BEA Working Paper Series, WP2024-5

Do Price Deflators for High-Tech Goods Overstate Quality Change?[1]

Authors Ana Aizcorbe and Daniel Ripperger-Suhler, U.S. Bureau of Economic Analysis

Contact Ana.Aizcorbe@bea.gov

Date August 2024

Abstract This paper studies chained price indexes for goods in high-tech sectors, how they handle quality change and whether they will likely suffer from chain drift issues. We argue that chained indexes do not handle quality change properly; though the underlying bilateral indexes hold quality constant just fine, the chained index does not, a problem we call comingling. When we explored multilateral methods as alternatives to chained indexes, we found that the Gini, Eltetö, Köves, and Szulc (GEKS) index that is often used to deal with the chain drift problem does not fix the comingling problem. Thus, the comingling issue is not just the chain drift problem in another guise; it can also exist in indexes that do not suffer from chain drift. Moreover, the practical implication of this finding is that we cannot use the GEKS index as benchmark against which to judge the numerical importance of these issues.

Using the weighted time product dummy (WTPD) index as a benchmark, we show that the changes in prices and expenditure shares over the product cycle that are typically exhibited by these high-tech goods can generate numerically important chain drift problems. Moreover, we show that the gap is negative: that is, the chained index will show faster price declines than the WTPD index. We illustrate these points using scanner data for six categories of consumer electronic goods.

Keywords Price Indexes, Inflation Measurement

JEL Code C43, E31

1. We would like to thank Erwin Diewert, Bart Hobijn, Paul Schreyer, seminar participants at the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis, and, especially, Jan de Haan and Frances Krsinich for many useful conversations that improved the quality of this paper.

Bureau of Economic Analysis
U.S. DEPARTMENT OF COMMERCE

1. Introduction

The fundamental role of price indexes in the national accounts is to decompose changes in nominal spending into a piece that measures changes in prices—called inflation—and another that measures the growth in "quantities" or real spending. The presence of quality change complicates the ability of price indexes to properly allocate changes in quality to real spending, not inflation. This problem is well understood in the context of bilateral (or direct) indexes (Diewert, 2019). Loosely speaking, price indexes typically measure inflation by "holding quality constant" which properly allocates any changes in quality to real spending. However, these bilateral indexes are often chained to obtain measures of price change over long spans of time. And how these chained indexes treat quality change has not been studied.

At the same time, it has been demonstrated that chained indexes constructed using very granular data—like scanner data—can display a numerically important problem called "chain drift" (Szulc (1983); Lent (2000)). This issue has been studied extensively in the context of consumer-packaged products sold in grocery stores, where the chain drift problem is thought to be related to consumers' responses to high-frequency sales and stockpiling behavior (Ivancic et al. (2011); De Haan and van der Grient (2011)). But, the possibility of numerically important chain drift problems in other sectors has received less attention (see De Haan and Krsinich (2014) for an exception).

This paper studies chained price indexes for goods in high-tech sectors, how they handle quality change and whether they will likely suffer from chain drift issues. We argue that chained indexes do not handle quality change properly; though the underlying bilateral indexes hold quality constant just fine, the chained index does not, a problem we call comingling. When we explored multilateral methods as alternatives to chained indexes, we found that the Gini, Eltetö, Köves, and Szulc (GEKS) index that is often used to deal with the chain drift problem does not fix the comingling problem. Thus, the comingling issue is not just the chain drift problem in another guise; it can also exist in indexes that do not suffer from chain drift. Moreover, the practical implication of this finding is that we cannot use the GEKS index as benchmark against which to judge the numerical importance of these issues.

Using the weighted time product dummy (WTPD) index as a benchmark, we show that the changes in prices and expenditure shares over the product cycle that are typically exhibited by these high-tech goods can generate numerically important chain drift problems. Moreover, we show that the gap is negative: that is, the chained index will show faster price declines than the WTPD index.

Our empirical work illustrates these points. Using scanner data for six consumer electronic goods, we find that chained indexes for many of these goods show faster declines than the WTPD index. For cutting-edge categories where quality change is rapid (e.g., TVs and computers), chained Törnqvist indexes fall faster than our benchmark, the WTPD index. We show that prices and market shares for these goods do, indeed, display the patterns over the product cycle that we believe give rise to chain drift. There are also categories that use older technologies—like calculators and dot matrix printers—and for them, the differences between chained and WTPD indexes tend to be small and often work in the other direction. Unlike the cutting-edge categories, prices and quantities are more volatile, often with obvious seasonal patterns (e.g., calculator sales at the beginning of the school year).

2. Chained Indexes and the Comingling Problem

It is well known that superlative index number formulas, like the Törnqvist, have potential chain drift issues (Diewert, 2022). In this section, we ask how chaining affects the ability of these indexes to properly account for quality change. Computing chained indexes involves two steps. First, one constructs price indexes for adjacent periods; these indexes are called bilateral or direct indexes because they use data for only two periods. Second, the price changes for those adjacent periods are cumulated (or chained) over time. We discuss each of these steps in turn.

