Alternative Methods for Calculating Fair Market Rents (FMRs) in Rental Markets with Rapidly Rising Rents

U.S. Department of Housing and Urban Development | Office of Policy Development and Research

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Prepared for
U.S Department of Housing and Urban Development
Office of Policy Development and Research

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January 2022

Acknowledgments

The authors would like to thank the U.S. Department of Housing and Urban Development's Office of Policy Development and Research assistance, especially Adam Bibler, Kurt Usowski, Chalita Brandly, and Marie Lihn, for providing invaluable guidance throughout the study.

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Executive Summary

The U.S. Department of Housing and Urban Development (HUD) determines the expected cost of a standard-quality rental housing unit. It sets the "Fair Market Rent" (FMR), which serves as a benchmark for the Housing Choice Voucher and other public programs. HUD calculates the FMR at the 40th percentile of the metropolitan area or nonmetropolitan county rents. Using the FMR as the benchmark, local housing authorities set a local payment standard (PS), usually 90 to 110 percent of FMR.

A key objective when setting the FMR is to maintain an adequate supply of low-income housing, which makes accurate FMR calculations especially important, particularly in markets experiencing rapidly rising rents. Reliable data from sources such as the American Community Survey (ACS) often lag by several years, making accurate FMR estimation more difficult. Recently, HUD has taken several steps to improve FMR calculations, such as using local and regional trend factors to forecast rent and implementing Small Area Fair Market Rents (SAFMRs) in some metropolitan areas. However, improving the accuracy of FMR calculations for areas witnessing rapid rent increases merits additional research.

This project identifies regions with rapidly rising rents by analyzing the ACS data. Two new methods are proposed for calculating FMR, especially for regions witnessing rapid rent increases. The first method uses rent indices from Axiometrics to update data from ACS. The second method calculates the price-to-rent ratio using the Zillow home value index and the rent data from ACS and then uses that ratio with the Zillow home value index to calculate FMR. In addition, we estimate the rent using the House Price Index (HPI) dataset provided by the Federal Housing Finance Agency (FHFA) instead of using the Zillow data. These methods can be used as additional inputs to determine the FMR.

1. Introduction

The U.S. Department of Housing and Urban Development (HUD) annually estimates the Fair Market Rent (FMR) for more than 600 metropolitan areas and about 2,000 nonmetropolitan areas. FMRs are estimates of gross rent and are used as a benchmark for HUD's assisted housing programs. Accurate measures of the FMR are needed to accomplish HUD's goal of successfully housing as many families receiving vouchers as possible. An FMR that is too low will severely limit the selection of units and neighborhoods, whereas an FMR that is too high will reduce the number of low-income families whom HUD can serve.

Generally, the FMR is the gross rent (shelter plus utilities) that would need to be paid in an area for a modest (nonluxury) rental unit. The FMR is targeted at the 40th percentile of the distribution of gross rents (CFR 888.113).

Currently, HUD's FMR calculation is based on three components:

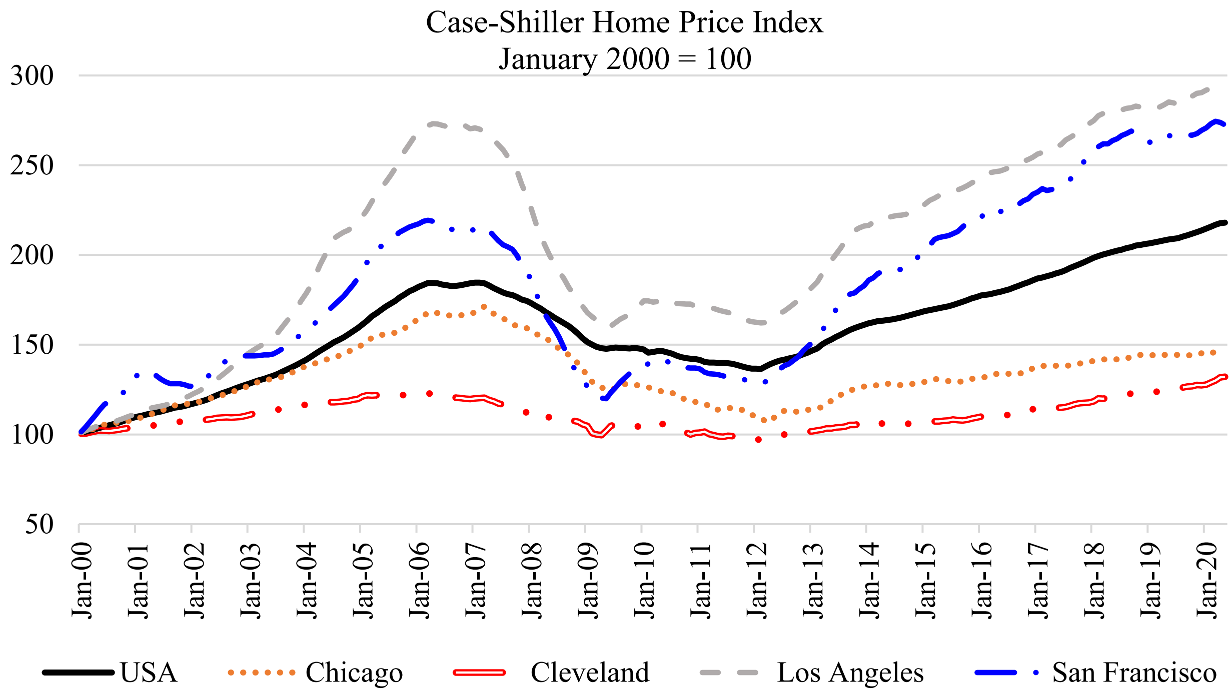
1. **A base rent,** calculated using the Census Bureau's 5-year American Community Survey (ACS) data and a recent-mover factor based on 1-year ACS data.
2. **An inflation factor,** estimated using the Consumer Price Index (CPI), is used to update the ACS to the current level. Local CPIs are used for the 22 metro areas where they are available; otherwise, a regional index is used.
3. **A trend factor,** used to forecast the rent values for the next fiscal year. In fiscal year 2020, HUD replaced the national trend factor with local and regional trend factors to improve the accuracy of rent calculations.

HUD makes additional adjustments for the number of bedrooms. Moreover, in some metropolitan areas, payment standards are based on Small Area Fair Market Rents (SAFMRs), which are calculated at the ZIP Code level.

The ACS is conducted annually and has replaced the "long-form" data, which were collected once every 10 years during the decennial census. Although the advantage of the ACS is that it allows more current data to be used, the ACS rents still lag behind the timing of the FMR by three years. In contrast to the 10-year cycle of the census, the annual nature of the ACS helps to account for variations in rents over the business cycle, including both booms and busts, although with somewhat delayed timing. For instance, using this methodology, the 2008 Great Recession would not be reflected in the data for at least a year, at which point the economy may have already started to recover. To update the ACS to the current levels, HUD relies on the CPI.

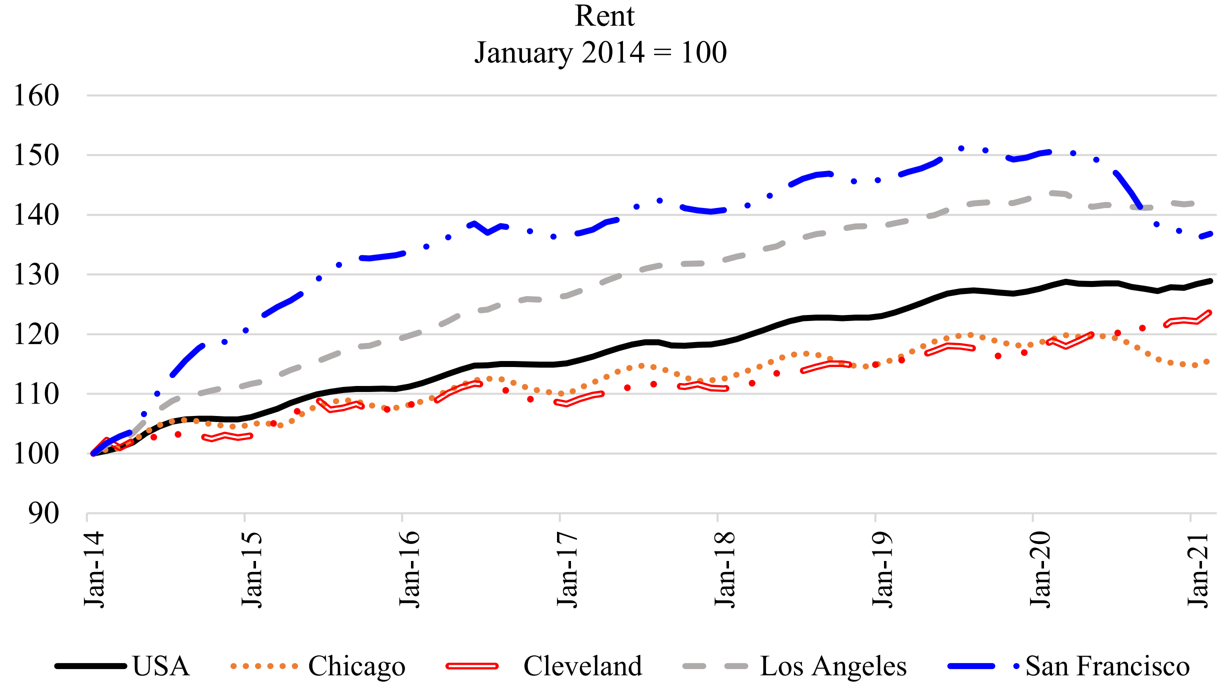
More importantly, different FMR areas are likely to be at different stages of the real estate cycle. Exhibit 1.1 shows the Case-Shiller Home Price Index for a selected set of large metro areas. The graph clearly indicates substantial heterogeneity in both the timing of the bust and recovery and the magnitude of price changes. This substantial heterogeneity in price is also likely to be reflected in divergences in rent changes across those regions.

