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Early Results from the RESET Demonstration Project:

Inflation in Food at Home

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ABSTRACT

This paper presents preliminary results from the RESET Demonstration Project, which builds price and sales indices from item-level transactions data. The RESET Demonstration project aims to establish the feasibility and benefits of using modern transactions data for economic measurement, showing the way forward for official economic statistics to be re-engineered based on 21st century information and information technology. The paper's preliminary results present new inflation measures for Food at Home and evaluate them both in comparison to current official statistics and as novel measures that better account for the dynamics of consumer choice. The paper addresses challenges of building reliable and credible official statistics from item-level transactions data and presents findings about recent inflation in Food at Home.

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. (2025) 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, 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. (2025) 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., 2025 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 entire period they indicate slightly lower inflation in Food at Home than the CPI-like indices, consistent with consumer substitution behavior within 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. The low-level price quotations in the CPI are calculated as geometric means of price relatives, which would reflect consumer substitution behavior 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.

With monthly scanner data, a key challenge for chained indices—including the Tornqvist—is chain drift. Our results show that chain drift is substantial in this setting. Accordingly, our

[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.

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 in Ehrlich et al. (2025), 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., 2025; Cafarella et al., 2023). The RESET DP—funded in 2025 by the Alfred P. Sloan Foundation and 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 initial 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 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

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

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

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

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:

$$s_{kt}^{\mathbb{C}_{t-1,t}} = \frac{p_{kt}q_{kt}}{\sum_{k\in\mathbb{C}_{t-1,t}} p_{kt}q_{kt}}. \tag{2}$$

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:

$$s_{kt-1}^{\mathbb{C}_{t-1,t}} = \frac{p_{kt-1}q_{kt-1}}{\sum_{k\in\mathbb{C}_{t-1,t}} p_{kt-1}q_{kt-1}}. \tag{3}$$

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:

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

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

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

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 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. Addressing product turnover is central to the RESET approach. We address the conceptual issues involved in Ehrlich et al. (2025). Implementing procedures that allow for entry and exit to be accounted for "at scale" is deferred to subsequent analysis. 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, the most familiar of which are 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) Standard Indices; Chaining

We first consider standard 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

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

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

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

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) Trailing-Share Laspeyres Index; BLS CPI

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

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

In this paper, we focus on a 12-month trailing-share Laspeyres index, so that we capture the preceding year's worth of expenditures in calculating the relevant expenditure shares, $s_{k12}^{\mathbb{t}-1,t}$. Because we do not consider alternative periods for the trailing-share index, we omit the subscript N hereafter. The trailing-share Laspeyres is intended to mimic aspects of the CPI's methodology. It also has other features, notably, the trailing-share index reduces the scope for chain drift and noise in the data more generally to affect measured prices by considering a year-long period to measure expenditure shares. The trailing share Laspeyres index is also consistent in aggregation.[5]

Note that 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

[5] 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 $t-1$.

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.

Note that 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 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

the next section. 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.

c) 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. This pattern might arise for a number of reasons, a prominent one being consumers' tendency to stockpile goods during temporary sales or promotions. Chain drift can in principle be positive or negative, but most of the empirical evidence is that it is negative, i.e., the evidence suggests that simple chained indices typically yield a downward bias in the measured 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.[6] As we summarize in Section V below, several national statistical agencies outside of the United States

[6] 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.

have adopted the RYGEKS Tornqvist index to measure inflation using scanner data. We likewise focus on the Tornqvist index as the elementary index into the RYGEKS procedure.

To compute the RYGEKS Tornqvist, 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

$$\Psi_{e,f}^{TQ} = \prod_{k \in \mathbb{C}_{e,f}} \left(\frac{p_{ke}}{p_{kf}} \right)^{\frac{s_e^{\mathbb{C}_{e,f}} + s_{kf}^{\mathbb{C}_{e,f}}}{2}} . \tag{12}$$

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

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

where the terms $\ln\Psi_{x,x}^{TQ} = 0$. 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.[7] 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).[8] Importantly, the RYGEKS Tornqvist price index is not consistent in aggregation. We discuss this issue further below.

