Inflation Measurement with Scanner Data and an Ever-Changing Fixed Basket

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Abstract – Statistics Sweden introduced scanner data into parts of the consumer price index several years ago, with the concern to ensure comparability over time and between countries. In this article, we discuss the issue of preserving the fixed basket approach and whether the traditional manual item replacement strategy, with quality and quantity adjustments, is still a relevant method to ensure comparability despite the change in data collection mode and extensiveness of data. Biases from improper quantity adjustments are discussed and illustrated through numeric examples based on real changes in the Swedish market of daily necessity products. Manual adjustments of quality and quantity are implemented by following a small random sample of representative items, i.e. a fixed basket, which therefore leads to imprecision or variance in the consumer price index. This may be a questionable approach given the availability of census-like scanner data, thus the bias-variance trade-off is addressed. The sample size related variance is estimated through a jackknife method and contrasted with quality/quantity adjustments.

JEL Classification: E31, C15, C83, C80
Keywords: scanner data, consumer price index, CPI, fixed basket, hidden inflation, jackknife variance

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Scanner data from retailers were introduced in the Swedish Consumer Price Index (CPI) as of year 2012, and started with the daily necessities. At the time of the introduction, Statistics Sweden had no conceptual questions concerning the amount of data to use. It was commenced with a one-to-one exchange of manually collected prices for scanner data from the (at the time) one retailer that provided these data, retaining the sample structure for both outlets and items. Prior to implementing scanner data in the CPI production, several internal studies were conducted to ensure that the new data source complied with the basic expectancy of no impairing impact on the CPI.

With time, the amount of included scanner data as well as the number of retailers that most kindly provided, and still provide, scanner data has increased to cover more than 80% of the Swedish daily necessities market in terms of turnover.[1] As a positive spillover effect from this experience in daily necessities, other parts of the Swedish CPI are now being produced with the help of new, alternative data sources comprising real transactions. Despite the increase in data volumes that are available for use, especially within daily necessities, the Swedish CPI production continues with the established product and store sampling strategy. The sampling strategy is principally independent of the data collection mode but rather adapted – only minor methodological changes and perhaps merely small divergences occured with the introduction of this alternative and very promising new data source.

However, being in the "Big Data" era and having the potential buzz from this echoing into statistical methodology, this somewhat conservative standing point of Statistics Sweden may be questioned: why not continuously use all, or as much as possible, of the data, what seems interesting and more up-to-date? The issue of preserving conventional CPI methodology in the presence of scanner data is discussed in this paper. The approach undertaken by Statistics Sweden, which combines big data and conventional approaches, is seeking to deal adequately with the phenomenon of relaunches. This means that when products change in some characteristic, for instance in size such that the new product is almost similar as the discontinued product, then some price adjustment with respect to the quantity change must be made to preserve comparability over time. Impacts from improper assessments of quantity/quality ajustments will be discussed regarding the use of automatic baskets with scanner data.

The purpose of this paper is to study the trade-off between the accuracy of the inflation measured and the bias from disregarding explicit quantity adjustments. Although the focus is on daily consumer products, the analysis is relevant for the overall CPI.

The paper is organized as follows. The next section gives an overview of the use of scanner data in the CPI production at Statistics Sweden. This is a descriptive section on this relatively new data collection mode and primarily aimed at readers who are not familiar with the topic. In the following section, a jackknife variance estimator is applied to assess the index variance in a simplified setting. Then we turn to the quantity/quality issue, which is described and supported with numeric examples based on actual changes that have taken place in the Swedish daily necessities market. The paper concludes with some general remarks and contextualisation of the results.

Scanner Data for Daily Necessity Products in the Swedish CPI

This section outlines some methodological issues that had to be addressed prior to implementing scanner data. But first, it proposes a small digression concerning terminology, and some elements on the arrival of scanner data at Statistics Sweden two decades ago.

Scanner Data, Transaction Data and Big Data

In the context of consumer sales, scanner data is perhaps a somewhat sloppy expression for "transaction data" of sales in the consumer market.[2] The word "scanner" stems from the use of bar codes[3] adhered to goods' packages that are scanned in order to register the items at the purchase point, e.g. the cash register/check-out

1. Market statistics can be obtained from the Swedish Trade Research Agency in a cooperation between market actors. See HUI Research (2017).

2. There is a distinction between scanner data and Electronic Point of Sales (EPOS) data in the CPI Manual (§6.117, ILO 2004) not adhered to here.

3. The bar code relates the item, through its package, to a distinct article number according to the standard of EAN/GTIN (European Article Number or Global Trade Item Number), provided by an international market actor.

point. The more general term "transaction data" can be used interchangeably whenever possible as it also has a wider scope: digital data of sales/consumption of services as well as goods. Transaction data of sales are, by and large, well-structured data stemming from a business system and should not be confused with for instance unstructured "big" data. Transaction data may be large, high-frequency, obtainable virtually in real-time, and they are similar to administrative data in that they are not intended for official statistics, but rather for management purposes, such as inventory management, or sales or profit monitoring.

Scanner Data's Way into the Swedish CPI

This digital data source is not a new phenomenon to Statistics Sweden. In the mid-1990s, when digital data itself was a new phenomenon, contacts were initiated with market sales analysts in Sweden in order to have a first look at this new and supposedly promising data source – the potential interest for the CPI was obvious and appealing. Nevertheless, a significant price tag was attached to these data which therefore remained inaccessible for a government agency operating in the context of the most serious national economic crisis in the post-war era (cf. Bäckström, 1997; or Englund, 2015, for economic-political details). Today, some twenty years later, this data source is an established and natural part of the monthly Swedish CPI data collection, and Statistics Sweden receives data from many retailers, free of charge, on the basis of bilateral non-profit agreements. This is merely for the sample of stores included in the CPI in a specific year. As the retail chains provide data *pro bono*, Statistics Sweden has kept data demands at rather modest levels, which is also in one sense a factor of confidence because the retailers do not provide complete high-frequency business information.

