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U.S. Department of Labor
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Brian Adams, U.S. Bureau of Labor Statistics
Lara Loewenstein, Federal Reserve Bank of Cleveland
Hugh Montag, U.S. Bureau of Labor Statistics
Randal Verbrugge, Federal Reserve Bank of Cleveland

Working Paper 555
October 6, 2022

Disentangling Rent Index Differences: Data, Methods, and Scope*

Brian Adams¹, Lara Loewenstein², Hugh Montag¹, and Randal Verbrugge²

¹US Bureau of Labor Statistics

²Federal Reserve Bank of Cleveland

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Abstract

Prominent rent growth indices often give strikingly different measurements of rent inflation. We create new indices from Bureau of Labor Statistics (BLS) rent microdata using a repeat rent index methodology and show that this discrepancy is almost entirely explained by differences in rent growth for new tenants relative to the average rent growth for all tenants. Rent inflation for new tenants leads the official BLS rent inflation by 4 quarters. As rent is the largest component of the consumer price index, this has implications for our understanding of aggregate inflation dynamics and guiding monetary policy.

*The views expressed in this paper are solely those of the authors and do not reflect the opinions of the Federal Reserve Bank of Cleveland or the Federal Reserve System. Emails: adams.brian@bls.org, lara.loewenstein@clev.frb.org, montag.hugh@bls.org, randal.verbrugge@clev.frb.org

1 Introduction

Shelter is by far the largest component of the Consumer Price Index (CPI), accounting for 32 percent of the index.¹ Accurate inflation measurement therefore depends critically on accurate rent inflation measurement, which is the primary input to both tenant and owner-equivalent rent. It is therefore concerning that rent indices differ so greatly. For example, in 2022q1 inflation rates in the Zillow Observed Rent Index (ZORI; see Clark (2020)) and the Marginal Rent Index (Ambrose et al. (2022)) reached an annualized 15 percent and 12 percent, respectively, while the official CPI for rent read 5.5 percent (see Figure 1).

If the Zillow reading were to replace the official rent measure in the CPI, then the 12-month headline May 2022 CPI reading of 8.6 percent would have read more than 3 percentage points higher. These are consequential discrepancies, larger than any of the historical CPI biases noted by the Boskin commission (Boskin et al. (1997)) and much greater than any of the current biases noted in Lebow and Rudd (2003) and Moulton (2018). Differences of this magnitude have consequences for housing economics, monetary policy, contract escalation, and GDP and welfare measurement (Ambrose et al. 2018; Hill et al. 2020; Ambrose et al. 2022). Furthermore, other rent indices are also more cyclical and less sticky than the CPI rent index, leading to important implications for macroeconomic modeling. For instance, Appendix D shows that Phillips curve parameter estimates (following Ashley and Verbrugge (2022)) and estimated impulse response functions of New Keynesian models (following Gelain and Manganelli (2020)) are very sensitive to the rent inflation measure used.

Why are these alternative rent measures reading so much hotter? Is the divergence because these measures focus on different segments of the rental market? The CPI rent sample is fully representative of the rental housing stock in US cities. In contrast, the Corelogic Single Family Rent Index (SFRI) covers mainly higher-tier detached rental units that advertise in the Multiple Listing Service (MLS), and the MRI covers larger apartment complexes in a restricted number of cities (Ambrose et al. 2018). Is it because they are constructed differently? The CPI for rent and owners' equivalent rent use 6-month changes in average rent growth over a fixed sample of rental units; in contrast, ZORI and the SFRI are both repeat-rent indexes, while the MRI is the product of two aggregate indexes, a price and an expected cap rate (Ambrose et al. 2022). Is it because these alternative measures measure the average rent increase facing a new tenant, while the CPI for rent measures average rent growth across all occupants?

This article uses the microdata underlying the official BLS rent index to assess the differences between the official BLS rent index and other measures of rent growth. Unlike the data underlying other rent indices, the survey data the BLS uses is a carefully constructed,

¹This is the sum of the aggregation weight of rent and owners' equivalent rent (which is also driven by rent growth) in the CPI. By comparison, food accounts for approximately 14 percent.

nationally representative random sample designed for measuring rent growth. The BLS takes great care, for example, to control for aging and to document what utilities are and are not included in rent. Data are of high quality; for instance, any unusual rent observation is flagged for review by BLS analysts. Alternative rent measures use data sources that are not designed to isolate growth in contract rent, are not carefully screened, do contain little information on utilities, do not control for aging, and are less representative.

We use the BLS microdata to create weighted repeat rent indices in the style of Case and Shiller (1989). We create a weighted new-tenant repeat rent (NTRR) index (using only leases of tenants that recently moved in) and weighted all-tenant repeat rent (ATRR) index (using all tenants, whether they recently moved in or not). Most alternative rent indices, specifically the CoreLogic Single Family Rent Index (SFRI) and ZORI, are new-tenant repeat rent indices. These repeat rent indices allow us to find whether the differences in the official BLS rent index and alternative indices are due to differences in the underlying data, scope, or methodology.

We find that most of the discrepancy between the official BLS rent index and other measures is due to scope, i.e., due to the differences in rent increases for *all* tenants versus *new* tenants. In 2022q2, our ATRR index was recording 6.68 percent year-over-year inflation, while the NTRR inflation rate was at 11.49 percent. The published BLS rent index was at 4.78 percent.

The CoreLogic SFRI, despite being based on single family rent listings from the Multiple Listing Service (MLS) (Boesel et al. 2021; Nothaft 2018), has been a fair approximation to our NTRR index. After rescaling, the MRI of Ambrose, Coulson, and Yoshida (2022) also has approximated our NTRR, even though its underlying data references only large multifamily housing.

Ambrose et al. (2015, 2022) criticized the all-tenant approach because it does not capture the cost of signing a new lease. They assert that, as a result, the BLS rent index tends to lag other rent indices and does not reflect current rental market conditions for lease-seekers. Yet, the price statistics literature generally favors the use of an all-tenant index in the CPI, as this more accurately reflects the change in purchasing power of a typical renter. We contribute to this debate by clarifying the difference that the use of a new-tenant index would make, using the same data source that underlies the CPI, and noting practical challenges that would accompany such usage.²

More generally, a price index measure should be chosen based upon its intended purpose.

²A related argument against using a new-tenant rent index in inflation measurement is that if the fraction of households that move varies significantly over time, we could be capturing price changes for an ever-changing portion of the market. We show that, consistent with other research (Ganong and Shoag 2017; Molloy et al. 2011), the share of units with new tenants has slowed in the BLS housing sample over time and shows a seasonal pattern.

For studying generalized changes in living standards over time or for escalation of social security benefits, an average tenant rent inflation measure is preferred, since it reflects what is happening to the typical household. In such contexts, data revisions — an inherent feature of repeat-rent measures — are somewhat problematic. Conversely, new tenant rent inflation measures are marginal measures that more quickly reflect changes in market conditions, making them a better comparison for alternative marginal measures of housing costs (such as monthly house prices or user costs). Also, they provide an earlier signal of inflationary pressures. In terms of such timing considerations, the CPI rent index lags our NTRR index by about four quarters, while it lags our ATRR index by about one quarter. The MRI lags our new-tenant rent index by perhaps one quarter, perhaps reflecting an information lag in the expectations of property sellers; and the SFRI and ZORI are roughly coincident with our new-tenant index.

For monetary policy considerations, it is not immediately clear which price index would be preferred. Different models yield different conclusions. In some models, the central bank should distinguish between price developments in different sectors, and (for instance) target more persistent prices (e.g., (La’O and Tahbaz-Salehi 2022)). But these models tend to take existing component indexes as given, and merely consider optimal weighting. Furthermore, relatively few models studying optimal policy include housing. As far as we know, no model has addressed the topic of optimal rental inflation measurement *per se*.

2 Rent data and price indices

2.1 BLS rent data

We use the BLS Housing Survey data, which the BLS uses to compute its CPI rent index. The Housing Survey follows a sample of renter-occupied housing units, surveying the same rental units every six months. Observations include the contract rent, the utilities and services included with the rent, the tenant’s move-in date, and many other unit and renter characteristics. Units are not necessarily surveyed at the start of leases; many observations are of continuing renters in the middle of a lease or after a lease renewal.

The BLS Housing Survey uses a multistage sampling design meant to draw a sample representative of rental expenditure.³ The first stage selects large geographic areas, called “Primary Sampling Units” (PSUs), chosen to represent all metropolitan and micropolitan areas in the United States.⁴ Each PSU is divided into segments, which become the funda-

³Table 1 demonstrates that this sample closely resembles that of the American Housing Survey (AHS), described in Appendix A.

⁴The BLS redesigned its geographic sample in 2018; now, PSUs definitions match Core-Based Statistical Areas. Previously, PSUs had been modified Metropolitan Statistical Areas and groups of counties with

mental units for sampling and weighting. In the CPI, segments consist of one or more contiguous Census blocks, often Census block groups. Segments are selected using a probability-proportional-to-size (PPS) method, where “size” is an estimate of total shelter expenditure within the segment. Finally, the BLS randomly samples enough rental units to yield at least five responding units per segment. The sample size is typically around 40,000 units.

The BLS selected a new sample in 1999. Subsequently, the survey lost units to demolition, to conversion to other uses, or to respondent non-cooperation.⁵ The survey periodically added new units sampled from construction permit data. However, more recently it has implemented a rolling sample replacement design, with new sample being drawn starting in 2012. Since 2016, units remain in the sample for only six years and one-sixth of the sample is replaced annually.

Repeat rent indices require paired observations of the same unit. Because units are surveyed every six months, an all-units repeat rent index can be calculated from nearly the beginning of the data in 1999. A repeat-rent index based on observations of new tenants can only add a unit to its calculation after the second observed move-in. Figure 5 shows between 13 and 25 percent of units have new tenants in a month. Several years are needed for a new tenant repeat rent index to achieve a steady sample size.

The official CPI dates observations to their survey collection month. A rent change in a unit may happen several months before the rent-collection period. Our repeat rent indexes instead date observations either to their recorded move-in date, or the completion of the most recent six-month interval since move-in.⁶ This is the most likely date of the rent change, because most rental contracts in the U.S. are annual, and six-month contracts are also common. Because we identify the date of the rent change (and use that month in our index construction, rather than the collection period), and because the rent change typically occurs in some month prior to the collection period, our indexes will reflect rent changes sooner than will official indexes.

The CPI Rent index and our repeat rent indexes use a rent measure called “economic rent.” Economic rent accounts for services rendered in lieu of rent, and adjusts for changes in utilities bundled with rent. It makes a hedonic adjustment for the aging of units (Crone et al. (2010); Gallin and Verbrugge (2007)). The CPI Rent index further includes vacancy adjustments and adjustments for structural change. Instead of estimating the value of structural changes, we exclude observations for which the number of rooms changes, the number

smaller towns (Paben et al. 2016).

