Estimating Quality-Adjusted Unit Value Indexes: Evidence from Scanner Data

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Abstract

An important issue in price index construction is how to deal with a variable set of commodities. A well-known approach is to impute the 'missing prices' of disappearing and new commodities (models), in particular using hedonic regression. The imputation approach can be problematic at the theoretical level, however. This paper discusses the use of a 'quality-adjusted unit value index' to tackle the issue. Using adjustment factors that eliminate the price differences due to differences in quality between a benchmark model, or numéraire, and the remaining models, quality-adjusted prices are obtained. The adjusted prices could be averaged in order to estimate quality-adjusted unit values for the base period and the current period and thus to estimate a quality-adjusted unit value index. It is argued that the quality-adjustment factors must be independent of time to give a sensible interpretation to the implicit quantity index. An estimator of a quality-adjusted unit value index is derived, based on a semi-log hedonic regression model. The estimator depends on the choice of the numéraire unless the characteristics parameters are constant over time. The assumption of constant parameters assures that the quality-adjustment factors are time independent. It makes it also possible to pool the data from adjacent periods and to employ the adjacent-period time dummy hedonic model, thereby preserving degrees of freedom. Empirical evidence is provided for PCs and some other durable goods using scanner data for the Netherlands.

Keywords: consumer price index; hedonic regression; quality adjustment; scanner data; unit values.

JEL classification: C43; E31; L63; L68.

1. INTRODUCTION

For a sufficiently homogeneous commodity a unit value is the appropriate price concept and the unit value index the appropriate measure of price change (Balk, 1998).[1] Index number theory tells us that for a heterogenous commodity group the price changes of the commodities should be aggregated using index formulas such as those of Laspeyres or Paasche, but preferably using superlative formulas like those of Fisher or Törnqvist (Diewert, 1976, 1995). The use of the latter (symmetric) index formulas is not without problems. Apart from practical problems statistical agencies face, for example finding real time expenditure data at detailed levels for the current period, there are some more fundamental issues. This paper addresses one conceptual issue, namely how to handle a variable set of commodities. I am interested in the population or universe rather than in samples, particularly in a set of commodities 'serving the same basic purpose' from the consumer's point of view.[2] For durable goods this is typically the set of commodities producing similar services; an example might be the set of televisions or some subset thereof, such as wide-screen tv's. The set may coincide with the elementary aggregation level statistical offices currently distinguish but it may also be a higher or lower level. The individual commodities are referred to as models. This paper does not address the treatment of a wholly new good, that is a set of models serving a basic purpose that did not exist before.

Quality adjustment is an element of price measurement where conceptual issues are easily mixed up with sampling issues. From time to time a statistical agency replaces an initially sampled model by a newly selected one. If the new model differs in quality from the 'old' model a quality adjustment is made, either explicitly or implicitly. When looking at the population or universe the term quality adjustment is ambiguous. If the population has not changed (the static-universe case), there can only be a change in the

[1] This has recently been questioned by Bradley (2003) who concludes that "except for extreme conditions the unit value is an inappropriate aggregate price measure, and will lead to inconsistent estimates when it is used in a price index or in the estimation of a demand system."

[2] The commodities belonging to this set are close, albeit imperfect, substitutes in the sense of having high substitution elasticities. The products falling into the scope of the Consumer Price Index (CPI) are usually classified according to purpose. I deliberately use the notion of *basic purpose* because it plays a dominant role in discussions on the conceptual foundations of the European Harmonized Index of Consumer Prices (Haschka, 2003). See Diewert (2002) for a critical assessment of harmonized indexes.

product mix, that is a change in relative quantities. Although the 'average quality' has probably changed, quality adjustment does not come into play because all models are matched: they are available in both periods. Superlative indexes take account of this change in the product mix. In a *dynamic universe* there are unmatched models as well. Unless the size of the population (the number of different models) has not changed, it is impossible to match disappearing and new models in a synthetic way through quality adjustment. An obvious pragmatic solution seems to impute the 'missing prices'. The imputation method should answer the question what the prices of the unmatched models would have been, had they been available.[3] But the use of such imputed prices may be unsatisfactory since "under imperfect competition, if an additional variety or model had actually been offered for sale, the prices of other products might also have changed" (Schultze and Mackie, 2001, p. 150).

Is there a way to circumvent the imputation of 'missing prices'? As a first step we could identify products by their performance characteristics instead of the model descriptions provided by the manufacturer. This probably increases the number of matched products. However, it is most likely that unmatched products will still exist and the imputation of 'missing prices' would still be needed. This paper investigates whether the use of a so-called quality-adjusted unit value index can tackle the problem.[4] The idea is as follows. Suppose the price differences between a certain benchmark model, or numéraire, and the remaining models can be attributed to differences in quality plus random errors. If we could eliminate the first part, using quality-adjustment factors, the resulting quality-adjusted prices could be averaged to calculate a quality-adjusted unit value. The ratio of the quality-adjusted unit values in two periods is taken as a measure of aggregate price change, which takes into account any changes in the size of the population. Aggregation to higher levels should be done using regular index formulas. This approach may seem paradoxical: by looking at characteristics, which is essentially a form of disaggregation, the level of aggregation where price index formulas are applied is raised.

[3] For a Fisher index this approach has been described in De Haan (2002) and applied to cars in De Haan and Opperdoes (2002).

[4] Dalén (2001) argues that a quality-adjusted unit value index should be the statistical target if hedonic regression is applied. With respect to deflation in the national accounts, Eurostat (2001) mentions the use of unit value indexes provided that they are sufficiently adjusted for quality changes. Silver and Heravi (2003) define quality-adjusted unit values to estimate 'exact' hedonic price indexes (see Feenstra, 1995). However, they still implicitly impute 'missing prices' for individual models.

The use of unit value indexes might also help to overcome a related issue in statistical practice. The base period of price indexes is usually one year. For high-turnover durable goods the annual expenditure weights of individual models may not adequately reflect their economic importance, though. This is because many models are available only for a very short period. For example, the initial market share of a new model is generally quite small but expanding. When this new model is introduced, say, in December of the base year, its weight will be too small compared to similar models that were introduced earlier. So statistical agencies face a weighting problem.

The quality-adjusted unit value index relates to the set of models serving the same basic purpose. I will interpret this rather vague description as the set of models for which the same hedonic function holds, which seems quite natural. A hedonic function expresses the price of a model as a function of its performance characteristics and an error term. After estimating this function from observed data, we obtain predicted prices. Based on those predicted values we might be able to estimate quality-adjusted prices and thus a quality-adjusted unit value index. Because I want to avoid issues arising from sampling, the empirical part of the paper utilizes scanner data covering the entire Dutch consumer market for some durable goods.

Section 2 explains in detail what is meant by a quality-adjustment factor and a quality-adjusted unit value index.[5] It starts off with a simple two-model case and generalises the idea to a commodity group with a large number of models. It is argued that, in order to obtain a sensible interpretation of the implicit quantity index, the adjustment factors must be time independent. Section 3 uses a semi-log hedonic regression model to derive an estimable expression for the quality-adjusted unit value index. The estimator depends on the choice of the numéraire unless the parameters of the characteristics are constant over time. Under the constant-parameters assumption a time dummy variable model can be applied. Section 4 describes the scanner data set, which contains prices (unit values), quantities sold and characteristics for personal computers, televisions, refrigerators, and washing machines. This section also presents the estimation of the time dummy models. Section 5 provides empirical evidence on the quality-adjusted unit value index. Section 6 concludes.

[5] Diewert (2003a), discussing the estimation of housing price indexes, defines similar quality-adjustment factors, reflecting the quality of the housing units relative to ‘average’ quality. Note that ‘average’ quality changes over time.

2. QUALITY-ADJUSTED UNIT VALUES AND UNIT VALUE INDEXES

2.1 The two-model case

Before turning to the general case where we look at the entire population it is instructive to start with a simple two-model case.[6] Suppose that a statistical agency wishes to link a disappearing model to a newly selected one in a synthetic way. Both models serve the same basic purpose and are close substitutes so that we could speak of a disappearing model and its natural successor. Model 1 (the 'old' model) has been sold in period $t-1$; it may be sold in period t also, but we expect it to be sold no longer during period $t+1$. The quantities are thus $q_1^{t-1} > 0$; $q_1^t \geq 0$; and $q_1^{t+1} = 0$. Replacement model 2 was not yet sold in period $t-1$ but is sold in period t and presumably in period $t+1$ as well. So we have $q_2^{t-1} = 0$; $q_2^t > 0$; and (presumably) $q_2^{t+} > 0$.

Suppose next that a quality-adjustment factor $\lambda_{2/1}^t$ can be found that serves to 'change the quantity bought of model 2 in period t into a quantity of model 1'. It is assumed that the representative consumer attains the same level of satisfaction, or utility, from buying one unit of model 2 as from buying $\lambda_{2/1}^t$ units of model 1. In other words, the consumer is indifferent between buying q_2^t units of model 2 and buying $\lambda_{2/1}^t q_2^t$ units of model 1. Denoting the prices by p_1^t and p_2^t, an average price in period t can be defined as

$$\tilde{\tilde{p}}^t = \frac{q_1^t p_1^t + \lambda_{2/1}^t q_2^t \tilde{p}_2^t}{q_1^t + \lambda_{2/1}^t q_2^t} = \frac{q_1^t p_1^t + q_2^t p_2^t}{q_1^t + \lambda_{2/1}^t q_2^t} \qquad (1)$$

I will call $\tilde{p}_2^t = p_2^t / \lambda_{2/1}^t$ the quality-adjusted price of model 2, so that $\tilde{\tilde{p}}^t$ defined by (1) can be called a quality-adjusted unit value. To calculate a price index going from $t-1$ to t we could use the price p_1^{t-1} and the average price $\tilde{\tilde{p}}^t$, and to calculate a price index from t to $t+1$ the average price $\tilde{\tilde{p}}^t$ and p_2^{t+1}. Notice that $\tilde{\tilde{p}}^t$ reduces to an ordinary unit value if $\lambda_{2/1}^t = 1$, i.e. when both models are identical from the consumer's point of view.