Exhibit 1.1. Case-Shiller Home Price Index



Source: Federal Reserve Economic Data (FRED)

Exhibit 1.2. Zillow Rent Index



Source: Zillow

The substantial heterogeneity across the regions indicates a need to use a local trend factor while adjusting the ACS rent values to current levels. HUD uses a regional inflation factor for most areas (except 22 metro areas where local CPI is available, although the top 22 metro areas account for 40 percent of the country's population). The regional indices ignore local variation, and rents may vary even within an urban area. Using regional trend factors (HUD started using local trend factors in FY 2020) might lead to significant differences between the FMR and actual market rents, especially in regions with rapidly rising rents.

We suggest alternative methods for calculating FMR that might improve its accuracy, especially for regions with rapidly rising rents. We propose two new methods to supplement the current methodology used to calculate FMR. The two methods are as follows:

1. Using Axiometrics data to adjust ACS values.
2. Applying price-to-rent ratio using Zillow data and FHFA's HPI.

We also reviewed the current method used by HUD to estimate the local trend factors using autoregressive integrated moving average (ARIMA) models. We did not have any additional suggestions to substantially improve the currently used procedure.

1.1 Study Objective

The purpose of this study is to present alternative methods to calculate the FMR in rental markets with rapidly rising rents. More specifically, we will answer the following research questions:

What criteria should be used to define a housing market with rapidly rising rents?

What criteria should be used to evaluate which alternative methods are better than the current ones?

Under what conditions should HUD implement the alternative method for calculating FMRs, and at what point are the alternative methods no longer needed?

What data that are not currently being used should HUD use to calculate FMRs in housing markets with rapidly rising rents?

Beyond alternative sources of data, what calculation techniques should HUD use when calculating FMRs in markets with rapidly rising rents and more generally?

For metropolitan areas, how do the alternative methods for calculating FMRs change the calculation of metropolitan-area-wide FMRs and SAFMRs?

2. Data

The key data we use in this project are the 5-year ACS data for all renters for two-bedroom units. We also use commercial data sources such as Axiometrics and Zillow to supplement our analysis. Apart from those commercially available datasets, we use the House Price Index (HPI) provided by FHFA and CPI data.

2.1 Axiometrics Data

The Axiometrics data are a survey of rental properties and include data on asking rent, effective rent, occupancy rate, number of units, average size of units, etc. The data are available at the individual property level and include the property's geographic coordinates, which enables the creation of summary statistics (median, 40th percentile, etc.) for various geographies. The key variable that we analyze is the effective rent, which is the asking rent minus concessions. We use effective rent because it might reflect current rent more accurately as concessions might vary depending on the demand for the apartment units.

We aggregate the data at the Core Based Statistical Area (CBSA) level for our analysis. We construct the effective yearly rent by taking the average of the four quarters. For the rest of the analysis, we use this panel of effective rent data at the CBSA year level.

A disadvantage of the Axiometrics data is that the data track only apartments and student housing. Therefore, understanding the trends in rental data for single-family housing is not possible using this data. Second, several CBSAs have fewer than 30 properties with rent data in every period, which is likely to make the data less accurate for those CBSAs due to the small sample size.

2.2 Zillow Data

The Zillow Home Value Index (ZHVI) is a smoothed, seasonally adjusted measure of typical home value in the 35th to 65th percentiles. It can be used to measure market changes across a given region and housing type. The ZHVI is based on "Zestimates" calculated on more than 100 million new homes, including new homes and homes that have not had any transactions in many years. The Zestimate is based on machine learning models and uses data from various sources, including public data, user-generated data, and data from multiple listing services. We use the ZHVI at the CBSA level. Zillow provides the data at the metropolitan level (using its own definitions of metropolitan areas), and we use a crosswalk to match the metropolitan areas to the CBSA to make the data comparable. We create a yearly estimate of Zillow home value at the CBSA level by taking the average of the monthly value.

We downloaded the Zillow Observed Rent Index (ZORI), a smoothed measure of the typical observed market rent across a given region. Similar to ZHVI, ZORI is a repeat-rent index, and the index is dollar-denominated and calculated by taking the mean of the middle 20 percent (the 40-to-60th percentile) of the asking rent. The index is weighted to reflect the rental housing stock to ensure that the rent index is representative of the market and not just homes currently listed for rent. We did not use ZORI in our analysis but recommend that this rent index be used with ZHVI to determine the trend in the price-to-rent ratio. As discussed later, the price-to-rent ratio should be adjusted if the ratio (computed using Zillow home values and Zillow rent) changes drastically from one year to another.

One of the disadvantages of the Zillow Indexes is that they are a "black box," and we do not know the exact model being used and the assumptions being made. Additionally, the Zillow data are only available from 2014, providing a limited number of years in which to evaluate the data compared to the ACS.

2.3 House Price Index From the Federal Housing Finance Agency

The FHFA index is computed using sales prices and appraisal values for mortgages bought or guaranteed by Fannie Mae and Freddie Mac.[1] The FHFA HPI is a weighted, repeat-sales index, which measures average price changes in repeat sales or refinancings on the same properties. Those indices are available monthly and quarterly at various levels of geographic aggregation. The main advantage of this index is its length, as the series data are available starting in 1975. We use the HPI at the CBSA year level for our analysis.

[1] The FHFA index that was downloaded is the All-Transactions Indexes (estimated using sales prices and appraisal data), metropolitan statistical areas and divisions (not seasonally adjusted).

3. Methodological Framework

In this section, we discuss the methodological framework that we use to answer the research questions.

3.1 Identifying Markets with Rapidly Rising Rents

Rents have appreciated significantly over the past few years. Rising rents coupled with stagnant incomes have led to an affordability crisis. In this project, we begin by identifying areas that have witnessed a rapid rent increase.

To identify the area with rapidly rising rents, we use 5-year ACS data for 2005 through 2009 to 2014 through 2018 for all renters and focus on the two-bedroom units. We calculate the change in 5-year estimates of the 40th percentile of the CBSA rent and then compute the average increase in rents over our sample period, and sort the data in descending order of rent increase.[2] Then, we select the 60 areas with the highest average rent increase over this period.[3] We use the 5-year ACS data to provide better geographic coverage. However, about 50 percent of those areas also have the highest annual rent increases using the ACS 1-year data. When we use the 1-year ACS data, we find that 33 of the 60 areas selected are among the top 60 areas with the highest average annual rent increase using the 1-year ACS data.

We supplement that analysis with additional data. Some of the areas meet one or more of the following criteria:

Areas that conducted an ad hoc rent survey.

Areas that requested revaluation between FY 2016 and FY 2021.

Areas with payment standards higher than 120 percent at least once between 2002 and 2017.

Areas with low supply elasticity using Saiz's measure. Saiz (2010) calculates the supply elasticities for metro areas with a population greater than 500,000.