The CPI Basket, Transaction Data and Exceptions

The CPI Basket

The CPI basket is presented in Table 1 according to the international nomenclature COICOP[4] (two-digit divisions). Prices are collected for defined products within these consumption categories. There are several computation steps between the total CPI value and the defined products – the CPI is simply a hierarchy in which price data is aggregated in steps.

A defined product at a specific retailer, the subject for price measurements, is referred to as a product offer. Observed prices are aggregated through index formulae and according to within-year fixed weights for the product groups, which often can be first-level indices, i.e. elementary aggregates. An example of a product group is milk: prices for varieties of all brands and stores and types of saturations (regarding fat) are assembled in one common product group, as are for instance flavored sodas, with or without sugar and regardless of size.

The weights for the product groups reflect their share of private consumption at a previous time point, in our case the previous full year prior to the index base year. The index base year is December y–1 and current months for price measurements are during year y, so weights are (normally) from year y–2 for the monthly index. The CPI is a series of indices chained over years and the discussion here concern the monthly (within-year) index links.

Transaction Data in the Basket

Transaction data are used for price measurements in several consumption categories, and are also a source of information for calculating weights. For daily consumer products, it comprises weekly turnover at item and store level, i.e. specific information on actual consumption. Some products, e.g. alcoholic beverages, pharmaceutical drug sales in pharmacies and dental care are covered monthly through complete census data. Besides this, aggregated annual scanner data for entire Sweden have been available to Statistics Sweden since the mid-1990s and used for basket construction.

As seen in Table 1, transaction data are used for price measurements but not in all parts of the basket – the main exceptions are given in Box 1.

4. COICOP (Classification of Individual Consumption According to Purpose). See the related United Nations web page (UN, 2017).

Table 1
CPI basket weights for year 2016

Code	Heading	Weight in basket (‰)	Transaction data
01	Food and non-alcoholic beverages	139	Yes
02	Alcoholic beverages, tobacco and narcotics	39	Yes
03	Clothing and footwear	53	No
04	Housing, water, electricity, gas and other fuels	251	Yes
05	Furnishing, household equipment and routine household maintenance	55	No
06	Health	38	Yes
07	Transport	135	No
08	Communication	35	No
09	Recreation and culture	120	No
10	Education	5	No
11	Restaurants and hotels	67	No
12	Miscellaneous goods and services	63	Yes
Total	CPI	1,000	

Notes: According to COICOP divisions (two-digit) for household consumption. Transaction data is indicated whenever included for price measurements. Two additional COICOP divisions, codes 13 and 14, exist but cover non-household consumption and are out of the scope of the consumer price index.

Box 1 – **Exceptions from Scanner Data in Daily Necessity Products: Non-Providers and Fresh Items**

In the first two COICOP divisions, 01 and 02, transaction data are used almost exclusively, with two specific exceptions. First, some retailers within division 01, Food and non-alcoholic beverages, do not provide transaction data which thus still requires manual price collection. Second, manual price collection has been continued within fresh fruit, fresh vegetables, fresh meat and cheese. Such items are usually sold by weight or sometimes by unit, e.g. avocados or lemons.

As of year 2017, scanner data were introduced for the fresh items' survey, starting with one retailer (Tongur & Sandén, 2016) and as of 2018, the duality in data collection, manual beside digital, was ended and a full transition to scanner data accomplished for retailers that provide scanner data (Bilius *et al.*, 2017). On related topics, see the publications from Statistics Norway (Nygaard, 2010 or Rodriguez & Haraldsen, 2005), or from Statistics Netherlands (van der Grient & de Haan, 2010).

Implementing the New Data Source in the Swedish CPI

As Statistics Sweden has experienced more than half a decade with scanner data in monthly CPI production, we propose here to review some of the choices that have been made along the way.

Alternatives for How to Use Scanner Data

Continuing with the fixed basket approach was decided by Statistics Sweden and the CPI Board (Box 2) in 2011 as it was considered the least intrusive way of using scanner data.[5] Implementation was immediate, as of year 2012 and more or less consisted of a change in the way of collecting data. This was considered to have the smallest impact on overall CPI production as well as related IT systems. The decision was based on several studies and analyses of data and comparisons with manual price collection (Norberg *et al.*, 2011). Besides the question of how to use scanner data in practice, it was also necessary to decide whether the data should actually be used. Four principally different ways of using scanner data were identified by Norberg *et al.* (2011), all having merely daily necessity products data in mind. The options are outlined in Box 3.

5. The decision was made upon approval from the CPI Board which had regulatory mandate at the time.

Box 2 – **The Swedish CPI Board**

The Swedish CPI Board (*Nämnden för Konsumentprisindex* in Swedish) is a scientific and interdisciplinary external methodological advisory board for the production of CPI. The Swedish CPI is not merely a statistic but also a decision made monthly, non-revisable. The board meets usually twice a year, at Statistics Sweden.

The board was installed many decades ago and serves at present, as of 2017, as a non-stipulating advisory council in questions of principal matter that are substantial for the CPI. Members are appointed by Statistics Sweden and are representatives of the CPI-related public institutions, e.g. the Central Bank of Sweden (Riksbanken), other governmental agencies and universities. Additionally, the Norwegian CPI unit is represented in order to exchange experience and to increase Nordic collaboration. Such input has been of specific help in the introduction of scanner data as Statistics Norway is one of the pioneering countries in this field. External experts of international standing are also appointed as board members.