In practice the statistical agency does not calculate the quality-adjusted unit value but applies some form of synthetic linking or quality adjustment. For example, the agency might use overlap pricing, provided that model 1 is sold during period t ($q_1^t > 0$). This means setting $\lambda_{2/1}^t = p_2^t / p_1^t$, so that $\tilde{p}_2^t = p_1^t$. Under perfect competition theory predicts

[6] This subsection is a slighly revised version of appendix 1 in De Haan (2002).

that the price difference between close substitutes reflects the consumer's evaluation of the difference in quality when both models are available at the same time: the *law of one quality-adjusted price* holds. Usually there will still exist random disturbances, and this makes the overlap pricing method problematic. Moreover, imperfect competition caused by market segmentation seems to be the rule rather than the exception. Of course, other quality adjustment methods could also be applied.

2.2 A generalisation

Hereafter only two time periods will be considered: the base period 0 and the current or comparison period 1. Suppose the total set of models I^t in period *t* (*t*= 0,1) belonging to a certain commodity group has N^t different models, numbered $i = 1,....,N^t$. There are N_M^{01} models available in both periods, forming the set of matched models $I_M^{01} = I^0 \cap I^1$ (where $I_M^{01} \neq \emptyset$ by assumption, hence $N_M^{01} \geq 1$). To define a quality-adjusted unit value for the population a benchmark model, or numéraire, must be chosen. The numéraire should be the same in both periods, so an obvious choice would be one of the matched models.[7] It will be designated number 1. Denoting the *quality-adjustment factor* of *i* in period *t* by λ_i^t ($\lambda_1^t = 1$) and defining its quality-adjusted price as $\tilde{p}_i^t = p_i^t / \lambda_i^t$ ($\tilde{p}_1^t = p_1^t$), the quality-adjusted unit value is given by

$$\tilde{\tilde{p}}_I^t = \frac{\sum_{i \in I^t} \lambda_i^t \tilde{p}_i^t q_i^t}{\sum_{i \in I^t} \lambda_i^t q_i^t} = \frac{\sum_{i \in I^t} p_i^t q_i^t}{\sum_{i \in I^t} \lambda_i^t q_i^t}, \tag{2}$$

which is a straightforward generalisation of (1). A convenient way of writing (2) is

$$\tilde{\tilde{p}}_I^t = \left[\sum_{i \in I^t} s_i^t (\tilde{p}_i^t)^{-1} \right]^{-1}. \tag{2'}$$

Equation (2') expresses the quality-adjusted unit value as a weighted harmonic mean of the quality-adjusted prices, with the expenditure shares $s_i^t = p_i^t q_i^t / \sum_{i \in I^t} p_i^t q_i^t$ serving as weights. The ratio of the quality-adjusted unit values in period 1 and period 0 yields the *quality-adjusted unit value index*:

[7] That the numéraire should be the same in both periods does not necessarily imply that it should be one of the matched models. It could also be a fictitious model, defined by some average of the characteristics.

$$\widetilde{P}^{01}_{I,UV} = \frac{\sum_{i \in I^1} p_i^1 q_i^1}{\sum_{i \in I^0} p_i^0 q_i^0} \left[\frac{\sum_{i \in I^1} \lambda_i^1 q_i^1}{\sum_{i \in I^0} \lambda_i^0 q_i^0} \right]^{-1} = \left[\frac{\sum_{i \in I^1} s_i^1 (\widetilde{p}_i^1)^{-1}}{\sum_{i \in I^0} s_i^0 (\widetilde{p}_i^0)^{-1}} \right]^{-1} . \tag{3}$$

The principal objective of index number theory is to derive optimal ways to decompose the change in the value of a certain aggregate into a price change and a quantity change. It is therefore useful to look at the quantity index implicitly defined by (3):

$$Q_I^{01} = \frac{\sum_{i \in I^1} p_i^1 q_i^1}{\sum_{i \in I^0} p_i^0 q_i^0} \frac{1}{\widetilde{P}^{01}_{I,UV}} = \frac{\sum_{i \in I^1} \lambda_i^1 q_i^1}{\sum_{i \in I^0} \lambda_i^0 q_i^0} . \tag{4}$$

In (4) the quantities are simply added after expressing them in *constant-quality units* (of the numéraire). This is the basic idea behind the quality-adjusted unit value index. One of the approaches in index number theory is the axiomatic or test approach. Balk (1998) discusses this approach for the ordinary unit value index. It is not so easy to tell which tests the quality-adjusted unit value index (3) and the quantity index (4) should satisfy. I suggest one requirement. Suppose the population has not changed (hence, all models are matched; $I^1 = I^0$) and there have been no changes in quantities ($q_i^1 = q_i^0$ for all *i*). Then it seems natural to require that $Q_I^{01} = 1$, especially when period 0 and period 1 are not too far apart. This requirement will be met with certainty only if the adjustment factors are constant over time, that is if $\lambda_i^1 = \lambda_i^0 = \lambda_i$ for all *i*.

3. USING HEDONIC REGRESSION

3.1 A semi-log regression model

Empirical studies often prefer the logarithmic hedonic model to the linear one. This is in agreement with Diewert's (2003b, 2003c) point of view. He argues, among other things, that the residuals from a logarithmic model are less likely to be heteroskedastic. The semi-log (log-linear) hedonic regression model can be expressed as

$$\ln p_i^t = \alpha^t + \sum_{k=1}^{K} \beta_k^t x_{ik} + \varepsilon_i^t ; \qquad (t = 0,1), \tag{5}$$

where x_{ik} is the k-th characteristic of model i and β_k^t the corresponding parameter (k= 1,….,K); ε_i^t is an error term with an expected value of zero. Note that the parameters are modelled time dependent for the time being as there is no a priori reason to believe they must be constant over time.

The quality-adjustment factors cannot be observed directly. How can they be measured? I will define, or approximate, them as the ratio of the systematic parts of the prices of model i (the exponent, or antilog, of $\alpha^t + \sum_{k=1}^{K} \beta_k^t x_{ik}$) and the numéraire; compare the overlap pricing quality adjustment method mentioned in subsection 2.1. This leads to

$$\lambda_i^t = \exp\left[\sum_{k=1}^{K} \beta_k^t (x_{ik} - x_{1k})\right]. \tag{6}$$

If all models had identical characteristics ($x_{ik} = x_{1k}$ for all k and all i) then $\lambda_i^t = 1$ for all i, and the quality-adjusted unit value index reduces to the ordinary unit value index.[8] This is a very desirable property since models with identical characteristics, including outlet-specific conditions, yield the same utility to the consumer and ought to be treated as identical goods. The unit value $\bar{p}_I^t = \sum_{i \in I^t} p_i^t q_i^t / \sum_{i \in I^t} q_i^t$ then is the preferred price concept. Estimating (5) and taking antilogarithms yields $\hat{p}_i^t = \exp(\hat{\alpha}^t + \sum_{k=1}^{K} \hat{\beta}_k^t x_{ik})$ for $i = 1,...., N^t$. The estimator of the quality-adjustment factor given by (6) becomes[9]

$$\hat{\lambda}_i^t = \exp\left[\sum_{k=1}^{K} \hat{\beta}_k^t (x_{ik} - x_{1k})\right] = \frac{\hat{p}_i^t}{\hat{p}_1^t}. \tag{7}$$

Expression (7) can be seen as a cross-sectional application of what Triplett (2003) calls hedonic quality adjustment. I assume that data on prices, quantities and characteristics for the whole population are known and that the hedonic model and the quality-adjusted unit value index will be estimated on these data. In this case we do not need to calculate the quality adjustment factors (7) explicitly. Let $u_i^t = \ln \hat{p}_i^t - \ln p_i^t$ denote the regression residuals. Taking antilogs gives $\exp(u_i^t) = \hat{p}_i^t / p_i^t$. By rewriting $\hat{\lambda}_i^t$ as $\exp(u_i^t)(p_i^t / \hat{p}_1^t)$, we can express the estimated quality-adjusted price as $\hat{\tilde{p}}_i^t = p_i^t / \hat{\lambda}_i^t = \hat{p}_1^t / \exp(u_i^t)$. The estimator of the quality-adjusted unit value index (3) reads

[8] Of course, when all models have identical characteristics one cannot estimate the hedonic model.

[9] Note that (7) is not an unbiased estimator of (6) due to the nonlinear structure. See Goldberger (1968) for a correction term. In practice the bias can be ignored unless the number of observations is very small.

$$\hat{\tilde{P}}^{01}_{I,UV} = \frac{\hat{p}^1_1}{\hat{p}^0_1}\left[\frac{\sum_{i\in I^1} s^1_i \exp(u^1_i)}{\sum_{i\in I^0} s^0_i \exp(u^0_i)}\right]^{-1}. \tag{8}$$

The factor between square brackets in (8), being the ratio of two weighted averages of the exponentiated residuals, is expected to have a value close to 1. In subsection 3.3 the question is raised under what circumstances this factor may differ from unity.

Conditional on the hedonic model and the estimation method there are N^{01}_M (the number of matched models) different estimators of $\tilde{P}^{01}_{I,UV}$.[10] Thus, the quality-adjusted unit value index depends on the choice of the numéraire and is not invariant to changes in the units of measurement. This is a major flaw. As is shown by equation (6), parameter constancy automatically implies constancy of the quality-adjustment factors. In section 2 this was argued to be a necessary condition in the short run for a sensible interpretation of the implicit quantity index. For adjacent periods the constant-parameters assumption seems reasonable. This calls for chaining period-to-period quality-adjusted unit value indexes. Under the assumption of constant parameters and by pooling data the dependency of $\hat{\tilde{P}}^{01}_{I,UV}$ on the choice of the numéraire disappears, as will be shown below.

3.2 Pooling data

If $\beta^1_k = \beta^0_k = \beta_k$ holds for all *k*, hedonic model (5) reduces to

$$\ln p^t_i = \alpha + \delta D_i + \sum_{k=1}^{K} \beta_k x_{ik} + \varepsilon^t_i; \qquad (t = 0,1), \tag{9}$$

which can be estimated on the pooled data of both periods. I assume, as usual, that the errors are independently and identically distributed. The advantage of pooling data is an expected gain in efficiency by saving degrees of freedom. The time dummy variable D_i takes on the value of 1 if the *i*-th observation comes from period 1 and the value of 0 otherwise. This method is known as the adjacent-period time dummy method. Because $\hat{p}^1_1 / \hat{p}^0_1 = \exp(\hat{\delta})$, *independent of the numéraire*, estimator (8) of the quality-adjusted unit value index becomes

[10] The number of different estimators will be less than the number of matched models if some of them had identical characteristics. Note that if we do not restrict the choice of the numéraire to the set of matched models, the number of different estimators will grow almost infinite. See also footnote 7.

$$\hat{\tilde{P}}^{01}_{I,UV} = \exp(\hat{\delta})\left[\frac{\sum_{i\in I^1} s_i^1 \exp(u_i^1)}{\sum_{i\in I^0} s_i^0 \exp(u_i^0)}\right]^{-1} = \exp(\hat{\delta})\left[\frac{\sum_{i\in I^1} s_i^1 (\hat{p}_i^1 / p_i^1)}{\sum_{i\in I^0} s_i^0 (\hat{p}_i^0 / p_i^0)}\right]^{-1}, \tag{10}$$

where u_i^t (t= 0,1) are now the residuals from the pooled regression.