Exhibit 3.1. Metro Areas with Rapidly Rising Rents

CBSA Code	CBSA Name
10540	Albany, OR MSA
11020	Altoona, PA MSA
12420	Austin-Round Rock, TX MSA
13740	Billings, MT MSA
13900	Bismarck, ND MSA
13980	Blacksburg-Christiansburg-Radford, VA MSA
14500	Boulder, CO MSA

[2] CBSA definitions are periodically changed by the Office of Management and Budget. Therefore, not all of the CBSAs are comparable over time. The main change was between 2013 and 2014. In our sample of 60 metropolitan areas, the following metro areas had changed: Charleston, WV MSA; Elizabethtown-Fort Knox, KY MSA; Manhattan, KS MSA; and Victoria, TX MSA.

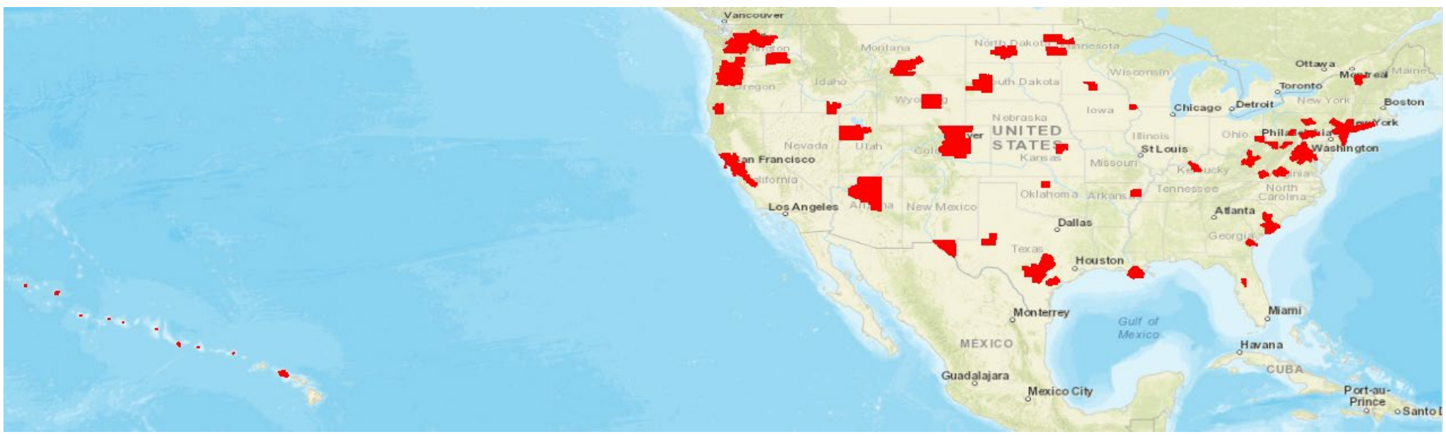
[3] For some CBSAs, the data are available for a shorter period, so the average rent increase is computed using the shorter period for which data are available.

14740	Bremerton-Silverdale, WA MSA
15540	Burlington-South Burlington, VT MSA
16220	Casper, WY MSA
16620	Charleston, WV MSA
16700	Charleston-North Charleston, SC MSA
17820	Colorado Springs, CO MSA
18700	Corvallis, OR MSA
19060	Cumberland, MD-WV MSA
19740	Denver-Aurora-Lakewood, CO MSA
20220	Dubuque, IA MSA
21060	Elizabethtown-Fort Knox, KY MSA
21340	El Paso, TX MSA
21420	Enid, OK MSA
22020	Fargo, ND-MN MSA
22380	Flagstaff, AZ MSA
22660	Fort Collins, CO MSA
24220	Grand Forks, ND-MN MSA
24420	Grants Pass, OR MSA
24540	Greeley, CO MSA
25420	Harrisburg-Carlisle, PA MSA
25980	Hinesville, GA MSA
26380	Houma-Thibodaux, LA MSA
27860	Jonesboro, AR MSA
28420	Kennewick-Richland, WA MSA
30140	Lebanon, PA MSA
31340	Lynchburg, VA MSA
31740	Manhattan, KS MSA
31860	Mankato-North Mankato, MN MSA
33260	Midland, TX MSA
34060	Morgantown, WV MSA
34900	Napa, CA MSA
35620	New York-Newark-Jersey City, NY-NJ-PA MSA
36220	Odessa, TX MSA
36500	Olympia-Tumwater, WA MSA
38900	Portland-Vancouver-Hillsboro, OR-WA MSA
39660	Rapid City, SD MSA
41420	Salem, OR MSA
41620	Salt Lake City, UT MSA
41700	San Antonio-New Braunfels, TX MSA
41860	San Francisco-Oakland-Hayward, CA MSA
41940	San Jose-Sunnyvale-Santa Clara, CA MSA
42220	Santa Rosa, CA MSA
42660	Seattle-Tacoma-Bellevue, WA MSA

44940	Sumter, SC MSA
45540	The Villages, FL MSA
46300	Twin Falls, ID MSA
46520	Urban Honolulu, HI MSA
47020	Victoria, TX MSA
47460	Walla Walla, WA MSA
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV MSA
48300	Wenatchee, WA MSA
48540	Wheeling, WV-OH MSA
48700	Williamsport, PA MSA

These areas are located throughout the country, as can be seen in exhibit 3.2.

Exhibit 3.2. The 60 Metro Areas with Rapidly Rising Rents



Source: Arc GIS, NHGIS, Author’s calculations

3.2 Alternative Methods for Calculating FMR

In this section, we present two alternative methods for calculating FMR.

1. **Using Axiometrics Data**

We find a strong positive correlation between effective rent data in Axiometrics and the 5-year ACS data. However, we find that the percentage change in 5-year ACS data and the percentage change in effective rent using Axiometrics data are very different for some metro areas. In some instances, the change in the effective rents using Axiometrics data is much bigger than the ACS change. Thus, we propose using the local correlation to predict FMR.

2. **Price-to-Rent Ratio**

The second method uses the price-to-rent ratio to estimate FMR because (at the margin) a household is likely to be indifferent about whether they obtain housing services through renting or through owning. Thus, in equilibrium, the cost of renting should be equal to the annual cost of owning.

Price-to-Rent Ratio Using Zillow Data

We calculate the price-to-rent ratio for each CBSA by dividing the average Zillow home value over 5 years by the 40th percentile of rent from the ACS 5-year file. Then, we use this price-to-rent ratio with the Zillow home value index to estimate rent.

Price-to-Rent Ratio Using Federal Housing Finance Agency's House Price Index

This method is similar to the second method previously discussed, but instead of using Zillow data, we use other price indices that are readily available: the HPI dataset provided by FHFA. We first forecast home values using the HPI and then use it with the price-to-rent ratio to estimate rent.

This price-to-rent approach provides a clear advantage because getting reliable house price indices is much easier, but that is not the case for rent indices.

We do not prefer one index over the other and recommend that both be used to obtain a range of FMR estimates.

First, the authors calculate the 5-year moving average of median effective rent using Axiometrics data for each metro area. Next, we run a simple linear regression with the 5-year ACS as the dependent variable, and the results of the analysis are summarized in exhibit 3.3.

Exhibit 3.3. Regression Results of 5-Year ACS on 5-Year Effective Rent

	5-year ACS							
	1	2	3	4	5	6	7	8
5-year effective rent	0.6289***	0.7191***	1.0961***	1.2156***	1.1534***	1.1328***	-0.0382	0.0183
	(0.0124)	(0.1331)	(0.2344)	(0.2650)	(0.2968)	(0.3143)	(0.0568)	(0.0554)
Lag of 5-year effective rent		-0.1022	-1.0927**	-1.4467**	-1.2600*	-1.3001*	0.1423	0.0361
		(0.1423)	(0.4484)	(0.6068)	(0.6881)	(0.7388)	(0.1302)	(0.1259)
Lag 2 of 5-year effective rent			0.6298***	0.8899	0.7422	0.9408	0.1391	0.2100
			(0.2418)	(0.6052)	(0.7981)	(0.9227)	(0.1614)	(0.1542)
Lag 3 of 5-year effective rent				-0.0213	-0.1066	-0.0524	-0.0989	-0.2809*
				(0.2751)	(0.6773)	(0.9385)	(0.1638)	(0.1606)
Lag 4 of 5-year effective rent					0.1096	-0.4758	-0.2997**	-0.0614
					(0.3027)	(0.7991)	(0.1395)	(0.1422)
Lag 5 of 5-year effective rent						0.3969	0.1457**	0.0735
						(0.3637)	(0.0636)	(0.0624)
Lag 1 of ACS 5-year							1.0401***	1.3895***
							(0.0132)	(0.0762)
Lag 2 of ACS 5-year								-0.3680***
								(0.0791)
Observations	464	409	353	300	251	202	202	202
Adjusted R-Squared	0.8480	0.8528	0.8586	0.8640	0.8692	0.8756	0.9962	0.9966
AIC	5522.5	4863.9	4195.8	3567.1	2986.0	2405.0	1700.8	1681.3
BIC	5530.8	4876.0	4211.3	3585.6	3007.2	2428.1	1727.2	1711.1

ACS = American Community Survey. AIC = Akaike information criterion. BIC = Bayesian information criterion.
* = Significant at 90th percent confidence level. ** = Significant at 90th percent confidence level. *** = Significant at 99th percent confidence level.

