Forecasting the Price of Shelter: The Importance of the Market–Shelter Gap

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Monday 10th March, 2025

Abstract

The price of shelter is an important component of price indexes, comprising 45.5 percent of core CPI. The gap between market rent and the price of shelter varies greatly over time due to the slow movement of the price of shelter. I demonstrate that this "market–shelter gap" strongly predicts the evolution of CPI shelter. A forecast model for CPI shelter including the market–shelter gap performs much better than existing forecast models, especially in periods when the gap is large. I explore the implications of this finding for the current policy environment.

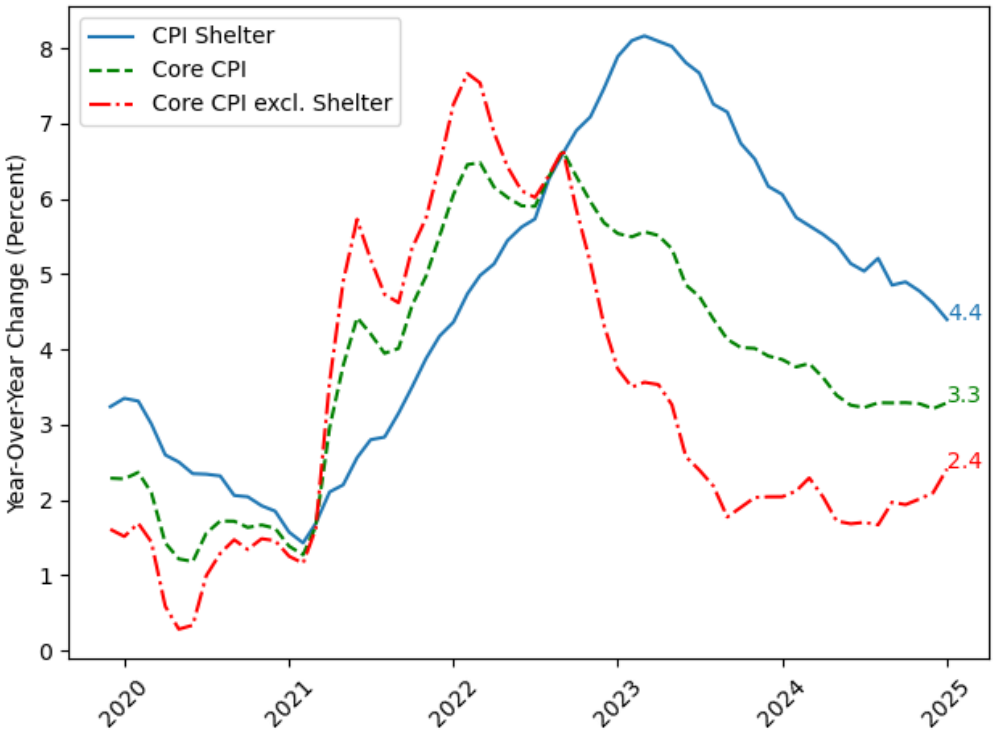
JEL Codes: E37, E31, E17
Keywords: CPI, shelter, housing, rent, market–shelter gap

*The views expressed herein are those of the author and do not indicate concurrence by the Federal Reserve Bank of Boston, the principals of the Board of Governors, or the Federal Reserve System. Thank you to Pratik Bhandari and John O'Shea for excellent research assistance, and to Vaishali Garga, Giovanni Olivei, Jenny Tang, and Egon Zakrajsek for very helpful suggestions and feedback.

1 Introduction

Shelter is the largest component of the Consumer Price Index (CPI), comprising 35.4 percent of headline CPI and 44.3 percent of core CPI as of January 2025. Figure 1 shows the year-over-year change in CPI shelter (the blue unbroken line), core CPI (the green dashed line), and core CPI excluding shelter (the red dotted/dashed line) since December 2019. In 2021 and early-2022, CPI shelter was much lower than other components of core CPI, which brought down overall core CPI. Since late-2022, however, CPI shelter has grown much more quickly than other components of core CPI. Indeed, without shelter, core CPI has been growing at about 2 percent on a year-over-year basis since mid-2023. Housing comprises a smaller portion of the Personal Consumption Expenditure (PCE) price index, which is the Federal Reserve's preferred measure of inflation, making up 15.6 percent of headline PCE and 17.6 percent of core PCE in December 2024. However, as I show in Figure A.1, it has still played an important role in raising inflation above the Federal Reserve's 2 percent target over the past year. Consequently, the price of shelter can drive inflation dynamics and inform central bank decisions.

Figure 1: Recent CPI and CPI Shelter Dynamics



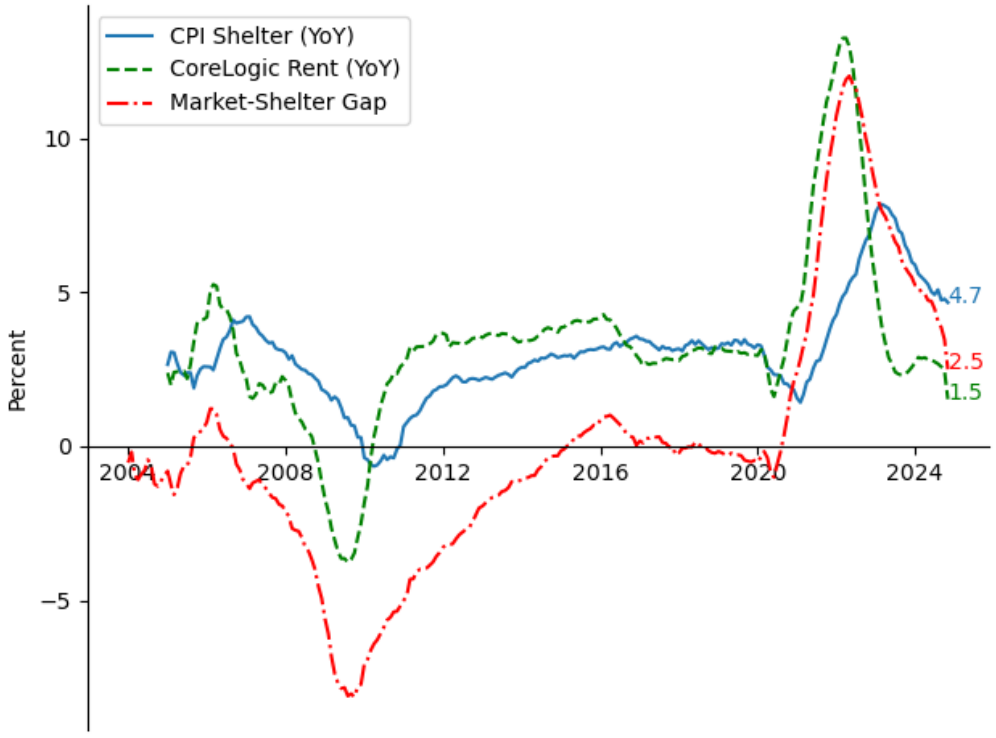
Source(s): US Bureau of Labor Statistics.

An important distinction between the price of shelter and market rent is the tenant composition of each measure. Market rent is the average rent paid by new tenants. CPI shelter is measured using the rent that all tenants pay, including tenants who have not moved.[1] Since rents change more quickly for new tenants than existing tenants, CPI shelter tends to lag market rent by about three to four quarters (Adams et al. (2024)).

[1]CPI shelter is made up of two main components: (1) CPI rent, which is the direct costs to tenants of renting a home, and (2) CPI owners' equivalent rent, which is the indirect costs to owners of living in a home. The latter captures the rent a person would have to pay if they rented rather than owned their home and is constructed using CPI rent.

Figure 2 shows how these dynamics play out in the data. The solid blue line shows year-over-year CPI-shelter growth. The dashed green line shows year-over-year market-rent growth measured using CoreLogic data. For example, in August 2009, during the Great Recession, year-over-year market-rent growth fell to a trough of –3.6 percent, while year-over-year CPI-shelter growth fell to a low of –0.7 percent eight months later, in April 2010. Similarly, in April 2022, during the COVID-19 pandemic, year-over-year market-rent growth climbed to a peak of 13.6 percent, while year-over-year CPI-shelter growth reached a peak of 7.8 percent 11 months later, in March 2023. Due to these dynamics, future growth in CPI shelter is typically forecast using lags of recent market rent growth.

Figure 2: CPI-shelter and Market-rent Dynamics



Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): CPI shelter and CoreLogic rent are measured on a year-over-year basis. The market–shelter gap (log market rent minus log CPI shelter) is shown relative to its historical mean.

However, forecasting CPI shelter using only the recent growth in market rent may miss important, longer-term dynamics. I plot the difference in the levels of market rent and CPI shelter (relative to its mean) in the red dotted/dashed line in Figure 2, which I call the "market–shelter gap." When market–shelter gaps open, such as around the Great Recession and (so far) in the post-pandemic period, they eventually close. This makes sense because it would be expected that the rent paid by new tenants (market rent) would, in the long term, grow the same amount as the rent paid by existing tenants (CPI shelter). For example, before and during the Great Recession, market rent contracted 1.6 percent from September 2006 to August 2009. Over the same period, CPI shelter grew 6.4 percent. As a result, the market–shelter gap expanded (in absolute terms) from –0.1 percent in June 2007 to –8.1 percent in August 2009 as shown in Figure 2. CPI shelter year-over-year growth fell and reached a nadir of –0.7 percent year-over-year in April 2010 when the market–shelter gap was –6.4 percent . However, it took another five years (until March 2015) for the market–shelter gap to close, during which CPI

shelter grew on average 1.3 percent slower than market rent. More formally, market rent and CPI shelter are cointegrated and the market–shelter gap is an error-correction term.

In this paper, I study the implications of the market–shelter gap for forecasting CPI shelter. The paper makes three main contributions. First, I show that the market–shelter gap strongly predicts the evolution of CPI shelter across a wide range of specifications. Second, I show that forecasts for CPI shelter incorporating the market–shelter gap generally perform better than forecasts excluding the market–shelter gap, especially in periods when there are large market–shelter gaps. Third, I apply this forecasting model to the current policy environment.

I start by looking in detail at how the market–shelter gap predicts growth in CPI shelter. I consider results for both national and MSA-level data. The results using MSA-level data tend to be identified with greater significance because they incorporate the cross-sectional variation between MSAs as opposed to only the variation across time. I show that the market–shelter gap is a strong predictor of changes in CPI shelter over the subsequent year using both national and MSA-level data. Indeed, in the MSA-level data the market–shelter gap is significant at the 0.1 percent level across all the specifications I consider. In the baseline specification, I find that a 1 percentage point larger market–shelter gap predicts that CPI shelter growth will be about 0.2 percentage point larger over the subsequent year.

Next, I examine the performance of different forecast models for CPI shelter. I construct historical forecasts for each month from December 2009 onward using the data available in that month. I compare the performance of different specifications with and without the market–shelter gap. I find that a model including the market–shelter gap and estimated using MSA-level data performs best at forecasting the year-over-year change in CPI shelter with a mean forecast error squared (MFES) of only 0.17. It performs much better than the equivalent forecast excluding the market–shelter gap, which has an MFES of 0.58. I also find across other specifications that including the market–shelter gap leads to better forecast performance.

The performance of the forecast including the market–shelter gap is even better when the absolute size of the market–shelter gap is large. When the absolute size of the gap is more than 2 percent, the MFES is 0.16 when including the market–shelter gap and rises to 1.01 when excluding the market–shelter gap. As can be observed in Figure 2, there have been two periods with pronounced market–gaps. In the aftermath of the Great Recession, market rents fell quickly while CPI shelter responded more slowly leading to a large negative gap. In the post-pandemic period, market rents rose quickly while CPI shelter responded more slowly leading to a large positive gap. In contrast, in the late-2010s, the market–shelter gap was close to zero. During this period, forecasts including the market–shelter gap differ little from forecasts excluding the market–shelter gap.

Forecasting the price of shelter is especially relevant for policy in recent years. From July 2020 to May 2022, market rent grew by 19.7 percent, while CPI shelter grew by 7.1 percent. As a result, the market–shelter gap grew from -0.6 percent to 12.0 percent over the same period. As Figure 1 demonstrates, the price of shelter is a key reason why inflation has not returned to target. Indeed, in December 2023 and March 2024, the median Federal Open Market Committee (FOMC) member estimated that there would be three cuts in interest rates in 2024, but as of June 2024, the number of estimated cuts in 2024 fell to just one. High CPI shelter growth leading to upside inflation surprises was likely a key factor in these revisions. This in turn shows the importance of having accurate forecasts of the price of shelter. The Federal Reserve still faces a "last-mile" problem in bringing average inflation back to 2 percent so the price of shelter remains a continued focus.

