Early Results from the RESET Demonstration Project:

Inflation in Food at Home

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ABSTRACT

This paper presents early results from the RESET Demonstration Project, an initiative that constructs price and sales indices using item-level transactions data. The project's overarching goal is to demonstrate the feasibility and advantages of leveraging modern transactions data for economic measurement by pointing toward a future in which official economic statistics are rebuilt on 21st-century data and technology. The paper's results introduce new inflation measures for Food at Home and evaluates them on two fronts: how they compare to current official statistics and what they offer as novel measures that capture more accurately the dynamics of consumer choice. The paper also addresses the challenges of producing reliable and credible official statistics from item-level transactions data and reports findings on recent Food at Home inflation trends.

I. Introduction

This paper introduces and presents early results from a new infrastructure—Re-Engineering Statistics using Economic Transactions (RESET) Demonstration Project—on the behavior of inflation in Food at Home since 2020. The RESET Demonstration Project (henceforth, the "DP") is building indices of price and sales from item-level transactions data using data from Circana, a leading aggregator of retail transactions data. The RESET DP aims to demonstrate how official statistics can be built from the ground up levering the infrastructure businesses use to process and record transactions. The paper addresses challenges of building reliable and credible official statistics from transactions data, shows that it is feasible to construct such indices that are comparable in timeliness and scope to official statistics, and examines the properties of reengineered measures of inflation—both in comparison to current official measures and as independent and potentially superior measures of the ground truth of the economy.

These reengineered key economic indicators will have a number of advantages over conventional measures produced by statistical agencies. Taking full advantage of item-level transactions data (also called point-of-sale [POS] or scanner data) allows simultaneous and timely measurement of price and quantity, meaning that superlative price indices can be constructed to account for consumer substitution behavior at all levels of aggregation. In contrast, current official statistics such as the chained CPI and PCE price indices only are superlative price indices at high levels of aggregation. Moreover, these official indices are constructed from price and sales data collected from completely different samples and available at different frequencies.[1] Thus, this paper contributes both to economic measurement and to understanding recent inflation.

[1] See Ehrlich et al. (2022) and Ehrlich et al. (2026) for further discussion of the limitations of the existing data infrastructure. The RESET DP also aims to use item-level transactions data to account for quality

The paper presents early estimates from the RESET DP for inflation in Food at Home. The paper considers several different measures of inflation: first, Laspeyres and related price indices designed to approximate the official CPI, and second, superlative price indices that to a second-order approximation fully account for consumer substitution at all levels of aggregation.

The first approach allows us to compare price indices constructed from Circana's infrastructure with the official price indices. We show that "CPI-like" indices constructed from the transactions data follow the official CPI for Food at Home closely, with modest differences arising during certain times during our sample period. One notable exception is a substantial deviation in the CPI for several months in Spring 2020 when, owing to the outbreak of the COVID-19 pandemic, the Bureau of Labor Statistics (BLS) changed its mode of data collection by largely replacing in-store enumeration with internet and phone data collection. Nonetheless, the overall comparison suggests that BLS's enumeration of prices otherwise aligns well with the transactions data for Food at Home. Verifying this alignment is an important step in promoting acceptance of the use of item-level data for official statistics to achieve the benefits of greater granularity, consistency, accuracy, and timeliness afford by the transactions data.

Based on preliminary work done by the RESET DP in General Merchandise categories, where product turnover is more widespread, the alignment we see between the transactions-based CPI-like indices and the current CPI is unlikely to be as close outside of Food at Home. Work on General Merchandise categories is ongoing, but the early indications are that price

change at the item level, and therefore account for the effects of entry and exit of products. This paper will focus on "matched-model" price indices, and therefore will not account for quality change and product turnover. Ehrlich et al. (2026) reports measurable quality change in Food at Home items, but it is much smaller than in General Merchandise. Hence, Food at Home is a natural starting point for evaluating the RESET DP approach because reasonable statistics can be reported without getting into the complex problem of accounting for quality change.

inflation measured by CPI-like indices in the transactions data is likely to be lower than is measured by the official CPI (see Ehrlich et al., 2026 and Johnson, 2025).

The second approach allows us to evaluate the promise of the RESET DP to deliver improved measures of inflation. We calculate superlative Tornqvist indices that account for consumer substitution in the transactions data. We show that over the sample period, bilateral geometric Paasche indices indicate lower inflation than bilateral geometric Laspeyres in Food at Home, which indicates consumer substitution behavior both at the item level within product categories and between product categories. The ability to measure this low-level substitution behavior is a key advantage of the DP's new infrastructure. In contrast, official statistics using superlative indices, such as the BEA's Personal Consumption Expenditure (PCE) price indices and the BLS's chained CPI, are superlative indices only at a high level. The CPI computes geometric-mean level Entry Level Item (ELI) indices for items in geographical regions (an item-area cell), which are aggregated into the chained CPI using a superlative index formula based on monthly expenditure weights from the Consumer Expenditure Survey. The BEA aggregates the CPI lower-level indices using PCE categories, which generally are more aggregate than ELIs. Low-level price quotations in the CPI are calculated as geometric means of price relatives. This would be exact only if the elasticity of substitution across items were one (Cobb-Douglas utility).[2] The RESET infrastructure accounts for substitution effects down to the item level. At the item level, the elasticity of substitution is much higher than Cobb-Douglas. Additionally, BLS samples items from a fixed sample of outlets that rotate in overlapping four-year periods.

[2] In the CPI, geometric means are used to construct low-level price indices. The CPI low-level geometric mean is implicitly sales-weighted because products are sampled probabilistically in proportion to their sales. See the discussion below.

Our item-level transaction data reflect contemporaneous substitution across outlets at the item-level.

With monthly scanner data, a key challenge for chained bilateral indices—including the Tornqvist—is *chain drift*, which is defined as the tendency for chained high-frequency indices to indicate non-zero cumulative price change even if all prices and quantities return to their initial period values in the final period of the index (e.g., International Monetary Fund, 2025, chapter 7). Our results show that chain drift is substantial in this setting. Accordingly, our headline Tornqvist measure in the preliminary analysis applies the rolling-year GEKS (RYGEKS) procedure (e.g., Ivancic et al., 2011), which is designed to address this problem. The RYGEKS Tornqvist is also the method commonly used by statistical agencies that incorporate scanner data into their official statistics (Office for National Statistics, 2025; Central Bureau of Statistics, 2026).

The analysis in this paper, which focuses on price indices for Food at Home, represents only a first step for the RESET DP. The advantages of using item-level data are likely even greater in product categories beyond Food at Home where product turnover is widespread. Official CPI methods for tracking expenditure shares and sampling products for which to obtain price quotes involve substantial lags, which are particularly problematic in categories with high turnover. Moreover, as emphasized by Erickson and Pakes (2011) and Ehrlich et al. (2026), product turnover and quality change go hand in hand, yet official CPI statistics account for quality change only in a limited way. Although we outline future plans for the RESET DP project throughout the paper, we emphasize that the step taken here is foundational and essential for moving toward the re-engineered architecture envisioned by the RESET Project.

II. Description of the RESET Project

The RESET DP proposes a new architecture for building official measures of inflation and spending from granular, item-level transactions data, offering internally consistent measures of real expenditures and inflation. The RESET DP architecture aims to replace the existing 20th-century infrastructure for official statistics, which relies on disparate surveys and enumerations, with one built on 21st-century information systems. The RESET Project asks how the system of economic measurement might be designed if starting from scratch, with the information technology and data that drive the 21st-century information economy? A "full reset" of the infrastructure for economic measurement builds on a century of progress in the theory and practice of economic measurement. Yet it aims to dispense with many compromises in current practice, which owe to the legacy of reliance on surveys and the myriad sensible expedients that have accumulated to address gaps and lags in the availability of source data.

The RESET Project—funded by the Alfred P. Sloan Foundation—has worked for several years to address the conceptual, methodological, and logistical challenges of using retail scanner data for price and quantity measurement (Ehrlich et al., 2019; Ehrlich et al., 2022; Ehrlich et al., 2026; Cafarella et al., 2023). The RESET DP—funded in 2025 by the Alfred P. Sloan Foundation and by the National Science Foundation—aims to show that large-scale innovation in the measurement of prices and quantities is both feasible for implementation by the statistical agencies and that it can lead to substantial improvements in the quality of official economic statistics.

To accomplish this aim, the RESET DP will release real-time monthly indices of inflation and sales covering the majority of retail goods in the United States—accounting for about eighteen percent of the CPI and fourteen percent of GDP. The early results reported in this paper

are for Food at Home, which is about eight percent of the CPI. The RESET DP will eventually encompass all goods in scope for the Circana universe, which is essentially all retail trade consumer goods excluding automobiles, gasoline, furniture, and prescription drugs. The RESET DP therefore aims to emulate the work of statistical agencies in producing credible, consistent, transparent, and intuitive statistics on a regular basis. In doing so, the RESET DP will show that, at least for a portion of the economy, re-engineering the work of the agencies based on 21st-century infrastructure and data is feasible. While the RESET DP will show that aggregate statistics can readily be produced from item-level transactions data, it requires addressing many challenges, such as classifying goods, assessing coverage, seasonal and trading day adjustment, and assuring longitudinal consistency.

These issues are the normal functions of statistical agencies. While the RESET Project aims at fundamental changes in the source data of official statistics and in how they are collected and processed, many of the core functions of statistical agencies remain necessary to produce reliable statistics. The RESET DP, by attempting to emulate the work of statistical agencies, will both produce practical knowledge about how these functions can be carried out using 21st-century infrastructure and identify remaining challenges that agencies would need to confront to translate the work of the RESET DP into a production environment.

The RESET DP is a joint research project between academic and agency researchers and Circana. As part of this project, Circana provides the RESET DP with access to the item-level national aggregates of store-level transactions data. The RESET research team does not have access to store-level data or retailer-level identifiers. The work with the item-level data is conducted by the project researchers within Circana's computational infrastructure. The grant funding supports the costs of providing and supporting the use of this infrastructure.

A central question concerning the use of item-level transactions data by statistical agencies is how the agencies will acquire such data, maintain the data's consistency across time, and be able to produce credible and transparent statistics without compromising the privacy and business interests of firms that provide data. The RESET DP does not aim to solve all of these issues. Doing so may require new contractual or legal frameworks. It certainly would require changes in how statistical agencies and firms interact. Additionally, there will be budgetary implications. Using transactions data could reduce the cost of data collection by surveys and enumerations, but may involve different costs, notably including procuring and processing data. The RESET Project aims to shine a light on these costs and benefits, and to demonstrate the measurement advantages of incurring the costs and savings of transitioning to a 21st century infrastructure of economic measurement.