Exhibit 3.3 indicates a strong positive correlation between the 5-year ACS and the 5-year moving average of effective rent using Axiometrics data. The analysis using the asking rents variable in Axiometrics is similar, with a high correlation between asking rent and effective rent. We use effective rent for our analysis because forecasts of effective rent are available for some metro areas, which might be helpful in forecasting FMR rents for the next fiscal year.

Next, we analyze the correlation between 5-year ACS and 1-year effective rent, and we again find a high correlation. The regression results are summarized in exhibit 3.4.

Exhibit 3.4. Regression Results of 5-Year ACS on 1-Year Effective Rent

	5-year ACS	
	1	2
Effective rent	0.5411***	0.2643***
	(0.0114)	(0.0590)
Lag of effective rent		0.2963***
		(0.0624)
Observations	461	440
Adjusted R-Squared	0.8296	0.8382
AIC	5539.5	5271.3
BIC	5547.8	5283.5

ACS = American Community Survey. AIC = Akaike information criterion. BIC = Bayesian information criterion.
* = Significant at 90th percent confidence level. ** = Significant at 90th percent confidence level. *** = Significant at 99th percent confidence level.

Lastly, we analyze the correlation between change in 5-year ACS and the change in effective rent and lagged values of change in effective rent. The regression results are summarized in exhibit 3.5.

Exhibit 3.5. Regression Results of Change in 5-Year ACS on Change in Effective Rent

	Change in 5-year ACS			
	1	2	3	4
Change in effective rent	0.0124	0.0069	0.0016	0.0032
	(0.0140)	(0.0130)	(0.0123)	(0.0128)
Lag of change in effective rent	0.0412***	0.0485***	0.0505***	0.0433***
	(0.0143)	(0.0134)	(0.0128)	(0.0141)
Lag 2 of change in effective rent	0.0556***	0.0694***	0.0756***	0.0784***
	(0.0145)	(0.0137)	(0.0132)	(0.0140)
Lag 3 of change in effective rent	0.1013***	0.0891***	0.0843***	0.0888***
	(0.0142)	(0.0141)	(0.0134)	(0.0151)
Lag 4 of change in effective rent		0.0739***	0.0879***	0.0909***
		(0.0149)	(0.0143)	(0.0165)
Lag 5 of change in effective rent		0.0888***	0.0751***	0.0682***
		(0.0151)	(0.0153)	(0.0167)
Lag 6 of change in effective rent			0.1091***	0.1044***
			(0.0158)	(0.0167)
Lag 7 of change in effective rent			0.0013	-0.0005
			(0.0164)	(0.0176)
Lag 8 of change in effective rent				-0.0335*
				(0.0187)
Lag 9 of change in effective rent				-0.0254
				(0.0166)
Observations	346	314	294	254
Adjusted R-Squared	0.2396	0.4251	0.5253	0.5458
AIC	3019.5	2670.0	2454.6	2128.9
BIC	3038.7	2696.3	2487.7	2167.8

ACS = American Community Survey. AIC = Akaike information criterion. BIC = Bayesian information criterion. * = Significant at 90th percent confidence level. ** = Significant at 90th percent confidence level. *** = Significant at 99th percent confidence level.

The exhibits indicate an overall high correlation between effective rent data in Axiometrics and the 5-year ACS data. Therefore, Axiometrics data offer potential improvements in FMR calculation in areas with rapidly rising rents, given that they are available ahead of ACS releases.

3.3 Predicting Rent Using Axiometrics Data

We find a strong positive correlation between effective rent data in Axiometrics and the 5-year ACS data. However, we find that the percentage change in 5-year ACS data and the percentage change in effective rent using Axiometrics data are very different for some metro areas. In some instances, the change in effective rents is much bigger than the ACS change. We propose using the local correlation to predict FMR.

We calculate the 5-year moving average of effective rent using Axiometrics data for each metro area. Next, we calculate the ratio as the 5-year ACS divided by the 5-year moving average of effective rent in 2017. Finally, we predict the rent in 2018 by multiplying this ratio by the 5-year moving average of effective rent in 2018.

To assess the accuracy of this alternative measure, we benchmark it against rents from the ACS data. We calculate the percentage error using the following formula:

$$\text{Error} = \frac{(\text{Predicted rent} - \text{ACS 5 year rent})}{\text{ACS 5 year rent}} * 100$$

Using the steps previously described, when we predict the rent in 2018, we get an error that is summarized in exhibit 3.6.

Exhibit 3.6. Comparison of Predicted Rents Using Axiometrics Data to ACS Values

Summary statistics of the error (%)	
Minimum	-7.4399
10th percentile	-3.9521
25th percentile	-2.0174
50th percentile	-0.5430
75th percentile	0.6800
90th percentile	2.0964
Maximum	5.4160
Mean	-0.8047
Standard Deviation	2.4234
Observations	56

ACS = American Community Survey.

The number of observations in the previous analysis is 56 because Axiomertics data do not cover all of the 60 areas of rapidly rising rents that we identified. The four CBSAs that Axiometrics does not cover are—

- Dubuque, IA MSA.
- Grants Pass, OR MSA.
- Twin Falls, ID MSA.
- Urban Honolulu, HI MSA.

The minimum and maximum of this error are smaller than 8 percent, so even if we cannot predict the FMR correctly, this small error can easily be corrected by using 90 to 110 percent of the payment standards.

The overall error is small, in the range of -7.5–5.5 percent. A negative error indicates that the ACS rent is higher than the predicted rent, whereas a positive error indicates that the ACS rent is lower than the predicted rent. The median error for the sample is -0.54 percent.

Exhibit 3.7 shows the predicted rent for each of the CBSAs. The variable definitions are as follows:

5-year ACS in 2018: 40th percentile of the 5-year ACS rent in 2018.

Effective rent in 2018: Yearly effective rent from Axiometrics in 2018.

5-year effective rent in 2018: 5-year moving average of effective rent.

Ratio in 2017: Ratio of 5-year ACS and 5-year effective rent for 2017.

Predicted rent in 2018: Ratio multiplied by the 5-year effective rent in 2018.

Error (%): Percentage difference between predicted rent and 5-year ACS in 2018.

Exhibit 3.7. Predicted Rent Using Axiometrics Data

CBSA Code	CBSA Name	5-Year ACS in 2018 ($)	Effective Rent in 2018 ($)	5-Year Effective Rent in 2018 ($)	Ratio in 2017	Predicted Rent in 2018 ($)	Error (%)
10540	Albany, OR MSA	857	1,004.25	881.13	0.9946	876.37	2.26
11020	Altoona, PA MSA	713	907.50	911.88	0.7585	691.68	-2.99
12420	Austin-Round Rock, TX MSA	1,184	1,152.75	1,095.10	1.0634	1,164.53	-1.64
13740	Billings, MT MSA	816	970.75	877.10	0.9195	806.53	-1.16
13900	Bismarck, ND MSA	814	991.75	986.25	0.8033	792.21	-2.68
13980	Blacksburg-Christiansburg-Radford, VA MSA	733	1,154.25	1,082.55	0.6838	740.21	0.98
14500	Boulder, CO MSA	1,319	1,597.00	1,445.00	0.9071	1,310.72	-0.63
14740	Bremerton-Silverdale, WA MSA	1,063	1,388.25	1,240.35	0.8613	1,068.27	0.50
15540	Burlington-South Burlington, VT MSA	1,212	1,644.50	1,642.00	0.7090	1,164.10	-3.95
16220	Casper, WY MSA	783	776.25	841.90	0.8984	756.40	-3.40
16620	Charleston, WV MSA	714	746.50	725.60	0.9822	712.68	-0.19
16700	Charleston-North Charleston, SC MSA	978	1,130.00	1,033.75	0.9525	984.62	0.68
17820	Colorado Springs, CO MSA	959	1,049.25	940.45	1.0206	959.79	0.08