Prior to 2017, the board was at a stipulating mandate. It had the right to make decisions on CPI-issues of principally influential nature. Also, their decision could not formally be appealed, according to the legal instructions for Statistics Sweden. The Board included also a permanent member from the parent ministry. However, in 2012, a review of the Swedish Official Statistics system and Statistics Sweden's role as the major governmental agency in statistics was carried out (SOU, 2012). The review was commissioned by the government and, concerning the CPI, the recommendation was that the CPI Board should no longer have stipulating mandate as it was questionable from the point of view of the agency's independence, and not in line with European Code of Practice for Official Statistics.

Box 3 – **Four Ways of Using Scanner Data in the CPI Production**

A - Replacing the manually collected price data with scanner data for the ordinary sample of outlets and products
This would imply only minor changes/adaptations to the current established CPI production and a total compliance with HICP[(a)] regulations.

B - Using scanner data as auxiliary information
This would require choosing between two possible approaches and still continue sampling price quotations manually. Either i) the sample would be calibrated with the corresponding periods' scanner data, or ii) the scanner data would be calibrated with the respective manual collection.

C - Computing index from a census of all products for which scanner data is available
Either the fixed basket approach is conducted on a large scale, with accompanying basket attrition during the year, or a complete change of methodology is introduced, most likely by adapting the Dutch or the Norwegian methods[(b)] with monthly chaining.

D - Using scanner data for auditing and quality control
This is the most minimalist possible use of scanner data in CPI production. Obviously, it would be a complete waste of resources if this was to be their only use.

(a) Cf. regulations for the Harmonised Indices for Consumer Prices, HICP (Eurostat, 2013).
(b) As outlined by van der Grient & de Haan (2010), Nygaard (2010) and through early discussions with Statistics Norway (Statistisk sentralbyrå in Norwegian).

The alternatives shown in Box 3 addressed the question of how to use data and, if at all, for anything more than quality control of the manually collected prices, which is option D. Option B appeared as possible but not optimal given the other options. As scanner data were obtained and implemented gradually, the first alternative, option A was a straightforward choice, which in a way preserved *status quo* of the CPI construction regarding index calculations and sample design. The choice of method has been debated in the limelight of option C (the opportunity of "Big Data") and with new methods emerging in the field, in which Statistics Netherlands and Statistics Norway have been pioneering. However, facing time and economic constraints and realizing the need for maturity with the new data source, i.e. gaining experience, option A appears to be justifiable as a beginning in the transition to new data sources. Option C was not the option preferred at the very first step but appears nevertheless as a goal.

Fixed Basket vs Dynamic Basket

The standard fixed basket approach was the point of departure when implementing the new data source in 2012. However, other countries use a more active approach, namely the dynamic basket. An outline of the two approaches can be found in the Eurostat practical guidelines for processing supermarket scanner data (Eurostat, 2017a). These have been established by Eurostat through input from participating countries, in order to formalize the approaches they applied and thus to strive for harmonization in the HICP for new countries using scanner data. The two approaches are presented below regarding main differences, benefits and drawbacks.

The Fixed Basket Approach

A fixed basket approach means that in all months *t* (or quarters) during the current year *y*, the basket is kept constant as far as possible. Prices of items in the given basket are observed (if possible) and are related, referenced, to the yearly starting point of measurements, normally December *y*–1, the base period. This is a direct comparison of each month with the base month price.

The Ever-Changing Basket and the Replacement Problem

The perhaps greatest drawback of this rather conservative approach is that it does not take advantage of the data richness or updated market information. It relies on a limited maintainable basket – the constraint is in reality the monthly maintenance of the basket, i.e. replacements. The replacement issue is central to preserving comparability over time, and perhaps the strongest argument for preserving the traditional approach: quality and quantity changes in replacements are explicitly dealt with. Whenever items are non-observable in the data, a choice must be made between making replacements to measure another comparable item, which in best case may be a relaunch of the same item, or, if not possible, to discontinue the item. In extreme cases, basket attrition may result in a non-representative basket[6] based on remaining items. The problem can be circumvented, i.e. not solved, through the more automated alternative for scanner data: the dynamic basket.

The Dynamic Basket Approach

A dynamic approach to using scanner data means that the measured prices stem from a continuously updated basket. This is operationalized such that a monthly matched items' index is calculated for the price ratios of exact matched items between adjacent months, (*t, y)* relative to (*t*–1, *y*), and this monthly index link is then chained back to the index base month (December *y*–1). This approach coincides with the fixed basket approach if all items (and weights) are identical at all periods, c.f. e.g. the HICP Methodological Manual, formulas 8.11 and 8.14 (Eurostat, 2017b), Eurostat (2017a) or Fisher (1922).

The dynamic approach retains the most recent universe of items in the basket, i.e. an updated sample, and such a coverage cannot be contested regarding representativeness and completeness. As pointed out by e.g. Boskin *et al*. (1997), such a data source should be used for reducing costs of data collection and to increase the assortment of goods and services in the CPI.

For regularity purposes, i.e. 1) basket stability, 2) representativeness over time and 3) data parsimony to avoid noise, it is necessary to exclude from the basket products for which the share of consumption in the month is too low, as stated by Eurostat (2017a) and by van der Grient & de Haan (2010), or to apply other regulatory filters to avoid for instance prices subject to dumping. Even with these precautions the problem of chain drift may occur, due to price bouncing, i.e. prices may decline or increase strongly in some periods, driving the index down/up in that specific period. When such changes influence the chain without the index returning to its previous level the following month, it is referred to as chain drift.

An illustration of this problem can be the following. Assume for instance that a size filter is applied such that e.g. the top 10 items with respect to turnover are selected a specific month (which were already included in the basket in the previous period). Some of the items may be "temporary" in terms of high turnover, whether due to significant campaigning or seasonality, e.g. Christmas. The next month, these "temporary" items are most likely not sold at the same prices, some may be dumped substantially or not exist anymore. Consequently, the same items

6. *In this situation, the basket will have incomplete coverage and thus not be representative of the target consumption.*

will not qualify into the top 10 or will be at strictly different price levels, and the chained index will not return to its preceding level, i.e. drift away.