⁵Gallin and Verbrugge (2016) suggest sample attrition was concentrated in higher-quality units; this influences aging bias estimates, among other things.

⁶For example, consider a tenant that moved into a housing unit in February 2011, and the housing unit is sampled on a April-October cycle. If the BLS microdata shows that the rent changed from October 2011 to April 2012, we assume that the month it changed was February 2012, a 6-month multiple of the move-in date.

of bathrooms or half-bathrooms changes, or a field note includes the words “remodel,” “renovate,” or “refurbish.” Instead of imputing rents for vacant units, we exclude these observations. For housing units that exit the sample, we also exclude all observations after the last date at which a new tenant moves in to mitigate the vacancy bias described in Sommers and Rivers (1983). No other index in this study makes adjustments for structural change, aging, or changes in the provision of utilities and services.

The CPI rent index uses average six-month change in that month’s sample. The index converts it into a monthly change by taking its sixth root. Let $\text{rent}_i^*(t)$ denote economic rent. Then the rent index at time t for a particular geographic region is constructed as

$$I^R(t) = \left(\frac{\sum_i w_i \text{rent}_i^*(t)}{\sum_i w_i e^{F_i, t} \text{rent}_i^*(t-6)} \right)^{1/6} I^R(t-1) \quad (1)$$

where w_i is the unit-specific weight⁷ and F_i, t is an age-bias factor that lowers the rent level in period $t-6$ to account for the fact that the observed change in rent will understate the constant-quality change in rent.⁸

2.2 Other Rent Data Sources and Indices

2.2.1 CoreLogic SFRI

The CoreLogic SFRI employs a repeat-rent methodology using rental listings of single family homes by realtors on the multiple listing services (MLS). Corelogic collects these data from participating realtor boards. In February 2014, over 90 boards participated, providing coverage for approximately 56 percent of all active listings nationwide. On average by 2020, CoreLogic had 10 years of history for these boards, and it had more than 20 years of data in some markets. The data contain information from rental listings including the list and closing rent for each unit, and the owner of the rental property.

The underlying MLS data is not representative of the general rental market. The Census’s 2018 Rental Housing Finance Survey estimates only 11 percent of single-unit rental properties are listed using a real estate agent (and thus listed on MLS).⁹ On average, rental listings on MLS are more expensive, larger and newer than newly-occupied rental units in the AHS (see Table 1). The SFRI is constructed using only single-family properties in the MLS.

⁷For each unit, there is a segment-level weight (corresponding to the segment that the unit is in), and then a second segment-specific weight that makes the unit’s weight either specific to the renter universe (for Rent). These weights also reflect the current number of units in the sample that responded in a given month.

⁸For more details on BLS index construction, see, e.g., Verbrugge and Poole (2010) or the BLS Handbook of Methods.

⁹See (Choi and Young 2020) for differential advertising strategies of landlords.

2.2.2 Marginal Rent Index

The Marginal Rent Index (ACY MRI) of Ambrose et al. (2022) uses data on large multifamily properties that have sold more than once since 2000. It multiplies a national repeat-sale index and sellers’ forward-looking estimates of average multifamily income yield (termed the capitalization rate). This produces a baseline net rent index that the ACY MRI rescales. The scaling targets matching the Repeat Rent Index of Ambrose et al. (2015) over the period for which both indexes are available. The Repeat Rent Index was calculated from Experian RentBureau data, but ended in 2009. The ACY MRI covers 20 states and 34 metropolitan areas.

2.2.3 Zillow data and microdata

The ZORI is a repeat-rent index (see Section 3.1) that begins in 2014. The ZORI makes use of its own proprietary data and MLS listing data, and uses American Community Survey data for weighting (by structure type, age, and year) with the goal of making the index representative for the entire rental stock. First, equation 2 is estimated (unweighted). The standard heteroskedasticity correction (see Ambrose et al. (2015)) had little effect; instead, Zillow runs a second-stage regression in which the squared residuals from 2 are regressed on the aggregation weights, and the predicted values from this second stage are used in a weighted least squares regression of equation 2; this index forms the ZORI. Once the index is constructed, it is smoothed using a three month exponentially weighted moving average.

3 Constructing a Repeat Rent Index

Most price indices attempt to compare prices over time for equivalent items. Otherwise, changes in quality or the composition of items sampled would be mislabeled as price changes. Because housing unit quality is so idiosyncratic, price indices use repeat observations of the same unit. Thus, the BLS returns to the same sample repeatedly and many other indices use repeated transactions for the same unit. When transactions occur with irregular frequency, the repeat sales method of Bailey et al. (1963) allows the price change between transactions to inform index levels for all periods between transactions. Because it uses observed unit-level changes in price, it controls for the time-invariant components of unobserved quality. Repeat-transaction indices have been used for house prices (Case and Shiller 1989) and rents Ambrose et al. (2015); Boesel et al. (2021); Clark (2020).

Suppose our dataset of rental prices spans N periods, such that observations are sampled from periods $\{1, \dots, N\}$. Let a unit i have rent observations in period s and period $t > s$. This observation pair enters a regression as

$$\ln P_{it} - \ln P_{is} = \gamma_2 D_{i2} + \dots + \gamma_N D_{iN} + u_{it}, \quad (2)$$

where $D_{ij} = 1$ if the second observation in the pair took place in period j , and $D_{ij} = -1$ if the first observation in the pair took place in period j , and for each other period $D_{ij} = 0$. For our example observation, $D_t = 1$ and $D_s = -1$. By using log prices, the parameters γ approximate percentage differences in prices from the base year; the base year index value is normalized to 1.

Using the BLS housing survey data, we construct two repeat rent indices, which differ only in their scope. The first is the new-tenant repeat rent (NTRR) index; like the SFRI and its peers, it is constructed using only observations with a new tenant. Observation pairs thus bookend the tenure of a renter within a housing unit: the first date records when the renter moved in, and the second date when a new renter moves in. Tenure lengths average about three years but can vary substantially. The NTRR reflects prices that a new renter would face if they changed their housing unit every period.

The second repeat rent index is an all-tenant repeat rent (ATRR) index. Its scope is broader: its sample includes all housing units and dates. In this case, each observation pair is based on the two consecutive occasions that a housing unit is surveyed as part of the BLS rental dataset. The ATRR represents the prices paid by an average renter (new and continuing). Thus, it differs in scope from the NTRR, SFRI, and several other rent indices. Comparisons of the ATRR with the NTRR will isolate the effects of changing the scope, since both draw from the same sample and share the repeat-rent methodology.

Our repeat-rent indexes are estimated using weights from the CPI rent index. First, we use segment weights (which correspond to the importance of segments within a given PSU) to estimate equation 2 for each PSU; these yield PSU-specific rent indexes. Next, we use a second set of weights, “upper” weights that represent the relative expenditure on rent for different PSU’s across the U.S., to aggregate the PSU-specific rental indexes into a national index.

The BLS collects rents every month, so we can create monthly repeat rent indices. However, volatility considerations required us to create quarterly repeat rent indices. At the PSU-level, particular months may have few observations. But repeat-rent indexes require a considerably large sample to yield inflation rate estimates which are well-behaved. The high volatility of monthly indexes, and their associated wide confidence intervals, implies that we cannot meaningfully compare our NTRR to other rent indexes at the monthly frequency.

Differences in tenure lengths may make the error term in equation 2 heteroskedastic, particularly for our NTRR index. Case and Shiller (1989) and Goetzmann (1992) propose a three-stage procedure to address it. First, we estimate equation 2 and obtain the residuals. Second, we regress the residuals squared on a constant and the time between observations.

Third, we use the resulting predicted values to estimate a GLS version of equation 2. Like Clark (2020), we found that this heteroskedasticity correction is of negligible importance in rental data. We estimate standard errors using a bootstrap method described in Appendix C.

4 Results and Discussion

4.1 Disentangling Rent Index Differences

4.1.1 Similar methods and scope, different data: NTRR and CoreLogic SFRI

Our NTRR and the CoreLogic SFRI have similar time series. Between 2005q1 and 2022q2, their inflation rates seldom show statistically-significant differences. In Figure 1, the SFRI generally appears to be a smoothed version of NTRR. Their quarterly year-on-year inflation rates never differ by more than 3.6 percentage points and have an average absolute difference of 0.89 percentage points. Quarterly changes in the two indices are highly correlated ($\rho = .92$), and neither series leads the other. Figure 3 depicts the intertemporal cross-correlations of SFRI, MRI, ATRR and the CPI for rent (denoted by “SEHA”, its item code) versus NTRR.

The similarity of NTRR and SFRI suggests the lack of representativeness of SFRI data is not driving the divergence between the SFRI and the official BLS rent index. Instead, differences mainly stem from methodology (repeat rent versus the CPI method), scope (new tenant versus all tenant), or rent adjustments (the BLS performs quality adjustments that the SFRI does not). The SFRI data approximate rent change in the BLS data, which might support their use in macroeconomic and housing studies. Because the SFRI and NTRR are similar, comparing NTRR and ATRR — which changes scope, holding methodology constant — can show how much of the difference between the SFRI and the BLS rent index is due to scope.

4.1.2 NTRR and other indices

The ZORI begins in 2014, providing a shorter comparison period with our NTRR. The ZORI quarterly year-on-year rent inflation rate is often similar to the NTRR, but not always. Indeed, in recent quarters, the ZORI inflation rate exceeds not only our NTRR, but all other rental inflation rates. Nevertheless, ZORI and the NTRR are highly correlated ($\rho = .93$).

The MRI is more volatile than NTRR (see Figure 1). It lags NTRR by about one quarter (see Figure 3, perhaps reflecting an information lag in the expectations of property sellers. Ambrose et al. (2022) rescale their net rent index to construct the MRI, and an alternative rescaling may improve its similarity with NTRR; section 5.2 explores this.

4.1.3 Same data and methods, different scope: NTRR and ATRR

We next compare our NTRR and ATRR; see Figure 2. The two indices differ mostly in their scope (new tenants versus all tenants), so their difference will reflect the importance of scope. We find that scope is of central importance in explaining the difference between the CPI for rent and other rent indexes, both in timing and in volatility.

The NTRR leads the ATRR considerably. This is evident both in a visual comparison of their time series (in Figure 2) and in their intertemporal cross-correlations (Figure 3). The NTRR's trough in rents after the housing crisis is deepest in 2009q3, whereas ATRR reaches its trough notably later in 2010q3. Likewise, we observe that the current price spike begins in NTRR well before it begins in ATRR.