I apply the forecast model to the current policy environment. While high CPI shelter growth has closed

much of the market–shelter gap, my baseline measure of the market–shelter gap suggests that there remains a moderate gap—2.5 percent as of November 2024 (see Figure 2). In this case, there would continue to be upward pressure on CPI shelter growth moving forward. Under the baseline forecast model, I find that CPI shelter will continue to grow quickly but at a diminishing rate in the medium-term. I find that CPI shelter will grow by 3.6 percentage points over the first half of 2025, 2.6 percentage points over the second half of 2025, and 2.3 percentage points over the first half of 2026 on an annualized basis. The evolution of market rent is uncertain with factors that may influence it including the degree of construction and immigration. I examine how the evolution of CPI shelter under different realizations of market rent growth. Market rent growth has little impact on CPI shelter growth over the next six months but has larger impacts moving into the second half of 2025 and 2026. I also show the importance of CPI shelter for broader inflation indexes. Under my baseline forecast, I find that high shelter prices will raise the headline CPI by 0.40 percentage point and core CPI by 0.51 percentage points in 2025 relative to if shelter prices grew at 2 percentage points. The effect on the PCE is smaller due to the lower weight placed on shelter, but the effect would still be 0.17 percentage point on the headline index and 0.20 percentage point on the core PCE.

This paper relates most closely to Bolhuis, Cramer, and Summers (2022), who examine the impact of the large rise in market rents in 2021 on the price of shelter. With significant foresight, the authors correctly predicted the large rise in CPI shelter in 2022. Their model forecasts components of CPI shelter using recent changes in market rent, CPI shelter, and house prices in an elastic net regression model. However, they do not incorporate a measure of the market–shelter gap, and I find that their forecast model does not perform as well as one including the market–shelter gap especially when the market–shelter gap is large (see Figure 6). Kmetz, Louie, and Mondragon (2023) construct a forecast of CPI shelter with disaggregated data using local projections based on recent lags of market rent and house price data, but excluding the market–shelter gap. They predicted that market shelter would decline quickly due to falling market rent and property prices in late 2023 and 2024, though they noted that there was significant uncertainty. Jordà and Yalcin (2024) construct a forecast of CPI shelter using the gap between new household formation and units completed, new units under construction, and Zillow data on asking rents, but excluding the market–shelter gap. Their forecast matches the qualitative movements in CPI shelter but suggests that CPI shelter would return more quickly to normal levels than it did in the post-pandemic period. Adams et al. (2024) construct separate rent indexes for new tenants and all tenants from the data underlying the CPI shelter. They confirm that the dynamics of new-tenant rent measured using CPI shelter data are similar to those of market rent, which suggests that the differences between market rent and the price of shelter are driven by tenant composition. Gallin et al. (2025) look at the dynamics of the market–shelter gap, which they term the rent gap, using the microdata underlying CPI shelter.[2] They examine the frequency of tenants moving over time, factors that affect the size of the gap including the length of a tenancy and rent inflation, and the impact of a gap on tenant behavior.

2 Empirical Approach

I combine two main data sets for my study. First, I obtain data on CPI shelter from the BLS. The BLS provides CPI shelter for the United States as a whole and for 24 MSAs.[3] The second data set contains information on

[2]To my knowledge, the authors have not yet released a formal working paper but have discussed these results at several conferences. I am citing slides presented at the BLS.

[3]The BLS has been measuring CPI shelter for many years for most MSAs, but updated its coverage at the end of 2017, adding several new MSAs and stopping the measurement for Cleveland.

Table 1: MSA Details

MSA Name	State	First Date	Last Date	Pop. (000)
Atlanta-Sandy Springs-Roswell	GA	200812m	202411m	6106
Baltimore-Columbia-Towson	MD	200807m	202411m	2844
Boston	MA	200511m	202411m	4944
Chicago-Naperville-Arlington Heights	IL	200701m	202411m	9450
Cleveland-Elyria	OH	200704m	201712m	2185
Dallas-Plano-Irving	TX	200401m	202411m	7637
Detroit-Dearborn-Livonia	MI	200401m	202411m	4392
Honolulu (Urban)	HI	201712m	202411m	1016
Houston-The Woodlands-Sugar Land	TX	200401m	202411m	7149
Los Angeles-Long Beach-Glendale	CA	200401m	202411m	13200
Miami-Miami Beach-Kendall	FL	200911m	202411m	6138
Minneapolis-St. Paul-Bloomington	MN-WI	201712m	202411m	3690
New York-Jersey City-White Plains	NY-NJ	200401m	202411m	20081
Philadelphia	PA	200807m	202411m	6245
Phoenix-Mesa-Scottsdale	AZ	201712m	202411m	4851
Riverside-San Bernardino-Ontario	CA	201712m	202411m	4599
San Diego-Carlsbad	CA	201712m	202411m	3298
San Francisco-Redwood City-South San Francisco	CA	200401m	202411m	4748
Seattle-Bellevue-Everett	WA	200401m	202411m	4018
St. Louis	MO-IL	201712m	202411m	2820
Tampa-St. Petersburg-Clearwater	FL	201712m	202411m	3175
Washington-Arlington-Alexandria	DC-VA-MD-WV	200807m	202411m	6278

Source(s): US Bureau of Labor Statistics, US Census Bureau, CoreLogic. Note(s): Population data are from the US Census Bureau and are measured at the MSA level for 2023.

market rent from CoreLogic. I use CoreLogic's "Single-Family Combined" measure, which includes single-family detached and single-family attached (condos) properties. The measure is provided for MSAs and nationally. I match 22 of the 24 MSAs to the CoreLogic data. The two MSAs for which I do not have CoreLogic market rent data are Denver and Urban Alaska (Anchorage). I seasonally adjust the CoreLogic data using X13-ARIMA with default parameters. I obtain a monthly data set for 22 MSAs and nationally, which is summarized in Table 1. The data set covers January 2004, which is when the CoreLogic national data begin, through to November 2024.[4] Coverage begins later for some MSAs.

I also draw on other data sources. I obtain data on CPI rent, CPI owners' equivalent rent (OER), and the New Tenant Rent Index (NTRI) from the BLS. CPI rent and CPI OER are both available at the MSA level, whereas the NTRI is available only nationally. I get alternative measures of national market rent from Zillow, Costar, and Apartment List.[5] I additionally obtain Zillow market rent data at the MSA level. When replicating the forecast model of Bolhuis, Cramer, and Summers (2022), I incorporate national house price data from Zillow.

The key variable of interest in this paper is the market–shelter gap. I define the market–shelter gap at the national level in Equation (1).[6] In words, the market–shelter gap is the difference between the level of market rent and CPI shelter in logs relative to the mean of this difference using all available time periods. One alternative would be to define the market–shelter gap relative to a month when market rent and CPI shelter

[4]This is the latest CoreLogic data I have available as of February 19, 2025. The data is released with a 2–3 month lag.

[5]I seasonally adjust the NTRI and Apartment List using X13-ARIMA with default parameters. I also convert quarterly NTRI and Costar data into monthly data by setting the value for the third month of a quarter to be the release for that quarter and the interpolating the values for the other months.

[6]T repesents the number of all data points in the sample, so the second half of the equation is just the mean of the difference between log market rent and log CPI shelter for the whole sample.

Table 2: Johansen Test

Maximum rank	Params	Log Likelihood	Eigenvalue	Trace Statistic	Critical Value 5%
0	14	2531.4015	-	53.4755	15.41
1	17	2557.1703	0.1932	1.9378*	3.76
2	18	2558.1393	0.008		

Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): To read this table, observe that the trace statistic for a rank of zero is higher than the critical value, so we reject that the maximum rank is zero. The trace statistic for a rank of one is lower than the critical value, so we do not reject that the maximum rank is one.

appear to be stable. One such month could be December 2019, when market rent and CPI shelter had grown at similar rates for several years. However, using this alternative approach leads to only a small difference in the market–shelter gap of 0.5 percentage point for April 2024. The market–shelter gap would be 3.0 percent under the alternative approach as opposed to 2.5 under the baseline approach. I plot the market–shelter gap under this alternative approach in Figure B.1. I verify that CPI shelter and market rent (measured using CoreLogic rent data) are cointegrated. Table 2 summarizes the results of a Johansen test. As expected, the test rejects that there is no cointegration and instead finds a rank of one. I also define the market–shelter gap similarly at the MSA level. I provide plots of the market–shelter gap, CPI shelter, and market rent for each MSA in Appendix D.

$$MarketShelterGap_t = \log(MarketRent_t) - \log(CPIShelter_t) - \frac{1}{T}\sum_{i=1}^{T}(\log(MarketRent_i) - \log(CPIShelter_i)) \quad (1)$$

The baseline specification for MSA-level data is given in Equation (2). The equivalent specification for national data is given in Equation (3). t represents the month, and msa represents the MSA. I look at how log CPI shelter responds over various time horizons to the market–shelter gap. β captures how much a 1 percentage point rise in the market–shelter gap at time t raises CPI shelter growth, in percentage points, from time t to time $t + m$. This follows the local projection approach suggested in Jordà (2005). I include 12 lags of the monthly difference in CPI shelter and market rent to capture differences in the future path of the dependent variables that are not due to the market–shelter gap. I choose one year of lags on the basis that maximum effect of market rent changes on CPI shelter occurs three to four quarters later. These lags are measured for the MSA under consideration in MSA-level data and nationally in national data. In MSA-level data, I can also control for MSA fixed effects, γ_{msa}, and time fixed effects, α_t. Controlling for MSA fixed effects allows me to capture differences in the average growth of CPI shelter or the explanatory variables across MSAs. Controlling for time fixed effects allows me to remove aggregate variation, which can be noisy, and look at only MSA-level differences. I use Driscoll and Kraay (1998) standard errors, allowing for the possibility of heteroskedasticity, autocorrelation (I allow for a maximum of 12 lags), and correlation between groups.

Table 3: Impact of Market–Shelter Gap on CPI Shelter Growth: Baseline Specification

$\Delta_{0,12}\log(CPIShelter_z)$	(1)	(2)	(3)	(4)	(5)	(6)
$MarketShelterGap_{z,t}$	0.380***	0.283***	0.342***	0.152***	0.191***	0.158***
	(0.023)	(0.041)	(0.065)	(0.022)	(0.023)	(0.016)
N	239	227	3618	3354	3354	3354
R^2	0.915	0.956	0.420	0.672	0.705	0.778
R^2_{adj}	0.915	0.950	0.419	0.669	0.701	0.759
National/MSA	National	National	MSA	MSA	MSA	MSA
CPI Shelter 12 Lags		*		*	*	*
Market Rent 12 Lags		*		*	*	*
Constant	*	*	*	*		
MSA Fixed Effects					*	*
Time Fixed Effects						*

Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): Driscoll-Kraay standard errors with 12 lags. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively.

$$\Delta_t^{t+m}\log(CPIShelter_{msa}) = \alpha_t + \gamma_{msa} + \beta MarketShelterGap_{msa,t} + \sum_{i=0}^{11}\delta_i\Delta\log(MarketRent)_{msa,t-i} + \sum_{i=0}^{11}\theta_i\Delta\log(CPIShelter)_{msa,t-i} + u_{msa,t+m} \quad (2)$$

$$\Delta_t^{t+m}\log(CPIShelter) = \alpha + \beta MarketShelterGap_t + \sum_{i=0}^{11}\delta_i\Delta\log(MarketRent)_{t-i} + \sum_{i=0}^{11}\theta_i\Delta\log(CPIShelter)_{t-i} + u_{t+m} \quad (3)$$

3 Measuring the Impact of the Market–Shelter Gap on CPI Shelter

Table 3 presents results on the impact of the market–shelter gap on future CPI shelter growth over the next 12 months. More precisely, the regressions in this table predict CPI shelter growth from time t to time $t + 12$ using the market–shelter gap at time t. The first two columns present results using national data (Equation (3)), while the latter four columns present results using MSA-level data (Equation (2)). Results with and without the controls are shown. I find that a 1 percentage point larger market–shelter gap predicts that CPI shelter growth will be 0.152 to 0.380 percentage point larger. In other words, 15.2 to 38.0 percent of a positive market–shelter gap closes over the subsequent 12 months due to increased CPI shelter growth. All the results are significant at the 0.1 percent level. Therefore, the market–shelter gap appears to be an important predictor of CPI shelter growth.

