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Housing Boom and Headline Inflation: Insights from Machine Learning

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Housing Boom and Headline Inflation: Insights from Machine Learning

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ABSTRACT: Inflation has been rising during the pandemic against supply chain disruptions and a multi-year boom in global owner-occupied house prices. We present some stylized facts pointing to house prices as a *leading* indicator of headline inflation in the U.S. and eight other major economies with fast-rising house prices. We then apply machine learning methods to forecast inflation in two housing components (rent and owner-occupied housing cost) of the headline inflation and draw tentative inferences about inflationary impact. Our results suggest that for most of these countries, the housing components could have a relatively large and sustained contribution to headline inflation, as inflation is just starting to reflect the higher house prices. Methodologically, for the vast majority of countries we analyze, machine-learning models outperform the VAR model, suggesting some potential value for incorporating such models into inflation forecasting.

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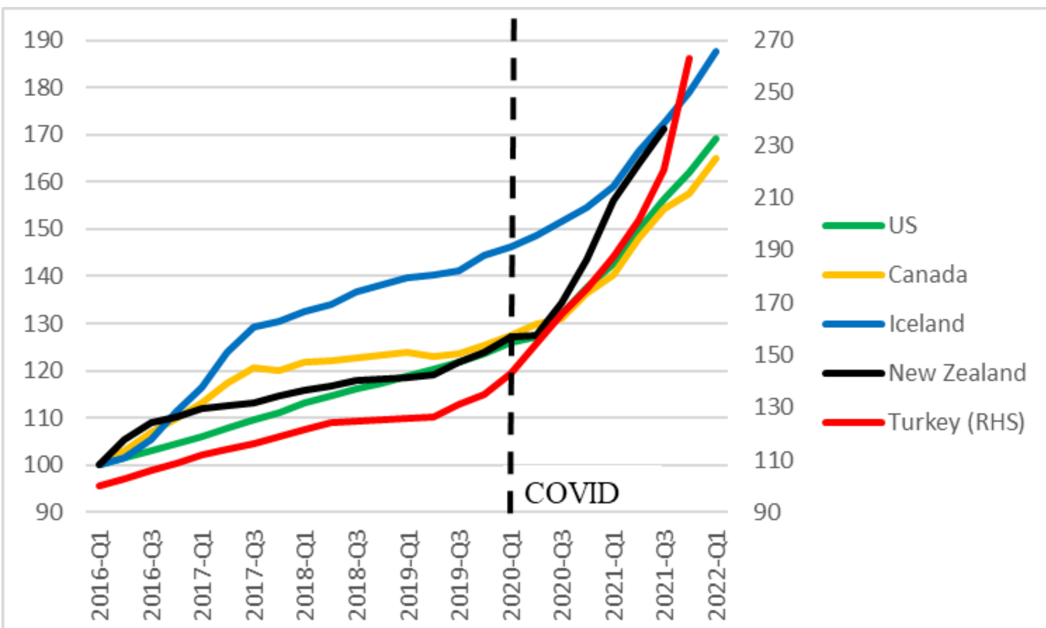
I. Introduction

The COVID-19 pandemic has extended further the multi-year housing boom. This boom is found in advanced economies and emerging markets alike and across continents. For example, nominal owner-occupied house prices in Turkey have more than doubled between 2016Q1 and 2021Q4 (the latest data point) (Figure 1, right axis). In the U.S., nominal house prices have risen by more than 60 percent between 2016Q1 and 2022Q1 and are recently growing at a rate higher than that during the pre-GFC period (Figure 1, left axis; and Figure 2a; see also Zhao, 2020). Due to concerns about financial, macroeconomic, and social stability,[2] the sharp rise and high level of house prices have received increasing attention by policymakers. For example, in its first strategy review since 2003 (completed in July 2021), President Lagarde noted that the ECB heard "loud and clear" that the top two concerns were climate change and the cost of housing (*Financial Times*, July 12, 2021).

Figure 1. Nominal Owner-occupied House Price Indices in Selected Countries

(2016Q1-2022Q1; 2016Q1=100)



Sources: OECD and authors' calculations.

This housing price boom coincides with decades-high headline inflation, raising a natural question of how much the rising housing price has contributed to the headline inflation. Against these backdrops, we shed some light on three related questions in this paper.

[2] For example, in September 2021, twenty thousand residents protested against unaffordable rents in Berlin, an issue closely related to the rising house sales prices (WSWS.org, September 13, 2021).

First, does high headline inflation follow high growth in owner-occupied housing prices? Conceptually, the answer is unclear. In addition to country-specific structural factors, such as segmented rental markets and housing policies, the type of the shock matters as well: if the higher housing price reflects higher *overall* demand for "housing space" due to (for example) a higher need for working from home, then rent (and thus headline inflation) could go up in tandem with housing price. But if the higher housing price reflects a preference *shift* for greater homeownership relative to renting, it may not lead to higher rent (and thus higher headline inflation. In addition, the net effect also depends on spillovers of the higher housing price to non-housing sectors' inflation, the wealth channel, and the credit channel (see literature review). Empirically, it is also difficult to rigorously establish the causal relationship between housing price growth and headline inflation. In this context, we provide some stylized facts suggesting that house price growth appears to be a *leading* indicator of headline inflation in the U.S. and some selected countries.

Second, which methods perform best in forecasting inflation in rents and (if applicable) owner-occupied housing costs with housing prices? We find that for eight of the nine countries we analyze, a country-specific machine-learning models outperform the vector autoregression (VAR) model in an out-of-sample forecast performance comparison. This possibly reflects the benefits of machine-learning models in macroeconomic forecasting, such as the ability to capture nonlinearities. Our country-specific machine-learning models can be explored by macroeconomic forecasters to predict the inflation of rents and (if applicable) owner-occupied housing costs, which can then be used to calculate the contributions to headline inflation and inform their own forecasts.

Third, how much does inflation in housing components (rent and owner-occupied housing cost) directly contribute to headline inflation, without considering the general equilibrium effects and policy responses? We find that the direct contribution of housing components to headline inflation in most countries we study was disproportionally higher than their weights in headline inflation during 2020, as rent and owner-occupied housing cost decreased more slowly than headline inflation in 2020. The contribution then dropped significantly in 2021, as rent and owner-occupied housing cost started catching up with the rapid housing price growth experienced in 2020, and as inflation in non-housing components played a dominant role in driving headline inflation due to (for example) supply chain disruptions. Looking ahead, our forecasting models suggest that due to lagged responses of rent and owner-occupied housing cost to the rapid housing price growth experienced so far, the contribution of such housing components to headline inflation will rise over the medium term; in some cases, they could even contribute to more than half of headline inflation projected by the WEO, highlighting the importance of carefully modeling the inflationary pressures in the housing components. These results suggest that even after the supply disruptions to the non-housing sectors and the associated inflationary pressures ease, the pressure from the rising housing price (and the rising rent and owner-occupied housing cost) will continue building up. This, in turn, would make the headline CPI inflation more persistent, complicating monetary policymaking.

We would like to note that our methodology only focuses on the *direct* effect of housing price growth on headline inflation. It does not account for general equilibrium effects (such as spillovers of housing to non-housing sectors)[3], nor does it account for potential de-anchoring of inflation expectations, policy responses, and feedback from headline inflation to housing price. As such, our forecasts are subject to biases in both directions. Relatedly, our methodology serves as a *complementary* tool to assist with the forecasting of headline inflation, rather than as a *substitute* to current inflation forecasting models.

The rest of the paper is structured as follows. Section II reviews related literature; Section III analyzes the case of the U.S., given that the impact of the U.S. housing boom on inflation has implications for the Fed's policy, and thus global spillover effects; Section IV analyzes some other countries with rapid housing price growth; Section V concludes and discusses potential operational implications. The appendices collect some technical details.

II. Literature Review

Our paper is related to three strands of literature. First, it is related to the literature on the interaction between housing price and *headline* inflation. On the theoretical front, a higher housing price could lead to higher headline inflation through the wealth channel and the credit channel: the former occurs as existing homeowners feel wealthier and consume more (see, e.g., Mishkin, 2007), and the latter occurs as the higher net worth of homeowners leads to more valuable collateral and enables them to take a higher home equity loan (see, e.g., Bernanke and Gertler, 1995). On the empirical front, Goodhart and Hofmann (2000) find that among all the asset prices considered, house prices have the largest power for predicting CPI inflation. And using cross-country forecasting models for nine countries, De Haan and Van den End (2017) find that high asset prices (including house prices) often signal high inflation. However, the opposite is true for some countries, highlighting the need for building country-specific models.

Second, our paper is related to the literature on the link between house prices and housing cost *components* in headline inflation (such as rent). In this regard, an extensive literature studies the house price-to-rent ratio. In theory, house prices and rents are expected to be broadly aligned, as no-arbitrage conditions imply that prices should equal the discounted flow of future rents.

[3] Some empirical studies, such as Iacoviello (2010), find that for the U.S., "Movements in the price of housing are only loosely connected to movements in other prices." That is, the spillovers of housing to non-housing sectors are empirically small in the U.S. However, for other countries, such spillovers can be large.

However, in practice, rents and house prices can move in different directions for various reasons such as macroprudential policies and demographic factors. For example, Cronin and McQuinn (2016) find that a reduction in the loan-to-value ratio leads to a greater demand for rental units and a lower price-to-rent ratio. In addition, Begley, Loewenstein, and Willen (2019) find that the price-rent ratio moves similarly across all property types but varies significantly by geography, which can be partially explained by differing expectations of population growth.

Moreover, rents can respond to house prices with a lag due to market frictions and other factors. For example, Zhou and Dolmas (2021) find that house price growth has led rent inflation and OER inflation in the U.S. by somewhat less than two years. Similarly, Brescia (2021) finds that house price gains historically lead the changes in the CPI shelter cost measures (including rent and owners' equivalent rent) by about five quarters in the U.S. Both papers suggest that the lagged effects of the house price appreciation during the COVID-19 crisis could keep the headline inflation in the U.S. longer than expected. And an October 2021 WEO chapter by IMF (2021a) estimates that a one-percentage-point, year-on-year increase in nominal house prices in the quarter ahead is associated with a cumulative increase of 1.4 percentage points in annual rent inflation over two years, although this study does not examine the lagged responses of rent (and other equivalent concepts) to house price growth.

Our paper is closely related to these three studies, with the following main differences: (i) We apply machine-learning models from the latest literature and select the best-performing models based on back-testing results, complementing the approaches in these studies (a three-variable VAR model in Zhou and Dolmas, 2021; linear regressions in Brescia, 2021; and local projections in IMF, 2021a). (ii) We cover multiple countries experiencing rapid house price growth recently (as opposed to the U.S.-centric studies in Zhou and Dolmas, 2021, and Brescia, 2021). But to account for country-specific institutional features, we construct country-specific forecasting models for each country we cover (as opposed to the single cross-country model in IMF, 2021a).

Third, our paper is related to the literature on inflation forecasting and macroeconomic forecasting. Accurate inflation forecasts are essential for central banks to inform monetary policymaking and anchor inflation expectations. But conventional wisdom suggests that it is challenging to improve simple models such as the random walk model in Atkeson and Ohanian (2001) or the time-varying unobserved components model in Stock and Watson (2007), as noted by Stock and Watson (2010) and supported by a large literature (Faust and Wright, 2013).

However, as Medeiros et al. (2021) point out, this literature has largely not yet incorporated the recent applications of machine learning and big data methods in economics. Definitions of "machine learning" vary, but a distinguishing feature of machine-learning applications is their focus on prediction (IMF, 2021b), which is helpful in terms of enhancing the accuracy of inflation forecasting. Medeiros et al. (2021) show that in a data-rich environment (with 122 variables in their case), the gains of using machine-learning models can be as large as 30 percent in terms of mean squared errors, and that such models can help uncover the main drivers for future inflation. Similar insights are documented in Masini, Medeiros, and Mendes (2021) in their survey of the most recent advances in supervised machine-learning and high-dimensional models for time series forecasting, as well as in Hall (2018) in the context of unemployment forecasting, who highlights one key advantage of machine learning, i.e., automating as many of modeling choices as possible in a manner that is not subject to the discretion of the forecaster.[4] [5]

III. THE U.S. CASE

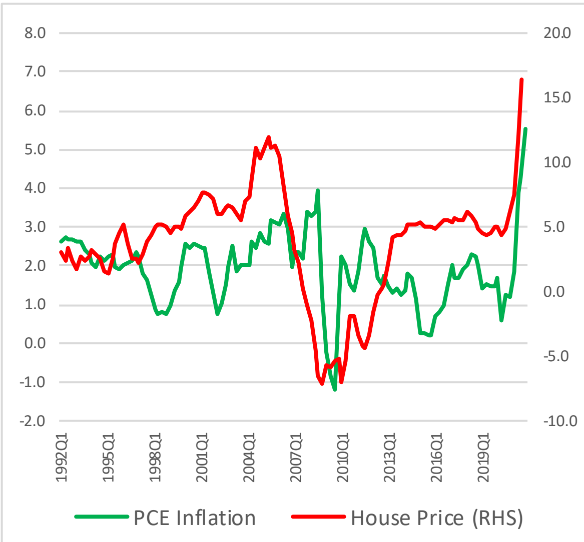
A. Stylized Facts

In the U.S., the growth of owner-occupied housing prices leads inflation. Headline inflation has accelerated, reaching its highest level in four decades (Figure 2). House price growth appears to lead the Fed's main target for monetary policy, Personal Consumption Expenditures (PCE) inflation, including during the early stage of the housing boom starting in the late 1990s, the housing bust during the GFC and the subsequent recovery, as well as the COVID-19 pandemic (Figure 2a). A similar relationship exists between the U.S. headline CPI inflation and house price growth (Figure 2b).

[4] Some studies apply machine-learning models to nowcast key macroeconomic indicators, such as Cerdeiro et al. (2020), in the context of nowcasting global trade. Some other studies, including Joseph (2019) and Zhao and Hastie (2019), contribute to the interpretability of machine learning models.

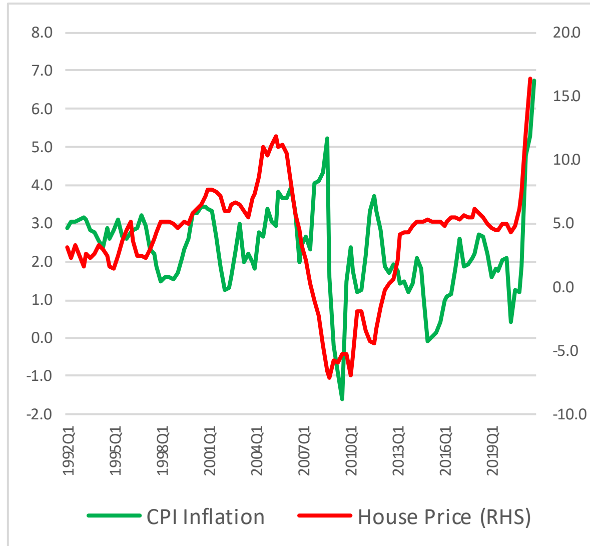
[5] There have also been some recent studies applying machine-learning methods to macroeconomic forecasting or nowcasting with limited data. For example, Cook and Hall (2017) find that all the four types of machine-learning models studied by them outperform the benchmark (and inherently linear) models at short time horizons in the context of forecasting the U.S. unemployment rate with limited data. Also in a "data-poor" environment (with quarterly observations from 1996 to 2010 in the training set and with 19 variables), Tiffin (2016) applies two "popular and successful" machine-learning models—Elastic Net regression and the Random Forest—to nowcast Lebanon's GDP growth, noting that these techniques are intuitively familiar to most economists, and in the particular case of Lebanese GDP, they provide plausible out-of-sample results.