The antilogarithm of $\hat{\delta}$ is generally viewed as a (quality-adjusted) measure of aggregate price change. The *time dummy price index* can be estimated directly from the estimated hedonic regression model, which is probably why this method is sometimes referred to as the direct hedonic approach. The time dummy index has also been called a regression index for obvious reasons. It was not always clear to everyone 'what happens inside the regression', and the method has been criticised for its black-box nature. There is now some literature on the interpretation of the time dummy price index. Van der Grient and De Haan (2003) present a decomposition of this index when Weighted Least Squares (WLS) regression is used. Diewert (2003b) shows that the time dummy index provides a generalisation of the Törnqvist price index using a specific type of WLS. The matched models should be weighted by the average expenditure shares of both periods while the unmatched models should be weighted by the expenditure shares of the period in which they are available. For a general discussion of the use of weights in hedonic regressions, see Silver (2003).

But if $\exp(\hat{\delta})$ itself can be interpreted as a measure of aggregate price change, it may seem strange at first sight to have a second factor in (10). The question arises, however, whether it is necessary, or even whether it is useful, to interpret $\exp(\hat{\delta})$ as such. From an econometric perspective, δ in model (9) can be viewed as a common shift parameter needed to justify the pooling of data from two data sets, pertaining to two periods, under the assumption of constant parameters when explaining price levels rather than price changes. De Haan (2004a) applies (9) in a hedonic imputation approach and calls this an *indirect* time dummy approach. Equation (10) applies an indirect time dummy method to estimate a quality-adjusted unit value index. The weighting of observations is still an issue but only from an econometric point of view. Econometrics textbooks recommend the use of WLS to reduce the standard errors of the regression coefficients, leaving their unbiasedness unaffected, if there is evidence of heteroskedasticity. The weights can take any form as long as they are exogenous. When the errors have constant variances, as I assumed above, Ordinary Least Squares (OLS) will suffice.

If the time dummy model (9) happens to fit the data perfectly ($R^2 = 1$), then the quality-adjusted unit value index estimator $\hat{\tilde{P}}_{I,UV}^{01}$ coincides with the antilog of the estimated common adjustment factor $\hat{\delta}$. This is a trivial case because the observed price relatives of all matched models would be the same. The factor between square brackets in (10) adjusts for the fact that in practice we will never find a perfect fit and most observations (log of prices) will lie off the regression hyperplane.

3.3 The quality-adjusted unit value index versus the time dummy index

An important question is under what circumstances $\hat{\tilde{P}}_{I,UV}^{01}$ will differ in a systematic way from $\exp(\hat{\delta})$. Under perfect competition the 'law of one quality-adjusted price' predicts there are no models whose prices are relatively high or low given their characteristics: there should be no *unusual prices*, apart perhaps from random disturbances. In that case we expect the numerator and the denominator of the bracketed factor in expression (10) to be approximately equal to 1, and therefore $\hat{\tilde{P}}_{I,UV}^{01} \approx \exp(\hat{\delta})$.

Under imperfect competition, on the other hand, such unusual prices might be expected, especially for new and disappearing models (Silver and Heravi, 2002; Triplett, 2003). Let I_N^1 and I_D^0 be the subset of new models in period 1 and the subset of disappearing models in period 0, respectively. Further, let s_M^t denote the matched-model expenditure share in period *t* (*t*= 0,1), $s_N^1 = 1 - s_M^1$ the (period 1) expenditure share of new models and $s^0 = 1 - s_M^0$ the (period 0) expenditure share of disappearing models. Equation (10) can now be written as

$$\hat{\tilde{P}}_{I,UV}^{01} = \exp(\hat{\delta}) \left[\frac{s_M^1 \sum_{i \in I_M^{01}} s_{iM}^1 (\hat{p}_i^1 / p_i^1) + s_N^1 \sum_{i \in I_N^1} s_{iN}^1 (\hat{p}_i^1 / p_i^1)}{s_M^0 \sum_{i \in I_M^{01}} s_{iM}^0 (\hat{p}_i^0 / p_i^0) + s_D^0 \sum_{i \in I_D^0} s_{iD}^0 (\hat{p}_i^0 / p_i^0)} \right]^{-1}, \qquad (10')$$

where $s_{iM}^t = p_i^t q_i^t / \sum_{i \in I_M^{01}} p_i^t q_i^t$ is the period *t* expenditure share of model *i* within the set of matched models, etc. Suppose that matched models do not display unusual prices, so that $\sum_{i \in I_M^{01}} s_{iM}^1 (\hat{p}_i^1 / p_i^1)$ and $\sum_{i \in I_M^{01}} s_{iM}^0 (\hat{p}_i^0 / p_i^0)$ will be close to 1. Suppose furthermore that retailers succeed in selling new models at unusually high prices, so that $p_i^1 > \hat{p}_i^1$ for $i \in I_N^1$; it is sometimes said that there are 'hidden' price increases. They may also sell disappearing models at unusually low prices, implying $p_i^0 < \hat{p}_i^0$ for $i \in I_D^0$. We would then have $\hat{\tilde{P}}_{I,UV}^{01} > \exp(\hat{\delta})$. Stated otherwise, the antilogarithm of $\hat{\delta}$ could underestimate the quality-adjusted unit value index, especially for high-turnover durable goods having relatively small matched expenditure shares. The quality-adjusted unit value index may thus be welcomed by those who have doubts about the strong price declines frequently measured by the time dummy index and by other hedonic price indexes. But this is just an example of what might happen. Other situations are conceivable as well, depending on the prevailing market circumstances and the pricing policies of manufacturers and retailers. The difference between $\exp(\hat{\delta})$ and the quality-adjusted unit value index is an empirical matter, which will be investigated in section 5.

One issue remains. The hedonic function has been defined for all models alike, both for matched and unmatched models. We may ask whether the hedonic function is correctly specified when there are systematic patterns in the residuals. If the answer would be no, then any observed systematic differences between $\exp(\hat{\delta})$ and the quality-adjusted unit value index could result from an incorrectly specified hedonic model, leading to biased estimators, rather than from a real phenomenon like the one mentioned above. De Haan (2004a) proposes to incorporate dummy variables for new and disappearing models into the hedonic model to cope with such systematic effects. As this is controversial and also because it complicates matters, this approach will not be followed here.

4. DATA AND HEDONIC MODELS

4.1 The data

Statistics Netherlands purchased scanner data from GfK-Benelux to perform research into hedonics and related issues. The data have already been described elsewhere (Van der Grient, 2004), so I will only present a short overview here. Our database contains prices (unit values), quantities and an extensive set of characteristics per type of outlet for each model sold during 1999-2001. We have monthly data at our disposal for PCs, and bimonthly data for televisions, refrigerators and washing machines. For the major outlet types the data pertain to all consumer transactions in the Netherlands. For the other outlet types GfK has drawn a sample of outlets and raised the sample data to obtain population estimates. We checked the data on plausibility and consistency. In general the data quality seemed fine, although a limited number of implausible records were deleted.

The number of transactions involved is huge. For example, each year about a million televisions were sold in the Netherlands. Computer sales increased strongly during the three year period, from 370,000 in 1999 to 650,000 in 2001. What surprised us was the clear seasonal pattern in the sales of all durable goods; see figure 1. Personal computers, televisions, and, albeit less pronounced, also washing machines display similar patterns, with sales reaching maximum levels towards the end of the year. Refrigerators show more or less the reverse pattern. The extra peak in the sales of televisions during the summer of 2000 was probably stimulated by the European Championships Football and the Olympic Games.

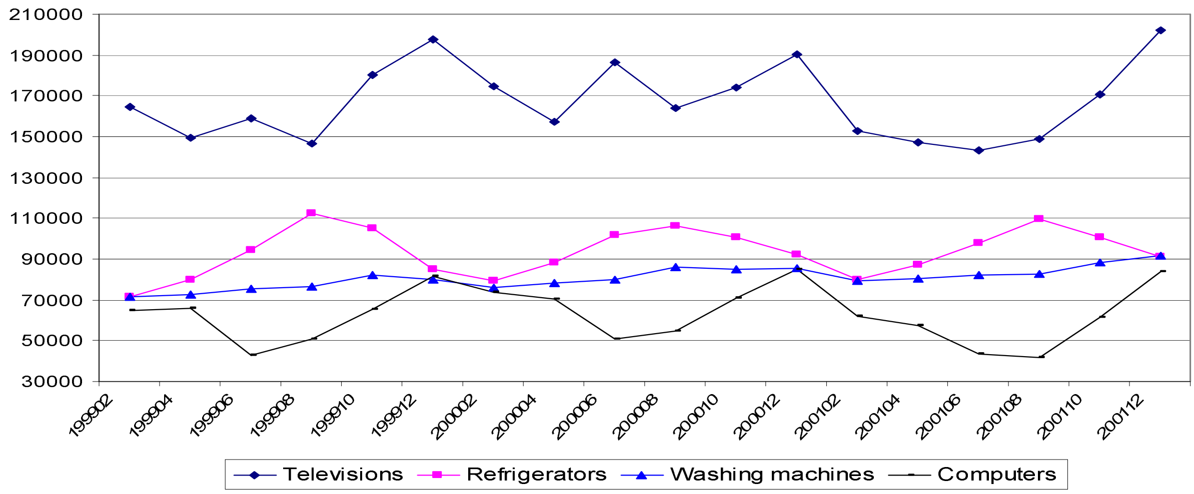

Figure 1. Bimonthy sales, 1999-2001

Chapter 22 of the new CPI manual (ILO, 2004) deals with the treatment of seasonal products. Products that are available throughout the year but feature regular fluctuations in prices or quantities that are synchronized with the season or the time of the year are called weakly seasonal products. Unfortunately the manual says little about problems possibly created by the existence of weakly seasonal products.[11] One of them might be chain drift when using high-frequency chaining. I doubt whether there is a satisfactory solution to this problem – if it is a problem at all. As will be shown below, the fraction of disappearing and new models is so large that a fixed-base index cannot sensibly be constructed. Chaining is needed also because the assumption of constant characteristics parameters should not be made for such a long time period.

