Forecasting State- and MSA-Level Housing Returns of the US: The Role of Mortgage Default Risks

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Abstract

We analyze the ability of an index of mortgage default risks (MDRI) for 43 states and 20 metropolitan statistical areas (MSA) of the US derived from Google search queries, in predicting (in- and out-of-sample) housing returns of the corresponding states and MSAs, based on various panel data and time-series approaches. In general, our results tend to prefer the panel data model based on common correlated effects estimation. We highlight that growth in MDRI negatively impacts housing returns within-sample, with predictive gains primarily concentrated beyond a year. These results are robust to alternative out-of-sample periods and econometric frameworks. Given the role of house prices as a leading indicators, our results are of value to policymakers, especially at the longer-run.

Keywords: Mortgage Default Risks, Housing Returns, States and MSAs, Panel Data Predictive Models

JEL Codes: C23, C53, R31

1. Introduction

As observed during the global financial crisis of 2007-2008, elevated mortgage delinquencies and defaults can dampen future house prices,[1]raise pessimism among consumers and investors, and wreak havoc on the macroeconomy and financial markets. Naturally, the financial concerns of homeowners are of paramount importance to the economy of the United States (US). While aggregate financial risk has been captured by an array of generalized market indices (such as the

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[1]Indeed, Lambie-Hanson (2015) finds that seriously delinquent homeowners neglect housing maintenance, subsequently depressing neighboring property values (Gerardi et al., 2015) and leading to further increases in mortgage defaults (Chan et al., 2013). Anenberg and Kung (2014) also find that higher levels of foreclosures can increase housing supply and thus depress property values.

Volatility Index (VIX) of the Chicago Board Options Exchange (CBOE), for instance), none of these measures provided timely insights that are specific to mortgage default risks during run-up to the crisis. In addition, the few available measures of mortgage default risks only captured information known to lenders or financial market participants and thus neglected potentially sensitive information on mortgage distress emanating directly from households. Given this, Chauvet et al., (2016) use Google search query data to develop broad-based and real-time index of mortgage default risk (MDRI) for the US. Unlike the existing indicators, the MDRI developed by these authors directly reflect households' concerns regarding their risk of mortgage default. More importantly, the MDRI is shown to predict national-level housing returns, mortgage delinquency indicators, and subprime credit default swaps, both within and out-of-samples, and across various (daily, monthly, weekly) data frequencies.

The finding that MDRI can provide information on the future path of housing returns, is of paramount importance to policymakers, given that house prices are historically known to be a leading indicator for both output and inflation of the aggregate US economy (Stock and Watson, 2003; Balcilar et al., 2014; Leamer, 2015; Nyakabawo et al., 2015). The role of regional house prices in predicting regional output of the US has also been highlighted by the work of Emirmahmutoglu et al., (2016). Against this backdrop, the objective of our analysis is to check whether MDRIs available for 43 states and 20 major Metropolitan Statistical Areas (MSAs), as developed by Chauvet et al., (2016) using Google search query data), can be used to forecast the housing returns of the corresponding states and MSAs. Note that, Chauvet et al., (2016) did provide in-sample evidence of predictability of housing returns for the 20 MSAs using the MDRIs for these metros. However, as pointed out by Campbell (2008),the ultimate test of any predictive model (in terms of the econometric methodologies and the predictors used) is in its out-of-sample performance, and hence, we analyze the importance of MDRI by relying primarily on a full-fledged forecasting exercise for not only 20 MSAs, but also 43 states of the US economy. Further, the ability of the MDRI to forecast aggregate housing returns, does not necessarily guarantee that the same will continue to hold at the regional-level, since local factors, over and above a national housing factor, could play important role in explaining the variability of housing returns at the MSA and state-levels (Del Negro and Otrok, 2007; Fairchild et al., 2015). Moreover, with regional business cycles not necessarily aligned with the aggregate business cycle (Gupta et al., 2018), accurate forecasting of housing returns for MSAs and states are of tremendous value to policy authorities.

To the best of our knowledge, this is the first attempt to predict (in- and out-of-sample) housing returns at the MSA- and state-levels based on the information content of corresponding information on risks associated with mortgage default risks. In the process, our paper adds to the large existing literature[2]on forecasting regional house price (returns) in the US, which in turn has looked into various types of econometric frameworks ranging from univariate to multivariate, linear to nonlinear, and a wide array of predictors involving just lagged values of house prices (returns) to macroeconomic, financial and behavioral aspects.

As far as our econometric modeling is concerned in forecasting regional housing returns, we first use a baseline framework of stationary augmented lag panel models with heterogeneous constants and slope coefficients as proposed by Chudik and Pesaran (2015) estimated at different prediction time horizons. The forecasting performance of these models is assessed not only by simple forecasting accuracy measures (such as the root mean square forecast error), but also via statistical

[2]See for example, Rapach and Strauss (2009), Das et al., (2010), Gupta and Das (2010), Gupta et al., (2011), Gupta and Miller (2012a, 2012b), Gupta (2013), Balcilar et al., (2015), Bork and Møller (2015, 2019).

tests of forecast encompassing. Several researchers have shown that if cross-sectional heterogeneity in the estimated parameter coefficient estimates is left unaccounted for, it will possibly result in inefficient and inconsistent estimates of the panel data coefficient parameters, along with biased standard errors. Pesaran and Smith (1995) show that the pooled estimator becomes inconsistent for a dynamic panel data model if the model slope coefficients exhibit heterogeneity. Recent econometric advances highlight the importance of estimating panel regression models which account for possible cross-sectional dependence in the error process.

One approach that has become popular in the literature involves estimating dynamic panels under cross sectional error dependence with a fixed number of unobserved and observed common factors, namely the common correlated effects estimation (CCE) approach originally introduced by Pesaran (2006). This approach involves approximating the unobserved common factors by the cross section averages of the dependent and the independent variables and using them as regressors in the main model specification. Chudik et al., (2011) show that the CCE approach exhibits robustness to the presence of an unknown number of unobserved common factors, as well as, to serial correlation of unknown form in the error respectively. Kapetanios et al., (2011) show the implementation of the CCE approach does not require the unobserved common factors to be stationary, integrated of an arbitrary order, or cointegrated of an arbitrary order. Given these points, we rely on dynamic panel data models with CCE over the monthly period of 2004:01 to 2017:12 for our analysis. The remainder of the paper is organized as follows: Section 2 discusses the data and methodology, Section 3 presents the in- and out-of-sample results, with Section 4 concluding the paper.

2. Data and econometric methodology

2.1. Data

Our analysis covers the monthly period of 2004:01 to 2017:12, with the start and end dates being driven purely by the availability of data on the MDRI, at the time of writing this paper. Monthly data of MDRI for 43 states and 20 MSAs are obtained from MDRI database developed by Chauvet et al., (2016).[3] These authors using Google search query data, collect sensitive information directly from individuals seeking assistance via internet search on issues of mortgage default and home foreclosure. Specifically, Chauvet et al. (2016) aggregate Google search queries for terms like "foreclosure help" and "government mortgage help" to compile a novel MDRI in real-time. The corresponding seasonally adjusted nominal house price data for the 43 states[4] and 20 MSAs[5] are derived from the Freddie Mac,[6] with the indices based on an ever-expanding database of loans purchased by either Freddie Mac or Fannie Mae. For the states, we use the non-farm employment (NFE) as a control obtained from the US Bureau of Economic Analysis (BEA), while for the MSAs, we use the monthly economic activity indices as developed by Arias et al., (2016) and available for download from the FRED database of the Federal Reserve Bank of St. Louis. These authors derived each of these indices from a Dynamic Factor Model (DFM) based on twelve underlying variables capturing various aspects of metro area economic activity. Seven (five) of the variables are monthly (quarterly). The variables include seven labor-market measures(average

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[3]The data can be accessed from: https://chandlerlutz.shinyapps.io/mdri-app/.
[4]The sates considered are: Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Florida, Georgia, Hawaii, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Maryland, Massachusetts, Michigan, Minnesota, Mississippi, Missouri, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, Tennessee, Texas, Utah, Virginia, Washington, West Virginia, and Wisconsin
[5]The MSAs considered are: Atlanta, Boston, Charlotte, Chicago, Cleveland, Dallas, Denver, Detroit, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa, and Washington DC.
[6]http://www.freddiemac.com/research/indices/house-price-index.page.

weekly hours worked, unemployment rate, private sector goods-producing employment, private sector services-producing employment, government sector employment, real average hourly earnings, real average quarterly wages), building permits, real personal income per capita, and three financial metrics (return on average assets, net interest margin, loan loss reserve ratio). Arias et al., (2016) estimate the DFM by using a maximum likelihood approach that allows for arbitrary patterns of missing data to accommodate mixed-frequency and differences in publication lags. These indices are stationary by design and hence, we use them directly in our panel data-based models without any further transformations, but we use returns of housing prices (*HPR*) and growth rates of the MDRI (*MDRIR*) and NFE (*NFER*) to ensure that these variables have no unit root issues.

2.2. Methodology

In this section we briefly describe the methodology that is implemented for the analysis of the relation between the regional housing returns of the US based on MDRI, given additional controls of non-firm employment at the state-level and economic activity index of the MSAs. Our baseline model is a long horizon heterogeneous stationary panel data regression with common correlated effects. Our model falls in the category of the stationary autoregressive distributed lagged (ARDL) panel data models introduced by Chudik and Pesaran (2015), where a mean group-type estimator is used to account for cross-sectional heterogeneity of the model parameter coefficients.

2.2.1. Dynamic panel models with common correlated effects

Let $HPR_{i,t} = \left(HPR_{1,t}, HPR_{2,t}, ..., HPR_{N,t}\right)'$ be a vector of housing price returns for t=1,2,…,T, i =1,2,…,N, where T and N represent the number of monthly observations and states, respectively. The following covariance stationary ARDL model is used to deal with heterogeneous slopes:

$$HPR_{i,t} = a_{i0} + \sum_{j=1}^{q} \beta_{ij} HPR_{i,t-j} + \sum_{j=1}^{q} \gamma_{ij} MDRIR_{i,t-j} + \sum_{j=1}^{q} \pi_{ij} X_{i,t-j} + u_{i,t} \ , \tag{1}$$

$$u_{i,t} = \theta_i f_t + e_{i,t} , \tag{2}$$

where $MDRIR_{i,t}$ are the growth rates of mortgage default risks, f_t represents a vector of unobserved common factors , $X_{i,t}$ is an observed control variable, θ_i and π_i are heterogeneous factor loadings of f_t and $X_{i,t}$ respectively, α_{i0} is the intercept for each cross-section unit, $\beta_{ij}, \gamma_{ij}, \pi_{ij}$ are the parameter coefficients, q is the lag order and $e_{i,t} \sim IID(0, \Sigma)$ across i and t. The errors $e_{i,t}$ may be allowed to be spatially correlated, whereas the roots of $\left(1 - \beta_{i1} L - ... - \beta_{iq} L^q\right) HPR_{i,t}$ must lie inside the unit circle. We assume that the heterogeneous parameter coefficients of model (1) are randomly distributed around a common mean:

$$\mathbf{g}_i = \mathbf{g} + \mathbf{z}_i , \; i = 1,2,.., N \tag{3}$$

where $\mathbf{g}_i = \left(a_{i0}, \beta_{ij}, \gamma_{ij}, \pi_{ij}\right)'$, $\mathbf{g} = \left(a_0, \beta_j, \gamma_j, \pi_j\right)'$ and $\mathbf{z}_i \sim IID\left(0, \Sigma_g\right)$ is a $\left(1 + 4 * j\right) \times N$ matrix of identically and independently distributed error terms with zero mean and positive definite covariance matrix Σ_g.

