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POTENTIAL REASONS FOR CPI CHAIN DRIFT BIAS WHILE USING ELECTRONIC TRANSACTION DATA

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Abstract. Scanner data mean electronic transaction data that specify product prices and their expenditures obtained from supermarkets' IT systems by scanning bar codes (i.e. GTIN or SKU). Scanner data are a relatively new and cheap data source for the calculation of the Consumer Price Index (CPI) and the biggest advantage of scanner data is the full product information they provide already at the lowest level of aggregation. Thus, the digitization of the public sector becomes not only something that is needed but an actual necessity resulting from organisational and economic premises (e.g.: reduction of costs or time related to obtaining data). One of main challenges while using scanner data is the choice of the right price index. The list of potential price indices, which could be used in the scanner data case, is quite wide, i.e. bilateral and multilateral indices are used in practice. One of the most important criterion in selecting index formula for scanner data case is the potential reduction of the chain drift bias. The chain drift occurs if the index differs from unity when prices and quantities revert back to their base level. In the paper we present situations on the market leading to the serious chain drift bias. Our main hypothesis is that lagging consumers' reaction to price changes is the cause of the chain drift effect. Moreover, the article is an attempt to answer the question whether the correlation of prices and quantities may have an influence on the scale and sign of the bias of the measurement of price dynamics. The study focuses also on the scale of over- and underestimation the target full-window multilateral indices by their corresponding splicing extensions. Finally, the paper verifies a hypothesis that the identity test is a key property in reducing chain drift bias. In order to verify the above research problems, both empirical and simulation studies were carried out. Our main result is the confirmation of earlier suspicions that delayed consumer response and price-quantity correlation are determinants of chain drift bias.

Keywords: scanner data, electronic transaction data, digital transformation in public statistics, big data, Consumer Price Index, chain drift, chain indices, multilateral indices, splice indices, PriceIndices package.

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Introduction

Technological changes affect the functioning of various sectors of the economy. Digitisation, together with digitalisation, are starting to have an increasing impact on the day-to-day functioning of not only the private sector but also the public sector (Małkowska et al., 2021). In the case of the latter, it is no longer just about e-government, the purpose of which is to provide various stakeholders with public services by electronic means. The public sector must keep up with modern IT solutions and demonstrate that it is innovative in order to respond to the needs and expectations of the modern information society. Therefore, also official statistics is changing its face. Providing citizens with universal access to regularly/periodically updated data banks is not the only challenge faced by official statistics. It becomes necessary to use tools that allow for the creation of a huge volume of data, enabling significant automation of the process of collecting data with a relatively low cost of obtaining information (Andronie et al., 2021; Dijmărescu et al., 2022). Bearing in mind that digitisation is a series of activities of converting previously analogue resources into digital equivalents, the transition from traditionally collected data to scanner data in the measurement of inflation is an excellent example of digitisation in the public sector. In addition, changes in the measurement of inflation are not just current challenges faced by official statistics but also a key issue in assessing the macroeconomic stability of individual European and world economies (Roszko-Wójtowicz & Grzelak, 2020).

Scanner data mean transaction data that specify turnover and numbers of items sold by barcodes, e.g. GTIN, formerly known as the EAN code (International Labour Office, 2004). These data are a quite new data source for statistical agencies and the availability of electronic sales data for the calculation of the Consumer Price Index (CPI) has increased over the past 20 years. They can be obtained from a wide variety of retailers (supermarkets, home electronics, Internet shops, etc.). Scanner data have numerous advantages compared to traditional survey data collection because such data sets are much bigger and cheaper than traditional ones and they contain complete transaction information, i.e. information about prices and quantities. Scanner data sets have huge volume and may provide some additional information about products (such as the following attributes: size, grammage, sale unit, colour, package quantity, etc.). These attributes may be useful in aggregating items into homogeneous groups. Nevertheless, there are lots of challenges while using these data. In the era of a pandemic, when the field work of the interviewers was significantly limited, scanner data allowed for the supplementation of the missing data. With the restrictions in movement and numerous cases of COVID-19, the data from supermarkets proved to be an important source of information concerning the prices and quantity of goods purchased by Poles. A wider use of scanner data in the assessment of inflation leads to the improvement of the data collection process and a better reflection of changes that occur in consumer behaviour. In the long-term perspective, the digital transformation of official statistics also contributes to the improvement of democratisation and leads to the development of the information society.

The first challenge connected with scanner data concerns item codes. The following codes may be used: global trade article number GTIN, price look-up (PLU) and stock-keeping units (SKUs). The next challenge is detecting items which were returned within the given period after the purchase. Since typically, 10000–25000 item codes are used in the supermarket, a huge challenge is to create the appropriate, preferably automatic (or at least almost fully automatic) IT system which is able to go through with the above-mentioned detections and which takes into consideration seasonal goods, replacements, as well as disappearing and appearing item codes in the sample. Finally, one of new challenges connected with scanner data is the choice of the index formula which should be able to reduce the chain drift bias and the substitution bias (Białek, 2020; Chessa, 2015; Chessa et al., 2017). The chain drift problem arises when all prices and quantities in the current period return to the value of the base period but the price index differs from unity (International Labour Office, 2004). It seems to be natural that the chain drift effect concerns mainly seasonal products.

This paper focuses on the above-mentioned chain drift issue. Based on the literature review and practical experiences, the Authors formulate the following research question: What are the potential causes of the chain drift effect (not only in relations to chain indices)? The aim of the paper is to investigate the phenomenon of chain drift accompanying weighted chain indices and spliced multilateral indices. In particular, the specific objectives are: (a) to investigate whether and how a delayed consumer response to price changes affects the scale of chain drift bias; (b) to check whether the direction of the correlation between prices and quantities may also influence the sign of the index bias due to chain drift. A derivative goal, resulting from the emergence of new multilateral index formulas in the literature, is to check whether the group of multilateral indices meeting the so-called identity test is less prone to chain drift bias than the remaining index group. The paper verifies our main hypothesis that chain drift bias is primarily dependent on the scale of delay in consumer response to changes in product prices and the direction of the correlation between product prices and quantities. The paper consists of an introduction, five sections proper and a conclusion, which includes a description of planned future research. Section 1 is a literature review. The Authors thoroughly discuss there the problem of chain drift in the context of different classes of price indices. In the Section 2 data sources and sources for computer scripts are presented. Section 3 consists of two separate subsections. Paragraph 3.1 indicates potential reasons of the chain drift effect while using chain indices and paragraph 3.2 indicates main sources of chain drift bias while extending multilateral indices by using splicing methods. Section 4 presents an empirical study and a discussion of results. We examine here the scale of over- and underestimation of the target full-window multilateral indices by their corresponding splicing extensions. The last section lists the most important conclusions of the research carried out.

1. Literature review – price indices and chain drift problem

In the case of traditional data collection, where interviewers collect information about prices from the field and the consumption level is evaluated via household budget surveys, statistical agencies use bilateral index numbers (von der Lippe, 2007; Białek & Roszko-Wójtowicz, 2021). Nevertheless, the dynamics of scanner data does not seem to be correctly reflected by these types of indices. One way to deal with a problem with huge product churn is to choose chained indices where the base period is updated frequently and the resulting bilateral indices are chain-linked. However, it can be shown (Chessa, 2015) that frequently chained weighted indices lead to chain drift bias. The chain drift can be formalised in terms of the violation of the *multi period identity test*. The above-mentioned test states, that when all prices and quantities in a current period return to their values from the base period, then the index should equal one. Even chained superlative indices, such as the chain Fisher or Törnqvist index, may suffer from the chain drift problem (Chessa, 2015). On the other hand, the use of some chained unweighted index formulas (e.g. the chain Jevons or Dutot index), which are free from the chain drift problem, does not take into account different levels of consumption of individual products in the analysed periods. Nevertheless, the use of the chain Jevons index seems to be justified within the so-called *dynamic approach*, where the sample is selected by applying appropriate data filters, e.g. extreme price filter or low sales filter (van Loon & Roels, 2018). For some discussion of the scale of the chain drift effect and its potential source when using chain indices, see Sections 3.1 and 4.

The multilateral price index is calculated for a given time window consisting of $T + 1$ consecutive months, which we number 0, 1, 2, ..., T (typically $T = 12$). Multilateral indices use all prices and quantities of individual products, which are available in a set time window. Multilateral indices are *transitive* (Australian Bureau of Statistics, 2016), which eliminates the chain drift problem. Although Ivancic et al. (2011) postulated that the use of multilateral indices can solve the chain drift problem, most statistical offices using scanner data still compute the monthly chained Jevons index (Chessa et al., 2017). However, many countries are experimenting with multilateral indexes and even implementing them into regular price index production. (Australian Bureau of Statistics (2016), Griffioen and ten Bosch (2016), Krsinich (2014), Inklaar and Diewert (2016), Chessa (2016, 2019); Chessa et al. (2017), Lamboray (2017), Guerreiro et al. (2018), Diewert and Fox (2018), Białek and Bobel (2019), as well as de Haan et al. (2021)). Unfortunately, chain drift problem returns when we want to update the multilateral index value after acquiring data for the new month. In this paper, we consider commonly used rolling-window updating methods which shift the estimation window (often 13 months) forward each month and then splice the new indices onto the existing time series. As it was shown (Chessa et al., 2017), splicing methods lead to the chain drift bias but still an open problem in the context of chain drift bias generation seems to be the choice of the time window length and the splicing method (see our discussions in Sections 3.2 and 4).

Following the *identity test* (International Labour Office, 2004; von der Lippe, 2007), it should be observed that even when only prices revert to their base values and quantities do not, the index becomes one. This test is more restrictive than the requirement about lack of chain drift and that is why statisticians are not unanimous on the need to include this test. Nevertheless, it is often mentioned among the axioms regarding multilateral indices (Eurostat, 2020; Zhang et al., 2019). A natural question arises as to whether a class of multilateral price indexes that satisfy the identity test (e.g. the GEKS-L, GEKS-GL, GEKS-AQU or GEKS-AQI indices – for more details see Białek (2022a) or Białek (2022b) – is less prone to chain drift when splicing methods are used (Section 4).