Bilateral Adjacent-Period Indexes

There is a literature that documents how different bilateral price indexes handle quality change. Some of these papers provide expressions that make the issue of quality vs. constant-quality price change very transparent (see, for example, Diewert et al. (2009), de Haan (2009), de Haan and Diewert (2017), and Aizcorbe and De Haan (2024)). We introduce those expressions for bilateral indexes in this section and apply them to chained indexes in the next.

The full imputation Törnqvist index uses the familiar Törnqvist price index formula but replaces actual prices with predicted values from a hedonic regression. Specifically, the formula for the full imputation Törnqvist is:

$$lnP_{FIT}^{t-1,t} \equiv \sum_{i\in S^t US^{t-1}} \frac{(s_i^t+s_i^{t-1})}{2}\,(\widehat{ln\,p}_i^t - \widehat{ln\,p}_i^{t-1}) \qquad (1)$$

where S^t denotes the goods sold in period t, $s_i^t = p_i^t q_i^t / \sum_{i\in S^t} p_i^t q_i^t$ are the expenditure shares for good i, and and p_i^t and q_i^t are the price and quantity sold of good i. Using imputed prices provides a way to deal with turnover so the index can include goods sold in either period: $(S^t US^{t-1})$. For example, for a good that enters at time t, the good will be included in the index with an imputed price relative and an expenditure share of zero in the period before entry. Exit is handled in a similar way.

The imputations are done using predicted values from the following hedonic regressions:

$$ln\,p_i^t = \alpha^t + \sum_{k=1}^K \beta_k^t z_{ik} + \varepsilon_i^t, \quad (t = 0,\ldots,T) \qquad (2)$$

where z_{ik} is (the quantity of) characteristic k $(k = 1,\ldots,K)$ for product i, β_k^t is the coefficient for k, α^t is the intercept term, and ε_i^t is an error term with mean 0. Following Pakes (2003) and others, we interpret the regression as a reduced form, where changes in the hedonic coefficients reflect the effect of changes in demand or supply on prices.

These are cross-sectional regressions that are estimated separately for each period using weighted least squares. Once estimated, the (logged) predicted prices in (1) can be replaced using the predicted values from the hedonic regression: $\widehat{ln\,p}_i^t = \hat{\alpha}^t + \sum_{k=1}^K \hat{\beta}_k^t z_{ik}$. As shown in De Haan (2009) and De Haan and Diewert (2017), doing so and simplifying provides an expression for the full imputation Törnqvist index in terms of the hedonic arguments:

$$ln\hat{P}_{FIT}^{t-1,t} = \hat{\alpha}^t - \hat{\alpha}^{t-1} + \sum_{k=1}^K \frac{(\bar{z}_k^{t-1}+\bar{z}_k^t)}{2}\left(\hat{\beta}_k^t - \hat{\beta}_k^{t-1}\right), (t = 0,\ldots,T) \qquad (3)$$

where the $\bar{z}_k^t$'s are weighted averages of the characteristics: $\bar{z}_k^t = \sum_{i\in S^t} s_i^t z_{ik}$.

Diewert (2019) provides two interpretations of this index that highlight the importance of choosing a reference point (or market basket) at which to evaluate price change. First, one can view this as an index that holds quality constant at $\left(\bar{z}_k^{t-1} + \bar{z}_k^t\right)/2$, a characteristics vector that is representative of the set of products that exist in both periods. He explains that choosing this reference point is what allows the index to compare "like with like." Second, he shows that (3) can be interpreted as the average of two indexes: one that uses $\bar{z}_k^{t-1}$as the reference point and another that uses $\bar{z}_k^t$. Again, the key to "holding quality constant" is to choose a single reference point at which to measure price change.

Finally, the index measures only changes in the hedonic coefficients to measure price change and does not include any terms that measure changes in characteristics (quality).

Chained Index

The chained index cumulates the price growth from these bilateral indexes. Letting $ln\ P_{FIT}^{\tau-1,\tau}$ denote bilateral indexes for adjacent periods, the chained index simply sums over those indexes to obtain price change from t_0 to t:

$$lnP_{CFIT}^{t_0,t} = \sum_{\tau=t_0+1}^{t} ln\ P_{FIT}^{\tau-1,\tau} \qquad (4)$$

Chain drift occurs when a chained index over some time period, $lnP_{CFIT}^{t_0,t}$, does not give the same answer as a bilateral index that measures price change from the first to last period, $lnP_{FIT}^{t_0,t}$. This test is called the multilateral identity test and can be applied by calculating the difference in the chained and bilateral versions of the indexes (Diewert, 2022). There is a chain drift problem if this gap does not equal zero.

To analyze the chained index, we examine the gap between the chained and bilateral indexes using a simple example that measures price change from t=0 to t=2. Using the predicted values from (3) in (4) and simplifying, that gap is:[2]

$$ln\hat{P}_{CFIT}^{0,2} - ln\hat{P}_{FIT}^{0,2} = \frac{1}{2}\sum_{k=1}^{K}\left(\hat{\beta}_k^2\right)(\bar{z}_k^1 - \bar{z}_k^0) + \frac{1}{2}\sum_{k=1}^{K}\left(\hat{\beta}_k^0\right)(\bar{z}_k^2 - \bar{z}_k^1) + \frac{1}{2}\sum_{k=1}^{K}\left(\hat{\beta}_k^1\right)(\bar{z}_k^0 - \bar{z}_k^2) \qquad (5)$$

2. Diewert (2001) equation 65 provides an expression for the gap between the two indexes that we can use to assess whether conditions in this sector are likely to give rise to a numerically important chain drift problem.