Pesaran (2006) filters out parametrically the unobserved cross-sectional dependence in the error term by including cross-sectional averages of the dependent and the explanatory variables in the main specification model. The new estimator, denoted hereafter as CCE, requires only that a relatively large cross-sectional sample is available, i.e., that $N \to \infty$ .His simulation results indicate that the use of the CCE estimator ensures an enhanced finite sample performance.

Furthermore, Chudik et al., (2011) show that the CCE estimator performs well even under the presence of multiple unobserved factors in the error process. It is also shown that the number of the multiple unobserved factors, which in practical situations is unknown, does not have to be smaller than the number of the cross-sectional averages. Moreover, the theoretical and simulation results of Kapetanios et al., (2011) indicate that the integration properties of the unobserved common factors do not affect the efficiency of the CCE estimation approach. Therefore, f_t may represent multiple unobserved stationary (or possibly non-stationary) common factors, which in turn can be approximated by the following cross-sectional means:

$$\overline{w}_{1t} = \frac{1}{N}\sum_{i=1}^{N} HPR_{i,t},\ \overline{w}_{2t} = \frac{1}{N}\sum_{i=1}^{N} MDRIR_{i,t}\ \ \overline{w}_{3t} = \frac{1}{N}\sum_{i=1}^{N} X_{i,t}, \tag{4}$$

The following dynamic specification is estimated by OLS for each individual cross-sectional unit i= 1,2, …, N:

$$HPR_{i,t} = a_{i0} + \sum_{j=1}^{q} \beta_{ij} HPR_{i,t-j} + \sum_{j=1}^{q} \gamma_{ij} MDRIR_{i,t-j} + \sum_{j=1}^{q} \pi_{ij} X_{i,t-j} + \sum_{j=1}^{q_T} \delta_{ij}' \overline{w}_{t-j} + \phi_i \overline{w}_{1t} + u_{i,t}\ , \tag{5}$$

where $\overline{w}_t = \left(\overline{w}_{1t}, \overline{w}_{2t}, \overline{w}_{3t}\right)'$.

Then, the CCE group mean estimator is calculated as the arithmetic average of the OLS estimates $\hat{\varphi}_i = \left(\hat{\alpha}_{i0}, \hat{\beta}_{ij}, \hat{\gamma}_{ij}, \hat{\pi}_{ij}, \hat{\delta}_{ij}, \hat{\phi}_i\right)'$ taken from (5):

$$\hat{\varphi}_{GM} = \frac{1}{N}\sum_{i=1}^{N}\hat{\varphi}_i \tag{6}$$

Pesaran (2006) shows that the CCE-group mean estimator is consistent and asymptotically distributed as normal in the context of a static panel model framework where the included explanatory variables are dependent to unobserved factors. However, Chudik and Pesaran (2015) argue that the CCE-group mean estimator becomes inconsistent for dynamic panels where the lagged dependent variable is included in the right-hand side of the model, even when *N* is large. According to Chudik and Pesaran (2015), consistency of the mean group estimator is ensured when equation (5) is augmented by a number of $q_T = \left\lfloor \sqrt[3]{T} \right\rfloor$ lagged cross-sectional mean terms, with $\lfloor . \rfloor$ denoting the integer function. Since our sample consists of 168 monthly observations for each cross-section, we will add six lagged of cross-sectional averages of the dependent and independent variables. They also prove that the dynamic CCE group mean estimator is asymptotically distributed as normal. Their Monte Carlo simulation experiments show that the new approach enjoys good finite sample properties under the condition that we have a relatively large time dimension.

2.2.2. Predictive panel regressions

Multi-horizon versions of equation (5) are used to examine whether MDRIs have predictive power for forecasting housing pricing returns at short and long forecast periods. Our approach regresses a multi-period ahead value of the housing price returns on lagged values of the housing price returns and the growth rates of the default risks. This approach is very popular in the literature of financial time series econometrics, referred to as the direct multistep forecast approach (see, Marcellino et al., (2006)).The main model specification that we consider is:

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{q} \beta_{ij} HPR_{i,t-j} + \sum_{j=1}^{q} \gamma_{ij} MDRIR_{i,t-j} + \sum_{j=1}^{q} \pi_{ij} X_{i,t-j} + \sum_{j=1}^{q_T} \delta'_{ij} \overline{w}_{t-j} + \phi_i \overline{w}_{1t} + u_{i,t+h} \ , \qquad (7)$$

where $HPR_{i,t+h} = \log\left(HP_{i,t+h} / HP_{i,t}\right)$, while h represents the forecast horizon. The estimation procedure described in equations (1)-(6) is adopted here: individual specific regressions of the form presented in (7) are estimated by means of least squares and then the N estimates of the parameters coefficients are averaged. The original CCE estimation framework requires that the right hand side of the regression (7) is augmented by the cross-sectional average of the dependent variable. Since our main goal in this investigation is to use the estimated parameter coefficients of this regression to generate forecasts of housing prices at future h periods ahead, we are restricted to use data up to period t and not period $t + h$. Therefore, we do not include cross section averages of $HPR_{i,t+h}$ as a regressor in equation (7); instead, we use the cross-section average of $HPR_{i,t}$ as a proxy for the cross-section of the dependent variable.

Due to overlapping observations, the residuals $u_{i,t+h}$ evolve as a moving average (MA) process of order (h-1). Therefore, we calculate autocorrelation and heteroscedasticity consistent (HAC) standard errors of the CCE group estimators following Newey and West (1987). The bandwidth parameter of the HAC estimator is selected to be equal to h -1. These standard errors are robust to temporal dependence.

3. Empirical Results

This section describes the results of the in-sample and out-of-sample analyses of housing returns with respect to the growth of MDRI for both the states and the MSAs, by controlling for growth of non-farm employment and the economic activity index respectively.

3.1. In-sample predictability

For the state-level data we estimate our baseline ARDL-CCE specification given in Eq.7 with $X_{it} \equiv NFER_{it}$:

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_{ij} HPR_{i,t-j} + \sum_{j=1}^{3} \gamma_{ij} MDRIR_{i,t-j} + \sum_{j=1}^{3} \pi_{ij} NFER_{i,t-j} + \sum_{j=1}^{6} \delta'_{ij} \overline{w}_{t-j} + \phi_i \overline{w}_{1t} + u_{i,t+h} \text{ ,}$$

(8)

where $NFER_{i,t}$ are the non-farm employment growth rates.

For comparison purposes, we also report the estimates the following ARDL fixed effects (ARDL-FE) panel regression model:

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_j HPR_{i,t-j} + \sum_{j=1}^{3} \gamma_j MDRIR_{i,t-j} + \sum_{j=1}^{3} \pi_j NFER_{i,t-j} + u_{i,t+h} \text{ .} \quad (9)$$

Table 1 demonstrates the estimated coefficients and the corresponding *p*-values in parentheses of the dynamic panel models (8) and (9) at the state-level. The dynamic ARDL-CCE model is estimated as described in the previous section, while the ARDL-FE model is estimated by using the(cross-sectional) dummy variables least squares method on the pooled data. Panel A reports the estimated coefficients of *HPR*, *MDRIR* and *NFER*, while Panel B reports the parameter coefficient estimates s of the lagged cross-sectional means of the MDRI growth rate variable.[7] Both ARDL-CCE and ARDL-FE models are fitted for forecast horizons 1, 3, 6, 12, and 24 months ahead. The standard errors of the estimated parameter coefficients of both models are computed by implementing the HAC estimator.

Examining the findings in Panel A, we see that the ARDL-CCE coefficients for the MDRIR are insignificant at all forecast horizons. However, moving to Panel B, we observe that the coefficients of the MDRI cross-sectional averages parameters are highly statistically significant particularly for horizons larger than three months-ahead. For three months-ahead period, three coefficients of lagged $\overline{w}_{2t}$ are statistically significant at level 5%, whereas for twelve and 24 months-ahead, all six coefficients are significant at 1% level. Thus, although there is no evidence of predictability from the MDRI variable, the cross-sectional averages of MDRIs are significant predictors at long horizons. The sign of all MDRI coefficients is negative, highlighting the negative reaction of individual housing prices to aggregate default risk movements. The values of the lagged MDRI and cross sectional MDRI averages coefficients range from -0,003 to -0,000 and -0.032 to -0.000, respectively.

The results of the ARDL-FE models reveal different predictability patterns. In particular, all lagged MDRI coefficients are negative and statistically significant over the range of 1 to 24 months ahead. Furthermore, they are similar in magnitude with the corresponding, ARDL-CCE coefficients. Hence, evidence from the ARDL_FE suggests that MDRIs have predictive housing price returns at both short and long-time horizons at the state-level.

[7] We do not report the coefficient estimates of the cross-sectional averages of the other explanatory variables due to limited space.

The findings from both models indicate that non-farm employment growth rates induce a significant positive effect on housing price returns at all forecast periods. Interestingly, we document that all lagged NFER coefficients in both ARDL-CCE and ARDL-FE dynamic specifications are highly statistically significant when we consider a forecast horizon of 24 months-ahead. Thus, there is some evidence in favor of long-horizon predictability of non-farm employment for housing price returns. Examining the autoregressive coefficient estimates of both dynamic models, we observe that housing prices returns display mostly significant positive and weak persistence at all forecast horizons.

