Alternative Fair Market Rents for Local Housing Markets

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

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Prepared for

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Contents

List of Exhibits

Executive Summary

Every year, HUD estimates Fair Market Rents (FMRs), which are used to determine payment standards and rental assistance levels for housing programs. Accurate FMRs play a critical role in whether voucher households can secure safe, decent, and affordable housing through the private market. If HUD inaccurately calculates FMR estimates and FMRs do not keep pace with rising rents, families may face limited housing options, have to devote a large portion of their income to housing costs, or fail to find a decent unit to lease with a voucher. Therefore, accurately estimating FMRs is vital to ensuring that renters with vouchers can maintain access to stable and decent housing. In places where rents rise more rapidly than FMR estimates, the negative implications of low or inaccurate FMRs may be even more severe.

This research examined avenues for identifying areas with rapidly rising rents and providing viable approaches to improving HUD's FMR calculations. We explored models that leverage local data to forecast whether a county will likely see rapidly rising rents in the future. We also used local data to improve the predictive ability of time series models, building on prior work and HUD's current methods. In our analysis, we found that incorporating timely data on vacancies, housing starts, population growth, unemployment, home values, and interest rates can improve models' performance in forecasting rents at the metropolitan and regional levels. We then applied these models to county-level data and calculated six sets of alternative FMRs. When compared with historical data, the alternative FMR estimates tended to outperform HUD–produced FMRs from the same period.

Findings

One overarching question drove our research: **what method should HUD use to calculate FMRs in markets with rapidly rising rents so that families using housing choice vouchers (HCVs) can find and lease suitable housing?** Although the agency's current estimation approach accounts for regional, metro-level, and national trend factors, our research examined whether incorporating timely county-level data can improve FMR estimates in markets with rapidly rising rents. We found the following:

- Between 2009 (2009–2010) and 2019 (2018–2019), an average of 19.5 percent of counties saw rapidly rising rents from the previous year. These counties are located across the country but are concentrated in the West—particularly in Montana, North Dakota, Alaska, and

Colorado—with fewer counties in the industrial Midwest. We also captured rising rents in urban areas along the Pacific Coast.

- We explored models using local area unemployment rates, vacancy rates, the share of building permits per 1,000 housing units, and growth in the number of housing units to predict which counties will experience rapidly rising rents before rental data become available. Our models showed relationships between vacancy rates and unemployment and the likelihood of rapidly rising rents. However, in a validation sample, the models could not accurately predict which counties had rapidly rising rents.
- We found that an Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model that incorporates data on vacancies, building permits, housing unit growth, unemployment, home values, and mortgage interest rates tends to provide better predictions of future changes in gross rent levels across metropolitan areas or for regional aggregates of midsize cities than a pure time series Autoregressive Integrated Moving Average (ARIMA) model.
- We saw promising results when we applied six alternative models to county-level data to generate FMRs and assessed their performance. We calculated six sets of alternative FMRs for U.S. counties that use local data to create unique forecasts for each. We designed these alternatives to maximize the accuracy of forecasts by county and did not include adjustments to increase FMRs above statewide minimums or 90 percent of the previous year's FMR. Looking across counties in 2018, five of the six alternative models were more accurate than HUD's FMRs according to root mean squared error. However, when FMRs were more than 10 percent off from actual rents, HUD more frequently set FMRs too high, whereas our models more frequently forecasted FMRs that were too low. Relative to HUD's FMRs, the six sets of alternative FMRs performed similarly in counties with rapidly rising rents.

The importance of accurate FMRs cannot be overstated. FMRs that fail to keep up with rising rents can limit housing choice, hinder the ability of new voucher holders to find eligible rental units, and increase housing instability. Our research shows that rents have risen rapidly in many U.S. counties; however, it is difficult to forecast which counties will have rapidly rising rents in any given year. In addition, the county-level FMRs we developed performed relatively well compared with HUD's FMRs, including the 2020 FMRs that calculated local and regional trend factors. Taken together, the best path to improve FMR calculations in areas with rapidly rising rents appears to be improving FMR calculations overall. HUD could take steps to improve FMR calculations by using county-level local data, as we did, although further refinements to our methods are needed.

As an alternative, HUD could incorporate local data and generate more local trend factors while staying within the basic framework of its current FMR calculation process. Our research shows that using more precise local data and focusing on smaller geographies could improve FMR calculations. In addition, HUD's shift toward using Small Area Fair Market Rents (SAFMRs) makes such local data even more important. Many of the datasets used in this study, for example, provide county-level but not ZIP Code–level information. As housing searches, job searches, and permitting continue to move online, new types of data collection could help develop more accurate FMR calculations in the near future.

Alternative Fair Market Rents for Local Housing Markets

Every year, HUD estimates Fair Market Rents (FMRs), which determine payment standards and rent levels for housing programs. Accurate FMRs play a critical role in whether voucher households can secure safe, decent, and affordable housing through the private market. If HUD calculates FMR estimates inaccurately and they do not keep pace with rising rents, families may face limited housing options, need to devote a large portion of their income to housing costs, or fail to find a decent unit to lease with a voucher. Therefore, accurately estimating FMRs is vital to ensuring that renters with vouchers can maintain access to stable and decent housing. In places where rent increases outpace FMR estimates, the negative implications of low or inaccurate FMRs may be even more severe.

Our research explored avenues for identifying areas with rapidly rising rents and providing viable approaches to improving HUD's FMR calculations. We began our analysis by defining a market with rapidly rising rents as any county with a 10 percent year-over-year increase in rents or any high-cost county (in the top quintile) with a 5 percent year-over-year increase in rents. We show that this definition picks up both high-cost urban areas with steady high-dollar rent increases and more affordable rural areas that saw rapid spikes in rents over the study period. We explored models that could leverage local data to forecast whether a county would likely see rapidly rising rents in the future. Our models, however, have limited predictive capabilities.

To improve the predictive ability of time series models, we incorporated timely data on vacancies, housing starts, population growth, unemployment, home values, and interest rates and found that these data can improve the performance of models that forecast rents at the metropolitan and regional levels. We then applied these models to county-level data and calculated six sets of alternative FMRs; these alternative FMR estimates show promise and tend to outperform the HUD–produced FMRs over the same period.

In this report, we provide background on how HUD calculates FMRs and present additional research on the process for calculating FMRs. We then detail the methods and data used in this study. Finally, we share findings from the main components of the study and conclude with a brief overview of the implications of this report for policy and future research.

Background

Congress created the Housing Choice Voucher (HCV) program (formerly known as Section 8) as part of the Housing and Community Development Act of 1974. For the first time, this legislation allowed HUD to provide assistance to households with low incomes to rent from private landlords, thus expanding the volume of housing units available to elderly renters and renters with low incomes or disabilities.

Under the federal HCV program, households identify a rental unit to live in; if the landlord accepts their rental application, they can use their voucher to pay all or a portion of their rent (HUD, 1999). Rental units participating in the program need approval from the local public housing agency. Before receiving approval to use a voucher on a housing unit, the public housing agency inspects the housing unit to verify that it conforms to health and safety standards. The local public housing agency also determines the level of rent support on the basis of the area's FMR, cost of the rental unit, household size, and household income. If a renter chooses a rental unit that exceeds the calculated value of the HCV, the renter pays the difference.

To support the HCV program, HUD must produce FMR estimates to cover the entire country. FMRs approximate the market rate of decent, affordable housing and are calculated at the 40th percentile of the local distribution of rental units occupied by recent movers. Public housing agencies use FMRs to determine payment standards for the HCV program and rent levels—such as initial rents and rent ceilings—for many other housing programs, including public housing, Section 8 project-based rental assistance, the Moderate Rehabilitation Single Room Occupancy program, HOME Investment Partnerships, and Emergency Solutions Grants (HUD, n.d.). Agencies also use FMRs to determine award amounts for Continuum of Care grantees and rent limits for Continuum of Care funds (HUD, n.d.). See exhibit 1 for more on the value of effective housing affordability programs.

The official definition of FMRs has changed since 1974. HUD originally set FMRs at the 50th percentile of area rents until 1984, when it changed to the 45th percentile. FMRs remained at the 45th percentile until 1995, when this threshold changed to the 40th percentile. In 2000, HUD began setting FMRs at the 50th percentile in areas where households needed higher FMRs to find and lease decent, affordable units. The agency phased out the use of 50th percentile FMRs between 2017 and 2020. During this period, it calculated FMRs for HUD Metropolitan FMR Areas (HMFAs)—a HUD-designated geography that largely maps onto U.S. Office of Management and Budget-designated counties and metropolitan statistical areas. HUD also divides some metropolitan statistical areas into smaller HMFAs, such as the Dallas/Fort Worth HMFAs and San Francisco/Oakland HMFAs.

Exhibit 1. Value of Effective Housing Affordability Programs

Research documents the effects of housing instability—which we define as living with rent burden, living in poor-quality housing,[1] being behind on rent, making frequent moves, being evicted, or experiencing homelessness—on families and children, which can negate or greatly diminish the benefits of HCVs. Inaccurate FMR calculations can exacerbate these issues.

Further, housing instability affects all aspects of people's lives, including long-term financial stability, health and health care insecurity, and food insecurity.

- **Long-term financial stability.** Housing instability in the form of high-cost burdens and evictions can lead to a self-perpetuating poverty cycle because affected individuals have a harder time retaining a job and making positive long-term financial savings and investments (Desmond and Gershenson, 2016; Verma and Hendra, 2003). In addition, an initial shock to housing instability can begin a cycle of worsening housing instability (Collinson and Reed, 2018; Harrison et al., 2021; Robinson and Steil, 2020).
- **Health and health care.** Responding to the immediate pressures of housing instability can crowd out proactive healthy behavior. Housing instability is associated with the lack of a primary care doctor or health insurance, postponement of needed or preventative medical care and medications, an increase in emergency department use, and an increase in hospitalization (Hatef et al., 2019; Kushel et al., 2005; Reid, Vittinghoff, and Kushel, 2008).
- **Food insecurity.** Several studies document the tradeoff between housing and food, finding that housing and food insecurity are deeply interlinked (Kirkpatrick and Tarasuk, 2011; Meyers et al., 2005; Mueller and Tighe, 2007). These harms can become self-reinforcing.

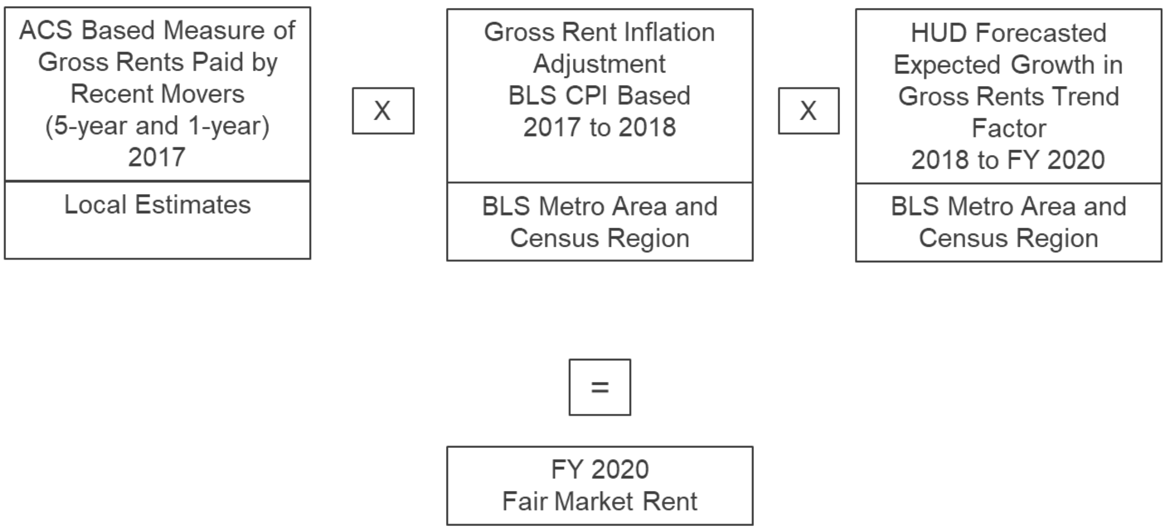
In recent years, HUD began calculating FMRs for individual ZIP Codes in response to calls for more granularity within HMFAs with high variations in rent. These localized FMRs, called Small Area Fair Market Rents (SAFMRs), mostly exist in areas where a single FMR for the entire HMFA would not accurately capture the area's diverse rent costs, especially in high-opportunity neighborhoods. In practice, these areas also tend to be HMFAs with high concentrations of voucher holders. Currently, HUD mandates the use of SAFMRs for some metropolitan areas. (Federal Register, 2016b).

[1] Poor quality is defined here as a combination of two elements: (1) housing deterioration (for example, peeling paint and holes in floor), and (2) housing disarray (for example, dark, crowded, and noisy) (Suglia, Duarte, and Sandel, 2011).

How HUD Forecasts Fair Market Rents

To calculate FMRs, HUD approximates the 40th percentile gross rent—contract rent plus utilities—paid by people who recently moved into standard-quality units within the FMR area (HUD, 2018). This process involves three steps, as shown in exhibit 2.

Exhibit 1. Fair Market Rent Calculations Process



ACS = American Community Survey. BLS = Bureau of Labor Statistics. CPI = Consumer Price Index. FY = fiscal year.
Note: All years refer to calendar year unless otherwise noted.
Source: HUD Fair Market Rents Introductory Overview PowerPoint slides

For each FMR area, HUD calculates a local gross rent basis using special American Community Survey (ACS) tabulations from the U.S. Census Bureau.[2] HUD starts with a 5-year ACS tabulation of 40th percentile estimates of gross rents paid by all renters and adjusts it using a recent mover adjustment. The recent mover adjustment is calculated by dividing the 1-year, 40th percentile, recent mover ACS tabulation for the smallest available geography by the 5-year, 40th percentile, all-renters tabulation for the corresponding geography. For small areas, HUD applies the recent mover adjustment at a higher level of geography than the gross rent basis.[3] HUD calculates the gross rent basis using the

[2] If public housing agencies supply HUD with local survey data that are more recent than American Community Survey data, we used the local survey data to create the gross rent basis.

[3] For example, the gross rent basis for a nonmetropolitan county FMR in 2021 could be calculated as the 2014-to-2018 5-year estimate of the 40th percentile of gross rents paid for *all renters* in the county, times the 2018 1-year estimate of the 40th percentile of *recent* movers across nonmetropolitan areas in the state, divided by the 2014-to-2018 5-year estimate of the 40th percentile of *all renters* across nonmetropolitan areas in the state.

most recent data available from the ACS. For example, for 2020 FMRs—which are calculated in 2019—the gross rent basis approximated rent levels in 2017.

The gross rent basis is then adjusted to account for inflation over the past year using an inflation factor. The inflation factor is calculated as a weighted average of two Consumer Price Index (CPI) series: rent of primary residence and housing fuels and utilities. CPI data are available for the four census regions (Northeast, Midwest, South, and West) by metropolitan area size, the 21 largest metropolitan areas, urban Alaska, and urban Hawaii. We refer to these regions as CPI geographies. HUD derives weights to account for the share of gross rent (comprising contract rent and utilities) and the share of renters with utilities included in their contract rent within each CPI geography.

Finally, HUD accounts for expected growth in rent prices between the previous calendar year and the forthcoming fiscal year using a trend factor. The agency currently estimates gross rent trend factors for CPI geographies. For each metro area and region, HUD estimates the trend factor using Autoregressive Integrated Moving Average (ARIMA) or Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) models that forecast changes in the rents of primary residences and housing fuels and utilities CPI series (Federal Register, 2019).

HUD policy also includes two rules that set floors for FMRs. First, HUD sets a state minimum FMR based on the population-weighted median of unadjusted nonmetropolitan FMRs in each state. Second, the agency sets a floor for the FMR in each area at 90 percent of the prior fiscal year's FMR.

RECENT IMPROVEMENTS IN FMR CALCULATIONS

HUD has updated its method of calculating FMRs over time. The first two steps of the current process (exhibit 1), with slight adjustments, have been in place since fiscal year 2012, as that was the first year for which 5-year ACS data were available. Before the FY 2020 FMRs, HUD used a national trend factor to account for expected growth in rent prices. Before the FY 2016 FMRs, the national trend factor was the average annual rent growth over the past five years. Between FY 2017 and FY 2019, HUD used a time series model to forecast a national trend factor. For the FY 2020 FMRs, HUD asked its multidisciplinary research team[4] to explore approaches to deriving more localized trend factors.

[4] From HUD (2015), "PD&R developed the Multidisciplinary Research Team (MDRT) vehicle to manage a team of qualified researchers. Researchers are selected for their expertise to produce an array of high quality, short-turnaround research. MDRT researchers use a variety of HUD and external data sources to answer research questions relating to HUD's priority policies and strategic goals."

In the report “Deriving Local Trend Factors for Fair Market Rent Estimation,” HUD’s multidisciplinary research team explored approaches to incorporate local market conditions into FMR calculations, starting with HUD’s existing methodology, followed by methods using alternate data sources and empirical strategies (2M Research, 2019). HUD used autoregressive integrated moving average models with exogenous variables (ARIMAX models) to estimate different trend factors for local metropolitan areas with more than 2.5 million people and aggregates for each in the same census region.

To estimate local rent and utilities (the two components of the gross rent index), the research team used three potential ARIMAX models:

1. A univariate time series model without exogenous variables.
2. A multivariate model with national exogenous variables.
3. A multivariate model with local exogenous variables to estimate the local rent and utilities.

Comparing the forecast errors for all three models for each geographic region using the root mean squared error (RMSE), the study found that the multivariate model with national exogenous variables provided the most accurate forecast for rent, and the univariate time series model without exogenous variables provided the most accurate forecast for the utilities series (2M Research, 2019).

Following the release of the 2019 report, HUD announced its plan to update the FMR estimation process to include local and regional trend factors (Federal Register, 2019).

Improving FMR Estimates

FMR estimation is complicated by the lack of rental data that are high quality, comprehensive, local, and timely. ACS estimates of gross rents are high quality, have broad geographic coverage, and include all types of rental units (HUD, 2018). However, 5-year estimates suffer from significant lag, and 1-year ACS estimates are not available for communities with smaller populations. By contrast, rent data collected by the Bureau of Labor Statistics (BLS) are more current and released more regularly, but they are available only for large metropolitan areas and regional aggregates of smaller cities.

Other sources of rent data are private or proprietary or oversample multifamily rental units (Feldman and MacDonald, 2019). Proprietary rent datasets such as CoStar, Reonomy, or Zillow may contain more up-to-date information than publicly available data. However, they often oversample multi-unit developments and undersample single-family rentals and rentals that are not professionally managed.

Therefore, these sources may not be comprehensive enough to incorporate into FMR calculations and may be biased toward higher rent prices (Feldman and MacDonald, 2019). Data aggregated from rental listing websites are also timely but include only asking prices and not final contracted rents (Boeing, Wegmann, and Jiao, 2020). If HUD were to use proprietary rent data, which often come from surveys of renters and landlords, they may have access to more contemporary information, which would, in turn, allow them to produce more timely and accurate rent estimates—provided biases in the data could be addressed.

Even without better rental data, there are at least two possible avenues to improve FMR calculations and estimates' usefulness. First, HUD could consider developing FMRs for smaller geographies. HUD already calculates SAFMRs at a more granular level (the ZIP Code tabulation area level) within some HMFAs, but apart from the geography for the gross rent basis, FMR and SAFMR calculations are otherwise identical (Federal Register, 2016a). Therefore, if gross rent inflation or trend factors change unevenly within a metropolitan area or region, SAFMRs within that area or region would not reflect relative intra-metro and intra-region changes in gross rent inflation or trend factors; consequently, the accuracy of SAFMRs would decrease. Inaccurate FMRs and SAFMRs that arise from intra-regional variations in rent inflation adversely affect renters with HCVs because accurate projections of annual changes in gross rent help HCV users find or stay in housing.

Second, HUD could improve its forecasts by using timelier data and including factors that are more closely tied to local predictors of rent changes. In a basic supply and demand model, rents increase when the demand for rental units is higher than the number of units available and fall if more units are available than prospective renter households. This study explores the use of timely, public-use data on factors that previous research suggests may correlate with rent changes: vacancies, employment, population growth, and residential construction.

- **Vacancies.** One way to determine whether the demand or supply of rental units is greater at current prices is by examining vacancy rates, which indicate whether or not the housing market is at equilibrium; declining vacancy rates, for example, are a sign that demand is growing more quickly than supply. Research shows a link between vacancy rates and rent changes, with much of it focusing on the so-called natural vacancy rate (Hagen and Hansen, 2010; Rosen and Smith, 1983; Smith, 1974). Conceptually, the natural vacancy rate is the level of vacancies in a housing market with neither excess supply nor excess demand. Vacancy rates below the natural rate indicate excess demand and are predictive of increases in future rents (Hagen and Hansen, 2010; Rosen and Smith, 1983; Smith, 1974). HUD's aggregated U.S.

Postal Service administrative data on address vacancies provide quarterly data on vacancies for a variety of geographies.

- **Employment.** The unemployment rate serves as a proxy for local economic conditions that affect demand. Statistics on income might align better with demand, but BLS local area unemployment statistics data are timelier than data on income at the county level. In addition, other studies have shown that rent is associated with the national employment rate (2M Research, 2019).
- **Population growth.** Analyses of long-run demographic changes show how population growth and household formation affect housing demand. The growth in the number of households in a county also implies an increase in demand for housing (Mankiw and Weil, 1989). All else constant, population increases have been shown to lead to higher rents (Saiz, 2003).
- **Residential construction.** Increased construction and maintenance may lead to higher rents. Home values and rents rise more steeply in markets that are constrained by geographic features such as a coastline (Saiz, 2010), and research has consistently shown that home values and rents rise because of regulatory constraints on housing supply (Glaeser, Gyourko, and Saks, 2005; Glaeser and Ward, 2009; Quigley and Raphael, 2005). The number of new building permits could serve as a leading indicator of future housing supply and current tightness in the housing market. Alternatively, construction could look forward—a rise in the number of building permits, for example, could indicate growing housing demand and the expectation of higher home values and rents. The Census Bureau's Building Permits Survey provides data on the number of new housing units authorized by building permits at the county level. We combine these data with address counts from the aggregated U.S. Postal Service dataset to calculate a housing start rate.

Research Design

One overarching question drove our research: **what method should HUD use to calculate FMRs in markets with rapidly rising rents so families using HCVs can find and lease suitable housing?** Although HUD's current estimation approach accounts for regional, metropolitan-area, and national trend factors, our research examines whether incorporating timely county-level data can improve the estimation of FMRs in markets with rapidly rising rents. Our research design includes five analytical components:

- Defining areas with rapidly rising rents.

- Predicting areas with rapidly rising rents.
- Estimating time series models with local data.
- Creating alternative FMR calculations.
- Assessing the alternative FMR calculations.

We began our analysis by defining and identifying areas with rapidly rising rents. Although it is important to have accurate FMR calculations in all areas, policymakers have expressed specific concern about the ability of current methodologies to accurately forecast market rents in areas where rents are rising more quickly relative to the rest of the country.[5] In the absence of an official definition of what defines an area with rapidly rising rents, we proposed a county-level rubric.

We explored models that can forecast which counties are experiencing rapidly rising rents before rental data become available. The models use predictors that we hypothesized are leading indicators of housing supply and demand, available at the county level: vacancy rate, number of building permits, unemployment rate, and changes in the number of housing units.

We then developed alternative methods for calculating FMRs by fitting time series models to quarterly CPI regional and metropolitan area rent data and introduced vacancy rate, number of building permits, unemployment rate, and changes in the number of housing units as potential predictors. To improve model performance, we also explored adding mortgage interest rates and regional measures of home values as predictors in the time series models.

Finally, we used the models developed using regional and metropolitan-area rent data for county-level data to create a set of county-specific FMR alternatives. We examined the performance of each of these six alternative FMRs by comparing them with county-level rent data from 2017 to 2020. We also assessed the performance of HUD's FMRs over the same period and compared the performance of our alternative FMRs with that of HUD's FMRs.

