ELSEVIER

Journal of Econometrics 68 (1995) 243–268

JOURNAL OF
Econometrics

Econometric estimates of price indexes for personal computers in the 1990's

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Abstract

In this paper we construct a number of quality-adjusted price indexes for personal computers in the US marketplace over the 1989–92 time period. We generalize earlier work by incorporating simultaneously the time, age, and vintage effects of computer models and then develop a corresponding specification test procedure. When data on new and surviving models are used in the estimation of hedonic price equations, a variety of quality-adjusted price indexes decline at about 30% per year, with a particularly large price drop occurring in 1992. We conclude that taking quality changes into account has an enormous impact on the time pattern of price indexes for PC's.

Key words: Personal computers; Price indexes; Hedonics; Panel data; Divisia index
JEL classification: C23; C43; L63

1. Introduction

The rapid technological and market developments in the personal computer industry are widely known and have received a great deal of public attention. One way of summarizing these major changes is to look at the unweighted arithmetic mean of prices and technological characteristics of personal

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We gratefully acknowledge the financial support of the Alfred P. Sloan Foundation, the National Science Foundation, and the Bradley Foundatin to the National Bureau of Economic Research Joanna Stavins, Lau Christensen, and participants in the NBER Productivity Group provided helpful comments and assistance.

SSDI 0304407694016 5 1 F

computer models sold in the last four years in the U.S. Based on data as reported by DATAPRO, in Table 1 we present such a summary.

As is seen in the final column of Table 1, mean nominal prices of PC models dropped slightly between 1989 ($4616) and 1991 ($4320), but then fell sharply in 1992 (to $3378), thereby changing at an overall average annual growth rate (*AAGR*) of − 10.97%. Even as the unweighted mean of computer 'box' prices fell at about 11% per year, dramatic quality improvements occurred in the performance and characteristics of PC models. For example in 1989, 37.3% of PC models had a 32-bit processor, but by 1992 this had doubled to 76.7%; over the same time, the percent of PC models having an 8-bit processor fell from 8.0% to zero. As a result, microprocessor (CPU) speed increased by about 80% from 15.06 to 27.78 MHZ. Furthermore, mean RAM capacity almost quadrupled from 1227 kilobytes (KB) in 1989 to 4755 KB in 1992, while hard disk capacity increased from 45 to 123 megabytes (MB). Even more dramatically, all this increased capacity and performance was compressed into an ever smaller and lighter 'box'; while mean size fell from 1695 to 1419 cubic inches between 1989 and 1992, weight fell even more rapidly from 30.43 to 25.60 pounds.

The measurement of price indexes in the presence of such rapid technological change is of course a difficult task. One measurement procedure is to construct a 'matched model' index, a procedure that is often used by government statistical agencies. With a matched model index, prices of products are compared only for models which survive unchanged from one year to the next. Since the quality of the product is constrained to be unchanged, any price variability represents a 'pure' or 'quality-constant' price change.

Using the same DATAPRO data, we have constructed a PC matched model index for the 1989–1992 time period. A matched model is defined here in a rather restrictive manner, having identical characteristics in the two adjacent time periods (e.g., speed, memory, storage capacity) – not just the same model name and number. This limits the number of matches. As is seen in Table 2, the matched model index implies that prices of PC's declined at an *AAGR* of about 19%, with a rather steep decline of 44% in 1992.

Table 1
Mean values of characteristics and prices of PC models sold, 1989–1992

Year	No. of models	*PERCENT* *PROC8*	*PROC32*	*RAM* in KB	*SPEED* MHZ	*HRDDSK* in MB	*SIZE* in IN^3	*WEIGHT* in LBS	*AGE* in years	Nominal price
1989	225	8.0%	37.3%	1227	15.06	45.00	1695	30.43	0.467	4616
1990	575	4.7%	46.1%	1608	18.40	55.75	1638	30.71	0.473	4405
1991	453	3.1%	41.9%	1829	19.35	48.85	1469	27.87	0.547	4320
1992	630	0.0%	76.7%	4755	27.78	122.52	1419	25.60	0.654	3378
Total/ mean	1883	3.1%	54.3%	2691	21.37	75.10	1531	28.28	0.551	4066
1982–88 mean	1265	32.0%	13.0%	561	8.35	17.20	NA	NA	0.600	2847

Table 2
PC price index based on matched model procedure

Year	No. of versions sold	Matches from previous year	Percent matches	Mean percent price change
1989	225			
1990	575	18	8.00%	– 7.860%
1991	453	185	32.17%	– 0.874%
1992	630	14	3.09%	– 42.561%
1992/1989 *AAGR* of price changes:		– 19.348%		

Though the decline of this matched model price index is almost double that of the unweighted mean price change for all models (– 19.35% vs. – 10.97%), it is reasonable to expect that even the matched model procedure understates true price declines. By examining only those models which survive unchanged year-to-year, any incremental improvements in a particular model (e.g., a faster processor) disqualify it from the index. New models are ignored entirely, as of course are models that exited the market. Moreover, with the matched model procedure, since the percentage of matches in the data ranges from 3% in 1991–92 to 32% in 1990–91, a clear majority of observations are ignored. Finally, it is plausible to argue that the fewest matches occur precisely during the most active periods of product improvement – and thus that the matched model procedure might substantially understate quality-adjusted price changes.

An increasingly useful alternative to the matched model procedure involves using econometric estimates of hedonic price equations to construct price indexes that hold quality fixed.[1] In an exploratory econometric study, Berndt and Griliches (1993) have estimated hedonic price equations based on computer magazine advertisement data for 1265 computers, beginning with the introduction of the IBM PC in 1982 and ending in 1988. The results they obtained were remarkably robust across alternative functional forms, and implied about a 28% annual decline in real quality-adjusted PC prices.[2,3]

[1] For historical discussions and references to appropriate studies, see Berndt (1991, Ch. 4), Cole et al. (1986), Dulberger (1989), Fisher et al. (1983), Gordon (1989, 1990), Griliches (1961, 1971, 1988, 1990), Hall (1971), Sinclair and Catron (1990), and Triplett (1986, 1989, 1990).

[2] Year-to-year real price changes based on their preferred *T–A* pooled model were, from 1982–83 to 1987–88, respectively, – 33%, – 1%, – 36%, – 34%, – 28%, and – 35%, implying an *AAGR* of – 28.7%.

[3] In a very recent paper paper by Nelson, Tanguay, and Patterson (1994), the authors use a sample of 1841 IBM-compatible PC models (but excluding laptops and notebooks) from 1984 through 1991 and similar estimation procedures. They find an *AAGR* of – 23.4%; for the common period of 1984–88, the Berndt and Griliches estimate of price change is an *AAGR* of – 25.5%, while that for Nelson et al. is a comparable – 24.5%.

In this paper we extend research on PC price indexes in a number of ways. First, because the data employed consists of an unbalanced panel, and because there is an identity relating the age of a model, its vintage, and the year in which the model is observed, important issues emerge involving the interpretation of dummy variable coefficients. Some of these issues were addressed by Berndt and Griliches. Here we extend that discussion by introducing a 'saturated' parameter model that permits a much richer parameterization, and also allows for a more complete set of specification tests in the unbalanced panel context. Second, in this paper we consider more completely the issue of parameter stability and equality. This is particularly important in the PC context, where new markets have emerged (notebooks vs. desktop models), technological change is dramatic, and where equation specifications need to be sufficiently general to capture possible nonlinearities. Third, this study incorporates data through 1992, and therefore updates results from previous studies. As we shall see, 1992 was a most remarkable year in terms of quality-adjusted price declines.