Table 4 summarizes results for additional specifications analyzing the impact of the market–shelter gap on future CPI shelter growth. The coefficients in each row show how much a 1 percentage point larger market–shelter gap raises CPI shelter growth in percentage terms one, three, six, and 12 months in the future. Each row

Table 4: Impact of Market–Shelter Gap on CPI Shelter Growth: Extended Specifications

$\Delta_{t,t+m} \log(CPIShelter)_z$. Months Ahead (m)	1	3	6	12
Panel A: National				
A1. National Baseline	0.019***	0.057***	0.110***	0.283***
A2. National 2004–2020	0.016	0.044^{+}	0.096*	0.308***
A3. National 2021+	0.200***	0.483***	0.373***	0.106
Panel B: MSA Baseline				
B1. MSA Baseline	0.022***	0.056***	0.100***	0.158***
Panel C: Time Subsets (MSA)				
C1. MSA 2004–2020	0.022***	0.053***	0.093***	0.149***
C2. MSA 2021+	0.078***	0.213***	0.384***	0.480***
Panel D: Alternative Controls (MSA)				
D1. No Time Dummies/Lag Controls	0.024***	0.063***	0.114***	0.191***
D2. No Lag Controls	0.025***	0.071***	0.130***	0.221***
D3. No Market Rent Controls	0.024***	0.063***	0.110***	0.163***
D4. No CPI Controls	0.027***	0.072***	0.134***	0.229***
D5. Two Years of Lags	0.022***	0.056***	0.099***	0.149***
Panel E: Alternative Variables (MSA)				
E1. Zillow	0.040***	0.099***	0.172***	0.269***
E2. CPI Rent	0.013***	0.041***	0.084***	0.146***
E3. CPI Owners' Equivalent Rent	0.013***	0.040***	0.086***	0.157***
Panel F: Misc (MSA)				
F1. Detrended Error Correction	0.031***	0.078***	0.139***	0.214***
F2. MSAs Beginning A through I	0.035***	0.090***	0.157***	0.241***
F3. MSAs Beginning J through Z	0.015***	0.039***	0.076***	0.140***
F4. Balanced Panel	0.021***	0.051***	0.092***	0.143***

Source(s): US Bureau of Labor Statistics, CoreLogic, Zillow. Note(s): Coefficients from a regression of the change in CPI shelter from month t to month $t+m$ on the market–shelter gap at time t, where m is one, three, six, and 12. Each regression contains 12 lags of month-over-month market rent and CPI shelter unless specified otherwise. Each regression in Panels B through F contain MSA and time fixed effects unless specified otherwise. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively, under Driscoll-Kraay standard errors with 12 lags.

represents a different specification. By default, I include 12 monthly lags of market rent and CPI shelter in each specification. Panel A shows specifications using national data. Specification A1 is the baseline specification that corresponds to column (2) in Table 3. Specifications A2 and A3 restrict the time period considered to 2004 through 2020 and 2021 onward. I consider 2004 through 2020 (rather than 2004 through 2019) because the large recent rise in market rent and subsequent rise in CPI shelter took place in the post-pandemic period from 2021 onwards. The results for shorter months make less sense under the restricted time periods. Specification A3 suggests that higher CPI shelter growth closes 20 percent of the market–shelter gap one month later and 48.3 percent three months later but only 10.6 percent 12 months later, which seems implausible. The results for specification A2 also seem uneven with a much stronger coefficient for 12 months later and are not as significant for other months. Therefore, while the national results make sense and correspond to the MSA-level results overall, they appear less consistent when restrictions are applied. As a result, I focus on MSA-level specifications. Specification B1 reports the baseline MSA results, which correspond to column (6) in Table 3. For the panel data specifications in Panels B through F, I also include MSA and time fixed effects unless otherwise specified.

Panel C of Table 4 examines how the coefficients have changed after the pandemic. In the 2004–2020 period, a 1 percentage point larger market–shelter gap predicts that CPI shelter will grow an additional 0.15 percent

over the subsequent 12 months. This jumps to an additional 0.48 percent in the post-pandemic period. I have analyzed this further in a policy note (Cotton, 2024). There are several reasons why the passthrough into CPI shelter could be faster in the post-pandemic period. First, market rents have risen in the post-pandemic period, meaning that rents of existing tenants now lag behind rents of new tenants. Landlords may be quicker to raise rents of existing tenants when market rents rise than to lower rents of existing tenants when market rents fall (as they did during the Great Recession). Second, the size of the market rent rise may mean that there is greater awareness among landlords that rents of existing tenants are below market rents, prompting quicker rises. Third, the growing presence of larger providers offering rentals or tools that allow landlords to measure the appropriate rent to set in their market might mean that market rents pass through more quickly into CPI shelter now.

The market–shelter gap appears to strongly predict changes in CPI shelter regardless of the specification. Panels D through F present other specifications. Panel D shows the impact of removing controls, which does not affect the results much. Panel E shows the impact of using alternative variables. The results for Zillow are stronger than with CoreLogic, but this is likely because the Zillow market rent data do not begin until 2012, so the sample is more focused on the period when the pass-through was stronger. The coefficients for the impact on 12-months-ahead CPI rent and CPI owners' equivalent rent are similar to the results for CPI shelter. Panel F shows alternative specifications. One concern might be that there could be long-term differences between the levels of market rent and CPI shelter, perhaps because the areas or types of homes covered by CPI shelter and market rent may differ. One way to control for this is to detrend the market–shelter gap for each MSA. I show the impact of doing this on the results in specification F1. The market–shelter gap has a slightly stronger impact, but the difference is not that large. I also consider restricting to only half of the MSAs in specifications F2 and F3 to verify that the results are not caused by one MSA. And I demonstrate in specification F4 that restricting the sample to only MSAs for which I have data for all the dates I consider so that I have a balanced panel also does not appear to affect the results. In each of these MSA-level specifications and across all timeframes, the market–shelter gap has a significant impact on CPI shelter growth one month, three months, six months, and 12 months in the future, and this impact is significant at the 0.1 percent level.

An alternative approach would be to estimate the impact 12 months in the future by summing the zero-to-one-month impact, the one-to-two-month impact and so on up to the 11-to-12-month impact. I consider this in Table C.1. This yields a coefficient for the market–shelter gap of 0.152, relative to 0.158 in the baseline case (B1). Therefore, the alternative method yields quite similar results. Moreover, the market–shelter gap is significant at the five percent level for each of the twelve separate regressions.

4 Forecasting with the Market–Shelter Gap

4.1 Forecast Construction

We have seen that the market–shelter gap appears to be an important predictor of CPI shelter growth in national and MSA-level data when measured using CoreLogic market rent data. The reason I have focused on CoreLogic so far is because, to my knowledge, it is the only measure at the MSA level that dates back as far as 2004. However, there are other measures of market rent at the national level (the NTRI, Costar) or at the MSA level (Zillow, Apartment List) that we could use for forecasting. In Figure 3, I show the national market–shelter

gap since December 2019 constructed with different measures of market rent. Each line on this figure reports the difference between the log of the market rent measure and the log of CPI shelter relative to that difference in December 2019. CoreLogic (shown in blue) and Zillow (shown in green) each offer multiple measures of market rent. I show attached unit measures in the dashed lines, detached unit measures in the dotted/dashed lines, and combined measures in the unbroken lines. One of each of these measures is provided by CoreLogic and Zillow.[7] I provide two other market rent measures from Costar and ApartmentList.[8] Finally, I provide the New Tenant Rent Index, which is constructed using only new tenants, from the data underlying the CPI rent index following the approach set out in Adams et al. (2024).

While there is significant dispersion between measures, one notable pattern is that attached measures (dashed lines) show low and mostly negative market–shelter gaps, whereas detached measures (dotted/dashed lines) show the most positive market–shelter gaps. It makes sense that attached rent indexes show lower market–shelter gaps than detached rent indexes because single-family rents rose much more during and after the pandemic as households moved away from cities and in search of more space. The two combined measures from CoreLogic and Zillow (the unbroken blue and green lines) fall between the attached and detached measures as would be expected. The New Tenant Rent Index measure, however, is much lower and shows a negative market–shelter gap. One alternative would be to estimate the market–shelter gap using the microdata underlying CPI shelter. Gallin et al. (2025) are working on this—their preliminary estimates appear in line with my primary measure of the market–shelter gap.[9]

I choose to focus on constructing the market–shelter gap using the CoreLogic combined market rent index for several reasons. First, CoreLogic is the median of the three measures comparing both detached and attached homes. It currently has a market–shelter gap of 3.0 percent measured relative to December 2019 compared with 6.0 percent for the Zillow combined measure and –3.8 percent for the NTRI. Second, the NTRI is constructed using a relatively small sample of only the new renters among the 24,000 homes in the CPI Housing Survey. It therefore shows more volatility in its measure than market rent measures constructed using MLS data, such as CoreLogic (Adams et al., 2024).[10] Third, when I construct estimates using MSA-level data, the CoreLogic national measure is likely to be more directly applicable to the MSA-level coefficients. Fourth, as I show later in this section, CoreLogic appears to yield the most accurate past forecasts. I also show results under alternative market rent indexes.

I obtain forecasts from period T, the last period for which data are available, to period $T + m$ (where m is usually 12) in two steps: First, I estimate either Equation (2) using the MSA-level data or Equation (3) using the national data.[11] Second, I apply the coefficients from the model to the national data at time T to obtain the forecast. I can directly apply the estimates when I estimate the model with national data. However, when I estimate the model with MSA-level data, I need to obtain an appropriate constant for the national data (as opposed to the MSA fixed effects in the MSA model). To do this, I set the constant to be such that the mean

[7] All of CoreLogic units are single family units compiled from Multiple Listing Service (MLS) data, but they provide separate measures for single-family attached, single-family detached, and single-family combined units.

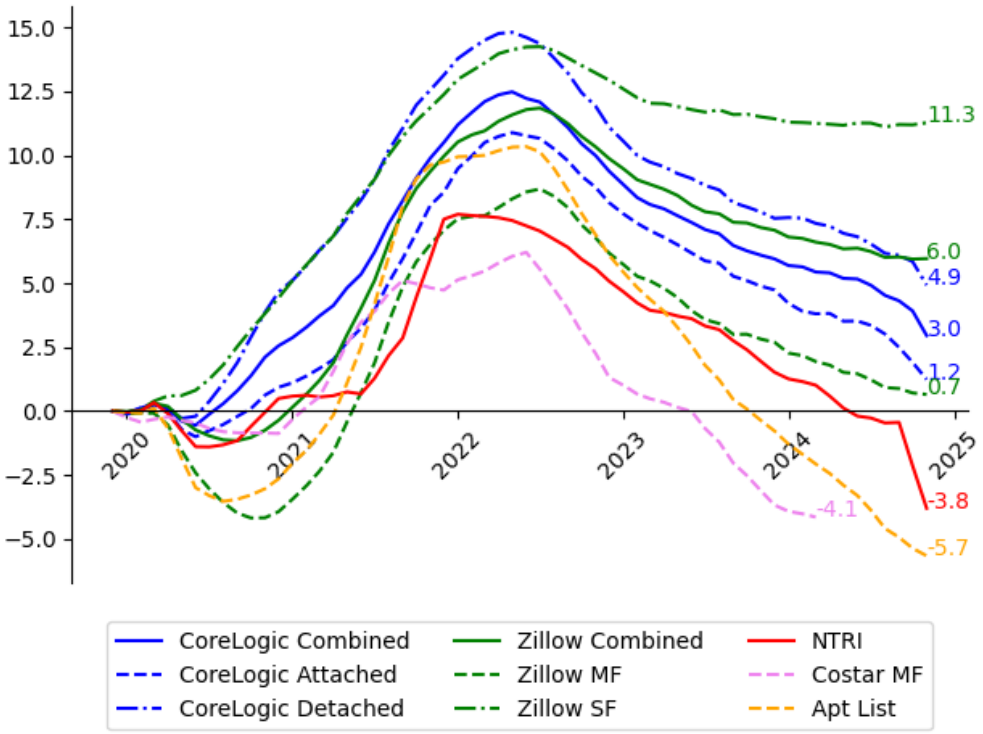
[8] Costar looks at only multifamily homes with at least five units. Apartment List is not explicitly an attached measure, but its website states that its measure is weighted more heavily toward professionally managed apartment buildings.