Figure 2a. U.S.: PCE Inflation and House Price Growth (1992Q1 - 2021Q4, Percent)



Sources: WEO, Haver, and authors' calculations.

Figure 2b. U.S.: CPI Inflation and House Price Growth (1992Q1 - 2021Q4, Percent)



Sources: WEO, Haver, and authors' calculations.

To better understand why this is the case, one needs to dig into the mechanism through which the headline inflation captures the housing costs. There are two types of residential houses: rental houses and owner-occupied houses. In the U.S., owner-occupied housing price transmits to headline inflation via rents and owners' equivalent rents (OER). The two housing components, rent and owners' equivalent rent (OER), account for a combined weight of nearly one third in inflation measures in the CPI in the U.S. (Table 1).[6] By comparison, the housing component in the European harmonized index of consumer prices is between 10-12 percent (Gonçalves et al., 2021). The combined weight of rent and OER in PCE inflation (15.0 percent of total), however, is in line with that of the housing component in Europe's inflation.

[6] Rent is the actual rental cost currently being paid by renters residing in a renter-occupied housing unit, and OER is the implicit rent that owner-occupants would have to pay if they were renting their homes (BLS, 2009). The data on both items are collected through the CPI Housing Survey every six months, considering that rents change relatively infrequently (BLS, 2009).

Table 1. Weights of Rent and OER in Major Inflation Measures
(Percent; as of 2021Q4)

	PCE	CPI
Rent	3.6	7.5
Owners' equivalent rent	11.4	23.8
Total	15.0	31.3

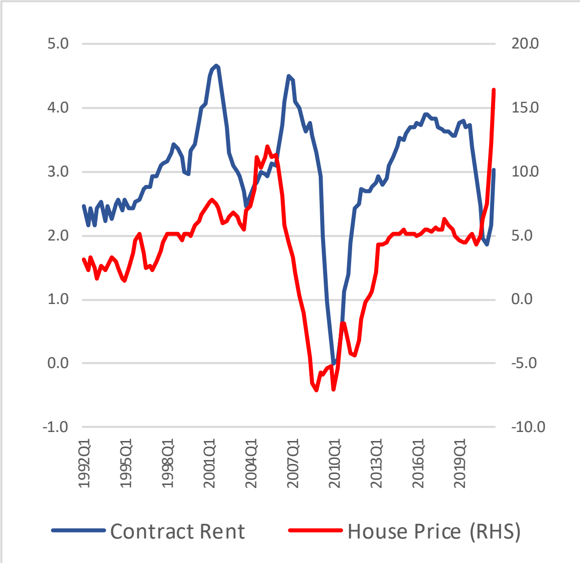
Sources: Haver and authors' calculations.

House price growth in the U.S. appears to lead the growth in the rent component of the headline inflation. The rent component that enters headline inflation measures captures current rents set in *contracts*, rather than vacant housing units' asking rents on the *market*. In the U.S., leases are typically set for a year; and even when a rental contract is up for renewal, landlords are either legally unable or are hesitant to increase rents as strongly as the market for existing renters. Hence, contract rents adjust slowly to market rents, which in turn lag house prices. This lagged response of contract rent to house price growth is shown in Figure 3a, and our paper focuses on this channel without considering general equilibrium effects of housing price growth on headline inflation (as discussed subsequently).

Moreover, house price growth also appears to lead the growth in the OER component of the headline inflation. Similar to rent, OER growth also seems to follow the house price growth with a lag (Figure 3b). This seems intuitive because the OER data are collected only every six months. As such, when house prices on the market are rising rapidly, owners tend to ask for a higher (implicit) rent, which is the definition of OER.

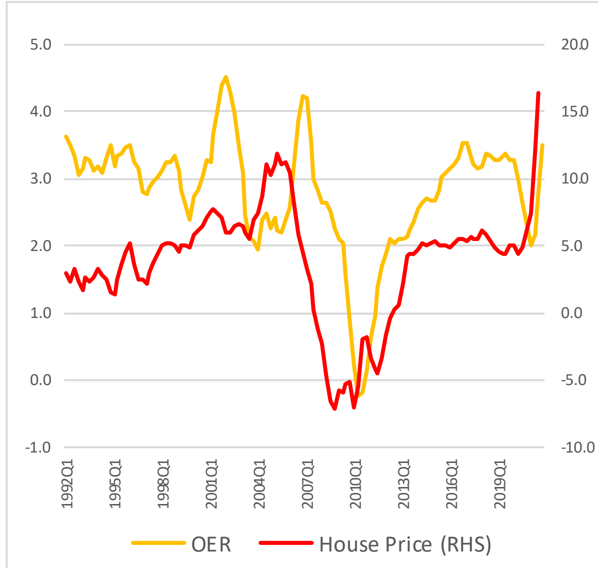
Note that these stylized facts may reflect pure correlations rather than causal relationships, although the lagged responses of rent and OER to owner-occupied housing prices seem intuitive given the way the headline inflation incorporates the housing components. Fortunately, in practice, accurately forecasting headline inflation without necessarily teasing out the causal relationships among variables is also informative and policy-relevant (and how much the housing price forecasts inflation will be picked up in the machine learning model). Therefore, in the subsequent section, we add more features in addition to housing price growth, build various models, forecast the inflation in housing components, and shed some light on their contribution to headline inflation.

Figure 3a. U.S.: Growth of House Price and Contract Rent (1992Q1 - 2021Q4, Percent)



Sources: BIS, Haver, and authors' calculations.

Figure 3b. U.S.: Growth of House Price and OER (1992Q1 - 2021Q4, Percent)



Sources: BIS, Haver, and authors' calculations.

B. Methodology and Data

Overview of Empirical Strategy

Our first goal is to explore what is a "good" way to incorporate owner-occupied housing prices into headline inflation forecasts. To this end, we apply some machine-learning models used by the literature under a similar setting (i.e., macroeconomic forecasting) to forecast the inflation in rent and OER. We then compare the forecasts with those obtained from a "traditional" model, i.e., a reduced-form VAR model. Our criterion of comparison is the out-of-sample root mean squared errors (RMSE).

Our second goal is to shed light on the direct contribution of housing components (rent and OER) to headline inflation, without considering the general equilibrium effects. To this end, we take the weighted sum of the rent inflation forecast and OER inflation forecast. We then compare it with the IMF U.S. team's WEO forecasts of the headline inflation to shed light on the quantitative importance of housing to inflation. This comparison only provides a suggestive conclusion because our results do not account for general equilibrium effects, whereas the WEO forecasts do. However, as discussed below, accounting for such effects is likely to raise the contribution of the housing price increase to headline inflation because a higher housing price could lead to higher non-housing inflation through some indirect channels. In this sense, our estimates are likely to provide a lower bound of the contribution of the housing price growth to headline inflation. Nonetheless, we still do not consider other factors such as monetary policy responses, and thus the direction of bias is unclear, which is a caveat of our analysis.

Implementation

Accordingly, our main results are based on a *two-step* machine learning-based methodology. First, we apply machine-learning models to forecast the rent inflation (i.e., the year-on-year growth of rent) and the OER inflation, respectively. Second, we take the weighted sum of the rent inflation forecast and OER inflation forecast and compare it with the WEO forecasts of the headline inflation.

Compared with conventional linear regressions, one advantage of our methodology is that it accounts for potential nonlinearity between the key macrofinancial indicators and rent inflation (OER inflation), as well as the interactions among the various macrofinancial indicators. Even though the (reduced-form) VAR approach also accounts for such nonlinearity to some extent, our methodology allows for more variables than a typical VAR model, which generally cannot include many variables due to concerns about high dimensionality (for example, the VAR model considered in Zhou and Dolmas (2021) includes three variables only). Moreover, our methodology conducts model selection based on back-testing results, which Zhou and Dolmas (2021) do not conduct. Finally, unlike panel regressions, our methodology is country-specific, which is useful for capturing the complex institutional arrangements of the housing markets that may vary substantially across countries.

The data we use for the U.S. are the publicly available quarterly data from 1982Q4 to 2021Q4, and the sources for the specific indicators are provided in Appendix Table 1. We take a forecasting horizon of two years, in line with the literature, for example, Hall (2018). A longer forecasting horizon is not used mainly due to the well-established difficulty of accurately forecasting inflation further into the future.

During the first step, we use the following variables—or "features" in machine-learning language—to forecast rent inflation and OER inflation include: (1) nominal GDP growth, capturing the state of the broad economy and the *real* sector; (2) disposable income growth, mainly capturing tax policies and *fiscal* stimulus (an important factor during economic crises); (3) M2 growth, an important driver of inflation from the *monetary* perspective; (4) the change of policy interest rate, capturing the impact of the central bank's *monetary policy*; (5) the contemporaneous year-on-year growth rate of the nominal *housing* price; (6) the lagged year-on-year growth rates of the nominal housing price, including one-quarter, two-quarter, three-quarter, four-quarter, and eight-quarter lags (reflecting the two-year forecasting horizon).[7] The selection

[7] To avoid excessive reduction of the degree of freedom, we do not include the fifth, sixth, and seventh lags.

of these variables is in line with the literature on inflation forecasting, such as Medeiros et al. (2021), although we have added the various lagged housing price growth rates to capture the potential lagged response of (rent and OER) inflation to house price developments, a pattern highlighted in the previous section of the paper.[8] In the robustness check section, we also consider some supply-side factors (such as rental vacancy rate), as well as inflation expectations.

We would like to note that even without using big data, machine-learning methods alone still have the potential to bring substantial benefits in the context of macroeconomic forecasting. For example, Coulombe et al. (2020) find that the nonlinearity associated with many machine-learning models is the true game-changer for improving the accuracy of macroeconomic predictions, which is also the case in a "data-poor environment". Their results further document clear historical situations where nonlinearity consistently helps: (i) when the level of macroeconomic uncertainty is high (consistent with Bloom, 2009); (ii) when financial conditions are tight (consistent with Adrian et al., 2019, and Beaudry et al., 2020); and (iii) during housing bubble bursts (consistent with Iacoviello, 2005, Mian and Sufi, 2009, as well as Shiller, 2014). Such findings suggest that even though the machine-learning models in our paper do not employ a large number of variables, they can still enhance the forecasting accuracy by capturing the nonlinear effects. We choose not to employ a large number of variables because we want to propose methodologies that are still applicable in the presence of limited data. In addition, since the time series is short, using a large number of variables can lead to over-fitting.

We then conduct a horse race of models to select the best-performing forecasting model. The candidate models we consider are VAR, Lasso, Elastic Net, and Random Forest models. For each of the models, we first do the time-split K-fold cross-validation and calculate RMSE for each fold. We then calculate the average RMSE and choose the hyperparameter values that produce the lowest average RMSE. And all these steps are done on the training set. See, for example, Pedregosa et al. (2011); and as Kohavi (1995) and Hastie, Tibshirani, and Friedman (2009) point out, K-fold cross-validation is a popular practice in terms of enhancing the forecasting performance of machine-learning models with limited data.

After we pin down the hyperparameters for each model class, we then conduct *back-testing* using observations in 2020Q1-2021Q4,[9] that is, we forecast the rent inflation (and OER

[8] We have the growth rate of nominal rent on the left-hand-side because it is part of the CPI inflation (which is a nominal concept). For the right-hand-side variables, we also use growth rates of nominal variables because our goal is to obtain the highest *forecasting* performance rather than to provide a *causal* interpretation. And for forecasting performance, it is more preferable to use nominal variables to forecast another nominal variable. For example, if we use the nominal GDP growth as one of the factors while forecasting the nominal rent growth, then we could better account for the unobservable or omitted nominal factors (i.e., those not included in our forecasting model) that affect nominal rent growth.

[9] Although this period coincides with the outbreak of the COVID-19 pandemic (which had important effects for housing markets in terms of construction halts, supply shortages, and perceived changes in

inflation) using the trained model, calculate the root mean squared errors (RMSE) for each model, and select the model with the lowest RMSE during the back-testing.[10] Finally, to shed light on the "absolute performance" of the best-performing model that emerges from the back-testing exercise, we also compare its performance with a "constant model" that forecasts the rent inflation (OER inflation) in 2020Q1-2021Q4 by the average rent inflation (OER inflation) in 2018Q1-2019Q4. Such a constant model represents a simple approach used by some practitioners, partially motivated by the hypothesis that inflation during a block of time periods (eight quarters in this case) broadly follows a random walk process.

During the second step, we calculate the weighted sum of the rent inflation forecast and OER inflation forecast for 2022Q1-2023Q4, using the corresponding weights of rent and OER in the headline CPI inflation in the U.S. This weighted sum is the total contribution of the rent inflation and OER inflation to the headline CPI inflation forecast. Since we do not produce the headline inflation forecast, we proxy it with the IMF U.S. team's WEO forecast for the headline CPI inflation. Despite the simplicity of this approach, it has the advantage of avoiding the potentially large error in forecasting the headline inflation itself, while still being able to shed light on the quantitative importance of the rent and OER components relative to the headline CPI inflation. Moreover, we also calculate the contributions of the actual rent inflation and actual OER inflation to the actual headline CPI inflation for 2020Q1-2021Q4; we then plot them together with the forecasted contributions for 2022Q1-2023Q4 to provide a broader context about the evolution.

We would like to note that our methodology does not account for general equilibrium effects (such as spillovers of housing to non-housing sectors), nor does it account for potential de-anchoring of inflation expectations, policy responses, and feedback from headline inflation to housing price. As such, our forecasts are subject to biases in both directions. Specifically:

- Spillovers to non-housing inflation (potentially *downward* bias). Our methodology only forecasts two components in the headline inflation rather than the headline inflation itself, thereby not capturing potential spillovers of housing inflation to the non-housing sectors. We choose to do so because headline inflation is much more complex and difficult to forecast. Moreover, some empirical studies such as Iacoviello (2010) find that for the U.S., "Movements in the price of housing are only loosely connected to movements in other prices." Still, for other countries, the headline inflation can rise more than our forecast due to

housing preferences), we still use it as our back-testing period for the following reasons: (1) Our robustness checks have already considered the supply-side factors (rental vacancy). (2) Our forecasting horizon (2022-23) is still likely to be affected by the COVID crisis, so a model that performs the best during 2020-2021 would better suit our needs. (3) Dropping the 2020-2021 data would lead to a loss of observations.

[10] For the VAR model, we use cross validation to determine the optimal lags.

the spillovers that occur through: higher home prices stimulating housing construction, which raises prices for various materials as well as labor; reduced affordability for renters or potential home buyers increases demand for higher wages; or higher home prices for home-owners make them feel wealthier and spend more money (including by allowing them to borrow more via home equity loans).

- Inflation expectations (potentially *downward* bias). Inflation can rise more rapidly than our forecast if inflation expectations are de-anchored, e.g., due to households' belief that the rising house prices are signs of more persistent and broad-based inflation. In the robustness check section, we include inflation expectations as an additional feature in inflation forecasting.
- Policy responses (potentially *upward* bias). Inflation can go down more rapidly, for instance, in case of faster-than-expected Fed tightening or the adoption of housing policies intended to rein in the rising house prices (such as rent controls and macroprudential measures).[11]
- Feedback from headline inflation to housing price (direction of bias *unclear*). On the one hand, a higher headline inflation could induce households to engage in more hedging by switching to real assets such as housing, pushing up the housing price. On the other hand, a higher headline inflation could erode households' real income and purchasing power, including the purchasing power for houses, depressing the housing price.