In the remainder of this section, we describe the data sources and methods used in each component.

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[5] House Report 116-106. "Transportation, Housing and Urban Development, and Related Agencies Appropriations Act, 2020," House Appropriations Committee. https://appropriations.house.gov/sites/democrats.appropriations.house.gov/files/HR%201865%20-%20Division%20H%20-%20THUD%20SOM%20FY20.pdf.

Data

Our analysis draws from various publicly available datasets and HUD–provided datasets that shed light on the supply of and demand for rental units and allow us to validate our analysis. These datasets and their use in our analyses are described in exhibit 3.

Exhibit 2. Datasets by Source and Use

Dataset (Provider)	Data of Interest	Analysis and Use	Years	Geography
Aggregated U.S. Postal Service administrative data on address vacancies (HUD)	Vacancy rates as a predictor of housing market disequilibrium	Predicting areas with rapidly rising rents Predictor variable for trend factors	2006–2019	Counties, aggregated to CPI geographies and FMR areas
American Community Survey (Census Bureau) special extract for HUD	40th percentile gross rent, 40th percentile gross rent of recent movers	Primary source of rent measurements	2009–2013 to 2015–2019 5-year averages; 2011–2019 1-year estimates	FMR areas, counties, metropolitan statistical areas, state nonmetro areas
Building permits survey (Census Bureau)	Number of permits	Predicting areas with rapidly rising rents; predictor variable for trend factors	2006–2019	Counties, aggregated to CPI geographies, FMR areas, and metropolitan statistical areas
Population Estimates Program (Census Bureau)	Number of housing units	Standardized number of housing units; predicting areas with rapidly rising rents	1997–2019	CPI geographies, FMR areas, metropolitan statistical areas, counties
Fair Market Rents (HUD public-use data)	FMRs	Assessment of alternate FMRs	2017–2020	FMR areas
Consumer Price Indices (Bureau of Labor Statistics)	Rent of primary residence CPI; housing fuels and utilities CPI; energy CPI, electricity CPI	Estimation of trend factors	1997–2020	CPI geographies
House Price Index (Federal Housing Finance Agency)	HPI	Local input to trend factors	1997–2019	CPI geographies
30-year fixed mortgage interest rates (Federal Reserve)	Mortgage interest rates	National input to trend factors	1997–2019	National
Local area unemployment statistics (Bureau of Labor Statistics)	Unemployment rate	Predicting areas with rapidly rising rents; predictor variable for trend factors	1997–2019	Counties, aggregated to CPI geographies, FMR areas, and metropolitan statistical areas

Dataset (Provider)	Data of Interest	Analysis and Use	Years	Geography
Zillow observed rent index (Zillow)	Zillow observed rent index	Assessing alternative FMRs	2014–2020	Metro (analogous to metropolitan statistical area), ZIP Code (analogous to ZIP Code tabulation area)
HUD-provided dataset	CPI weights used in FMR calculations	Creating gross rent CPI series	2020 (held constant for all years)	CPI geographies

CPI = Consumer Price Index. FMR = Fair Market Rent. HPI = House Price Index.

Defining Areas with Rapidly Rising Rents

We began our analyses by defining and identifying counties with rapidly rising rents. To start, we calculated county-level recent mover–adjusted rents for 2008 to 2018. We used HUD's 40th percentile county-level ACS rent estimates and applied the recent mover adjustment at the smallest available level of geography. We then calculated year-over-year changes in rents from 2009 to 2019.

We explored multiple definitions of counties with rapidly rising rents and determined that a two-tiered definition best accounted for both large percentage point changes in rents and impactful increases in rents in high-cost areas.

Our preferred definition for counties experiencing rapidly rising rents includes—

- Counties with rents in the top 20th percentile nationally that experience a rent increase of greater than 5 percent.
- Counties with rents in the bottom 80th percentile nationally that experience a rent increase of greater than 10 percent.

We provide additional information on the analysis that led to this definition in appendix A.

Predicting Areas with Rapidly Rising Rents

We developed models to predict areas with rapidly rising rents using the following data:

- **Annual estimated housing unit counts**, by county, from the Census Bureau's Population Estimates Program.

- **Aggregate vacancy and address data** from HUD's aggregated U.S. Postal Service administrative data on address vacancies, updated quarterly.[6]
- **Data on the number of new housing units** authorized annually through building permits from the Census Bureau's Building Permits Survey, by county.
- **Unemployment data at the county level** from BLS local area unemployment statistics.

We then calculate the housing growth rate, the rate of new housing starts, and vacancy rates with the following formulas:

$$Housing\ growth\ rate = 100 \times \frac{\text{number of housing units } - \text{prior year number of units}}{\text{prior year number of units}}$$

$$Rate\ of\ new\ housing\ starts = 1000 \times \frac{\text{the number of housing starts}}{\text{the number of households}}$$

$$Vacancy\ rate = 100 \times \frac{\text{the number of vacant residential units}}{\text{the sum of vacant and occupied residential units}}$$

To account for lags in data availability, our analysis attempts to forecast whether a county will have rapidly rising rents (between year t and year t+1) using the unemployment rate, vacancy rate, and housing growth rate for the prior year (t−1) and the rate of housing starts two years prior (t−2).

Our final dataset is a repeated cross-section of counties from 2009 to 2016, with data from previous years used to calculate housing growth rates, identify counties with rapidly rising rents, and measure lags of predictor variables.[7]

[6] The U.S. Postal Service vacancy data from HUD include three categories for each address: vacant, occupied, and "no stat." No stat addresses include rural route addresses that are vacant for 90 days or longer, addresses for businesses or homes under construction that are not yet occupied, and addresses in urban areas identified by a carrier as not likely to be active for some time. Because no stat addresses could signal that housing supply is rising (in the case of new construction) or falling (in the case of units being removed from the market), we exclude them from this analysis.

[7] We chose to end the analysis in 2016 so that we could use predictions about which counties had rapidly rising rents to create alternative FMR calculations. However, because the predictive models performed poorly, we elected not to use the predictions.

METHODOLOGY

To evaluate the out-of-sample performance of our models, we randomly divide the counties such that 70 percent of counties are in an estimation sample and 30 percent are in a validation sample. Next, we developed two types of models using the estimation sample and evaluated the models' predictive ability using the validation sample.

The first type of model is a Boolean function that would identify any county with statistics above or below some threshold as likely to have rapidly rising rents. (For example, is there a vacancy rate below which counties are more likely to have rapidly rising rents?) These models take the following form:

$$E[R_i\,] = 1 \text{ if } v_i < V^* \text{ OR}$$

$$E[R_i\,] = 1 \text{ if } v_i < V^*, e_i < E^*, s_i < S^*, \text{and } g_i < G^*$$

where R_i is equal to 1 for rapidly rising counties, the local vacancy rate is v_i, the local unemployment rate is e_i, the local housing start rate is s_i, and the housing growth rate is g_i. The goal of these Boolean models is to determine if there are simple rules that might help forecast which counties are likely to see rapidly rising rents.

We calculated whether the models correctly identified each county using 100 values of $V, E, S,$ and G individually, as in the second equation. We then selected the parameters V^*, E^*, S^* and G^* (from the 100 tested values) that maximized the share of counties that the model correctly identified. Next, we estimated whether the model correctly identified each county using every potential combination from 10 values each of $V, E, S,$ and G in the third equation—producing 10,000 estimates—and again identified the parameters that maximized the share of correctly identified counties.

The second type of model is a logit model, which takes the following form:

$$\log \frac{P(R_i = 1)}{1 - P(R_i = 1)} = \beta_0 + \beta_1 v_i + \beta_2 e_i + \beta_3 s_i + \beta_4 g_i$$

where β_0, β_1, β_2, β_3, and β_4 are estimated coefficients representing the relationship between the predictor variables and the log of the likelihood that a county has rapidly rising rents. We also estimated an expanded logit model with inverse measures of vacancy rates, unemployment, housing start rate, and housing growth rate.[8]

For each model, we calculate an F-score using the validation sample. In the validation sample, we categorize each county-year combination in the validation set as either—

- A true positive (correctly identified as a place with rapidly rising rents).
- A true negative (correctly identified as a place without rapidly rising rents).
- A false positive (predicted to have rapidly rising rents but did not).
- A false negative (predicted not to have rapidly rising rents but did).

Next, we calculate the number of counties that appear in each of these four categories along with accuracy, recall, precision, and the F-score, as follows:

- **Accuracy** is the percentage of the total that is either a true positive or a true negative.
- **Recall** is the percentage of places with rapidly rising rents that were correctly identified (true positives divided by the sum of true positives and false negatives).
- **Precision** is calculated as true positives divided by the sum of true positives and false positives.
- **F-score** is the harmonic mean of recall and precision.

Estimating Rent Time Series Models with Local Data

We modeled gross rent series[9] for the large metropolitan areas that BLS identifies as primary sampling units (PSUs) and all the regional series comprising urban areas with fewer than 2.5 million people (classified as size class B/C by the BLS) in each census region using new predictor variables. We examined predictors that are available at the county level but also included some variables at larger

[8] Hagen and Hansen (2010) show that there are benefits to using both vacancy rate and inverse vacancy rate in modeling changes in rents because the relationship between vacancy and changes in rents is nonlinear. They estimate a negative coefficient on vacancy rate and a positive coefficient on inverse vacancy rate.

[9] Because we estimate the ARIMAX model with the same sets of predictor variables used for the ARIMA model for rent of primary residence CPI and the fuels and utilities CPI, we create a combined gross rent CPI series with HUD gross rent component shares weight.

geographies as indicators for overall economic conditions and housing prices that would affect rent levels and affordability. In sum, we included the following:

- **Annual estimated housing unit counts** at the county level and aggregated to PSU and census region from the Census Bureau's Population Estimates Program.
- **Aggregate vacancy and address data** from HUD's aggregated U.S. Postal Service administrative data on address vacancies, by tract and aggregated to PSU and census region.
- Data on the number of **new housing units authorized annually through building permits,** by county and aggregated to PSU from the Census Bureau Building Permits Survey.
- **Unemployment data,** by PSU and census region from BLS local area unemployment statistics.
- **30-year national fixed mortgage interest rate** from the Federal Reserve.
- **House Price Index,** by PSU and census region, from the Federal Housing Finance Agency.

For vacancy rate, mortgage interest rate, and unemployment rate, we used a 1-year lag to account for the time it takes for the rental market to respond to changes in these predictor levels. For building permits per 1,000 housing units, we used a 2-year lag; for House Price Index and housing stock, we calculated the percentage change in the 1-year lag and 2-year lag values.

For the ARIMA models, the datasets included quarterly rent and utilities data from 1997 to 2019, aggregated into our composite gross rent CPI. For the ARIMAX models, we also used 2005 to 2018 quarterly data, for which 2005 is the earliest year of vacancy data available. **For data that are only available on a yearly basis, we used linear interpolation to impute quarterly data; we assume the same numeric change for each of the four quarters in each year.**

METHODOLOGY

We first identified the best-fitting ARIMA model for each metropolitan area or region. Suppose Y_t is the variable of interest (gross rent CPI) and let y_t be the *d*th differential of gross rent CPI. We want to fit an ARIMA (*p*, *d*, *q*) model, with the forecasting equation given by

$$y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$$

where *i* = 1 to *p*, *j* = 1 to *q*.

The ARIMA model helped produce forecasts based on prior values in the time series (AR terms) and the errors made by previous predictions (MA terms). These models rapidly adjusted for sudden changes in trends, resulting in increased forecast accuracy.

We used the Dickey-Fuller Generalized Least Squares (DF-GLS) test to examine the stationarity of the gross rent CPI series, assess whether the ARIMA assumptions are met, and determine the degree of integration "d" in the model specification. Our test output revealed that gross rent CPI in all geographies achieved stationarity after first differencing.

To select the AR and MA terms in the model, we conducted repeated test models with different specifications and used the Schwarz Bayesian Information Criterion (SBC)—which penalizes additional model parameters to avoid overfitting—to select our best model. Lower SBC is preferable because it indicates the optimum tradeoff between the number of explanatory variables and better fit. Exhibit 4 shows the selection process for the Seattle-Tacoma-Bellevue, Washington, metropolitan area and the class size B/C series in the Midwest region. We present the results for the rest of the geographies in exhibit 28 in appendix B. We applied the autocorrelation function (ACF) and partial autocorrelation function (PACF) to confirm the stationarity of the series if the model residuals are white noise and not correlated.

Exhibit 3. ARIMA Model Identification for the Seattle-Tacoma-Bellevue, Washington, Metropolitan Area and Midwest Region (Size Class B/C)

Area	Autoregressive Terms (p)	Level of Integration (d)	Moving Average Terms (q)	Schwarz Bayesian Information Criterion
Seattle-Tacoma-Bellevue, WA	0	1	1	352.35
Seattle-Tacoma-Bellevue, WA	0	1	2	355.45
Seattle-Tacoma-Bellevue, WA	1	1	0	345.13
Seattle-Tacoma-Bellevue, WA	***1***	***1***	***1***	***343.05***
Seattle-Tacoma-Bellevue, WA	1	1	2	347.21
Seattle-Tacoma-Bellevue, WA	2	1	0	347.62
Seattle-Tacoma-Bellevue, WA	2	1	1	347.42
Midwest (Size Class B/C)	0	1	1	264.10
Midwest (Size Class B/C)	0	1	2	265.99
Midwest (Size Class B/C)	1	1	0	265.52
Midwest (Size Class B/C)	***1***	***1***	***1***	***262.96***
Midwest (Size Class B/C)	1	1	2	267.36
Midwest (Size Class B/C)	2	1	0	269.26
Midwest (Size Class B/C)	2	1	1	255.06

Source: Urban Institute analysis of Bureau of Labor Statistics CPI data

Once we identified the best fitting ARIMA model, we added local and national predictors, X, to the model (for example, local vacancy rate and national mortgage interest rate) using an ARIMAX model defined as

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{k=1}^{b} \beta_k X_{t-k} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$$

where *i* = 1 to *p*, *j*= 1 to *q*, and *k* = 1 to *b* (number of lags of the exogenous predictors, X).

With several predictors, we risked issues with multicollinearity between predictors that bias the estimation of coefficients. We examined the correlation between the predictor variables to avoid multicollinearity that could bias the model results, and exhibit 5 demonstrates the correlation matrix of the predictors.

House Price Index and vacancy rate are the most closely correlated predictor variables at –0.66 and significant at 0.01 significance level, followed by mortgage rate and House Price Index at −0.57 at 0.01 significance level (exhibit 5). For our select predictors ARIMAX model, we included the three least-correlated variables: House Price Index, unemployment rate, and building permits per 1,000 housing units. Building permits per 1,000 housing units incorporates a measure of housing stock and mortgage interest rate as a national-level predictor and does not vary by area. For the expanded ARIMAX model, we include all the predictor variables in the model.

Exhibit 4. Correlation Between the Predictor Variables

	Vacancy	Mortgage	Unemployment Rate	Building Permits per 1,000 Housing Units	Housing Units
Mortgage interest rate	0.12***				
Unemployment rate	0.31***	−0.35***			
Building permits per 1,000 housing units	−0.24***	0.20***	−0.33***		
Housing units	−0.18***	−0.06**	0.12***	0.45***	
House Price Index	−0.66***	−0.57***	**–0.03**	**0.06***	0.13***

* Significance level of 0.05.
** Significance level of 0.01.
*** Significance level of 0.001.
Sources: Urban Institute analysis of Bureau of Labor Statistics CPI and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau Building Permits Survey and Population Estimates Program data; Federal Housing Finance Agency House Price Index data; Federal Reserve mortgage interest rate data

Creating Alternative FMR Calculations

We calculated alternative FMRs by applying the coefficients from the ARIMA and ARIMAX models to quarterly county-level data. To create this dataset, we took the annual 40th percentile gross rent series that we constructed to define and predict areas with rapidly rising rents and expanded it to quarterly data, fitting a cubic spline to the natural log of annual gross rent (exhibit 6).[10] We followed the same procedure for the estimated number of housing units and unemployment rate. We also included quarterly county-level vacancy data, the metro/regional HPI, and the national mortgage interest rate. Just as when we defined and predicted areas with rapidly rising rents, we excluded counties in the six New England states because New England HMFAs do not align with counties.

For each year from 2017 to 2020, we created a dataset that includes only data that would have been able to forecast the FMR for that fiscal year. For example, while producing alternative FMRs for FY 2018, we use an ACS–derived gross rent series that runs from 2005 through 2015, BLS CPI data that run through 2016, and local area unemployment data that run through 2017.

Exhibit 5. Construction of County-Level Dataset

Data	Geography	Adjustments	Timeframe	Models
Gross rent series	County	Quarterly imputed from annual calculations	Quarterly change	ARIMA, select predictors ARIMAX, and expanded ARIMAX
Vacancy rates	County	None	1-year lagged	Expanded ARIMAX
Building permits per 1,000 housing units	County	Quarterly imputed from annual calculations	2-year lagged	Select predictors ARIMAX and expanded ARIMAX
House Price Index	Metro/Region	None	Percentage change between 1-year lagged and 2-year lagged	Select predictors ARIMAX and expanded ARIMAX
Mortgage interest rates	National	None	1-year lagged	Expanded ARIMAX
Unemployment rate	County	Quarterly unemployment rates imputed from annual BLS estimates	1-year lagged	Select predictors ARIMAX and expanded ARIMAX
Change in housing units	County	Quarterly count of housing units imputed from annual estimates	Percentage change between 1-year and 2-year lagged	Expanded ARIMAX

[10] We converted annual data to quarterly data using the expand procedure in Statistical Analysis System (SAS). Linear interpolation, which was used for predictor variables to estimate the local rent time series, produced unrealistic results at the county level.

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. BLS = Bureau of Labor Statistics.

Source: Urban Institute analysis of Bureau of Labor Statistics CPI and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau Building Permits Survey and Population Estimates Program data; Federal Housing Finance Agency House Price Index data; Federal Reserve mortgage interest rate data

MODELING

We explored three models: the ARIMA model, the select predictors ARIMAX model, and the expanded ARIMAX model. We separately estimated each model using CPI series that end in 2015, 2016, 2017, and 2018. We then applied these models to the county-level data as follows.

First, we assigned each county (in each year) to a set of models. If counties are within a metropolitan area that has a BLS rent series, they are assigned to models estimated for their metro area. Otherwise, counties are assigned to models for their census region. Within metropolitan areas and regions, we assigned the model based on the most recent data that would be available. For the FY 2017 FMRs, we applied the ARIMA and ARIMAX models calculated using CPI data through 2015 to county-level rent data from the ACS that runs through 2014. We calculated alternative FY 2018 FMRs using rent data through 2015 and models fit CPI data through 2016; FY 2019 FMRs using rent data through 2016 and models fit CPI data through 2017; and FY 2020 FMRs using rent data through 2017 and models fit CPI data through 2018.

We used two techniques for implementing the regional models to forecast gross rent series. The techniques differ in how they account for rent changes over the previous year. Method A uses county-level forecasts, and Method B uses regional and metro-level inflation data. By comparing the two methods, we can see if local forecasting can outperform regional and metro-level inflation adjustments. The two techniques are implemented as follows:

- **Method A.**
    1. Because the *d* term in all the ARIMA and ARIMAX models is 1, we took the first difference of the county gross rent series, creating series of quarterly changes in rents.
    2. We applied the ARIMA and ARIMAX models to the first-differenced gross rent series and accompanying predictor variables to create forecasted first differences.
    3. We calculated predicted rent levels based on the forecasted first differences. For FY 2018, we calculated out 11 quarters, or through the third quarter of 2018.
    4. We calculated alternative FMRs as the average across the four quarters of that fiscal year.

- **Method B.** This technique takes advantage of available metro-level and regional CPI data.
    1. We estimated four additional quarters of gross rents by 1 year using the regional or metropolitan area CPI data. For example, for FY 2018 FMRs, we estimated calendar year 2016 gross rents using CPI data.
    2. We took the first difference of the county gross rent series, creating series of quarterly changes in rents.
    3. We applied the ARIMA and ARIMAX models to the first-differenced gross rent series and accompanying predictor variables to create forecasted first differences.
    4. We calculated predicted rent levels based on the forecasted first differences. For FY 2018, we calculated out seven quarters, or through the third quarter of 2018.
    5. We calculated alternative FMRs as the average across the four quarters of that fiscal year.

From these two methods and the three models, we estimated six sets of alternative FMRs each year. To assess the accuracy of our methods, we did not adjust our alternative FMRs based on a state minimum, nor did we adjust FMRs to ensure that they did not fall below 90 percent of the previous year's FMR.

Assessing Alternative FMR Calculations

To assess the performance of our alternative FMRs, we compared the six alternative FMR values and HUD's FMR values with the actual 40th percentile gross rent to examine whether any of our alternative FMRs outperformed HUD's FMRs.

To evaluate our results, we compiled the following data by fiscal year:

- 40th percentile gross rents in 2017 and 2018, calculated retrospectively from HUD's ACS extracts
- 40th percentile gross rents, for a subset of counties, constructed by adjusting the 2018 gross rents by the change in rent prices from Zillow's ZIP Code–level observed rent index (ZORI) for 2019 and 2020.

At the time of the analysis, county-level ACS data for 2019 and 2020 were not available. To calculate goodness of fit in 2019 and 2020, we used ZORI and a ZIP Code-to-county crosswalk from Geocorr to adjust the gross rent series for inflation. Because ZORI is only available for certain ZIP Codes, our sample size for comparison in 2019 and 2020 is much smaller than in 2017 and 2018.

METHODOLOGY

To evaluate the predictive power of the proposed methods, we calculated the RMSE for each of the six sets of alternative FMRs in each year and overall.[11] For each year of the analysis, we also calculated the share of counties for which the actual 40th percentile gross rent fell below 90 percent of the alternative FMR, between 90 and 110 percent of the alternative FMR, or above 110 percent of the alternative FMR.

These metrics allowed us to see whether FMRs tend to be too high or too low. We selected the 90 and 110 percent thresholds because public housing agencies have the option to set payment standards between 90 and 110 percent of FMRs without special approval from HUD and because HUD used similar metrics in its 2018 report.

We explored performance across all counties in 2017 and 2018 and across a subset of counties (for which Zillow data are available) in 2019 and 2020 against these metrics. We then conducted further subgroup analyses to assess the alternative FMRs' performance among metropolitan and nonmetropolitan counties, in counties with high or rapidly rising rents, and in counties for which SAFMRs are calculated.

Limitations

Several limitations of the study design may influence the research findings, including how we defined and predicted areas with rapidly rising rents and how we assessed our alternative FMR calculations. We detail major limitations and how they affect our evaluation below.

Data availability. FMR calculations and the analysis described above are limited by data availability. Most of our analyses focused on housing markets defined at the county level. This offers the potential for more granularity than current FMR calculation methods, but counties vary greatly in both geographic size and population. Ideally, we would have examined smaller areas, such as ZIP Codes or census tracts. At these lower levels, however, the best available data likely come from ACS 5-year

[11] The RMSE is the square root of the sum of squared differences between the alternative FMR (or HUD's official FMR) and the 40th percentile gross rent calculated retrospectively.

estimates, meaning we could not take advantage of timelier data from the BLS's local area unemployment statistics or the Census Bureau's Population Estimates Program and Building Permits Survey.

Limitations of available datasets. The timely, county-level datasets we used each have their limitations. Notably, the BLS Local Area Unemployment Statistics are modeled—meaning they include modeling error—and the Census Bureau's Building Permits Survey data are affected by nonresponse bias and imputation error. In addition, each of our predictor variables had some gaps in geographic coverage. As a result, the alternative FMRs that we generate with ARIMAX models exclude some counties.