As Figure 3 shows, NTRR leads ATRR by about three quarters, while it leads the CPI for rent by about four quarters. This one-quarter differential is the average time between BLS collection and actual rent change. This collection days and the smoothing induced by using 6th root of a 6-month change, are of secondary importance for explaining why the CPI for rent lags other indexes. Instead, our findings indicate that most of the lag between the CPI for rent and indices like NTRR (and SFRI) is due to scope: the CPI measures the prices that all tenants pay, while other indexes measure only the prices of new tenant leases.

The NTRR is much more volatile than the ATRR. The large rent decline in 2009-2010 and the inflation spike in 2021-2022 are more extreme in the NTRR, but even lesser fluctuations throughout the 2010s are more pronounced in the NTRR. Standard errors on the ATRR are small, averaging .04 percentage points.

In contrast, the NTRR has larger standard errors, averaging .65 percentage points. The chief reason for this difference is that the NTRR is calculated from subset of the observations in the ATRR — those with newly moved-in tenants. But a second reason is that continuing renters in the ATRR, even when signing new leases, tend to have sticky rents.

4.1.4 Same data and scope, different methods: ATRR and CPI Rent

Finally, we compare the ATRR to the CPI for rent. Differences between these indexes reflect several methodological differences. First, the index construction method differ. Second, the CPI must apply a vacancy correction and thus includes more imputed rents, while the ATRR addresses vacancy correction by dropping units. Third, the CPI applies a quality adjustment for large structural changes, while ATRR drops such observations. Fourth, the CPI applies an aging bias adjustment. Fifth, the CPI uses all rental observations in its microdata, while the ATRR sample removes outliers and observations with large structural changes. The ATRR leads the Rent CPI slightly, chiefly because ATRR observations are backdated to the move-in date.

5 Additional Results

5.1 Repeat rent end-sample variability (and effective sample size over time)

A new price observation for a unit i in period s informs repeat-rent index estimates for previous periods, since this observation provides a new data point for estimating the index in unit i 's previous observation. The sample size available to estimate the index at time s is smallest at time s , and grows for time $t > s$. Thus, the index estimate for period s gradually improves, as more rent observations accumulate in later periods.

The effect is quantitatively important. First, we examine the evidence in a snapshot of sample over time, namely a graph of the current sample size by quarter; see the upper panel in Figure 5. In this figure, we observe a clear seasonal pattern, reflecting the seasonal pattern of moving (relocations are higher in summer and fall). We also observe a decline in sample size starting in 2012. The lower panel displays new tenancies as a fraction of all tenancies in the BLS rent microdata. The decline in new tenancies in our data is mainly driven by two factors. First, there is the “smallest sample-size” effect just discussed, that there are few observations towards the end of the sample. This effect is seen dramatically in the last two quarters. But presumably this effect mainly influences the last few years, since the average tenure length in a rental unit is roughly three years. Second and more important, there is an influence unique to BLS microdata. Starting in 2012, the BLS sample began converting to a six-year rotation (see Section 2.1) — thus, a given rental unit is included in the sample only for six years. Prior to this, a unit would typically remain in the sample for much longer. Why does this six-year rotation matter? Because of right-truncation. Given an average rental tenure rates of about three years, then on average, we will observe only a single rent pair (i.e., observe only two new tenancies) for each unit over that unit's lifetime in the sample, even though the BLS will have collected 12 rent observations over this period.

Second, we provide an example of inflation-estimate revision in Figure 6. In this figure, the red line depicts the historical inflation rate that would have been estimated using only the data available up through 2015Q4. The black line depicts the historical inflation rate using all of the data (through 2022Q2). The deviation represents the influence of additional sample. Notice that in the 2015Q4 estimates, quarters 2015Q1-Q4 display much wider confidence intervals, and received large revisions as more data became available. Repeat-rent indexes are inherently prone to this behavior, although the effect will be exacerbated if the sample size is small to begin with.

5.2 Rescaling the MRI

The MRI displays higher volatility than the SFRI and NTRR, though all should be measuring approximately the same thing — growth in new-tenant rents. The MRI is a rescaled version of a net rent index (see Section 2.2.2), and we conjecture that its deviations from NTRR could be diminished by a suitable rescaling. Accordingly, we rescale the year-on-year percentage change in MRI to minimize its mean squared error versus year-on-year percentage change of NTRR. In particular, the minimization problem is

$$\min_{r,a} \sum_t \left(r \left(\pi_{t,rMRI}^{y/y} \right) + a - \pi_{t,NTRR}^{y/y} \right)^2 \quad (3)$$

where $\pi_{t,rMRI}^{y/y}$ is the year-over-year inflation in the MRI, $\pi_{t,NTRR}^{y/y}$ is the year-over-year inflation in the NTRR, r is the scaling factor, and a is a constant. We term the resulting (rescaled) index the RMRI. The mean squared error-minimizing value of r is 0.443 and a is 1.55. The RMRI matches the dynamics of the NTRR and the SFRI fairly well; it generally lies within the error bounds of the SFRI except briefly in 2011 and 2012. We hypothesize that due to the forward-looking nature of the MRI data, the MRI changes with the same timing as our NTRR, albeit by different magnitudes.

5.3 Dynamic relationships

To explore the dynamic relationships between the various rent index inflation rates, as well as to assess potential forecast gains for CPI rent using SFRI, we estimate vector error-correction (VECM) models on pairwise sets of series. These highlight both the long-term relationship, and their shorter-run dynamics. The VECM models are specified as

$$\Delta y_t = \alpha(\beta' y_{t-1}) + v + \sum_{i=1}^3 \Lambda \Delta y_{t-i} + \epsilon_t \quad (4)$$

where $y_t = (y_{1,t}, y_{2,t})'$ is a bivariate vector, $\Delta y_t = (y_t - y_{t-1})$, v is a vector, Λ is a matrix of coefficients on lag terms, the vector $\beta = (\beta_1, \beta_2)'$ describes the long-term cointegration relationship between y_1 and y_2 such that $\beta' y_{t-1}$ is stationary, and α determines the speed at which each variable adjusts back towards this relationship. β_1 is normalized to 1. We estimate these relationships on pre-pandemic data, to avoid overfitting based on one extreme episode. Table 2 reports the values of α and β along with some standard errors. In this table, “SEHA” refers to CPI-rent. The other coefficient estimates are provided in table 2.

Long-term relationship estimates suggest that long-term averages of all four of the series investigated will coincide. In responding to deviations from the long-term relationship,

NTRR and ATRR do most (or all) of the adjusting to eliminate said deviations; NTRR also does most of the adjusting towards ATRR, and towards SEHA. Conversely, and somewhat surprisingly, in SEHA-CoreLogic relationship, neither variable strongly moves to eliminate the gap.

We explore the predictive content of SFRI for SEHA using the Bayesian Information Criterion (BIC). Dropping all SFRI terms from Equation (4) — i.e., using a univariate model in $\Delta SEHA_t$ — the BIC is -0.127. Inclusion of lags of SFRI cause the BIC to fall to -0.491, indicating substantial predictive content for these terms. However, if one then adds the cointegration term ($\beta'y_{t-1}$), the BIC rises to -0.456, indicating that omitting this term is preferred.

6 Conclusion

Housing occupies a prominent place in aggregate price indexes, so accuracy in rent inflation measurement is crucial for accurate inflation measurement. But recently, the accuracy of CPI rent inflation measurement has been called into question, prompted mainly by divergent signals from other rent measures. These differences are consequential. For example, replacing CPI rent with Zillow’s ZORI would have raised headline CPI inflation in May 2022 by more than 3 percentage points. Moreover, alternative rent indexes have different dynamic properties, so their inclusion in aggregate indexes could have first-order influence on parameter estimates of macroeconomic and financial models. Thus, an important question is: what drives the differences between these rent indexes?

To answer this question, we construct repeat rent indexes using the confidential rent microdata used for CPI rent index. These data represent the only data source suitable for this analysis, because they are the high-frequency rent data that are fully representative of the U.S. rental market. We demonstrate that the discrepancy between CPI rents and other rent indexes is almost entirely driven by differences in rent growth for new tenants relative to the average rent growth for all tenants.

CoreLogic’s SFRI has a surprisingly close relationship to our new tenant repeat-rent index over our sample period, despite the fact that SFRI data are not representative: they pertain only to larger and more expensive single-family units, and are not fully geographically representative. SFRI rent movements help predict CPI rent movements.

Which rent index is most suitable for use in the CPI? Index purpose should guide index design. Many of the important uses of the CPI, such as contract escalation and social security indexation, favor the use of average rents rather than new-tenant rents. But an important question for future research relates to macroeconomic modeling by central bankers. New-tenant rent indexes more quickly reflect inflationary pressures, which in turn will strongly

influence model parameter estimates. The issue of which rent index best relates to central bankers' objectives is not a trivial one. We contribute to this debate chiefly by highlighting the different dynamic properties of these indexes, and by raising two key operational issues: repeat-rent indexes are noisy in real time and can experience large revisions for a few years.

References

- Adams, Brian and Randal Verbrugge (2021). “Location, location, structure type: Rent divergence within neighborhoods.” Working Paper 21-03, Federal Reserve Bank of Cleveland. URL <https://www.clevelandfed.org/en/newsroom-and-events/publications/working-papers/2021-working-papers/wp-2103-location-and-structure-type-rent-divergence-within-neighborhoods.aspx>.
- Ambrose, Brent W, N Edward Coulson, and Jiro Yoshida (2015). “The repeat rent index.” *Review of Economics and Statistics*, 97(5), pp. 939–950. doi:10.1162/REST_a_00500.
- Ambrose, Brent W, N Edward Coulson, and Jiro Yoshida (2018). “Reassessing Taylor rules using improved housing rent data.” *Journal of Macroeconomics*, 56, pp. 243–257. doi:10.1016/j.jmacro.2018.03.001.
- Ambrose, Brent W, N Edward Coulson, and Jiro Yoshida (2022). “Housing rents and inflation rates.” doi:10.2139/ssrn.2787193.
- Ashley, Richard and Randal Verbrugge (2022). “An intermittent Phillips curve: finding a stable (but persistence-dependent) Phillips curve model specification.” Manuscript, Federal Reserve Bank of Cleveland.
- Bailey, Martin J, Richard F Muth, and Hugh O Nourse (1963). “A regression method for real estate price index construction.” *Journal of the American Statistical Association*, 58(304), pp. 933–942. doi:10.1080/01621459.1963.10480679.
- Boesel, Molly, Shu Chen, and Frank E. Nothaft (2021). “Housing preferences during the pandemic: effect on home price, rent, and inflation measurement.” *Business Economics*, 56, pp. 200 – 211. doi:10.1057/s11369-021-00241-4.
- Boskin, Michael J, Ellen R Dulberger, Robert J Gordon, Zvi Griliches, and Dale W Jorgenson (1997). “The CPI commission: Findings and recommendations.” *The American Economic Review*, 87(2), pp. 78–83. URL <https://www.jstor.org/stable/2950888>.
- Case, Karl E and Robert J Shiller (1989). “The efficiency of the market for single-family homes.” *The American Economic Review*, 79(1), p. 125. URL <https://www.jstor.org/stable/1804778>.
- Choi, Jung Hyun and Caitlin Young (2020). “Owners and renters of 6.2 million units in small buildings are particularly vulnerable during the