The chain drift effect, which occurs while using weighted chain indices, is well documented in the literature. The results of works dealing with this subject, however are not always unanimous. For instance, Feenstra and Shapiro (2003) examine scanner data on canned tuna and find that the chain Törnqvist price index (Törnqvist, 1936) leads to upward chain drift caused by sales. In the paper by de Haan (2008), the same price index formula is used but the author, studying data on detergents, finds that sales lead to downward bias. Several studies of scanner data (de Haan, 2008; de Haan & van der Grient, 2011) show that pendular quantities cause downward chain drift. In the paper by Feenstra and Shapiro (2003) a delayed quantity reaction to price reduction is considered ("sticky quantities"). In the above-mentioned paper it is demonstrated that the upward chain drift resulting from sticky quantities dominates the downward chain drift arising from pendular quantities. An interesting study on "unconventional" consumer behaviour, such as stocking and delayed quantity responses to price changes, and its impact on chain drift bias can be found in the paper by von Auer (2019). The contribution of this article consists in the following: a) the impact of the scale of the delay in consumer response to price changes at the level of chain drift bias is analysed; b) it has been shown that the sign of the correlation between product prices and quantities may affect the sign of the index bias due to chain drift; c) the study included completely new multilateral formulas that meet the identity test.

2. Materials and methods

Before the research problem is implemented in an empirical and simulation study (Section 3 and Section 4), data sources and sources for computer scripts that were used in the work will be indicated. Let us first note that the simulation and empirical research was carried out in the R environment with open access (R Core Team, 2019). In particular, the original R script, which is done for analysis of the Divisia price index (see Section 3.1.1), is available at: https://github.com/JacekBialek/important_documents/blob/main/TEDE_2022_Divisia.Rmd.

The above-mentioned script considers three artificial products sold in the unit time interval and it is assumed that prices and quantities are periodic processes over time.

The R script that performs chain drift bias estimation for chain indexes and window splice methods is available at: https://github.com/JacekBialek/important_documents/blob/main/TEDE_2022_distances.Rmd.

The above-mentioned script generates an artificial scanner data set containing transactions of ten products sold in the period December 2019 – December 2021, and it considers two cases: Case 1 (negative correlations between prices and quantities) and Case 2 (positive correlations between prices and quantities). The user can control the level of delay in the reaction of consumers to price changes (*delta* parameter). The script compares first the chain Jevons and chain Fisher indices with the target GEKS price index (see Section 3.1.2) and then the script performs an analogical comparison for splice GEKS indices (see Section 3.2).

Whenever scanner data are filtered and multilateral indexes are determined, scripts written in the R environment use the *PriceIndices* R package (see Białek (2021a) or Białek (2021b)), which is available on the CRAN (https://cran.r-project.org/web/packages/PriceIndices/index.html) and GitHub (https://github.com/JacekBialek/PriceIndices) servers.

In the case of the real scanner data used in the conducted empirical study (see Section 4), the authors did not receive permission to make them available from the data owner (Statistics Poland).

Likewise, the retailer transferring this data also refused to do so.

3. Results of preliminary simulation studies

3.1. Chaining as a generator of chain drift

In the "direct" approach, while measuring price dynamics on the time interval $[0, t]$, the resulting price index $P^{0,t}$ depends only on prices and quantities from the base period 0 and the current period t. In other words, for a given set of matched products $G_{0,t}$ and for a given set of prices $\{(p_i^0, p_i^t) : i \in G_{0,t}\}$ and quantities of products $\{(q_i^0, q_i^t) : i \in G_{0,t}\}$, the direct (or bilateral) price index is a function of prices and quantities from the base and current period, i.e. $P^{0,t} = P^{0,t}(p^0, p^t, q^0, q^t)$.

The idea of chain indices is that a longer interval is partitioned into a subset of smaller intervals on which bilateral indices are calculated and subsequently combined (chained). In other words, a chain index measures the cumulative effect of successive intervals from 0 to 1, 1 to 2, ..., $t - 1$ to t (von der Lippe, 2007). In general, the chain index can be expressed as follows:

$$P_{ch}^{0,t} = \prod_{s=1}^{t} P^{s-1,s}, \tag{1}$$

where the linking formula $P^{s-1,s}$ is any bilateral price index. For example, the chain Fisher price index can be considered:

$$P_{ch-F}^{0,t} = \prod_{s=1}^{t} P_F^{\,s-1,s}, \tag{2}$$

in which the bilateral Fisher index (1922) is a geometric mean of the Laspeyres (1871) and Paasche (1874) indices, i.e.

$$P_F^{s-1,s} = \sqrt{P_{La}^{s-1,s} P_{Pa}^{s-1,s}}, \tag{3}$$

where

$$P_{La}^{s-1,s} = \frac{\sum_{i \in G_{s-1,s}} q_i^{s-1} p_i^s}{\sum_{i \in G_{s-1,s}} q_i^{s-1} p_i^{s-1}}; \tag{4}$$

$$P_{Pa}^{s-1,s} = \frac{\underset{i\ \ G_{s-1,s}}{} q_i^s p_i^s}{\underset{i\ \ G_{s-1,s}}{} q_i^s p_i^{s-1}}. \tag{5}$$

As it was above-mentioned, even chained superlative indices, e.g. the chain Fisher (1922) or Törnqvist (1936) index, may suffer from the chain drift problem (Chessa, 2015). One way to deal with this problem is to use chain (unweighted) Jevons (1865) index with the following linking index formula calculated for $N_{s-1,s} = card(G_{s-1,s})$ products:

$$P_J^{s-1,s} = \prod_{i \in G_{s-1,s}} \left(\frac{p_i^s}{p_i^{s-1}}\right)^{\frac{1}{N_{s-1,s}}}. \tag{6}$$

Nevertheless, the use of the chain Jevons index $P_{ch\ J}^{0,t}$ does not take into account different levels of consumption of individual products in the analysed period $[0, t]$.

A natural question arises about the potential causes of the chain drift effect (not only in relation to chain indices). The article verifies our main hypothesis that chain drift bias is primarily dependent on the scale of delay in consumer reaction to changes in product prices and the direction of correlation between product prices and quantities.

3.1.1. Divisia price index

Let us assume that we observe continuous price and quantity processes of N products on a time interval $[0, t]$, where $p_i(t)$ and $q_i(t)$ denote a price and quantity of i-th product at time t respectively. The key element of Francois Divisia's (1925) approach was to treat time as a continuous variable and his price index $P_{Div}(0,t)$, under some technical assumption (e.g. differentiability of the price and quantity functions), can be expressed as follows:

$$P_{Div}(0,t) = \exp\left(\int_0^t \frac{q_i(\tau)\frac{dp_i(\tau)}{d\tau}}{V(t)} d\tau\right), \tag{7}$$

where the value function $V(t)$ can be written as

$$V(t) = \sum_{i=1}^{N} p_i(t) q_i(t). \tag{8}$$

Although in practice we do not observe prices and quantities continuously over time, the Divisia's formula is regarded as mathematically elegant and theoretically perfect (von der Lippe, 2007), in the sense that all index formulas used in practice should approximate it. On the bases of theoretical considerations, chain indices are often regarded as being discrete time approximations of Divisia's index. Consequently, it can be expected that the phenomenon of chain drift has a similar origin and effect both in the case of chain indices and the Divisia's index. Therefore, before we apply our considerations to chain indexes, let us take a look at the following example:

Example 1. Let us consider a group of $N = 3$ products observed on time interval [0, 1] and characterized by the following price and quantity processes:

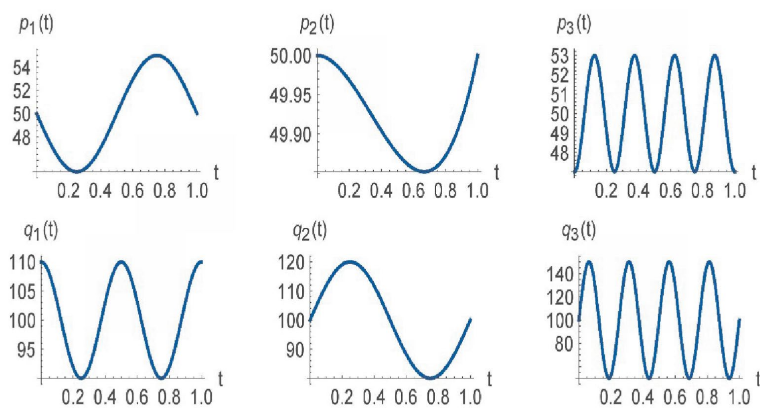

Figure 1. Comparison of price and quantity processes for three considered products

i.e. where $p_1(t) = 50 - 5\sin(2\pi \cdot t)$, $p_2(t) = 50 + t^3 - t^2$, $p_3(t) = 50 - 3\cos(8\pi \cdot t)$, and $q_1(t) = 100 + 10\cos(4\pi \cdot t)$, $q_2(t) = 100 + 20\sin(2\pi \cdot t)$, $q_3(t) = 100 + 50\sin(8\pi \cdot t)$. Please note, that the price and quantity processes were selected so that after a unit time their level would return to the initial value (see Figure 1), i.e. we have: $p_i(0) = p_i(1) = 50$ and $q_i(0) = q_i(1) = 100$ for any $i \in \{1,2,3\}$. Unfortunately, the problem of chain drift occurs because $P_{Div}(0,1) = 1.089 \neq 1$.

3.1.2. Chain Jevons and chain Fisher price indices

In the "classical" price index theory, the Fisher price index is treated as being ideal since it satisfies the *factor reversal test* and the *time reversal test* (von der Lippe, 2007). Moreover, in the filed the so called *economic approach* in index theory, superlative indices (e.g. the Fisher index) are proved to be the best approximation of the Cost of Living Index (COLI). Nevertheless, as it was above-mentioned, even chain superlative Fisher index may lead to chain drift bias. As it is commonly known, some countries use the chain Jevons index to deal with chain drift problem while using scanner data, however, the Jevons formula does not consider changes in consumers' consumption. Finally, multilateral price indices seem to be accurate for scanner data analysis since they are free from chain drift (Chessa, 2015; Chessa & Griffioen, 2016) and due to their unweighted or weighted (preferred) form. In this section, we hypothesize that chain drift, which may be generated by chain indices, depends on the price-quantity correlation and the scale of the delay in consumer reactions to price changes. However, this hypothesis requires further research and, above all, a definition of the measure of the delay in the response of quantity to price changes. This is the direction of further work of the author of the article.