18700	Corvallis, OR MSA	920	1,117.75	998.40	0.9237	922.20	0.24
19060	Cumberland, MD-WV MSA	644	799.75	789.75	0.7618	601.62	-6.58
19740	Denver-Aurora-Lakewood, CO MSA	1,228	1,468.00	1,339.45	0.9076	1,215.64	-1.01
21060	Elizabethtown-Fort Knox, KY MSA	703	729.00	713.30	0.9445	673.71	-4.17
21340	El Paso, TX MSA	745	737.25	716.70	1.0197	730.80	-1.91
21420	Enid, OK MSA	746	702.25	739.75	0.9334	690.50	-7.44
22020	Fargo, ND-MN MSA	775	767.75	731.60	1.0415	761.98	-1.68
22380	Flagstaff, AZ MSA	1,084	1,372.00	1,253.95	0.8826	1,106.73	2.10
22660	Fort Collins, CO MSA	1,052	1,361.50	1,299.90	0.7824	1,017.04	-3.32
24220	Grand Forks, ND-MN MSA	785	907.50	868.85	0.9002	782.12	-0.37
24540	Greeley, CO MSA	888	1,237.50	1,039.95	0.8816	916.77	3.24
25420	Harrisburg-Carlisle, PA MSA	912	973.25	920.55	0.9971	917.91	0.65
25980	Hinesville, GA MSA	782	1,091.00	1,058.65	0.7342	777.21	-0.61
26380	Houma-Thibodaux, LA MSA	788	867.00	837.65	0.9075	760.19	-3.53
27860	Jonesboro, AR MSA	684	648.00	702.90	0.9637	677.39	-0.97
28420	Kennewick-Richland, WA MSA	867	1,015.00	956.45	0.8884	849.70	-2.00

30140	Lebanon, PA MSA	822	954.00	874.40	0.9211	805.44	-2.02
31340	Lynchburg, VA MSA	730	863.25	827.25	0.8781	726.43	-0.49
31740	Manhattan, KS MSA	853	764.00	793.95	1.0593	841.02	-1.41
31860	Mankato-North Mankato, MN MSA	823	1,345.00	1,231.25	0.7046	867.57	5.42
33260	Midland, TX MSA	1,163	1,473.00	1,161.83	1.0224	1,187.81	2.13
34060	Morgantown, WV MSA	781	697.75	679.60	1.1157	758.21	-2.92
34900	Napa, CA MSA	1,492	2,077.00	1,954.70	0.7722	1,509.41	1.17
35620	New York-Newark-Jersey City, NY-NJ-PA MSA	1,396	2,150.00	2,055.50	0.6723	1,381.97	-1.01
36220	Odessa, TX MSA	1,018	1,329.50	1,108.65	0.9198	1,019.72	0.17
36500	Olympia-Tumwater, WA MSA	1,040	1,214.75	1,043.70	1.0241	1,068.87	2.78
38900	Portland-Vancouver-Hillsboro, OR-WA MSA	1,096	1.349.75	1.218.20	0.8943	1.089.47	-0.60
39660	Rapid City, SD MSA	820	949.00	842.85	0.9795	825.60	0.68
41420	Salem, OR MSA	854	1.003.50	861.50	1.0066	867.22	1.55
41620	Salt Lake City, UT MSA	969	1.132.25	1.008.95	0.9677	976.35	0.76
41700	San Antonio-New Braunfels, TX MSA	949	928.25	860.70	1.1008	947.47	-0.16
41860	San Francisco-Oakland-Hayward, CA MSA	1,709	2.602.00	2.406.20	0.7082	1.703.99	-0.29

41940	San Jose-Sunnyvale-Santa Clara, CA MSA	1,948	2.819.75	2.625.85	0.7267	1.908.11	-2.05
42220	Santa Rosa, CA MSA	1,445	2.059.50	1.833.30	0.7994	1.465.48	1.42
42660	Seattle-Tacoma-Bellevue, WA MSA	1,292	1.640.00	1.453.90	0.8857	1.287.76	-0.33
44940	Sumter, SC MSA	690	831.25	726.45	0.9523	691.81	0.26
45540	The Villages, FL MSA	770	975.75	831.02	0.9456	785.83	2.06
47020	Victoria, TX MSA	866	857.25	855.40	0.9596	820.85	-5.21
47460	Walla Walla, WA MSA	833	865.50	875.00	0.9003	787.72	-5.44
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV MSA	1,532	1,656.38	1,578.93	0.9507	1,501.06	-2.02
48300	Wenatchee, WA MSA	839	1,349.25	1,200.40	0.6895	827.66	-1.35
48540	Wheeling, WV-OH MSA	660	719.75	695.13	0.9530	662.47	0.37
48700	Williamsport, PA MSA	763	913.00	850.75	0.9053	770.18	0.94

Next, we compare the errors in predicted rents using Axiometrics data with those in predicted rents using the gross rent Consumer Price Index factor provided by HUD. To predict rents in 2018 using the CPI factor, we multiplied the 40th percentile of ACS 5-year rent in 2017 with the CPI factor in 2017 through 2018. The key objective in all our analyses has been to estimate the 5-year ACS for the next year; hence we again benchmark the predicted rent using the CPI factor against the 40th percentile of ACS 5-year rent in 2018. Thus, we calculate errors using the following formula:

$$\text{Error} = \frac{(\text{Predicted rent in 2018 using CPI factor} - \text{ACS 5} - \text{year rent in 2018})}{\text{ACS 5} - \text{year rent in 2018}} * 100$$

Using the steps previously described, we get an error that is summarized in exhibit 3.8. For comparison, we restrict the sample to CBSAs for which we had Axiometrics data.

Exhibit 3.8. Comparison of Predicted Rents Using CPI Factor for 2018

Summary statistics of the error (%)	
Minimum	-5.1676
10th percentile	-3.9490
25th percentile	-2.4676
50th percentile	-1.4095
75th percentile	-0.5573
90th percentile	0.1531
Maximum	1.6521
Mean	-1.5404
Standard Deviation	1.5038
Observations	56

CPI = Consumer Price Index.

As shown in exhibit 3.8, for 2018, predicted rents using the CPI factor were marginally lower than the corresponding ACS 5-year rent for most of the sample. The median error using the CPI factor for this sample is -1.41 percent, and the mean is -1.54 percent.

3.4 Price-to-Rent Ratio Using Zillow Data

We calculate the price-to-rent ratio for each CBSA by dividing the average Zillow home value over 5 years by the 40th percentile of rent from the ACS 5-year file (referred to as “Rent” in the following formula). For this analysis, the authors use the Zillow Home Value Index All Homes (SFR, Condo/Co-op) Time Series, Raw, Mid-Tier ($) provided by Zillow. It is a monthly series, and we take the average to calculate the home values at the yearly frequency. Thus, the price-to-rent ratio is calculated using the following formula:

$$\text{Price} - \text{to} - \text{rent ratio in the year 2018} = \frac{\text{Average Zillow value during } 2014 - 2018}{\text{40th percentile of rent in 2018 from the ACS } 5 - \text{year file}}$$

Next, to predict the rent in 2019, we use the following equation:

$$\text{Predicted rent in 2019 } = \frac{\text{Average Zillow value during } 2015 - 2019}{\text{Price} - \text{to} - \text{rent ratio in the year 2018}}$$

To assess the accuracy of this alternative measure, we benchmark it against gross rents from the ACS data. We calculate the percentage error using the following formula:

$$\text{Error} = \frac{(\text{Predicted rent} - \text{Rent})}{\text{Rent}} * 100$$

When using the method, we assume that the price-to-rent ratio that we have calculated using the 5-year ACS data and the 5-year moving average of the Zillow home value index does not change much from year to year. If one expects the price-to-rent ratio to change significantly, then adjusting the price-to-rent ratio in that direction might be a good idea. One can compute the price-to-rent ratios by looking at price and rent data from various sources. For instance, one can compute the price-to-rent ratio using Zillow's value and rent data. An alternative could be to use the HPI available from FHFA or Fannie Mae and use the owners' equivalent rent of residences (OER), a subcomponent of the shelter component of the Consumer Price Index for All Urban Consumers (CPI-U).

In the method previously discussed, we use the 40th-percentile rents from the ACS 5-year survey. We repeat the analysis using the gross median rent using the 5-year ACS, and the results are summarized in the appendix. As seen in appendix exhibit A.1, the prediction error using the median rent is very similar to those obtained using the 40th percentile. We use the 40th percentile of the rent in our preferred specification because FMR is based on the 40th percentile of the distribution. However, when calculating the price-to-rent ratio, we use the median Zillow value and the 40th percentile of the rent distribution. Ideally, calculating the price-to-rent ratio for the same portion of the distribution would have been better. However, we do not have the 40th percentile of ZHVI.

