

INDEX NUMBER THEORY AND MEASUREMENT ECONOMICS

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Chapter 17. Scanner Data and the Rolling Year Methods for Constructing Indexes

1. Introduction

When detailed price and quantity information is available for components of the CPI, it becomes possible to produce month to month superlative indexes for these components. As we saw at the end of the last Chapter, these superlative month to month indexes can be subject to a considerable amount of chain drift. Thus in this Chapter, we will review recent methods that have been suggested to overcome this problem.

In section 2 below, we note that the GEKS multilateral index number method that was studied in Chapter 2 can be applied in the time series context and the resulting indexes are free from chain drift. However, they have the disadvantage that as a new month is added, all of the old parities between periods will change.

In section 3, a solution to the problem raised in section 2 is suggested: namely that a rolling window of 13 consecutive months should be used to produce GEKS indexes and the rate of change over the last 2 months in the window should be used to update the index level for the previous month. This method is known as the Rolling Year GEKS method.

In section 4, the Rolling Year GEKS method is adapted to situations where timely expenditure information is not available.

Sections 5 and 6 apply the ideas in the previous sections to suggest a “new” method for constructing elementary indexes: the Rolling Year Time Dummy method,² which is an adaptation of the Country Product Dummy method that is used in making comparisons of prices between countries.

Section 7 adapts some of the ideas that were suggested in this Chapter and the previous Chapter to deal with fashion goods. These are goods whose price drops as the time on the marketplace increases.

2. The Multilateral GEKS Method Applied in the Time Series Context

¹ This Chapter was prepared for the Preconference Training Sessions on Price Measurement held on August 23-24, 2014, sponsored by the 33nd General Conference of the International Association for Research in Income and Wealth held in Rotterdam, Netherlands, August 24-30, 2014.

² This method has recently been suggested by de Haan and Krsinich (2012).

Recall our discussion of the GEKS method for making index number comparisons between multiple time periods or countries in Chapter 3. This method is due to Gini (1931; 12) and it was derived in a different fashion by Eltetö and Köves (1964) and Szulc (1964) and thus the method is known as either the GEKS or EKS method for making multilateral comparisons. In this Chapter, we will apply the method in the time series context.

Some new notation will be introduced in order to explain the method in the time series context. Denote the price and quantity data for the past thirteen months by the superscript $c = 1, 2, \dots, 13$. Thus when c equals 13, the data refer to the current month and when $c = 1$, the data refer to the same month one year ago from the current month. We call these thirteen months the *current augmented year*. As usual, let there be N commodities that are available in at least one month of the current augmented year and let p_n^c and q_n^c denote the price and quantity of commodity n that is in the marketplace in month c of the current augmented year. If the commodity is unavailable in month c , define p_n^c and q_n^c to be 0.³ Let $p^c \equiv [p_1^c, p_2^c, \dots, p_N^c]$ and $q^c \equiv [q_1^c, q_2^c, \dots, q_N^c]$ be the price and quantity vectors for month c in the current augmented year. Let $S(i, j)$ be the *set of commodities that is present in months i and j of the current augmented year*, for $i, j = 1, 2, \dots, 13$. Then the *maximum overlap Laspeyres, Paasche and Fisher indexes* that compare the prices in month j to month i in the current augmented year are defined as follows:

$$\begin{aligned} (1) P_L(j/i) &\equiv \frac{\sum_{n \in S(i,j)} p_n^j q_n^i}{\sum_{n \in S(i,j)} p_n^i q_n^i}; & i, j = 1, 2, \dots, 13; \\ (2) P_P(j/i) &\equiv \frac{\sum_{n \in S(i,j)} p_n^j q_n^j}{\sum_{n \in S(i,j)} p_n^i q_n^j}; & i, j = 1, 2, \dots, 13; \\ (3) P_F(j/i) &\equiv [P_L(j/i) P_P(j/i)]^{1/2}; & i, j = 1, 2, \dots, 13. \end{aligned}$$

The Fisher indexes $P_F(j/i)$ will have the usual satisfactory axiomatic properties, including satisfying the time reversal test ($P_F(i/j) = 1/P_F(j/i)$) and the identity test ($P_F(i/i) = 1$).