2. The data sets

The data sets for this paper were obtained for the most part from Datapro Information Services Group, a division of McGraw-Hill (DATAPRO).[4] As is seen in Table 1, the data consists of an unbalanced panel of 1883 observations on PC's during the four-year 1989–1992 timeframe. To avoid the extreme-end 'toy' and 'file server' computer models, we have restricted the sample to models having at least 512KB of RAM, a speed of at least 7.8MHZ (thereby still including the IBM-XT), and having a hard disk capacity of no more than 500 MB.

In previous work, we used data from personal computer advertisements, such as those for mail-order purchases, to obtain measures of a particular model's characteristics and price. The advantage of that approach is that the resulting price data more closely approximates actual transactions prices than does, say, a list price. The disadvantage is that typical advertisements frequently provide less than full information on the particular combination of attributes 'packaged together' in the model by the vendor. The DATAPRO data set has the advantage of providing far more complete technical specifications than does the typical magazine advertisement; DATAPRO provides technical information on approximately 40 characteristics in a consistent form across manufacturers, models, and years. However, the price data from DATAPRO is for the list price of the particular base model, rather than a transactions price. Although in our previous study we found that 'street' prices were frequently 35% lower than list

[4] Datapro Information Services Group, Delran, NJ 08075.

prices, whether this discount proportion has changed substantially over time is not clear. Using 1970–86 data from the US mainframe computer market, Oliner (1993) reports that rates of growth in list prices were very similar to those of transactions prices. To the extent that percent discounts from list price to transactions price have increased as competitive pressures in the PC market have intensified in the past few years, the price indexes resulting from our use of DATAPRO data might understate somewhat the true rate of price decline of PC's. On the other hand, the share of sales accounted for by mail order models has plausibly increased since 1989. Since in the mail order market there is no apparent distinction between list and transactions prices, the use of list price data for the entire 1989–92 time period might overstate the average transaction price decline. Moreover, it is widely known that in 1992 major brand manufacturers changed pricing strategies and brought list prices down considerably to match others' transactions prices. Which of these various offsetting effects is dominant is, unfortunately, unknown.

It would of course be desirable to link the 1989–92 data of this study with the Berndt–Griliches 1982–88 data. Because the 1989–92 data employ list prices, there is no feasible link between the 1988 prices based on magazine advertisements and the 1989–92 DATAPRO price series. A preliminary attempt to merge the data sets resulted, not surprisingly, in very large and unrealistic price increases from 1988 to 1989. Unfortunately, DATAPRO data series prior to 1989 are not currently available. Consequently, the results of this study are not directly comparable to those presented by Berndt and Griliches.

The technical characteristics data we employ from the DATAPRO data base include measures of the following variables: *PRICE* (in current dollars); *RAM* (installed random access memory capacity, in kilobytes); *MAXRAM* (maximum amount of addressable RAM capacity possible); *MHZ* (speed of processor chip, in megahertz); *HRDDSK* (hard disk capacity, in megabytes); *SIZE* (in cubic inches); *WGT* (in pounds); *DENSITY* (*WGT*/*SIZE*); *AGE* (age of the model, i.e., a model introduced in year t and observed in year t is zero years old, a model introduced in year $t - 1$ and observed in year t is one year old, etc). The sample is confined to models three years of age and younger. Dummy variables *AGE0*, *AGE1*, *AGE2*, and *AGE3* are defined accordingly; *DFLP23* is a dummy variable equal to one if the model has two or more floppy drives; and *DNOHDDSK* is a dummy equal to one if the model does not have a hard disk. Other dummy variables include *DPROC* (a series of dummy variables for whether the processor chip is 8-bit – *DPROC8*, 16-bit – *DPROC16*, or 32-bit – *DPROC32*); *DMOBILE* (a dummy variable equal to one if the computer is defined by DATAPRO as notebook, laptop, portable, or transportable, as distinct from desktop or floorstanding); a series of brand dummy variables equal to one if the computer brand is ALR (*DALR*), Apple (*DAPPLE*), AST (*DAST*), Compaq (*DCMPQ*), CompuAdd (*DCOMPUAD*), Dell (*DDELL*), Digital Equipment Corporation (*DDEC*), Hewlett Packard (*DHP*), IBM (*DIBM*), NEC (*DNEC*),

Table 3
Summary of DATAPRO personal computer data, 1989–1992

Variable	Mean	Minimum value	Maximum value
PRICE	4066.31	525.00	22655.00
RAM	2690.92	512.00	32000.00
MAXRAM	21207.61	512.00	256000.00
MHZ	21.37	7.83	66.00
HRDDSK	75.10	0.00	440.00
SIZE	1530.82	34.20	7020.00
WGT	28.28	2.80	110.00

Sample means of dummy variables

PROC8	0.0313	*V89*	0.1540
PROC16	0.4259	*V90*	0.3404
PROC32	0.5428	*V91*	0.2693
DFLP23	0.2103	*V92*	0.1620
DMOBILE	0.2268	*DALR*	0.0313
AGE0	0.6150	*DAPPLE*	0.0409
AGE1	0.2560	*DAST*	0.0308
AGE2	0.0924	*DCOMPAQ*	0.0531
AGE3	0.0366	*DCOMPUAD*	0.0361
T89	0.1194	*DDEC*	0.0531
T90	0.3054	*DDELL*	0.0935
T91	0.2406	*DHP*	0.0483
T92	0.3346	*DIBM*	0.0669
V86	0.0016	*DNEC*	0.0526
V87	0.0478	*DTOSH*	0.0292
V88	0.0250	*DZEN*	0.0228
		DOTHER	0.4414

Sample size: 1883

Toshiba (*DTOSH*), Zenith (*DZEN*), or all other brands (*DOTHER*).[5] Finally, we have constructed dummy variables *T89, T90, T91*, and *T92* that equal one if the computer model is being observed in that particular year, and seven vintage dummy variables (*V86* through *V92*) corresponding to the vintage of the particular model (the year it was first introduced on the market).[6] This data is summarized in Table 3.

[5] Brand-specific dummy variables were introduced for all brands having a market share of 2.0% or more, where market share here means the number of model versions of a particular brand divided by the total number of all model versions (1883) from 1989 to 1992.

[6] DATAPRO reports the date of the first sale of each computer model.

As is seen in Table 3 from means of the dummy variables, the data set is dominated by new models (*AGE0* = 0.62) that are desktop or floorstanding (not laptops or notebooks, for *DMOBILE* = 0.23), having either zero or only one floppy disk drive (*DFLP23* = 0.22) and a hard disk drive (*DNOHDDSK* = 0.25, implying 75% of models have a hard disk), and by brands other than those from the nine leading vendors (*OTHER* = 0.44, but with Dell, IBM, Compaq, DEC and NEC having the largest number of models).