[9] I do not have access to this data because it is only available to BLS economists (it is not one of the data sets available to external researchers). This also means that it would not be possible to update this measure regularly unless the BLS makes such a series available, which makes it less convenient to use to construct up-to-date forecasts. Similar to my estimate of the market–shelter gap, Gallin et al. (2025) measure the market rent part of the gap using market rent data from CoreLogic as well as Costar.

[10] See Appendix B of the October 2022 working paper version of Adams et al. (2024) for more details.

[11] Note that when estimating the model with both national and MSA-level data, I normally include 12 lags of market rent and CPI shelter. I also include MSA fixed effects in the MSA model, but I normally exclude time fixed effects because these lead to worse forecasts (perhaps because the time fixed effects capture some of the variation that would otherwise be attributed to the lags of market rent and CPI shelter, meaning the lags are less well estimated).

Figure 3: Market–Shelter Gap Measures: During and after the Pandemic



Source(s): Apartment List, US Bureau of Labor Statistics, CoreLogic, Costar, Zillow. Note(s): Computed as $\log(MarketRent_t) - \log(CPIShelter_t)$ adjusted to be zero in December 2019.

residuals in the national model equal zero.[12] I obtain a 10 percent confidence interval for the forecasts by computing the 5th percentile and the 95th percentile of the in-sample forecast errors and adding these to the forecast.

4.2 Forecast Comparison

I compare the forecasting effectiveness of different specifications, including and excluding the market–shelter gap. I report the forecast performance of the specifications in Table 5. I typically compute forecasts for the 12-month-ahead growth in CPI shelter. I use rolling data so that I estimate the growth in CPI shelter from period T to $T + 12$ using only the data available at T. The first date I consider for the rolling window is December 2009.[13] In other words, I estimate the model using data from January 2004 to December 2009 and use this model to forecast the growth in CPI shelter from December 2009 to December 2010. Next, I estimate the model using data from January 2004 to January 2010 and forecast CPI-shelter growth from January 2010 to January 2011, and so forth. Each panel shows a different specification, and the two rows in a panel show the performance of that specification excluding and including the market–shelter gap. The second and third column show statistics relating to the mean forecast error squared. The mean forecast error squared is the mean of the constructed forecast for CPI shelter growth over the next 12 months minus the actual realization of CPI shelter growth over that time squared. The second column shows the mean forecast error squared for the whole sample. The third column shows the mean forecast error squared only in periods when there is a large market–shelter gap, which I specify to be a market–shelter gap that is in absolute terms more than 2 percent. The fourth and fifth column present statistics relating to the Diebold-Mariano test, which tests whether two forecasts are statistically different. For each panel specification, I test whether the forecast including the market–shelter gap is significantly different from the forecast excluding the market–shelter gap and report the t-statistic and p-value in the fourth and fifth columns, respectively.

With CoreLogic data, including the market–shelter gap generally leads to a significant improvement in forecasting. Panel A shows the results of forecasting using the baseline MSA model measured using CoreLogic data (corresponding to column (5) in Table 3). Excluding the market–shelter gap, the mean forecast error squared is 0.58. Including the market–shelter gap, the mean forecast error squared drops to 0.17. The difference is even more pronounced in periods when there is a large market–shelter gap. In that case, the mean forecast error squared is 1.01 when excluding the market–shelter gap but 0.13 when including the market–shelter gap. The two forecasts are highly significantly different according to the Diebold-Mariano test. The improved performance when including the market–shelter gap can also be seen in Figure 4 and Figure 6. Panels B through D show variations on the baseline MSA model measured using CoreLogic data. Panel B shows the results using two years of monthly lags of market rent and CPI shelter rather than one year of lags. The model excluding the market–shelter gap (B1) performs similarly to the baseline (A1). The model including the market–shelter gap (B2) performs better than when the market–shelter gap is excluded (B1) but worse than the baseline (A2). This may be because once the market–shelter gap is included, longer lags are not needed in the model and instead introduce noise through overfitting. Panel C shows the results using a 10-year-model window; that is, when I estimate the coefficients of the model, I consider only the last 10 years of available data.

[12] Mathematically, I set the constant, $\hat{\alpha}$, such that $\hat{\alpha} = \bar{y}_{nat} - \bar{X}_{nat}\hat{beta}_{msa}$ where $\bar{y}_{nat}$ is the mean of the dependent variable, $\hat{\beta}_{msa}$ are the coefficients from the MSA model, and $\bar{X}_{nat}$ are the mean of the independent variables stacked as a matrix.

[13] When constructing models with national data (Panels E, F, and G in Table 5), there is less variation available, so I set the start date at December 2013. Zillow MSA data are available only from January 2012 onward, so to ensure I have six years of data before constructing forecasts, the first date I consider for the rolling window is December 2018 (Panel H in Table 5).

Table 5: Forecast Error of Different Specifications

Forecast Type	MFE2: All	MFE2: $\lvert MSG\rvert > 2\%$	DM T-Stat	DM P-Val
Panel A: Baseline				
A1: Excl. MS gap	0.58	1.01		
A2: Incl. MS gap	0.17	0.16	10.07	0.000
Panel B: Two Years of Lags				
B1: Excl. MS gap	0.61	1.09		
B2: Incl. MS gap	0.28	0.41	10.01	0.000
Panel C: 10-Year Window				
C1: Excl. MS gap	1.14	2.19		
C2: Incl. MS gap	0.38	0.57	8.48	0.000
Panel D: Including Time Dummies				
D1: Excl. MS gap	0.98	1.75		
D2: Incl. MS gap	0.39	0.57	8.32	0.000
Panel E: National Data				
E1: Excl. MS gap	0.44	0.90		
E2: Incl. MS gap	0.36	0.60	1.16	0.247
Panel F: Bolhuis et al (2022)				
F1: Excl. MS gap	0.89	2.33		
F2: Incl. MS gap	0.43	0.86	4.73	0.000
Panel G: NTRI Model/Forecast				
G1: Excl. MS gap	1.25	2.50		
G2: Incl. MS gap	1.41	3.11	-2.85	0.005
Panel H: Zillow Model/Forecast				
H1: Excl. MS gap	3.16	4.50		
H2: Incl. MS gap	1.45	0.71	3.85	0.000
Panel I: CoreLogic Model/NTRI Forecast				
I1: Excl. MS gap	0.86	1.28		
I2: Incl. MS gap	1.07	1.45	-6.52	0.000
Panel J: CoreLogic Model/Zillow Forecast				
J1: Excl. MS gap	1.09	1.57		
J2: Incl. MS gap	0.72	0.53	2.86	0.005
Panel K: One Month Ahead				
K1: Excl. MS gap	0.013	0.019		
K2: Incl. MS gap	0.010	0.013	2.25	0.026
Panel L: Three Months Ahead				
L1: Excl. MS gap	0.053	0.081		
L2: Incl. MS gap	0.037	0.043	2.92	0.004
Panel M: Six Months Ahead				
M1: Excl. MS gap	0.15	0.25		
M2: Incl. MS gap	0.08	0.08	4.99	0.000

Source(s): US Bureau of Labor Statistics, CoreLogic, Zillow. Notes: Each row shows a specification. The second to fifth columns show the mean forecast error squared for all periods, the mean forecast error squared when the absolute value of the market shelter gap is greater than 2 percent, the Diebold-Mariano statistic for the specification including the market–shelter gap relative to the specification excluding the market–shelter gap, and the p-value for the Diebold-Mariano test. Forecast errors are computed for December 2009 until one year before the last date of the sample except for Panels E, F, and G, where they are computed from December 2013, and Panel H where they are computed from December 2017.

Including the market–shelter gap (C2) performs better than excluding the market–shelter gap (C1). However, the forecasts perform worse than the baseline. Panel D shows the results when I include time dummies in the model (unlike in the baseline model in Panel A). Again, including the market–shelter gap (D2) leads to better forecasts than excluding the market–shelter gap (D1), but the forecasts perform less well than in the baseline case.[14]

In Panels E and F, I explore the performance of models using CoreLogic market-rent data but at the national level. In Panel E, I compute the baseline model with national rather than MSA data (corresponding to column (2) in Table 3). In this case, the model including the market–shelter gap (E2) performs similarly to the model excluding the market–shelter gap (E1), although when the market–shelter gap is large, the model including the market–shelter gap performs better. Both models perform worse than the baseline model including the market–shelter gap (A2). Forecasts constructed using national data perform worse than models constructed using MSA data because there are fewer national data points available, so the coefficients are less precisely estimated and show more variation across different samples. In Panel F, I show the performance of the forecast from Bolhuis, Cramer, and Summers (2022), which uses 24 year-over-year lags of CPI shelter, market rent, and house prices in an elastic net regression model. Including the market–shelter gap (F2) significantly improves the forecast gap relative to excluding it (F1), but the forecasts perform worse than the baseline case (A2).

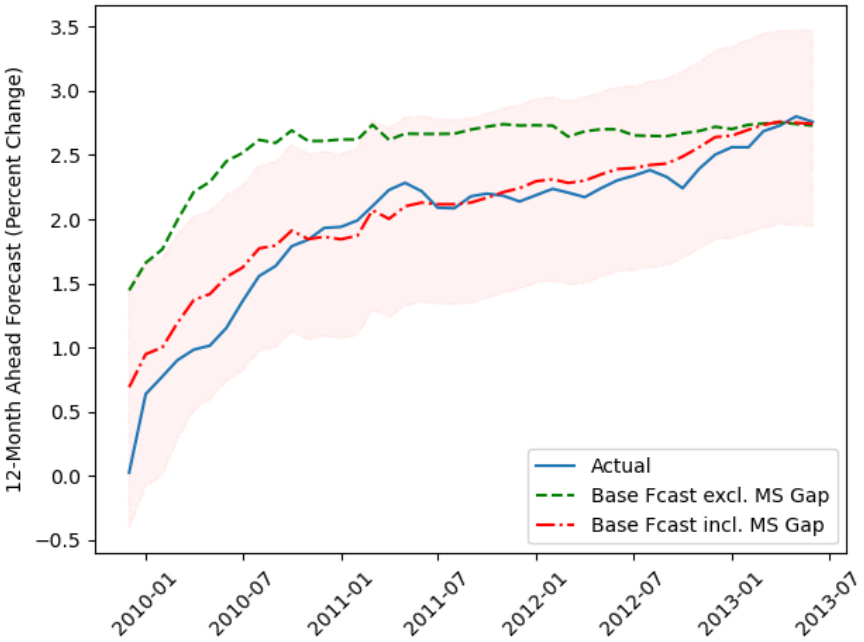
Forecasts with alternative measures of market rent perform worse than CoreLogic, and including the market–shelter gap improves forecasts for Zillow but not for the NTRI. In Panel G, I compute the model and the forecast using the NTRI, which is available only at a national level. Including the market–shelter gap leads to somewhat worse forecast performance, but the forecasts are less accurate than in the baseline case (A2). In Panel H, I compute the model and the forecast using Zillow data. Including the market–shelter gap leads to better forecast performance though the forecast remains relatively inaccurate. In Panels I and J, I compute the model using CoreLogic MSA data but then apply the model to national data in which the market rent is measured using the NTRI and Zillow data, respectively. I again find that including the market–shelter gap worsens the forecast with the NTRI and improves the forecast with Zillow but that both forecasts perform worse than in the baseline case (A2).

Including the market–shelter gap improves forecasting for shorter horizons as well. I have focused on the 12-month ahead horizon, since it is a standard horizon that is likely to be important for policy makers. However, I also examine the performance of forecasts over the one, three, and six-month horizons in Panels K, L, and M, respectively. The forecast errors are smaller than for the 12-month horizon, since the forecast is made for a closer period. However, in each case, the market–shelter gap still improves the performance of the forecast.