[INSERT TABLE 1]

Table 2 demonstrates the estimation results for the MSA data. In this case, we estimate similar ARDL-CCE and ARDL-FE model specifications with the state data (Eq. 8 and Eq.9), and replace the non-farm employment (NFER) with economic activity (EA):

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_{ij} HPR_{i,t-j} + \sum_{j=1}^{3} \gamma_{ij} MDRIR_{i,t-j} + \sum_{j=1}^{3} \pi_{ij} EA_{i,t-j} + \sum_{j=1}^{6} \delta'_{ij} \overline{w}_{t-j} + \phi_i \overline{w}_{1t} + u_{i,t+h} , \quad (10)$$

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_{j} HPR_{i,t-j} + \sum_{j=1}^{3} \gamma_{j} MDRIR_{i,t-j} + \sum_{j=1}^{3} \pi_{j} EA_{i,t-j} + u_{i,t+h} . \quad (11)$$

Table 2 reports the estimation results from models (10) and (11). We begin our analysis by focusing on the coefficients of the MDRI parameters of the models which account for common correlated effects. For forecast horizons up to six months ahead, there is no evidence of predictability since all coefficients are statistically not different from zero. On the other hand, for forecasting horizons *h* equal to 12 and 24 months-ahead, all MDRI parameter coefficients are statistically significant. Results reported in Panel B suggest that the predictive ability of the MDRI cross-sectional averages is enhanced when we consider longer forecast horizons. For horizons 1 to 3 months-ahead, we document three statistically significant coefficients, while, for horizons 6 to 24 months-ahead all coefficients are highly significant. Overall, compared to the results at the state level reported in Table 1, in the case of the MSA data we document stronger evidence of long horizon predictability. Our findings are supported by the results of the ARDL-FE model which suggest that MDRI is a significant predictor of housing price returns at horizons larger than six months-ahead. The sign of the statistically significant MDRI coefficients is negative as in Table 1.

However, looking at the magnitude of the MDRI coefficient estimates, we document substantial differences between the values of the two models at large horizons. For instance, at h =12, the coefficients of the ARDL-FE model are 6, to 10 times the corresponding values of the CCE-based model. We draw a similar picture at h = 24; the coefficients of the ARDL-FE model are 10 to 19 times the corresponding estimates of the ARDL-CCE model. These differences can be attributed to the presence of significant cross-sectional dependence in processes under study. As we can see from the ARDL-CCE estimation results, at these horizons, the estimated coefficients of the MDRI cross-sectional average terms are large in magnitude and statistically significant, which is clearly an evidence of the presence of cross-sectional dependence in our data. This suggests that the error term in fixed effects (FE) models is cross-sectionally dependent. Consequently, FE models may suffer from heterogeneous slope coefficient bias which inflates the marginal impact of MDRI on housing price returns.

We find mixed evidence on the predictive ability of economic activity for forecasting future housing price returns. The economic activity coefficients of the CCE-models are statistically different from zero at the 1, 6 and 24 month horizons for 5% significance level. The CCE-based regressions deliver positive and relatively large coefficients (smaller than one) except for the 24-

month horizon, where we document an estimate of -1,231. The FE models yield more clear-cut evidence of long horizon predictability; the coefficients are always positive and statistically significant at the 5% level for horizons h = 12, 24.

[INSERT TABLE 2]

3.2. Out-of-sample forecasting

The above results suggest that the growth rates of MDRIs have predictive power for forecasting housing prices returns mainly at long time horizons. Therefore, an issue that arises is whether the models presented earlier can provide improved forecasting performance for housing price returns over different alternative predictors.

In this section we conduct two out-of-sample forecasting exercises in order to investigate the predictive ability of MDRI growth rates for forecasting housing price returns at multiple time horizons, at the state- and MSA- levels. Different nested dynamic panel and time series model specifications are used as competing forecast models. The forecasting performance of the models is examined by means of the root mean squared forecast error criterion, an accuracy measure of the forecasted direction of change, and statistical tests of forecast encompassing. In this paper, the predictive accuracy of the models is compared on the aggregate level, i.e., two alternative forecasts are tested to be equally accurate when averaged both over the cross-sectional and the time dimension.

3.2.1 Out-of-sample forecasting within the baseline ARDL-CCE framework

We use three competing models to generate the forecasts of housing prices at the state level and MSA level which are described by the following equations:

$$HPR_{i,t+h} = \bar{a}_0 + \sum_{j=1}^{3} \bar{\beta}_j HPR_{i,t-j} + \sum_{j=1}^{3} \bar{\gamma}_j MDRIR_{i,t-j} + \sum_{j=1}^{3} \bar{\pi}_j X_{i,t-j} + \sum_{j=1}^{6} \bar{\delta}_j' \bar{w}_{t-j} + \bar{\phi}\, \bar{w}_{1t} + u_{i,t+h} , \tag{12}$$

where $\bar{w}_t = (\bar{w}_{1t}, \bar{w}_{2t}, \bar{w}_{3t})$,

$$HPR_{i,t+h} = \bar{a}_0 + \sum_{j=1}^{3} \bar{\beta}_j HPR_{i,t-j} + \sum_{j=1}^{3} \bar{\pi}_j X_{i,t-j} + \sum_{j=1}^{6} \bar{\delta}_j' \bar{w}_{t-j} + \bar{\phi}\, \bar{w}_{1t} + u_{i,t+h} , \tag{13}$$

where $\bar{w}_t = (\bar{w}_{1t}, \bar{w}_{3t})$, and

$$HPR_{i,t+h} = \bar{a}_0 + \sum_{j=1}^{3} \bar{\beta}_j HPR_{i,t-j} + \sum_{j=0}^{6} \bar{\phi}_j \bar{w}_{1t-j} + u_{i,t+h} , \tag{14}$$

In the case of the state level data we set $X_{i,t} \equiv NFER_{i,t}$, while in the case of MSA data $X_{i,t} \equiv EA_{i,t}$. Cross-sectional mean variables $\bar{w}_{1t}$, $\bar{w}_{2t}$, and $\bar{w}_{3t}$, are defined in Eq.4.

Forecasting equations (12) and (13)-(14) correspond to the ARDL-CCE baseline model given in Eq.7 and nested models, respectively. The coefficients $\bar{a}_0, \bar{\beta}_j, \bar{\gamma}_j, \bar{\pi}_j, \bar{\delta}_j, \bar{\phi}$ represent the ARDL-CCE estimates of the corresponding parameters $a_{i0}, \beta_{ij}, \gamma_{ij}, \pi_{ij}, \delta_{ij}, \phi_i$ in the baseline model.

The forecasting exercise is conducted by splitting the sample into an estimation sample, used for parameter estimation, and a test sample, used for evaluation of the forecast performance. Three estimation windows are considered; the first window includes approximately the first half of our sample (80 monthly periods, beginning at 2010:08), the second window consists is a 5 year period (60 observations, beginning at 2008:12 which corresponds to the peak of the recent European sovereign debt crisis) and the third includes approximately 30% of the observations of our sample (50 monthly periods, starting in 2008:02 which corresponds to the peak of the recent global financial crisis. A rolling window of fixed length is implemented to estimate the coefficients of the models and then h-step-ahead forecasts are generated recursively for each cross-sectional unit using the estimated coefficients. Our approach removes one observation from the beginning of the estimation sample and adds one new observation at the end of it. Therefore, each forecast adjusts as the forecasting equation is successively updated by re-estimating the model parameters with the addition of one data point to the estimation sample.

3.2.2 Measures and tests of forecast accuracy

Let us denote the actual aggregate housing returns by $HPR_{t+h} = \frac{1}{N}\sum_{i=1}^{N} HPR^{*}_{i,t+h}$, $t = R, \ldots, T - h$, where $HPR^{*}_{i,t+h} = \log(HP_{i,t+h}) - \log(HP_{i,t})$, and R is the length of the estimation sample. Denote the forecasted aggregate housing prices by $\hat{H}PR_{t+h} = \frac{1}{N}\sum_{i=1}^{N} \hat{H}PR^{*}_{i,t+h}$, where $\hat{H}PR^{*}_{i,t+h}$, are the h-step-ahead forecasts generated recursively by any of the equations described in equations (12)-(14).

A selection of measures and statistical tests is used to evaluate the forecast performance of the models. Let the pseudo-out-of-sample forecast error be $e_{t+h} = HPR_{t+h} - \hat{H}PR_{t+h}$. The root mean squared forecast error criterion (RMSFE) is calculated as

$$\text{RMSFE} = \sqrt{\frac{1}{T-h-R+1}\sum_{t=R}^{T-h} e^{2}_{t+h}}\ . \tag{15}$$

The accuracy of the forecasted direction of change is estimated as

$$\text{Sign} = \frac{1}{N}\sum_{i=1}^{N} \hat{S}_i , \tag{16}$$

where $\hat{S}_i = \frac{1}{T-h-R+1}\sum_{t=R}^{T-h} I\left\{HPR_{i,t+h}\hat{H}PR_{i,t+h} > 0\right\}$, $I\{.\}$ is an indicator function that assigns the value one when the condition inside the brackets is satisfied and zero otherwise.

Along with the metrics mentioned above, it is important to apply a formal statistical evaluation of the accuracy of two alternative forecasts, which in turn have been generated by nested prediction models. A popular approach in the literature is to evaluate the predictive performance of nested models by testing for forecasting encompassing (see Nelson (1972), Granger and Newbold (1973), Chong and Hendry (1986), Fair and Shiller (1989), Harvey et al. (1998)). Denote by $\left\{\hat{H}PR_{1t+h}\right\}, t = R,..,T-h,$ and $\left\{\hat{H}PR_{2t+h}\right\}$, two series of competing forecasts, whereas let $\left\{e_{1t+h}\right\}$, and $\left\{e_{2t+h}\right\}$, be the corresponding pseudo-out-of-sample forecast errors, respectively. Suppose we want to test whether we cannot improve the accuracy of the first series of forecasts through linear combination with the second series of forecasts, in other words, that $\left\{\hat{H}PR_{1t+h}\right\}$ encompasses $\left\{\hat{H}PR_{2t+h}\right\}$. Define the loss differential series as

$$d_t = e_{1t}\left(e_{1t} - e_{2t}\right) \tag{17}$$

According to Harvey, et al., (1998), the null hypothesis of forecast encompassing can be expressed in terms of the loss differential series:

$$H_0 : E\left(d_t\right) = 0 \tag{18}$$

They suggest that a Diebold and Mariano (1995)-type test can be used to test null hypothesis (18). In particular, they propose the following test:

$$\text{ENCT} = P^{1/2}\frac{\bar{d}}{\sqrt{\hat{V}}} \tag{19}$$

Where and $\bar{d}$ are the length and average of the loss differential series, respectively, while $\hat{V}$ is the long-run variance of d_t which is estimated by using a HAC estimator. The test statistic is asymptotically distributed under the null hypothesis as standard normal. It is assumed that the combination weights are positive, which implies that the alternative hypothesis is always $E(d_t) > 0$. Hence, the test statistic in (19) is one-sided to the right. The loss differential series exhibits correlation of MA(h – 1) form, and therefore the bandwidth parameter used in the HAC estimation is set to be equal to h – 1. For the calculation of the HAC estimator, we use the quadratic spectral kernel.

Clark (1999) argues that there are situations where the HAC estimator yields a negative value of the long-run variance, especially when evaluating the predictive accuracy of long horizon forecasts. A straightforward consequence of a negative long-run variance estimate is that the test statistic (19) cannot be computed. Several solutions to this problem have been proposed in the literature. We followed a rather conservative approach by setting the ENCT test to be zero whenever the HAC estimate is negative, as in Harvey et al., (2016).