III. Methodology

A. Price Index Formulae

i. Defining prices and shares

We begin this section by developing the notation we will use throughout the paper. We denote the volume of sales of item k in period t as q_{kt}.[3] We further denote dollar spending on item k in period t as y_{kt}. We denote the average sale price of item k in period t as p_{kt}, which we calculate as

$$p_{kt} = \frac{y_{kt}}{q_{kt}}. \tag{1}$$

[3] The transactions data includes information both for unit sales (e.g., packages of cookies or bottles of cola) and for volume sales (e.g., ounces of cookies or fluid ounces of cola). Throughout the paper, we use volume sales as our measure of quantity.

In the results in this paper, dollar spending and volume sales for item *k* are measured aggregating the item by store by week data to the item by month national level.[4] We describe the construction of months from the Circana weekly calendar in Section III.B.ii below.

We define "continuing items" as items which are sold both in periods $t-1$ and t; we denote the set of continuing items as $\mathbb{C}_{t-1,t}$. We construct price indices at various levels of aggregation such as total Food at Home and at the CPI's Entry Level Item (ELI) level. We discuss our mapping from Circana's product hierarchy to ELIs in Section III.B.i below. We discuss the aggregation procedures from the ELI to higher level aggregates below.

For any level of aggregation, we will use $s_{kt}^{\mathbb{C}_{t-1,t}}$ to represent the share of expenditure devoted to item k at time t among continuing items:

$$s_{kt}^{\mathbb{C}_{t-1,t}} = \frac{y_{kt}}{\sum_{l \in \mathbb{C}_{t-1,t}} y_{lt}}. \tag{2}$$

We use $s_{kt-1}^{\mathbb{C}_{t-1,t}}$ to refer to the share of expenditure devoted to item k at time $t-1$ among continuing items:

$$s_{kt-1}^{\mathbb{C}_{t-1,t}} = \frac{y_{kt-1}}{\sum_{l \in \mathbb{C}_{t-1,t}} y_{lt-1}}. \tag{3}$$

We also use a lagged expenditure share to approximate CPI methodology. The example below is to use a rolling *N*-month average lagged expenditure share, which will be denoted by $s_{kN}^{\mathbb{L}_{t-1,t}}$. This is the share of expenditures for item k over months $t-1$ to $t-N$ for items present in $t-1$ and t. It can be computed in three steps:

[4] The data used in this paper cover the lower 48 states and the District of Columbia.

$$y_{kN}^{\mathbb{C}_{t-1,t}} = \sum_{j=1}^{N} y_{kt-j}^{\mathbb{C}_{t-1,t}}, \tag{4}$$

$$y_{agg,N}^{\mathbb{C}_{t-1,t}} = \sum_{k \in \mathbb{C}_{t-1,t}} y_{kN}^{\mathbb{C}_{t-1,t}}, \tag{5}$$

$$s_{kN}^{\mathbb{L}_{t-1,t}} = \frac{y_{kN}^{\mathbb{C}_{t-1,t}}}{y_{agg,N}^{\mathbb{C}_{t-1,t}}}. \tag{6}$$

This approach computes this lagged share by taking ratios of sums, treating missing expenditures as zeros. Missing expenditures could be due to a number of factors such as recent entry or stockouts.

Geographical and time aggregation. The fundamental data are at the item-store-week level. The RESET project does not have direct access to item-store-week level data because it would reveal proprietary information about individual retailers. For the analysis in this paper, Circana researchers aggregated the data to the item-national-week level for the RESET DP's use, though the project intends to use subnational data both for index number construction and potentially for index publication as described below. The project will report monthly indices. Section III.B.ii describes our approach to aggregating the data from the weekly to monthly frequency.

ii. Price Index Formulas

This paper presents matched-model price indices, which do not adjust for the entry or exit of products from the market over time. As documented in Kaplan and Schulhofer-Wohl (2017) and Ehrlich et al. (2026), among others, product turnover at the UPC level is very rapid. Addressing product turnover is therefore central to the RESET approach. We address the conceptual issues involved and propose potential solutions in Ehrlich et al. (2026). Implementing procedures that

allow for entry and exit to be accounted for "at scale" is deferred to subsequent analysis.[5] The focus of this paper on Food at Home, where product turnover is less important than for other goods, allows us to focus on key issues for continuing-goods price indices, and allows us to share early results from the Demonstration Project.

We consider a number of indices starting with the monthly chained geometric Laspeyres and Paasche indices and the Tornqvist index. We also consider a "trailing-share index" meant to approximate aspects of the CPI's methodology. Finally, we consider rolling-year GEKS Tornqvist indices. Both of the latter two indices are meant to minimize the effect of chain drift.

a) Basic Indices; Chaining

We first consider basic price indices between time *t*-1 and time *t* where the shares are calculated at the same period as the price relatives. The *geometric Laspeyres index* is given by

$$\Psi_{t-1,t}^{L_{geo}} = \prod_{k \in \mathbb{C}_{t-1,t}} \left(\frac{p_{kt}}{p_{kt-1}} \right)^{s_{kt-1}^{\mathbb{C}_{t-1,t}}} . \tag{7}$$

The *geometric Paasche index* is given by

$$\Psi_{t-1,t}^{P_{geo}} = \prod_{k \in \mathbb{C}_{t-1,t}} \left(\frac{p_{kt}}{p_{kt-1}} \right)^{s_{kt}^{\mathbb{C}_{t-1,t}}} . \tag{8}$$

The *Tornqvist index* is the geometric average of the geometric Laspeyres and Paasche indices, so

$$\Psi_{t-1,t}^{TQ} = \sqrt{\Psi_{t-1,t}^{L_{geo}} \Psi_{t-1,t}^{P_{geo}}} = \prod_{k \in \mathbb{C}_{t-1,t}} \left(\frac{p_{kt}}{p_{kt-1}} \right)^{\frac{s_{kt-1}^{\mathbb{C}_{t-1,t}} + s_{kt}^{\mathbb{C}_{t-1,t}}}{2}} . \tag{9}$$

[5] Ehrlich et al. (2026) show that hedonic methods allowing for time-varying valuations of unobservable product characteristics can be applied in transactions data using modern machine learning methods that greatly reduce the need for "house-to-house combat," i.e., detailed analysis by human researchers at the product group level. The RESET DP plans to apply these hedonic methods to the transactions data for general merchandise to account for product entry and exit.

To produce an index over multiple time periods, the *chained index* is the product of these basic indices, i.e.,

$$\Psi_{t-\tau,t}^{chained} = \prod_{s\in t-\tau+1}^{t} \Psi_{s-1,s}. \quad (10)$$

Importantly, all of these geometric price indices (Laspeyres, Paasche, and Tornqvist) are consistent in aggregation. As such, there is no difference between the price indices computed as a single stage for all items in Food at Home relative to first computing ELI level price indices and then aggregating with the appropriate consistent weights.

b) Laspeyres Indices in Practice: BLS CPI and Trailing-Share Laspeyres Index

There are many ways to compute the lagged expenditure shares in a Laspeyres-style index. In equation (7), we define the geometric Laspeyres index where the lagged share is measured over the same time interval as the denominator of the price relative. This computation is feasible in the transactions data because expenditures are measured consistently and simultaneously with prices in the item-level transactions data.

In practice, statistical agencies must typically use longer lags to compute Laspeyres-style indices such as the CPI because the expenditure data needed to compute the weights are available with considerable lags. Currently, the CPI is computed based on annual (12-month, January to December) weights obtained from the Consumer Expenditure (CE) survey. For example, the CPI in 2025 was based on expenditure weights for calendar year 2023. These weights are updated annually, so the CPI in 2026 uses 2024 weights. The BLS has, over time, used more timely weights. Prior to 2002, the expenditure base period was updated approximately every 10 years. Effective with the release of January 2002 data, month-to-month changes in the CPI-U were based on weights drawn from 1999 and 2000 calendar year expenditures (see Greenlees and Williams 2009). In 2002, it switched to using trailing weights calculated over two

years lagged for two years and switched to the current practice of using weights over one year lagged for two years in 2023. This progressive updating of the weights addresses one of critiques of the Boskin Commission (Boskin et al., 1998). Following the approach BLS uses for the C-CPI-U, it might be possible to have only one-year lags in the CE weights, but even more timely updates are likely not feasible.

We compute the *trailing-share geometric Laspeyres* indices as

$$\Psi_{t-1,t,N}^{trailing\ L_{geo}} = \prod_{k \in \mathbb{C}_{t-1,t}} \left(\frac{p_{kt}}{p_{kt-1}} \right)^{s_{kN}^{\mathbb{L}_{t-1,t}}} . \tag{11}$$

The trailing-share geometric Laspeyres index uses the preceding year's worth of expenditures in calculating the relevant expenditure shares, $s_{k12}^{L_{t-1,t}}$. See equations (4)–(6). The trailing-share Laspeyres is a step towards mimicking aspects of the CPI's methodology. It also has other features. Notably, the trailing-share index reduces the scope for chain drift and volatility in the data by considering a year-long period to measure expenditure shares. The trailing-share Laspeyres index is also consistent in aggregation.[6]

We use a rolling monthly window to define our trailing-year weights in equation (11). We do so for multiple reasons. First, by updating the weights each month *t* rather than a fixed (or infrequently updated) calendar as in the CPI, we include items that are present in the data through month *t*-1. Procedures that use weights ending early implicitly exclude items that entered between the end-date of the share calculation and *t*-1. For example, suppose we fixed the trailing-share weights as the average expenditure shares in the preceding calendar year. Then if

[6] The trailing-share Laspeyres index requires 13 months of data. Our sample begins in January 2020, so the first period for which we can implement the formula described above is January 2021. To report trailing-share Laspeyres indices for month t beginning in February 2020, we calculate expenditure weights from January 2020 through month $t-1$.

an item was first introduced in mid-2025, its weight based on 2024 expenditure shares would be zero, and it would not be included in the index until the next calendar year. The use of a fixed or infrequently updated period for calculating the expenditure weights therefore produces a selected and more limited sample of products in the index than using a rolling monthly window.