3. 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 *TIME* be a variable equal to the year in which a model was observed (say, *TIME* = 1991); let *VINTAGE* be a variable equal to the year in which the model was first introduced into the market (e.g., *VINTAGE* = 1989); and let *AGE* be a variable equal to the number of years that a particular model has been in the market (e.g., *AGE* = 2). For any model-observation, we therefore have the identity

$$TIME \equiv VINTAGE + AGE. \tag{1}$$

Because of this identity, one cannot include continuous linear versions of all three of the *TIME*, *VINTAGE*, and *AGE* variables into a regression equation, else exact collinearity would occur; only two of the three could be included directly, and indirect estimates for the impact of the third variable could be computed using Eq. (1). Note that regardless of which two of the three variables were included in the estimated regression equation, direct and implicit parameter estimates would be identical, as would be the equation R^2.

To capture nonlinearities in the data, one could of course specify the time, age, and vintage variables in dummy variable form. Recall that we have constructed four time dummy variables (*T89* through *T92*), seven vintage dummy variables (*V86* through *V92*), and four age dummy variables (*AGE0* through *AGE3*). As was noted by Berndt and Griliches, when the coefficients on these variables are held constant over time and/or vintage, then the simple adding-up conditions implied by Eq. (1) no longer hold. This raises significant issues concerning the interpretation of dummy variable coefficients, as well as the maximal parameterization possible that avoids exact collinearity.

Consider a traditional time–age (*T–A*) hedonic price equation relating $\ln P_{ivat}$, the natural logarithm of the price of the *i*th model of vintage *v*, age *a*, and time *t*, to a constant term, a vector of time dummies T (T = *T90*, *T91*, *T92*, with *T89* excluded), a vector of age dummies A (A = *AGE1*, *AGE2*, *AGE3*, with *AGE0* excluded), and a number of model-i-specific characteristic variables (called X's), as well as a random disturbance term u_{ivat}:

$$\ln P_{ivat} = \alpha + T'\alpha_t + A'\alpha_a + X'\beta + u_{ivat}. \tag{2}$$

In this model, the vintage dummies are excluded. This raises the question: Is it really necessary to discard entirely the information on one of the three sets of dummy variables? Can one not employ a specification that efficiently combines information simultaneously from the T, A, and V dummy variables, yet avoids exact collinearity?

In fact, as Hall (1971) has shown in a somewhat different context (a balanced panel data set for second-hand trucks), this can be done. In the current context, the maximal parameterization consistent with avoiding exact collinearity is one in which five of the seven vintage dummy variables are added to the T–A specification of Eq. (2). We write such a T–A–V specification as

$$\ln P_{ivat} = \gamma + T'\gamma_t + A'\gamma_a + V'\gamma_v + X'\beta + u_{ivat}, \tag{3}$$

where the T vector excludes, say, *T89*, the A vector excludes *AGE0*, and the V vector now excludes two vintages – say, *V86* and *V92*. To the extent that quality improvements are not captured by the included X's but are embodied in successive vintages, one might expect that the γ_v coefficients capture effects of omitted variables. However, as Hall noted, estimates of the γ_v coefficients should be interpreted as *differences* from the average rate of growth of technical progress embodied but unobserved in pairwise comparisons of vintages. Deleting the *V86* and *V92* dummy variables allows us to interpret the remaining coefficients as measuring the acceleration or deceleration of technological progress from the average rate between 1986 and 1992. In the current context with *V*86 and *V92* omitted, the coefficient on, say, the *V90* dummy variable should therefore be interpreted as the *difference* between the average 1990 effect and the mean of the average vintage effects over the entire 1986–92 set of vintages.

This type of reasoning led Berndt and Griliches to a specification test: A necessary condition for a hedonic price equation, such as Eq. (2), to be satisfactory empirically is that the portion of quality change not captured by the characteristics variables should be unrelated to vintages, i.e., in a desirable specification, the γ_v in Eq. (3) should be approximately zero. Based on this specification test, Berndt and Griliches then proceeded to choose a preferred model.

Although this specification test has obvious utility and interpretation, we now show that an alternative model can be developed, one that is richer in parameters and therefore permits greater flexibility in hypothesis tests and choice of specifications. Specifically, since unbalanced panel data are available on seven vintages, four age dummies, and four time dummies, one can envisage a fully saturated hedonic price equation specification in which there is no intercept, but there are separate coefficients for each of the sixteen time–vintage 'interaction' variables: *V86T89, V87T89, V88T89, V89T89, V87T90, V88T90, V89T90, V90T90, V88T91, V89T91, V90T91, V91T91, V89T92, V90T92, V91T92,* and *V92T92,* where each of these interaction dummy variables is an element-by-element product of $Vv \cdot Tt$, for $v = 86, \dots, 92$ and $t = 89, \dots, 92$.

With this fully saturated parameter model as the most general specification, it can easily be shown that for the T–A model to be valid, the following restrictions must be placed on coefficients of the dummy variables:[7]

$$\begin{aligned}
T\text{–}A\text{:}\quad V90T90 - V89T89 &= V89T90 - V88T89 = V88T90 - V87T89 \\
&= V87T90 - V86T89, \\
V91T91 - V89T89 &= V90T91 - V88T89 = V89T91\text{–}V87T89 \\
&= V88T91\text{–}V86T89, \\
V92T92 - V89T89 &= V91T92 - V88T89 = V90T92 - V87T89 \\
&= V89T92 - V86T89.
\end{aligned}$$

Note that with these nine independent restrictions, the number of time and age dummy variable coefficients, plus the intercept term, is seven. Incidentally, the interpretation of these restrictions is that in this model, the time effect is the same for all ages in 1990, in 1991, and in 1992.[8]

Hence, roughly speaking, the saturated model places no restrictions on the acceleration or deceleration of vintage and age effects over time, the T–A–V model of Hall places parameter restrictions on this acceleration or deceleration, while the T–A model constrains this deceleration or acceleration of vintage effects to be zero. Specifically, relative to the fully saturated model, the T–A–V model involves two constraints on the age effects,

$$\begin{aligned}
T\text{–}A\text{–}V\text{:}\quad & (V90T92 - V91T92) - (V90T91 - V91T91) \\
& = (V88T90 - V89T90) - (V88T90 - V89T89) \\
& = \alpha_2 - 2\alpha_1, \\
& (V89T92 - V90T92) - (V89T91 - V90T91) \\
& = (V87T90 - V88T90) - (V87T89 - V88T89) \\
& = \alpha_3 - 2\alpha_2 + \alpha_1,
\end{aligned}$$

[7] The restrictions are based on the assumption that *T89* and *AGE0* are the omitted dummy variables in the T–A model having an intercept term.

[8] That the effect of age is the same for all time periods turns out to involve redundant restrictions.

where the α's are coefficients on age dummies, as well as two restrictions on the vintage effects over time,

$$(V91T92 - V90T91) - (V90T92 - V89T91)$$

$$= (V91T91 - V90T90) - (V90T91 - V89T90) = \alpha_{91} - 2\alpha_{90} + \alpha_{89},$$

$$(V90T92 - V89T91) - (V89T92 - V88T91)$$

$$= (V90T91 - V89T90) - (V89T91 - V88T90) = \alpha_{90} - 2\alpha_{89} + \alpha_{88},$$

where the α's are coefficients on vintage dummies.