Example 2. Let us consider an artificial scanner data set for $N = 10$ products sold during the time interval: December, 2019 – December, 2021. We will consider two cases for the price and quantity processes, i.e. *Case 1* (negative price-quantity correlation) and *Case 2* (positive price-quantity correlation). Of course, in practice, Case 1 applies to most products in any supermarket. We will assume that product quantities in both cases can be described by the following function (sales unit and currency are irrelevant to our considerations):

$$q_i^t = \begin{cases} 210 - t : 0 \le t \le 12 + \delta \\ 210 - i(12+\delta) + i(12+\delta)(t - 12 - \delta)/(12 - \delta) : 13 + \delta \le t \le 24 \end{cases} \tag{9}$$

and product prices, depending on the case, are described as follows:

Case 1

$$p_i^t = \begin{cases} 140 + it : 0 \le t \le 12 \\ 140 + i(24 - t) : 13 \le t \le 24 \end{cases}; \tag{10}$$

Case 2

$$p_i^t = \begin{cases} 140 - it : 0 \le t \le 12 \\ 140 - i(24 - t) : 13 \le t \le 24 \end{cases}, \tag{11}$$

where i denotes product number $(i \in \{1,2,...,10\})$, t is the number of month $(t \in \{0,1,...,24\})$ and δ means delay (in months) in consumer reaction to price changes $(\delta \in \{2,4,6,8\})$. Let us note that the price and quantity processes are selected so that, regardless of the value of the parameter δ, their values return to the initial state, i.e. we have $p_i(0) = p_i(24) = 140$ and

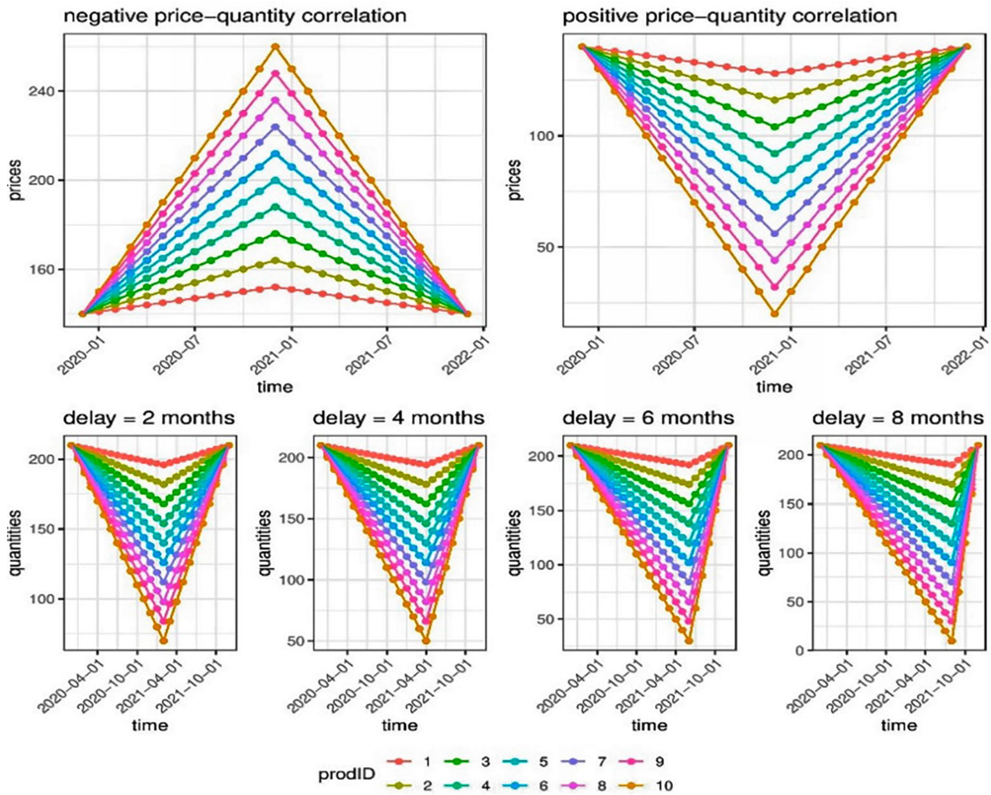

Figure 2. Price and quantity processes for ten considered products depending on the price-quantity correlation and the level of delay in consumer reaction

$q_i(0) = q_i(24) = 210$ (see Figure 2). Pearson's linear correlation coefficients determined for the price and quantity processes are the same for each product but they depend on δ parameter value, i.e. for $\delta \in \{2,4,6,8\}$ these correlation coefficients are {–0.956, –0.849, –0.701, –0.522} (Case 1) and {0.956, 0.849, 0.701, 0.522} (Case 2) respectively.

In our analysis, a target index is the GEKS formula as being free of chain drift, i.e.

$$P_{GEKS}^{0,t} = \prod_{\tau=0}^{T} (P_F^{0,\tau} P_F^{\tau,t})^{\frac{1}{T+1}} \tag{12}$$

which is based on the superlative Fisher index and is calculated for the full time window [0, T] = [0,24]. A comparison of chain Jevons and chain Fisher indices to the GEKS price index, performed for the most extreme delay in consumer reaction (δ = 8 months) is presented in Figure 3.

Of course, regardless of the value of the parameter δ, the Jevons chain index and the GEKS index revert to one. The Fisher chain index seems to overestimate the target index (full-time GEKS) in the case of a negative price-quantity correlation and underestimates the target index when the corresponding correlation is positive. The question remains whether the difference between chain indices and the target index depends on the scale of the delay in consumer reaction to price changes. The answer to this question is positive, i.e. the mean absolute difference between any of chain indices and the GEKS index is an increasing function of δparameter (see Table 1 and Table 2). In other words, this simple example shows that there may be a relation between the scale of consumer reaction lag and the bias of the price index due to the chain drift effect.

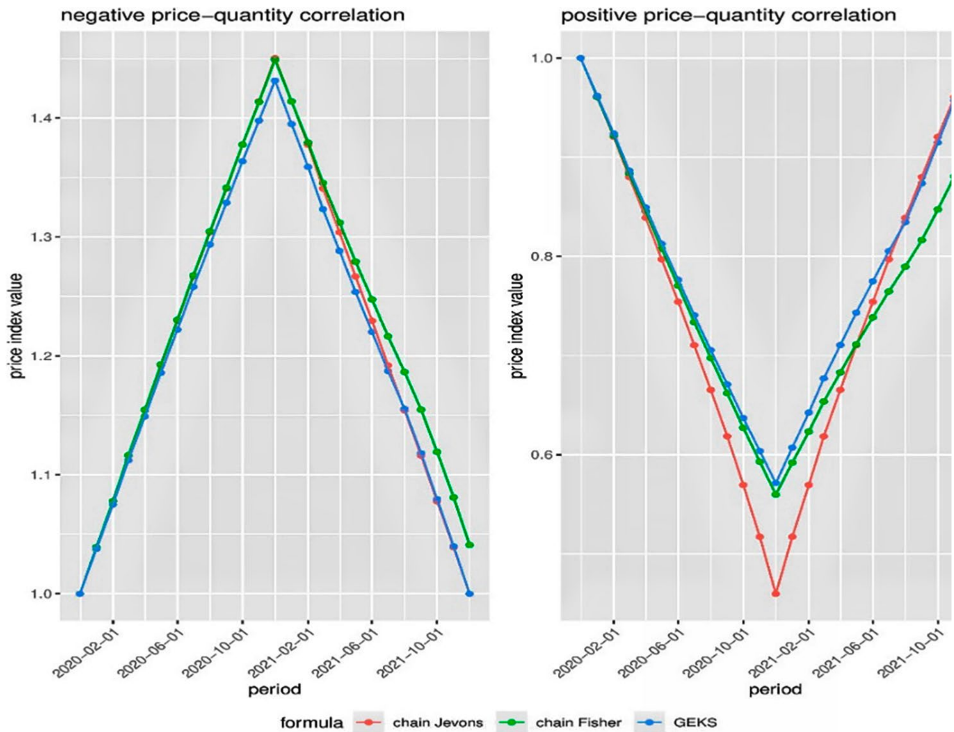

Figure 3. Comparison of selected chain indices to the GEKS method for Cases 1 and 2 and for δ = 8

Table 1. Mean absolute distances between considered chain indices and the target GEKS price index (p.p): Case 1

Index:	δ = 0	δ = 2	δ = 4	δ = 6	δ = 8
chain Jevons (without filtering)	0.126	0.319	0.503	0.675	0.879
chain Jevons (with filtering)	0.126	0.665	1.383	2.013	2.406
chain Fisher (without filtering)	0.161	0.632	1.096	1.540	1.945

Table 2. Mean absolute distances between considered chain indices and the target GEKS price index (p.p): Case 2

Index:	δ = 0	δ = 2	δ = 4	δ = 6	δ = 8
chain Jevons (without filtering)	2.620	2.799	2.957	3.096	3.319
chain Jevons (with filtering)	2.049	1.966	2.285	2.355	2.300
chain Fisher (without filtering)	0.058	0.825	1.538	2.096	2.503

Please note, that according to the so-called *dynamic approach*, Table 1 and Table 2 also consider the Jevons chain index calculated after applying the *low sales filter* on a given data set. While using this filter, the dynamic basket is determined using turnover figures of individual products in two adjacent months, i.e. the product is included in the sample if its turnover is above a fixed threshold determined by the number of products in a given product group. We consider the following condition for the above mentioned rule, which indicates whether the i-th product is taken into consideration in the comparison of months $t-1$ and t:

$$\frac{s_i^{t-1}+s_i^t}{2} > \frac{1}{N\lambda}, \tag{13}$$

where s_i^t denotes expenditure share of i-th product at time t, N is the number of products and λ is a set real parameter.

At this point, the reader should be provided with the reason why it was assumed in the paper that $\lambda = 1.25$. For this purpose, it should be mentioned that two approaches can be considered when constructing the sample of scanner products, i.e. a fixed basket approach and a dynamic approach. The fixed basket approach means that the basket is kept constant as far as possible in all months during the current year. The above-mentioned dynamic approach to using scanner data means that the measured prices stem from a continuously updated basket and thus this approach retains the most recent universe of items in the basket (Eurostat, 2018). In fact, the dominant belief is that the processing of scanner data in the dynamic approach should include filtering before the final calculation of price indices. Data filters should remove, or at least flag, products with extreme price fluctuations, products falling off sales, or just insignificant sales. Countries that have implemented a dynamic approach usually build a monthly sample in accordance with the procedure recommended by Eurostat, which is referred to as low sales filter: 'A low-sales filters out item codes with very low sales, or, conversely, ensures that the selected codes represent a sufficiently high proportion of turnover (between 50 and 80%)'. The λ parameter, which is involved in building the product sample selection criterion, is any real and positive number and is constant for all COICOP categories and throughout time. In the paper by van der Grient and de Haan (2010), the authors draw the following conclusion: "The threshold ($\lambda = 1.25$) was chosen such that roughly 50% of the items in an elementary aggregate will be selected, representing 80–85% of the expenditures". This value of the λ parameter was later used in many studies and by many authors, including the work of Guerreiro et al. (2018); van Loon and Roels (2018); Białek and Beręsewicz (2021). In view of the above-presented recommendations, in this study the authors also adopted the value of the λ parameter equal to 1.25.

