An Almost Ideal Hedonic Price Index for Televisions

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Abstract: The time dummy approach, where the hedonic model is estimated by (a certain type of) weighted least squares regression, implicitly leads to a generalised Törnqvist price index. We present a decomposition of this almost ideal index and investigate when it reduces to the matched-model Törnqvist index. The analysis is illustrated using scanner data for televisions during the period 1999-2001. The matched-model price index appears to approximate the generalised version quite well.

Keywords: consumer price index, hedonic regression, scanner data.

1. Introduction

Statistics Netherlands is conducting research into the treatment of durable goods in the Consumer Price Index (CPI); see Van der Grient (2001) for the project plan. One of the aims is to investigate how to incorporate scanner data (obtained directly from retailers) for household appliances and electronic equipment. The central question is whether hedonic quality adjustments are necessary or a matched-model approach suffices. This question can only be answered properly if we had a benchmark at our disposal. By this we mean a price index for the population – so that sampling aspects do not come into play – which has been constructed using a sound methodology, including hedonic quality adjustments. This paper addresses the compilation of such a benchmark index for televisions.

One of the methods to compile a hedonic price index is the time dummy approach. We will consider two periods, denoted by 0 and 1. The semi-log (log-linear) hedonic model reads

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

where p_i^t denotes the price of model (good) i in period t, x_{ik} its k-th characteristic (k= 1,…,K), β_k the corresponding parameter, ε_i^t an error term with an expected value of zero, and D_i^t a dummy variable that takes on the value of 1 when the observation comes from period 1 (otherwise 0). Notice that the β_k's are assumed constant over time. This restriction does not pose a serious problem if 0 and 1 are adjacent, short periods. Model (1) will be estimated by least squares regression on the pooled data from both periods. The estimated or

[1] The views expressed in this paper are those of the author and do not necessarily reflect the policies of Statistics Netherlands.

predicted price of i is $\hat{p}_i^t$, the residual $u_i^t = \ln(p_i^t) - \ln(\hat{p}_i^t) = \ln(p_i^t / \hat{p}_i^t)$. The antilogarithm (exponential) of the time dummy coefficient $\hat{\delta}$ yields a quality-adjusted price change.

In most empirical studies Ordinary Least Squares (OLS) has been used to estimate (1). Silver (2002) criticises this approach. Because this particular hedonic technique directly estimates a price index, the observations should be weighted according to their economic importance. Thus, a certain type of Weighted Least Squares (WLS) is needed. Diewert (2002) suggests to use the average expenditure shares as weights in the WLS-procedure for a model that has been sold in both periods. If there happen to be no new or disappearing models, in which case there are only matched models, the WLS-estimator coincides with the Törnqvist index. For new and disappearing models, which are by definition available in one period only, the expenditure shares relating to that period should serve as weights. According to Diewert the resulting WLS-estimator provides a generalisation of the Törnqvist index. Since the Törnqvist index belongs to the class of superlative indexes, we take it for granted that his choice for the weights, when applied to the whole population, leads to the desired benchmark price index.

In this paper we analyse the difference between the generalised Törnqvist index and its matched-model counterpart. The second one is much easier to construct because product characteristics do not have to be collected. Section 2 derives a general expression for the WLS time dummy price index and formulates two requirements which the weights must satisfy. By doing so it will immediately become clear why Diewert's choice is the most logical one. Next we show under what assumption the generalised Törnqvist price index can be written as the product of the matched-model Törnqvist price index and a factor containing the average residuals of new and disappearing models. Section 3 illustrates the decomposition using scanner data for televisions. Section 4 concludes.

2. The WLS time dummy price index

2.1 A decomposition

We will start by introducing some notation. U^t denotes the population of models belonging to a certain product group in period t (t= 0,1). The matched population is defined as $U_M = U^0 \cap U^1$; it is assumed throughout that $U_M \neq \emptyset$. U_D is that part of U^0 that is no longer available in period 1 (the disappearing part), and U_N is that part of U^1 that did not exist in period 0 (the new part). Regression model (1) will be estimated by WLS, in which w_i^0 en w_i^1 denote the weights for $i \in U^0$ and $i \in U^1$, respectively. Since the regression residuals sum to zero in each period, the following relation holds:

$$\prod_{i \in U_M} \left(\frac{p_i^0}{\hat{p}_i^0} \right)^{w_i^0} \prod_{i \in U_D} \left(\frac{p_i^0}{\hat{p}_i^0} \right)^{w_i^0} = \prod_{i \in U_M} \left(\frac{p_i^1}{\hat{p}_i^1} \right)^{w_i^1} \prod_{i \in U_N} \left(\frac{p_i^1}{\hat{p}_i^1} \right)^{w_i^1} = 1. \tag{2}$$

