Cepni, Oguzhan; Gupta, Rangan; Pierdzioch, Christian

Book

Forecasting growth-at-risk of the United States : housing price versus housing sentiment or attention

University of Pretoria
Department of Economics Working Paper Series

Forecasting Growth-at-Risk of the United States: Housing Price versus Housing Sentiment or Attention

Oguzhan Cepni
Copenhagen Business School and Ostim Technical University
Rangan Gupta
University of Pretoria
Mawuli Segnon
Helmut Schmidt University
Working Paper: 2024-01
January 2024

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Forecasting Growth-at-Risk of the United States: Housing Price versus Housing Sentiment or Attention

Submission: January 2023

Oguzhan Cepni[*], Rangan Gupta[†], Christian Pierdzioch[‡]

Abstract

We examine the predictive power of national housing market-related behavioral variables, along with their connectedness at the state level, in forecasting US aggregate economic activity (such as the Chicago Fed National Activity Index (CFNAI) and real Gross Domestic Product (GDP) growth), as opposed to solely relying on state-level housing price return connectedness. Our results reveal that while standard linear regression models show statistically insignificant differences in forecast accuracy between the connectedness of housing price returns and behavioral variables, quantile regression models, which capture growth-at-risk, demonstrate significant forecasting improvements. Specifically, state-level connectedness of housing sentiment enhances forecast accuracy at lower quantiles of economic activity, indicative of downturns, whereas connectedness of housing attention is more effective at upper quantiles, corresponding to upturns. The results for GDP growth, however, are less conclusive. These findings underscore the importance of incorporating regional heterogeneity and behavioral aspects in economic forecasting.

JEL Classifications: C22; C32; C53; E30; R31.

Keywords: Housing price; Housing sentiment and attention; Connectedness; Economic activity; Forecasting; Quantile predictive regressions.

Conflicts of interest: The authors declare no conflict of interest.

Funding statement: The authors declare that they did not receive any funding for this research.

[*]Copenhagen Business School, Department of Economics, Porcelaenshaven 16A, Frederiksberg DK-2000, Denmark; Ostim Technical University, Ankara, Turkiye. Email address: oce.eco@cbs.dk.

[†]Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa. Email address: rangan.gupta@up.ac.za.

[‡]Department of Economics, Helmut Schmidt University, Holstenhofweg 85, P.O.B. 700822, 22008 Hamburg, Germany. Email address: macroeconomics@hsu-hh.de.

1 Introduction

The United States (US) residential real estate represents about 85.08% of total household non-financial assets, 33.16% of total household net worth, and 35.29% of US net wealth (Financial Accounts of the US, Third Quarter, 2023).[1] These figures indicate a notable relation between housing price movements and the predictive capacity for various measures of real economic activity, as explored in several studies (see, for example, Balcilar et al. (2014), Apergis et al. (2015), Nyakabawo et al. (2015), Emirmahmutoglu et al., (2016), Piazzesi and Schneider (2016), Christiansen et al. (2019)). Furthermore, with the US housing market known to be (partially) segmented (see the discussions in Antonakakis et al. (2020), Chowdhury et al. (2023) and Gabauer et al. (2024)), researchers also have documented that synchronized movements of regional housing price returns drive aggregate economic activity (Del Negro and Otrok, 2007; Arias et al., 2016; Hernández-Murillo et al., 2017; Gupta et al., 2023; Payne and Sun, 2023). At the same time, recent advancements in behavioral economics have led to the development of metrics of aggregate and regional housing market indexes of sentiment and media attention, which have been shown to explain a significant portion of the total variation in future house prices at the state- and overall-level, even after accounting for economic fundamentals, i.e., traditional predictors used to predict housing price movements (see, for instance, Bork et al. (2020), Balcilar et al. (2021), Cepni (2023), Cepni and Khorunzhina (2023)). This growing body of evidence highlights the relevance of behavioral factors in the housing market, offering potential additional insights that extend beyond traditional price-based analysis.