Now choose month k as the base month. Using k as the base month and the Fisher indexes as our formula, a complete set of index numbers for the augmented year can be obtained as the following sequence of 13 fixed base numbers: $P_F(1/k)$, $P_F(2/k)$, ..., $P_F(13/k)$. In the international comparisons literature, this set of price indexes for a fixed k is called the set *Fisher star PPPs with country k as the star*.⁴ The final set of GEKS indexes for the 13 months is simply geometric mean of all 13 of the specific month star parities; i.e., the final set of *GEKS indexes for the months in the augmented year* is any normalization of the following indexes:⁵

$$(4) \left[\prod_{k=1}^{13} P_F(1/k) \right]^{1/13}, \left[\prod_{k=1}^{13} P_F(2/k) \right]^{1/13}, \dots, \left[\prod_{k=1}^{13} P_F(13/k) \right]^{1/13}.$$

³ If quantity information for the current augmented year is not available but price and expenditure information, p_n^c and e_n^c , is available, then if $e_n^c > 0$, define $q_n^c \equiv e_n^c/p_n^c$ and if $e_n^c = 0$, define $q_n^c \equiv 0$.

⁴ This terminology follows that of Kravis (1984). In our present context, the “countries” are now the 13 months in the current augmented year.

⁵ Balk (1981; 74) derived the GEKS parities using this type of argument rather than the usual least squares derivation of the GEKS parities; see Balk (1996) and Diewert (1999) for these alternative derivations.

The above GEKS indexes have a number of important properties:⁶

- They satisfy Walsh's (1901; 401) *multi-period identity test* so that if any two months in the augmented year have exactly the same price and quantity vectors, then the above index values will coincide for those two months; i.e., *the above indexes are free from chain drift*.
- The above indexes do not asymmetrically single out any single month to play the role of a base period; all possible base months contribute to the overall index values.⁷
- The above indexes make use of all possible bilateral matches of the price data between any two months in the augmented year.
- Strongly seasonal commodities make a contribution to the overall index values.

The last property explains why the augmented year should include at least 13 consecutive months, so that strongly seasonal commodities can make a contribution to the overall index.

The major problem with the GEKS indexes defined by (4) is that the indexes change as the data for a new month becomes available. A headline CPI cannot be revised from month to month due to the fact that many contracts are indexed to a country's headline consumer price index. A solution to this no revisions problem will be described in the following subsection.

3. Rolling Year GEKS Indexes

Ivancic, Diewert and Fox (2011) dealt with the fact that the addition of a new month's data would cause the GEKS indexes for past periods to change in the following way. Their method adds the price and quantity data for the most recent month to the augmented year and drops the oldest month from the old augmented year in order to obtain a new augmented year. The GEKS indexes for the new augmented year are calculated in the usual way and the ratio of the index value for the last month in the new augmented year to the index value for the previous month in the new augmented year is used as an *update factor* for the value of the index for the last month in the previous augmented year. The resulting indexes are called *Rolling Year GEKS indexes*.

Numerical experiments with Australian and Dutch scanner data from grocery chains show that the Rolling Year GEKS indexes work well when up to date price and quantity data are made available to the statistical agency; see Ivancic, Diewert and Fox (2011) and de Haan and van der Grient (2011). In particular, adding and dropping a month of data

⁶ The basic idea of adapting a multilateral method to the time series context is due to Balk (1981) who set up a framework that is very similar to the one explained here (which follows Ivancic, Diewert and Fox (2011) more closely). Balk (1981) used an index number formula due to Vartia (1976a) (1976b) in place of maximum overlap bilateral Fisher indexes as his basic building blocks and he considered augmented years of varying length instead of a 13 month augmented year but the basic idea of adapting multilateral methods to the time series context is due to him.

⁷ Thus the above GEKS procedure is an improvement over the suggestion of Feenstra and Shapiro (2003) who chose only a single base month.

and recomputing the GEKS indexes does not seem to change past index values very much.⁸