3.2.3. Out-of-sample forecasting results

Tables 3 and 4 report the results of the out-of-sample forecasting exercise using state- and MSA-level data, respectively. Specifically, the tables report the RMSFEs, sign measures and forecast encompassing test results for forecast horizons 1, 3, 6, 12, 18 and 24 months. Panels A, B and C present the results for estimation windows of 50, 60 and 80 monthly observations, respectively.

Forecast encompassing tests are applied in order to examine whether linear combinations of forecasts generated from dynamic models that include growth rates of MDRI and/or NFER can yield more accurate forecasts than alternative models. Encompassing test (ENCT) results are also reported along with the corresponding p-values.

[INSERT TABLE 3]

Results for the state- and MSA-level data reported in Tables 3 and 4, respectively, suggest only minor differences in RMSFEs across different forecasting models and different estimation windows. As expected, RMSFE is an increasing function of the forecast horizon for all models. However, our results clearly suggest that ARDL-CCE specifications with MDRI as regressor are superior according to the RMSFE metric for horizons larger than 12 months-ahead. The forecasting encompassing test results are in line with this finding. Specifically, when we consider a forecast horizon h = 18 or 24 months-ahead, the null hypothesis that the forecasts from the ARDL-CCE specification with NFER and MDRI (Eq.12) are encompassed by the forecasts from the ARDL-CCE specification with NFER alone (Eq.13), is rejected at the 5% significance level for all estimation windows. Furthermore, our results indicate that the 18 and 24 months ahead forecasts from the simple ARDL-CCE model (Eq.14) fail to encompass the forecasts the specification with MDRI (Eq.12) at level of statistical significance 5%. Therefore, the use of MDRI improves the forecasting accuracy of the dynamic CCE model at long forecast horizons. We also observe that the MDRI specifications always predict more accurately the direction of change in housing price returns at long forecast periods. In the case of state data, estimation window of 80 and h = 24 the sign metric of ARDL-CCE models with MDRI is 83.1%, while for the ARDL-CCE with and without NFER is 75.3% and 72%, respectively. The same regularities hold for the case of the MSA data; when a forecast horizon of two years and estimation window of 80 are considered, forecasting equation with MDRI (Eq.12) generates a sign value of 87.9%

while forecasting equations with and without EA (Eq.13 and Eq.14) yield 74% and 70.2%, respectively.

[INSERT TABLE 4]

3.2.4 Robustness Analysis

In order to examine the robustness of the results, we repeat the forecasting analysis within two alternative frameworks, the ARDL-FE framework and the time series ARDL framework.

Following the analysis reported in the previous subsection, we consider three competing forecasting models within the ARDL-FE framework:

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_j HPR_{i,t-j} + \sum_{j=1}^{3} \gamma_j MDRIR_{i,t-j} + \sum_{j=1}^{3} \pi_j X_{i,t-j} + u_{i,t+h} \; , \tag{20}$$

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_j HPR_{i,t-j} + \sum_{j=1}^{3} \pi_j X_{i,t-j} + u_{i,t+h} \; , \tag{21}$$

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_j HPR_{i,t-j} + u_{i,t+h} \; , \tag{22}$$

Models (20), (21) and (22) are estimated using the dummy variables least squares method. Time series ARDL framework consists of the time series versions of the previous forecast models:

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_{ij} HPR_{i,t-j} + \sum_{j=1}^{3} \gamma_{ij} MDRIR_{i,t-j} + \sum_{j=1}^{3} \pi_{ij} X_{i,t-j} + u_{i,t+h} \; , \tag{23}$$

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_{ij} HPR_{i,t-j} + \sum_{j=1}^{3} \pi_{ij} X_{i,t-j} + u_{i,t+h} \; , \tag{24}$$

$$HPR_{i,t+h} = a_{i0} + \sum_{j=1}^{3} \beta_{ij} HPR_{i,t-j} + u_{i,t+h} \; , \tag{25}$$

Equations (23)-(25) are estimated using least squares for each cross-sectional unit. In the case of the state-level data, we set $X_{i,t} \equiv NFER_{i,t}$, while in the case of MSA data $X_{i,t} \equiv EA_{i,t}$.

Tables 5 and 6 report the results of the out-of-sample forecasting exercise when ARDL-FE models are applied at the state and MSA-level, respectively. Tables 7 and 8 report the results of the out-of-sample forecasting exercise when ARDL time series models are applied at the state and MSA-level, respectively. For every forecasting model we demonstrate the results for estimation windows of 50, 60 and 80 monthly observations. The analysis done within the ARDL-CCE framework and reported in the previous sub-section is repeated for FE and time series ARDL frameworks. Consequently, in each table we report RMSFE and sign forecast accuracy metrics, as well as the encompassing tests results, for forecast horizons 1, 3, 6, 12, 18 and 24 months-ahead.

[INSERT TABLE 5]

From the inspection of Tables 5 and 6, it is evident that FE specifications with MDRI growth rates generate superior forecasts in terms of the RMSFEs and the sign metrics for horizons greater than one year-ahead. The evidence from the forecasting encompassing tests support this finding. In the case of state- (MSA-) level data, for forecast horizons 24 and 18 months-ahead, the null hypothesis that the forecasts from the ARDL-FE specification with NFER (EA) and MDRI are encompassed by the forecasts from the ARDL-FE specification with NFER (EA) alone is rejected at 5% and 10% levels of statistical significance, respectively. Furthermore, for $h = 24$ (18) the forecasts from the simple ARDL-FE model do not encompass the forecasts from MDRI specification again at the 5% (10%) level of significance. Additionally, FE specifications with MDRI tend to predict more accurately the direction of change in housing price returns especially at long forecast periods.

Therefore, there is much to be gained by using MDRI growth rates in a dynamic model for forecasting housing returns at long horizons. These results hold for all estimation window lengths.

[INSERT TABLE 6]

Next, we repeat the out-of-sample forecasting analysis in a time series context. The forecasting regularities observed in the ARDL-CCE and ARDL-FE frameworks are also present in the time series framework. Results reported in Tables 7 and 8 for state- and MSA-level, respectively, show that forecast accuracy measures support the superiority of the MDRI based models for long horizon forecasting. Furthermore, forecasting encompassing tests reject the null hypothesis that the forecasts from the time series specification with NFER (EA) and MDRI are encompassed by the forecasts from the time series specification with NFER (EA) for all forecasting horizons at the 10% significance level. Furthermore, the ENCT test results suggest that for forecasting horizons greater than one year, the simple ARDL model (Eq.25) fail to encompass the forecasts from competing time series specifications at the 5% level of significance. Additionally, time series specifications with MDRI tend to predict more accurately the direction of change in housing price returns especially at long forecast periods. Therefore, there is much to be gained by using MDRI growth rates in a dynamic model for forecasting housing returns at long horizons.

[INSERT TABLES 7 and 8]

Overall, the examination of the ARDL-FE and time series ARDL forecasting results shown in Tables 5-8, reveals similar patterns to those documented for the ARDL-CCE baseline framework (Tables 3 and 4). Specifically, all specifications with MDRI growth rates generate superior forecasts in terms of the RMSFEs and the sign metrics for horizons greater than one year-ahead compared to their corresponding specifications without MDRI as regressor. As in the case of the baseline forecasting model, the evidence from the forecasting encompassing tests supports this finding. Encompassing tests results suggest that forecasts from specifications with MDRI as regressor are not encompassed by the forecasts of competing specifications which do not include MDRI. Therefore, there is much to be gained by using MDRI growth rates in a dynamic model for forecasting housing returns at long horizons. These results are not sensitive to the selection of the estimation window.

3.2.5 Sensitivity analysis: estimation bias reduction

The purpose of this sub-section is twofold. First, we want to investigate the sensitivity of our results to the possible presence of small time dimension bias in the least squares estimator of the panel data models. To the extent that there is bias in the estimated parameter coefficients, the generated forecasts will be inaccurate, while the forecast encompassing test statistics will result in misleading inference. Nickel (1981) shows that the within group estimator delivers biased coefficient estimates of a dynamic panel model when a small T sample is available. Second, since our evaluation so far has shown that the CCE and the fixed effects models dominate in terms of forecasting accuracy (the first at the MSA-level data and the second at the state level data), we find of great interest to compare their forecasting performance after we apply small-sample bias corrections to the parameter coefficient estimates. Contrasting the CCE and FE models, a small T bias is expected to cause a stronger effect in the coefficient estimates of the former, and as a consequence to its forecasting performance. For example, consider that when we forecast housing price returns at the state level based on an estimation window of 80 monthly observations, 80 observations are used to estimate the 29 unknown parameters of the state-specific ARDL-CCE model with MDRI and NFER. Then, these coefficients are averaged on the cross-sectional dimension. On the other hand, $80\times 43=3440$ observations will be used to estimate the 52 parameters of the corresponding ARDL-FE model. Thus, compared to the fixed effects models, the CCE models appear to be possibly more prone to small *T* bias, since they use a much smaller number of time observations to estimate a relatively large number of parameters.

Small *T* bias correction is performed by estimating the panel data models via the jackknife bias reduction method of Chudik and Pesaran (2015). Their method first, splits the estimation sample into two sample windows of equal length, and then uses the two generated sample windows to re-estimate the model parameter coefficients. The new parameter coefficient estimates are denoted as $\hat{\varphi}_{GM}^{(A)}$ and $\hat{\varphi}_{GM}^{(B)}$, respectively. Finally, the parameter coefficient estimates are adjusted by applying the following transformation: $\hat{\varphi}_{GM}^{*}=2\hat{\varphi}_{GM}-0.5*\hat{\varphi}_{GM}^{(A)}-0.5*\hat{\varphi}_{GM}^{(B)}$. The same method is also applied to the parameter coefficients of the FE panel regressions.

The results of the estimations are presented in Table 9. The analysis is based on an estimation window of 80-monthly observations. The differences in *p*-values are comparatively minor with only exception being the larger *p*-values for $h=18$ at the state-level. The net result is strong long horizon predictability of the MDRI specifications at both datasets. Thus, we draw similar conclusions with our prior analysis. Compared to Table 3, we observe a sizable reduction in the magnitude of the RMSFEs of the CCE models. We document that the CCE method outperforms the FE models in terms of forecast accuracy at both the state and MSA-level. There is much to be gained also in terms of the accuracy of the forecasted direction of change by using the bias-corrected CCE models. At long horizons, the implementation of the jackknife bias reduction on the CCE models yields much higher sign values when compared to those of the fixed effects panel regressions.