The drift is even more marked when the quantities sold, known from scanner data, are used in the index formula to aggregate prices. Chain drift is an issue in a whole way, which has been thoroughly examined (cf. Johansen & Nygaard, 2011; Nygaard, 2010; van der Grient & de Haan, 2011).

The Dynamic Approach and Replacements/ Relaunches: A Non-Issue

The major drawback with the dynamic approach is that it only takes into account the products present two successive months for the calculation of the index of a given month: only existing pairs of items are included. However, a relaunch can be accompanied by a price increase (either the price is unchanged for a lower quantity or the price increases without a tangible improvement in quality/quantity). Such changes will be "hidden" if not explicitly dealt with. Indeed, with the dynamic approach, no quality adjustment is made because all the items in the dynamic basket are by definition present two adjacent months, a feature that unfortunately impairs the validity of this approach: "*Relaunches and replacements are a potential problem for this method because the system does not automatically link a disappearing item code with its relaunch or replacement item code*" (Eurostat, 2017a, p. 28).

Weekly Data in a Monthly Index: How to Aggregate?

Having data at higher frequency raises the question of multiple data: should the points be combined? And if yes, how? Manual price collection was, and is, undertaken once a month per store, which implies single spot prices. As stipulated by the HICP guidelines (Eurostat, 2013), the standard operating procedure is to measure prices during the week in which the midpoint of the month (the 15^{th}) occurs, or additionally one week prior to/one week after the midweek. Usually, price measurements (in sampled stores) are *a priori* allocated over the three weeks to increase precision over the month.

With scanner data came the possibility of obtaining weekly consumption, i.e. weekly turnover and purchased quantities. The data follows calendar weeks, Monday-Sunday, which restricts consistent use of more than the three full weeks due to weeks that do not start and end in the same month. Using the midweek and the two adjacent weeks provides at best three data points per product offer. Thus, the sample precision increases but this occurs in a dimension that is not so frequently addressed in standard methodology literature, due to the nature of economic statistics: discrete measurements of continuous time data (cf. the CPI Manual §15.70, ILO, 2004).

Two intuitive possibilities for combining the weekly data points into one single price per product offer and month are the geometric mean and the arithmetic mean, which are both relevant. In the very first implementation, the CPI Board concluded that an unweighted geometric mean over the (maximally) three weeks would be appropriate to obtain the monthly price for each product offer from scanner data. In this way, the scanner data from the single providing retailer would match the remaining non-scanner data subset of product offers. The idea was that the three weeks from scanner data could be considered as three data collection rounds rather than one single spot collection, as the remaining product offers. The unweighted geometric mean approach to aggregation was also in accordance with the actual index construction, which is a geometric mean value (a Jevons index).

The question of week to month aggregation was re-addressed when data from more retail chains were obtained and again, the CPI Board was consulted (Sammar & Norberg, 2012). This time, considering the increase in coverage, the Board opted for a weighted arithmetic mean over three weeks as it would be reflecting monthly unit prices, in line with the actual data (weekly). "Weighted" means that the turnovers of at most three weeks are aggregated and divided by the sum of quantities from the weeks, resulting in a monthly average unit price.

The behavior of the two candidate mean values was studied (Norberg *et al.*, 2012) in a price index context and it was realized that they differed in some situations. For more than 90% of the observations, the two means differed only subtly. The difference were accentuated when weighting played in extensively, for instance in periods of holidays with low prices. It was realized also that shocks on the base period subsequently affected the relative aggregated price (i.e. the index) throughout the year even if the two means would coincide in the specific month.

Sample Monitoring

Transitioning to scanner data entailed that replacements/item substitution for obsolete basket items had to be done by the CPI team through monitoring basket attrition. In order to mitigate potential sample depletion, a very simple basket monitoring system was operationalized: comparing sales in the current month t with the base period December y–1. The monitoring covers the number of stores in which the product has been sold and the number of sold packages, i.e. a two-dimensional analysis. This is done *a posteriori* for each completed month. Doing so, the CPI sample remains representative (presumably) at the expense of at most one working days' effort every month for searching the scanner data for substitutes. No imputations are done for missing prices nor are stores replaced, should they have closed between the annual sample updates. However, object non-response, i.e. store obsolescence, is a rare event, especially for well-established or high-turnover stores.

Estimating Item Related Variance

We now look at the contribution of an article to the price index variance in the case of a fixed basket, using all or part of the scanner data. After a brief outline of the sampling design, the construction of the index for the elementary aggregate is presented, then the jackknife variance estimation. The section ends with a discussion of the finite population properties of the sample of daily necessity products.

Item and Store Sampling

The sampling design has two dimensions: location and product (items available for purchase). By location is meant the actual store from which purchases of products for private consumption takes place. Items are selected through annual sampling, regardless of the collection mode. For both scanner data and remaining manual price collection, order probability proportional to size, or order PPS, is applied in the two dimensions (cf. Ohlsson, 1990; Rosén, 2000).

Item Sampling

From each of the retail chains covered with scanner data, some 800 items are included in the annual sample. The sample frames are defined every year based on annual aggregate scanner data from the year previous to the base month. Extensive linking is done between the item identifier in the scanner data, the EAN/GTIN code and finer levels of the COICOP classification. Matching with the weekly scanner data produces the desired sample. The item samples for the retail chains are drawn with negative sample coordination of the frames between the chains. However, many items of well-known brands can be found at all retailers and are high-volume sales. Such items are often common to several of the retailer-specific samples.

