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The Effect of Component Disaggregation on Measures of the Median and Trimmed-Mean CPI*

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Abstract

For decades, the Federal Reserve Bank of Cleveland (FRBC) has produced median and trimmed-mean consumer price index (CPI) measures. These have proven useful in various contexts, such as forecasting and understanding post-COVID inflation dynamics. Revisions to the FRBC methodology have historically involved increasing the level of disaggregation in the CPI components, which has improved accuracy. Thus, it may seem logical that further disaggregation would continue to enhance its accuracy. However, we theoretically demonstrate that this may not necessarily be the case. We then explore the empirical impact of further disaggregation along two dimensions: shelter and non-shelter components. We find that significantly increasing the disaggregation in the shelter indexes, when combined with only a slight increase in non-shelter disaggregation, improves the ability of the median and trimmed-mean CPI to track the medium-term trend in CPI inflation and marginally increases predictive power over future movements in CPI inflation. Finally, we examine the practical implications of our preferred degree of disaggregation. Our preferred measure of the median CPI suggests that trend inflation was lower pre-pandemic, while both our preferred median and trimmed-mean measures suggest a faster acceleration in trend inflation in 2021. We also find that higher disaggregation marginally weakens the Phillips curve relationship between median CPI inflation and the unemployment gap, though it remains statistically significant.

Keywords: inflation measurement, median CPI, trimmed-mean CPI, trend inflation, disaggregates of inflation

JEL Codes: E31, E37, E52, C8

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1 Introduction

Measuring the medium-term trend (MTT) in inflation is important for several reasons. First, it is a matter of central importance for monetary policy. Second, because the real interest rate matters for intertemporal decisions, estimating the MTT in inflation is useful in practically any real-world situation where intertemporal tradeoffs are involved. Third, it is useful in removing noise from the inflation series, noise that otherwise might obscure relationships and cloud empirical work involving inflation.[1]

While there are many approaches to estimating the MTT in inflation, a simple method is using a limited-influence statistic, such as a median, instead of the sample mean to estimate the center of the current cross-sectional distribution of price changes in CPI or PCE components. Limited-influence statistics are useful for estimating the center of the inflation distribution because the sample distribution of price changes in CPI components is highly leptokurtic, i.e., it frequently has big outliers. Official measures of inflation are computed as a sample mean across component price changes, but sample means are very sensitive to outliers. Thus, limited-influence statistics are more efficient estimators of the center of the distribution. And in practice, the current center of the distribution has been shown to be a good estimate of the MTT in inflation.

Bryan and Pike (1991) and Bryan and Cecchetti (1994) introduced the median CPI and trimmed-mean CPI, and shortly thereafter, the Federal Reserve Bank of Cleveland (FRBC) began producing these series. These two series have been shown to be useful signals of the MTT in CPI inflation.[2] For this reason, these and other similar measures have been gaining traction and are increasingly used in empirical studies, not only in the forecasting context (e.g., Smith, 2004; Meyer, Venkatu and Zaman, 2013; Liu and Smith, 2014; Meyer and Zaman 2019; Verbrugge and Zaman, 2023a,b; Ocampo, Schoenle and Smith 2023) but also in many other contexts as well, including: establishing and testing the robustness of stylized inflation facts (Bryan and Cecchetti, 1999; Verbrugge, 1999; Fang, Miller and Yeh, 2010); understanding inflation uncertainty (Metiu and Prieto, 2023); discriminating

[1]Mazumder (2017), Kishor and Koenig (2022), and de Veirman (2023) also make this point, and it is implicit in Andrle, Bruha and Solmaz (2017). The reduction of noise helps explain why Phillips curves estimated with, e.g., trimmed-mean inflation, are much more successful. To our knowledge, Alves (2014) is the only extant study using trimmed inflation in a DSGE model.

[2]In like manner, the trimmed-mean PCE has been shown to be a very good signal of the MTT in PCE inflation; see Mertens (2016).

between models of price adjustment (Ashley and Ye, 2012); locating a stable Phillips curve (Ball and Mazumder, 2011; Ball and Mazumder, 2019; Stock and Watson, 2020; Ashley and Verbrugge, 2023); studying the effects of oil supply shocks (Kilian, 2008); understanding inflation expectations and their relationship to inflation (Verbrugge and Zaman, 2021); and understanding post-Great Recession and post-COVID inflation dynamics (Ball and Mazumder, 2011; Mazumder, 2018; Ball et al., 2021; Ball, Leigh, and Mishra 2022; Verbrugge and Zaman 2023b; Cotton et al., 2023). They have also been suggested as a superior measure for monetary policy targeting and communication (Cecchetti and Groshen, 2001; Dolmas and Koenig, 2019; Verbrugge, 2022).[3]

Given the growing importance of the median and trimmed-mean CPI, it is worth exploring opportunities to enhance the existing FRBC measures. One potential approach lies in increasing the level of disaggregation, i.e., the number of CPI components used to calculate the median and trimmed-mean. Such changes have precedent. The earliest precursor to today's median and trimmed-mean CPI had just seven components. When formally introduced, it had 36 components, which was later increased to 41. Subsequent research demonstrated that it would be desirable to increase the number of components to 45, where it stands today. But is this level of disaggregation *optimal*? Notably, trimmed-mean *PCE* inflation and median *PCE* inflation are calculated using significantly larger baskets of 178 and 201 PCE components, respectively (Dolmas 2009; Carroll and Verbrugge 2019). This paper investigates whether further disaggregation would enhance the existing FRBC measures.

We first demonstrate theoretically that, when estimating the weighted median of the underlying distribution of CPI indexes, if some of those underlying indexes are unobserved because they are unpublished, as is the case with the CPI, the weighted median of the most highly disaggregated basket that is feasible (based upon indexes that are observed) is not necessarily the minimum mean squared error (MSE) estimator. Hence, the optimal level of disaggregation becomes an empirical question.

We therefore conduct such an empirical investigation, systematically investigating the impact of the level of disaggregation, taking the current FRBC median and trimmed-mean CPI basket as our starting point. We disaggregate the CPI basket along two dimensions: shelter and non-shelter components. For shelter components, our starting point is the current FRBC methodology, which

[3] Verbrugge (2022), in particular, highlights the severe theoretical and empirical deficiencies of "core" inflation measures.

splits Owners' Equivalent Rent (OER) into four regional components. We then further divide each regional OER component into two components based on city size classes. For Rent, we apply the same disaggregation, resulting in a total of eight OER indexes and eight Rent indexes at the highest level of shelter disaggregation. For non-shelter components, we use the current FRBC non-shelter component basket as our baseline and then construct four additional non-shelter component baskets using the disaggregation structure of the CPI. This results in a total of 15 candidate baskets of CPI components, ranging in size from the current FRBC basket of 45 components to a basket of 148 components. Next, we derive new measures of median and trimmed-mean CPI inflation from each basket. We then evaluate the performance of each new median and trimmed-mean CPI measure using criteria from the core inflation literature. Two in particular are worth highlighting. First, we assess how disaggregation affects the accuracy of median and trimmed-mean inflation in tracking an ex-post measure of the MTT in CPI inflation. Second, we examine the extent to which disaggregation impacts the predictive power of each measure over future movements in CPI inflation.

For median CPI, we find disaggregating both OER and Rent into eight components, in combination with only slightly more non-shelter disaggregation relative to the FRBC basket, to be the optimal mix of disaggregation in terms of tracking the ex-post MTT in CPI inflation and maximizing in-sample predictability over future movements in CPI inflation. Notably, for MTT tracking, further disaggregation of non-shelter components generally results in clear performance losses. For trimmed-mean CPI, results are generally similar—though the general performance of the trimmed mean does not seem sensitive to the level of disaggregation in shelter. Thus, our findings are somewhat counterintuitive: increasing the level of disaggregation as far as possible is not the best thing to do.

Our work extends a long thread of the literature that has derived or extended measures of trend CPI and PCE inflation using limited- influence estimators (e.g. Bryan and Pike 1991; Bryan and Cecchetti 1994; Bryan, Cecchetti, and Wiggins 1997; Dolmas 2005; Brischetto and Richards 2007; Dolmas 2009; Higgins and Verbrugge 2015; Carroll and Verbrugge 2019; Rich, Verbrugge, and Zaman 2022). Our work also contributes to a large literature which has evaluated competing measures of the MTT in inflation in terms of metrics such as forecasting, explaining future headline inflation, and tracking ex-post measures of trend inflation (e.g., Clark 2001; Marques, Neves, and Sarmento

2003; Rich and Steindel 2005; Rich and Steindel 2007; Meyer and Pasaogullari 2010; Crone et al. 2013; Higgins and Verbrugge 2015; Gamber and Smith, 2019; Verbrugge and Zaman 2023a,b). We also contribute to the literature examining how the properties of derived measures of inflation change as one changes the level of disaggregation of the components underlying the headline price indexes (e.g., Mahedy and Shapiro 2017; Zaman 2019; Stock and Watson 2020). However, in contrast to prior work, we are the first to derive a theoretical result regarding the optimal level of disaggregation for a weighted-median estimator. Further, we are the first to propose disaggregating OER into 8 components, and disaggregating Rent at all, in the calculation of limited influence estimators of MTT inflation. We are also the first to investigate the performance of MTT inflation measures by level of disaggregation in a systematic manner. Finally, we are also the first to demonstrate that there is no simple relationship between the frequency with which shelter components are selected as the median, and the strength of the Phillips curve relationship in the resulting median CPI measure.

The rest of the paper is organized as follows. In Section 2, we provide a brief history of the FRBC median and 16 percent trimmed-mean CPI inflation measures, along with an overview of the methodology behind their calculation. In Section 3, we prove that the optimal level of disaggregation need not be the highest level of disaggregation possible. In Section 4, we propose a scheme for defining several collections of CPI shelter and non-shelter components at increasingly finer levels of disaggregation than the set of 45 components currently used to compute the FRBC measures. Section 5 examines how varying the level of CPI component disaggregation affects the ability of median and trimmed-mean CPI inflation measures to track an ex-post estimate of the MTT in CPI inflation and explain future inflation. In Section 6, we discuss some practical implications of our preferred degree of disaggregation for the median and trimmed-mean CPI. First, we examine the implications for trend CPI inflation: our preferred median and trimmed-mean CPI measures suggest that trend inflation was lower pre-pandemic, and accelerated faster in 2021. Second, we look at how changing the degree of component disaggregation alters the distribution of components chosen as the median component over time. Finally, we highlight that higher disaggregation weakens the Phillips curve relationship between median CPI inflation and the unemployment gap; our preferred median CPI measure has the weakest relationship, though it remains firm and statistically significant. Section 7 concludes.

2 The FRBC Median and Trimmed-Mean CPI

2.1 A brief history

The FRBC median and 16 percent trimmed-mean CPI inflation originated from the seminal work of Bryan and Pike (1991) and Bryan and Cecchetti (1994), who were the first to propose a theoretical and statistical justification for the use of the median or trimmed-mean as measures of "core" (or trend) inflation (Dolmas and Wynne (2008)).[4] While the FRBC has published these limited-influence estimators of the MTT in CPI inflation for decades, the components of CPI inflation from which these measures are calculated have evolved over time.[5]

Prior to 1998, the FRBC calculated the median and trimmed-mean CPI using 36 CPI components. In 1998, the Bureau of Labor Statistics (BLS) carried out its sixth comprehensive revision of the CPI, leading the FRBC to modify its component basket, for a revised total of 41 components.[6] Importantly, prior to 1998, median and trimmed-mean CPI used the shelter component, whereas after 1998, Shelter was split into: Rent of primary residence (Rent); Lodging away from home; Owner's Equivalent Rent of primary residence (OER); and Tenants' and household insurance.[7]

In July 2007, the FRBC again revised the median and trimmed-mean CPI. Under this new "revised methodology," OER was split into four regional OER subindexes, one each for the Northeast, Midwest, South, and West. This change was prompted by research by Brischetto and Richards (2007)–later confirmed by the FRBC (2007)–that found that breaking up OER improved the ability of trimmed-mean measures to track the trend in CPI inflation. Concurrently, the FRBC added the component leased cars and trucks, bringing the total to 45 CPI components.[8]

Since its introduction in 2007, small methodological adjustments have since been made to the "revised methodology" median and trimmed-mean CPI to ensure that it reflects the most recent

[4]The earliest precursor to today's median CPI in Bryan and Pike (1991) was derived from just seven CPI components.

[5]The FRBC updates the median and trimmed-mean CPI each month immediately following a new CPI data release by the Bureau of Labor Statistics (BLS) and makes these data available at https://www.clevelandfed.org/en/indicators-and-data/median-cpi.

[6]For more on this and other revisions, see https://www.bls.gov/cpi/additional-resources/historical-changes.htm

[7]We refer to measures calculated from either set of components as the "old methodology" median and trimmed-mean CPI. The "old methodology" data begin in 1967 through July 2007. See Appendix 1 for both the pre-1998 and post-1997 sets of components used under the "old methodology."

[8]Data for the "revised methodology" measures begin in 1983, as this is when the BLS introduced the rental equivalence method of measuring the cost of owner-occupied shelter. See Appendix 2 for a list of the components used under the "revised methodology."

statistical techniques and data availability. For example, the BLS does not seasonally adjust the four regional OER subindexes despite the presence of seasonality in each (FRBC (2007)). Since the FRBC median and trimmed-mean CPI indexes use seasonally-adjusted data (see Higgins and Verbrugge (2014) for a discussion), the FRBC seasonally adjusts the regional OER series. Whereas the FRBC originally used the Census Bureau's X-12-ARIMA procedure to do this, it has since switched to the newer X-13-ARIMA-SEATS procedure.

In the next section, we review in detail the current methodology for constructing the FRBC median and trimmed-mean CPI. We begin by explaining the procedure for calculating the monthly expenditure weights, and seasonally adjusting CPI indexes, for the four regional components of OER. We then enumerate the steps we take to calculate the median and trimmed-mean from any collection of CPI components.

2.2 Methodology

2.2.1 OER

CPI expenditure weights (in CPI parlance, "relative importances") are estimated annually and released in December, based upon direct measures of consumer expenditures. Over the course of the following year, they are updated every month to reflect relative price movements that have occurred. Essentially, these describe or approximate how expenditure weights change, based upon changes in relative prices.[9]

In order to split OER into regional components and incorporate them into median and trimmed-mean CPI calculations, each component is weighted by its appropriate share in the overall CPI-U. Unlike for most components, the BLS does not publish the relative importances of each regional OER component relative to overall CPI-U. The FRBC must therefore compute these itself. Computing these weights is a two-step process.

First, we calculate the **annual** relative importances for each region x by multiplying: (1) the relative importance of region x relative to the overall CPI-U; and (2) the relative importance of OER in region x relative to the overall CPI for that same region x. Why? Suppose we know that

[9] The updating procedure makes no attempt to approximate substitution behavior across components. Such substitution is picked up annually – with a very long lag – when the December relative importances are recomputed based upon Consumer Expenditure Survey data.

the weight of x in X is x/X and that the weight of X in Y is X/Y. What is the weight of x in Y, i.e., x/Y? It is simply x/Y = (x/X)*(X/Y). For example, taking the West region for concreteness, we know the weight of West OER (x) in the West CPI (X) is x/X, and we also know that the weight of the West (X) in the national CPI-U (Y) is X/Y. So to get the weight of West OER in the national CPI, we multiply the weight of the West OER in the West CPI by the weight of the West region in the national CPI.

Given these annual relative importances, each month we pull the monthly price indexes for each regional OER component and proceed to follow the BLS methodology to compute the current **monthly** relative importances for each regional OER component based upon price movements that occurred that month. Let us consider a concrete example. Suppose we are in March and are given: (1) the values of the non-seasonally adjusted (NSA) price index of component x for December (I^x_{Dec}) through March (I^x_{Mar}); (2) the values of the same for the headline CPI-U (I^{CPI}_{Dec} through I^{CPI}_{Mar}); and (3) the annual (December) relative importance of x, R^x_{Dec}. We wish to compute R^x_{Mar}. The current BLS method to construct the non-normalized weight R^x_{Mar} is given by:

$$R^x_{Mar} = R^x_{Dec} * \left(\frac{I^x_{Mar}}{I^x_{Dec}}\right)$$

To construct the normalized weight, one adjusts all the relative weights so as to ensure that they all add up to 100 by simply dividing the non-normalized weight by the analogous "updated relative importance" for the entire CPI – which has an initial "relative importance" of 100 in December – which is given by:

$$R^{CPI}_{Mar} = 100 * \left(\frac{I^{CPI}_{Mar}}{I^{CPI}_{Dec}}\right)$$

Hence the normalized weight for x, Φ^x_{Mar}, equals:

$$\Phi^x_{Mar} = \frac{R^x_{Mar}}{R^{CPI}_{Mar}}$$

One can also rewrite this as a recursive formula. Clearly:

$$R^x_{Mar} = R^x_{Dec} * \left(\frac{I^x_{Mar}}{I^x_{Dec}}\right) = R^x_{Dec} * \left(\frac{I^x_{Feb}}{I^x_{Dec}}\right)\left(\frac{I^x_{Mar}}{I^x_{Feb}}\right) = R^x_{Feb}\left(\frac{I^x_{Mar}}{I^x_{Feb}}\right)$$

Similarly:

$$R^{CPI}_{Mar} = R^{CPI}_{Feb}\left(\frac{I^{CPI}_{Mar}}{I^{CPI}_{Feb}}\right)$$

This implies:

$$\Phi^x_{Mar} = \frac{R^x_{Mar}}{R^{CPI}_{Mar}} = \frac{R^x_{Feb}}{R^{CPI}_{Feb}} * \frac{(I^x_{Mar}/I^x_{Feb})}{(I^{CPI}_{Mar}/I^{CPI}_{Feb})} = \Phi^x_{Feb}\frac{(I^x_{Mar}/I^x_{Feb})}{(I^{CPI}_{Mar}/I^{CPI}_{Feb})}$$

With this methodology, we compute for each month t the weights Φ^c_t for each component c in the Northeast OER, Midwest OER, South OER, and West OER.

This leaves the monthly CPI indexes for each component. The BLS produces both a seasonally adjusted and non-seasonally adjusted version of the headline CPI-U index and most components. As the BLS explains:

> "Seasonally adjusted data are computed using seasonal factors derived by the X-13ARIMA-SEATS Seasonal Adjustment Method. These factors are updated with the release of January data in February and reflect price movements from the previous calendar year. The new factors are used to revise the previous 5 years of seasonally adjusted data; older seasonally adjusted indexes are considered to be final."[10]

However, the BLS does not publish seasonally adjusted price indexes for the four regional OER indexes despite the presence of seasonality in each series. As a result, the FRBC seasonally adjusts these series using the BLS methodology described above.

2.2.2 Calculating median and trimmed-mean CPI inflation

For a given collection of CPI components C, denote as

$$\pi^c_t = 100\left(\frac{I^c_t}{I^c_{t-1}} - 1\right)$$

[10] For more information on seasonal adjustment in the CPI, see https://www.bls.gov/cpi/seasonal-adjustment/.

the monthly inflation rate of component c in month t. For a regional OER component, I_t^c is the corresponding NSA CPI index that has been seasonally adjusted, as explained in the previous section. For other components, I_t^c is the seasonally adjusted (SA) index published by the BLS. (If a given index I_t^c is only available in NSA form, since that component does not display significant seasonality, we use the NSA index for that component.) For each component c, in addition to π_t^c, we have available Φ_t^c, calculated as explained in the previous section for each regional OER component and taken from the BLS otherwise. To calculate the median and trimmed-mean in month t:

1. For each $c \in C$, if either π_t^c or Φ_t^c is missing, component c is dropped from any further calculations. Denote as $\tilde{C}$ the set of components C excluding components with missing data.[11]

2. Renormalize the weights such that for each $c \in \tilde{C}$: $\tilde{\Phi}_t^c = 100(\Phi_t^c / \sum_{c \in \tilde{C}} \Phi_t^c)$.

3. For all $c \in \tilde{C}$, sort π_t^c from smallest to largest. More formally, define a one-to-one mapping $c \leftrightarrow j$, $j = 1, ..., J$, where j denotes the relative position of π_t^c. For example, $c \leftrightarrow j = 1$ if π_t^c is the smallest monthly inflation rate, and $c \leftrightarrow j = J$ if π_t^c is the largest.