[7] 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.

[8] We plan on investigating alternative procedures such as the Window and Mean splice. An advantage of the movement splice is that revisions are not required. However, there are desirable features of using alternative splicing procedures.

Although several statistical agencies have successfully implemented such RYGEKS procedures, this multilateral approach does pose tradeoffs.[9] 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.

d) Price Level Indices and Year-over-Year Indices

The month-over-month indices discussed enable constructing price level indices with chaining and in turn to compute indices such as year-over-year (YOY) indices. Constructing these indices is straightforward but we bring attention to these indices as it is instructive to compare and contrast the year-over-year indices from the monthly chaining relative to direct YOY indices. A *chained* price level index is produced from a base year with the recursive formula

$$I_t = I_{t-1} * \psi_{t-1,t} \tag{14}$$

for any month-over-month price index $\psi_{t-1,t}$. With the price level index computed, a YOY indices from the chained index is computed as $\psi^C_{t-12,t} = I_t / I_{t-12}$.

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

Alternatively, Direct indices can also be computed, where the price change is based on a long difference. In this paper, we will present Direct YOY price changes, that is, where the long difference is computed over 12-month rolling windows. Consider, for example, a Direct YOY Tornqvist:

$$\psi_{t-12,t}^{TQ,D} = \prod_{k \in \mathbb{C}_{t-12,t}} \left(\frac{p_{kt}}{p_{kt-12}} \right)^{\frac{s_{kt-12}^{\mathbb{C}_{t-12,t}} + s_{kt}^{\mathbb{C}_{t-12,t}}}{2}} \tag{15}$$

Direct indices such as this Direct YOY Tornqvist have multiple attractive features. Such measures are consistent in aggregation. They also are not subject to chain drift by construction. Since Direct YOY Geometric Laspeyres and Geometric Paasche indices can readily be computed, these indices provide guidance about substitution bias present in the transactions data in an internally consistent manner using indices that abstract from chain drift.

There are limitations, of course, since these Direct YOY indices restrict attention to items present in both t-12 and *t*. This is related to the limitations of RYGEKS in the presence of product turnover, where the Direct YOY is the longest of the many direct indices going into the 12-month RYGEKS Tornqvist. It would be possible to compute direct indices over longer than 12-month windows. In addition to posing computational burdens for the RYGEKS (the number of computations increases exponentially with the number of periods included in the window), increasing the window size also makes the effect of product turnover more severe as there are fewer continuing goods over longer windows.

e) Two-Stage Aggregate Food at Home Price Indices

All of the preliminary results for Food at Home presented in this paper are calculated by pooling the data for the 65 ELIs in Food at Home and applying the index formulas described in subsections a) through c) above. In other words, we have computed our Food at Home price

indices using all products in Food at Home in a set of "single-stage" indices. For the geometric Laspeyres, Paasche, Tornqvist and trailing share geometric Laspeyres this is not an issue in terms of the implied total Food at Home price indices since these methods are all consistent in aggregation.

We are also examining two methods of addressing aggregation issues for indices that are not consistent in aggregation. [The remainder of this subsection discusses calculations that are not in this draft, but will be included in the post-conference draft.]

First, 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.[10] In the initial 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, we intend to explore indices built from sub-national geographical data.

As a closer approximation to the CPI formula than the version of the trailing-share Laspeyres index defined in equation (11) and included in the figures and tables of this draft, we will

[10] 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 projected 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.

consider a two-stage hybrid index using 12-month trailing share. In the first stage, we compute a trailing-share geometric Laspeyres index for each ELI (denoted by m) as[11]

$$\Psi_{t-1,t,12}^{trailing\ \mathrm{L}^{m}_{geo}} = \prod_{k \in \mathbb{C}_{t-1,t}} \left(\frac{p_{kt}}{p_{kt-1}} \right)^{s_{k12}^{\mathbb{L}^{m}_{t-1,t}}} . \tag{16}$$

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

$$\Psi_{t-1,t}^{two\ stage} = \sum_{m \in \mathbb{M}} s_{m12}^{agg} \Psi_{t-1,t,12}^{trailing\ geo^{m}} \tag{17}$$

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

$$s_{m12}^{agg} = \frac{s_{Agg,12}^{\mathbb{C}^{m}_{t-1,t}}}{s_{Agg,12}^{\mathbb{C}_{t-1,t}}}. \tag{18}$$

This 2-stage CPI-like index is meant to facilitate further the comparison between our results and the official CPI.