A more recent paper that describes the Dutch experience with Rolling Year GEKS is by van der Grient and de Haan (2011) and we will briefly describe the contents of this important paper. The authors note that in 2010, Statistics Netherlands expanded the use of scanner data in their CPI using the monthly unit value data by detailed product provided by six supermarket chains. The six chains for which scanner data were included in the January 2010 CPI have an aggregate market share of some 50% and a weight of slightly over 5% in the CPI. They also described the new method that utilized this scanner data in the Dutch CPI. Monthly chained Jevons price indexes are now computed at the lowest aggregation level. However, not all item prices are used: the authors noted that using all item prices in the various elementary indexes overstates the importance of low expenditure items. Thus in the Dutch CPI, an item price is used in the computation of the price index between two adjacent months if its average expenditure share in the current and preceding month with respect to the set of matched items is above a certain threshold value. The threshold (for including the item in the Jevons elementary aggregate) was chosen so that roughly 50 percent of the items are selected, representing 80 to 85 percent of aggregate expenditure. This cut-off sampling was done at the elementary aggregation level; i.e., for each product category at the most detailed level within each supermarket chain. Van der Grient and de Haan (2011) noted that the lack of weighting at the item level is an obvious weakness. Thus the Dutch Central Bureau of Statistics is also computing Rolling Year GEKS indexes to compare with their cut-off sampling method for constructing elementary aggregates, which are used in their official CPI. In order to make an informed decision about possible implementation of the Rolling Year GEKS method, Statistics Netherlands has a shadow system running which computes rolling year GEKS indexes for each COICOP category and each supermarket chain. Van der Grient and de Haan (2011) fully describe both the official Dutch cut-off sampling method and the Rolling Year GEKS method and they present monthly index numbers for 2009 and 2010. At the all items level, they find that the two methods yield similar results. However, as might be expected, at lower levels of aggregation, there appear to be some marked differences.⁹

The problems associated with the treatment of quality change have not been mentioned in this report but quality adjusting prices of products that are subject to rapid technological change is an important problem. One important method for the treatment of quality change is the *hedonic regression* technique. This method regresses the price of the product on its price determining characteristics. It is outside the scope of this report to discuss this method in detail but an important new paper by de Haan and Krsinich (2012) shows how hedonic regression techniques can be combined with the Rolling Year GEKS method in the scanner data context.

⁸ Balk (1981; 77) also observed the same phenomenon as he computed his GEKS indexes using successively larger data sets.

⁹ Other countries who are experimenting with using supermarket scanner data in their consumer price indexes are Norway and Australia.

Our conclusion at this point is that Rolling Year GEKS appears to be the “best” method for constructing elementary aggregates, provided supermarket chains and other major retailers are willing to provide the statistical agency with the required data on prices and quantities.

4. Approximate Rolling Year GEKS Indexes

The methodology that is used in constructing Rolling Year GEKS indexes for some elementary aggregates can be adapted for use in situations where the statistical agency has only “traditional” elementary aggregate information (based on a sample of item prices) and base year expenditure information for a rolling year in the past.¹⁰

The notation that was explained in section 2 above will be used here, with some modifications. Denote the (elementary) price index data for the past thirteen months by the superscript $c = 1, 2, \dots, 13$. Thus when c equals 13, the data refer to the current month and when $c = 1$, the data refer to the same month one year ago from the current month. As in section 2, we call these thirteen months the *current augmented year*. Suppose that there are N elementary aggregates and let p_n^c denote the elementary price index level for stratum n in month c of the current augmented year for $n = 1, \dots, N$. If the stratum n corresponds to strongly seasonal items and in month c , no items are available, then define p_n^c to be 0. It is assumed that quantity or expenditure information for the current augmented year is not available but expenditure information by month is available for each stratum for an augmented base year b . Reorder the augmented base year expenditure information so that the monthly expenditures by month in the augmented base year line up with the months in the current augmented year. Thus if month 13 in the current augmented year is July of the current year, e_n^{13*} corresponds to the July expenditures for elementary stratum n in the base year; e_n^{12*} corresponds to the base year expenditures for stratum n in June of the base year and so on. These augmented base year expenditures by stratum and month can be converted into implicit quantities by dividing the augmented base year expenditures by the corresponding elementary price indexes p_n^{c*} . Thus if $e_n^{c*} > 0$, define $q_n^{c*} \equiv e_n^{c*}/p_n^{c*}$ and if $e_n^{c*} = 0$, define $q_n^{c*} \equiv 0$. Define the vector of elementary price indexes for month c of the current augmented year as $p^c \equiv [p_1^c, p_2^c, \dots, p_N^c]$ and define the vector of quantities for month c in the augmented base year as $q^{c*} \equiv [q_1^{c*}, q_2^{c*}, \dots, q_N^{c*}]$ for $c = 1, \dots, 13$. Let $S(i, j)$ be the *set of elementary strata that have positive elementary indexes for months i and j of the current augmented year*, for $i, j = 1, 2, \dots, 13$. Then the *approximate maximum overlap Laspeyres, Paasche and Fisher indexes* that compare the prices in month j to month i in the current augmented year are defined as follows:

$$\begin{aligned}
 (5) \quad P_{AL}(j/i) &\equiv \sum_{n \in S(i,j)} p_n^j q_n^{i*} / \sum_{n \in S(i,j)} p_n^i q_n^{i*}; & i, j = 1, 2, \dots, 13; \\
 (6) \quad P_{AP}(j/i) &\equiv \sum_{n \in S(i,j)} p_n^j q_n^{j*} / \sum_{n \in S(i,j)} p_n^i q_n^{j*}; & i, j = 1, 2, \dots, 13; \\
 (7) \quad P_{AF}(j/i) &\equiv [P_{AL}(j/i) P_{AP}(j/i)]^{1/2}; & i, j = 1, 2, \dots, 13.
 \end{aligned}$$

¹⁰ This base year expenditure information is required for each month in the base year in order to implement the method suggested here.

The indexes defined by (5)-(7) are the approximate counterparts to the “true” Laspeyres, Paasche and Fisher indexes defined earlier by (1)-(3): basically, current month c implicit quantity vectors q^c are replaced by their base year counterparts, q^{c*} .

Once the above approximate indexes have been defined, we can follow the methodology explained in section 2 above. Thus define the set of *approximate GEKS indexes for the months in the augmented year* as any normalization of the following indexes:

$$(8) \left[\prod_{k=1}^{13} P_{AF}(1/k) \right]^{1/13}, \left[\prod_{k=1}^{13} P_{AF}(2/k) \right]^{1/13}, \dots, \left[\prod_{k=1}^{13} P_{AF}(13/k) \right]^{1/13}.$$

The above approximate GEKS indexes have a number of important properties:

- They satisfy a modification of Walsh’s multiperiod identity test so that if any two months in the augmented year have exactly the same price vectors and the implicit quantity vectors for those two months in the base augmented year are the same, then the above index values will coincide for those two months; i.e., *the above indexes are free from chain drift*.
- The above indexes do not asymmetrically single out any single month to play the role of a base period; all possible base months contribute to the overall index values.¹¹
- Strongly seasonal commodities make a contribution to the overall index values.

Now follow the Rolling Year GEKS methodology explained in section 3 above. Thus we add the price data for the most recent month to the current augmented year and drop the price data for the oldest month in order to obtain a new augmented year for prices. Similarly, we add an additional month of quantity data to the base year for expenditures and implicit quantities and drop the oldest month of quantity data for the augmented base year. The approximate GEKS indexes for the new augmented years are calculated in the usual way and the ratio of the index value for the last month in the new augmented year to the index value for the previous month in the new augmented year is used as an *update factor* for the value of the index for the last month in the previous augmented year. The resulting indexes are called *Approximate Rolling Year GEKS indexes*.¹²

Since this method has not been suggested before, there have been no numerical experiments to see how it performs in practice. A priori, this method appears to be an improvement over traditional annual basket methods but it will have to be tested before it can be used by national statistical agencies in their consumer price indexes.

Some of the methods described in this section can be adapted to the elementary index context as will be seen in the following section.

¹¹ Thus the above GEKS procedure is an improvement over the suggestion of Feenstra and Shapiro (2003) who chose only a single base month.

¹² The resulting indexes no longer satisfy Walsh’s multiperiod identity test exactly but it is likely that they will satisfy this test to a high degree of approximation and so the resulting chained indexes will be largely free of chain drift.

5. The Time Product Dummy (TPD) Method for Constructing Elementary Indexes

Recall the simple stochastic approach to elementary indexes that was explained in section 6 of Chapter 4. In that approach, a statistical model was proposed that used only the data of two consecutive periods. A problem with this approach is that if there are strongly seasonal commodities in the elementary aggregate, they can have no influence on the elementary aggregate unless the commodity is present in both periods under consideration. Thus it seems more appropriate to extend the model in Chapter 4 to cover the data for an augmented year so that strongly seasonal commodities will have an influence on the elementary indexes. The basic hypothesis is that prices within the elementary stratum vary proportionally over time except for random errors. Thus if a sample of M items in the elementary stratum are priced over the thirteen months in the current augmented year, let $S(c)$ denote the set of items that are actually priced during month c of the augmented year and denote the price of item m in month c of the augmented year by p_m^c for $c = 1, 2, \dots, 13$ $m \in S(c)$ and $c = 1, 2, \dots, 13$. The counterparts to equations (37) and (38) in Chapter 4 are the following equations:

$$(9) \quad p_m^1 \approx \beta_m; \quad m \in S(1);$$

$$(10) \quad p_m^c \approx \alpha^c \beta_m; \quad c = 2, 3, \dots, 13; m \in S(c).$$