This selection arising from choice of windows over which to calculate shares is non-random, for example, entering goods may be higher quality than continuing goods. Second, using an infrequently updated weights produces a discrete change in the index periodically, whereas using a rolling window produces smoother changes. Third, by defining the trailing shares over a moving 12-month interval, we facilitate comparison with the rolling-year GEKS introduced in below. Fourth, the seasonality of many items' sales patterns motivates our choice of a 12-month window rather than a shorter period, a consideration which also motivates our choice of window for the rolling-year GEKS. International Monetary Fund (2004) also suggests using rolling-year indices to deal with seasonal products.

c) Two-Stage Aggregate Food at Home Price Indices

To mimic BLS CPI procedures more closely, we extend the analysis discussed above to two-stage indices. To motivate the two-stage approach, consider the official CPI. It is neither an arithmetic Laspeyres nor a geometric Laspeyres, but a hybrid. It is (approximately) a geometric Laspeyres at low levels of aggregation (product group by geographic area), which is aggregated via an arithmetic Laspeyres formula at higher levels of aggregation. In the early results presented in this paper, we build all of our price indices from item-national-month level data, which does not mimic geographical stratification and aggregation used by the BLS to produce the two-stage

process of the CPI. In future work under the DP, we intend to explore indices built from sub-national geographical data.[7]

As a closer approximation to the CPI formula than the single-stage trailing-share Laspeyres index defined in equation (11), we consider a two-stage hybrid index using 12-month trailing shares. In the first stage, we compute a trailing-share geometric Laspeyres index for each ELI (denoted by m) as[8]

$$\Psi_{t-1,t,12}^{trailing\ \mathrm{L}^{m}_{geo}} = \prod_{k \in \mathbb{C}_{t-1,t}} \left(\frac{p_{kt}}{p_{kt-1}} \right)^{s_{k12}^{\mathbb{L}^{m}_{t-1,t}}} . \tag{12}$$

In the second stage, we compute a trailing-share arithmetic Laspeyres index aggregated across ELIs as

$$\Psi_{t-1,t}^{two\ stage} = \sum_{m \in \mathbb{M}} s_{m12}^{agg} \Psi_{t-1,t,12}^{trailing\ geo^{m}} \tag{13}$$

where the weights s_{m12}^{agg} are given by

$$s_{m12}^{agg} = \frac{y_{agg,12}^{\mathbb{C}^{m}_{t-1,t}}}{y_{agg,12}^{\mathbb{C}_{t-1,t}}}. \tag{14}$$

In equation (14) we apply the definition in equation (5) for N=12 for the continuing items in *t-1* and *t* for ELI *m* for the numerator and for all continuing items in *t-1* and *t* in the denominator.

[7] The CPI computes the lower-level price indices at the Product group (Item) by Area level where the Areas are the 32 Primary Sampling Units. Using the two-stage national indices described in this section, RESET DP future work plans to explore estimates with a geographical dimension. This planned work will address several issues. (1) It will allow the project to produce two-stage Item by Area estimates that mimic the CPI procedures. (2) The RESET DP will not be limited to urban areas, as are all CPI measures. Note importantly that in the current draft, the national indices are computed for the entire country, i.e., they reflect prices faced and purchases made by the roughly 10 percent of the populations that is out-of-scope for the CPI (and therefore also for the consumer price deflators in the BEA national income statistics). (3) The RESET Project plans to produce regional-level indices of both price and sales.

[8] In future iterations when we consider the BLS procedure of aggregating from the geographic by ELI level, *m* can be a geographic by product group cell.

This two-stage CPI-like index is meant to facilitate further the comparison between our results and the official CPI. We refer to this price index as the "trailing-share Laspeyres 2 stage UA," where "2 stage UA" denotes two-stage, upper-level arithmetic aggregation.

Second, we compute indices designed to approximate the procedures BLS uses for the CCPI (chained CPI) and BEA uses for the PCE price index. For the CCPI, the BLS uses the same lower-level price indices as the CPI (i.e., geographic area by ELI geometric means) and Tornqvist aggregation at the upper level.

To illustrate the approach, let $\Psi_{t-1,t}^{F,m}$ represent any first-stage price index *F* for ELI m. A second-stage Tornqvist Food at Home price index $\Psi_{t-1,t}^{F,TQ}$ aggregating these first-stage indices is given by

$$\Psi_{t-1,t}^{F,TQ} = \prod_{m \in \mathbb{M}} \left(\Psi_{t-1,t}^{F,m} \right)^{\frac{s_{mt}^{agg} + s_{mt-1}^{agg}}{2}} \tag{15}$$

where $\mathbb{M}$ is the aggregate set of all ELIs and the expenditure share of ELI *m* in the aggregate (*agg*) is

$$s_{mt}^{agg} = \frac{\sum_{l \in \mathbb{C}_{t-1,t}^{m}} y_{lt}}{\sum_{l \in \mathbb{C}_{t-1,t}} y_{lt}}. \tag{16}$$

When we apply this methodology to the trailing share geometric Laspeyres at the *m* (ELI) level, we refer to this index as the "trailing share Laspeyres 2 stage UT," where "2 stage UT" denotes two-stage, upper-level Tornqvist aggregation.

d) Rolling-Year GEKS Tornqvist Index

The literature that implements price indices in scanner data has generally found "chain drift" to be a prominent pattern in the resulting indices (e.g., Ivancic et al., 2011). Chain drift is typically

associated with high frequency price volatility and is said to be present over some multi-period horizon if the chained price index does not return to unity (i.e., no inflation cumulatively) if all prices and quantities in the final period revert to the same prices and quantities as in the base period. More broadly, this reflects the fact that chained price indices are not transitive. Several factors may produce chain drift, but a leading explanation is consumers' tendency to stockpile goods during temporary sales or promotions (Feenstra and Shapiro, 2002). While chain drift can in principle be either positive or negative, the empirical literature has predominantly found it to be negative, meaning that simple chained indices tend to understate the true rate of inflation.

The literature has developed multilateral methods to address this challenge. The multilateral measures combine price indices computed over multiple horizons. We consider the rolling-year GEKS (RYGEKS) method (e.g., Ivancic et al., 2011), which uses only backward-looking data and thus does not require revision and can be computed in real time. Feasibility in real time is clearly essential for approaches designed to replace the current CPI methodology. Additionally, the CPI is currently defined so it is not revised, which may also be a desirable feature.[9] As we summarize in Section V below, several national statistical agencies outside of the United States have adopted the RYGEKS Tornqvist index to measure inflation using scanner data. We likewise focus on the Tornqvist index as the elementary index in the RYGEKS procedure. Because the RYGEKS Tornqvist is not consistent in aggregation, we follow the practice of national statistical agencies (see Eurostat, 2022) and aggregate the RYGEKS Tornqvist ELI indices via Tornqvist aggregation.

[9] That the CPI is not revised makes it useful for indexation of contracts and government programs, e.g., Social Security benefits, the inflation-adjustment of Treasury Inflation Protected Securities, and private union contracts. Note, however, that since the 2017 tax legislation, tax brackets are adjusted using the chained CPI.

To compute the RYGEKS Tornqvist at the ELI level, one first chooses a window over which to construct all possible combinations of Tornqvist indices and then constructs a geometric mean of these indices. Specifically, define a Tornqvist price index from month e to month f as for product group m as:

$$\Psi_{e,f}^{TQ,m} = \prod_{k \in \mathbb{C}_{e,f}^{m}} \left(\frac{p_{ke}}{p_{kf}} \right)^{\frac{s_e^{\mathbb{C}_{e,f}^{m}} + s_{kf}^{\mathbb{C}_{e,f}^{m}}}{2}} . \tag{17}$$

Then for the 13-month window from month $t-12$ to month t, the RYGEKS Tornqvist index is given by

$$\ln\left(\Psi_{t-1,t}^{RYGEKS,m}\right) = \frac{1}{13}\left[\sum_{\tau=t-12}^{t} \ln\left(\Psi_{\tau,t}^{TQ,m}\right) + \ln\left(\Psi_{t-1,\tau}^{TQ,m}\right)\right] = \frac{1}{13}\left[\sum_{\tau=t-12}^{t} \ln\left(\Psi_{\tau,t}^{TQ,m}\right) - \ln\left(\Psi_{\tau,t-1}^{TQ,m}\right)\right] \tag{18}$$

where the terms $\ln\left(\Psi_{x,x}^{TQ,m}\right) = 0$. For each pair of months $t-1$ and t, we calculate the RYGEKS Tornqvist index using the rolling window from month $t-12$ to month t; we then chain the resulting RYGEKS indices to measure price changes over multiple months.[10] This procedure is often called the "movement splice" (see, e.g., Office for National Statistics, 2022 for a description of the movement splice and alternative procedures).[11] Importantly, the RYGEKS Tornqvist price index is not consistent in aggregation. We discuss this issue further below.

[10] The 12-month RYGEKS requires 13 months of price data. Our sample begins in January 2020, so the first period for which we can implement the formula described above is January 2021. To report RYGEKS indices for months in 2020, we follow a common practice (e.g., Ivancic et al., 2011) to handle the start-up period by using the initial 13-month sample, January 2020 through January 2021, as the window over which to compute the GEKS indices.

[11] We plan on investigating alternative procedures such as the Window and Mean splices as well as allowing for window lengths longer than 13 months. An advantage of the movement splice is that revisions are not required. However, methods have been developed for the Mean splice without requiring revisions of the price indices (see Office of National Statistics, 2022).

Although several statistical agencies have successfully implemented such RYGEKS procedures, this multilateral approach does pose tradeoffs.[12] These methods address potential chain drift by including as components price indices that occur over longer horizons than one month. For example, one of the components of the RYGEKS Tornqvist is the Tornqvist from $t-12$ to t. Yet this component index includes only products present in $t-12$ and t, so any product entry and exit within that period is excluded from this component. If product turnover is associated with quality upgrading, this directly computed year-over-year index will overstate the rate of inflation over this 12-month period (e.g., Krsinich, 2024). Similar remarks apply to each of the price indices computed on a direct basis over a multi-month horizon in the RYGEKS index. These limitations may be mitigated by hedonic methods that allow the inclusion of entering and exiting goods in the component price indices. The RESET project intends to produce such hedonic indices in future work.

To aggregate the RYGEKS from the product group *m* level to Food at Home, we use equation (15) to aggregate low-level RYGEKS indices using the Tornqvist aggregation at upper level. The resulting index is often referred to as the RYGEKS Tornqvist 2 stage.

B. Measurement Challenges

For the early results from the DP presented in this paper, Circana aggregates the transactions data that we use to the national level at a weekly frequency prior to our use of the data (as noted, we will explore sub-national data in future work). For each individual product, the dataset contains information on total spending, unit sales, volume sales, and the product's place within Circana's internal product hierarchy. We map products from Circana's hierarchy to ELIs using a concordance that we have developed as described in subsection i. below. We also aggregate

[12] Agencies make different choices in the implementation of RYGEKS. For example, the UK and Australia both use 25-month windows.

product information to the monthly level using a calendar developed for the purposes of this project as described in subsection ii. Because the transactions data can be noisy—either from the fundamental volatility of retail marketing and shopping behavior or potentially because of measurement issues, we discuss some potential data cleaning steps that we are exploring. Dealing with the volatility of retail outcomes also drives decisions about index-number specification and estimation.[13]

i. Concordance between Circana's Proprietary Product Hierarchy and the CPI

At the broadest level, Circana's Food at Home products are divided into Components for edible packaged goods and perimeter goods. Within Components, products are further organized into Departments, Aisles, Categories, and Subcategories, with Departments being the broadest categorization and subcategories being the narrowest categorization. Component, Department, and Aisle correspond loosely to the traditional physical layout of a grocery store with Component being edible packaged goods or perimeter (fresh and refrigerated foods), Department being broad groups such as "Frozen," Aisle being groups such as "Frozen Proteins," Category being groups such as "Frozen Seafood," and Subcategory being groups such as "Frozen Raw Shrimp." Circana's product hierarchy for Food at Home contains 3,479 unique subcategories in the data extract we used to produce the results in this paper. Table 1 summarizes the hierarchy and gives counts of the number of elements in each level of the hierarchy.