Second, we compute indices designed to approximate the procedures BLS uses for the CCPI-U and BEA uses for the PCE price index. BLS uses a Tornqvist aggregation of lower level (geographic area by ELI) approximately geometric Laspeyres price indices for the CCPI-U. BEA uses a Fisher aggregation of lower-level price indices drawn from the CPI (for Food at Home this includes 18 product groups). We plan on using similar procedures to approximate the approaches of BLS and BEA for these price indices. Relatedly but distinctly, since the RYGEKS Tornqvist is not consistent in aggregation, we plan to follow the practice of national statistical agencies (see Eurostat, 2022) and aggregate the RYGEKS Tornqvist ELI indices via Tornqvist aggregation. We will compare the two-stage RYGEKS with the single-stage method for the

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

higher level of aggregation reported in the current paper. To illustrate the planned approach, a second-stage Tornqvist Food at Home price index computed from first price indices using formula F is given by

$$\Psi_{t-1,t}^{F,TQ} = \prod_{m \in \mathbb{M}} \left(\Psi_{t-1,t}^{F,m} \right)^{\frac{s_{mt}^{agg} + s_{mt-1}^{agg}}{2}} \tag{19}$$

where $\Psi_{t-1,t}^{F,m}$ represents a first-stage price index for ELI m calculated using formula F, and the weights s_{mt}^{agg} are given by

$$s_{mt}^{agg} = \frac{s_{m,t}^{\mathbb{C}_{t-1,t}}}{s_{Agg,t}^{\mathbb{C}_{t-1,t}}}. \tag{20}$$

B. Measurement Challenges

In our preliminary results for the DP to date, 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 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.[12]

[12] 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,

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.

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.

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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.

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 nominal 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., 2025) 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., 2025), 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 preliminary 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 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 geometric Laspeyres index that uses a trailing 12-month weighting scheme designed to approximate CPI methodology, and (ii) the RYGEKS-Tornqvist index. Figure 2 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 the them is effectively unity. Mean differences are modest. Over the full sample, the CPI records an average year-over-year increase of 4.77%, compared with 4.49% for the trailing-share geometric Laspeyres and 4.47% for the RYGEKS-Tornqvist.

These small full-sample differences obscure notable variation across subperiods. Table 4 reports annualized monthly averages by calendar year. In 2020, the CPI rises markedly faster 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 in Figure 3, 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 future work, we may be able to investigate the impact of the mode transition across further categories.

In 2025, a new divergence emerges, with the CPI rising noticeably more quickly than the transactions-based indices; the annualized difference in average monthly inflation exceeds 1.5 percentage points for both comparisons. Identifying the sources of these recent discrepancies remains an active area of ongoing research.

Even with some notable differences, a key finding is that the trailing share geometric 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 trailing-share geometric 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.

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

Figure 4 adds the geometric Laspeyres, geometric Paasche, and Tornqvist defined in equations (7)–(9) alongside the three indices shown in Figure 2. 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, i.e., the multiplicative cumulation in equation (14). The 12-month rates of price change are computed by taking the percent change from the chained index 12 months ago. 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 measure, which is based on a superlative index formula that explicitly mitigates chain-drift bias. Figure 4 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 2, despite the differences in means. For example, the chained Tornqvist and the RYGEKS Tornqvist have a correlation close to one, but the mean of the chained Tornqvist is more than 3 percentage points lower than the RYGEKS Tornqvist. 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 has long been recognized in the use of transactions data. 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. Ehrlich et al. (2025, Appendix D.2) discusses how end-of-product-cycle clearance sales can affect indices. 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. (2025) 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.

Indeed, 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, 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 or direct comparison indices, and in future work, also with hedonics.