4. For each j, compute cumulative weight $w(j) = \sum_{k=1}^{j} \tilde{\Phi}_t^j$ where $\tilde{\Phi}_t^j \equiv \tilde{\Phi}_t^c$ if and only if $c \leftrightarrow j$.

5. Find the first j for which $50 \leq w(j)$. Denoting this index as j^{MED}, the median component is the component c^{MED} satisfying $c^{MED} \leftrightarrow j^{MED}$, and the median inflation rate is $\pi_t^{c^{MED}}$.

6. To calculate the 16 percent trimmed-mean:

   (a) Find the first j for which $8 < w(j)$. Denote this index as j_S and set its normalized relative importance to $\tilde{\Phi}_t^{j_S} \equiv \tilde{\Phi}_t^j - 8$.

   (b) Find the first j for which $92 \leq w(j)$. Denote this index as j_E and set its normalized relative importance to $\tilde{\Phi}_t^{j_E} \equiv \tilde{\Phi}_t^j - \tilde{\Phi}_t^{j-1}$.

   (c) Calculate the trimmed mean:

$$\pi_t^{TM} = \frac{\sum_{j \in [j_S, j_E]} \pi_t^j \tilde{\Phi}_t^j}{\sum_{j \in [j_S, j_E]} \tilde{\Phi}_t^j} = \frac{\sum_{j \in [j_S, j_E]} \pi_t^j \tilde{\Phi}_t^j}{84}$$

[11] Missing data are rare, but can happen if the BLS has insufficient source data to publish the component.

3 More Disaggregation Need Not Be Better: A Theoretical Result

Given the historical record of improvements to the median CPI, and given the much higher level of disaggreation in the median PCE (for example) compared to the median CPI, it may seem obvious that increasing the level of disaggregation in the median CPI even further will lead to improvement. Moreover, even laying aside the empirical performance gains that have historically accompanied increased disaggregation, there is a more theoretical argument that seems to support the notion that "more disaggregation must be better." At the lowest level of aggregation —namely, no disaggregation at all —the median equals the mean, i.e., equals headline CPI. Next, consider a very low level of disaggregation, splitting the CPI into just core goods, core services, and energy. Most of the time, core services is likely to be chosen as the median. It is clear that the resulting median will be highly volatile, and also clear that very little has been gained over just using headline CPI. As the level of disaggregation increases, it seems obvious that the distinction between the mean and the median would sharpen, and that the median would become a closer and closer approximation to the "true median"—namely, the median of the full scope of underlying indexes that the statistical agency generates (even if it does not publish all of those indexes, owing to concerns such as inadequate sample sizes or confidentiality). However, it turns out that this intuition is incorrect. In this section, we prove that if researchers do not have access to the full scope of underlying indexes that the statistical agency generates in order to produce a weighted average statistic like the CPI, and wish to compute the weighted median of the sample distribution, it is not always better to use the most disaggregated data that are available. Thus, the optimal level of disaggregation in any particular case is an empirical issue: one must assess how the weighted average computed based upon various levels of disaggregation performs along a number of dimensions, such as accuracy, against ex-post estimates of the MTT.

We begin with some definitions. Consider a discrete collection of N random variables: $A = \{X_j : j = 1, ...N\}$, each with an associated non-negative weight $w_j : j \in A$ with $\sum_{j=1}^{N} w_j = 1$. Denote a member of the set A by V. We define the weighted sample median as follows. After the random variables are realized, sort the random variables from smallest to largest, indexed by k, so that v_k is the k^{th} largest realization. The cumulative sum weight through index l is defined by $\sum_{k=1}^{l} w_k$. Then the weighted median of the sample of random variables A is defined as follows:

$wmed\,(A) = v_l : \sum_{k=1}^{l} w_k \leq 0.5$ and $\sum_{k=1}^{l+1} w_k > 0.5$.

Proposition 1. *Suppose that there is a collection of N random variables: $B = \{X_j : j = 1, ...N\}$, each with an associated non-negative weight $w_j : j \in B$ with $\sum_{j=1}^{N} w_j = 1$. Suppose that there exists a set $C \subset B$, of cardinality r, whose elements are unobserved; instead, what is observed is their weighted mean $Y = \sum_{j \in C} w_j X_j$. Without loss of generality, assume that the indexes of the random variables in C are $\{M - r, M - r + 1, ..., M\}$. Moreover, there exists a second set $D \subset B$, of cardinality s, with $C \cap D = \emptyset$, with a weighted mean $Z = \sum_{j \in D} w_j X_j$. Without loss of generality, assume that the indexes of the random variables in C are $\{M - r - s, M - r - s + 1, ..., M - s - 1\}$.*

Let

$$G = \{Y, X_j : j = 1, ..., M - r - 1\}$$

and let

$$H = \{Y, Z, X_j : j = 1, ..., M - r - s\}$$

Then the following inequality need not hold:

$$E\,[wmed\,(G) - wmed\,(B)]^2 \leq E\,[wmed\,(H) - wmed\,(B)]^2$$

Proof. We prove this via a counterexample. We consider a collection of 7 random variables $B = \{X_i, i = 1, ..., 7\}$, each equally weighted. For simplicity, one of these, X_4, has the Dirac delta function (centered on 0) as its distribution. The distributions of all the random variables are as follows:

$$X_1 \sim U\left[-6,-5\right]$$
$$X_2 \sim U\left[-4,-3\right]$$
$$X_3 \sim U\left[-2,-1\right]$$
$$X_4 \sim \left\{\delta\left(t\right)=0, t\neq 0\right\}$$
$$X_5 \sim U\left[1,2\right]$$
$$X_6 \sim U\left[3,4\right]$$
$$X_7 \sim U\left[5,6\right]$$

Given these distributions, the "true" weighted sample median $wmed(B)$ is always $X_4 = 0$. But suppose that X_1 and X_5 are unobserved; only their weighted average Y is observed. Clearly, $Y \sim U\left[-5,-3\right]$. The most disaggregated observed collection of random variables is the set $G = \{Y, X_2, X_3, X_4, X_6, X_7\}$, with $wmed(G) = x_3$, which is at most -1. However, consider aggregating X_3 and X_7 into a variable Z. Clearly, $Z \sim U\left[3,5\right]$ and the weighted median of the set $H = \{Y, X_2, X_4, X_6, Z\}$ is always equal to 0. Hence, the most disaggregated set available, G, does not necessarily yield the most accurate weighted median estimate. $\square$

The theoretical result in this paper is reminiscent of some results in the factor estimation literature. For instance, Boivin and Ng (2006) show that increasing the number of underlying indexes used to estimate factors is not necessarily better. However, the concern in that part of the literature is related to estimating a modest number of common factors, not a weighted median. Typically, in the factor literature, the researcher is considering additional series for inclusion that are of varied types, and not part of a unified group of series constructed and released by a statistical agency under a common sampling design. And even when the discussion is related to using aggregates versus more disaggregated series, aggregation in that literature is often seen as desirable in that it can remove idiosyncratic noise (e.g., Alvarez, Camacho and Perez-Quiros, 2016). “Beneficial aggregation” may also be driving the results of Gamber and Smith (2019), who find that—when constructing estimators of the MTT in PCE inflation using a principal components approach—computing principal components using 17 PCE components yielded superior MTT estimates compared with using 50 components. However, in our context, the true weighted median is a function of all of that idiosyncratic noise.

4 Finer Disaggregations of the CPI

Having established theoretically that more disaggregation is not necessarily better, we turn to an empirical investigation. We first describe our approach to disaggregation. To systematically explore the effect of disaggregation of CPI components on median and trimmed-mean CPI inflation, we derive several novel splits of the CPI by disaggregating it along two distinct dimensions: shelter components (OER and Rent), and non-shelter components. We begin by outlining our methodology for achieving increasingly finer splits of the non-shelter components of the CPI and then detail our splits for the shelter components. Finally, we combine each non-shelter split with every shelter split to form several new complete sets of CPI subcomponents.

To split the non-shelter components, we begin with the eight major groups of the CPI: Food and Beverages, Shelter, Apparel, Transportation, Medical Care, Recreation, Education and Communication, and Other Goods and Services. Next, we break up each of these components to the next lowest level possible by following the CPI item aggregation tree.[12] For example, Food and Beverages is split into two components, Food and Alcoholic Beverages, while shelter is split into three components, namely, Shelter, Fuels and utilities, and Household furnishings and Operations. We then repeat this process until we cannot achieve a finer level of disaggregation on any CPI component. For a given CPI component, we do not split it further if one of the following criteria holds:

1. A component only has a single subcomponent. For example, Personal care services has only one subcomponent, Haircuts and other personal care services.

2. Splitting the component would introduce an "unsampled" item for which the BLS does not publish a price index. For example, splitting "Information technology, hardware, and services" would introduce the component "Unsampled information and information processing."[13]

3. Splitting a component would introduce items at indent level 8 in the December 2022 release of the annual relative importance of components in the CPI.[14]

[12]As downloaded in August 2023. This tree is available from the BLS as a downloadable spreadsheet from https://www.bls.gov/cpi/additional-resources/cpi-item-aggregation.htm

[13]We note that, for consistency with the current FRBC median and trimmed-mean CPI, we make an exception and split "New and used motor vehicles," even though this introduces the component "Unsampled new and used motor vehicles." We also note that, due to the split of "New and used motor vehicles," the relative importances for the components in collections C3, C4, and C5 will add up to slightly less than 100.

[14]There are 8 such components: four that would result from splitting component "Beef and veal" and four that

This gives us six different collections of components, which we label C0, C1, C2, C3, C4, and C5, where ascending numbers indicate finer levels of disaggregation.[15] From the 8 components in C0, we get 25 in C1, 56 in C2, 90 in C3, 102 in C4, and 134 in C5. Importantly, OER and Rent first appear in C2 and when we refer to Ci, $i = 2, 3, 4, 5$, we are referring to the collection of CPI components Ci where both OER and Rent are present and **not** split. Next, we collect the monthly relative importances as published by the BLS for each component, as well as the seasonally adjusted price index for each component where available, and the not seasonally adjusted price index otherwise.[16] We collect these data beginning in 2009M12, since going back further in time would begin to introduce structural breaks in the list of components in one or more collections.[17]

We proceed to define three splits of OER and Rent:

- **OER4**: OER4 breaks apart the national OER price indexes and weights into four regional OER price indexes and weights, one for each of the four Census regions Northeast, Midwest, South, and West, as is done with the current "revised methodology" FRBC median and trimmed-mean CPI. The component Rent is not split.

- **OER8**: OER8 further splits each regional OER index into two parts, one for city size class A (corresponding to population size greater than 2.5 million) and size class B/C (population size 2.5 million or less), where size classes are defined by the BLS. The component Rent is not split.

- **OER8-RENT8**: OER8-RENT8 retains the OER8 split of OER and additionally splits Rent along the same eight regions as OER8.[18]

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would result from splitting component "Pork." The 2022 annual relative importances are available from the BLS as a downloadable spreadsheet from https://www.bls.gov/cpi/tables/relative-importance/home.htm.

[15] Technically, this procedure actually yields seven different levels of disaggregation: C0,...,C6. However, C6 has just 15 more components than C5, all of which are relatively small components by weight within the Food at Home category. Therefore, we skip C5 and re-label C6 as C5.

[16] Data are collected using Haver Analytics except where otherwise noted. For a list of the components in each collection and the Haver codes for each relative importance and price index series, see Appendix 3.

[17] We manually verify this using: (1) the 2008, 2009, and 2022 annual relative importances as published by the BLS and available at https://www.bls.gov/cpi/tables/relative-importance/home.htm; and (2) the databases of both current and discontinued CPI series as available at https://www.bls.gov/cpi/data.htm.

[18] Prior to December 2017, there were actually three city size classes: Size A (cities with a population size over 2.5 million), Size B/C (cities with a population size between 50 thousand and 2.5 million), and Size D (cities with a population less than 50,000). However, the BLS only published price indexes and relative importances for Size D cities in the Midwest and South regions, and not for the Northeast and West regions. Therefore, between December 2009 and November 2017, we use **nine** regional indexes for both the OER8 and RENT8 splits: the eight mentioned

As Table 1 shows, on the basis of component weights, OER8 is more disaggregated than OER4, and OER8-RENT8 is more disaggregated than OER8. For both OER and Rent, we calculate the relative importance and seasonally adjust the index for each region as outlined previously in the Methodology section.[19]

Table 1: Summary Statistics of Housing Split Component Weights

	OER4	OER8	OER8-RENT8
Count	5.00	9.00	16.00
Mean	6.59	3.66	2.06
Std	1.88	1.84	1.45
Min	4.65	1.90	0.41
1st Quantile	4.66	1.90	0.42
5th Quantile	4.69	1.91	0.43
10th Quantile	4.73	1.92	0.53
25th Quantile	4.84	2.76	1.06
50th Quantile	6.81	3.07	1.72
75th Quantile	7.53	3.74	2.95
90th Quantile	8.48	6.09	3.56
95th Quantile	8.80	6.81	4.24
99th Quantile	9.06	7.38	5.44
Max	9.12	7.53	5.74

Notes: Component weights as published December 2022 by the BLS.

OER and Rent first appear in C2. Since our focus is on the effect of varying the degree of disaggregation in both shelter and non-shelter components, in the remainder of the paper, we drop collections C0 and C1 from further consideration. Additionally, as a baseline, we also add collection "FRBC" consisting of the components currently used to derive the official FRBC median and trimmed-mean CPI indicators. As seen in Table 2, the FRBC collection is overall the least disaggregated of the non-shelter component collections.

previously, as well as the index and weights for all Size D cities. Data for Size D cities were downloaded directly from the BLS Consumer Price Index (CPI) Databases website using the BLS Data Finder tool.

[19] All Haver codes for the input price indexes and relative importances of OER8 and RENT8 are listed in Appendix 4.

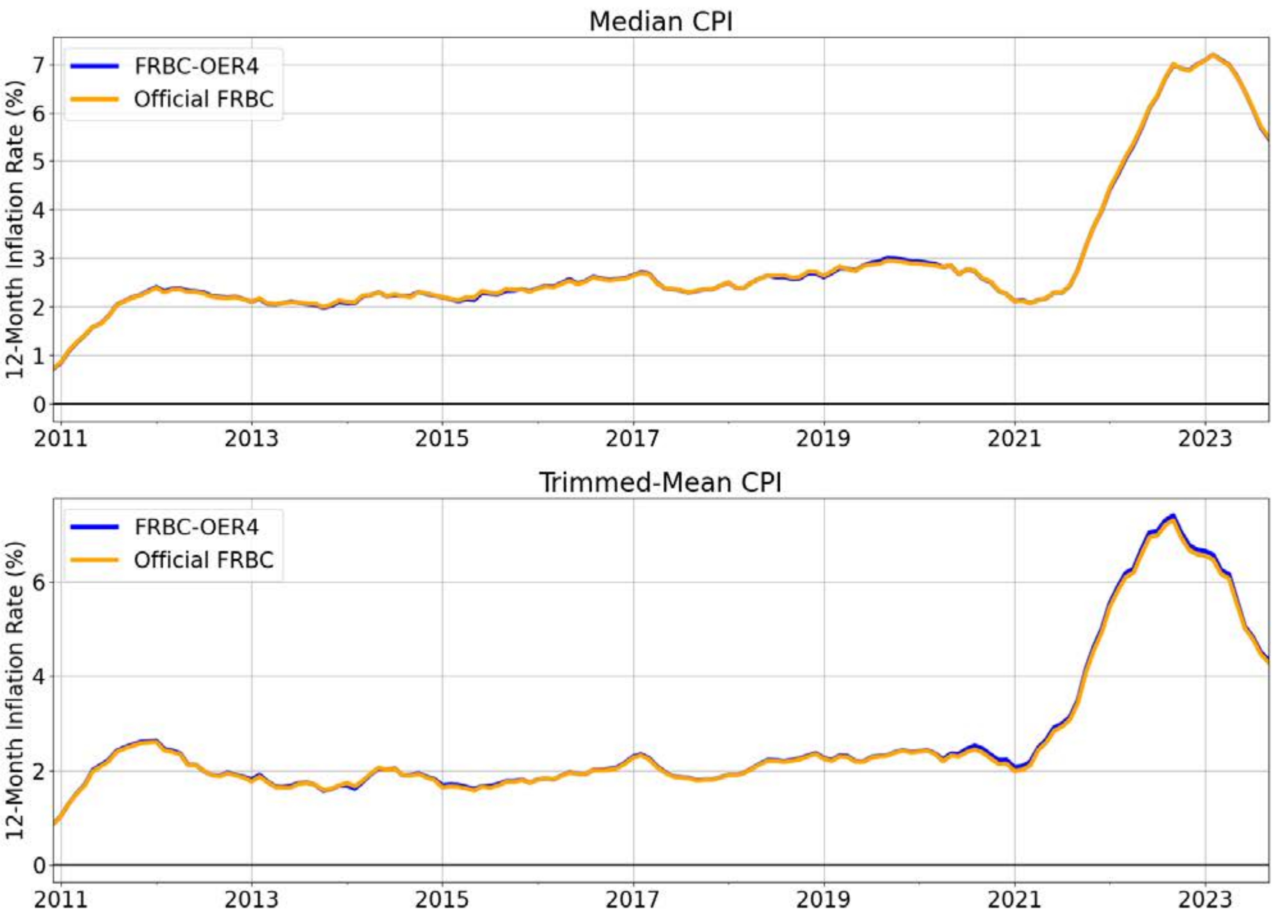
Table 2: Summary Statistics of Component Weights in Each Collection

	FRBC	C2	C3	C4	C5
Count	40.00	54.00	88.00	100.00	132.00
Mean	1.67	1.24	0.76	0.67	0.51
Std	1.68	1.78	0.87	0.79	0.71
Min	0.10	0.04	0.01	0.01	0.01
1st Quantile	0.11	0.05	0.02	0.02	0.01
5th Quantile	0.15	0.09	0.06	0.06	0.05
10th Quantile	0.22	0.11	0.09	0.09	0.07
25th Quantile	0.50	0.22	0.16	0.16	0.11
50th Quantile	1.02	0.60	0.42	0.33	0.22
75th Quantile	2.39	1.17	0.97	0.85	0.55
90th Quantile	4.36	3.43	2.01	1.81	1.26
95th Quantile	5.27	4.05	2.45	2.32	2.20
99th Quantile	6.16	8.39	3.55	3.18	3.02
Max	6.65	8.73	4.31	4.31	4.31

Notes: Component weights as published December 2022 by the BLS. Components summarized in this table do not include the shelter split components.

The complete splits of the CPI are then the cross-product of non-shelter component splits (FRBC, C2, C3, C4, C5) with shelter splits (OER4, OER8, OER8-RENT8). This gives us 15 component collections in total. FRBC-OER4, the least disaggregated CPI split, is our baseline and, although there are minor methodological differences, produces median and trimmed-mean measures essentially identical to the current official FRBC measures (see Figure 1). C5-OER8-RENT8, the most disaggregated split, has 148 components.

Figure 1: Comparing the FRBC-OER4 Median and Trimmed-Mean CPI to the Official Federal Reserve Bank of Cleveland Measures



5 Results

From each of our 15 previously defined splits of the CPI, it is straightforward using the methodology outlined in Section 2.2.2 to derive measures of 12-month median and trimmed-mean CPI inflation. Hereafter, when we refer to inflation, we are speaking of the 12-month rate of change, measured as a percent. In addition, we will refer to median or trimmed-mean CPI inflation as derived from a particular split of the CPI simply by the name of the split; for example, taking split FRBC-OER8-

RENT8 for concreteness, we refer to median CPI inflation as derived from split FRBC-OER8-RENT8 as "median FRBC-OER8-RENT8 inflation." Our sample starts in 2010M12 and ends in 2023M09.

