Differences in Hedonic and Matched-Model Price Indexes: Do the Weights Matter?

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This note uses scanner data for over 60 segments of consumer information technology (IT) and electronic goods to construct matched-model indexes. Virtually all of the segment-level indexes constructed with these data show price declines that reflect quality increases—a typical exception is floppy disks, a category that shows price declines that reflect falling average prices. Our first pass at these data show that in all but nine of the categories, unweighted geometric mean price indexes falls faster than weighted superlative indexes (Fisher and Tornquist). Part of the reason for this appears to be that, within each segment, goods with relatively low market shares tend to show faster price declines than those with high market shares. Although it would be interesting to explore whether life-cycle effects over the life of each good also contribute to this result, the time-series dimension of our data is short and precludes an analysis of pricing over the product cycle.

Because dummy variable hedonic measures (DV) are also unweighted, our preliminary finding suggests that, all else held equal, DV indexes will tend to show faster price declines than their superlative counterparts. Of course, hedonic techniques arguably do a better job of capturing quality change and will tend to show faster price declines for that reason. Our only point is that maybe the weights matter too.

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1. INTRODUCTION

Price measurement poses two types of challenges: splitting out pure price change from quality change and aggregating over goods.[1] The literature on hedonic techniques emphasizes the first issue; there, the quality of a good is defined in terms of its characteristics, and for the dummy variable price index, the regression of prices on these characteristics allows one to hold quality constant and, thus, construct constant-quality price measures (Rosen(1974)). The literature on index number theory has focused on the aggregation issue; there, the emphasis is on using weights that are in some sense "ideal." This literature offers the so-called superlative indexes--like the Tornquist and the Fisher Ideal Indexes—that are "ideal" in that they possess properties that are superior to the alternatives (Diewert (1976)). Moreover, the Fisher Index has the advantage that it has a cost-of-living interpretation (Triplett(2004)). The simplest versions of these superlative indexes rely on the "matched-model" (MM) assumption to split out quality differences across goods and pure price change.

Many feel that this assumption does not provide an adequate means to capture quality change. Loosely speaking, the empirical evidence is consistent with this view. The stylized fact is that measures obtained from matched-model techniques typically show slower rates of quality increases than do hedonic-based measures, suggesting that hedonic techniques are able to better capture quality change than matched-model methods.[2] For goods whose constant-quality price indexes typically show price declines that reflect quality increases over time—like computers—the stylized fact is often stated as "matched-model indexes typically show slower rates of price decline than do hedonic-based indexes."

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[1] For a full discussion of these issues see the National Academy Report on Price Measurement (Schultze et. al.(2000) and the price measurement handbooks sponsored by the OECD (Triplett(2000)) and the ILO(Diewert(2004)).

[2] As discussed in Triplett's paper, differences can, and often do, go in the other direction. Nonetheless, the folklore is that matched-model indexes capture less quality change than hedonic methods and, indeed, most of the papers in Triplett's review find this.

Elsewhere in this volume, Jack Triplett carefully examines estimates reported in the literature to show that these methods can, and do, yield very different estimates of price change, even when constructed from the same data. His paper documents that price measures calculated using dummy variable (DV) price indexes obtained from hedonic regressions can be quite different from those obtained using superlative indexes calculated through either matched-model or imputation methods. His paper also provides an important summary of the theoretical factors that give rise to those differences, with an emphasis on how the different methods handle quality change.

This note complements Triplett's work by focusing on the other dimension to the problem: the weights used for aggregation. Matched-model and hedonic methods differ not only in how they handle quality change but also in how they aggregate over goods: DV price indexes are unweighted while superlative indexes use expenditure weights to aggregate over goods. Below, a first pass at scanner data for over 60 classes of consumer electronic and IT goods suggests that differences in the weights matter. In particular, for these data, unweighted indexes typically fall faster than expenditure-weighted indexes. Part of the reason for this seems to be that, within each segment, goods with a relatively low market share tend to show faster price declines than goods with a high market share. Although it would be interesting to explore whether life-cycle effects also contribute to this finding, the time-series dimension of our data is relatively short (three years for IT goods and two years for consumer electronics goods) and does not allow us to say much about pricing over the product cycle.[3]

Because the DV hedonic price index is also unweighted, our finding suggests that, all else held equal, DV indexes will tend to show faster rates of price declines than their superlative counterparts because they use different weights. Of course, because hedonic regressions do a better job of capturing quality change, one can expect hedonic indexes to show faster quality change and, thus, faster price declines than matched-model indexes. Our only point is that the weighting issue may also matter. Thus, in interpreting results reported in the literature, care should be taken to note not just the methods used to split out quality vs. pure price change, but also the particular weights used to aggregate over goods.

2. THE INDEXES

We begin by briefly reviewing the construction of DV price indexes and that of superlative indexes calculated using either matched-model or imputation method.

Unweighted Price Measures

The typical hedonic regression explains the prices of each variety or model of a good that is produced and sold at time t ($P_{m,t}$, m = 1 … M) as a function of the quantities of its characteristics ($C_{k,m,t,}$ k = 1, …K) and time dummy variables ($D_{m,t}$, t = 1, …T). Typically, the hedonic regression is specified with a semi- logarithmic functional form:

$$(1) \qquad \ln P_{m,t} = \Sigma_k \beta_k C_{k,m,t} + \Sigma_t \delta_t D_{m,t} + \varepsilon_{m,t}$$

where $D_{m,t}$ = 1 if a price for model m is observed at time t, and = 0 otherwise.

β_k and δ_t are econometric estimates and $\varepsilon_{m,t}$ is an error term. Each model has K characteristics that influence its price, and, in the general, the quantity of each characteristic in a model can change over time.

[3] See Silver and Heravi (2004) for an interesting discussion of firms' pricing strategies and their potential impact on the measurement of quality change.