Streamlining decisions. We also made several decisions to streamline our analysis that introduced potential study limitations. First, we focused on two-bedroom FMRs. If rent changes for larger or smaller units deviated significantly over time, our analysis misses this nuance. Second, we excluded New England counties and Puerto Rico's municipios from our analysis of counties with rapidly rising rents and our alternative FMR calculations. Although there is no obvious reason that the analysis would have substantively different findings if these places were included, we cannot say this with certainty. Third, our alternative FMRs deviated from HUD's in various ways, and we did not systematically examine the influence of each decision on the differences between our estimates and those from HUD. We developed our time series models to predict composite gross rent CPI instead of following the current FMR methodology of estimating separate models for rent CPI and utility CPI. We introduced new predictor variables to the ARIMAX models and applied the coefficients from regional and metropolitan-area models to county-level data. In addition, we did not adjust FMRs based on the state minimum or the previous year's FMR. Any of these differences could be responsible for the differences between our alternative FMRs and HUD's FMRs. HUD also changed its FMR methodology during our study period, and we did not examine how HUD's current methods would have performed over the earlier period.

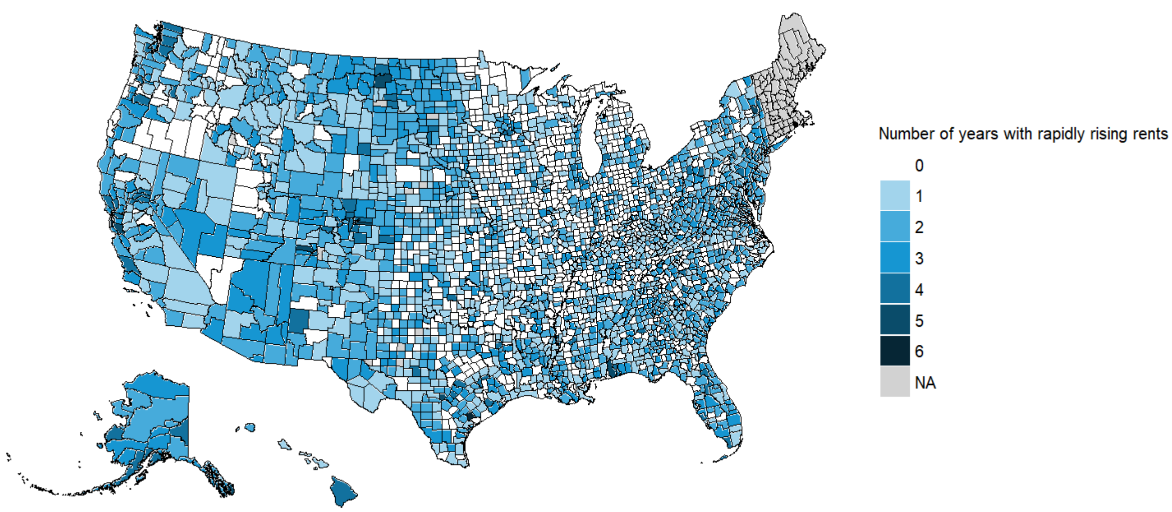
Findings

As we described in the previous section, we designed this study to develop insights that may help HUD improve FMR calculations, particularly in areas with rapidly rising rents. In this section, we discuss the geographic distribution of the counties we defined as having rapidly rising rents. We then present the results of our attempts to develop models that predict areas with rapidly rising rents using data from 2009 to 2016. Next, we describe the models that we estimated to fit gross rent price data at the regional and metropolitan-area levels. Finally, we assess the performance of alternative, county-level FMRs relative to actual rent levels and the FMRs used between 2017 and 2020.

Defining Areas with Rapidly Rising Rents

Using the definition proposed in the Research Design section of this report, we found that an average of 19.5 percent of counties had rapidly rising rents between 2009 (2009–2010) and 2019 (2018–2019). Exhibit 7 illustrates the counties that saw rapidly rising rents during this period and the number of years during which the county experienced rapidly rising rents. These counties are more heavily concentrated in Western states, including Montana, North Dakota, Alaska, and Colorado, and are less concentrated in the industrial Midwest. Exhibit 2 also captures rising rents in urban areas along the Pacific Coast, which could pose a concern for policymakers and local public housing agencies.

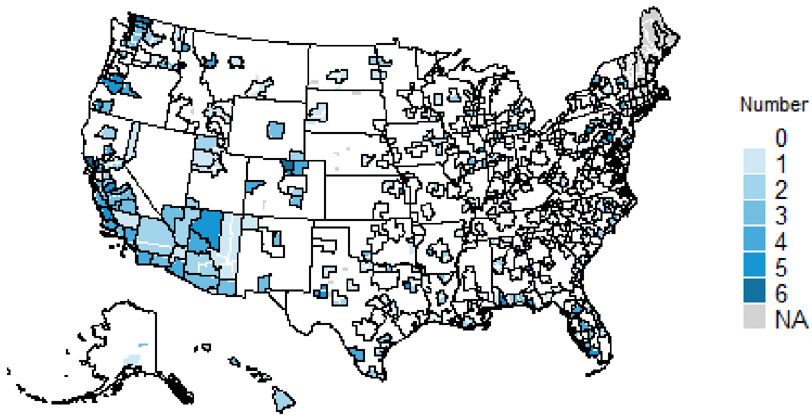
Exhibit 6. Number of Years in Which Counties Saw Rapidly Rising Rents, 2009–2010 to 2018–2019



Note: We define a county as having rapidly rising rents if (1) the county has rents in the top 20th percentile nationally and experiences a rent increase of greater than 5 percent, or (2) the county has rents in the bottom 80th percentile nationally and experiences a rent increase of greater than 10 percent.
Source: Urban Institute analysis of HUD American Community Survey extracts of gross rents from 2009 to 2019

Although our research focuses on rent changes at the county level, HUD's current methodology estimates rents for FMR areas that generally align with metropolitan areas, small areas (such as ZIP Codes) within metropolitan areas, and nonmetropolitan counties. For comparison, exhibit 8 identifies metropolitan and state nonmetropolitan areas in which more than one-half of households live in counties with rapidly rising rents under our preferred definition. The map shows rapidly rising rents for more than 1 year within metropolitan areas in Alaska, Hawaii, North Dakota, and the Pacific Coast.

Exhibit 7. Number of Years in Which the Majority of Households in Metropolitan and State Nonmetropolitan Areas Saw Rapidly Rising Rents, 2009–2010 to 2018–2019



Notes: We define a county as having rapidly rising rents if (1) the county has rents in the top 20th percentile nationally and experiences a rent increase of greater than 5 percent, or (2) the county has rents in the bottom 80th percentile nationally and experiences a rent increase of greater than 10 percent. Metro and state nonmetropolitan areas are designated as having rapidly rising rents if more than 50 percent of households in the area live in counties with rapidly rising rents.
Source: Urban Institute analysis of HUD American Community Survey extracts of gross rents from 2009 to 2019

Predicting Areas with Rapidly Rising Rents

We explored two sets of models that could be used to predict which counties are experiencing rapidly rising rents before rental data become available. The first is Boolean models, which set thresholds above or below which we predict counties will have rapidly rising rents. The second is logit models, which estimate the likelihood function. Both models used predictors that we hypothesize are leading indicators of housing supply and demand available at the county level: vacancy rates, number of building permits, unemployment rate, and changes in the number of households. Throughout the analysis period (2009 to 2016), 18.8 percent of counties experienced rapidly rising rents. Additional descriptive statistics appear in appendix B.

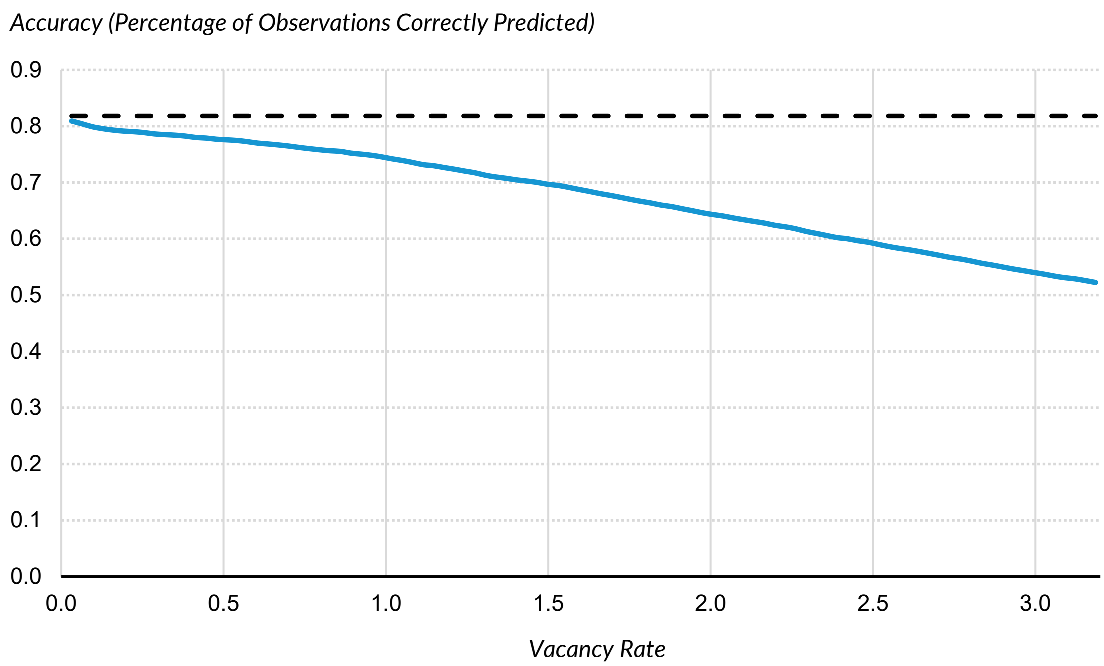
BOOLEAN MODELING RESULTS

For each of the predictors examined, we identified cut-off thresholds $V^*, E^*, S^*,$ and G^* that maximized the accuracy of our prediction as to which counties had rapidly rising rents. We found that accuracy is maximized when our models predicted that few or no counties would have rapidly rising rents.

Exhibit 9 displays the results of the Boolean model using only vacancy rate as a predictor and varying the threshold V, below which we forecast that counties will have rapidly rising rents. The top panel shows the percentage of counties with vacancy rates below a given threshold. As the vacancy rate threshold V increases, the fraction of counties below V—the counties we would predict to have rapidly rising rents—falls. The bottom panel shows the accuracy of the Boolean model. We see that efficiency is maximized at $= 0$, the point at which the fraction of counties predicted to have rapidly rising rents falls to zero. The dashed line in the lower panel represents the accuracy of a null hypothesis that no counties have rapidly rising rents. Put more simply, if we predict that no counties have rapidly rising rents, we are correct 81 percent of the time—and no Boolean model using only vacancy rate improves on this level of accuracy.

The same pattern holds for unemployment, rate of housing starts, and housing growth rate when each is modeled on its own. In a combined model, we found that some combinations of V^*, E^*, S^* and G^* led to accuracy rates marginally higher than a null assumption that no counties have rapidly rising rents. However, these combinations are all edge cases predicting that fewer than 10 of 14,081 county-by-year observations are instances of rapidly rising rents, and none of these combinations increased accuracy by as much as one-tenth of 1 percent beyond the null assumption that no place has rapidly rising rents.

Exhibit 8. Boolean Model Accuracy with Vacancy Rate



Notes: The top panel shows the percentage of counties with vacancy rates below a given threshold. The bottom panel shows the accuracy of the Boolean model, which predicts that counties below a certain vacancy rate have rapidly rising rents and counties above that vacancy rate do not have rapidly rising rents.
Sources: Urban Institute analysis of BLS unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

LOGIT MODELING RESULTS

Next, we examined whether we could use logit models to predict whether counties experience rapidly rising rents. To accommodate the two-part definition of rapidly rising rents, we estimated logit models separately for places in the top 20th percentile of rents, the bottom 80th percentile of rents, and all together, all based on 40th percentile recent-mover–adjusted rents in 2009. Because counties with smaller populations tend to have larger margins of error around estimates of rent and the unemployment rate, we also estimated the model using a subset of counties with at least 20,000 households. For ease of interpreting analysis findings, we calculated odds ratios for each logit model. Odds ratios show how each predictor affects the likelihood of having rapidly rising rents. An odds ratio of 0.9 means that an increase in the predictor of 1 reduces the odds of having rapidly rising rents by 10 percent, and an odds ratio of 1.1 means that an increase in the predictor of 1 increases the odds of having rapidly rising rents by 10 percent.

The 95 percent confidence intervals for the odds ratios appear in exhibit 10, and the low and high columns show each side of the confidence interval. If the low end falls above 1, we have 95 percent confidence in a positive relationship; if the high end falls above 1, we have 95 percent confidence that the relationship is positive.

Some evidence indicates that higher vacancy rates are associated with a decreased likelihood of having rapidly rising rents. The estimated odds ratio for all counties implies that a 1 percentage point increase in vacancy rate decreases the likelihood of having rapidly rising rents by between 1 and 4 percent. Places with higher unemployment rates also appear less likely to have rapidly rising rents. The 95 percent confidence intervals for the variables that appear only in the expanded model span 1.000, which indicates that we cannot identify whether the relationship is positive or negative.

Exhibit 9. Predicting the Likelihood of Having Rapidly Rising Rents

Logit Model Results (95 Percent Confidence Odds Ratios), 2009–2010 to 2015–2016

	All Counties		**Rent in Top 20%**		**Rent in Bottom 80%**		**At Least 20K Households**	
	Low	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
Base model								
Vacancy rate	**0.957**	**0.987**	0.931	1.003	0.986	1.022	**0.898**	**0.958**
Housing start rate	**1.008**	**1.034**	0.982	1.022	0.998	1.031	0.991	1.027
Unemployment rate	0.971	1.001	**0.944**	**0.997**	0.963	1.000	0.956	1.003
Growth rate	0.989	1.168	0.859	1.113	0.944	1.101	0.949	1.214
Observations	14,081		3,063		11,018		5,770	
Expanded model								
Vacancy rate	**0.955**	**0.986**	0.926	1.000	0.985	1.022	**0.892**	**0.953**
Inverse vacancy rate	0.997	1.001	0.996	1.002	0.997	1.002	0.994	1.001
Housing start rate	**1.006**	**1.034**	0.982	1.023	0.999	1.035	0.991	1.028
Inverse housing start rate	0.958	1.017	0.959	1.046	0.979	1.048	0.959	1.038
Unemployment rate	0.977	1.036	0.911	1.012	**1.018**	**1.094**	0.905	1.001
Inverse unemployment rate	**0.748**	**9.846**	0.031	8.685	7.241	145.1	0.013	2.594
Housing growth rate	0.983	1.161	0.861	1.118	0.929	1.081	0.956	1.225
Inverse housing growth rate	0.999	1.002	0.997	1.005	0.999	1.002	0.999	1.004
Observations	13,865		3,054		10,811		5,756	

Notes: Top 20 percent and bottom 80 percent are based on 40th percentile recent-mover–adjusted rents in 2009. Relationships that are nonzero with 95 percent confidence are in bold.
Sources: Urban Institute analysis of BLS unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Exhibit 11 displays forecast validation statistics for the logit models. We compared the logit model with a null assumption that no county has rapidly rising rents. Because we identified 19 percent of our county-by-year observations as having rapidly rising rents and 81 percent as not having rapidly rising rents, the null assumption that no county has rapidly rising rents has an accuracy rate of 81 percent. Because the null never correctly identifies counties with rapidly rising rents, its recall—the percentage of places with rapidly rising rents that were correctly identified—is zero. Precision and F-score are undefined for the null hypothesis; because the null never predicts that rents are rising, there are no true or false positives (only true and false negatives). Neither logit model was more accurate than the null across all counties or for any of the three county subsets we examined. Recall was greater than zero for both models using any set of counties, but neither model correctly identified even one in four counties with rapidly rising rents across all counties.

Exhibit 10. Performance of Logit Model Predicting Areas with Rapidly Rising Rents, 2009–2010 to 2015–2016

	Null	Base Model				Expanded Model			
		All Counties	Rent in Top 20%	Rent in Bottom 80%	At Least 20K Households	All Counties	Rent in Top 20%	Rent in Bottom 80%	At Least 20K Households
True positives	0	293	176	143	201	293	177	128	203
False positives	0	940	292	639	473	920	282	610	466
True negatives	5,251	4,311	654	3,666	1,481	4,264	663	3,629	1,479
False negatives	1,199	906	299	581	443	894	296	586	440
Accuracy	0.814	**0.714**	0.584	0.757	0.647	**0.715**	0.592	0.759	0.650
Recall	0.000	**0.244**	0.371	0.198	0.312	**0.247**	0.374	0.179	0.316
Precision	n/a	**0.238**	0.376	0.183	0.298	**0.242**	0.386	0.173	0.303
F-Score	n/a	**0.241**	0.373	0.190	0.305	**0.244**	0.380	0.176	0.309

Note: Top 20 percent and bottom 80 percent are based on 40th percentile recent-mover–adjusted rents in 2009.
Sources: Urban Institute analysis of BLS unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Estimating Rent Time Series Models with Local Data

Our next section of analysis focuses on predicting gross rent CPI with additional predictor variables. To evaluate whether the additional predictor variables improve the fitness of the time series model, we calculated the RMSE to compare forecast errors for the ARIMA, select predictors ARIMAX, and expanded ARIMAX models. This reveals how well the selected model predicts compared with the actual gross CPI for the forecast periods we chose.

Specifically, we estimated each model specification over four overlapping sample periods: 2005 to 2015, 2005 to 2016, 2005 to 2017, and 2005 to 2018. Next, we calculated the predicted gross rent CPI over the following seven quarters and calculated RMSE, mimicking models used to forecast FMRs in FY 2017, FY 2018, FY 2019, and FY 2020, respectively.

We found mixed results in improvements to the ARIMA model. In general, the ARIMAX models had lower RMSE and performed better than the ARIMA model, but this is not always the case. As demonstrated in exhibit 12, for example, the ARIMA model performed best for the Seattle-Tacoma-Bellevue, Washington, metropolitan area during the 2005–2018 estimate period, and the ARIMAX model performed better for the other periods. Exhibit 13 shows the number of times each model performed the best for Seattle and the Midwest. Statistics describing the model performance for all other PSUs can be found in exhibit 31 in appendix B. Overall, the expanded ARIMAX model performed the best nationally more than one-half of the time (53 percent), followed by the ARIMAX model with selected predictors (34 percent); this is intuitive because we introduced additional predictor variables that capture trends in rent CPI and, therefore, reduce RMSE. The ARIMA model only performed better than the ARIMAX model in 13 percent of the models we estimated.

Exhibit 11. Root Mean Squared Error for ARIMA and ARIMAX Models Comparison, Seattle-Tacoma-Bellevue, Washington, Metropolitan Area and Midwest Region (Size Class B/C)

FMR Prediction Year	Estimate Time Period	RMSE for ARIMA	RMSE for Select Predictors ARIMAX	RMSE for Expanded ARIMAX
Seattle-Tacoma-Bellevue, WA				
FY 2020	2005–2018	**1.799**	2.059	2.300
FY 2019	2005–2017	2.098	**1.924**	2.324
FY 2018	2005–2016	1.861	1.804	**1.017**
FY 2017	2005–2015	2.064	1.682	**1.417**
Midwest (Size Class B/C)				
FY 2020	2005–2018	0.588	0.554	**0.479**
FY 2019	2005–2017	0.618	**0.552**	0.588
FY 2018	2005–2016	0.773	**0.685**	0.720
FY 2017	2005–2015	1.075	**1.043**	1.080

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. FY = fiscal year. RMSE = root mean squared error.

Notes: Size Class B/C consists of urban areas with a population of 2.5 million or fewer. Results for all regions appear in exhibit 32.

Source: Urban Institute analysis of HUD FMR program data and BLS Consumer Price Index data

Exhibit 12. Summary of ARIMA and ARIMAX Model Performance

Area	ARIMA	Select Predictors ARIMAX	Expanded ARIMAX
Northeast (Size Class B/C)	3	0	1
Midwest (Size Class B/C)	0	3	1
South (Size Class B/C)	0	2	2
West (Size Class B/C)	0	1	3
Boston-Cambridge-Newton, MA-NH	1	1	2
New York-Newark-Jersey City, NY-NJ-PA	1	1	2
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	1	0	3
Chicago-Naperville-Elgin, IL-IN-WI	0	2	2
Detroit-Warren-Dearborn, MI	0	3	1
Washington-Arlington-Alexandria, DC-VA-MD-WV	1	1	2
Miami-Fort Lauderdale-West Palm Beach, FL	0	2	2
Atlanta-Sandy Springs-Roswell, GA	0	2	2
Baltimore-Columbia-Towson, MD	0	1	3
Dallas-Fort Worth-Arlington, TX	0	2	2
Los Angeles-Long Beach-Anaheim, CA	0	0	4
San Francisco-Oakland-Hayward, CA	1	1	2
Seattle-Tacoma-Bellevue, WA	1	1	2
Total	**9**	**23**	**36**

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables.

Note: Size Class B/C consists of urban areas with a population of 2.5 million or fewer.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index data; Federal Reserve mortgage interest rate data

We found that no single predictor variable performs the best as a predictor for change in gross rent CPI across all geographies. Exhibits 14 and 15 present the coefficients and standard deviations for the predictor variables in the ARIMAX models for the Seattle metropolitan area and the Midwest region. In Seattle, for the select predictors used in the ARIMAX model (House Price Index, unemployment rate, and building permits per 1,000 housing units), the number of building permits and the House Price Index are statistically significant. The negative coefficient for building permits per 1,000 housing units indicates that an increase in building permits predicts a smaller increase in gross rent in the future, although the magnitude and significance vary in other locations. Conversely, House Price Index is significant and positive for the Seattle-Tacoma-Bellevue analysis, indicating that as the House Price Index increases, larger gross rent increases follow; as with the building permits coefficient, the magnitude and significance vary for other locations. In contrast, we find much smaller coefficients on relationships between predictor variables and the gross rent series for the Midwest (size class B/C).

Exhibit 13. Coefficients for Select Predictors Using the ARIMAX Model for 2005–2018, Seattle-Tacoma-Bellevue, Washington, Metropolitan Area and Midwest Region

Predictor	Coefficient	Standard Error
Seattle-Tacoma-Bellevue, WA		
Building permits per 1,000 housing units*	-0.433*	0.173
House Price Index*	0.172**	0.051
Unemployment rate	-0.006	0.004
Midwest (Size Class B/C)		
Building permits per 1,000 housing units	0.015	0.178
House Price Index	0.063	0.108
Unemployment rate	0.000	0.002

* Significance level of 0.05.

** Significance level of 0.01.

*** Significance level of 0.001.

Notes: Size Class B/C consists of urban areas with a population of 2.5 million or fewer. Results for all regions appear in exhibit 32.

Sources: Urban Institute analysis of Bureau of Labor Statistics unemployment statistics, U.S. Department of Housing and Urban Development FMR program data, Census Bureau Building Permits Survey data, and Federal Housing Finance Agency House Price Index.

Exhibit 14. Coefficients for Expanded ARIMAX Model for 2005–2018, Seattle-Tacoma-Bellevue, Washington, Metropolitan Area and Midwest Region (Size Class B/C)

Predictor	Coefficient	Standard Error
Seattle-Tacoma-Bellevue, WA		
Permits per 1,000 housing units	-0.296	1.317
House Price Index**	0.207	0.082
Unemployment rate	-0.002	0.005
Mortgage interest rate	-0.004	0.008
Vacancy rate	-0.148	1.435
Housing growth rate	0.464	13.56
Midwest (Size Class B/C)		
Permits per 1,000 housing units	-0.049	1.541
House Price Index	0.012	0.147
Unemployment rate	-0.001	0.003
Mortgage interest rate	0.000	0.006
Vacancy rate	0.07	0.823
Housing growth rate	0.511	16.547

* Significance level of 0.05.
** Significance level of 0.01.
*** Significance level of 0.001.
Note: Size Class B/C consists of urban areas with a population of 2.5 million or fewer. Results for all regions appear in exhibit 33.
Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics CPI and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index data; Federal Reserve mortgage interest rate data

In exhibit 16, we summarize the frequency of significance of the predictor variables for the select predictors ARIMAX model for 2005–2018. House Price Index appears to be the predictor that is most often significant, although the direction of coefficient may vary by region. Detailed coefficient and standard error values for each PSU and size class B/C series for each region can be found in exhibits 32 and 33 in appendix B. We do not show counts of significance for the expanded ARIMAX model because the predictors are correlated, so statistical significance does not necessarily identify the most important predictors in the expanded ARIMAX model.

