, for all three overlapping models, whatever the effects of omitted and unobserved characteristics, they do not appear to be systematic among vintage comparisons.

17. The corresponding Bayes-Leamer criterion value is 7.09, only slightly larger than the calculated F-statistic of 5.94.

18. The corresponding Bayes-Leamer test criteria for the three overlapping models are 5.23, 6.20, and 6.72, respectively, each of which is larger than the calculated F-statistic.

Table 2.7 **Parameter Estimates for Pooled Overlapping Samples and for Pooled Sample for 1982–88 with Time Interactions**

	Overlapping Pooled Samples						Pooled Sample 1982–88 with Time Interactions	
	1982–84		1984–86		1986–88			
Variable	Estimate	*t*-Stat.	Estimate	*t*-Stat.	Estimate	*t*-Stat.	Estimate	*t*-Stat.
Intercept	4.1805	19.447	4.6522	22.881	4.5653	29.790	3.7782	25.066
LRAM	0.4622	9.872	0.1925	4.768	0.1652	6.883	0.6297	15.857
LRAM * TC							−0.0855	−9.416
LMHZ	0.0818	1.047	0.4041	6.521	0.4580	9.427	0.1968	2.846
LMHZ * TC							0.0370	2.228
LHRDDSK	0.2405	7.591	0.2090	12.190	0.1603	20.061	0.2302	7.612
LHRDDSK * TC							−0.0137	−2.301
LNUMFLP	0.6089	5.880	0.3916	4.976	0.1625	2.753	0.3271	6.644
LSLOTS	0.2429	5.453	0.2613	8.136	0.1134	4.930	0.1556	7.965
AGE1	0.1527	2.030	0.1321	2.725	0.1593	5.134	0.1410	4.835
AGE2	0.0217	0.172	0.0793	0.983	0.1701	3.841	0.1593	3.733
AGE3	0.3827	2.644	0.1758	1.070	0.1907	2.342	0.2496	3.525
PROC16	0.1429	1.751	0.1255	2.302	0.2824	7.338	0.2170	6.315
PROC32			0.2736	1.097	0.6040	9.392	0.6152	9.573
DBW	0.1538	2.163	0.0644	1.387	−0.1190	−3.771	0.0013	0.046
DCOLOR	0.3498	1.547	−0.0070	−0.042	−0.0249	−0.340	0.0590	0.831
DPORT	0.0770	0.890	0.4723	7.067	0.5019	11.217	0.3967	10.365
DEXTRA	0.0283	0.166	0.2670	2.201	0.3137	3.092	0.2132	2.615
DDISC	−0.3445	−5.196	−0.2430	−4.778	−0.3053	−9.508	−0.2946	−10.061

(continued)

Table 2.7 (continued)

	Overlapping Pooled Samples						Pooled Sample 1982–88 with Time Interactions	
	1982–84		1984–86		1986–88			
Variable	Estimate	*t*-Stat.	Estimate	*t*-Stat.	Estimate	*t*-Stat.	Estimate	*t*-Stat.
DAPPLE	0.2993	1.925	0.4641	4.158	0.2439	2.911	0.2199	3.047
DCMDRE	−0.4662	−2.331	−0.3954	−2.681	−0.3076	−3.292	−0.3672	−4.409
DCMPQ	0.4631	2.535	0.2757	2.756	0.0913	1.395	0.1929	3.109
DNEC	0.2916	1.686	−0.0582	−0.482	0.0580	−0.770	0.0399	0.578
DRDIOSH	0.4379	3.113	−0.0387	−0.335	−0.3162	−3.964	0.0704	1.056
DPCLIM			−0.3583	−1.988	−0.5025	−5.331	−0.5136	−5.247
DOTHER	0.2680	2.408	0.1467	1.996	−0.1316	−2.878	0.2607	3.498
DOTHER * TC							−0.0648	−4.405
T83	−0.5203	−5.631					−0.2552	−3.144
T84	−0.6203	−6.173					0.0029	0.034
T85			−0.4015	−7.196			−0.0787	−0.710
T86			−0.7694	−12.584			−0.0319	−0.218
T87					−.3365	−9.915	0.1372	0.722
T88					−.7561	−18.667	0.2680	1.110
R^2		0.8310		0.7336		0.7810		0.7668
N		247		428		904		1,265
Root MSE		0.4183		0.3889		0.3595		0.3965

Note: Coefficients on the time dummy variables across estimated models are not comparable since different base years are implicit.

Table 2.8 **Test Results for Null Hypothesis That Vintage Effects Are Zero in the Pooled Overlapping Samples and in the Pooled Sample for 1982–88 Model with Time Interactions**

Pooled Samples	Calculated F-Statistic	.01 Critical F-Value	% Change in RMSE
Overlapping 1982–84	2.72	3.32	1.45
Overlapping 1984–86	3.30	3.78	0.84
Overlapping 1986–88	5.85	3.32	1.08
1982–88 with time interactions	3.55	2.51	0.82

With the pooled 1982–88 time-interaction model, results are roughly similar to those from the overlapping models. The calculated F-statistic is larger than the .01 critical value, and the improvement in the RMSE when vintage variables are added is less than 1 percent.[19] Thus, there is little basis to choose among these two specifications. However, we expect that the constant change in parameters implied by the interactive time counter would become increasingly inappropriate as additional time observations were added. On this criterion, therefore, we have a mild preference for the specification involving three overlapping regressions.