As shown in Triplett and MacDonald (1977), Silver and Heravi (2000), Aizcorbe, Corrado and Doms(2000) and others, if goods are homogeneous—i.e., if characteristics don't change over the life of each good—then $C_{k,m,t} = C_{k,m,t-1}$, and the DV price index reduces to a weighted average of 1) a geometric mean for models that appear in both periods (i.e., a matched-model geometric mean) and 2) a term that adjusts that index for quality change associated with turnover. For example, in the case where a new good enters the market at time t, the (logged) DV measure may be stated as:

$$(2) \qquad \ln I_{t,t-1}^{DV} = \delta_t - \delta_{t-1} = (M_{t-1}/M_t)\,[\,\Sigma_{m\in M(t,t-1)}(\ln P_{m,t} - \ln P_{m,t-1})\,/\,M_{t-1}\,]$$

$$+(1/M_t)\,[\ln P_{N,t} - \Sigma_k\, ß_k C_{k,N,t}) - \Sigma_{m\in M(t,t-1)}(\ln P_{m,t-1} - \Sigma_k\, ß_k C_{k,m,t-1})\,/M_{t-1}]$$

where the M_s 's denote the number of goods sold at time s and $\Sigma_{m\in M(t,t-1)}$ denotes a sum taken over goods that were sold in both periods.

This expression shows that the DV measure is made up of two terms. The first term is a (logged) matched-model geometric mean:

$$(3) \qquad \ln I_{t,t-1}^{GEO} = \Sigma_{m\in M(t,t-1)}(\ln P_{m,t} - \ln P_{m,t-1})\,/\,M_{t-1}$$

This is a "matched-model" index because it only considers goods available in both periods (it only sums over goods for which prices are observed in both periods). That term is weighted by the share of goods available in both periods (M_{t-1}/M_t).

The second term adjusts the matched-model geomean for any quality change associated with the entry of the new good by comparing the quality-adjusted price of the new good at time t to the average quality-adjusted price of goods existing at time t-1. As discussed in Triplett(2004), differences in the treatment of quality change can generate differences between hedonic and matched-model indexes. In this context, the second term in (2) captures the difference between the price measure from the DV index (2) and the matched-model geometric mean (3).

Weighted Price Measures

Superlative indexes—like the Fisher and Tornquist indexes—use the relative importance of each good to aggregate price change over goods. The Tornquist index, for example, uses expenditure shares from time t-1 and t for aggregation. In logged form, the matched-model index is:

$$(4) \quad \ln I_{t,t-1}^{TORN} = \Sigma_{m\in M(t,t-1)} (\omega_{m,t} + \omega_{m,t-1})/2 \left(\ln P_{m,t} - \ln P_{m,t-1} \right)$$

where the expenditure weights are $\omega_{m,t} = P_{m,t}\, Q_{m,t} \,/(\Sigma_{m\in M(t,t-1)} P_{m,t}\, Q_{m,t})$. Note that the (logged) Tornquist in (4) and the Geometric mean index in (3) differ only in that the Tornquist is weighted while the Geomean is not and they are similar in that they are both matched-model indexes.

Similarly, a Fisher Index boils down to a function of weighted averages:

$$(5) \quad I^{FISHER}_{t,t-1} = [\, \Sigma_{m\in M(t,t-1)}\ \omega_{m,t-1} (P_{m,t} / P_{m,t-1}) / \Sigma_{m\in M(t,t-1)}\ \omega_{m,t} \ (P_{m,t-1} / P_{m,t})\,]^{1/2}$$

Although the functional forms for the Fisher and Tornquist are quite different, the two formulas typically yield very similar price measures.[4]

[4] See Ehemann(2004) for an important exception.

In all of these matched-model indexes, price change for each good (the price relative: ($P_{i,t} / P_{i,t-1}$)) provides a control for quality change *over the life of each good* only when the data are such that the "good" is homogeneous over time (i.e., its attributes don't change over time). In that case, the price relative compares prices while holding quality constant and the resulting index is a constant-quality index. The Achilles heel of MM methods, however, is in how they handle quality change that is associated with *the turnover of goods*. For example, in the formulas for the geomean, Tornquist and Fisher matched-model indexes in (3)-(5), price change for a new good is undefined because a price does not exist at time t-1, the period before the good was introduced. A similar problem arises when goods exit the market. The standard MM index ignores observations where one of the prices in the price relative is missing and uses only goods for which prices exist in both periods.

The imputation method combines hedonic and superlative approaches to adjust the matched-model indexes for this type of quality change. In particular, predicted values from a hedonic regression are used to predict unobserved prices when turnover occurs so that the price index can include all goods sold in either period (Pakes (2003) provides theoretical underpinnings to justify this approach).

To see this, suppose again that a new good enters at time t . In the case of the Tornquist index, for example, the imputation method measures price change from time t-1 to time t by including a predicted price for the new good at time t-1, $\rho_{N,t-1}$, in the Tornquist index formula:

$$(4') \quad \ln\ I_{t,t-1}^{TORNIM} = \Sigma_{m\in M(t,t-1)} (\omega_{m,t} + \omega_{m,t-1})/2\ (\ln P_{m,t} - \ln P_{m,-1})$$
$$+ (\omega_{N,t} + 0)/2\ (\ln P_{N,,t} - \ln \rho_{N,t-1})$$

The first term is similar to the matched-model Tornquist in that it sums only over matched models but is different in that the expenditure weights for all goods at time t now include the expenditures on the new good in the denominator: $\omega_{m,t}=P_{m,t}Q_{m,t}$ $/(\Sigma_{m\in M(all)} P_{m,t}\, Q_{m,t})$. The second term uses the imputed price for the new good to form the price relative.

As in Triplett (2005), a comparison of the matched-model and imputation-based Tornquist indexes in (4) and (4') would show how different treatments of quality change can affect the measure of price change. In (4'). the second term provides a direct measure of that effect.

Summary

Table 1 summarizes the four types of indexes discussed above. For our purposes, the question of interest is "To what extent does the use of different weights in hedonic vs. matched model indexes generate numerical differences in the price measures?" To get at this question, one can compare price measures that use the same method for quality change: the DV vs imputation Tornquist indexes or the Matched-model Geometric Mean vs. Tornquist indexes. In his analysis of existing studies, Triplett (2004) reports the results of studies that constructed both of these indexes using the same data and found that, in some cases, the unweighted DV index falls faster than the imputation hedonic (e.g., Lim and McKensie(2002) and vanMulligen(2003)) while in other cases they can be quite close (Dulberger(1989)).