To evaluate these measures, we primarily focus on two criteria that are standard in the core/MTT inflation evaluation literature. First, we evaluate how accurately each measure of median and trimmed-mean inflation tracks medium-term movements in CPI inflation. We do so along two dimensions: first, we assess how closely the mean of each candidate measure matches that of CPI inflation over our sample; and second, we examine how accurately each candidate measure tracks changes in a standard ex-post proxy of the "true" underlying MTT in CPI inflation. We find that the highest level of shelter disaggregation OER8-RENT8, when combined with slightly more non-shelter disaggregation as found in C2, leads to substantial improvement in accuracy, in an MSE sense, versus the ex-post MTT trend estimate. Trimmed-mean CPI is insensitive to increasing shelter disaggregation, but also benefits from increasing the level of non-shelter disaggregation from FRBC to C2.

Second, we assess the extent to which each candidate measure has predictive power over future movements in CPI inflation. We find that the level of shelter disaggregation has essentially no effect on the ability of either the median or trimmed-mean CPI to explain future CPI inflation at the 12-month horizon. In contrast, we find a marginal benefit to the predictive ability at the 24- and 36-month horizons from further non-shelter disaggregation; however, beyond moving to the C2, there is little benefit to additional non-shelter disaggregation.

Our key finding is that while greater shelter disaggregation helps median inflation more accurately estimate the MTT in inflation (and marginally helps its predictive ability), greater non-shelter disaggregation generally does not.

5.1 Accuracy in estimating the MTT in CPI inflation

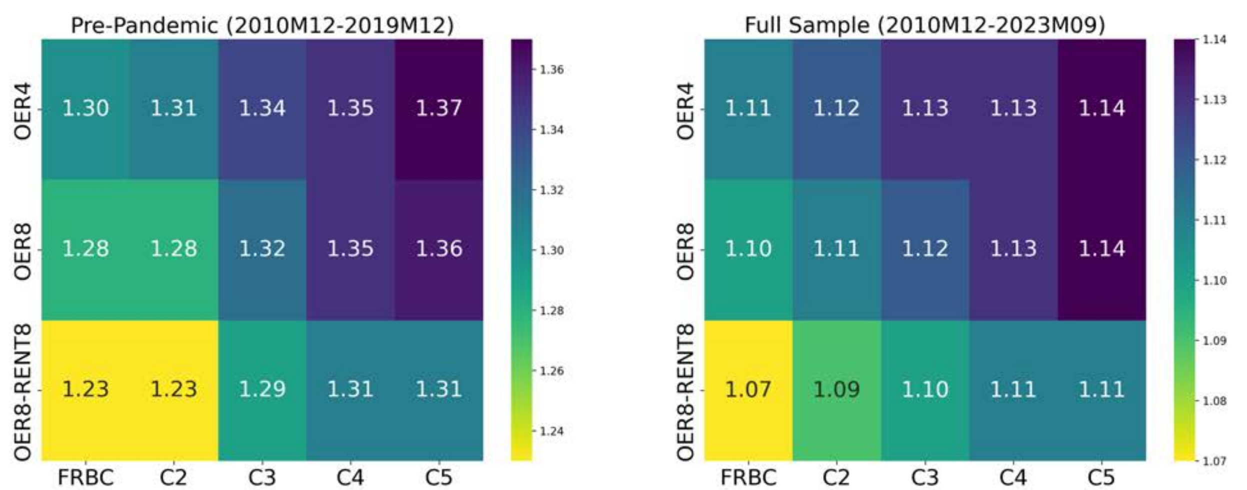
5.1.1 Accuracy in mean

An MTT estimator should, over a long period of time, have an average as close as possible to the average rate of headline CPI inflation (Clark 2001; Rich and Steindel 2007; Higgins and Verbrugge 2015; Stock and Watson 2016). Therefore, we first examine how close the mean of each median and trimmed-mean CPI inflation measure was to the mean of CPI inflation over the pre-pandemic

(2010M12-2019M12) and full (2010M12-2023M09) samples.

Beginning with the median CPI, we find that while the mean of each median CPI measure overstates the mean of CPI inflation over the pre-pandemic period, FRBC-OER8-RENT8 and C2-OER8-RENT8 overstate it the least, at 23 percent higher (Figure 2). This is a 7 percent reduction relative to the benchmark FRBC-OER4 median inflation, the mean of which overstated that of headline CPI inflation by 30 percent. Expanding to the full sample, the qualitative results are similar: average median FRBC-OER8-RENT8 inflation still overstates average CPI inflation the least, at 7 percent, with C2-OER8-RENT8 close behind at 9 percent higher. Overall, results in Figure 2 show that (1) as we move across a given row (i.e., as we increase the degree of non-shelter disaggregation), the mean of the median inflation series moves further away the mean of headline CPI; and (2) as we move down any column (i.e. as we increase the degree of shelter disaggregation) the mean of the median inflation series moves closer to the mean of headline CPI.

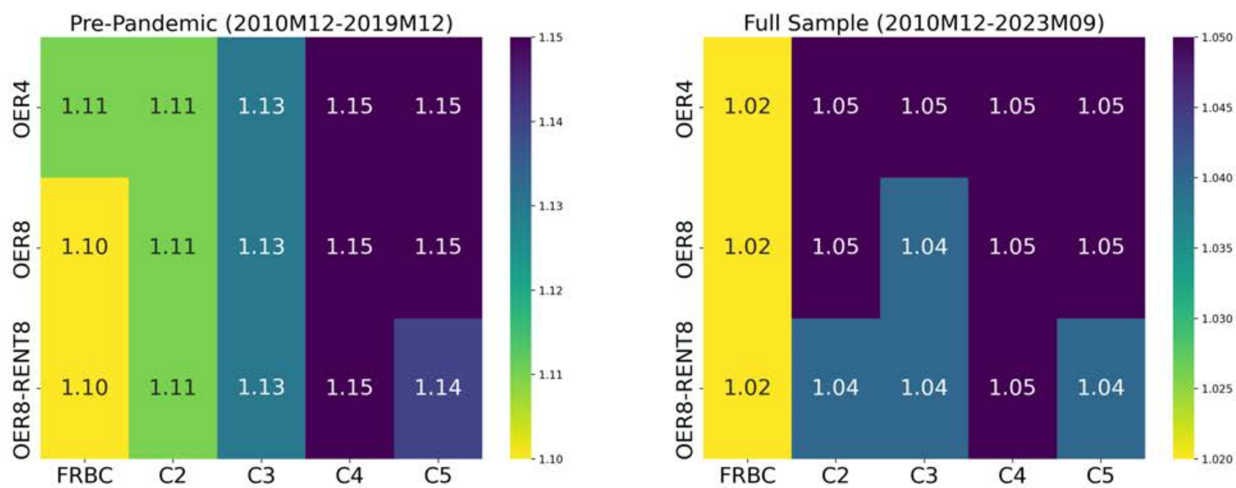
Figure 2: Mean of Median Inflation Measures Relative to Mean of Headline CPI Inflation



Notes: Reported figures are the ratio of the average of the median inflation rate and the average of headline CPI inflation. Both averages are computed as the mean of 12-month inflation rates, measured by percent changes, over the indicated period.

We now repeat the prior analysis for trimmed-mean inflation measures derived from each split (Figure 3). Once again, pre-pandemic, mean trimmed-mean inflation from the FRBC and C2 splits overstate mean CPI inflation by the least, at just 10 percent and 11 percent, respectively. Expanding to the full sample, the qualitative results are similar: average trimmed-mean FRBC-OER8-RENT8 inflation still overstates average CPI inflation the least, at 2 percent. C2-OER8-RENT8 is close behind, at 4 percent higher. Unlike with median inflation, shelter disaggregation makes essentially no difference in the tracking ability of trimmed-mean measures. Additionally, while differences between trimmed-mean measures lie primarily between non-shelter splits, the difference between these is fairly small, particularly in the full sample, in which all trimmed-mean measures overstated CPI inflation by between just 2 percent-4 percent.

Figure 3: Mean of Trimmed-Mean Inflation Measures Relative to Mean of Headline CPI Inflation



Notes: Reported figures are the ratio of the average trimmed-mean inflation rate and the average headline CPI inflation. Both averages are computed as the mean of 12M inflation rates, measured by percent changes, over the indicated period.

5.1.2 Accuracy versus a standard ex-post MTT estimate

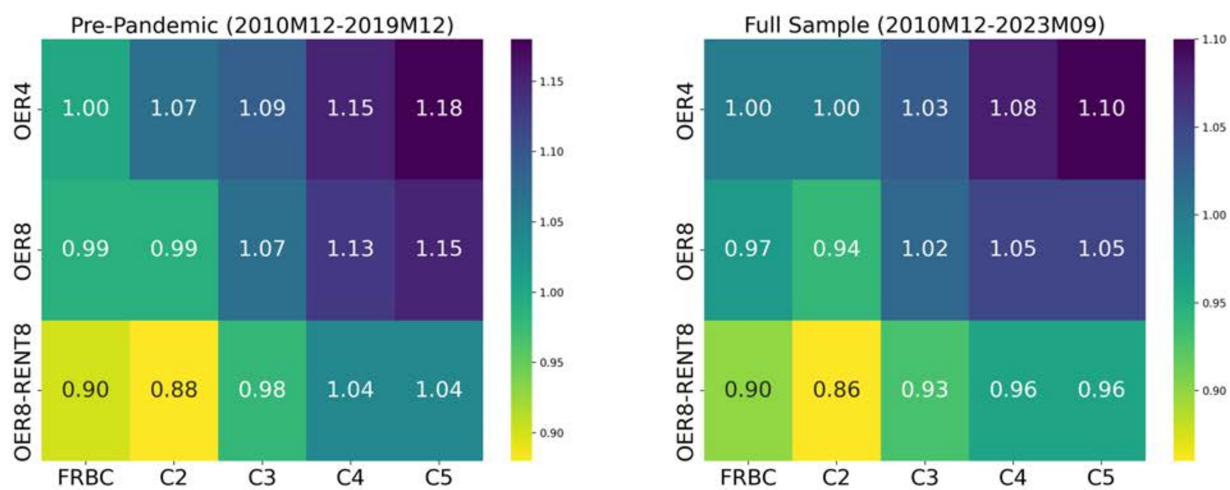
An MTT estimator should closely track ex-post estimates of that MTT, thereby helping to distinguish persistent movements in underlying trend inflation from transitory price shocks (Clark 2001; Rich and Steindel 2007; Higgins and Verbrugge 2015). Following Bryan, Cecchetti, and Wiggins (1997), we use a 36-month centered moving average of 12-month CPI inflation as our ex-post estimate, or proxy, of the MTT. That is, in a given month, the proxy is equal to the average of inflation in the current month, the preceding 18 months, and the subsequent 18 months. We examine the RMSE of deviations between each median or trimmed-mean inflation measure and the MTT proxy. Hence, for each of our candidates j, $j = 1, ..., 15$, we compute:

$$(1) \qquad RMSE(\hat{\pi}^{MTT} - \hat{\pi}_j) = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\pi}_t^{MTT} - \hat{\pi}_{j,t})^2}$$

where $\hat{\pi}^{MTT}$ denotes the MTT proxy, $\hat{\pi}_j$ is a candidate median or trimmed-mean CPI inflation measure, and $(\hat{\pi}_t^{MTT} - \hat{\pi}_{j,t})$ measures the deviation between the two at month t.

Beginning again with the median CPI, in Figure 4, we report the RMSE of each measure of median inflation relative to the RMSE of median FRBC-OER4 inflation. By this metric, C2-OER8-RENT8 outperforms all other median candidates, in many cases by a wide margin. The RMSE of C2-OER8-RENT8 is 12 percent lower than that of median FRBC-OER4 inflation pre-pandemic, and 14 percent lower in the full sample. As before, the results in Figure 4 show that greater shelter disaggregation improves the ability of the derived median inflation measure to track the trend inflation proxy, while greater non-shelter disaggregation worsens it.

Figure 4: $RMSE(\hat{\pi}^{MTT} - \hat{\pi}_j)$ of Median Inflation Measures, Relative to FRBC-OER4

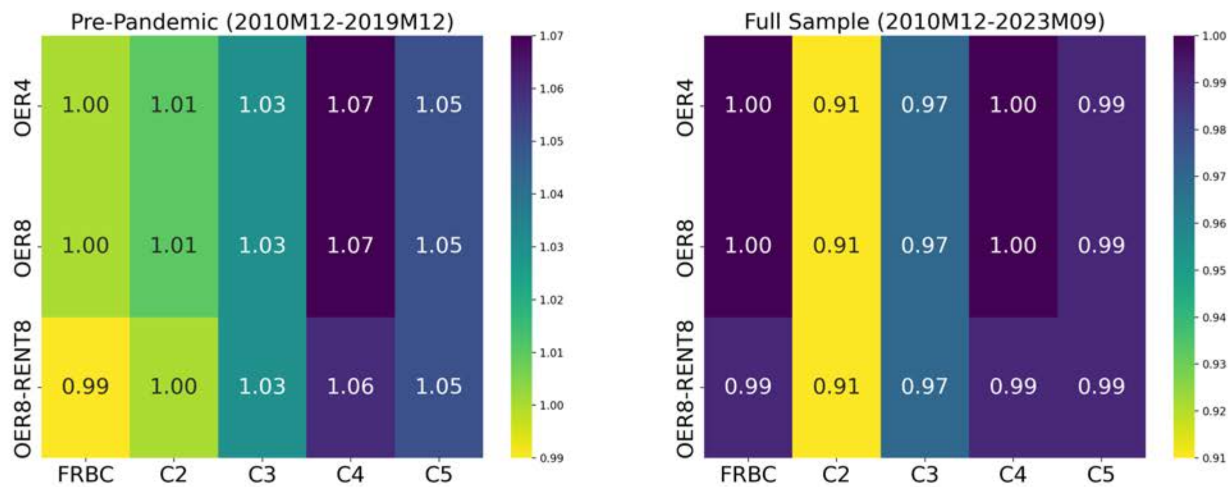


Notes: Reported figures are the RMSE of deviations of the median inflation measure from a 36-month centered moving average of CPI inflation, divided by the same for median FRBC-OER4 inflation. In the pre-pandemic sample, the moving average is computed using CPI inflation through December 2019 only.

In Figure 5, we present $RMSE(\hat{\pi}^{MTT} - \hat{\pi}_j)$ for each trimmed-mean candidate measure, relative to the RMSE for trimmed-mean FRBC-OER4 inflation. Once again, we find that trimmed-mean measures are fairly insensitive to the level of shelter disaggregation. Pre-pandemic, the FRBC and

C2 non-shelter splits do about equally well, while more disaggregated non-shelter splits increase deviations from the trend inflation proxy. Notably, in the full sample, trimmed-mean C2 inflation achieves a 9 percent lower RMSE than the baseline trimmed-mean FRBC-OER4 inflation, a significant reduction relative to all the other non-housing splits.

Figure 5: $RMSE(\hat{\pi}^{MTT} - \hat{\pi}_j)$ of Trimmed-Mean Inflation Measures, Relative to FRBC-OER4



Notes: Reported figures are the RMSE of deviations of the trimmed-mean inflation measure from a 36-month centered moving average of CPI inflation, divided by the same for median FRBC-OER4 inflation. In the pre-pandemic sample, the moving average is computed using CPI inflation through December 2019 only.

We now briefly compare the MTT-tracking performance of our median inflation measures versus our trimmed-mean measures. In short, trimmed-mean measures are superior. First, as seen above in Figure 2 and Figure 3, trimmed-mean measures overall overstated the mean of headline CPI inflation less than median measures. Below, in Figure 6 and Figure 7 we present the level of the RMSEs for both median and trimmed-mean measures, respectively. We note that trimmed-mean measures, including C2-OER8-RENT8, outperform median measures by a fairly wide margin in terms of better tracking the trend inflation proxy.

Figure 6: $RMSE(\hat{\pi}^{MTT} - \hat{\pi}_j)$ of Median Measures

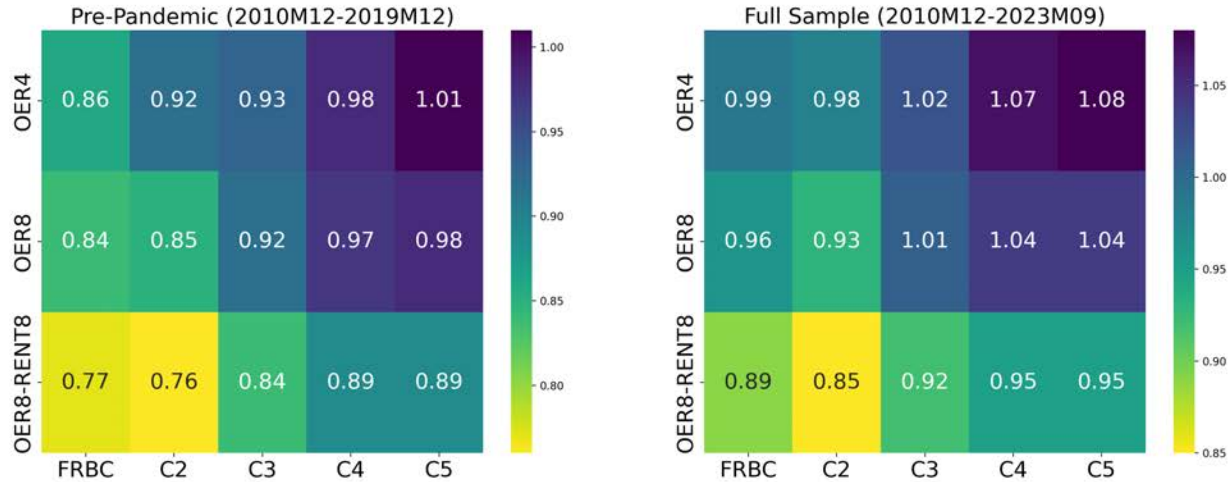
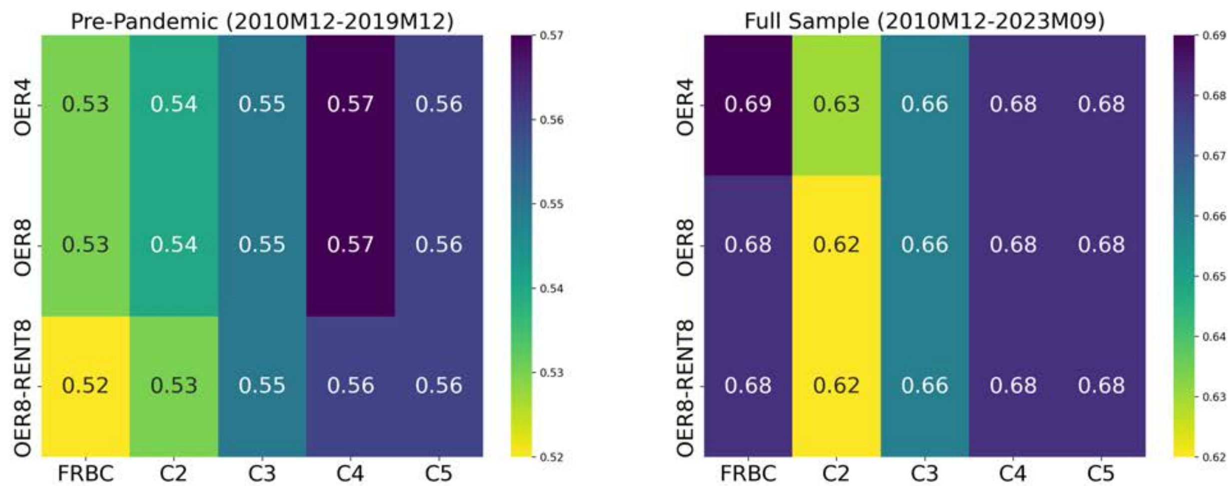


Figure 7: $RMSE(\hat{\pi}^{MTT} - \hat{\pi}_j)$ of Trimmed-Mean Measures



5.1.3 Digging into performance differences: The role of variability

Overall, C2-OER8-RENT8 outperforms the other splits in terms of deviations from the trend inflation proxy and is nearly even with FRBC-OER8-RENT8 on the comparability of means metrics. What could help account for this result? One possibility is the variability of each candidate measure. In the simplest model of an MTT estimator π_j, the estimated rate of MTT inflation today is equal to the true MTT in inflation π_t^{MTT} plus an idiosyncratic error term ϵ_t:

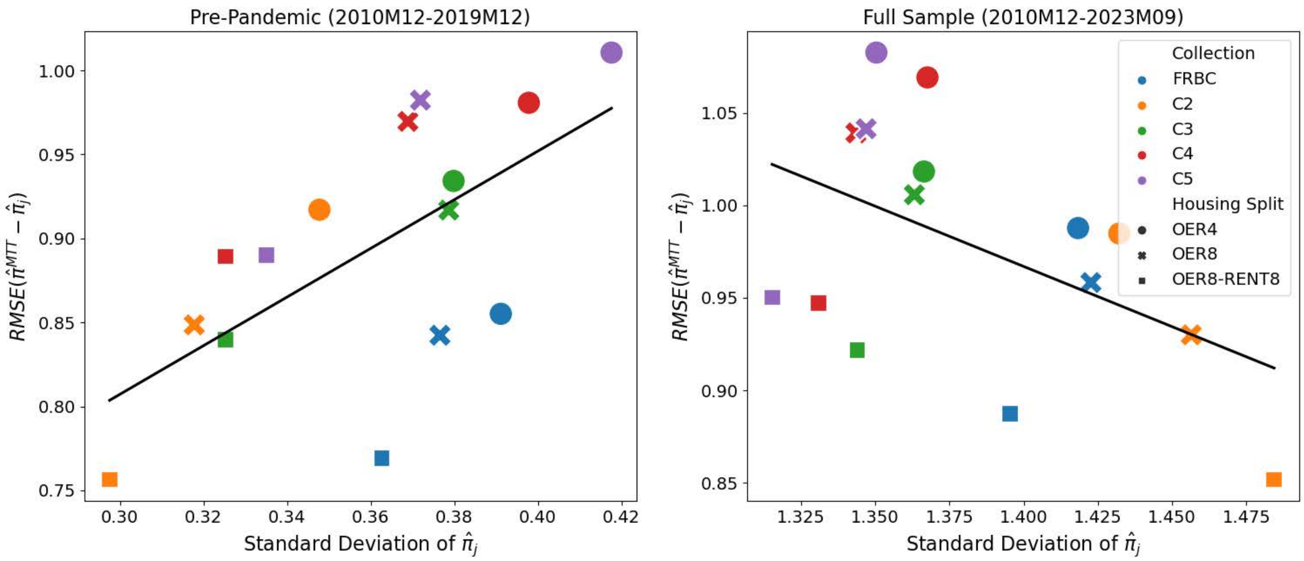
$$\hat{\pi}_{j,t} = \pi_t^{MTT} + \epsilon_t \tag{2}$$

Since trend inflation is generally assumed to be persistent and to evolve slowly, we would expect better estimates of the MTT to be associated with lower levels of variability (e.g., Brischetto and Richards, 2007).[20] To assess the role that variability plays in our results, for each median inflation measure, we plot the $RMSE(\hat{\pi}^{MTT} - \hat{\pi}_j)$ as calculated in the prior section against the variability of the measure as measured by its standard deviation.