[INSERT TABLE 9]

4. Conclusions

In this paper we analyze the ability of an index of mortgage default risks (MDRI) for 43 states and 20 MSAs of the US derived from Google search queries, in predicting (in- and out-of-sample) housing returns of the corresponding states and MSAs, based on various panel data approaches. The in-sample analysis of the dynamic models with common correlated effects (CCE) based on state-level- data reveals that the MDRI growth rates do not predict housing prices returns over any forecast horizons. However, we document evidence of long-horizon predictability of the cross-section averages of the MDRI growth rates. The sign of the MDRI and the corresponding cross-sectional averages coefficients is negative highlighting the negative relation of individual housing prices to aggregate default risk movements. The estimation results of the dynamic fixed effects panel regressions draw a very different picture of predictability. In particular, changes in MDRI growth rates are found to cause a negative impact on housing price returns at both short and long-time horizons. However, the parameter coefficient estimates of these models appear to be severely inflated possibly due to the presence of cross-sectional dependence in the error term. As a consequence, this raises a reasonable amount of uncertainty about the reliability of the statistical inference.

On the other hand, the in-sample results of the dynamic models with common correlated effects based on the MSA-level data indicate the MDRIs induce a significant and negative effect on housing price returns at long forecast horizons. Again, the coefficient estimates of the fixed effects panel regressions appear to be biased.

The out-of-sample forecasting analysis based on the state-level data confirms the evidence on the long horizon predictability of the MDRIs. We summarize our main findings as follows: First, specifications which include MDRI growth rates outperform the competing models at forecast horizons larger than 12 months-ahead in terms of the RMSFEs and the accuracy of the predicted direction of change. Second, the forecast encompassing tests show that at long forecasts horizons the accuracy of forecasts is improved when the growth rates of MDRI and non-farm employment are combined in a single dynamic forecast model. Third, this finding is robust with respect to the estimation method (dynamic model with CCE, fixed effects panel regressions, and time-series based-models), as well as to the length of the estimation sample. Fourth, along with the use of the jackknife bias reduction, the CCE models are found to dominate across the forecast models in terms of predictive accuracy.

The out-of-sample forecasting analysis of the MSA-level data reveals stronger evidence on the long horizon predictability of the MDRIs. The comparison of the forecast accuracy measures shows that the MDRI based specifications have superior performance over the competing specification at long horizons. The inferential analysis indicates that there is much to be gained by generating forecasts of housing prices based on a specification that uses MDRI growth rates. This finding holds for different modeling approaches and estimation sample lengths. The CCE approach is found again to be the dominant forecast model.

From the perspective of a policymaker, trying to utilize the information on regional housing returns for predicting regional business cycles, our results imply that, information on mortgage default risks can be utilized in a statistically significant manner primarily in the long-run, i.e., from one-year onwards, in forecasting the future path and the direction of the growth of housing prices. As part of future research, it would be interesting to extend our analysis to studying the predictability of regional housing market volatility using a panel-Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach, as shown to exist for the national-level housing returns by Bouri et al., (forthcoming) using time-series based approaches.

Data Availability Statement:

The data that support the findings of this study are available from publicly available databases: the Mortgage Default Risks Index (MDRI) database, Freddie Mac, US Bureau of Economic Analysis (BEA), and FRED database of the Federal Reserve Bank of St. Louis.

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[Dataset]

Data: MDRI by Chauvet et al. (2016): https://chandlerlutz.shinyapps.io/mdri-app/); House Price: Freddie Mac: http://www.freddiemac.com/research/indices/house-price-index.page; Non-Farm Employment: Regional Accounts Database of the US Bureau of Economic Analysis (BEA), and; Monthly economic activity indices of MSAs as developed by Arias et al., (2016): FRED database of the Federal Reserve Bank of St. Louis.

Table 1: In-sample predictability of housing price returns at the state level

Panel A: estimates of the main parameter coefficients of the models

Models	$h = 1$		$h = 3$		$h = 6$		$h = 12$		$h = 24$	
	ARDL-CCE	ARDL-FE	ARDL-CCE	ARDL-FE	ARDL-CCE	ARDL-FE	ARDL-CCE	ARDL-FE	ARDL-CCE	ARDL-FE
Constant	0.001	0.001	0.005	0.004	0.010	0.007	0.016	0.034	0.028	0.120
	(0.148)	(0.653)	(0.116)	(0.664)	(0.013)	(0.701)	(0.235)	(0.314)	(0.518)	(0.140)
$HPR_{i,t-1}$	0.060	0.103	0.101	0.249	0.150	0.440	0.251	0.805	0.295	1.192
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$HPR_{i,t-2}$	-0.041	-0.048	-0.073	-0.102	-0.074	-0.149	-0.104	-0.261	-0.134	-0.343
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$HPR_{i,t-3}$	0.023	0.034	0.067	0.104	0.122	0.177	0.139	0.226	0.131	0.022
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)	(0.000)	(0.159)	(0.768)
$NFER_{i,t-1}$	0.004	-0.000	0.010	-0.008	0.022	-0.016	0.037	0.000	0.091	0.264
	(0.099)	(0.738)	(0.213)	(0.071)	(0.259)	(0.129)	(0.195)	(0.986)	(0.000)	(0.000)
$NFER_{i,t-2}$	0.004	-0.003	0.016	-0.007	0.030	-0.011	0.060	0.027	0.153	0.292
	(0.055)	(0.020)	(0.036)	(0.136)	(0.128)	(0.348)	(0.087)	(0.264)	(0.000)	(0.000)
$NFER_{i,t-3}$	0.005	0.000	0.017	0.004	0.039	0.011	0.090	0.084	0.182	0.323
	(0.009)	(0.904)	(0.006)	(0.407)	(0.023)	(0.320)	(0.002)	(0.000)	(0.000)	(0.000)
$MDRIR_{i,t-1}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	-0.002	-0.002	-0.008
	(0.570)	(0.000)	(0.369)	(0.000)	(0.208)	(0.000)	(0.318)	(0.000)	(0.310)	(0.000)
$MDRIR_{i,t-2}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	-0.003	-0.003	-0.010
	(0.371)	(0.000)	(0.180)	(0.000)	(0.222)	(0.000)	(0.269)	(0.000)	(0.250)	(0.000)
$MDRIR_{i,t-3}$	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	-0.002	-0.003	-0.007
	(0.112)	(0.013)	(0.073)	(0.000)	(0.268)	(0.000)	(0.226)	(0.000)	(0.236)	(0.000)

Panel B: estimates of the coefficients of the MDRI cross-sectional averages

	$h = 1$	$h = 3$	$h = 6$	$h = 12$	$h = 24$
$\overline{w}_{2t-1}$	0.000	0.000	-0.001	-0.007	-0.021
	(0.813)	(0.986)	(0.000)	(0.000)	(0.000)
$\overline{w}_{2t-2}$	0.000	0.000	-0.002	-0.009	-0.026
	(0.083)	(0.182)	(0.000)	(0.000)	(0.000)
$\overline{w}_{2t-3}$	0.000	-0.001	-0.004	-0.012	-0.032
	(0.872)	(0.020)	(0.000)	(0.000)	(0.000)
$\overline{w}_{2t-4}$	-0.000	-0.001	-0.004	-0.013	-0.030
	(0.120)	(0.001)	(0.000)	(0.000)	(0.000)
$\overline{w}_{2t-5}$	-0.000	-0.001	-0.002	-0.009	-0.020
	(0.296)	(0.012)	(0.000)	(0.000)	(0.000)
$\overline{w}_{2t-6}$	0.000	-0.000	-0.000	-0.005	-0.012
	(0.665)	(0.601)	(0.138)	(0.000)	(0.000)

Notes: This table presents the estimation results for the dynamic models ARDL-CCE and ARDL-FE, described in Equations (8)-(9), at various monthly forecast periods *h*. The panel data consist of 43 cross-sectional units spanning the period 1/1/2004- 1/12/2017. Panels A and B present the findings for the main parameter coefficients of the models and the cross-sectional averages of MDRI, respectively. The specifications of the ARDL-CCE and the ARDL-FE model are given in equations (8) and (9), respectively. The estimation procedure for the ARDL-CCE models is described in Equations (1)-(6). The ARDL-FE models are estimated by using the cross-sectional dummy variables least squares method. $HPR_{i,t}$ are the state-specific housing price returns for month *t*, $MDRIR_{i,t}$ are the state-specific growth rates of Mortgage default risks for month *t*, and $NFER_{i,t}$ are the growth rates of non-farm employment for month *t*. *p*-values are in parentheses.

Table 2: In-sample predictability of housing price returns at the MSA level

Panel A: estimates of the main parameter coefficients of the models

	$h = 1$		$h = 3$		$h = 6$		$h = 12$		$h = 24$	
Models	ARDL-CCE	ARDL-fixed effects	ARDL-CCE	ARDL-fixed effects	ARDL-CCE	ARDL-fixed effects	ARDL-CCE	ARDL-fixed effects	ARDL-CCE	ARDL-fixed effects
Constant	0.000	0.000	0.000	0.000	0.000	-0.001	-0.007	-0.008	-0.045	-0.035
	(0.726)	(0.774)	(0.942)	(0.778)	(0.774)	(0.729)	(0.001)	(0.476)	(0.000)	(0.295)
$HPR_{i,t-1}$	0.552	1.110	1.219	3.078	1.947	5.905	2.787	10.752	2.765	15.066
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$HPR_{i,t-2}$	-0.213	-0.383	-0.328	-0.847	-0.278	-1.536	-0.385	-2.757	-0.222	-3.588
	(0.002)	(0.000)	(0.047)	(0.000)	(0.157)	(0.000)	(0.080)	(0.000)	(0.472)	(0.000)
$HPR_{i,t-3}$	0.258	0.174	0.666	0.311	1.027	0.235	1.135	-1.027	1.905	-5.476
	(0.000)	(0.000)	(0.000)	(0.005)	(0.004)	(0.377)	(0.117)	(0.080)	(0.004)	(0.000)
$EA_{i,t-1}$	0.014	0.011	0.040	0.027	0.268	0.030	0.589	-0.032	1.740	0.750
	(0.516)	(0.169)	(0.552)	(0.311)	(0.045)	(0.607)	(0.210)	(0.796)	(0.053)	(0.021)
$EA_{i,t-2}$	-0.017	-0.008	0.046	-0.023	0.003	-0.037	0.316	-0.012	0.087	0.200
	(0.567)	(0.454)	(0.633)	(0.409)	(0.974)	(0.472)	(0.080)	(0.913)	(0.477)	(0.333)
$EA_{i,t-3}$	0.054	-0.001	0.082	0.007	0.101	0.054	-0.126	0.389	-1.231	0.632
	(0.011)	(0.874)	(0.331)	(0.798)	(0.642)	(0.348)	(0.624)	(0.020)	(0.000)	(0.002)
$MDRIR_{i,t-1}$	0.000	-0.001	0.000	-0.004	0.001	-0.015	-0.008	-0.053	-0.017	-0.169
	(0.472)	(0.023)	(0.754)	(0.014)	(0.703)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
$MDRIR_{i,t-2}$	0.001	-0.001	0.001	-0.003	0.002	-0.016	-0.006	-0.061	-0.012	-0.199
	(0.250)	(0.297)	(0.651)	(0.098)	(0.162)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
$MDRIR_{i,t-3}$	0.000	0.000	0.000	-0.003	0.001	-0.013	-0.005	-0.050	-0.008	-0.154
	(0.524)	(0.656)	(0.757)	(0.083)	(0.526)	(0.001)	(0.020)	(0.000)	(0.059)	(0.000)