In principle, the Jevons chain index after using the *low sale filter* should not deviate substantially from the weighted multilateral index. However, as the results from Table 1 and Table 2 show, that chain indices (including the chain Jevons index) may differ from the GEKS index noticeably and this difference may be crucial especially when the price-quantity correlation is positive (Case 2) and there is a big delay in consumer reaction on price changes. Our results also show, that in case of positive correlation between prices and quantities and no delay or small delay in consumer reaction on price changes, the chain Fisher index values are much closer to values of the GEKS index than the chain Jevons index values are

(Table 2). Finally, quite surprisingly, our example shows that there are potential situations in the supermarket, when a "simple" chain Jevons index used for non-filtered data set, provides much better results than the chain Jevons index with data filtering or chain Fisher index using expenditure shares as weights (Table 1).

3.2. Splicing as a generator of chain drift

The known and popular multilateral methods include the GEKS method (Gini, 1931; Eltetö & Köves, 1964), the Geary-Khamis (GK) method (Geary, 1958; Khamis, 1972), the CCDI method (Caves et al., 1982) or the Time Product Dummy Methods (de Haan & Krsinich, 2018). Recently, in the literature on the subject, there have also been proposed multilateral indexes that work on the time window and at the same time meet the identity test. Therefore, we may consider the GEKS-L and GEKS-GL indices based on the Laspeyres and geometric Laspeyres formulas, respectively, as well as the GEKS-AQU and GEKS-AQI formulas, which require quality adjusting (Białek, 2022a).

Unfortunately, adding information from a new month can change the values of quality adjustment parameters and it may influence on the corresponding multilateral indices. In the paper, we take into consideration four commonly used rolling-window updating methods, which shift the estimation window forward in each month and then splice the new indices onto the existing time series. We consider the following splicing methods:

3.2.1. The movement splice method

In the case of the movement splice method (de Haan & van der Grient, 2011), the following recursive formula can be used:

$$P_{MS}^{0,t} = P_{MS}^{0,t-1} \cdot P_{t-T,t}^{t-1,t}, \tag{14}$$

where P is any multilateral index formula, the subscript makes reference to the used time window and the superscript indicates months for which the index is calculated (see van Loon & Roels, 2018).

3.2.2. The window splice method

The window splice method proposed by Krsinich (2014) is used to calculate the price index for the new month by chaining the indices of the shifted window to the index of T months ago. It can be written in the following way:

$$P_{WS}^{0,t} = P_{WS}^{0,t-1} \cdot \frac{P_{t-T,t}^{t-T,t}}{P_{t-T-1,t-1}^{t-T,t-1}}. \tag{15}$$

3.2.3. The half splice method

The half splice "works" at $t_0 = (T + 1)/2$ if T is an odd integer and at $t_0 = T/2$ if T is an even integer (de Haan, 2015). A corresponding recursive formula can be expressed as follows:

$$P_{HS}^{0,t} = P_{HS}^{0,t-1} \cdot \frac{P_{t-T,t}^{t-t_0,t}}{P_{t-T-1,t-1}^{t-t_0,t-1}}. \tag{16}$$

3.2.4. The mean splice method

The mean splice method (Diewert & Fox, 2018) uses the geometric mean of all possible choices of splicing, i.e. all months {1, 2, ..., T} which are included in the current window and the previous one. The general formula for the mean splice method can be written as:

$$P_{GMS}^{0,t} = P_{GMS}^{0,t-1} \cdot \prod_{t_0=1}^{T} \left(\frac{P_{t-T,t}^{t-t_0,t}}{P_{t-T-1,t-1}^{t-t_0,t-1}} \right)^{\frac{1}{T}} . \tag{17}$$

As it was shown (Chessa et al., 2017), splicing methods may lead to the substantial chain drift bias. The following example shows that the sign of this bias may depend on the sign of the price-quantity correlation and its value may depend on the level of delay in consumer reactions on price changes.

Example 3. Let us continue the case study presented in Example 2, i.e. with exactly the same *Case 1* (negative price-quantity correlation) and *Case 2* (positive price-quantity correlation). Figure 4 and Figure 5 show a comparison between splice GEKS indices and the full-window GEKS index for the biggest delay in consumers reaction on price changes (δ = 8).

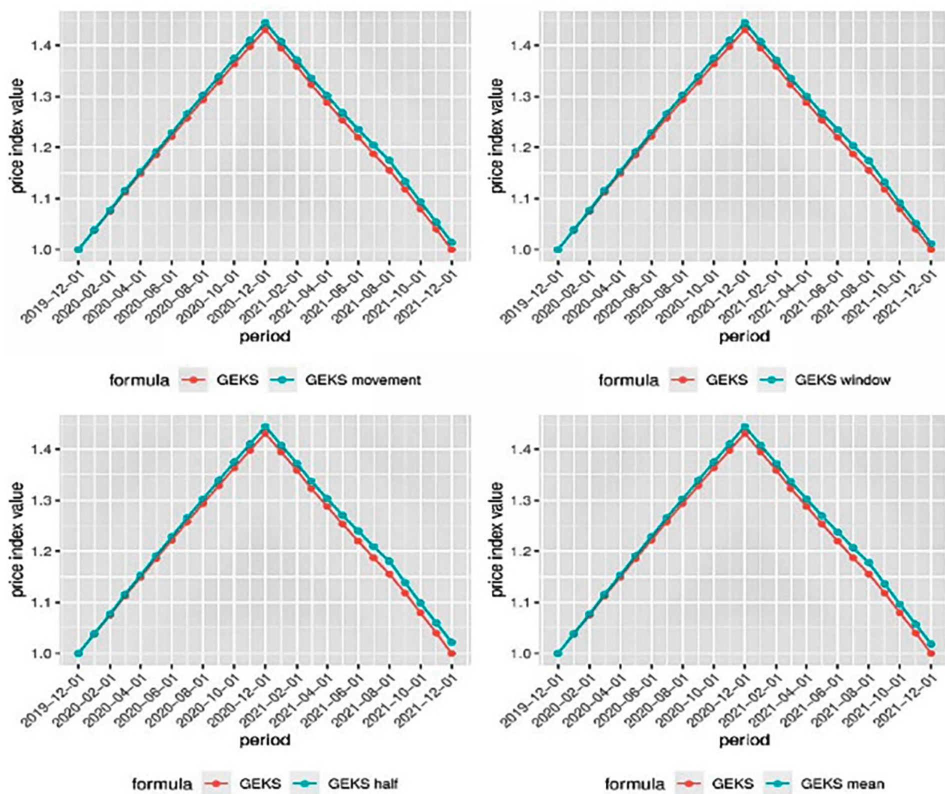

Figure 4. Comparison of selected splice GEKS indices to the full-window GEKS method for Case 1 and for δ = 8

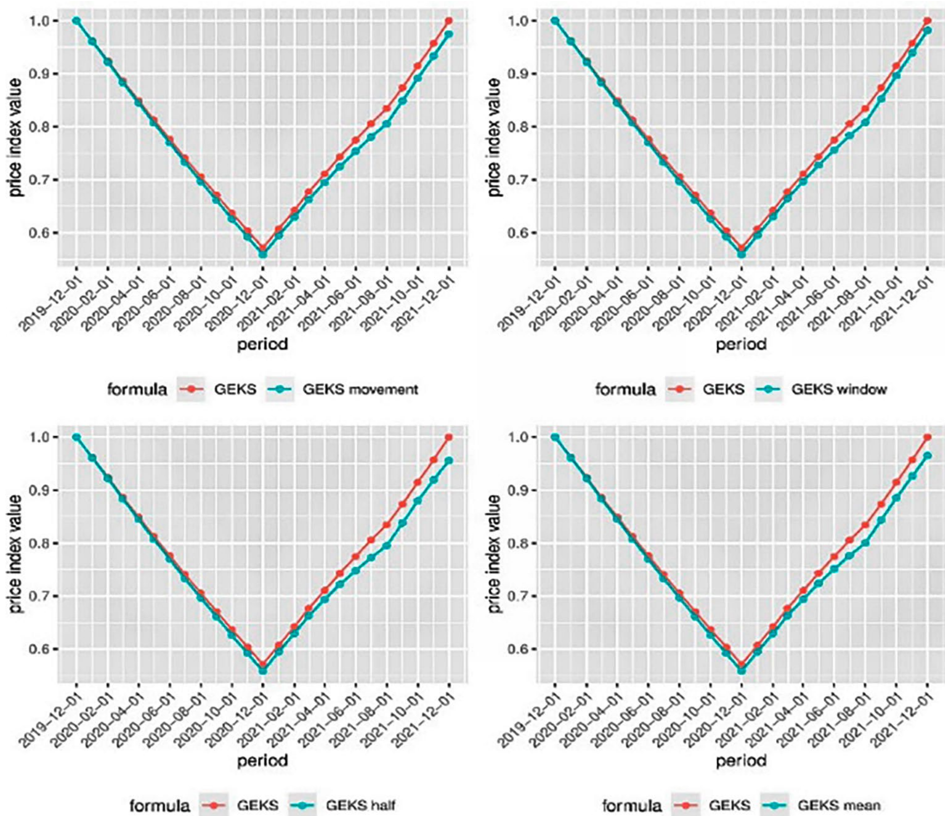

Figure 5. Comparison of selected splice GEKS indices to the full-window GEKS method for Case 2 and for δ = 8

Table 3. Mean absolute distances between considered splice GEKS indices and the target full window GEKS price index (p.p): Case 1

Index:	δ = 0	δ = 2	δ = 4	δ = 6	δ = 8
GEKS movement	0.040	0.166	0.430	0.744	1.094
GEKS window	0.020	0.162	0.403	0.699	1.040
GEKS half	0.017	0.255	0.577	0.929	1.287
GEKS mean	0.019	0.218	0.509	0.840	1.197

Table 4. Mean absolute distances between considered splice GEKS indices and the target full window GEKS price index (p.p): Case 2

Index:	δ = 0	δ = 2	δ = 4	δ = 6	δ = 8
GEKS movement	0.023	0.281	0.600	0.974	1.386
GEKS window	0.012	0.205	0.479	0.825	1.229
GEKS half	0.008	0.371	0.815	1.290	1.725
GEKS mean	0.010	0.315	0.691	1.111	1.546

Table 3 and Table 4 present mean absolute distances between splice GEKS indices and the target full-window GEKS price index (p.p) for all considered values of the above-mentioned delay ($\delta \in \{2, 4, 6, 8\}$). In our study, in the situation with negative price-quantity correlation, splice indices overestimate real price changes, i.e. splicing leads to overestimating the target full-window GEKS index (see Figure 4). When the price-quantity correlation is positive, splice indices underestimate the target GEKS index and the chain drift bias is even bigger in this Case 2 (see Figure 5 and Table 4). It is interesting that the chain drift bias is reasonably small when there is no delay in consumers reactions but this bias increases substantially as the level of delay in consumer response becomes bigger (Table 3 and Table 4).