C. Back Testing and Model Selection

With the aforementioned caveats in mind, we now turn to the back testing and model selection for the U.S. Figure 4 plots the back-testing results, i.e., the rent inflation forecasts (year-on-year growth rates of contractual rent) in 2020Q1-2021Q4, by the four models with four lags of the housing price growth—VAR, Lasso, elastic net, and random forest, along with the true contractual rent inflation in the CPI data (black dots).[12] It is evident from the figure that the forecast by the VAR model tracks the actual data most closely and captures the recent rising trend, although it performs poorly during 2021.[13]

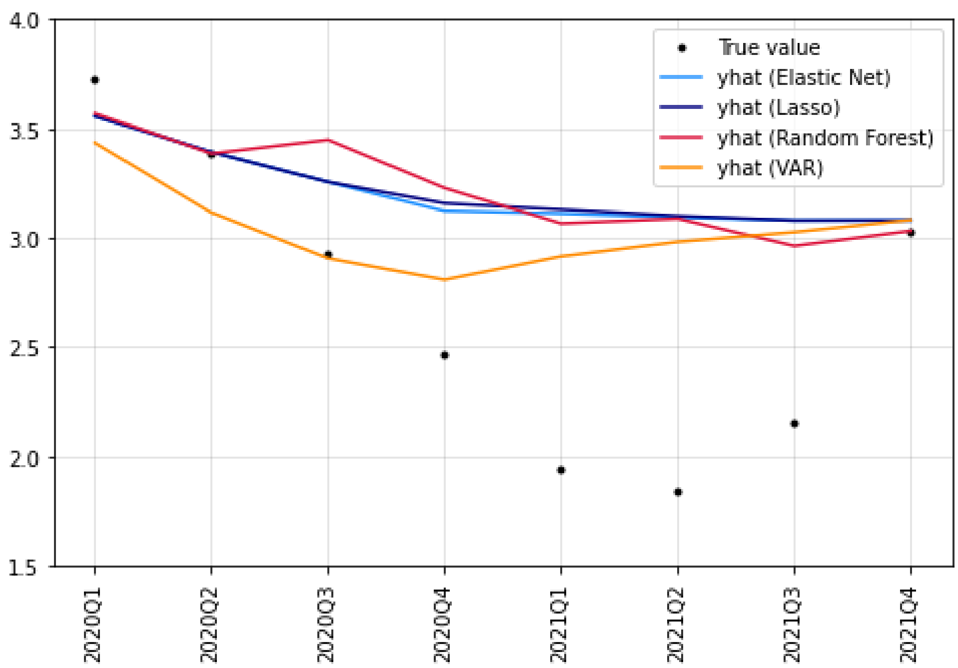
[11] While examining the risks of high housing prices to systemic financial stability is beyond the scope of this analysis, consideration of such risks may trigger policymakers to tighten macroprudential measures, lowering house prices and weakening the transmission from house prices to headline inflation.

[12] The VAR model is an exception, which allows for 1st-8th lags of housing price growth in all cases. This is because the VAR model is a dynamic model; we want to allow for longer dynamics in the VAR model by using the cross validation to determine the optimal lags (instead of constraining the maximum number of lags to 4). To save space, the forecasts of the three non-VAR models with 1st-4th and the 8th lags are not plotted in the figure, as they still underperform the VAR model (suggested by the higher RMSE in Table XX). But these forecasts are available upon request.

[13] In the robustness check subsection, the "best-performing" rent inflation forecasting model (i.e., after adding the inflation expectation and rental vacancy rate) significantly outperforms the VAR model.

A similar conclusion can be drawn from Table 2, which shows the specific numerical values of the performance measure—root mean squared errors (RMSEs)—of the various rent inflation forecasting models during the back-testing period. The second column of the table also presents the RMSEs for the models with the 1st-4th and the 8th lags of the housing price growth. As indicated by the green color, the VAR model has the lowest RMSEs (best performance) among the four models for both the 1st-4th-lag case and the case with an additional 8th lag. We would like to highlight that although Figure 4 suggests that even the best-performing VAR model does not appear to have a high fit, Table 2 shows that all the four models have much lower RMSEs than the simple constant model, i.e., they are much more accurate than the simple constant model that forecasts rent inflation in the next two years by the average of the rent two years. As such, we select the VAR model and use it to conduct the rent inflation forecasts for 2022-2023.

Figure 4. Back-Testing Results for Rent Inflation in the U.S.



Sources: Haver and authors' calculations.

Table 2. Back-Testing RMSEs for Rent Inflation in the U.S.

	1-4 Lags	1-4 & 8 Lags
Elastic Net	27.436	24.958
Lasso	27.786	25.393
Random Forest	27.601	26.976
VAR 1/	23.835	23.835
Constant Model	101.650	101.650

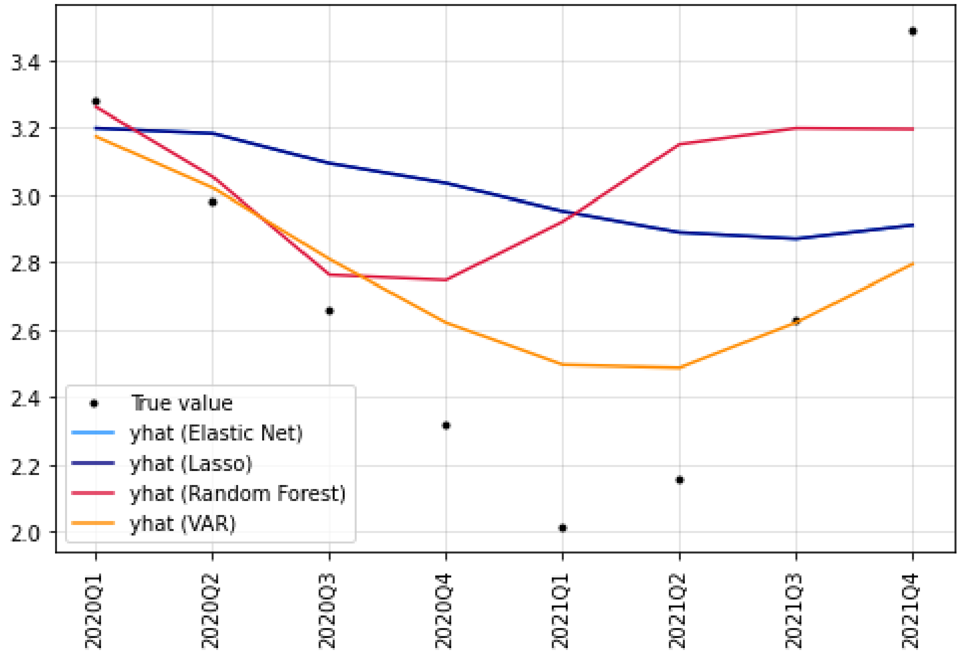
1/ Allows for 1-8 lags in all cases.

Sources: Authors' calculations.

Similarly, we conduct the back testing for the OER inflation in the U.S. It turns out that the VAR model with eight lags of the housing price growth is also the best-performing model among the four forecasting models. And this is true for both the 1st-4th-lag case (i.e., the other three non-VAR models include the 1st-4th lags of housing price growth) and the case with an additional 8th lag (i.e., the other three models include the 1st-4th and the 8th lags). Figure 5 plots the OER inflation forecasts in 2020Q1-2021Q4 by the four models with four lags of the housing price growth.[14] The figure makes it clear that the forecast by the VAR model tracks the actual OER inflation data (black dots) most closely and also captures the recent rising trend; in fact, it appears to have a better fit than the VAR model for the rent inflation (Figure 5 and Table 3). A possible explanation is that homeowners filling out the OER survey are more aware of housing price trends, although we do not test this hypothesis in the paper.

[14] The VAR model is again an exception, which allows for 1st-8th lags of housing price growth in all cases.

Figure 5. Back-Testing Results for OER Inflation in the U.S.



Sources: Haver and authors' calculations.

Table 3. Back-Testing RMSEs for OER Inflation in the U.S.

	1-4 Lags	1-4 & 8 Lags
Elastic Net	20.969	19.217
Lasso	20.968	19.225
Random Forest	21.253	24.501
VAR 1/	12.786	12.786
Constant Model	100.491	100.491

1/ Allows for 1-8 lags in all cases.

Sources: Authors' calculations.

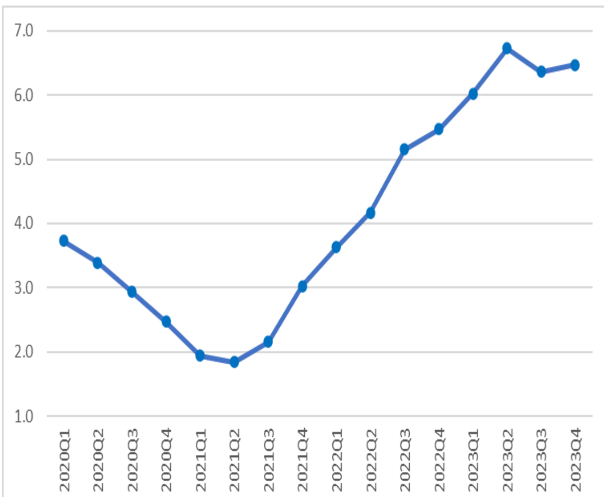
D. Forecasting Results

Using the selected forecasting models, which turn out to be VAR in both the rent inflation and OER inflation cases, we forecast the year-on-year rent inflation and OER inflation in 2022Q1-2023Q4 in the U.S., at a quarterly frequency. We then take the weighted sum to estimate the contribution of these two housing components to the headline CPI inflation.

Figure 6a plots the rent inflation forecast in the two-year-ahead horizon (2022Q1-2023Q4). According to our model, the rent inflation in the U.S. will continue its sharply rising trend that started in 2021Q3. The trend will continue until 2023Q2, reaching 6.7 percent year-on-year, after which point the rent inflation will hover around 6.5 percent in 2023Q3-Q4. It is worth mentioning that our rent inflation forecasts have a similar trend and magnitude to the IMF U.S. team's forecasts of "housing services inflation" (which combines the rent and OER inflation), despite the dramatically different approaches used by these two sets of forecasts. This suggests that the IMF U.S. team's housing services inflation forecasts have largely incorporated the lagged response of the housing costs to the growth of the sales price of housing highlighted in the stylized facts section.[15]

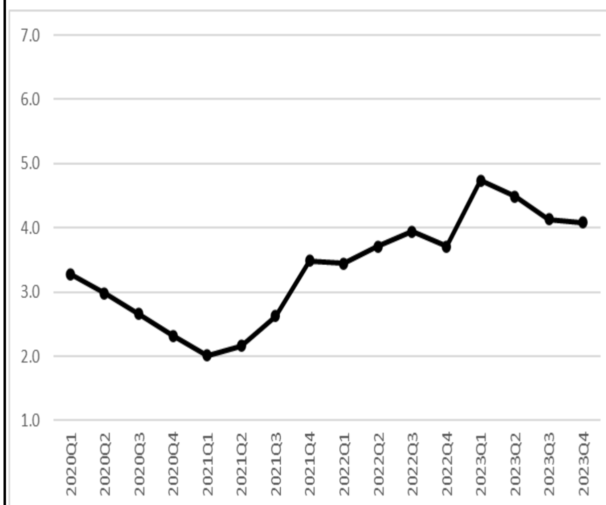
Figure 6. Model Forecasts for the U.S.
(Percent)

a. Rent Inflation



Note: 2020Q1-2021Q4 values are actual data.
Sources: Haver and authors' calculations.

b. OER Inflation



Note: 2020Q1-2021Q4 values are actual data.
Sources: Haver and authors' calculations.

Figure 6b plots the OER inflation forecast in 2022Q1-2023Q4. According to our model, the OER inflation in the U.S. will continue its rising trend that started in 2021Q2. The trend will continue until 2023Q1, reaching 4.7 percent year-on-year, after which point the rent inflation will drop over time to 4.1 percent in 2023Q4. Our OER inflation forecasts have a similar trend to the IMF U.S. team's forecasts of "housing services inflation" (which combines the rent and OER inflation), although our forecasts are somewhat lower than theirs, most likely driven by the different forecasting models and variables involved.

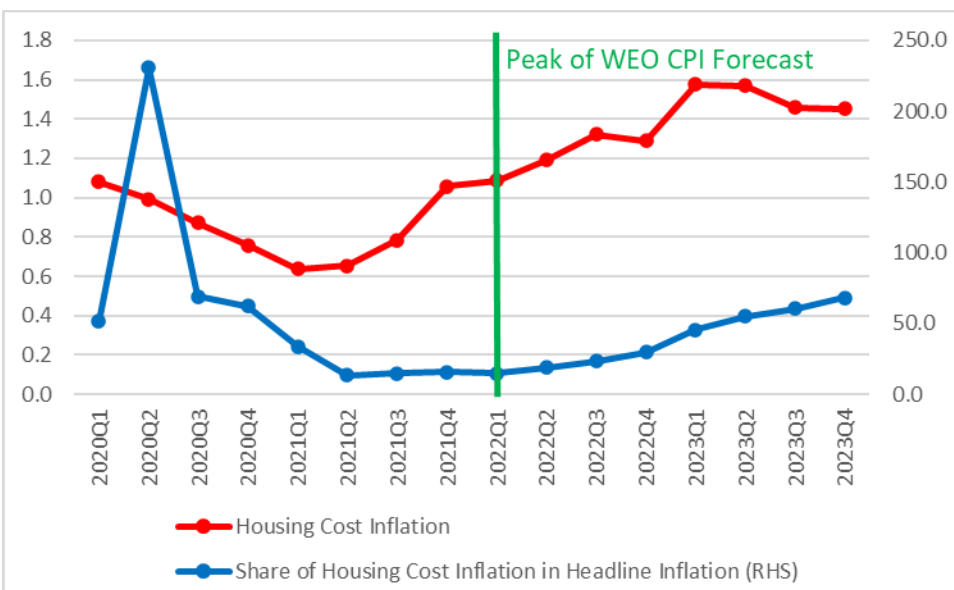
We multiply our rent inflation forecast and the OER inflation forecast by their respective weights in the headline CPI to obtain the weighted housing cost inflation. We then divide the

[15] To mitigate the impact of other exogenous factors on inflation forecasts, this comparison is made using the IMF US team's forecasts before the war in Ukraine broke out.

weighted housing cost inflation by the absolute value of the headline CPI inflation to measure the contribution of the housing cost components to the CPI inflation. Figure 7 plots the forecast of the weighted housing cost inflation (left axis), along with its contribution to the headline CPI inflation forecast by the IMF's U.S. team (right axis), from 2020Q1 to 2023Q4. It shows that inflation of housing cost components would peak in 2023Q1, one year *after* the expected peak (the green vertical line) of headline CPI inflation by the IMF U.S. team (as in their February 2022 WEO submission before the war in Ukraine broke out).

Moreover, the figure shows that this contribution reached 231 percent in 2020Q2 and 69 percent in 2020Q3. Note that a contribution of higher than 100 percent indicates that although the non-housing components in 2020Q2 experienced deflation, the housing components continued to experience inflation that more than offset the deflationary pressure and drove the overall headline CPI inflation positive. In addition, we would like to highlight that these high ratios in 2020 and 2021 are based on calculations from the actual observed data, rather than our forecasts. The share of housing cost inflation in the headline CPI then dropped starting in 2020Q3, mostly reflecting the emerging inflationary pressures on the headline CPI from the non-housing sectors (particularly due to supply disruptions). However, our forecasts suggest that the share would rise again in 2022Q2 and reach 68 percent in 2023Q4, which is *more than double* the 31 percent weight of the housing costs in CPI.