Exhibit 15. Significant Predictor Variables and Select Predictors for ARIMAX Model, 2005–2018

	Unemployment Rate	Building Permits per 1,000 Housing Units	House Price Index
Select predictors ARIMAX model	0	2	8

ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables.

Notes: Significance test is based on a significance level of 0.05. See exhibit 32 for complete results.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics CPI and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

Assessing Alternative FMR Calculations

To assess the performance of our alternative FMR estimates, we compared estimates calculated from the six alternative models and HUD–calculated FMRs with the actual 40th percentile gross rent.

USING THE RMSE AS AN ASSESSMENT STRATEGY

Although the ARIMAX models tend to better fit the metropolitan and regional gross rent CPI series (exhibit 13), the ARIMA model better predicted county gross rents while using RMSE. Exhibit 17 displays the RMSE for estimates from the six alternative FMR models and the HUD FMRs between 2017 and 2020. We calculated RMSE in terms of nominal dollars and with each county weighted equally. Alternative formulations of RMSE with errors calculated as a percentage of actual rent and weighted by the number of housing units in each county appear in exhibits 55 and 56. For each of the ARIMA and ARIMAX models, alternative A shows the results when we apply the model directly to the county gross rent series and forecast 11 quarters forward to estimate FMRs. Alternative B shows the results when we use regional and metropolitan-area CPI data to forecast gross rent for four quarters and then use the ARIMA and ARIMAX models to forecast the next seven quarters.

Based on RMSE, version A of the ARIMA model performed best in 2017 and 2018 (exhibit 17). The A version of the select predictors ARIMAX model provided the best fit for the data in 2019 and 2020, but our calculated gross rents in those years include less than 10 percent of all counties and include only four nonmetropolitan counties. Forecasting directly from the county gross rents (rows marked

"A" in exhibit 17) tended to provide a better fit than forecasting after using 1 year of metropolitan area or regional inflation adjustments. However, version B using the select predictors ARIMAX model performed better in 2017 and 2018. Results are similar when we calculate RMSE using errors measured as a percentage of actual rents. Weighting by the number of housing units, version B using the select predictors ARIMAX model performs best in 2017 and 2018, and the expanded ARIMAX model performs worse (exhibits 55 and 55).

Exhibit 16. Goodness of Fit Measures at the County Level (RMSE in Nominal Dollars)
HUD FMRs and Alternatives by Year

FMR Definition	2017	2018	2019	2020
HUD FMR	111	109	184	188
ARIMA (A)	**84**	**90**	143	131
ARIMA (B)	85	90	148	136
Select predictors ARIMAX (A)	125	113	**118**	**113**
Select predictors ARIMAX (B)	113	107	118	114
Expanded ARIMAX (A)	91	95	150	137
Expanded ARIMAX (B)	94	101	160	143
Observations (counties)	2,634	2,613	218	218

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent.

Notes: Exhibit displays root mean squared prediction errors calculated between HUD's two-bedroom FMR or proposed alternatives and actual 40th percentile gross rents for two-bedroom units. For 2019 and 2020, we adjusted the 2018 gross rents to 2019 and 2020 levels using ZIP Code-level ZORI estimates from Zillow. Because ZORI estimates are available for select ZIP Codes, the sample size is smaller in 2019 and 2020.
Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics CPI and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

We expect that HUD FMRs will have larger RMSEs compared with county gross rents than our alternatives for three reasons: first, many FMRs are developed for multicounty HMFAs; second, HUD used national trend factors in 2017, 2018, and 2019 to calculate FMRs in those fiscal years; and third, HUD adjusts FMRs based on the state minimum and previous year's FMR floors but we did not. For each year in the study period, FMRs calculated from the ARIMA model and the expanded ARIMAX model better fit the data than HUD’s FMRs. The select predictors model, however, did not universally outperform HUD’s FMRs in terms of minimizing relative RMSE. In 2017, neither technique using the select predictors ARIMAX model had a lower RMSE than HUD’s FMRs, and in 2018, only version “B” of the select predictors ARIMAX model had a lower RMSE than HUD’s FMRs. Notably, all our alternatives performed better than HUD’s FMRs in 2020, when HUD began using local trend factors at the metropolitan and regional levels.

USING TRUE VALUE WITHIN 10 PERCENT RANGE AS AN ASSESSMENT STRATEGY

To more practically evaluate how well our alternative models perform, we also examined whether actual 40th percentile gross rents were within 10 percent of our alternative FMRs, less than 90 percent of our alternative FMRs, or more than 110 percent of our alternative FMRs (exhibit 18). If actual rents are lower than FMRs, public housing agencies and some households with HCVs may be able to lease more expensive units than the program was designed to subsidize, leading to higher costs per assisted household and, potentially, fewer households served. If actual rents are higher than FMRs, however, households with HCVs may have difficulty finding decent-quality rental units. We considered this latter issue to be of greater concern than the former. All else equal, we considered FMRs that overestimate rent (producing instances in which actual rent is less than 90 percent of the FMR) preferable to FMRs that underestimate rent (producing instances in which actual rent is greater than 110 percent of the FMR). HUD’s use of a state minimum and floor set at 90 percent of the previous year’s FMR helps minimize instances in which FMRs might be too low. Because we did not replicate this policy, we expect that actual rents will be more than 110 percent of HUD’s FMRs less frequently than our alternatives.

Exhibit 17. Ratio of Actual Gross Rent to FMRs for HUD FMRs and Alternatives by Year

	40th Percentile Gross Rents			
	Less than 90% of FMR	*90–110% of FMR*	*Greater than 110% of FMR*	**Observations**
2017				2,634
HUD FMR	***35%***	***60%***	***5%***	
ARIMA (A)	7%	70%	23%	
ARIMA (B)	6%	68%	26%	
Select predictors ARIMAX (A)	57%	36%	7%	
Select predictors ARIMAX (B)	43%	49%	8%	
Expanded ARIMAX (A)	10%	66%	24%	
Expanded ARIMAX (B)	9%	64%	27%	
2018				2,613
HUD FMR	***32%***	***62%***	***6%***	
ARIMA (A)	5%	68%	27%	
ARIMA (B)	5%	67%	28%	
Select predictors ARIMAX (A)	45%	47%	8%	
Select predictors ARIMAX (B)	35%	55%	10%	
Expanded ARIMAX (A)	6%	66%	28%	
Expanded ARIMAX (B)	7%	63%	30%	
2019				218
HUD FMR	***21%***	***56%***	***23%***	
ARIMA (A)	3%	56%	41%	
ARIMA (B)	3%	54%	43%	
Select predictors ARIMAX (A)	12%	76%	12%	
Select predictors ARIMAX (B)	14%	74%	12%	
Expanded ARIMAX (A)	3%	53%	44%	
Expanded ARIMAX (B)	3%	51%	46%	
2020				218
HUD FMR	19%	55%	26%	
ARIMA (A)	3%	59%	38%	
ARIMA (B)	3%	56%	41%	
Select predictors ARIMAX (A)	12%	80%	8%	
Select predictors ARIMAX (B)	12%	80%	8%	
Expanded ARIMAX (A)	3%	59%	38%	
Expanded ARIMAX (B)	3%	56%	41%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent.

Notes: Exhibit displays percentage of counties for which the actual 40th percentile gross rent (calculated using ACS data) is less than 90 percent of, between 90 and 110 percent of, or greater than 110 percent of HUD's two-bedroom FMR or proposed alternatives. Alternative FMRs are the average of the four quarters of the fiscal year. For 2019 and 2020, we adjusted the 2018 gross rents to 2019 and 2020 levels using ZIP Code-level ZORI estimates from Zillow. Because ZORI estimates are available for select ZIP Codes, the sample size is smaller in 2019 and 2020.

Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics CPI and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

The ARIMA model produced FMRs that were closest to actual rents most frequently, using data from 2017 and 2018. Actual rents were within 10 percent of the ARIMA model FMRs 70 and 68 percent of the time in 2017 and 68 and 67 percent of the time in 2018. The expanded ARIMAX model performed similarly on this metric. However, the ARIMA and expanded ARIMAX models were more likely to underestimate actual rents than either the selected predictors ARIMAX model or HUD's FMRs. In 2018, the ARIMA model created FMRs that were too low in 27 and 28 percent of counties, and the expanded ARIMAX model created FMRs that were too low in 28 and 30 percent of counties. Of our alternative FMRs, the two generated from the select predictors ARIMAX model were least likely to undershoot the actual gross rent. In 2017, only 7 and 8 percent of counties had actual rents greater than 110 percent of these predicted FMRs, and in 2018, only 8 and 10 percent of counties had actual rents greater than 110 percent of the predicted FMRs.

In 2017 and 2018, HUD's FMRs were rarely lower than any of our alternative estimates—in 2017 and 2018, the actual 40th percentile gross rent was more than 110 percent of HUD's FMR in only 5 and 6 percent of counties. In 2017 and 2018, 90 to 110 percent of HUD's FMRs covered the actual 40th percentile rent level more frequently than the alternatives based on the select predictors ARIMAX model but less frequently than the alternatives based on either the ARIMA or expanded ARIMAX models.

For the 218 counties for which we calculated actual rents for 2019 and 2020, the select predictors ARIMAX model performed better than HUD's FMRs and alternative FMRs based on the ARIMA and expanded ARIMAX models. In 2019, actual rents were within 10 percent of the FMRs produced by the select predictors ARIMAX model 74 and 76 percent of the time. In 2020, actual rents were within 10 percent of the FMRs from the select predictors ARIMAX model 80 percent of the time. Finally, the select predictors ARIMAX model produced FMRs that were too low only 12 percent of the time in 2019 and only 8 percent in 2020.

SUBGROUP ANALYSIS

In this section, we examine how well the models performed based on calculations using data from different types of counties. We focus here on FY 2018, the most recent year for which we have broad coverage on alternative FMRs generated without using metropolitan area or regional inflation adjustments (version A). Results for other years are presented in appendix B.

We first look at counties within the top 20th percentile of rents in 2009 and those identified as having rapidly rising rents in 2018 (exhibit 19). With respect to RMSE, all the models perform similarly well in counties with higher rents compared with HUD's FMRs. Examining the distribution, however, we see that the expanded ARIMAX and ARIMA models tend to underestimate rent levels.

We find similar results in counties with rapidly rising rents. The ARIMA and expanded ARIMAX models have a lower RMSE among counties with rapidly rising rents, but they are more likely than HUD's previous methodology to produce FMRs lower than the actual 40th percentile gross rent.

Exhibit 18. Performance of HUD FMRs and Alternatives in Counties with High or Rapidly Rising Rents, 2018

	RMSE	**40th Percentile Gross Rents**			
	(dollars)	*Less than 90% of FMR*	*90–110% of FMR*	*Greater than 110% of FMR*	**Observations**
Counties with higher rents (top 20th percentile)					529
HUD FMR	153	19%	63%	18%	
ARIMA (A)	143	4%	57%	39%	
Select predictors ARIMAX (A)	**143**	**19%**	**63%**	**18%**	
Expanded ARIMAX (A)	151	4%	55%	41%	
Counties with rapidly rising rents					593
HUD FMR	124	**39%**	**55%**	**6%**	
ARIMA (A)	**92**	10%	67%	23%	
Select predictors ARIMAX (A)	126	47%	46%	7%	
Expanded ARIMAX (A)	94	9%	67%	24%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. RMSE = root mean squared error.

Notes: Exhibit displays root mean squared prediction errors and percentage of counties for which the actual 40th percentile gross rent (calculated using American Community Survey data) is less than 90 percent, between 90 and 110 percent, or greater than 110 percent of HUD's two-bedroom FMR or proposed alternatives. Alternative FMRs are the average of the four quarters of the fiscal year. Categories are not mutually exclusive—some counties appear in both groups.

Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics CPI and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Exhibit 20 shows results for counties broken down by metropolitan and nonmetropolitan status in 2018. HUD's FMRs, which are calculated directly for nonmetropolitan counties, perform better by RMSE among nonmetropolitan counties than they do in metropolitan areas, where a single FMR may be used for a multicounty HMFA. Our alternative FMRs also perform well among nonmetropolitan counties, whether evaluated based on RMSE or distribution of the actual 40th percentile rents relative to HUD–estimated FMRs.

Comparing alternatives, the ARIMA model has the lowest RMSE and is most frequently within 10 percent of the actual gross rent level in both metropolitan and nonmetropolitan counties, but it is also most likely to set FMRs too low so that the true 40th percentile of rents is more than 110 percent of FMRs. In nonmetropolitan areas, the select predictors ARIMAX model leads to FMRs that tend to be too high; the 40th percentile of gross rent was less than 90 percent of the alternative FMR in 59 percent of counties.

Exhibit 19. Performance of HUD's FMRs and Alternatives in Metropolitan and Nonmetropolitan Counties, 2018

		40th Percentile Gross Rents			
	RMSE (dollars)	*Less than 90% of FMR*	*90–110% of FMR*	*Greater than 110% of FMR*	**Observations**
Counties in metropolitan areas					1,035
HUD FMR	138	**30%**	**60%**	**10%**	
ARIMA (A)	**116**	4%	62%	34%	
Select predictors ARIMAX (A)	125	34%	55%	11%	
Expanded ARIMAX (A)	122	5%	60%	35%	
Counties in nonmetropolitan areas					**1,578**
HUD FMR	84	**33%**	**64%**	**3%**	
ARIMA (A)	**68**	6%	72%	22%	
Select predictors ARIMAX (A)	105	53%	41%	6%	
Expanded ARIMAX (A)	72	7%	70%	23%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. RMSE = root mean squared error.

Note: Exhibit displays root mean squared prediction errors and percentage of counties for which the actual 40th percentile gross rent (calculated using American Community Survey data) is less than 90 percent, between 90 and 110 percent, or greater than 110 percent of HUD's two-bedroom FMR or proposed alternatives. Alternative FMRs are the average of the four quarters of the fiscal year.

Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics CPI and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Finally, we examine the performance of our alternative FMRs in 139 counties in metropolitan areas that calculate SAFMRs (exhibit 21). In these counties, the selected predictors ARIMAX model has the lowest RMSE; the actual 40th percentile of rents was within 10 percent of the predicted FMR 72 percent of the time; and the actual 40th percentile was more than 110 percent of the predicted FMR

12 percent of the time. However, in 2017, the ARIMA model had a lower RMSE, but FMRs from the select predictors ARIMAX model performed better according to the distributional metrics (appendix B).

Exhibit 20. Performance of HUD's FMRs and Alternatives in Counties with SAFMRs, 2018

	RMSE (dollars)	40th Percentile Gross Rents Less than 90% of FMR	90–110% of FMR	Greater than 110% of FMR	Observations
Counties with SAFMRs					**139**
HUD FMR	226	38%	45%	17%	
ARIMA (A)	165	5%	59%	36%	
Select predictors ARIMAX (A)	**158**	**16%**	**72%**	**12%**	
Expanded ARIMAX (A)	179	6%	58%	36%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. RMSE = root mean squared error. SAFMR = Small Area Fair Market Rent.

Notes: Exhibit displays root mean squared prediction errors and percentage of counties for which the actual 40th percentile gross rent (calculated using American Community Survey data) is less than 90 percent, between 90 and 110 percent, or greater than 110 percent of HUD's two-bedroom FMR or proposed alternatives. Alternative FMRs are the average of the four quarters of the fiscal year.

Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics CPI and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Implications for Policy and Future Research

The research presented in this report aims to help HUD determine the best method for calculating FMRs in markets with rapidly rising rents. We began our work by defining markets with rapidly rising rents, which we apply to U.S. counties. We recommend a two-tiered definition: rents are rapidly rising if gross rents fall in the top 20 percent nationally and rise 5 percent year over year, or if rents are not in the top 20 percent nationally but increase 10 percent year over year. This definition captures rural or lower-cost areas that see sharp increases in rents in percentage terms and higher-cost areas that see moderate increases in rent in percentage terms that are large in terms of the dollar amount for renters.

Next, we developed predictive models to forecast counties likely to have rapidly rising rents, using local data that are available more quickly than rental data. We focused on local area unemployment rates, vacancy rates, the number of building permits per 1,000 housing units, and growth in the number of housing units. Our models showed that places with higher vacancy and unemployment rates were less likely to have rapidly rising rents. However, the models could not accurately predict which counties had rapidly rising rents in a validation sample.

Our predictive models used simple approaches that produced results that are relatively easy to interpret. We explored a Boolean model that sought to find thresholds and a logit model that assumed that predictors were independently associated with the probability of rapidly rising rents. Unfortunately, these approaches failed to make accurate predictions, leaving several avenues open for future work in forecasting areas with rapidly rising rents. Future work could examine—

- The functional form of the predictive models and the potential interactions between the predictor variables.
- Interactions between predictor variables or incorporating thresholds into logit, probit, or linear probability models.
- More complex classification schemes, such as Bayesian models, random forests, or other machine learning algorithms that might prove effective at identifying areas with rapidly rising rents.
- A prediction process built on the ARIMA and ARIMAX models that have proven relatively effective at forecasting rent levels.

We also estimated time series models with local data, using ARIMA and ARIMAX models based on BLS rent and utilities prices (aggregated into a gross rent series). We show that an ARIMAX model that incorporates data on vacancies, building permits, population growth, unemployment, home values, and mortgage interest rates tends to provide better predictions of future changes in gross rent levels across metropolitan areas than a pure time series ARIMA model. Adding these predictors to the ARIMAX models could improve the estimation of local trend factors at the county level, even while staying within the basic framework of HUD's current FMR calculation process.

Future research should explore refinements to our ARIMA and ARIMAX models. We used lags of predictor variables to account for the timeliness of data releases and educated guesses about long-term relationships between those predictors and the rental market. But the ideal number of lags may depend on each geography's preexisting conditions and unique trends in those factors. Future research could further refine the models designed to predict areas with rapidly rising rents and the ARIMAX models by identifying the number of lags needed to maximize the predictive capability of each predictor variable.

In our analysis, we applied the coefficients from regional and metropolitan-area ARIMA and ARIMAX models to county-level data to generate six alternative FMRs and assess their performance. We designed our alternative FMRs to maximize accuracy at the county level and did not include adjustments that HUD makes to maintain FMRs above statewide and previous-year floors. The results were promising. Looking across counties in 2017, four of our FMRs more accurately predicted the true 40th percentile rent (had a smaller RMSE) than HUD's FMRs. In 2018, five of our alternatives had lower county-level RMSEs than HUD's FMRs, and in 2019 and 2020, all six sets of alternative FMRs had lower RMSEs than HUD's FMRs. These results generally held both in metropolitan areas and nonmetropolitan areas. Looking only at counties with rapidly rising rents, we found that our six sets of FMRs performed similarly, relative to HUD FMRs and to each other, as they had across the full sample of counties.

Our research suggests that we can predict FMRs at a local level by predicting changes in rent locally rather than applying regional inflation and trend factors. We can apply a similar process to ZIP Codes to calculate SAFMRs. Although many predictor variables are not available at the ZIP Code level, the ARIMA model could be applied to an imputed ZIP Code-level gross rent series. Future work could examine estimating county- or even ZIP Code–specific ARIMA and ARIMAX models.

We also found that although the local predictors tended to improve the fit of time series models of gross rent, the ARIMAX-based FMRs did not always outperform the ARIMA-based models when applied to the county data. Further research could examine additional predictors, new combinations of predictors, and more systematic testing of the predictive capacity of each.

In addition, as discussed in the limitations section, our research made several simplifications—notably, excluding New England and Puerto Rico and focusing only on two-bedroom FMRs—that could be explored individually. Our alternative FMRs differed from HUD's FMRs in several ways: introducing new predictor variables, using a single gross rent series rather than separate utility and rent series, applying the model rather than the implied trend factor to local data, and using county-level FMRs. Future research could also explore how each difference affects FMR calculations and which differences have the largest impact.

Finally, it is important to note that during our study period, we see no evidence that HUD systematically set FMRs too low. Rather, in 2017 and 2018, HUD rarely set the two-bedroom FMRs much lower than actual rents. In 2017, actual rents were more than 10 percent higher than the FMR in only 5 percent of counties, and in 2018, actual rents were more than 10 percent higher than the FMR in only 6 percent of counties. FMRs appear to have been too low more frequently in 2019 and 2020, but we were only able to examine a smaller set of counties in those years.

Conclusion

The importance of accurate FMRs cannot be overstated. FMRs that fail to keep up with rising rents can limit housing choice, hinder the ability of new entrants into the voucher program to find eligible rental units, and increase housing instability. Our research shows that rents have risen rapidly in many U.S. counties; however, it is difficult to forecast which counties will have rapidly rising rents in any given year. In addition, the county-level FMRs that we developed performed relatively well compared with HUD's FMRs, including the 2020 FMRs that calculated local and regional trend factors. Taken together, the best path to improve FMR calculations in areas with rapidly rising rents appears to be improving FMR calculations overall. HUD could take steps to improve FMR calculations by calculating FMRs at the county level using local data, as we did, although further refinements to our methods are needed. Alternatively, HUD could incorporate local data and generate more local trend factors while staying within the basic framework of its current FMR calculation process.

Our research also shows that using more precise local data and focusing on smaller geographies could improve FMR calculations. HUD's shift toward increased use of SAFMRs makes such local data even more important. Many of the datasets we used in this study, for example, are available at the county level but not the ZIP Code level. As housing searches, job searches, and permitting continue to shift online, more data collection could help develop more accurate FMR calculations in the near future.

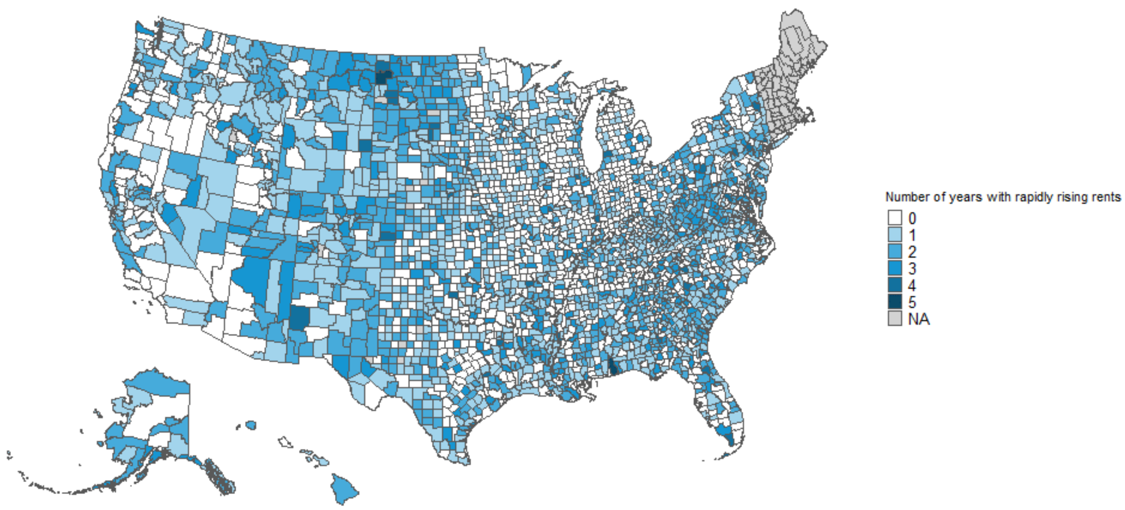
Appendix A. Exploring Alternative Definitions of Rapidly Rising Rents

In this appendix, we identify areas of the country experiencing rapidly rising rents, which we define as increases in rent that drive renters to seek alternative housing. We originally envisioned this designation as including any U.S. county where rent values increased by more than 10 percent in a single year. The 10 percent threshold aligns with previous research that examined Fair Market Rent (FMR) areas with rents between 90 and 110 percent of the FMR (HUD, 2018). However, a preliminary analysis showed that a 10 percent threshold would only classify between 5 and 15 percent of all U.S. counties as having rapidly rising rents each year. Moreover, the 10 percent threshold did not include many of the most populous and expensive cities, where rising rents pose a major policy concern.