Although further experimentation with other combinations of characteristics variables would most likely be useful, we now move on to using several of the most promising specifications to construct quality-adjusted price indexes for PCs.

2.5 Price Indexes

On the basis of the results of these various hedonic price equations, we can construct price indexes in a variety of ways. Although possibilities are limited when quantity sales data on the various models are unavailable, numerous procedures can be implemented given enough available data. In this section, we construct and comment on several price indexes, all based on our hedonic regression equations but varying in their interpretation and in their use of parameter estimates and quantity weights.

We begin with price indexes based on direct transformations of estimated hedonic price coefficients, interpreted as price indexes holding quality constant over time. In the first three rows of table 2.9, we present implicit PC price indexes computed directly from the three T-A regression equations reported in table 2.5, constructed simply as the exponentiated estimated coefficients on the time dummy variables, with T82 set to zero. The values in parentheses are percentage changes from the previous year, computed as

19. The Bayes-Leamer criterion in this case is 7.07, about twice the size of the calculated F-statistic.

Table 2.9 Alternative Implicit Quality-Adjusted Relative Price Indexes for Microcomputers Based on Direct Hedonic Regression Estimates

Procedure	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	AAGR 1982–88
T-A pooled				1.000	0.672	0.665	0.425	0.279	0.200	0.131	
					(−33)	(−1)	(−36)	(−34)	(−28)	(−35)	−28.7
T-A list				1.000	0.803	0.705	0.466	0.307	0.219	0.138	
					(−20)	(−12)	(−34)	(−34)	(−29)	(−37)	−28.1
T-A discount				1.000	0.448	0.746	0.458	0.282	0.187	0.141	
					(−55)	(−67)	(−39)	(−38)	(−34)	(25)	−27.9
V-A pooled	4.869	2.859	1.561	1.000	1.179	0.828	0.577	0.377	0.274	0.163	
		(−41)	(−45)	(−36)	(18)	(−30)	(−30)	(−35)	(−27)	(−41)	−26.1
V-A list	3.322	2.579	1.649	1.000	1.099	0.796	0.556	0.366	0.265	0.152	
		(−29)	(−36)	(−39)	(10)	(−28)	(−43)	(−34)	(−28)	(−43)	−26.9
V-A discount	6.969	3.212	1.410	1.000	1.424	0.932	0.661	0.424	0.269	0.256	
		(−54)	(−56)	(−29)	(42)	(−35)	(−29)	(−36)	(−43)	(−14)	−20.3
New models only				1.000	0.716	0.620	0.420	0.266	0.195	0.116	
					(−28)	(−13)	(−32)	(−37)	(−27)	(−41)	−30.2
Overlapping				1.000	0.594	0.538	0.360	0.249	0.178	0.117	
					(−41)	(−9)	(−33)	(−31)	(−29)	(−34)	−30.1
Time interactions				1.000	0.560	0.494	0.296	0.182	0.129	0.086	
					(−44)	(−12)	(−40)	(−39)	(−29)	(−33)	−33.6

Note: The price indexes are relative to the CPI. Values in parentheses are percentage changes form the previous year, computed as 100 * $(PI_t - PI_{t-1})/PI_{t-1}$, where PI is the relative price index.

$100 * (PI_t - PI_{t-1})/PI_{t-1}$, where PI is the price index. Note that the price indexes in the *T-A* model are the estimated time effects from regressions holding age and other characteristics constant. Overall, we see that average annual growth rates (AAGRs) are similar for the pooled, list, and discount equations (about −28 percent per year), although the estimated indexes for discounted models tend to be somewhat unstable from 1983 to 1985.

In the second set of three rows in table 2.9, implicit price indexes are presented that are based on direct exponentiation of the estimated vintage coefficients from the *V-A* specifications in table 2.6. The interpretation of these price indexes is slightly different—they are time effects reflecting the year of introduction and hence the average pace of technological change. As is seen in table 2.9, these price indexes suggest slightly slower declines in quality-adjusted prices than those based on *T-A* regressions (especially for discount models) and also reveal greater instability, particularly between 1982 and 1985.

One might think of these *V-A* price indexes as tracing out quality-adjusted price indexes for various vintages having AGE = 0 (since price indexes for 1979–88 are computed directly from the V79–V88 vintage coefficients, assuming AGE = 0), but estimation of the underlying coefficients is based on a sample including models of all ages. An alternative procedure for constructing a price index for new models only—an index that might be construed as tracing out the technological "frontier"—is to estimate parameters from a data sample restricted to new models, that is, to models with AGE = 0. Implicit price indexes computed from such a regression are reported in the row "new models only" in table 2.9.[20] There it is seen that a "new model only" price index declines more rapidly than those based on full-sample *T-A* and *V-A* specifications; in particular, the AAGR from 1982 to 1988 is −30.2 percent.

