Does Zillow Rent Measure Help Predict CPI Rent Inflation?

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Abstract

This paper examines the usefulness of the Zillow Observed Rent Index (ZORI) in predicting CPI rent inflation. Using data from February 2015 to October 2023, we demonstrate that while ZORI provides valuable insights into future movements in CPI rent inflation, its effectiveness is limited to periods when there is a significant disparity between these two rent series. By employing Giacomini and Rossi's (2010) forecast fluctuations test, we find that, before the pandemic, there was no statistically significant difference between models that incorporated Zillow rent inflation and those that did not. However, starting in June 2020, models incorporating Zillow rent inflation began to outperform forecasting models without it in predicting CPI rent inflation. This performance advantage coincides with the two-year post-pandemic period when Zillow rent inflation significantly diverged from CPI rent inflation.

Keywords: Rent Inflation Forecasting, Zillow Rent Index, Direct Forecasts.
JEL Classifications: E01, E31, E37, R21, R31.

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1 Introduction

The rapid surge in inflation during the year 2022 emerged as one of the most significant economic consequences resulting from the global COVID-19 pandemic. This sudden spike in inflation took policymakers and businesses by surprise, as its speed and intensity were unprecedented. Notably, one facet of this inflationary episode that garnered substantial attention from both the private sector and policymakers was the behavior of rent inflation. Rent constitutes a substantial proportion of the two most widely monitored price indices: the Consumer Price Index (CPI) and the Personal Consumer Expenditure (PCE) index, accounting for a substantial 32 percent of the CPI. During the immediate aftermath of the COVID-19 pandemic, there was a burgeoning interest in the Zillow Observed Rent Index (ZORI). This interest stemmed from ZORI's ability to provide real-time insights into the rental market, particularly for new tenants, making it an invaluable tool for understanding dynamic market conditions.[1]

Furthermore, ZORI exhibited a remarkable divergence from the official CPI rent measures, especially during periods of rapid market shifts. For instance, in early 2022, while ZORI's annualized inflation rates soared to approximately 15%, the official CPI for rent remained at 5.5%.[2] While ZORI may not be tailored for use in official cost-of-living indices like the CPI, its focus on new-tenant inflation offered crucial insights for policymakers. It served as an early indicator of changes in rental market conditions, aiding in the integration of new-tenant inflation into inflation forecasts and monetary policy decisions. ZORI also presented an alternative perspective compared to all-tenant indices such as the Bureau of Labor Statistics (BLS) index. This divergence was essential for various economic analyses and models, particularly those related to inflation measurement and macroeconomic forecasting. The methodological distinctions between ZORI and conventional indices, notably ZORI's utilization of the repeat-rent method, further piqued the interest of researchers and policymakers. These methodological variations unveiled diverse facets of rent inflation and

[1] See Adams et al. (2023).

[2] The Marginal Rent Index proposed by Ambrose et al. (2022) also reached 12 percent in 2022.

housing market dynamics, making ZORI a point of interest in economic and policy circles.

With the growing disparity between rents in private markets and government-measured residential services inflation, academic research began exploring the predictive potential of ZORI for the rent inflation components of CPI and PCE. Researchers such as Bolhuis, Cramer, and Summers (2022) examined the predictive power of private market rent indices, suggesting that if historical trends persist, residential inflation components of the CPI and PCE could reach approximately 7% in 2022, significantly contributing to overall inflation. Additionally, studies like Lansing, Oliveira, and Shapiro (2022) examined the influence of rising rents on future inflation, predicting a substantial increase in rent inflation for 2022 and 2023, potentially adding 0.5 percentage points to personal consumption expenditures price inflation annually, which could impact the Federal Reserve's 2% inflation target. Adams et al. (2023) showed that discrepancy between two measures are largely explained by differences in rent growth for new tenants relative to all tenants.[3]

In light of these findings, this paper seeks to address two important questions: Do the in-sample forecasting results reported in the literature hold up in an out-of-sample forecasting exercise? And, do these forecasting results exhibit stability across different time periods? These questions assume particular significance as the years following the COVID-19 pandemic witnessed highly unusual behavior in the housing market and overall inflation. The record-high divergence between ZORI and CPI rent indices prompts us to consider that predictive patterns in ZORI inflation for official rent inflation may only emerge in cases of extreme divergence, with little marginal content in past movements of ZORI inflation for CPI rent inflation during normal periods.

Our in-sample results, utilizing data from January 2015 to October 2023, affirm the existing findings that Zillow rent inflation indeed possesses predictive content for future movements in CPI rent inflation especially at 6-12 months horizon. Adding Zillow rent inflation as a predictor significantly improves forecasting performance, especially at longer

[3] Ambrose et al. (2015) also provide an alternate rent index, Marginal Rent Index (ACY MRI) that employ a weighted repeat rent estimator to construct quarterly indexes. They find that the repeat rent and Bureau of Labor Statistics indexes differ due to sampling and construction methods.

horizons[4]. House price growth as a predictor does not offer substantial additional information for CPI rent inflation. Furthermore, a 3-variable model with PCE and Zillow rent inflation as predictors consistently performs better than bivariate models that does not include Zillow measure, demonstrating the value of including Zillow rent inflation in forecasting. We also explore the use of information in level of variables and use the cointegration between level of different rent indices. We find that incorporating the cointegrating residual into the forecasting model leads to a substantial improvement in forecasting accuracy for various horizons, suggesting the value of utilizing the long-run relationships between rent measures. However, concerns arise about look ahead bias when using the full sample for estimation, as the forecasting performance improvement disappears when employing the pseudo real-time version of the cointegrating residual, raising questions about the stability of forecasting models that use this approach.