B. Substitution Bias: Evidence from Direct YOY Indices

The RYGEKS Tornqvist index is, as noted above, a preferred price index for national statistical agencies working with transaction-level data because it is built from superlative indices in a way that mitigates chain drift. A limitation, however, is that it is not consistent in aggregation. Relatedly, comparing the RYGEKS Tornqvist with, for example, the trailing-share geometric Laspeyres does not provide direct evidence on the importance of substitution bias from the item level upward. To assess this issue, we examine evidence from direct year-over-year (YOY)

indices. These indices are also of independent interest because they serve as diagnostics relative to the chained YOY indices.

Figure 5 presents direct YOY geometric Laspeyres, geometric Paasche, and Tornqvist indices. The year-over-year change in the CPI is included as a point of reference. The results indicate non-trivial substitution bias: the gap between the direct YOY geometric Laspeyres and geometric Paasche exceeds half a percentage point per year. The direct YOY Tornqvist is approximately 0.27 percentage points per year lower than the direct YOY Geometric Laspeyres. The gap is again largest during the high inflation period in 2021 and 2022. In August 2022, direct YOY Geometric Laspeyres was 14.1 percent and the direct YOY Tornqvist 13.1 percent – a large gap of 1 percentage point.

Aside from 2022, when inflation accelerated and the dispersion of relative prices increased, substitution bias in Food at Home over our sample period is relatively modest and consistent with the evidence in O'Flaherty (2026) using item-level transactions data from NielsenIQ. Ehrlich et al. (2025) also using NielsenIQ data find evidence of more substantial substitution bias in Food at Home for the 2006–2015 period. Moreover, the latter paper finds much larger substitution effects in consumer tech and apparel goods.

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, and 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, like 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). And 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, like 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 and examine its potential causes.

We believe that these initial 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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Figure 1: Price Indices, Food at Home, 2020–2025