I have focused on testing whether the performance of the forecast improves when the market–shelter gap is included by testing whether out-of-sample forecasts improve using the Diebold-Mariano statistic. This is a standard approach in macroeconometrics. However, Diebold (2015) points out that while this approach yields a valid test, it is not the most efficient test in some cases. Diebold argues that when testing the forecasting power of two known models it may be best to compare model selection criteria for the full sample for each model. I take this alternative approach in Table C.2. I find that the model selection criteria (both Akaike Information Criterion and Bayesian Information Criterion) decrease when the market–shelter gap is included in all cases except for the Bayesian Information Criterion when the forecast is constructed using the NTRI

[14]This may be because including time fixed effects is likely to soak up variation in the MSA model that would otherwise be captured by lags, but when the model is then applied to forecast the future, there is no way to measure a time fixed effect and the lag coefficients are imperfectly measured. This is why I do not include time fixed effects when forecasting by default.

Figure 4: CPI Shelter Forecast: December 2009 through June 2013



Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): The lines show the realized/forecast growth in CPI shelter beginning at the date shown on the x-axis and ending 12 months later.

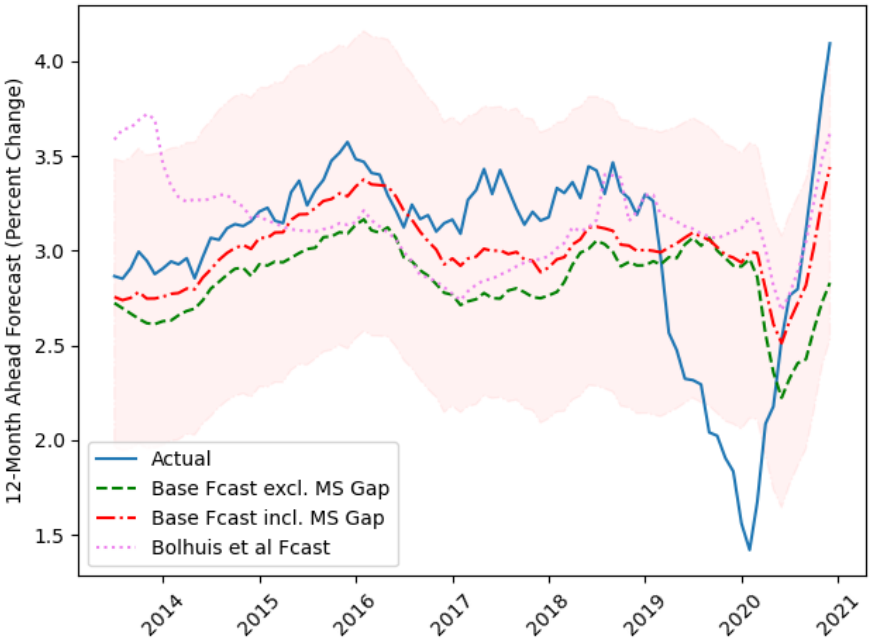
rather than CoreLogic data. This further supports the idea that forecasting is improved by introducing the market–shelter gap.

4.3 Historical Forecasts

I now examine in more detail the performance of the baseline forecast excluding and including the market shelter gap over time, which are respectively models A1 and A2. I break down the analysis into three periods with corresponding graphs. I also show the forecasts in a single graph in Figure C.1.

Following the Great Recession, forecasts including the market–shelter gap better predicted the low growth in CPI shelter. From September 2006 to December 2009 (when my forecasts begin), market rent contracted 1.6 percent while CPI shelter grew 6.4 percent. As a result, the market–shelter gap expanded in absolute terms from –0.1 percent to –8.1 percent. Figure 4 shows the baseline forecasts for the growth in CPI shelter over the next 12 months excluding the market–shelter gap (green dashed line) and including the market–shelter gap (red dotted/dashed line) following the Great Recession. The shaded area shows the 10 percent confidence interval around the forecast including the market–shelter gap. The realized growth in CPI shelter is shown in the blue unbroken line. The forecast including the market–shelter gap performs well whereas the forecast excluding the market–shelter gap overstates CPI shelter growth to a large degree and is significantly different from the forecast including the market–shelter gap for much of this period. The reason for this is that the forecast excluding the market–shelter gap estimates future CPI shelter growth using lagged market rent, which recovered quickly after the Great Recession, and ignores the market–shelter gap, which took longer to recover and depressed CPI shelter growth.

Figure 5: CPI Shelter Forecast: July 2013 through December 2020



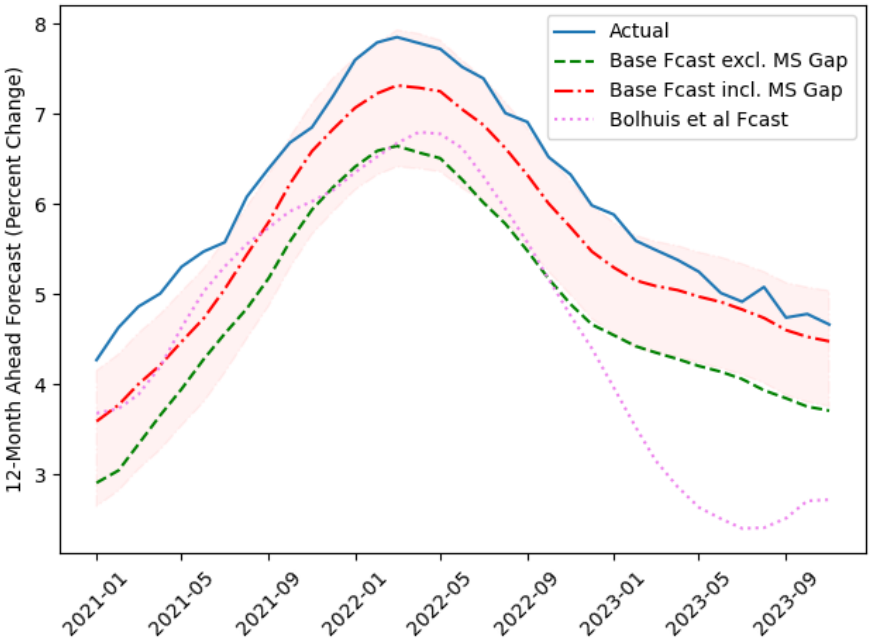
Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): The line shows the realized/forecast growth in CPI shelter beginning at the date shown on the x-axis and ending 12 months later. The actual CPI shelter growth over the next 12 months ends early because it is only available up to 12 months before the end of the data set.

The forecasts including and excluding the market–shelter gap then performed similarly while the market–shelter gap remained close to zero up until the post-pandemic period. Figure 5 presents my baseline forecast including and excluding the market–shelter gap during this period. I also show the forecast using the approach in Bolhuis, Cramer, and Summers (2022) in the violet dotted line. The model from Bolhuis, Cramer, and Summers (2022) uses national data and applies lags of market rent and CPI shelter as well as lags of property prices, but excludes the market–shelter gap.[15] The forecasts generally perform similarly during this period. They closely predict year-ahead CPI shelter until the pandemic, which begins to affect the graphs starting in March 2019 since I am considering year-ahead forecasts/realizations. From that point onward, there are fluctuations in CPI shelter due to the pandemic, although these are small relative to the deviations in the Great Recession and post-pandemic period. All the forecasts fail to capture the dip in year-ahead in CPI shelter due to the pandemic and only partly capture the rise in year-ahead CPI shelter in the immediate post-pandemic period.

In the post-pandemic period when the market–shelter gap was large, forecasts including the market–shelter gap performed much better than forecasts excluding the market–shelter gap. From July 2020 to May 2022, market rent grew by 19.7 percent, while CPI shelter grew by 7.1 percent. As a result, the market–shelter gap grew from -0.6 percent to 12.0 percent over the same period. Figure 6 shows how year-ahead CPI shelter forecasts evolved from 2021 onward in the presence of a large market–shelter gap. The baseline forecast including the market–shelter gap performs well throughout the period, although it does slightly undershoot realized year-

[15] I did not consider the model from Bolhuis, Cramer, and Summers (2022) in Figure 4 because the model requires two years of yearly lags (meaning three years of lagged data) plus one year forward, which means that there are only 24 data points with which to estimate the forecast model in December 2009. This is less of an issue with the MSA model, which also yields cross-sectional variation and uses fewer lags.

Figure 6: CPI Shelter Forecast: January 2021 through December 2023



Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): The line shows the realized/forecast growth in CPI shelter beginning at the date shown on the x-axis and ending 12 months later. The actual CPI shelter growth over the next 12 months ends early because it is only available up to 12 months before the end of the data set.

ahead CPI shelter growth. This relates to the faster passthrough of market–shelter gaps observed in the post-pandemic period (Table 4). The baseline forecast excluding the market–shelter gap was significantly lower than the forecast including the market–shelter gap during the latter half of this sample and has persistently underestimated year-ahead CPI shelter growth by around one percent throughout this period. The Bolhuis, Cramer, and Summers (2022) forecast performs well during the first half of the period but poorly later in the second half where it predicts a large unrealized drop in shelter growth.[16] Again, the logic is that by ignoring the large positive market–shelter gap and focusing instead on market rent lags, which quickly returned to approximately their pre-pandemic norms, the forecast models excluding the market–shelter gap understate the continued upward pressure on CPI shelter.

5 Current Policy Environment

In Table 6, I apply the forecast models I developed in Section 4 to estimate how CPI shelter will evolve and to consider the implications for monetary policy. I report annualized forecasts for the first and second halves of 2025 and 2026. Each row shows a different specification. The first row (A1) shows the forecast for the baseline specification. I find that CPI shelter will continue to grow quickly but at a rate that diminishes with CPI shelter growing 3.6 percent in the first half of 2025, 3.1 percent in the second half of 2025, and 2.3 percent in the first half of 2026. This makes sense because the rate should slow as the market–shelter gap closes. The moderately fast but diminishing growth is not surprising since under the baseline model, there remains, as of April 2024, a

[16]The large slowdown is likely because house price growth, which are also used as a predictor in the Bolhuis, Cramer, and Summers (2022) model, slowed in the latter part of the sample.

Table 6: Current Forecast

Model	24m12–25m06	25m06–25m12	25m12–26m06	26m06-26m12
Panel A: Baseline				
A1: Baseline	3.6	2.6	2.3	2.1
A2: Excl. Market-Shelter Gap	3.1	2.1	1.8	2.0
Panel B: Future Market Rent				
B1: Market Rent grows at -3%	3.3	1.6	0.8	-0.1
B2: Market Rent grows at 0%	3.6	2.5	2.2	1.7
B3: Market Rent grows at 3%	3.9	3.4	3.7	3.4

Source(s): US Bureau of Labor Statistics, CoreLogic, Zillow. Notes: Each row shows a specification. The second through fifth columns show the forecast annualized CPI shelter growth from December 2024 to June 2025, June 2025 to December 2025, January 2026 to June 2026, and June 2026 to December 2026. Models A1 and A2 in this table correspond to models A2 and A1, respectively, in Table 5.

market–shelter gap of 2.5 percent, which will continue to close if CPI shelter grows more quickly than market rent. I also show how excluding the market–shelter gap affects the forecast initially (A2). I find this reduces the CPI shelter growth forecast by about 0.5 percentage points on an annualized basis over the next 18 months. By the end of 2026, by which point the market–shelter gap will have further closed, the two forecasts are similar.

Future CPI shelter growth depends on how market rent will evolve. I forecast CPI shelter growth while allowing the future path of market rent growth to vary. To do this, I assume market rent grows at a set rate from November 2024 (the last available period in my data set) onward. I then estimate a one-month-ahead model using the baseline approach (column (5) in Table 3). This allows me to estimate CPI shelter and the market–shelter gap at time $T + 1$, which I can then use to estimate CPI shelter and the market–shelter gap at time $T + 2$, and so forth. I forecast how market shelter growth of –3 percent, 0 percent, and 3 percent will affect CPI shelter (under the baseline forecast approach) in Table 6. I forecast that CPI shelter will grow fairly quickly over the next six months regardless of how market rent evolves in the short term. However, I find large differences in CPI shelter growth in the latter half of 2025 and 2026 depending on the future evolution of market rent growth. The slow response of CPI shelter to future changes in market rent is not surprising since CPI shelter lags market rent by three to four quarters (Adams et al., 2024).

