The Effects of the Quality Adjustment Method on Price Indices for Digital Cameras

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Abstract

In this paper we test different hedonic and conventional quality adjustment methods in a uniform, but somewhat unconventional, descriptive framework. The main aim is to address questions on hedonic quality adjustment methods and their robustness in index compilation. We do this by giving an empirical example with digital camera prices. We will show how conventional quality adjusting methods may be treated parallel with hedonic ones and how these methods may be evaluated similarly with regression based methods. Contrary to structural models that many hedonic quality adjusted price indices are based on, the hedonic models in this paper are all used as forecast models which, we believe, add to the robustness and practical utility of hedonics as a day-to-day tool for statistical agencies using quality adjustment.

The empirical part of the paper is based on findings from a quarterly digital camera database including some 1,200 prices from over 250 different digital camera models over the years 1998 to 2002. The main findings indicate that, in an aggregate context, such as price index, relatively simple hedonic models may be sufficient for accurate quality controlling even in high technology products. Further, if compared with a matched model framework, the collection of character data for hedonics may not need to exceed the precision already needed in the matched model. This suggests that it may be feasible to use hedonic indices even in high frequency index compilation.

I. Introduction

Adjustment for quality change in price indexes for high technology goods is the topic of a literature that stretches back for many years. This article contributes to this literature by investigating alternative methods of quality adjustment for digital cameras.

The need to adjust price measures for changes in the quality of goods and services has long been recognized by statistical agencies and by academic researchers. To this end, hedonic regression methods have been used in a variety of ways in index number calculations. Methods have been developed for high frequency indices, such as a CPI or a PPI,[1] but it is often unclear which method to choose. The range of possible methods raises the question of how sensitive the results are to the choice of technique. This paper investigates this question for the case of a high technology good that has received relatively little attention, digital cameras. The main finding is that all reasonable methods give approximately the same answer.

Section II of this paper introduces six different methods within a unified estimation framework. These are:

- grand unit-value;
- class unit-value;
- matched model;
- time dummy pooled regression;
- time dummy 2-period regression; and
- "full" hedonic regression imputation.

We compare the results of applying these methods to the digital camera data. Although a number of previous studies have mainly focus on differences between matched model and hedonic methods,[2] few studies have been made on differences that result from applying different hedonic methods

[1] See, for example, Gordon (1990), Fixler and Zieschang (1992), Feenstra (1995), Diewert (2001) and Pakes (2002).

[2] See, for example, Silver (1999), Moulton et al. (1999), Silver et. Heravi (2000), and Aizcorbe et. all (2001).

In section III, we discuss the advantages and shortcomings of each method, including the plausibility of the implicit assumptions each method imposes. In section IV we lay out the data for digital cameras and discuss the sample frame and some reservations. In section V we present the results for the six different methods introduced earlier. Finally, we give conclusions and propose some additional topics to be investigated.

All the long run indices are constructed by chaining indexes of consecutive periods. For some of the methods tested, an equivalent direct index would be identical and hence would give exactly the same result.

II. Methods to be Tested

A. Set up

A time-dependent joint distribution of price and quality characteristics exists for all goods in the marketplace. Unfortunately only a fraction of the potentially important characteristics can be included in our models. In addition, we assume that the various digital camera models that are on the market are separable from other goods and services, so that possible cross dependencies need not be modeled.[3]

We use the natural logarithm of the price as the dependent variable in the hedonic regression models because it has nice properties of symmetry, summation over time, congruence with geometric mean indices, and ease of interpretation. Empirical evidence also supports this specification in many studies, including the present one.[4] The models tested are linear in the quality

[3] For example, if falling prices for digital storage raise the demand for high pixel counts, we might see a growing coefficient for this characteristic, but we do not attempt the model the source of the coefficient drift. The effect of complementary and substitute good prices on hedonic prices for characteristics is interesting topic, despite being beyond the scope of the present paper.

[4] See e.g. Diewert (2002) and a summary treatment in Triplett (2002) or ILO (2004).

variables, either as originally measured, or after a possibly non-linear transformation of that measure.[5] $p_{it} = X_{it}\beta_{it} + \varepsilon_{it}$

B. Methods

We consider six different methods of quality adjustment. They are the following.

I) Grand unit-value

The grand unit-value price index is calculated as the geometric average of all the sampled prices in period *t* divided by the geometric average of all the prices in the sample in period *t*–1. (Note that the use of geometric averages is a departure from the usual practice in calculating unit-value indexes, which begins by dividing total revenues by the number of units sold.) The grand unit-value index is a good method for very homogenous items, because quality differences are ignored. If all observations are present in both time periods, a grand unit value index calculated from geometric means is identical to the matched model index discussed below.

II) Class unit-value

The class unit-value index takes quality differences between classes of digital cameras into account by grouping the observations into classes and calculating separate averages for each class. Class unit-values are also often used in practice for imputing missing prices for use with the matched model approach.

III) Matched model

As its name suggests, for this method, the price of the same model is tracked over time. New models are linked into the price index when their prices are available in two time periods. The

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[5] For functional forms and economic approach to hedonic indices, see Rosen (1974), Diewert (2001) and Triplett (2002). Here the question of model selection and functional form is not discussed further. Including the prices of other goods in ***x*** would also allow imputations based on e.g. average price or average price change of other goods, which are methods widely used by statistical agencies. We follow the descriptive approach introduced by Koskimäki and Vartia (2001).

matched model method may be seen as an extreme case of the class unit-value method where each observation forms a separate class. Many national statistical agencies have long used the matched model approach to control for quality change in price index construction. Keeping the same models in the sample is consistent with fixed basket framework that many statistical agencies use for their price indexes. In addition, this method can control for effects of quality changes without the difficult and expense of collecting detailed information on item characteristics and running hedonic regressions.

The major drawback of the matched model approach is that the sample may become unrepresentative if it is not updated frequently enough. This often occurs for high technology goods, such as digital cameras, which typically undergo rapid turnover in the models available in the marketplace. If a new model enters with a quality-adjusted price lower than was previously offered and incumbents do not drop their prices to match the new model's price, the price index would fail to reflect the reduction in the price level. In addition to failing to account for direct effects of introductions of new models, matched model indexes would omit any direct effect of disappearances of old ones.

IV) Pooled time dummy hedonic regression

In this widely used hedonic specification, the effect of quality characteristics X_{it} on the log price p_{it} of digital camera model i is assumed to be constant over time. If the sample contains N camera models and T time periods, the hedonic regression equation is:

$$p_{it} = a_t + X_{it}\beta_i + \varepsilon_{it} \qquad i = 1,\ldots,N;\ t = 1,\ldots,T$$

The price index comparing time t to time t–1 is calculated in logarithmic form as the difference between the estimate of a_t and the estimate of a_{t-1}.

Time dummy hedonic price indexes are simple to calculate because unmatched observations need not be discarded, as is necessary for the matched model indexes. They work well in cases when the coefficients on the characteristics are relatively stable over time. One of their disadvantages is that sudden changes in coefficients may go unnoticed if the number of periods used to estimate the character coefficients is large. Another is that the quality correction factor is same for all observations at the magnitude given by the time indicator coefficient, which makes this method unsuitable for imputing missing prices for use in a matched model index.