In light of these developments, our study bridges two crucial strands of research: the impact of housing prices on economic activity and the predictive role of housing market-related behavioral variables. We investigate whether national housing market-related behavioral variables and their total connectedness at the state level can forecast aggregate economic activity more effectively than the connectedness of state-level housing price returns. The answer to this query is indeed of importance to policymakers in terms of timely design of monetary and/or fiscal policies responses to prevent possible economic slowdowns, especially when we forecast broad (derived from the combination of information on many real economy-related variables) and high-frequency (monthly) indexes of economic

[1] https://www.federalreserve.gov/releases/z1/20231207/z1.pdf.

activity, as we do in our predictive analysis covering the sample period from 1978:02 to 2021:11.

Our methodology extends beyond the traditional conditional mean-based predictive model by incorporating insights from the recent literature on growth-at-risk (Adrian et al., 2019; 2022). To this end, we conduct our forecasting experiment using a quantile regression framework. This approach is more informative relative to a conditional mean-based predictive model because it investigates the ability of the predictors to forecast the entire conditional distribution of economic activity, rather than being restricted just to the conditional mean, with the upper and lower conditional quantiles corresponding to expansionary and recessionary episodes (without having to identify them explicitly using a business-cycle-dating approach). In this regard, density forecasts have become important tools for central banks and policy institutions to estimate and report the degree of uncertainty around their forecasts, while making policy decisions (Rossi, 2014). Furthermore, a quantile regression framework retains the simple structure of a linear predictive regression model for any given quantile but, simultaneously, renders it possible to add an element of underlying non-linearity to our empirical research strategy in that the coefficients of the predictors are allowed to vary across the different quantiles of the conditional distribution of economic activity.

It is important to contextualize our study within the broader spectrum of existing literature. The relationship between real estate markets and economic activity has been extensively studied, with a focus on understanding how changes in real estate prices can serve as a barometer for broader economic health. For instance, Case and Shiller (2003) and Leamer (2007, 2015) provide foundational insights into the predictive power of housing markets for economic cycles. Their work emphasizes the lead-lag relationship between housing market trends and overall economic performance, suggesting that housing market indicators can be a precursor of economic shifts. Furthermore, the role of behavioral economics in real estate markets has gained prominence, with researchers like Case et al. (2012), Shiller (2015) and Shiller and Thompson (2022) exploring the psychological factors that influence housing market dynamics. These studies have shed light on how sentiment, media attention, and investor psychology can impact housing prices, often independent of traditional economic fundamentals. This body of work underscores the importance of considering behavioral aspects in real estate market analyses. In addition, recent studies have increasingly focused on regional housing market dynamics and their impact on national economic trends. The works of Glaeser et al. (2014) and Mian and Sufi (2014) offer insights into how localized housing market shocks can propagate to the national economy, highlighting the interconnectedness of regional and national economic systems. Their research illustrates the complex interplay between local housing markets and national economic indicators, reinforcing the need to consider both micro and macro perspectives in housing market analyses.

Our paper makes a significant contribution to the literature by effectively intertwining the concepts of housing market sentiment and attention with economic forecasting. Our approach centers on the examination of national and state-level housing market-related behavioral variables, particularly their connectedness, and their capacity to forecast US aggregate economic activity. Unlike previous studies that have primarily focused on housing price returns, our research underscores the predictive power of behavioral variables in the housing market. Our findings reveal that, while traditional linear regression models show negligible differences in forecast accuracy between housing price returns and behavioral variables, quantile regression models, which account for growth-at-risk, indicate a marked improvement in forecasting capabilities. Specifically, the connectedness of state-level housing sentiment proves to be a more accurate predictor during economic downturns, while housing attention is more effective during upturns. These insights not only broaden the academic understanding of housing markets and their impact on the economy but also hold substantial implications for policymakers. The ability to accurately forecast economic activities based on housing market sentiment and attention could lead to more informed and timely policy interventions, potentially mitigating economic downturns and tempering inflationary pressures. Therefore, our study serves as a pivotal link between regional housing market dynamics and macroeconomic forecasting, offering a fresh perspective that could reshape policy formulation and economic analysis.