Store Sampling

The store sample for daily consumer products includes about 60 stores, representing the whole country. The design is Poisson sampling which is a method for size-proportional sampling based on permanent random numbers (Ohlsson, 1990). Through this, rotations can be achieved. However, Statistics Sweden's standard rotation scheme (annually 20%) is not strictly applied here. Rotation is applied if it is justified from a probabilistic point of view (i.e. representativeness) in order to avoid excess burden on data providers to change their transmitted data content. For statistical reasons, stores are subject to resampling every year but are only replaced if their relative importance is significantly altered in comparison with previous years' sampling.

Estimation Outline

Estimating the variance in a consumer price index is an intricate problem. Variance comes from two-dimensional sampling, at the store and item levels; formal variance assessments can be found in Balk (1989, 1991), Dalén & Ohlsson (1995) and Norberg (2004).

The Lowest Level Index: Elementary Aggregates

The elementary aggregates, or lowest level index formulation are computed as the geometric average[7] of the relative prices of

7. This index formulation is one of the two explicitly recommended methods for the HICP (Eurostat, 2013) at the lowest level.

items belonging to a product group, and over all stores. Ratios of prices in the observation period t in the current year y relative to the prices in the base month 0, $P_{t,i}$ and $P_{0,i}$, formulate the index $I_g^{0,t}$:

$$I_g^{0,t} = \prod_{i=1}^{k_g} \left(\frac{P_{t,i}}{P_{0,i}} \right)^{w_i} \quad (1)$$

where the sum is calculated over the k_g product offers i in product group g in which each product offer may have a distinct weight w_i. In the Swedish case, the weights w_i are computed as a function of the store and item probabilities. Most are unit weights, i.e. equal (e.g. $w_i = 1$) whereas a few are sometimes larger to reflect for instance a well-sold coffee brand in a large hypermarket.

If all weights are equal (which is equivalent to no weighting) equation (1) is referred to as an unweighted Jevons index. If the included sample elements reflect the outcome of a size-proportional sampling procedure, inclusion probabilities and weights cancel out, i.e. implicit weighting. When the weights reflect the respective consumption share of the items, the expression is referred to as a geometric Young index (cf. the CPI Manual, formula 1.9, ILO, 2004).

The Jackknife Method for Stratified Sampling

The jackknife method suggested here is used to approximate the variance contribution of the n^{th} element in the existing sample. The method is explained in Wolter (1985), and a similar analysis on scanner data can be found in Leaver & Larson (2001) from the U.S. CPI at the Bureau of Labor Statistics (BLS).

The computation strategy is to make an estimation of the target parameter, in this case an aggregate index of the product group price indices (equation 1) while excluding, one by one, every element in the existing sample once, i.e. retaining n–1 elements in each estimation and computing the target parameter based on the remaining elements. Running this procedure over all n elements renders an average contribution to variation. The selected store sample is kept fixed, i.e. the item sample is taken as conditional on the existing sample of stores. The approach is assumed to suffice for the proof of concept – namely the trade-off between the item contribution to variance and the bias from disregarding explicit quantity adjustments.

The Jackknife Estimation Scheme

The approximately 800 sampled items for which scanner data are available at each of the three retail chains constitute altogether some 90 product groups within daily necessities in the COICOP hierarchy. These product groups are by definition the elementary aggregates for which a price index is computed with equation (1) for all products and chains, i.e. one aggregate for all items within a product group. Items are classified and coded according to the product group to which they belong, hence an *item* is synonymous to a product.

The stratification scheme is outlined in Table 2, showing the exclusion scheme for each of the n–1 runs. In this scheme, product groups are crossed with each retail chain to define the strata, rendering some 270 strata from which items are excluded. Equation (1) is estimated over all product groups rendering the target parameter – the aggregate daily consumer products price index for COICOP 01.

By design, 90 product groups crossed with maximally three retail chains render approximately $L = 270$ strata. In total, the almost 800 products sampled within each retailer chain can add up to a total of some 2 400 products, with variations due to variation in assortments. A retailer stratum h has n_h items/products.The n_h varies between the strata within the same product group which thus has k_g products in total; $k_g = \sum_{h=1}^{H} n_h, h \in g$. Within each k_g there can be $H = 3$ strata, whereas the h sum to $L = 270$, for all g: $h \in (g, L)$.

In a few strata, only one product is found and those are omitted from computations since the n–1 procedure renders zero remaining products, meaning that no variance can be estimated in the specific stratum. Assortments and samples vary between chains, sometimes substantially, so not all product groups necessarily comprise all three chains.

Each estimation excludes, sequentially, one row (as displayed in Table 2), i.e. each product in a stratum, hence there is no random element added in the estimation procedure. Instead, randomness in the original sample is reflected between runs by altering the composition of the given sample.

The Parameter of Interest

Equation (1) can be expressed in logarithmic form, giving the following sum for each product group, followed by exponentiation:

$$I_g^{0,t} = \prod_{i=1}^{k_g} \left(\frac{P_{t,i}}{P_{0,i}} \right)^{w_i} = \exp\left[\sum_{i=1}^{k_g} w_i \left(\ln\left(P_{t,i}\right) - \ln(P_{0,i}) \right) \right] \quad (2)$$

The expression in brackets on the right hand side of equation (2) is a linearized version of (1), similar to the formulation used by Leaver & Larson (2001). This will be the parameter of interest when the elimination of the products/items, n–1, is done in each stratum h within product group g.