[13] One additional measurement challenge that we do not address in this paper is the effect of sales and excise taxes on inflation. The CPI includes taxes paid by consumers on retail goods. In some cases, indirect taxes are included in the prices used to calculate the CPI (e.g., cigarettes), while in other cases, the applicable sales tax rates are determined from secondary data sources (Bureau of Labor Statistics, 2025). The RESET Project intends explore the effects of sales and excise taxes in future work. Note, however, that taking into account sales taxes would have little effect on Food at Home studied in this paper because Food at Home is typically untaxed and, in any case, all price indices used in this paper are affected only by changes in sales taxes, not their levels.

We matched these 3,479 subcategories to one of 65 Food at Home Entry Level Items (ELI) from the Bureau of Labor Statistics. Two RESET project researchers independently reviewed the information in Circana's hierarchy and picked the ELI that best fit that subcategory. A third researcher reconciled the assignments where they diverged. We referenced the CPI handbook of methods and CPI ELI checklists, which are the list of example products and product characteristics that the collectors use to select a product for each ELI, and obtained confirmation from the CPI information staff when needed. The mapping was reviewed by two researchers afterward.

For the most part, each subcategory could be clearly mapped to one ELI, but there were some cases in which the mapping was unclear. In some cases, a subcategory could in principle map to multiple ELIs; we mapped each subcategory to one unique ELI for our concordance to avoid allocating portions of sales across ELIs. In other cases, subcategory descriptions do not provide enough information to indicate clearly which ELI they should map to. For example, the subcategory, "Dried Beans/Grains," would fall both under Dried fruits and vegetables (FM031) and under Rice, pasta, cornmeal and other cereal products (FA031) because dried beans belong under FM031, but dried grains fall under FA031. We mapped some subcategories that did not correspond clearly to another ELI to FT062, Other Miscellaneous Food. Table 2 shows some examples of the mapping of Circana subcategories.

An initial analysis of the concordance compared the expenditure shares for the 65 categories obtained from the Circana data to those obtained using the BLS CE survey data. The correlation between the monthly expenditure shares (weights) is high and stable, hovering around 87.5 percent. Further analysis of the relationship between BLS CE and Circana ELI level shares will be an important component of our work. Discrepancies are a potential source of difference in the

price indices. As discussed above, the CE weights used for calendar year *t* price indices are from year *t*-2. Thus, even if CE and Circana weights track each other relatively well in a contemporaneous fashion, the significant timing differences may be important. The real-time Circana-based indices offer one of the many advantages of the RESET DP architecture.

ii. Calendar

Circana's transactions data are natively available at a weekly cadence, generally covering weeks ending on Sundays. Unless explicitly noted otherwise, all of the work in this paper uses data that has been aggregated to the monthly frequency for consistency with the official statistics. We have developed a custom calendar that maps weeks to months for the purposes of the RESET DP. The two main objectives in choosing the calendar were to map four- or five-week periods as closely as possible to calendar months and to allow for reporting as promptly as possible. Formally, if a Monday through Sunday week that splits across the end of one month and the beginning of the following month ends in the first two days of the later month, we assign it to the prior month. Otherwise, we assign the split week to the later month. Table 3 displays this calendar for 2025.

The RESET DP calendar offers advantages and disadvantages relative to the widely used "4-5-4 calendar" maintained by the National Retail Federation (2026), or "NRF calendar." Two advantages of the NRF calendar are first, that it is widely used, and second, that a month can be compared to its companion in the prior quarter or the prior year, as each will have the same number of weeks. One disadvantage of the NRF calendar is that it occasionally requires 53-week years, which could create challenges for the longitudinal consistency of our price and sales indices. An additional advantage of our calendar is that it includes the four or five weeks ending on Sundays that most closely reflect the calendar month.

Seasonal adjustment. In this paper, the price indices are not seasonally adjusted. In future work, the RESET DP will investigate seasonal adjustment challenges associated with using transactions data. These include accounting for calendar, holiday, and trading day effects, as well as challenges of applying standard seasonal adjustment filters. These issues are much more substantial for measuring sales than prices given the huge swings in activity over the year.

iii. Addressing Challenges in Measuring Price Change in Transactions Data

Although Circana invests substantial resources into cleaning the transactions data that we use in this project, some anomalies inevitably remain. In our prior work with data from NielsenIQ and Circana (see Ehrlich et al., 2026) we have used outlier filters such as winsorization of price relatives. In addition, for methods that incorporate the role of product turnover into price indices (such as the Feenstra, 1994 index considered in Ehrlich et al., 2026), we have explored methods that require thresholds of activity for determining which products should be considered continuing goods or entering and exiting goods. Our prior research shows that entering new products require time to build up market share and exiting products likewise take time to exit. We have conducted preliminary analysis of these methods in Circana's Food at Home data, but we do not apply them in the results presented in this paper. Likewise, our early results at this point do not construct price indices that explicitly incorporate product turnover. We plan to consider these issues in future work.

Another issue that requires further research is random-weight and ring-on products. Random-weight products are products whose weights or volumes are not fixed at the product ID level such as ground beef or chicken thighs. The transactions data include information on volume sold for each product in addition to unit count sold. We are therefore able to normalize expenditure on each product by the volume sold each month to account for the variability in

random weight products. Related but distinct are ring-on categories where heterogeneous items are packaged *ad hoc* and sold without an identifying UPC or SKU. POS systems record the price and the department, typically Meat or Produce, to which the package's revenue is credited. Such Ring-on goods represented 0.05 percent of Food at Home dollar sales in 2025.

iv. Assessing Circana Coverage

For both the price and quantity indices that are planned for the DP, characterizing and assessing Circana's coverage of the Food at Home universe is essential. The coverage for Consumer Packaged Goods (CPG), which includes Food at Home, is exceptional. Circana's transactions data includes coverage of grocery stores, mass merchandisers, dollar and club stores, online retailers, convenience stores, and military stores. Much of the coverage is literally a census of stores (e.g., all stores in a given retail chain) and for non-census cases Circana has representative samples (for category, store-size and geographic cells) with accompanying sample weights. Similar remarks apply to General Merchandise and Specialty (e.g., Shoe) stores, which are an important part of next phases of the DP. Nonetheless, the RESET DP is conducting a thorough assessment of coverage taking advantage of comparisons between the 2022 Retail Economic Census and the Circana universe. The joint measurement of price, sales, and quantity is central to the RESET Demonstration Project and will be featured in future work.

IV. Results: Inflation Trends in Food at Home

A. Headline Inflation Indices

The results in this section report price indices for Food at Home comparing the RESET price indices for Food at Home. The sample period is January 2020 through November 2025 for the reported results. The underlying Circana item-level data reflect more than 500 thousand continuing items (i.e., items with positive sales in t-1 and t) in any given month.

Figure 1(a) presents price indices for Food at Home from January 2020 through November 2025. The indices are shown at a monthly frequency and are normalized to equal 100 in January 2021. The figure compares the CPI for Food at Home to two indices constructed from Circana's item-level transactions data: (i) a two-stage Laspeyres index that uses a trailing 12-month weighting scheme designed to approximate CPI methodology using a geometric Laspeyres at the lower level and an arithmetic Laspeyres for upper-level aggregation (2 stage UA) and (ii) the two-stage RYGEKS Tornqvist index. Figure 1(b) reports the year-over-year inflation rates for the same indices.

The three indices exhibit very similar overall dynamics. Each shows a sharp acceleration in inflation beginning in July 2021, peaking in August 2022, and then declining to considerably lower rates by 2024. Year-over-year inflation rates are highly correlated: both transaction-based measures have pairwise correlations of 0.99 with the CPI, while the correlation between them is effectively unity. Mean inflation differs noticeably over the sample period across these measures: Over the full sample, the CPI records a compound annual growth rate of 4.51%, compared with 4.05% for the trailing-share Laspeyres 2 stage UA and 4.12% for the RYGEKS Tornqvist 2 stage.

These small full-sample differences obscure notable variation across subperiods. Table 4 reports compound annual growth rates by calendar year. In 2020, the CPI rises markedly more quickly than the transactions-based indices. During the pandemic, the BLS rapidly shifted many CPI price quotations from in-store collection to online sources. As illustrated by monthly inflation rates shown in Figure 2, the divergence is concentrated in the early pandemic months—April through June 2020—when the CPI increases substantially more than the measures based on transactions data. Monthly inflation differences exceed 1 percentage point, implying annualized

gaps greater than 12 percentage points. By July 2020, however, the CPI again tracks the transactions-based indices closely, suggesting that the BLS transition period was relatively brief. Hence, this evidence suggests that the mode transition might have pushed the level of the food index up (see Bowman, 2025, for overall CPI). Given the way this component of the CPI is constructed, the effect on the level of the CPI is permanent, as is the effect on the level of the corresponding BEA indicators that use the CPI.

In 2025, a new divergence emerges, with the CPI rising noticeably more quickly than the transactions-based indices; the compound annualized growth rate for the CPI is 0.41 percentage points higher than in the transactions-based price indices. We explore potential sources of this discrepancy below.

Even with some notable differences, a key finding is that the trailing-share Laspeyres 2-stage UA index tracks the CPI closely for Food at Home. These results suggest that the prices sampled by the BLS under routine field collection procedures provide a good approximation to Circana's transactions-based data. It also helps validate our approach to computing price indices from the transactions data by showing that our two-stage Laspeyres is a good approximation to the CPI formula in the case of Food at Home where the prices sampled by BLS align relatively closely with those in the Circana data.[14]

We caution, however, that the approximation of the official CPI is not likely to hold in contexts outside of Food at Home. In particular, for general merchandise goods that are presently being examined by the RESET DP, product turnover is so ubiquitous as to make any

[14] In the appendix, we also consider the single-stage trailing-share geometric Laspeyres index. This index closely approximates the two-stage trailing-share Laspeyres index we consider in the main text. The compound annual growth rate for the single-stage index is 3.88% compared to 4.05% for the two-stage index.

match-model index constructed from transactions data differ substantially from the CPI (Johnson, 2025).