Next, we use the method previously discussed to estimate rents for 2019. The sample consists of the 60 CBSAs identified as having rapidly rising rents—except for the Victoria, TX MSA—because Zillow data are missing for a few years.

Using the steps previously described, we calculate the prediction error for rent for 2019, and is summarized in exhibit 3.9.

Exhibit 3.9. Comparison of Predicted Rents Using Zillow Data to ACS Values

Summary Statistics of the Error (%)	
Minimum	-2.7304
10th percentile	-1.3250
25th percentile	0.1518
50th percentile	1.3528
75th percentile	3.0209
90th percentile	4.7082
Maximum	6.9743
Mean	1.6169
Standard deviation	2.1525
Observations	59

When the error calculated in exhibit 3.9 is negative, it indicates that the ACS rent is higher than the predicted rent. For this sample, the error is very small and is in the range of – 2.7 to +7.0 percent. The mean and median are positive, indicating that the predicted rent is higher than the 40th percentile of the ACS rent. Zillow also provides data at the ZIP Code level, which can be used for estimating the SAFMRs using the methodology previously illustrated.

Exhibit 3.10. Predicted Rents Using Zillow Data

CBSA Code	CBSA Name	Zillow Region Name	5-Year ACS in 2019 ($)	Average 5-Year Zillow Value in 2019 ($)	Price-to-Rent Ratio in 2018	Predicted Rent in 2019 ($)	Error (%)
10540	Albany, OR MSA	Albany, OR	892	228,628	242.90	941.24	5.52
11020	Altoona, PA MSA	Altoona, PA	713	110,269	149.88	735.74	3.19
12420	Austin-Round Rock, TX MSA	Austin, TX	1,241	320,234	255.73	1,252.25	0.91
13740	Billings, MT MSA	Billings, MT	834	249,339	299.20	833.35	-0.08
13900	Bismarck, ND MSA	Bismarck, ND	824	268,046	326.06	822.07	-0.23
13980	Blacksburg-Christiansburg, VA MSA	Blacksburg, VA	768	174,999	231.23	756.80	-1.46
14500	Boulder, CO MSA	Boulder, CO	1,418	510,072	359.17	1,420.15	0.15
14740	Bremerton-Silverdale, WA MSA	Bremerton, WA	1,138	326,979	282.89	1,155.87	1.57
15540	Burlington-South Burlington, VT MSA	Burlington, VT	1,236	281,522	224.73	1,252.72	1.35
16220	Casper, WY MSA	Casper, WY	778	208,397	264.49	787.93	1.28
16620	Charleston, WV MSA	Charleston, WV	714	99,037	138.14	716.91	0.41
16700	Charleston-North Charleston, SC MSA	Charleston, SC	1,017	2,48375	241.16	1,029.92	1.27
17820	Colorado Springs, CO MSA	Colorado Springs, CO	1,021	270,377	262.68	1,029.31	0.81
18700	Corvallis, OR MSA	Corvallis, OR	997	329,001	336.26	978.42	-1.86

19060	Cumberland, MD-WV MSA	Cumberland, MD	655	91,769	138.75	661.39	0.98
19740	Denver-Aurora-Lakewood, CO MSA	Denver, CO	1,328	394,280	296.73	1,328.74	0.06
20220	Dubuque, IA MSA	Dubuque, IA	751	170,235	224.21	759.26	1.10
21060	Elizabethtown-Fort Knox, KY MSA	Elizabethtown, KY	723	139,365	189.40	735.81	1.77
21340	El Paso, TX MSA	El Paso, TX	756	126,590	166.24	761.49	0.73
21420	Enid, OK MSA	Enid, OK	768	83,472	107.73	774.79	0.88
22020	Fargo, ND-MN MSA	Fargo, ND	800	220,696	275.34	801.55	0.19
22380	Flagstaff, AZ MSA	Flagstaff, AZ	1,170	327,901	288.12	1,138.06	-2.73
22660	Fort Collins, CO MSA	Fort Collins, CO	1,120	369,552	326.65	1,131.35	1.01
24220	Grand Forks, ND-MN MSA	Grand Forks, ND	800	193,311	235.08	822.31	2.79
24420	Grants Pass, OR MSA	Grants Pass, OR	875	259,506	291.39	890.56	1.78
24540	Greeley, CO MSA	Greeley, CO	942	327,706	339.27	965.92	2.54
25420	Harrisburg-Carlisle, PA MSA	Harrisburg, PA	937	177,204	189.27	936.27	-0.08
25980	Hinesville, GA MSA	Hinesville, GA	804	135,556	163.76	827.75	2.95
26380	Houma-Thibodaux, LA MSA	Houma, LA	793	149,715	185.04	809.08	2.03
27860	Jonesboro, AR MSA	Jonesboro, AR	690	117,971	166.92	706.77	2.43
28420	Kennewick-Richland, WA MSA	Kennewick, WA	912	246,120	257.58	955.50	4.77

30140	Lebanon, PA MSA	Lebanon, PA	850	173,017	204.86	844.57	-0.64
31340	Lynchburg, VA MSA	Lynchburg, VA	732	165,258	217.82	758.68	3.64
31740	Manhattan, KS MSA	Manhattan, KS	843	185,087	209.25	884.55	4.93
31860	Mankato-North Mankato, MN MSA	Mankato, MN	835	194,911	224.64	867.66	3.91
33260	Midland, TX MSA	Midland, TX	1,201	231,184	189.52	1,219.85	1.57
34060	Morgantown, WV MSA	Morgantown, WV	793	162,401	201.94	804.20	1.41
34900	Napa, CA MSA	Napa, CA	1,605	651,950	414.95	1,571.14	-2.11
35620	New York-Newark-Jersey City, NY-NJ-PA MSA	New York, NY	1,445	446,149	308.49	1,446.22	0.08
36220	Odessa, TX MSA	Odessa, TX	1,035	158,275	146.06	1,083.61	4.70
36500	Olympia-Tumwater, WA MSA	Olympia, WA	1,077	285,433	254.78	1,120.30	4.02
38900	Portland-Vancouver-Hillsboro, OR-WA MSA	Portland, OR	1,175	374,163	318.60	1,174.41	-0.05
39660	Rapid City, SD MSA	Rapid City, SD	830	213,192	249.33	855.07	3.02
41420	Salem, OR MSA	Salem, OR	900	252,896	270.08	936.36	4.04
41620	Salt Lake City, UT MSA	Salt Lake City, UT	1,023	319,323	304.85	1,047.48	2.39
41700	San Antonio-New Braunfels, TX MSA	San Antonio, TX	987	186,669	186.16	1,002.76	1.60

41860	San Francisco-Oakland-Hayward, CA MSA	San Francisco, CA	1,827	1,003,347	548.34	1,829.80	0.15
41940	San Jose-Sunnyvale-Santa Clara, CA MSA	San Jose, CA	2,115	1,065,204	516.60	2,061.97	-2.51
42220	Santa Rosa, CA MSA	Santa Rosa, CA	1,541	605,944	398.49	1,520.58	-1.33
42660	Seattle-Tacoma-Bellevue, WA MSA	Seattle, WA	1,379	447,637	318.69	1,404.63	1.86
44940	Sumter, SC MSA	Sumter, SC	675	115,806	160.64	720.91	6.80
45540	The Villages, FL MSA	The Villages, FL	790	255,149	321.24	794.27	0.54
46300	Twin Falls, ID MSA	Twin Falls, ID	734	17,829	229.03	785.19	6.97
46520	Urban Honolulu, HI MSA	Urban Honolulu, HI	1,591	683,860	426.48	1,603.51	0.79
47020	Victoria, TX MSA	Victoria, TX	899	NA	NA	NA	NA
47460	Walla Walla, WA MSA	Walla Walla, WA	884	237,520	263.51	901.37	1.97
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV MSA	Washington, DC	1,577	408,016	259.48	1,572.44	-0.29
48300	Wenatchee, WA MSA	Wenatchee, WA	870	303,935	333.64	910.96	4.71
48540	Wheeling, WV-OH MSA	Wheeling, OH	673	89,346	128.32	696.28	3.46
48700	Williamsport, PA MSA	Williamsport, PA	761	146,713	185.86	789.36	3.73

Next, we compare the errors in predicted rents using Zillow data with those in predicted rents using the gross rent CPI factor provided by HUD. To predict rents in 2019 using the CPI factor, we multiplied the 40th percentile of ACS 5-year rent in 2018 with the CPI factor in 2018 through 2019. The key objective in all our analyses has been to estimate the 5-year ACS for the next year; hence we again benchmark the predicted rent using the CPI factor against the 40th percentile of ACS 5-year rent in 2019. Thus, we calculate errors using the following formula:

$$\text{Error} = \frac{(\text{Predicted rent in 2019 using CPI factor } - \text{ACS 5} - \text{year rent in 2018})}{\text{ACS 5} - \text{year rent in 2018}} * 100$$

Using the steps previously described, the error we get is summarized in exhibit 3.11. For comparison, we restrict the sample to CBSAs for which we had Zillow data. As can be seen in exhibit 3.11, the mean error in predicted rents for 2019 using the CPI factor is 0.02 percent when benchmarked against the ACS 5-year rent in 2019, whereas the median error is 0.004 percent.