The sequence of numbers $1, \alpha^2, \alpha^3, \dots, \alpha^{13}$ are the desired factors of proportionality over the 13 months in the current augmented year and they represent the sequence of elementary indexes for the stratum under consideration for the augmented year. The parameters $\beta_1, \beta_2, \dots, \beta_M$ represent quality adjustment factors that adjust for the differing quality of the outlets sampled and the items chosen. Adding multiplicative error terms to the right hand sides of (9) and (10) and taking logarithms of both sides of the resulting equations leads to the following system of linear in parameters estimating equations:

$$(11) \quad \ln p_m^1 = b_m + \varepsilon_m^1; \quad m \in S(1);$$

$$(12) \quad \ln p_m^c = a^c + b_m + \varepsilon_m^c; \quad c = 2, 3, \dots, 13; m \in S(c)$$

where $b_m \equiv \ln \beta_m$ for $m = 1, \dots, M$ and $a^c \equiv \ln \alpha^c$ for $c = 2, 3, \dots, 13$.

Once the a^c parameters have been estimated, estimates of the α^c can be obtained by exponentiating the a^c . It can be seen that the model defined by (11) and (12) is formally identical to Summers' (1973) *Country Product Dummy* model for generating elementary indexes except that the time periods in the current augmented year replace the countries in Summer's method. Thus it seems appropriate to term the present time series model the *Time Product Dummy* model for generating elementary indexes.¹³

¹³ Balk (1980; 70) proposed a weighted version of this model in the time series context and Diewert (2004) proposed a weighted version of this model in the multilateral context. Following up on the earlier work of Aizcorbe, Corrado and Doms (2003), de Haan and Krsinich (2012) proposed this model and called it the Time Dummy Product Model.

Some of the advantages of the TPD method of constructing elementary aggregates over traditional method that rely on the Jevons, Carli or Dutot formulae as aggregation techniques are as follows:

- The TPD estimates do not single out a single month's prices as the base prices as is done using the current ONS methodology for the RPI that uses Carli indexes with a January base month; the TPD method treats all months in the current augmented year in a completely symmetric manner.
- The TPD method makes use of all of the price information collected for the current augmented year and so there is maximal (implicit) matching of prices within the augmented year.
- There is no need for special methods (like carry forward missing prices) to deal with missing prices or strongly seasonal commodities: the TPD method automatically deals with these problems.
- The TPD method generates standard errors for the resulting elementary indexes.
- The TPD method generates elementary indexes that satisfy Walsh's multiperiod identity test; i.e., if the prices for two months in the augmented year are identical, then the resulting TPD index values will be identical for those two months. Thus TPD indexes will be free of chain drift.

Of course, a problem with the TPD indexes is that they will change as data for a new month becomes available. In the following subsection, we use the Rolling Year methodology to overcome this difficulty.

6. The Rolling Year Time Product Dummy (RYTPD) Method for Constructing Elementary Indexes

As usual, the Rolling Year GEKS methodology explained in section 3 above can be adapted to deal with the problem identified at the end of the last subsection. Thus we add the price data for the most recent month to the current augmented year and drop the price data for the oldest month in order to obtain a new augmented year for prices. A new model defined by (11) and (12) for the new augmented year is estimated and new index values say α^{12*} and α^{13*} are generated for the new augmented year. The value of the index for the last month in the previous augmented year is multiplied by $\alpha^{13*}/\alpha^{12*}$ in order to obtain an updated index for the last month in the new augmented year. The resulting indexes are called *Rolling Year Time Product Dummy (RYTPD) elementary indexes*.¹⁴

A more general version of the RYTPD method (that also adjusts for quality changes) has been implemented recently by de Haan and Krsinich (2012). Since the basic method has not been implemented, there have been no numerical experiments to see how it performs in practice.¹⁵ A priori, this method appears to be an improvement over traditional

¹⁴ This method was also proposed by de Haan and Krsinich (2012).