After some rearranging and substitution of $\hat{p}_i^1 / \hat{p}_i^0 = \exp(\hat{\delta}_{WLS})$ for $i \in U_M$ we obtain the following general expression for the WLS time dummy price index:

$$P_{TD} = \exp(\hat{\delta}_{WLS}) = \prod_{i \in U_M} \left(\frac{p_i^1}{p_i^0} \right)^{\frac{w_i^1}{w_M^1}} \prod_{i \in U_M} \left(\frac{p_i^0}{\hat{p}_i^0} \right)^{\frac{w_i^1 - w_i^0}{w_M^1}} \prod_{i \in U_N} \left(\frac{p_i^1}{\hat{p}_i^1} \right)^{\frac{w_i^1}{w_M^1}} \prod_{i \in U_D} \left(\frac{p_i^0}{\hat{p}_i^0} \right)^{\frac{-w_i^0}{w_M^1}}, \tag{3}$$

where $w_M^1 = \sum_{i \in U_M} w_i^1$.

A first requirement is that the resulting index should be wholly based on observed prices when there are no new or disappearing models. Quality changes do not occur in that case (although the quality mix usually does change because of changes in the quantities sold), and we want the outcome to be independent of the chosen set of characteristics. Yet the resulting price index is in a certain sense model dependent: it will automatically have a geometric structure due to the log-linear specification of the regression model, in which the weights play a crucial role. If $U^0 = U^1 = U_M$, then (3) reduces to

$$P_{TD} = \prod_{i \in U_M} \left(\frac{p_i^1}{p_i^0} \right)^{\frac{w_i^1}{w_M^1}} \prod_{i \in U_M} \left(\frac{p_i^0}{\hat{p}_i^0} \right)^{\frac{w_i^1 - w_i^0}{w_M^1}} = \prod_{i \in U_M} \left(\frac{p_i^1}{p_i^0} \right)^{\frac{w_i^1}{w_M^1}} \prod_{i \in U_M} \left[\exp(u_i^0) \right]^{\frac{w_i^1 - w_i^0}{w_M^1}} . \qquad (3')$$

The second factor of (3') contains the period 0 residuals. This factor depends on the choice of the characteristics and usually differs from 1. Hence, the first requirement will generally not be met. We therefore impose the restriction $w_i^0 = w_i^1 = w_i$ for $i \in U_M$, which assures that the time dummy index equals the matched-model index $P_M = \prod_{i \in U_M} (p_i^1 / p_i^0)^{w_i / w_M}$. Summarising: the use of time-dependent weights for the matched models, whether that be (relative) expenditures or quantities, must be avoided. No weighting at all of the observations, i.e. the use of OLS, does satisfy the requirement.

A second requirement is that the resulting index can be defended on the grounds of index number theory. This implies that the price relatives of the individual models must somehow be weighted by expenditure shares, and not for example by (relative) quantities. The use of OLS, which leads to the unweighted geometric or Jevons price index, is no longer an option. For the matched models we have expenditure shares of both period 0 and period 1, denoted by s_i^0 and s_i^1. For reasons of symmetry their unweighted average is a natural choice, which also meets the first requirement. This is precisely what Diewert (2002) proposes. For disappearing and new models we only have expenditure shares for period 0 and period 1, respectively. Substitution of $w_i^0 = w_i^1 = (s_i^0 + s_i^1)/2$ for $i \in U_M$, $w_i^0 = s_i^0$ for $i \in U_D$ and $w_i^1 = s_i^1$ for $i \in U_N$ in the general WLS expression (3) yields a decomposition of Diewert's generalised Törnqvist price index:

$$P_{GT} = \left(P_{MGL} \right)^{\frac{s_M^0}{s_M^0 + s_M^1}} \left(P_{MGP} \right)^{\frac{s_M^1}{s_M^0 + s_M^1}} \left[\exp(\bar{u}_N) \right]^{\frac{2(1 - s_M^1)}{s_M^0 + s_M^1}} \left[\exp(-\bar{u}_D) \right]^{\frac{2(1 - s_M^0)}{s_M^0 + s_M^1}} , \qquad (4)$$

where s_M^t denotes the period t share (t= 0,1) of the matched population in the total expenditure; $\bar{u}_N = \sum_{i \in U_N} s_i^1 u_i^1 \Big/ \sum_{i \in U_N} s_i^1$ and $\bar{u}_D = \sum_{i \in U_D} s_i^0 u_i^0 \Big/ \sum_{i \in U_D} s_i^0$ are the expenditure-weighted average residuals of new and disappearing models. The other part of (4) is the weighted geometric average of two matched-model price indexes: the geometric Laspeyres index $P_{MGL} = \prod_{i \in U_M} (p_i^1 / p_i^0)^{s_{iM}^0}$ and what we will call the geometric Paasche index $P_{MGP} = \prod_{i \in U_M} (p_i^1 / p_i^0)^{s_{iM}^1}$, with $s_{iM}^t = s_i^t / s_M^t$ being the share of i in the period t expenditures on all matched models.

2.2 *Two assumptions*

The matched-model Törnqvist price index is defined as the unweighted geometric average of P_{MGL} and P_{MGP}, i.e. $P_{MT} = (P_{MGL} P_{MGP})^{1/2}$. We need two assumptions to achieve that this index coincides with the generalised Törnqvist index:

Assumption *i*: $s_M^1 = s_M^0$.

Replacing s_M^1 by s_M^0 in decomposition (4) gives

$$P_{GT(i)} = P_{MT}\left[\exp(\overline{u}_N - \overline{u}_D)\right]^{\frac{1}{s_M^0}-1}. \tag{5}$$

Assumption *ii)*: $\overline{u}_N = \overline{u}_D$.

Under this assumption $P_{GT(i)}$ reduces to P_{MT}. Note that it is not the variability of the quality-adjusted prices of unmatched models that matters. Rather it is *systematic* effects – giving rise to positive or negative *average* residuals – that matter. Whether *ii*) holds depends on the prevailing market circumstances. Under perfect competition the 'law of one quality-adjusted price' predicts that the average residuals $\overline{u}_D$ en $\overline{u}_N$ will be (close to) zero. However, firms can try to reduce competition, for example through market segmentation. Also, consumers may not be completely informed or they may be faced with search costs. When such market imperfections exist it is conceivable that new and disappearing models have unusual prices, i.e. prices that are relatively high or low given their characteristics, so that assumption *ii*) becomes questionable. One possibility is that manufacturers or retailers manage to enforce 'hidden' price increases during the introduction of new models, so that $\overline{u}_N > 0$. Furthermore, old models may be sold at unusually low prices ('sales'), in which case $\overline{u}_D < 0$. If both phenomena occur simultaneously, the error caused by assumption *ii*) might be large. Of course, other situations can arise too.

While systematic differences between quality-adjusted prices are unlikely to occur under perfect competition, the law of one quality-adjusted price will not perfectly hold. At a given point in time there will be random differences. Indeed, one might even view these differences as evidence of heavy competition since firms compete by (temporarily) lowering their prices. Such short-term relative price decreases can cause substantial relative quantity changes. This makes the use of a superlative chain index formula like the Törnqvist particularly meaningful.

2.3 *Identification of goods*

An important topic, which has not been discussed so far, is how goods should be identified. Almost every consumer durable has a model (or type) number attached to it, which is usually available in scanner data sets. This number is in principle unique and can serve as an identification key. The set of matched models, for example, can be found by matching model numbers (in a certain outlet type) in adjacent periods. However, changes in model numbers do not necessarily imply real quality changes. A matched-model approach is problematic if model-number changes coincide with price changes. The effects should be visible in the average residuals of new models.