To examine if the forecasting performance is stable, we utilize Giacomini and Rossi's (2010) fluctuations test. The results suggest that before the pandemic, there was no statistically significant difference between models incorporating Zillow rent inflation and those without it. However, starting in 2020:M6, models incorporating Zillow rent inflation outperform univariate forecasting models in predicting CPI rent inflation. This performance advantage aligns with the two-year post-pandemic period when Zillow rent inflation significantly diverged from CPI rent inflation. This divergence suggests that Zillow's data may have captured market dynamics or rent trends not fully reflected in the CPI rent inflation data during the post-pandemic period

Splitting the forecast sample into pre-pandemic and post-pandemic subsamples confirms these findings, with the post-pandemic period exhibiting a substantial improvement in forecasting performance when Zillow rent inflation is included as a predictor at medium and long horizons.. The findings underscore the need for adaptive and flexible forecasting models that can incorporate and weigh various data sources based on their predictive power in different economic contexts. This adaptability is crucial for accurately forecasting economic indi-

[4] We use Clark-West (2007) forecast comparison test to evaluate the performance of alternate nested forecasts.

cators in rapidly changing environments, such as those experienced during the COVID-19 pandemic.

The rest of the paper is structured as follows: Section 2 provides a description of the data used in our empirical analysis, Section 3 reviews empirical models and results, Section 5 presents out-of-sample forecasting results, and Section 6 concludes.

2 Data Description

Our data covers the period from February 2015 to October 2023. The start date is determined by the availability of rent inflation measure from Zillow. The CPI is a crucial economic indicator used to measure inflation and plays a significant role in comprehending price changes in various goods and services. Specifically, the assessment of shelter prices within the CPI heavily relies on rental data. Shelter, the largest component in the CPI, allocates 8 percent of relative importance, while owner-occupied housing contributes an additional 24 percent. This is measured using the owners' equivalent rent (OER) method, which means that rents ultimately influence around 32 percent of the CPI. The U.S. Bureau of Labor Statistics (BLS) has historically served as the official source of rental data and is the primary data provider for CPI calculation.

The Bureau of Economic Analysis (BEA) produces the PCE Price Index, which differs from the CPI and is used in economic analysis and policy formulation[5]. Notably, both the BEA and BLS assign significantly different weights to housing components within their respective indices. In the PCE, shelter accounts for over 15 percent.

However, in recent years, alternative rental datasets have become available, including the rental price index from the online real estate marketplace, Zillow. Zillow's data exhibits distinct features compared to BLS rental data, making both datasets potentially valuable in various policy contexts. Notable distinctions include Zillow's more comprehensive and geographically granular coverage compared to BLS data. Additionally, the Zillow index

[5] For a discussion of how PCE differs from CPI for housing and other categories, most notably healthcare, see Johnson (2017).

specifically focuses on new tenants, whereas the BLS rent measure encompasses all tenants, with new rental leases contributing to only about 20 percent of its weight[6]. Consequently, the Zillow series offers a more timely snapshot of current rental dynamics, but it may exhibit higher volatility and cyclical movements, capturing short-term fluctuations not reflected in the BLS measure. The Zillow Observed Rent Index (ZORI) has been available since 2014 and leverages Zillow's extensive database of rental prices to monitor changes in asking prices for rental properties. To monitor changes in home prices, we rely on the S&P/Case-Shiller US National Home Price Index. This widely recognized index offers a comprehensive view of home price movements in the United States, providing valuable insights into the housing market's performance and trends. This is motivated by the work of Brescia (2021) and Dolmas and Zhou (2021) who use housing prices to forecast rents.

Tables 1a and 1b show correlation and summary statistics for the data used in this paper. Figure 1 shows different rent measures. Not surprisingly, we find a high correlation of 0.91 between rent inflation measures of CPI and PCE. However, Zillow rent inflation although positively correlated with both these measures is not as high with a correlation of 0.25 with CPI rent inflation and a correlation of 0.15 with PCE rent inflation. The contemporaneous correlation of house price growth is surprisingly negative with CPI and PCE rent inflation. However, it is positive with Zillow measure with a correlation of 0.58. Table 1b show the descriptive statistics for these four variables.