Figure 7. US: Housing Cost Inflation and Contribution to Headline CPI
(Percent)



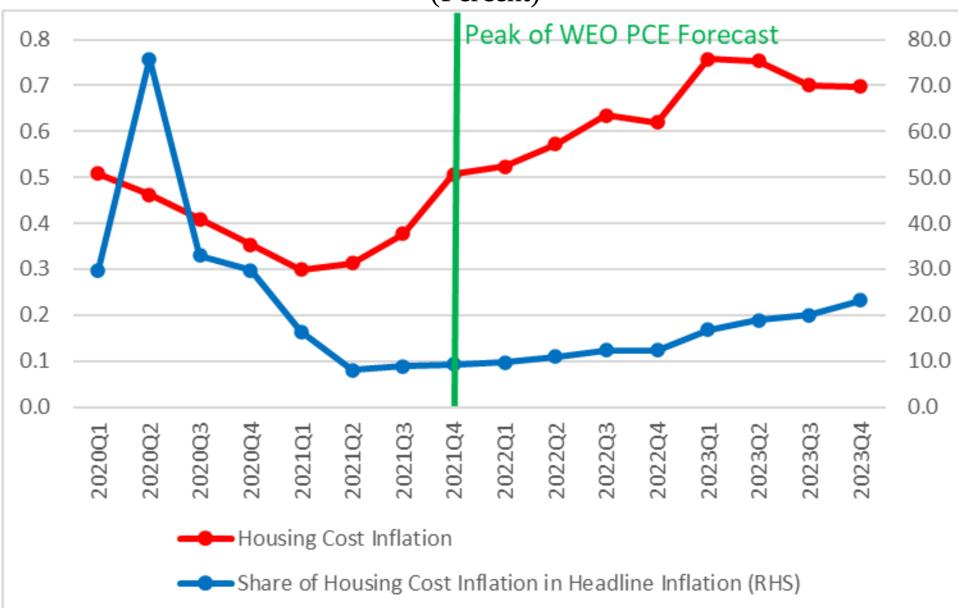
Note: 2020Q1-2021Q4 values are actual data.

Sources: WEO, Haver, and authors' calculations.

Given that the Fed targets the PCE inflation rather than the CPI inflation, we also calculate the weighted housing cost inflation using the weights of rent and OER in PCE. Figures 8 plots the evolution of this weighted housing cost inflation and its contribution to the U.S. headline PCE inflation forecast by the IMF's U.S. team, respectively. The patterns are very similar to the CPI case: the inflation of housing cost components would peak in 2023Q1, five quarters *after* the peak of headline PCE inflation expected by IMF's U.S. team in late February 2022; the share of the weighted housing cost inflation in headline PCE inflation reached 76 percent in 2020Q2 and 33 percent in 2020Q3, dropped afterward, but will keep rising to 23 percent in 2023Q4, which is also significantly higher than the 15 percent weight of the housing costs in PCE.

Figure 8. U.S.: Housing Cost Inflation and Contribution to Headline PCE

(Percent)



Note: 2020Q1-2021Q4 values are actual data.

Sources: WEO, Haver, and authors' calculations.

These results suggest that inflationary pressure from the rising housing price (and the rising rent/OER) could continue build for several more quarters, as reflected by the rising rent and OER inflation. This, in turn, would make the headline CPI inflation persistent, complicating monetary policymaking.

E. Robustness Checks

In this subsection, we conduct robustness checks by incorporating inflation expectation and rental vacancy rate into our forecasting models for the U.S.[16] The first variable captures the forward-looking behavior of landlords and tenants while determining the rents and OERs, as a higher inflation expectation would lead to higher rent and OER, all else being equal. The second variable captures the tightness in the rental market and the supply-side condition, as a lower rental vacancy rate would also lead to higher rent and OER, all else being equal. Note that we use the *rental* vacancy rate not only in the forecasting models for rent inflation but also in those for OER inflation. This is because a tighter rental market is likely to affect the implicit rent that homeowners would pay to themselves, which is the definition of OER.[17] Data on inflation expectation are from Consensus Forecast (starting from 1993Q1), and data on rental vacancy rate are from Haver (starting from 1970Q1).

The back-testing performance for the robustness checks is presented in Table 4. As before, the number in red indicates the best performance for each column. Based on these performance measures, we select the Elastic Net model with the 1st-4th and the 8th lags of housing price growth to forecast both the rent inflation and the OER inflation. Note that the "best-performing" *rent* inflation forecasting model in the robustness checks (i.e., after adding the inflation expectation and rental vacancy rate) has a slightly *higher* performance than that in the main model (i.e., without these two extra variables; see Table 4a vs. Table 2); however, the "best-performing" *OER* inflation forecasting model in the robustness checks has a *lower* performance than that in the main model (see Table 4b vs. Table 3).[18] But in both cases, the machine-learning models significantly outperform the VAR models.

[16] The IMF US team has also considered these two factors in their housing cost inflation forecasting, although using a different forecasting model.

[17] As for forecasting the OOHC growth, one should ideally also include the vacancy rate for *owner-occupied* houses as well. However, this data is not readily available for the countries we cover. But given that we have also controlled for the housing price itself while forecasting the OOHC growth, the impact of the *owner-occupied* house vacancy rate on the OOHC may be largely captured by the housing price.

[18] Note that the performance presented here is for the back-testing. For the performance on the training set, the model with more variables still outperforms that with fewer variables. However, for the purpose of improving forecasting accuracy, back-testing performance should be relied on.

Table 4. Back-Testing RMSEs for the U.S.: Robustness Checks

a. Rent Inflation

	1-4 Lags	1-4 & 8 Lags
Elastic Net	30.933	23.689
Lasso	30.732	23.700
Random Forest	28.533	30.076
VAR 1/	41.756	41.756
Constant Model	101.746	101.736

1/ Allows for 1-8 lags in all cases.

b. OER Inflation

	1-4 Lags	1-4 & 8 Lags
Elastic Net	18.397	15.800
Lasso	18.388	15.862
Random Forest	19.221	19.351
VAR 1/	21.604	21.604
Constant Model	100.686	100.697

1/ Allows for 1-8 lags in all cases.

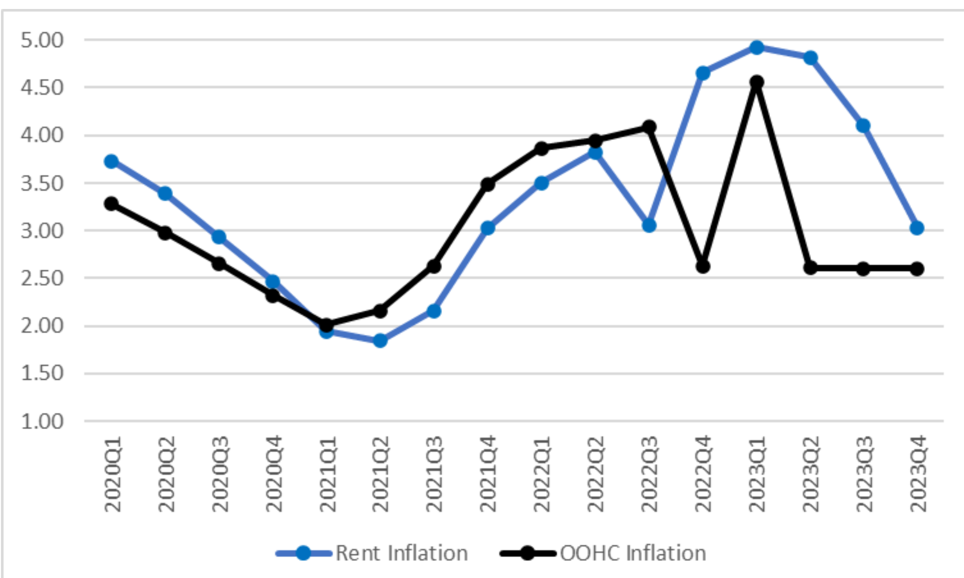
Sources: Authors' calculations.

Interestingly, after considering these two additional variables, our forecasts of the rent growth rates and OER growth rates (Figure 9) are lower than those without them. The forecasting models themselves do not shed light on why this is the case, as these results are also obtained with the best-performing machine-learning models that significantly outperform the benchmark of a constant forecasting model (Table 4).

Nonetheless, the weighted housing cost inflation displays the same pattern as before: it would peak after the expected peak of the headline CPI inflation in the WEO forecasts, and its contribution to the headline CPI would keep rising in the medium term to a share that is significantly larger than the housing weights in the headline (Figure 10). This is also the case for the headline PCE inflation (Figure 11).

Figure 9. Forecasts of Rent Inflation and OER Inflation in the U.S.: Robustness Checks

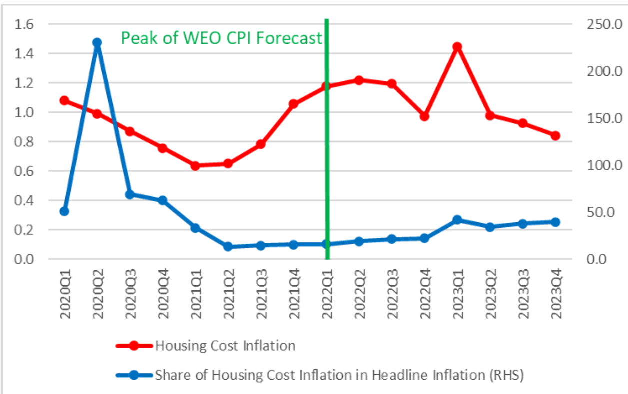
(Percent)



Note: 2020Q1-2021Q4 values are actual data.

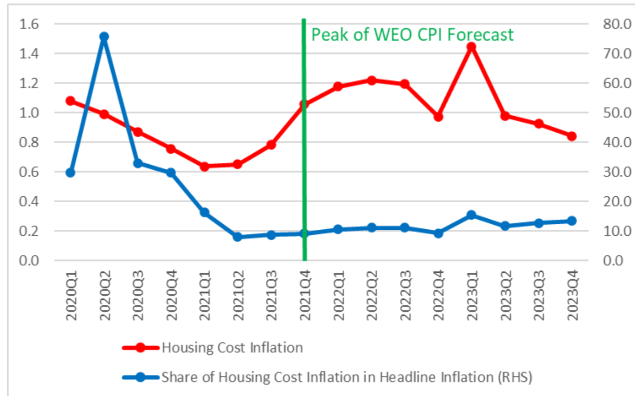
Sources: Haver and authors' calculations.

Figure 10. U.S.: Housing Cost Inflation and Contribution to CPI (Robustness check) (Percent)



Sources: WEO, Haver, and authors' calculations.

Figure 11. U.S.: Housing Cost Inflation and Contribution to PCE (Robustness check) (Percent)



Sources: WEO, Haver, and authors' calculations.

IV. Other Selected Countries

A. Stylized Facts

We now turn to some other countries. To this end, it is necessary to provide more institutional background on the construction of housing-related inflation and how it is reflected in the CPI inflation. As discussed earlier, the housing components of the headline CPI typically consist of renters' housing costs and owner-occupied housing costs (OOHC) in most countries. Whereas the former is usually measured by the actual rents in the rental contracts, the latter is less straightforward, and its estimation approaches differ across countries. In the U.S., this is estimated by the owners' equivalence rent, an approach used by Mexico and Sweden as well. However, some other countries apply the "user cost approach" by summing up the recurring actual costs (such as home insurance, maintenance, property taxes, and mortgage interest payments) and estimated depreciation costs. This applies to Canada and the U.K. in our sample.[19] Finally, there are also countries, like Korea and Luxembourg in our sample, that use only "actual rentals for housing" and do not include the owner-occupied housing costs when calculating the

[19] Iceland: Selected Issues; IMF Country Report No. 18/319. Besides the rental equivalence and user cost approaches, another common approach for estimating the OOHC is the acquisitions approach. This approach covers the cost of purchasing and owning a dwelling, including renovations, home insurance, maintenance, and transfer costs. None of the countries in our sample use this approach. In addition, the approach used by Brazil is unclear based on the CPI decomposition data in Haver, so we use the country's condo costs (one relatively large item in its CPI) to proxy its OOHC.

CPI. Note that following the Strategy Review completed in July 2021, ECB decided to incorporate owner-occupied house prices into its Harmonized Consumer Price Index (HCPI) through a multi-year project (link).[20]

Table 5 summarizes the OOHC estimation approaches and the weights of rent/OOHC in the headline CPI. As shown in the Table, the combined weight for the two housing components (rent and OOHC) is the highest in the U.S., close to one third. This is followed by the U.K., Canada, and Iceland, with a combined weight of 27.9, 26.3, and 20.4 percent, respectively. The other countries in our sample have lower weights, with Sweden, Mexico, and Korea in the range of 10-15 percent, and Luxembourg and Brazil in the range of 4-7 percent.

Table 5. OOHC Estimation Approaches and Weights in Headline CPI 1/

Country	OOHC estimation approach	OOHC weight in CPI	Rent weight in CPI	Total weight in CPI
Brazil	Unclear; proxied by condo cost	1.6	3.6	5.2
Canada	User cost	19.7	6.5	26.2
Iceland	User cost	16.0	4.4	20.4
Korea	N.A. (OOHC not included) 2/	0.0	9.8	9.8
Luxembourg	N.A. (OOHC not included) 3/	0.0	6.7	6.7
Mexico	Rental equivalence	12.0	2.2	14.2
Sweden	Modified user cost 4/	6.9	7.3	14.2
U.K. 5/	User cost	18.5	9.4	27.9
U.S.	Rental equivalence	23.8	7.5	31.3

1/ All weights are as of 2021Q4.
2/ Although maintenance cost is included in Korea's headline CPI, we exclude it from the OOHC following the *CPI and Housing in Advanced Inflation Targeting Economies* Table in IMF Country Report No. 18/319.
3/ The weights are for the CPI rather than the harmonized consumer price index (HCPI).
4/ Since 2017, Sweden has made adjustments to address conceptual issues with the user-cost approach: the impact of mortgage rates is removed, and the house price series is smoothed with a 30-year moving average to deliver a modified inflation index (the CPIF) (Iceland: Selected Issues; IMF Country Report No. 18/319).
5/ In March 2017, the CPIH became the headline measure of inflation in the U.K. The CPIH is a measure of CPI that includes a measure of owner occupiers' housing costs.
Source: Haver and authors' calculations.

Like in the U.S. case, house price growth in the U.K. also appears to lead the growth in the rent component of the headline inflation, which is also the contract rent currently paid by tenants. For example, during the GFC, the rent growth rate fell sharply in 2008Q3, four quarters

[20] The Governor of Central Bank of Luxembourg Governor also noted that "while the HICP remains the appropriate price measure for monetary policy purposes, there is scope and need for further improvement, in particular in the coverage of housing expenditures." (November 2021; link)

after the significant deceleration in house price growth in 2007Q3; the house price growth also recovered earlier than the rent price growth. During the recent COVID-19 crisis, the rent growth rate started its acceleration in 2021Q4, five quarters after the acceleration in house price growth in 2020Q3. This lagged response of contract rent to house price growth is shown in Figure 12a. The OOHC growth rate in the U.K. appears to lag the house price growth as well, particularly during the GFC and the COVID-19 crisis, as shown in Figure 12b. These lagged responses are summarized in Table 6. Partially reflecting the lagged responses of the rent and OOHC components, the headline CPI inflation (the one that includes a measure of owner occupiers' housing costs) also displays a lagged response to the house price growth (Figure 12c).

As shown in Table 6 and Figures 13-15, a similar pattern appears to exist for Canada, Iceland, and Korea: both the rent growth and the OOHC growth tend to react a few quarters after the change in the house price growth rate, a pattern that is most evident during the GFC and the COVID-19 crises. It is also interesting that the OOHC appears to react sooner than the rent during the GFC and the COVID-19 crises, probably because the construction of the OOHC implies that it is more flexible than (say, one-year) rental contracts in terms of responding to house price movements. Note that for Korea, the OOHC results are not available because the OOHC is not included in the country's headline CPI.