CPI shelter is likely to continue to have important implications for monetary policy moving forward. As Figure 1 demonstrates, the slow response of CPI shelter initially held down broader inflation indexes in the aftermath of the COVID-19 pandemic. Since mid-2022, however, high CPI shelter has raised aggregate inflation substantially. In Table 7, I consider how much aggregate inflation will rise if CPI shelter grows at the pace predicted under the baseline forecast in Table 6, that is, 3.1 percent from December 2024 to December 2025, relative to if CPI shelter grows at 2 percent. I find large impacts on headline and core CPI, which grow by an additional 0.39 and 0.49 percent, respectively. There is a smaller but still notable impact on the headline and core PCE, as shelter makes up a smaller share of those price indexes.

6 Conclusion

In this paper, I investigated the role that the market–shelter gap can play in forecasting the price of shelter. I started by demonstrating that a higher market–shelter gap predicts higher CPI shelter growth. I found that this holds across a range of different specifications. Next, I examined how well a range of different models perform

Table 7: Potential Impact of Shelter on Aggregate Inflation (June 2024 to June 2025)

	Share of Shelter/Housing (%)	Impact (p.p.) relative to 2% Shelter Growth
CPI	35.4	0.39
CPI Core	44.3	0.49
PCE	15.6	0.17
PCE Core	17.6	0.20

Source(s): US Bureau of Labor Statistics, CoreLogic. Notes: The second column shows the share of shelter/housing in the CPI/PCE, respectively. The CPI weights are taken from the June 2024 release, and the PCE weights are taken from the May 2024 release. The third column shows the amount by which aggregate inflation indexes will increase if CPI shelter rises by 4.2 percent, which is the amount forecast for June 2024 to June 2025 in the baseline forecast, rather than 2 percent.

in predicting CPI shelter growth both including and excluding the market–shelter gap. I found that a model including the market–shelter gap and applied to MSA-level data performs best at forecasting the change in CPI shelter. Across most of the specifications, I found that including the market–shelter gap leads to better forecast performance, especially in the case where there is a large market–shelter gap. The reason for this is that it can take a long time for CPI shelter to catch up with market rent, which is not captured as well by models with only past lags. Looking forward, my baseline forecast model suggests that CPI shelter will continue to grow quickly but at a diminishing rate in the medium term. In particular, I estimate that CPI shelter will grow 3.6 percent in the first half of 2025, 3.1 percent in the second half of 2025, and 2.3 percent in the first half of 2025, although it is important to note the uncertainty around current market rent trends.

Shelter prices play an important role in overall inflation aggregates, comprising 44.3 percent of core CPI and 17.6 percent of core PCE, and making it an important determinant of monetary policy. As a result, high shelter prices can raise overall inflation and have been a key roadblock in the "last-mile" problem of bringing inflation back to an average of 2 percent in recent months. Indeed, in December 2023 and March 2024, the median FOMC member estimated that the committee would make three interest rate cuts in 2024, but as of June 2024, this estimate had dropped to only a single cut in 2024. High CPI shelter leading to upside inflation surprises was likely a key factor in these revisions. The price of shelter is likely to remain an important determinant of monetary policy for the foreseeable future.

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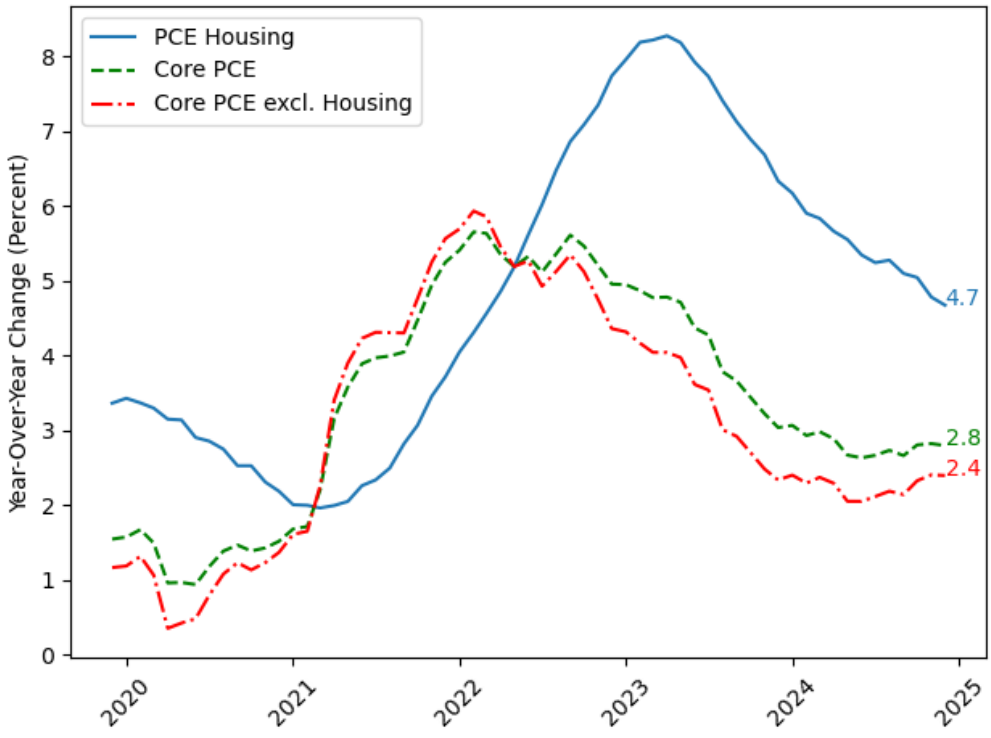
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Online Appendix

A Aggregate Inflation: Additional Graphs

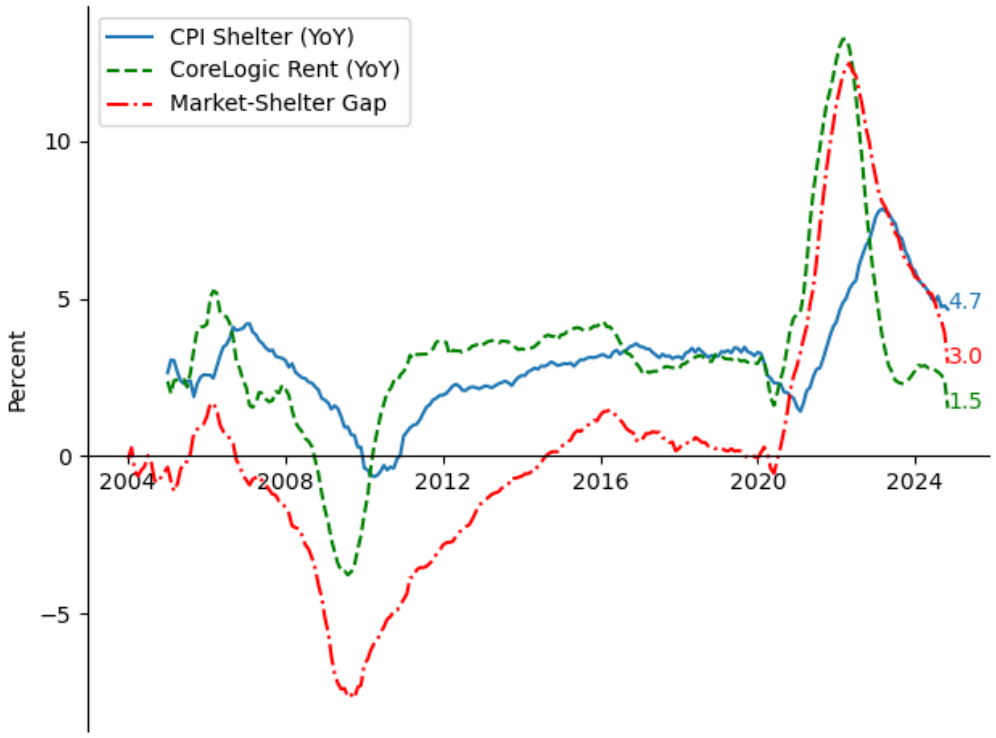
Figure A.1: Recent PCE and PCE Housing Dynamics



Source(s): US Bureau of Economic Activity.

B CPI-shelter and Market-rent Dynamics: Additional National Graphs

Figure B.1: CPI Shelter and Market Rent Dynamics: Market–Shelter Gap Relative to December 2019



Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): CPI shelter and CoreLogic rent are measured on a year-over-year basis. The market–shelter gap (log market rent minus log CPI shelter) is set to zero in December 2019.

C Additional Empirics

Table C.1: Market–Shelter Coefficients: Month-by-Month

$\Delta_{i,i+1}\log(CPIShelter_z)$	0	1	2	3	4	5	6	7	8	9	10	11
$MarketShelterGap_{z,t}$	0.024***	0.018***	0.018***	0.017***	0.016***	0.014***	0.012***	0.009**	0.007*	0.007*	0.008***	0.009***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
N	3354	3354	3354	3354	3354	3354	3354	3354	3354	3354	3354	3354
R^2	0.293	0.267	0.264	0.265	0.262	0.262	0.258	0.258	0.259	0.266	0.264	0.264
R^2_{adj}	0.230	0.202	0.199	0.200	0.196	0.197	0.193	0.193	0.194	0.202	0.199	0.199

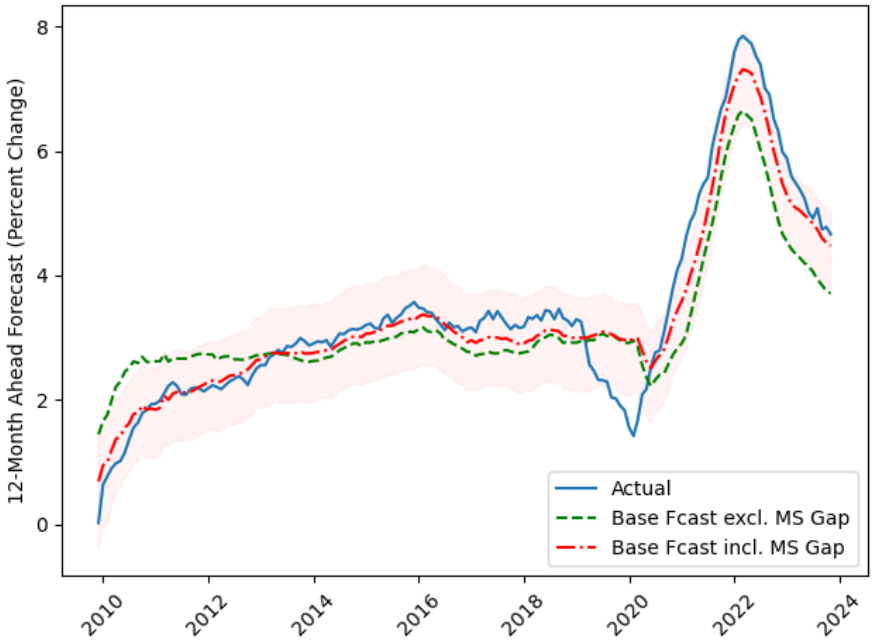
Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): Coefficients from a regression of the change in CPI shelter from month $t+i$ to month $t+i+1$ on the market–shelter gap at time t plus 12 lags of month-over-month market rent and CPI shelter, and MSA and time fixed effects. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively, under Driscoll-Kraay standard errors with 12 lags.

Table C.2: Model Selection Criteria of Different Specifications

Forecast Type	AIC	Δ AIC	BIC	Δ BIC
Panel A: Baseline				
A1: Excl. MS gap	-18318.36		-18036.94	
A2: Incl. MS gap	-18931.17	-612.80	-18643.62	-606.69
Panel B: Two Years of Lags				
B1: Excl. MS gap	-17164.80		-16742.29	
B2: Incl. MS gap	-17602.06	-437.26	-17173.51	-431.22
Panel C: Including Time Dummies				
C1: Excl. MS gap	-18961.52		-17297.45	
C2: Incl. MS gap	-19436.56	-475.04	-17766.37	-468.92
Panel D: National Data				
D1: Excl. MS gap	-1758.88		-1673.26	
D2: Incl. MS gap	-1867.02	-108.13	-1777.97	-104.71
Panel E: NTRI Model/Forecast				
E1: Excl. MS gap	-1467.54		-1383.51	
E2: Incl. MS gap	-1467.81	-0.27	-1380.42	3.09
Panel F: Zillow Model/Forecast				
F1: Excl. MS gap	-9257.18		-9000.79	
F2: Incl. MS gap	-9838.14	-580.96	-9576.29	-575.51
Panel G: One Month Ahead				
G1: Excl. MS gap	-27623.24		-27338.61	
G2: Incl. MS gap	-27714.51	-91.27	-27423.69	-85.08
Panel H: Three Months Ahead				
H1: Excl. MS gap	-23902.33		-23618.27	
H2: Incl. MS gap	-24136.77	-234.44	-23846.54	-228.27
Panel I: Six Months Ahead				
I1: Excl. MS gap	-21170.37		-20887.17	
I2: Incl. MS gap	-21578.16	-407.80	-21288.81	-401.64

Source(s): US Bureau of Labor Statistics, CoreLogic, Zillow. Notes: Each row shows a specification. The second to fifth columns show the Akaike Information Criterion (AIC), the change in the AIC when the market–shelter gap is included relative to when it is not, the Bayesian Information Criterion (BIC), and the change in the BIC when the market–shelter gap is included relative to when it is not.