The two final implicit price indexes computed directly from hedonic regression equations without use of quantity sales weights are given in table 2.9 in the last two rows—"overlapping" and "time interactions." The overlapping price indexes are based on the three overlapping regressions reported in table 2.7. They are computed by directly exponentiating the coefficient estimates on the time dummy variables, linked so that, for example, the implicit 1985 and 1986 price indexes are the products of the exponentiated coefficients for 1984 and 1985 and for 1984 and 1986, respectively. Notice that, with an overlapping index procedure, the quality weights are constant only for subperiods and that coefficient estimates reflect varying sample means among subperiods. Interestingly, the overlapping price indexes fall at almost the same AAGR as that based on a "new models only" regression, although the overlapping price indexes fall more rapidly in the earlier years.

20. The underlying regression equation is of the same form as in table 2.5, except that age variables are deleted. Price indexes are computed directly by exponentiating the estimated coefficients on the time dummy variables.

The computation of price indexes based on the time-interaction model requires use of sample characteristics data, not just values of estimated coefficients. For example, using parameter estimates on the time interaction terms reported in table 2.7 for the log change in quality-adjusted prices between year t and year $t - 1$, we first compute

$$\begin{aligned} \ln \tilde{p}_t - \ln \tilde{p}_{t-1} &= (\alpha_t - \alpha_{t-1}) - .0855 * \text{LRAM}_t' \\ &\quad + .0370 * \text{LMHZ}_t' - .0137 * \text{LHRDDSK}_t' \\ &\quad - .0648 * \text{TC}_t * \text{DOTHER}_t', \end{aligned} \tag{10}$$

where the $'_t$ on LRAM, LMHZ, LHRDDSK, and DOTHER refer to the sample mean of these variables between year t and year $t - 1$. To calculate the price index, we simply cumulate the values in (10) over 1982–88 (letting $\alpha_{1982} = 0$) and then exponentiate them. This price index moves more rapidly—a decline of 33.6 percent per year—than that based on either new models or overlapping regressions. This large decline reflects the fact that sample means of the variables are all increasing with time, and these means are multiplied by the relatively large negative coefficients in (10).

One important problem with each of the above price indexes is that they fail to reflect changes over time in the mix of models. Recall that the direct hedonic regression coefficients in the *T-A* models can be interpreted as holding quality constant either by fixing the base of characteristic values over time or by fixing their valuation (parameter estimates). In a world with rapidly evolving new technologies, the notion of a fixed characteristic base as portraying representative transactions becomes increasingly inappropriate. What would be preferable is an index number procedure that accounts for compositional changes in models over time.[21] Such a computation requires, of course, quantity and revenue sales data by model year. As our final index number computations, we now consider a Divisia index that weights quality-adjusted prices of models by their revenue shares.

Specifically, our calculation of a (Tornqvist approximation to the) Divisia index proceeds as follows. First consider a model j observed in both period 0 and period 1. Let

$$\ln P_{1,j} = Z_{1,j}'\hat{\beta} + \hat{\alpha}_1 + \varepsilon_{1j}, \tag{11a}$$

$$\ln P_{0,j} = Z_{0,j}'\hat{\beta} + \hat{\alpha}_0 + \varepsilon_{0j}, \tag{11b}$$

where $Z_{1,j}$ and $Z_{0,j}$ are vectors of all regression variables except for the time dummy variables in year 1 and 0, the $\hat{\alpha}$'s are estimated coefficients on the time dummy variables, and the ε's are least squares residuals. This implies that

$$\ln P_{1,j} - \ln P_{0,j} = (Z_{1,j}' - Z_{0,j}')\hat{\beta} + (\hat{\alpha}_1 - \hat{\alpha}_0) + (\varepsilon_{1j} - \varepsilon_{0j}),$$

21. For a recent discussion of weighting issues in the context of compositional changes, see Triplett (1989b) and the references cited therein.

which can be rearranged to yield the expression

$$(12)\quad \ln P_{1,j} - \ln P_{0,j} - (Z'_{1,j} - Z'_{0,j})\hat{\beta} = (\hat{\alpha}_1 - \hat{\alpha}_0) + (\varepsilon_{1j} - \varepsilon_{0j}).$$

The left-hand side of (12) states that the log change in the quality-adjusted price of model j from 0 to 1 equals the change in observed prices minus the change in quality, where quality is evaluated using least squares regression coefficients and values of the characteristics. Alternatively, the right-hand side of (12) states that an equivalent way of computing the log change in the quality-adjusted price of model j is simply to sum the difference in estimated time dummy coefficients (which, implicitly, hold quality characteristics constant) plus the difference in the computed residuals (which reflects changes in the unmeasured attributes of the model). The choice of which of these two methods to employ in computer quality-adjusted prices can be based on relative computational convenience.