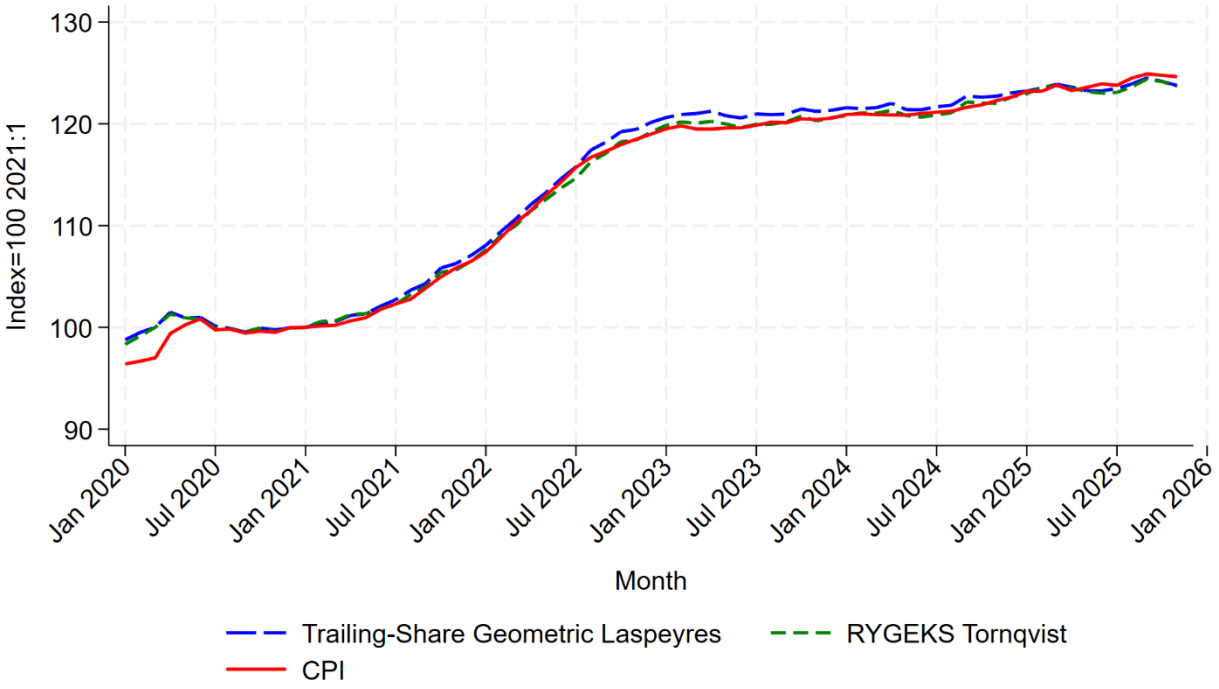


Figure 2: Twelve-month Price Change, Food at Home, 2020–2025

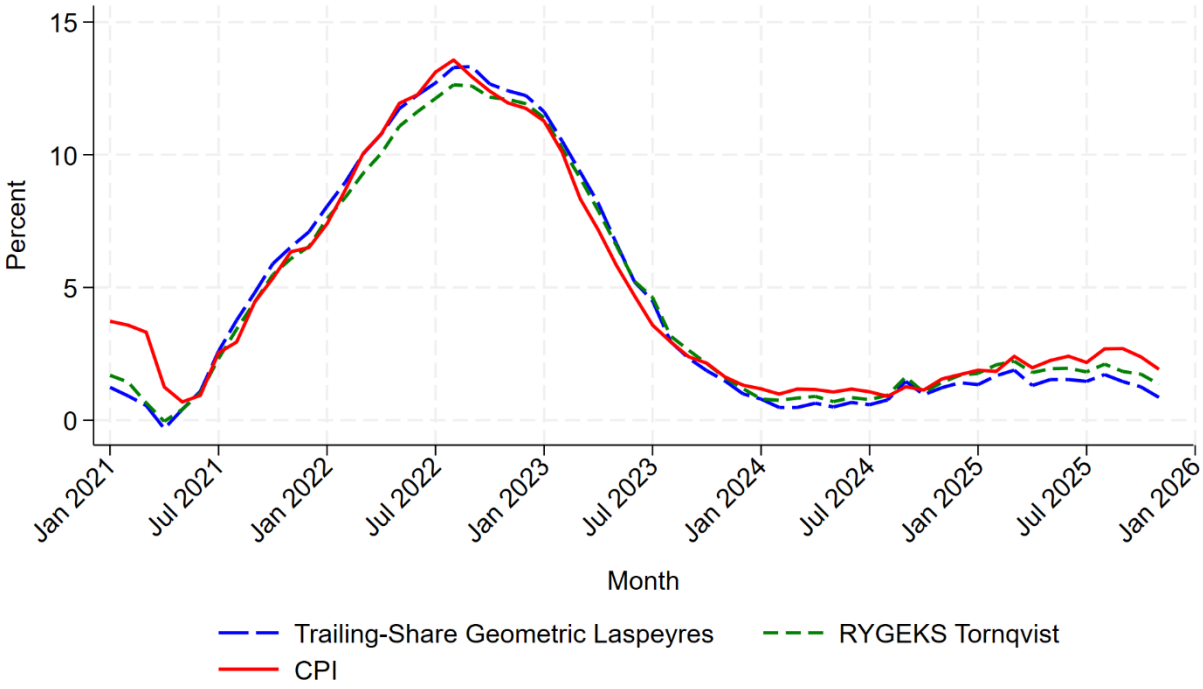


Figure 3: Monthly Price Change, Food at Home: 2020

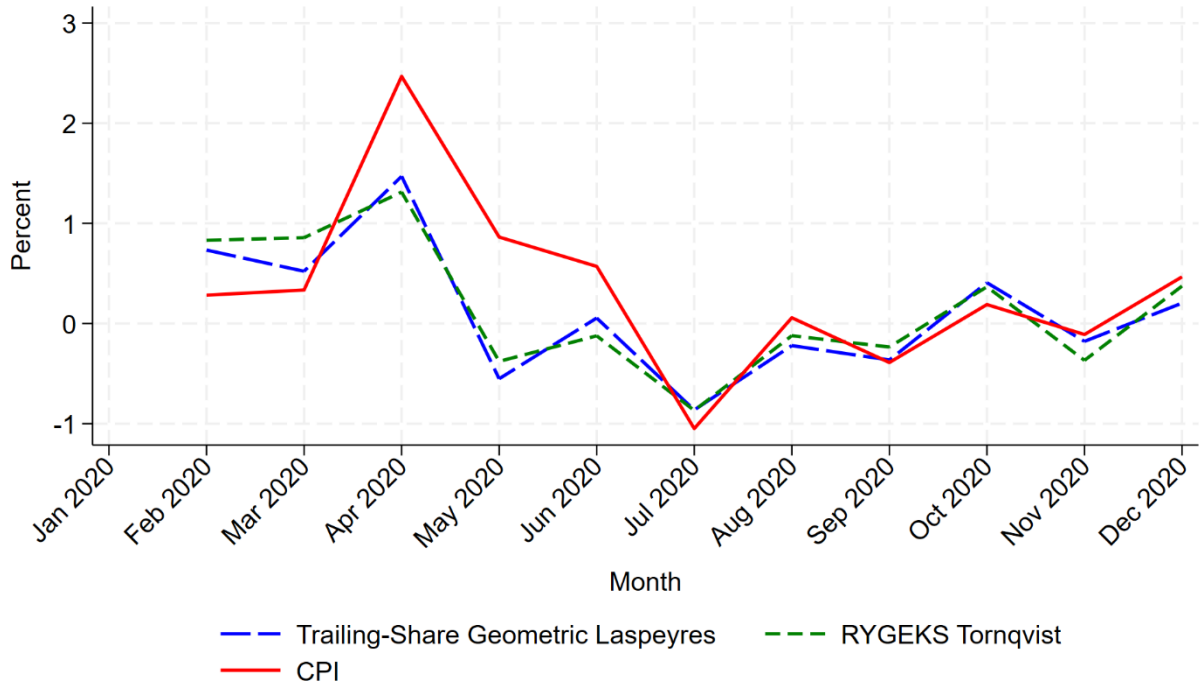


Figure 4: Twelve-month Price Change, Food at Home, 2021–2025