Exhibit 3.11. Comparison of Predicted Rents Using CPI Factor for the Year 2019

Summary statistics of the error (%)	
Minimum	-5.0263
10th percentile	-2.8007
25th percentile	-1.4589
50th percentile	0.0038
75th percentile	1.2619
90th percentile	2.6717
Maximum	5.5849
Mean	0.0211
Standard Deviation	2.1298
Observations	59

CPI = Consumer Price Index.

3.5 Price-to-Rent Ratio Using the FHFA House Price Index

In this section, we explore the price-to-rent methodology using another price index that is readily available—namely, the HPI dataset provided by FHFA. In the following analysis, we use the Metropolitan Statistical Areas and Divisions: All Transactions Index (not seasonally adjusted) for this analysis, which is estimated using sales price and appraisal data.

We use this dataset with the ACS 5-year dataset to forecast rents. We perform the following steps:

We begin by forecasting home values.

Because we are using the 5-year ACS house value,[4] we first create a 5-year moving average of the HPI. (The 5-year moving average index in 2010 is the average HPI for the period 2006–2010.)

Next, we calculate the change in this 5-year moving average index as follows:

$$\text{Change in index} = \frac{(5-\text{year moving average in year t}) - (5-\text{year moving average in year t}-1)}{5-\text{year moving average in year t}-1}$$

Next, we merge it with the ACS 5-year data and forecast value as—

Forecast value in year *t* = House value in year *t*-1 + (House value in year *t*-1 * change in the index in year *t*)

We calculate the forecast error as—

$$\text{Error in value in year } t = \frac{\text{Forecast value in year } t - \text{ House value in year } t}{\text{House value in year } t} * 100$$

The forecast error is summarized in exhibit 3.12.

Exhibit 3.12. Summary Statistics of Errors for House Values Forecasts

Summary statistics of the error (%)	
Minimum	-6.9396
10th percentile	-3.1726
25th percentile	-1.7990
50th percentile	-0.5236
75th percentile	0.6617
90th percentile	1.5868
Maximum	6.5750
Mean	-0.6267
Standard Deviation	1.8789
Observations	501

We calculate the price-to-rent ratio as—

$$\text{Price} - \text{to} - \text{rent ratio in the year t} = \frac{\text{Median Value from the ACS 5} - \text{year file}}{\text{Median Gross Rent from the ACS 5} - \text{year file}}$$

[4] https://data.census.gov; ACS table ID: B25077

Next, to predict rent, we use the following equation:

$$\text{Predicted rent in year t } = \frac{\text{Forecast value in year t}}{\text{Price} - \text{to} - \text{rent ratio in year t} - 1}$$

To assess the accuracy of this alternative measure, we benchmark it against gross rents from the ACS data. We calculate the percentage error using the following formula:

$$\text{Error in year } t = \frac{(\text{Predicted rent in year } t - \text{Gross rent in year } t)}{\text{Gross rent in year } t} * 100$$

One of the advantages of using the FHFA HPI for this project is that it allows us to test the accuracy of the rent predictions for a longer period.

We estimate the errors using the steps previously described and are summarized in exhibits 3.13 and 3.14.

Exhibit 3.13. Comparison of Predicted Rent Using the FHFA House Price Index to ACS Values

Summary statistics of the error (%)	
Minimum	-15.0421
10th percentile	-5.8179
25th percentile	-3.3072
50th percentile	-1.0341
75th percentile	1.3355
90th percentile	2.8242
Maximum	8.3926
Mean	-1.2608
Standard Deviation	3.5127
Observations	501

ACS = American Community Survey. FHFA = Federal Housing Finance Agency.

Exhibit 3.14. Comparison of Predicted Rent Using the FHFA House Price Index to ACS Values from 2014 Forward

Summary statistics of the error (%)	
Minimum	-7.5760
10th percentile	-2.8913
25th percentile	-1.3538
50th percentile	0.3220
75th percentile	2.1515
90th percentile	3.2103
Maximum	8.3926
Mean	0.3630
Standard Deviation	2.4925
Observations	336

ACS = American Community Survey. FHFA = Federal Housing Finance Agency.

If one looks at the absolute value of median error after 2013, it is lower than the median error for the entire sample. The error distribution for the pre-2014 period reveals large negative errors, which imply that the gross rent is higher than the predicted rent. To analyze the possible reason for this relatively large negative error, we selected two metropolitan areas—San Francisco-Oakland-Fremont, CA Metro Area, and San Jose-Sunnyvale-Santa Clara, CA Metro Area. We found that the price-to-rent ratio for those two metro areas decreased from 2010 through 2014 (for this analysis, we computed the price-to-rent ratio by dividing the ACS 5-year value by the ACS 5-year gross rent). To predict rent, we divide the house price by the price-to-rent ratio; using a larger price-to-rent ratio will result in lower rent. Thus, as discussed earlier, when a large fluctuation occurs in the price-to-rent ratio from one year to another, the ratio can be adjusted to reflect that movement. Exhibit 3.15 summarizes the error for each year.

The sample consists of the 60 CBSAs with rapidly rising rents (see exhibit 3.1) and those in the bulleted list that follows because the HPI for these CBSAs is broken down into separate metropolitan statistical area divisions (MSADs). One can aggregate the MSADs to form the corresponding CBSA by taking a simple average or a population-weighted average. For this analysis, we excluded the following CBSAs to alleviate measurement error concerns when aggregating data across MSADs.

- New York-Newark-Jersey City, NY-NJ-PA Metro Area
- San Francisco-Oakland-Berkeley, CA Metro Area
- Seattle-Tacoma-Bellevue, WA Metro Area
- Washington-Arlington-Alexandria, DC-VA-MD-WV Metro Area

FHFA HPI is also available at the ZIP Code level, so it can be used to estimate the SAFMRs using the methodology previously described.

Exhibit 3.15. Comparison of Predicted Rent Using the FHFA House Price Index to ACS by Year

		Summary statistics of the error (%)			
Year	Observations	Mean	Std. Dev.	Minimum	Maximum
2011	55	-5.2951	3.1151	-15.0421	-1.0740
2012	55	-4.7587	2.7876	-11.5672	-0.2621
2013	55	-3.6486	2.6425	-10.1195	0.9204
2014	56	-1.9466	2.3158	-7.5760	8.3926
2015	56	0.6455	1.9241	-4.2821	5.1143
2016	56	0.8907	2.5594	-5.2989	6.9322
2017	56	0.3639	2.5773	-5.2919	7.0710
2018	56	0.7147	2.2005	-4.9569	6.6130
2019	56	1.5095	1.8657	-3.3672	5.8224

ACS = American Community Survey. FHFA = Federal Housing Finance Agency. Std. Dev. = standard deviation.

3.6 Autoregressive Integrated Moving Average (ARIMA) Models

In addition to proposing those two new methods, we also reviewed the current procedure HUD uses to calculate the trend factor by using the autoregressive integrated moving average (ARIMA) models. We did not have any additional suggestions to substantially improve the currently used procedure. The only recommendation is that HUD consider using FHFA HPI, Axiometrics, or Zillow data to further localize the inflation factors for areas where CPI is unavailable. Also, FHFA House Price Index/Zillow/Axiometrics data can be an additional input in calculating the trend factors using the ARIMA model.

4. Conditions Under Which HUD Should Use Alternative Methods

HUD should use these new proposed methods to supplement its existing analysis. We recommend that HUD calculates the rent using all three data sources discussed—Axiometrics, Zillow, and FHFA. It is also important to remember that the proposed method using the price-to-rent ratio assumes that the price-to-rent ratio does not change much in a year. If one expects that the price-to-rent ratio has changed significantly, one will need to adjust the ratio by looking at the contemporaneous price and rent data.

To begin with, HUD should continue using its existing method and do a more careful evaluation of the metropolitan areas for which the rents using the existing method deviate significantly from FMR estimates currently being used by HUD.