4. Empirical study and discussion of results

The aim of our empirical study is indicating potential differences between full-time window multilateral indices and corresponding splicing methods with respect to the sign of these differences and the used index formula. In the study, scanner data from one retail chain in Poland were used, i.e. monthly data on *ground coffee* (subgroup of COICOP 5 group: 012111), *drinking yoghurt* (subgroup of COICOP 5 group: 011441) and *white sugar* (subgroup of COICOP 5 group: 011811) sold in 212 outlets during the period from December 2020 to December 2021. Before price index calculations, the database was carefully prepared. First, after deleting missing and duplicated data, the sold products were classified first into the relevant elementary groups and their subgroups (COICOP 6 level). Product classification was done via *data_selecting* and *data_classification* functions from the *PriceIndices* R package (Białek, 2021b). The first function required manual preparation of dictionaries of phrases and keywords which are able to identify individual product groups. The *data_classification* function, which is based on *machine learning* techniques, was used for problematic, previously unclassified products and required manual preparation of learning data sets. This step of classification was based on random trees and the *XGBoost* algorithm (Chen & Guestrin, 2016). Next, the product matching was carried out based on the available GTIN bar codes, internal retailer codes and product labels. To match products over time we run the *data_matching* function from the *PriceIndices* package. All products with two identical codes or one of the codes identical and an identical label were automatically matched. Products were also matched if they had identical one of the codes and the Jaro-Winkler (1989) distance of their labels (descriptions) was smaller than the fixed precision value: 0.02. In the last step before calculating indices, two data filters were applied to remove unrepresentative products from the data set, i.e. the *data_filtering* function from the *PriceIndices* package was applied. The *extreme price filter* (Białek & Beręsewicz, 2021) was used to eliminate items with more than three-fold price increase or more than double price drop from period to period. The *low sale filter* (van Loon & Roels, 2018) was run to roll out products with relatively low sales (almost 30% of products were removed). The study focuses on two classes of multilateral indices (see Appendix): G_{IDT} – multilateral indices which satisfy the *identity test* (GEKS-L, GEKS-GL, GEKS-AQU, GEKS-AQI) and G^{c}_{IDT} – selected multilateral indices which do not satisfy *identity test* and are commonly accepted in the literature (GEKS, CCDI, Geary-Khamis, TPD). The graphical results for differences between full-time window multilateral indices and corresponding splicing methods are presented in Figures A1–A6 (see Appendix). Tables 5–7 summarise these differences with respect to the sign of these differences and the used multilateral index formula. To be more precise: Tables 5–7 present mean absolute distances between full-window target index and splicing methods (*ALL* column), and analogical mean semi-distances on the basis of cases when splice indices overestimate (*OVER* column) and underestimate (*UNDER* column) the target full-time index values. Our main conclusions from this study are as follows: overestimating or underestimating the full-time index is consistent in the index classes G_{IDT} and G_{IDT}^{c}, i.e. either all indices from a given group strongly overestimate the target index or underestimate it most often. The hypothesis that splice indices from class G_{IDT} generate smaller distances than their full-window version (lower bias) has not been confirmed. In other words, the *identity test* does not play an important role in eliminating the chain drift bias of splice indices. In the group of indices from the class G_{IDT}, the smallest chain drift bias of their splicing extensions was generated after using the *window splice* method (2/3 of the cases) or the *movement splice* method (1/3 of the cases). In the group of indices from the class G_{IDT}^{c} there was no clear favourite among splicing methods: the *movement splice* method was the best in 1/6 of the cases, the *window splice* method in 2/6 of the cases, the *half splice* method in 1/6 of the cases and the *mean splice* in 2/6 of the cases. However, considering both index classes, the *window splice* method seems to be the best choice. In turn, the *half splice* method almost always turned out to be the worst (18 cases out of 24 examined cases).

Table 5. Mean absolute distances between considered splice indices and the corresponding target full-window index for sugar products (p.p)

Index:	ALL	OVER	UNDER	Index:	ALL	OVER	UNDER
GEKS movement	0.151	0.011	0.140	GEKS half	0.184	0.079	0.105
GEKS window	0.160	0.051	0.109	GEKS mean	0.152	0.038	0.114
CCDI movement	0.150	0.011	0.139	CCDI half	0.179	0.073	0.106
CCDI window	0.168	0.062	0.106	CCDI mean	0.152	0.041	0.111
TPD movement	0.652	0.013	0.638	TPD half	0.317	0.052	0.265
TPD window	0.331	0.149	0.182	TPD mean	0.290	0.064	0.226
GK movement	0.781	0.011	0.770	GK half	0.355	0.052	0.303
GK window	0.360	0.145	0.215	GK mean	0.343	0.069	0.274
GEKS-L movement	0.346	0.343	0.003	GEKS-L half	0.380	0.377	0.003
GEKS-L window	0.167	0.149	0.018	GEKS-L mean	0.243	0.233	0.010
GEKS-GL movement	0.233	0.219	0.014	GEKS-GL half	0.281	0.277	0.004
GEKS-GL window	0.117	0.102	0.015	GEKS-GL mean	0.161	0.151	0.010
GEKS-AQI movement	0.264	0.257	0.007	GEKS-AQI half	0.412	0.409	0.03
GEKS-AQI window	0.174	0.136	0.038	GEKS-AQI mean	0.235	0.227	0.008
GEKS-AQU movement	0.333	0.309	0.024	GEKS-AQU half	0.378	0.372	0.006
GEKS-AQU window	0.166	0.143	0.023	GEKS-AQU mean	0.237	0.220	0.017

Table 6. Mean absolute distances between considered splice indices and the corresponding target full-window index for joghurt products (p.p)

Index:	ALL	OVER	UNDER	Index:	ALL	OVER	UNDER
GEKS movement	0.698	0.084	0.614	GEKS half	0.942	0.076	0.866
GEKS window	0.522	0.104	0.418	GEKS mean	0.767	0.076	0.691
CCDI movement	0.654	0.084	0.570	CCDI half	0.917	0.074	0.843
CCDI window	0.521	0.118	0.403	CCDI mean	0.747	0.079	0.668
TPD movement	1.227	0.013	1.214	TPD half	0.741	0.013	0.728
TPD window	0.849	0.013	0.836	TPD mean	0.864	0.013	0.851
GK movement	1.203	0.012	1.191	GK half	0.716	0.012	0.704
GK window	0.822	0.012	0.810	GK mean	0.840	0.012	0.827
GEKS-L movement	0.540	0.059	0.481	GEKS-L half	0.922	0.040	0.882
GEKS-L window	0.636	0.054	0.581	GEKS-L mean	0.801	0.050	0.751
GEKS-GL movement	0.540	0.059	0.469	GEKS-GL half	0.941	0.061	0.880
GEKS-GL window	0.615	0.082	0.533	GEKS-GL mean	0.798	0.071	0.727
GEKS-AQI movement	0.502	0.070	0.432	GEKS-AQI mean	0.785	0.052	0.733
GEKS-AQI window	0.641	0.052	0.589	GEKS-AQI half	0.906	0.042	0.864
GEKS-AQU movement	0.502	0.080	0.422	GEKS-AQU half	0.848	0.047	0.801
GEKS-AQU window	0.571	0.074	0.498	GEKS-AQU mean	0.743	0.059	0.684

Table 7. Mean absolute distances between considered splice indices and the corresponding target full-window index for coffee products (p.p)

Index:	ALL	OVER	UNDER	Index:	ALL	OVER	UNDER
GEKS movement	0.706	0.704	0.002	GEKS half	0.976	0.974	0.002
GEKS window	0.548	0.527	0.021	GEKS mean	0.813	0.811	0.002
CCDI movement	0.774	0.770	0.004	CCDI half	1.011	1.007	0.004
CCDI window	0.649	0.639	0.010	CCDI mean	0.894	0.890	0.004
TPD movement	0.338	0.225	0.113	TPD half	0.517	0.411	0.106
TPD window	0.421	0.369	0.052	TPD mean	0.324	0.267	0.057
GK movement	0.394	0.296	0.098	GK half	0.607	0.525	0.082
GK window	0.485	0.433	0.052	GK mean	0.416	0.364	0.052
GEKS-L movement	0.983	0.972	0.011	GEKS-L half	1.378	1.367	0.011
GEKS-L window	0.861	0.731	0.130	GEKS-L mean	1.120	1.109	0.011
GEKS-GL movement	1.073	1.067	0.006	GEKS-GL half	1.323	1.317	0.006
GEKS-GL window	0.848	0.733	0.115	GEKS-GL mean	1.119	1.113	0.006
GEKS-AQI movement	1.601	1.589	0.012	GEKS-AQI half	1.263	1.212	0.051
GEKS-AQI window	1.452	0.868	0.584	GEKS-AQI mean	1.102	1.054	0.048
GEKS-AQU movement	1.000	0.990	0.010	GEKS-AQU half	1.405	1.395	0.010
GEKS-AQU window	0.836	0.739	0.097	GEKS-AQU mean	1.157	1.147	0.010

Conclusions and future works

In the case of scanner data, which is characterized by a big product churn and a high percentage of seasonal products, the use of classical bilateral indices would be burdened with too much measurement bias. In turn, chain indices that take into account all months in the analysed time window generate a chain drift effect. It therefore seems that multilateral indexes that take into account the entire time window and are also free from chain drift, are the ideal choice for scanner data. But even in the case of multilateral indices, when there is a need to use their so-called extensions (e.g. splice methods), the problem of chain drift returns.