- pandemic.” *Urban Wire*. URL <https://www.urban.org/urban-wire/owners-and-renters-62-million-units-small-buildings-are-particularly-vulnerable-during>
- Clark, Joshua (2020). “Methodology: Zillow Observed rent Index (zori).” <https://www.zillow.com/research/methodology-zori-repeat-rent-27092/>. Accessed: 2021-03-02.
- Crone, Theodore M, Leonard I Nakamura, and Richard Voith (2010). “Rents have been rising, not falling, in the postwar period.” *The Review of Economics and Statistics*, 92(3), pp. 628–642. doi:10.1162/REST_a_00015.
- Foote, Christopher L, Lara Loewenstein, and Paul S Willen (2020). “Cross-Sectional Patterns of Mortgage Debt during the Housing Boom: Evidence and Implications.” *The Review of Economic Studies*, 88(1), pp. 229–259. doi:10.1093/restud/rdaa034.
- Gallin, Joshua and Randal J. Verbrugge (2007). “Improving the CPI’s age-bias adjustment: Leverage, disaggregation and model-averaging.” Working Paper 411, US Bureau of Labor Statistics. URL <https://www.bls.gov/osmr/research-papers/2007/pdf/ec070100.pdf>.
- Gallin, Joshua and Randal J. Verbrugge (2016). “Panel data estimates of age-rent profiles for rental housing.” Working Paper 16-30, Federal Reserve Bank of Cleveland. URL <https://www.clevelandfed.org/en/newsroom-and-events/publications/working-papers/2016-working-papers/wp-1630-age-rent-profiles.aspx>.
- Ganong, Peter and Daniel Shoag (2017). “Why has regional income convergence in the us declined?” *Journal of Urban Economics*, 102, pp. 76–90. doi:10.1016/j.jue.2017.07.002.
- Gelain, Paolo and Simone Manganelli (2020). “Monetary policy with judgment.” Working Paper 2404, European Central Bank. URL <https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2404~bce81d28a5.en.pdf>.
- Goetzmann, William Nelson (1992). “The accuracy of real estate indices: Repeat sale estimators.” *The Journal of Real Estate Finance and Economics*, 5(1), pp. 5–53. doi:10.1007/BF00153997.
- Hill, Robert J., Miriam Steurer, and Sofie R. Walzl (2020). “Owner occupied housing, inflation and monetary policy.” Working Paper 2020-18, University of Graz. URL <http://www100.uni-graz.at/vwlwww/forschung/RePEc/wpaper/2020-18.pdf>.
- La’O, Jennifer and Alireza Tahbaz-Salehi (2022). “Optimal monetary policy in production networks.” *Econometrica*, 90(3), pp. 1295–1336. doi:10.3982/ECTA18627.

- Lebow, David E and Jeremy B Rudd (2003). “Measurement error in the Consumer Price Index: where do we stand?” *Journal of Economic Literature*, 41(1), pp. 159–201. doi:10.1257/002205103321544729.
- Molloy, Raven, Christopher L Smith, and Abigail Wozniak (2011). “Internal migration in the United States.” *Journal of Economic Perspectives*, 25(3), pp. 173–96. doi:10.1257/jep.25.3.173.
- Moulton, Brent R (2018). “The measurement of output, prices, and productivity.” Technical report, Hutchins Center on Fiscal & Monetary Policy at Brookings, Washington, DC. URL <https://www.brookings.edu/research/the-measurement-of-output-prices-and-productivity/>.
- Nothaft, Frank (2018). “Single-family rental: Measuring rent growth and return.” *Realtor University: The Journal of the Center for Real Estate Studies*, 6(1), pp. 5–14.
- Paben, Steven P., William H. Johnson, and John F. Schilp (2016). “The 2018 revision of the consumer price index geographic sample.” *Monthly Labor Review*. URL <https://www.bls.gov/opub/mlr/2016/article/the-2018-revision-of-the-CPI-geographic-sample.htm>.
- Sommers, J.P. and J.D. Rivers (1983). “Vacancy imputation methodology for rents in the cpi.” In *Proceedings of the American Statistical Association, Business and Economic Statistics Section*. American Statistical Association, Alexandria, VA.
- Verbrugge, Randal (forthcoming). “Is it time to reassess the focal role of core PCE inflation in assessing the trend in PCE inflation?” *Economia*.
- Verbrugge, Randal and Robert Poole (2010). “Explaining the rent–OER inflation divergence, 1999–2007.” *Real Estate Economics*, 38(4), pp. 633–657. doi:10.1111/j.1540-6229.2010.00278.x.
- Wolter, Kirk M. (2007). *Introduction to Variance Estimation*. Springer, New York, 2nd edition. doi:10.1007/978-0-387-35099-8.

	All rental units		Units with new tenants		
	AHS	BLS	AHS	BLS	MLS
Rent (2015 \$)	1,043	1,046	1,017	1,043	1,739
Years Between Obs.	2.8	0.7	4.1	1.4	2.5
Characteristics					
Year Built	1967	1973	1970	1977	1981
Rooms (#)	5	4	4	4	6
Bedrooms (#)	2	2	2	2	3
Bathrooms (#)	2	1	2	2	2
Air Conditioning					
Central (%)	59.3	57.1	64.9	64.0	76.2
Other or None (%)	40.7	42.9	35.1	36.0	18.7
Property Type					
Detached (%)	28.1	21.9	25.5	15.0	46.5
Semidetached (%)	8.8	15.1	8.6	14.0	28.0

Table 1. SUMMARY STATISTICS. *Note:* Values from the AHS are from the 2015, 2017, and 2019 surveys. Values from MLS are from 2015 onwards. *Source:* AHS, MLS.

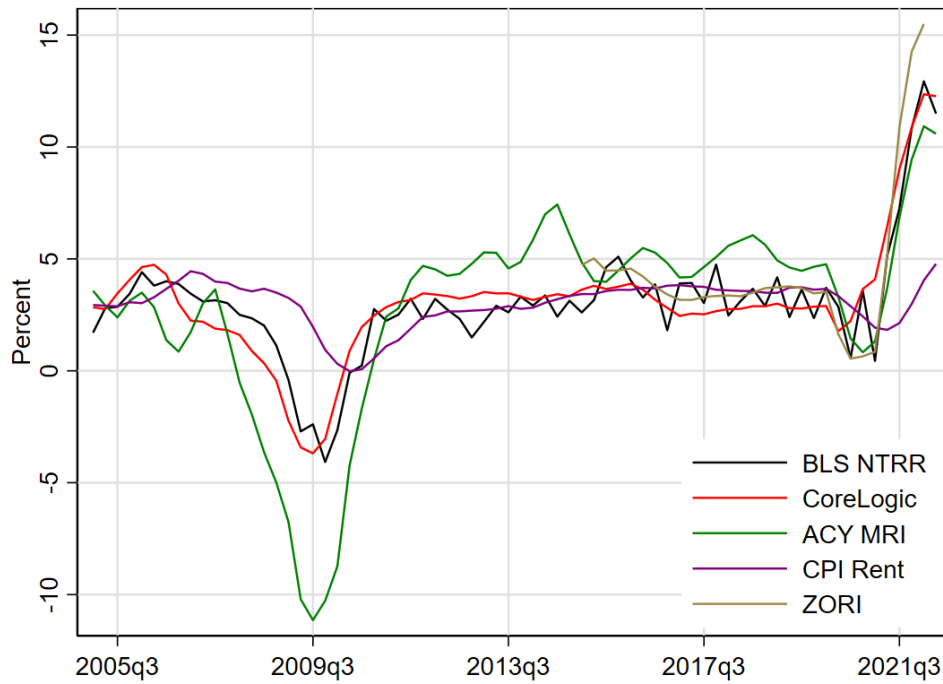


Figure 1. COMPARISONS OF RENT INDICES. *Note:* A comparison of BLS Shelter Index, Publicly Available Rent Indices, and Our New-Tenant Repeat Rent Index whose construction is described in Section 3. *Source:* BLS Housing Survey, Corelogic SFRI, Zillow (ZORI) and Ambrose et al. (2022) for the ACY MRI.

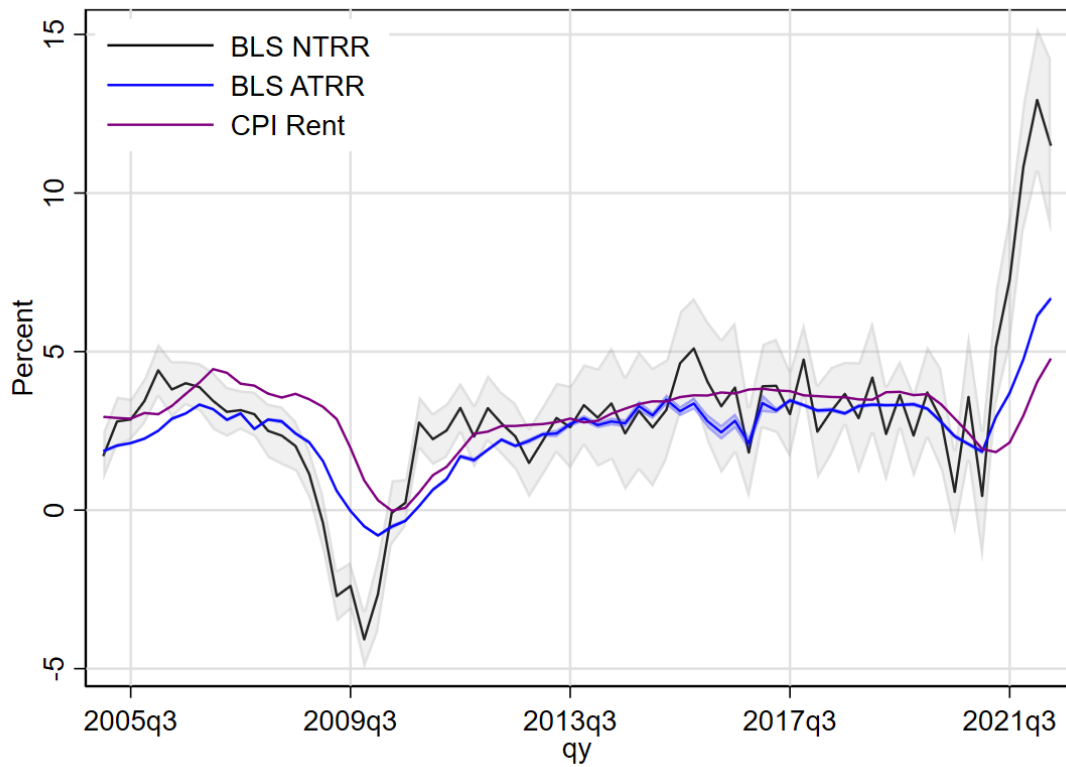


Figure 2. NTRR VERUS ATRR. *Note:* CPI Rent is rent of primary residence. The construction of ATRR and NTRR are described in Section 3. *Source:* BLS Housing Survey.