The existence of this more general specification suggests a somewhat different specification test procedure than was used in Berndt and Griliches. First, we undertake yearly regressions; since these regressions involve only one time period, the age and vintage dummies are perfectly colinear, and thus we can estimate these equations with either (but not both) the age or vintage dummies. Second, we test for parameter stability by pooling the 1989–92 data and estimating the fully saturated time–vintage interaction specification described above. If these parameter stability restrictions are satisfied empirically, then we will estimate and test for restrictions incorporated in the T–A–V and T–A models. As a preferred specification, we will choose that model consistent with the data but most parsimonious in parameterization. We will also examine whether there is empirical support for the traditional T–A model. Third, if the above test for 1989–92 parameter stability is rejected, we will test for a weaker type of parameter stability over time by undertaking adjacent (two-) year regressions and comparing them with the yearly regressions. If the parameter constraints from adjacent year regressions are not rejected, we will compare the corresponding fully saturated, T–A–V and T–A models and choose a preferred specification. If, however, the parameter constraints of these adjacent year models are rejected, we will choose as the preferred model the yearly regressions.

The above tests can be carried out using the standard F-test methodology. Among others, however, Arrow (1960) and Ohta and Griliches (1976) have noted that when samples are large and 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. We do that here by choosing 0.01 significance levels. Second, since in our hedonic regressions the dependent variable is the natural logarithm of price, the root mean squared error (RMSE) measures the unexplained variation in prices in, roughly, percentage units. A reasonable criterion is to employ the difference in the RMSE of the constrained and unconstrained regressions as a relevant measure of the explanatory power of a particular model. As an alternative test criterion, therefore, we will reject the null hypothesis when the RMSE under the alternative results in a reduction of more than 5% in the RMSE (the standard deviation of the unexplained variation in log prices). With a typical 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 corresponding to the null hypothesis.

Two other comments concerning hypothesis testing are appropriate here: (a) Since heteroskedasticity may be present, we will compute standard errors and variance–covariance matrices of the coefficients using the White (1980) heteroskedasticity-robust procedure. Traditional F-tests involving joint hypotheses, not just t-tests, will therefore be adjusted to accommodate the heteroskedasticity-consistent variance–covariance matrix; and (b) as an additional check on the various model specifications, we will assess the sensitivity of computed price indexes to various parameter restrictions, including some of those rejected by the above test criteria. If growth in the price indexes is robust to alternative models, the empirical significance of rejections of particular models will, for our purposes, be diminished.

4. Functional forms, stability, and results of specification tests

We now turn to a discussion of empirical findings. Results from preliminary regressions suggested that parameters differed significantly for mobile and desktop models, and thus we proceeded by disaggregating PC's into these two groups.[9] We now discuss the two sets of findings separately.

4.1. Results for desktop models

We began by estimating yearly regression equations using an expanded version of the T–A functional form specified by Berndt and Griliches, where squared values of *LRAM*, *LMAXRAM*, *LMHZ*, *LHDDSK*, *LRAM*, *LSIZE*, and *LWGT* (variables identified by the suffix *SQ*), as well as interaction variables *LRAMHARD*, *LMHZSIZE*, and *LWGTSIZE* were included as regressors.[10] We also added a dummy variable *DNOHDDSK* for models having no hard disk. With our basic model refined in this manner, we then examined parameter stability issues further.

[9] The F-test statistic for the null hypothesis of parameter equality across mobile and desktop models was 13.47, while the 0.01 critical value is 1.49; the $\Delta RMSE$ was 14.05%. The rejection was also decisive when a *DMOBILE* dummy variable was included.

[10] The L prefix denotes a natural logarithm transformation. Following Berndt and Griliches, we defined *LHDDSK* and *LHDDSKSQ* as $\log(MB + 1)$ and $[\log(MB + 1)]^2$, respectively. Note that the interaction variables are calculated as the product of the logs, and not as the log of the product.

Our first result is that for desktop models from 1989 to 1992, there is little support for parameter stability. Comparing the yearly regressions with the 1989–92 pooled fully saturated model, we reject the hypothesis of parameter stability using both the traditional F-test (test statistic of 4.11, 0.01 critical value of 1.39) and the 5% *ΔRMSE* criteria (*ΔRMSE* is 9.70%). Moreover, this rejection of parameter stability largely remains even when one compares yearly with adjacent (two-) year regressions. Specifically, for 1989–90 and 1991–92, the F-test statistics of 4.35 and 3.22 exceed the 0.01 critical values of 1.71 and 1.79, while for 1990–91 there is marginal support for parameter stability (test statistic of 1.52 compared to 1.70 critical value). Similar conclusions emerge when using the *ΔRMSE* criterion (the 1989–90, 1990–91, and 1991–92 *ΔRMSE* are 7.67%, 1.35%, and 5.10%, respectively).

Given this rejection of parameter stability for the desktop models and our testing methodology, we terminate our testing procedure for further functional form restrictions, such as those for the *T–A* model. However, several other results are worth noting. First, with each yearly regression, results from Box–Cox regressions strongly supported the log–log specification.[11] Second, as is seen in Table 4 where results from yearly regressions are presented, a number of reasons underly the rejection of parameter stability. In 1989 and 1992, for example, the coefficients on *LRAM* and *LRAMSQ* are statistically significant, but are reversed in sign; similar significant sign reversals occur in 1991 and 1992 for *LMAXRAM* and *LMAXRAMSQ*. Trends in other coefficients are also evident, such as those for *LHDDSKSQ*, *LRAMHARD*, *LWGT*, and *LWGTSQ*. Of special interest are coefficients on several premium brand name dummy variables. For *IBM*, *DELL*, *CMPQ*, *APPLE*, and *ZEN*, the 1992 estimates indicate sharp declines from earlier years, corroborating the highly publicized aggressive changes in pricing strategy adopted by these companies in 1992 to meet competitive market pressures. In fact, by summing the company and company-1992 coefficients, we find that in 1992 quality-adjusted list prices for *IBM*, *DELL*, and *CMPQ* were not significantly different from the '*OTHER*' brand names, *ZEN* had become somewhat cheaper, and while *APPLE* still commanded a premium price, this premium had been approximately halved. Third, even though parameters vary considerably by year, the yearly estimates are plausible. In Fig. 1, for example, we plot the fitted price of desktop PC models as a function of speed (in *MHZ*) for 1989 and for 1992, where all other variables are measured at their yearly sample means and *MHZ* is plotted over the observed range of values for that year. As is seen in Fig. 1, the price frontier is upward-sloping, but has fallen sharply between 1989 and 1992. A similar pattern

[11] Estimates of the Box–Cox λ parameter and values of the χ^2 test statistic for the null hypothesis that $\lambda = 0$ are, respectively, -0.05 and 0.35 for 1989, 0.02 and 0.27 for 1990, 0.06 and 1.56 for 1991, and -0.30 and 3.33 for 1992.