[11] Many, if not most, models are available for less than a year. So it is in fact difficult to speak of (weak) seasonality at the level of individual models, notwithstanding the seasonal pattern at the aggregate level.

Durable goods are identified by model numbers or (in our case) bar codes provided by the manufacturer. Purchases of the same durable good sold in different outlets do not necessarily yield the same utility to the consumer. Durable goods having identical bar codes but sold in different types of outlets are therefore treated as different items. Seven outlet types are distinguished. For television sets, refrigerators, and washing machines the most important ones are chains, buying combinations, and independents. The larger part of computers is sold by specialized stores. Figure 2 shows the percentage of items (combinations of models and outlet types) available in adjacent periods. It highlights the market dynamics. In case of televisions, refrigerators and washing machines on average 20 to 25% of the items disappear every two months. For PCs the attrition rate is even much higher: each month one third of the items disappear.[12]

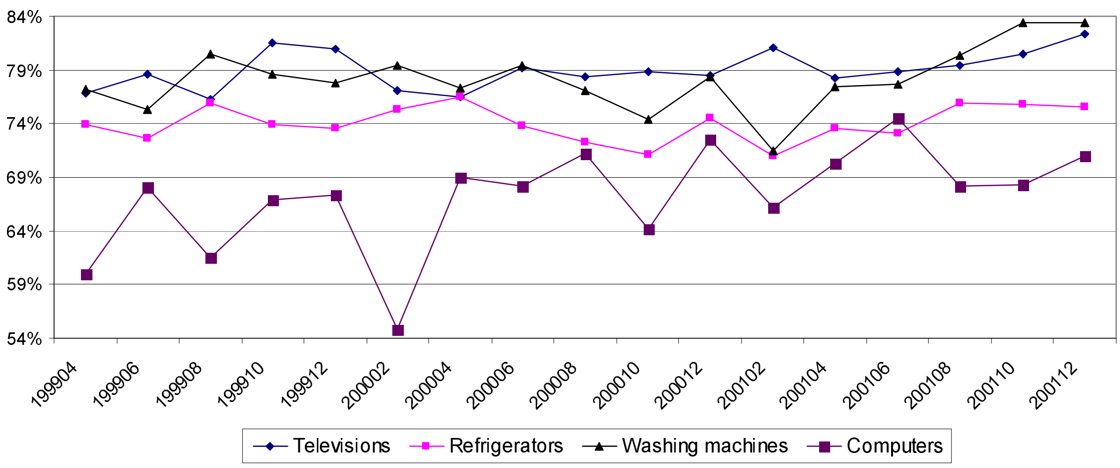

Figure 2. Percentage of matched items between period t and period t-1 (uneven months are not shown for computers)

Figure 2 should be interpreted with caution. Firstly, there is a positive relation between the number of months a particular item is available and its monthly sales or turnover: the 'lifetime' is the longest for the best selling items.[13] Computers are a good example. During 1999-2001 only 5% of the items stay on the market for more than a year, but they nevertheless account for 30% of total turnover. And while 80% of the items are

[12] Statistical agencies should thus continually update their item samples. Silver and Heravi (2002), using scanner data on washing machines, describe the possible consequences of sample degradation.

[13] Proportional to expenditure sampling is a natural strategy for compiling a CPI since the most important items, in terms of expenditures, are given the highest inclusion probability (De Haan et al., 1999). The fact that these items stay on the market for a relatively long time has a practical advantage for statistical agencies. Yet the problem mentioned in the introduction of finding annual weights – in this case inclusion probabilities – for items that are available for less than a year remains.

available less than half a year, their share in turnover is only one third. Secondly, some items reappear shortly after they disappeared. This is a well-known property of scanner data. Reappearing items have been treated as new ones. Thus, in a way figure 2 slightly overstates the true attrition rates.

4.2 The hedonic models

Statistics Netherlands' experiences with hedonic modelling are documented extensively in Van der Grient (2003a,b), Oei (2003) and Van Mulligen (2003). See Van der Grient (2004) for a summary. During an early stage of our research various functional forms were evaluated. Not surprisingly, the log-linear model outperformed the linear model. Our hedonic models incorporate many explanatory variables, most of which are dummy variables. To give an example: the model for televisions includes about thirty technical characteristics, (e.g. screen size, which is a continuous variable, availability of teletext, etc.), almost fourty brand-name dummies, and four dummies for type of outlet. Most coefficients differ significantly from zero at the 5%-level and their signs accord with a priori expectations. We found no evidence of heteroskedasticity.

Except for PCs the assumption of constant coefficients during adjacent periods has been tested.[14] The OLS parameter estimates are fairly stable in the short run; adjacent-period parameter stability was never rejected at the 5%-level. As a matter of fact, stability was not rejected over a period of four months either, that is by comparing period t and t+2. The conclusion must be that pooling data is acceptable for televisions, refrigerators, and washing machines, while for computers the assumption of constant parameters might be violated.

The appendix lists some results. To save space only the pooled OLS regressions for the first two periods of each year are shown. The remainder, and the results using Diewert's (2003b) WLS method, are available on request. The time series for $\exp(\hat{\delta})$ is shown in section 5 below. For PCs the fit of the model is disappointing, with the adjusted R^2 not exceeding 0.71. For the other durables the adjusted R^2 is satisfactory but diminishes slightly over time. A possible explanation might be that relevant new characteristics are missing in our database. If so, the parameter estimators will be biased in later periods.

[14] This was done using a Chow-test (Chow, 1960) that compares the residual sums of squares from the separate regressions of two periods with the residual sum of squares from the pooled regression model. The latter includes a time dummy variable to allow the intercept term to shift, and thus equals model (9).

5. EMPIRICAL RESULTS

Figures 3-6 depict the price changes of televisions, refrigerators, washing machines and PCs as measured by the quality-adjusted unit value index (QAUVI) as well as the time dummy index (TDI), both for OLS and WLS according to Diewert (2003b). Since there was no evidence of heteroskedasticity, OLS is preferred in case of the quality-adjusted unit value index. For the time dummy index WLS is preferred since (expenditure-share) weighting of observations should be better than not weighting them at all. Thus, it is most interesting to compare QAUVI OLS and TDI WLS. For televisions and PCs the price changes according to both measures are more or less the same, whereas for refrigerators and especially for washing machines the WLS time dummy index is below the OLS quality-adjusted unit value index. Notice that weighting observations can have a substantial impact on the quality-adjusted unit value index numbers: for televisions and refrigerators QAUVI WLS clearly overstates QAUVI OLS. For washing machines, on the other hand, they almost coincide.

All durable goods declined in price but at different average rates of change, irrespective of the measure used. As expected, PCs showed the largest average price decrease, about 2% per month. The price decline of refrigerators and washing machines was relatively modest. There is another marked difference between PCs and the other three durables: computer prices have been declining steadily, while the prices of the other goods rose or were stable during the first half of 2001. The underlying causes of these differing price trends are beyond the scope of this paper.

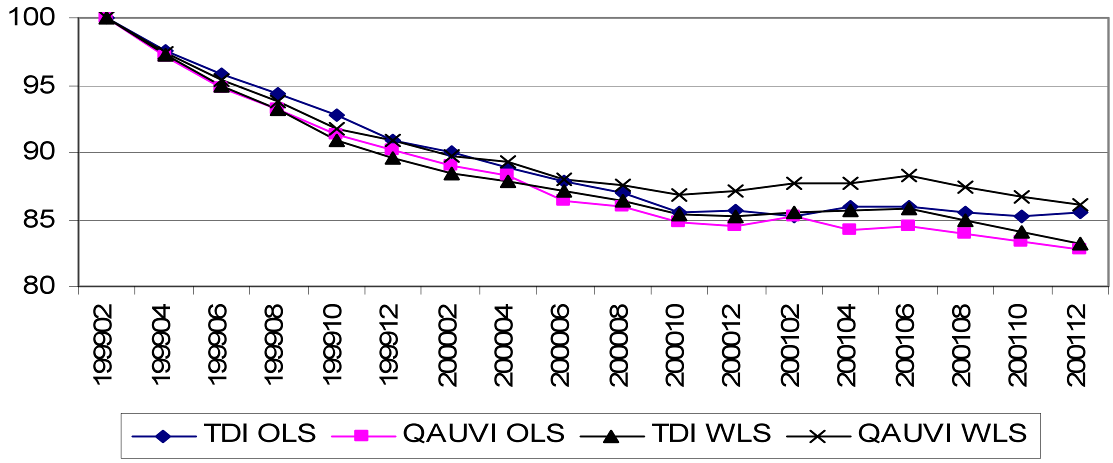

Figure 3. Price indexes of televisions (Jan-Feb 1999= 100)

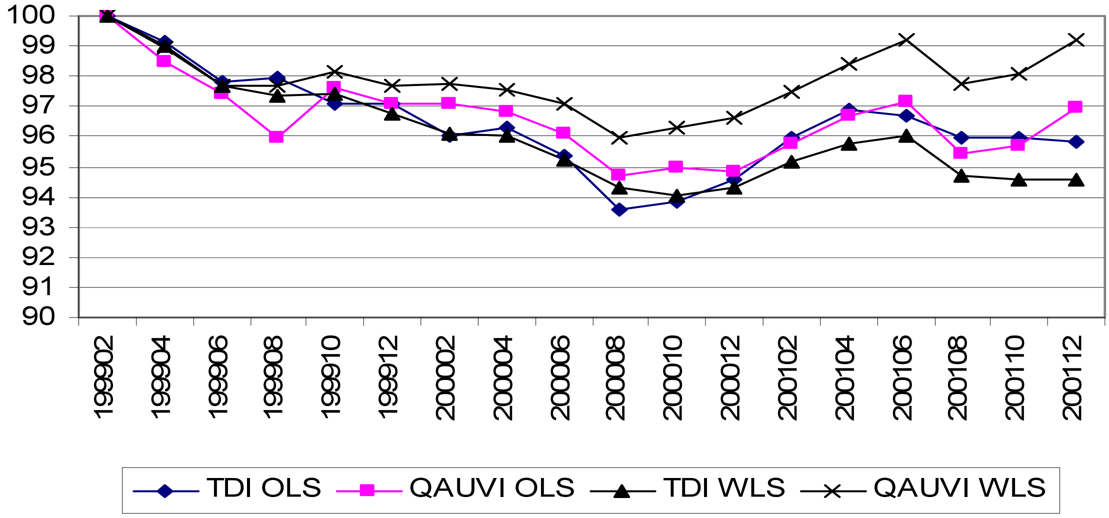

Figure 4. Price indexes of refrigerators (Jan-Feb 1999= 100)