The well-known conditions under which this gap will equal zero (Diewert, 2022) are not likely to hold in high-tech sectors. First, these terms equal zero if quality does not change (i.e., the $\bar{z}_k^t$'s are constant). But, increases in quality over time is the rule more than the exception in these sectors so the terms that measure changes in quality will likely not be zero. The other sufficient condition that would remove this gap is less obvious. The gap is removed if the hedonic coefficients do not change over time ($\hat{\beta}_k^t = \hat{\beta}_k^s$ for all s). Unfortunately, empirical tests of the stability of hedonic coefficient have typically found significant changes over time (Berndt and Rappaport (2001), Heravi and Silver (2002) and Pakes (2003)) and so that condition is not likely to hold either.

What does this gap between the chained and bilateral index tell us about how the chained index deals with quality change? Our result follows directly from (5). The gap is made up of terms that measure changes in the average characteristics and this points to a problem with the chained index. The aim of these price indexes is to hold quality constant, so that the resulting measure of inflation will not include changes in prices that result from changes in quality. As we have seen, the bilateral indexes (like (3)) measure price change using only changes in the hedonic coefficients, not measures in the characteristics. However, (5) says that the gap between the bilateral and chained indexes is a function of changes in the average characteristics. Because the bilateral index is not a function of the characteristics, this says that the chained index incorrectly includes quality change and, therefore, does not properly account for quality change. We call this a comingling problem.

Another, simpler, way to show that the chained index includes terms that measure changes in the characteristics is to rewrite the chained index as:

$$lnP_{CFIT}^{02} = (\hat{\alpha}^2 - \hat{\alpha}^0) + \sum_{k=1}^{K} \frac{(\bar{z}_k^1 + \bar{z}_k^2)}{2} \left(\hat{\beta}_k^2\right) - \sum_{k=1}^{K} \frac{(\bar{z}_k^0 + \bar{z}_k^1)}{2} \left(\hat{\beta}_k^0\right) + \sum_{k=1}^{K} \frac{(\bar{z}_k^0 - \bar{z}_k^2)}{2} \left(\hat{\beta}_k^1\right) \tag{6}$$

The last term is a function of changes in the characteristics which says that the price index will include changes in quality.

This occurs because the chained index does not use a single reference point to measure price change. For our simple example, the two reference points are $\left(\bar{z}_k^0 + \bar{z}_k^1\right)/2$ and $\left(\bar{z}_k^1 + \bar{z}_k^2\right)/2$.

$$\begin{aligned} lnP_{CFIT}^{02} &= lnP_{FIT}^{0,1} + lnP_{FIT}^{1,2} \\ &= (\hat{\alpha}^1 - \hat{\alpha}^0) + \sum_{k=1}^{K} \left(\bar{z}_k^0 + \bar{z}_k^1\right)/2 \left(\hat{\beta}_k^1 - \hat{\beta}_k^0\right) \\ &\quad + (\hat{\alpha}^2 - \hat{\alpha}^1) + \sum_{k=1}^{K} \left(\bar{z}_k^1 + \bar{z}_k^2\right)/2 \left(\hat{\beta}_k^2 - \hat{\beta}_k^1\right) \end{aligned} \tag{7}$$

Recall that a bilateral index "holds quality constant" at some level and calculates constant-quality price change at that point. When the chained index sums over the two underlying bilateral indexes, it is using two different reference points: one for the 0,1 index and another for the 1,2 index. This change in the reference point creates problems when the reference points involve different levels of quality. In this sense the chained index does not hold quality constant and will, in general, include part of the difference in quality from the two reference points as price change.

To sum up, we have shown that a chained full imputation Törnqvist includes terms that measure the change in goods' characteristics (or quality). This means that the index does not hold quality constant. We believe the problem is related to using more than one market basket (or reference point). As such, other versions of the Törnqvist (single imputation or matched model) are likely to have similar problems.

3. Does fixing the chain drift problem fix the comingling problem?

Multilateral methods have been developed to resolve the chain drift problem (Eurostat, 2022). In this section, we ask whether applying these methods can resolve the comingling problem. One popular method is the GEKS index (see Ivancic et al. (2011), National Academy of Sciences, 2022). The GEKS index for a full imputation Törnqvist that measures price change from t_0 to t is written:

$$lnP_{GEKS,FIT}^{t_0,t} = \sum_{\tau=0}^{T}[\, lnP_{FIT}^{t_0,\tau} + lnP_{FIT}^{\tau,t}\,]/(T+1) \quad (8)$$

It is a simple average of price indexes calculated over $T+1$ paths, each called a "link," where the number of paths is chosen by the researcher. The time periods used in the index are determined by the choice of T. So, for example, in measuring price change from $t=0$ to $t=10$, one could, in general, choose a $T>10$.