Although we have restricted the analysis in this project to areas with rapidly rising rents, we believe these methods can be applied to all areas. One of the constraints in using the proposed methods for all FMR areas will be the availability of the data, as the commercially available data sources will not cover numerous geographic areas. Some of these methods can also be used to estimate SAFMRs because data from Zillow and FHFA HPI are also available at the ZIP Code level.

These methods will also be very useful if, for some reason, the ACS decides not to publish its 1-year estimates, as was the case this year. The Census Bureau is not releasing its 1-year estimates for 2020 because the data collection was affected by the COVID-19 pandemic. Such circumstances will make estimating FMR difficult for HUD. HUD can update the FMR estimate by having alternative methods that do not rely on the release of ACS annual estimates.

Some of the shortcomings of the proposed methods are that the commercial datasets will not be available for all the locations, and the length of the time series of some commercial datasets are relatively short. Thus, HUD must continue to rely on the methodology it currently uses for most regions and use the methods proposed in the current study to supplement its current analysis.

Appendix A

In appendix exhibit A.1, we summarize the percentage error when we use the Zillow home value index and the median gross rent from ACS.[5] The errors are very similar to the one obtained using the 40th percentile of the rent distribution.

Appendix Exhibit A.1. Price-to-Rent Ratio Using ACS Median Rent and Zillow Home Value Index

Summary statistics of the error (%)	
Minimum	-2.8298
10th percentile	-0.7812
25th percentile	0.4110
50th percentile	1.4483
75th percentile	3.0605
90th percentile	4.7882
Maximum	6.3990
Mean	1.7376
Standard Deviation	2.0399
Observations	59

ACS = American Community Survey.

[5] We also predict rent using 1-year gross rent instead of the ACS 5-year survey, but the errors using the 1-year survey data were much higher. Given that the 5-year ACS data are likely to be more representative of the rent distribution in the area, we prefer to use that dataset.

Appendix B

Appendix Exhibit B.1. Crosswalk Between CBSA, FMR Area, and Zillow Region

CBSA Name	FMR Area Name	Zillow Region Name
Albany, OR MSA	Albany, OR MSA	Albany, OR
Altoona, PA MSA	Altoona, PA MSA	Altoona, PA
Austin-Round Rock, TX MSA	Austin-Round Rock, TX MSA	Austin, TX
Billings, MT MSA	Billings, MT HUD Metro FMR Area	Billings, MT
Bismarck, ND MSA	Bismarck, ND HUD Metro FMR Area	Bismarck, ND
Blacksburg-Christiansburg, VA MSA	Blacksburg-Christiansburg-Radford, VA HUD Metro FMR Area	Blacksburg, VA
Boulder, CO MSA	Boulder, CO MSA	Boulder, CO
Bremerton-Silverdale, WA MSA	Bremerton-Silverdale, WA MSA	Bremerton, WA
Burlington-South Burlington, VT MSA	Burlington-South Burlington, VT MSA	Burlington, VT
Casper, WY MSA	Casper, WY MSA	Casper, WY
Charleston, WV MSA	Charleston, WV HUD Metro FMR Area	Charleston, WV
Charleston-North Charleston, SC MSA	Charleston-North Charleston, SC MSA	Charleston, SC
Colorado Springs, CO MSA	Colorado Springs, CO HUD Metro FMR Area	Colorado Springs, CO
Corvallis, OR MSA	Corvallis, OR MSA	Corvallis, OR
Cumberland, MD-WV MSA	Cumberland, MD-WV MSA	Cumberland, MD
Denver-Aurora-Lakewood, CO MSA	Denver-Aurora-Lakewood, CO MSA	Denver, CO
Dubuque, IA MSA	Dubuque, IA MSA	Dubuque, IA
El Paso, TX MSA	El Paso, TX HUD Metro FMR Area	El Paso, TX
Elizabethtown-Fort Knox, KY MSA	Elizabethtown, KY HUD Metro FMR Area	Elizabethtown, KY
Enid, OK MSA	Enid, OK MSA	Enid, OK
Fargo, ND-MN MSA	Fargo, ND-MN MSA	Fargo, ND
Flagstaff, AZ MSA	Flagstaff, AZ MSA	Flagstaff, AZ
Fort Collins, CO MSA	Fort Collins, CO MSA	Fort Collins, CO

Grand Forks, ND-MN MSA	Grand Forks, ND-MN MSA	Grand Forks, ND
Grants Pass, OR MSA	Grants Pass, OR MSA	Grants Pass, OR
Greeley, CO MSA	Greeley, CO MSA	Greeley, CO
Harrisburg-Carlisle, PA MSA	Harrisburg-Carlisle, PA MSA	Harrisburg, PA
Hinesville, GA MSA	Hinesville, GA HUD Metro FMR Area	Hinesville, GA
Houma-Thibodaux, LA MSA	Houma-Thibodaux, LA MSA	Houma, LA
Jonesboro, AR MSA	Jonesboro, AR HUD Metro FMR Area	Jonesboro, AR
Kennewick-Richland, WA MSA	Kennewick-Richland, WA MSA	Kennewick, WA
Lebanon, PA MSA	Lebanon, PA MSA	Lebanon, PA
Lynchburg, VA MSA	Lynchburg, VA MSA	Lynchburg, VA
Manhattan, KS MSA	Manhattan, KS MSA	Manhattan, KS
Mankato-North Mankato, MN MSA	Mankato-North Mankato, MN MSA	Mankato, MN
Midland, TX MSA	Midland, TX HUD Metro FMR Area	Midland, TX
Morgantown, WV MSA	Morgantown, WV MSA	Morgantown, WV
Napa, CA MSA	Napa, CA MSA	Napa, CA
New York-Newark-Jersey City, NY-NJ-PA MSA	New York, NY HUD Metro FMR Area	New York, NY
New York-Newark-Jersey City, NY-NJ-PA MSA	Jersey City, NJ HUD Metro FMR Area	New York, NY
New York-Newark-Jersey City, NY-NJ-PA MSA	Newark, NJ HUD Metro FMR Area	New York, NY
Odessa, TX MSA	Odessa, TX MSA	Odessa, TX
Olympia-Tumwater, WA MSA	Olympia-Tumwater, WA MSA	Olympia, WA
Portland-Vancouver-Hillsboro, OR-WA MSA	Portland-Vancouver-Hillsboro, OR-WA MSA	Portland, OR
Rapid City, SD MSA	Rapid City, SD HUD Metro FMR Area	Rapid City, SD
Salem, OR MSA	Salem, OR MSA	Salem, OR
Salt Lake City, UT MSA	Salt Lake City, UT HUD Metro FMR Area	Salt Lake City, UT
San Antonio-New Braunfels, TX MSA	San Antonio-New Braunfels, TX HUD Metro FMR Area	San Antonio, TX
San Francisco-Oakland-Hayward, CA MSA	San Francisco, CA HUD Metro FMR Area	San Francisco, CA

San Francisco-Oakland-Hayward, CA MSA	Oakland-Fremont, CA HUD Metro FMR Area	San Francisco, CA
San Jose-Sunnyvale-Santa Clara, CA MSA	San Jose-Sunnyvale-Santa Clara, CA HUD Metro FMR Area	San Jose, CA
Santa Rosa, CA MSA	Santa Rosa, CA MSA	Santa Rosa, CA
Seattle-Tacoma-Bellevue, WA MSA	Seattle-Bellevue, WA HUD Metro FMR Area	Seattle, WA
Sumter, SC MSA	Sumter, SC MSA	Sumter, SC
The Villages, FL MSA	The Villages, FL MSA	The Villages, FL
Twin Falls, ID MSA	Twin Falls County, ID	Twin Falls, ID
Urban Honolulu, HI MSA	Urban Honolulu, HI MSA	Urban Honolulu, HI
Victoria, TX MSA	Victoria, TX MSA	Victoria, TX
Walla Walla, WA MSA	Walla Walla County, WA HUD Metro FMR Area	Walla Walla, WA
Washington-Arlington-Alexandria, DC-VA-MD-WV MSA	Washington-Arlington-Alexandria, DC-VA-MD HUD Metro FMR Area	Washington, DC
Wenatchee, WA MSA	Wenatchee, WA MSA	Wenatchee, WA
Wheeling, WV-OH MSA	Wheeling, WV-OH MSA	Wheeling, OH
Williamsport, PA MSA	Williamsport, PA MSA	Williamsport, PA

FMR = Fair Market Rent. CBSA = Core Based Statistical Area. MSA = Metropolitan Statistical Area.

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U.S. Department of Housing and Urban Development
Office of Policy Development and Research
Washington, DC 20410-6000

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April 2023