For the estimations in this study, the index calculation of the elementary aggregate (2) is slightly different with regard to the weighting, compared to the actual weighting.[8] The difference is that observations, relative prices, within each retail chain (= stratum) are averaged and summarized to the product group by weighting with the average market share of each retailer to result in (2) for the complete product group. This replaces individual items' weights w_i and this is necessary since alternation in the number of products offsets the existing implicit weighting due to size-proportional samples. The weights are normalized so that depending on the number of retail chains within each product group, the retailers' average relative price is assigned an *a priori* known weight.[9] This changes equation (2) to (2'):

$$\begin{aligned} I_g^{0,t} &= \prod_{h=1}^{H} \left[\prod_{i=1}^{n_{h,g}} \left(\frac{P_{t,i}}{P_{0,i}} \right) \right]^{w_h} \\ &= exp\left[\sum_{h=1}^{H} w_h \sum_{i=1}^{n_{h,g}} \left(\ln\left(P_{t,i}\right) - \ln(P_{0,i}) \right) \right] \end{aligned} \quad (2')$$

The final estimate of the daily necessity products price index is a weighted arithmetic average over all computed products groups' indices according to

$$I^{0,t} = \sum_{g=1}^{G} w_g I_g^{0,t} \quad (3)$$

where the product group weights w_g are normalized so they sum to one, cf. their aggregate share in terms of the total basket in Table 1.

By analogy with the definitions in Wolter (1985) for estimation under stratification, the price index in (3) is computed when the $(h,i)^{th}$ observation is deleted. This is done for all deletions within a stratum and over all strata, resulting in as many estimates as there are items/products,

8. This is the case for Statistics Sweden at present. Other options are possible; Statistics Netherlands (CBS) applies index computations, elementary aggregates, to individual retail chains, which is a slightly finer level than is the case here (van der Grient & de Haan, 2010).

9. In reality, some products have individual weights to reflect high-volume consumption. This is disregarded here in order to avoid volatility in the variance estimations merely due to weighting. All products in the sample are taken as an outcome of simple random sampling.

Table 2
Outline of the jackknife estimation scheme

Estimation run	Product group	Product code	Stratum h	Chain
1	1113	1113001	1	1
2		1113002	1	1
3		1113003	2	2
4		1113004	3	3
5		1113005	3	3
6		1113006	3	3
7	1114	1114001	4	1
.	.	.	.	.
.	.	.	.	.
n = 2 400	.	.	L = 270	.

Notes: The numbers n = 2 400 and L = 270 are approximate and for illustrative purposes. Exact numbers are reported in the estimations subsection. The light grey fields illustrate the stratification for the chain.

i.e. approximately n = 2,400 runs. There are at most approximately L = 270 averages (strata) to obtain from the runs to obtain the variance estimate, see (5) below. These L averages are computed, for each stratum h as the average parameter estimate over the n_h parameter estimates,

$$\hat{\theta}_{(h\bullet)} = \sum_{i=1}^{n_h} \hat{\theta}_{(hi)} \, / \, n_h \,, \qquad (4)$$

so each deletion $(n - 1)$ provides the parameter $\hat{\theta}_{(hi)}$ in (4), i.e. an estimate of the total daily consumer products price index in (3), $\hat{\theta} = I^{0,t}$, with the i^{th} item deleted.

The index jackknife variance estimator finally computed over all product groups within daily consumer products is:

$$v\left(\hat{\theta}\right) = \sum_{h=1}^{L} \frac{w_h}{n_h} \sum_{i=1}^{n_h} \left(\hat{\theta}_{(hi)} - \hat{\theta}_{(h\bullet)}\right)^2 \qquad (5)$$

It should be noted that w_h in (5) is a stratum-wise correction factor; $w_h = \left(n_h - 1\right)\left(1 - \frac{n_h}{N_h}\right)$ without replacement sampling.

Estimation Results

Based on n = 2,066 runs from the L = 231 complete strata (n>1), the estimated standard error of the change in the index with scanner data is 0.168 index units on average over the twelve months in year 2016, i.e. the monthly change in relation to the base period. This means that for an index value of e.g. 102, the uncertainty in a 95% confidence interval becomes [101.67 ; 102.33]. The monthly standard error estimates are given in Table 3.

The results in Table 3 must be considered in the context of practical reality. If the samples were in fact due to simple random sampling and if, at the same time, consumption of goods was equally distributed between all products within each product group, i.e. consumer preferences were identically heterogeneous and dispersed equally over all items, then the results obtained could easily be multiplied to the universe of all products. In such an as-if situation, and having in mind that a typical daily consumer products store contains more than say 10,000 items, the Swedish CPI sample of 800 items would imply an 8% coverage transferred to the variance computation through the finite population correction, (1 – (n/N)). If the sample size is n = 800 and the population size is N = 10,000, the finite population correction would be (1 – (800/10,000)) reported in Table 3.

The estimated standard errors can be assessed in the context of total CPI standard error. The daily products share of CPI is 13.9% as reported in Table 1, whereas the total CPI standard error for the yearly inflation rate is estimated to 0.12 index units (SCB, 2017). If the estimated standard error for daily necessity products is related to this total standard

Table 3
Standard error estimates

Month in 2016	Standard error
January	0.1725
February	0.1464
March	0.1514
April	0.1668
May	0.1692
June	0.1705
July	0.1825
August	0.2047
September	0.1651
October	0.1684
November	0.1805
December	0.1426

Notes: Values in index units. Daily necessities index with scanner data. 2066 products and 231 strata.

error accordingly with weighting, then only 4 percent of the CPI variance is due to daily products (the weight is squared as well as the standard errors in order to obtain correct levels). Due to this low variance contribution, an increase in sample size cannot contribute to a much higher precision of the overall CPI even if the included items are due to simple random sampling.

The item weighting, explicit or implicit through size-proportional sampling, offsets this linear calculation as it is a sampling design effect. Hence, having a sample of the few most sold items and a few representative items for the rest implies in practice a smaller variance contribution than that obtained from a simple variance estimation as done here. The contrasting approach would be to take the dynamic basket with a cut-off for the most sold items. Of course, applying such cut-off in terms of value share per product group implies higher precision, but is not necessarily better for estimating inflation – it is simpler but most likely only slightly more precise since consumption is not equally distributed over all items.