Figure 3 adds the geometric Laspeyres, geometric Paasche, and Tornqvist defined in equations (7)–(9) alongside the three indices shown in Figure 1(b). Recall that the geometric Laspeyres, geometric Paasche, and Tornqvist are defined using concurrent monthly shares, i.e., over the same time interval as the monthly price relative. Indices are then constructed using chaining. The 12-month rates of price change are computed by taking the percent change from the chained index 12 months ago. As expected, the chained geometric Laspeyres, geometric Paasche, and Tornqvist indices display substantial negative chain drift. In particular, they show deflation in Food at Home from around mid-2023 through the end of our sample. This evidence motivates our focus on the RYGEKS Tornqvist 2-stage measure, which is based on a superlative index formula that explicitly mitigates chain-drift bias. Figure 3 also shows that the movements in measured inflation rates over time are similar between the indices using monthly weights and the indices considered previously in Figure 1(b), despite the differences in whole sample means. For example, the chained Tornqvist and the RYGEKS Tornqvist 2 stage have a correlation close to one, but the mean of the chained Tornqvist is more than 3 percentage points lower than the RYGEKS Tornqvist's. Further, the geometric Laspeyres lies above the geometric Paasche, with the largest gap during the high inflation period in 2021 and 2022. This evidence is consistent with substitution bias, although the simultaneous presence of chain drift complicates the interpretation of these differences.

The chain drift that arises in price indices constructed from item-level transactions data is not a statistical artifact. Rather it can arise from equilibrium outcomes in the retail sector related to retailers' marketing strategies, consumer response to changing prices, seasonality of demand for

specific items, and other such factors that can lead to dramatic swings in prices and quantities. This possibility has long been recognized in the use of transactions data to construct price indices. Often in these data, prices and quantities do not comove negatively, as they would if consumers were moving along stable demand curves. In real data, demand can shift—owing to many factors including promotion by retailers and seasonal demand (e.g., for candy at Halloween and cookies at Christmas). This reality can result in seemingly perverse results with price indices. See, for example, Feenstra and Shapiro (2003), who found that the Tornqvist index showed higher change than the Laspeyres for tuna fish because consumers appeared to stock up when the item was being promoted, even if the promoted price was not necessarily the lowest price. The effects of such behavior on price indices can be mitigated by using lower-frequency measurements such as quarterly. The RESET DP, however, aims to produce data at the same monthly frequency used by the CPI and PCE.

Ehrlich et al. (2026, Appendix D.2) discusses how end-of-product-cycle clearance sales can affect price indices constructed from transactions data. Redding and Weinstein's (2020) CES Unified Price Index offers an alternative approach to handling chain drift because it uses an exact price index, though Ehrlich et al. (2026) shows its restrictions on functional form and the economic environment are strong, which causes unfavorable consequences when these restrictions do not hold in the economy.

The chain drift present in the geometric Laspeyres, Paasche, and Tornqvist indices is especially pronounced in some ELIs with distinct holiday price and expenditure patterns. For example, the product groups (ELIs) Cookies, Cakes, and Candy show very large expenditures in December followed by much smaller expenditures in January, along with price declines from December to January. These patterns are consistent with holiday promotions in December for

these high-demand items, which are then followed by clearance sales at lower prices in January. Mechanically, the geometric Laspeyres will show very large declines under these conditions—with a high weight from holiday spending multiplying the dramatic price drop when these items go on post-holiday clearance. The availability of very cheap (and perhaps somewhat stale) Christmas cookies in January mechanically pulls down the geometric Laspeyres index. Christmas cookies in January are not really the same good as Christmas cookies in December, even if they have the same bar code. Edge cases such as this are not a reason to abandon transactions-based price indices, but they need to be addressed. We do so with our consideration of RYGEKS and in future work, also with hedonics.

B. Substitution Bias at Upper Levels of Aggregation

To assess the extent of substitution bias at the upper level of aggregation, we compare two transactions-based price indices that differ only in their upper-level aggregation method: the two-stage trailing-share Laspeyres with upper-level arithmetic aggregation, and the two-stage trailing-share index with upper-level Tornqvist aggregation. The key distinction is that the arithmetic index uses trailing-share weights, while the Tornqvist index uses average $t-1$ to t weights. This comparison is directly analogous to the relationship between the CPI and the CCPI: the CPI uses upper-level arithmetic aggregation with two-year-lagged expenditure weights; the CCPI uses upper-level Tornqvist aggregation with average *t-1* and *t* weights.

Figure 4(a) plots all four price indices in levels — the two transactions-based indices alongside the CPI and CCPI. The results from the indices constructed from transactions data reveal substantial high-level substitution effects. From January 2020 to November 2025, the cumulative inflation gap between the transactions-based upper-level Tornqvist (UT) and upper-

level arithmetic Laspeyres (UA) is 1.76 percentage points. The corresponding cumulative gap between the CPI and CCPI is 1.38 percentage points, which is also significant though smaller.

Figure 4(b) presents the implied year-over-year (YOY) inflation rates from these same series. As is evident from both Figure 4(b) and Table 4, the gap between inflation measured with upper-level arithmetic Laspeyres aggregation and upper-level Tornqvist aggregation is evidenced across the sample period. The same pattern holds in the comparison between the CPI and the CCPI.

That said, substitution bias in the Food at Home category over our sample period is relatively modest. This result is consistent with O'Flaherty (2026), who uses item-level transactions data from NielsenIQ and reaches a similar conclusion. Ehrlich et al. (2026), also working with NielsenIQ data, document more substantial substitution bias in Food at Home for the 2006–2015 period and find considerably larger substitution effects in consumer electronics and apparel.

C. Exploring Differences Between CPI and Trailing-Share Laspeyres Price Indices

Although the CPI and the trailing-share Laspeyres 2-stage UA indices track each other closely, notable discrepancies arise in certain periods, particularly in 2020 and 2025. These discrepancies could stem from a number of sources. In this section, we investigate one candidate explanation: differences in upper-level expenditure weights. To this end, we conduct two related but distinct exercises. For these exercises, it is instructive to compare and contrast the CPI and the trailing share two stage monthly inflation rates:

$$\pi_t^{CPI} = \sum_{m \in \mathbb{M}} RI_{mt-1} \pi_{mt}^{CPI}, \quad \pi_t^{two\ stage} = \sum_{m \in \mathbb{M}} s_{m12}^{agg} \pi_{mt}^{\text{trailing geo}} \tag{19}$$

where π_t^{CPI} is the monthly CPI inflation rate for food at home, $\pi_t^{two\ stage}$ is the monthly two-stage inflation rate for food at home measured from the transactions data (using an arithmetic Laspeyres index at the upper level of aggregation), $RI_{m,t-1}$ is the relative importance weight for

ELI m in the CPI, s_{m12}^{agg} is the expenditure weight of ELI m in the two-stage trailing share Laspeyres UA index defined as in equation (13), π_{mt}^{CPI} is the monthly CPI inflation rate for ELI m, and $\pi_{mt}^{\text{trailing geo}}$ is the monthly inflation rate for our trailing share geometric Laspeyres for ELI m.[15]

We begin by considering an exercise in which we exchange upper-level weights between the CPI and the trailing-share Laspeyres two-stage UA indices. First, we construct an alternative CPI that uses ELI-level monthly CPI inflation rates together with transactions-based expenditure weights (or "POS weights") at the upper level of aggregation (i.e., the same upper-level weights used in the two-stage Laspeyres). Second, we construct an alternative two-stage trailing-share Laspeyres using trailing-share geometric Laspeyres monthly inflation rates at the ELI level together with the relative importance weights at the upper level (i.e., the same upper-level weights used in the CPI). Using the exchanged weights monthly inflation rates, we compute the chained price indices and in turn the YOY rates of inflation from the chained price indices.

Figure 5 displays the results of these two exercises focusing on the YOY inflation rates. Two findings stand out. First, each "exchanged-weight" series tracks its corresponding series with its own upper-level weights reasonably well. Second, and more importantly, differences in

[15] Monthly inflation rates are calculated as $\pi_t^F = 100*(\psi_t^F - 1)$ for any monthly price index ψ_t^F. Relative importance weights are adjusted expenditure weights from the CE taking into account the inflation since the most recent direct measurement of the weight (see U.S. Bureau of Labor Statistics, 2026). For these calculations, we use the published cost share weights from BLS found here: https://www.bls.gov/cpi/tables/relative-importance/cost-weights.htm. We follow BLS methodology for using translating these cost share weights to relative importance weights: https://www.bls.gov/cpi/factsheets/constructing-special-cpis.htm. We have verified that the relative importance weights derived from the cost share weights replicate reported relative importance weights in BLS news releases of the CPI. Conceptually, the relationship between the base period CE weights and relative importance weights is given by $RI_{m,t-1} = \frac{s_{m0} I_{m,t-1}}{\sum_{m \in \mathbb{M}} s_{m0} I_{m,t-1}}$, where s_{m0} is the base-period CE weight for ELI m, and $I_{m,t-1}$ is the chained price index in levels for ELI m in period t-1. In the CPI, the base-period CE weight for any month in the current year is the annual weight from two years prior.

upper-level expenditure weights do not account for the divergence between the CPI and the two-stage Laspeyres observed in 2025.

Building on this finding, we turn to an exact decomposition of the difference between the CPI and our two-stage Laspeyres monthly inflation rates. The difference can be decomposed as follows:

$$\pi_t^{CPI} - \pi_t^{two\ stage} = \sum_{m \in \mathbb{M}} \overline{s}_{mt} (\pi_{mt}^{CPI} - \pi_{mt}^{\text{trailing geo}}) + \sum_{m \in \mathbb{M}} \overline{\pi}_{mt} (\text{RI}_{mt-1} - s_{m12}^{agg}) \quad (20)$$

where $\overline{s}_{mt} = (\text{RI}_{mt-1} + s_{m12}^{agg})/2$ and $\overline{\pi}_{mt} = (\pi_{mt}^{CPI} + \pi_{mt}^{\text{trailing geo}})/2$. The first term on the right-hand side of equation (20) is the "price component," capturing differences in inflation rates between the CPI and the trailing-share geometric Laspeyres at the ELI level, weighted by the average of the relative importance and trailing-share weights. The second term is the "weight component," capturing differences between the relative importance and trailing-share weights, weighted by the average of the CPI and trailing-share geometric Laspeyres inflation rates at the ELI level.

Figure 6 presents the results of this decomposition of the difference in monthly inflation rates. The elevated CPI inflation relative to the two-stage trailing-share Laspeyres is most pronounced in 2020, at the height of the pandemic, and again in several months of 2025. Across the full sample, the price component accounts for the dominant share of the variation in the gap between the two inflation measures—87 percent of that variation is attributable to this component.[16] This decomposition reinforces the conclusion that differences in upper-level aggregation weights are not the primary driver of the gap between the CPI and the two-stage Laspeyres; instead, the divergence originates at the ELI level. Further research is needed to

[16] This calculation is based on the contribution of the variance of the price component plus half of the contribution of the covariance between the two components.

identify the nature and sources of ELI-level inflation differences between the CPI and the transactions-based index.