3 Empirical Model and Results

3.1 In-Sample Predictability

While the correlation results presented in the above section are informative, they do not provide any information on the marginal predictive power of these variables on future rent inflation. Moreover, those correlation measures are contemporaneous and do not capture the dynamic relationship among those variables over time. To examine this question, we

[6]See Adams et al. (2023) for an excellent discussion on the differences between different rent indices.

perform a Granger causality test for different variables in our study. The results are shown in Table 2. The results from the Pairwise Granger Causality Tests reported in Table 2 show that Zillow rent inflation Granger causes CPI rent inflation but not vice versa. In the case of PCE and CPI rent inflation, we find that predictive causality runs in both directions. We also examine whether Zillow rent inflation contains marginal information about future movements in PCE inflation that is not already contained in its own lags. The results do indicate that this is the case, and there is no evidence for the reverse relationship. Overall, these tests indicate that Zillow rent inflation has significant in-sample predictive power over CPI and PCE rent inflation. The same cannot be said about the predictive ability of official rent inflation for Zillow rent inflation.

When we perform the Granger causality test for house price growth, it is evident that there is no significant predictive relationship between house price growth and CPI rent inflation. In contrast, house price growth shows a significant ability to predict both Zillow and PCE Rent inflations, as evidenced by very low p-values. However, this predictive relationship does not work in reverse; Zillow Rent Inflation does not predict house price growth, and similarly, CPI and PCE rent inflation lack predictive power over house price growth. Although PCE Rent Inflation demonstrates some potential in predicting house price growth.

4 Out-of-Sample Forecasting

Our empirical analysis so far has focused on the in-sample predictive relationship between different measures of rent and house price indicators. While informative, the results presented so far do not provide us with information on the usefulness of these predictors in an out-of-sample context. In particular, how do these predictors perform when information from the full sample is not included? For this purpose, we perform a recursive out-of-sample forecasting exercise for CPI rent inflation in this sample. We focus on CPI rent inflation because of its overall importance in the CPI inflation.

We estimate the following regression specification for different forecast horizons:

$$y_{t+i} = \alpha + \sum_{j-1}^{p} \beta_j y_{t-j} + \sum_{k=1}^{q} \theta_k x_{t-k} + \varepsilon_{t+j} \tag{1}$$

where y_t is CPI rent inflation, and x_t is set of predictors. For bivariate regression, we estimate three separate models in which lagged values of PCE rent inflation, Zillow rent inflation, and house price growth are included in addition to CPI rent inflation as a predictor. We also consider trivariate models where, in addition to lags of CPI rent inflation, we also include lags of two of the three predictors in our model.

This forecasting model is referred to as the Direct Forecast approach in the literature. Direct forecasts are made using horizon-specific estimated models, where the dependent variable is the multiperiod ahead value being forecasted. This method circumvents the problem of misspecification that the forecasts generated from the VAR model may be prone to, by performing a direct estimation of the model for different horizons, 'i', instead of iterative forecasting as done in the VAR approach. Direct forecasts are made using a horizon-specific estimated model, where the dependent variable is the multiperiod ahead value being forecasted.[7] This approach is less prone to misspecification, especially for long horizon forecasts, as highlighted by Marcellino, Stock, and Watson (2006).

Our sample begins in 2015:M2 and runs through 2023:M10. Our first set of forecasts covers the period from 2018:M3 to 2019:M2 and uses sample information until 2018:M2. The estimation sample for the first forecasts is from 2015:M2 to 2018:M2. We then advance one month, re-estimate the model, and forecast from 2018:M4 to 2019:M3, and so on. Our final set of forecasts covers the period from 2022:M11 to 2023:M10. We consider various monthly horizon forecasts up to M=12. In addition to these monthly forecasts, we also examine the average over the next 12 months. These averages are used in the analysis to mitigate the noise associated with monthly projections.

Our forecasts are based on the direct estimation of the model in Equation 1. The results for this exercise are shown in Table 3. We report the ratio of root mean squared errors from

[7] This approach offers advantages over iterative VAR forecasts. In addition to forecasting the variable of interest, in this case, CPI rent inflation, we also forecast the other variables to obtain multi-period ahead forecasts (for example, house price growth).

a forecasting model compared to a random walk model. A ratio less than unity indicates that the model has superior forecasting performance compared to the RW model, with the benchmark model being a RW model. In the first step, we examine whether a parsimonious univariate forecasting model, such as an AR(1) model, has a forecasting advantage over a RW model. The results shown in the table suggest that this is not the case. Except for a very minor advantage at 1- and 12-month ahead forecasts, the forecasts generated from an AR(1) model perform poorly compared to a RW model. In fact, the 1-12 month average forecast generated from an AR(1) model has a 12 percent higher RMSE than the RW model.

In the next step, we examine whether the addition of other measures of rent inflation improves the forecasting performance of CPI rent inflation. '+' in the table indicates the inclusion of a variable in the univariate forecasting model of CPI rent inflation. The results suggest that the inclusion of PCE rent inflation does not improve the out-of-sample forecasts of CPI rent inflation. The results are much more promising when Zillow rent inflation is used as a predictor. Although the forecasting performance does not improve at short horizons (h=1,3), the improvement is substantial at longer horizons. At a 12-month ahead forecasting horizon, the inclusion of Zillow rent inflation in a model of CPI rent inflation leads to a forecasting improvement of 28 percent over a RW model. On average, Zillow rent inflation reduces the RMSE of CPI rent inflation compared to a RW model by 21 percent when evaluating the forecast for h=1-12 month averages. As shown earlier, this improvement is not occurring because of the predictive power of CPI rent inflation's own lags (AR(1) model), but rather because of the inclusion of Zillow rent inflation.