¹⁵ Although the unweighted rolling year method has not been precisely implemented, Balk (1980c) more or less implemented a weighted version of the model using his Dutch data set on greenhouse fruits and

elementary index methods but it will have to be tested before it can be used by national statistical agencies in their consumer price indexes. The axiomatic properties of the method seem to be attractive. A big advantage the RYTPD method has over the methods that rely on comparing monthly prices for items with a corresponding base month price (typically either a December or January price) is that the RYTPD method treats all months in the rolling year in a symmetric fashion; i.e., no single month is singled out to play the role of a numeraire item price. The problem with relying on a numeraire month's price is that it could be atypical or in the case of strongly seasonal commodities, it could even be nonexistent. The method appears to be very promising.

In the following section, we will apply the material in this Chapter and the previous Chapter to comment on the problems raised by fashion goods.

7. The Problem of Fashion Goods

A *fashion good* is a good which comes on the market with a price premium due to its newness and then declines in price as its "newness" wears off. Examples of fashion commodities are certain items of women's clothing, automobiles, electronic games and movies.

One of the best papers which deals with fashion goods in a systematic manner is by Greenlees and McClelland (2010). They obtained scanner data on apparel sales of "women's tops" in the US for a number of years and they tried a wide variety of techniques to deal with the problems associated with fashion goods. The basic problem is that at the beginning of the fashion season, a fashion good comes into the marketplace at a high price and then as time passes, the price of the same item declines rapidly. Thus if any kind of matched model price index is used, the resulting index will show a tremendous downward movement throughout the year. When a new fashion item that is somewhat comparable is introduced at the beginning of the following season is linked in with the last price of last year's comparable fashion item, then the index will rapidly decline to a very low level. However, if one uses annual unit value prices for the fashion items, there is very little change in these prices over time.

How can a fashion good be detected? In the case of a clothing item, a useful test would be a persistent decline in the price of the item after its introduction. Greenlees and McClelland (2010) document the decline in price of a women's fashion item (misses' tops) for a major department store chain in the U.S. from the start of each March over the years 2004-2007. Only 2 percent of transactions in this item take place at the introductory price at the start of each season. The average selling price is about one half of the starting

vegetables for 72 months. Balk computed his weighted TPD indexes, starting with the first 4 months of data, then adding one more month of data and ending up using all 72 months of data. He found that once 48 months of data were used, adding an additional month of data to the previous regression model did not significantly change the earlier model price levels. Thus for his data set, a rolling window of length 48 months would probably work well. Ivancic, Diewert and Fox also experimented with a weighted version of the Rolling Year Time Dummy Product method and obtained results that were quite similar to their Rolling Year GEKS results in Ivancic, Diewert and Fox (2012). See also Diewert (2005) (2006) for related materials in the bilateral context.

price. Non fashion items tend to sell at prices that may fluctuate but do not persistently decline.

There are two problems that are associated with the use of average prices to reflect the movements in the prices of fashion items:

- Average prices fail to account for any changes in average item characteristics or “quality” over time.
- The effects of the product cycle for these fashion goods leads to tremendous fluctuations in the month to month indexes. These fluctuations are not “real” because the same physical item in the middle of the year is not the same (in the eyes of purchasers) as the item when it is “newer”.

The answer to the above problems is to treat each fashion good in each month of its life as a *separate good*. These separate goods cannot be directly compared across the months within the fashion cycle but a brand new car of a certain model and type can be compared with the comparable brand new car that is introduced at the start of the next fashion cycle. The effect of this treatment is to make each vintage of a fashion good a *strongly seasonal commodity* that can be compared across fashion seasons (for models of the same vintage) but cannot be directly compared within the fashion season.¹⁶ Basically, comparing prices of a particular fashion item as it “ages” in the market place is not comparing like with like: an older vintage of a fashion good gives less utility to purchasers as compared to a new vintage. Index number theory rests on the assumption that we are comparing the same good (that gives purchasers the same utility) at two or more time periods and fashion goods do not satisfy this criterion: different vintages of the same physical fashion good give purchasers differing amounts of utility.

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¹⁶ Of course, there is a practical problem facing price collectors in following this advice: it may be difficult to determine if a particular fashion item just introduced in the current month is comparable to last season’s just introduced fashion item.

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