To see that a GEKS index has a comingling problem, we rewrite the GEKS index for $T=t$ as the sum of three types of terms: (1) a link where $\tau = t_0$, (2) another where $\tau = t$, and (3) the sum of the remaining links that use the other τ 's:

$$\begin{aligned} ln\hat{P}_{GEKS,FIT}^{t_0,t} = \{\, & [ln\hat{P}_{FIT}^{t_0,t_0} + ln\hat{P}_{FIT}^{t_0,t}] + [ln\hat{P}_{FIT}^{t_0,t} + ln\hat{P}_{FIT}^{t,t}] \\ & + \textstyle\sum_{\tau=t_{0+1}}^{t-1}[ln\hat{P}_{FIT}^{t_0,\tau} + ln\hat{P}_{FIT}^{\tau,t}]\}/(T+1) \end{aligned} \quad (9)$$

The first two terms reduce to bilateral indexes: two of the indexes will show no price change ($ln\hat{P}_{FIT}^{t_0,t_0}$= $ln\hat{P}_{FIT}^{t,t}$= 0) and the other two are bilateral indexes ($ln\hat{P}_{FIT}^{t_0,t}$). So these terms do not include quality change.

The remaining links are made up of indexes that sum price growth using two underlying bilateral indexes. They measure price change from t_0 to t in two steps; and although the steps do not involve adjacent indexes, these terms have the same structure as the chained indexes in (7) and which we have shown comingles price and quality change.

To be clear, one such link that uses some τ other than t_0 to t, expressed in terms of the hedonic arguments is the analog to (7):

$$ln\hat{P}_{FIT}^{t_0,\tau} + ln\hat{P}_{FIT}^{\tau,t} = (\hat{\alpha}^{\tau} - \hat{\alpha}^{t_0}) + \sum_{k=1}^{K} \frac{\left(\bar{z}_k^{t_0} + \bar{z}_k^{\tau}\right)}{2} \left(\hat{\beta}_k^{\tau} - \hat{\beta}_k^{t_0}\right)$$

$$+ (\hat{\alpha}^{t} - \hat{\alpha}^{\tau}) + \sum_{k=1}^{K} \frac{\left(\bar{z}_k^{\tau} + \bar{z}_k^{t}\right)}{2} \left(\hat{\beta}_k^{t} - \hat{\beta}_k^{\tau}\right) \quad (10)$$

And the analog to (6) is:

$$lnP_{CFIT}^{t_0,t} = (\hat{\alpha}^{t} - \hat{\alpha}^{t_0}) + \sum_{k=1}^{K} \frac{\left(\bar{z}_k^{\tau} + \bar{z}_k^{t}\right)}{2} \left(\hat{\beta}_k^{t}\right) - \sum_{k=1}^{K} \frac{\left(\bar{z}_k^{t_0} + \bar{z}_k^{\tau}\right)}{2} \left(\hat{\beta}_k^{t_0}\right) + \sum_{k=1}^{K} \frac{\left(\bar{z}_k^{t_0} - \bar{z}_k^{t}\right)}{2} \left(\hat{\beta}_k^{\tau}\right) \quad (11)$$

where the last term incorrectly includes changes in characteristics.

This has two implications. Obviously, in sectors where purchases gravitate towards higher-quality goods over time, the GEKS index could inappropriately include the effect of some changes in quality in the price deflator. The second implication is more practical. The recent literature has used GEKS indexes as a benchmark against which to assess the relative importance of chain drift (by comparing GEKS to a chained index), and the relative merits of other multilateral indexes (by comparing the index to a GEKS index) and interpreting any gaps to bias in the other method. The comingling problem in the GEKS index suggests it would be better to use a benchmark that has neither a chain drift nor comingling problem.

4. Measuring chain drift using the weighted time product dummy index as a benchmark

Another multilateral method that has been used to assess the numerical importance of chain drift is the weighted time product dummy (WTPD) index. That method uses a pooled regression that explains prices using fixed effects for both time periods and for goods' characteristics:

$$ln\, p_i^t = \alpha + \sum_{t=1}^{T} \hat{\delta}^{\mathrm{t}} D_i^t + \sum_{i=1}^{N-1} \gamma_i D_i + \varepsilon_i^t \tag{12}$$

where, D_i^t is time dummy variable with the value 1 if the observation pertains to period t and 0 otherwise; D_i a dummy variable that has the value of 1 if the observation relates to item i and zero otherwise; and dummies for $i = N$ and period 0 are omitted. Finally, the time dummy parameters in (12) yield the price index between periods 0 and t: $lnP_{WTPD}^{0\mathrm{t}} = \hat{\delta}^{\mathrm{t}}$.

The parameters γ_i are fixed effects and represent the quality adjustment factors for the i goods, though they are also called "references prices" in the literature. Work by De Haan, Willenborg, and Chessa (2016) showed that if (12) is estimated using expenditure shares as weights in weighted least squares, then the fixed effects can be interpreted as weighted geometric averages of the deflated prices, with the WTPD index serving as deflator:

$$\gamma_i = \sum_{\tau \; in \; S^i} = \frac{s_i^\tau}{\sum_{i \in S^i} s_i^\tau} \left(ln\, p_i^\tau - \; lnP_{WTPD}^{0\mathrm{t}}\right) \tag{13}$$

This says that the reference price for good i is calculated as the average deflated price of good i, where the average is taken over all the periods when good i was sold. Goods' reference prices are fixed over time. This interpretation of the $\gamma_i{}'$s will help us sign the difference between the WTPD and Törnqvist indexes below.