As shown in Figure 8, the correlation between lower variability and better MTT inflation tracking depends on the sample. While in the pre-pandemic sample, the standard deviation of median inflation is positively correlated with its $RMSE(\hat{\pi}^{MTT} - \hat{\pi}_j)$, in the full sample this flips to a negative correlation. Focusing on median C2-OER8-RENT8 inflation, we see that while it had the lowest tracking RMSE in both periods, it flipped from having the lowest variability of all measures in the pre-pandemic sample to having the highest in the full sample. One possible explanation, given how quickly the trend inflation rose in 2021, is that C2-OER8-RENT8's greater flexibility in following trend inflation's upward trajectory contributed to both C2-OER8-RENT8's higher variability and lower RMSE.

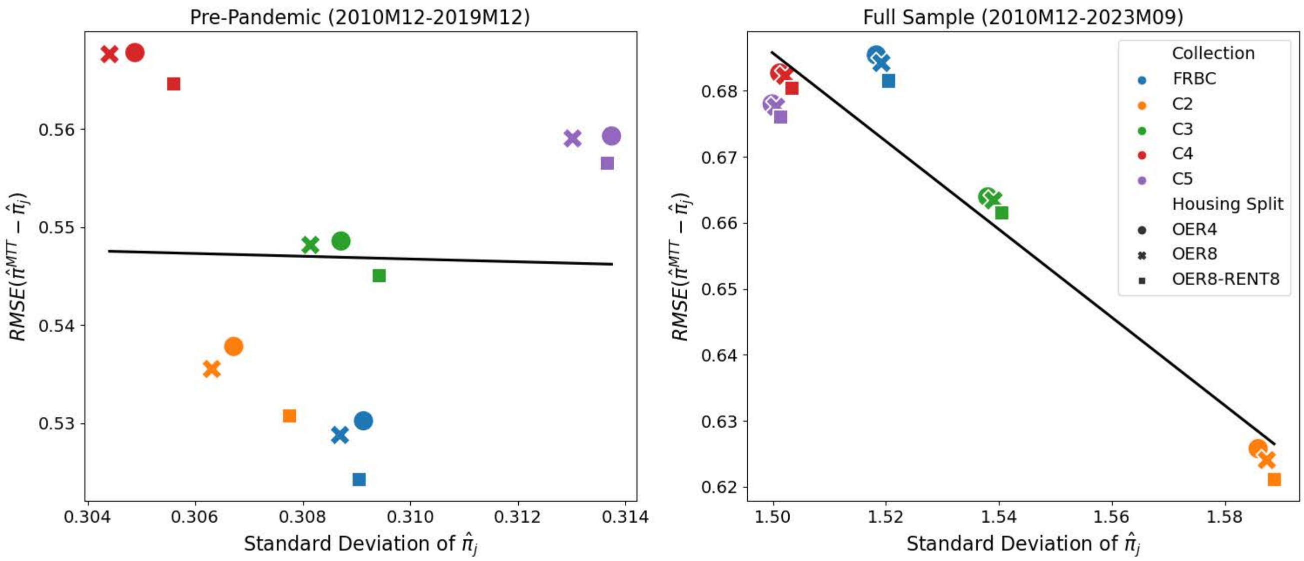
[20]Indeed, the core inflation literature often identifies lower variability itself as a desirable criterion for an MTT estimator.

Figure 8: Standard Deviation of Median Inflation Measures Relative to RMSE of Deviations from a 36-Month MA of CPI Inflation



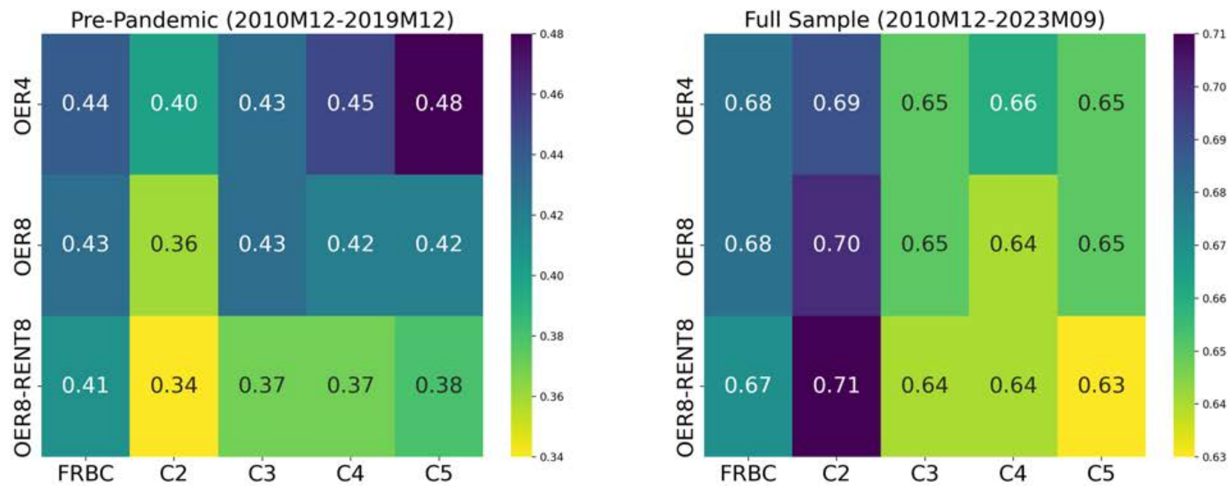
Unlike with median inflation, we find a weak pre-pandemic relationship between the standard deviation of trimmed-mean inflation and the RMSE of deviations around the MTT inflation proxy. More generally, there is little variation in the variability of different trimmed-mean inflation measures. On the other hand, we again find a negative relationship between the RMSE and the standard deviation in the full sample, with C2-OER8-RENT8 once again achieving both the lowest RMSE and the highest standard deviation (Figure 9).

Figure 9: Standard Deviation of Trimmed-Mean Inflation Measures Relative to RMSE of Deviations from a 36-Month MA of CPI Inflation



In Figure 10, we present the standard deviation of each median inflation measure relative to the standard deviation of CPI inflation over the specified period. Increasing shelter disaggregation is nearly always associated with decreasing variability; however, this effect is much larger in the pre-pandemic sample, and is increasing in higher levels of non-shelter disaggregation, suggesting an interaction between the two dimensions of disaggregation. These results echo those of Brischetto and Richards (2007), who found that splitting OER into four regional subcomponents lowered the variability of monthly trimmed-mean inflation rates across a wide range of trim sizes.

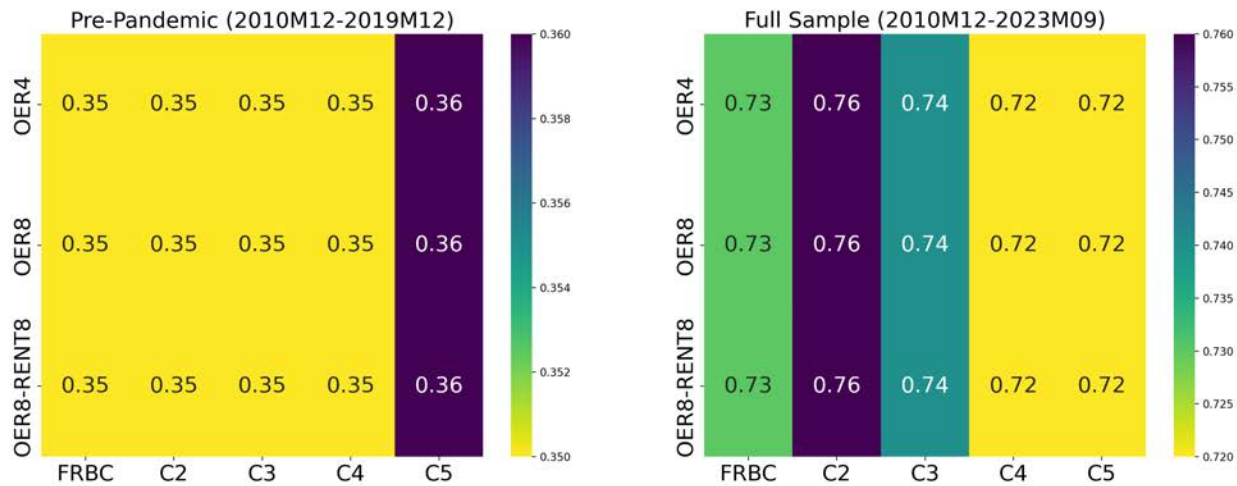
Figure 10: Standard Deviation of Median Inflation Measures Relative to the Standard Deviation of CPI Inflation



Notes: Reported figures are the standard deviation of the median inflation rate over the indicated period, divided by the same for headline CPI inflation.

Finally, in Figure 11, we present the standard deviation of each trimmed-mean inflation measure relative to the standard deviation of CPI inflation over the specified period. Recalling that trimmed-mean C2-OER8-RENT8 outperforms median C2-OER8-RENT8 inflation in tracking the MTT in the CPI, it is interesting to note that pre-pandemic, median and trimmed-mean C2-OER8-RENT8 inflation had essentially the same variability, while in the full sample, the standard deviation of the trimmed-mean measure was 5 percent higher than that of the median measure. This further reinforces our earlier result showing that there is not a one-to-one correspondence between the lower variability of an MTT estimator and better tracking of the medium-run trend.

Figure 11: Standard Deviation of Trimmed-Mean Inflation Measures Relative to the Standard Deviation of CPI Inflation



Notes: Reported figures are the standard deviation of the median inflation rate over the indicated period, divided by the same for headline CPI inflation.

5.2 In-sample explanatory power

It is desirable for an MTT estimator to have explanatory power over future inflation. To assess the in-sample explanatory power of each of our measures of median and trimmed-mean inflation, we follow previous research (e.g., Clark 2001; Rich and Steindel 2007) and estimate regressions of the form:

$$\pi_{t+h} - \pi_t = \alpha_{j,h} + \beta_{j,h}(\pi_t - \hat{\pi}_{j,t}) + \epsilon_{j,t+h} \tag{3}$$

where:

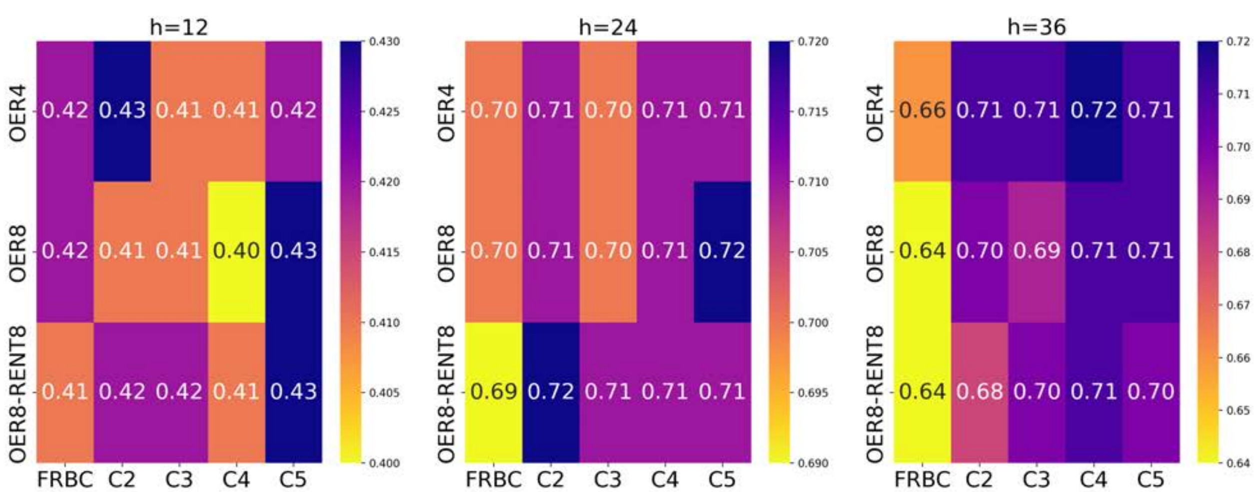
- $\pi_{t+h} = 100 \cdot (P_{t+h}/P_{t+h-12} - 1)$ is the year-over-year rate of CPI inflation h months ahead;
- $\pi_t = 100 \cdot (P_t/P_{t-12} - 1)$ is the current month t year-over-year rate of CPI inflation; and
- $\hat{\pi}_{j,t}$ is the current month t year-over-year median or trimmed-mean CPI inflation rate, for candidate j.

Notice that the intercept, $\alpha_{j,h}$, allows for (fixed) bias adjustment for each candidate j - so that if a particular MTT estimator has a large bias versus headline inflation, the intercept will correct for that bias. Thus, candidates with higher bias are not automatically penalized.

We present the adjusted R^2 from these regressions for each measure of median and trimmed-mean inflation. We do so for the 12-, 24-, and 36-month horizons h. If we were to estimate these regressions through the full sample, each would be contaminated by several observations in which post-pandemic inflation realizations would be regressed on pre-pandemic or pandemic inflation. As these observations are unlikely to be informative about the quality or lack thereof of our MTT estimators, we present results for the pre-pandemic sample only.

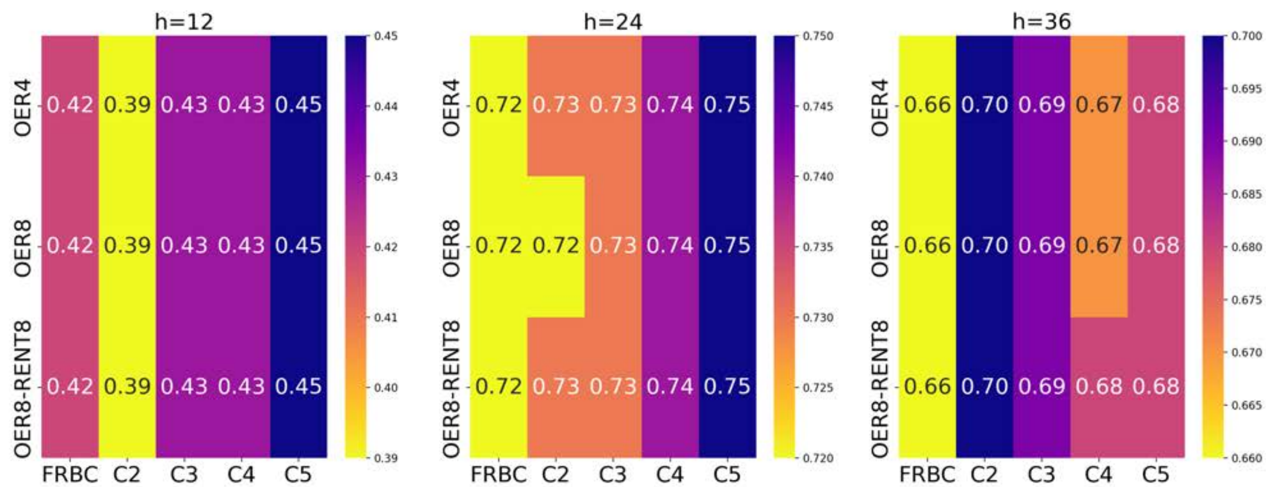
In Figure 12 we report the adjusted R^2 from fitting Equation 3 on data in the pre-pandemic sample, using median inflation as the measure of the MTT. Overall, differences in predictive accuracy between candidates are small. At all horizons, by the adjusted R^2 metric, the C2-OER8-RENT8 candidate is as accurate as, or more accurate than, the FRBC-OER4 benchmark. At the 12-month and 24-month horizons, the C2-OER8-RENT8 candidate is either nearly the most, or the most, accurate candidate. At the 36-month horizon, the C2-OER8-RENT8 candidate is marginally less accurate than the other non-FRBC candidates.

Figure 12: In-Sample Adjusted R^2 of Equation 3, Pre-Pandemic Sample, Median Measures



In Figure 13 we report the adjusted R^2 from fitting Equation 3 on data in the pre-pandemic sample using trimmed-mean inflation as the MTT. We first note that shelter disaggregation makes no difference to the results, such that we can refer to competing splits by referring to their non-shelter split alone. We find that C2 measures are marginally more accurate at the 24- and 36-month horizons than the baseline FRBC-OER4. At the 12-month horizon, C2 measures are marginally inferior to the other candidates.

Figure 13: In-Sample Adjusted R^2 of Equation 3, Pre-Pandemic Sample, Trimmed-Mean Measures



5.3 Summary

Our analysis focused on two criteria: how accurately each measure tracks a standard ex-post estimate of the MTT in inflation and how accurately each measure predicts future changes in inflation. Our findings suggest that for median measures, splitting shelter to the OER8-RENT8 level and splitting non-shelter components from the FRBC level to the C2 level improves the comparability of means and tracking the proxy of the MTT in CPI inflation. Regarding predictive ability, this candidate always matches or dominates the FRBC-OER4 baseline. For trimmed-mean measures, splitting non-shelter components from the FRBC level to the C2 level results in a meaningful improvement in performance across metrics. We conclude that the C2-OER8-RENT8 split provides the highest net benefit across median and trimmed-mean measures.

6 Practical Implications

In this section, we explore some of the practical implications of finer disaggregations of CPI components on median and trimmed-mean CPI inflation.

First, given our focus on tracking the medium-run trend in CPI inflation, we compare the historical time-paths of the baseline FRBC-OER4 median and trimmed-mean to those from our preferred measure, C2-OER8-RENT8, over our sample period. By doing so, we aim to determine how inferences about the medium-run trend in inflation would change when using one measure versus the other.