V) Time dummy 2-period hedonic regression

In this method, the coefficients on the characteristics are held constant for just two periods at a time. If, for example, we have 20 time periods in our data set, instead of estimating just one regression model, we estimate 19 models. As in pooled time dummy method, the index between adjacent time periods can be deduced directly from the estimated time dummy indicators. Over longer time intervals, the index must be constructed by chaining the time dummy coefficients.

An advantage of 2-period hedonic regression over pooled hedonic regression is that the characteristic coefficients are free to evolve over time. In addition, 2-period hedonic regression allows some flexibility over time in specification, as the set of quality characteristics included in the model need not be constant.

VI) Full hedonic imputation

This method lets the relationship between price and quality change freely from period to period. The model is simply the same as:

$$p_{it} = a_{it} + X_{it}\beta_{it} + \varepsilon_{it} \qquad i = 1,\ldots,N;\ t = 1,\ldots,T$$

To calculate the index from period t–1 to period t, the estimated coefficients from period t–1 regression are used to predict the prices of cameras with the characteristics observed in period t, and the coefficients from the period t regression are used to predict the prices of cameras with the period t–1 characteristics. One index is calculated from the differences between the observed and predicted values of the period t log prices, and another index is calculated from the differences between the observed and predicted values of the period *t*–1 log prices. These indexes are then averaged geometrically to obtain a kind of Törnqvist index.

Apart form the matched model method, all the methods previously discussed are special cases or simplifications of full hedonic method, even the unit-value indices. However, one might expect indexes calculated by the full hedonic model to differ only slightly from indexes calculated by 2-period time dummy model because the number of estimated models is only one more. Note that hedonic regressions generally cannot be interpreted as structural models with direct economic interpretations for the coefficients such as shadow prices, marginal utilities or marginal quality costs.

IV Description of the Data Set

The author collected quarterly data on digital camera prices from 1996 to mid-2002 from advertisements in issues of the *Journal of Popular Photography* on microfilm. When more than one retailer advertised the same model, an average of their prices was used as the price observation. Additional price data for two last quarters of 2002 were collected from the Internet at *www.pricescan.com*, resulting in over 1300 observations on 288 different digital camera models. Data on the models' quality characteristics were compiled mainly from the website *dpreviw.com*. Not all the observations were used in the empirical investigation of quality adjustment methods, however. Missing data on characteristics prevented the use of the 59 observations for the years 1996 and 1997, and SLR (single lens reflex) digital cameras were excluded because their characteristics were not comparable with characteristics of other types of digital cameras. These exclusions left a total of 1155 price observations, with the distribution described in table 1.

The need to gather data from historical sources precluded the use of random sampling. Before the third quarter of 2002, all prices quoted for the models advertised in the *Journal of Popular Photography* were recorded. For some advertised models, no price observation was available because readers were told to call for the price. For late 2002, when prices were collected from the Internet, generally the lowest available price was recorded, and most of the makes and models on the market were included in the sample. New models were included in the sample when they were first advertised; no attempt was made to track a fixed sample of models, as is typically done by statistical agencies.

The quality characteristics may have some variation between retailers. The most important source of variation is differences in the memory cards included in cameras. For this reason, memory was excluded from some of the regression models.

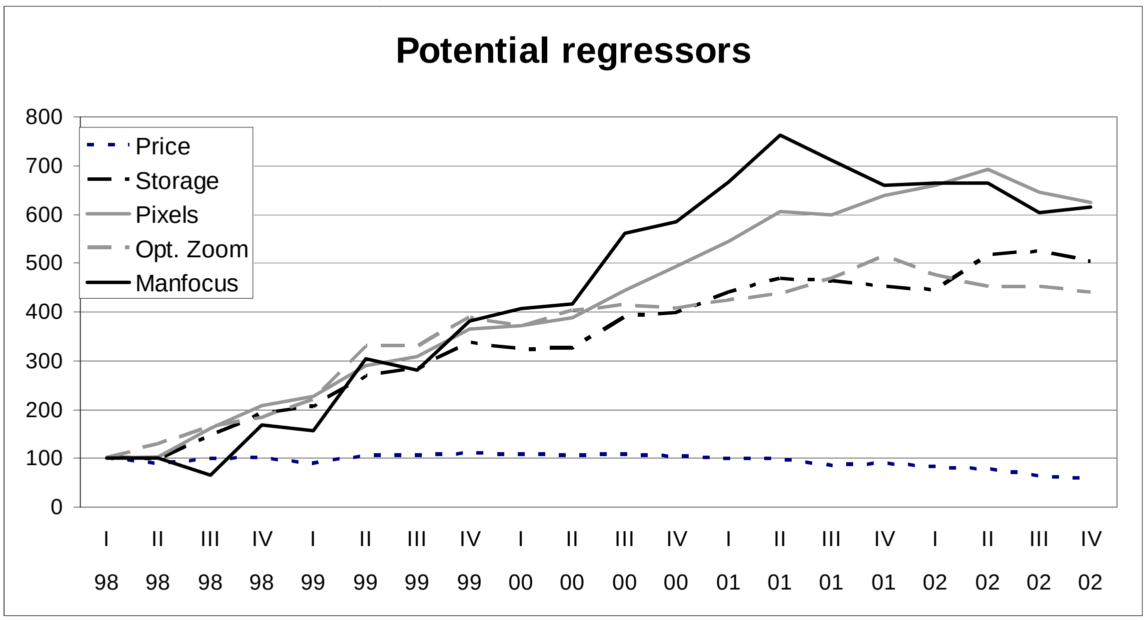
No explicit data were available for the weights, so all indexes are calculated as equally weighted geometric means. Thus, each model has an equal weight. Out of all observations Sony counted for the most observations (18%), followed by Olympus (15%), Kodak (13%), Fuji (12%), Canon (11%), Nikon (8%) and 13 additional manufacturers. Differences in pricing between manufacturers seemed to be minor.

A possible source of downward bias in indexes for the second quarter of 2002 is in the change to the Internet for collecting price data. The prices reported by Pricescan.com are usually for a "best price", which is the lowest advertised price within a selection of online retailers. Also, these prices usually do not include shipping. This may be problematic if there is a tendency for the low price retailers to charge more for the shipping than others.

Table 1. Distribution of the price observations

Quarter/ Year	1998	1999	2000	2001	2002
Q1	19	41	79	75	50
Q2	20	34	44	29	94
Q3	27	54	63	83	155
Q4	37	31	55	41	124
Total	103	160	241	228	423

Figure 1. Some scaled average quality variables



Quality characteristics

Changes in the average quality characteristics are large in time compared to the evolution of average prices. Of these variables, the manual focus is a binary variable and the index presentation should be interpreted as the evolution of the share of digital cameras having the feature in question. When used in average form e.g. in imputation, all binary variables should be interpreted similarly. All available variables in the data set are presented in table 2 in Appendix 1. The most useful are the ones indicating a sharpness of the picture, a memory capacity, an optical zoom ratio, and manual focus, an external flash and movie options.