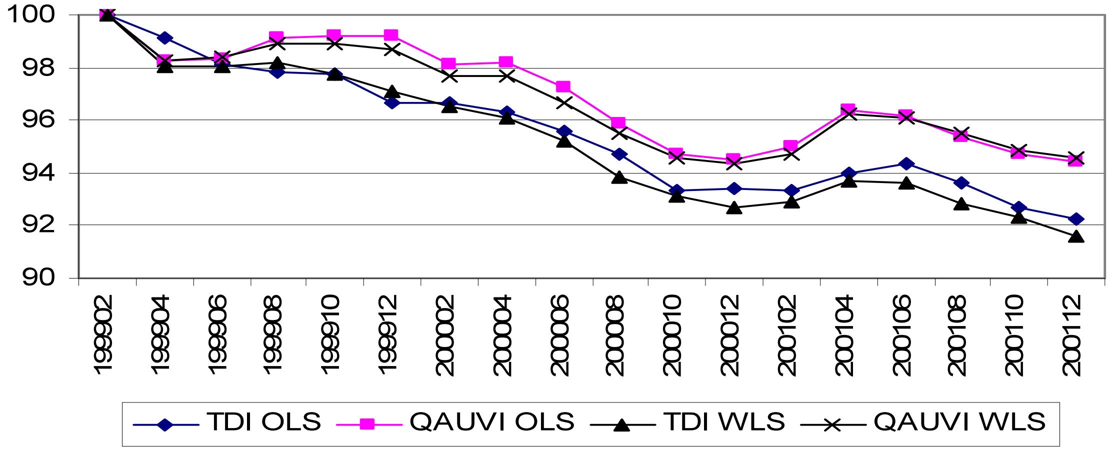

Figure 5. Price indexes of washing machines (Jan-Feb 1999= 100)

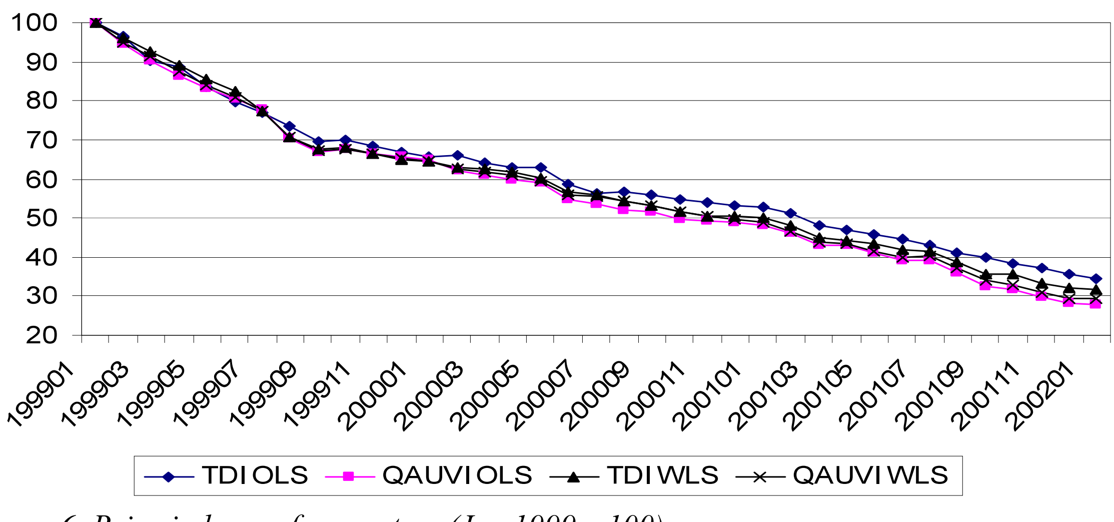

Figure 6. Price indexes of computers (Jan 1999= 100)

In subsection 3.3 it was argued that a systematic difference between the quality-adjusted unit value index and the time dummy price index could point to imperfect competition. Comparing QAUVI OLS with TDI OLS in figures 3-6 reveals that such differences do exist for washing machines and computers but not for televisions and refrigerators. The components of the bracketed factor in expression (10') may give some further insight into this issue. Table 1 shows the average values of those components. Unfortunately the findings appear to be of little help. Contrary to what has been argued earlier, the values for the matched items differ substantially from unity in many cases, suggesting that high-expenditure matched items had unusually high or low prices. I find this rather puzzling. In the case of televisions the values for the matched items in period 1 (1.032) and period 0 (1.030) are of the same order of magnitude and cancel out. The high value for disappearing PCs (1.184) is mainly due to extremely high values at the end of the period, up to 4.241 for the last regression.

*Table 1. Components of equation (10'), unweighted averages**

	Televisions	Refrigerators	Washing machines	Computers
$\sum_{i \in I_M^{01}} s_{iM}^1 (\hat{p}_i^1 / p_i^1)$	1.032	1.012	1.005	1.010
$\sum_{i \in I_N^1} s_{iN}^1 (\hat{p}_i^1 / p_i^1)$	1.001	1.026	0.996	1.021
$\sum_{i \in I_M^{01}} s_{iM}^0 (\hat{p}_i^0 / p_i^0)$	1.030	1.013	1.007	0.992
$\sum_{i \in I_D^0} s_{iD}^0 (\hat{p}_i^0 / p_i^0)$	0.955	1.021	0.996	1.184

* Based on adjacent-period pooled OLS regressions

Finally I turn to the quantity indexes calculated implicitly using QAUVI OLS and TDI WLS, shown in figures 7-10. The quantity changes are so huge that the choice between both price measures is perhaps irrelevant. Even for washing machines, where the price measure does matter, the differences between the implicit quantity index numbers are only minor compared to the quantity change itself. It is highly unlikely that if QAUVI OLS and TDI WLS had been estimated from samples, as usual, the quantity indexes would have been significantly different from each other. Thus, if our main concern would be deflating consumer expenditure in the national accounts, the use of QAUVI OLS and TDI WLS would both yield satisfactory results.

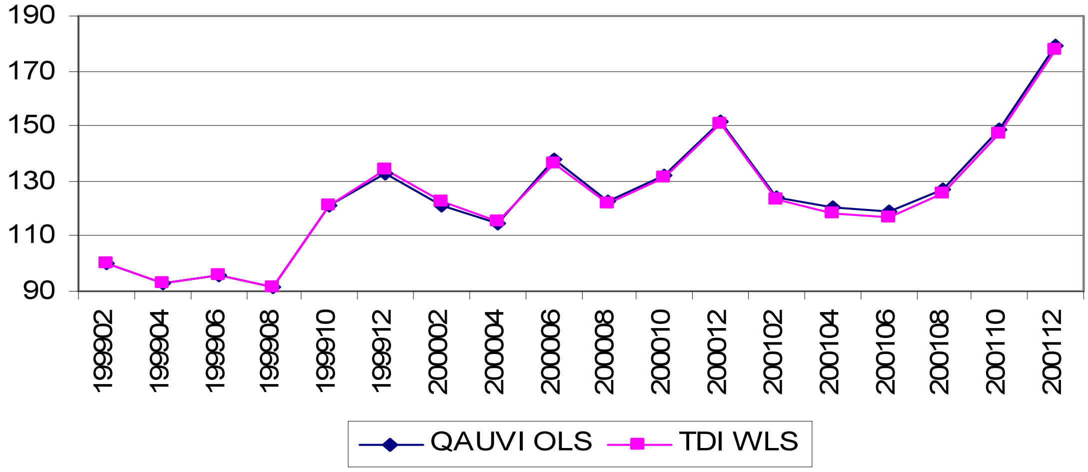

Figure 7. Implicit quantity indexes of televisions (Jan-Feb 1999=100)

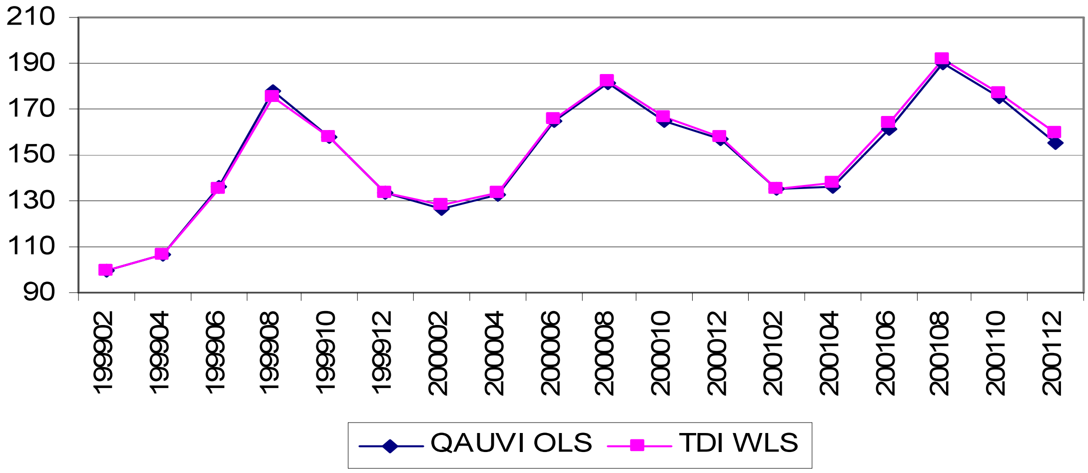

Figure 8. Implicit quantity indexes of refrigerators (Jan-Feb 1999=100)