There are some benefits to using WTPD as a benchmark (Krsinich, 2016). It is based on a fairly general regression specification that does not require a specific functional form for quality differences across goods as other methods do (time dummy hedonic method). Moreover, its use of fixed effects provides a control for unobserved characteristics, something that matched-model indexes also do for continuing goods (Pakes, 2003).

However, several concerns have been raised about the index that we note here. Some of these are not relevant for our work. For example, in the economic approach to price indexes, the regression in (12) implicitly places restrictions on the underlying utility function. We do not view this as an issue because the use of price indexes as deflators does not require an economic approach interpretation to price indexes (Aizcorbe and De Haan, 2024). Second, it is often noted that the specification in (12) will ignore any entering or exiting goods but this is only relevant for bilateral indexes that only use two periods of data. It is less relevant for regressions that pool the sample as we do. The last two concerns that have been raised have not been thoroughly proven: 1) that the model in (12) leads to overfitting,[3] and 2) that the model will not adequately account for quality change.

To explore differences in the WTPD and chained Törnqvist indexes, we consider the case where there is no turnover. This comparison is relevant for both a full imputation Törnqvist index and the (simpler) matched-model Törnqvist. We use the matched-model index here, following the analysis in Diewert (2021).[4]

For the WTPD index, we suppose that one applies weighted least squares to a pooled sample to obtain estimates of the parameters in (12). As is well known, the resulting price index is $lnP_{WTPD}^{0t} = \hat{\delta}^{t}$.

Our comparison to the chained index becomes transparent if we rewrite this index as a quality-adjusted index:

$$lnP_{WTPD}^{t-1,t} = \sum_i s_i^t (ln\, p_i^t - \hat{\gamma}_i - \hat{\varepsilon}_i^t)/2 - \sum_i s_i^{t-1} (ln\, p_i^{t-1} - \hat{\gamma}_i - \hat{\varepsilon}_i^{t-1}) \qquad (14)$$

The formula for the matched model Törnqvist index is a version of (1) that uses actual (not predicted) prices:

$$lnP_{MMT}^{t-1,t} \equiv \sum_{i \in S^t \cup S^{t-1}} \frac{(s_i^t + s_i^{t-1})}{2} (ln\, p_i^t - ln\, p_i^{t-1}) \qquad (15)$$

Subtracting the two indexes and simplifying gives:

$$lnP_{WTPD}^{t-1,t} - lnP_{MMT}^{t-1,t} = \sum_i \left(s_i^t - s_i^{t-1}\right) \left(\frac{(ln\, p_i^t + ln\, p_i^{t-1})}{2} - \hat{\gamma}_i \right) + \sum_i \left(s_i^t \varepsilon_i^t\right) - \sum_i \left(s_i^{t-1} \varepsilon_i^{t-1}\right) \qquad (16)$$

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3. We do not understand this objection. One can take the specification in (12) and obtain both types of parameters using simple averaging. In particular, one can first-difference the data (to remove the γ_i's) and take averages of the resulting $ln\, p_i^t - ln\, p_i^{t-1}$ to obtain the δ^t. Then, one can deflate the price data using these δ^t's and take averages across goods of the adjusted prices to back out the γ_i's. This seems to be another way to get the De Haan et al (2016) result. In any case, how does overfitting relate to this?

4. Diewert (2021) has looked at this case. He uses a slightly different expression to try to sign the difference in the two indexes but using his expression to sign the gap for high-tech goods leads to the same conclusion.

The last two terms are weighted averages of the error terms and equal zero. As in Diewert's analysis, the first two terms can be interpreted as a covariance. If these covariances are positive, then WTPD will be larger (show faster growth or slower declines) than the matched model index.

To sign the covariances, we consider how prices and market shares change over the product cycle. Recall that $\widehat{\gamma_i}$ the average (deflated price) for each good i. For many information technology (IT) goods, early in the good's life, prices are higher than average ($\frac{(ln\, p_i^{\tau} + \; ln\, p_i^{\tau-1})}{2} - \widehat{\gamma_i}$ >0) and market shares are increasing ($s_i^{\tau} - s_i^{\tau-1}$ >0). So, the product of the two terms for good i in (16) is positive. Later in the good's life, prices are lower than average ($\frac{(ln\, p_i^{\tau} + \; ln\, p_i^{\tau-1})}{2} - \widehat{\gamma_i}$ < 0) and market shares are declining ($s_i^{\tau} - s_i^{\tau-1}$ <0), so the product of the two terms is still positive.

Given the patterns we observe for prices and market shares, these terms will be positive for all adjacent period indexes. Summing over all goods (the covariance) will simply sum over these positive differences and, so, will be positive. This means that the WTPD price index will be numerically larger than the Törnqvist (for example, .94 > .92). This is what we see in the data.

5. Empirical Work

Our empirical work is based on a scanner dataset for consumer electronic goods sold at retail establishments that we obtained from Circana data (formerly known as NPD). Our dataset provides sales estimates (quantities and dollars) at monthly frequencies for highly granular product classes (barcode-level) from 2011 to 2020. As is usually done, we calculate prices as unit values (dollars/quantities).