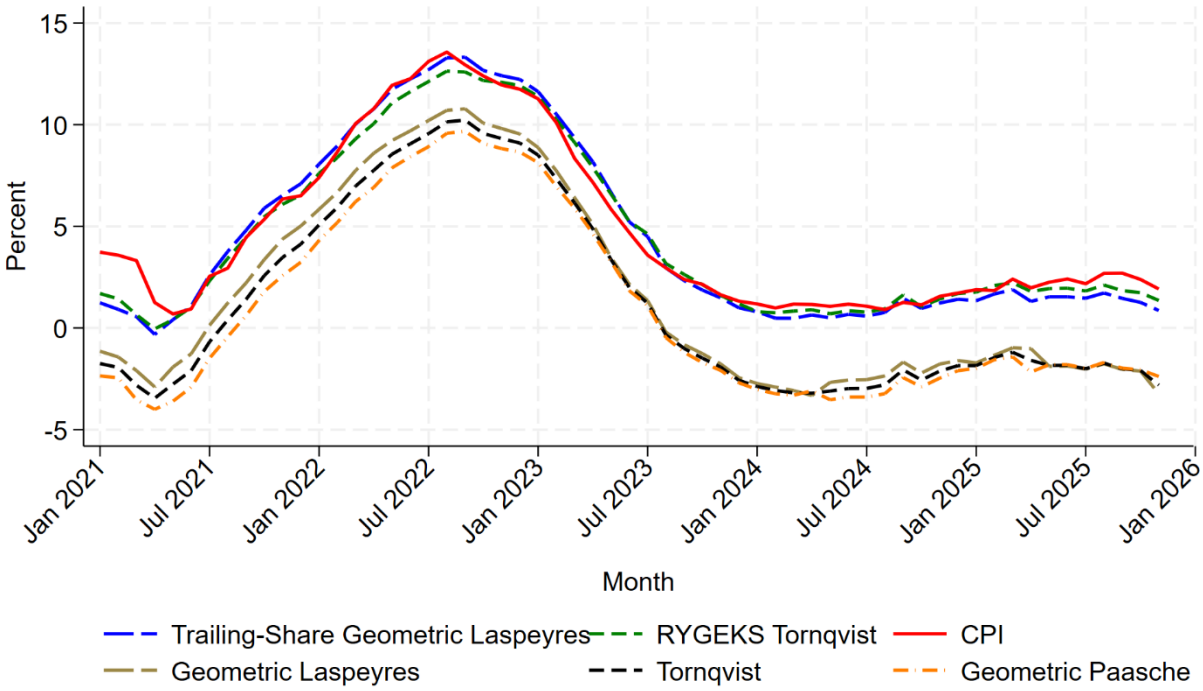


Figure 5: Direct Year-over-Year Price Change, Food at Home

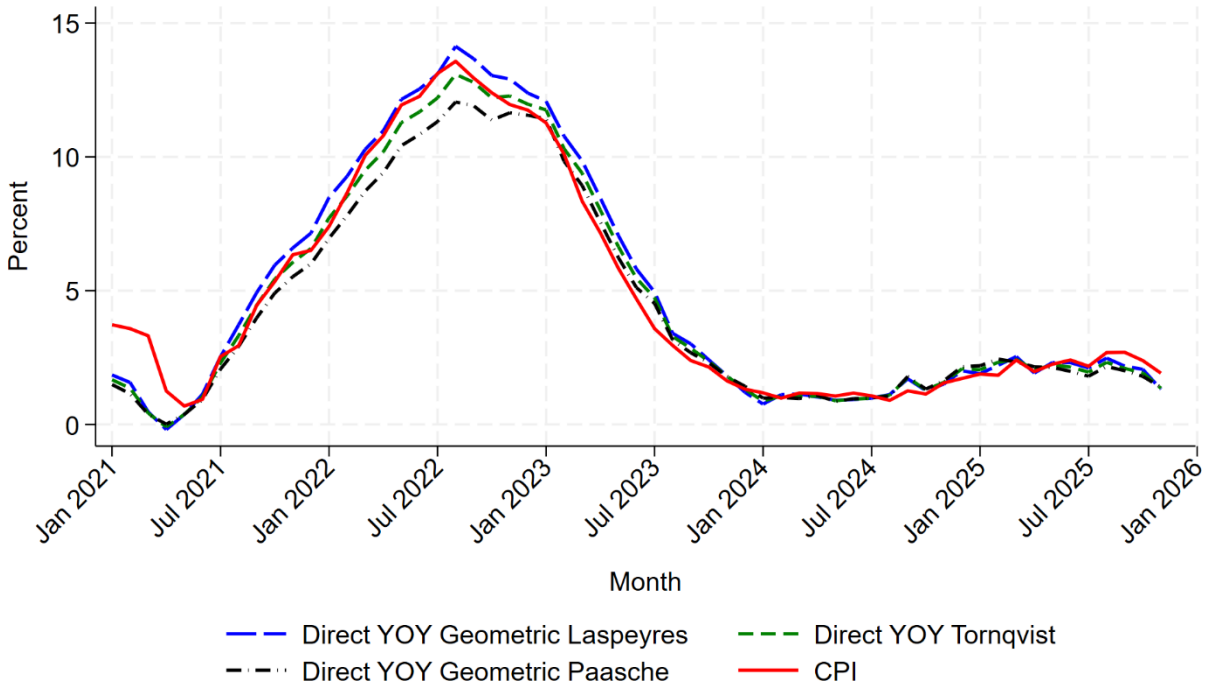


Table 1: Circana's Proprietary Product Hierarchy, Food at Home

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

	Trailing-Share Geometric Laspeyres	RYGEKS Tornqvist	CPI
2020	1.3	1.8	4.1
2021	7.1	6.6	6.5
2022	12.2	11.9	11.8
2023	1.0	1.2	1.3
2024	1.4	1.7	1.7
2025	0.6	0.9	2.5

Note: Annual inflation rates are computed as the annual arithmetic average of monthly percent changes. For 2020, data are February through December only. The 2025 data are through November.