V Results

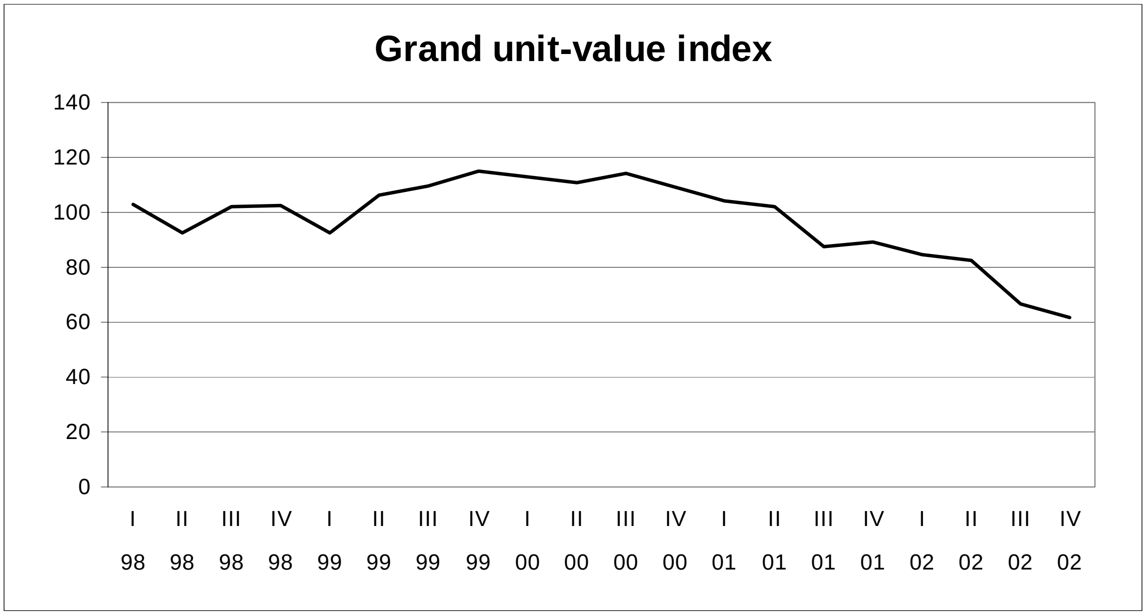
As is shown in figure 1, average prices were flat from 1998 to 2001, after which they began to fall substantially. In addition, the average value of many measures of quality rose steadily throughout the sample period. Figure 1 shows indexes of storage capacity, pixels per image, percent of models with an optical zoom, and percent of models with manual focus availability. For many high technology goods the average price does not seem to change very much, while average quality characteristics change considerably. This is true for digital cameras too.

The price for a typical new digital camera model often starts with a stable introductory price (may be set by the manufacturer) and then the dispersion of offer prices becomes larger in time. Often the highest asking price stays the same (or decreases moderately) while the lowest price declines sharply. We use just one price for a model at one time, representing either the average offered price (until mid-2002), or the lowest offered price.

I) Grand unit-value

The average price of a digital camera fluctuated around $500 until early 2001 and then dropped to under $350 in late 2002. The grand unit-value index based on the geometric mean of offered prices is shown in figure 2. Of course, this index does not account for the changes in performance of the equipment. The drop during the last two quarters may partly reflect the change in data collection method – both because the Internet price refers to the lowest price and also because there may be more 'low end' models in the Internet data set.

Figure 2. Unit value index series (1998 = 100)



II) Class unit-value

For the sake of illustration, we classify the cameras into groups of similar models and calculate the group mean price changes. This classification method is actually often used by statistical agencies for missing observations or replacements and may be a good method in connection with some products.

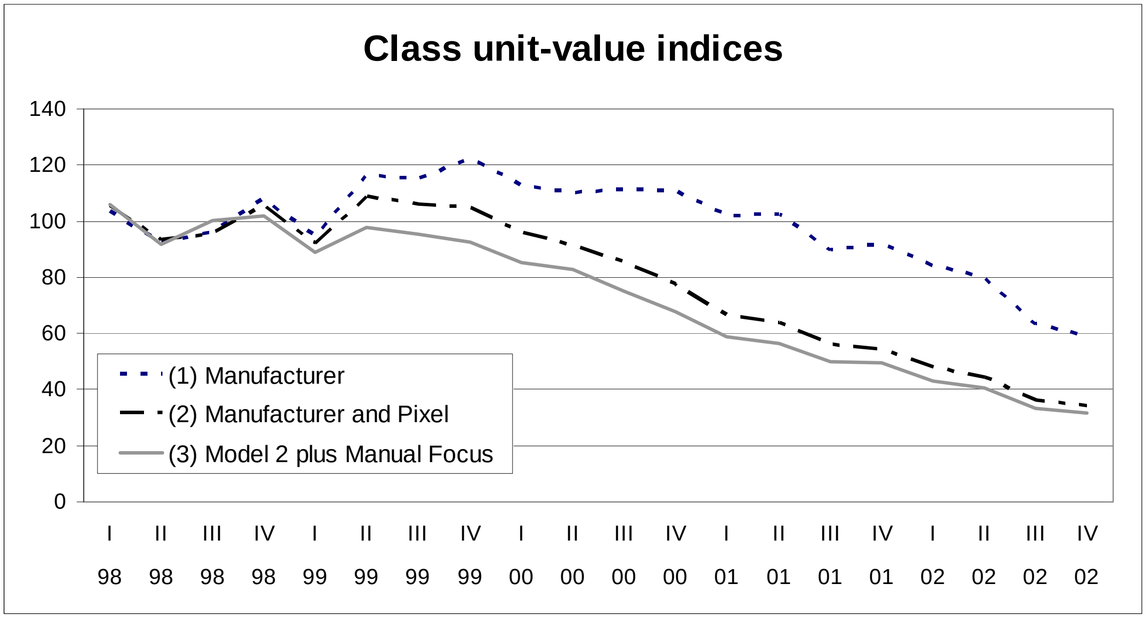
The classification method is based on classifying the cameras according to some rule – most likely by their characteristics – and calculating the class means. The matched model index above is an extreme case of this method. Each model is classified as its own group and 'empty' classes appear every time when the model is not found in the next period.

The first classification model in figure 2 is based on the manufacturer. The index may be calculated from the changes in make-specific average prices[6]. The second model adds pixel count group – a variable, which classifies the camera models into five categories according to the granularity of the picture (less that 1 megapixel, 2 Mp, 3Mp and over 4 Mp cameras). The third model further classifies the data to models with or without a manual focus option (autofocus is the

[6] The actual calculation is based on a time dummy regression model with indicator variables for each manufacturer.

norm). As with unadjusted averages, we do not actually calculate the class means but instead use regression models (without cross effects).[7]

Figure 3. The class unit-value method



Compared to the matched model index, these indices have more volatility around the trend in the first two years. Adding the classifying factors clearly smoothens the series, but practical usability suffers because the number of class means to be calculated grows rapidly and empty classes start to appear.