For the other four countries covered by our machine learning analyses (Mexico, Brazil, Sweden, and Luxembourg), we also find that contract rent growth, OOHC growth (if available), and headline CPI inflation lag house price growth (Appendix Figures 1-4).[21] However, the pattern appears less clear than the five countries discussed above, possibly due to some data issues and country-specific institutional details. Nonetheless, given that these are presented as stylized facts rather than causal analysis, they may not substantially affect the main conclusions presented below.

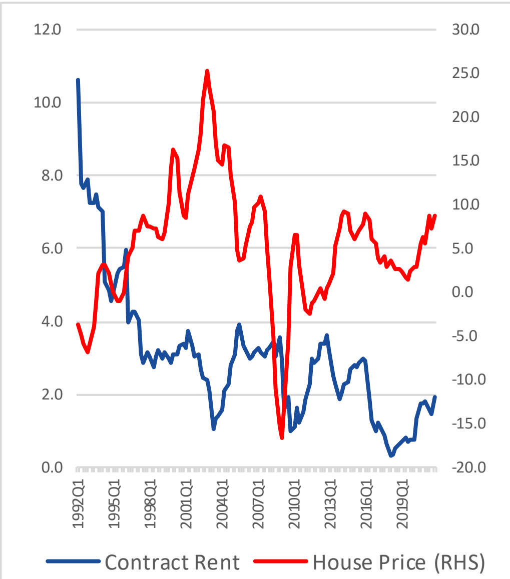
Table 6. Lagged Responses of Rent and OOHC to House Price Inflation

Country	**GFC *(Deceleration)***			**COVID *(Acceleration)***		
	Starting time of house price deceleration	Lag of rent deceleration	Lag of OOHC deceleration	Starting time of house price acceleration	Lag of rent acceleration	Lag of OOHC acceleration
Canada	2007Q2	4 quarters	4 quarters	2020Q2	4 quarters	2 quarters
Iceland	2008Q2	4 quarters	0 quarters 1/	2020Q2	6 quarters 2/	3 quarters
Korea	2007Q2	2 quarters	N.A.	2020Q2	1 quarter	N.A.
U.K.	2007Q3	4 quarters	4 quarters	2020Q3	5 quarters	2 quarters
U.S.	2006Q1	5 quarters	4 quarters	2020Q3	4 quarters	3 quarters

1/ The zero lag is most likely because Iceland calculates the OOHC directly from the house price (IMF Country Report 18/319).
2/ Excluding the temporary increases in 2020Q4 and 2021Q1.
Source: BIS, Haver, and authors' calculations.

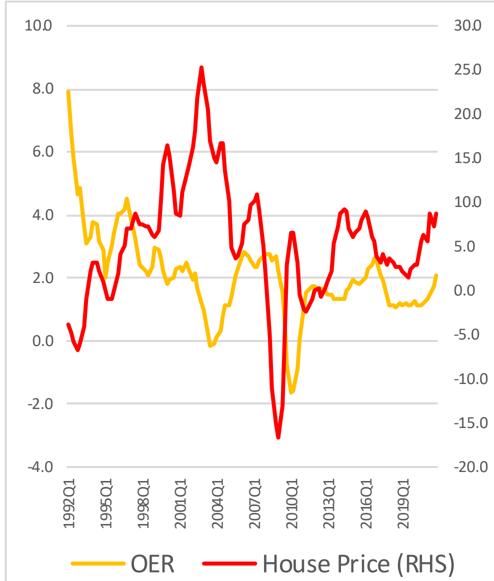
[21] Note that Luxembourg's authorities have frozen the rent during the pandemic and extended the freeze in response to inflationary pressures and rising housing affordability concerns.

Figure 12a. U.K.: Growth of House Price and Rent (1992Q1 – 2021Q4, Percent)



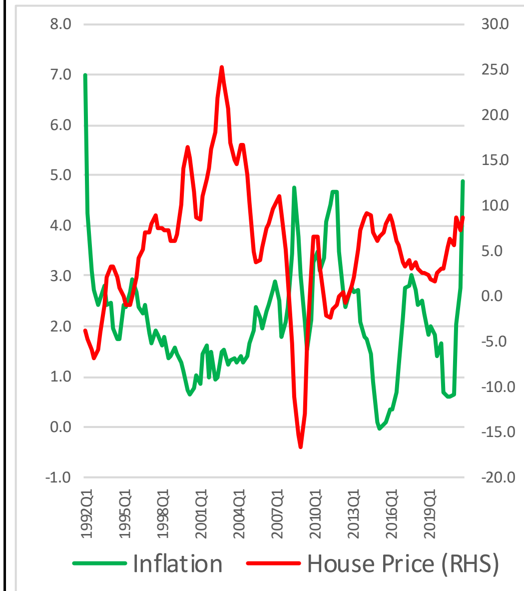
Sources: BIS, Haver, and authors' calculations.

Figure 12b. U.K.: Growth of House Price and OER (1992Q1 - 2021Q4, Percent)



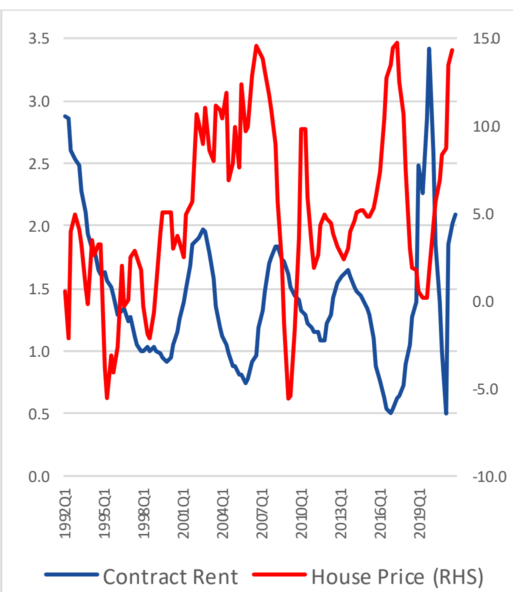
Sources: BIS, Haver, and authors' calculations.

Figure 12c. U.K.: CPI Inflation and House Price Growth (1992Q1 - 2021Q4, Percent)



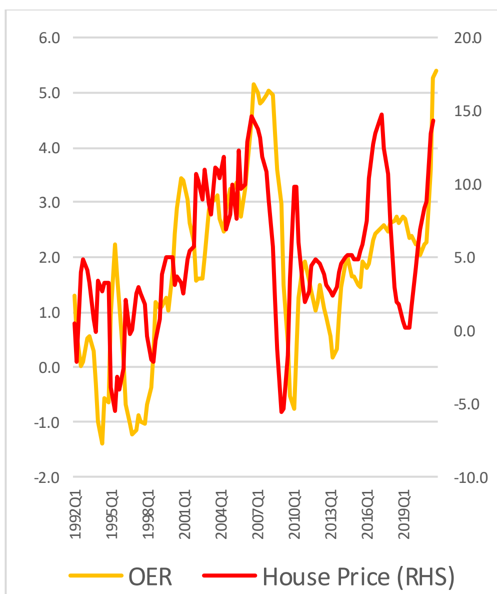
Sources: WEO, BIS, and authors' calculations

Figure 13a. Canada: Growth of House Price and Rent (1992Q1 - 2021Q4, Percent)



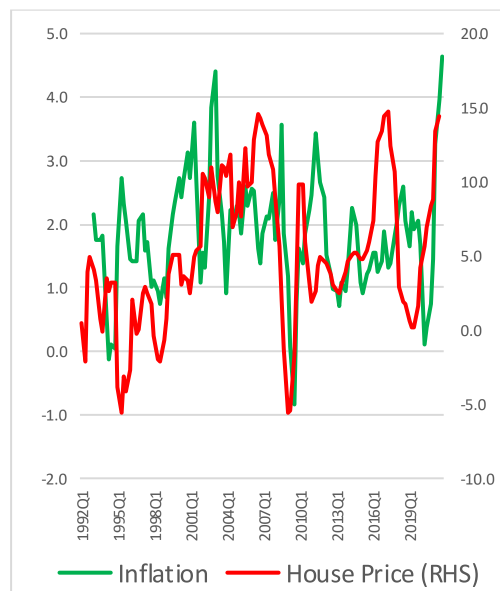
Sources: BIS, Haver, and authors' calculations.

Figure 13b. Canada: Growth of House Price and OER (1992Q1 - 2021Q4, Percent)



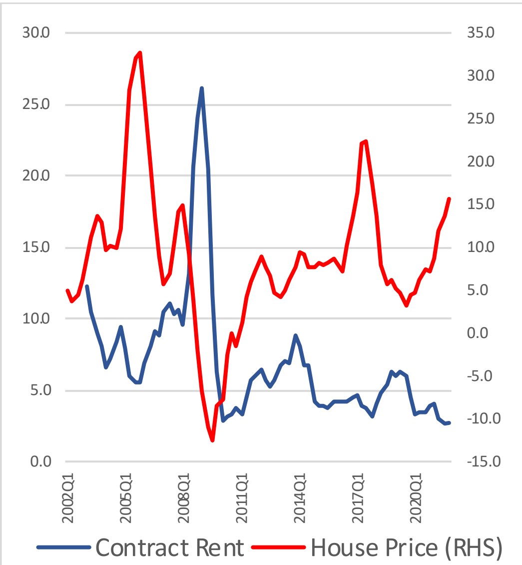
Sources: BIS, Haver, and authors' calculations.

Figure 13c. Canada: CPI Inflation and House Price Growth (1992Q1 - 2021Q4, Percent)



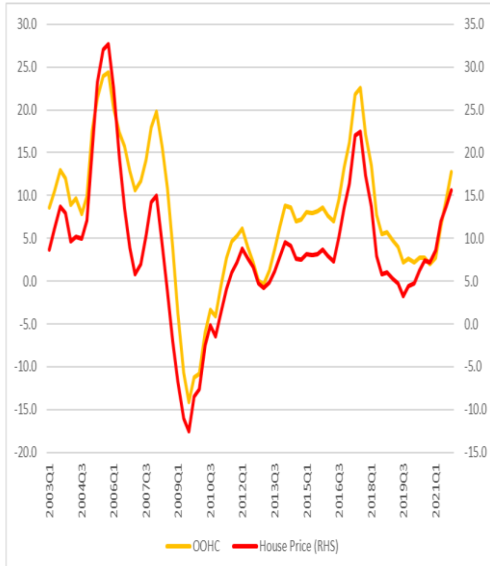
Sources: WEO, BIS, and authors' calculations.

Figure 14a. Iceland: Growth of House Price and Rent (2002Q1 - 2021Q4, Percent)



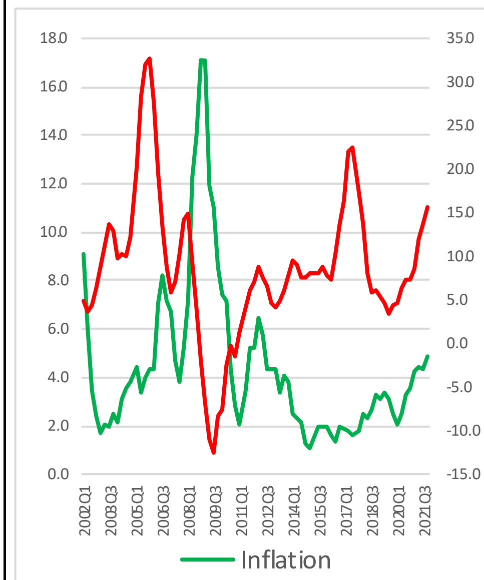
Sources: BIS, Haver, and authors' calculations.

Figure 14b. Iceland: Growth of House Price and OER (2003Q1 - 2021Q4, Percent)



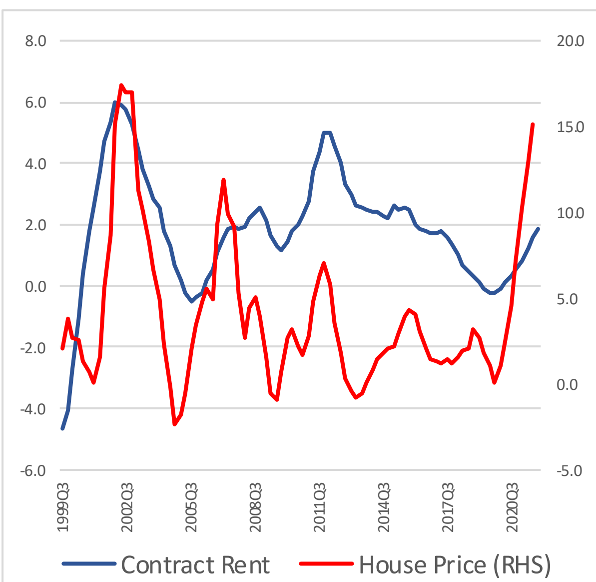
Sources: BIS, Haver, and authors' calculations.

Figure 14c. Iceland: CPI Inflation and House Price Growth (2002Q1 - 2021Q4, Percent)



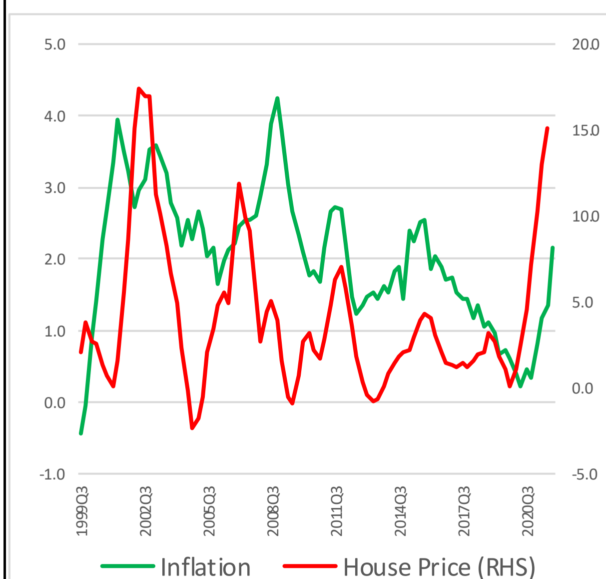
Sources: WEO, BIS, and authors' calculations.

Figure 15a. Korea: Growth of House Price and Rent (1999Q3 - 2021Q3, Percent)



Sources: BIS, Haver, and authors' calculations.

Figure 15b. Korea: CPI Inflation and House Price Growth (1999Q3 - 2021Q3, Percent)



Sources: WEO, BIS, and authors' calculations.

B. Methodology and Data

Like the U.S. case, our main results for the other countries are also based on the two-step machine learning-based methodology explained above – first applying machine-learning models to forecast the rent inflation and the inflation in owner-occupied housing costs, and then calculating the weighted sum of these two components and comparing with the WEO forecasts of the headline inflation. Such a two-step procedure does not account for general equilibrium effects, such as spillovers of housing to non-housing inflation, de-anchoring of inflation expectations, policy responses, and feedback from headline inflation to housing price, although it is unclear how these effects would alter the sign of our inflation forecast (as discussed in the U.S. section).

Our country coverage is confined by the availability of key indicators at the quarterly frequency. Machine learning models also require longer time series to have a larger training dataset and yield less biased results. Despite these data challenges, we manage to construct a quarterly database for eight countries (besides the U.S.) covering both advanced economies and emerging market economies across North America, Latin America, Europe, and Asia. These include Brazil, Canada, Iceland, Korea, Luxembourg, Mexico, Sweden, and the U.K. The starting time for each country varies based on data availability (see Table 7).