Exhibit 22 displays the number of times (maximum of six) each county experienced rents that rose by more than 10 percent between 2009–2010 and 2015–2016. Counties experiencing rapidly rising rents by this definition appear concentrated along a region extending south from North Dakota and

Montana to west Texas and some counties in the Southeast. This definition finds fewer coastal, highly populated, and high-cost counties with rapidly rising rents. Our researchers were concerned about missing high-cost areas in which a rent increase of less than 10 percent may still represent a significant cost increase in dollars. For example, although we might expect Los Angeles County to experience rapidly rising rents—when the 40th percentile rent for a two-bedroom rose by more than $100 between 2015 and 2016—this definition would omit the county.

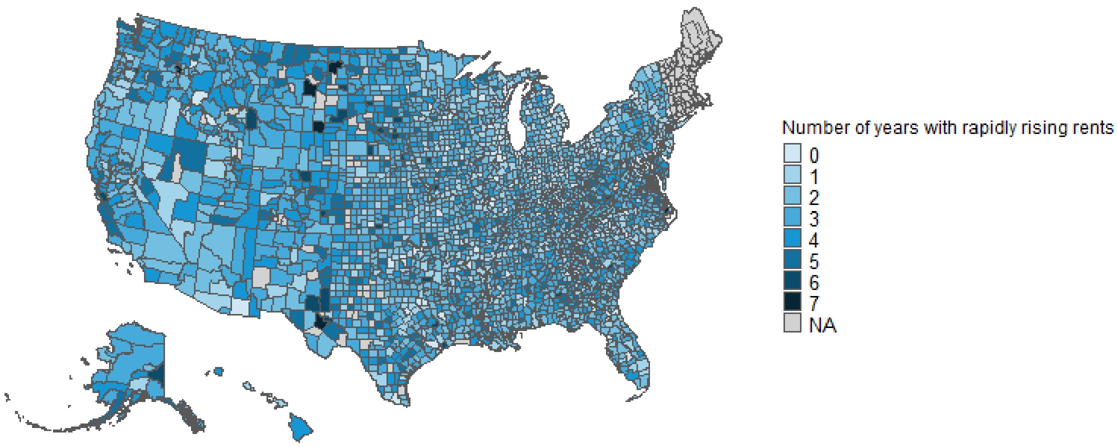
Exhibit 21. Number of Years Counties Saw More than a 10 Percent Increase in Rents, 2009–2010 to 2015–2016



Source: Urban Institute analysis of HUD American Community Survey extracts of gross rents from 2009 to 2016

We next explored lower thresholds of 5 and 8 percent for rapidly rising rents. The 5 percent threshold (exhibit 23) would designate almost every county in the United States as having experienced rapidly rising rents at least once during the study period, which means that the standard is too sensitive to positive changes in rent. We expect some changes in rent year to year—for example, inflation drives the absolute cost of rent upward. However, this study intends to identify counties where renters are priced out of their housing, not just counties where rents are rising.

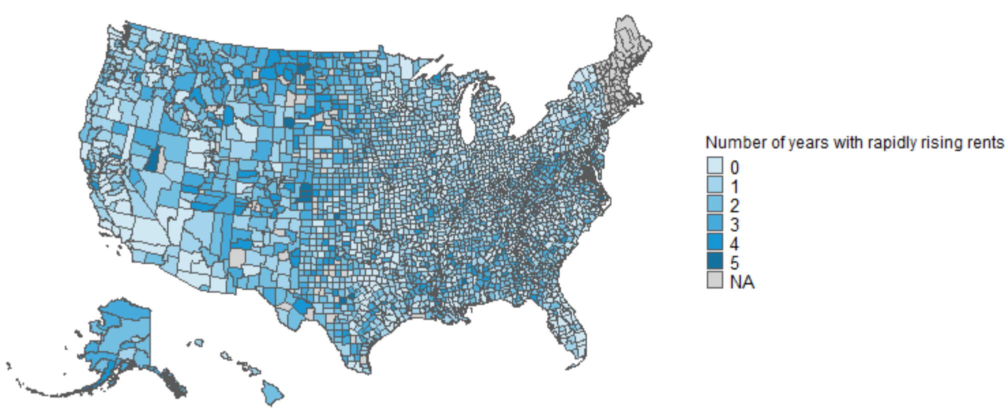
Exhibit 22. Number of Years Counties Saw More than a 5 Percent Increase in Rents, 2009–2010 to 2015–2016



Source: Urban Institute analysis of HUD American Community Survey extracts of gross rents from 2009 to 2016

Similarly, the 8 percent threshold (exhibit 24) picks up about one-half of U.S. counties but drops off known high-cost counties with tight rental markets, such as areas around Silicon Valley, New York City, and southern Florida.

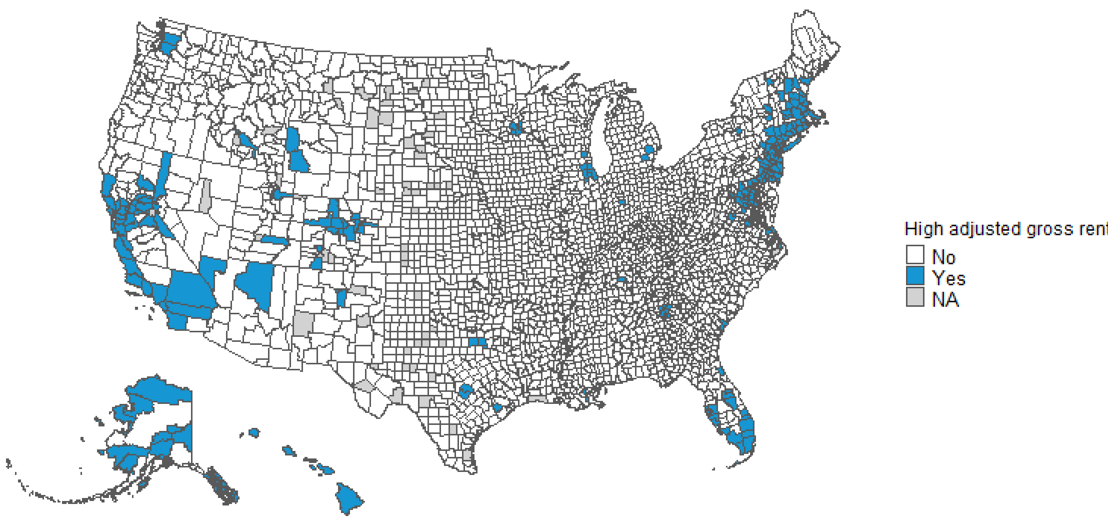
Exhibit 23. Number of Years Counties Saw More than an 8 Percent Increase in Rents, 2009–2010 to 2015–2016



Source: Urban Institute analysis of HUD American Community Survey extracts of gross rents from 2009 to 2016

To ensure that our final definition of rapidly rising rents accounted for high-cost areas where larger dollar-delineated increases in rent still fall below the 10 percent and 8 percent thresholds, we examined a graduated definition wherein counties with rents in the top 20th percentile nationally that experience a rent increase of greater than 5 percent and counties with rents in the bottom 80th percentile nationally that experience a rent increase of greater than 10 percent are considered rapidly rising. Exhibit 25 identifies counties in the top 20th percentile of rents in 2009. As expected, these areas are concentrated in California, the Northeast Corridor, Florida, Alaska, and Hawaii. We determined that the two-tiered definition best identified places where rents are rising either in dollars or as a percentage of previous rent levels. This preferred definition appears in exhibit 7 of this report.

Exhibit 24. Counties Where 2009 Rents Were in the Top 20th Percentile Nationally



Source: Urban Institute analysis of HUD ACS extracts of gross rents from 2009 to 2016

Appendix B. Supplemental Exhibits

This appendix contains exhibits that describe the data we used to predict rapidly rising rents and estimate rent time series models. It supplements the sections on analyses A and B from this report.

Predicting Areas with Rapidly Rising Rents

Exhibit 25. Predictors of Rapidly Rising Rents and Counties with Rapidly Rising Rents, 2009–2016

Summary Statistics

	Mean (percent)	Standard Deviation (percent)	Observations (counties x years)
Housing growth rate	0.40	1.80	25,142
Vacancy rate	3.89	3.08	23,250
Housing starts per 1,000 units	4.27	4.86	22,270
Unemployment rate	7.48	3.04	25,124
County has rapidly rising rents	18.8	39.0	24,504

Sources: Urban Institute analysis of Bureau of Labor Statistics unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Exhibit 26. Correlation Between Indicator for Rapidly Rising Rents and Predictor Variables (2009–2016)

	Rapidly Rising County	Housing Growth Rate	Vacancy Rate	Housing Starts per 1,000 Units
Housing growth rate	0.06 (24,492)			
Vacancy rate	-0.05 (22,680)	-0.14 (23,238)		
Housing starts per 1,000 units	0.06 (21,707)	0.72 (22,268)	-0.18 (21,056)	
Unemployment rate	-0.03 (24,494)	-0.13 (25,106)	0.13 (23,238)	-0.17 (22,267)

Sources: Urban Institute analysis of Bureau of Labor Statistics unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Estimating Rent Time Series Models with Local Data

Exhibit 27. Preferred ARIMA Model Specification by Area

Area	Geographic Code	p	d	q	SBC
Atlanta-Sandy Springs-Roswell, GA	S35C	2	1	0	456.3099
Baltimore-Columbia-Towson, MD	S35E	0	1	1	389.0183
Boston-Cambridge-Newton, MA-NH	S11A	0	1	1	373.2472
Chicago-Naperville-Elgin, IL-IN-WI	S23A	0	1	1	328.7474
Dallas-Fort Worth-Arlington, TX	S37A	0	1	1	344.9239
Detroit-Warren-Dearborn, MI	S23B	0	1	1	322.7242
Los Angeles-Long Beach-Anaheim, CA	S49A	1	1	1	245.7559
Miami-Fort Lauderdale-West Palm Beach, FL	S35B	1	1	1	286.5353
New York-Newark-Jersey City, NY-NJ-PA	S12A	1	1	0	261.5284
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	S12B	0	1	1	293.1719
San Francisco-Oakland-Hayward, CA	S49B	1	1	0	304.0293
Seattle-Tacoma-Bellevue, WA	S49D	1	1	1	343.0479
Washington-Arlington-Alexandria, DC-VA-MD-WV	S35A	1	1	0	299.1943
Midwest (Size Class B/C)	N200	2	1	1	256.8544
Northeast (Size Class B/C)	N100	0	1	1	221.9262
South (Size Class B/C)	N300	0	1	1	215.8605
West (Size Class B/C)	N400	2	1	0	214.4220

SBC = Schwarz Bayesian Information Criterion.

Note: The following models failed to converge during the maximum likelihood estimated and were not considered: Atlanta-Sandy Springs-Roswell, GA 2,1,2; Boston-Cambridge-Newton, MA-NH 2,1,1; Baltimore-Columbia-Towson, MD 2,1,2; Miami-Fort Lauderdale-West Palm Beach, FL 2,1,2; New York-Newark-Jersey City, NY-NJ-PA 0,1,2; Philadelphia-Camden-Wilmington, PA-NJ-DE-MD 1,1,2; and Washington-Arlington-Alexandria, DC-VA-MD-WV 0,1,1 and 0,1,2; West region 2,1,1 only converged for some years in the ARIMAX model, so we updated to 2,1,0 because the SBC is very close (214.422) to the SBC for 2,1,1 (214.302).

Sources: Urban Institute analysis of Bureau of Labor Statistics Consumer Price Index; HUD FMR program data

Exhibit 28. Summary Statistics for Predictor Variables for the ARIMAX Model

Variable	Mean	Standard Deviation	Minimum	Maximum
Vacancy rate	0.027	0.013	0.006	0.076
Housing units	4058911	6709509	128250	38208553
Building permits	37242	65109	99	583518
Unemployment rate	5.639	2.290	2.000	22.567
House Price Index	217.33	89.24	84.88	605.82
Mortgage rate	5.30	1.42	2.76	8.32

Sources: Urban Institute analysis of Bureau of Labor Statistics unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

Exhibit 29. Correlation of Predictor Variables for the ARIMAX Model

	Vacancy Rate	Mortgage	Unemployment Rate	Building Permits per 1,000 Housing Units	Housing Stock
Vacancy rate	1.00				
Mortgage	0.12***	1.00			
Unemployment rate	0.31***	-0.35***	1.00		
Building permits per 1,000 housing units	-0.27***	0.20***	-0.34***	1.00	
Housing stock	-0.19***	-0.06**	0.12***	0.47***	1.00

* Significance level of 0.05.

** Significance level of 0.01.

*** Significance level of 0.001.

Sources: Urban Institute analysis of Bureau of Labor Statistics unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

Exhibit 30. Time Series Model Performance

Area	Time Period	ARIMA	ARIMAX, Selected	ARIMAX, Expanded
Northeast (Size Class B/C)	2005–2018	0.4612	0.4537	**0.4124**
Northeast (Size Class B/C)	2005–2017	**0.6936**	0.7380	0.7748
Northeast (Size Class B/C)	2005–2016	**0.9094**	0.9103	0.9408
Northeast (Size Class B/C)	2005–2015	**0.9803**	1.0004	1.0286
Midwest (Size Class B/C)	2005–2018	0.5885	0.5541	**0.4795**
Midwest (Size Class B/C)	2005–2017	0.6180	**0.5520**	0.5883
Midwest (Size Class B/C)	2005–2016	0.7733	**0.6849**	0.7203
Midwest (Size Class B/C)	2005–2015	1.0746	**1.0433**	1.0804
South (Size Class B/C)	2005–2018	0.4793	0.4263	**0.3941**
South (Size Class B/C)	2005–2017	0.4934	0.4715	**0.4312**
South (Size Class B/C)	2005–2016	0.8391	**0.7427**	0.8137
South (Size Class B/C)	2005–2015	0.9359	**0.8667**	0.9115
West (Size Class B/C)	2005–2018	0.9545	0.6379	**0.3446**
West (Size Class B/C)	2005–2017	1.0980	0.7838	**0.5184**
West (Size Class B/C)	2005–2016	0.7866	0.6017	**0.4856**
West (Size Class B/C)	2005–2015	0.7143	**0.5152**	0.5441
Boston-Cambridge-Newton, MA-NH	2005–2018	**2.3692**	2.5680	2.7837
Boston-Cambridge-Newton, MA-NH	2005–2017	2.8881	2.9493	**2.5398**
Boston-Cambridge-Newton, MA-NH	2005–2016	3.4299	3.2090	**1.2153**
Boston-Cambridge-Newton, MA-NH	2005–2015	1.1490	**0.9139**	2.5486
New York-Newark-Jersey City, NY-NJ-PA	2005–2018	1.1568	1.0628	**0.9534**
New York-Newark-Jersey City, NY-NJ-PA	2005–2017	0.9651	**0.9629**	1.0173
New York-Newark-Jersey City, NY-NJ-PA	2005–2016	0.7842	0.9406	**0.6355**
New York-Newark-Jersey City, NY-NJ-PA	2005–2015	**0.6139**	0.6358	0.6770

Area	Time Period	ARIMA	ARIMAX, Selected	ARIMAX, Expanded
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	2005–2018	1.0918	1.0826	**1.0249**
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	2005–2017	0.9815	0.9391	**0.7373**
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	2005–2016	0.8095	0.7961	**0.6806**
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	2005–2015	**0.6352**	0.6396	0.7634
Chicago-Naperville-Elgin, IL-IN-WI	2005–2018	0.8744	**0.8743**	1.1023
Chicago-Naperville-Elgin, IL-IN-WI	2005–2017	1.1765	1.1371	**1.0998**
Chicago-Naperville-Elgin, IL-IN-WI	2005–2016	0.9684	0.8842	**0.7786**
Chicago-Naperville-Elgin, IL-IN-WI	2005–2015	0.5974	**0.5777**	0.9772
Detroit-Warren-Dearborn, MI	2005–2018	1.4253	**1.2686**	1.3662
Detroit-Warren-Dearborn, MI	2005–2017	1.1480	**0.8930**	0.9373
Detroit-Warren-Dearborn, MI	2005–2016	0.8134	**0.5716**	0.6480
Detroit-Warren-Dearborn, MI	2005–2015	0.8749	0.7460	**0.6921**
Washington-Arlington-Alexandria, DC-VA-MD-WV	2005–2018	1.0594	**1.0332**	1.0576
Washington-Arlington-Alexandria, DC-VA-MD-WV	2005–2017	1.5264	1.6118	**1.3712**
Washington-Arlington-Alexandria, DC-VA-MD-WV	2005–2016	1.4640	1.5420	**0.6203**
Washington-Arlington-Alexandria, DC-VA-MD-WV	2005–2015	**0.7643**	0.9622	1.4950
Miami-Fort Lauderdale-West Palm Beach, FL	2005–2018	2.1331	2.0704	**1.9103**
Miami-Fort Lauderdale-West Palm Beach, FL	2005–2017	1.9146	**1.8169**	1.9334

Area	Time Period	ARIMA	ARIMAX, Selected	ARIMAX, Expanded
Miami-Fort Lauderdale-West Palm Beach, FL	2005–2016	0.9807	0.8907	**0.8356**
Miami-Fort Lauderdale-West Palm Beach, FL	2005–2015	1.3858	**0.8764**	0.9910
Atlanta-Sandy Springs-Roswell, GA	2005–2018	2.8459	**2.5256**	2.6581
Atlanta-Sandy Springs-Roswell, GA	2005–2017	3.5624	**2.5187**	2.8014
Atlanta-Sandy Springs-Roswell, GA	2005–2016	5.0632	4.1900	**3.6340**
Atlanta-Sandy Springs-Roswell, GA	2005–2015	4.7300	3.8223	**3.6732**
Baltimore-Columbia-Towson, MD	2005–2018	2.4664	2.3244	**2.2723**
Baltimore-Columbia-Towson, MD	2005–2017	3.0461	2.8998	**1.9417**
Baltimore-Columbia-Towson, MD	2005–2016	4.0981	4.0842	**3.2566**
Baltimore-Columbia-Towson, MD	2005–2015	3.1826	**3.1526**	3.7167
Dallas-Fort Worth-Arlington, TX	2005–2018	1.2348	**0.9822**	1.0809
Dallas-Fort Worth-Arlington, TX	2005–2017	2.0476	1.7321	**1.1061**
Dallas-Fort Worth-Arlington, TX	2005–2016	2.6743	1.8452	**1.3216**
Dallas-Fort Worth-Arlington, TX	2005–2015	2.3954	**1.2631**	1.3339
Los Angeles-Long Beach-Anaheim, CA	2005–2018	1.4437	1.2717	**1.0798**
Los Angeles-Long Beach-Anaheim, CA	2005–2017	1.2790	1.0193	**0.7637**
Los Angeles-Long Beach-Anaheim, CA	2005–2016	0.5525	0.4779	**0.4018**
Los Angeles-Long Beach-Anaheim, CA	2005–2015	1.1340	1.0122	**0.6322**
San Francisco-Oakland-Hayward, CA	2005–2018	3.7575	3.7399	**3.6236**

Area	Time Period	ARIMA	ARIMAX, Selected	ARIMAX, Expanded
San Francisco-Oakland-Hayward, CA	2005–2017	**1.7655**	2.0420	2.4209
San Francisco-Oakland-Hayward, CA	2005–2016	1.9465	1.9410	**0.8633**
San Francisco-Oakland-Hayward, CA	2005–2015	1.4152	**0.7045**	2.0023
Seattle-Tacoma-Bellevue, WA	2005–2018	**1.7994**	2.0593	2.3000
Seattle-Tacoma-Bellevue, WA	2005–2017	2.0977	**1.9241**	2.3245
Seattle-Tacoma-Bellevue, WA	2005–2016	1.8613	1.8041	**1.0168**
Seattle-Tacoma-Bellevue, WA	2005–2015	2.0640	1.6821	**1.4167**

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables.

Note: We calculated root mean squared error for forecasts 2 years out based on the specified period.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

Exhibit 31. Coefficients for ARIMAX with Selected Predictor, 2005–2018

Area	Predictor	Coefficient	Standard Deviation	Statistically Significant (nonzero)
Seattle-Tacoma-Bellevue, WA	Permits per 1,000 housing units*	-0.433	0.173	Yes
Seattle-Tacoma-Bellevue, WA	House Price Index**	0.172	0.051	Yes
Seattle-Tacoma-Bellevue, WA	Unemployment rate	-0.006	0.004	
New York-Newark-Jersey City, NY-NJ-PA	Permits per 1,000 housing units	0.077	0.109	
New York-Newark-Jersey City, NY-NJ-PA	House Price Index**	0.089	0.034	Yes
New York-Newark-Jersey City, NY-NJ-PA	Unemployment rate	0.001	0.001	
Boston-Cambridge-Newton, MA-NH	Permits per 1,000 housing units	-0.175	0.390	
Boston-Cambridge-Newton, MA-NH	House Price Index**	0.125	0.106	
Boston-Cambridge-Newton, MA-NH	Unemployment rate	-0.003	0.005	
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Permits per 1,000 housing units	-0.093	0.180	
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	House Price Index**	0.132	0.054	Yes
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Unemployment rate	0.001	0.001	
Chicago-Naperville-Elgin, IL-IN-WI	Permits per 1,000 housing units	-0.057	0.070	
Chicago-Naperville-Elgin, IL-IN-WI	House Price Index	0.088	0.060	
Chicago-Naperville-Elgin, IL-IN-WI	Unemployment rate	0.000	0.001	
Detroit-Warren-Dearborn, MI	Permits per 1,000 housing units	-0.015	0.065	
Detroit-Warren-Dearborn, MI	House Price Index	0.054	0.030	
Detroit-Warren-Dearborn, MI	Unemployment rate	-0.001	0.001	
Baltimore-Columbia-Towson, MD	Permits per 1,000 housing units	0.409	0.466	
Baltimore-Columbia-Towson, MD	Housing price index	0.007	0.094	
Baltimore-Columbia-Towson, MD	Unemployment rate	0.002	0.003	
Miami-Fort Lauderdale-West Palm Beach, FL	Permits per 1,000 housing units	0.009	0.054	

Area	Predictor	Coefficient	Standard Deviation	Statistically Significant (nonzero)
Miami-Fort Lauderdale-West Palm Beach, FL	House Price Index***	0.100	0.019	Yes
Miami-Fort Lauderdale-West Palm Beach, FL	Unemployment rate	0.000	0.001	
Los Angeles-Long Beach-Anaheim, CA	Permits per 1,000 housing units	-0.068	0.272	
Los Angeles-Long Beach-Anaheim, CA	House Price Index**	0.070	0.025	Yes
Los Angeles-Long Beach-Anaheim, CA	Unemployment rate	-0.002	0.002	
San Francisco-Oakland-Hayward, CA	Permits per 1,000 housing units	-1.272	0.221	Yes
San Francisco-Oakland-Hayward, CA	House Price Index***	0.097	0.026	Yes
San Francisco-Oakland-Hayward, CA	Unemployment rate	-0.012	0.002	
Dallas-Fort Worth-Arlington, TX	Permits per 1,000 housing units	-0.055	0.076	
Dallas-Fort Worth-Arlington, TX	House Price Index	0.163	0.118	
Dallas-Fort Worth-Arlington, TX	Unemployment rate	-0.002	0.004	
Atlanta-Sandy Springs-Roswell, GA	Permits per 1,000 housing units	-0.041	0.033	
Atlanta-Sandy Springs-Roswell, GA	House Price Index*	0.163	0.077	Yes
Atlanta-Sandy Springs-Roswell, GA	Unemployment rate	-0.001	0.003	
Washington-Arlington-Alexandria, DC-VA-MD-WV	Permits per 1,000 housing units	-0.036	0.128	
Washington-Arlington-Alexandria, DC-VA-MD-WV	House Price Index	0.032	0.036	
Washington-Arlington-Alexandria, DC-VA-MD-WV	Unemployment rate	-0.002	0.003	
Northeast (Size Class B/C)	Permits per 1,000 housing units	0.027	0.267	
Northeast (Size Class B/C)	House Price Index	0.018	0.104	
Northeast (Size Class B/C)	Unemployment rate	0.000	0.002	
Midwest (Size Class B/C)	Permits per 1,000 housing units	0.015	0.178	
Midwest (Size Class B/C)	House Price Index	0.063	0.108	

Area	Predictor	Coefficient	Standard Deviation	Statistically Significant (nonzero)
Midwest (Size Class B/C)	Unemployment rate	0.000	0.002	
South (Size Class B/C)	Permits per 1,000 housing units	0.023	0.078	
South (Size Class B/C)	Housing price index	0.104	0.062	
South (Size Class B/C)	Unemployment rate	0.001	0.002	
West (Size Class B/C)	Permits per 1,000 housing units	-0.066	0.105	
West (Size Class B/C)	House Price Index**	0.028	0.039	Yes
West (Size Class B/C)	Unemployment rate	-0.002	0.002	

* Significance level of 0.05.