In what follows, we take a more indirect approach to this issue and compare price change for Geometric and Tornquist matched model indexes. Evidence that the geometric means fall consistently faster than the Tornquist indexes would support the view that, all else held equal, DV indexes will tend to fall faster than Tornquist index constructed using the imputation method. As shown below, for the data used here, the (unweighted) Geometric means do tend to fall faster than the (weighted) Tornquist.

3. THE DATA

Scanner data on over 60 classes of consumer IT and consumer electronic goods sold at US retail outlets were used to assess this issue. Briefly, the data sets contain average prices and quantities for goods sold in US outlets that are tracked by a consulting firm called NPD Techworld (A data appendix contains a full description of the data). The prices are unit values averaged over outlets and time (to monthly frequencies) but are for highly granular products (at the "bar code" or "SKU" level). The consumer electronics data have been used by William Thompson for VCRs (BLS), Mary Kokoski, Keith Waehrer, and Patricia Rozaklis for consumer audio products, Ruder and To (for stereo receivers).

The data on IT products are described in table 2. Our goal is to construct matched-model indexes for adjacent observations and than chain those indexes to measure price change over a longer period of time. Thus, the feature of the data that is relevant for us is the degree to which model can be matched in adjacent periods.[5] Information on this point is given in the table: the total number of observations in each category (column 1), the percent of observation included in the matched model indexes (column 2), and the expenditure shares associated with the excluded observations (column 3). The remaining columns explain why the observations were excluded using expenditure shares: some observations represent the "birth" of the good (column 4), sometimes a particular model has no observation in the dataset (column 5), or a data point exists but the unit and dollar sales are listed as zeroes (column 6). Finally, as detailed in the appendix, when a model is sold in only a few outlets, the data are suppressed; in the IT dataset, those observations are shown together in an "All Other" category (column 7) while the consumer electronics database does not report the suppressed items.

As may be seen, the data cover a broad range of IT goods, components and peripherals over the thirty-six months ending in September 2004. The "quality" of the data varies across categories. An example of "good data" is the data on personal computers, where there are over 17,000 observations, about 60 percent of which can be included in the matched model indexes.

[5] This is very different from what is done by statistical agencies. If, instead, we were constructing indexes that use a fixed base, then issues of "sample degradation" (Silver and Heravi(2000) and selection bias (of the type discussed in Pakes(2003) would become relevant.

Though the number of excluded observations is high, they make up only about 20 percent of expenditures. Of the excluded observations, about 15 percent of expenditures represent births of new goods and another 2-1/2 percent represent data that were suppressed to prevent disclosure of the outlets; less than one percent of expenditures represent missing observations—cases where no items were sold in a period and, thus, generated an observation that can't be matched.

An example of "bad data" is the data for tape drives. Although there are about 1,000 observations, only 8 percent of the observations (making up about 7 percent of the market) could be used in the matched-model indexes. Most of the observations are excluded owing to disclosure problems—67 percent of expenditures—while another 10 percent represents births and another 10 percent or so are periods with no sales for specific products.

Table 2b provides similar information for the consumer electronics data. Note that, unlike in the IT file, this file excludes observations for which there is a disclosure problem.

4. MATCHED-MODEL INDEXES

These data were used to construct chained, matched-model Geometric and Tornquist indexes at monthly frequencies.[6] The indexes were constructed for each category (e.g., desktop PCs) and each month in the data set and the average price change across all periods is reported in Table 3a for IT goods and Table 3b for consumer electronics. Several points seem noteworthy.

First, for both IT goods and consumer electronics, the matched model indexes (shown in the first three columns of the tables) show declines for most of the categories. This indicates that, on average, prices for these goods are falling over time. This is consistent with recent reports based on highly granular point-of-sale data for durable goods ranging from televisions (Silver and Heravi (2004)), motor vehicles (Corrado, Dunn and Otoo(2004)), and memory chips (Aizcorbe, Corrado and Doms(2000)). But, here we also observe falling prices for less durable goods (floppy disks).

In fact, the result is fairly widespread and holds up across a broad array of goods. We see price declines for goods in relatively new and mature segments (PDAs and corded telephones); goods in fairly competitive as well as concentrated segments (memory cards and PCs), and both high-tech and relatively low-tech goods (PCs and calculators).

For personal computers—an area that has been studied extensively—the matched-model Tornquist calculated here for desktop computers falls at a compound annual growth rate of twenty-eight percent annual rate, well within the (wide) range of matched-model superlative indexes reported in the literature: previous studies report declines that range from –8.5 percent in Dulberger (1989) to –42.7 percent in Okamato and Sato (2001). Similarly, the matched-model Geometric mean index calculated here falls at about 40 percent per year, not far from the DV estimates reported in the literature for recent periods—DV indexes for PCs in the 1990s ranged from –31 to –52 percent—and a bit higher than the rates calculated for previous periods.

Quality Change vs. Pure Price Change

The sharp declines in the Tornquist index given in column 1 for computers and some of the underlying peripherals—like hard drives, scanners and printers—just verify what previous studies have found and seem intuitive given our knowledge of the rapid rates of innovation in those sectors. In other cases—like floppy disks or CD Media—the price indexes also show nontrivial monthly declines that could reflect quality increases or pure price declines. To assess the extent to which these declines represent quality change vs. demand and supply forces (like increased competition or a fall in demand), the change in an average price series is compared to the Tornquist index to get a crude measure of quality change. In particular, the change in the average price is defined as the (logged) change in a geometric mean of the price levels and shown in the fourth column. The difference between changes in this average price and the Tornquist index is defined

[6] The individual indexes are available from the authors.

as quality change and shown in the column 5. As may be seen, most of the declines in the Tornquist indexes reflect quality increases.