But what constitutes a genuine quality change? The hedonic hypothesis states that a good should be viewed as a specific combination of quality-determining attributes or characteristics; a correct hedonic model contains all characteristics that determine the performance of the good in question. From an economic point of view, therefore, it would be preferable to identify a good based on its characteristics. Models (model numbers) with identical characteristics – including outlet-specific conditions – yield the same utility to the consumer and are in fact identical goods.[2] A new good should be defined as a combination of characteristics that did not exist before. It may be a new combination of already existing characteristics or the addition of entirely new characteristics. The time dummy method permits adding (dummy variables for) new characteristics, which is an advantage compared to most other hedonic methods, in particular the hedonic imputation approach. It is most likely that the number of new and disappearing goods measured by their characteristics is smaller than the number of new and disappearing models, and the impact of hedonic modelling will diminish accordingly.

Despite its attractiveness we will not identify products based on their characteristics and restrict ourselves to identification by model numbers. This is because our study aims at finding practical solutions for implementing scanner data obtainable directly from Dutch retailers themselves, who are generally unable or unwilling to provide Statistics Netherlands with product characteristics.

3. An illustration on scanner data for televisions

3.1 The data and the hedonic model

For research purposes Statistics Netherlands has bought scanner data from market research company GfK for a limited number of durable goods. They refer to 18 two-month periods for the years 1999-2001. The data sets contain (per type of outlet) for all models many characteristics, unit values, and quantities sold. Expenditures and expenditure shares can easily be computed. One of the product groups is television sets. Van der Grient (2002) describes this group and compares the scanner data with the CPI data. We did some data cleaning and deleted models that were only sold incidentally. Still, as many as 24 773 observations (unit values per model per period per outlet type) remained in the televisions data set, covering 97.8% of total sales.

Van der Grient (2003) gives a thorough description of the selection of the hedonic model utilized in our study.[3] The model incorporates 71 explanatory variables, most of which are dummies. These include 29 technical characteristics (e.g. size of screen and availability of teletext), 38 brand names, and 4 outlet types. The R^2 was 0.96 in case of OLS, and 0.97 in case of WLS. Almost all coefficients were statistically significant and their signs accorded with a priori expectations. The assumption of constant coefficients during adjacent periods has been tested and was not rejected. As a matter of fact the coefficients for the most important technical characteristics appeared to be extremely stable over the entire three-year period.

The unit values indicated that the average price of television sets increased by 18%. This increase has nothing to do with inflation, however, but is due to the appearance on the market

[2] The unit value (average transaction price) over all relevant models sold in a particular outlet type then is the natural price concept.

[3] Regression results are available from the authors. Statistics Netherlands investigated earlier the possibility of estimating a hedonic model for TVs using data from a ‘price comparison website’ called Consumerdesk (Van der Grient and Oei, 2001).

of models with higher-valued characteristics. As will be shown below, quality-adjusted prices decreased by some 17%.

3.2 Results

Figure 1 clearly demonstrates the importance of weighting in the regression. Three different time dummy price indexes are shown: one using OLS, the second using WLS with time-specific expenditure shares serving as weights and the third using Diewert's WLS proposal.[4] The OLS version approximates the generalised Törnqvist index surprisingly well, although both series seem to diverge at the end of the period studied. The use of time-specific expenditure shares as weights, on the other hand, gives rise to upward bias.

The official CPI, which is presented in figure 1 for comparison, also overstates the generalised Törnqvist index.[5] One should bear in mind that the CPI methodology and the data used differ a lot from the time dummy indexes. The CPI is based on a sample of only 20 television models and is a Laspeyres-type index; the (constant) weights reflect the 1995 expenditure pattern. Moreover, explicit quality adjustments have not been carried out; a matched-model approach has been applied.