The structure of our paper is organized in the following manner: Section 2 details the data utilized in our research. In Section 3, the methodology for constructing the connectedness measures is explained. The forecasting models employed in this study are delineated in Section 4. Section 5 is dedicated to discussing our primary findings. The paper is brought to a conclusion in Section 6.

2 Data

As far as our dependent variable involving monthly economic activity is concerned, we use two alternative measures. The first is the Chicago Fed National Activity Index (CFNAI), which is a weighted average of 85 monthly indicators of national economic activity derived from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories.[2] A zero value for the CFNAI has been associated with the national economy expanding at its historical trend (average) rate of growth; negative values with below-average growth (in standard deviation units); and positive values with above-average growth. Secondly, we utilize a metric of real Gross Domestic Product (GDP)-based economic growth derived from the Mixed-Frequency-Vector Autoregressive (MF-VAR) model of Koop et al. (2023).[3] The authors make use of quarterly real income and expenditure-side GDP, along with monthly data on unemployment, hours worked, the consumer price index, the industrial production index, personal consumption expenditure, the federal funds rate, the Treasury bond yield, and the S&P 500 index.

Following the growth-at-risk literature, we first control for the financial state of the economy by using the Chicago Fed's National Financial Conditions Index (NFCI), which, in turn, provides a comprehensive weekly update on US conditions in money markets, debt and equity markets, and the traditional and "shadow" banking systems.[4]

As far as the national- and state-level housing price log-returns data is concerned, we rely on the seasonally-adjusted house price indexes provided by Freddie Mac, which are based on an ever-expanding database of loans purchased by either Freddie Mac or Fannie Mae.[5] Based on the work of Cepni and Khorunzhina (2023) at the quarterly-frequency, we construct monthly state-level housing-sentiment indexes using consumer attitudes and expectations about home-buying conditions from the Survey of Consumers of the Univer-

[2] The data is publicly available at: https://www.chicagofed.org/research/data/cfnai/current-data.

[3] The data is downloadable from: https://sites.google.com/view/aubreybcpoon/research?authuser=0.

[4] The weekly data, which is averaged to monthly frequency, can be retrieved from: https://www.chicagofed.org/research/data/nfci/current-data.

[5] The data is available for download from: https://www.freddiemac.com/research/indices/house-price-index.

sity of Michigan, with the corresponding version for the overall US utilized in its original form to capture national housing market sentiment. As in the original work, we exploit the regional identifier of the survey, which allows us to extract regional variation in the composition of sentiment. Then, using Partial Least Squares (PLS), we construct state-level housing-sentiment indexes by linking the regional variation in sentiment composition with the target variable of the state-level housing price returns. Finally, as in Cepni (2023), who introduces quarterly aggregate- and state-level housing media attention indexes based on the Bloomberg Terminal News Trends (NT) function, we create corresponding monthly versions of these indexes based on news counts of 20 housing market related topics.[6] Note that the Bloomberg Terminal News Trends (NT) function collects articles from various news and social media sources and identifies their content using artificial intelligence tools.

The state-level data on housing price returns, sentiment, and attention indexes are then utilized to obtain corresponding total connectedness indexes using the recently proposed model-free approach of Gabauer et al. (2023), with the technical details outlined at the end of the paper (Appendix 3), which, in turn, allows us to consider large number (such as 50, in our case) of time series in the network. Based on data availability, the models involving the national housing price returns versus housing sentiment, and housing price returns and housing attention index cover the monthly periods of 1978:02 to 2021:11, and 1999:01 to 2021:11, respectively. The corresponding models involving the connectedness of the relevant variables, due to a 60-month rolling-window approach, utilized to obtain the associated time series covers 1983:01 to 2021:11, and 2003:12 to 2021:11, respectively.

We plot our data in Figures 1 to 4.