Importance of Weighting

A comparison of the matched-model Tornquist and (unweighted) geomean indexes provides information on the importance of weighting. Column 6 in tables 3a and 3b subtract the average declines in the Geomean (in column 3) from that of the Tornquist (column 1): a positive number indicates that the Geomean falls faster (rises slower) than the Tornquist. The result is also shown visually in Chart 1. For IT goods, in 27 out of 34 segments, the Geometric mean falls faster than the Tornquist index. In these cases, the differences (column 6) range from essentially zero for notebook PCs (line 2) to 1.8 percentage points for floppy drives. In the seven cases where the effect works in the other direction, the measured differences tend to be small—less than one percentage point—except for tape drives, a category where the data are thin. Similar results hold in the consumer electronics data.

Because the Geometric mean weights price change equally across goods and the Tornquist uses each good's average market share in the two periods, our finding reflects the fact that prices fall faster for observations with low market shares in these data. The top panel of chart 2 provides a scatter plot of the measured price change for each observation on personal computers—calculated as the logged price relative that enters into the Tornquist price index—plotted against the market share for that observation. As may be seen, prices fall more often than they rise—most observations lie below horizontal line at zero. The presence of both price increases and decreases at low market shares suggests that these relatively large price declines may just reflect the presence of sales in the data: the price relative for a sales month will show a decline while that in the following month will show a large price increase (as the discount is removed). There is some evidence that period sales are influencing the pattern in observations with low market shares: when price change in adjacent months are plotted in a scatter diagram, there appears to be a negative correlation between price change in adjacent months, consistent with the presence of sales in one month followed by a removal of the special in the next.

The feature of the data that generates geomeans that fall faster than the weighted indexes is that the observed price declines are larger for observations with low market share than for observations with high market share. Part of the reason for this seems to be that models with small market shares tend to show faster price declines than models with large market shares. The bottom panel provides a plot where data on the PC *observations* shown in the top panel have been aggregated over time to obtain measures for individual *models:* Each dot in the chart is a model's average price change and average market share over all periods that it is sold. As may be seen, the same pattern seen in the top panel seems to hold for individual models indicating that goods with lower market shares (perhaps the less popular goods) tend to show faster price declines.

Unfortunately, both of the datasets used here are fairly short (24-36 months) and do not allow a careful analysis of pricing over the life of each model to see if there are any systematic patterns in the market share and price relatives. Loosely speaking, based on observations where we observe the birth of the good, goods tend to come in at a high market share that falls back after a few months. At the same time, prices tend to fall over the life of the good. If these price declines are more pronounced once the goods' market shares have fallen, one would expect to see positive correlations between the price relatives and market shares.

An examination of these correlations showed no discernible pattern. For example, for desktop PCs, there were many models with positive correlations but almost just as many with negative correlations. Moreover, in many cases the correlations are not significantly different from zero.

Robustness of Results

We did further analysis to check whether two features of the data could be causing the geomeans to fall faster. First, the high degree of product granularity in the data gives rise to “spikes” in the price relatives for some of the observations. Although this occurs rarely—in less than one percent of the observations—one might be concerned that the outliers are nonetheless influencing the indexes. Second, as detailed in the appendix, the weekly data are organized into monthly data using the “Atkins Month Definition,” where the first, second and third weeks of the quarter include four, four and five weeks, respectively. This means that two of the monthly price indexes computed each quarter measure price change over periods with different number of weeks. This feature of the data may help explain the negative correlations seen in chart 1: the recorded price declines from a period of 4 weeks to one with 5 weeks will be greater than that from a period of 5 weeks to one with 4 weeks. In that sense, adjacent months that show largish price declines (from 4-5 week months) will be followed by smallish price declines (from 5-4 weeks). This feature of the data is potentially problematic in that it could potentially generate correlations between the expenditure weights and the price relatives that could distort the price indexes. (See Szulc (1983), Reinsdorf (1998) and Lent(2000) for a discussion of these issues).

However, our preliminary investigations suggest that our result is not affected by this feature of the data. To smooth the spikes in the data, we simply aggregated the monthly data at the SKU-level to annual data and construct annual price indexes. With regard to the unusual calendar used by NPD to report the data, we constructed price indexes where only 4/5 of the measured price change for the months that span 5 weeks is used in the index, which yields indexes that use equal time intervals to compare price change. Neither of these changes in the data overturned the result that unweighted indexes tend to fall faster than weighted ones.

SUMMARY

In these data, indexes that weigh price change equally across goods appear to fall faster than indexes that use expenditure weights. This suggests that one reason that DV indexes tend to fall faster than superlative indexes is that they use different weights. Of course, this hypothesis cannot be pinned down without undertaking hedonic analysis for each of the segments and making direct comparisons of the resulting DV indexes to the superlative indexes in table 3. That exercise is left for future work. In the meantime, the indirect evidence reported here suggests that doing so might provide useful information on the differential rates of decline in matched-model vs. hedonic measures.

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Data Appendix

The data are point-of-sale transaction data (i.e., scanner data) sent to NPD Techworld via automatic feeds from their participating outlets on a weekly basis.

- "Point-of-sale" means that any rebates or other discounts (coupons, for example) that occur at the cash register are netted out of the price; "mail in rebates" and other discounts that occur after the sale are not. Another potential source of variation in the transaction price is that it is net of any returns.
- Purchases made at NPD's participating outlets—retail establishments like Best Buys and Circuit City—will be reflected in the data, as will any catalog sales where the transaction occurs at an NPD retailer. Importantly, sales that occur directly to the consumer from manufacturers like Dell are not included in the NPD data.
- The data are suppressed when the sales of a particular model in a particular month came from fewer than five of NPD's retailers. Those observations are grouped together and reported as a model labeled "All Other." As discussed in the text, these observations are excluded because the attributes of the goods are not held constant over time for this "model." All sales for the outlet's own label are also grouped into a "model" labeled "Private label" to prevent disclosing the retailer. These observations are also excluded.
- The data also occasionally include sales of "refurbished" goods—models that were returned, sent to the manufacturer for any adjustments, and returned to the retail outlet for sale. These models are excluded from the data, as we wish only to measure sales of new models.
- The weekly data are organized into monthly data using the "Atkins Month Definition," where the first, second and third weeks of the quarter include four, four and five weeks, respectively. Because calendar years typically include 365 days and Atkins years only include 364, every six years or so, when the two calendars are off 0by exactly one week, NPD reports the extra week in the December.
- In a small number of cases, we found models with duplicate model numbers listed separately in the data. For those models that were listed in the same category, we used an aggregate of the data in the two entries (unit value as the revenues for both models divided by the unit sales of both). For those that were listed in separate categories, we treated the models as if they were separate goods.