V. International Practice

Over the past decade, there has been an expansion in the use of transactions data in national price statistics worldwide. Currently, at least 18 countries use transactions data in their official price indexes for food. Many countries use the transactions data in other product categories. Australia makes extensive and long-standing use of price quotations for Food at Home. The Australian Bureau of Statistics (ABS, 2017) obtains transactions data directly from supermarket chains and creates Tornqvist price indexes for about 30 food categories. It then uses RYGEKS methods to reduce chain drift and aggregate to a total food index using Tornqvist and the aggregation weights implied by the transactions data. Slightly different from our approach, ABS uses a 25-month window and a mean splicing method (as opposed to our movement splicing method—see Cage et al., 2021). Beginning in 2026, ABS uses the transactions data to construct the national accounts estimates of household spending (similar to the U.S. PCE data). Similar to our approach, ABS is using both the prices and quantities to create a consistent measure of real expenditures.

Statistics Netherlands (CBS, 2026), Statistics New Zealand, and the Office for National Statistics (ONS, 2025) in the UK use a similar method for most of their food categories. They both use transactions data directly from supermarkets to create prices and expenditure weights, the RYGEKS method, and Tornqvist aggregation.

Statistics Canada follows the most common approach in the use of item-level transactions data by incorporating price observations into their current methods for creating price indexes. While some of the product groups use both prices and quantities, the aggregation across food

products uses the current weighting methods. Statistics Canada uses alternative data (both web-scraped and transactions data) in over 75% of the price quotes for over 50% of the market basket. Some countries, such as Iceland and the Netherlands (see Chessa, 2026), have been using transactions data for particular consumer goods for almost 20 years, and Norway and Switzerland have used transactions data from supermarkets since the early 2000s (see EFTA, 2020). Furthermore, some countries incorporate hedonics in the RYGEKS price indexes. For example, New Zealand estimates a GEKS index usings scanner data and hedonics for consumer electronics (see de Haan et al., 2021).

International groups such as EUROSTAT, UNECE, and the Ottawa Group, have started to include standard methods to use transactions data in price indexes (see Eurostat, 2022). The new International Labor Office CPI Handbook includes an entire chapter on transactions data and multilateral indexes (International Monetary Fund, 2025). A recent CNSTAT report (National Academies of Sciences, Engineering, and Medicine, 2022) recommends that BLS incorporate transactions data into the CPI.

VI. Conclusion

This paper provides early results from the RESET Demonstration Project on the behavior of Food at Home inflation over the past several years. Inflation measures produced from the transactions-based indices generally track the official CPI for Food at Home closely, yet some differences are apparent. First, the CPI shows substantially higher inflation in Spring 2020, during the BLS's mode shift, than the transactions-based indices. Second, the CPI has been measuring higher inflation than the transactions-based indices in 2025. We will monitor whether this divergence persists going forward.

We believe that these early results provide encouraging evidence that the transactions-based indices can be used to reengineer the traditional statistics for retail trade, which is a substantial portion of the economy. We expect the differences between the official statistics and the transactions-based statistics to be larger outside of Food at Home in product groups with high product turnover, highlighting the value of moving to the new paradigm suggested by the RESET Demonstration Project.

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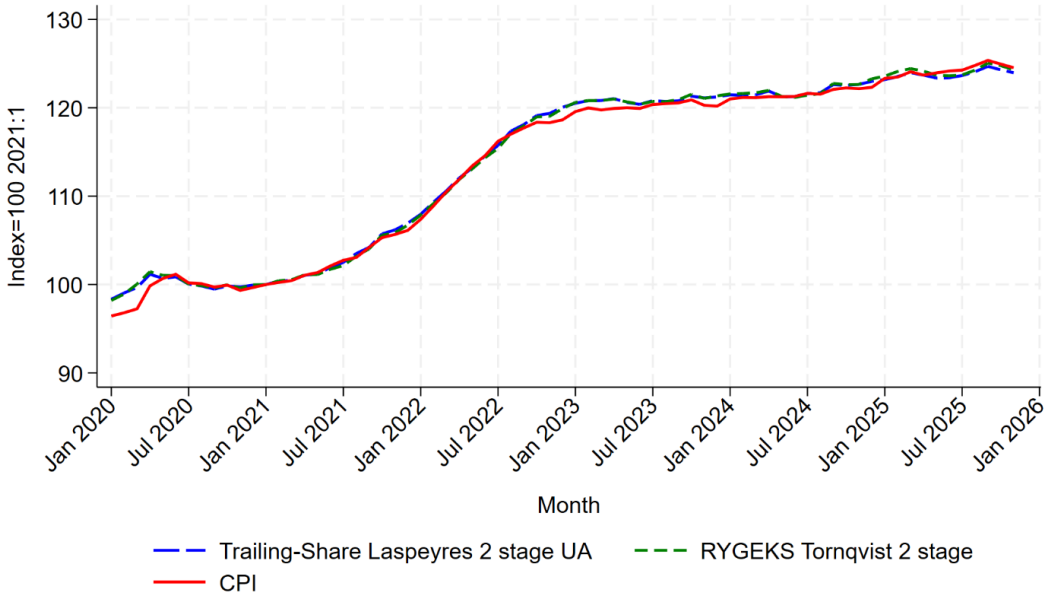
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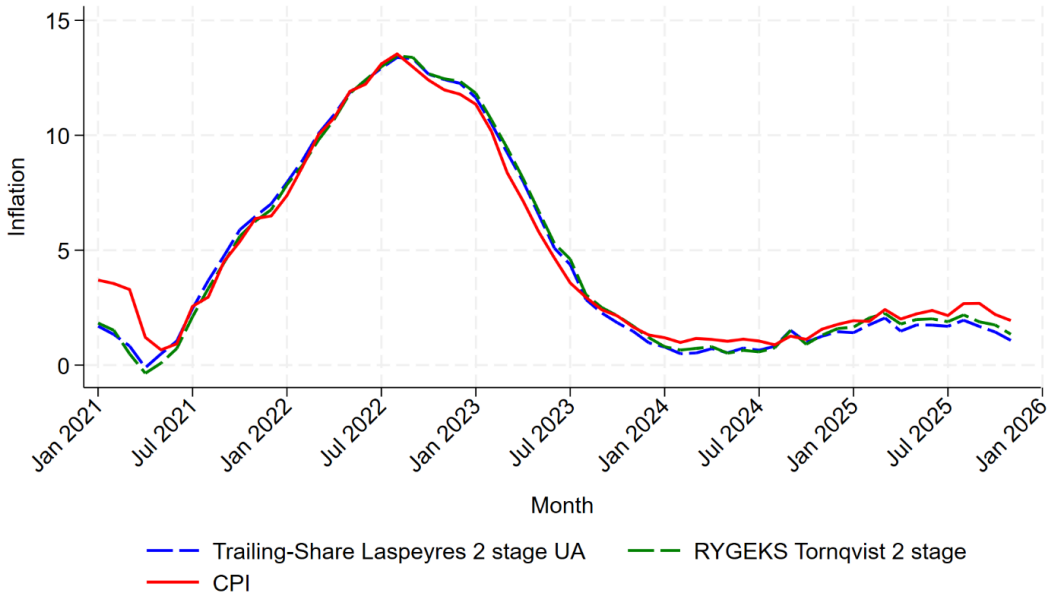
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Figure 1: Price Indices and Inflation Rates, Food at Home, 2020–2025