– Figures 1 and 4 about here. –

3 Model-Free Estimate of Connectedness

To measure the propagation mechanism among the three separate categories of the state-level housing variables (housing price returns, housing sentiment indexes, and housing

[6]The topics considered are: “home sales, “home price”, “housing price”, “housing demand”, “housing supply”, “housing market”, “housing cost”, “home buyers”, “home inventory”, “homeownership”, “real estate agencies”, “real estate”, “real estate listing”, “mortgage rate”, “mortgage demand”, “mortgage credit”, “subprime mortgage”, “residential property price”, “home foreclosure”, and “mortgage affordability”.

media attention indexes), we employ the recently developed model-free connectedness approach of Gabauer et al. (2023). They have shown that the unscaled generalized forecast error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998) can be formulated in terms of variance-covariances:

$$\phi_{i\leftarrow j}^{gen} = \frac{\mathbf{\Sigma}_{ij}^2}{\mathbf{\Sigma}_{jj}\mathbf{\Sigma}_{ii}} = \left(\frac{\mathbf{\Sigma}_{ij}}{\sqrt{\mathbf{\Sigma}_{jj}\mathbf{\Sigma}_{ii}}}\right)^2 = \rho_{ij}^2 = R_{ij}^2. \tag{1}$$

This measure remains invariant to the forecast horizon, being the squared Pearson correlation coefficient,[7] defined as the R^2 goodness-of-fit measure for a bivariate linear regression between series i and j. This definition implies $R_{ii}^2 = 1$ and $R_{ij}^2 = R_{ji}^2$.

Utilizing the normalization technique proposed by Diebold and Yilmaz (2012), the (scaled) GFEVD can be formulated as follows:

$$gSOT_{i\leftarrow j} = \frac{R_{ij}^2}{\sum_{l=1}^k R_{il}^2} \tag{2}$$

where $\sum_{j=i}^k gSOT_{i\leftarrow j} = 1$ and $\sum_{j=i}\sum_{i=i}^k gSOT_{i\leftarrow j} = k$.

The total connectedness index (TCI) of Diebold and Yilmaz (2009, 2012, 2014) is given by

$$TCI = \frac{\sum_{i,j=1,i\neq j}^k gSOT_{i\leftarrow j}(H)}{k-1}. \tag{3}$$

The TCI illustrates the average contribution of one series to all others, and vice versa, the average contribution of all other series to one series. A low (high) TCI indicates a low (high) level of network interconnectedness and market risk.

4 Predictive Regressions

Our forecasting model uses, in addition to a specific housing market-related variable, X_t, lagged economic activity, EA_t, and National Financial Conditions Index, $NFCI_t$, as control variables. Note that for EA_t we use the monthly estimate of GDP, as well as the Chicago

[7] For robustness purposes, the Spearman and Kendall correlation coefficients are used. The Spearman correlation coefficient is equal to the Pearson correlation coefficient between the ranked series, $\frac{cov(R(x),R(y))}{\sigma(R(x))\sigma(R(y))}$, while the (transformed) Kendall rank correlation coefficient is equal to $sin(\frac{\pi}{n(n-1)}\sum_{i<j} sgn(x_i - x_j)sgn(y_i - y_j))$

Fed National Activity Index (CFNAI). As far as X_t is concerned, it includes the national housing returns (NHPR), national housing sentiment index (NHSI), national housing attention index (NHAI), connectedness of these three state-level housing market variables (hpr, hsi and hai) considered independently, based on Pearson, Spearman, and Kendall correlation approaches. We estimate this forecasting model by the ordinary-least-squares (OLS) technique. The forecasting model is given by the following equation:

$$EA_{t+h} = \beta_0 + \beta_1 EA_t + \beta_2 NFCI_t + \beta_3 X_t + u_{t+h}, \tag{4}$$

where $\beta_j, j = 0, .., 3$ are the coefficients to be estimated, u_{t+h} denotes a disturbance term, and EA_{t+h} is the average economic activity over the forecast horizon, h, where we set $h = 1, 6, 12$ for our monthly data.