Interactions and Finite Population Characteristics

There may exist relationships in price levels between items and outlets and, in turn, within brands. Such interaction can be relevant to account for regarding variance estimation of the CPI, as explained by Norberg (2004). However, as the outlet sample is considered fixed in this study, any potential interaction is disregarded in what follows, assuming that it does not impair the results.

Another characteristic of the existing item sample is the finite population property. Item samples are, as mentioned, obtained from complete frames with practically perfect coverage of the respective year, *y*–2. Since the sampling design is probability proportional to size, some sampled items/products are the most sold ones and thus included with certainty. A consequence is that the actual variance due to the survey design is smaller than what is estimated here, because the jackknife procedure treats all items with equal probability, whereas in reality their probability of being included varies. The proportional trade-off suggested here is the worst-case scenario, as if all items were sampled with equal probability.

Quantity Changes in Daily Consumer Products

We address now the issue of quantity changes, using the example of changes actually occurred in the Swedish market of daily necessity products, in order to assess their possible impact on the CPI should these products be included in the sample.[10] The following bias estimates are empirical and based on knowledge from media coverage of CPI-related products. So far, our experience of packages growing in size is limited, whereas the issues outlined here concern packages diminishing in size, i.e. decreasing quantities. Where necessary, quantity adjustments are made for newly entered (replacement) items to express their prices in comparable units with their predecessors (as used in the base period). Quantity can in one sense be seen as a quality aspect, and the two terms are sometimes used interchangeably, cf. the CPI Manual (§7.77, ILO 2004).

Item Substitution and Adjustments to Comparable Units

The sampling design and the introduction of replacements are of specific interest for the CPI to ensure comparability over time within the year, as can be easily understood from the emphasis in the CPI Manual (ILO, 2004, Ch. 8) in which also the scanner data situation is addressed. For instance, the following is stated: "*Where nothing much in the quality and range of goods available changes, use of the matched models method presents many advantages. The matched models method compares like with like, from like outlets*", "*Where there is a very rapid turnover in items such that serious sample depletion takes place quickly, replacements cannot be relied upon to make up the sample. Alternative mechanisms, which sample from or use the double universe of items in each period, are required. These include chained formulations and hedonic indices* […]" (*ibid.*, § 8.62).

It is clear that in the presence of basket attrition, or more correctly, loss of representativeness, some kind of a more rapid updating monthly chaining and resampling procedure should be more efficient and appropriate for scanner data.

10. The actual CPI basket content with respect to specific products cannot be stated due to confidentiality. However, these examples are publicly known and are here related to potential effects on the CPI "as-if".

However, one may also read out from the same paragraph (§ 8.62) that quantity changes in relaunched products are not accounted for in a matched model method – they should be explicitly dealt with and not circumvented. The main difference between the monthly chained index formulation and the fixed basket formulation is that quantity changes, if not addressed, affect the fixed basket as a function of time – the number of remaining months until the sample is annually updated determines the bias. A monthly chaining procedure simply chains away the problem directly from the inclusion month.

A related issue is that of unit values. In a research paper, von Auer (2011) discusses unit value indices when products are similar but not identical, and unit values over time. One criteria for similarity is the package size, i.e. commensurability, for which an "amended unit value" strategy is outlined. The amended unit value is about transforming/recalculating, linearly, package sizes to common units between the similar products in order to preserve comparability with base period.[11] Although not directly transferable to our analysis, the outline is very much relevant: proper unit values are in some sense carried back to the base period. Such an approach produces a unit-value basket and not merely a unit-value index. The concern here is to be able to make relevant comparisons and not to circumvent the problem.[12] In particular, whether with the concept of changing price levels or the conventional CPI methodology, the linearity of the calculation of the proportional unit value can be questioned. Internal work at Statistics Sweden has shown that size-price relationships are not proportional but rather exponential, below the unit level, i.e. a doubling of size results in less than a doubling in price.

Quantity Changes on the Swedish Market

Over the past few years, several changes in product package have taken place on the Swedish daily necessities market. Some of these changes have directly affected the CPI calculations through corresponding quantity adjustments of base period prices for the fixed basket. However, if not addressed, this may possibly result in a noteworthy bias in the CPI in terms of hidden inflation. Some examples are given here below.

Coffee: In the last years, many coffee packages have downsized from a previously "standard" 500 grams to 450 grams, or -10%. In fact, most packages on the market are now less than 500 grams. Coffee prices can be rather volatile and bundled sales are very common, e.g. buy three and pay for two, so this is by nature an intriguing item in the CPI basket. The 10% change in package sizes was manually accounted for according to standard operating procedures for the CPI when identified in the samples. However, concerning real price changes, the point is debatable.[13] In fact, the alleged implicit price increases due to package size changes was subject to media coverage of a dispute between the largest daily necessities retailer on the Swedish market and a coffee producer with substantial market share. This change would go unseen with a monthly chaining procedure. The weight for the product group Coffee is 0.39%, which means that if not adjusted for, an inflation of 0.039 would be unaccounted for due to the 0.1 units size change, although perhaps blurred by the general confusion over coffee prices.

Sour Milk: In year 2015, at least one dairy producer changed the box content of a specific kind of Swedish sour milk (*filmjölk* in Swedish) from liters to grams. *Filmjölk* is a very popular creamy milk similar to yoghurt, original to Sweden and coming in various flavors and fat contents. The change went almost unnoticed until daily press and public radio[14] announced it in a news flash. Having in mind that liter is a volume measure and gram is a weight measure and the fact that the density of a dairy product depends on its fat content[15] (FAO, 2012), this was not an easy quantity assessment to make. Adjustments were done pragmatically for all observed brands and varieties in the CPI sample.