What happens to the forecasting performance if Case-Shiller house price growth is added as a predictor? Based on the results reported in the table, we can conclude that house price growth does not provide additional information about CPI rent inflation that is not already present in its own lags. There is some improvement at the 12-month ahead forecast horizon, but the forecasting performance is worse compared to a RW model for most of the forecasting horizons.

We also assess the forecasting performance for a 3-variable model, where in addition to lags of CPI rent inflation, we also include lags of two other predictors. For example, '+PCE+Zillow' reports the forecasting results for a 3-variable model that includes lags of CPI rent inflation and lags of PCE and Zillow rent inflation. The results suggest that there is a benefit in including both Zillow and PCE rent inflation as predictors, as the RMSE for this model is lower than for either the bivariate model with PCE or with Zillow at all forecast horizons. At h=1-12 horizons, there is almost a 10 percent decline in RMSE. If PCE and house price growth are added to a model of CPI rent inflation, we again find a benefit in the inclusion of these two variables, as the RMSE is lower than in the models where these two variables are included by themselves. If we compare all these models, it is clear that models that include Zillow rent inflation yield better forecasting results.

4.1 Information in the Level of Rent Prices

Our results suggest that Zillow rent inflation provides valuable information about future movements in CPI rent inflation that is not already contained in its own lags. This raises the question of whether we could also use the information in the levels of these rent measures in addition to the first differences. As is widely known in the literature, valuable information can be lost if one does not utilize the information present in the long-run comovement of non-stationary variables. In other words, can we utilize the fact that a linear combination of CPI rent, PCE rent, and Zillow rent is cointegrated? Figure 2 shows the cointegrating residual of a model when a cointegration model is estimated using the logarithm of CPI rent, the logarithm of PCE rent, and the logarithm of Zillow rent. The estimated cointegrated residual is stationary, indicating the existence of a long-run equilibrium relationship.

Table 4 presents the results of the forecasting model when we augment the +PCE+Zillow model from the earlier section with the cointegrating residual. The results show a substantial improvement in RMSE at almost all forecasting horizons. For h=1-12 months, we observe that the RMSE ratio declines from 0.72 to 0.58. This suggests that utilizing the long-run relationship between different measures of rent leads to an improvement in forecasting performance. One concern with the cointegration model is that the cointegrating residual is based on the estimated parameters of the full sample and may, therefore, suffer from look ahead bias. The recursive forecast generated from a model with a variable that uses information from the full sample cannot be characterized as an out-of-sample forecasting exercise. To address this, we estimated a real-time cointegration model where we reestimated the cointegration relationship between CPI rent, PCE rent, and Zillow rent as our sample size expanded, adding one more observation to our recursive exercise. Our initial sample for this exercise includes the first three years of our data. The estimated cointegration vector is updated as the sample size expands. As we expand the sample size by one observation, we save the residual for the last observation in the sample. This process is repeated until we reach the end of the sample. The forecasting results for this exercise are reported in the column named 'PCE+Zillow+Residual (RT).' We find that the improvement in forecasting performance disappears when we utilize the real-time version of the cointegrating residual. This implies that the use of the full sample in the estimation of the cointegration vector may be playing an outsized role in the improvement of forecasting performance when the cointegrating residual was added as an extra predictor. This switch in the forecasting performance raises questions about the stability of forecasting performance of different models, which we address in the next section.

4.2 Forecast Instability

The results presented in the earlier section, where we used the real-time version of the cointegrated residual, suggest that the forecasting performance of our models may be influenced by the sample size. To examine this possibility, we employ Giacomini and Rossi's (2010) test for examining forecast instability. Rossi and Sekhposyan (2010), Giacomini and Rossi (2010), and Rossi (2019) provide numerous examples where relative forecast performance is not robust to the evaluation period: one model produces out-of-sample forecasts that are superior to another's, on average, over some interval, but the performance advantage disappears or even reverses in one or more subintervals. Giacomini and Rossi (2010) propose a "fluctuations test" for detecting such performance instabilities. The forecasts are for CPI rent inflation at the 1-to-12-month horizon, compared over rolling 36-month intervals. The interval length is such that the first and last intervals do not overlap. We use the variant of the fluctuations test that is appropriate for models estimated recursively. See Giacomini and Rossi (2010).

Figure 3 displays the fluctuations test statistic plot. The figure shows that +Zillow and +PCE+Zillow outperform the RW model starting in 2020:M6. Before 2020:M6, for every subinterval within our evaluation period, the difference is typically not statistically significant. Notably, performance differences are significant for two years in the post-pandemic period. This is also the period when Zillow rent inflation deviated significantly from CPI rent inflation. The results overall indicate that the predictive power of Zillow rent inflation for CPI rent inflation in the full sample is mainly driven by the period that followed immediately after the Covid lockdown.