Figure 1: Price change of televisions; three time dummy indexes and the CPI

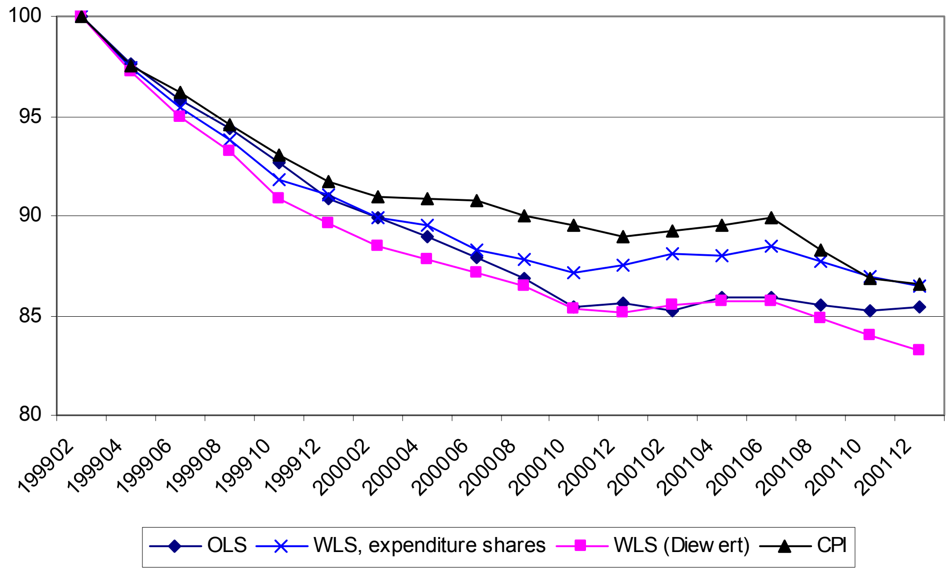


Table 1 decomposes the generalised Törnqvist price index according to expression (4). 'Factor L/P' denotes the weighted average of the matched-model Laspeyres and Paasche indexes and 'Factor residuals' denotes the remaining part of the right-hand side of (4). The latter appears to be negligible.

Table 2 shows for all adjacent periods the expenditure shares of the matched models in both period t-1 and period t to infer to what extent assumption i) $s^1_M = s^0_M$ holds. The matched

[4] All price index numbers can be found in appendix 1.
[5] Statistics Netherlands does not publish a separate CPI for television sets. We computed this index ourselves from the official CPI data.

expenditure share s_M^t in period t is on average about 95% and slightly smaller than the share s_M^{t-1} in the preceding period, which is on average about 98%. So while the shares are not exactly equal, the differences are very small.

Table 1: P_{GT} and factors of decomposition (4)

	P_{GT}	Factor L/P	Factor residuals
199902	100.00	100.00	1.000
199904	97.26	96.95	1.003
199906	94.97	94.87	1.001
199908	93.24	93.24	1.000
199910	90.86	91.10	0.997
199912	89.62	89.79	0.998
200002	88.43	88.72	0.997
200004	87.81	87.63	1.002
200006	87.16	87.31	0.998
200008	86.44	86.62	0.998
200010	85.31	85.76	0.995
200012	85.17	85.40	0.997
200102	85.55	85.70	0.998
200104	85.72	85.68	1.000
200106	85.75	85.74	1.000
200108	84.90	84.75	1.002
200110	83.99	84.08	0.999
200112	83.25	83.42	0.998

Table 2: Expenditure shares of the matched models in period *t*-1 and period *t*

t-1	*t*	s_M^{t-1}	s_M^t
199902	199904	0.98	0.95
199904	199906	0.98	0.98
199906	199908	0.98	0.95
199908	199910	0.99	0.93
199910	199912	0.98	0.96
199912	200002	0.98	0.98
200002	200004	0.97	0.97
200004	200006	0.98	0.95
200006	200008	0.98	0.95
200008	200010	0.97	0.93
200010	200012	0.97	0.95
200012	200102	0.99	0.98
200102	200104	0.97	0.97
200104	200106	0.98	0.97
200106	200108	0.98	0.97
200108	200110	0.98	0.95
200110	200112	0.98	0.98

Table 2 suggests that the bias caused by assumption *i*) will be small as well. This is indeed confirmed by table 3, which contains both factors from the right-hand side of decomposition (5). P_{MT} exceeds the weighted average of the geometric Laspeyres and Paasche indexes ('Factor L/P' in table 1) by no more than 0.02 index points in December 2001.[6] The impact on

[6] The geometric Paasche index turns out to be higher than the geometric Laspeyres index (86.25 against 80.73 in December 2001).

'Factor residuals' is somewhat larger and in the opposite direction. On balance $P_{GT(i)}$ exhibits a downward bias of 0.28 index points with respect to the generalised Törnqvist index.