Panel B: estimates of the coefficients of the MDRI cross-sectional averages

	$h = 1$	$h = 3$	$h = 6$	$h = 12$	$h = 24$
$\overline{w}_{2t-1}$	-0.002	-0.003	-0.025	-0.097	-0.348
	(0.080)	(0.388)	(0.025)	(0.000)	(0.000)
$\overline{w}_{2t-2}$	0.000	-0.005	-0.038	-0.158	-0.448
	(0.934)	(0.372)	(0.020)	(0.000)	(0.000)
$\overline{w}_{2t-3}$	-0.004	-0.023	-0.076	-0.251	-0.613
	(0.019)	(0.007)	(0.002)	(0.000)	(0.000)
$\overline{w}_{2t-4}$	-0.004	-0.022	-0.068	-0.246	-0.540
	(0.030)	(0.006)	(0.001)	(0.000)	(0.000)
$\overline{w}_{2t-5}$	-0.003	-0.015	-0.041	-0.168	-0.355
	(0.034)	(0.017)	(0.003)	(0.000)	(0.000)
$\overline{w}_{2t-6}$	-0.001	-0.002	-0.015	-0.104	-0.205
	(0.384)	(0.469)	(0.006)	(0.000)	(0.000)

***Notes*:** This table presents the estimation results for the dynamic models described in Equations (10)-(11) at various monthly forecast periods *h*. The panel data consist of 20 cross-sectional units spanning the period 1/1/2004- 1/12/2017. Panels A and B present the findings for the main parameter coefficients of the models and the cross-sectional averages of MDRI, respectively. The specifications of the ARDL-CCE and the ARDL-fixed effects model are given in equations (10) and (11), respectively. The estimation procedure for the ARDL-CCE models is described in Equations (1)-(6). The ARDL-fixed effects models are estimated by using the cross-sectional dummy variables least squares method. $HPR_{i,t}$ are the MSA-specific housing price returns for month *t*, $MDRIR_{i,t}$ are the MSA-specific growth rates of Mortgage default risks for month *t*, and $EA_{i,t}$ denote the MSA-specific economic activity for month *t*. *p*-values are in parentheses.

Table 3: Out-of-sample forecasting results of housing prices at the state level within the ARDL-CCE framework

Estimation window	80			60			50		
Models	ARDL – CCE	ARDL-CCE with NFER	ARDL-CCE with NFER, MDRI	ARDL – CCE	ARDL-CCE with NFER	ARDL-CCE with NFER, MDRI	ARDL – CCE	ARDL-CCE with NFER	ARDL-CCE with NFER, MDRI
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Comparing models :	(1)-(2)	(2)-(3)	(1)-(3)	(1)-(2)	(2)-(3)	(1)-(3)	(1)-(2)	(2)-(3)	(1)-(3)
					Forecast Horizon *h* = 1				
RMSFE	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Sign	0.884	0.888	0.881	0.871	0.869	0.864	0.872	0.867	0.861
ENCT test	0.000	0.000	0.000	1.216	0.399	1.164	0.963	0.808	1.368
	(0.500)	(0.500)	(0.500)	(0.112)	(0.345)	(0.122)	(0.168)	(0.210)	(0.086)
					Forecast Horizon *h* = 3				
RMSFE	0.005	0.006	0.006	0.007	0.007	0.007	0.007	0.007	0.007
Sign	0.901	0.903	0.899	0.878	0.877	0.874	0.876	0.876	0.873
ENCT test	0.000	0.000	0.000	1.066	0.209	0.949	0.469	0.000	0.231
	(0.500)	(0.500)	(0.500)	(0.143)	(0.417)	(0.171)	(0.319)	(0.500)	(0.409)
					Forecast Horizon *h* = 6				
RMSFE	0.015	0.016	0.016	0.018	0.018	0.017	0.018	0.018	0.018
Sign	0.907	0.908	0.908	0.888	0.887	0.888	0.892	0.892	0.889
ENCT test	0.000	1.368	0.000	0.766	1.534	1.049	0.654	0.144	0.619
	(0.500)	(0.086)	(0.500)	(0.222)	(0.062)	(0.147)	(0.256)	(0.443)	(0.268)
					Forecast Horizon *h* = 12				
RMSFE	0.048	0.051	0.049	0.045	0.049	0.048	0.047	0.049	0.048
Sign	0.867	0.864	0.876	0.863	0.853	0.861	0.882	0.862	0.866
ENCT test	0.000	2.131	0.000	0.000	1.150	0.042	0.065	1.166	0.563
	(0.500)	(0.017)	(0.500)	(0.500)	(0.125)	(0.483)	(0.474)	(0.122)	(0.287)
					Forecast Horizon *h* = 18				
RMSFE	0.082	0.082	0.075	0.079	0.078	0.074	0.077	0.073	0.068
Sign	0.816	0.794	0.854	0.848	0.835	0.851	0.864	0.883	0.876
ENCT test	0.098	3.746	2.499	1.042	1.636	1.905	2.099	1.969	2.799
	(0.461)	(0.000)	(0.006)	(0.149)	(0.051)	(0.028)	(0.018)	(0.024)	(0.003)
					Forecast Horizon *h* = 24				
RMSFE	0.111	0.108	0.096	0.117	0.109	0.104	0.116	0.101	0.095
Sign	0.720	0.753	0.831	0.802	0.836	0.880	0.852	0.897	0.912
ENCT test	0.651	8.224	2.962	2.591	1.907	2.894	2.819	2.125	2.924
	(0.258)	(0.000)	(0.002)	(0.005)	(0.028)	(0.002)	(0.002)	(0.017)	(0.002)

Notes: The table demonstrates the out-of-sample rolling window forecast results of monthly housing prices based on a panel of 43 cross-sectional units for the period 1/1/2004- 1/12/2017 for forecast horizons 1, 3, 6, 12, 18, and 24 months-ahead and for three estimation windows, 80, 60 and 50 monthly observations. RMSFEs, the sign accuracy measure of the predicted direction and the ENCT encompassing test statistics results are reported. ENCT denote the Harvey, at al. (1998) forecast encompassing test. p-values are in parentheses. Models' (1) (2) and (3) specifications are described in equations (14), (13), (12), respectively. Models are compared according to their encompassing ability using the ENCT test.

Table 4: out-of-sample forecasting results of housing prices at the MSA-level within the ARDL-CCE framework

Estimation window	80			60			50		
Models	ARDL – CCE (1)	ARDL-CCE with EA (2)	ARDL-CCE with EA, MDRI (3)	ARDL – CCE (1)	ARDL-CCE with EA (2)	ARDL-CCE with EA, MDRI (3)	ARDL – CCE (1)	ARDL-CCE with EA (2)	ARDL-CCE with EA, MDRI (3)
Comparing models :	(1)-(2)	(2)-(3)	(1)-(3)	(1)-(2)	(2)-(3)	(1)-(3)	(1)-(2)	(2)-(3)	(1)-(3)
				Forecast Horizon *h* = 1					
RMSFE	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
sign	0.944	0.946	0.949	0.921	0.917	0.915	0.923	0.911	0.910
ENCT test	0.000	1.556	0.165	0.289	1.931	1.408	2.701	2.697	3.578
	(0.500)	(0.060)	(0.434)	(0.386)	(0.027)	(0.080)	(0.003)	(0.003)	(0.000)
				Forecast Horizon *h* = 3					
RMSFE	0.008	0.009	0.009	0.011	0.011	0.011	0.011	0.010	0.010
sign	0.945	0.941	0.943	0.917	0.904	0.900	0.923	0.913	0.912
ENCT test	0.000	2.174	0.000	0.912	1.162	1.227	1.997	1.008	2.080
	(0.500)	(0.015)	(0.500)	(0.181)	(0.123)	(0.110)	(0.023)	(0.157)	(0.019)
				Forecast Horizon *h* = 6					
RMSFE	0.026	0.028	0.027	0.030	0.029	0.028	0.034	0.030	0.029
sign	0.928	0.913	0.918	0.905	0.881	0.885	0.908	0.900	0.893
ENCT test	0.000	1.968	0.000	0.792	1.522	1.132	1.401	1.294	1.498
	(0.500)	(0.025)	(0.500)	(0.214)	(0.064)	(0.129)	(0.081)	(0.098)	(0.067)
				Forecast Horizon *h* = 12					
RMSFE	0.081	0.084	0.076	0.081	0.080	0.072	0.097	0.083	0.079
sign	0.871	0.861	0.901	0.869	0.864	0.872	0.876	0.899	0.896
ENCT test	0.000	1.621	1.207	1.255	1.671	1.846	1.727	1.503	2.001
	(0.500)	(0.052)	(0.114)	(0.105)	(0.047)	(0.032)	(0.042)	(0.066)	(0.023)
				Forecast Horizon *h* = 18					
RMSFE	0.130	0.127	0.108	0.144	0.136	0.121	0.153	0.127	0.114
sign	0.801	0.832	0.915	0.834	0.869	0.909	0.869	0.905	0.922
ENCT test	0.814	2.176	1.871	1.926	1.778	2.270	2.002	1.716	2.406
	(0.208)	(0.015)	(0.031)	(0.027)	(0.038)	(0.012)	(0.023)	(0.043)	(0.008)
				Forecast Horizon *h* = 24					
RMSFE	0.168	0.156	0.128	0.216	0.190	0.175	0.228	0.176	0.162
sign	0.702	0.740	0.879	0.787	0.834	0.894	0.874	0.883	0.900
ENCT test	1.269	5.815	2.507	2.257	2.104	3.103	1.960	1.981	2.316
	(0.102)	(0.000)	(0.006)	(0.012)	(0.018)	(0.001)	(0.025)	(0.024)	(0.010)

Notes: *Notes*: The table demonstrates the out-of-sample rolling window forecast results of monthly housing prices based on a panel of 20 cross-sectional units for the period 1/1/2004- 1/12/2017 for forecast horizons 1, 3, 6, 12, 18, and 24 months-ahead and for three estimation windows, 80, 60 and 50 monthly observations. RMSFEs, the sign accuracy measure of the predicted direction and the ENCT encompassing test statistics results are reported. ENCT denote the Harvey, at al. (1998) forecast encompassing test. p-values are in parentheses. Models' (1) (2) and (3) specifications are described in equations (14), (13), (12), respectively. Models are compared according to their encompassing ability using the ENCT test.