As is the case with many data products, quantities and dollar sales are often suppressed to protect retailers and manufacturers.[5] Moreover, some categories were not covered in all years. For our sample, we chose 6 categories where price and quantity data were available all 10 years, and where suppression rates were low.

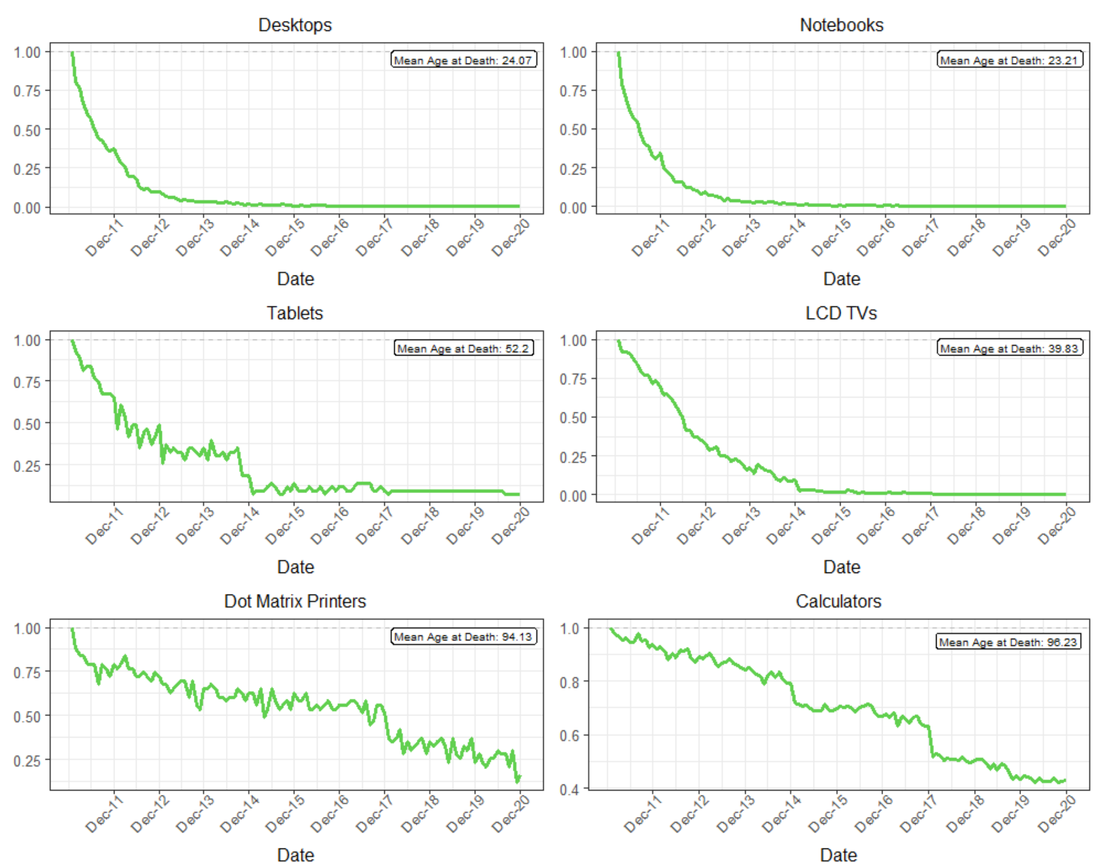
5. For example, 55 percent of spending and units sold for servers over the entire period is suppressed. This prevents us from constructing price indexes.

A caveat to our preliminary work is that these are “literal read” estimates—other than the suppression issue, we did not clean the data to handle outliers or other anomalies. Our view is that any emblematic feature for these markets will cut through the imperfections.

Product Cycles and Turnover

Two important features of sectors with rapid product innovation are short product cycles and a high degree of entry and exit (sometimes called product turnover or churn). As has been noted, both of these features present challenges for the calculation of price indexes. Figure 1 provides information on the average length of product cycles and the resulting survival rates. For example, desktop computers show the shortest product cycle in our data where the average age at death over all models is 24 months. This makes it virtually impossible to calculate direct (or bilateral) indexes of price changes for the 20-year span of the data and is precisely the reason that many indexes for IT goods were calculated as chained indexes. Figure 1 also shows survival rates for the models that were sold in the first period (1/2011). For desktops, the share of models remaining falls over the first two year to about 10 percent

Figure 1. Survival Rates for Models Sold in January 2011



by month 25 and essentially falls to zero by the end of the sample (12/2020). Of the other categories, the ones we could call high-tech (desktops, notebooks, tablets, and TVs) show very similar patterns—very few goods survive to year 10. The lower-tech categories (dot matrix printers and calculators) show slower declines but, even so, very few models survive to the end of the sample.