(a) Price Indices

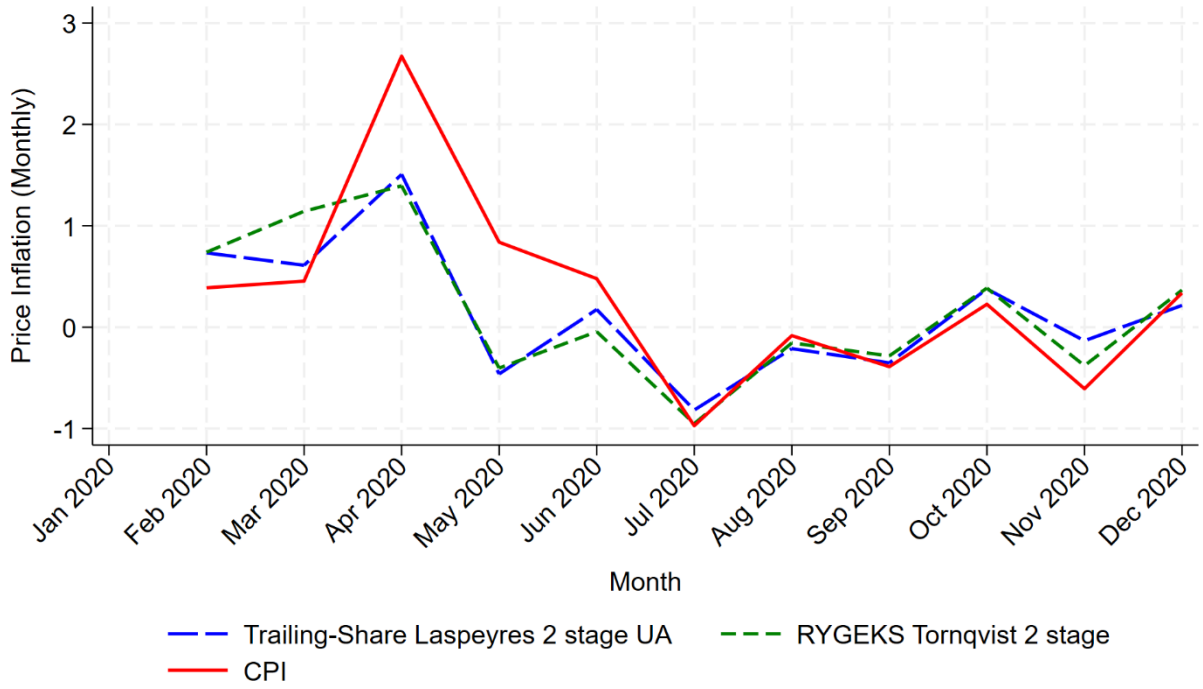


(b) Inflation Rates



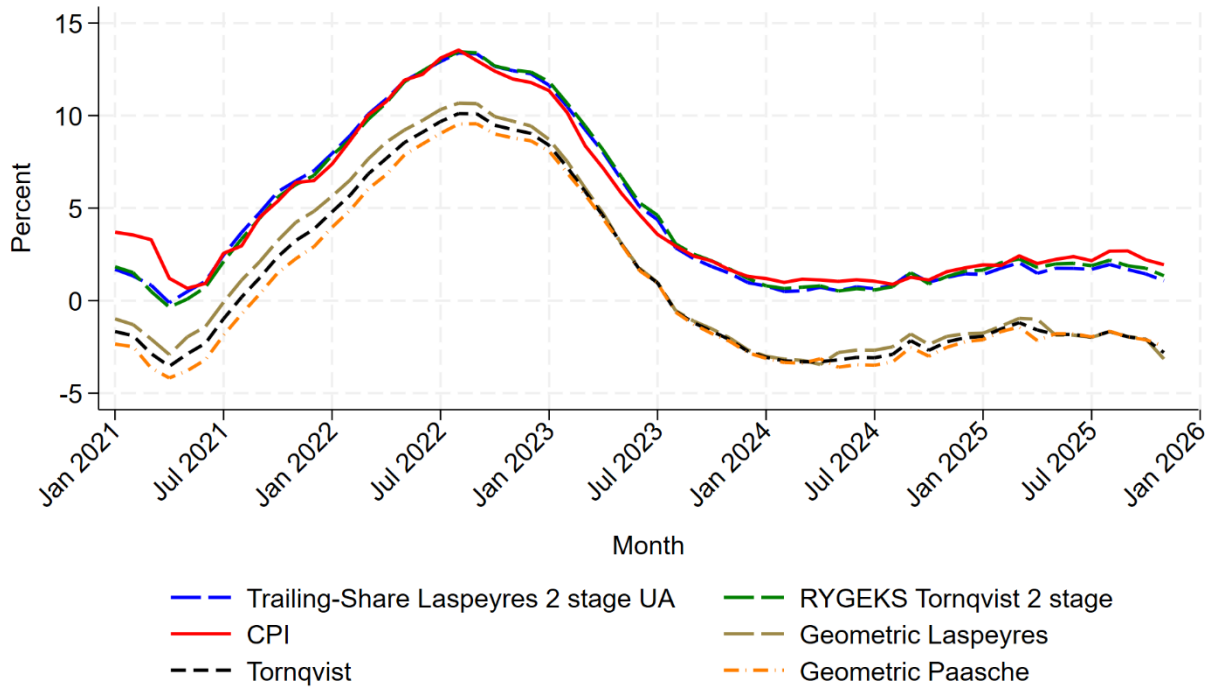
Note: Trailing-Share Laspeyres 2 stage UA is a geometric Laspeyres at lower level (within ELIs) and an arithmetic Laspeyres at the upper level (across ELIs) using 12-month trailing share weights in both stages. RYGEKS Tornqvist 2 stage is a rolling-year GEKS Tornqvist at lower level and Tornqvist (using t-1, t weights) at upper level. All inflation rates in Panel (b) are from chained YOY indices.

Figure 2: Monthly Price Change, Food at Home: 2020



Note: Trailing-Share Laspeyres 2 stage UA is a geometric Laspeyres at lower level (within ELIs) and an arithmetic Laspeyres at the upper level (across ELIs) using 12-month trailing share weights in both stages. RYGEKS Tornqvist 2 stage is a rolling-year GEKS Tornqvist at lower level and Tornqvist (using t-1, t weights) at upper level.

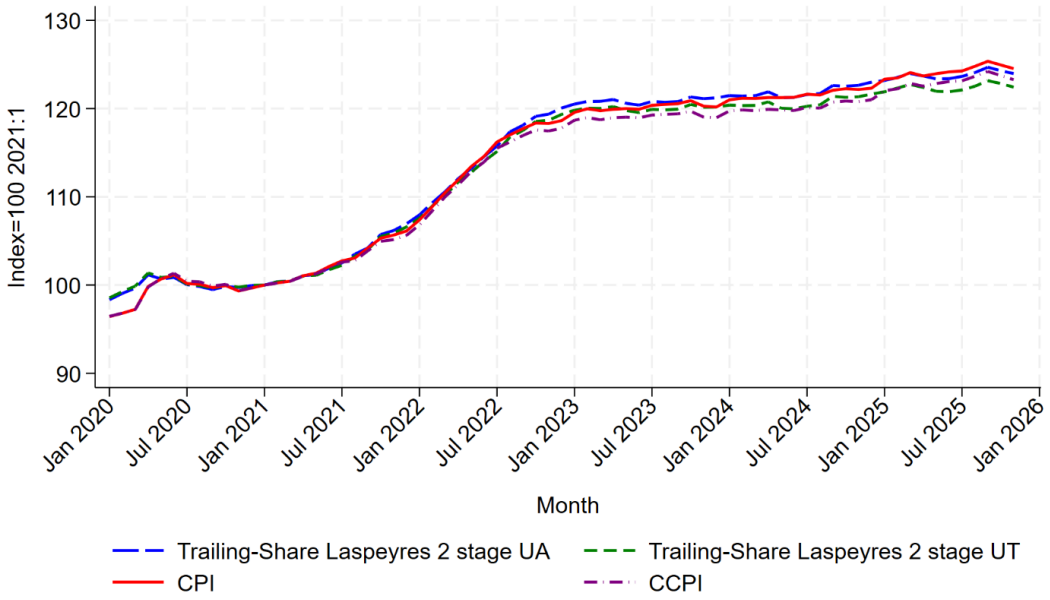
Figure 3: Twelve-month Price Change, Food at Home, 2021–2025



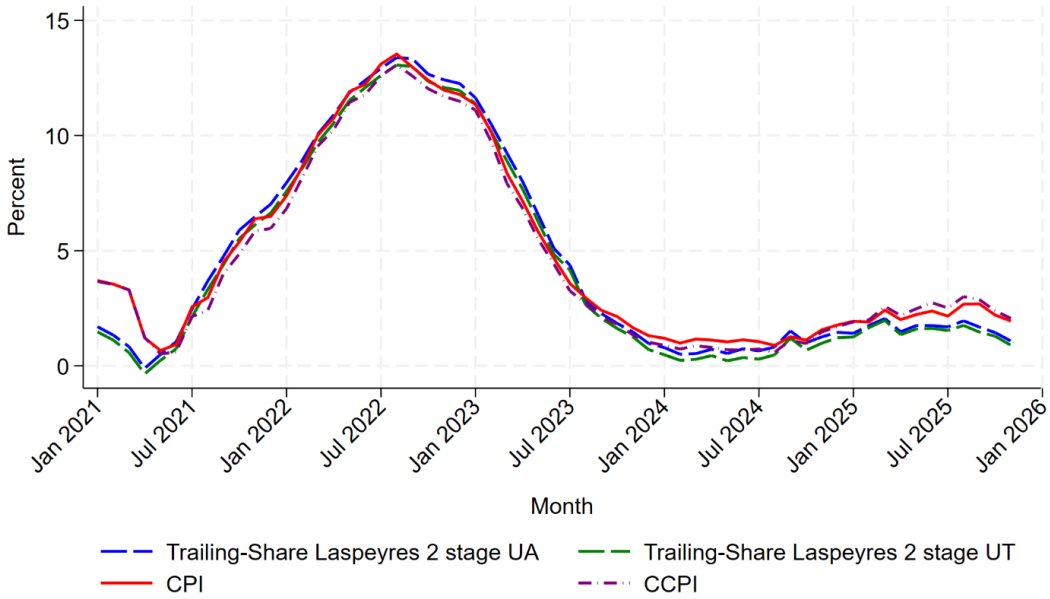
Note: All indices chained YOY. Trailing-Share Laspeyres 2 stage UA is a geometric Laspeyres at lower level (within ELIs) and an arithmetic Laspeyres at the upper level (across ELIs) using 12-month trailing share weights in both stages. RYGEKS Tornqvist 2 stage is a rolling-year GEKS Tornqvist at lower level and Tornqvist (using t-1, t weights) at upper level. Geometric Laspeyres, Geometric Paasche and Tornqvist are bilateral indices.

Figure 4: Price Indices and Inflation Rates, Food at Home, 2020–2025: Comparison with Tornqvist Upper-Level Aggregation