Table 3: $P_{GT(i)}$ and factors of decomposition (5)

	$P_{GT(i)}$	P_{MT}	Factor residuals
199902	100.00	100.00	1.000
199904	97.01	96.95	1.001
199906	94.73	94.87	0.998
199908	92.99	93.25	0.997
199910	90.75	91.10	0.996
199912	89.44	89.79	0.996
200002	88.24	88.72	0.995
200004	87.61	87.63	1.000
200006	87.07	87.31	0.997
200008	86.34	86.63	0.997
200010	85.27	85.77	0.994
200012	85.01	85.42	0.995
200102	85.34	85.71	0.996
200104	85.48	85.70	0.997
200106	85.52	85.76	0.997
200108	84.56	84.77	0.998
200110	83.68	84.10	0.995
200112	82.97	83.44	0.994

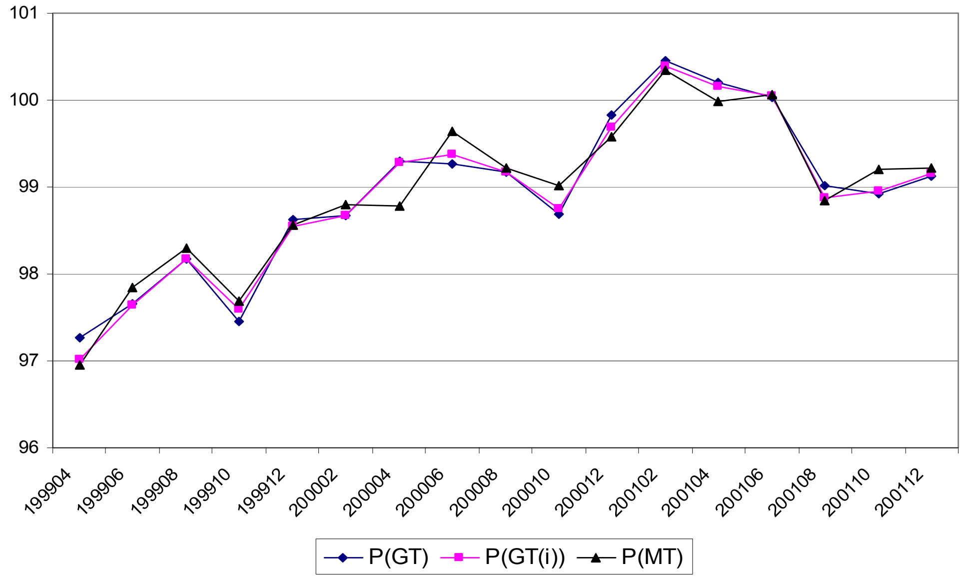
Table 4 shows to what extent assumption *ii*) $\bar{u}_N = \bar{u}_D$ holds. The average residuals fluctuate around zero but the positive values predominate. In general, the average residuals of the disappearing models exceed those of the new models. Assumption *ii*) more than offsets the downward bias caused by assumption *i*). In December 2001 the matched-model Törnqvist index (see table 3) overstates the generalised version by 0.19 index points.

Table 4: Weighted average residuals of new and disappearing models (assumption *ii*)

t-1	t	$\bar{u}_N$	$\bar{u}_D$
199902	199904	0.08	0.04
199904	199906	0.01	0.12
199906	199908	0.01	0.07
199908	199910	-0.02	0.04
199910	199912	0.04	0.04
199912	200002	0.03	0.10
200002	200004	0.12	-0.04
200004	200006	-0.03	0.10
200006	200008	0.00	0.03
200008	200010	-0.01	0.07
200010	200012	0.07	0.03
200012	200102	0.07	0.04
200102	200104	0.05	-0.02
200104	200106	-0.01	0.00
200106	200108	0.08	0.06
200108	200110	-0.01	0.11
200110	200112	-0.04	0.00

Both assumptions are thus approximately valid. This is again illustrated in Figure 2, which depicts the period-to-period changes of the generalised Törnqvist index and its approximations $P_{GT(i)}$ en P_{MT}.

Figure 2: Price indexes of televisions, changes with respect to the preceding period



4. Conclusion

The matched-model Törnqvist price index for televisions approximated Diewert's (2002) generalised Törnqvist index well during the years 1999-2001. There are two reasons for this: the expenditure share of the matched models was very high, and the average residuals of the new and disappearing models were small. This means that explicit quality adjustments were not necessary so that the matched-model Törnqvist index sufficed. This result seems fairly robust. In any case the average residuals did not display a striking pattern, not even during the turning point in the business cycle around 2000. In this respect it is a pity the data did not cover the conversion of the Dutch guilder to the euro in January 2002. That would have provided us with an additional check on the robustness of the results, since it is conceivable that markets were less transparent at that time.