This work explores the nature of chain drift, although it should be treated rather in terms of preliminary study. Our examples 1–3 allow us to hypothesize that the conditions for the formation of the chain drift effect are the same for chain indices and multilateral extensions. Numerical examples supported by simulations of the level of delay in consumer reaction to price changes indicate that perhaps the scale of chain drift can be explained through the prism of this delay. Moreover, it also appears that the direction of the correlation between prices and quantities may also influence the sign of the index bias due to chain drift. In our simple numerical studies (Examples 2–3) we found that the chain drift bias increases substantially as the level of delay in consumer response on price changes becomes bigger. Moreover, the chain and splice indices overestimated the target full-window GEKS index in the situation with negative price-quantity correlations and they underestimated the same target price index when price-quantity correlations were positive. So perhaps the chain drift effect also depends on the direction and strength of the relationship between prices and quantities. However, both hypotheses require further research and, above all, a definition of the measure of the delay in the response of quantity to price changes.

Finally, in the conducted empirical study, we decided to investigate the scale of a possible overestimation or underestimation of the full-window multilateral index depending on the choice of the splicing method. We were disappointed to find that the identity test does not play an important role in eliminating the chain drift bias of splice indices. Taking into account all 24 examined empirical cases (see Tables 5–7) we conclude that the window splice method is the best choice and, in turn, the half splice method almost always leads to the worst results (in terms of the size of the chain drift bias). Please note that we restrict our conclusions only to the splicing methods included in the study (i.e. the movement splice, window splice, half splice and mean splice method). Similar research, which would also cover modifications of these methods based on published indexes (WISP or HASP), is one of the author's future research goals.

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References

Andronie, M., Lăzăroiu, G., Ștefănescu, R., Ionescu, L., & Cocoșatu, M. (2021). Neuromanagement decision-making and cognitive algorithmic processes in the technological adoption of mobile commerce apps. *Oeconomia Copernicana*, *12*(4), 1033–1062. https://doi.org/10.24136/oc.2021.034

Australian Bureau of Statistics. (2016). *Making greater use of transactions data to compile the Consumer Price Index* (Information Paper 6401.0.60.003).

Białek, J. (2020). Proposition of a hybrid price index formula for the Consumer Price Index measurement. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *15*(4), 697–716. https://doi.org/10.24136/eq.2020.030

Białek, J. (2021a). *PriceIndices: Calculating Bilateral and Multilateral Price Indexes*. R package version 0.0.9.

Białek, J. (2021b). PriceIndices – a new R package for bilateral and multilateral price index calculations. *Statistika – Statistics and Economy Journal*, *36*(2), 122–141.

Białek, J., & Beręsewicz, M. (2021). Scanner data in inflation measurement: From raw data to price indices. *The Statistical Journal of the IAOS*, *37*(4), 1315–1336. https://doi.org/10.3233/SJI-210816

Białek, J. (2022a, June). The general class of multilateral indices and its two special cases. In *17th Meeting of the Ottawa Group on Price Indices*. Rome, Italy.

Białek, J. (2022b). Improving quality of the scanner CPI: Proposition of new multilateral methods. *Quality and Quantity*. https://doi.org/10.1007/s11135-022-01506-6

Białek, J., & Bobel, A. (2019, May). *Comparison of price index methods for CPI measurement using scanner data* [Conference presentation]. 16th Meeting of the Ottawa Group on Price Indices. Rio de Janeiro, Brazil.

Białek, J., & Roszko-Wójtowicz, E. (2021). Dynamics of price level changes in the Visegrad group: Comparative study. *Quality and Quantity*, *55*, 357–384. https://doi.org/10.1007/s11135-020-01021-6

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). Multilateral comparisons of output, input, and productivity using superlative index numbers. *Economic Journal*, *92*(365), 73–86. https://doi.org/10.2307/2232257

Chen, T., & Guestrin, C. E. (2016). XGboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). San Francisco, CA, USA, ACM. https://doi.org/10.1145/2939672.2939785

Chessa, A. (2015). Towards a generic price index method for scanner data in the Dutch CPI. In *14th Meeting of the Ottawa Group* (pp. 20–22). Tokyo.

Chessa, A. (2016). A new methodology for processing scanner data in the Dutch CPI. *Eurostat review of National Accounts and Macroeconomic Indicators*, *1*, 49–69.

Chessa, A. (2019, May). A comparison of index extension methods for multilateral methods. In *16th Meeting of the Ottawa Group on Price Indices*. Rio de Janeiro, Brazil.

Chessa, A., & Griffioen, R. (2016). *Comparing scanner data and web scraped data for consumer price indices* (Report). Statistics Netherlands.

Chessa, A. G., Verburg, J., & Willenborg, L. (2017). A comparison of price index methods for scanner data. In *15th Meeting of the Ottawa Group* (pp. 10–12). Eltville am Rhein.

de Haan, J. (2008). Reducing drift in chained superlative price indexes for highly disaggregated data. In *The Economic Measurement Workshop*. Centre for Applied Economic Research, University of New South Wales.

de Haan, J. (2015). A framework for large scale use of scanner data in the Dutch CPI. In *Report from Ottawa Group 14th Meeting, International Working Group on Price Indices* (pp. 1–43). Ottawa Group.

de Haan, J., & Krsinich, F. (2018). Time dummy hedonic and quality-adjusted unit value indexes: Do they really differ? *Review of Income and Wealth*, *64*(4), 757–776. https://doi.org/10.1111/roiw.12304

de Haan, J., & van der Grient, H. A. (2011). Eliminating chain drift in price indexes based on scanner data. *Journal of Econometrics*, *161*(1), 36–46. https://doi.org/10.1016/j.jeconom.2010.09.004

de Haan, J., Hendriks, R., & Scholz, M. (2021). Price measurement using scanner data: Time-product dummy versus time dummy hedonic indexes. *Review of Income and Wealth*, *67*(2), 394–417. https://doi.org/10.1111/roiw.12468

Diewert, W. E., & Fox, K. J. (2018). *Substitution bias in multilateral methods for CPI construction using scanner data* (UNSW Business School Research Pape No. 2018-13). https://doi.org/10.2139/ssrn.3276457

Dijmărescu, I., Iatagan, M., Hurloiu, I., Geamănu, M., Rusescu, C., & Dijmărescu, A. (2022). Neuromanagement decision making in facial recognition biometric authentication as a mobile payment technology in retail, restaurant, and hotel business models. *Oeconomia Copernicana*, *13*(1), 225–250. https://doi.org/10.24136/oc.2022.007

Divisia, F. (1925). L'indice montaire et la theorie de la monnaie. *Revue d'Economique Politique*, *40*(1), 49–81.

Eltetö, O., & Köves, P. (1964). On a problem of index number computation relating to international comparison. *Statisztikai Szemle*, *42*(10), 507–518.

Eurostat. (2018). *Practical guide for processing supermarket scanner data*. Harmonised Index of Consumer Prices.

Eurostat. (2020). *Practical guide on multilateral methods in the HICP* (*draft*). European Commission. Version September 2020.

Feenstra, R., & Shapiro, M. (2003). High-frequency substitution and the measurement of price indexes. *Studies in Income and Wealth*, *64*, 123–146.

Fisher, I. (1922). *The making of index numbers: A study of their varieties, tests, and reliability*. Houghton Mifflin.

Geary, R. C. (1958). A note on the comparison of exchange rates and purchasing power between countries. *Journal of the Royal Statistical Society. Series A* (*General*), *121*(1), 97–99. https://doi.org/10.2307/2342991

Gini, C. (1931). On the circular test of index numbers. *Metron*, *9*(9), 3–24.

Griffioen, A. R., & Ten Bosch, O. (2016, May). On the use of internet data for the Dutch CPI. In *The UNECE-ILO Meeting of the Group of Experts on Consumer Price Indices*. Geneva, Switzerland.

Guerreiro, V., Walzer, M., & Lamboray, C. (2018). The use of supermarket scanner data in the Luxembourg consumer price index. *Economie et Statistiques*, *97*, 1–17.

Inklaar, R., & Diewert, W. E. (2016). Measuring industry productivity and cross-country convergence. *Journal of Econometrics*, *191*(2), 426–433. https://doi.org/10.1016/j.jeconom.2015.12.013

International Labour Office. (2004). *Consumer price index manual: Theory and practice*. Geneva.

Ivancic, L., Diewert, W. E., & Fox, K. J. (2011). Scanner data, time aggregation and the construction of price indexes. *Journal of Econometrics*, *161*(1), 24–35. https://doi.org/10.1016/j.jeconom.2010.09.003

Jaro, M. (1989). Advances in record-linkage methodology as applied to matching the 1985 census of Tampa, Florida. *Journal of the American Statistical Association*, *84*(406), 414–420. https://doi.org/10.1080/01621459.1989.10478785

Jevons, W. S. (1865). On the variation of prices and the value of the currency since 1782. *Journal of the Statistical Society of London*, *28*(2), 294–320. https://doi.org/10.2307/2338419

Khamis, S. H. (1972). A new system of index numbers for national and international purposes. *Journal of the Royal Statistical Society: Series A* (*General*), *135*(1), 96–121. https://doi.org/10.2307/2345041

Krsinich, F. (2014). The FEWS index: Fixed effects with a window splice. Non-revisable quality adjusted price indexes with no characteristic information. In *Meeting of the Group of Experts on Consumer Price Indices* (pp. 26–28). Geneva, Switzerland.

Lamboray, C. (2017). The Geary Khamis index and the Lehr index: How much do they differ. In *15th Meeting of the Ottawa Group* (pp. 10–12).

Laspeyres, K. (1871). IX. Die Berechnung einer mittleren Waarenpreissteigerung. *Jahrbücher für Nationalökonomie und Statistik*, *16*(1), 296–318. https://doi.org/10.1515/jbnst-1871-0124

Małkowska, A., Urbaniec, M., & Kosała, M. (2021). The impact of digital transformation on European countries: Insights from a comparative analysis. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *16*(2), 325–355. https://doi.org/10.24136/eq.2021.012

Paasche, H. (1874). Über die Preisentwicklung der letzten Jahre nach den Hamburger Börsennotirungen. *Jahrbücher für Nationalökonomie und Statistik*, *23*(2–4), 168–178.

R Core Team. (2019). *R: A language and environment for statistical computing. R Foundation for Statistical Computing*. Vienna, Austria.