Table 4
Parameter estimates of year-by-year regressions for desktop computers (t-statistics from heteroskedasticity-robust standard errors in parentheses)

Variable	1989	1990	1991	1992
Constant	7.565	10.49	17.36	14.00
	(0.73)	(4.11)	(3.72)	(4.14)
LRAM	3.832	− 0.369	− 0.297	− 2.173
	(2.74)	(0.71)	(0.38)	(4.12)
LRAMSQ	− 0.231	0.051	0.042	0.157
	(2.32)	(1.44)	(0.78)	(4.65)
LMAXRAM	− 0.395	0.071	− 1.446	1.145
	(1.14)	(0.26)	(3.55)	(2.13)
LMAXRMSQ	0.018	0.003	0.084	− 0.042
	(0.85)	(0.20)	(3.89)	(1.62)
LMHZ	2.556	0.175	1.018	1.140
	(1.18)	(0.23)	(0.94)	(1.29)
LMHZSQ	0.001	0.114	− 0.528	− 0.108
	(0.01)	(0.95)	(3.10)	(1.26)
LHDDSK	0.017	0.205	− 0.130	− 0.185
	(0.04)	(0.82)	(0.33)	(0.69)
LHDDSKSQ	0.019	0.051	0.060	0.092
	(0.36)	(2.00)	(1.25)	(3.90)
LRAMHARD	− 0.012	− 0.064	− 0.030	− 0.062
	(0.26)	(4.76)	(1.42)	(4.32)
LSIZE	− 5.790	− 1.181	− 1.663	− 0.945
	(1.44)	(2.05)	(1.47)	(1.98)
LSIZESQ	0.503	0.072	0.009	− 0.120
	(1.30)	(1.26)	(0.08)	(2.87)
LWGT	1.896	− 0.516	0.152	− 2.747
	(0.72)	(0.78)	(0.16)	(4.42)
LWGTSQ	− 0.166	− 0.148	− 0.305	− 0.444
	(0.66)	(1.10)	(1.40)	(2.24)
LMHZSIZE	− 0.311	− 0.059	0.351	0.004
	(1.24)	(0.63)	(2.20)	(0.04)
LWGTSIZE	− 0.118	0.191	0.227	0.808
	(0.22)	(1.34)	(0.95)	(3.43)
DFLP23	0.037	− 0.315	− 0.242	− 0.040
	(0.36)	(5.17)	(3.77)	(0.53)
DNOHDDSK	− 0.643	− 0.471	− 0.498	− 1.373
	(0.71)	(0.94)	(0.61)	(2.42)

Table 4 (continued)

Variable	1989	1990	1991	1992
DAGE1	− 0.128	− 0.028	0.132	0.199
	(1.30)	(0.44)	(2.37)	(5.02)
DAGE2	0.030	0.057	0.293	0.344
	(0.38)	(0.82)	(2.13)	(7.62)
DAGE3	0.043	0.122	0.489	0.214
	(0.36)	(2.51)	(6.16)	(2.94)
DPROC8	− 0.342	− 0.019	− 0.265	na
	(2.10)	(0.13)	(0.98)	
DPROC32	0.303	0.222	0.228	0.090
	(2.62)	(4.16)	(2.73)	(1.94)
DALR	na	na	na	− 0.285
				(3.12)
DAPPLE	0.514	0.627	0.446	0.279
	(3.84)	(8.25)	(3.21)	(2.53)
DAST	0.551	− 0.455	− 0.230	0.021
	(4.10)	(4.04)	(1.41)	(0.26)
DCMPQ	0.589	0.465	0.592	0.114
	(5.33)	(7.72)	(6.05)	(1.17)
DCOMPUAD	na	na	na	− 0.295
				(3.81)
DDEC	na	na	na	0.142
				(2.50)
DDELL	0.761	0.310	0.385	0.033
	(6.46)	(4.11)	(4.88)	(0.40)
DHP	0.349	0.395	0.521	0.282
	(3.10)	(6.97)	(7.92)	(4.00)
DIBM	0.344	0.475	0.509	0.021
	(3.21)	(8.60)	(6.28)	(0.24)
DNEC	0.464	0.086	− 0.061	− 0.012
	(5.67)	(0.85)	(0.35)	(0.19)
DTOSH	na	na	na	1.042
				(7.82)
DZEN	na	0.259	0.350	− 0.215
		(3.27)	(4.62)	(3.61)
R^2	0.832	0.830	0.769	0.824
RMSE	0.341	0.306	0.370	0.248
N	173	457	321	504

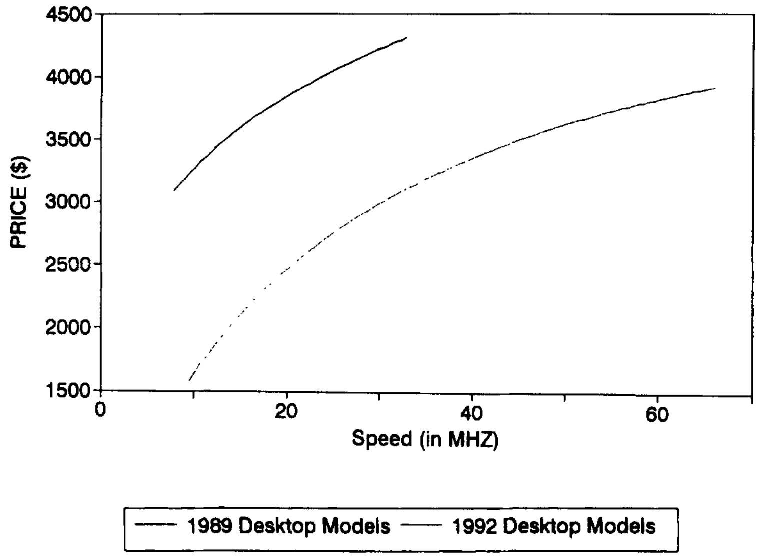

Fig. 1. Desktop computer price vs. speed.

is displayed in Fig. 2, where desktop computer price is plotted as a function of hard disk capacity.

4.2. Results for mobile models

The results we obtained from regressions with mobile (laptop, notebook, and transportable) models differed considerably from those of the desktop models. First, the considerable nonlinearities among variables such as *MHZ*, *RAM*, *HDDSK*, and *MAXRAM* were not significant in the mobile model regressions. This led us to stay with a more parsimonious and linear specification. Second, somewhat surprisingly, there was some support for parameter stability over time in the mobile model regressions. Specifically, when the pooled fully saturated regression (with 1992 dummy intercepts for premium brands) was compared with the yearly regressions, the parameter restrictions of the former did not reduce goodness of fit significantly; the traditional F-statistic was 0.97 (with a 0.01 critical value of 1.60), while the $\Delta RMSE$ was 1.00%. However, this nonrejection of parameter stability over the entire time period masks somewhat the possibility that 1992 may be different. In particular, based on a comparison of yearly with adjacent-year regressions, the null hypothesis of parameter stability (except for time dummies) is clearly not rejected in 1989–90 and 1990–91 (F-test statistics of 0.46 and 0.49, 0.01 critical values of 2.01 and 2.07, and $\Delta RMSE$ of -2.72% and -2.04%), but is rather marginal for 1991–92