Whether implementation in the CPI of scanner data for televisions – let alone for all electronic equipment – without hedonic quality adjustments is acceptable, remains debatable. We will repeat our exercise for video recorders, refrigerators, washing machines, and PCs. PCs in particular are a suitable test case, because the dynamics are far greater here than for the other commodity groups. However, even if we would find similar results, there is still no guarantee that the same will hold in the future. Note that Statistics Netherlands brings in new televisions almost always by initially assigning them the aggregate price change of the other models; see Van der Grient (2002). This method is known as linking, or bridged overlap in HICP jargon. We refer to it as a matched-model procedure, albeit not exactly a good one. Explicit quality adjustments for television sets are thus not made in current Dutch practice either, and an almost automatic procedure is applied.

Although Diewert's (2002) WLS time dummy index can be defended on the grounds of index number theory, we nevertheless make some critical remarks. First, the data may contain outliers that have a substantial influence on the outcome. This concerns especially outliers which receive large weights in the WLS procedure. Silver (2002) suggests to delete such influential outliers. We did not follow his suggestion as that might have affected the population character of the index too heavily. We did clean the database for obvious errors, though.

Second, weighting of observations is only necessary in order to interpret the antilog of the time dummy coefficient as a certain type of price index. In econometrics WLS is recommended if there is evidence of heteroskedasticity (non-constant variance of the errors). Diewert (2002) notes that the log-linear model is preferred over its linear counterpart, because heteroskedasticity is less likely in that case. WLS might now introduce heteroskedasticity. As such, this is not problematic: as long as the weights are exogenous, the estimators remain unbiased. The weights (expenditure shares) in Diewert’s procedure are not exogenous, however, since they contain the explained variable (price), which makes them stochastic variables. This introduces a bias in the WLS estimator.

Third, there seems to be an inconsistency in the time dummy approach, irrespective of the weighting procedure. The hedonic regression model should hold for all goods (TV models), both for matched models and new and disappearing ones. Is it then not a bit strange if the residuals of new and disappearing models exhibited a systematic pattern? De Haan (2003) proposes to incorporate dummy variables for those models. A drawback is that the antilogarithm of the time dummy coefficient can no longer be interpreted as a price index, so that one has to use the hedonic imputation method. Since this approach is controversial we did not try it.

So there is something to be said against the WLS procedure used on econometric grounds, the more so because the time dummy approach assumes constancy of the parameters. The generalised Törnqvist index may thus not be the final answer, but the advantages surely counterbalance the problems. The qualification ‘almost ideal’ seems in place – and that is what the title of our paper refers to.

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Appendix 1: Price index numbers for televisions (199902=100)

	P_{GT}	$P_{GT(i)}$	P_{MT}	WLS time dummy *)	OLS time dummy	CPI
199902	100.00	100.00	100.00	100.00	100.00	100.0
199904	97.26	97.01	96.95	97.42	97.57	97.5
199906	94.97	94.73	94.87	95.42	95.78	96.2
199908	93.24	92.99	93.25	93.84	94.42	94.5
199910	90.86	90.75	91.10	91.82	92.70	93.1
199912	89.62	89.44	89.79	91.02	90.87	91.7
200002	88.43	88.24	88.72	89.90	89.94	90.9
200004	87.81	87.61	87.63	89.53	88.91	90.8
200006	87.16	87.07	87.31	88.30	97.89	90.8
200008	86.44	86.34	86.63	87.82	86.90	90.0
200010	85.31	85.27	85.77	87.18	85.45	89.6
200012	85.17	85.01	85.42	87.51	85.64	89.0
200102	85.55	85.34	85.71	88.13	85.22	89.3
200104	85.72	85.48	85.70	87.99	85.87	89.5
200106	85.75	85.52	85.76	88.48	85.95	89.9
200108	84.90	84.56	84.77	87.75	85.57	88.3
200110	83.99	83.68	84.10	86.98	85.21	86.9
200112	83.25	82.97	83.44	86.45	85.45	86.6

*) Time-specific expenditure shares as weights.