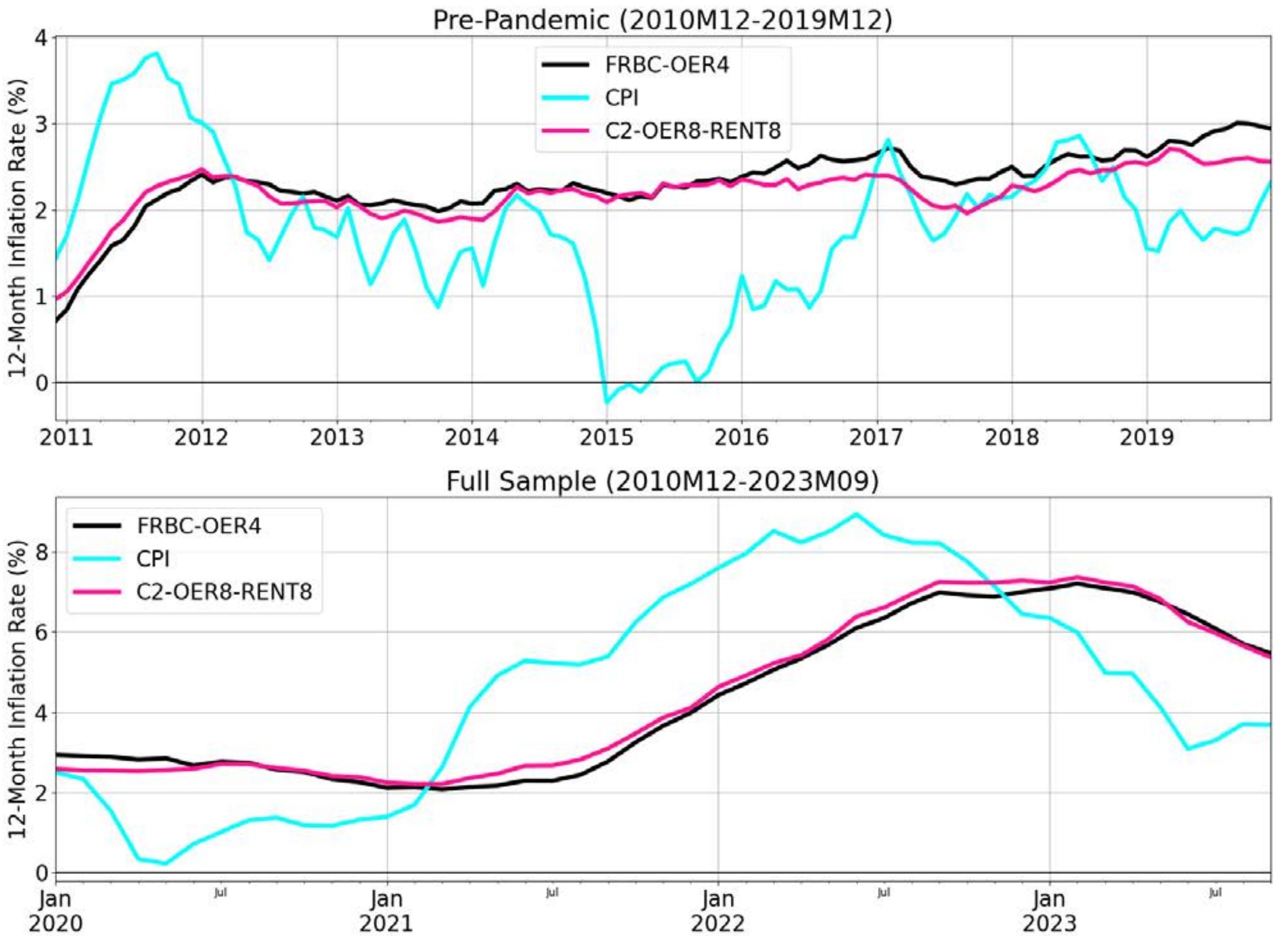
Second, we investigate how varying the level of disaggregation affects the frequency with which the OER, Rent, and non-Shelter (i.e., non-OER, non-Rent) components are chosen as the median component in the median CPI inflation measure.

Lastly, we examine empirically how increasing disaggregation can alter the relationship between median and trimmed-mean CPI and other key economic variables. To do this, we estimate a parsimonious empirical Phillips curve between either the median or trimmed-mean and the unemployment gap. This analysis allows us to observe how changing disaggregation affects the strength of that relationship.

6.1 The historical trend in CPI inflation

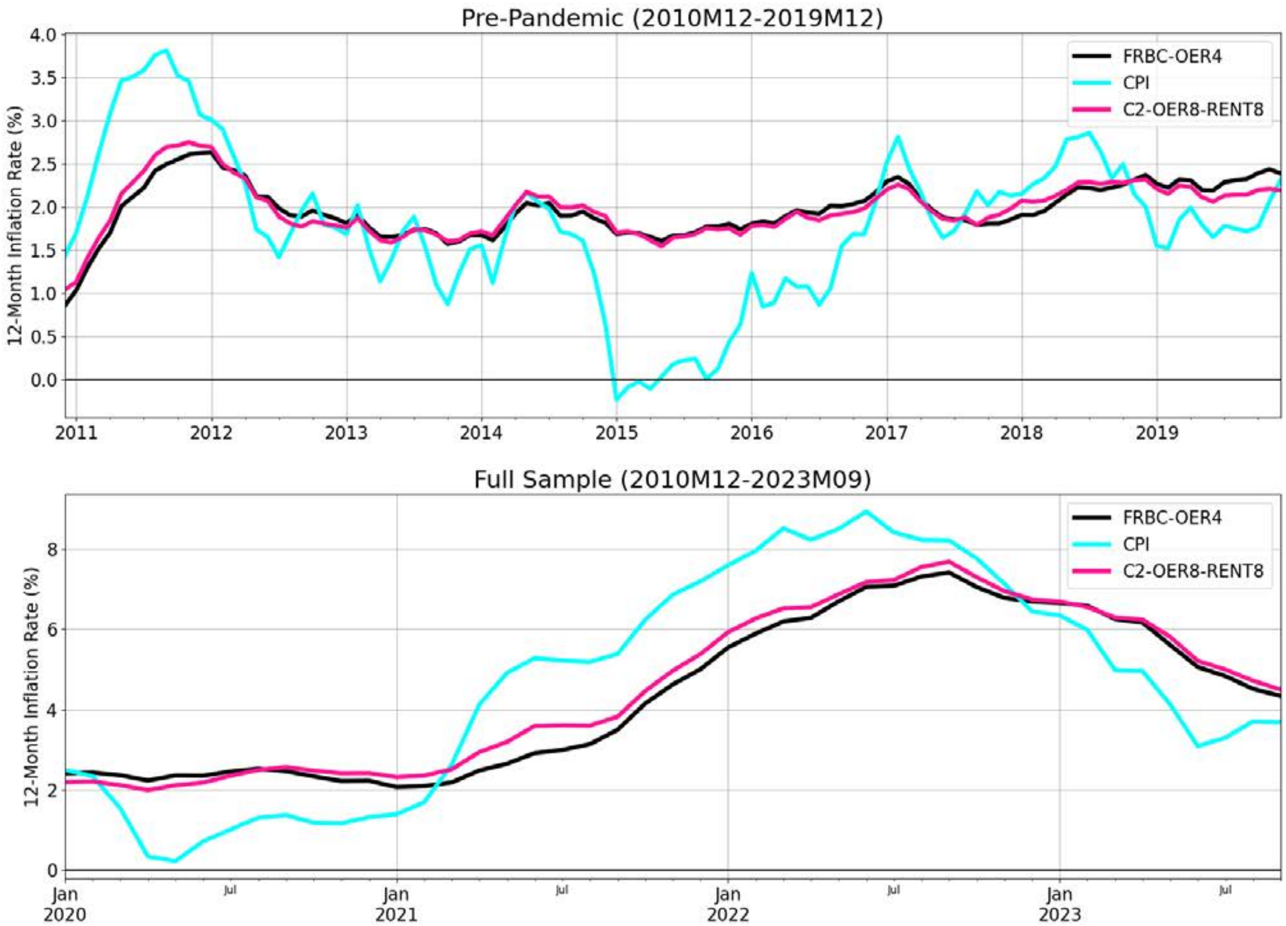
In Figure 14, we compare the evolution of C2-OER8-RENT8 inflation relative to CPI inflation and the FRBC-OER4 baseline for the median rates. During most of the pre-pandemic period, median C2-OER8-RENT8 inflation was consistently lower than median C2-OER4 inflation, particularly after mid-2015. Conversely, post-pandemic, the reverse is true.

Figure 14: Comparing the FRBC-OER4 and C2-OER8-RENT8 Measures of Median CPI Inflation



In Figure 15, we compare the evolution of C2-OER8-RENT8 inflation relative to CPI inflation and the FRBC-OER4 baseline for the trimmed-mean rates. Pre-pandemic, trimmed-mean C2-OER8-RENT8 and trimmed-mean FRBC-OER4 inflation tracked each other closely. However, post-pandemic, the former tended to exceed the latter, similar to the median rates.

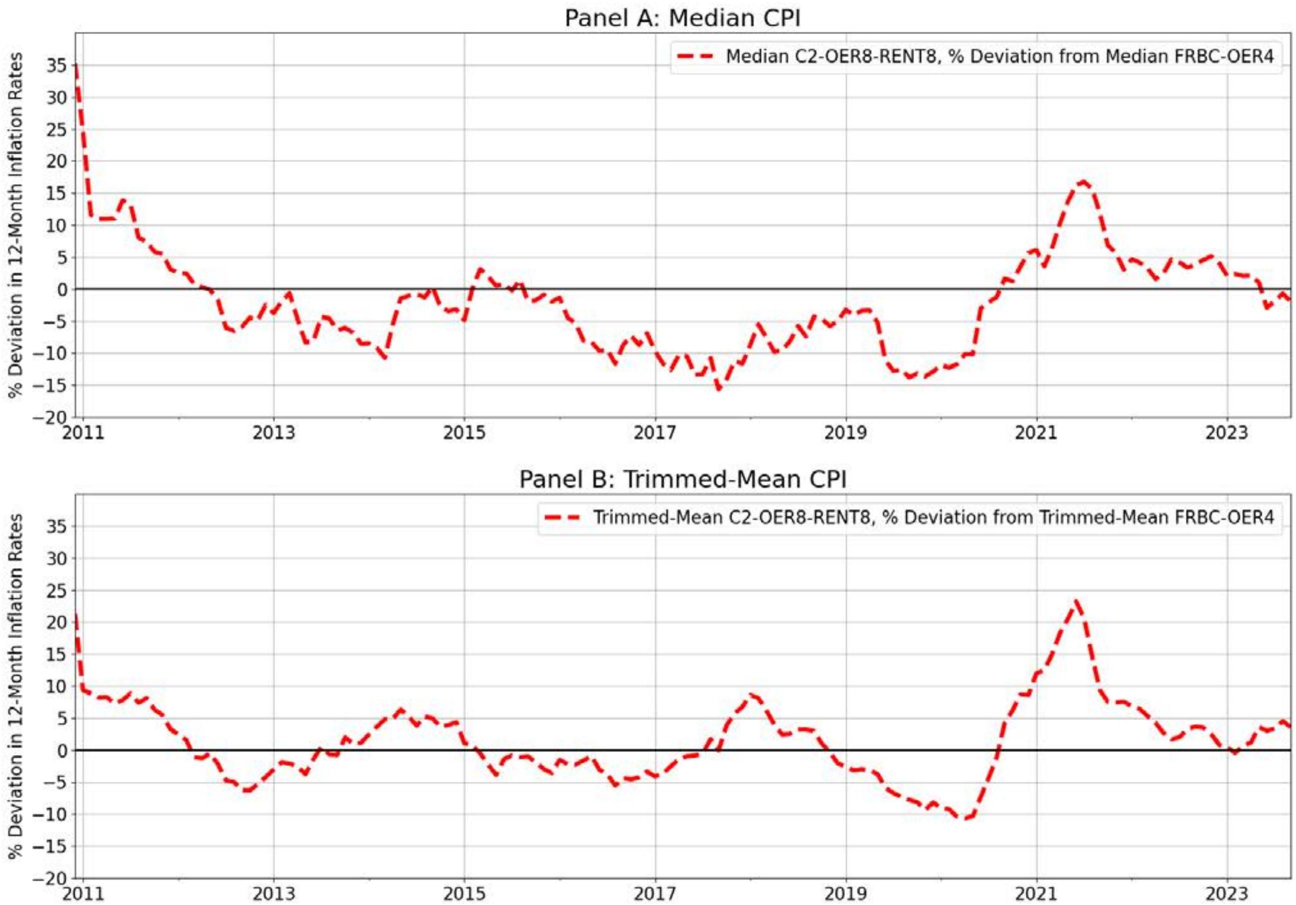
Figure 15: Comparing the FRBC-OER4 and C2-OER8-RENT8 Measures of Trimmed-Mean CPI Inflation



To quantify these qualitative differences, in Figure 16, we plot the percentage difference between C2-OER8-RENT8 and FRBC-OER4 for the median (Panel A) and trimmed-mean (Panel B) rates. Both median and trimmed-mean CPI inflation measures can systematically and persistently diverge across time, with differences of up to 35 percent for the median and nearly 25 percent for the trimmed-mean.

Two episodes stand out. At its July 2019 meeting, the FOMC began a rate-cut cycle, citing "muted inflation pressures" in its statement. Both the C2-OER8-RENT8 median and trimmed-mean were more consistent with this view than the FRBC-OER4 median and trimmed-mean, with the former nearly 15 percentlower than the latter in the case of the median and approaching 10 percent lower in the case of the trimmed-mean. More notably, both median and trimmed-mean C2-OER8-RENT8 provided an early warning in late 2020 about the surge in CPI inflation that was about to arrive in Q2 of 2021, relative to FRBC-OER4. By January 2021, median C2-OER8-RENT8 already exceeded median FRBC-OER4 by 6 percent, the largest gap since the aftermath of the Great Recession. Thereafter, this gap increased to a high of just under 17 percent in July 2021, just as CPI inflation was exceeding 5 percent, also for the first time since the Great Recession. The C2-OER8-RENT8 trimmed-mean inflation rate provided an even starker early warning: a gap of 12 percentwith its FRBC-OER4 counterpart in January 2021 soared to 23 percent in June 2021, the highest gap in our entire sample. Our analysis demonstrates that both median and trimmed-mean C2-OER8-RENT8 inflation measures offer valuable insights into trend inflation dynamics that diverge from those provided by existing baseline measures.

Figure 16: Comparing the FRBC-OER4 and C2-OER8-RENT8 Measures of Median and Trimmed-Mean CPI Inflation



6.2 Variation in the median component of median CPI

In any given month, a particular component is chosen as the median. In the past, there has been considerable interest in the frequency with which shelter components are chosen as the median. Indeed, already at median CPI's inception, Bryan and Cecchetti (1994) noted the disproportionate frequency with which shelter was chosen as the median component. Brischetto and Richards (2007) found that splitting OER into four subcomponents both decreased the frequency with which OER was selected as the median component (from 58 percent of the time to 37 percent) and improved the performance of trimmed-mean CPI inflation across a range of trims.[21] Given the direct link between splitting OER and the improvement in the quality of derived limited-influence estimators of the MTT in inflation, a reasonable inference would be that further splitting OER would reduce the frequency with which OER is chosen as the median component, and yield further performance gains in these estimators. In this context, we note a common misconception related to the properties of the median CPI, and how they depend upon the component chosen as the median component. For instance, some have argued that since an OER index is often chosen as the median component, this makes the median behave like OER. However, this argument might be flipping the actual direction of causality on its head. Suppose, for instance, that OER is highly cyclical, but the remaining components that are typically near the median of the distribution are not. In that case, whenever cyclical forces are strong, they would pull OER away from the median of the distribution, such that OER would not be chosen as the median. The fact that an OER series is often chosen as the median simply means that this OER component generally reflects what is happening to components near the center of the distribution.[22]

Nonetheless, given the degree of interest in the distribution of the median component, we provide in Figure 17 and Figure 18 the frequency with which the following types of components are chosen as the median component: OER, Rent, and non-Shelter (i.e., non-OER, non-Rent) components. Figure 17 covers the pre-pandemic period, while Figure 18 covers the full sample.

[21]Stock and Watson (2020) also draw attention to the frequency with which shelter components are chosen; see Section 6.3

[22]This insight comes from Larry Ball (private communication). His example involves annual measurements of the height of each student in a given class, from first grade through twelfth grade. It would not be surprising to discover that a particular student would frequently be the sample median.

Figure 17: Percentage Frequency of Selection as the Median Component, 2010M12-2019M12

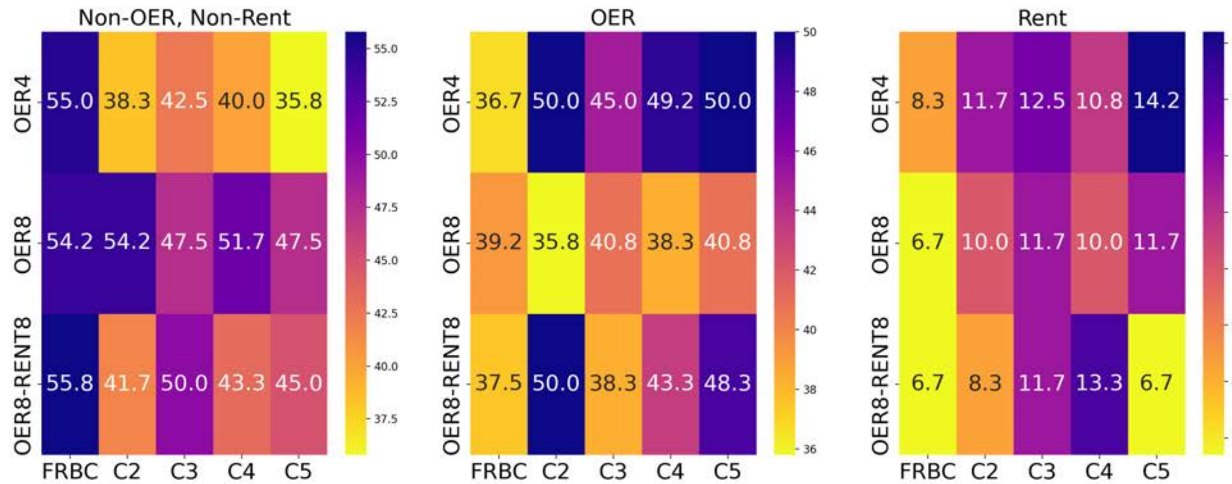
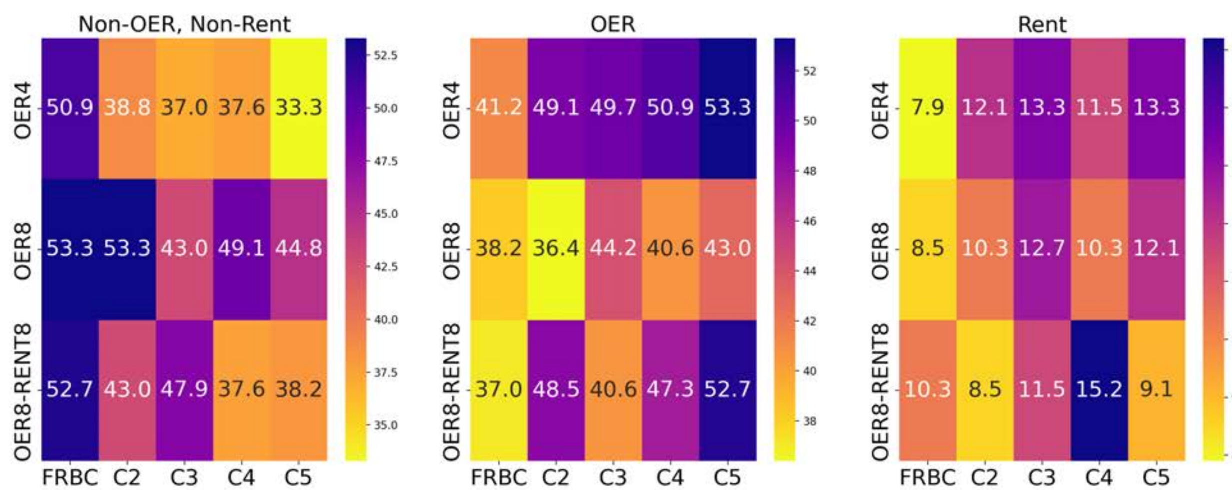


Figure 18: Percentage Frequency of Selection as the Median Component, 2010M12-2023M09



Once again, we obtain somewhat counterintuitive results. Focusing on the full sample, we see that further splitting OER from four subcomponents to 8 does, as one would expect, reduce the frequency with which OER was chosen as the median component. It also nearly always reduces the frequency with which Rent is chosen as the median component, with the exception of the FRBC split. Conversely, the impact of splitting Rent into 8 components is usually associated with an *increase* in the probability that a shelter component is chosen as the median (and for most levels of disaggregation - namely, for C2, C4 and C5 - an *increase* in the probability that an OER component is chosen).