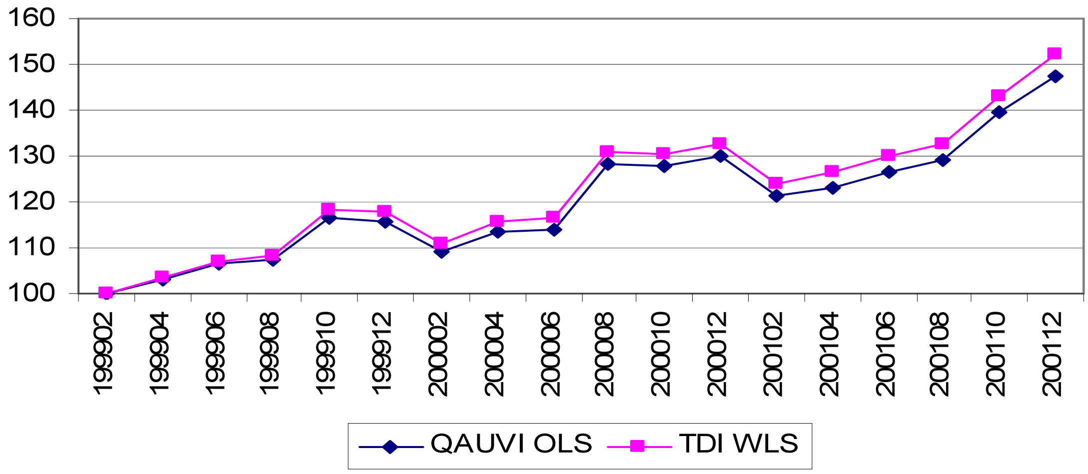

Figure 9. Implicit quantity indexes of washing machines (Jan-Feb 1999=100)

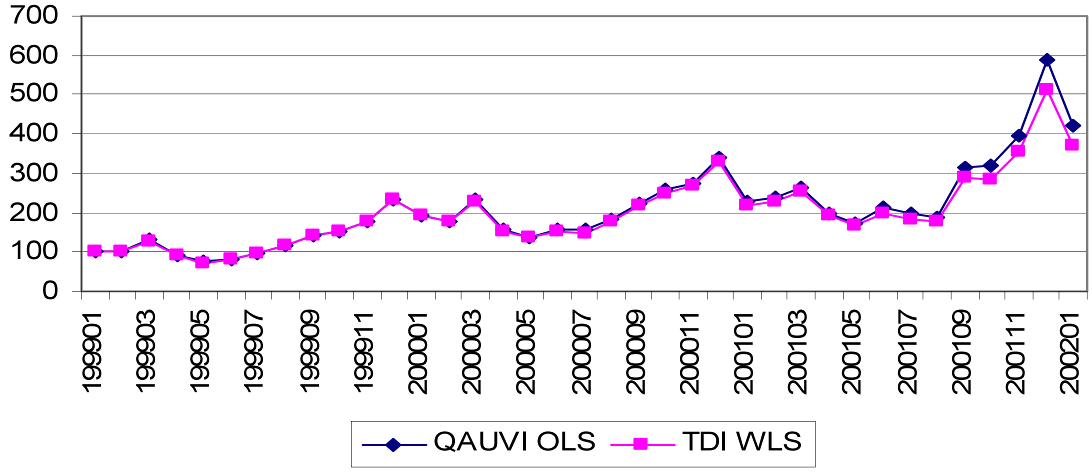

Figure 10. Implicit quantity indexes of computers (Jan 1999=100)

6. CONCLUDING REMARKS

This paper discusses the usefulness of a so-called quality-adjusted unit value index as an alternative measure of aggregate price change. Essentially the idea is that the quantities of commodities or models 'serving the same basic purpose' (that is, models for which the same hedonic function holds) can be added after expressing them in constant-quality units (of a numéraire). I leave it up to index number theorists to decide whether this idea is acceptable or not. But there are some disadvantages that need attention.

First, to justify the approach the characteristics parameters of the hedonic model must be constant over time, at least between adjacent short periods. Although in practice the assumption of constant parameters does not seem very restrictive, it is a disadvantage compared with hedonic imputation price indexes. Second, the estimation of the quality-adjusted unit value index is very data demanding: it needs data on prices, quantities or expenditures, and characteristics for each period. For practical purposes it would not be necessary to have data for the whole population, but a fairly large sample seems to be called for to avoid highly volatile time series. Third, and most importantly, the approach is model based. The quality-adjustment factors cannot be observed directly and must be estimated using the hedonic model. As no model is perfect, the estimator of the quality-adjusted unit value index is not design unbiased. This of course also applies to hedonic price indexes. The problem is that the quality-adjusted unit value index uses hedonics even if all models were matched. It would be better to have a (non parametric) measure of price change which is fully based on actual price and quantity observations and does not rely on econometric modelling when there are no new and disappearing models.

To assess the quality-adjusted unit value index it is useful to have another look at the (WLS) time dummy index. The latter index suffers from the first two drawbacks too but not from the third, provided that the regression weights for the matched models are the same in both periods (Van der Grient and De Haan, 2003). Equal weighting, i.e. the use of OLS, satisfies this condition as does Diewert's (2003b) proposal. By using OLS, for example, the time dummy index would equal the unweighted geometric mean matched-model index. What, then, might be the justification for using the quality-adjusted unit value index instead of the time dummy index?[15]

Most importantly, the quality-adjusted unit value index does not rely on imputed values for the 'missing prices', which was the motivation behind this paper. The time dummy index, on the other hand, does implicitly depend on such imputations. Let w_i^t denote the regression weight for item *i* in period *t*. De Haan (2004b) has shown that under the restriction of constant regression weights $w_i^0 = w_i^1 = w_i$ for the matched models, the WLS time dummy index $P_{I,TD}^{01}$ can be decomposed as

$$P_{I,TD}^{01} = \exp(\hat{\delta}) = \left[\prod_{i \in I_M^{01}} \left(\frac{p_i^1}{p_i^0} \right)^{w_i} \prod_{i \in I_D^0} \left(\frac{\hat{p}_i^1}{p_i^0} \right)^{w_i^0} \prod_{i \in I_N^1} \left(\frac{p_i^1}{\hat{p}_i^0} \right)^{w_i^1} \right]^{\frac{1}{w_M + w_D^0 + w_N^1}}, \quad (11)$$

where $w_M = \sum_{i \in I_M^{01}} w_i$, $w_D^0 = \sum_{i \in I_D^0} w_i^0$, and $w_N^1 = \sum_{i \in I_N^1} w_i^1$. From decomposition (11) it can immediately be seen that, in order to interpret $\exp(\hat{\delta})$ as a 'genuine' price index, the regression weights should be some form of (average) expenditure shares, possibly following Diewert (2003b).[16] However, a WLS procedure may not be optimal from an

[15] As mentioned earlier, the quality-adjusted unit value index reduces to the ordinary unit value index if all models had identical characteristics, which does not hold for the time dummy index and other hedonic price indexes. But this advantage disappears if items had been identified by their characteristics instead of the model numbers or bar codes.

[16] De Haan (2004b) shows that, when the regression weights are properly chosen, the WLS time dummy index can be interpreted as a special case of the Törnqvist index where the 'missing prices' are imputed. It is furthermore argued that the set of weights proposed by Diewert (2003b) overstates the impact of new and disappearing models. This follows directly from equation (11). Silver and Heravi (2004) discuss the difference between the Törnqvist index in which the prices of all models (including the matched ones) are estimated from an hedonic model and the time dummy index.

econometric point of view. It might introduce heteroskedasticity and thus raise the standard errors of the estimators. Also, weighting can give rise to bias if the weights are not exogenous. Expenditure shares are not exogenous since they implicitly contain the explained variable (price). The quality-adjusted unit value index does not depend on a specific type of WLS. Weighting is motivated by econometric rather than by index number considerations. Moreover, it can be argued that this approach applies hedonics for which it is meant in the first place: to explain price differences in a *cross section*. The pooling of data has merely been done to constrain the coefficients to be the same in both periods, thereby saving degrees of freedom. When looking at the empirical results, and especially when focussing on the quantity index numbers, the choice between the quality-adjusted unit value index and Diewert's WLS time dummy index does not seem that important after all.

In the introduction the question was raised whether the use of the quality-adjusted unit value index might help to overcome the practical problem of finding annual expenditure weights for models that are available less than a year. It would be necessary to estimate a quality-adjusted unit value for the base year instead of a base month. The difficulty is that we have to assume constancy of the parameters throughout the year. Except for PCs we tested this very stringent assumption and had to reject it (Van der Grient, 2004). So the quality-adjusted unit value index is not of much use in this respect.

APPENDIX: REGRESSION RESULTS

*Table 2. Televisions; pooled OLS semi-log regressions**)

Variable	199902/04 Coefficient	Standard error	200002/04 Coefficient	Standard error	200102/04 Coefficient	Standard error
(Intercept)	**4.783**	0.033	**4.651**	0.035	**4.604**	0.036
Time dummy	**-0.025**	0.005	-0.012	0.006	**0.008**	0.006
Technical characteristics						
Diameter	**0.050**	0.001	**0.052**	0.001	**0.053**	0.001
Scrtype2	**0.049**	0.012	**0.076**	0.013	**0.061**	0.014
Syst2	0.012	0.010	0.006	0.009	0.016	0.010
Syst4	**0.065**	0.015	0.023	0.015	0.029	0.015
Syst6	**0.061**	0.026	**0.080**	0.034	0.010	0.050
Syst7	0.048	0.025	0.028	0.029	0.038	0.034
Syst8	**0.129**	0.028	-0.056	0.042	-0.064	0.062
Model1	0.002	0.008	0.016	0.010	-0.016	0.012
S_vhs1	**0.067**	0.008	-0.003	0.008	**0.018**	0.008
Nicam1	0.010	0.010	0.015	0.009	-0.007	0.009
Scratio2	**0.223**	0.009	**0.229**	0.009	**0.205**	0.010
Freq100	**0.316**	0.011	**0.343**	0.011	**0.335**	0.011
Wattage	**0.003**	0.000	**0.002**	0.000	**0.002**	0.000
Dolby1	0.026	0.015	0.025	0.013	**0.049**	0.012
Portab	**0.062**	0.013	**0.079**	0.015	**0.099**	0.016
Sound0	**-0.143**	0.012	**-0.164**	0.014	**-0.142**	0.015
Text0	**-0.222**	0.015	**-0.191**	0.016	**-0.191**	0.017
Text1	**-0.081**	0.011	**-0.064**	0.011	**-0.052**	0.010
Text3	**0.112**	0.014	**0.082**	0.014	**0.034**	0.012
Flatscr	**0.322**	0.019	**0.301**	0.014	**0.331**	0.010
Pip1	**0.062**	0.024	0.031	0.031	0.030	0.034
Mltpip1	**0.080**	0.025	-0.014	0.022	**0.101**	0.019
Mltpip2	0.023	0.015	**-0.035**	0.016	**0.036**	0.015
Freez1	**0.055**	0.017	0.034	0.020	-0.006	0.016
Sattune1	**-0.175**	0.044	-0.043	0.074	**-0.410**	0.158
Dvd					**0.596**	0.093
Remote0	-0.046	0.056	**0.204**	0.073		
Pc_conn	0.070	0.041	**0.173**	0.053	0.090	0.069
Brand dummies						
Brand1					**-0.075**	0.036
Brand2	**-0.070**	0.017	**-0.112**	0.018	**-0.131**	0.026
Brand3	**-0.232**	0.034	**-0.285**	0.033	**-0.198**	0.034
Brand4	**1.178**	0.039	**1.357**	0.045	**1.484**	0.043
Brand5	**-0.257**	0.068	**-0.244**	0.070	**-0.209**	0.071
Brand6			0.022	0.103	0.117	0.158
Brand7	**-0.144**	0.017	**-0.177**	0.019	**-0.175**	0.021
Brand8	**-0.265**	0.020	**-0.294**	0.022	**-0.455**	0.037
Brand9					**-0.092**	0.039
Brand10	**0.046**	0.015	**0.073**	0.016	**0.113**	0.017
Brand11			**-0.498**	0.103	**-0.358**	0.066