Table 1. Average Quantity and Expenditure Shares for Goods, by Turnover Status

	Quantity shares		
	Continuing	Entering	Exiting
Desktop computers	79.6%	10.3%	10.1%
Notebook computers	79.4%	10.4%	10.2%
Calculators	97.0%	1.5%	1.6%
Tablets	91.2%	5.6%	3.2%
Dot matrix printers	95.7%	1.6%	2.7%
LCD TV	90.6%	4.6%	4.9%
	Expenditure shares		
	Continuing	Entering	Exiting
Desktop computers	92.0%	6.0%	1.9%
Notebook computers	90.3%	7.7%	1.7%
Calculators	98.2%	0.9%	0.9%
Tablets	94.7%	4.4%	0.9%
Dot matrix printers	97.6%	1.2%	1.2%
LCD TV	97.1%	1.9%	1.1%

Information on product turnover is given in table 1. For each period, we identify observations that involve entry (goods that appear in the sample for the first time), exit (goods that will exit the sample in the next period), and continuing goods (goods that were sold in all three periods). We then calculate shares for each category both in terms of quantities (number of goods) and dollars (spending on those goods) and provide the resulting averages in table 1.

The entry and exit shares calculated as quantities (percent of goods in the top panel) are higher than when calculated as a percent of spending. For example, for desktops, on an average month, about 10 percent of the models sold have just entered the market, another 10 percent or so will exit the market in the next period, and the remaining 80 percent are “continuing models” that were sold in all three periods. Measured in terms of expenditure shares, the share of spending associated with each group is 6 percent for entering goods, 2 percent for exiting, and 92 percent for continuing goods. Because these indexes use expenditure shares as weights, the potential numerical importance of how one handles turnover is about expenditure (not quantity) shares. In our empirical work, we calculate both matched model and imputation versions of the Törnqvist to assess the potential importance of these turnover observations.

Price Indexes

Finally, we compare several price indexes to gain some sense for the potential numerical magnitude of the chain drift problem for IT goods.

- Matched model Törnqvist: A chain drift problem in the matched model Törnqvist, in and of itself, will drive a wedge between that index and the WTPD. To the extent that turnover has an appreciable impact on the price indexes, though, the matched model and WTPD indexes have different ways to handle turnover and that, too, could drive a wedge between the two indexes.

- To control for these differences in the treatment of turnover, we also compute a single imputation Törnqvist that imputes any missing prices using the WTPD prediction for that price. That is, this index uses imputations for entry and exit using the same method as WTPD. The resulting index treats matched models the same as the matched model Törnqvist but uses imputations to deal with turnover. Differences in the single imputation and matched model indexes tells us something about the importance of handling turnover for these goods.

- Finally, we construct WTPD indexes to obtain our estimate for the numerical importance of chain drift. We calculate this as the difference between the single imputation Törnqvist and the WTPD index, given as equation (15) in the text.

Table 2 summarizes our results by providing compound annual growth rates for the three indexes and a calculation of chain drift. Indexes for most of the categories show price declines; the two lower-tech categories are the exception. The matched model and single imputation Törnqvist indexes show very similar rates of decline. This is consistent with our priors that the expenditure shares associated with turnover are sufficiently small that imputation does little to change the growth rate.

Our estimates of chain drift (the difference between the single imputation Törnqvist and the WTPD indexes) show that the chain drift problem could be numerically important for goods in this sector. For the four high-tech categories, the Törnqvist indexes fall faster than the WTPD index and the differences can be large: for example, declines of 26.9 percent vs 17.5 percent for TVs. The two low-tech sectors show smaller positive differences.

Table 2. Growth Rates for Selected Price Indexes, 1/2011 to 12/2020
(Compound Annual Growth Rates in Percent)

	Chained Törnqvist		WTPD	Chain drift
	Matched model	Single imputation		
	(1)	(2)	(3)	(2)-(3)
Desktop computers	-11.9	-11.6	-5.7	-5.9
Notebook computers	-16.5	-15.7	-7.6	-8.1
Tablets	-17.4	-16.7	-13.8	-2.9
LCD TV	-27.1	-26.9	-17.5	-9.4
Dot matrix printers	0.7	0.5	0.2	.3
Calculators	1.3	-0.0	1.2	-1.2

To explain these differences in the results for the high- and low-tech goods, the first two panels of figure 2 measure the evolution of log prices and log expenditure shares over the lifetime of a good. For an individual good, the price level at a given age in months is the difference in the log price at that age and the log price when the good first enters the sample. The overall term is computed by taking the unweighted average of the log price relatives for all goods at each age in months. The expenditure share term is calculated using the same procedure.

For high-tech goods, the prices and market shares display the pattern typically seen for goods in markets with rapid product innovation. Prices start high and decline over the life of the good. Below, the expenditure shares tend to rise over the beginning of a model's life and then eventually fall back for the rest of the product cycle. As discussed above, it is the combination of changes in prices and shares that give the positive correlation that we argued will cause a chained Törnqvist index to fall faster than the weighted time product dummy index. And as seen in the bottom panel of figure 2, this is indeed the case; the chained indexes for the four high-tech goods fall faster than the WTPD benchmark.

The last two columns provide similar plots for the two lower-tech categories—dot matrix printers and calculators. As may be seen, prices and shares for the lower-tech goods do not follow the pattern that we saw earlier. And, as seen below, the chained indexes tend to be above the WTPD index.