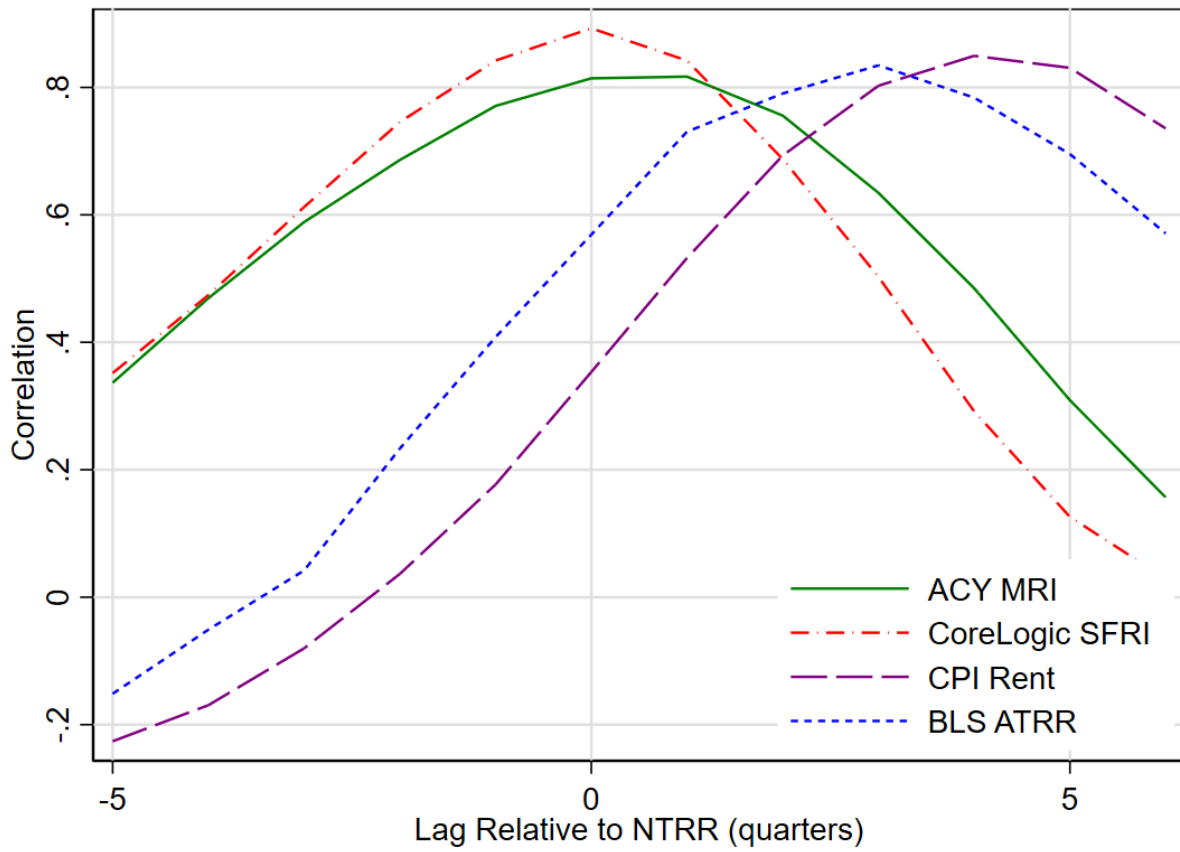


Figure 3. LAGGED CORRELATION WITH THE NTRR. *Source:* Authors' calculations on data from BLS, Corelogic, Zillow and Ambrose et al. (2022).

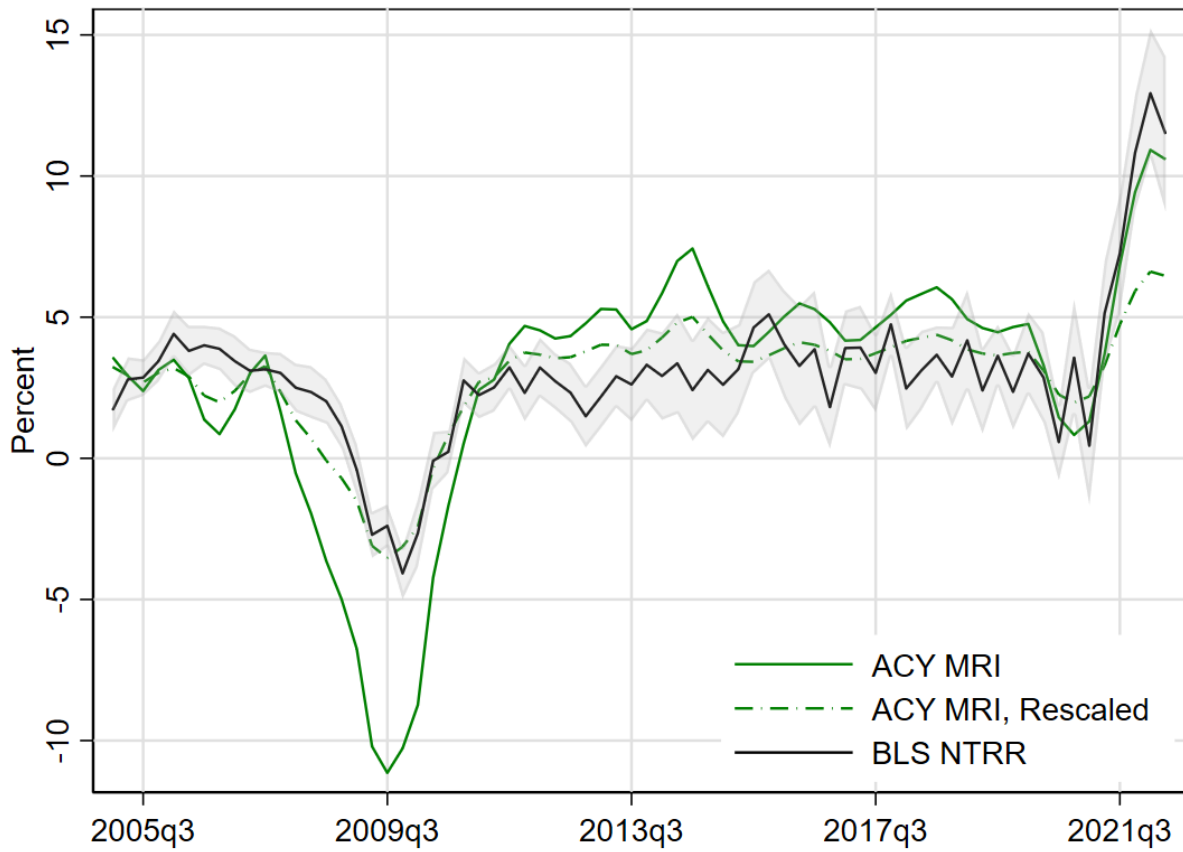


Figure 4. RESCALED VERSION OF MARGINAL RENT INDEX FROM AMBROSE ET AL. (2022). *Note:* Source: BLS and Ambrose et al. (2022).

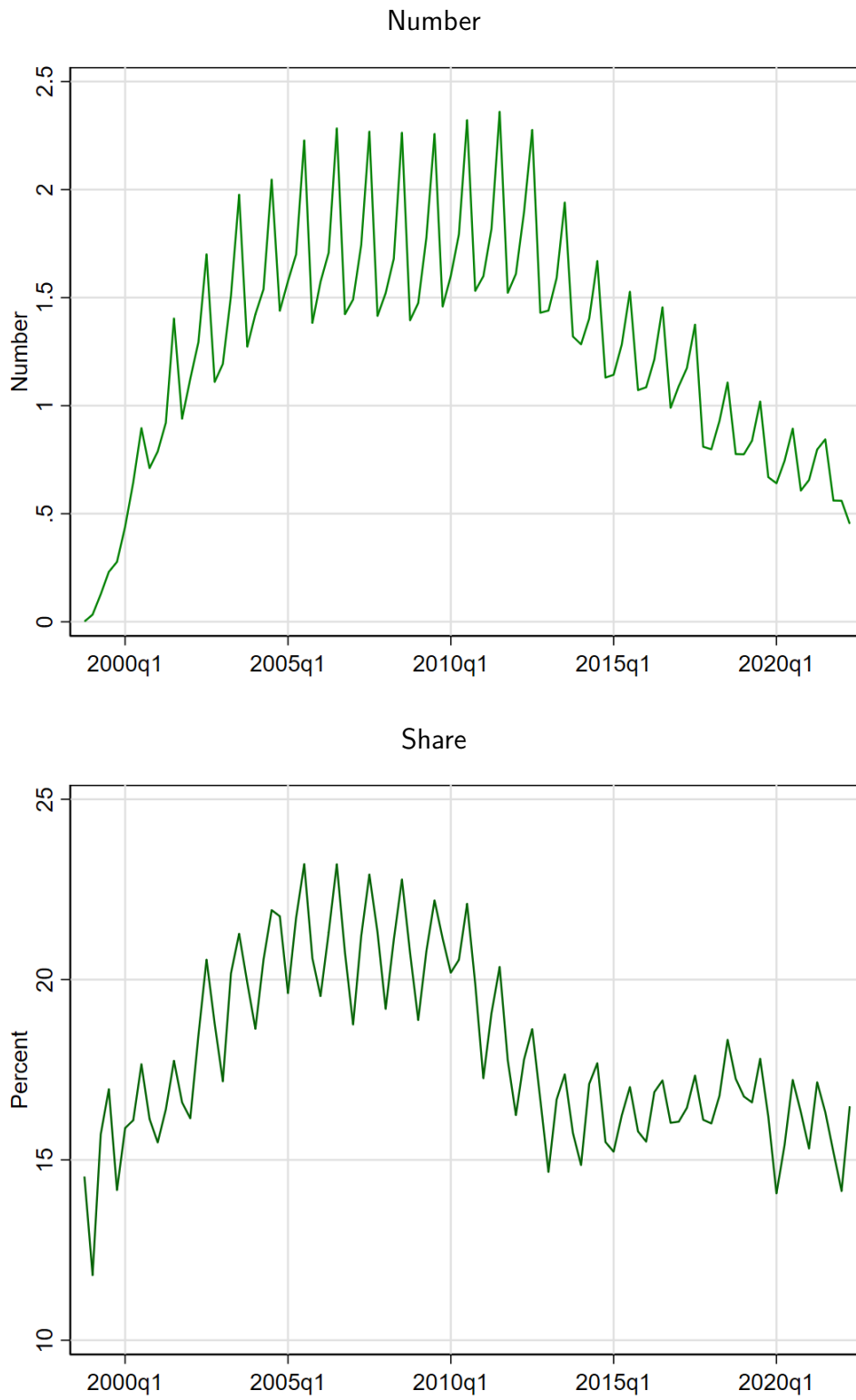


Figure 5. SHARE AND NUMBER OF OBSERVATIONS USED IN CONSTRUCTION OF NEW TENANT REPEAT RENT INDEX. *Note:* .Source: BLS.