Each observation in the NPD data is an aggregate of the transaction-level data for each barcode (or SKU) across outlets. As described in Kokoski et. al. (2000):

"The price and quantity observations supplied by NPD are national estimates. NPD receives data from a subset of all the outlets that sell consumer audio electronics products. The unit sales reported by these chains are then extrapolated to reflect national aggregate sales and expenditures. The extrapolation process is straightforward. First, the chains within the sample are categorized into channels. Then, the chains within each channel are assigned to cells depending on their total revenue and the number of stores in the chain. Each chain is then assigned an adjustment factor corresponding to the number of chains with similar size characteristics, nationally divided by the number of chains with similar characteristics in the NPD sample. This adjustment factor is used as a weight when aggregating chain level data on units sold and total expenditures. The average price reported for each model is then calculated by dividing total expenditures on that model by the total number of units of that model sold."

Below is a data point for a particular type of printer paper:

ID	INDSTRY	INDSEG	CATGRP	CATGORY	SUBCAT	TIMEPER	BRAND	MODELA	MODDESC	UNITS	DOLLARS
1	Total IT	IT Hardware	Consumables	Technology Papers	Thermal	October 2001	Fujifilm	B20HG	HG GRADE THERMO-AUTOCHRO ME PPR	43	526

Table 1. Summary of Price Measures

	Method for Quality Change	
	Hedonic	Matched-Model
Unweighted	DV Index (2)	Geometric Mean (3)
Weighted	Imputation Method-Tornquist (4’)	Matched-model Tornquist (4)

Table 2a. Disposition of Observations: IT Goods
Pooled Monthly Data for the Years 2001 through 2004

Line No.	Categories	N	Percent included: Obser-vations	Percent included: Expenditure Shares	Expenditure Shares, Reason for Exclusion: Birth	Missing: Obs	Missing: Data	Disclosure Problem
	Computing devices:							
1	Desktop PCs	17,846	66.3	81.2	16.6	0.3	0.0	2.4
2	Notebook PCs	19,415	70.6	90.7	8.8	0.2	0.0	0.4
3	PDAs	4,433	84.6	96.0	3.9	0.0	0.0	0.0
	Printers:							
4	Dot Matrix	1,787	79.2	93.8	4.4	1.3	0.0	0.5
5	Ink Jet	7,361	82.3	96.2	3.6	0.1	0.0	0.0
6	Laser	5,624	77.2	96.9	2.6	0.4	0.0	0.0
	External Peripherals:							
7	Multimedia Speaker	8,068	78.2	95.6	2.4	0.0	0.0	2.0
8	Fax Machines	1,873	81.8	96.7	3.2	0.1	0.0	0.0
9	Scanners	8,167	77.7	94.5	4.2	0.4	0.0	0.8
10	Multifunction Dev.	4,660	83.3	97.2	2.7	0.1	0.0	0.0
11	Monitors	23,972	74.1	92.5	3.9	0.2	0.1	3.5
12	Keyboard	9,011	75.2	93.5	2.2	0.0	0.0	4.4
13	Mice	11,356	74.0	94.1	2.6	0.0	0.1	3.4
14	Game Pad	1,903	77.5	93.3	2.9	0.0	0.0	3.9
15	Joysticks	2,140	72.8	95.9	3.2	0.0	0.0	0.9
	Drives:							
16	Hard Drives	8,519	64.2	95.3	3.8	0.2	0.0	0.7
17	Tape Drive	1,155	12.0	10.4	10.1	12.2	0.2	67.4
18	CD ROM DVD Reader	4,186	68.5	82.3	5.8	1.2	0.1	10.8
19	CD-R/RW DVD-R	12,528	75.4	92.2	4.7	0.2	0.1	3.0
20	Floppy Drives	1,359	50.5	70.2	2.1	0.1	0.0	28.0
	Internal Components:							
21	Networking Dev.	48,340	65.9	96.8	2.2	0.4	0.2	0.6
22	Sound Cards	1,771	70.0	91.8	4.0	0.1	0.0	4.3
	Media:							
23	Floppy Disks	6,511	77.9	86.8	3.9	0.0	0.0	9.5
24	Data Cartridges	5,714	67.9	87.3	6.6	2.3	0.0	3.8
25	DVD Media	8,330	80.5	90.2	2.0	0.1	0.0	7.9
26	CD Media	20,346	78.3	87.0	3.4	0.3	0.0	9.6
27	Memory Cards	17,175	76.1	97.1	1.2	0.1	0.0	1.8
	Other:							
28	Calculators	9,952	63.4	90.4	2.1	0.0	0.0	7.7
29	Reference Databanks	1,343	85.7	96.6	3.0	0.0	0.0	0.4
30	PC Projectors	3,576	71.0	94.8	3.4	1.5	0.1	0.3
31	Personal Organizer	2,790	68.2	85.7	6.4	0.1	0.2	8.0
32	Laser-copier Toner	37,996	77.5	92.6	2.5	0.1	0.0	4.9
33	Inkjet Cartridge	33,911	79.5	96.6	2.3	0.1	0.0	1.1
34	Notebook Batteries	5,382	55.0	75.2	4.4	1.2	0.1	19.8

Table 2b. Disposition of Observations: Consumer Electronic Goods
Pooled Monthly Data for the Years 2000 through 2002