III) Matched models

Before the real hedonic specification, we first calculate a digital camera price index based on a matched model method. As mentioned above, the sampling frame was not meant to be used for calculation of matched model index. In a sense, this sampling could be described as "quarterly re-sampling"[8]. Since we did not initially plan to calculate the matched model index at all, it is provided

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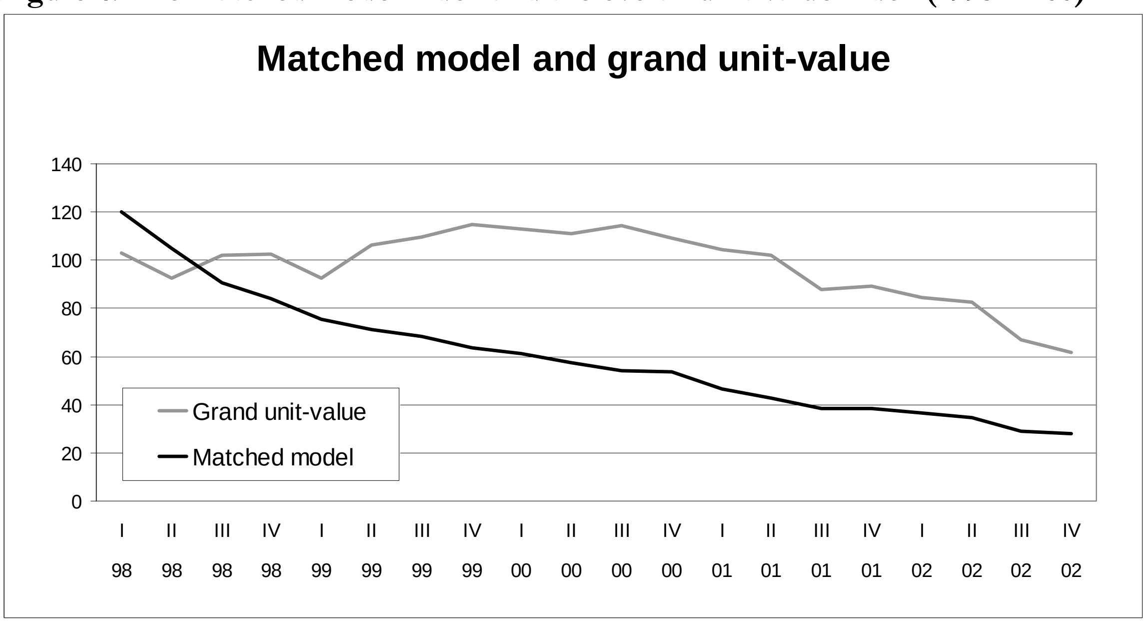
[7] We are actually not cross-classifying the models, but using the 'main effects', in terms of analysis of variance.

[8] It would not be true to claim that the samples were truly independent from one another since we used the same magazine having mostly the same advertisers over time. However, the notion of independence should not be too far from true and we would expect it to have only minor effect for the price index.

only as an example and methodological criticism should not focus on inadequacy of this matched model method.

There were observations from at least two quarters for almost all of the 288 models in the data set. However, the turnover of camera models was rather fast. The number of models for which price were found over more than 4 quarters period was 167 and over 6 quarters just 52. In traditional statistical agency practice, this would have meant a large number of replacement models to be found and an alternative method to account for those models at times of no price observation. Our matched model index does not include estimates for the missing models, either for the ones entering or exiting. The observed price change over more than one quarter is divided by the number of quarters and addressed only to the first quarter. With these reservations, the (geometric average price) index series are presented in figure 4 together with a grad unit-value price index. As can be seen, especially in the first six to eight quarters, the two methods differ considerably, and the matched model index is much smoother in decline.

Figure 4. The matched model index and the overall unit-value index (1998 = 100)



IV) Time dummy pooled hedonic regression

In this section period t models are estimated as

$$\ln\left(\hat{p}_i^t\right) = x_i^{t}{}'\hat{\beta} = \hat{\alpha} + \hat{\beta}_1 x_{i1}^t + \cdots + \hat{\beta}_K x_{iK}^t + \sum\nolimits_{t=2}^{T} \delta^t D^t ,$$

where an indicator variable D_t gets value 1 at period t and 0 otherwise. We will use four slightly different models to illustrate how the model selection affects the quality correction and the index. The models that will be used for all hedonic methods and their corresponding explanatory powers for pooled time dummy model are following:

Model 1: manual focus + ln(megapixels) [R-square 66%]

Model 2: manual focus + ln(megapixels) + ln(megabytes) [75%]

Model 3: manual focus + ln(megapixels) + optical zoom [77%]

Model 4: manual focus + ln(megapixels) + optical zoom + ln(megabytes) + ext. flash [80%].

Adding more quality characteristics increase the overall model fit somewhat, and the differences with quality correction factors from each model become even smaller. A summary table for the coefficients and quality correction terms (as the difference between the quality adjusted price index and the grand unit-value index) of the below models is presented in appendix 2.

As one can see there is some variation between the four models when the OLS adjusts the hyperplane in price-quality coordination. The feature of forecast model is that by adding explanatory variables into the model the individual coefficients, and quality correction factors, adjust so that best overall fit is achieved. This means that the individual quality corrections factors contribute a part of their value to the new variable depending on the amount of multicollinearity it has with the variables already in the model. However, when taken together with all quality characteristics in the model, the total quality correction factor may have very little 'dispersion' between models.

Table 3. Quality adjusted pooled time indices

Year	Quarter	Model 1	Model 2	Model 3	Model 4
98	I	124.8	125.7	125.1	124.4
98	II	106.7	108.2	107.0	106.8
98	III	85.5	85.2	86.6	86.7
98	IV	83.0	80.9	81.3	82.1
99	I	71.2	69.2	69.2	70.0
99	II	67.9	64.6	66.1	67.2
99	III	67.9	64.8	63.7	64.9
99	IV	62.4	59.0	58.9	59.9
00	I	59.1	56.0	55.9	56.7
00	II	56.7	53.9	53.5	54.1
00	III	54.4	50.6	50.1	50.4
00	IV	46.6	44.0	45.9	45.9
01	I	40.1	37.7	39.6	39.0
01	II	36.5	34.3	36.2	35.7
01	III	34.1	32.0	32.8	31.6
01	IV	34.1	32.3	32.3	31.1
02	I	30.6	29.2	29.7	28.5
02	II	28.0	26.3	28.0	26.7
02	III	23.0	21.5	23.1	21.8
02	IV	21.8	20.3	21.8	20.6

The overall picture of the quality adjusted price index for 1999 – 2002 does not really change when adding new quality variables into the hedonic regression. Hence, in practice it may be feasible to collect high frequency data on just few quality characteristics together with an existing matched model price collection.

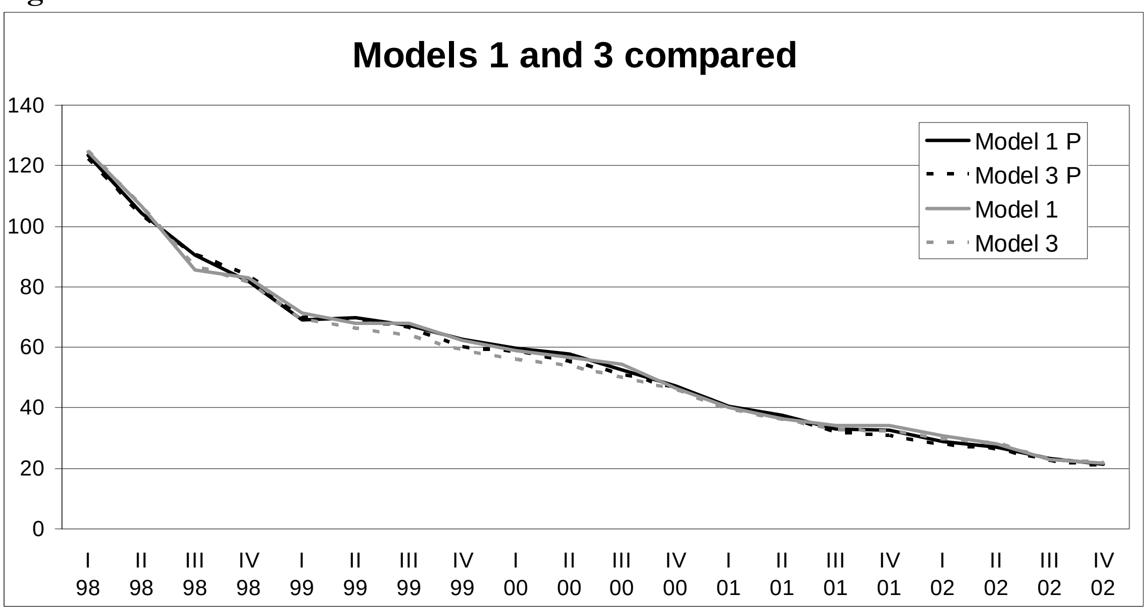
V) Time dummy 2-period hedonic regression