The corresponding product group, covering both yoghurt and sour milk, accounts for 0.419% of the basket. A quantity reduction of for instance 3%, which, for simplicity is an approximate attribution of the change in volume, means that 1000 milliliters are now 970 milliliters. Given

11. von Auer (2011) treats Change in Price Levels, CPL, which differs from the more established concepts of Average of Price Changes in CPI.
12. Chaining and the hubris of price statisticians was well addressed by the now late Professor Peter von der Lippe. Cf. www.von-der-lippe.org (2017-07-19).
13. A coffee producer in Sweden commented that consumer market prices are due to retailers pricing policy and not due to producers pricing policy (Berge, 2016).
14. Cf. the experiment by the Swedish national radio broadcasting service (Sveriges Radio) in Bressler & Näslund (2015).
15. Scientific sources on the internet can be consulted for milk density calculations. We do not have exact numbers for this specific Swedish product.

that no price changes are made at sales points, this would result in a bias of 0.03 units for several products that are included in the CPI through the aggregate weight of 0.419% of the basket. If at least one third of the product group consists of these products the bias would be 0.013%. Taken in isolation, this is a very small value but in the broader context, adding (or multiplying) these bias from all items may be substantial over time, and change the path of index.

Tobacco: Over the past few years, products in the group of tobacco products, which consists of cigarettes and the Swedish moist tobacco known as s*nus*, have changed package content sizes, due to EU regulations. Cigarette packages have alternated between 19 and 20 cigarettes. Such changes must be accounted for in the fixed basket when making replacements. Otherwise, if the prices do not change with the package size, this 0.05 units change would result in a bias on tobacco items. The weight for tobacco products is 1.545% of the basket, of which cigarettes represent 1.01 weight units, hence a bias of 0.05 due to cigarettes only.

All in all, if the three contributions to bias presented here are hidden in chaining, a total bias of approximately 0.1% may be present (≈ 0.039 + 0.013 + 0.05 percent of weights). This can be compared to the standard error of 0.168 index units with a simple random sampling, i.e. an overestimation of the actual standard error.

* *
*

The advent of new data sources opens up new possibilities. Coverage, a feature of massive digital datasets such as transaction data, is unquestionable in terms of context and scope. These data are in the range of censuses, less than a century after the introduction of random sampling theory, which aimed to preserve representativeness through small and cost-efficient samples (on random sampling theory, see Neyman, 1934; more generally on sample surveys, see the fascinating anthology by Betlehem, 2009).

The arrival of scanner data has somewhat challenged the traditional CPI production methodology, especially with the development of new methods to deal with massive data, borrowed from mass data analysis (e.g. machine learning). From this point of view, Statistics Sweden has taken cautious steps, initially on a small scale, to preserve comparability over time and with other countries for the purposes of harmonised consumer price indices, and to ensure transparency.

In this article, we have focused on the case of scanner data for daily consumer products and their inclusion in the CPI, particularly regarding the issue of the trade-off between item related variance and the bias from disregarding explicit quantity adjustments. One implicit assumption is the absence of technological change, i.e. that technological developments do not have a direct impact on food and drink prices in the short term, so that the traditional fixed basket approach can be maintained throughout the year. In addition, manual price collection remains the most common way to produce the CPI, including direct comparisons and quantity adjustments in the event of item replacement. We have seen that the contribution to the variance/standard error from a randomly sampled item in the daily products survey is rather small and would tend to decrease with appropriate sampling. Given that the samples are based on size-proportional sampling strategies, precision is actually higher than the findings in this article suggest – although lower than that obtained in dynamic approaches covering larger sales volumes. This must be acknowledged as an advantage of dynamic methods, yet the extent of the improvement in precision is not certain, particularly due to the dependencies between daily products and retailers.[16] As shown in the article, uncontrolled mechanical approaches can be questioned, not in terms of coverage but because the index they generate may mask inflation rather than show it if quantity changes are ignored.

Although the focus was on daily necessities, this is an issue for the overall CPI, highlighting one possible drawback with using scanner data: important details like quantity adjustments can now be blurred in the data deluge – as if coverage alone was the panacea for obtaining accurate measures of inflation (or deflation).

However, this should not lead to ignoring or denying the opportunities offered by scanner

16. *As mentioned earlier, item samples can be retailer specific or common between retailers, e.g. high-volume sales of well-known brands. Inflation is most unlikely to affect the basket only through a few independent items due to manufacturer dependency so item and/or store samples are not strictly independent, regardless of sampling procedure. The question of true effective samples sizes is so far unaddressed for the Swedish CPI. The interaction term between the two sampling dimensions is addressed in Norberg (2004).*

data. Extensive development is taking place in other countries, as attested by the meetings of the Ottawa Group, the most important global forum for price indices. It is worth noting that Statistics Netherlands (CBS) have been forging ahead in this field, as shown by the various research reports published. Nevertheless, from a comparative point of view, using scanner data with isolated methods that cannot be compared but modify the CPI methodology significantly can be questionable. The endeavour might also be disproportionate in order to gain a modest increase in overall precision: we have seen here that the variances of the price index of daily consumer products (excluding fruit and vegetables) are small, which can be contrasted to other sources of error that may affect the CPI.

Finally, the arrival of Big Data should invite us to keep in mind that the production of statistics requires a quality assessment of the complete process, not only the data, as stressed by e.g. Biemer *et al.* (2014) and Biemer & Lyberg (2003). This means thinking in terms of "total survey error" (Biemer *et al.*, 2017). For scanner data, and especially dynamic sampling, this implies quality control at the codification level within the COICOP nomenclature. Otherwise, the data may not fit into the basket as intended. Ensuring that data are consistent with the survey methodology is a matter of precaution, as highlighted, for example, by Couper (2013), who points out that the data must be in accordance with the topic rather than the topic distorted to adapt it to the data.

For the time being, Statistics Sweden has been sticking to the traditional CPI methodology while some other countries have gone further with "big data" approaches. But further steps in the use of scanner data are likely in the near future. ☐

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