(a) Price Indices

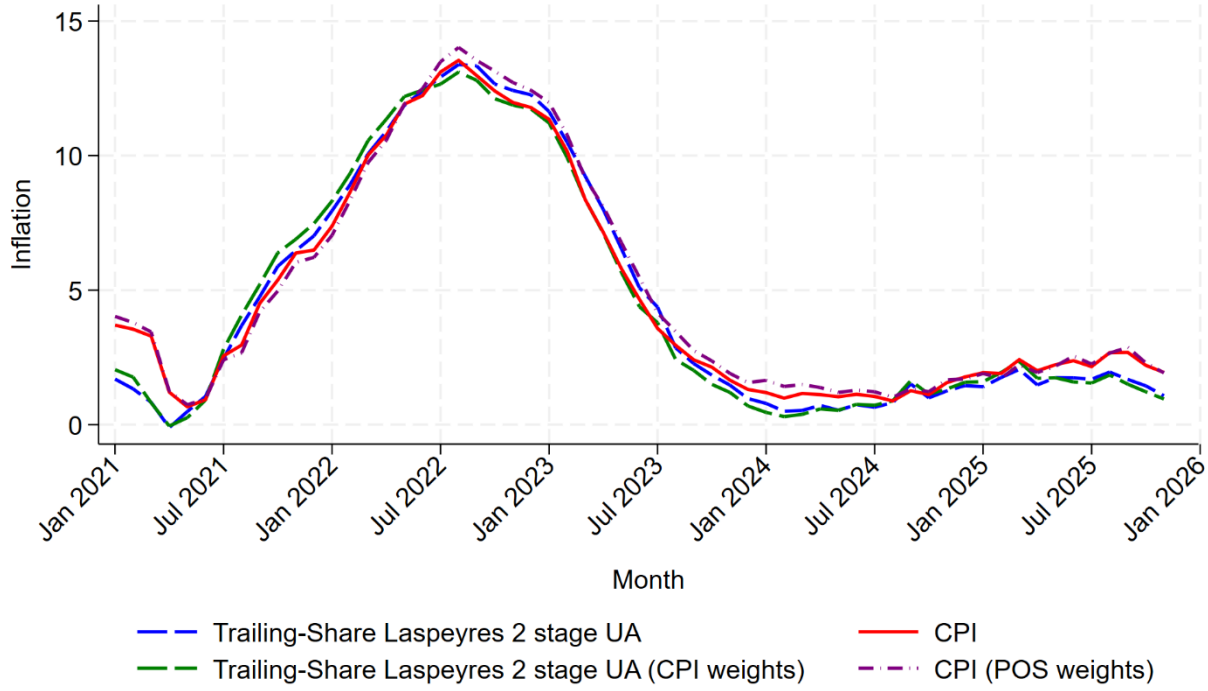


(b) Inflation Rates



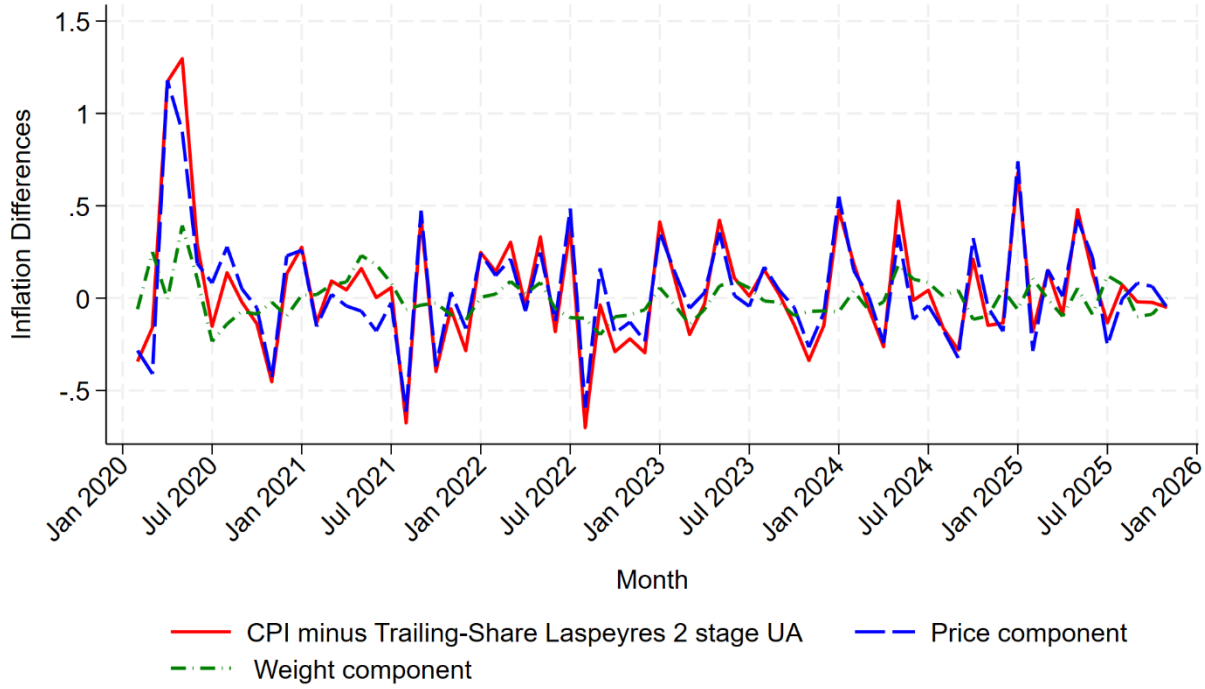
Note: Trailing-Share Laspeyres 2 stage UA is a geometric Laspeyres at lower level (within ELIs) and an arithmetic Laspeyres at the upper level (across ELIs) using 12-month trailing share weights in both stages. Trailing-Share Laspeyres 2 stage UT is geometric at lower level using trailing share weights and Tornqvist at upper level using (*t-1,t*) weights. CCPI is the BLS chained CPI, which uses Tornqvist aggregation at the upper level (using *t-1,t* CEX weights). All inflation rates in Panel (b) are from chained YOY indices.

Figure 5: 12-Month Price Change, Food at Home, 2020–2025:
Exchanging Upper-Level Weights



Note: All indices chained YOY. Trailing-share Laspeyres 2 stage UA is a geometric Laspeyres at lower level (within ELIs) and an arithmetic Laspeyres at the upper level (across ELIs) using 12-month trailing share weights in both stages. Trailing-Share Laspeyres 2 stage UA (CPI weights) is geometric Laspeyres at lower level using trailing share weights and arithmetic Laspeyres at the upper level using relative importance weights. CPI (POS weights) is CPI at the ELI level and arithmetic Laspeyres at upper level using trailing-share expenditure weights calculated from the Circana transactions data.

Figure 6: Decompositon of Difference in Monthly Inflation Rate (CPI minus Trailing-Share Laspeyres 2 stage UA), Food at Home: 2020-2025



Note: The difference in monthly inflation rates between the CPI and the Trailing-Share Laspeyres 2 stage UA is decomposed into a "Price Component" (the contribution of differences in rates of inflation at the ELI level using the average ELI weight for the CPI and the Trailing Share approach) and a "Weight Component" (the contribution of differences in the expenditures weights at the ELI level using the average ELI inflation rate for the CPI and Trailing Share Approach). See Section IV.C for the definition of the decomposition formula.

Table 1: Circana's Proprietary Product Hierarchy, Food at Home

Component	Department	Aisle	Category	Subcategory
2	11	63	588	3,479

Table 2: Illustrative Mapping from Circana's Proprietary Product Hierarchy to ELIs

ELI Number	ELI Title	Number of Matched Subcategories	Example (Category, Subcategory)
FB011	Bread	53	Pitas, Wheat
FF011	Chicken	69	Thighs, Chicken
FM031	Dried fruits and vegetables	24	Dried Fruit, Dried Figs
FT062	Other miscellaneous foods	691	Meat -SS[Shelf Stable], Meat Alternatives

Table 3: Weeks to Months, RESET Demonstration Project Calendar, 2025

Calendar Month	Final Day of Calendar Month	Day of Week	Final Day of RESET Month (Sunday)	Weeks in RESET Month
Jan-25	1/31/2025	Friday	2/2/2025	5
Feb-25	2/28/2025	Friday	3/2/2025	4
Mar-25	3/31/2025	Monday	3/30/2025	4
Apr-25	4/30/2025	Wednesday	4/27/2025	4
May-25	5/31/2025	Saturday	6/1/2025	5
Jun-25	6/30/2025	Monday	6/29/2025	4
Jul-25	7/31/2025	Thursday	7/27/2025	4
Aug-25	8/31/2025	Sunday	8/31/2025	5
Sep-25	9/30/2025	Tuesday	9/28/2025	4
Oct-25	10/31/2025	Friday	11/2/2025	5
Nov-25	11/30/2025	Sunday	11/30/2025	4
Dec-25	12/31/2025	Wednesday	12/28/2025	4

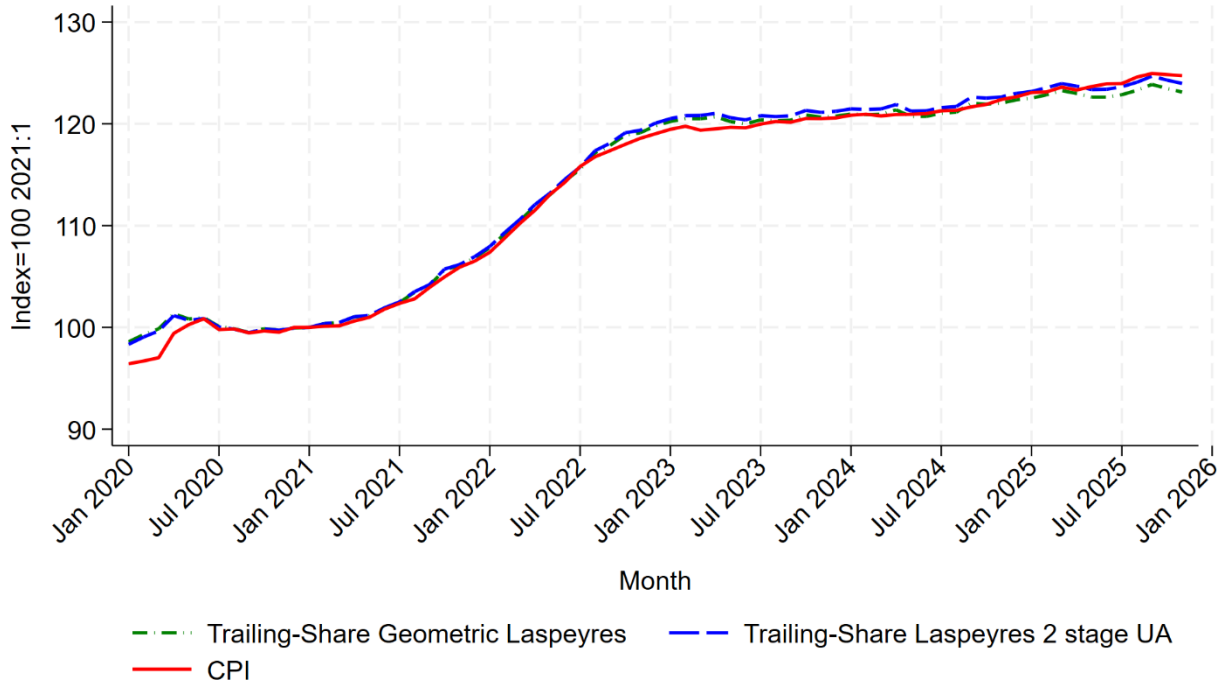
Table 4: Annual Price Change (Percent), Food at Home, 2020-2025

Period	Trailing-Share Laspeyres 2 stage UA	Trailing-Share Laspeyres 2 stage UT	RYGEKS Tornqvist 2 stage	CPI	CCPI
1/20 to 1/21	1.7	1.5	1.8	3.7	3.7
1/21 to 1/22	8.0	7.6	7.9	7.4	6.8
1/22 to 1/23	11.6	11.4	11.8	11.4	11.1
1/23 to 1/24	0.8	0.5	0.8	1.2	0.9
1/24 to 1/25	1.4	1.3	1.7	1.9	1.9
1/25 to 11/25	0.8	0.5	0.8	1.2	1.2
1/20 to 11/25	4.1	3.8	4.1	4.5	4.3

Note: Annual inflation rates are computed as the compound annual growth rate over reported horizon. Trailing-Share Laspeyres 2 stage UA is a geometric Laspeyres at lower level (within ELIs) and an arithmetic Laspeyres at the upper level (across ELIs), using 12-month trailing share weights in both stages. Trailing-Share Laspeyres 2 stage UT=Geometric at lower level using trailing share weights, Tornqvist at upper level using (t-1,t) weights. RYGEKS Tornqvist 2 stage is a rolling-year GEKS Tornqvist at lower level, and a Tornqvist (using t-1, t weights) at upper level. CCPI is the CCPI-U, which uses Tornqvist aggregation at the upper level (using t-1,t CEX weights).

Appendix

Figure A1: Price Indices, Food at Home, 2020–2025



Note: Trailing-Share Geometric Laspeyres is single-stage index calculated using pooled data across all ELIs in Food at Home. Trailing-Share Laspeyres 2-stage UA is a geometric Laspeyres at lower level (within ELIs) and an arithmetic Laspeyres at the upper level (across ELIs), using 12-month trailing share weights in both stages.