Several other features of (12) are worth noting. First, if there is no change in the characteristics of model j between 0 and 1 (i.e., the model has not become a new version in period 1), then $(Z'_{1,j} - Z'_{0,j}) = 0$ in (12), and, in essence, the quality-adjusted log price change is computed using the traditional matched-model procedure. Second, if the least squares residual is the same in the two time periods (i.e., if $\varepsilon_{1j} - \varepsilon_{0j} = 0$), then the log change in quality-adjusted prices is simply equal to the change in the time dummy coefficients. Note that residuals have a useful interpretation in the hedonic price equation, for they provide evidence on whether, relative to the overall market, a particular model is over- or underpriced.[22] An interesting issue concerns the relation between these residuals and the revenue shares garnered by each model. Since for each year the sum of residuals is zero, we would expect that, if shares are uncorrelated with residuals, it would also be the case that $\Sigma\, s_j\varepsilon_j \approx 0$.

Once (12) is computed for every model j in years 0 and 1, the log change in quality-adjusted prices over all models is calculated as the revenue share–weighted sum of the individual model j log changes in quality-adjusted prices,

$$(13)\quad \begin{aligned} \ln \tilde{P}_1 - \ln \tilde{P}_0 &= \sum_{j=1}^{J} \bar{s}_j(\ln \tilde{P}_{1,j} - \ln \tilde{P}_{0,j}) \\ &= \sum_{j=1}^{J} \bar{s}_j(\varepsilon_{1j} - \varepsilon_{0j}) + \hat{\alpha}_1 - \hat{\alpha}_0, \end{aligned}$$

where the ~, superscript is the quality-adjusted price (computed for individual j models using either side of eq. [12]), $\bar{s}_j$ is the arithmetic mean of $s_{j,1}$ and $s_{j,0,}$ and s_j is the share of model j's value of shipments in the total value of shipments over all models in the appropriate time period.

22. This under- or overpricing might also of course reflect the effects of unobserved omitted variables or of differential market power in differing segments of the PC market.

The calculation in (12) is feasible only when model j is part of a surviving cohort of models. In fact, however, some models exit the market each year, while others enter. To account for these entering and exiting models, several adjustments must be made to (12) and (13).

Consider the case of a model that enters the market in time period 1. Obviously, its price cannot be observed in period 0, and thus use of (12) to compute a quality-adjusted price index is not feasible. One can, however, use the estimated hedonic regression equation to predict such missing prices. Specifically, we substitute the right-hand side of (11b) into (12), set $Z_{1j} = Z_{0j}$ and $\varepsilon_0 = 0$, and then rearrange. This yields an expression for quality-adjusted log-price changes for entering models in period 1, computed in two alternative but equivalent ways as

$$\ln P_{1,j} - Z'_{1,j}\hat{\beta} - \hat{\alpha}_0 = \hat{\alpha}_1 - \hat{\alpha}_0 + \varepsilon_{1j}. \tag{14}$$

Similarly, for exiting models that were observed in period 0 but not in period 1, we employ hedonic regression procedures to predict the price of that model would it have survived to period 1. Specifically, we substitute (11a) into (12), set $Z_{1j} = Z_{0j}$ and $\varepsilon_1 = 0$, and then rearrange. This yields the appropriate log change in the quality-adjusted prices for existing models as

$$Z'_{0,j}\hat{\beta} + \hat{\alpha}_1 - \ln P_{0,j} = \hat{\alpha}_1 - \hat{\alpha}_0 = \varepsilon_{0j}. \tag{15}$$

Once these log changes in quality-adjusted prices are computed for all incumbent, entering, and exiting models, we calculate revenue shares (setting $s_{0,j}$ to zero for entering models and $s_{1,j}$ to zero for exiting models, thereby effectively using half the last or first observed share weight) and then compute an aggregate log change in quality-adjusted prices over all models using (13).

Several other points are worth noting. First, an interesting feature of (12), (14), and (15) is that they employ as information the values of the least squares residuals. Hence, the Divisia quality-adjusted index number procedure takes into account whether those models that exited (or entered) had prices above or below the average quality-adjusted prices. Note, however, that the weight given these exiting and entering models is likely to be minor since their average revenue share in periods 0 and 1 is in most cases rather small.

Second, empirical implementation of this Divisia index number procedure requires data on value of shipments by model. Proprietary data on shipments, installations, and value of shipments by model and year for about 950 of the 1,265 models in our estimation sample were kindly provided by the International Data Corporation (IDC). These data formed the basis of the share weights used in (13).

Restricting our sample to models covered by the IDC data set and computing revenue values by model year as the product of the IDC estimates of average price paid and number of models shipped, we computed Divisia quality-adjusted price indexes separately for incumbent, entering, and exiting models and for selected aggregates.[23] Our results, using parameter estimates from the *T-A* pooled and *T-A* overlapping regressions, are presented in table 2.10. A number of results are worth noting.