Table 5: Out-of-sample forecasting results of housing prices at the state level within the ARDL-FE framework

Estimation Window	80			60			50		
Models	ARDL (4)	ARDL with NFER (5)	ARDL with NFER, MDRI (6)	ARDL (4)	ARDL with NFER (5)	ARDL with NFER, MDRI (6)	ARDL (4)	ARDL with NFER (5)	ARDL with NFER, MDRI (6)
Comparing models :	(4)-(5)	(5)-(6)	(4)-(6)	(4)-(5)	(5)-(6)	(4)-(6)	(4)-(5)	(5)-(6)	(4)-(6)
				Forecast Horizon *h* = 1					
RMSFE	0.001	0.001	0.001	0.002	0.002	0.002	0.002	0.002	0.002
Sign	0.858	0.859	0.854	0.848	0.850	0.842	0.852	0.855	0.850
ENCT test	0.000	1.702	0.000	1.041	2.174	1.599	1.010	1.242	1.304
	(0.500)	(0.044)	(0.500)	(0.149)	(0.015)	(0.055)	(0.156)	(0.107)	(0.096)
				Forecast Horizon *h* = 3					
RMSFE	0.006	0.006	0.006	0.008	0.008	0.008	0.008	0.008	0.008
sign	0.871	0.870	0.868	0.853	0.857	0.853	0.861	0.864	0.861
ENCT test	0.000	2.448	0.000	0.234	2.757	0.924	0.147	2.046	0.622
	(0.500)	(0.007)	(0.500)	(0.407)	(0.003)	(0.178)	(0.442)	(0.020)	(0.267)
				Forecast Horizon *h* = 6					
RMSFE	0.016	0.016	0.016	0.019	0.020	0.019	0.019	0.020	0.019
sign	0.879	0.875	0.875	0.855	0.852	0.853	0.868	0.864	0.863
ENCT test	0.000	1.679	0.000	0.000	1.743	0.268	0.000	1.341	0.000
	(0.500)	(0.047)	(0.500)	(0.500)	(0.041)	(0.394)	(0.500)	(0.090)	(0.500)
				Forecast Horizon *h* = 12					
RMSFE	0.046	0.046	0.046	0.039	0.041	0.040	0.039	0.042	0.041
sign	0.849	0.851	0.856	0.827	0.816	0.826	0.849	0.838	0.838
ENCT test	0.000	2.012	0.198	0.000	1.332	0.210	0.000	1.172	0.000
	(0.500)	(0.022)	(0.422)	(0.500)	(0.091)	(0.417)	(0.500)	(0.121)	(0.500)
				Forecast Horizon *h* = 18					
RMSFE	0.074	0.073	0.071	0.064	0.062	0.059	0.058	0.058	0.055
sign	0.819	0.830	0.844	0.811	0.812	0.829	0.841	0.836	0.837
ENCT test	1.112	2.838	4.817	1.132	1.564	3.089	0.631	1.410	2.716
	(0.133)	(0.002)	(0.000)	(0.129)	(0.059)	(0.001)	(0.264)	(0.079)	(0.003)
				Forecast Horizon *h* = 24					
RMSFE	0.094	0.092	0.087	0.097	0.092	0.087	0.090	0.084	0.080
sign	0.780	0.808	0.826	0.781	0.809	0.833	0.823	0.828	0.845
ENCT test	2.913	15.059	6.219	2.589	2.357	4.076	6.901	1.929	4.601
	(0.002)	(0.000)	(0.000)	(0.005)	(0.009)	(0.000)	(0.000)	(0.027)	(0.000)

Notes: The table demonstrates the out-of-sample rolling window forecast results of monthly housing prices based on a panel of 43 cross-sectional units for the period 1/1/2004- 1/12/2017 for forecast horizons 1, 3, 6, 12, 18, and 24 months-ahead and for three estimation windows, 80, 60 and 50 monthly observations. RMSFEs, the sign accuracy measure of the predicted direction and the ENCT encompassing test statistics results are reported. ENCT denote the Harvey, at al. (1998) forecast encompassing test. p-values are in parentheses. Models' (4), (5) and (6) specifications are described in equations (22), (21), (20), respectively. Models are compared according to their encompassing ability using the ENCT test.

Table 6: out-of-sample forecasting results of housing prices at the MSA-level within ARDL-FE framework

Estimation window	80			60			50		
Models	ARDL (4)	ARDL with EA (5)	ARDL with EA, MDRI (6)	ARDL (4)	ARDL with EA (5)	ARDL with EA, MDRI (6)	ARDL (4)	ARDL with EA (5)	ARDL with EA, MDRI (6)
Comparing models :	(4)-(5)	(5)-(6)	(4)-(6)	(4)-(5)	(5)-(6)	(4)-(6)	(4)-(5)	(5)-(6)	(4)-(6)
					Forecast Horizon *h* = 1				
RMSFE	0.002	0.002	0.002	0.003	0.003	0.003	0.003	0.003	0.003
Sign	0.923	0.923	0.922	0.909	0.910	0.908	0.911	0.913	0.912
ENCT test	0.000	0.608	0.000	1.096	2.700	1.436	0.789	3.431	1.199
	(0.500)	(0.272)	(0.500)	(0.136)	(0.003)	(0.076)	(0.215)	(0.000)	(0.115)
					Forecast Horizon *h* = 3				
RMSFE	0.010	0.010	0.010	0.013	0.013	0.013	0.012	0.013	0.013
Sign	0.917	0.917	0.918	0.905	0.900	0.900	0.908	0.905	0.907
ENCT test	0.000	1.332	0.000	0.402	2.769	0.843	0.128	2.622	0.468
	(0.500)	(0.091)	(0.500)	(0.344)	(0.003)	(0.200)	(0.449)	(0.004)	(0.320)
					Forecast Horizon *h* = 6				
RMSFE	0.029	0.030	0.030	0.032	0.033	0.033	0.034	0.037	0.036
Sign	0.908	0.899	0.908	0.894	0.880	0.885	0.897	0.900	0.902
ENCT test	0.000	1.383	0.000	0.000	1.853	0.390	0.000	1.797	0.000
	(0.500)	(0.083)	(0.500)	(0.500)	(0.032)	(0.348)	(0.500)	(0.036)	(0.500)
					Forecast Horizon *h* = 12				
RMSFE	0.082	0.085	0.083	0.077	0.081	0.078	0.091	0.096	0.092
Sign	0.853	0.852	0.863	0.862	0.836	0.838	0.875	0.887	0.889
ENCT test	0.000	1.505	0.000	0.000	1.332	0.919	0.000	1.381	0.411
	(0.500)	(0.066)	(0.500)	(0.500)	(0.091)	(0.179)	(0.500)	(0.084)	(0.341)
					Forecast Horizon *h* = 18				
RMSFE	0.128	0.129	0.124	0.134	0.131	0.125	0.151	0.146	0.138
Sign	0.785	0.804	0.819	0.831	0.818	0.824	0.853	0.872	0.883
ENCT test	0.000	1.734	1.499	0.928	1.427	2.352	1.088	1.430	2.440
	(0.500)	(0.041)	(0.067)	(0.177)	(0.077)	(0.009)	(0.138)	(0.076)	(0.007)
					Forecast Horizon *h* = 24				
RMSFE	0.162	0.158	0.150	0.201	0.187	0.180	0.232	0.205	0.196
Sign	0.707	0.756	0.770	0.796	0.797	0.827	0.835	0.858	0.874
ENCT test	1.273	3.148	2.753	1.475	1.998	2.346	2.055	1.732	2.573
	(0.102)	(0.001)	(0.003)	(0.070)	(0.023)	(0.009)	(0.020)	(0.042)	(0.005)

Notes: *Notes*: The table demonstrates the out-of-sample rolling window forecast results of monthly housing prices based on a panel of 20 cross-sectional units for the period 1/1/2004- 1/12/2017 for forecast horizons 1, 3, 6, 12, 18, and 24 months-ahead and for three estimation windows, 80, 60 and 50 monthly observations. RMSFEs, the sign accuracy measure of the predicted direction and the ENCT encompassing test statistics results are reported. ENCT denote the Harvey, at al. (1998) forecast encompassing test. p-values are in parentheses. Models' (4), (5) and (6) specifications are described in equations (22), (21), (20), respectively. Models are compared according to their encompassing ability using the ENCT test.

Table 7: Out-of-sample forecasting results of housing prices at the state level within the time series ARDL framework

Estimation window	80			60			50		
Models	ARDL	ARDL with NFER	ARDL with NFER, MDRI	ARDL	ARDL with NFER	ARDL with NFER, MDRI	ARDL	ARDL with NFER	ARDL with NFER, MDRI
	(7)	(8)	(9)	(7)	(8)	(9)	(7)	(8)	(9)
Comparing models :	(7)-(8)	(8)-(9)	(7)-(9)	(7)-(8)	(8)-(9)	(7)-(9)	(7)-(8)	(8)-(9)	(7)-(9)
					Forecast Horizon *h* = 1				
RMSFE	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
Sign	0.852	0.851	0.850	0.841	0.846	0.844	0.851	0.860	0.858
ENCT test	0.000	2.950	0.226	1.051	3.435	1.807	1.292	3.390	2.074
	(0.500)	(0.002)	(0.411)	(0.147)	(0.000)	(0.035)	(0.098)	(0.000)	(0.019)
					Forecast Horizon *h* = 3				
RMSFE	0.006	0.007	0.006	0.008	0.008	0.008	0.008	0.008	0.008
Sign	0.850	0.851	0.853	0.835	0.839	0.846	0.851	0.856	0.859
ENCT test	0.000	3.599	0.086	0.385	3.748	1.088	0.374	3.111	0.943
	(0.500)	(0.000)	(0.466)	(0.350)	(0.000)	(0.138)	(0.354)	(0.001)	(0.173)
					Forecast Horizon *h* = 6				
RMSFE	0.018	0.019	0.018	0.021	0.021	0.021	0.020	0.021	0.021
Sign	0.844	0.846	0.851	0.827	0.833	0.836	0.851	0.858	0.862
ENCT test	0.000	2.315	0.000	0.009	2.248	0.571	0.000	1.898	0.352
	(0.500)	(0.010)	(0.500)	(0.496)	(0.012)	(0.284)	(0.500)	(0.029)	(0.363)
					Forecast Horizon *h* = 12				
RMSFE	0.053	0.054	0.053	0.050	0.052	0.050	0.050	0.053	0.051
Sign	0.790	0.797	0.806	0.802	0.802	0.807	0.837	0.838	0.843
ENCT test	0.000	1.991	0.145	0.000	1.538	0.822	0.000	1.512	0.699
	(0.500)	(0.023)	(0.442)	(0.500)	(0.062)	(0.206)	(0.500)	(0.065)	(0.242)
					Forecast Horizon *h* = 18				
RMSFE	0.090	0.090	0.086	0.090	0.087	0.082	0.086	0.083	0.078
Sign	0.724	0.740	0.752	0.788	0.793	0.801	0.828	0.838	0.842
ENCT test	1.116	2.010	2.918	1.207	1.598	2.626	1.432	1.601	2.640
	(0.132)	(0.022)	(0.002)	(0.114)	(0.055)	(0.004)	(0.076)	(0.055)	(0.004)
					Forecast Horizon *h* = 24				
RMSFE	0.125	0.121	0.114	0.140	0.131	0.124	0.136	0.126	0.120
Sign	0.646	0.668	0.688	0.753	0.769	0.782	0.803	0.824	0.836
ENCT test	2.219	3.518	2.949	1.780	2.052	2.680	2.251	1.989	2.730
	(0.013)	(0.000)	(0.002)	(0.038)	(0.020)	(0.004)	(0.012)	(0.023)	(0.003)

Notes: *Notes*: The table demonstrates the out-of-sample rolling window forecast results of monthly housing prices based on a panel of 43 cross-sectional units for the period 1/1/2004- 1/12/2017 for forecast horizons 1, 3, 6, 12, 18, and 24 months-ahead and for three estimation windows, 80, 60 and 50 monthly observations. RMSFEs, the sign accuracy measure of the predicted direction and the ENCT encompassing test statistics results are reported. ENCT denote the Harvey, at al. (1998) forecast encompassing test. p-values are in parentheses. Models' (7), (8) and (9) specifications are described in equations (25), (24), (23), respectively. Models are compared according to their encompassing ability using the ENCT test.