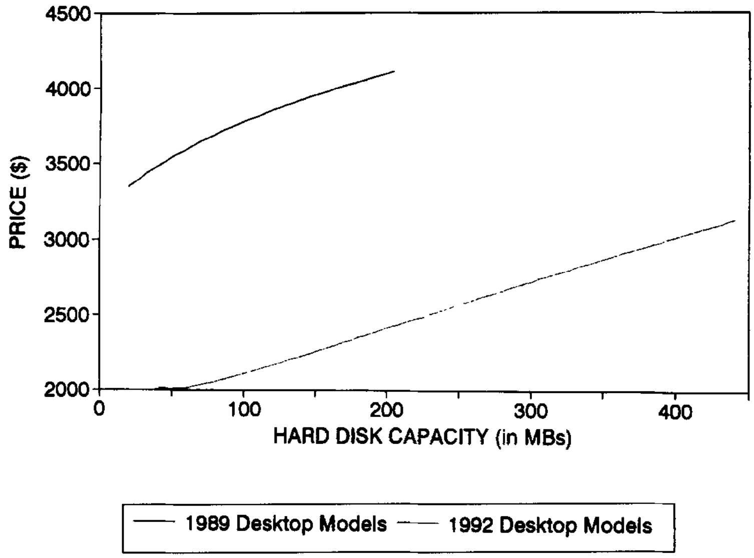

Fig. 2. Desktop computer price vs. hard disk.

(F-statistic of 2.07, 0.01 critical value of 2.18, and $\Delta RMSE$ of 4.70% being very close to our 5% threshold). We consider this 1992 result further in Section 5 below.

Based on the pooled model, when the more restrictive T–A models was compared to the fully saturated model, again the loss of fit was insignificant; the F-statistic for the nine restrictions of the T–A model was 1.60 (0.01 critical value of 2.41), while the $\Delta RMSE$ was 0.82%. With this T–A model, the specification test outlined in Section 3 yields supportive results; T–A as a special case of the fully saturated model is not rejected.[12] Finally, with T–A, a Box–Cox transformation yields further support for the log–log model; the estimate of λ is 0.1854 and its 99% confidence interval ranges from -0.1958 to 0.4094, thereby including the $\lambda = 0$ (log–log) specification.

Parameter estimates from the pooled T–A model are given in Table 5. As expected, coefficient estimates on $LRAM$, $LMHZ$, $LMAXRAM$, and $LHDDSK$ are positive and significant, with that on $LHDDSK$ being particularly large (1.27). Since the $LDENSE$ variable is defined as $\log(WGT/SIZE)$, the total effect of $LWGT$ on $LPRICE$ is the sum of the coefficients on $LWGT$ and $LDENSE$ – about -0.20. The marginal effect of $LSIZE$ on $LPRICE$ is the negative of the $LDENSE$ parameter estimate – therefore about -0.19. Hence increases in

[12] The F-test statistic is 1.60, while the 0.01 critical value is 2.41; the $\Delta RMSE$ is 0.82%

Table 5

Parameter estimates of pooled T–A regression for mobile computers (t-statistics from heteroskedasticity-robust standard errors in parentheses)

Variable	Estimate	Variable	Estimate	Variable	Estimate	Variable	Estimate
Constant	1.2085 (1.80)	*DNOHARD*	0.8221 (5.63)	*DAST*	−0.2093 (2.71)	*DNEC*	0.2295 (4.08)
LRAM	0.7769 (10.38)	*DPROC8*	−0.1399 (2.06)	*DCMPQ*	0.5279 (11.49)	*DTOSH*	0.1152 (2.30)
LMHZ	0.1862 (1.75)	*DPROC32*	0.3143 (7.51)	*DCMPQ92*	−0.6416 (6.22)	*DTOSH92*	0.0925 (1.12)
LMAXRAM	0.0779 (2.26)	*DAGE1*	0.0645 (1.63)	*DCOMPUAD*	−0.3924 (4.34)	*DZEN*	0.4413 (7.12)
LHDDSK	1.2739 (7.98)	*DAGE2*	0.2446 (3.16)	*DDELL*	−0.1109 (2.34)	*DZEN92*	−0.5852 (6.52)
LWGT	−0.3927 (3.18)	*DAGE3*	0.0483 (0.73)	*DDELL92*	−0.1249 (1.51)	*D90*	−0.1393 (2.79)
LDENSE	0.1913 (3.22)	*DAPPLE*	0.5175 (8.06)	*DHP*	0.3525 (3.76)	*D91*	−0.2595 (4.09)
LRAMHARD	−0.1504 (7.51)	*DAPPLE92*	−0.6547 (5.89)	*DIBM*	0.0975 (1.28)	*D92*	−0.7634 (7.27)
DCOLOR	0.4601 (9.99)	*DALR*	−0.0263 (0.30)	*DIBM92*	−0.4315 (4.15)	R^2	0.6890
						RMSE	0.2660
						N	427

weight and in size, *ceteris paribus*, reduce prices of mobile models, but there is also a premium for density. The estimate of the *DCOLOR* parameter is positive, as is that on *DNOHARD*, and both are substantial (the no-hard-disk models tended to be very small, powerful, and expensive models). Although the *DAGE* dummy variables have positive parameter estimates consistent with the notion of 'survival of the fittest', the number of *AGE3* models is very small, and thus the insignificance of this parameter is not surprising. In terms of brand effects, the *APPLE*, *CMPQ*, and *ZEN* premia are substantial until 1992, but the large negative estimates of *DAPPLE92*, *DCMPQ92*, *DIBM92*, and *DZEN92* reveal a sharp change in pricing strategies by these companies to meet heightened competition. Interestingly, the slightly positive estimate of *DTOSH92* suggests that Toshiba did not follow the other major brands in reducing 1992 prices. Finally, the very large and negative estimate of the *D92* dummy variable suggests that in 1992, quality-adjusted prices of mobile computer models dropped significantly. This raises issues of price index measurement, to which we now turn our attention.

5. Price index results

Price indexes based on the various hedonic price equations can be constructed in a variety of ways, often reflecting different assumptions concerning what is being held fixed over time. In this section we construct and comment on several price indexes, based for the most part on our hedonic regression equations, but varying in their interpretation and in their use of parameter estimates and quantity weights.

5.1. Price indexes for mobile computer models

Recall from the introduction that a crude measure of price increase is simply the change over time in the unweighted sample means of models. For mobile computer models, as is shown in the first row of Table 6, for 1989–92 this yields an *AAGR* of − 10.6% Since no matched models occur between 1989 and 1990, one cannot replicate the BLS-like matched model procedure for the mobile PC models.[13] Based on the various estimated hedonic price equations, however, one can construct a number of quality-adjusted price indexes.

One simple procedure for constructing price indexes is to use the dummy variable coefficient on the last-year time dummy in adjacent year regressions,

[13] For 1990–91 and 1991–92, however, matched models do occur. Based on these matched models, price indexes for 1991 and 1992 are 0.9966 and 0.5673, respectively. Thus the 1990–92 *AAGR* for matched mobile models is − 24.7% which is about twice the comparable growth rate based on arithmetic means (− 12.5%).