In case of rapid quality change, the assumption that quality – price relation stays the same except from the constant term over a long period of time should be questioned. We will use two different methods to allow more flexibility in the models. The first one is to apply the time indicator model to data that pools data together only two consecutive periods, and estimate 19 independent time indicator models (for all pairs). The second is to estimate separate models for each 20 quarters and impute the matching prices as suggested by the index formulas. With the latter we calculate different log-Laspeyres and “log-Paasche” indices using the model from period *t* and *t-1*, respectively and present the hedonic Törnqvist price index. We call these models pairwise pooled and full hedonic models.

As the results will show, again there are no large changes in the quality-adjusted indices and thus we will use just two models, Model 1 and Model 3 from the previous section.

Now, the model R^2s vary between 60 and 85%. The resulting index series for pairwise pooled indices are presented in figure 5 together with ones from the previous section. The P refers to 2-period pooled model, and as one can see, the two quality correction magnitudes are very similar with the completely pooled data models.

Figure 5. Pooled estimation models

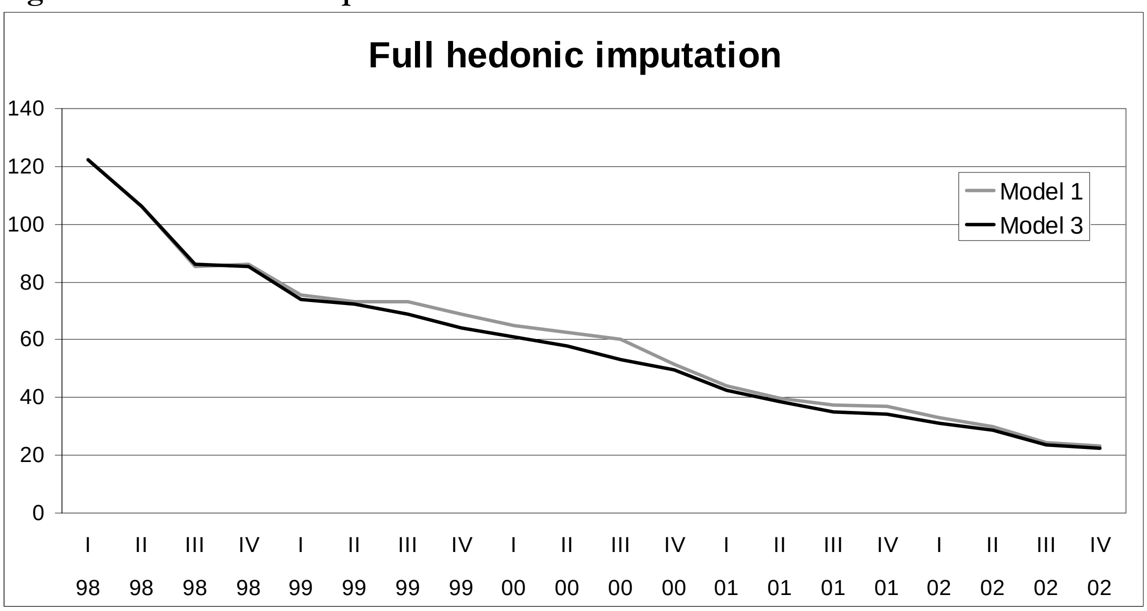


In this case individual observations have much more effect for the coefficients, especially in the early years. Consequently, the quality correction factors for individual characteristics do vary little more, but the total quality correction factors are not affected as much, as expected. One could modify this method by adding the number of consecutive periods to the estimation, which would have a further smoothing effect but still gradually take into account possible changes in quality – price relation.

VI) Full hedonic imputation

The second method could be called a true full hedonic method. Estimated models stay the same but instead of calculating just one index we will use all the data and present the resulting quality adjusted price indices as a Törnqvist index[9]. This would theoretically be the most comparable with an index based on time indicator model[10]. See result in the summary table in Appendix 2. The two indices are presented in figure 6.

Figure 6. Full hedonic imputation models 1 and 3



While it may be difficult to see real difference in the quality adjusted price indices, there are some differences in the quality correction factors. The difference between the two model pairwise quality correction factors is some 8% at maximum. With the pooled data the difference is at most

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[9] Difference of chained Laspeyres and Paasche are at most 7 index points and average to very close to 0.

[10] Since both use the data from the two periods to estimate the model(s). See appendix 1.

6%. With individually estimated Törnqvist quality correction factors between the two models differ again at most some 8%.

VII) Summary

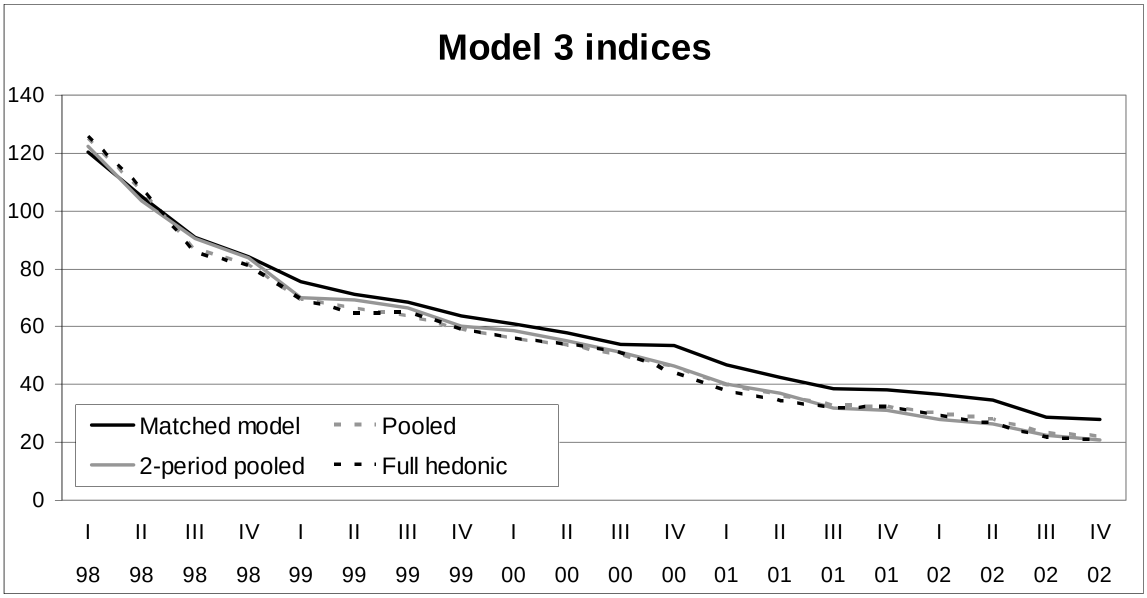
Applying the different quality adjustment methods described in section II seems not to affect the resulting price index very much.