Brand12	**0.146**	0.019	0.032	0.018	**0.076**	0.019
Brand13	**0.608**	0.045	**0.673**	0.047	**0.741**	0.048
Brand14			**-0.112**	0.025	**-0.121**	0.021
Brand15	**0.330**	0.021	**0.493**	0.020	**0.525**	0.019
Brand16	0.025	0.019	**0.135**	0.033	**0.143**	0.061
Brand17	-0.058	0.127			0.056	0.159
Brand18			-0.166	0.103	**-0.208**	0.080
Brand19	**0.073**	0.016	**0.066**	0.016	**0.082**	0.017
Brand20	**0.077**	0.013	**0.080**	0.013	**0.098**	0.014
Brand21			**-0.224**	0.060	-0.092	0.080
Brand22			**-0.336**	0.103		
Brand23	**-0.395**	0.127			**-0.443**	0.158
Brand24	**-0.120**	0.047	**-0.222**	0.044	**-0.170**	0.052
Brand25	**-0.223**	0.053	**-0.236**	0.061		
Brand26	**-0.201**	0.047	**-0.234**	0.061	-0.132	0.080
Brand27	**-0.088**	0.028	**-0.161**	0.050	**-0.282**	0.112
Brand28	**-0.053**	0.018	**-0.064**	0.017	-0.035	0.019
Brand29					**-0.367**	0.061
Brand30	**-0.120**	0.016	**-0.092**	0.017	**-0.072**	0.019
Brand31	**0.141**	0.018	**0.160**	0.019	**0.174**	0.020
Brand32	**-0.244**	0.036	**-0.262**	0.033	**-0.236**	0.046
Brand33	**-0.494**	0.065	**-0.446**	0.066	**-0.448**	0.080
Brand34	**0.411**	0.043	**0.083**	0.026	0.012	0.022
Brand35			**-0.340**	0.085	0.042	0.113
Brand36	**-0.194**	0.043	**-0.304**	0.038	**-0.255**	0.047
Brand37	**-0.299**	0.046	**-0.291**	0.044	**-0.456**	0.054
Outlet-type dummies						
Outlet1	**-0.071**	0.008	**-0.062**	0.008	**-0.090**	0.008
Outlet2	**0.037**	0.010	**0.041**	0.011	0.007	0.012
Outlet3	**-0.023**	0.008	-0.010	0.008	**-0.052**	0.008
Outlet4	**-0.063**	0.009	**-0.068**	0.011	**-0.159**	0.013
Adjusted R2	0.970		0.961		0.959	
SEE	0.126		0.144		0.157	
Number of cases	2237		2670		2919	
Number of variables	60		65		68	

*) Explanatory variables which are not incorporated into the model in those periods but are incorporated in other periods have been left out. Coefficients that differ significantly from zero at the 5% level are in bold.

*Table 3. Refrigerators; pooled OLS semi-log regressions**)

Variable	199902/04 Coefficient	199902/04 Standard error	200002/04 Coefficient	200002/04 Standard error	200102/04 Coefficient	200102/04 Standard error
(Intercept)	**5.397**	0.023	**5.430**	0.022	**5.379**	0.027
Time dummy	-0.009	0.007	0.003	0.007	0.010	0.009
Technical characteristics						
Doors_1	**0.053**	0.016	0.010	0.016	**0.059**	0.020
Doors_3	**0.436**	0.043	**0.392**	0.054	**0.397**	0.067
No_frost	0.001	0.029	**0.090**	0.027	0.048	0.033
Combi	**0.358**	0.021	**0.403**	0.022	**0.277**	0.025
Star_0	-0.023	0.016	**-0.069**	0.017	**-0.056**	0.020
Star_1	**-0.328**	0.034	**-0.302**	0.031	**-0.216**	0.048
Star_2	**-0.253**	0.022	**-0.210**	0.025	**-0.243**	0.035
Star_3	0.033	0.023	0.011	0.027	-0.030	0.044
Groscool	**0.002**	0.000	**0.003**	0.000	**0.003**	0.000
Grosfrez	**0.003**	0.000	**0.002**	0.000	**0.003**	0.000
Syst_2	**-0.093**	0.021	**-0.132**	0.022	-0.049	0.025
No_label	**-0.154**	0.026	**-0.168**	0.028	**-0.248**	0.038
X_label	0.006	0.093	0.064	0.169	0.156	0.101
B_label	**-0.094**	0.011	**-0.099**	0.010	**-0.093**	0.012
C_label	**-0.130**	0.013	**-0.102**	0.014	**-0.072**	0.018
D_label	**-0.181**	0.020	**-0.144**	0.023	**-0.101**	0.037
E_label	**-0.169**	0.033	**-0.075**	0.038	-0.046	0.050
F_label	**-0.229**	0.037	-0.130	0.071	**-0.202**	0.103
G_label	**-0.439**	0.061	**-0.249**	0.083	**-0.601**	0.093
A1_label	**0.076**	0.025	**0.126**	0.027	**0.148**	0.028
Brand dummies						
Brand1	**0.052**	0.020	-0.017	0.021	**-0.050**	0.024
Brand2	**-0.415**	0.054	**-0.521**	0.055	**-0.570**	0.089
Brand3	**0.302**	0.082	**0.426**	0.127	**0.336**	0.071
Brand4	-0.046	0.025	-0.056	0.031	-0.077	0.044
Brand5	**0.834**	0.062	**0.641**	0.065	**0.570**	0.068
Brand6			**-0.265**	0.047	**-0.340**	0.056
Brand7	**-0.054**	0.019	**-0.141**	0.021	**-0.171**	0.028
Brand8	**-0.191**	0.036	**-0.325**	0.040	**-0.322**	0.046
Brand9					**-0.458**	0.083
Brand10	-0.161	0.130			0.203	0.216
Brand11			-0.017	0.065	**-0.200**	0.036
Brand12	**-0.220**	0.034	**-0.172**	0.032	**-0.174**	0.033
Brand13	**-0.464**	0.036	**-0.483**	0.046	**-0.391**	0.067
Brand14	**-0.292**	0.040	**-0.460**	0.041	**-0.460**	0.047
Brand15	**-0.414**	0.131	**-0.415**	0.099	**-0.419**	0.126
Brand16					-0.080	0.091
Brand17	**-0.447**	0.049	**-0.496**	0.062	**-0.627**	0.109
Brand18	**-0.265**	0.022	**-0.299**	0.023	**-0.335**	0.028
Brand19	0.012	0.076	0.007	0.121	-0.139	0.216
Brand20	**0.243**	0.096	0.067	0.170	-0.055	0.217
Brand21	**-0.486**	0.035	**-0.558**	0.036	**-0.485**	0.048
Brand22					**-0.163**	0.068

Brand23	**-0.287**	0.022	**-0.352**	0.030	**-0.457**	0.034
Brand24	**-0.375**	0.046	**-0.377**	0.044	**-0.410**	0.055
Brand25					**0.635**	0.218
Brand26			**0.412**	0.171	**0.622**	0.218
Brand27					-0.208	0.216
Brand28	**0.375**	0.035	**0.340**	0.053	-0.052	0.089
Brand29			**-0.295**	0.099	**-0.246**	0.044
Brand30	**-0.401**	0.093				
Brand31	**-0.127**	0.028	**-0.249**	0.029	**-0.204**	0.049
Brand32			**-0.556**	0.120	**-0.756**	0.216
Brand33	**-0.251**	0.026	**-0.361**	0.034	**-0.388**	0.055
Brand34	**-0.361**	0.025	**-0.432**	0.024	**-0.504**	0.029
Brand35					-0.172	0.093
Brand36	**0.122**	0.016	**0.096**	0.018	**0.083**	0.021
Brand37	-0.015	0.021	-0.014	0.027	**-0.125**	0.036
Brand38	0.018	0.019	0.003	0.020	0.006	0.026
Brand39	**-0.202**	0.028	**-0.219**	0.031	**-0.272**	0.036
Brand40	**0.351**	0.028	**0.335**	0.035	**0.182**	0.049
Brand41	**-0.264**	0.048	**-0.365**	0.061	**-0.469**	0.069
Brand42	**-0.137**	0.047	**-0.143**	0.061		
Brand43	**-0.155**	0.025	**-0.331**	0.029	**-0.295**	0.035
Brand44	0.129	0.098	**0.196**	0.090	**0.259**	0.095
Brand45	0.005	0.014	**-0.043**	0.017	**-0.049**	0.021
Brand46	**0.893**	0.098	**0.800**	0.102	**0.706**	0.114
Brand47					**-0.801**	0.153
Brand48	**-0.142**	0.014	**-0.169**	0.017	**-0.247**	0.021
Brand49	**-0.157**	0.026	**-0.235**	0.028	**-0.269**	0.041
Brand50	**-0.139**	0.016	**-0.145**	0.017	**-0.196**	0.022
Outlet-type dummies						
Outlet1	**-0.064**	0.008	**-0.052**	0.010	**-0.074**	0.011
Outlet2	**0.040**	0.014	**0.034**	0.016	0.020	0.020
Outlet3	**0.027**	0.010	0.010	0.012	-0.013	0.017
Outlet4	**0.110**	0.027	**0.289**	0.026	**0.355**	0.030
Adjusted R2	0.932		0.903		0.857	
SEE	0.129		0.168		0.215	
Number of cases	1542		2041		2153	
Number of variables	64		67		74	

*) Explanatory variables which are not incorporated into the model in those periods but are incorporated in other periods have been left out. Coefficients that differ significantly from zero at the 5% level are in bold.