Table 6
Alternative quality-adjusted price indexes for mobile personal computers (percent change from previous year in parentheses)

Procedure	1989	1990	1991	1992	1989–92 *AAGR*
Arithmetic means	1.0000	0.9323 (– 6.8%)	0.8723 (– 6.4%)	0.7144 (– 18.1%)	– 10.60%
Adjacent year regressions	1.0000	0.8741 (– 12.6%)	0.7666 (– 12.3%)	0.4526 (– 41.0%)	– 23.22%
Saturated model	1.0000	0.8832 (– 11.7%)	0.8271 (– 6.3%)	0.3968 (– 52.0%)	– 26.52%
Pooled *T–A* model	1.0000	0.8699 (– 13.0%)	0.7714 (– 11.3%)	0.4422 (– 42.7%)	– 23.81%
Laspeyres – Pooled *T–A* parameters, fixed 1989 quality	1.0000	0.9975 (– 0.2%)	0.8911 (– 10.7%)	0.5305 (– 40.5%)	– 19.05%
Laspeyres – Yearly parameters, fixed 1989 quality	1.0000	0.8627 (– 13.7%)	0.7339 (– 14.9%)	0.5696 (– 22.4%)	– 17.11%
Paasche – Yearly parameters, updated quality	1.0000	0.9350 (– 6.5%)	0.9198 (– 1.6%)	0.4887 (– 46.9%)	– 21.23%
Divisia – Yearly parameters	1.0000	1.0005 (+ 0.5%)	0.9762 (– 2.4%)	0.4408 (– 54.8%)	– 23.90%

and simply exponentiate it. For example, letting the price index for 1989 be 1.0, exponentiate the *T90* time dummy from the 1989–90 adjacent year regressions, and set this equal to the 1990 price index. For 1991, exponentiate the *T91* time dummy from the 1990–91 adjacent year regression, and multiply this by the 1990 price index; do an analogous calculation for the 1992 price index, based on the 1991–92 adjacent year regression. The results of such calculations are given in the second row of Table 6.[14] There it is seen that the quality-adjusted price index falls about 13% in 1990, another 12% in 1991, and then drops more dramatically by about 41% in 1992. The average annual growth rate (*AAGR*) over the three-year time period is about – 23%. This is more than twice as large a price decline as that based on simple arithmetic means.

[14] Since the 1991–92 adjacent year regressions have 1992-specific brand dummy variables (see Table 5), it is necessary to weight the 1992 brand coefficients by the 1991–92 mean proportion of that brand's models, and add this weighted sum to the 1992 time dummy before exponentiation.

An alternative price index calculation can be undertaken using the saturated dummy variable model, estimated over the 1989–92 time period. Analogous to the matched model procedure used by the BLS, one can envisage a matched vintage price index procedure. Specifically, note that from 1989 to 1990, three vintages overlap – 1987, 1988, and 1989. Using overall 1989–92 sample means for all other right-hand variables, we construct a fitted price for 1989 and for 1990, where the vintage–time interaction coefficients on the 1987–89 overlapping vintages are weighted by the sample means of the vintage–time dummy variables in the two years, where these weights sum to unity. Then we construct a 1990 price index as the 1990 fitted price divided by the 1989 fitted price. We do similar calculations involving three overlapping vintages for successive years 1991 and 1992. The results of this calculation are given in the third row of Table 6, where it is seen that the matched vintage price index based on the saturated model yields price indexes that fall at a slightly larger rate than the hedonic price index from the adjacent year regressions (an *AAGR* of -26.5% vs. -23.2%).

Recall from Section 4.2 that there was some empirical support for the 1989–92 pooled *T–A* specification, although there was also evidence pointing to the 1992 parameters being different. In the pooled model, if one exponentiates the 1990, 1991, and 1992 time dummy coefficients (with 1992 modified to account for the brand-specific dummies as noted in the previous footnote), one obtains another set of price indexes, which we present in row four of Table 6. The *T–A* model yields *AAGR's* slightly smaller than those based on the saturated model (-23.8% vs. -26.5%), but very similar to those based on adjacent year regressions (-23.8% vs. -23.2%). This similarity in *AAGR*'s of quality-adjusted price indexes is not surprising, since the adjacent year, fully saturated, and *T–A* models were not rejected as valid special cases of the yearly regression models. Moreover, the price index calculation for the saturated model is based on a matched vintage notion, which is not quite the same as that based on time dummies, and thus the slight difference among them is not surprising.

Each of the above price indexes is based on a regression equation that implicitly weights each observation equally. An alternative price index concept is one we call a fixed-weight Laspeyres index. In this index, one employs the parameter estimates (which reflect implicit characteristic quality prices) and fixed base-period quantity weights for the characteristics (sample means of the regressors in the base year, say 1989) to compute fitted prices for 1989, 1990, 1991, and 1992. The ratio of the various yearly fitted values to the 1989 value is then the Laspeyres quality fixed (1989) price index. Such a calculation could be done with yearly or pooled parameters. Since the evidence presented above is somewhat marginal concerning 1992, we employ and compare results based on both the yearly and pooled coefficients. With pooled coefficients, as seen in Table 6, the resulting Laspeyres index declines at a smaller rate than the pooled

T–A index (-19.0 vs. -23.8%), even though both are based on identical parameter estimates; when yearly coefficients are employed, the *AAGR* becomes -17.1%. Both these values are considerably smaller (in absolute value) than that based on the pooled T–A model. The reason for this difference is that the use of 1989 fixed quality weights does not capture adequately the significant change in quality that occurred for mobile models between 1989 and 1992.

To shed more light on this weighting issue, we also compute a Paasche-type quality updated price index. For 1990, this Paasche index computes a fitted price using the pooled and 1990-specific parameters along with the 1990 quality (mean characteristics) weights, and for 1989 the fitted price is computed using the same 1990 quality weights, but the pooled and 1989-specific parameters. The 1990 Paasche index is then calculated as the ratio of 1990 to 1989 fitted prices. For 1991, the quality weights are updated to 1991, and fitted prices are calculated for 1991 using pooled and 1991-specific parameters, while for 1989 the pooled and 1989-specific parameters are employed with 1991 quality weights. The 1991 price index is then computed as the ratio of these 1991 and 1989 fitted prices. A similar quality updating occurs for 1992. Hence, unlike the case with the Laspeyres fixed 1989 quality price index, with this Paasche updated quality price index the changes over time in quality are explicitly incorporated as changing weights. As shown in Table 6, with the Paasche index the *AAGR* declines slightly more rapidly than the Laspeyres indexes (-21.2% vs. -17.1 to -19.1%).

Yet another set of possible weights to employ in calculating an aggregate price index is based on model-specific revenue shares that vary over time. Following procedures detailed in Berndt and Griliches (1993), we calculate a Divisia price index, using the yearly coefficients and models for which we were able to obtain quantity sales data.[15] It is worth noting here that with the mobile models, there was very little overlap of models between years; indeed in 1992, all mobile models for which sales data were available were new. This implies that the Berndt–Griliches Divisia index procedure, a procedure that compares the fitted price of a model in, say, 1992 with a fitted price of an unobserved model having 1992 characteristics but fictitiously existing in 1991, is not likely to be as reliable when there is no model overlap between years. Somewhat surprisingly, therefore, as is shown in the bottom panel of Table 6, with this share-weighted Divisia procedure, the decline in the price index is -23.9% per year – very similar to price index trends based on the adjacent year and pooled T–A model regressions.[16]

[15] Proprietary sales data were provided us by the International Data Corporation.