Table 4. Model 3 hedonic indices

Year	Quarter	Matched model	Pooled	2-period pooled	Full hedonic
98	I	120.2	125.1	122.4	125.7
98	II	104.9	107.0	103.5	108.2
98	III	90.8	86.6	90.4	85.2
98	IV	84.1	81.3	83.6	80.9
99	I	75.6	69.2	69.9	69.2
99	II	71.0	66.1	69.0	64.6
99	III	68.3	63.7	66.6	64.8
99	IV	63.6	58.9	60.2	59.0
00	I	61.0	55.9	58.4	56.0
00	II	57.6	53.5	55.1	53.9
00	III	54.0	50.1	51.0	50.6
00	IV	53.5	45.9	46.4	44.0
01	I	46.6	39.6	40.2	37.7
01	II	42.6	36.2	37.1	34.3
01	III	38.5	32.8	32.0	32.0
01	IV	38.3	32.3	30.9	32.3
02	I	36.4	29.7	28.0	29.2
02	II	34.5	28.0	26.3	26.3
02	III	28.9	23.1	22.4	21.5
02	IV	27.9	21.8	20.8	20.3

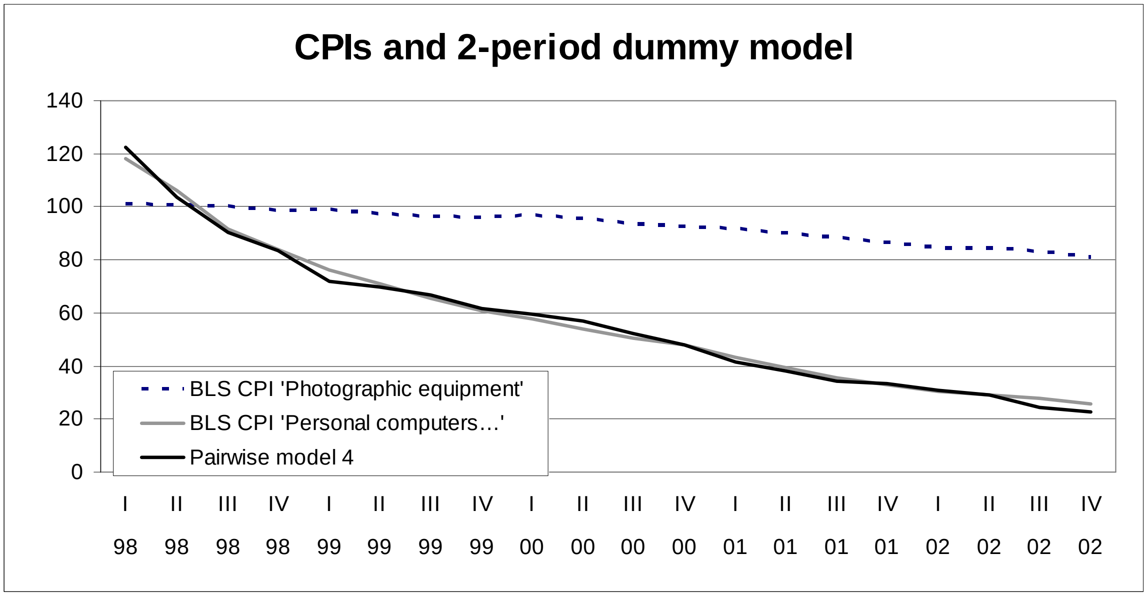
As we can see either from the table above or figure 7 below, the matched model index stays above the hedonic indices but differences between the three different hedonic model 3 indices are not large. The pooled grand unit-value index was estimated using just one regression model, while 2-period pooled unit-value has 19 estimations. Full hedonic index is calculated as a Törnqvist index using 20 models to impute the prices total of 40 times, twice for each period.

Figure 7. Model 3 quality adjusted price indices



How much have the prices of quality adjusted digital cameras changed? Let's compare them with personal computers since the BLS uses hedonic methods to control for quality change in personal computers. The similarity with computer price evolution is striking. In figure 8, the BLS computer price index and photographic equipment indices are presented with our digital camera price index re scaled to 1998=100. The rate of decline is almost identical. The BLS photographic equipment index is the best public series we could find for comparison. It is clearly not directly comparable since it is an aggregate of a number of individual goods' indices, many of which probably experience little of no technological changes in quality.

Figure 8. Comparison between digital cameras and personal computers



VI. Conclusions

As shown above, regardless of different methods and regression specifications used to adjust for quality changes in digital camera price index all reasonable models produce indices that come very close to each other. By reasonable we mean that the model accounts for changes in major quality dimensions. Since applying forecast models, we prefer a simpler model if no substantial benefit is achieved from adding more variables into the hedonic model. If one has to choose between a simple model and more complicated one we think the simpler is better.

As a starting point we should expect and allow the models or at least character coefficients to differ between periods. Only if there is no evidence against changing coefficients should we use time restricted models. However, if data allows the use of pooled regressions, time dummy hedonic models seem to be rather robust in choice of model specification, especially over relatively short periods. The advantages from using somehow pooled data are that it gives more stable regression coefficients and it is relatively simple to apply. Especially with high frequency indices it may also make the hedonics more feasible since it may demand less data. This again is not a bad thing.

Since relatively simple models seem to work rather well large scale characteristics collection may not be necessary. This means that using hedonic regression models may not be of any greater restraint for statistical agencies than a matched model approach requires. The matched model approach already needs the same (or even more) information of the quality characteristics, as Pakes (2004) also notes. Information that is already collected in some form could be used as input for the regression models of section II.

As long as the matched model index does not produce sample selection bias it works very well. However, there are two issues that require attention. First, if the distribution of characteristics changes in time, as it does with high technology products, frequent sampling is needed and quality changes in mismatches must be dealt somehow. Typical statistical agency quality adjustment procedures may not be suitable for simultaneously dealing with both quality change and sampling. Second, matching does not solve the missing observation problem and some quality adjustment method is needed anyhow. We argue that hedonic approach is a good and could often be feasible way to produce indices so that sampling may be separated from the quality adjustment process. One could still take into account sample design and the theoretical target index.

The main findings indicate that, in an aggregate context such as price index, relatively simple hedonic models may be sufficient for accurate quality controlling even in high technology products with rapid quality changes. Further, compared with a matched model framework, the collection of characteristic data for hedonics may not need to exceed the precision already needed to "make the match". This suggests that it may be feasible to use hedonic indices even in high frequency index compilation.

Regression based methods could be implemented for all elementary aggregate indices regardless of whether the model is grand unit-value, matched model, or one exploiting quality character data (or prices from non-missing observations) of various precision. In some cases relatively simple unit-value indices may be sufficient while others could include more rigorous regression models. We believe that with today's technology continuous updating of the regression models could be automated to a large degree.

References

Aizcorbe, A., Corrado, C. and Doms, M. (2001), Constructing Price and Quantity Indexes for High Technology Goods, Industrial Output Section, Division of Research and Statistics, Washington, D.C.: Board of Governors of the Federal Reserve System.