4.3 Sub-sample Analysis

The forecast stability test reported earlier showed instability in the forecasting performance of models that include Zillow rent inflation as an additional predictor compared to a benchmark random walk model. To further investigate this, we split our forecast sample into two samples: pre-pandemic and post-pandemic. The results are shown in Tables 5-6. Table 5 confirms the result presented using the Giacomini and Rossi (2010) "fluctuations test." We do not find a significant difference in the forecasting performance of an AR1 model and the model that contains Zillow rent inflation as a predictor for all forecast horizons. If PCE inflation is added as an additional predictor to a model with CPI inflation, then forecasting performance remains the same. However, the results change when we look at the post-pandemic sample beginning in 2020:M6. The results for this exercise are shown in Table 6. The reported results for the second subsample are consistent with the full sample. Models that include Zillow rent inflation lead to a significant improvement in forecasting performance according to the Clark-West test. The difference compared to a univariate model is significant at almost all forecasting horizons.

5 Conclusion

The rapid surge in inflation during 2022, driven by the global COVID-19 pandemic, had profound economic implications. Of particular interest was the behavior of rent inflation, a substantial component of widely monitored price indices like the Consumer Price Index (CPI) and the Personal Consumer Expenditure (PCE) index. During the pandemic aftermath, the Zillow Observed Rent Index (ZORI) gained prominence for its real-time insights into the rental market, especially for new tenants. ZORI exhibited a significant divergence from official CPI rent measures during periods of rapid market shifts, providing policymakers with valuable early indicators of changes in rental market conditions.

This paper's findings address two important questions: the stability and reliability of in-sample forecasting results in an out-of-sample context. The results confirm that Zillow rent inflation possesses predictive content for CPI rent inflation, extending to significant out-of-sample forecasting performance from 2019 through 2022. However, this predictive power did not extend to house price growth forecasting. Importantly, evidence of forecasting performance instability in Zillow rent inflation emerged. Models incorporating Zillow rent inflation outperformed univariate models in predicting CPI rent inflation starting in 2020, aligning with the post-pandemic period of significant divergence between ZORI and CPI rent inflation. In summary, the paper highlights the potential value of ZORI in forecasting rent inflation, particularly during periods of extreme divergence from official measures. The research underscores the importance of considering dynamic market conditions and methodological distinctions when analyzing rent inflation, offering valuable insights for policymakers and researchers alike.

References

[1] Adams, B., Loewenstein, L., Montag, H., & Verbrugge, R. (2023). Disentangling rent index differences: data, methods, and scope. Federal Reserve Bank of Cleveland Working Paper.

[2] Ambrose, B. W., Coulson, N. E., and Yoshida, J. (2015): The repeat rent index, Review of Economics and Statistics 97, 939–950.

[3] Ambrose, B. W., Coulson, N. E., & Yoshida, J. (2023). Housing Rents and Inflation Rates. Journal of Money, Credit and Banking.

[4] Bolhuis, M. A., Cramer, J. N., & Summers, L. H. (2022). The coming rise in residential inflation. Review of Finance, 26(5), 1051-1072.

[5] Brescia, E. (2021): Housing poised to be strong driver of inflation. Fannie Mae Housing Insights.

[6] Clark, Todd E. and Kenneth D. West (2007),"Approximately Normal Tests for Equal Predictive Accuracy in Nested Models," Journal of Econometrics, 138, pp. 291-311.

[7] Dolmas, J., & Zhou, X. (2021). Surging house prices expected to propel rent increases, push up inflation. Fed Dallas Working Paper.

[8] Giacomini, Raffaella and Barbara Rossi (2010), "Forecast Comparisons in Unstable Environments," *Journal of Applied Econometrics*, 25, pp. 595-620.

[9] Johnson, N. (2017). A comparison of PCE and CPI: Methodological Differences in US Inflation Calculation and their Implications November 2017.

[10] Lansing, K. J., Oliveira, L. E., & Shapiro, A. H. (2022). Will rising rents push up future inflation?. FRBSF Economic Letter, 3.

[11] Marcellino, M., Stock, J. H., & Watson, M. W. (2006). A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of econometrics*, 135(1-2), 499-526.

[12] McAdam, P. (2023). Comparing Measures of Rental Prices Can Inform Monetary Policy. Economic Bulletin, 1-4.

[13] Rossi, Barbara (2019), "Forecasting in the Presence of Instabilities: How Do We Know Whether Models Predict Well and How to Improve Them," *Barcelona GSE Working Paper Series*, No. 1161.

[14] Rossi, Barbara and Tatevik Sekhposyan (2010), "Have Economic Models' Forecasting Performance for U.S. Output Growth and Inflation Changed Over Time?," *International Journal of Forecasting*, 26, pp. 808-835.