We begin with results from the *T-A* pooled regressions. First, inspection of the top row of table 2.10 reveals that the quality-adjusted Divisia relative price index for all PC models declined at an AAGR of −28.2 percent from 1982 to 1988, virtually identical to the AAGR of −28.7 percent for the direct hedonic *T-A* pooled price index.

Second, although the AAGRs over the entire period are nearly equal for these indexes, the Divisia index reveals a much smoother decline over time, with year-to-year declines ranging between 20 and 37 percent, whereas year-to-year declines for the direct *T-A* pooled index vary from 1 to 36 percent.

Third, changes in the price indexes for the incumbent models are quite different from those models entering and exiting between 1982 and 1988. As shown in the next three rows in table 2.10, the price declines of the incumbent models were on average larger (−30.6 percent) than those for the entering (−24.9 percent) and exiting (−20.0 percent) models. Note that these results can be reconciled with the econometric findings reported earlier for the *T-A* specification, for which estimated coefficients on the age variables were positive, provided one interprets the latter result as reflecting selectivity due, perhaps, to unobserved positive quality differentials among the survivors as vintages progress.

Fourth, the pricing strategies employed for entering and exiting models are quite different. Over the period 1982–88, the price declines for entering models (−24.9 percent) were on average larger than those for exiting models (−20.0 percent). However, while for exiting models prices were on average flat between 1982 and 1985, these models exhibited very large price declines from 1985 to 1988.

In the bottom panel of table 2.10, we present Divisia relative price indexes using parameter estimates from the overlapping regressions. The most interesting result is that, in spite of using a rather different set of regressions, the AAGR from 1982 to 1988 is hardly affected. Specifically, the AAGRs for the pooled and overlapping regressions for all computer models are −28.2 and −28.0 percent, respectively; for incumbent models, −30.6 and −30.5 percent; for entering models, −24.9 and −22.4 percent; and for exiting models, −20.0 and −23.7 percent. Although there are year-to-year variations between the Divisia pooled and overlapping regression price indexes, the AAGRs for 1982–88 are reasonably robust.

23. We divided revenues among list and discount listings of the same model in proportion to the relative number of listings. It is also worth noting that mean values of the revenue shares of continuing, entering, and exiting models from 1982 to 1988 are 54, 26, and 20 percent, respectively. There is considerable variation in these shares over our sample time period, however.

Table 2.10 Alternative Divisia Quality-Adjusted Relative Price Indexes for Microcomputers Based on *T-A* Pooled and *T-A* Overlapping Regression Estimates

Regression and Sample	1982	1983	1984	1985	1986	1987	1988	AAGR 1982–88 (%)
T-A pooled estimation:								
All computer models	1.000	0.638	0.510	0.385	0.283	0.188	0.136	−28.2
		(−36)	(−20)	(−25)	(−26)	(−34)	(−28)	
Incumbent models only	1.000	0.580	0.438	0.330	0.247	0.160	0.112	−30.6
		(−42)	(−24)	(−25)	(−25)	(−35)	(−30)	
Entering models only	1.000	0.716	0.562	0.379	0.270	0.201	0.179	−24.9
		(−28)	(−22)	(−33)	(−29)	(−26)	(−11)	
Exiting models only	1.000	0.804	1.188	1.005	0.682	0.410	0.263	−20.0
		(−20)	(48)	(−15)	(−32)	(−40)	(−36)	
T-A overlapping estimation:								
All computer models	1.000	0.576	0.465	0.359	0.282	0.193	0.140	−28.0
		(−42)	(−19)	(−23)	(−21)	(−32)	(−27)	
Incumbent models only	1.000	0.542	0.422	0.317	0.250	0.160	0.113	−30.5
		(−46)	(−22)	(−25)	(−21)	(−36)	(−29)	
Entering models only	1.000	0.756	0.586	0.453	0.355	0.261	0.218	−22.4
		(−24)	(−22)	(−23)	(−22)	(−26)	(−16)	
Exiting models only	1.000	0.591	0.780	0.638	0.440	0.299	0.197	−23.7
		(−41)	(32)	(−18)	(−31)	(−32)	(−34)	

Note: The price indexes are relative to the CPI. Values in parentheses are percentage changes from the previous year, computed as 100 * (PI_t − PI_{t-1})/PI_{t-1}, where PI is the relative price index.

2.6 Summary

The simultaneous existence of incumbent, entering, and exiting models raises issues of product heterogeneity in the microcomputer market and of the nature of price and quality competition and creates ambiguity in how one constructs and interprets price indexes. These are the issues on which we have focused attention in this paper.

Specifically, we have reported results from a variety of hedonic regression equations using an unbalanced panel data set for 1,265 model years from 1982 to 1988 and have developed and implemented empirically a specification test for selecting preferable hedonic price equations. We have discussed in detail the alternative interpretation of dummy variable coefficients in models having time and age, vintage and age, and all the time, age, and vintage dummy variables as regressors. On the basis of these estimated hedonic price equations, we then computed quality-adjusted price indexes using a variety of procedures. This provided us with indexes having varying interpretations—constant average quality price indexes, price indexes for new models only, and quality-adjusted price indexes portraying representative transactions that take into account the changing model composition in our sample over time. Not surprisingly, average annual growth rates for these varying price indexes also differed, although all showed a substantial decline in quality-adjusted prices over the period 1982–88.