Diewert, W. E. (2001), Hedonic Regressions: A Consumer Theory Approach, Discussion Paper No.: 01-12, University of British Columbia, Vancouver.

Diewert, W. E. (2002), Hedonic Producer Price Indexes and Quality Adjustment, Discussion Paper No.: 02-14, University of British Columbia, Vancouver.

Feenstra, R.C. (1995), “Exact Hedonic Price Indexes,” *Review of Economics and Statistics,* LXXVII, 634-54.

Fixler, D.J. and Zieschang, K.D. (1992), "User Costs, Shadow Prices, and the Real Output of Banks" in Zvi Griliches (ed.), *Output Measurement in the Service Sector*, University of Chicago Press, National Bureau of Economic Research Conference on Research in Income and Wealth, Studies in Income and Wealth, volume 56, pp. 219-242.

Gordon, R.J. (1990), The Measurement of Durable Goods Prices, Chicago: University of Chicago Press.

Heravi, S. and Silver, M. (2002), On the Stability of Hedonic Coefficients and their Implications for Quality-Adjusted Price Change Measurement, Cambridge, Mass: NBER Summer Institute 2002.

ILO/IMF/OECD/UNECE/Eurostat/The World Bank (2004): Consumer Price Index Manual: theory and practice, Geneva, International Labour Office.

Moulton, B.R., LaFleur, T. and Moses, K.E. (1999), ”Research on Improved Quality Adjustment in the CPI: The Case of Televisions”, in Lane, W. (ed.): Proceedings of the Fourth Meeting of the International Working Group on Price Indices.

Koskimäki, T. and Vartia, Y. (2001), "Beyond Matched Pairs and Griliches-type Hedonic Methods for Controlling Quality Changes in CPI Sub-indices. Mathematical Considerations and Empirical Examples on the Use of Linear and Non-linear Hedonic Models with Time-dependent Quality Parameters", paper presented at the 6th meeting of the International Working Group on Price Indices, Canberra.

Pakes, A. (2002): "A Reconsideration of Hedonic Price Indexes with an Application to PC's." *American Economic Review* 93, 1578-96.

Pakes, A. (2004): Hedonics and the Consumer Price Index, Harvard University.

Rosen, S. (1974): "Hedonic Prices and Implicit Markets: Product Differentation in Pure Competition". *Journal of Political Economy*, January-February 1974, 82(1), pp.34–55.

Silver, M (1999): "An Evaluation of the Use of Hedonic Regressions for Basic Components of Consumer Price Indices", *Review of Income and Wealth*, Vol. 45.

Silver, M. and Heravi, S. (2001), "Scanner Data and the Measurement of Inflation", *The Economic Journal*, 111 June.

Triplett, J.E. (2002), *Handbook on Quality Adjustment of Price Indexes for Information and Communication Technology Products*, Directorate for Science, Technology and Industry, Draft, Organisation for Economic Co-operation and Development, STI Working Paper 2004/9, Statistical Analysis of Science, Technology and Industry, 8 October 2004, OECD Paris.

Appendix 1: Average prices and indexes by the classification method

Table A1.1 Average prices

Year	Quarter	Quarterly mean prices $	Mean index
98	I	528.9	103.0
98	II	474.5	92.4
98	III	524.1	102.0
98	IV	527.0	102.6
99	I	474.4	92.4
99	II	546.0	106.3
99	III	562.4	109.5
99	IV	590.1	114.9
00	I	580.5	113.0
00	II	569.4	110.9
00	III	587.0	114.3
00	IV	561.4	109.3
01	I	535.7	104.3
01	II	524.2	102.1
01	III	463.6	87.7
01	IV	471.6	89.2
02	I	447.3	84.6
02	II	436.0	82.4
02	III	353.4	66.8
02	IV	315.8	61.5

Table A1.2 Data set variables

Variable	Description	type of measure
lnp	log of price	dollars
lnpix	log of sharpness	megapixels
lnsto	log of memory included	megabytes
movie	movie feature	0 - 1 variable
remote	remote control	0 - 1 variable
flash_ex	external flash	0 - 1 variable
manfocus	manual focus	0 - 1 variable
zoomo	optical zoom	scale of optical magnification
zoomd	digital zoom	scale of digital magnification
USB	usb connection	0 - 1 variable
serial	serial connection	0 - 1 variable
bat_re	battery recharger	0 - 1 variable
type	type of camera	compact, ultacomp, SLR-type
multires	choices of various resolutions	number, or '0 - 1 variable
ISO	number of different iso	number, or '0 - 1 variable
manufac	manufacturer	18 manufacturers

Table A1.3. Price Indexes by Classification method

Year	Quarter	Only Manufacturer (1)	Manufacturer and Pixel-group (2)	2 + Manual focus
1998	I	103.4	105.4	106.0
1998	II	92.3	93.3	91.9
1998	III	96.4	95.4	100.4
1998	IV	108.0	105.8	101.7
1999	I	94.6	92.0	88.9
1999	II	116.5	108.6	97.9
1999	III	114.8	106.0	95.3
1999	IV	122.2	104.9	92.6
2000	I	112.8	96.0	85.4
2000	II	109.8	91.3	82.8
2000	III	111.3	85.3	74.9
2000	IV	110.9	77.3	67.9
2001	I	102.0	66.5	59.0
2001	II	102.5	63.9	56.4
2001	III	89.6	55.8	49.9
2001	IV	91.9	54.4	49.5
2002	I	83.9	47.7	43.1
2002	II	80.1	44.1	40.4
2002	III	63.3	36.0	33.5
2002	IV	58.7	33.9	31.5

Appendix 2: Some regression results

Time indicator Model 4 estimation results. The model is estimated as

$$\ln\left(\hat{p}_i^t\right) = \hat{\beta}^t x_i^t =$$

$$\hat{\alpha} + \hat{\beta}_1 LNPIX + \hat{\beta}_2 LNSTO + \hat{\beta}_3 MANFOCUS + \hat{\beta}_4 ZOOMO + \hat{\beta}_5 FLASH\_EX + \sum_{t=10}^{28} \hat{\delta}^t Q_t$$

The REG Procedure
Model: Model 4
Dependent Variable: lnp

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	24	170.35142	7.09798	160.64	<.0001
Error	938	41.44658	0.04419		
Corrected Total	962	211.79800			

Root MSE	0.21020	R-Square	0.8043
Dependent Mean	6.05545	Adj R-Sq	0.7993
Coeff Var	3.47133		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	Intercept	1	6.56490	0.07584	86.57	<.0001
lnpix	ln(PIXEL)	1	0.50031	0.02129	23.50	<.0001
Manfocus	Manfocus	1	0.13551	0.01722	7.87	<.0001
ZoomO	Opt Zoom	1	0.06494	0.00562	11.56	<.0001
lnsto	ln(STORAGE)	1	0.12207	0.01539	7.93	<.0001
Flash_ex	Ext flash	1	0.11777	0.01872	6.29	<.0001
Q10		1	-0.16623	0.09449	-1.76	0.0789
Q11		1	-0.34812	0.08709	-4.00	<.0001
Q12		1	-0.49367	0.08241	-5.99	<.0001
Q13		1	-0.69502	0.08191	-8.48	<.0001
Q14		1	-0.77254	0.08240	-9.38	<.0001
Q15		1	-0.80633	0.07965	-10.12	<.0001
Q16		1	-0.90879	0.08450	-10.76	<.0001
Q17		1	-0.93108	0.07829	-11.89	<.0001
Q18		1	-0.97396	0.08171	-11.92	<.0001
Q19		1	-1.07752	0.08038	-13.41	<.0001
Q20		1	-1.15870	0.08123	-14.26	<.0001
Q21		1	-1.29944	0.08044	-16.15	<.0001
Q22		1	-1.37906	0.08708	-15.84	<.0001
Q23		1	-1.50989	0.08095	-18.65	<.0001
Q24		1	-1.52072	0.08508	-17.87	<.0001
Q25		1	-1.59569	0.08398	-19.00	<.0001
Q26		1	-1.65902	0.08160	-20.33	<.0001
Q27		1	-1.83195	0.07983	-22.95	<.0001
Q28		1	-1.90307	0.08005	-23.77	<.0001