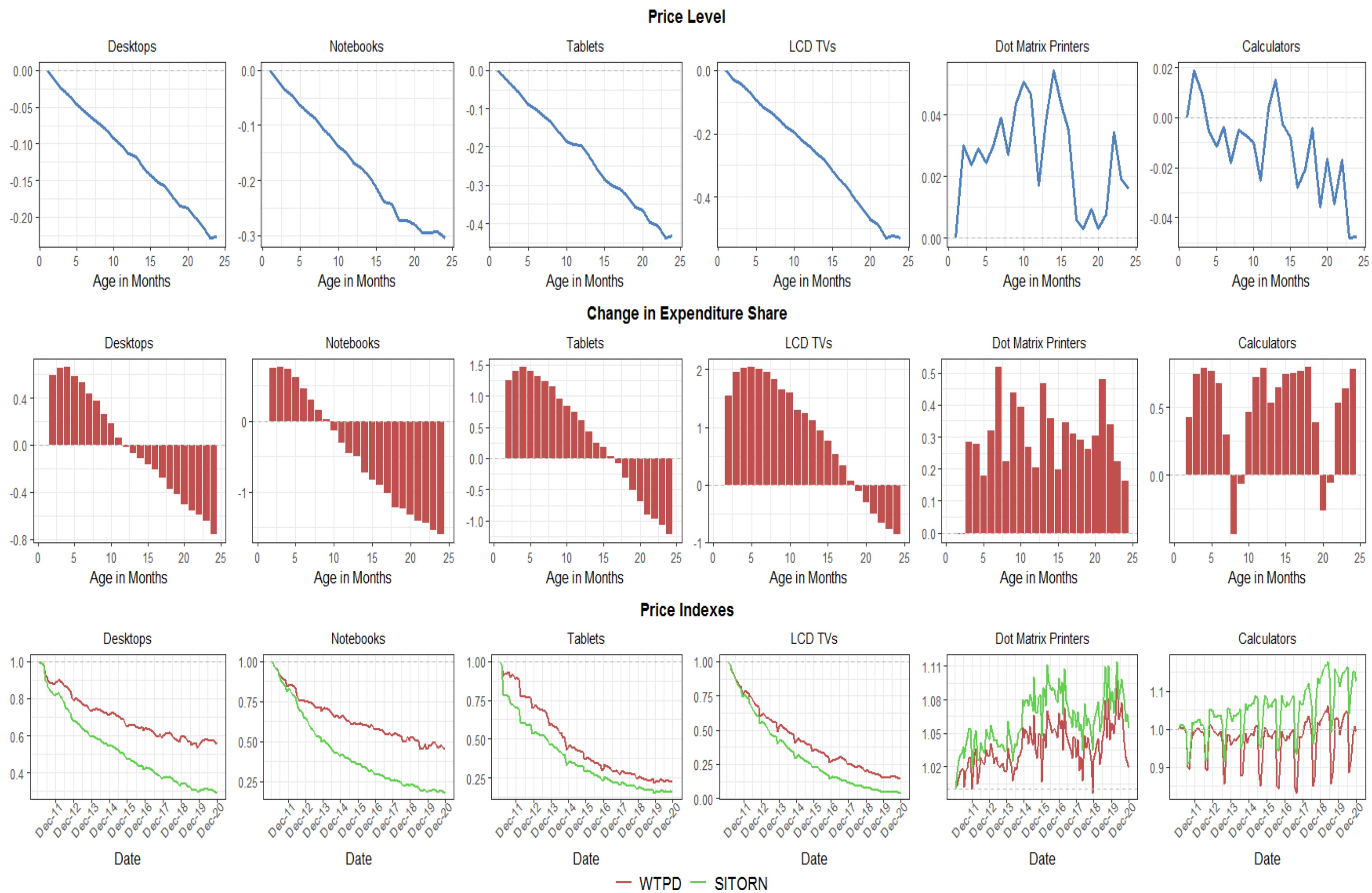
6. Summary and Conclusions

The chain drift problem has been almost exclusively studied in the context of sales at grocery stores and is thought to be related to high-frequency sales of those goods. In this paper, we show that chain drift can also be a problem for another important sector, IT goods. Our analysis ties the problem to patterns typically seen over the product cycle: prices that fall over the product cycle and expenditure shares that rise at first before falling back through the end of the good's life. Our empirical work uses scanner data for six IT categories to show that categories that show the above patterns are indeed related to chain drift. The higher-tech categories show those patterns and substantial chain drift—computers, laptops, tablets, and TVs. The lower-tech categories do not display these patterns and do not appear to have an obvious chain drift problem.

Along the way, we found an alternative interpretation for the well-known chain drift problem for superlative indexes like the Törnqvist. These chained price indexes are not able to hold quality constant, a problem we call comingling. When we extended our analysis to multilateral methods, we found that one of the multilateral methods used to solve the chain drift problem, the GEKS index, also has a comingling problem. Unfortunately, this means that we could not use the GEKS index as a benchmark against which to estimate the numerical importance of chain drift.

Our conclusions about chain drift and our analysis are only relevant for goods that display the kind of pricing/shares patterns that we see in our data. So, for example, although IT sectors that provide services do display rapid quality improvements, they do not show the price/share patterns over the product cycle that we see here so we cannot say much about the likelihood that those indexes will suffer chain drift problems. For the same reason, our analysis is likely not relevant for sales of consumer-packaged goods at grocery stores.

Figure 2. Product Lifecycle and Price Indexes



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