Table 7. Time Horizon Coverage

Country	Main Model: Rent	Main Model: OOHC
Brazil	2006Q3-2021Q4	2006Q3-2021Q4
Canada	1981Q1-2021Q4	1981Q1-2021Q4
Iceland	2002Q1-2021Q4	2003Q1-2021Q4
Korea	1999Q3-2021Q4	N.A.
Luxembourg	1999Q1-2021Q4	N.A.
Mexico	2005Q1-2021Q4	2005Q1-2021Q4
Sweden	2005Q1-2021Q4	1998Q1-2021Q4
U.K.	1988Q1-2021Q4	1988Q1-2021Q4
U.S.	1982Q4-2021Q4	1983Q1-2021Q4

Source: Haver and authors' calculations.

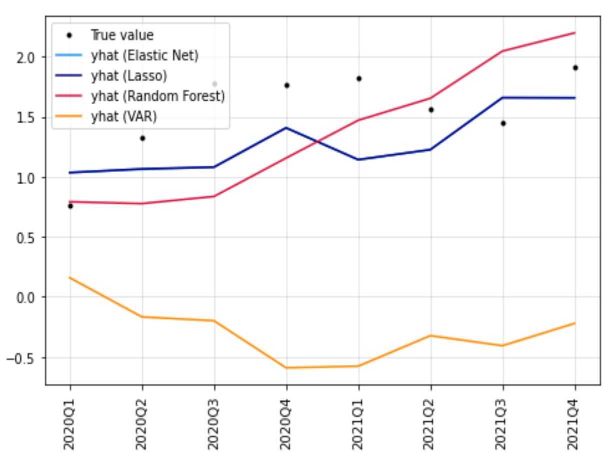
The house price data come from BIS. We use the nominal residential property prices of all new and existing dwellings in the whole country when feasible, and in urban areas/major cities if nationwide data is not available. Data on other variables, including GDP, household disposable income, M2, and monetary policy rate, are from publicly available sources (Appendix Table 1).

C. Back Testing and Model Selection

As in the U.S. case, we conduct the back testing for the various rent forecasting models and OOHC forecasting models. Figures 16a-b present the fit of each model for rent forecasting and OOHC forecasting, respectively. And Tables 7a-b present the specific RMSEs for all models. It is worth noting that, unlike the U.S. case, the best-performing models for the U.K. are machine-learning models: Lasso model with 1st-4th and the 8th lags for rent forecasting, and Random Forecast model with 1st-4th lags for OOHC forecasting. In both cases, the machine-learning models significantly outperform the VAR and constant models. In particular, in the rent forecasting case, the best-performing Lasso model has an RMSE of 27, in contrast to the VAR model's RMSE of 124.

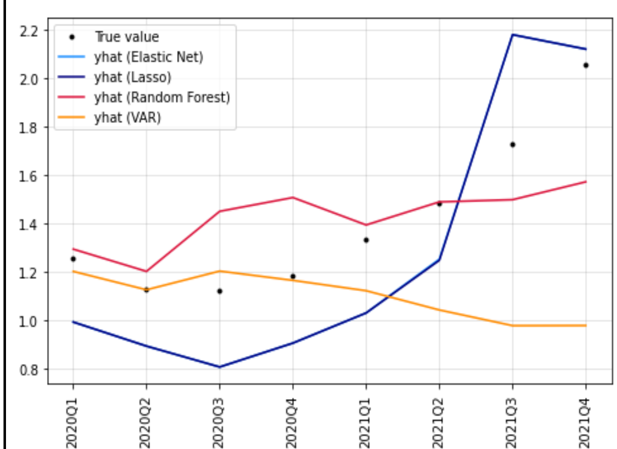
The best-performing models for other countries are summarized in Table 9. As shown in the table, *all* of the eight selected models are machine-learning models in the rent forecasting case, and *all* of the six selected models are machine-learning models in the OOHC forecasting case (the other two countries do not have OOHC included in their headline inflation). These results are consistent with the findings in the literature that machine-learning forecasting models have the advantages of, e.g., capturing nonlinear effects and can often outperform traditional models. Of course, given that our back-testing period (2020Q1-2021Q4) overlaps with the ongoing COVID-19 crisis, which may have had some unique impact on the housing markets compared with the past, one should not over-emphasize the importance of the back-testing performance.

Figure 16a. Back-Testing Results for Rent Inflation in the U.K. (Percent)



Sources: Haver and authors' calculations.

Figure 16b. Back-Testing Results for OOHC Inflation in the U.K. (Percent)



Sources: Haver and authors' calculations.

Table 8. Back-Testing Results for Rent Inflation in the U.K.

a. Rent Model Performance: Forecast RMSE

	1-4 Lags	1-4 & 8 Lags
Elastic Net	35.587	27.405
Lasso	35.601	27.397
Random Forest	33.901	33.983
VAR 1/	123.877	123.877
Constant Model	100.271	

1/ Allows for 1-8 lags in all cases.

Sources: Haver and authors' calculations.

b. OOHC Model Performance: Forecast RMSE

	1-4 Lags	1-4 & 8 Lags
Elastic Net	20.335	25.299
Lasso	20.370	25.299
Random Forest	20.047	17.766
VAR 1/	35.264	35.264
Constant Model	100.498	100.498

1/ Allows for 1-8 lags in all cases.

Sources: Haver and authors' calculations.

Table 9: Selected Models for Non-U.S. Countries

Country	Rent	OOHC
U.K.	Lasso (1-4 & 8 lags)	Random Forest (1-4 lags)
Canada	Elastic Net (1-4 lags)	Elastic Net (1-4 lags)
Iceland	Random Forest (1-4 lags)	Elastic Net (1-4 lags)
Korea	Random Forest (1-4 lags)	N.A.
Mexico	Elastic Net (1-4 lags)	Elastic Net (1-4 lags)
Brazil	Random Forest (1-4 & 8 lags)	Lasso (1-4 & 8 lags)
Sweden	Random Forest (1-4 & 8 lags)	Lasso (1-4 & 8 lags)
Luxembourg	Random Forest (1-4 lags)	N.A.

Source: Authors' calculations.

D. Forecasting Results

With the selected best-performing models, we then forecast the rent inflation over 2022Q1-2023Q4 (and OOHC inflation, if applicable). The results are similar to those in the U.S. case.

For the U.K. (Figure 17), inflation of housing components would peak in 2023Q1, three quarters *after* the expected peak (the green vertical line) of headline CPI inflation forecasts by the IMF's U.K. team in its January 2022 WEO submission. In addition, the contribution of the inflation of housing components to headline CPI inflation reached 67 percent in 2021Q1, which was *more than double* the 28 percent housing weight in CPI. It then dropped during the pandemic, and our forecasting results suggest that it will keep rising to 42 percent in 2023Q4, also significantly higher than the 28 percent weight in CPI. Note that to mitigate the impact of other exogenous factors on inflation forecasts, we use the WEO forecasts (as of January 2022) before the war in Ukraine broke out. This is the case for all countries analyzed in our paper.

For Canada (Figure 18), inflation of housing components would peak one quarter after the expected peak (the green vertical line) of headline CPI inflation in WEO. In addition, the contribution of the inflation of housing components to headline CPI inflation reached 404 percent in 2020Q2 and 110 percent in 2020Q3, much higher than the 26 percent housing weight in CPI. It then dropped during the pandemic, and our forecasting results suggest that it will rise to 50 percent in 2023Q2 before dropping, still about double the 26 percent weight in CPI.

For Iceland, as shown in Figure 19, the lagged response and the importance of housing cost inflation are even clearer: inflation of housing components would not peak until in 2023Q3, six quarters after the expected peak (the green vertical line) of headline CPI inflation in WEO. In addition, the contribution of the inflation of housing components to headline CPI inflation reached 244 percent in 2021Q3, that is, the inflation of housing components in the CPI (the weighted sum of rent and OOHC) still continued to accelerate in 2021Q3 even when the headline CPI inflation dramatically decelerated (from 2.4 percent in 2021Q2 to 0.7 percent in 2021Q3, not shown in Figure 19). The share of rent inflation dropped subsequently. However, our forecasting results suggest that it will eventually rise to about 150 percent in 2023Q4; that is, the acceleration in the inflation of housing components are projected to more than offset the deceleration in the non-housing inflation.

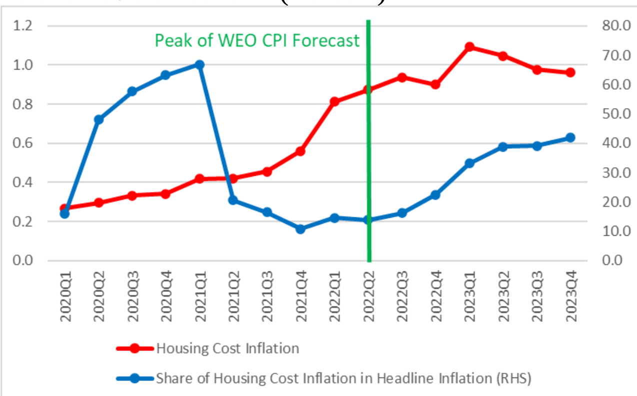
For Korea, only the rent component is considered because the OOHC does not enter the country's headline CPI calculation (based on the classification in IMF Country Report No. 18/319). As shown in Figure 20, inflation of rent in Korea would not peak until in 2022Q4, four quarters after the expected peak (the green vertical line) of headline CPI inflation in WEO. In addition, the contribution of the rent inflation to headline CPI inflation reached 44 percent in 2020Q2 and 12 percent in 2022Q4, both higher than the 9.4 percent housing weight in CPI. Like in other countries, the share of rent inflation in Korea then dropped during the pandemic, and our forecasting results suggest that it will keep rising to 13.6 percent in 2023Q4, exceeding the housing weight in CPI (which has become 9.8 percent since 2021Q1).

The forecasting results for the other four countries – Mexico, Brazil, Sweden, and Luxembourg – are presented in Appendix Figures 5-8. The patterns are similar: inflation of housing components would peak in 2022-2023 after the expected peak of headline CPI inflation in WEO; and the contribution of the inflation of housing components to headline CPI inflation dropped from a high level during the pandemic and will rise again during 2022-2023.[22] Note that

[22] As noted in the Eurostat methodological note issued in December 2020 (link), "the HICP weights used in 2020 were updated at the beginning of the year and they are kept constant throughout the year… As such, the weights used in 2020 do not reflect any impact of the COVID-19 crisis." And the methodological note explains how to reflect any impact of the COVID-19 crisis in the weights used in 2021's HICP. However, it turns out that for many countries (such as the U.K. and Luxembourg), the rent weights used by statistical agencies in 2021 were higher than those in 2020, suggesting that rental expenditures in these countries during the COVID accounted for a higher share in consumers' baskets

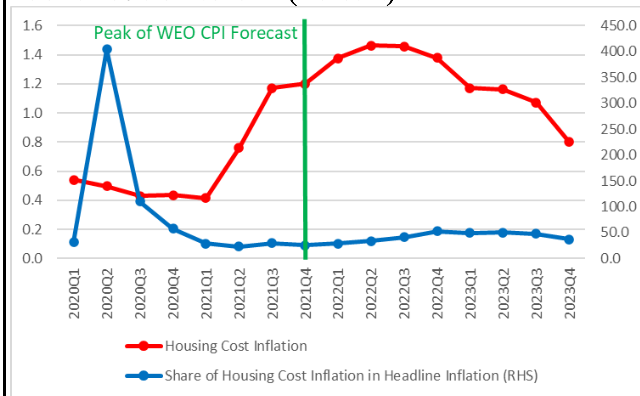
after 2023Q2, the results for Brazil are counter-intuitive and become negative, likely due to the smaller sample. However, the country still broadly follows the patterns described above.

Figure 17. U.K.: Housing Cost Inflation and Contribution to CPI (Percent)



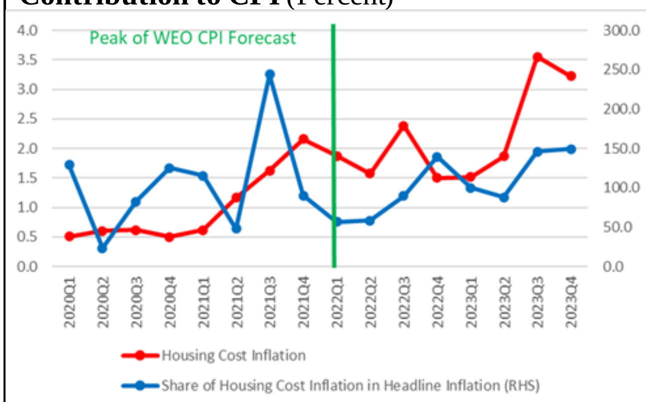
Sources: WEO, Haver, and authors' calculations.

Figure 18. Canada: Housing Cost Inflation and Contribution to CPI (Percent)



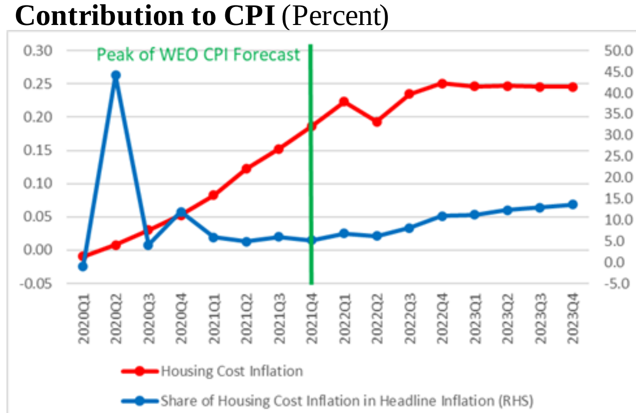
Sources: WEO, Haver, and authors' calculations.

Figure 19. Iceland: Housing Cost Inflation and Contribution to CPI (Percent)



Sources: WEO, Haver, and authors' calculations.

Figure 20. Korea: Housing Cost Inflation and Contribution to CPI (Percent)



Sources: WEO, Haver, and authors' calculations.

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than before. Therefore, our calculation of the contribution of housing cost inflation to headline inflation in 2020 may be an under-estimate of the true contribution.

E. Robustness Checks

As in the U.S. case, we also conduct robustness checks for the eight countries discussed above. We do so by incorporating inflation expectation and rental vacancy rate into our forecasting models: the first variable captures the forward-looking behavior of landlords and tenants, and the second variable captures supply-side conditions. Since such data are not available for Iceland and Luxembourg, the robustness check results for these two countries are not available. In addition, as discussed above, the robustness check results for Korea's OOHC case are not available either because the country does not include OOHC in its headline CPI. Data sources are presented in Appendix Table 1.

We follow the same two-step procedure by first selecting the best forecasting models for rent inflation and OOHC inflation, and then taking the weighted sum of the forecasts of these two components. Table 10 summarizes the selected models for the non-U.S. countries. It is worth noting that, as in the previous subsection, *all* of the best-performing models are machine-learning models, both for rent forecasting and for OOHC forecasting.

Using the best-performing models, we forecast the rent inflation and OOHC inflation from 2022Q1 to 2023Q4, calculate the weighted sum using their respective weights in headline CPI inflation, and compare it with IMF country teams' forecasts of the headline CPI inflation. The results are presented in Appendix Figures 9-14. For all the countries with available robustness check results, the weighted housing cost inflation displays a similar pattern as in the previous subsection: it would peak *after* the expected peak of the headline CPI inflation in the WEO forecasts; moreover, its contribution to the headline CPI would rise during 2022Q1-2023Q3, although by a somewhat less extent than in the case without considering the additional two variables.