We estimate our forecasting model using ten different estimation windows, each covering a range from 50% to 75% of the data (starting at the beginning of the sample period for which data on the connectedness measures are available).[8] We use the remaining test data along with the estimated forecasting models to compute forecasts of economic activity, which we then use to compute time series of forecast errors. Finally, we use the resulting time series of forecast errors to compute the root-mean-squared-forecast error (RMSFE), the mean-absolute forecast error (MAFE) and the test for comparing non-nested forecasts proposed proposed by Diebold and Mariano (1995) test, as modified by Harvey et al. (1997), which we denote as DM.

To enhance interpretability, we calculate ratios of the RMSFE (MAFE) statistic, and average the results across the ten different estimation windows. We call the resulting ratios the L2 and L1 ratios. Here, the L1 ratio represents the Absolute-forecasts-error loss function, and the L2 ratio represents the Squared-forecasts-error loss function. A ratio larger than unity indicates that a rival model using connectedness measure, $CO_{t,R}$, delivers more accurate forecasts than some benchmark model using a different connectedness measure, $CO_{t,B}$. It should be noted that the benchmark and rival forecasting models, thus, are non-nested forecasting models. Likewise, the Diebold-Mariano (DM) test serves as a one-sided test for the null hypothesis of equal predictive accuracy, where the alternative hypothesis

[8] We use the R language and environment for statistical computing (R Core Team, 2023) for our empirical analysis.

is that the rival model yields more accurate forecasts than the benchmark model.

As an extension, we also estimate our forecasting models by means of a quantile-regression model. A quantile-regression model has the advantage that we can trace out the incremental contribution of the rival models, in terms of forecasting performance relative to the benchmark model, across the quantiles of CFNAI and GDP growth.

$$\hat{\mathbf{b}}_{\mathbf{q}} = \arg\min \sum_{t}^{T} \rho_q \left(EA_{t+h} - \beta_{0,q} - \beta_{1,q} EA_t - \beta_{2,q} NFCI_t - \beta_{3,q} X_t \right), \tag{5}$$

where q denotes the quantile being studied, $\hat{\mathbf{b}}_{\mathbf{q}}$ denotes the quantile-dependent vec tor of coefficients to be estimated, and the function ρ_q, denotes the usual check function, defined as $\rho_q = qu_{t+h}$ in case $u_{t+h} > 0$, and $\rho_q = (q-1)u_{t+h}$ in case $u_{t+h} < 0$.

5 Empirical Results

We begin our presentation with a discussion of the OLS results for the aggregate data summarized in Table 1, as obtained for a fixed-estimation window. The results for the L1 and L2 ratios are smaller than unity, with only one exception. The ratios decrease in value when we increase the forecast horizon, irrespective of whether we study CFNAI or GDP growth as our left-hand-side variable. As a result, the benchmark NHPR model performs somewhat better than the NHSI and NHAI models, and this superior performance strengthens in the forecast horizon. This could be attributed to the model's ability to better capture and integrate long-term economic trends and cycles, which might not be as effectively represented in the NHSI and NHAI models. However, it's important to note that all Diebold-Mariano (DM) tests yield statistically insignificant results. This outcome implies that the differences in the forecasting performance of the NHPR model compared to the NHSI and NHAI models are not substantial enough to definitively favor one model over the others. In other words, while the NHPR model shows some advantages in our analysis, these are not strong enough to conclusively discount the utility of the NHSI and NHAI models. In other words, the hypothesis that there is no systematic difference in the performance of the forecasts derived from the NHPR vs. NHSI (NHPR vs. NHAI) models cannot be rejected.[9]

– Tables 1 and 2 about here. –

Table 2 summarizes the results for the aggregate data that we obtain when we base our empirical analysis on a quantile-regression model. The general picture that emerges from the results, again based on a fixed-estimation window, is that the L1 ratios (based on the check-function) show no systematic pattern across quantiles and forecast horizons except that, while few ratios exceed unity, the vast majority of the ratios is smaller than unity, indicating that the rival model does not outperform the benchmark model in a systematic quantile-dependent way.