However, as seen previously, median inflation tended to perform better as an MTT estimator once we split Rent in addition to OER. Pre-pandemic, the two best performing splits, FRBC-OER8-RENT8 and C2-OER8-RENT8, had strongly diverging median component profiles: while FRBC-OER8-RENT8 had the lowest OER frequency and the highest non-shelter frequency, C2-OER8-RENT8 had the *highest* OER frequency and the lowest non-shelter frequency. In the full sample, FRBC-OER8-RENT8 still had the lowest OER frequency and highest non-shelter frequency, while C2-OER8-RENT8 now had the second highest OER frequency and third lowest non-shelter frequency. This suggests that, on its own, choosing OER (or shelter more broadly) as the median component more frequently is simply a feature of the median CPI, and is not necessarily correlated with inferior performance by median CPI inflation as a measure of the MTT in inflation.

6.3 Phillips curve relationship

Recent research has shown that empirical Phillips curve-type relationships (i.e., estimated reduced-form regressions relating inflation to labor market slack) are strong and stable over time when the inflation variable used in regressions is the median PCE (Ball and Mazumder, 2019), trimmed mean PCE (Ashley and Verbrugge, 2023) or median CPI (Stock and Watson, 2020). Stock and Watson (2020) argue that this is because, month after month, the component selected as the median CPI is often an inflation component with a strong sensitivity to economic conditions, such as a shelter component. They show that the dynamics of median CPI inflation are "quite similar" to their cyclically sensitive inflation indicator. Above, we argued that the cyclical sensitivity of the median CPI results from the fact that components near the median of the distribution are cyclically sensitive, not because a shelter component per se is often selected. Nonetheless, the conjecture does raise the question: are candidate MTT estimators that select shelter components less frequently in turn relatively less cyclically sensitive? Once again, the answer we find is both interesting and counterintuitive: no!

To assess the cyclical sensitivity, for each of our median and trimmed-mean CPI indexes, we estimate a parsimonious Phillips curve formulation similar to the one used in Zaman (2019):

$$\pi_{j,t} = \alpha_j + \beta_j x_t + e_{j,t} \tag{4}$$

where $\pi_{j,t}$ is the 12-month inflation rate of the jth median or trimmed-mean CPI index, and x_t is defined as the average of the unemployment gap over the preceding 12 months,

$$x_t = \frac{1}{12}\Sigma_{i=1}^{12}(U_{t-i} - U_{t-i}^N) \tag{5}$$

where U_t is the overall unemployment rate and U_t^N is the Congressional Budget Office's (CBO) estimate of the long-run unemployment rate. β_j, which can be thought of as the slope of the Phillips curve, determines the strength of the cyclical relationship between the median or trimmed-mean inflation measure and the labor market slack.

To abstract from the extreme volatility in the unemployment rate data at the onset of and during the COVID-19 pandemic, we estimate using OLS the above Phillips curve model over the pre-COVID sample for each inflation measure. Table 3 reports the estimated β_j for each median and trimmed-mean index considered in this paper. Also reported are the p-values to provide an assessment of whether each estimated β_j is statistically different from zero.[23] As shown in the table, each median measure exhibits a statistically significant Phillips curve relationship. The β_j estimates also clearly indicate that for a given non-shelter split, the greater the shelter disaggregation, the weaker the estimated Phillips curve relationship. For example, the estimated β_j for median FRBC-OER4 inflation is -0.121, for FRBC-OER8 it is -0.100, and for FRBC-OER8-RENT8 it is -0.087. While our results show that the level of shelter disaggregation is inversely related to the strength of the Phillips curve relationship among the median CPI candidates, this inverse relationship is *not* driven by a reduction in the percentage of time a shelter component is chosen as the median. Recall from Section 6.2 that when we increase the level of shelter disaggregation by disaggregating Rent

[23]Similar to Zaman (2019), to account for the possibility of serial correlation in the regression residuals, Newey-West standard errors are computed. The lag length is set equal to $(4 * (T/100)^{2/9})$, where T refers to the size of the estimation sample.

into 8 components, a shelter component was (typically) chosen *more* frequently as the median - and yet, moving from OER8 rows to the OER8-RENT8 row always results in a weaker Phillips curve relationship.

In contrast to median CPI MTT estimators, trimmed-mean measures do not display any meaningful sensitivity to labor market slack, as evidenced by small β_j estimates that are not statistically different from zero.

Table 3: Estimated Phillips Curve Slope

Series	Median		Trimmed-Mean	
	Beta	P-value	Beta	P-value
FRBC-OER4	-0.121	0.00	-0.051	0.15
FRBC-OER8	-0.100	0.00	-0.048	0.17
FRBC-OER8-RENT8	-0.087	0.00	-0.048	0.18
C2-OER4	-0.116	0.00	-0.047	0.17
C2-OER8	-0.091	0.00	-0.045	0.19
C2-OER8-RENT8	-0.078	0.00	-0.045	0.19
C3-OER4	-0.139	0.00	-0.050	0.14
C3-OER8	-0.118	0.00	-0.048	0.15
C3-OER8-RENT8	-0.102	0.00	-0.049	0.15
C4-OER4	-0.147	0.00	-0.046	0.19
C4-OER8	-0.120	0.00	-0.045	0.21
C4-OER8-RENT8	-0.098	0.00	-0.045	0.20
C5-OER4	-0.156	0.00	-0.058	0.11
C5-OER8	-0.131	0.00	-0.057	0.12
C5-OER8-RENT8	-0.103	0.00	-0.057	0.12

Note: Estimation sample spans 2011m1-2019m12.

7 Conclusion

The median and trimmed-mean CPI measures developed by Federal Reserve Bank of Cleveland (FRBC) researchers are well-known estimators of the medium-term trend (MTT) in CPI inflation. Over time, various improvements to these two measures have been implemented. Historically, revisions to the underlying methodology have usually involved increasing the level of disaggregation; and whenever further disaggregation has been investigated, it has always improved the performance of the median CPI. Moreover, *less* disaggregation, in the limit, leads to an index identical to headline CPI, suggesting that more disaggregation should be better. Finally, the current level of disaggregation in the median and trimmed mean CPI is far lower than that used in, e.g., the median PCE. It may seem obvious that increasing the level of disaggregation would improve the performance of FRBC MTT estimators—and indeed, that increasing the level of disaggregation by as much as possible would result in the highest performance gains. But this paper provides evidence to the contrary.

We first demonstrate theoretically, in Proposition 1, that the minimum mean squared error estimator of the median of the underlying distribution need not be the one associated with the most disaggregated basket that is feasible. Hence, the optimal level of disaggregation must be established empirically.

We conduct this analysis using criteria well-established in the literature, focusing on two criteria in particular: accuracy vis-a-vis an ex-post estimate of the MTT, and predictive power for future movements in headline CPI inflation at various horizons. We systematically investigate the impact of further disaggregation by constructing 15 distinct median and trimmed-mean CPI inflation measures with varying levels of disaggregation. First, we evaluate how well each measure of median and trimmed-mean inflation tracks an ex-post estimate of the MTT in inflation. Second, we assess the extent to which each median and trimmed-mean measure has predictive power over future movements in headline CPI inflation.

For tracking the ex-post MTT in inflation, we find improvements in accuracy from disaggregating the shelter components (OER and Rent) by as much as possible. However, in accordance with Proposition 1, we find that only a small increase in the level of disaggregation for non-shelter components yields accuracy improvements, demonstrating empirically that increasing disaggregation does not always further enhance these measures. Our predictive accuracy findings are congruent: increasing housing disaggregation by as much as possible, but increasing non-shelter component disaggregation only a small amount, generally yields marginal gains in predictive accuracy. (We leave the exploration of relative performance over earlier time periods—an endeavor that would introduce breaks into the FRBC MTT estimator time series—for future work.)

We explore some of the practical implications of finer disaggregations of the CPI components on median and trimmed-mean CPI inflation. First, we show that prior to the COVID-19 pandemic, our preferred median and trimmed-mean CPI measures derived from our C2-OER8-RENT8 split of the CPI were more in line with the views of economists and monetary policymakers at the time, namely that medium-run trend inflation was more subdued than the headline inflation rate suggested. During the COVID-19 pandemic and beyond, our preferred measures more closely tracked the medium-run trend in CPI inflation, rising more quickly in 2021 than the official measures, suggesting they were more sensitive to the clear rise in the medium-term trend in inflation. Next, we show that increasing the level of shelter disaggregation does not necessarily increase the frequency of choosing a non-shelter component as the median. Finally, we show that similar to the official FRBC median measure, all median CPI measures we considered exhibit a statistically significant relationship with the labor market slack. Contrary to popular belief, there is not a simple relationship between the frequency with which a shelter component is selected as a median, and the strength of the resulting Phillips curve relationship.

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8 Appendix 1: "Old Methodology" FRBC Median and Trimmed-Mean CPI Components

Table 4: "Old Methodology" FRBC Median and Trimmed-Mean CPI Components

	Original Components	Post-1997 Components
0	Cereals and bakery products	Cereals and bakery products
1	Meats, poultry, fish and eggs	Meats, poultry, fish, and eggs
2	Dairy products	Dairy and related products
3	Other food at home	Fresh fruits and vegetables
4	Food away from home	Processed fruits and vegetables
5	Alcoholic beverages	Nonalcoholic beverages and beverage materials
6	Fuel oil and other household fuel commodities	Other food at home
7	Gas and electricity (energy services)	Food away from home
8	Men's and boys' apparel	Alcoholic beverages
9	Women's and girls' apparel	Rent of primary residence
10	Infants' and toddlers' apparel	Lodging away from home
11	Footwear	Owners' equivalent rent of primary residence
12	New vehicles	Tenants' and household insurance
13	Used cars, etc.	Fuel oil and other fuels
14	Motor fuel	Gas (piped) and electricity
15	Auto maintenance and repair	Water and sewer and trash collection services
16	Public transportation	Household furnishings and operations
17	Medical care commodities	Men's and boys' apparel
18	Medical care services	Women's and girls' apparel
19	Tobacco and smoking products	Footwear
20	Toilet goods and personal care appliances	Infants' and toddlers' apparel
21	Personal care services	Jewelry and watches
22	Fruits and vegetables	New vehicles
23	Shelter	Used cars and trucks
24	Other utilities and public services	Car and truck rental
25	Housefurnishings	Motor fuel
26	Housekeeping supplies	Motor vehicle parts and equipment

Continued on next page

Table 4: "Old Methodology" FRBC Median and Trimmed-Mean CPI Components

	Original Components	Post-1997 Components
27	Housekeeping services	Motor vehicle maintenance and repair
28	Other apparel commodities	Motor vehicle insurance
29	Apparel services	Motor vehicle fees
30	Other private transportation commodities	Public transportation
31	Other private transportation services	Medical care commodities
32	Entertainment commodities	Medical care services
33	Entertainment services	Recreation
34	School books and supplies	Education
35	Personal and educational services	Communication
36		Tobacco and smoking products
37		Personal care products
38		Personal care services
39		Miscellaneous personal services
40		Miscellaneous personal goods

9 Appendix 2: "New Methodology" FRBC Median and Trimmed-Mean CPI Components

Table 5: Pre-1998 Components, excluding OER Components

	Name	BLS Code (NSA)	BLS Code (SA)
1	Cereals and bakery products	MUUR0000SA1111	MUSR0000SA1111
2	Meats, poultry, fish, and eggs	MUUR0000SA1112	MUSR0000SA1112
3	Dairy products	MUUR0000SA1113	MUSR0000SA1113
4	Fruits and vegetables	MUUR0000SA1114	MUSR0000SA1114
5	Other food at home	MUUR0000SA1115	MUSR0000SA1115
6	Food away from home	MUUR0000SE19	MUSR0000SE19
7	Alcoholic beverages	MUUR0000SE20	MUSR0000SE20
8	Fuel oil and other household fuel commodities	MUUR0000SE25	MUSR0000SE25
9	Gas (piped) and electricity (energy services)	MUUR0000SE26	MUSR0000SE26
10	Other utilities and public services	MUUR0000SE27	MUSR0000SE27
11	Housefurnishings	MUUR0000SA231	MUSR0000SA231
12	Housekeeping supplies	MUUR0000SE33	MUSR0000SE33
13	Housekeeping services	MUUR0000SE34	MUSR0000SE34
14	Men's and boys' apparel	MUUR0000SA3111	MUSR0000SA3111
15	Women's and girls' apparel	MUUR0000SA3112	MUSR0000SA3112
16	Infants' and toddlers' apparel	MUUR0000SE41	MUSR0000SE41
17	Other apparel commodities	MUUR0000SA3114	MUSR0000SA3114
18	Footwear	MUUR0000SE40	MUSR0000SE40
19	Apparel services	MUUR0000SE44	MUSR0000SE44
20	New vehicles	MUUR0000SE45	MUSR0000SE45
21	Used cars	MUUR0000SE46	MUSR0000SE46
22	Motor fuel	MUUR0000SE4701	MUSR0000SE4701
23	Automobile maintenance and repairs	MUUR0000SE49	MUSR0000SE49
24	Other private transportation commodities	MUUR0000SA4151	MUSR0000SA4151
25	Other private transportation services	MUUR0000SA4152	MUSR0000SA4152
26	Public transportation	MUUR0000SE53	MUSR0000SE53
27	Medical care commodities	MUUR0000SA51	MUSR0000SA51
28	Medical care services	MUUR0000SA512	MUSR0000SA512
29	Entertainment commodities	MUUR0000SA61	MUSR0000SA61
30	Entertainment services	MUUR0000SE62	MUSR0000SE62
31	Tobacco and smoking products	MUUR0000SE63	MUSR0000SE63
32	Toilet goods and personal care appliances	MUUR0000SE64	
33	Personal care services	MUUR0000SE65	

Continued on next page

Table 5: Pre-1998 Components, excluding OER Components

	Name	BLS Code (NSA)	BLS Code (SA)
34	School books and supplies	MUUR0000SE66	MUSR0000SE66
35	Personal and educational services	MUUR0000SA7132	MUSR0000SA7132
36	Renters' costs	MUUR0000SA211	MUSR0000SA211
37	Household insurance	MUUR0000SE2202	MUSR0000SE2202
38	Household maintenance and repairs	MUUR0000SA213	MUSR0000SA213

Table 6: Post-1997 Components, exlcluding OER Components

	Name	Haver Price Code	Haver Weight Code
1	Cereals and bakery products	UFC@CPIDATA	RPCUFC@CPIDATA
2	Meats, poultry, fish and eggs	UFM@CPIDATA	RPCUFM@CPIDATA
3	Dairy and related products	UFY@CPIDATA	RPCUFD@CPIDATA
4	Fresh fruits and vegetables	UFFF@CPIDATA	URFFF@CPIDATA
5	Processed fruits and vegetables	UFFP@CPIDATA	URFFP@CPIDATA
6	Nonalcoholic beverages and beverage matls	UFBV@CPIDATA	RPCUFONB@CPIDATA
7	Other food at home	UFO@CPIDATA	RPCUFHO@CPIDATA
8	Food away from home	UFAH@CPIDATA	RPCUFA@CPIDATA
9	Alcoholic beverages	UAB@CPIDATA	RPCUAB@CPIDATA
10	Rent of primary residence	UHSP@CPIDATA	RPCUHSRR@CPIDATA
11	Lodging away from home	UHSL@CPIDATA	RPCUHSRO@CPIDATA
12	Tenants' and household insurance	UHROTN@CPIDATA	RPCUHSHI@CPIDATA
13	Fuel oil and other fuels	UHFHF@CPIDATA	RPCUHFO@CPIDATA
14	Energy services	UHFG@CPIDATA	RPCUHFG@CPIDATA
15	Water/sewer/trash collection services	UHFS@CPIDATA	RPCUHFS@CPIDATA
16	Household furnishings and operation	UHH@CPIDATA	RPCUHH@CPIDATA
17	Men's and boys' apparel	UAM@CPIDATA	RPCUACM@CPIDATA
18	Womens and girls apparel	UAW@CPIDATA	RPCUACW@CPIDATA
19	Footwear	UAF@CPIDATA	RPCUACF@CPIDATA
20	Infants and toddlers apparel	UAI@CPIDATA	RPCUACI@CPIDATA
21	Watches and jewelry	UAOW@CPIDATA	URAOW@CPIDATA
22	New vehicles	UTW@CPIDATA	RPCUTPV@CPIDATA
23	Used cars and trucks	UTD@CPIDATA	RPCUTPU@CPIDATA
24	Car and truck rental	UTK@CPIDATA	URTK@CPIDATA
25	Motor fuel	UTM@CPIDATA	RPCUTPM@CPIDATA
26	Motor vehicle parts and equipment	UTCA@CPIDATA	RPCUTPOC@CPIDATA
27	Motor vehicle maintenance and repair	UTR@CPIDATA	RPCUTPR@CPIDATA
28	Motor vehicle insurance	UTSI@CPIDATA	URTSI@CPIDATA
29	Motor vehicle fees	UTSEN@CPIDATA	URTSE@CPIDATA
30	Public transportation	UTU@CPIDATA	RPCUTU@CPIDATA
31	Medical care commodities	UMC@CPIDATA	RPCUMC@CPIDATA
32	Medical care services	UMS@CPIDATA	RPCUMS@CPIDATA
33	Recreation	UE@CPIDATA	RUEM@CPIDATA
34	Education	UDE@CPIDATA	RPCUOE@CPIDATA
35	Communication	UDM@CPIDATA	RPCUOC@CPIDATA
36	Tobacco and smoking products	UOT@CPIDATA	RPCUOT@CPIDATA

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Table 6: Post-1997 Components, exlcluding OER Components

	Name	Haver Price Code	Haver Weight Code
37	Personal care products	UOPPN@CPIDATA	RPCUOPA@CPIDATA
38	Personal care services	UOPSN@CPIDATA	RPCUOPS@CPIDATA
39	Miscellaneous personal services	UOPSM@CPIDATA	RPCUOPO@CPIDATA
40	Misc personal goods	UOEE@CPIDATA	UROEE@CPIDATA
41	Leased cars and trucks	UTL@CPIDATA	URTL@CPIDATA

Table 7: FRBC Regional OER Codes

Region	Annual weight, region relative to overall CPI-U	Annual weight, regional OER relative to regional CPI-U	NSA regional OER price indexes
Northeast	YNEN@CPIDATA	YHOANEN@CPIDATA	UHOANEN@CPIDATA
Midwest	YMWN@CPIDATA	YHOAMWN@CPIDATA	UHOAMWN@CPIDATA
South	YSON@CPIDATA	YHOASON@CPIDATA	UHOASON@CPIDATA
West	YWEN@CPIDATA	YHOAWEN@CPIDATA	UHOAWEN@CPIDATA

10 Appendix 3: C0-C5 Components

Table 8: C0 Components

	Name	Haver Price Code	Haver Weight Code
1	Food and beverages	UF@CPIDATA	RUFBM@CPIDATA
2	Housing	UH@CPIDATA	RUHM@CPIDATA
3	Apparel	UA@CPIDATA	RUAPM@CPIDATA
4	Transportation	UT@CPIDATA	RUTRM@CPIDATA
5	Medical care	UM@CPIDATA	RUMM@CPIDATA
6	Recreation	UE@CPIDATA	RUEM@CPIDATA
7	Education and communication	UD@CPIDATA	RUDCM@CPIDATA
8	Other goods and services	UO@CPIDATA	RUOM@CPIDATA