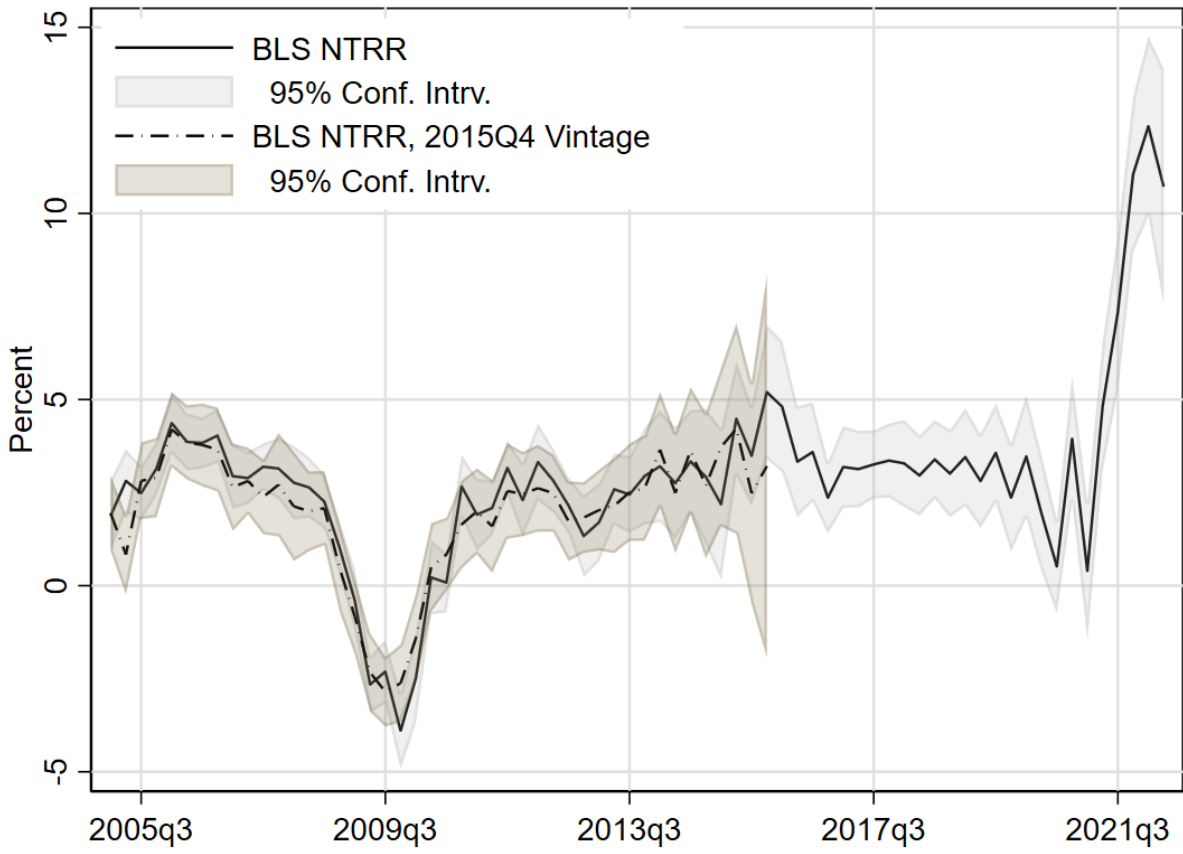


Figure 6. COMPARING REPEAT RENT INDICES USING DIFFERENT DATA VINTAGES. *Note: Source: BLS.*

	NTRR-CoreLogic	ATRR-CoreLogic	NTRR-CoreLogic	NTRR-CPI Rent	CPI Rent-CoreLogic	NTRR-ATRR
Cointegrating Equation						
β_1	1.000	1.000	1.000	1.000	1.000	1.000
β_2	-0.976	-1.017	-0.803	-1.290	-1.031	-1.031
(Std Error)	(0.070)	(0.094)	(0.047)	(0.116)	(0.046)	(0.046)
Speed of Adjustment						
α_1	-0.512	-0.146	-0.363	-0.053	-0.602	-0.602
(Std Error)	(0.029)	(0.002)	(0.028)	(0.000)	(0.025)	(0.025)
α_2	-0.094	0.041	0.081	0.039	0.036	0.036
(Std Error)	(0.007)	(0.004)	(0.001)	(0.003)	(0.003)	(0.003)

Table 2. Pairwise Vector Error Correction Results

Appendix A Representativity: Further Details

In the main body, we briefly discussed the representativity of data underlying the SFRI, the ZORI, the MRI, and indexes based upon BLS data. In this section, we discuss the sample representativity of two other data sources, as well as other information pertinent to comparison studies like this one.

A.1 American Housing Survey data

The AHS is a longitudinal housing unit survey conducted biennially by the U.S. Department of Housing and Urban Development in odd-numbered years and designed (after weighting) to represent the U.S. housing stock (and not U.S. housing expenditure). Based upon 1980 Census data, the national sample underwent a redesign in 1985, with a base sample size of approximately 47,000 housing units (owned and rented). However, few homes remained in the panel over its entire length; over the 1985-2013 period, 100,000 different homes were included.¹⁰ In 2005, the national sample was improved in two ways: first, mobile home coverage was adjusted by replacing the units currently in the sample with mobile homes selected from Census 2000 and, second, assisted living housing units selected from Census 2000 were introduced into the sample. A new representative national sample of approximately 85,000 housing units was drawn for the 2015 AHS using the Master Address File (MAF) as the sampling frame, with additional oversampling of selected metropolitan areas and HUD-assisted housing units. The total sample size beginning in 2015 is about 115,000 housing units.

The AHS collects information about units' physical characteristics (including the physical condition of homes), information on neighborhoods, information on the characteristics of people who live in the homes, vacancies, home improvements, and housing costs. In Table 1, we use the national sample in 2015; the AHS sample was redrawn at this date, so the sample is discontinuous there.¹¹ AHS data do not identify whether utilities are included in the contract rent.

A.2 American Community Survey

We provide information on the ACS because it is currently used in BLS sampling (and starting in 2019, for weights in ZORI) and because it is a source of national rental information,

¹⁰An interesting aspect of the AHS is that a housing unit's transitions between owner-occupied and renter-occupied are observable; see, e.g., Foote et al. (2020). Conversely, in BLS data, transitions from owner-occupied to renter-occupied occur outside of the sample, and a transition from renter-occupied to owner-occupied will typically imply that the unit drops from the sample.

¹¹We do not have access to Zillow microdata or to RCA CPPI microdata, so their corresponding summary statistics are not included in the Table.

although—given that it is not longitudinal data—it is not ideally suited for constructing rent indexes (it cannot be used to construct repeat-rent indexes, for example).

The ACS is an ongoing monthly survey (that started in 2005), designed to reflect the U.S. population (and provide information about “communities”). Given this focus, its hierarchy of geography is thus: nation, regions, divisions, states, counties, census tracts, and finally block groups. The Census Bureau mails questionnaires to approximately 295,000 addresses a month across the United States. Each address has about a 1-in-480 chance of being selected in a month, and no address may be selected more than once every 5 years. In other words, it is a repeated cross-section.

The ACS asks about tenure (owner/renter), acreage, rent, selected owner costs, age, value of home (if owned), rooms, bedrooms, whether occupants obtain government assistance, house heating fuel, kitchen facilities, and plumbing facilities, among other things. Public-use files, which we use, contain a subset of the ACS microdata. At the block group and tract level, only five-year estimates are available.

A.3 Geographic representativity

Geographic coverage of each data source was discussed above. RentBureau data and RCA CPPI data are highly geographically concentrated, and MLS data are modestly geographically concentrated. BLS data are representative of expenditures across urban areas in the U.S., and AHS data (and ACS data, to a somewhat lesser extent) are representative of housing units across the entire U.S. To convey a sense of the coverage of MLS data versus BLS data, Figure 10 maps what locations are most sampled in Los Angeles, where both data sources have many observations. The BLS sample is concentrated in its selected segments, but these segments are spread throughout the metropolitan area.

A.4 Importance of representativity

Why is sample representativity important? A non-representative sample is, effectively, a sample that has conditioned on a variable, such as geography or structure type. (Equivalently, non-response bias is a chief concern in many contexts.) In the rent context, “location-location-location” has been an aphorism in real estate since at least the 1920s, and rent growth can vary significantly within and across cities (e.g., Verbrugge and Poole (2010)). Real estate markets are segmented by location, but also by structure type (Adams and Verbrugge (2021)). Thus, rental market dynamics vary not only by location, but also by structure type (within a location). A data source that is restricted along one of these two dimensions will feature rent movements that differ from the average, at least over some periods.

Appendix B MLS-based repeat rent index

The Corelogic SFRI is based on housing units listed for rent on MLS. Because Corelogic also provides access to the underlying data, these data are often used by researchers. While the level of rents in the MLS data is not representative (see Table 1), our results suggest that over our sample period, the rent growth of properties listed in MLS is representative. Most researchers use these data for a specific area. We therefore created a series of rent indices using the MLS data for areas that match the PSUs in the BLS Housing Survey. Our methodology is identical to that described in Section 3, including that we remove any properties that the listing indicates were recently renovated or remodeled. We then compared the resulting MLS and CPI-data-based indices, and found that they consistently gave similar results — although the CPI-based indices are more volatile, reflecting their smaller sample size. Figure 7 contains three examples. Our findings should provide some confidence to researchers who wish to use the MLS data to measure local rent growth.

Appendix C Constructing variance estimates for repeat-rent indices

In those cases where we have access to the underlying microdata, these data either derive from a multistage sampling design (BLS data) or from an unknown selection mechanism (MLS data). These data are then used to create a repeat-rent index, whose four-quarter growth rate is then computed. This is a nonlinear function of the data. In such cases, variances are unknown. To determine whether these indices are statistically indistinguishable, we estimate variances of the quarterly estimates using a bootstrap analysis, following Wolter (2007). These methods are even applicable for estimators deriving from complex sample survey designs.