– Tables 3 and 4 about here. –

Next, we report the results, for a fixed estimation window, for the Pearson, Spearman, and Kendall connectedness measures in Tables 3 (OLS results) and 4 (results for the quantile regression model). The OLS results for both the L1 and the L2 ratio show that the sentiment and attention models often tend to outperform the benchmark (hpr) model in forecasting CFNAI, especially when the length of the forecast horizon increases. Such findings suggest that behavioral factors, encapsulated in sentiment and attention models, may have a more significant impact on economic activity than previously understood, especially over extended periods. This could be due to these models' ability to capture the nuanced and often rapidly changing economic sentiments and attentions, which traditional models might overlook. However, when it comes to forecasting GDP growth, in turn, the results are less decisive in this regard. Similarly, while there are few statistically significant DM test results for the CFNAI models, the test results are all insignificant for GDP growth.[10]

As for the quantile-regression model, we find that the sentiment and attention models outperform the benchmark (hpr) model in the majority of combinations of quantiles and

[9] A natural question is whether the results change when we opt for a recursive-estimation window, that is an estimation window that recursively expands until we reach the end of the sample period. The results, reported in Table A1 at the end of the paper (Appendix A1), are in line with the results for the fixed estimation window.

[10] As in the case of the aggregate data, the results for a recursive-estimation window corroborate the results for the fixed-estimation window (see Table A2). In terms of robustness, we report in Tables A3 (fixed-estimation window) and A4 (recursive-estimation window) some additional results based on metrics of short-term and long-term connectedness, derived from the time-varying general dynamic factor model (tvGDFM), as developed by Barigozzi et al. (2021). The results show again that, while sentiment and attention do add some value-added in some cases in terms of forecasting performance, especially for CFNAI, the differences as compared to the benchmark model are in general statistically insignificant.

forecast horizons when we study CFNAI. Interestingly, the sentiment models yield a superior performance mainly at the quantiles below the median, while the attention models tend to perform better than the benchmark model for the quantiles above the median. This implies that during periods of economic downturns or slower growth, sentiment indicators become more predictive. It could reflect how negative consumer or investor sentiment impacts economic activity. Conversely, attention models excel in higher quantiles, indicating their predictive power during periods of economic growth or expansion. This might be due to heightened media and public attention positively correlating with economic upturns.

When focusing on GDP growth, the short-term forecast horizon shows no significant difference between the benchmark and the behavioral models. This could suggest that in the immediate future, traditional economic indicators are just as effective as sentiment and attention metrics in predicting GDP growth. However, for longer forecast horizons, both sentiment and attention models demonstrate superior performance at lower quantiles. This trend again underscores the importance of behavioral indicators in anticipating periods of slower economic growth or potential downturns. The fact that these models are more predictive at lower quantiles for longer horizons could indicate their potential utility in long-term economic planning and risk assessment, especially in identifying early warning signs of economic deceleration.

– Table 5 about here. –

Results for the DM test reported in Table 5 show that for CFNAI, and as expected less so for GDP growth, this pattern of results for the sentiment and attention models are statistically significant in several cases. Hence, the forecasts derived from the sentiment models tend to outperform the forecasts extracted from the benchmark (hpr) model at the lower quantiles, while the forecasts produced by means of the attention model tend to be more accurate than the benchmark forecasts for the upper quantiles.