Line No.	Categories	N	Percent included: Obser-vations	Percent included: Expend-iture Shares	Expenditure Shares, Reason for Exclusion: Birth	Missing: Obs	Missing: Data	Disclosure Problem
	Video Products:							
1	Color Television	19,881	81.3	93.8	5.9	0.4	0.1	0.0
2	Web Browsers	381	89.8	87.7	12.3	0.0	0.0	0.0
3	Digital Set Top Box Decoder	237	77.2	97.5	2.3	0.2	0.0	0.0
4	TV Combinations	3,406	81.8	91.8	7.5	0.6	0.2	0.0
5	Video Cassette Recorders/Players	6,340	76.7	92.7	7.0	0.4	0.0	0.0
6	Remote Controllers	1,681	84.7	94.3	5.2	0.5	0.1	0.0
7	Camcorders	5,444	78.1	94.2	5.6	0.2	0.1	0.0
8	DBS Direct Broadcast Satellite/DSS	1,966	78.5	92.1	7.5	0.5	0.1	0.0
9	DVD	4,521	85.6	94.6	5.1	0.4	0.1	0.0
10	CD Players/Recorders	10,721	80.3	93.8	5.9	0.3	0.2	0.0
11	Personal Video Recorders	239	92.5	95.7	4.3	0.0	0.4	0.0
	Audio Products:							
12	Portable Home Radios	3,066	87.0	94.9	4.6	0.5	0.3	0.0
13	Solid State Voice Recorders	457	83.8	92.9	6.6	0.5	0.4	0.0
14	Portable Tape Recorders	1,189	83.9	92.8	5.8	1.3	0.0	0.0
15	Portable Radio/Cassette	440	89.8	90.9	9.0	0.1	2.4	0.0
16	Headset Stereos	3,149	83.5	93.4	5.8	0.7	0.0	0.0
17	Stereo Headphones	3,681	85.1	93.9	5.2	0.9	0.0	0.0
18	Receivers/Amps/Tuners	6,633	80.1	92.9	6.7	0.5	0.1	0.0
19	Cassette Decks	951	87.7	92.8	6.5	0.7	0.0	0.0
20	Home Speakers	14,006	82.1	93.1	5.9	1.0	0.1	0.0
21	One Brand Rack Systems	295	66.1	78.5	16.3	5.2	0.1	0.0
22	One Brand Shelf Systems	6,235	81.2	93.0	6.4	0.5	0.1	0.0
	Telecommunications:							
23	Corded Telephones	2,712	82.3	91.6	7.3	1.1	0.1	0.0
24	Cordless Telephones	5,331	77.8	92.7	6.7	0.6	0.4	0.0
25	Answering Devices	3,977	79.0	93.2	6.3	0.5	0.2	0.0
26	Caller I.D.	329	82.1	91.6	7.1	1.3	0.0	0.0
27	Two-way Radios	952	84.8	92.6	7.1	0.3	0.4	0.0
28	Headsets	1,826	83.6	89.8	7.9	2.2	0.2	0.0