Our research is preliminary, and much remains to be done. One item high on our research agenda involves obtaining model-specific performance measures for specific numerical tasks, such as the number of instructions executed per unit of time, and then redoing the hedonic regressions with such performance measures added as regressors. Moreover, issues of parameter instability and choice of variables to include in the set of characteristics are also potentially important and need further examination. Finally, given that the least squares residuals either provide economic information on over- or underpricing of models relative to the market as a whole or reflect the effects of omitted variables or differential market power in different PC market segments, an interesting extension would involve examining in greater detail the relations among residuals for entering, incumbent, and exiting models and realized market shares.

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Comment Rosanne Cole

These papers deal with the main outstanding empirical issues associated with the construction and interpretation of hedonic-based price indexes in general and computer price indexes in particular. In addition, the Oliner paper contains estimates of the rate of depreciation and of the retirement distribution for a set of computers and an assessment of the possible bias in BEA estimates of real gross and net stocks of this class of assets.

The contribution of the Berndt-Griliches paper is primarily methodological. The authors employ a sample of microcomputer list and discount prices to illustrate and deal with the econometric issues involved in estimating hedonic regressions from data in the form of an unbalanced panel. Of specific concern is the interpretation of the various time-related coefficients, given that one never really knows whether the included set of characteristics is the "correct" one. They develop and implement empirically a test for detecting inadequacy in the specification of hedonic equations—inadequacy of the set of included characteristics and/or invalid stability constraints on the characteristics' coefficients over time. Finally, they construct a variety of price indexes: constant average quality price indexes; price indexes reflecting changes over time in model mix or changing average quality; and price indexes for new, continuing, and exiting models only.

Berndt and Griliches regard their results for microcomputers as preliminary. Obtaining improved measures of characteristics (I return to this topic later) ranks high on their agenda for further work on these products. But their main contribution is the provision of a diagnostic tool whose use, when coupled with technical knowledge of the products under study, should benefit and improve the credibility of future hedonic studies.

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Computers have received considerable attention largely because of the difficulties these products pose for price measurement. They provide an example of products subject to rapid technological improvement in a rapidly changing marketplace. There is relatively frequent entry and exit of firms and a steady stream of models introduced and of models discontinued. Indeed, the market for computers has been characterized as in "disequilibrium" caused by technological change.

Multiple Prices

Previous work, especially Dulberger's (1989) study of intermediate and large-size computer processors (so-called mainframe computers), has emphasized one aspect of disequilibrium: the existence for a time of multiple quality-adjusted prices when models embodying new technology are introduced into the marketplace.

Oliner employs a largely untapped body of data, secondary market asking prices for IBM mainframe computers, to ask how these prices compare with list prices and whether Dulberger's finding of multiple prices was merely an artifact. His analysis confirms Dulberger's finding. The secondary market data show price premiums on old models comparable to those found in the list price data.[1]

The question has important practical implications. If the quality-adjusted prices of existing products adjust instantaneously and fully to the introduction of new models, then a price index covering only the most technologically advanced models would be the same as the price index covering all models that are sold. Moreover, these price indexes would be the same as a price index based on matched-models procedures so it might not even be necessary to turn to hedonic methods.

There are some suggestions of multiple prices for microcomputers reported by Berndt and Griliches in their table 2.10, but they are of a perverse nature. There, the quality-adjusted price indexes for entering models are persistently higher than those for continuing models. These price differentials are not of the Dulberger variety, which arise when models embodying new technology come into the marketplace, persist for a short time, and then vanish. The period of time that the differentials persist depends partly on the time it takes for new "families" of models to be brought into full production.

The rapid increase in production of new families of microcomputers and their short delivery schedules during 1982–88 (the period covered by the price

1. This result is a fairly strong one because it takes some time for models to appear in the *Price Guide*. For example, ten of the thirty-three models produced during the period studied by Dulberger, 1972–84, were not quoted in the *Price Guide* until they were out of production. Of the twenty-three models in current production and also quoted in the *Price Guide*, seven were first quoted at age 1, ten at age 2, five at age 3, and one at age 4. The majority (twenty-three of thirty-four) of models produced during 1985–88 were not quoted in this secondary market data until they were out of production. Moreover, it should be noted that Dulberger's sample was not limited to IBM models.

indexes in table 2.10) suggest that there was much less imbalance between the demand for and supply of these products than was typical historically for mainframes. One would therefore expect prices to adjust quickly and fully to the introduction of new models, but not to "overadjust." The price differentials in table 2.10 are, in my judgment, more of the ordinary garden variety, which arise when prices have not been adequately adjusted for quality differences among the products to which they refer.