6 Concluding Remarks

In recent research, national and state-level housing market sentiment and attention variables have been shown to possess additional information over fundamental variables in forecasting housing price returns of the US. At the same time, the role of aggregate and synchronized housing price returns across states have served as a leading indicator for economic activity. In the context of these two lines of research, we aim to determine whether the national housing market-related behavioral variables, and their total connectedness at the state-level, forecast aggregate economic activity relatively better than overall and total connectedness of state-level housing price returns. In this regard, we rely on both conditional-mean and quantiles-based predictive regressions over the monthly period of 1978:02 to 2021:11. We find statistically insignificant forecast comparison results between state-level connectedness of housing price returns and the two behavioral variables, in line with the corresponding national data, using a standard linear regression model. However, several results are statistically significant when we consider a quantile-regression model, capturing growth-at-risk. Relative to connectedness of housing price returns, a model using the total connectedness of state-level housing sentiment improves forecasting accuracy at the lower quantiles of the conditional distribution of the broad CFNAI, while the same for an attention model does so mainly at the upper quantiles. Results for the monthly-metric of GDP growth are less decisive.

Academically speaking, our findings highlight the importance of accounting for regional heterogeneity across the US housing market, as well as the need to go beyond models of conditional mean, and study the entire conditional distribution of economic activity via a quantiles-based framework. Keeping this in mind, our results are also policy relevant, since policmakers will be better off in utilizing housing market-related behavioral variables rather than housing price returns in forecasting growth-at-risk of especially a broad measure of economic activity. The fact that the connectedness of sentiment and attention can produce more accurate forecasts of downturns and upturns, respectively (while performing equally well to housing returns connectedness for other parts of the conditional distribution), and are likely to be available without publication delays and measurement errors as in house prices, policy authorities can design appropriate monetary and fiscal policy responses in a timely manner to prevent or reduce the likelihood of recessions and inflationary pressures.

Furthermore, understanding the relative strengths of different forecasting models can help policymakers in designing more targeted economic policies. For instance, in anticipating economic downturns, models that perform better at lower quantiles (like sentiment models) might be more useful. Investors could leverage these insights to adjust their portfolios based on the economic cycle, using different models to assess risk and return in different market conditions. Given the segmented nature of the US housing market, future research could focus on regional or state-level analysis to capture more localized economic dynamics.

References

Adrian, T., Boyarchenko, N., and Giannone, D. (2019). Vulnerable growth. American Economic Review, 109(4), 1263–1289.

Adrian, T., Grinberg, F., Liang, N., Malik, S., and Yu, J. (2022). The term structure of growth-at-risk. American Economic Journal: Macroeconomics, 14(3), 283–323.

Antonakakis, N., Chatziantoniou, I., and Gabauer, D. (2020). A regional decomposition of US housing prices and volume: market dynamics and Portfolio diversification. The Annals of Regional Science, 66(2), 279–307.

Apergis, N., Simo-Kengne, B.D., Gupta, R., and Chang, T. (2015). The dynamic relationship between house prices and output: evidence from US metropolitan areas. International Journal of Strategic Property Management, 19(4), 336–345.

Arias, M.A., Gascon, C.S., and Rapach, D.E. (2016). Metro business cycles. Journal of Urban Economics, 94(C), 90–108.

Barigozzi, M., Hallin, M., Soccorsi, S. and von Sachs, R. (2021). Time-varying general dynamic factor models and the measurement of financial connectedness. Journal of Econometrics, 222(1), 324–343.

Balcilar, M., Bouri, E., Gupta, R., and Kyei, C.K. (2021). High-frequency predictability of housing market movements of the United States: The role of economic sentiment. Journal of Behavioral Finance, 22(4), 490–498.

Balcilar, M., Gupta, R., and Miller, S.M. (2014). Housing and the Great Depression. Applied Economics, 46(24), 2966–2981.

Bork, L., Møller, S.V., and Pedersen, T.Q. (2020). A new index of housing sentiment. Management Science, 66(4), 1563–1583

Case, K.E., and Shiller, R.J. (2003). Is there a bubble in the housing market? Brookings Papers on Economic Activity, 2003(2), 299–362.

Case, K.E., Shiller, R.J., and Thompson, A.K. (2012). What have they been thinking? Home buyer behavior in hot and cold markets. Brookings Papers on Economic Activity, 2012(1), 265–315.