[15] Verbrugge, R., & Poole, R. (2010). Explaining the rent–OER Inflation divergence, 1999–2007. Real Estate Economics, 38(4), 633-657.

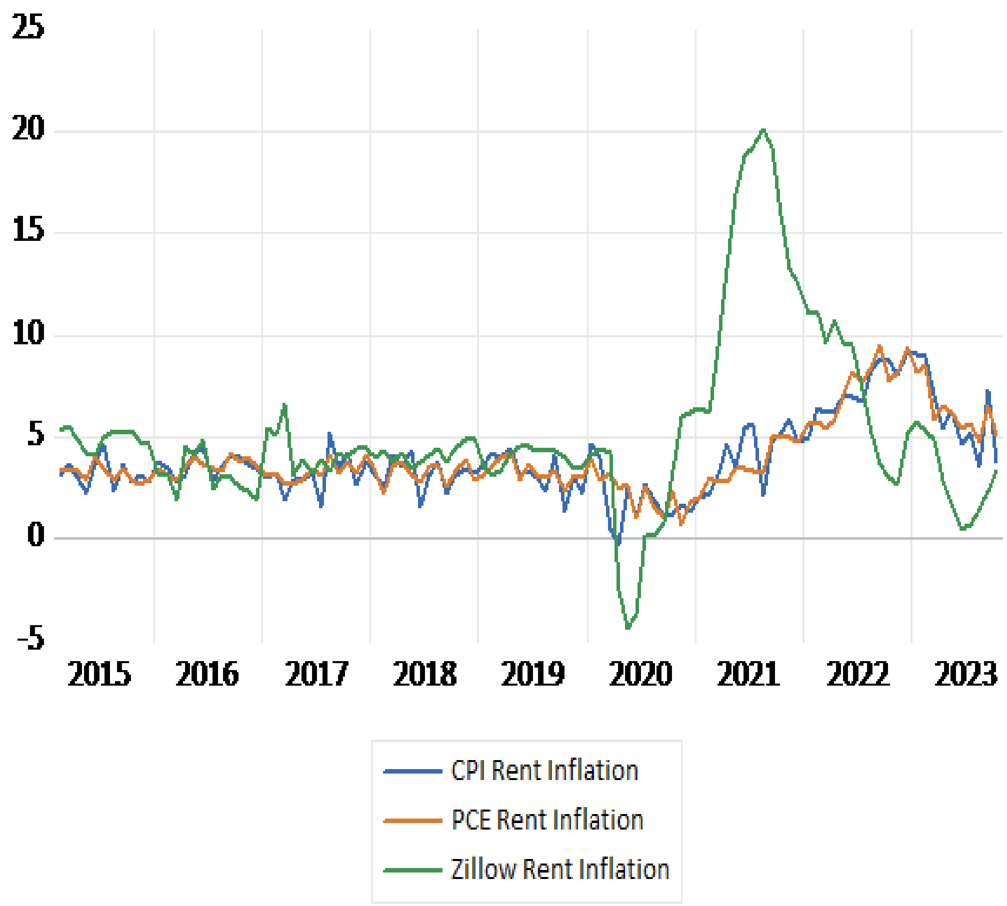

Figure 1: Different Measures of Rent Inflation

Notes: The sample period is 2015M2-2023M10. Inflation data is rate of change in monthly prices annualized.