Characteristics Measures

One of the problems encountered in implementing hedonic techniques to correct prices for quality differences is obtaining appropriate measures of characteristics. In the case of computers, the problem is especially severe for measures of speed. There is always a trade-off between measures that are adequate for the purpose at hand and measures that are also comparable across the range of products under consideration.

There is a second type of problem that is a level-of-aggregation issue. Computer processors are one component of a computing system (or network of system components); auxiliary storage devices (disk drives, tape drives) are another. Measures of speed that are adequate at a single component level are generally inadequate at a higher level of aggregation. Thus, for example, equivalent MIPS (millions of instructions processed per second) is an adequate measure of processor speed, but it is an inadequate measure of speed for small computers that house both the processor and the auxiliary storage devices under one cover ("box").

The speed measure employed for microcomputers in the Berndt-Griliches paper is at the lowest level, clock rate (logic cycles per second). Logic cycle time is the highest speed at which a microprocessor could theoretically operate (neglecting a memory speed constraint). Even though this measure is roughly comparable across the range of the *microprocessors* contained in the products that they consider, it is not an adequate measure of the speed of the *microcomputers* that they price. Preferable measures of speed are equivalent MIPS (which takes account of memory cycle time) at the processor level or a benchmark performance measure (which in addition takes account of the speed of the embedded auxiliary storage device) at the computer level.

A comparison of clock rate with other publicly available speed measures for a set of IBM PCs is given in table C.1: equivalent MIPS, at the processor level, and benchmark measures, at the computer level. Two types of benchmark measures are shown: the Whetstone, a widely used performance benchmark for scientific applications, and NSTL performance benchmarks.[2] The

2. The performance benchmark tests were conducted by National Software Testing Laboratories, Inc. (NSTL), Plymouth Meeting, PA (215-941-9600) and reported in the *PC Digest* "Ratings Report" (see the April 1987 issue).

Table C.1 Comparisons of Speed Measures, Selected IBM PCs

Model	Processor Speed (expressed relative to PC/XT): Clock Rate (MHz)		Vax Equivalent MIPS
PC/XT	4.77	1.0	1.0
PC/AT	6	1.3	2.96
PC/AT	8	1.7	4.14
PS/2:			
Model 30	8	1.7	
Model 50	10	2.1	5.17
Model 60	10	2.1	
Model 80	16	3.4	

	Computer Speed: Benchmarks (expressed relative to PC/XT)				
		NSTL Performance Benchmarks			
	Whetstone	Simple Average	Spreadsheet	World Processing	General Ledger
PC/XT	1.0	1.0	1.0	1.0	1.0
PC/AT (6MHz)	3.14	2.7	2.9	2.6	2.5
PC/AT (8MHz)	4.38	3.5	4.0	3.3	3.2
PS/2:					
Model 30		2.1	2.3	2.1	2.0
Model 50	5.47	4.4	4.9	4.2	4.0
Model 60		4.6	4.9	4.3	4.2
Model 80		7.6	9.0	7.2	6.6

Sources: VAX MIPS and Whetstone measures are constructed from a table sourced as Power Meter v. 1.2, The Database Group (testing performed by *PC Week* and reported in *PC Week*, (8 September 1987, 1). NSTL performance benchmark measures are constructed from results of performance benchmarks tests reported in the "Ratings Report" in *PC Digest*, April 1987, 16, 20, 23–28, and used with permission of NSTL, a Division of Datapro Research Group, Plymouth Meeting, Pa. 19462.

NSTL benchmark tests are unusual because they are conducted for a fairly wide range of applications (spreadsheet, word processing, relational data base, etc.) and performance of each application is tested under more than one application software package. Although the entries in table C.1 draw only on results for IBM PCs for three popular applications, results for other applications and for other brand-name PCs that rely on Intel microprocessors (Compac, Tandy, etc.) were also published in the same report.

The comparisons in table C.1 show that, on the basis of clock rate, the PS/2 model 30 has the same speed as one model of the PC/AT; all the NSTL measures show its speed to be slower. The speed of the PS/2 model 50 is twice that of the PC/XT based on the clock rate measure; all the alternatives show it to be four to five times as fast. The PS/2 model 80 is nearly three and a half times as fast as the PX/XT when measured by clock rate but six to nine times as fast on the basis of the NSTL measures of speed.[3]

This same measurement problem exists for the other brand-name microcomputers included in the data set studied by Berndt and Griliches. The error introduced is such that prices of higher-speed models are persistently undercorrected for quality change.[4] I suspect that this is the main reason for the perverse price differentials between entering and continuing models in the quality-adjusted price indexes shown in table 2.10 of Berndt and Griliches's paper.