Table 9: C1 Components

	Name	Haver Price Code	Haver Weight Code
1	Food	UFD@CPIDATA	RUFDM@CPIDATA
2	Alcoholic beverages	UAB@CPIDATA	RPCUAB@CPIDATA
3	Fuels and utilities	UHF@CPIDATA	RPCUHF@CPIDATA
4	Household furnishings and operation	UHH@CPIDATA	RPCUHH@CPIDATA
5	Shelter	UHS@CPIDATA	RPCUHS@CPIDATA
6	Men's and boys' apparel	UAM@CPIDATA	RPCUACM@CPIDATA
7	Women's and girls' apparel	UAW@CPIDATA	RPCUACW@CPIDATA
8	Footwear	UAF@CPIDATA	RPCUACF@CPIDATA
9	Infants' and toddlers' apparel	UAI@CPIDATA	RPCUACI@CPIDATA
10	Jewelry and watches	UAOW@CPIDATA	URAOW@CPIDATA
11	Private transportation	UTP@CPIDATA	RPCUTP@CPIDATA
12	Public transportation	UTU@CPIDATA	RPCUTU@CPIDATA
13	Medical care commodities	UMC@CPIDATA	RPCUMC@CPIDATA
14	Medical care services	UMS@CPIDATA	RPCUMS@CPIDATA
15	Video and audio	UEV@CPIDATA	RPCUEV@CPIDATA
16	Pets, pet products and services	UEPT@CPIDATA	UREPT@CPIDATA
17	Sporting goods	UEE@CPIDATA	UREE@CPIDATA
18	Photography	UEP@CPIDATA	UREP@CPIDATA
19	Other recreational goods	UEGO@CPIDATA	UREGO@CPIDATA
20	Other recreation services	UES@CPIDATA	URES@CPIDATA
21	Recreational reading materials	UER@CPIDATA	URER@CPIDATA
22	Education	UDE@CPIDATA	RPCUOE@CPIDATA
23	Communication	UDM@CPIDATA	RPCUOC@CPIDATA
24	Tobacco and smoking products	UOT@CPIDATA	RPCUOT@CPIDATA
25	Personal care	UOP@CPIDATA	RPCUOP@CPIDATA

Table 10: C2 Components

	Name	Haver Price Code	Haver Weight Code
1	Food at home	UFH@CPIDATA	RPCUFH@CPIDATA
2	Food away from home	UFAH@CPIDATA	RPCUFA@CPIDATA
3	Alcoholic beverages at home	UABH@CPIDATA	URABH@CPIDATA
4	Alcoholic beverages away from home	UABE@CPIDATA	URABE@CPIDATA
5	Household energy	UHFH@CPIDATA	RPCUHFF@CPIDATA
6	Water and sewer and trash collection services	UHFS@CPIDATA	RPCUHFS@CPIDATA
7	Window and floor coverings and other linens	UHHW@CPIDATA	URHHW@CPIDATA
8	Furniture and bedding	UHHF@CPIDATA	URHHF@CPIDATA
9	Appliances	UHHP@CPIDATA	URHHP@CPIDATA
10	Other household equipment and furnishings	UHHQ@CPIDATA	URHHQ@CPIDATA
11	Tools, hardware and outdoor equipment/supplies	UHHTH@CPIDATA	URHHTH@CPIDATA
12	Housekeeping supplies	UHHK@CPIDATA	URHHK@CPIDATA
13	Household operations	UHHRN@CPIDATA	RPCUHO@CPIDATA
14	Rent of primary residence	UHSP@CPIDATA	RPCUHSRR@CPIDATA
15	Lodging away from home	UHSL@CPIDATA	RPCUHSRO@CPIDATA
16	Oer	UHOA@CPIDATA	RPCUHSHA@CPIDATA
17	Tenants' and household insurance	UHROTN@CPIDATA	RPCUHSHI@CPIDATA
18	Men's apparel	UAMM@CPIDATA	URAMM@CPIDATA
19	Boys' apparel	UAMB@CPIDATA	URAMB@CPIDATA
20	Women's apparel	UAWW@CPIDATA	URAWW@CPIDATA
21	Girls' apparel	UAWG@CPIDATA	URAWG@CPIDATA
22	Men's footwear	UAFM@CPIDATA	URAFM@CPIDATA
23	Boys' and girls' footwear	UAFB@CPIDATA	URAFB@CPIDATA
24	Women's footwear	UAFW@CPIDATA	URAFW@CPIDATA
25	Infants' and toddlers' apparel	UAI@CPIDATA	RPCUACI@CPIDATA
26	Watches	UAOWW@CPIDATA	URAOWW@CPIDATA
27	Jewelry	UAOWJ@CPIDATA	URAOWJ@CPIDATA
28	New and used motor vehicles	UTV@CPIDATA	RPCUTV@CPIDATA

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Table 10: C2 Components

	Name	Haver Price Code	Haver Weight Code
29	Motor fuel	UTM@CPIDATA	RPCUTPM@CPIDATA
30	Motor vehicle parts and equipment	UTCA@CPIDATA	RPCUTPOC@CPIDATA
31	Motor vehicle maintenance and repair	UTR@CPIDATA	RPCUTPR@CPIDATA
32	Motor vehicle insurance	UTSI@CPIDATA	URTSI@CPIDATA
33	Motor vehicle fees	UTSEN@CPIDATA	URTSE@CPIDATA
34	Public transportation	UTU@CPIDATA	RPCUTU@CPIDATA
35	Medicinal drugs	UMG@CPIDATA	URMG@CPIDATA
36	Medical equipment and supplies	UMQN@CPIDATA	URMQ@CPIDATA
37	Professional services	UMSP@CPIDATA	RPCUMSP@CPIDATA
38	Hospital and related services	UMSH@CPIDATA	RPCUMSH@CPIDATA
39	Health insurance	UMSIN@CPIDATA	URMSI@CPIDATA
40	Video and audio	UEV@CPIDATA	RPCUEV@CPIDATA
41	Pets and pet products	UEPTP@CPIDATA	UREPTP@CPIDATA
42	Pet services including veterinarian services	UEPTS@CPIDATA	UREPTS@CPIDATA
43	Sporting goods	UEE@CPIDATA	UREE@CPIDATA
44	Photography	UEP@CPIDATA	UREP@CPIDATA
45	Other recreational goods	UEGO@CPIDATA	UREGO@CPIDATA
46	Other recreation services	UES@CPIDATA	URES@CPIDATA
47	Recreational reading materials	UER@CPIDATA	URER@CPIDATA
48	Educational books and supplies	UDES@CPIDATA	RPCUOES@CPIDATA
49	Tuition, other school fees and child care	UDET@CPIDATA	RPCUOEP@CPIDATA
50	Postage and delivery services	UDMP@CPIDATA	URDMP@CPIDATA
51	Information and information processing	UDI@CPIDATA	RPCUI@CPIDATA
52	Tobacco and smoking products	UOT@CPIDATA	RPCUOT@CPIDATA
53	Personal care products	UOPPN@CPIDATA	RPCUOPA@CPIDATA
54	Personal care services	UOPSN@CPIDATA	RPCUOPS@CPIDATA
55	Miscellaneous personal services	UOPSM@CPIDATA	RPCUOPO@CPIDATA

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Table 10: C2 Components

	Name	Haver Price Code	Haver Weight Code
56	Miscellaneous personal goods	UOEE@CPIDATA	UROEE@CPIDATA

Table 11: C3 Components

	Name	Haver Price Code	Haver Weight Code
1	Cereals and bakery products	UFC@CPIDATA	RPCUFC@CPIDATA
2	Meats, poultry, fish and eggs	UFM@CPIDATA	RPCUFM@CPIDATA
3	Dairy and related products	UFY@CPIDATA	RPCUFD@CPIDATA
4	Fruits and vegetables	UFF@CPIDATA	RPCUFF@CPIDATA
5	Nonalcoholic beverages and beverage materials	UFBV@CPIDATA	RPCUFONB@CPIDATA
6	Other food at home	UFO@CPIDATA	RPCUFHO@CPIDATA
7	Full service meals and snacks	UFAHF@CPIDATA	URFAHF@CPIDATA
8	Limited service meals and snacks	UFAHLN@CPIDATA	URFAHL@CPIDATA
9	Food at employee sites and schools	UFAHE@CPIDATA	URFAHE@CPIDATA
10	Food from vending machines and mobile vendors	UFAHVN@CPIDATA	URFAHV@CPIDATA
11	Other food away from home	UFAHM@CPIDATA	RPCUFAO@CPIDATA
12	Beer, ale and malt beverages at home	UABHB@CPIDATA	URABHB@CPIDATA
13	Distilled spirits at home	UABHD@CPIDATA	URABHD@CPIDATA
14	Wine at home	UABHW@CPIDATA	URABHW@CPIDATA
15	Alcoholic beverages away from home	UABE@CPIDATA	URABE@CPIDATA
16	Fuel oil and other fuels	UHFHF@CPIDATA	RPCUHFO@CPIDATA
17	Energy services	UHFG@CPIDATA	RPCUHFG@CPIDATA
18	Water and sewerage maintenance	UHFSW@CPIDATA	URHFSW@CPIDATA
19	Garbage and trash collection	UHFSG@CPIDATA	URHFSG@CPIDATA
20	Floor coverings	UHHWFN@CPIDATA	URHHWF@CPIDATA
21	Window coverings	UHHWW@CPIDATA	URHHWW@CPIDATA
22	Other linens	UHHWL@CPIDATA	URHHWL@CPIDATA
23	Furniture and bedding	UHHF@CPIDATA	URHHF@CPIDATA
24	Appliances	UHHP@CPIDATA	URHHP@CPIDATA
25	Clocks, lamps and decorator items	UHHQCN@CPIDATA	URHHQC@CPIDATA

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Table 11: C3 Components

	Name	Haver Price Code	Haver Weight Code
26	Indoor plants and flowers	UHHQI@CPIDATA	URHHQI@CPIDATA
27	Dishes and flatware	UHHQDN@CPIDATA	URHHQD@CPIDATA
28	Nonelectric cookware and tableware	UHHQK@CPIDATA	URHHQK@CPIDATA
29	Tools, hardware and outdoor equipment/supplies	UHHTH@CPIDATA	URHHTH@CPIDATA
30	Household cleaning products	UHHKC@CPIDATA	URHHKC@CPIDATA
31	Household paper products	UHHKRN@CPIDATA	URHHKR@CPIDATA
32	Miscellaneous household products	UHHKM@CPIDATA	URHHKM@CPIDATA
33	Household operations	UHHRN@CPIDATA	RPCUHO@CPIDATA
34	Rent of primary residence	UHSP@CPIDATA	RPCUHSRR@CPIDATA
35	Housing at school ex board	UHROS@CPIDATA	URHROS@CPIDATA
36	Other lodging away from home	UHROM@CPIDATA	URHROM@CPIDATA
37	Oer	UHOA@CPIDATA	RPCUHSHA@CPIDATA
38	Tenants' and household insurance	UHROTN@CPIDATA	RPCUHSHI@CPIDATA
39	Men's apparel	UAMM@CPIDATA	URAMM@CPIDATA
40	Boys' apparel	UAMB@CPIDATA	URAMB@CPIDATA
41	Women's apparel	UAWW@CPIDATA	URAWW@CPIDATA
42	Girls' apparel	UAWG@CPIDATA	URAWG@CPIDATA
43	Men's footwear	UAFM@CPIDATA	URAFM@CPIDATA
44	Boys' and girls' footwear	UAFB@CPIDATA	URAFB@CPIDATA
45	Women's footwear	UAFW@CPIDATA	URAFW@CPIDATA
46	Infants' and toddlers' apparel	UAI@CPIDATA	RPCUACI@CPIDATA
47	Watches	UAOWW@CPIDATA	URAOWW@CPIDATA
48	Jewelry	UAOWJ@CPIDATA	URAOWJ@CPIDATA
49	New vehicles	UTW@CPIDATA	RPCUTPV@CPIDATA
50	Used cars and trucks	UTD@CPIDATA	RPCUTPU@CPIDATA
51	Leased cars and trucks	UTL@CPIDATA	URTL@CPIDATA
52	Car and truck rental	UTK@CPIDATA	URTK@CPIDATA
53	Gasoline	UTMG@CPIDATA	RPCUTPMG@CPIDATA

Continued on next page

Table 11: C3 Components

	Name	Haver Price Code	Haver Weight Code
54	Other motor fuels	UTMO@CPIDATA	URTMO@CPIDATA
55	Tires	UTCT@CPIDATA	URTCT@CPIDATA
56	Vehicle accessories other than tires	UTCON@CPIDATA	URTCO@CPIDATA
57	Motor vehicle maintenance and repair	UTR@CPIDATA	RPCUTPR@CPIDATA
58	Motor vehicle insurance	UTSI@CPIDATA	URTSI@CPIDATA
59	Motor vehicle fees	UTSEN@CPIDATA	URTSE@CPIDATA
60	Public transportation	UTU@CPIDATA	RPCUTU@CPIDATA
61	Prescription drugs and medical supplies	UMP@CPIDATA	URMP@CPIDATA
62	Nonprescription drugs and medical supplies	UMGNN@CPIDATA	URMGN@CPIDATA
63	Medical equipment and supplies	UMQN@CPIDATA	URMQ@CPIDATA
64	Physicians' services	UMSPP@CPIDATA	URMSPP@CPIDATA
65	Dental services	UMSPT@CPIDATA	URMSPT@CPIDATA
66	Eyeglasses and eye care	UMSPE@CPIDATA	URMSPE@CPIDATA
67	Services by other medical professionals	UMSPS@CPIDATA	URMSPS@CPIDATA
68	Hospital services	UMSHS@CPIDATA	URMSHS@CPIDATA
69	Nursing homes and adult daycare	UMSNS@CPIDATA	URMSNS@CPIDATA
70	Care of invalids and elderly at home	UOEECN@CPIDATA	UROEEC@CPIDATA
71	Health insurance	UMSIN@CPIDATA	URMSI@CPIDATA
72	Video and audio	UEV@CPIDATA	RPCUEV@CPIDATA
73	Pets and pet products	UEPTP@CPIDATA	UREPTP@CPIDATA
74	Pet services including veterinarian services	UEPTS@CPIDATA	UREPTS@CPIDATA
75	Sporting goods	UEE@CPIDATA	UREE@CPIDATA
76	Photography	UEP@CPIDATA	UREP@CPIDATA
77	Other recreational goods	UEGO@CPIDATA	UREGO@CPIDATA
78	Other recreation services	UES@CPIDATA	URES@CPIDATA
79	Recreational reading materials	UER@CPIDATA	URER@CPIDATA
80	Educational books and supplies	UDES@CPIDATA	RPCUOES@CPIDATA

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Table 11: C3 Components

	Name	Haver Price Code	Haver Weight Code
81	Tuition, other school fees and child care	UDET@CPIDATA	RPCUOEP@CPIDATA
82	Postage	UDMPP@CPIDATA	URDMPP@CPIDATA
83	Delivery services	UDMPD@CPIDATA	URDMPD@CPIDATA
84	Telephone services	UDITN@CPIDATA	RPCUIT@CPIDATA
85	Information technology, hardware and services	UDII@CPIDATA	RPCUIX@CPIDATA
86	Tobacco and smoking products	UOT@CPIDATA	RPCUOT@CPIDATA
87	Personal care products	UOPPN@CPIDATA	RPCUOPA@CPIDATA
88	Personal care services	UOPSN@CPIDATA	RPCUOPS@CPIDATA
89	Miscellaneous personal services	UOPSM@CPIDATA	RPCUOPO@CPIDATA
90	Miscellaneous personal goods	UOEE@CPIDATA	UROEE@CPIDATA

Table 12: C4 Components

	Name	Haver Price Code	Haver Weight Code
1	Cereals and cereal products	UFCC@CPIDATA	URFCC@CPIDATA
2	Bakery products	UFCB@CPIDATA	URFCB@CPIDATA
3	Meats, poultry and fish	UFMF@CPIDATA	URFMF@CPIDATA
4	Eggs	UFME@CPIDATA	URFME@CPIDATA
5	Milk	UFYF@CPIDATA	URFYF@CPIDATA
6	Cheese and related products	UFYPC@CPIDATA	URFYPC@CPIDATA
7	Ice cream and related products	UFYPI@CPIDATA	URFYPI@CPIDATA
8	Other dairy and related products	UFYO@CPIDATA	URFYO@CPIDATA
9	Fresh fruits and vegetables	UFFF@CPIDATA	URFFF@CPIDATA
10	Processed fruits and vegetables	UFFP@CPIDATA	URFFP@CPIDATA
11	Juices and nonalcoholic drinks	UFBVJ@CPIDATA	URFBVJ@CPIDATA
12	Beverage materials including coffee and tea	UFBVM@CPIDATA	URFBVM@CPIDATA
13	Sugar and sweets	UFOS@CPIDATA	RPCUFOS@CPIDATA
14	Fats and oils	UFOT@CPIDATA	RPCUFOF@CPIDATA
15	Other food at home	UFOM@CPIDATA	RPCUFOO@CPIDATA
16	Full service meals and snacks	UFAHF@CPIDATA	URFAHF@CPIDATA
17	Limited service meals and snacks	UFAHLN@CPIDATA	URFAHL@CPIDATA
18	Food at employee sites and schools	UFAHE@CPIDATA	URFAHE@CPIDATA
19	Food from vending machines and mobile vendors	UFAHVN@CPIDATA	URFAHV@CPIDATA
20	Other food away from home	UFAHM@CPIDATA	RPCUFAO@CPIDATA
21	Beer, ale and malt beverages at home	UABHB@CPIDATA	URABHB@CPIDATA
22	Distilled spirits at home	UABHD@CPIDATA	URABHD@CPIDATA
23	Wine at home	UABHW@CPIDATA	URABHW@CPIDATA
24	Alcoholic beverages away from home	UABE@CPIDATA	URABE@CPIDATA
25	Fuel oil	UHFHOF@CPIDATA	URHFHOF@CPIDATA

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Table 12: C4 Components

	Name	Haver Price Code	Haver Weight Code
26	Propane, kerosene and firewood	UHFHOO@CPIDATA	URHFHOO@CPIDATA
27	Electricity	UHFGE@CPIDATA	URHFGE@CPIDATA
28	Utility (piped) gas service	UHFGU@CPIDATA	URHFGU@CPIDATA
29	Water and sewerage maintenance	UHFSW@CPIDATA	URHFSW@CPIDATA
30	Garbage and trash collection	UHFSG@CPIDATA	URHFSG@CPIDATA
31	Floor coverings	UHHWFN@CPIDATA	URHHWF@CPIDATA
32	Window coverings	UHHWW@CPIDATA	URHHWW@CPIDATA
33	Other linens	UHHWL@CPIDATA	URHHWL@CPIDATA
34	Furniture and bedding	UHHF@CPIDATA	URHHF@CPIDATA
35	Appliances	UHHP@CPIDATA	URHHP@CPIDATA
36	Clocks, lamps and decorator items	UHHQCN@CPIDATA	URHHQC@CPIDATA
37	Indoor plants and flowers	UHHQI@CPIDATA	URHHQI@CPIDATA
38	Dishes and flatware	UHHQDN@CPIDATA	URHHQD@CPIDATA
39	Nonelectric cookware and tableware	UHHQK@CPIDATA	URHHQK@CPIDATA
40	Tools, hardware and outdoor equipment/supplies	UHHTH@CPIDATA	URHHTH@CPIDATA
41	Household cleaning products	UHHKC@CPIDATA	URHHKC@CPIDATA
42	Household paper products	UHHKRN@CPIDATA	URHHKR@CPIDATA
43	Miscellaneous household products	UHHKM@CPIDATA	URHHKM@CPIDATA
44	Household operations	UHHRN@CPIDATA	RPCUHO@CPIDATA
45	Rent of primary residence	UHSP@CPIDATA	RPCUHSRR@CPIDATA
46	Housing at school ex board	UHROS@CPIDATA	URHROS@CPIDATA
47	Other lodging away from home	UHROM@CPIDATA	URHROM@CPIDATA
48	OER	UHOA@CPIDATA	RPCUHSHA@CPIDATA
49	Tenants' and household insurance	UHROTN@CPIDATA	RPCUHSHI@CPIDATA
50	Men's apparel	UAMM@CPIDATA	URAMM@CPIDATA