Table A2.1 Parameter estimates for pairwise dummy model and full dummy model 3

Year	Quarter	Intercept	lnpix	Manfocus	ZoomO	Time D
1998	I					
1998	II	6.81	0.65	0.07	0.06	-0.167
1998	III	6.52	0.52	0.13	0.07	-0.135
1998	IV	6.33	0.42	-0.06	0.08	-0.079
1999	I	6.25	0.43	0.04	0.07	-0.153
1999	II	6.09	0.49	0.05	0.08	-0.025
1999	III	6.05	0.54	0.14	0.07	-0.047
1999	IV	5.99	0.53	0.21	0.07	-0.078
2000	I	5.89	0.58	0.16	0.08	-0.037
2000	II	5.84	0.60	0.15	0.08	-0.045
2000	III	5.83	0.54	0.17	0.07	-0.085
2000	IV	5.76	0.55	0.14	0.07	-0.089
2001	I	5.66	0.60	0.14	0.07	-0.141
2001	II	5.51	0.61	0.16	0.06	-0.089
2001	III	5.41	0.59	0.08	0.09	-0.110
2001	IV	5.28	0.57	0.10	0.10	-0.015
2002	I	5.30	0.51	0.21	0.08	-0.083
2002	II	5.15	0.53	0.26	0.09	-0.054
2002	III	5.13	0.53	0.23	0.08	-0.186
2002	IV	5.03	0.46	0.23	0.08	-0.063
Full	Model	**6.69**	**0.53**	**0.18**	**0.08**	

Table A2.2 Parameter estimates for full hedonic model 4

Year	Quarter	Intercept	lnpix	Manfocus	ZoomO	Insto	Flash_ex
1998	I	6.63	0.59		0.05	0.16	
1998	II	6.58	0.71	-0.01	0.03	0.19	
1998	III	6.36	0.48	0.12	0.08	0.00	-0.05
1998	IV	6.12	0.36	-0.11	0.09	0.08	-0.02
1999	I	6.01	0.48	0.04	0.07	0.05	0.04
1999	II	5.80	0.47	0.12	0.03	0.16	0.14
1999	III	5.79	0.33	0.18	0.10	0.06	0.23
1999	IV	5.58	0.34	0.18	0.10	0.12	0.18
2000	I	5.50	0.52	0.09	0.12	0.13	0.11
2000	II	5.72	0.58	0.09	0.13	-0.02	0.05
2000	III	5.28	0.38	0.06	0.13	0.19	0.08
2000	IV	5.40	0.53	0.07	0.07	0.14	0.10
2001	I	5.26	0.57	0.15	0.02	0.14	0.13
2001	II	5.19	0.57	0.13	0.03	0.14	0.13
2001	III	5.08	0.66	0.01	0.07	0.08	0.10
2001	IV	5.15	0.73	0.07	0.05	0.02	0.18
2002	I	5.04	0.80	0.17	0.04	0.00	0.00
2002	II	4.72	0.62	0.14	0.07	0.15	0.12
2002	III	4.67	0.54	0.13	0.05	0.15	0.11
2002	IV	4.88	0.43	0.24	0.05	0.06	0.07

Table 2.3. Quality correction factors

Year	Quarter	Model 2P	Model 2Full	Model 4P	Model 4Full	Model 2	Model 4
1998	I						
1998	II	-0.04	-0.05	-0.02	-0.05	-0.03	-0.02
1998	III	-0.24	-0.25	-0.26	-0.30	-0.27	-0.31
1998	IV	-0.11	-0.16	-0.12	-0.18	-0.12	-0.13
1999	I	-0.06	-0.06	-0.06	-0.09	-0.06	-0.06
1999	II	-0.18	-0.20	-0.20	-0.26	-0.18	-0.20
1999	III	-0.03	-0.03	-0.02	-0.04	-0.03	-0.03
1999	IV	-0.13	-0.13	-0.14	-0.16	-0.13	-0.14
2000	I	-0.01	-0.01	0.02	0.01	-0.01	0.02
2000	II	-0.04	-0.04	-0.05	-0.05	-0.04	-0.05
2000	III	-0.10	-0.10	-0.10	-0.12	-0.10	-0.10
2000	IV	-0.06	-0.06	-0.04	-0.05	-0.06	-0.04
2001	I	-0.08	-0.07	-0.08	-0.08	-0.08	-0.08
2001	II	-0.08	-0.08	-0.10	-0.09	-0.09	-0.10
2001	III	-0.01	0.00	0.01	0.00	0.00	0.02
2001	IV	-0.06	-0.05	-0.06	-0.06	-0.06	-0.06
2002	I	0.00	0.00	-0.01	0.02	0.00	-0.01
2002	II	-0.01	-0.01	-0.04	-0.02	-0.01	-0.03
2002	III	0.05	0.05	0.05	0.04	0.05	0.05
2002	IV	0.02	0.02	0.02	0.03	0.02	0.02

Table A2.4. Quality correction factors (scaled cumulative series 1998=100)

Year	Quarter	Model 2P	Model 2Full	Model 4P	Model 4Full	Model 2	Model 4
1998	I	117.7	118.5	117.6	121.5	119.1	120.2
1998	II	113.4	115.0	114.9	117.6	115.2	117.5
1998	III	89.1	89.9	88.7	87.8	87.7	86.3
1998	IV	79.8	76.7	78.8	73.1	78.0	76.0
1999	I	75.5	71.8	74.0	67.0	73.7	71.4
1999	II	63.3	58.9	60.6	51.6	61.7	58.4
1999	III	61.3	57.0	59.4	49.8	59.7	56.9
1999	IV	53.7	50.0	51.5	42.3	52.4	49.4
2000	I	53.4	49.7	52.4	42.7	52.1	50.3
2000	II	51.2	47.9	49.9	40.8	49.9	47.9
2000	III	46.4	43.4	45.0	36.3	45.2	43.2
2000	IV	43.8	41.0	43.4	34.6	42.6	41.5
2001	I	40.6	38.1	39.9	31.8	39.5	38.2
2001	II	37.3	35.2	36.1	29.0	36.2	34.6
2001	III	37.1	35.2	36.6	29.0	36.2	35.2
2001	IV	35.0	33.6	34.5	27.5	34.2	33.2
2002	I	35.0	33.6	34.2	28.0	34.2	32.9
2002	II	34.6	33.1	33.0	27.3	33.8	31.8
2002	III	36.4	34.7	34.6	28.6	35.6	33.5
2002	IV	37.0	35.4	35.3	29.3	36.2	34.1