Given my view that the Berndt-Griliches study has produced questionable correction for quality change, I remain unconvinced that hedonic techniques are preferable to matched-models procedures for purposes of constructing quality-adjusted price indexes for microcomputers. This preference, however, is conditioned on the assumption that the sample of models priced is refreshed with sufficient frequency as to remain representative of models sold.[5]

Depreciation, Obsolescence, and the Concept of Age

Oliner's hedonic regressions can be regarded as treating the decline in market value of a computer as it ages as consisting of two components: the part attributable to the rate of technological obsolescence and the part attributable to the rate of change in the market value of the computer's characteristics. There are two concepts of age for purposes of estimating the obsolescence component of depreciation: one based on model age and one based on age of the technology embodied in the model. Judging by the regression results (reported in Oliner's tables 1.7 and 1.8), the preferred concept would be the one based on age of the technology embodied in the model, not the one based on model age. On an annual basis, the rates compound to 14.7 percent (table 1.7, col. 5) and 16.1 percent (table 1.7, col. 2), respectively.[6] Thus, it appears that the choice between the two concepts matters more for purposes of interpreting than for estimating a geometric rate of obsolescence of these products from hedonic regressions.

3. As a general rule, numerically intensive applications require a relatively small amount of data movement, or "disk accesses." Consequently, a spreadsheet or the Whetstone benchmark will show relative speed measures close to the measures of processor speed. In contrast, word processing or general ledger are applications that require considerable disk activity. Benchmarks based on this type of application will show relative speed measures for the computer that are slower than the processor speed measures. A summary measure of computer speed can be obtained by striking a simple or weighted average of the benchmark results.

4. The hedonic work underlying the Bureau of Labor Statistics (BLS) experimental price indexes for microcomputers employed the clock rate measure of speed and is subject to the same criticism.

5. But see Triplett's Comment (in this volume). One problem threading through the workshop sessions on computer price indexes and semiconductor price indexes was the difficulty of fitting these products into the producer price index (PPI) sampling methodology.

6. The estimated rates of depreciation are altered only slightly by allowing for disequilibrium: the 14.7 percent becomes 14.6 percent, and the 16.1 percent becomes 15.9 percent.

The two concepts of age produce very different patterns of depreciation, however, as a comparison of Oliner's figures 1.5 and 1.6 illustrates. Oliner has an interesting interpretation of the two. My own would be somewhat different. Since I would expect the depreciation pattern of these products to be dominated by technological obsolescence, I conclude that the results show that a new model embodying new technology declines in price as it ages far less rapidly than a new model embodying a three- or four-year-old technology. In summary, the model age–price profile is dominated by the age of the technology that the model contains.

Processors do not wear out with use, as do products with moving parts, nor do they suffer from metal fatigue. They become obsolete, not when repairs can no longer be justified, but when other complementary resouces are unjustifiably large compared with those required to operate models embodying the most advanced technology. The time pattern of the lines in fig. 1.6 suggests that it takes two generations of new technology to make the old fully obsolete; this seems consistent with the long tail on the retirement distribution that Oliner estimates.

Retirement, Depreciation, and "Real" Capital Stock Estimates

A major contribution of the Oliner paper is the evidence presented on the pattern of the distribution of retirements of this set of products. The Winfrey S-3 is clearly shown to be a poor approximation of reality. As one might guess from Oliner's results, it is probably also a poor approximation of the retirement distribution of other types of office and computing equipment.

Rather than having to rely on Winfrey approximations, it would of course be preferable to develop estimates of retirement distributions and average service lives from a historical set of data on maintenance contracts covering this (or any) class of assets. Such a data set is not publicly available, at least to my knowledge. Despite their "second-best" aspect, data on stocks are available (although not from a single or costless source) for other types of computing equipment. I endorse Oliner's recommendation for a further research effort along the lines that he describes.

Oliner's evidence on retirements and the decline in average service lives convinces me that the BEA estimates of real gross stocks of processors, relying as they do on a Winfrey S-3 distribution with a constant eight-year average service life, would overstate the growth of these stocks. I am glad he now agrees that an overly rapid rate of depreciation has historically been employed to obtain estimates of the net stocks from the gross stocks.[7] Only the obsolescence component, or partial depreciation, as Oliner calls it, should be applied.

Two factors account for the decline in average service lives and the increase in the depreciation rates that Oliner observes, and both can change direction

7. The first version of the paper did not distinguish partial depreciation for purposes of estimating real net stocks from real gross stocks.

over time. One is the pickup in the pace of introducing new technology. The second is an increase in the average age of the technology contained in the new models in his sample. On the basis of the data in Oliner's appendix tables 1.A.1 and 1.A.2, the 360 models embodied new technology, the new 370 models had an average technology age of two years, and the new 303X models had an average technology age of five years. These two factors together produced the earlier obsolescence and shorter service lives that Oliner notes (his fig. 1.3). An answer to the question of whether these findings would hold for other types of computers and computing equipment—and, for that matter, for other types of high-tech equipment—awaits further research. Certainly, Oliner's work is an important first step.

Reference

Dulberger, Ellen R. 1989. The application of a hedonic model to a quality-adjusted price index for computer processors. In *Technology and capital formation*, ed. Dale W. Jorgenson and Ralph Landau. Cambridge, Mass.: MIT Press.

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