Table 3a. Matched-Model Price Indexes for IT Goods

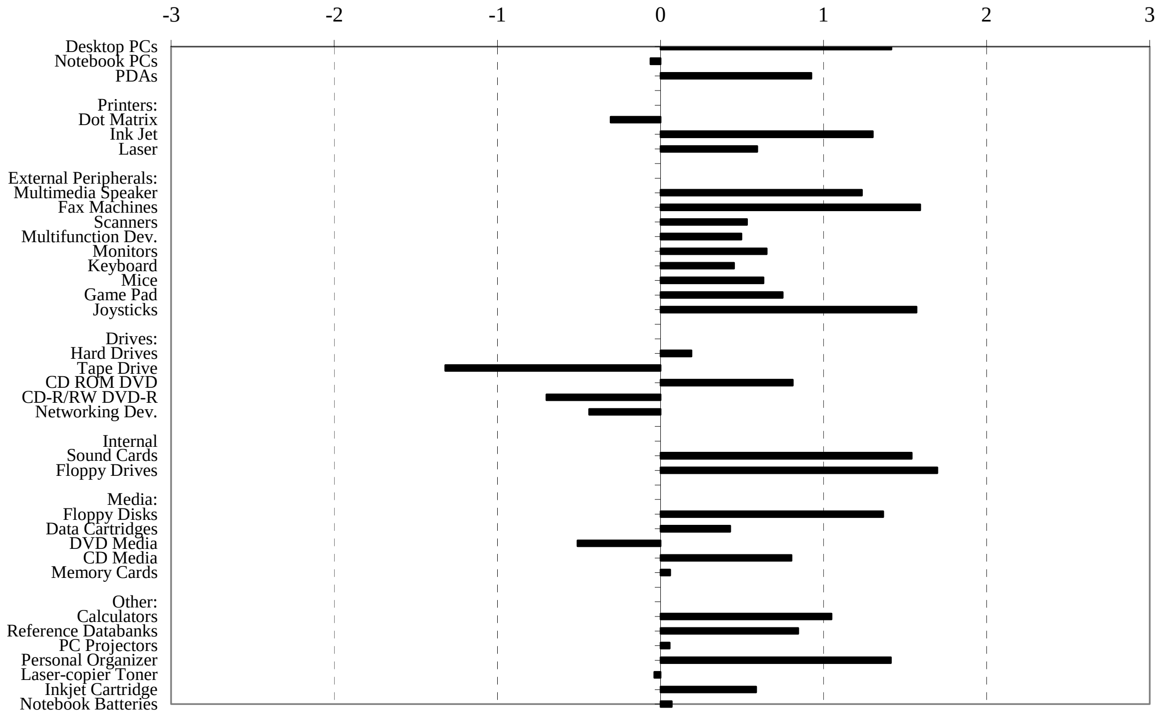
Line No.	Categories	Price Indexes (monthly rates) Tornquist (1)	Fisher (2)	Geomean (3)	Average (4)	Difference between Indexes: Average less Tornquist (5)	Tornquist less Geomean (6)
	Computing devices:						
1	Desktop PCs	-2.77	-2.71	-4.18	0.06	2.83	1.42
2	Notebook PCs	-3.97	-3.93	-3.90	-0.15	3.82	-0.06
3	PDAs	-2.99	-2.98	-3.91	-1.69	1.30	0.93
	Printers:						
4	Dot Matrix	-0.15	-0.15	0.16	-0.01	0.14	-0.31
5	Ink Jet	-2.23	-2.23	-3.53	0.50	2.72	1.30
6	Laser	-1.31	-1.30	-1.90	-0.56	0.76	0.59
	External Peripherals:						
7	Multimedia Speaker	-1.10	-1.13	-2.34	0.34	1.44	1.24
8	Fax Machines	-1.11	-1.02	-2.70	0.32	1.43	1.59
9	Scanners	-2.22	-2.22	-2.75	0.10	2.33	0.53
10	Multifunction Dev.	-2.37	-2.33	-2.86	0.31	2.68	0.50
11	Monitors	-1.60	-1.59	-2.25	-0.02	1.58	0.65
12	Keyboard	-0.97	-0.97	-1.42	0.30	1.27	0.45
13	Mice	-0.85	-0.85	-1.48	0.59	1.44	0.63
14	Game Pad	-0.56	-0.57	-1.31	0.19	0.75	0.75
15	Joysticks	-0.69	-0.70	-2.27	-0.30	0.39	1.57
	Drives:						
16	Hard Drives	-2.48	-2.53	-2.67	-0.43	2.04	0.19
17	Tape Drive	-15.57	-15.76	-14.25	0.40	15.97	-1.32
18	CD ROM DVD Reader	-1.26	-1.33	-2.07	-1.08	0.17	0.81
19	CD-R/RW DVD-R	-5.41	-5.40	-4.71	-2.35	3.07	-0.70
20	Networking Dev.	-2.30	-2.33	-1.86	-0.06	2.24	-0.44
	Internal Components:						
21	Sound Cards	-1.23	-1.40	-2.77	0.52	1.75	1.54
22	Floppy Drives	-0.72	-0.72	-2.42	-2.45	-1.73	1.70
	Media:						
23	Floppy Disks	-0.39	-0.38	-1.76	-0.38	0.01	1.37
24	Data Cartridges	-0.98	-0.96	-1.40	-0.06	0.91	0.43
25	DVD Media	-4.43	-4.46	-3.92	-0.38	4.05	-0.51
26	CD Media	-1.00	-1.01	-1.80	-0.70	0.30	0.80
27	Memory Cards	-3.04	-3.08	-3.10	-0.29	2.75	0.06
	Other:						
28	Calculators	-0.46	-0.44	-1.51	-0.39	0.07	1.05
29	Reference Databanks	-0.47	-0.46	-1.32	0.84	1.31	0.85
30	PC Projectors	-1.99	-1.97	-2.04	-2.33	-0.34	0.06
31	Personal Organizer	-1.20	-1.16	-2.61	-1.45	-0.26	1.41
32	Laser-copier Toner	0.02	0.02	0.06	-0.38	-0.40	-0.04
33	Inkjet Cartridge	0.02	0.03	-0.56	0.62	0.59	0.59
34	Notebook Batteries	-0.90	-0.67	-0.97	0.04	0.93	0.07

Table 3b. Matched-Model Price Indexes for Consumer Electronics

Line No.	Categories	Price Indexes (monthly rates) Tornquist	Fisher	Geomean	Average	Difference between Indexes: Average less Tornquist	Tornquist less Geomean
		(1)	(2)	(3)	(4)	(5)	(6)
	Video Products:						
1	Color Television	-1.18	-1.17	-1.70	0.75	1.93	0.52
2	Web Browsers	-2.03	-1.99	-3.47	-1.86	0.16	1.44
3	Digital Set Top Box Decoder	-0.38	-0.32	-1.83	-1.67	-1.29	1.45
4	TV Combinations	-1.07	-1.07	-1.47	-0.30	0.76	0.40
5	Video Cassette Recorders/Players	-0.95	-1.16	-2.39	-1.14	-0.19	1.44
6	Remote Controllers	-0.15	-0.15	-0.71	2.70	2.86	0.56
7	Camcorders	-1.86	-1.90	-3.26	-0.42	1.44	1.40
8	DBS Direct Broadcast Satellite/DSS	-1.58	-1.66	-2.73	-1.32	0.26	1.14
9	DVD	-2.15	-2.14	-2.98	-1.89	0.25	0.83
10	CD Players/Recorders	-1.03	-1.02	-1.79	-0.39	0.64	0.77
11	Personal Video Recorders	-2.85	-2.84	-3.10	-3.63	-0.78	0.25
	Audio Products:						
12	Portable Home Radios	-0.93	-0.93	-1.06	0.40	1.33	0.13
13	Solid State Voice Recorders	-1.55	-1.53	-0.81	2.60	4.15	-0.74
14	Portable Tape Recorders	-0.23	-0.22	-1.05	-0.56	-0.33	0.82
15	Portable Radio/Cassette	-0.39	-0.40	-0.68	-0.52	-0.13	0.29
16	Headset Stereos	-0.32	-0.31	-1.17	-0.61	-0.28	0.84
17	Stereo Headphones	-0.20	-0.21	-0.38	-0.06	0.14	0.17
18	Receivers/Amps/Tuners	-1.34	-1.32	-1.54	0.72	2.06	0.20
19	Cassette Decks	-0.34	-0.32	-0.84	-0.40	-0.06	0.51
20	Home Speakers	-0.89	-0.89	-1.46	-0.41	0.49	0.56
21	One Brand Rack Systems	-0.82	-0.80	-1.64	0.45	1.27	0.83
22	One Brand Shelf Systems	-1.37	-1.36	-1.94	-0.38	0.99	0.57
	Telecommunications:						
23	Corded Telephones	-0.71	-0.70	-0.95	0.08	0.79	0.24
24	Cordless Telephones	-2.07	-2.04	-2.20	-0.34	1.72	0.13
25	Answering Devices	-1.67	-1.66	-1.83	0.57	2.24	0.17
26	Caller I.D.	0.12	0.08	-0.39	-0.66	-0.77	0.51
27	Two-way Radios	-0.99	-1.03	-1.45	-1.14	-0.15	0.46
28	Headsets	-1.51	-1.51	-1.45	-1.08	0.43	-0.06