Roszko-Wójtowicz, E., & Grzelak, M. M. (2020). Macroeconomic stability and the level of competitiveness in EU member states: A comparative dynamic approach. *Oeconomia Copernicana*, *11*(4), 657–688. https://doi.org/10.24136/oc.2020.027

Törnqvist, L. (1936). The bank of Finland's consumption price index. *Bank of Finland Monthly Bulletin*, *16*(10), 1–8.

van der Grient, H., & de Haan, J. (2010, May). The use of supermarket scanner data in the Dutch CPI. In *Joint ECE/ILO Workshop on Scanner Data*. Geneva.

van Loon, K., & Roels, D. (2018, May). Integrating big data in the Belgian CPI. In *Meeting of the Group of Experts on Consumer Price Indices*. Geneva, Switzerland.

von Auer, L. (2019, May). The nature of chain drift. In *17th Meeting of the Ottawa Group on Price Indices*. Rio de Janerio, Brasil.

von der Lippe, P. (2007). *Index theory and price statistics*. Peter Lang. https://doi.org/10.3726/978-3-653-01120-3

Zhang, L.-C., Johansen, I., & Nyagaard, R. (2019). Tests for price indices in a dynamic item universe. *Journal of Official Statistics*, *35*(3), 683–697. https://doi.org/10.2478/jos-2019-0028

APPENDIX

Figures concerning the Empirical Study

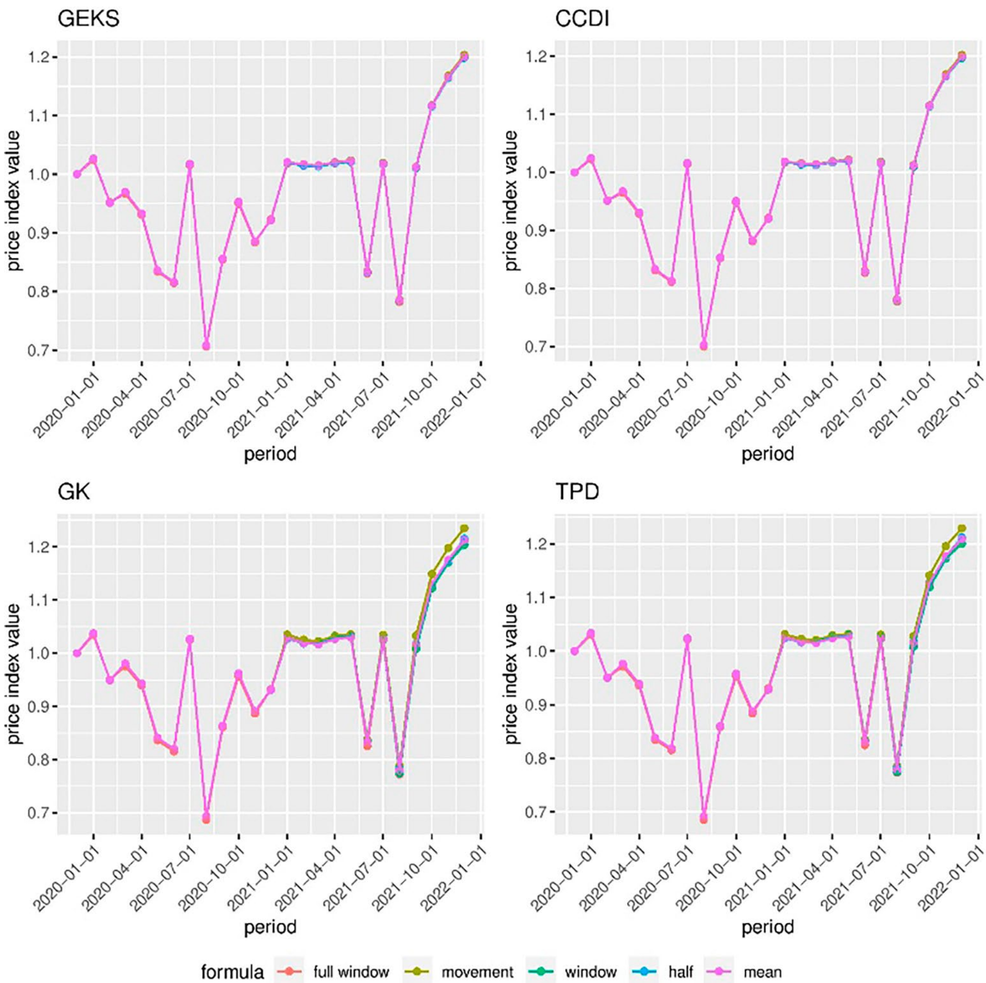

Figure A1. Comparison of G_{IDT}^{c} indices (splicing methods vs full time indices) for sugar products

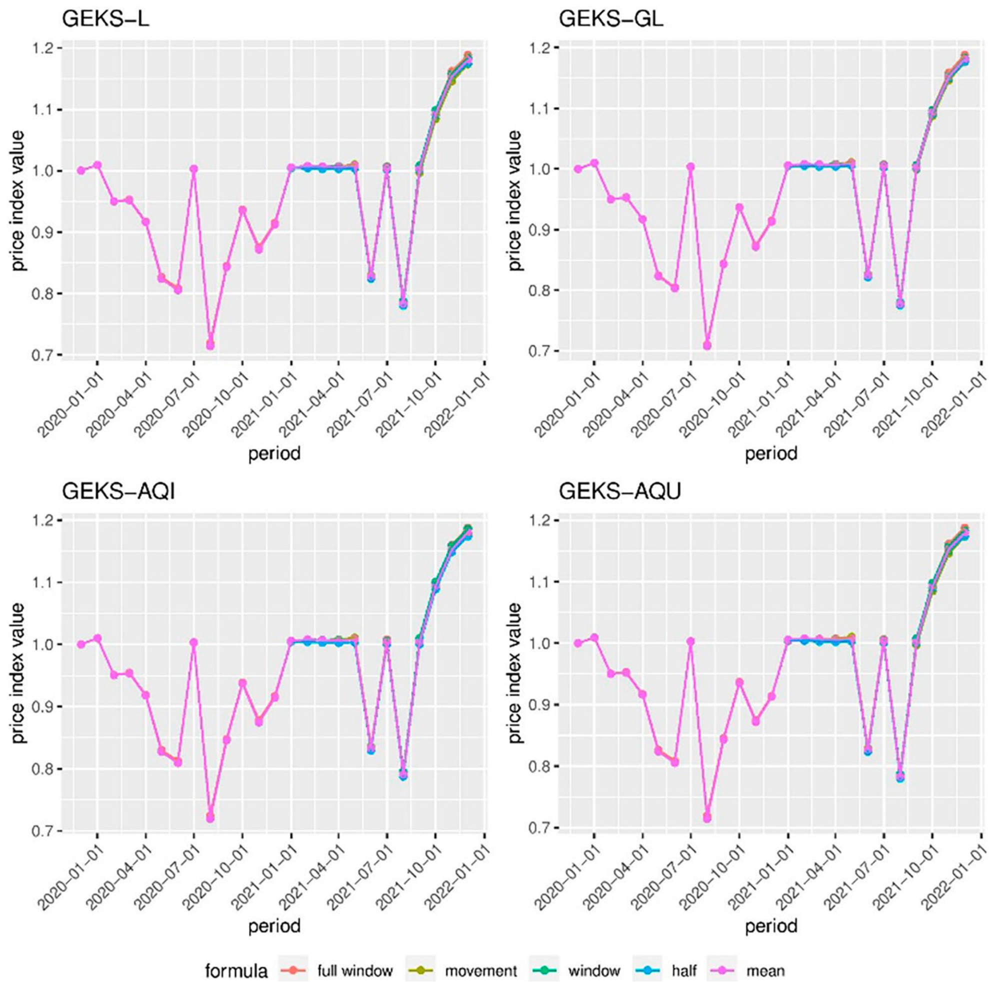

Figure A2. Comparison of G_{IDT} indices (splicing methods vs full time indices) for sugar products

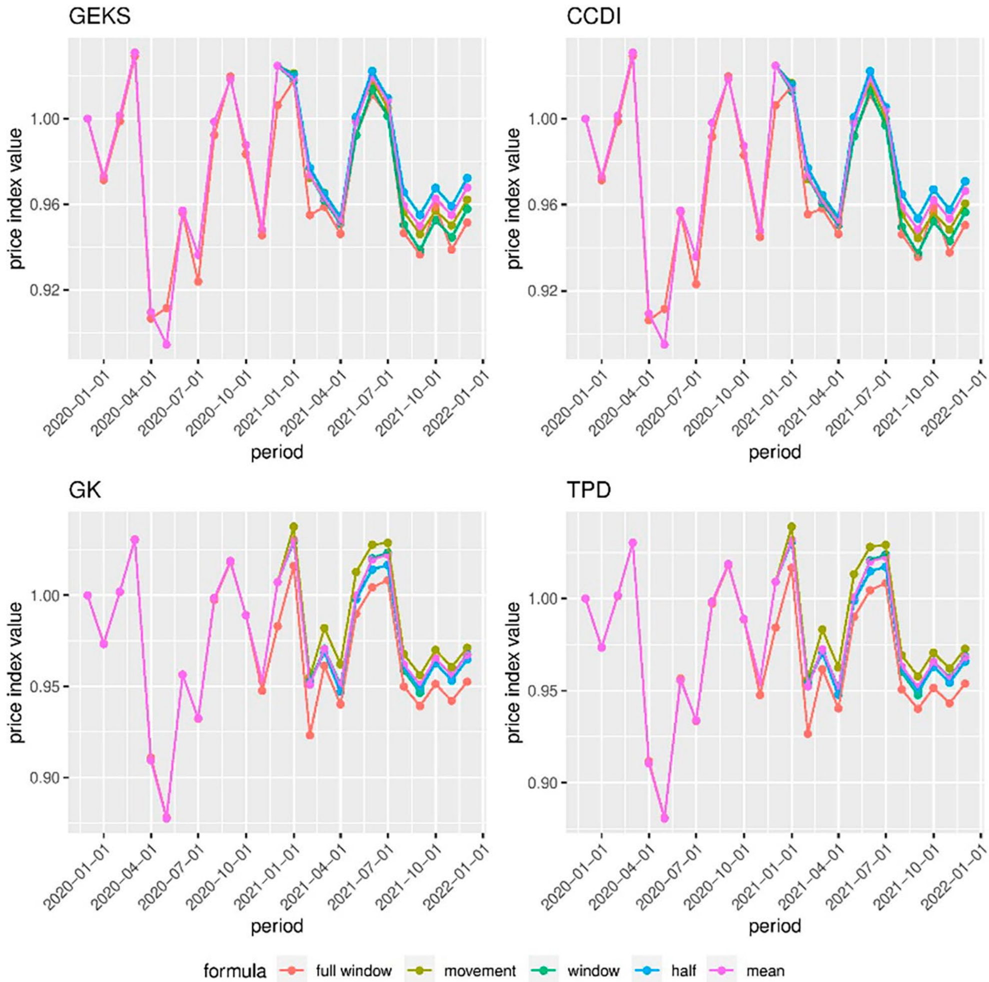

Figure A3. Comparison of G^{c}_{IDT} indices (splicing methods vs full time indices) for joghurt products