Table 10: Selected Models for Non-U.S. Countries: Robustness Checks

Country	Rent	OOHC
U.K.	Random Forest (1-4 lags)	Random Forest (1-4 lags)
Canada	Random Forest (1-4 & 8 lags)	Random Forest (1-4 & 8 lags)
Iceland	N.A.	N.A.
Korea	Random Forest (1-4 & 8 lags)	N.A.
Mexico	Random Forest (1-4 lags)	Lasso (1-4 lags)
Brazil	Random Forest (1-4 & 8 lags)	Lasso (1-4 & 8 lags)
Sweden	Random Forest (1-4 & 8 lags)	Lasso (1-4 & 8 lags)
Luxembourg	N.A.	N.A.

Source: Authors' calculations.

F. Heatmap for Ten More Countries with Rapid House Price Growth

Because rents are often an important driver of inflation, we assess what the trends in rents in other countries might imply for their overall inflationary pressures. Due to data limitations and differences in institutional features,[23] we cannot apply the same types of machine-learning models to other countries. Instead, we conduct a simple analysis to have a preliminary understanding of the additional inflation pressure.

Specifically, we first select countries that rank in the top ten in terms of the average quarterly year-on-year house price growth rate since 2020Q1, after excluding the nine countries analyzed in the machine-learning section. We then calculate the deviation of the latest house price growth rate from the average year-on-year growth rate right before the pandemic (2016-2019). We do the same for the deviation of the latest rent growth from the pre-pandemic average rent growth. Finally, we compare these two deviations to obtain a "Pressure Index", and we assign ratings using some judgment-based thresholds.

Table 11 presents the heatmap for the top ten countries that have experienced the highest average quarterly year-on-year house price growth rate since 2020Q1. For six out of the ten countries, the pressure is rated as "High" because the country's rent growth has significantly lagged behind its house price growth. For example, Turkey's latest year-on-year house price growth (30.2 percent as of 2021Q2) more than triples its average year-on-year growth of 9.0 percent observed right before the pandemic (2016-2019). By contrast, its latest year-on-year rent growth (10.3 percent) is more or less the same as the pre-pandemic average. Given our previous analyses in the stylized facts and the machine-learning sections, these results suggest potential upward pressure on rent and thus headline inflation in Turkey in the coming years.

As in the case of the nine countries analyzed in the machine-learning section, the analysis of these ten countries also do not account for potential de-anchoring of inflation expectations, spillovers to non-housing inflation, or policy responses. Moreover, it does not rule out the possibility of a structural break in the housing market, where households may have permanently shifted from renting to owning houses, and thus the rising house prices will unlikely be followed by rising rents. As such, the preliminary heatmap presented here only aims at providing suggestive evidence and serves as a first step for more rigorous analyses.

[23] One example of the data limitations is that the OER data are not available in these countries. One example of the differences in institutional features is that Czech does not use the rental equivalence approach to incorporate owners' housing costs into inflation; instead, it uses the net acquisition approach.

Table 11. Simple Analysis of House Price-Associated Inflation Pressure in Ten Countries

	Rank 1/	HP_Avg since 20Q1	HP_Avg 2016-19	HP_Latest 2/	Rent_Avg 2016-19	Rent_Latest 3/	Pressure Index 4/	Pressure 5/
Turkey	1	29.6	9.0	50.2	9.4	14.3	3.7	**High**
Russia	2	20.2	4.6	22.8	1.9	8.9	1.1	**Low**
New Zealand	3	17.0	6.9	27.6	2.4	3.8	2.5	**High**
Czech	4	12.2	9.2	22.0	2.5	4.2	1.4	**Medium**
Australia	5	11.4	2.1	23.7	0.6	0.4	18.8	**High**
Lithuania	6	10.4	7.1	18.9	6.1	8.0	2.0	**High**
Netherlands	7	10.2	7.3	16.7	2.1	0.7	6.5	**High**
Poland	8	9.5	5.2	9.0	3.3	7.8	0.7	**Low**
Estonia	9	9.2	5.8	17.4	6.9	14.5	1.4	**Medium**
Germany	10	9.0	6.5	12.0	1.4	1.4	1.8	**High**

1/ Ranked based on the average yoy house price growth since 2020Q1, excluding countries analyzed in the machine-learning section.
2/ As of 2021Q3, except Turkey and Australia (both 2021Q4).
3/ As of 2022Q1, except New Zealand and Australia (both 2021Q4).
4/ Equals the ratio of the latest house price growth to its pre-pandemic average, divided by the ratio of the latest rent growth to its pre-pandemic average.
5/ "High" if pressure index exceeds 1.50; "Medium" if it lies between 1.25 and 1.50; "Low" if it falls below 1.25.
Source: OECD and authors' calculations.

V. Conclusion and Operational Implications

In this paper, we present some stylized facts suggesting headline inflation generally lagging house price growth in nine AEs and EMs, including the U.S., the U.K., Canada, Iceland, Korea, Mexico, Brazil, Sweden, and Luxembourg. We then apply machine-learning models to forecast the two housing components in the headline inflation, i.e., rent and OOHC (which is OER in the U.S. case). We find that inflation of housing components in CPI (PCE) forecasts would peak *after* the expected peak of headline inflation in WEO forecasts, i.e., after the non-housing inflation pressure recedes. Moreover, the contribution of the inflation of housing components was disproportionally higher than the housing weight in headline inflation in 2020-2021, dropped significantly afterward, but is expected to keep rising over the medium term according to our machine learning-based forecasts. Finally, for some countries for which our machine-learning methodologies are not readily applicable, we present a preliminary heatmap map and provide suggestive evidence about the degree of potential pressures of rising housing costs on headline inflation, which serves as a first step for more rigorous analyses of the inflationary pressures in these countries.

Operationally, our paper highlights the need to carefully incorporate housing prices into the headline inflation forecasts. In view of the potential lagged responses of the housing cost components (rent and OOHC, if applicable) to house price growth, it would be useful to take a *granular* approach by forecasting the different housing cost components and then aggregating them into the headline inflation with the respective weights. Our models show that rent inflation and OOHC inflation are expected to increase significantly in 2022 for some countries and also in 2023 for a subset of these countries. Given their relatively high weights in the headline inflation indices, these housing cost components will contribute a high share to the headline inflation in 2022 and 2023. As such, rising inflation in rent and OOHC could potentially push headline inflation above central banks' targets in 2022 and 2023, even after current inflationary pressures from supply bottlenecks and labor shortages subside. In this regard, our machine-learning methodology provides a complementary approach (focusing on the direct impact on housing components) that macroeconomic forecasters can explore to incorporate the house price growth into the headline inflation forecasts and to cross-check their forecasts by other approaches. Indeed, for eight out of the nine countries we analyze, it turns out that machine-learning models outperform the VAR model, a model frequently used by practitioners.

As for the implications for monetary policy, more analysis of inflation dynamics is needed, particularly using structural and general equilibrium models. On the one hand, as discussed earlier, the monetary policy response will depend on the impact on inflation expectations and spillovers to non-housing inflation. Rising housing prices can increase households' expectations of headline inflation measures, and the spillovers to non-housing inflation could also intensify the *upward* pressure on inflation. On the other hand, monetary tightening itself can slow down the growth of house price or rent, which *mitigates* the impact on inflation and highlights the need for modeling the feedback loop among house price growth, inflation, and monetary policy (e.g., by introducing an endogenous monetary policy response function). Nonetheless, our paper highlights the importance of sufficiently accounting for the following side effect of keeping a loose monetary policy for long: doing so may fuel the continued growth of house prices, which could in turn lead to higher rent and OOHC, and ultimately higher headline inflation.

Finally, the relationship between house prices and inflation also raises the questions of *whether and how* to incorporate owner-occupied housing prices into inflation measures. Many countries such as the U.S. and Japan incorporate house prices into headline inflation measures only indirectly, through the rent and OER (i.e., using the "rental equivalence approach"). Against the backdrop of sharply rising house prices, many call for the need to revisit this approach. For example, the ECB's Strategy Review completed in July 2021 has decided that the ECB should incorporate owner-occupied housing prices and plan to use the "net acquisition approach" to this end. Indeed, appropriately incorporating housing costs into headline inflation increases the representativeness of the consumer price index and better reflects household expenditures.

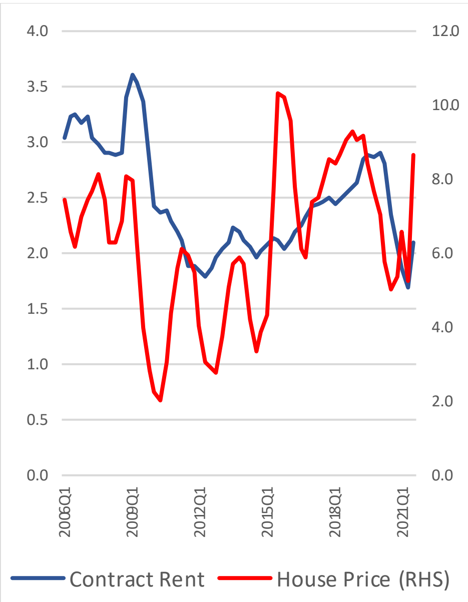
APPENDICES

Appendix Table 1. Data Sources

Indicator	Frequency	Sources
Rent	Quarterly	Haver
Weight of rent in headline inflation	Quarterly	Haver
OOHC	Quarterly	Haver
Weight of OOHC in headline inflation	Quarterly	Haver
Headline inflation	Quarterly	Haver, WEO
Housing price	Quarterly	BIS
Nominal GDP	Quarterly	IFS
M2	Quarterly	Haver
Policy rate	Quarterly	IFS, Federal Reserve Economic Data, CEIC
(Gross) Household disposable income	Quarterly	DataStream, CEIC
Inflation expectation	Quarterly	Consensus Forecast
Rental vacancy rate	Quarterly	Haver

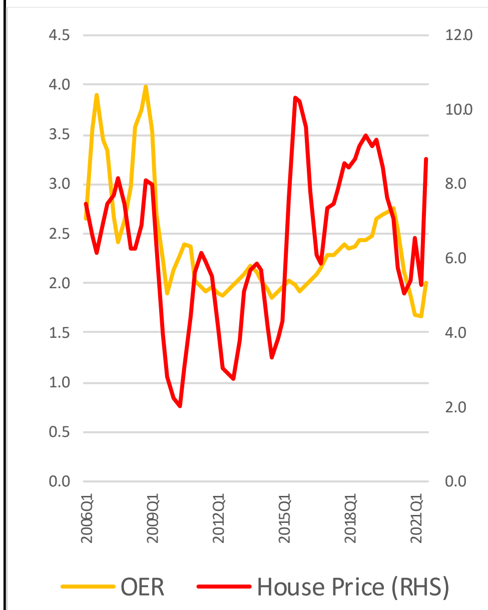
Source: Authors.

Appendix Figure 1a. Mexico: Growth of House Price and Rent
(2006Q1 - 2021Q3, Percent)



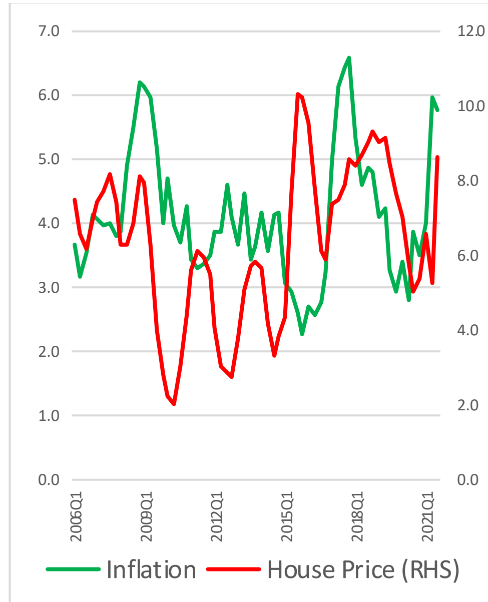
Sources: BIS, Haver, and authors' calculations.

Appendix Figure 1b. Mexico: Growth of House Price and OER
(2006Q1 - 2021Q3, Percent)



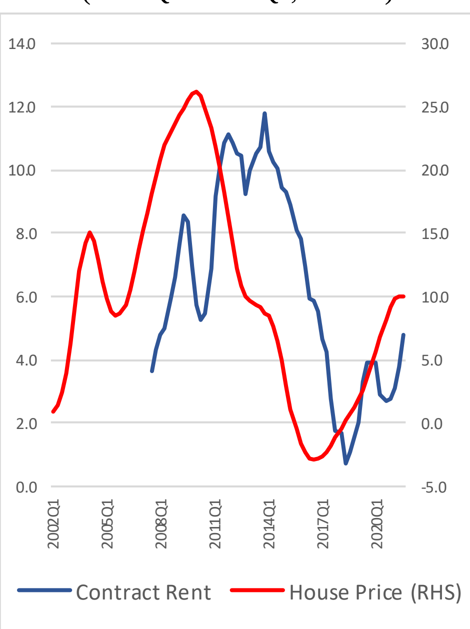
Sources: BIS, Haver, and authors' calculations.

Appendix Figure 1c. Mexico: CPI Inflation and House Price Growth
(2006Q1 - 2021Q3, Percent)



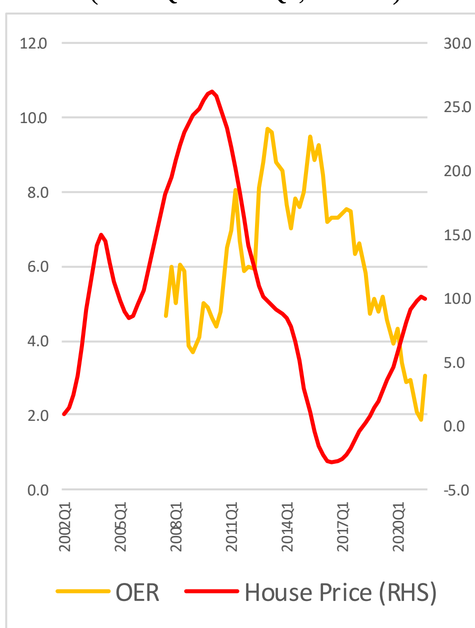
Sources: WEO, BIS, and authors' calculations.

Appendix Figure 2a. Brazil: Growth of House Price and Rent
(2002Q1 - 2021Q3, Percent)



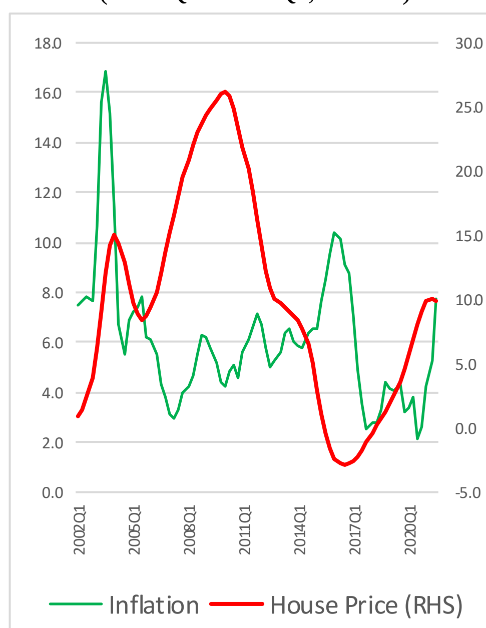
Sources: BIS, Haver, and authors' calculations.

Appendix Figure 2b. Brazil: Growth of House Price and OER
(2002Q1 - 2021Q3, Percent)



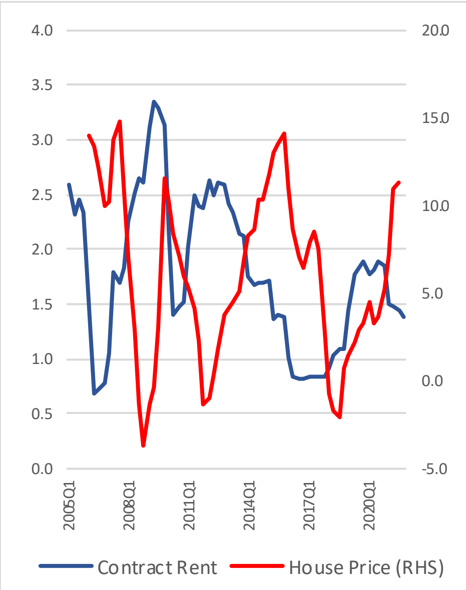
Sources: BIS, Haver, and authors' calculations.