** Significance level of 0.01.

*** Significance level of 0.001.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data.

Exhibit 32. Coefficients for the Expanded ARIMAX Model, 2005–2018

Area	Predictor	Coefficient	Standard Deviation	Statistically Significant (nonzero)
Seattle-Tacoma-Bellevue, WA	Unemployment rate	-0.002	0.005	
Seattle-Tacoma-Bellevue, WA	House Price Index**	0.207	0.082	Yes
Seattle-Tacoma-Bellevue, WA	Building permits per 1,000 households	-0.296	1.317	
Seattle-Tacoma-Bellevue, WA	Mortgage interest rate	-0.004	0.008	
Seattle-Tacoma-Bellevue, WA	Vacancy rate	-0.148	1.435	
Seattle-Tacoma-Bellevue, WA	Housing unit growth	0.464	13.560	
New York-Newark-Jersey City, NY-NJ-PA	Unemployment rate	-0.002	0.002	
New York-Newark-Jersey City, NY-NJ-PA	House Price Index	0.031	0.057	
New York-Newark-Jersey City, NY-NJ-PA	Building permits per 1,000 households	0.036	0.120	
New York-Newark-Jersey City, NY-NJ-PA	Mortgage interest rate	-0.003	0.004	
New York-Newark-Jersey City, NY-NJ-PA	Vacancy rate	2.330	1.218	
New York-Newark-Jersey City, NY-NJ-PA	Housing unit growth	0.916	2.031	
Boston-Cambridge-Newton, MA-NH	Unemployment rate	0.001	0.006	
Boston-Cambridge-Newton, MA-NH	House Price Index	-0.005	0.257	
Boston-Cambridge-Newton, MA-NH	Building permits per 1,000 households	-0.116	1.102	
Boston-Cambridge-Newton, MA-NH	Mortgage interest rate	-0.013	0.010	
Boston-Cambridge-Newton, MA-NH	Vacancy rate	-0.030	1.956	
Boston-Cambridge-Newton, MA-NH	Housing unit growth	5.876	9.214	
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Unemployment rate	0.003	0.002	
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	House Price Index**	0.284	0.087	Yes

Area	Predictor	Coefficient	Standard Deviation	Statistically Significant (nonzero)
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Building permits per 1,000 households	-0.532	0.894	
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Mortgage interest rate	0.004	0.004	
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Vacancy rate	-0.108	0.513	
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Housing unit growth	2.051	9.255	
Chicago-Naperville-Elgin, IL-IN-WI	Unemployment rate	0.003	0.002	
Chicago-Naperville-Elgin, IL-IN-WI	House Price Index	0.053	0.075	
Chicago-Naperville-Elgin, IL-IN-WI	Building permits per 1,000 households	0.355	3.255	
Chicago-Naperville-Elgin, IL-IN-WI	Mortgage interest rate	-0.013	0.007	
Chicago-Naperville-Elgin, IL-IN-WI	Vacancy rate	-0.085	0.823	
Chicago-Naperville-Elgin, IL-IN-WI	Housing unit growth	0.134	31.986	
Detroit-Warren-Dearborn, MI	Unemployment rate	-0.001	0.001	
Detroit-Warren-Dearborn, MI	House Price Index	0.012	0.062	
Detroit-Warren-Dearborn, MI	Building permits per 1,000 households	-0.041	0.450	
Detroit-Warren-Dearborn, MI	Mortgage interest rate	-0.004	0.004	
Detroit-Warren-Dearborn, MI	Vacancy rate	-0.155	0.662	
Detroit-Warren-Dearborn, MI	Housing unit growth	0.199	3.362	
Baltimore-Columbia-Towson, MD	Unemployment rate	0.005	0.003	
Baltimore-Columbia-Towson, MD	House Price Index	0.002	0.116	
Baltimore-Columbia-Towson, MD	Building permits per 1,000 households	1.366	0.893	
Baltimore-Columbia-Towson, MD	Mortgage interest rate	0.017	0.009	
Baltimore-Columbia-Towson, MD	Vacancy rate	2.206	2.328	
Baltimore-Columbia-Towson, MD	Housing unit growth	-7.916	7.685	
Miami-Fort Lauderdale-West Palm Beach, FL	Unemployment rate	0.002	0.002	

Area	Predictor	Coefficient	Standard Deviation	Statistically Significant (nonzero)
Miami-Fort Lauderdale-West Palm Beach, FL	House Price Index	0.053	0.038	
Miami-Fort Lauderdale-West Palm Beach, FL	Building permits per 1,000 households	0.185	0.649	
Miami-Fort Lauderdale-West Palm Beach, FL	Mortgage interest rate	-0.009	0.006	
Miami-Fort Lauderdale-West Palm Beach, FL	Vacancy rate	0.043	0.491	
Miami-Fort Lauderdale-West Palm Beach, FL	Housing unit growth	0.670	5.793	
Los Angeles-Long Beach-Anaheim, CA	Unemployment rate	0.001	0.003	
Los Angeles-Long Beach-Anaheim, CA	House Price Index***	0.087	0.023	Yes
Los Angeles-Long Beach-Anaheim, CA	Building permits per 1,000 households	-0.065	0.395	
Los Angeles-Long Beach-Anaheim, CA	Mortgage interest rate	-0.002	0.003	
Los Angeles-Long Beach-Anaheim, CA	Vacancy rate	-2.397	1.337	
Los Angeles-Long Beach-Anaheim, CA	Housing unit growth	1.949	5.613	
San Francisco-Oakland-Hayward, CA	Unemployment rate	-0.008	0.004	
San Francisco-Oakland-Hayward, CA	House Price Index***	0.153	0.040	Yes
San Francisco-Oakland-Hayward, CA	Building permits per 1,000 households	-0.937	0.486	
San Francisco-Oakland-Hayward, CA	Mortgage interest rate	0.005	0.007	
San Francisco-Oakland-Hayward, CA	Vacancy rate	-0.676	1.406	
San Francisco-Oakland-Hayward, CA	Housing unit growth	-0.970	4.917	
Dallas-Fort Worth-Arlington, TX	Unemployment rate	-0.001	0.004	
Dallas-Fort Worth-Arlington, TX	House Price Index	0.143	0.139	
Dallas-Fort Worth-Arlington, TX	Building permits per 1,000 households**	1.279	0.492	Yes
Dallas-Fort Worth-Arlington, TX	Mortgage interest rate	0.004	0.007	

Area	Predictor	Coefficient	Standard Deviation	Statistically Significant (nonzero)
Dallas-Fort Worth-Arlington, TX	Vacancy rate	1.481	0.890	
Dallas-Fort Worth-Arlington, TX	Housing unit growth	-13.193	4.781	
Atlanta-Sandy Springs-Roswell, GA	Unemployment rate	-0.003	0.005	
Atlanta-Sandy Springs-Roswell, GA	House Price Index	0.096	0.090	
Atlanta-Sandy Springs-Roswell, GA	Building permits per 1,000 households	0.084	1.218	
Atlanta-Sandy Springs-Roswell, GA	Mortgage interest rate	-0.016	0.010	
Atlanta-Sandy Springs-Roswell, GA	Vacancy rate	1.295	0.969	
Atlanta-Sandy Springs-Roswell, GA	Housing unit growth	-0.013	12.587	
Washington-Arlington-Alexandria, DC-VA-MD-WV	Unemployment rate	-0.010	0.003	
Washington-Arlington-Alexandria, DC-VA-MD-WV	House Price Index***	0.130	0.035	Yes
Washington-Arlington-Alexandria, DC-VA-MD-WV	Building permits per 1,000 households	-0.246	0.244	
Washington-Arlington-Alexandria, DC-VA-MD-WV	Mortgage interest rate	0.008	0.004	
Washington-Arlington-Alexandria, DC-VA-MD-WV	Vacancy rate	1.810	0.972	
Washington-Arlington-Alexandria, DC-VA-MD-WV	Housing unit growth	-2.890	1.839	
Northeast (Size Class B/C)	Unemployment rate	0.001	0.003	
Northeast (Size Class B/C)	Housing price index	0.057	0.138	
Northeast (Size Class B/C)	Building permits per 1,000 households	-0.095	2.098	
Northeast (Size Class B/C)	Mortgage interest rate	0.002	0.005	
Northeast (Size Class B/C)	Vacancy rate	-0.313	0.827	
Northeast (Size Class B/C)	Housing unit growth	0.504	21.946	
Midwest (Size Class B/C)	Unemployment rate	-0.001	0.003	
Midwest (Size Class B/C)	House Price Index	0.012	0.147	
Midwest (Size Class B/C)	Building permits per 1,000 households	-0.049	1.541	

Area	Predictor	Coefficient	Standard Deviation	Statistically Significant (nonzero)
Midwest (Size Class B/C)	Mortgage interest rate	0.000	0.006	
Midwest (Size Class B/C)	Vacancy rate	0.070	0.823	
Midwest (Size Class B/C)	Housing unit growth	0.511	16.547	
South (Size Class B/C)	Unemployment rate	0.000	0.002	
South (Size Class B/C)	House Price Index	0.088	0.093	
South (Size Class B/C)	Building permits per 1,000 households	0.003	1.258	
South (Size Class B/C)	Mortgage interest rate	0.000	0.005	
South (Size Class B/C)	Vacancy rate	0.586	0.684	
South (Size Class B/C)	Housing unit growth	-0.003	9.852	
West (Size Class B/C)	Unemployment rate	-0.001	0.002	
West (Size Class B/C)	House Price Index**	0.062	0.023	Yes
West (Size Class B/C)	Building permits per 1,000 households	-0.100	0.401	
West (Size Class B/C)	Mortgage interest rate	0.004	0.004	
West (Size Class B/C)	Vacancy rate	-0.437	0.464	
West (Size Class B/C)	Housing unit growth	-0.003	2.717	

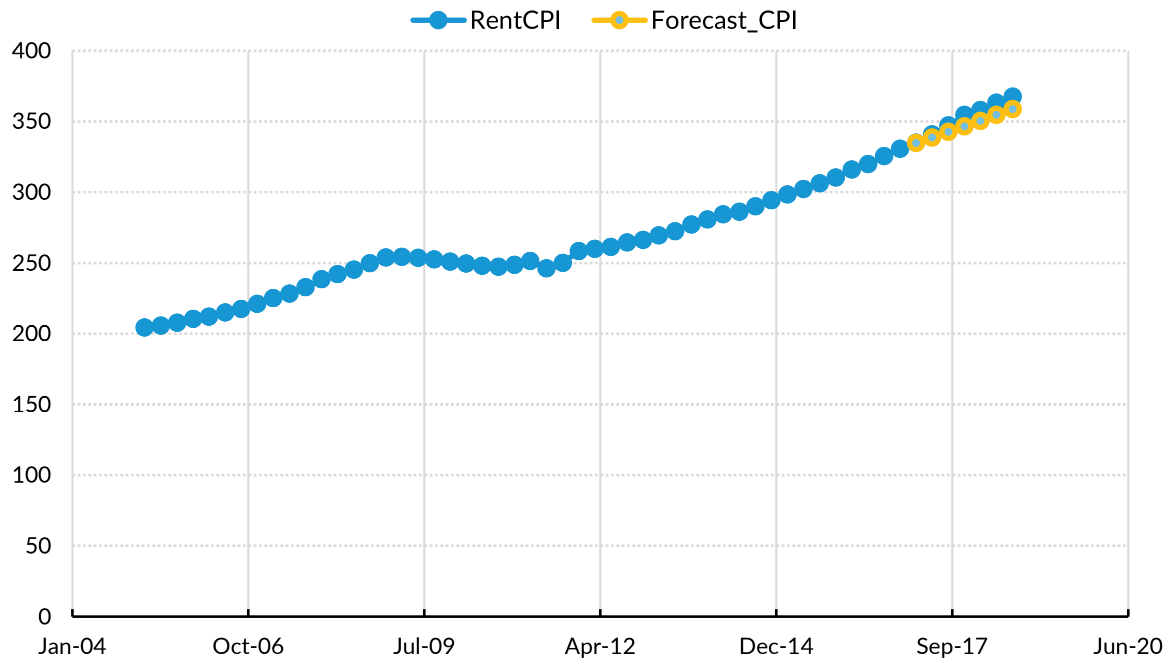
* Significance level of 0.05.

** Significance level of 0.01.

*** Significance level of 0.001.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

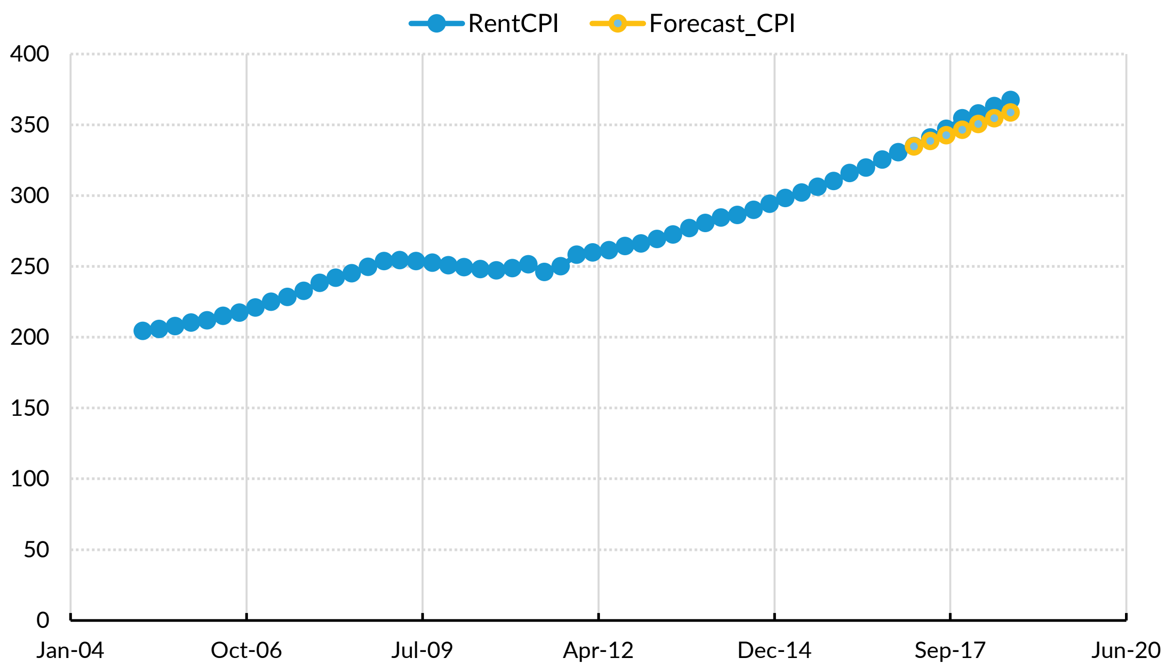
Exhibit 33. Gross Rent CPI Validation and Forecast for Seattle-Tacoma-Bellevue, Washington, Using ARIMAX with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

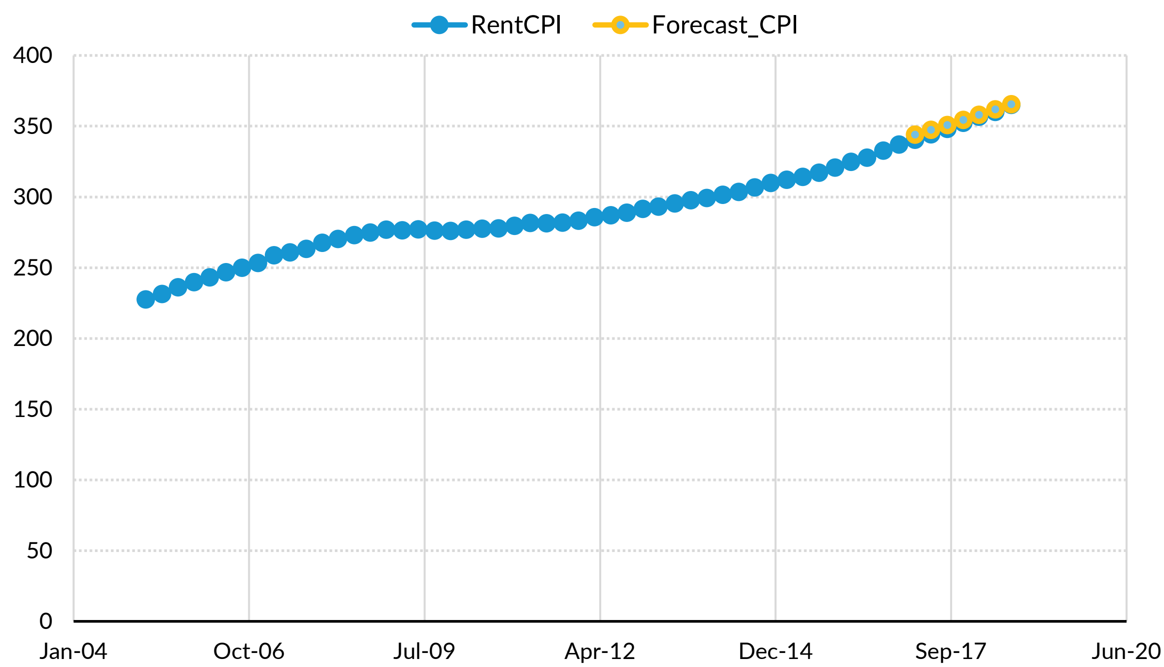
Exhibit 34. Gross Rent CPI Validation and Forecast for San Francisco-Oakland-Hayward, California, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

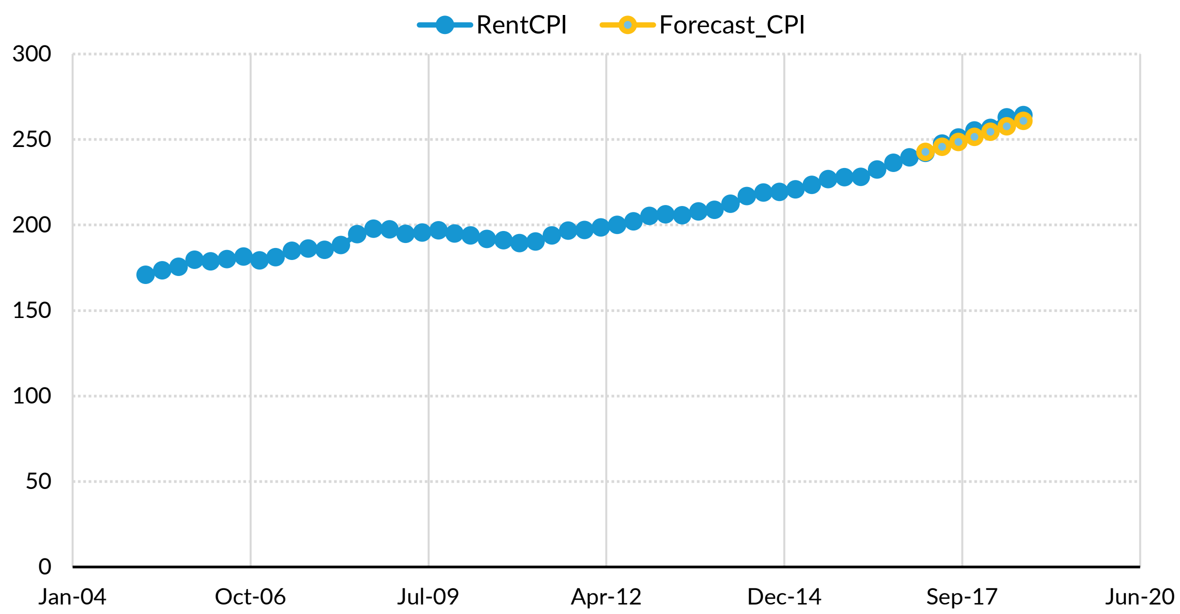
Exhibit 35. Gross Rent CPI Validation and Forecast for Los Angeles-Long Beach-Anaheim, California, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

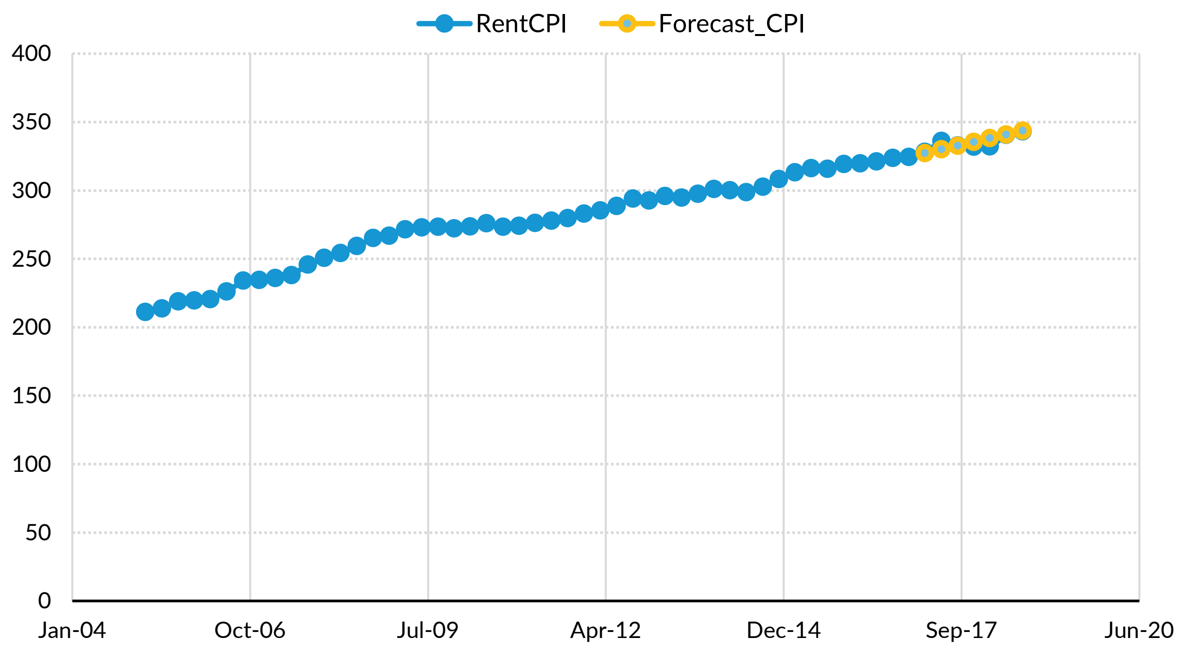
Exhibit 36. Gross Rent CPI Validation and Forecast for Dallas-Fort Worth-Arlington, Texas, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