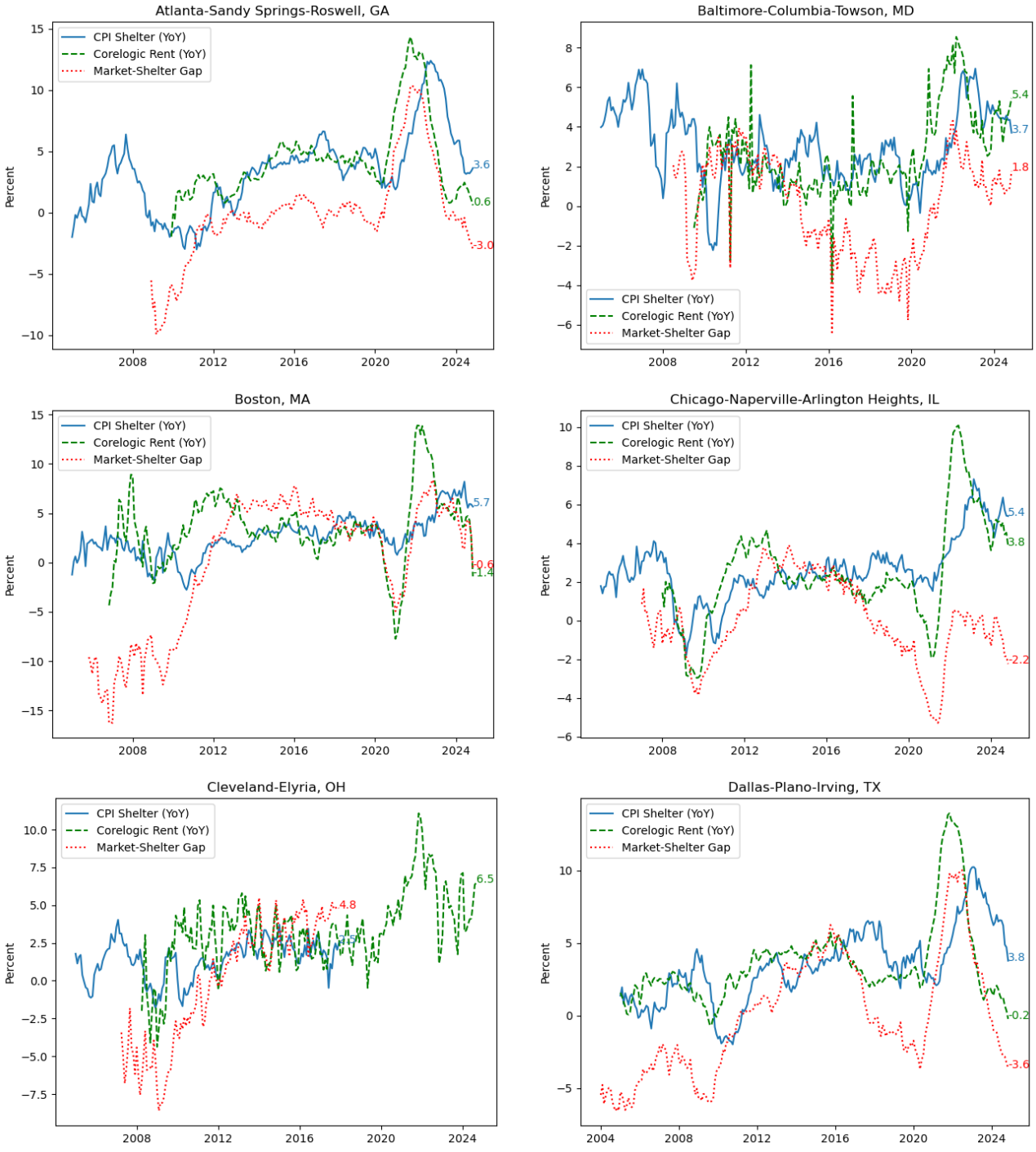
Figure C.1: CPI Shelter Forecast: Whole Sample



Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): The lines show the realized/forecast growth in CPI shelter beginning at the date shown on the x-axis and ending 12 months later.

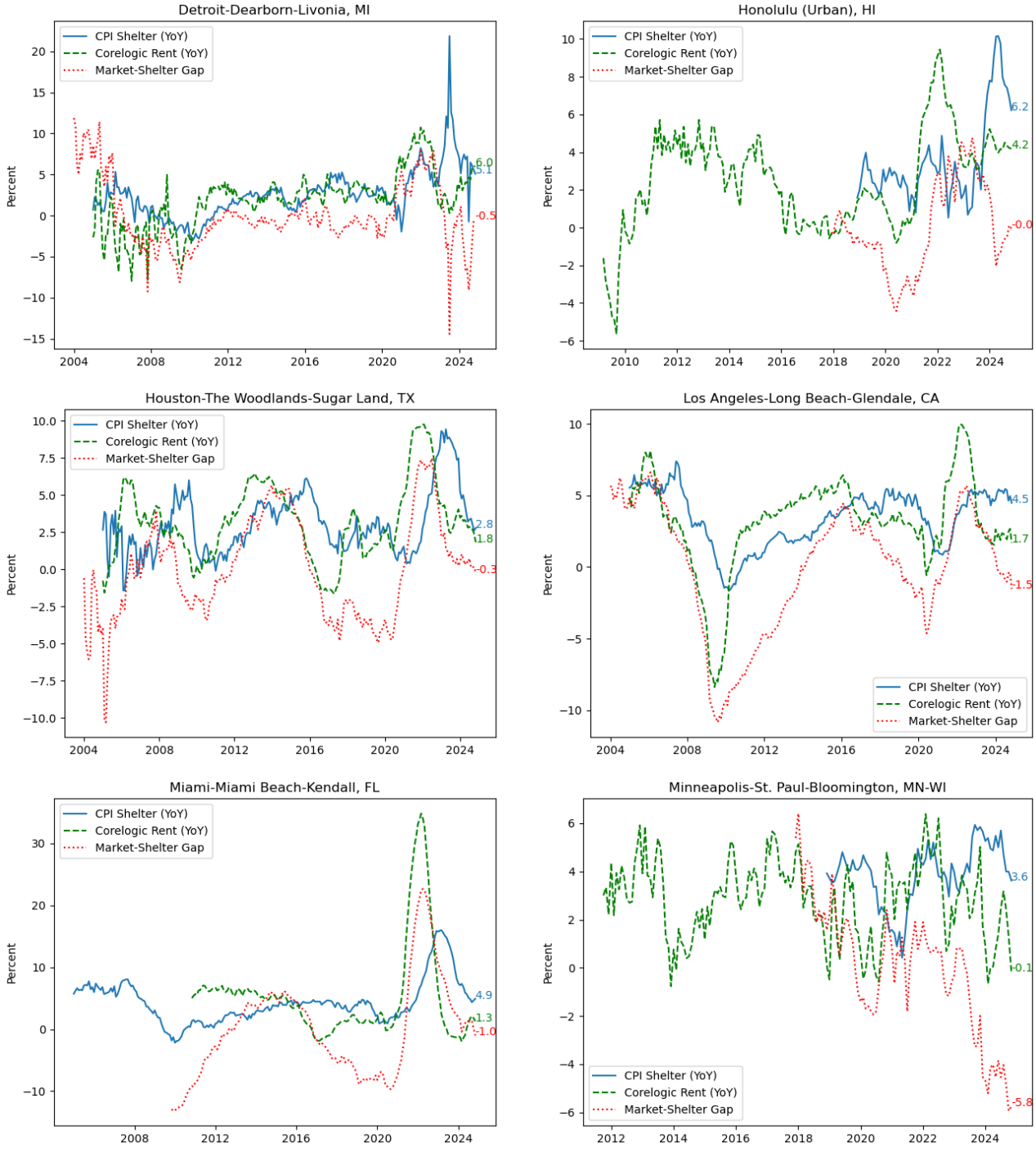
D CPI-shelter and Market-rent Dynamics: MSA Graphs

Figure D.1: CPI-shelter and Market-rent Dynamics: Atlanta–Dallas



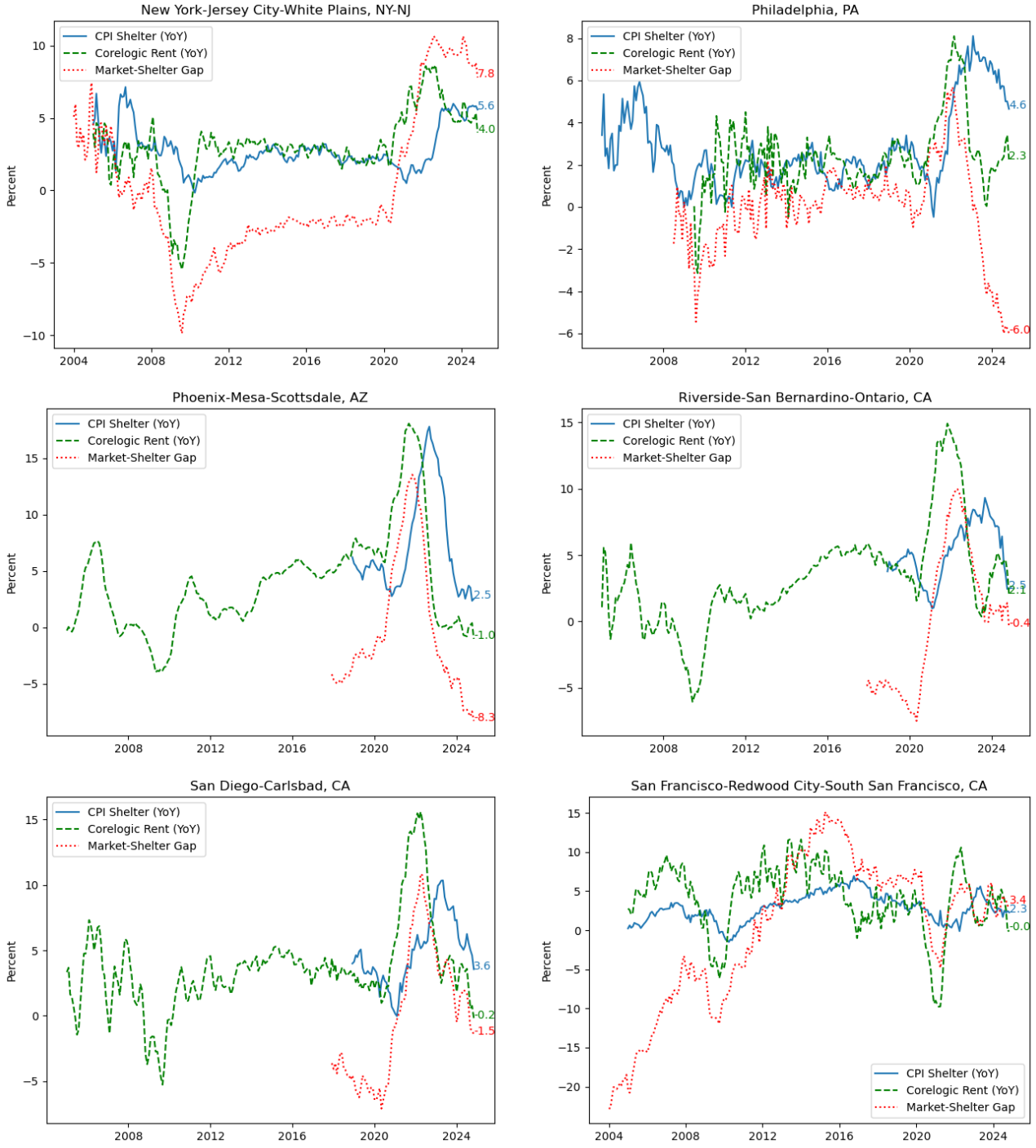
Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): CPI shelter and CoreLogic rent are measured on a year-over-year basis. The market–shelter gap is the difference of the logs of market rent and CPI shelter measured relative to its mean.