*Table 4. Washing machines; pooled OLS semi-log regressions**)

Variable	199902/04 Coefficient	Standard error	200002/04 Coefficient	Standard error	200102/04 Coefficient	Standard error
(Intercept)	**5.568**	0.024	**5.743**	0.024	**5.752**	0.026
Time dummy	-0.008	0.005	-0.003	0.006	0.007	0.006
Technical characteristics						
Rotspeed	**0.001**	0.000	**0.001**	0.000	**0.001**	0.000
Type_cw	**-1.398**	0.061	**-1.160**	0.059	**-1.139**	0.062
Type_l	**0.134**	0.009	**0.116**	0.010	**0.099**	0.010
Enerb	-0.002	0.007	**-0.061**	0.008	**-0.074**	0.009
Enerc	**-0.057**	0.012	**-0.050**	0.014	-0.033	0.019
Enerd	**-0.066**	0.030	0.004	0.031	0.060	0.042
Enere	-0.034	0.033	**-0.144**	0.046	-0.022	0.165
Enerf	0.143	0.089				
Centr_m	**-0.081**	0.008	**-0.081**	0.008	**-0.058**	0.008
Washresb	**-0.048**	0.008	**-0.092**	0.010	**-0.128**	0.010
Washresc	-0.021	0.014	**-0.064**	0.015	**-0.090**	0.017
Washresd	**-0.054**	0.026	0.022	0.037	-0.067	0.049
Washresf	**0.153**	0.065				
Washresg			**-0.226**	0.093	**-0.151**	0.073
Brand dummies						
Brand1			**-0.625**	0.064	**-0.744**	0.095
Brand2	**-0.233**	0.022	**-0.379**	0.030	**-0.324**	0.033
Brand3	**0.227**	0.025	**0.288**	0.032	**0.305**	0.056
Brand4			**-0.294**	0.053	**-0.189**	0.056
Brand5	**-0.116**	0.013	**-0.118**	0.013	**-0.087**	0.014
Brand6	**-0.398**	0.064	**-0.407**	0.090	**-0.437**	0.049
Brand7	**0.093**	0.024				
Brand8	**-0.485**	0.108	**-0.602**	0.065		
Brand9	0.007	0.011	-0.008	0.012	**-0.028**	0.013
Brand10	-0.053	0.063	**-0.075**	0.027	**-0.143**	0.018
Brand11	**-0.286**	0.019	**-0.344**	0.019	**-0.327**	0.020
Brand12			**-0.654**	0.128	**-0.558**	0.078
Brand13	**-0.128**	0.055	**-0.395**	0.064	**-0.372**	0.078
Brand14					**-0.349**	0.095
Brand15					**-0.302**	0.043
Brand16	**-0.329**	0.035	**-0.385**	0.041	**-0.378**	0.056
Brand17	**-0.368**	0.017	**-0.460**	0.018	**-0.379**	0.021
Brand18	-0.054	0.035	**-0.351**	0.057	**-0.248**	0.068
Brand19					**0.396**	0.135
Brand20					**-0.197**	0.056
Brand21	**-0.410**	0.043	**-0.416**	0.049	**-0.320**	0.136
Brand22	**-0.173**	0.063	-0.136	0.127		
Brand23	**-0.258**	0.025	**-0.269**	0.034	**-0.366**	0.033
Brand24	**-0.359**	0.109	**-0.486**	0.090		
Brand25	**-0.321**	0.041	**-0.437**	0.041	**-0.432**	0.070
Brand26	**-0.433**	0.017	**-0.505**	0.019	**-0.467**	0.017
Brand27					**-0.099**	0.036
Brand28	**-0.106**	0.022	**-0.129**	0.024	**-0.120**	0.031

Brand29	**0.284**	0.011	**0.263**	0.012	**0.316**	0.013
Brand30	**-0.304**	0.024	**-0.383**	0.027	**-0.282**	0.026
Brand31	**-0.436**	0.077			**-0.460**	0.068
Brand32	**-0.730**	0.055	**-0.736**	0.074	**-0.813**	0.068
Brand33	**-0.418**	0.040	**-0.496**	0.074	**-0.567**	0.134
Brand34	-0.107	0.108				
Brand35	**-0.273**	0.024	**-0.357**	0.021	**-0.365**	0.021
Brand36	**0.052**	0.012	0.003	0.012	**-0.052**	0.013
Brand37	**-0.153**	0.065	**-0.206**	0.082	-0.059	0.087
Brand38	**-0.268**	0.015	**-0.247**	0.016	**-0.230**	0.016
Brand39	**-0.063**	0.017	**-0.090**	0.020	**-0.113**	0.023
Brand40	**-0.220**	0.013	**-0.270**	0.016	**-0.213**	0.017
Outlet-type dummies						
Outlet1	**0.066**	0.007	**0.075**	0.007	**0.079**	0.007
Outlet2	**0.128**	0.010	**0.158**	0.011	**0.117**	0.012
Outlet3	**0.067**	0.008	**0.069**	0.009	**0.066**	0.010
Adjusted R2	0.919		0.894		0.863	
SEE	0.108		0.126		0.134	
Number of cases	1562		1814		1845	
Number of variables	50		49		52	

*) Explanatory variables which are not incorporated into the model in those periods but are incorporated in other periods have been left out. Coefficients that differ significantly from zero at the 5% level are in bold.

Table 5. Computers; pooled OLS semi-log regressions)*

Variable	199901/02 Coefficient	199901/02 Standard error	200001/02 Coefficient	200001/02 Standard error	200101/02 Coefficient	200101/02 Standard error
(Intercept)	**6.188**	0.074	**6.035**	0.090	**6.507**	0.041
Time dummy	**-0.035**	0.015	0.007	0.012	**-0.034**	0.011
Technical characteristics						
Speed	**0.002**	0.000	**0.002**	0.000	**0.001**	0.000
Hdisk	**0.000**	0.000	**0.000**	0.000	**0.000**	0.000
Memory	**0.002**	0.000	**0.002**	0.000	**0.001**	0.000
Monitor	**0.141**	0.020	**0.179**	0.021	**0.730**	0.037
Workstat	**0.255**	0.119	**0.374**	0.060	**0.494**	0.048
Usb	0.035	0.036	-0.003	0.061		
Processor1	**0.596**	0.161				
Processor2			-0.014	0.035	**-0.064**	0.020
Processor3	**-0.212**	0.026	**-0.185**	0.018	**-0.222**	0.017
Processor4	**-0.228**	0.040	**-0.198**	0.062	-0.052	0.071
Processor5			**-0.074**	0.024	**-0.118**	0.040
Processor6					-0.234	0.135
Processor7					**-0.096**	0.027
Processor8	-0.042	0.107				
Processor9					-0.169	0.101
Processor10	-0.283	0.263	-0.406	0.234		
Processor11	**-0.219**	0.030	**-0.235**	0.025	**-0.149**	0.028
Processor12			-0.127	0.226		
Processor13	**-0.258**	0.040	**-0.374**	0.076	0.032	0.158
Processor14	**-0.352**	0.059	**-0.275**	0.082	**-0.914**	0.208
Processor15	**-0.300**	0.055	**-0.224**	0.074		
Processor16	-0.039	0.065	**0.288**	0.126	**-0.665**	0.221
Processor17	0.074	0.110				
Processor18			0.191	0.171		
Processor19	**-0.126**	0.038	**-0.225**	0.070		
Processor20	**0.538**	0.263				
Processor21	**0.755**	0.262				
Processor22	**0.351**	0.057	0.080	0.052	**-0.547**	0.051
Processor23			**0.658**	0.064	**0.519**	0.051
Brand dummies						
Brand1	0.014	0.072	0.019	0.049	-0.031	0.086
Brand2			0.058	0.095		
Brand3	**-0.060**	0.028	**-0.114**	0.021	**-0.130**	0.019
Brand4	-0.468	0.266				
Brand5	0.169	0.090	-0.079	0.059	**-0.171**	0.030
Brand6					**-0.385**	0.039
Brand7	**-0.228**	0.041	**-0.207**	0.049	**-0.099**	0.029
Brand8	-0.008	0.057	0.049	0.040	-0.038	0.030
Brand9	**0.069**	0.029	**-0.078**	0.026	**-0.119**	0.058
Brand10	-0.273	0.261	-0.128	0.226		
Brand11	**-0.125**	0.037	**-0.150**	0.034	**-0.211**	0.036
Brand12	**-0.198**	0.053	-0.076	0.070		
Brand13			0.068	0.104	**-0.619**	0.208

Brand14	-0.038	0.028	**-0.054**	0.020	-0.026	0.018
Brand15	-0.259	0.279	0.233	0.162		
Brand16	**-0.162**	0.052	**0.083**	0.036		
Brand17	0.041	0.047	0.031	0.042	-0.065	0.121
Brand18	**-0.434**	0.044	**-0.409**	0.054	**-0.369**	0.033
Brand19	**-0.466**	0.103	**-0.564**	0.232		
Brand20	-0.323	0.186	-0.016	0.071	0.284	0.148
Brand21					-0.083	0.067
Brand22	**-0.200**	0.061	0.033	0.052	**-0.111**	0.046
Brand23	0.181	0.259	-0.063	0.160	-0.244	0.147
Brand24			**-0.344**	0.061	**-0.306**	0.068
Outlet-type dummies						
Outlet1	0.056	0.039	**0.082**	0.030	**0.090**	0.025
Outlet2	0.006	0.023	**0.044**	0.019	**0.067**	0.017
Outlet3	-0.009	0.028	**-0.085**	0.026	**0.105**	0.026
Outlet4	0.010	0.027	**-0.070**	0.020	0.005	0.020
Outlet5	**0.099**	0.035	**0.076**	0.026	**0.081**	0.023
Outlet6					0.017	0.208
Adjusted R2	0.639		0.712		0.711	
SEE	0.257		0.224		0.206	
Number of cases	1269		1394		1459	
Number of variables	47		49		43	

*) Explanatory variables which are not incorporated into the model in those periods but are incorporated in other periods have been left out. Coefficients that differ significantly from zero at the 5% level are in bold.

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