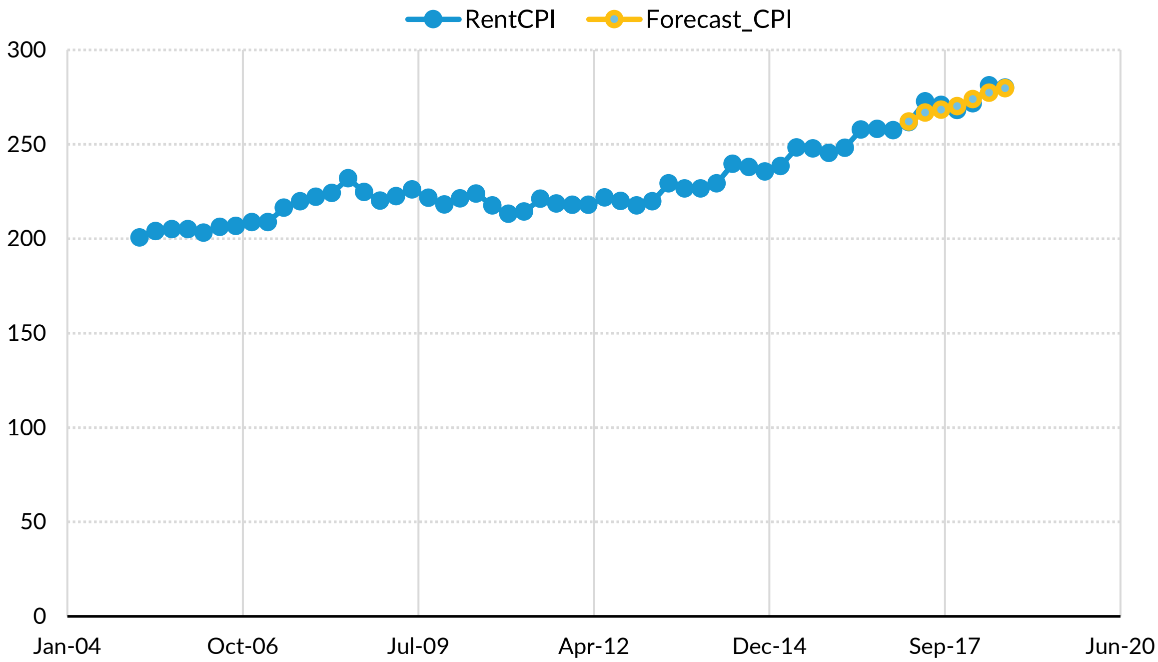
Exhibit 37. Gross Rent CPI Validation and Forecast for Baltimore-Columbia-Towson, Maryland, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

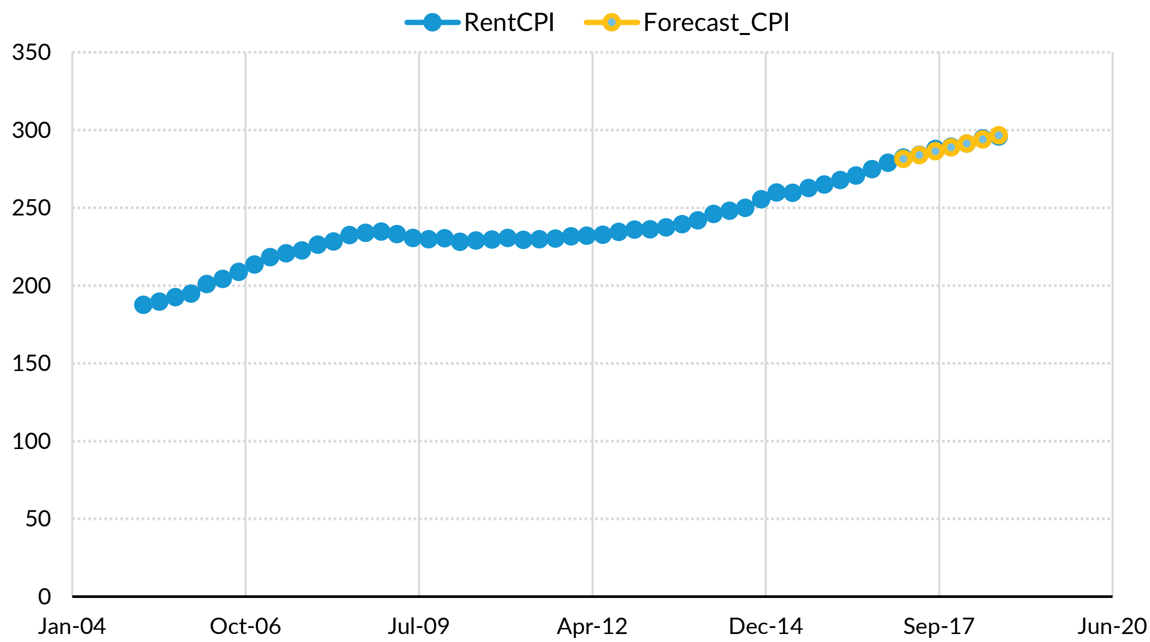
Exhibit 38. Gross Rent CPI Validation and Forecast for Atlanta-Sandy Springs-Roswell, Georgia, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

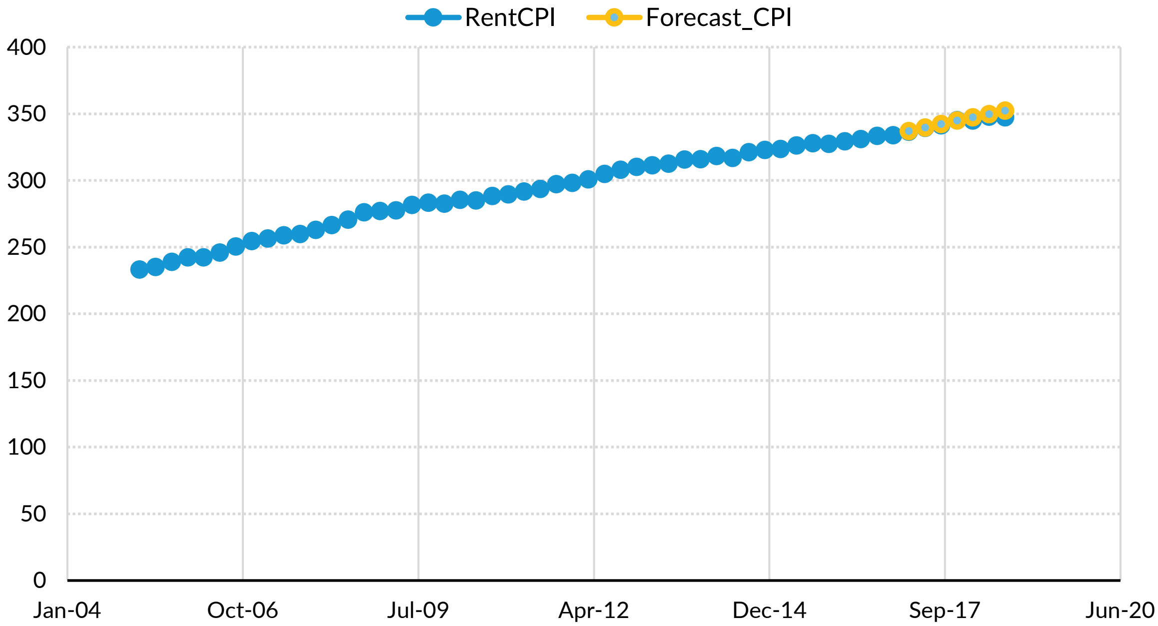
Exhibit 39. Gross Rent CPI Validation and Forecast for Miami-Fort Lauderdale-West Palm Beach, Florida, Using ARIMAX with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

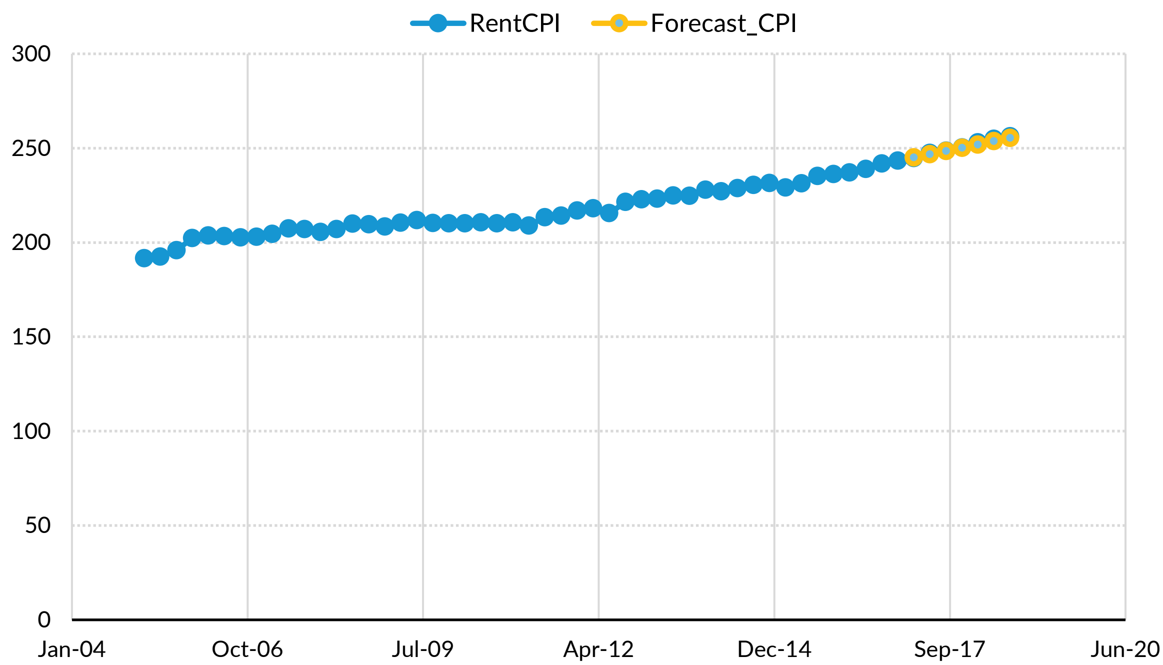
Exhibit 40. Gross Rent CPI Validation and Forecast for Washington-Arlington-Alexandria, DC-Virginia-Maryland-West Virginia, Using ARIMAX Model with Selected Predictors, 2005—2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

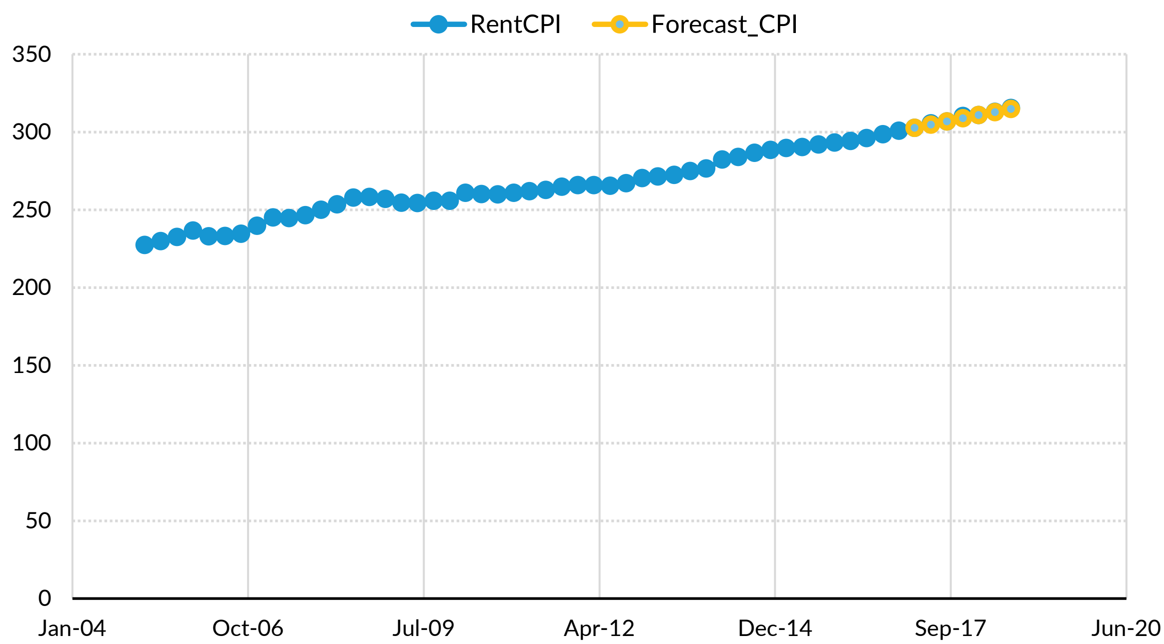
Exhibit 41. Gross Rent CPI Validation and Forecast for Detroit-Warren-Dearborn, Michigan, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

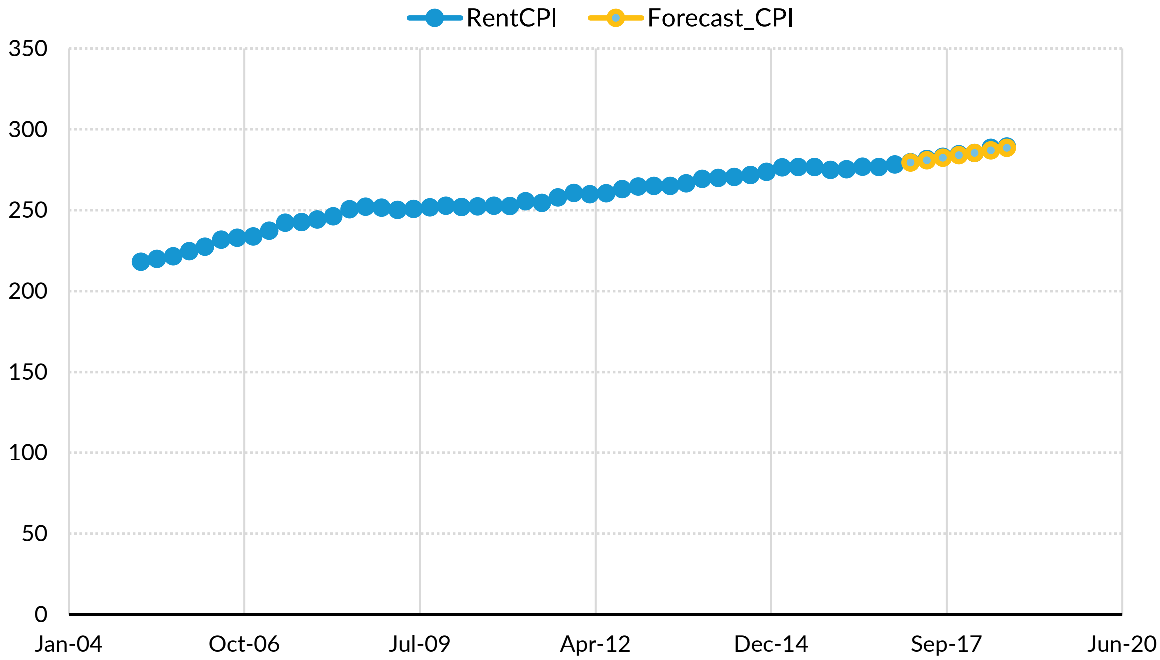
Exhibit 42. Gross Rent CPI Validation and Forecast for Chicago-Naperville-Elgin, Illinois-Indiana-Wisconsin, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

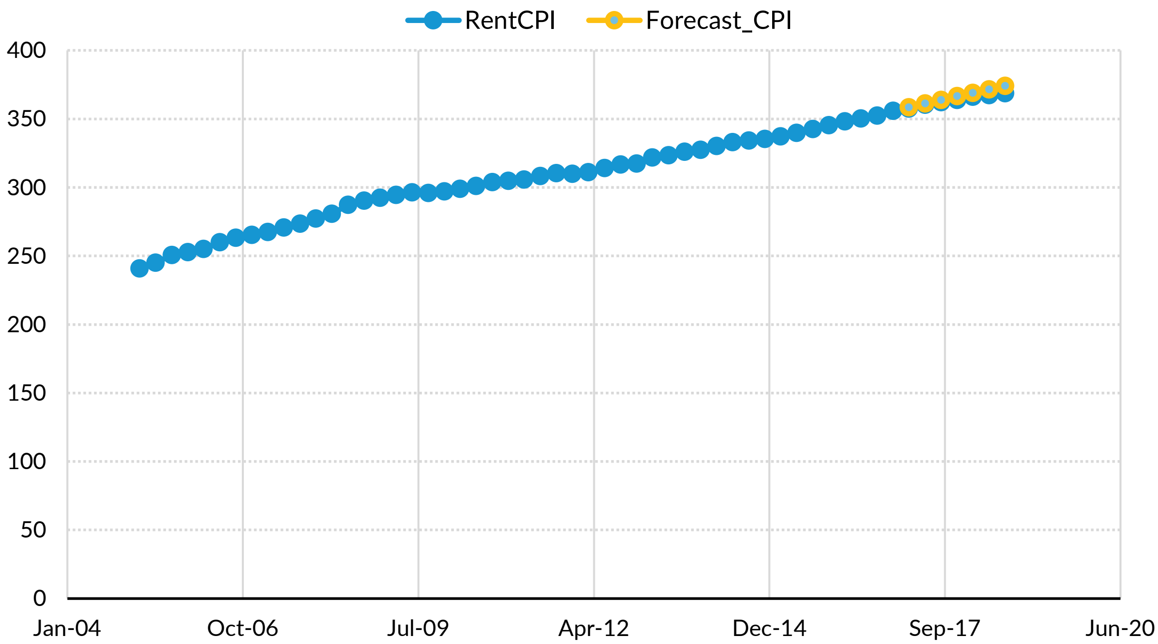
Exhibit 43. Gross Rent CPI Validation and Forecast for Philadelphia-Camden-Wilmington, Pennsylvania-New Jersey-Delaware-Maryland Metro Area, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

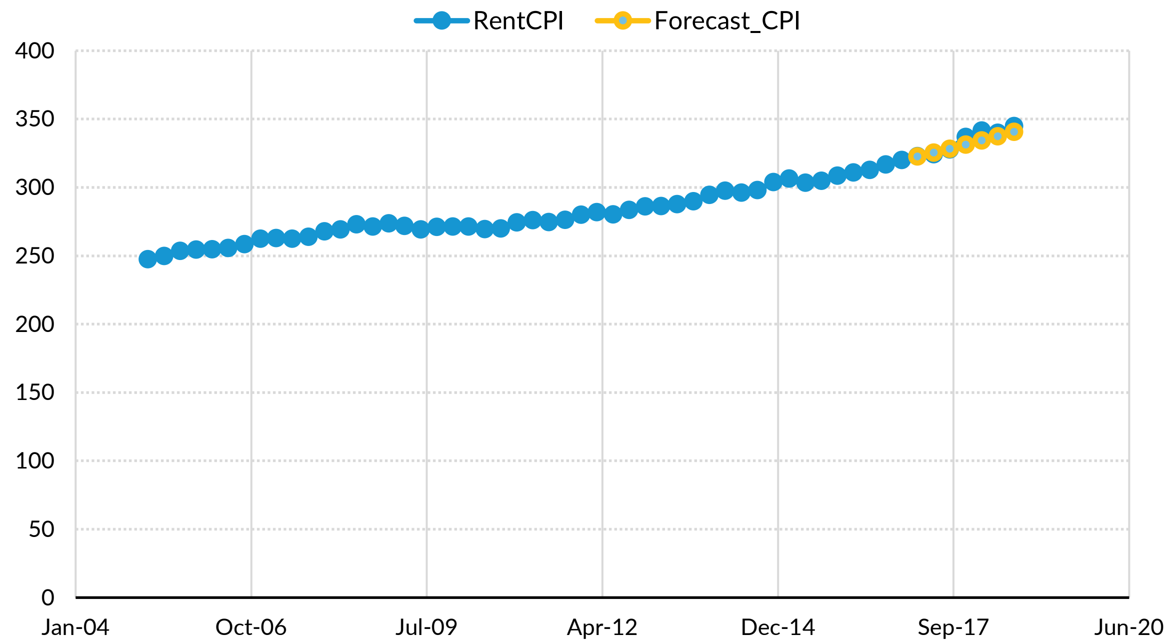
Exhibit 44. Gross Rent CPI Validation and Forecast for New York-Newark-Jersey City, New York-New Jersey-Pennsylvania, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

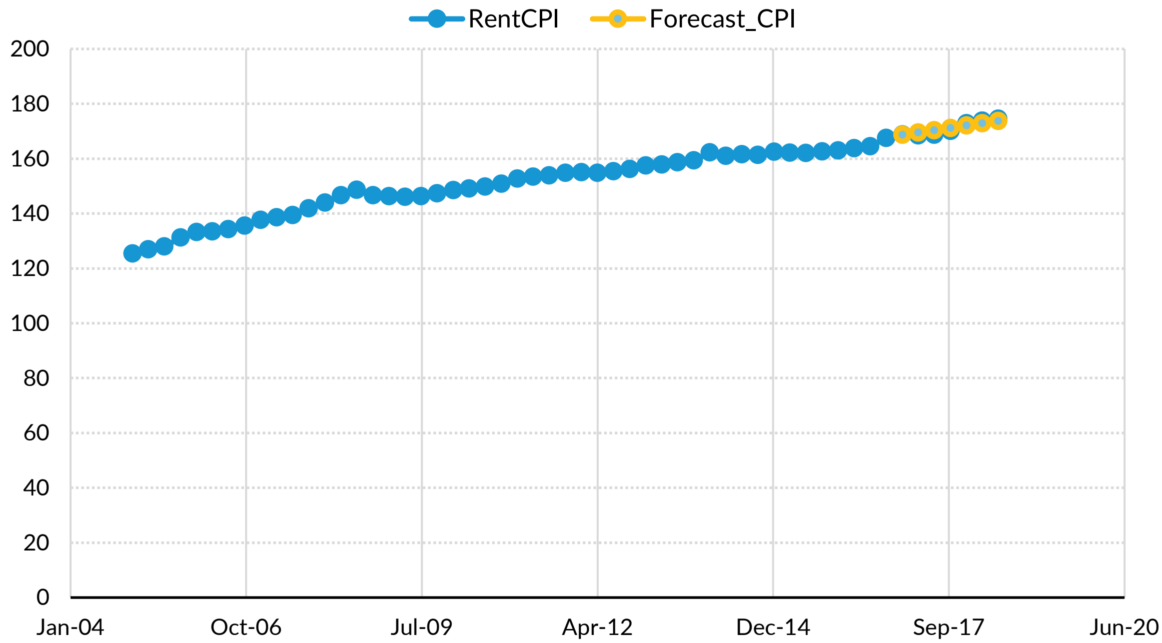
Exhibit 45. Gross Rent CPI Validation and Forecast for Boston-Cambridge-Newton, Massachusetts-New Hampshire, Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

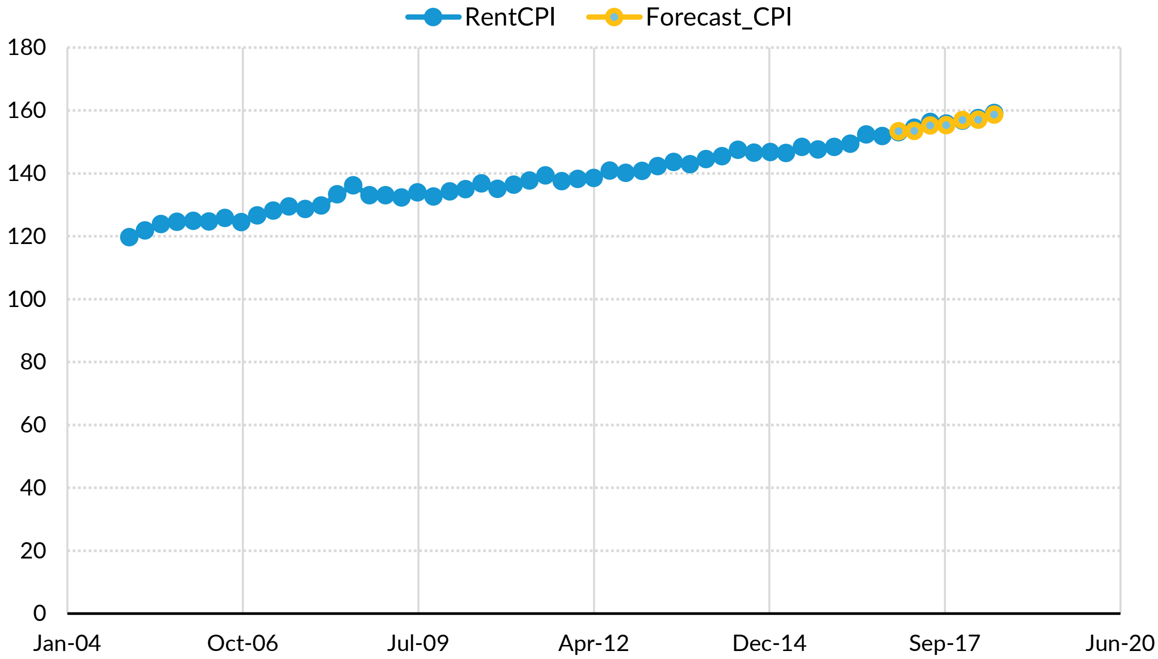
Exhibit 46. Gross Rent CPI Validation and Forecast for Midwest Region (Size Class B/C) Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