Chart 1. Matched-model Geometric Means vs. Tornquist Indexes (difference in average monthly percent changes)

Consumer IT Goods



Consumer Electronic Goods

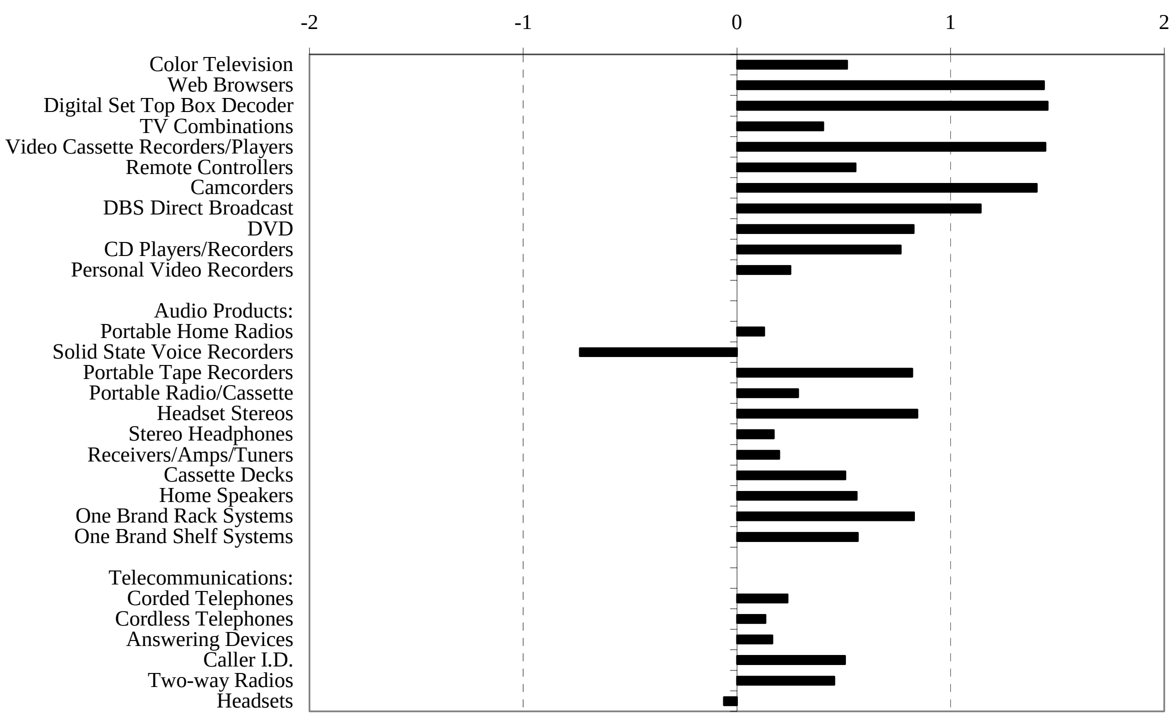
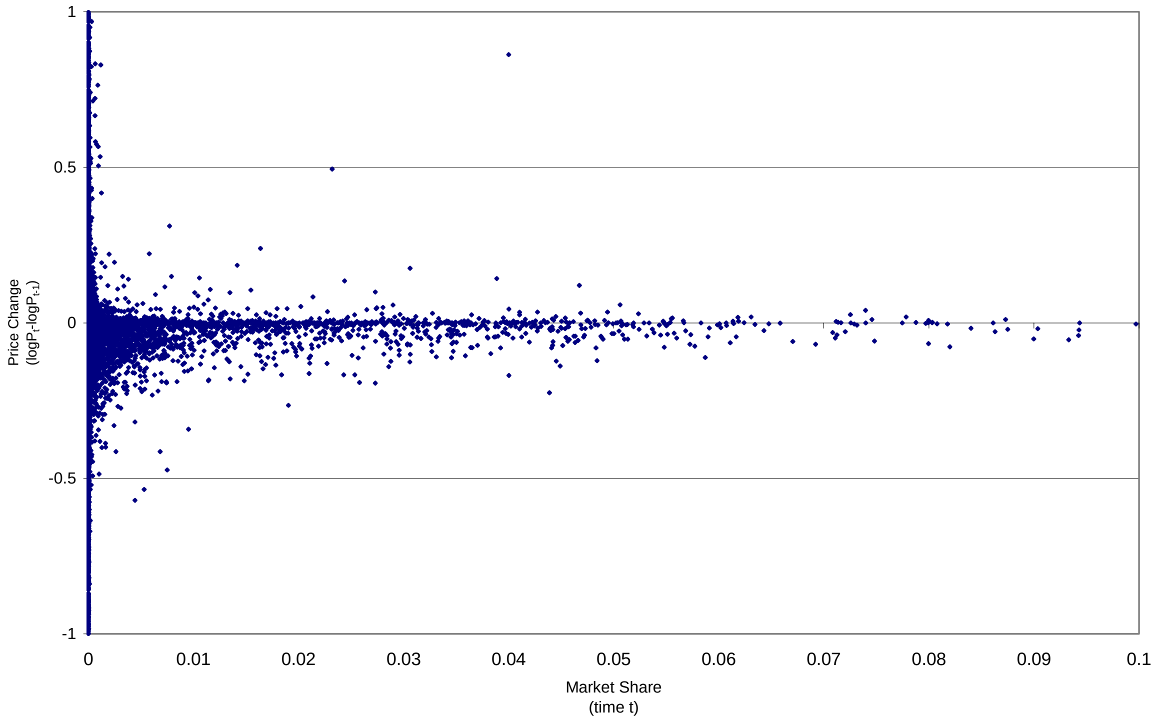


Chart 2. Price Change versus Market Share for Desktop Personal Computers

All observations



All models