[16] However, when we employed pooled coefficients, the 1990–92 Divisia price indexes were 0.9786, 1.0169, and 0.7935, implying an *AAGR* of -7.42%.

5.2. Price indexes for desktop computer models

We now turn to desktop models, which dominate mobile models in terms of numbers (1456 vs. 427) and on the basis of revenue shares (the yearly revenue shares of desktops in 1989–92 are 83%, 88%, 83%, and 76%). Again, we construct a variety of price indexes, reported in Table 7. A price index calculated as the simple arithmetic means of prices of all models by year, relative to 1989, declines at an annual rate of 9.7%, while one based on the matched model procedure declines about twice as rapidly, − 19.32%. Both these measures understate considerably the quality-adjusted decline in prices, however.

As seen in the third row of Table 7, when quality-adjusted price indexes are computed using the saturated model specification with pooled 1989–92 parameters, the index declines at a much larger rate of − 31.23%. This rate of decline is reasonably robust to alternative model specifications, being − 32.13% for the pooled T–A model, and − 31.15% based on the adjacent year regressions. It is even robust to the use of yearly coefficients and the Divisia index, which declines

Table 7
Alternative quality-adjusted price indexes for desktop personal computers (percent change from previous year in parentheses)

Procedure	1989	1990	1991	1992	1989–92 *AAGR*
Arithmetic means	1.0000	0.9601 (− 4.0%)	0.9620 (+ 0.2%)	0.7363 (− 23.5%)	− 9.70%
Matched models	1.0000	0.9214 (− 7.9%)	0.9134 (− 0.9%)	0.5251 (− 42.3%)	− 19.32%
Saturated model	1.0000	0.7428 (− 25.7%)	0.6717 (− 9.6%)	0.3253 (− 51.6%)	− 31.23%
Pooled T–A model	1.0000	0.7496 (− 25.0%)	0.6735 (− 10.2%)	0.3126 (− 53.5%)	− 32.13%
Adjacent year regressions	1.0000	0.8093 (− 19.1%)	0.7356 (− 9.1%)	0.3264 (− 55.6%)	− 31.15%
Laspeyres – Yearly parameters, fixed 1989 quality	1.0000	0.6732 (− 32.7%)	0.6403 (− 4.9%)	0.2550 (− 60.2%)	− 36.59%
Paasche – Yearly parameters, updated quality	1.0000	0.9282 (− 7.2%)	0.9304 (+ 0.2%)	0.4119 (− 55.7%)	− 25.60%
Divisia – Yearly coefficients	1.0000	0.9462 (− 5.4%)	0.9042 (− 4.4%)	0.3154 (− 65.1%)	− 31.93%

at an $AAGR$ of -31.93%. However, if one employs the fixed 1989 quality weights and computes a Laspeyres index analogous to that discussed above, the rate of decline increases to an $AAGR$ of -36.59%. By contrast, if one computes a Paasche price index, the decline is considerably smaller, an $AAGR$ of -25.6%. This suggests that with this data, the choice of weights appears to make a much more critical difference to price index calculations than does the choice of model specification. Price indexes based on (statistically rejected) models with parameter stability imposed are very similar to those based on yearly regressions and adjacent year regressions.

It is also worth noting that quality-adjusted prices for desktop models tended to decline more rapidly than for mobile models (the respective Divisia indexes decline at -31.93% and -23.90%). This raises the issue of how one might compute a price index for the combined desktop–mobile markets.

5.3. Price indexes for combined desktop and mobile computer models

One way of computing a composite PC price index is simply to pool the data, ignore differences in parameters between mobile and desktop models, and exponentiate the appropriate time dummy variable coefficients. Such a simple approach has some support, for the evidence presented above suggests that $AAGR$'s of price indexes are reasonably robust, even when calculated using hedonic models that are statistically rejected. Using a pooled T–A type hedonic model, we obtain 1989–92 price indexes of 1.000, 0.771, 0.694, and 0.358, yielding an $AAGR$ of -28.97%.

Alternatively, one could employ the separate regression models for the mobile and desktop models along with yearly coefficients, and then calculate a combined mobile–desktop Divisia index. When this is done, we obtain 1989–92 price indexes equal to 1.000, 0.963, 0.914, and 0.349, implying an $AAGR$ of -29.62%. Hence even though the procedures and models differ considerably, the resulting average growth trends are surprisingly similar – a 1989–92 price index for the total PC market declines on average between 29 and 30% per year.

6. Summary remarks

Our purpose in this paper has been to construct a number of quality-adjusted price indexes for personal computers in the US marketplace over the 1989–92 time period. To do this, we generalized earlier work on incorporating simultaneously time, age, and vintage effects into an unbalanced panel data set, and we developed a corresponding specification test procedure.

Our results can be summarized as follows. Parameters of hedonic price equations differed in the mobile and desktop PC markets. Although there was very little evidence supporting parameter stability over time in the desktop market, in the mobile market the evidence suggested overall parameter stability; however, even in the mobile market there was a suggestion of parameters being different in 1992. Given parameter stability in the mobile market, we also found substantial support for the traditional hedonic price equation involving time and age variables, in addition to the various measures of quality. In particular, the traditional *T–A* model was not rejected as a special case of the fully saturated dummy variable specification. For both the mobile and desktop markets, the Box–Cox model provided support for the log–log formulation.

A simple arithmetic mean of prices of models by year reveals a price decline of about 10% per year. The common government statistical agency procedure of using only matched model prices generates a much larger rate of price decline – about 19% per year. But this matched model procedure is also unreliable, for by construction it excludes new models. When data on new models, as well as surviving vintages, are employed in the estimation of hedonic price equations, a variety of quality-adjusted price indexes can be calculated, with varying interpretations. Although there are some differences, on average these quality-adjusted price indexes based on econometrically estimated hedonic price equations decline at about 30% per year. The average decline in the mobile market was about 24%, while that in the desktop market was larger at 32% per year. Together these results imply that taking quality changes properly into account has a very substantial impact on the time pattern of price indexes.

The research in this paper can be extended in a number of ways. First, the DATAPRO data set we have employed is based on list price data. If feasible, it would be useful to gather 'street' prices for as many models as possible from advertisements in appropriate magazines, newspapers, and journals. To the extent that increasing competition has widened the gap between list and transactions prices, the approximate 30% decline in quality-adjusted price indexes for personal computers may understate somewhat the true rate of price decline. On the other hand, the 1992 change by premium manufacturers in list price policy that more closely matched the transactions prices of mail order firms could generate overstated price declines. Which effect dominates is an important empirical issue worthy of further examination.

Second, it would be interesting to link the mobile and desktop markets, which are essentially separate in our analysis. One way of doing this would be to pool mobile and desktop models (with, perhaps, a separate intercept term for each) until mobile models became sufficiently important to generate a 'regime shift', and thereafter to treat them separately. The link could be constructed by comparing fitted prices for the various models pre-regime shift (using the pooled parameters) and post-regime fit (based on separate regressions), and then weighting by using a Divisia index.

Finally, the prices and technological change embodied in new models of personal computers have an obsolescing impact on older vintages. A most interesting line of research would be to gather data on prices of used computers, and then to model and estimate the price movements of used models over time in response to the persistent and dramatic technological change embodied in new models.

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