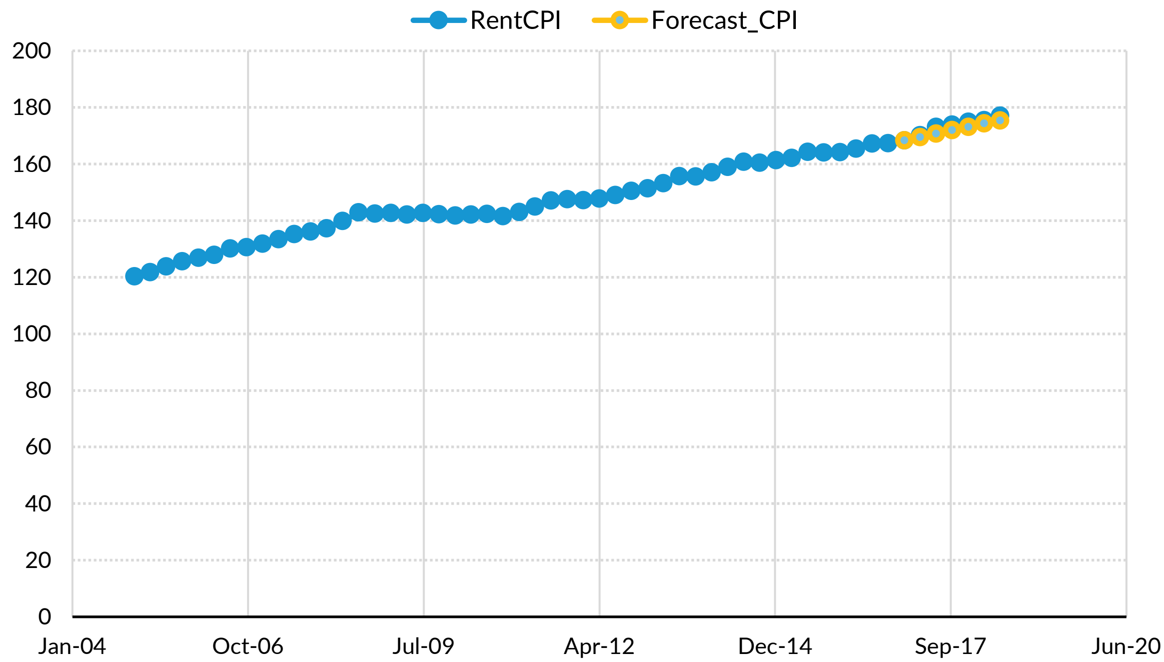
Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

Exhibit 47. Gross Rent CPI Validation and Forecast for the Northeast Region (Size Class B/C) Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.
Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

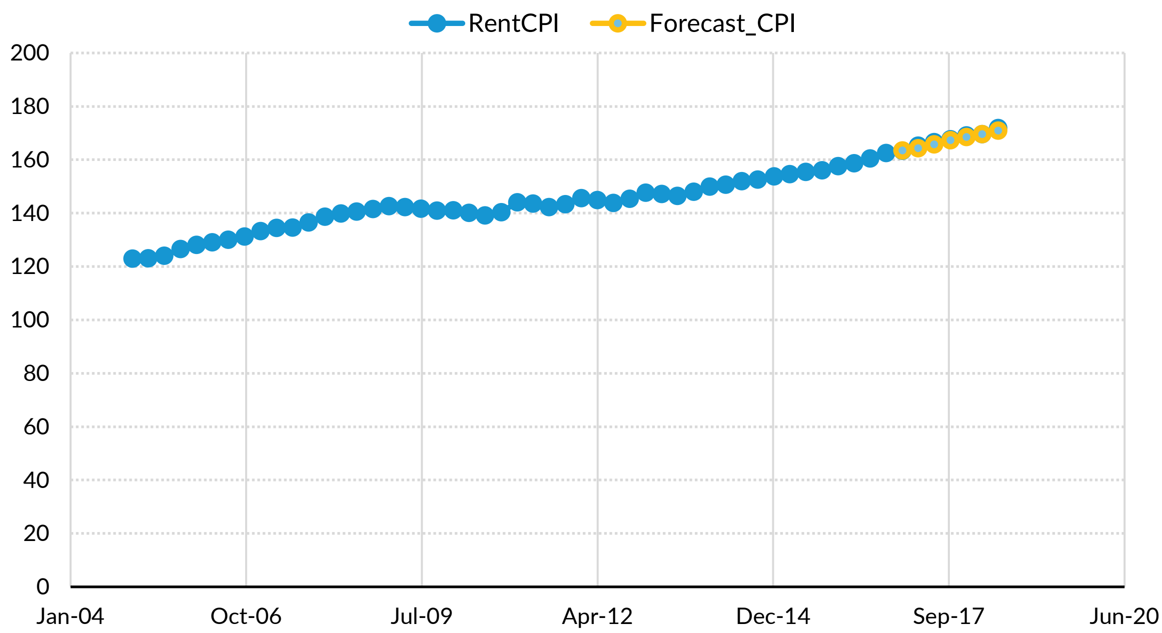
Exhibit 48. Gross Rent CPI Validation and Forecast for the Southern Region (Size Class B/C) Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

Exhibit 49. Gross Rent CPI Validation and Forecast for the Western Region (Size Class B/C) Using ARIMAX Model with Selected Predictors, 2005–2016



CPI = Consumer Price Index.

Sources: Urban Institute analysis of HUD FMR program data; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data; Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest rate data

Exhibit 50. Performance of HUD FMRs and Alternatives, 2017

	RMSE (dollars)	Percentage of Counties in Which 40th Percentile Gross Rents Are *Less than 90% of FMR*	*90–110% of FMR*	*Greater than 110% of FMR*	Observations
All counties					2,634
HUD FMR	111	35%	60%	5%	
ARIMA (A)	84	7%	70%	23%	
ARIMA (B)	85	6%	68%	26%	
Select ARIMAX (A)	125	57%	36%	7%	
Select ARIMAX (B)	113	43%	49%	8%	
Expanded ARIMAX (A)	91	10%	66%	24%	
Expanded ARIMAX (B)	94	9%	64%	27%	
Counties with higher rents (top 20th percentile)					529
HUD FMR	151	21%	66%	13%	
ARIMA (A)	129	4%	64%	32%	
ARIMA (B)	130	4%	61%	35%	
Select ARIMAX (A)	136	23%	62%	15%	
Select ARIMAX (B)	132	21%	63%	16%	
Expanded ARIMAX (A)	138	4%	62%	34%	
Expanded ARIMAX (B)	144	4%	59%	37%	
Counties with rapidly rising rents					597
HUD FMR	140	47%	49%	4%	
ARIMA (A)	100	14%	61%	25%	
ARIMA (B)	101	12%	60%	28%	
Select ARIMAX (A)	140	52%	38%	10%	
Select ARIMAX (B)	134	46%	43%	11%	
Expanded ARIMAX (A)	107	14%	58%	28%	
Expanded ARIMAX (B)	113	13%	56%	31%	
Counties in metropolitan areas					1,038
HUD FMR	140	33%	59%	8%	
ARIMA (A)	105	7%	66%	27%	
ARIMA (B)	106	6%	64%	30%	
Select ARIMAX (A)	128	42%	50%	8%	
Select ARIMAX (B)	120	34%	57%	9%	
Expanded ARIMAX (A)	110	7%	65%	28%	
Expanded ARIMAX (B)	114	6%	63%	31%	
Counties in nonmetropolitan areas					1,596

HUD FMR	87	37%	60%	3%	
ARIMA (A)	68	8%	72%	20%	
ARIMA (B)	69	8%	70%	22%	
Select ARIMAX (A)	123	67%	27%	6%	
Select ARIMAX (B)	108	48%	45%	7%	
Expanded ARIMAX (A)	76	12%	67%	21%	
Expanded ARIMAX (B)	78	11%	65%	24%	
Counties with SAFMRs					139
HUD FMR	225	41%	46%	13%	
ARIMA (A)	128	3%	65%	32%	
ARIMA (B)	129	3%	63%	34%	
Select ARIMAX (A)	135	26%	66%	8%	
Select ARIMAX (B)	127	28%	65%	7%	
Expanded ARIMAX (A)	144	5%	65%	30%	
Expanded ARIMAX (B)	151	4%	63%	33%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. RMSE = root mean squared error. SAFMR = Small Area Fair Market Rent.

Notes: Exhibit displays root mean squared prediction errors and percentage of counties for which the actual 40th percentile gross rent (calculated using American Community Survey data) is less than 90 percent, between 90 and 110 percent, or greater than 110 percent of HUD's two-bedroom FMR or proposed alternatives. Alternative FMRs are the average of the four quarters of the fiscal year. Categories are not mutually exclusive.

Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Exhibit 51. Performance of HUD FMRs and Alternatives, 2018

		Percentage of Counties in which 40th Percentile Gross Rents Are			
	RMSE (dollars)	*Less than 90% of FMR*	*90–110% of FMR*	*Greater than 110% of FMR*	**Observations**
All counties					2,613
HUD FMR	109	32%	62%	6%	
ARIMA (A)	90	5%	68%	27%	
ARIMA (B)	90	5%	67%	28%	
Select ARIMAX (A)	113	45%	47%	8%	
Select ARIMAX (B)	107	35%	55%	10%	
Expanded ARIMAX (A)	95	6%	66%	28%	
Expanded ARIMAX (B)	101	7%	63%	30%	
Counties with higher rents (top 20th percentile)					529
HUD FMR	153	19%	63%	18%	
ARIMA (A)	143	4%	57%	39%	
ARIMA (B)	144	4%	56%	40%	
Select ARIMAX (A)	143	19%	63%	18%	
Select ARIMAX (B)	139	19%	60%	21%	
Expanded ARIMAX (A)	151	4%	55%	41%	
Expanded ARIMAX (B)	165	4%	51%	45%	
Counties with rapidly rising rents					593
HUD FMR	124	39%	55%	6%	
ARIMA (A)	92	10%	67%	23%	
ARIMA (B)	90.4	9%	68%	23%	
Select ARIMAX (A)	126	47%	46%	7%	
Select ARIMAX (B)	120	41%	51%	8%	
Expanded ARIMAX (A)	94	9%	67%	24%	
Expanded ARIMAX (B)	99	10%	63%	27%	
Counties in metropolitan areas					1,035
HUD FMR	138	30%	60%	10%	
ARIMA (A)	116	4%	62%	34%	
ARIMA (B)	116	4%	61%	35%	
Select ARIMAX (A)	125	34%	55%	11%	
Select ARIMAX (B)	119	27%	60%	13%	
Expanded ARIMAX (A)	122	5%	60%	35%	
Expanded ARIMAX (B)	130	4%	58%	38%	
Counties in nonmetropolitan areas					1,578
HUD FMR	84	33%	64%	3%	
ARIMA (A)	68	6%	72%	22%	

ARIMA (B)	68	6%	71%	23%	
Select ARIMAX (A)	105	53%	41%	6%	
Select ARIMAX (B)	97	39%	53%	8%	
Expanded ARIMAX (A)	72	7%	70%	23%	
Expanded ARIMAX (B)	75	7%	67%	26%	
Counties with SAFMRs					139
HUD FMR	226	38%	45%	17%	
ARIMA (A)	165	5%	59%	36%	
ARIMA (B)	169	4%	60%	36%	
Select ARIMAX (A)	158	16%	72%	12%	
Select ARIMAX (B)	149	20%	68%	12%	
Expanded ARIMAX (A)	179	6%	58%	36%	
Expanded ARIMAX (B)	194	6%	57%	37%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. RMSE = root mean squared error. SAFMR = Small Area Fair Market Rent.

Notes: Exhibit displays root mean squared prediction errors and percentage of counties for which the actual 40th percentile gross rent (calculated using American Community Survey data) is less than 90 percent, between 90 and 110 percent, or greater than 110 percent of HUD's two-bedroom FMR or proposed alternatives. Alternative FMRs are the average of the four quarters of the fiscal year. Categories are not mutually exclusive.

Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Exhibit 52. Performance of HUD FMRs and Alternatives, 2019

	RMSE (dollars)	Percentage of Counties in which 40th Percentile Gross Rents Are: *Less than 90% of FMR*	*90–110% of FMR*	*Greater than 110% of FMR*	Observations
All counties					218
HUD FMR	184	21%	56%	23%	
ARIMA (A)	143	3%	56%	41%	
ARIMA (B)	148	3%	54%	43%	
Select ARIMAX (A)	118	12%	76%	12%	
Select ARIMAX (B)	118	14%	74%	12%	
Expanded ARIMAX (A)	150	3%	53%	44%	
Expanded ARIMAX (B)	160	3%	51%	46%	
Counties in metropolitan areas					214
HUD FMR	186	21%	55%	24%	
ARIMA (A)	144	4%	55%	41%	
ARIMA (B)	148	4%	53%	43%	
Select ARIMAX (A)	118	12%	76%	12%	
Select ARIMAX (B)	119	13%	74%	13%	
Expanded ARIMAX (A)	151	4%	53%	43%	
Expanded ARIMAX (B)	161	3%	51%	46%	
Counties with SAFMRs					101
HUD FMR	213	26%	49%	25%	
ARIMA (A)	151	3%	56%	41%	
ARIMA (B)	157	2%	53%	45%	
Select ARIMAX (A)	126	13%	77%	10%	
Select ARIMAX (B)	127	14%	75%	11%	
Expanded ARIMAX (A)	163	4%	51%	45%	
Expanded ARIMAX (B)	178	2%	50%	48%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. RMSE = root mean squared error. SAFMR = Small Area Fair Market Rent.

Notes: Exhibit displays root mean squared prediction errors and percentage of counties for which the actual 40th percentile gross rent (calculated using American Community Survey data) is less than 90 percent, between 90 and 110 percent, or greater than 110 percent of HUD's two-bedroom FMR or proposed alternatives. Alternative FMRs are the average of the four quarters of the fiscal year. Categories are not mutually exclusive.

Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; and Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Exhibit 53. Performance of HUD FMRs and Alternatives, 2020

	RMSE (dollars)	Percentage of Counties in which 40th Percentile Gross Rents Are: *Less than 90% of FMR*	*90–110% of FMR*	*Greater than 110% of FMR*	Observations
All counties					218
HUD FMR	188	19%	55%	26%	
ARIMA (A)	131	3%	59%	38%	
ARIMA (B)	136	3%	56%	41%	
Select ARIMAX (A)	113	12%	80%	8%	
Select ARIMAX (B)	114	12%	80%	8%	
Expanded ARIMAX (A)	137	3%	59%	38%	
Expanded ARIMAX (B)	143	3%	56%	41%	
Counties in metropolitan areas					214
HUD FMR	189	19%	55%	26%	
ARIMA (A)	132	4%	59%	37%	
ARIMA (B)	136	3%	57%	40%	
Select ARIMAX (A)	113	12%	80%	8%	
Select ARIMAX (B)	115	13%	79%	8%	
Expanded ARIMAX (A)	137	3%	60%	37%	
Expanded ARIMAX (B)	143	4%	56%	40%	
Counties with SAFMRs					101
HUD FMR	218	27%	50%	23%	
ARIMA (A)	132	4%	59%	37%	
ARIMA (B)	138	4%	55%	41%	
Select ARIMAX (A)	116	12%	80%	8%	
Select ARIMAX (B)	118	12%	80%	8%	
Expanded ARIMAX (A)	139	5%	58%	37%	
Expanded ARIMAX (B)	149	5%	52%	43%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. RMSE = root mean squared error. SAFMR = Small Area Fair Market Rent.

Notes: Exhibit displays root mean squared prediction errors and percentage of counties for which the actual 40th percentile gross rent (calculated using American Community Survey data) is less than 90 percent, between 90 and 110 percent, or greater than 110 percent of HUD's two-bedroom FMR or proposed alternatives. Alternative FMRs are the average of the four quarters of the fiscal year. Categories are not mutually exclusive.

Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; and Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Exhibit 54. Alternative Calculations of Root Mean Squared Error, 2017

	RMSE		Population-Weighted RMSE		
	(dollars)	(percent)	(dollars)	(percent)	Observations
All counties					2,634
HUD FMR	111	16.4%	152	11.3%	
ARIMA (A)	84	10.7%	118	9.6%	
ARIMA (B)	85	10.8%	122	9.9%	
Select ARIMAX (A)	125	19.1%	145	13.5%	
Select ARIMAX (B)	113	17.2%	116	11.5%	
Expanded ARIMAX (A)	91	11.7%	140	11.0%	
Expanded ARIMAX (B)	94	11.9%	146	11.7%	
Counties with higher rents (top 20th percentile)					529
HUD FMR	151	14.3%	176	11.0%	
ARIMA (A)	129	11.8%	135	9.8%	
ARIMA (B)	130	11.9%	140	10.1%	
Select ARIMAX (A)	136	13.9%	157	11.5%	
Select ARIMAX (B)	132	13.7%	124	9.3%	
Expanded ARIMAX (A)	138	12.4%	163	11.7%	
Expanded ARIMAX (B)	144	13.0%	169	12.5%	
Counties with rapidly rising rents					597
HUD FMR	140	20.4%	198	12.5%	
ARIMA (A)	100	13.2%	117	9.7%	
ARIMA (B)	101	13.2%	126	10.2%	
Select ARIMAX (A)	140	21.6%	135	11.9%	
Select ARIMAX (B)	134	20.3%	116	11.2%	
Expanded ARIMAX (A)	107	13.9%	156	12.1%	
Expanded ARIMAX (B)	113	14.4%	160	12.9%	
Counties in metropolitan areas					1,038
HUD FMR	140	17.8%	160	11.1%	
ARIMA (A)	105	11.6%	123	9.6%	
ARIMA (B)	106	11.6%	128	9.9%	
Select ARIMAX (A)	128	16.6%	147	12.4%	
Select ARIMAX (B)	120	15.7%	117	10.3%	
Expanded ARIMAX (A)	110	11.9%	148	11.1%	
Expanded ARIMAX (B)	114	12.2%	153	11.8%	
Counties in nonmetropolitan areas					1,596
HUD FMR	87	15.3%	79	12.5%	
ARIMA (A)	68	10.2%	70	9.5%	
ARIMA (B)	69	10.2%	70	9.5%	
Select ARIMAX (A)	123	20.6%	124	19.5%	

Select ARIMAX (B)	108	18.1%	110	17.5%	
Expanded ARIMAX (A)	76	11.5%	75	10.4%	
Expanded ARIMAX (B)	78	11.8%	78	10.7%	
Counties with SAFMRs					139
HUD FMR	225	21.5%	223	13.1%	
ARIMA (A)	128	10.2%	134	9.7%	
ARIMA (B)	129	10.5%	137	10.1%	
Select ARIMAX (A)	135	12.7%	148	11.2%	
Select ARIMAX (B)	127	12.7%	116	9.1%	
Expanded ARIMAX (A)	144	11.4%	161	12.1%	
Expanded ARIMAX (B)	151	12.3%	176	13.7%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. RMSE = root mean squared error. SAFMR = Small Area Fair Market Rent.
Notes: Exhibit displays root mean squared prediction errors calculated between HUD's two-bedroom FMR or proposed alternatives and actual 40th percentile gross rents for two-bedroom units. Weights are based on the number of rental units in each county. Alternative FMRs are the average of the four quarters of the fiscal year. Categories are not mutually exclusive.
Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

Exhibit 55. Alternative Calculations of Root Mean Squared Error, 2018

	RMSE		**Population-Weighted RMSE**		
	(dollars)	(percent)	(dollars)	(percent)	**Observations**
All counties					2,613
HUD FMR	109	15.3%	148	10.8%	
ARIMA (A)	90	10.5%	126	10.0%	
ARIMA (B)	90	10.5%	121	10.0%	
Select ARIMAX (A)	113	16.0%	175	13.4%	
Select ARIMAX (B)	107	15.0%	118	10.8%	
Expanded ARIMAX (A)	95	11.0%	146	11.3%	
Expanded ARIMAX (B)	101	11.5%	175	13.0%	
Counties with higher rents (top 20th percentile)					529
HUD FMR	153	14.1%	171	10.7%	
ARIMA (A)	143	12.2%	143	10.2%	
ARIMA (B)	144	12.4%	137	10.3%	
Select ARIMAX (A)	143	13.3%	201	13.0%	
Select ARIMAX (B)	139	13.3%	128	9.4%	
Expanded ARIMAX (A)	151	12.7%	169	12.0%	
Expanded ARIMAX (B)	165	13.7%	204	14.2%	

Counties with rapidly rising rents					593
HUD FMR	124	18.5%	124	10.4%	
ARIMA (A)	92	10.5%	126	9.2%	
ARIMA (B)	90	10.4%	109	8.9%	
Select ARIMAX (A)	126	17.6%	226	15.5%	
Select ARIMAX (B)	120	17.0%	122	10.9%	
Expanded ARIMAX (A)	94	10.9%	146	10.2%	
Expanded ARIMAX (B)	99	11.3%	170	11.5%	
Counties in metropolitan areas					1,035
HUD FMR	138	17.0%	156	10.7%	
ARIMA (A)	116	11.7%	132	10.1%	
ARIMA (B)	116	11.8%	126	10.2%	
Select ARIMAX (A)	125	14.8%	183	13.1%	
Select ARIMAX (B)	119	14.4%	120	10.0%	
Expanded ARIMAX (A)	122	12.1%	154	11.6%	
Expanded ARIMAX (B)	130	12.7%	185	13.4%	
Counties in nonmetropolitan areas					1,578
HUD FMR	84	14.1%	73	11.2%	
ARIMA (A)	68	9.6%	73	9.3%	
ARIMA (B)	68	9.5%	73	9.2%	
Select ARIMAX (A)	105	16.7%	104	15.6%	
Select ARIMAX (B)	97	15.5%	100	14.8%	
Expanded ARIMAX (A)	72	10.2%	76	9.8%	
Expanded ARIMAX (B)	75	10.5%	80	10.1%	
Counties with SAFMRs					139
HUD FMR	226	21.5%	221	13.1%	
ARIMA (A)	165	13.1%	148	10.4%	
ARIMA (B)	169	13.5%	150	10.8%	
Select ARIMAX (A)	158	14.3%	143	10.7%	
Select ARIMAX (B)	149	14.0%	113	8.6%	
Expanded ARIMAX (A)	179	14.4%	174	12.9%	
Expanded ARIMAX (B)	194	15.5%	194	14.6%	

ARIMA = Autoregressive Integrated Moving Average. ARIMAX = Autoregressive Integrated Moving Average with Exogenous Variables. FMR = Fair Market Rent. RMSE = root mean squared error. SAFMR = Small Area Fair Market Rent.

Notes: Exhibit displays root mean squared prediction errors calculated between HUD's two-bedroom FMR or proposed alternatives and actual 40th percentile gross rents for two-bedroom units. Weights are based on the number of rental units in each county. Alternative FMRs are the average of the four quarters of the fiscal year. Categories are not mutually exclusive.

Sources: Urban Institute analysis of Federal Housing Finance Agency House Price Index; Federal Reserve mortgage interest data; Zillow observed rent index; Bureau of Labor Statistics Consumer Price Index and unemployment statistics; HUD FMR program data and U.S. Postal Service vacancy data; Census Bureau American Community Survey, Building Permits Survey, and Population Estimates Program data

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