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Table 12: C4 Components

	Name	Haver Price Code	Haver Weight Code
51	Boys' apparel	UAMB@CPIDATA	URAMB@CPIDATA
52	Women's apparel	UAWW@CPIDATA	URAWW@CPIDATA
53	Girls' apparel	UAWG@CPIDATA	URAWG@CPIDATA
54	Men's footwear	UAFM@CPIDATA	URAFM@CPIDATA
55	Boys' and girls' footwear	UAFB@CPIDATA	URAFB@CPIDATA
56	Women's footwear	UAFW@CPIDATA	URAFW@CPIDATA
57	Infants' and toddlers' apparel	UAI@CPIDATA	RPCUACI@CPIDATA
58	Watches	UAOWW@CPIDATA	URAOWW@CPIDATA
59	Jewelry	UAOWJ@CPIDATA	URAOWJ@CPIDATA
60	New vehicles	UTW@CPIDATA	RPCUTPV@CPIDATA
61	Used cars and trucks	UTD@CPIDATA	RPCUTPU@CPIDATA
62	Leased cars and trucks	UTL@CPIDATA	URTL@CPIDATA
63	Car and truck rental	UTK@CPIDATA	URTK@CPIDATA
64	Gasoline	UTMG@CPIDATA	RPCUTPMG@CPIDATA
65	Other motor fuels	UTMO@CPIDATA	URTMO@CPIDATA
66	Tires	UTCT@CPIDATA	URTCT@CPIDATA
67	Vehicle accessories other than tires	UTCON@CPIDATA	URTCO@CPIDATA
68	Motor vehicle maintenance and repair	UTR@CPIDATA	RPCUTPR@CPIDATA
69	Motor vehicle insurance	UTSI@CPIDATA	URTSI@CPIDATA
70	Motor vehicle fees	UTSEN@CPIDATA	URTSE@CPIDATA
71	Public transportation	UTU@CPIDATA	RPCUTU@CPIDATA
72	Prescription drugs and medical supplies	UMP@CPIDATA	URMP@CPIDATA
73	Nonprescription drugs and medical supplies	UMGNN@CPIDATA	URMGN@CPIDATA
74	Medical equipment and supplies	UMQN@CPIDATA	URMQ@CPIDATA
75	Physicians' services	UMSPP@CPIDATA	URMSPP@CPIDATA
76	Dental services	UMSPT@CPIDATA	URMSPT@CPIDATA
77	Eyeglasses and eye care	UMSPE@CPIDATA	URMSPE@CPIDATA
78	Services by other medical professionals	UMSPS@CPIDATA	URMSPS@CPIDATA
79	Hospital services	UMSHS@CPIDATA	URMSHS@CPIDATA
80	Nursing homes and adult daycare	UMSNS@CPIDATA	URMSNS@CPIDATA
81	Care of invalids and elderly at home	UOEECN@CPIDATA	UROEEC@CPIDATA

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Table 12: C4 Components

	Name	Haver Price Code	Haver Weight Code
82	Health insurance	UMSIN@CPIDATA	URMSI@CPIDATA
83	Video and audio	UEV@CPIDATA	RPCUEV@CPIDATA
84	Pets and pet products	UEPTP@CPIDATA	UREPTP@CPIDATA
85	Pet services including veterinarian services	UEPTS@CPIDATA	UREPTS@CPIDATA
86	Sporting goods	UEE@CPIDATA	UREE@CPIDATA
87	Photography	UEP@CPIDATA	UREP@CPIDATA
88	Other recreational goods	UEGO@CPIDATA	UREGO@CPIDATA
89	Other recreation services	UES@CPIDATA	URES@CPIDATA
90	Recreational reading materials	UER@CPIDATA	URER@CPIDATA
91	Educational books and supplies	UDES@CPIDATA	RPCUOES@CPIDATA
92	Tuition, other school fees and child care	UDET@CPIDATA	RPCUOEP@CPIDATA
93	Postage	UDMPP@CPIDATA	URDMPP@CPIDATA
94	Delivery services	UDMPD@CPIDATA	URDMPD@CPIDATA
95	Wireless telephone services	UDITCN@CPIDATA	URDITC@CPIDATA
96	Residential telephone services	UDITAN@CPIDATA	URDITA@CPIDATA
97	Information technology, hardware and services	UDII@CPIDATA	RPCUIX@CPIDATA
98	Tobacco and smoking products	UOT@CPIDATA	RPCUOT@CPIDATA
99	Personal care products	UOPPN@CPIDATA	RPCUOPA@CPIDATA
100	Personal care services	UOPSN@CPIDATA	RPCUOPS@CPIDATA
101	Miscellaneous personal services	UOPSM@CPIDATA	RPCUOPO@CPIDATA
102	Miscellaneous personal goods	UOEE@CPIDATA	UROEE@CPIDATA

Table 13: C5 Components

	Name	Haver Price Code	Haver Weight Code
1	Flour and prepared flour mixes	UFCCF@CPIDATA	URFCCF@CPIDATA
2	Breakfast cereal	UFCCC@CPIDATA	URFCCC@CPIDATA
3	Rice, pasta and corn-meal	UFCCR@CPIDATA	URFCCR@CPIDATA
4	Bread	UFCBB@CPIDATA	URFCBB@CPIDATA
5	Fresh biscuits, rolls and muffins	UFCBM@CPIDATA	URFCBM@CPIDATA
6	Cakes, cupcakes and cookies	UFCBC@CPIDATA	URFCBC@CPIDATA
7	Other bakery products	UFCBP@CPIDATA	URFCBP@CPIDATA
8	Beef and veal	UFMB@CPIDATA	URFMB@CPIDATA
9	Pork	UFMP@CPIDATA	URFMP@CPIDATA
10	Other meats	UFMO@CPIDATA	URFMO@CPIDATA
11	Chicken	UFMPK@CPIDATA	URFMPK@CPIDATA
12	Other poultry including turkey	UFMPO@CPIDATA	URFMPO@CPIDATA
13	Fresh fish and seafood	UFMSF@CPIDATA	URFMSF@CPIDATA
14	Processed fish and seafood	UFMSS@CPIDATA	URFMSS@CPIDATA
15	Eggs	UFME@CPIDATA	URFME@CPIDATA
16	Milk	UFYF@CPIDATA	URFYF@CPIDATA
17	Cheese and related products	UFYPC@CPIDATA	URFYPC@CPIDATA
18	Ice cream and related products	UFYPI@CPIDATA	URFYPI@CPIDATA
19	Other dairy and related products	UFYO@CPIDATA	URFYO@CPIDATA
20	Apples	UFFFA@CPIDATA	URFFFA@CPIDATA
21	Bananas	UFFFB@CPIDATA	URFFFB@CPIDATA
22	Citrus fruits	UFFFC@CPIDATA	URFFFC@CPIDATA
23	Other fresh fruits	UFFFO@CPIDATA	URFFFO@CPIDATA
24	Potatoes	UFFVP@CPIDATA	URFFVP@CPIDATA
25	Lettuce	UFFVL@CPIDATA	URFFVL@CPIDATA
26	Tomatoes	UFFVT@CPIDATA	URFFVT@CPIDATA
27	Other fresh vegetables	UFFVO@CPIDATA	URFFVO@CPIDATA
28	Canned fruits and veg-etables	UFFPC@CPIDATA	URFFPC@CPIDATA
29	Frozen fruits and veg-etables	UFFPZ@CPIDATA	URFFPZ@CPIDATA

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Table 13: C5 Components

	Name	Haver Price Code	Haver Weight Code
30	Other processed fruits and vegetables	UFFPO@CPIDATA	URFFPO@CPIDATA
31	Carbonated drinks	UFBVJD@CPIDATA	URFBVJD@CPIDATA
32	Frozen noncarbonated juices and drinks	UFBVJZN@CPIDATA	URFBVJZ@CPIDATA
33	Nonfrozen noncarbonated juices and drinks	UFBVJJ@CPIDATA	URFBVJJ@CPIDATA
34	Coffee	UFBVMC@CPIDATA	URFBVMC@CPIDATA
35	Other beverage materials including tea	UFBVMT@CPIDATA	URFBVMT@CPIDATA
36	Sugar and artificial sweeteners	UFOSA@CPIDATA	URFOSA@CPIDATA
37	Candy and chewing gum	UFOSSN@CPIDATA	URFOSS@CPIDATA
38	Other sweets	UFOSO@CPIDATA	URFOSO@CPIDATA
39	Butter and margarine	UFOTM@CPIDATA	URFOTM@CPIDATA
40	Salad dressings	UFOTS@CPIDATA	URFOTS@CPIDATA
41	Other fats and oils including peanut butter	UFOTO@CPIDATA	URFOTO@CPIDATA
42	Soups	UFOMP@CPIDATA	URFOMP@CPIDATA
43	Frozen and freeze dried prepared foods	UFOMZ@CPIDATA	URFOMZ@CPIDATA
44	Snacks	UFOMK@CPIDATA	URFOMK@CPIDATA
45	Spices, seasonings, condiments, sauces	UFOMS@CPIDATA	URFOMS@CPIDATA
46	Baby food	UFOMBN@CPIDATA	URFOMB@CPIDATA
47	Other miscellaneous foods	UFOMO@CPIDATA	RPCUFOM@CPIDATA
48	Full service meals and snacks	UFAHF@CPIDATA	URFAHF@CPIDATA
49	Limited service meals and snacks	UFAHLN@CPIDATA	URFAHL@CPIDATA
50	Food at employee sites and schools	UFAHE@CPIDATA	URFAHE@CPIDATA
51	Food from vending machines and mobile vendors	UFAHVN@CPIDATA	URFAHV@CPIDATA
52	Other food away from home	UFAHM@CPIDATA	RPCUFAO@CPIDATA

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Table 13: C5 Components

	Name	Haver Price Code	Haver Weight Code
53	Beer, ale and malt beverages at home	UABHB@CPIDATA	URABHB@CPIDATA
54	Distilled spirits at home	UABHD@CPIDATA	URABHD@CPIDATA
55	Wine at home	UABHW@CPIDATA	URABHW@CPIDATA
56	Alcoholic beverages away from home	UABE@CPIDATA	URABE@CPIDATA
57	Fuel oil	UHFHOF@CPIDATA	URHFHOF@CPIDATA
58	Propane, kerosene and firewood	UHFHOO@CPIDATA	URHFHOO@CPIDATA
59	Electricity	UHFGE@CPIDATA	URHFGE@CPIDATA
60	Utility (piped) gas service	UHFGU@CPIDATA	URHFGU@CPIDATA
61	Water and sewerage maintenance	UHFSW@CPIDATA	URHFSW@CPIDATA
62	Garbage and trash collection	UHFSG@CPIDATA	URHFSG@CPIDATA
63	Floor coverings	UHHWFN@CPIDATA	URHHWF@CPIDATA
64	Window coverings	UHHWW@CPIDATA	URHHWW@CPIDATA
65	Other linens	UHHWL@CPIDATA	URHHWL@CPIDATA
66	Furniture and bedding	UHHF@CPIDATA	URHHF@CPIDATA
67	Appliances	UHHP@CPIDATA	URHHP@CPIDATA
68	Clocks, lamps and decorator items	UHHQCN@CPIDATA	URHHQC@CPIDATA
69	Indoor plants and flowers	UHHQI@CPIDATA	URHHQI@CPIDATA
70	Dishes and flatware	UHHQDN@CPIDATA	URHHQD@CPIDATA
71	Nonelectric cookware and tableware	UHHQK@CPIDATA	URHHQK@CPIDATA
72	Tools, hardware and outdoor equipment/supplies	UHHTH@CPIDATA	URHHTH@CPIDATA
73	Household cleaning products	UHHKC@CPIDATA	URHHKC@CPIDATA
74	Household paper products	UHHKRN@CPIDATA	URHHKR@CPIDATA
75	Miscellaneous household products	UHHKM@CPIDATA	URHHKM@CPIDATA
76	Household operations	UHHRN@CPIDATA	RPCUHO@CPIDATA
77	Rent of primary residence	UHSP@CPIDATA	RPCUHSRR@CPIDATA

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Table 13: C5 Components

	Name	Haver Price Code	Haver Weight Code
78	Housing at school ex board	UHROS@CPIDATA	URHROS@CPIDATA
79	Other lodging away from home	UHROM@CPIDATA	URHROM@CPIDATA
80	OER	UHOA@CPIDATA	RPCUHSHA@CPIDATA
81	Tenants' and household insurance	UHROTN@CPIDATA	RPCUHSHI@CPIDATA
82	Men's apparel	UAMM@CPIDATA	URAMM@CPIDATA
83	Boys' apparel	UAMB@CPIDATA	URAMB@CPIDATA
84	Women's apparel	UAWW@CPIDATA	URAWW@CPIDATA
85	Girls' apparel	UAWG@CPIDATA	URAWG@CPIDATA
86	Men's footwear	UAFM@CPIDATA	URAFM@CPIDATA
87	Boys' and girls' footwear	UAFB@CPIDATA	URAFB@CPIDATA
88	Women's footwear	UAFW@CPIDATA	URAFW@CPIDATA
89	Infants' and toddlers' apparel	UAI@CPIDATA	RPCUACI@CPIDATA
90	Watches	UAOWW@CPIDATA	URAOWW@CPIDATA
91	Jewelry	UAOWJ@CPIDATA	URAOWJ@CPIDATA
92	New vehicles	UTW@CPIDATA	RPCUTPV@CPIDATA
93	Used cars and trucks	UTD@CPIDATA	RPCUTPU@CPIDATA
94	Leased cars and trucks	UTL@CPIDATA	URTL@CPIDATA
95	Car and truck rental	UTK@CPIDATA	URTK@CPIDATA
96	Gasoline	UTMG@CPIDATA	RPCUTPMG@CPIDATA
97	Other motor fuels	UTMO@CPIDATA	URTMO@CPIDATA
98	Tires	UTCT@CPIDATA	URTCT@CPIDATA
99	Vehicle accessories other than tires	UTCON@CPIDATA	URTCO@CPIDATA
100	Motor vehicle maintenance and repair	UTR@CPIDATA	RPCUTPR@CPIDATA
101	Motor vehicle insurance	UTSI@CPIDATA	URTSI@CPIDATA
102	Motor vehicle fees	UTSEN@CPIDATA	URTSE@CPIDATA
103	Public transportation	UTU@CPIDATA	RPCUTU@CPIDATA
104	Prescription drugs and medical supplies	UMP@CPIDATA	URMP@CPIDATA
105	Nonprescription drugs and medical supplies	UMGNN@CPIDATA	URMGN@CPIDATA
106	Medical equipment and supplies	UMQN@CPIDATA	URMQ@CPIDATA
107	Physicians' services	UMSPP@CPIDATA	URMSPP@CPIDATA
108	Dental services	UMSPT@CPIDATA	URMSPT@CPIDATA

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Table 13: C5 Components

	Name	Haver Price Code	Haver Weight Code
109	Eyeglasses and eye care	UMSPE@CPIDATA	URMSPE@CPIDATA
110	Services by other medical professionals	UMSPS@CPIDATA	URMSPS@CPIDATA
111	Hospital services	UMSHS@CPIDATA	URMSHS@CPIDATA
112	Nursing homes and adult daycare	UMSNS@CPIDATA	URMSNS@CPIDATA
113	Care of invalids and elderly at home	UOEECN@CPIDATA	UROEEC@CPIDATA
114	Health insurance	UMSIN@CPIDATA	URMSI@CPIDATA
115	Video and audio	UEV@CPIDATA	RPCUEV@CPIDATA
116	Pets and pet products	UEPTP@CPIDATA	UREPTP@CPIDATA
117	Pet services including veterinarian services	UEPTS@CPIDATA	UREPTS@CPIDATA
118	Sporting goods	UEE@CPIDATA	UREE@CPIDATA
119	Photography	UEP@CPIDATA	UREP@CPIDATA
120	Other recreational goods	UEGO@CPIDATA	UREGO@CPIDATA
121	Other recreation services	UES@CPIDATA	URES@CPIDATA
122	Recreational reading materials	UER@CPIDATA	URER@CPIDATA
123	Educational books and supplies	UDES@CPIDATA	RPCUOES@CPIDATA
124	Tuition, other school fees and child care	UDET@CPIDATA	RPCUOEP@CPIDATA
125	Postage	UDMPP@CPIDATA	URDMPP@CPIDATA
126	Delivery services	UDMPD@CPIDATA	URDMPD@CPIDATA
127	Wireless telephone services	UDITCN@CPIDATA	URDITC@CPIDATA
128	Residential telephone services	UDITAN@CPIDATA	URDITA@CPIDATA
129	Information technology, hardware and services	UDII@CPIDATA	RPCUIX@CPIDATA
130	Tobacco and smoking products	UOT@CPIDATA	RPCUOT@CPIDATA
131	Personal care products	UOPPN@CPIDATA	RPCUOPA@CPIDATA
132	Personal care services	UOPSN@CPIDATA	RPCUOPS@CPIDATA
133	Miscellaneous personal services	UOPSM@CPIDATA	RPCUOPO@CPIDATA
134	Miscellaneous personal goods	UOEE@CPIDATA	UROEE@CPIDATA

11 Appendix 4: OER4, OER8, and Rent8 Components

Table 14: OER4 Codes

Region	Annual weight, region relative to overall CPI-U	Annual weight, regional OER relative to regional CPI-U	NSA regional OER price indices
Northeast	YNEN@CPIDATA	YHOANEN@CPIDATA	UHOANEN@CPIDATA
Midwest	YMWN@CPIDATA	YHOAMWN@CPIDATA	UHOAMWN@CPIDATA
South	YSON@CPIDATA	YHOASON@CPIDATA	UHOASON@CPIDATA
West	YWEN@CPIDATA	YHOAWEN@CPIDATA	UHOAWEN@CPIDATA

Table 15: OER8 Codes, excluding OER for Size D Cities

Region	City Size Class	Annual weight, region relative to overall CPI-U	Annual weight, regional OER relative to regional CPI-U	NSA regional OER price indexes
Northeast	A	YN1N@CPIDATA	YHOAN1N@CPIDATA	UHOAN1N@CPIDATA
	B	YN2N@CPIDATA	YHOAN2N@CPIDATA	UHOAN2N@CPIDATA
Midwest	A	YM1N@CPIDATA	YHOAM1N@CPIDATA	UHOAM1N@CPIDATA
	B	YM2N@CPIDATA	YHOAM2N@CPIDATA	UHOAM2N@CPIDATA
South	A	YS1N@CPIDATA	YHOAS1N@CPIDATA	UHOAS1N@CPIDATA
	B	YS2N@CPIDATA	YHOAS2N@CPIDATA	UHOAS2N@CPIDATA
West	A	YW1N@CPIDATA	YHOAW1N@CPIDATA	UHOAW1N@CPIDATA
	B	YW2N@CPIDATA	YHOAW2N@CPIDATA	UHOAW2N@CPIDATA

Table 16: Rent8 Codes, excluding Rent for Size D Cities

Region	City Size Class	Annual weight, region relative to overall CPI-U	Annual weight, regional Rent relative to regional CPI-U	NSA regional Rent price indexes
Northeast	A	YN1N@CPIDATA	YHSRN1N@CPIDATA	UHSRN1N@CPIDATA
	B	YN2N@CPIDATA	YHSRN2N@CPIDATA	UHSRN2N@CPIDATA
Midwest	A	YM1N@CPIDATA	YHSRM1N@CPIDATA	UHSRM1N@CPIDATA
	B	YM2N@CPIDATA	YHSRM2N@CPIDATA	UHSRM2N@CPIDATA
South	A	YS1N@CPIDATA	YHSRS1N@CPIDATA	UHSRS1N@CPIDATA
	B	YS2N@CPIDATA	YHSRS2N@CPIDATA	UHSRS2N@CPIDATA
West	A	YW1N@CPIDATA	YHSRW1N@CPIDATA	UHSRW1N@CPIDATA
	B	YW2N@CPIDATA	YHSRW2N@CPIDATA	UHSRW2N@CPIDATA