The basic idea involves forming random groups by resampling housing units at random with replacement within each PSU in the BLS rental sample. We create k groups of housing units for each PSU, and then use the groups to create k PSU-specific repeat rent indices. Next, we use the upper-level weights to aggregate the resampled PSU indices to create k national repeat rent indices. The estimate of the variance $v(\hat{\theta})$ in any given month is given by:

$$v(\hat{\theta}) = \frac{1}{k-1} \sum_{j=1}^k (\hat{\theta}_j - \hat{\theta})^2, \quad (5)$$

where $\hat{\theta}$ is the average estimate across the k groups, and $\hat{\theta}_j$ is the estimate from group j ,

and we have suppressed the time subscript. Since k is not large in our applications, the confidence interval takes the form

$$\hat{\theta} \pm t_{k-1, \alpha/2} \sqrt{v(\hat{\theta})}, \quad (6)$$

where $t_{k-1, \alpha/2}$ is the upper $\alpha/2$ percentage point of the t distribution.

To ensure that the random group estimator has acceptable statistical properties, the random groups must be formed so that each group has the same sampling design as the original sample. Thus, in the multistage sampling undertaken by the BLS for its rent sample, random groups must be formed by dividing the ultimate clusters, which are Census block groups, into k groups.

Appendix D Implications of alternative rent measures for macroeconomic modeling

In this section, we investigate the importance of using alternative rent measures in aggregate price measures for statistical inferences in Phillips curve estimation and in New Keynesian Dynamic Stochastic General Equilibrium (DSGE) models.

We start by describing the construction of an alternative price index, the “core SFRI” PCE price index. While the CPI is in widespread use in the economy — for instance, in contract escalation, in social security inflation adjustments, and in financial market contracts — the PCE price index dominates monetary policy decision-making. The inflation target is specified in terms of the headline PCE index, and core PCE (i.e., PCE-less-food-and-energy) plays a focal role in monetary policy deliberations — as it is thought to be an index that does a good job in removing noise from the headline PCE index.¹² Accordingly, Phillips curve models, and DSGE models that are focused on monetary policy (especially those within the Federal Reserve system), are often specified in terms of core PCE.

The rent data entering the PCE price index ultimately derive from CPI rent movements (either the CPI for rent, or the CPI for owners’ equivalent rent, which are both driven by rent movements in the CPI rental sample.) However, use of a new-tenant rent index in the PCE price index could potentially yield notably different dynamics. For illustrative purposes, we construct an alternative core PCE index, one in which all rent and owners’ equivalent rent categories in the core PCE are replaced by the CoreLogic SFRI rent.¹³ In particular,

¹²In this context, Verbrugge (forthcoming) argues that core PCE is long overdue for replacement.

¹³We are not the first to investigate the importance of alternative rent measures for inflation measurement and its many consequences. For instance, Ambrose et al. (2022) investigate the use of the MRI as the measure of rent and owners’ equivalent rent in the CPI index. Differences are quite stark. However, the CPI places a greater weight on housing consumption than does the PCE, so it is of interest to investigate the

we first seasonally-adjust monthly growth rates in SFRI. Then we replace monthly growth rates in “Tenant-occupied mobile homes,” “Tenant-occupied, stationary homes and landlord durables,” “Owner-occupied mobile homes,” and “Owner-occupied, stationary homes” with these SFRI monthly growth rates. These four PCE categories have an average core PCE aggregation weight of 17.5 percent from January 2004-June 2022. SFRI data are only available starting in January 2004, so our “core SFRI” index begins in February 2004.

We display the monthly growth rate of the new index in Figure 8, along with the growth rate of core PCE. While core SFRI is more volatile, in most months the difference between the inflation rates is modest, and usually those differences are not persistent. The median difference is a mere 0.08 percentage points. But in some periods, such as September 2008 - June 2009, differences exceed 0.5 percentage points — while in some other periods, such as from January to May of 2009, and from April 2021 to April 2022, differences exceed a full percentage point.

We next demonstrate that Phillips curve parameter estimates (following Ashley and Verbrugge (2022)), and parameter estimates and impulse response functions of New Keynesian models (following Gelain and Manganelli (2020)), are very sensitive to the rent inflation measure used in the core Personal Consumption Expenditures index. This is somewhat remarkable, given the shortness of the sample and what look to be modest differences between the two alternative core PCE indexes.

First, we specify a Phillips curve, following Ashley and Verbrugge (2022). Those authors demonstrate that the Phillips curve is persistence-dependent (fluctuations in inflation respond differently to persistent fluctuations in unemployment, versus less-persistent fluctuations in unemployment), and further that both of these relationships feature sign asymmetry.¹⁴ Let π_t^{core} denote monthly inflation in the core PCE index, $\pi_t^{coreSFRI}$ denote monthly inflation in the core SFRI index, $u_t^{neg.lowgap}$ denote the negative portion of persistent fluctuations in the unemployment rate gap, and $u_t^{pos.medgap}$ denote the positive portion of the moderately-persistent fluctuations in the unemployment rate gap. Below we display our specification; and immediately below the two Phillips curve coefficients ϕ^{low} and ϕ^{med} , we also display these coefficient estimates (and standard errors).

$$\pi_t^{core} = \alpha + \sum_{k=1}^3 \beta_k \pi_{t-k}^{core} + \underbrace{\phi^{low}}_{0.29 \text{ (0.47)}} u_{t-1}^{neg.lowgap} + \underbrace{\phi^{med}}_{0.82 \text{ (0.57)}} u_{t-2}^{pos.medgap} + e_t \quad (7)$$

$$\pi_t^{coreSFRI} = \alpha + \sum_{k=1}^3 \beta_k \pi_{t-k}^{coreSFRI} + \underbrace{\phi^{low}}_{0.30 \text{ (0.56)}} u_{t-1}^{neg.lowgap} + \underbrace{\phi^{med}}_{1.52 \text{ (0.70)}} u_{t-2}^{pos.medgap} + e_t \quad (8)$$

impact of alternative rent measures in the core PCE index.

¹⁴Given the dynamics of these persistence components, the resulting estimated Phillips curve has a natural interpretation in terms of a Phillips curve relationship that is “intermittent”: strong at the onset of a recession and for a few months after the unemployment rate peaks, nonexistent during the long recovery, and strong when the economy begins to overheat.

Over this sample period (February 2004 to June 2022), there is no evidence of a relationship between core PCE inflation and unemployment gap fluctuations; one would conclude that there is no Phillips curve relationship.¹⁵ Conversely, there is firm statistical evidence for a relationship between moderately-persistent fluctuations in the unemployment rate gap, and core SFRI inflation.

Next, we investigate the extent to which DSGE model parameter estimates are sensitive to the rent measure used in core PCE. In particular, we estimate the DSGE model in Gelain and Manganelli (2020), alternatively using core PCE and core SFRI PCE, and examine the resulting estimated impulse response error bands to the three structural shocks in the model.¹⁶ These are plotted in Figure 9.

Three observations stand out. First, the return of core-SFRI to its steady-state following a structural shock is noticeably more rapid. Second, the error bands around the core-SFRI IRFs are generally tighter. And third, the inflation IRFs are statistically distinct; in response to all 3 structural shocks, there is disjointness of the error bands, either up to 5 months, or after 5 months. For instance, in response to a monetary policy shock, core-SFRI returns much more rapidly to steady state, with disjoint IRF error bands after 3 months. In keeping with this, the policy rate and real GDP growth return much more rapidly to trend, with disjointness of IRF error bands after 3 months and 5 months, respectively.

In short, using an alternative rental series in core PCE leads to materially different inferences about the very existence of a Phillips curve, and about the responses of inflation (and other variables) to structural shocks in a DSGE model.

¹⁵Verbrugge (forthcoming) explains how deficiencies in the core PCE index as a measure of trend inflation lead to this negative result.

¹⁶IRFs are nonlinear functions of the model parameter estimates. These plot the dynamic response of the model's endogenous variables to a shock in an exogenous variable.

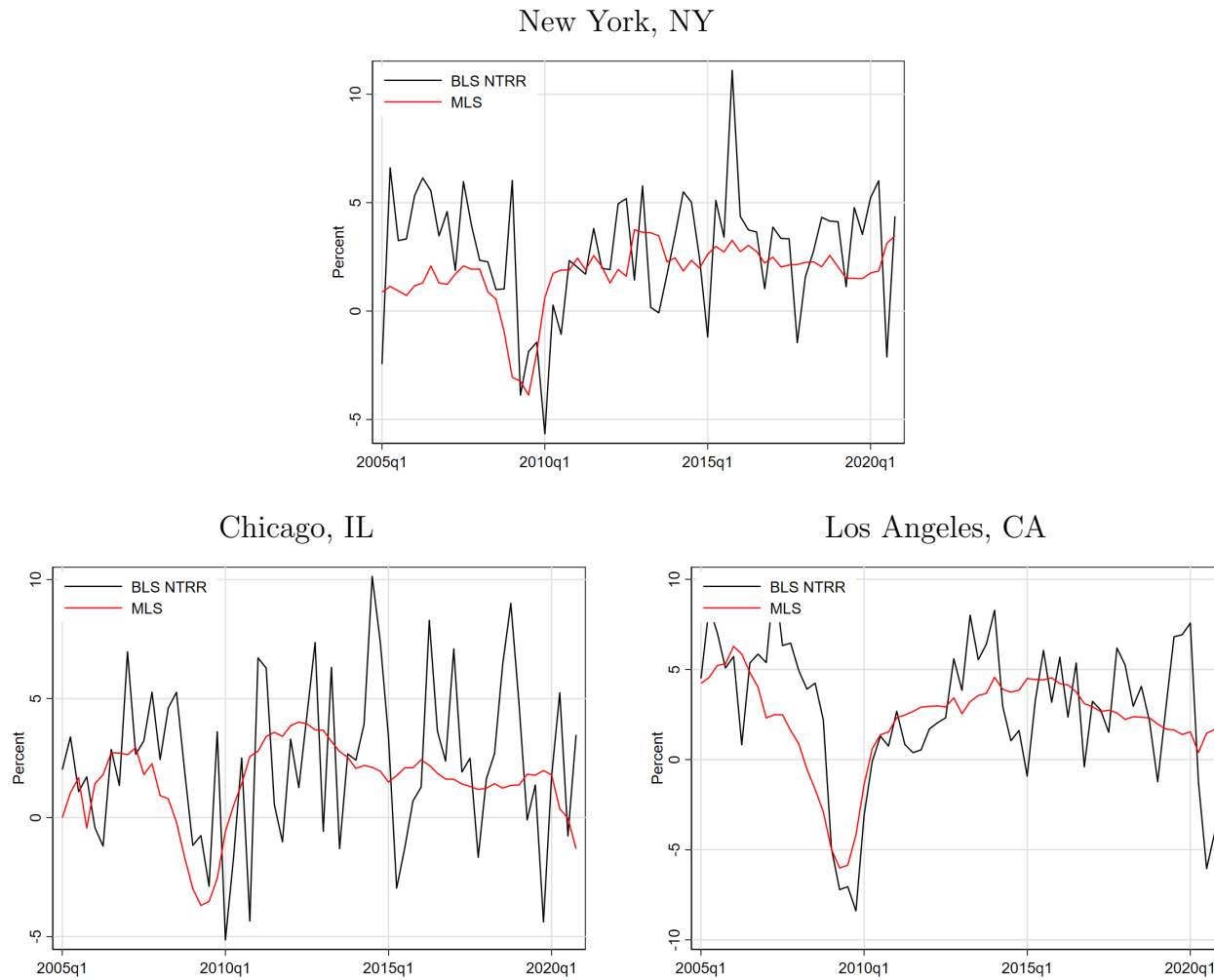


Figure 7. PSU-LEVEL INDICES USING BLS NEW TENANT DATA AND MLS RENTAL LISTINGS. *Note:* Areas are defined as the respective CBSA. *Source:* BLS Housing Survey and Corelogic Multiple Listing Service data.