Figure D.2: CPI-shelter and Market-rent Dynamics: Detroit–Minneapolis



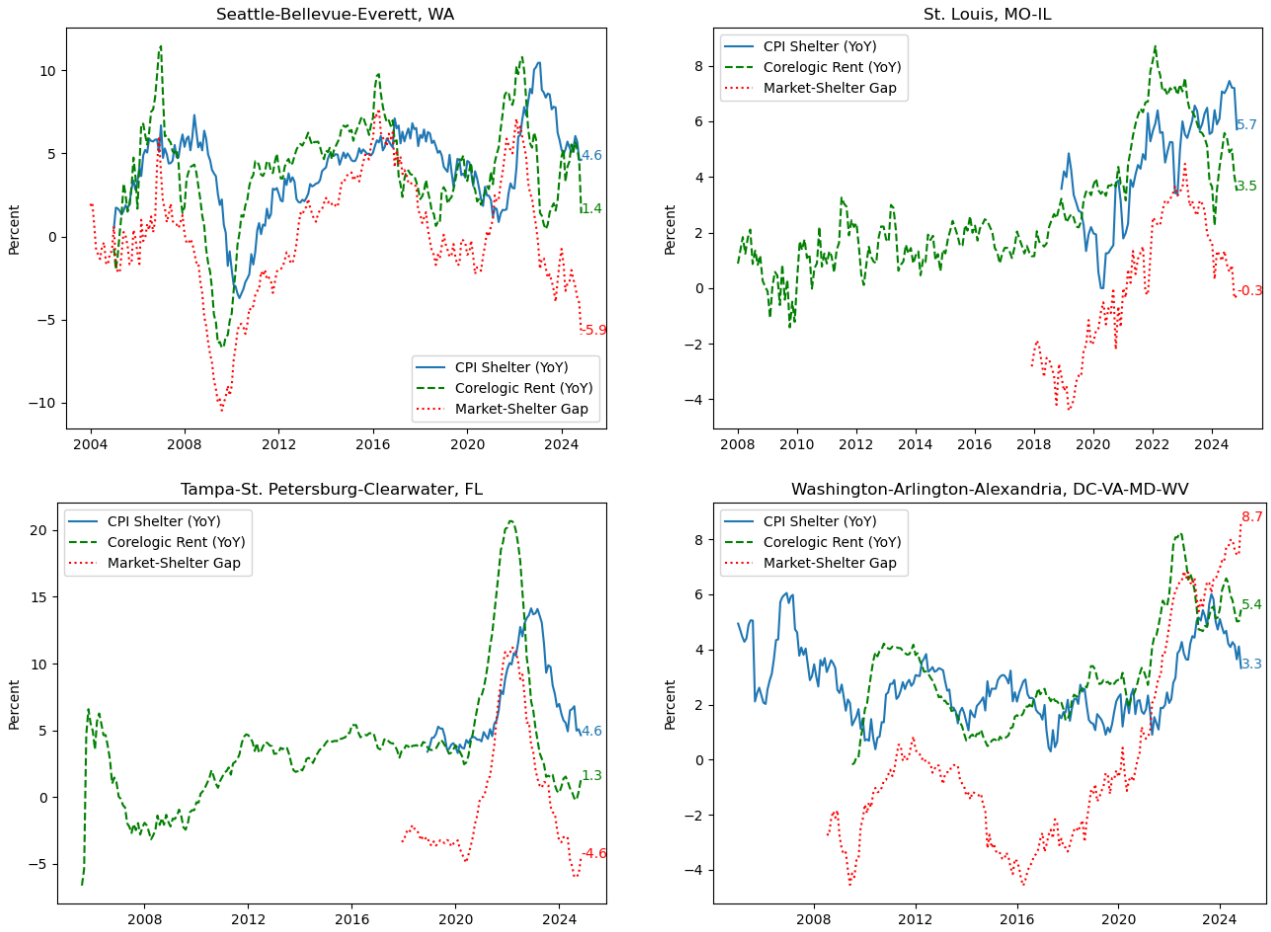
Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): CPI shelter and CoreLogic rent are measured on a year-over-year basis. The market–shelter gap is the difference of the logs of market rent and CPI shelter measured relative to its mean.

Figure D.3: CPI-shelter and Market-rent Dynamics: New York–San Francisco



Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): CPI shelter and CoreLogic rent are measured on a year-over-year basis. The market–shelter gap is the difference of the logs of market rent and CPI shelter measured relative to its mean.

Figure D.4: CPI-shelter and Market-rent Dynamics: Seattle–Washington, DC



Source(s): US Bureau of Labor Statistics, CoreLogic. Note(s): CPI shelter and CoreLogic rent are measured on a year-over-year basis. The market–shelter gap is the difference of the logs of market rent and CPI shelter measured relative to its mean.

E Robustness Checks for Main Specification

Table E.1: Alternative Specification: National Baseline

$\Delta_{0,m} \log(CPIShelter_{nat})$. Months ahead (m):	1	3	6	12
Intercept	0.002***	0.005***	0.009***	0.025***
	(0.000)	(0.001)	(0.002)	(0.004)
$MarketShelterGap_{nat,t}$	0.019***	0.057***	0.110***	0.283***
	(0.005)	(0.013)	(0.024)	(0.041)
N	238	236	233	227
R^2	0.743	0.891	0.934	0.956
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Baseline specification with national data.

Table E.2: Alternative Specification: National 2004–2020

$\Delta_{0,m} \log(CPIShelter_{nat})$. Months ahead (m):	1	3	6	12
Intercept	0.003***	0.007***	0.012***	0.028***
	(0.001)	(0.002)	(0.003)	(0.004)
$MarketShelterGap_{nat,t}$	0.033**	0.082**	0.154***	0.339***
	(0.010)	(0.026)	(0.038)	(0.052)
N	168	168	168	168
R^2	0.644	0.866	0.936	0.960
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.1 except that I only consider the 2004–2020 period.

Table E.3: Alternative Specification: National 2021+

$\Delta_{0,m} \log(CPIShelter_{nat})$. Months ahead (m):	1	3	6	12
Intercept	0.002***	0.007***	0.013***	0.038***
	(0.001)	(0.002)	(0.003)	(0.004)
$MarketShelterGap_{nat,t}$	0.026**	0.094***	0.200***	0.583***
	(0.009)	(0.028)	(0.050)	(0.086)
N	70	68	65	59
R^2	0.829	0.920	0.957	0.981
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.1 except that I only consider 2021 onwards.

Table E.4: Alternative Specification: MSA Baseline

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.022***	0.056***	0.100***	0.158***
	(0.003)	(0.008)	(0.013)	(0.016)
N	3596	3552	3486	3354
R^2	0.301	0.497	0.628	0.778
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Baseline specification with MSA data.

Table E.5: Alternative Specification: MSA 2004–2020

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.022***	0.054***	0.097***	0.159***
	(0.002)	(0.006)	(0.011)	(0.016)
N	2126	2124	2121	2115
R^2	0.361	0.498	0.587	0.706
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I only consider the 2004–2020 period.

Table E.6: Alternative Specification: MSA 2021+

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.046***	0.118***	0.207***	0.312***
	(0.012)	(0.030)	(0.055)	(0.071)
N	1470	1428	1365	1239
R^2	0.285	0.493	0.644	0.824
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I only consider 2021 onwards.

Table E.7: Alternative Specification: No Time Dummies/Lag Controls

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.024***	0.063***	0.114***	0.191***
	(0.004)	(0.009)	(0.016)	(0.023)
N	3596	3552	3486	3354
R^2	0.211	0.415	0.556	0.705
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I exclude time fixed effects, lag market rent controls, and lag CPI shelter controls.

Table E.8: Alternative Specification: No Lag Controls

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.025***	0.071***	0.130***	0.221***
	(0.003)	(0.009)	(0.018)	(0.031)
N	3860	3816	3750	3618
R^2	0.212	0.392	0.546	0.728
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I exclude lag market rent and lag CPI shelter controls.

Table E.9: Alternative Specification: No Market Rent Controls

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.024***	0.063***	0.110***	0.163***
	(0.003)	(0.007)	(0.012)	(0.015)
N	3680	3636	3570	3438
R^2	0.228	0.419	0.580	0.775
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I exclude lag market rent controls.

Table E.10: Alternative Specification: No CPI Controls

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.027***	0.072***	0.134***	0.229***
	(0.004)	(0.011)	(0.022)	(0.035)
N	3692	3648	3582	3450
R^2	0.292	0.484	0.605	0.741
CPI Shelter 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I exclude lag CPI shelter controls.

Table E.11: Alternative Specification: Two Years of Lags

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.022***	0.056***	0.099***	0.149***
	(0.003)	(0.008)	(0.014)	(0.017)
N	3332	3288	3222	3090
R^2	0.315	0.507	0.650	0.797
CPI Shelter 2 Year Lags	*	*	*	*
Corelogic Rent 2 Year Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I include 24 monthly lags for market rent and CPI shelter.

Table E.12: Alternative Specification: Zillow

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap(Zillow)_{msa,t}$	0.040***	0.099***	0.172***	0.269***
	(0.009)	(0.019)	(0.030)	(0.051)
N	1806	1804	1801	1729
R^2	0.255	0.464	0.638	0.800
CPI Shelter 12 Lags	*	*	*	*
Zillow Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, Zillow. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I measure market rent (including the market-shelter gap) using Zillow market rent data.

Table E.13: Alternative Specification: CPI Rent

$\Delta_{0,m} \log(CPIRent_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap(CPIRent)_{msa,t}$	0.013***	0.041***	0.084***	0.146***
	(0.002)	(0.005)	(0.011)	(0.017)
N	3596	3552	3486	3354
R^2	0.353	0.527	0.642	0.764
CPI Rent 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I consider CPI rent rather than CPI shelter.

Table E.14: Alternative Specification: CPI Owners' Equivalent Rent

$\Delta_{0,m} \log(CPIOER_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap(CPIOER)_{msa,t}$	0.013***	0.040***	0.086***	0.157***
	(0.001)	(0.004)	(0.009)	(0.016)
N	3596	3552	3486	3354
R^2	0.401	0.570	0.663	0.784
CPI OER 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I consider CPI owners' equivalent rent rather than CPI shelter.

Table E.15: Alternative Specification: Detrended Error Correction

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap(Detrended)_{msa,t}$	0.031***	0.078***	0.139***	0.214***
	(0.005)	(0.011)	(0.018)	(0.024)
N	3596	3552	3486	3354
R^2	0.305	0.505	0.638	0.786
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I use the detrended error correction term. To detrend the error correction term, I regress it on a time trend for each MSA separately.

Table E.16: Alternative Specification: MSAs Beginning A through I

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.035***	0.090***	0.157***	0.241***
	(0.009)	(0.020)	(0.031)	(0.034)
N	1682	1664	1637	1583
R^2	0.360	0.509	0.614	0.751
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I only consider MSAs with names beginning A–I.

Table E.17: Alternative Specification: MSAs Beginning J through Z

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.015***	0.039***	0.076***	0.140***
	(0.002)	(0.006)	(0.011)	(0.017)
N	1914	1888	1849	1771
R^2	0.404	0.611	0.735	0.849
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I only consider MSAs with names beginning J–Z.

Table E.18: Alternative Specification: Balanced Panel

$\Delta_{0,m} \log(CPIShelter_{msa})$. Months ahead (m):	1	3	6	12
$MarketShelterGap_{msa,t}$	0.021***	0.051***	0.092***	0.143***
	(0.004)	(0.008)	(0.012)	(0.014)
N	3196	3162	3111	3009
R^2	0.310	0.509	0.637	0.784
CPI Shelter 12 Lags	*	*	*	*
Corelogic Rent 12 Lags	*	*	*	*
MSA Fixed Effects	*	*	*	*
Time Fixed Effects	*	*	*	*

Source(s): BLS, CoreLogic. Note(s): Driscoll-Kraay standard errors. *, **, and *** represent < 0.05, < 0.01, and < 0.001 significance, respectively. Similar to Table E.4 except that I restrict to MSAs that are available for all dates in the sample.