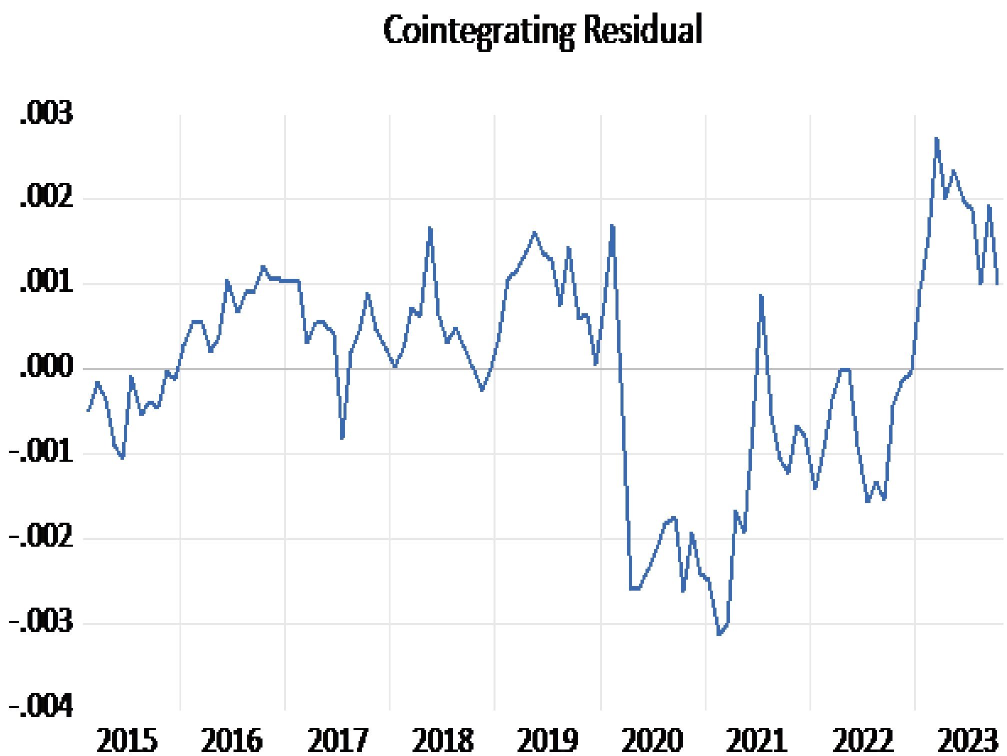

Figure 2: Cointegrating Residual

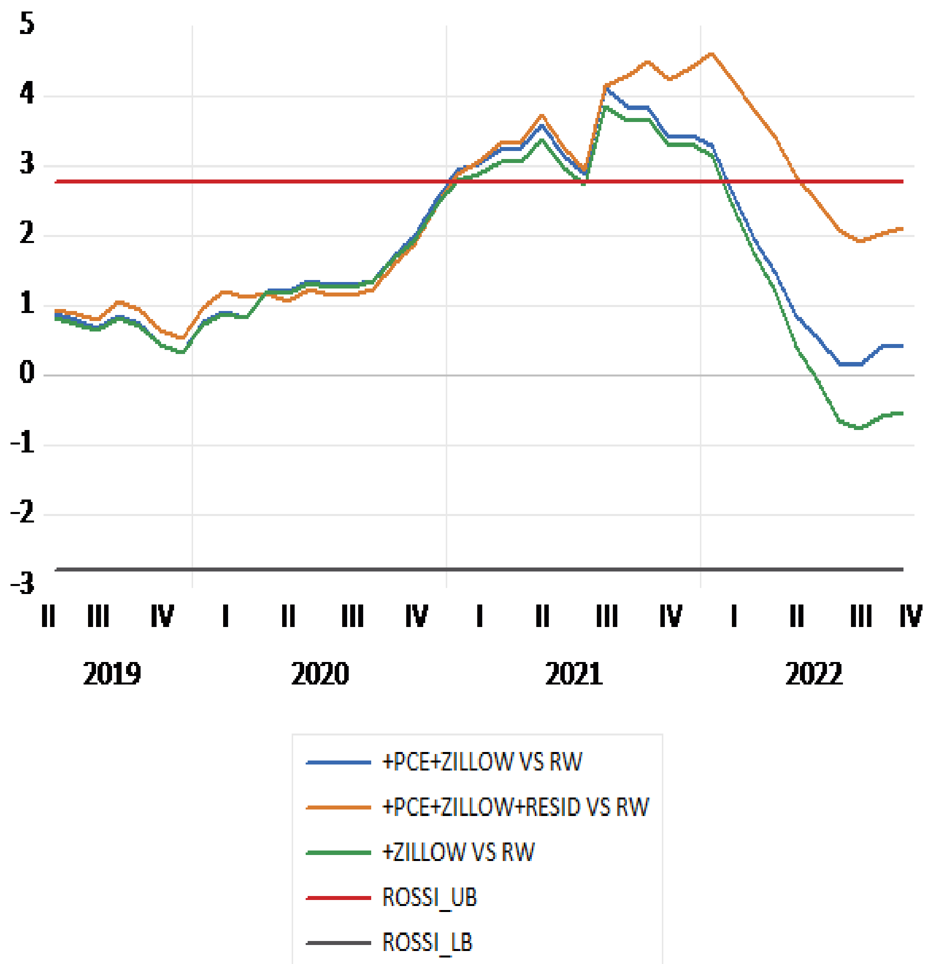

Figure 3: Giacomini-Rossi (2010) Fluctuations Test

Notes: Horizontal black and red lines are lower and upper bounds for Giacomini-Rossi (2010) test. Green line is test statistic for a 2-variable model (CPI and Zillow) vs a Random Walk. Blue line is test statistic for a 3-variable model (CPI+PCE+Zillow) vs a Random Walk. Orange line is test statistic for 4-variable model (CPI+PCE+Zillow+Cointegrating residual).

Table 1a. Rent Inflation Contemporaneous Correlation

Variable	CPI	PCE	Zillow	HPI
CPI	1.00			
PCE	0.91	1.00		
Zillow	0.25	0.15	1.00	
HPI	-0.18	-0.30	0.58	1.00

Notes: The sample period is 2015:M2-2023M10. All variables are in growth rates. HPI is S&P Case Shiller house price growth rate.

Table 1b. Rent Inflation Descriptive Statistic

Variable	Mean	Median	Std. Dev
CPI	3.93	3.50	1.95
PCE	3.96	3.41	1.79
Zillow	5.21	4.26	4.33
HPI	7.11	5.57	6.43

Notes: The sample period is 2015:M2-2023M10. All variables are in growth rates. HPI is S&P Case Shiller house price growth rate.