Appendix Figure 2c. Brazil: CPI Inflation and House Price Growth
(2002Q1 - 2021Q3, Percent)



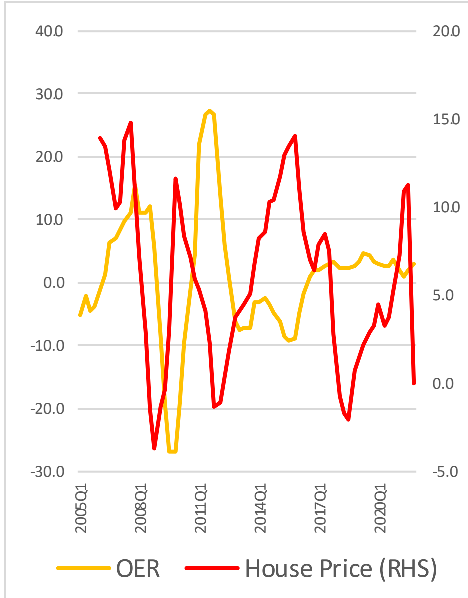
Sources: WEO, BIS, and authors' calculations.

Appendix Figure 3a. Sweden: Growth of House Price and Rent
(2005Q1 - 2021Q4, Percent)



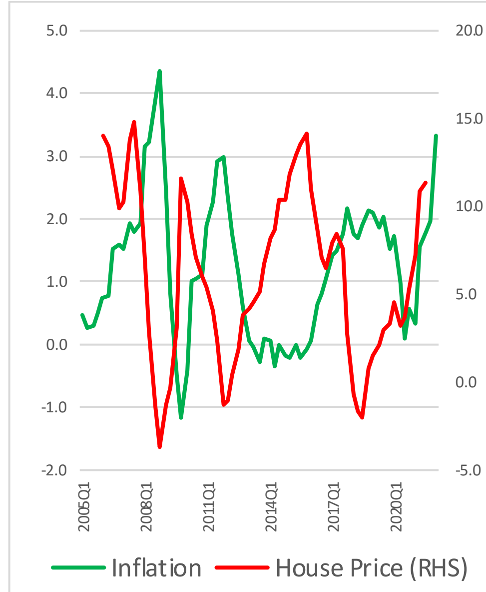
Sources: BIS, Haver, and authors' calculations.

Appendix Figure 3b Sweden: Growth of House Price and OER
(2005Q1 - 2021Q4, Percent)



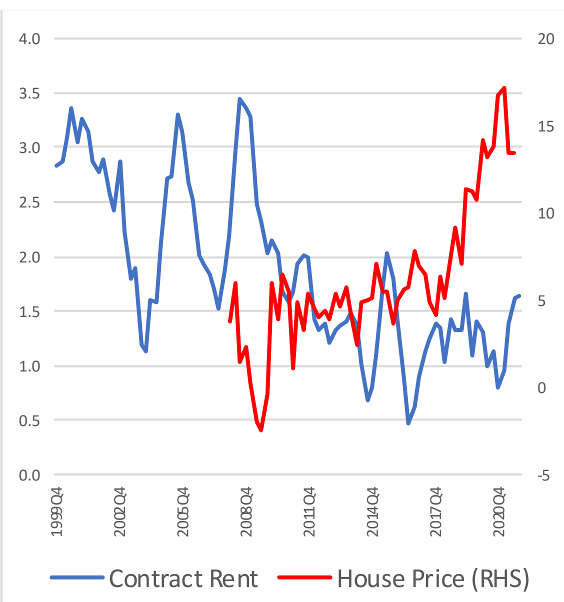
Sources: BIS, Haver, and authors' calculations.

Appendix Figure 3c Sweden: CPI Inflation and House Price Growth
(2005Q1 - 2021Q4, Percent)



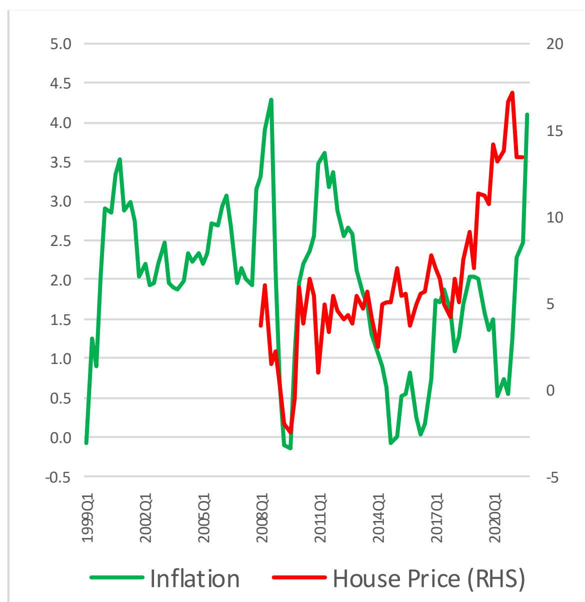
Sources: WEO, BIS, and authors' calculations.

Appendix Figure 4a. Luxembourg: Growth of House Price and Rent (1999Q1 - 2021Q4, Percent)



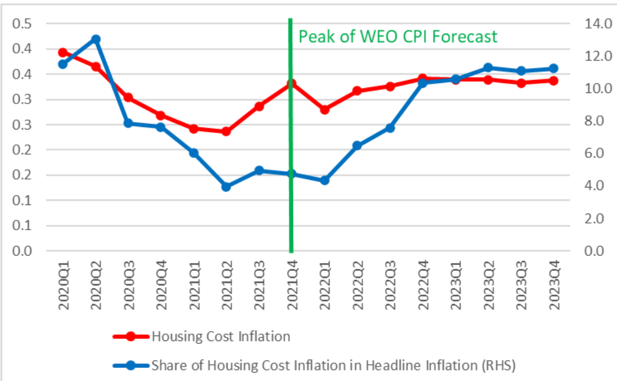
Sources: BIS, Haver, and authors' calculations.

Figure 4b. Luxembourg: CPI Inflation and House Price Growth
(1999Q1 - 2021Q4, Percent)



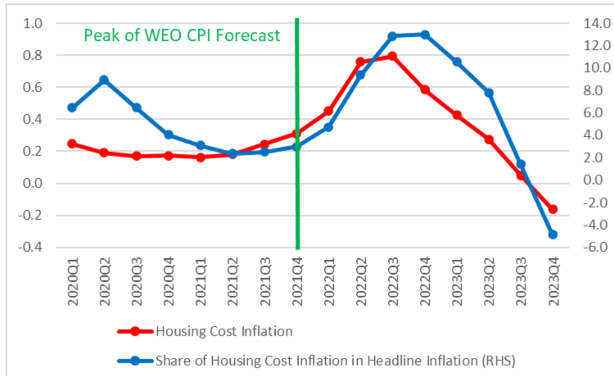
Sources: WEO, BIS, and authors' calculations.

Appendix Figure 5. Mexico: Housing Cost Inflation and Contribution to CPI (Percent)



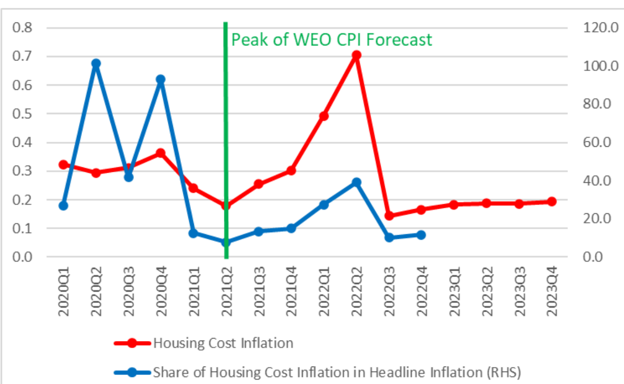
Sources: WEO, Haver, and authors' calculations.

Appendix Figure 6. Brazil: Housing Cost Inflation and Contribution to CPI (Percent)



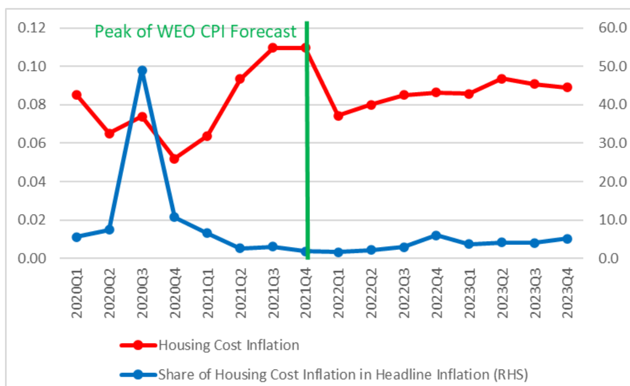
Sources: WEO, Haver, and authors' calculations.

Appendix Figure 7. Sweden: Housing Cost Inflation and Contribution to CPI (Percent)



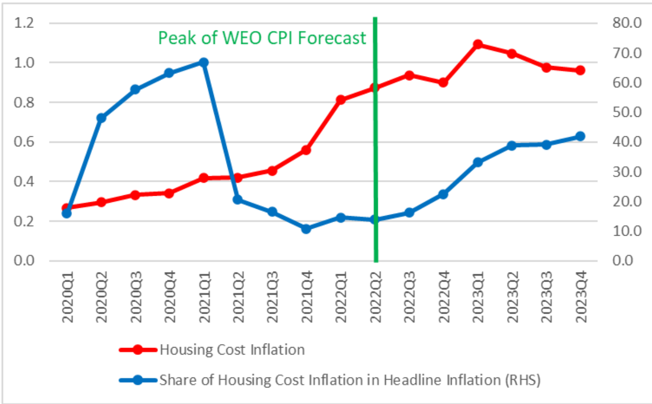
Sources: WEO, Haver, and authors' calculations.

Appendix Figure 8. Luxembourg: Housing Cost Inflation and Contribution to CPI (Percent)



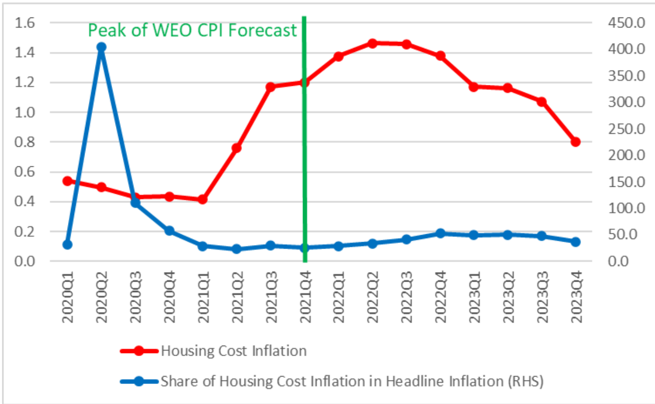
Sources: WEO, Haver, and authors' calculations.

Appendix Figure 9. U.K.: Housing Cost Inflation and Contribution to CPI (Percent)



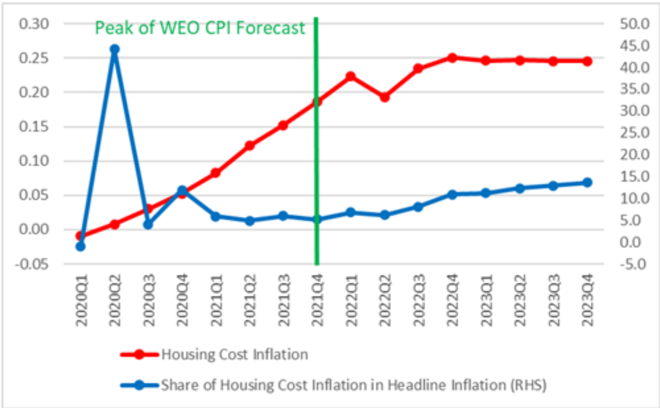
Sources: WEO, Haver, and authors' calculations.

Appendix Figure 10. Canada: Housing Cost Inflation and Contribution to CPI (Percent)



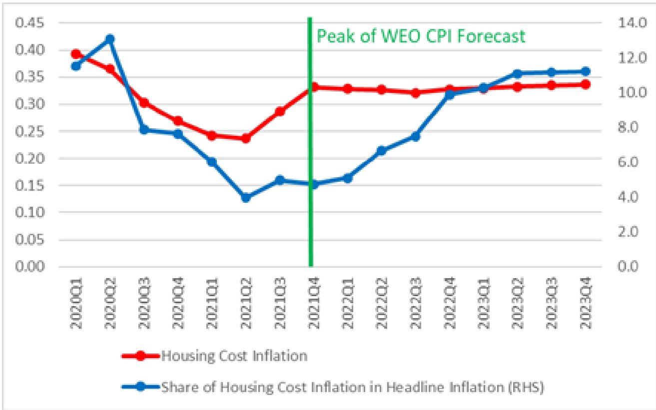
Sources: WEO, Haver, and authors' calculations.

Appendix Figure 11. Korea: Housing Cost Inflation and Contribution to CPI (Percent)



Sources: WEO, Haver, and authors' calculations.

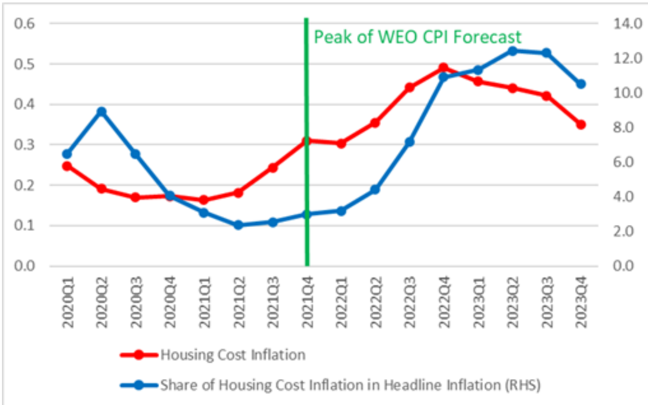
Appendix Figure 12. Mexico: Housing Cost Inflation and Contribution to CPI (Percent)



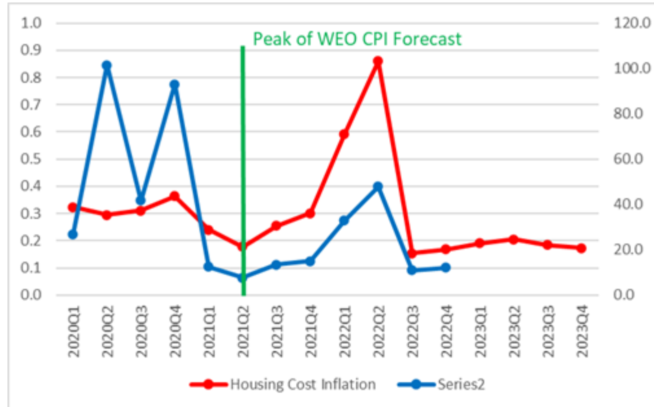
Sources: WEO, Haver, and authors' calculations.

Appendix Figure 13. Brazil: Housing Cost Inflation and Contribution to CPI (Percent)

Appendix Figure 14. Sweden: Housing Cost Inflation and Contribution to CPI (Percent)



Sources: WEO, Haver, and authors' calculations.



Sources: WEO, Haver, and authors' calculations.

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