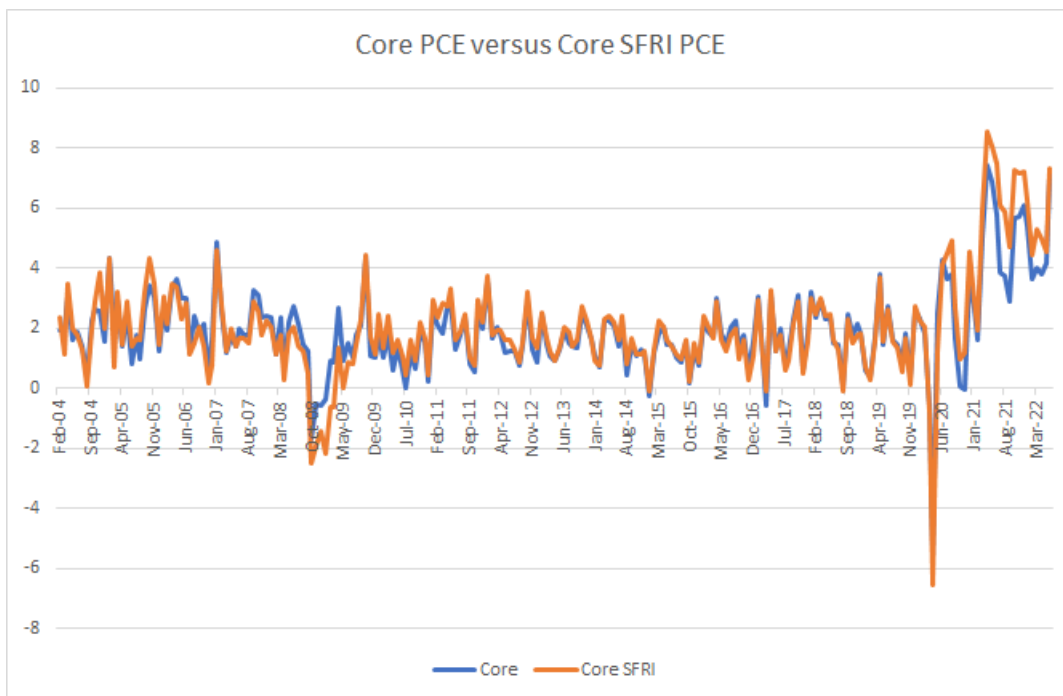


Figure 8. MONTHLY ANNUALIZED CORE PCE INFLATION VERSUS CORE-SFRI PCE INFLATION. *Source:* Bureau of Economic Analysis, CoreLogic, and authors' calculations.

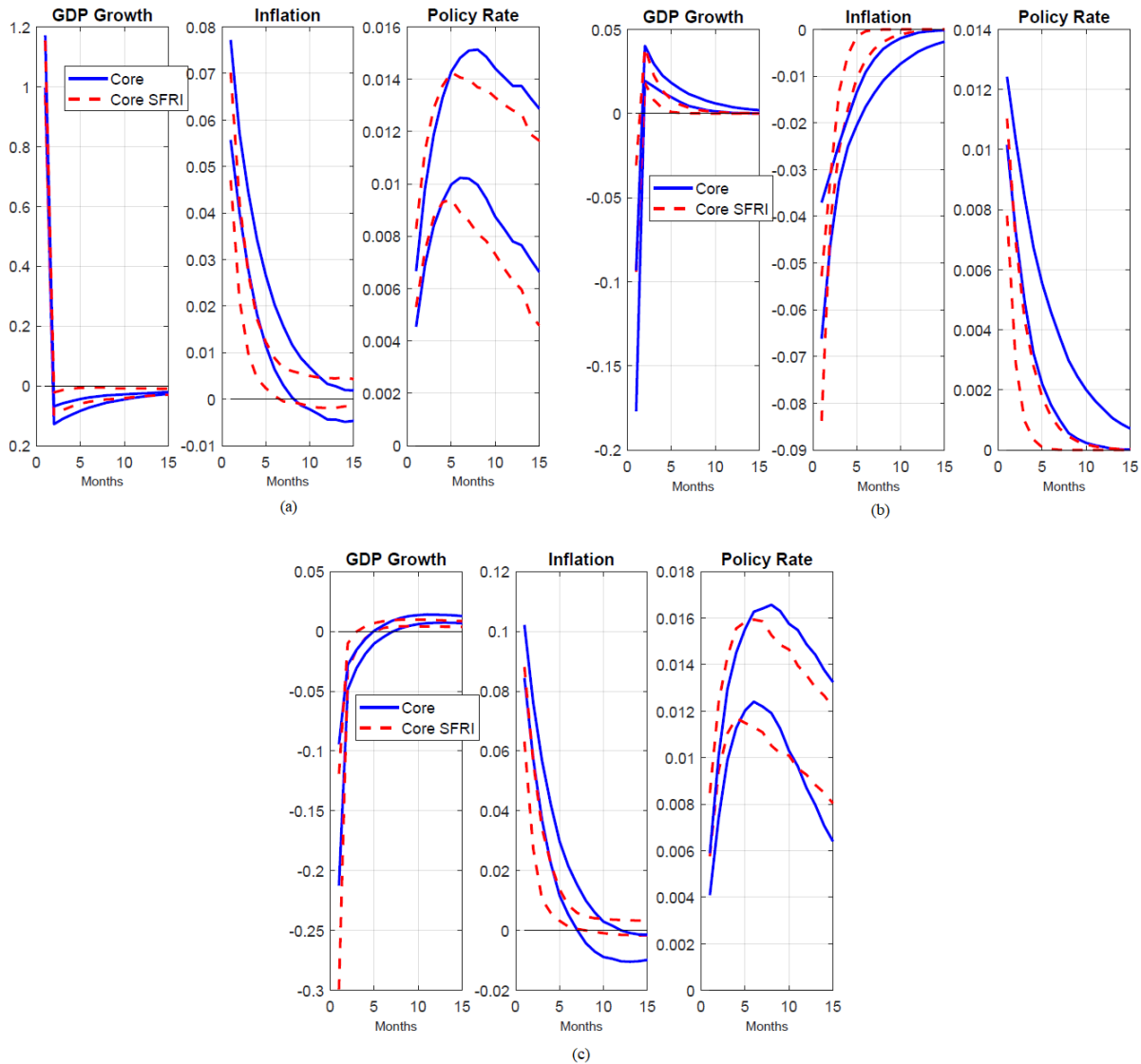
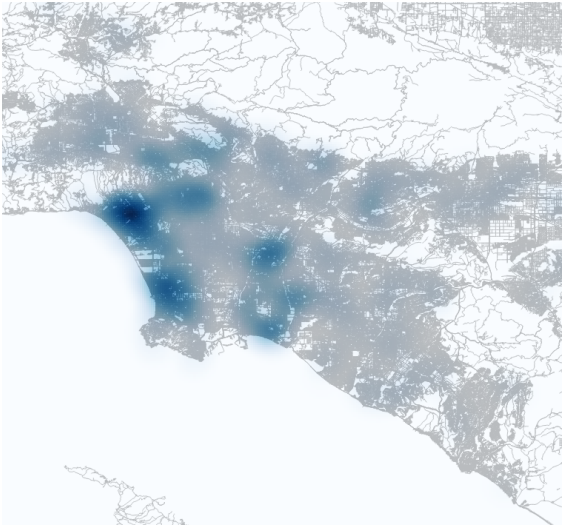


Figure 9. IMPULSE RESPONSE FUNCTIONS IN A NEW KEYNESIAN MODEL. *Note:* Impulse Response Functions (IRFs) display the dynamic response of endogenous variables to exogenous shocks in the model. They are nonlinear functions of model parameter estimates. We display only the IRF error bands, since our purpose is to assess whether IRFs for different inflation measures are statistically distinct. Panel (a) plots the IRF error bands to a government spending shock, panel (b) plots the IRF error bands to a monetary policy shock, and panel (c) plots the IRF error bands to a price markup shock.

BLS Housing Sample



MLS

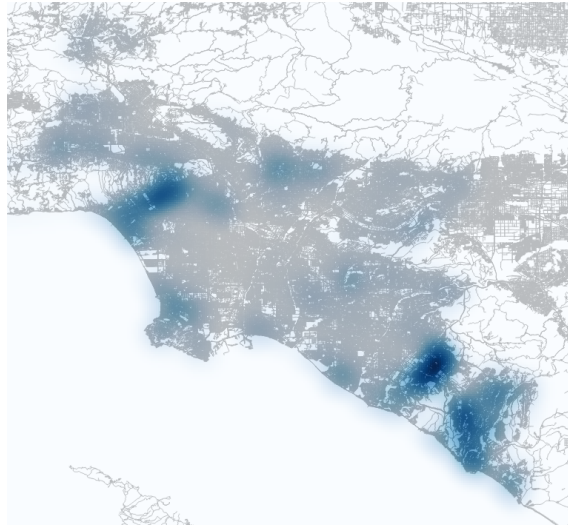


Figure 10. HEATMAP OF SAMPLE LOCATIONS IN LOS ANGELES. *Note:* The left panel shows the geographic distribution of sample in BLS Housing Survey. The right panel shows the geographic distribution in the MLS data. *Source:* BLS Housing Survey and CoreLogic.