Table 8: out-of-sample forecasting results of housing prices at the MSA-level within the time series ARDL framework

Estimation window	80			60			50		
Models	ARDL	ARDL with EA	ARDL with EA, MDRI	ARDL	ARDL with EA	ARDL with EA, MDRI	ARDL	ARDL with EA	ARDL with EA, MDRI
	(7)	(8)	(9)	(7)	(8)	(9)	(7)	(8)	(9)
Comparing models :	(7)-(8)	(8)-(9)	(7)-(9)	(7)-(8)	(8)-(9)	(7)-(9)	(7)-(8)	(8)-(9)	(7)-(9)
					Forecast Horizon *h* = 1				
RMSFE	0.002	0.002	0.002	0.003	0.003	0.003	0.003	0.003	0.003
Sign	0.918	0.916	0.919	0.904	0.904	0.904	0.911	0.913	0.912
ENCT test	0.000	2.653	0.000	0.882	3.370	1.196	0.789	3.431	1.199
	(0.500)	(0.004)	(0.500)	(0.189)	(0.000)	(0.116)	(0.215)	(0.000)	(0.115)
					Forecast Horizon *h* = 3				
RMSFE	0.010	0.010	0.010	0.013	0.013	0.013	0.012	0.013	0.013
Sign	0.907	0.899	0.903	0.896	0.887	0.890	0.908	0.905	0.907
ENCT test	0.000	2.199	0.000	0.312	3.070	0.686	0.128	2.622	0.468
	(0.500)	(0.014)	(0.500)	(0.377)	(0.001)	(0.246)	(0.449)	(0.004)	(0.320)
					Forecast Horizon *h* = 6				
RMSFE	0.029	0.032	0.031	0.033	0.035	0.033	0.034	0.037	0.036
Sign	0.891	0.892	0.893	0.881	0.877	0.879	0.897	0.900	0.902
ENCT test	0.000	1.796	0.000	0.000	2.381	0.340	0.000	1.797	0.000
	(0.500)	(0.036)	(0.500)	(0.500)	(0.009)	(0.367)	(0.500)	(0.036)	(0.500)
					Forecast Horizon *h* = 12				
RMSFE	0.084	0.090	0.086	0.083	0.089	0.085	0.091	0.096	0.092
Sign	0.836	0.852	0.847	0.843	0.851	0.854	0.875	0.887	0.889
ENCT test	0.000	1.563	0.000	0.000	1.531	0.382	0.000	1.381	0.411
	(0.500)	(0.059)	(0.500)	(0.500)	(0.063)	(0.351)	(0.500)	(0.084)	(0.341)
					Forecast Horizon *h* = 18				
RMSFE	0.135	0.136	0.128	0.148	0.147	0.138	0.151	0.146	0.138
Sign	0.776	0.805	0.810	0.818	0.831	0.844	0.853	0.872	0.883
ENCT test	0.000	1.706	1.994	0.599	1.510	2.079	1.088	1.430	2.440
	(0.500)	(0.044)	(0.023)	(0.274)	(0.066)	(0.019)	(0.138)	(0.076)	(0.007)
					Forecast Horizon *h* = 24				
RMSFE	0.175	0.167	0.155	0.227	0.204	0.193	0.232	0.205	0.196
Sign	0.698	0.738	0.760	0.786	0.812	0.832	0.835	0.858	0.874
ENCT test	1.986	3.002	2.478	1.664	1.960	2.464	2.055	1.732	2.573
	(0.024)	(0.001)	(0.007)	(0.048)	(0.025)	(0.007)	(0.020)	(0.042)	(0.005)

Notes: The table demonstrates the out-of-sample rolling window forecast results of monthly housing prices based on a panel of 20 cross-sectional units for the period 1/1/2004- 1/12/2017 for forecast horizons 1, 3, 6, 12, 18, and 24 months-ahead and for three estimation windows, 80, 60 and 50 monthly observations. RMSFEs, the sign accuracy measure of the predicted direction and the ENCT encompassing test statistics results are reported. ENCT denote the Harvey, at al. (1998) forecast encompassing test. p-values are in parentheses. Models' (7), (8) and (9) specifications are described in equations (25), (24), (23), respectively. Models are compared according to their encompassing ability using the ENCT test.

Table 9: Forecasting results of panel ARDL models with jackknife bias reduction

Models	Panel A: State-level data						Panel B: MSA-level data					
	ARDL – CCE	ARDL-CCE with NFER	ARDL-CCE with NFER, MDRI	ARDL-FE	ARDL-FE with NFER	ARDL-FE with NFER, MDRI	ARDL – CCE	ARDL-CCE with EA	ARDL-CCE with EA, MDRI	ARDL-FE	ARDL-FE with EA	ARDL-FE with EA, MDRI
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Comparing models :	(1)-(2)	(2)-(3)	(1)-(3)	(4)-(5)	(5)-(6)	(4)-(6)	(1)-(2)	(2)-(3)	(1)-(3)	(4)-(5)	(5)-(6)	(4)-(6)
Forecast Horizon *h* = 1												
RMSFE	0.001	0.001	0.001	0.003	0.001	0.001	0.002	0.002	0.002	0.006	0.003	0.003
sign	0.882	0.883	0.880	0.853	0.858	0.851	0.932	0.936	0.936	0.922	0.915	0.917
ENCT test	0.034	1.397	0.826	5.763	0.000	5.807	0.000	1.816	0.000	7.393	0.000	7.469
	(0.487)	(0.081)	(0.204)	(0.000)	(0.500)	(0.000)	(0.500)	(0.035)	(0.500)	(0.000)	(0.500)	(0.000)
Forecast Horizon *h* = 3												
RMSFE	0.005	0.005	0.005	0.010	0.006	0.006	0.007	0.009	0.009	0.019	0.011	0.011
sign	0.895	0.903	0.906	0.864	0.865	0.864	0.938	0.928	0.936	0.919	0.906	0.911
ENCT test	0.194	1.612	0.883	3.509	0.971	3.491	0.000	2.337	0.000	4.071	0.443	4.088
	(0.423)	(0.053)	(0.189)	(0.000)	(0.166)	(0.000)	(0.500)	(0.010)	(0.500)	(0.000)	(0.329)	(0.000)
Forecast Horizon *h* = 6												
RMSFE	0.012	0.014	0.013	0.023	0.016	0.016	0.022	0.029	0.026	0.044	0.033	0.033
sign	0.909	0.916	0.922	0.871	0.870	0.873	0.934	0.902	0.911	0.913	0.889	0.894
ENCT test	0.000	2.257	0.000	2.387	0.559	2.413	0.000	2.048	0.000	1.927	0.803	1.991
	(0.500)	(0.012)	(0.500)	(0.008)	(0.288)	(0.008)	(0.500)	(0.020)	(0.500)	(0.027)	(0.211)	(0.023)
Forecast Horizon *h* = 12												
RMSFE	0.034	0.040	0.036	0.059	0.045	0.044	0.063	0.080	0.066	0.102	0.092	0.089
sign	0.898	0.899	0.915	0.844	0.846	0.858	0.891	0.869	0.907	0.868	0.841	0.856
ENCT test	0.000	1.865	0.000	1.935	0.907	1.884	0.000	1.431	1.600	1.122	1.100	1.452
	(0.500)	(0.031)	(0.500)	(0.027)	(0.182)	(0.030)	(0.500)	(0.076)	(0.055)	(0.131)	(0.136)	(0.073)
Forecast Horizon *h* = 18												
RMSFE	0.054	0.059	0.048	0.093	0.066	0.065	0.091	0.098	0.076	0.143	0.129	0.123
sign	0.875	0.862	0.889	0.814	0.840	0.852	0.846	0.849	0.929	0.816	0.809	0.828
ENCT test	0.000	2.900	1.638	1.417	1.432	1.420	0.158	1.753	1.916	2.173	1.100	4.403
	(0.500)	(0.002)	(0.051)	(0.078)	(0.076)	(0.078)	(0.437)	(0.040)	(0.028)	(0.015)	(0.136)	(0.000)
Forecast Horizon *h* = 24												
RMSFE	0.072	0.075	0.057	0.112	0.077	0.073	0.111	0.091	0.077	0.169	0.147	0.137
sign	0.873	0.864	0.888	0.775	0.827	0.849	0.828	0.868	0.934	0.752	0.776	0.812
ENCT test	0.380	8.635	2.196	1.286	3.652	1.436	2.508	6.918	2.789	5.498	1.555	3.147
	(0.352)	(0.000)	(0.014)	(0.099)	(0.000)	(0.076)	(0.006)	(0.000)	(0.003)	(0.000)	(0.060)	(0.001)

Notes: The table demonstrates the results of the out-of-sample rolling window forecasts of housing prices based on ARDL-CCE and ARDL-FE models estimated by the jackknife bias reduction method of Chudik and Pesaran (2015) for forecast horizons 1, 3, 6, 12, 18, and 24 months-ahead. Panel A refers to state-level data (43 cross-sectional units and 168 monthly observations) case, while Panel B refers to the MSA-level data (20 cross-sectional units and 168 monthly observations). RMSFEs, the sign accuracy measure of the predicted direction and the ENCT encompassing test statistics results are reported. ENCT denote the Harvey, at al. (1998) forecast encompassing test. p-values are in parentheses. Models (1), (2), (3), (4), (5), (6) specifications are described in equations (14), (13), (12), (22), (21), (20), respectively. Models are compared for each dataset according to their encompassing ability using the ENCT test.