Table 2. In-Sample Predictability Results

Null Hypothesis	**P-Value**
CPI does not Granger cause Zillow	0.11
Zillow does not Granger cause CPI	0.04
PCE does not Granger cause CPI	0.00
CPI does not Granger cause PCE	0.03
Zillow does not Granger cause PCE	0.04
PCE does not Granger cause Zillow	0.15
HPI does not Granger cause CPI	0.64
CPI does not Granger cause HPI	0.55
HPI does not Granger cause Zillow	0.00
Zillow does not Granger cause CPI	0.90
HPI does not Granger cause PCE	0.00
PCE does not Granger cause HPI	0.25

Notes: The sample period is 2015:M2-2023M10. All variables are in growth rates. HPI is S&P Case Shiller house price growth rate.

Table 3. Forecasting CPI Rent Inflation

Horizon	RW	AR(1)	+PCE	+Zillow	+PCE+Zillow	+HPI	+PCE+HPI
1-step	1.000	0.996	0.936*	1.106	**0.922***	1.118	0.952
3-step	1.000	1.098	0.988*	1.060	**0.943***	1.104	1.003
6-step	1.000	1.151	0.983*	0.860**	**0.808****	0.976*	0.927
9-step	1.000	1.069	1.273	0.807**	**0.799****	1.292	0.911
12-step	1.000	0.988	0.916**	0.722**	**0.729****	0.865*	0.873
1-12-avg	1.000	1.120	0.994	0.791**	**0.723****	1.002	0.892

Notes:

The table shows RMSEs of different forecasting models that includes CPI rent inflation and other predictors. +refers to a model with lags of CPI rent inflation and lags of +variable. Our first set of forecasts is for 2018:M3 to 2019:M2; the final set of forecasts is for 2022:M11 to 2023:M10. h=1-12 denotes averages over next 12-months.* refers to significant forecast improvement over AR(1) model at 10% significance level. Lowest ratios are bolded.

Table 4. Forecasting CPI Rent Inflation

Horizon	RW	AR(1)	+PCE+Zillow	+PCE+Zillow+Residual	+PCE+Zillow+Residual (RT)
1-step	1.000	0.996	**0.922***	0.948*	0.951*
3-step	1.000	1.098	0.943*	**0.924****	0.946*
6-step	1.000	1.151	0.808**	**0.713****	0.801**
9-step	1.000	1.069	0.799**	**0.731****	0.799**
12-step	1.000	0.988	0.729**	**0.557****	0.683**
1-12-avg	1.000	1.120	0.723**	**0.589****	0.701**

Notes:

The table shows RMSEs of different forecasting models that includes CPI rent inflation and other predictors. +refers to a model with lags of CPI rent inflation and lags of +variable. Our first set of forecasts is for 2018:M3 to 2019:M2; the final set of forecasts is for 2022:M11 to 2023:M10. h=1-12 denotes averages over next 12-months.* refers to significant forecast improvement over AR(1) model at 10% significance level. Lowest ratios are bolded. RT refers to real-time estimate of cointegrating residual.

Table 5. Forecasting CPI Rent Inflation (Pre-Pandemic Sample)

Horizon	RW	AR(1)	+PCE	+Zillow	+PCE+Zillow
1-step	1.000	0.666	0.646	0.658	**0.642**
3-step	1.000	**0.790**	0.817	0.810	0.820
6-step	1.000	0.876	0.858	0.853	**0.849**
9-step	1.000	0.902	0.948	**0.895**	0.904
12-step	1.000	0.891	**0.850**	0.866	0.856
1-12-avg	1.000	0.737	0.707	**0.694**	0.699

Notes:

The table shows RMSEs of different forecasting models that includes CPI rent inflation and other predictors. +refers to a model with lags of CPI rent inflation and lags of +variable. Our first set of forecasts is for 2018:M3 to 2019:M2; the final set of forecasts is for 2022:M11 to 2023:M10. h=1-12 denotes averages over next 12-months.* refers to significant forecast improvement over AR(1) model at 10% significance level. Lowest ratios are bolded.

Table 6. Forecasting CPI Rent Inflation (Post-2020M6 Sample)

Horizon	RW	AR(1)	+PCE	+Zillow	+PCE+Zillow
1-step	**1.000**	1.158	1.081	1.314	1.062
3-step	1.000	1.212	1.056	1.156	**0.994***
6-step	1.000	1.235	1.024	0.862**	**0.792****
9-step	1.000	1.103	1.336	0.784**	**0.773****
12-step	1.000	1.100	0.928	**0.689****	0.700**
1-12-avg	1.000	1.174	1.035	0.806**	**0.726****

Notes:

The table shows RMSEs of different forecasting models that includes CPI rent inflation and other predictors. +refers to a model with lags of CPI rent inflation and lags of +variable. Our first set of forecasts is for 2018:M3 to 2019:M2; the final set of forecasts is for 2022:M11 to 2023:M10. h=1-12 denotes averages over next 12-months.* refers to significant forecast improvement over AR(1) model at 10% significance level. Lowest ratios are bolded.