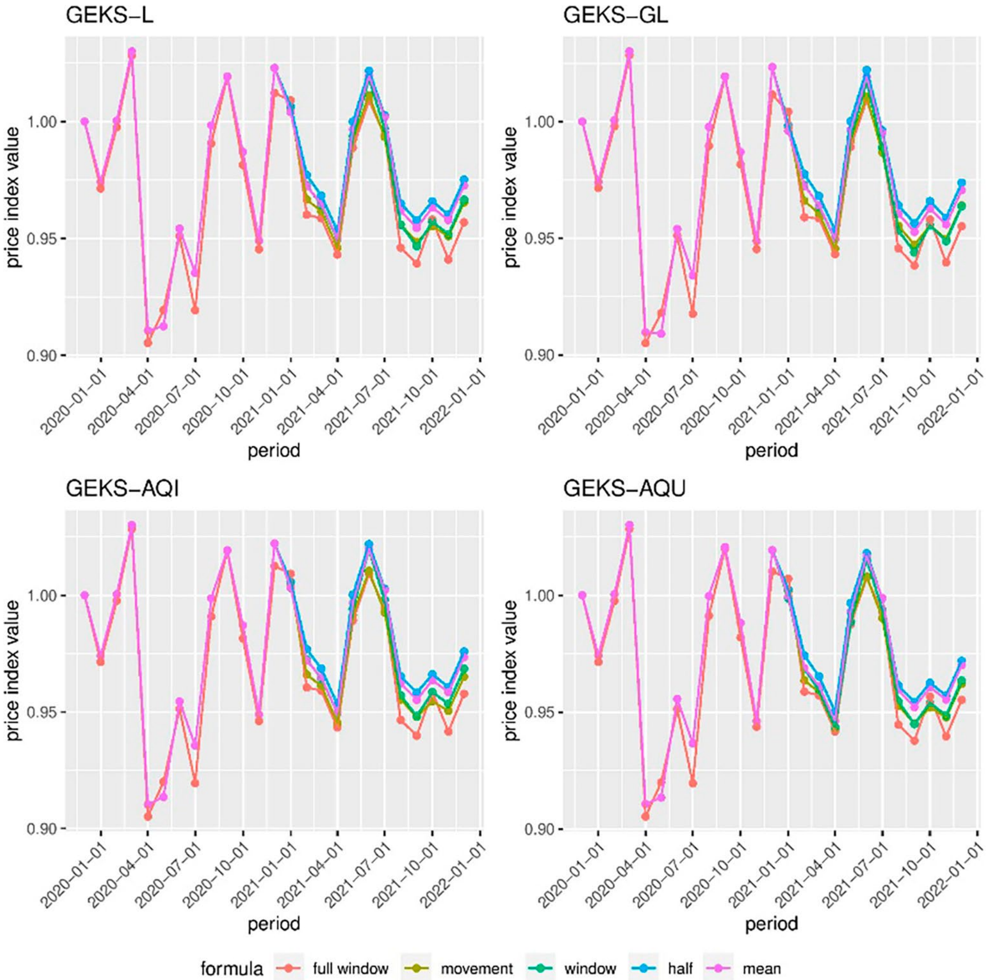

Figure A4. Comparison of G_{IDT} indices (splicing methods vs full time indices) for joghurt products

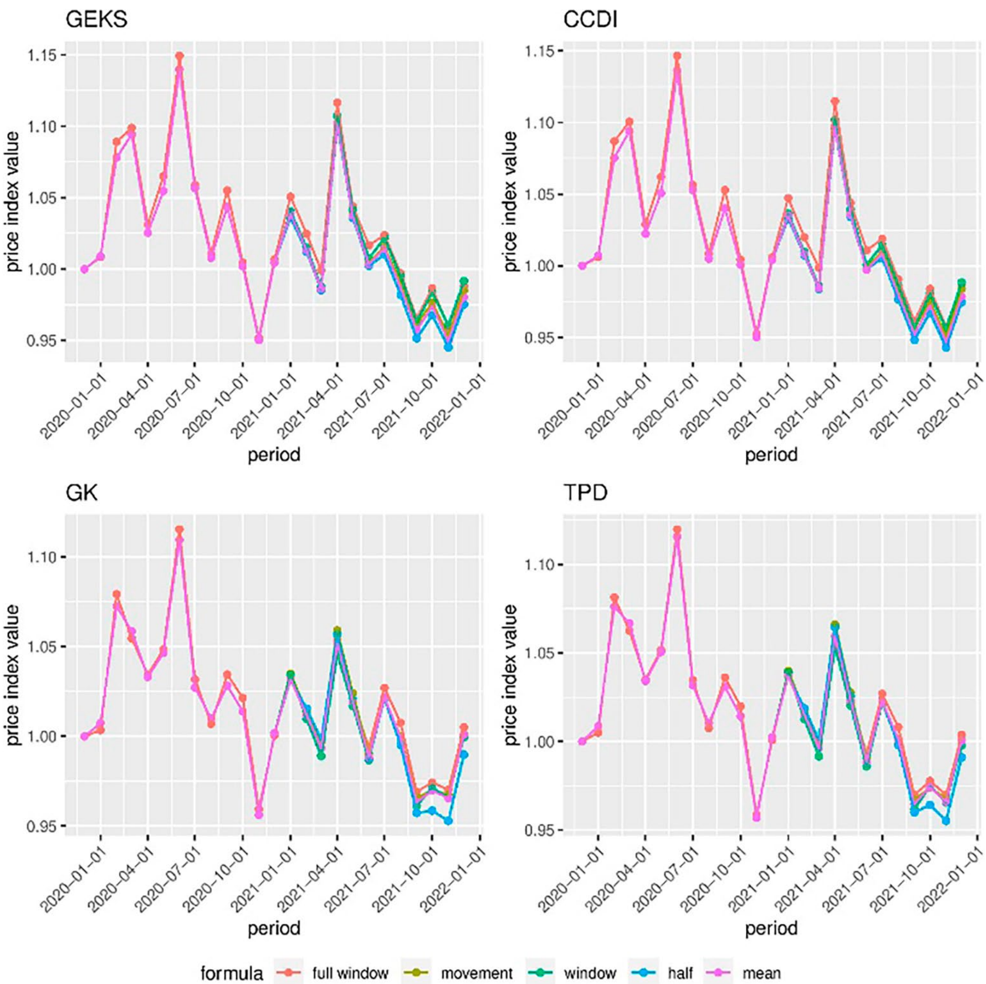

Figure A5. Comparison of G^{c}_{IDT} indices (splicing methods vs full time indices) for coffee products

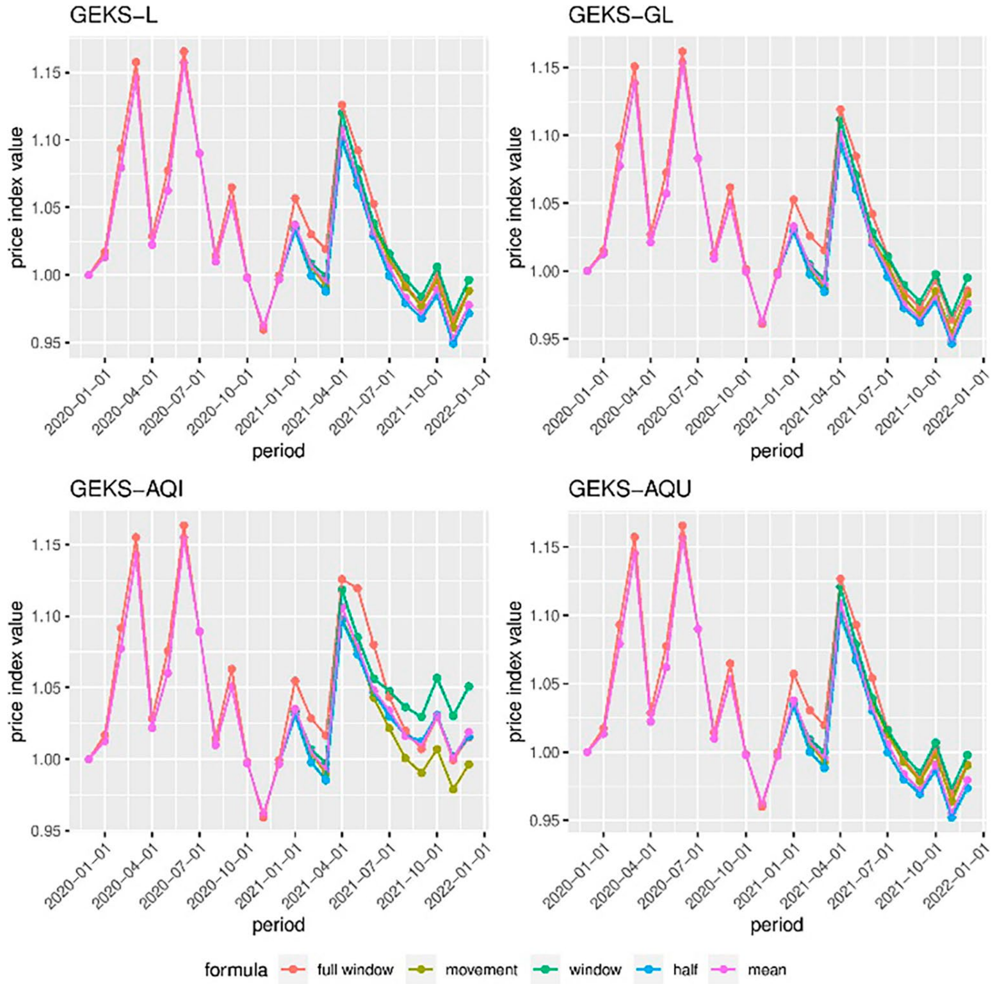

Figure A6. Comparison of G_{IDT} indices (splicing methods vs full time indices) for coffee products