Cepni, O. (2023). Fifty shades of the US States: How news media coverage drives house prices. Copenhagen Business School, Mimeo.

Cepni, O., and Khorunzhina, N. (2023). Geography of housing sentiment over business cycles. Available at SSRN: https://ssrn.com/abstract=4350783.

Chowdhury, S.R., Gupta, K., and Tzeremes, P. (2023). US housing prices and the transmission mechanism of connectedness. Finance Research Letters, 58 (Part D), 104636.

Christiansen, C., Eriksen, J.N., and Møller, S.V. (2019). Negative house price co-movements and US recessions. Regional Science and Urban Economics, 77(C), 382–394.

Del Negro, M., and Otrok, C. (2007). 99 Luftballons: monetary policy and the house price boom across US states. Journal of Monetary Economics, 54(7), 1962–1985.

Diebold, F.X., and Mariano, R.S. (1995). Comparing predictive accuracy. Journal of Business and Economic Statistics, 13(3), 253–263.

Diebold, F.X. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. Economic Journal, 119(534), 158–171.

Diebold, F.X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28(1), 57–66.

Diebold, F.X. and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, 182(1), 119–134.

Emirmahmutoglu, F., Balcilar, M., Apergis, N., Simo-Kengne, B.D., Chang, T., and Gupta, R. (2016). Causal relationship between asset prices and output in the US: Evidence from state-level panel Granger causality test. Regional Studies, 50(10), 1728–1741.

Gabauer, D. Chatziantoniou, I., and Stenfors, A. (2023). Model-free connectedness measures. Finance Research Letters, 54(1), 103804.

Gabauer, D., Gupta, R., Marfatia, H.A., and Miller, S.M. (2024). Estimating US housing price network connectedness: Evidence from dynamic Elastic Net, Lasso, and Ridge vector autoregressive models. International Review of Economics and Finance, 89(Part B), 349–362.

Glaeser, E.L., Gyourko, J., Morales, E., and Nathanson, C.G. (2014). Housing dynamics: An urban approach. Journal of Urban Economics, 81(C), 45–56.

Gupta, R., Ma, J., Theodoridis, K., and Wohar, M.E. (2023). Is there a national housing market bubble brewing in the United States? Macroeconomic Dynamics, 27(8), 2191–2228.

Harvey, D., Leybourne, S., and Newbold, P. (1997). Testing the equality of prediction mean squared errors. International Journal of Forecasting, 13(2), 281–291.

Hernández-Murillo, R., Owyang, M.T., and Rubio, M. (2017). Clustered housing cycles. Regional Science and Urban Economics, 66(C), 185–197.

Koop, G., McIntyre, S., Mitchell, J., and Poon, A. (2023). Reconciled Estimates of Monthly GDP in the US. Journal of Business and Economic Statistics, 41(2), 563–577.

Koop, G., Pesaran, M.H., and Potter, S.M. (1996). Impulse response analysis in nonlinear multivariate models. Journal of Econometrics, 74(1), 119–147.

Leamer, E.E. (2007). Housing is the business cycle. Proceedings - Economic Policy Symposium - Jackson Hole, Federal Reserve Bank of Kansas City, pages 149–233.

Leamer, E.E. (2015). Housing really is the business cycle: What survives the lessons of 2008–09? Journal of Money, Credit and Banking, 47(S1), 43–50.

Mian, A., and Sufi, A. (2014). What explains the 2007 – 2009 drop in employment? Econometrica, 82(6), 2197–2223.

Nyakabawo, W.V., Miller, S.M., Balcilar, M., Das, S. and Gupta, R. (2015). Temporal causality between house prices and output in the U.S.: A bootstrap rolling-window approach. North American Journal of Economics and Finance, 33(C), 55–73.

Payne, J.E., and Sun, X. (2023). Time-varying connectedness of metropolitan housing markets. Real Estate Economics, 51(2), 470–502.

Pesaran, H.H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. Economics Letters, 58(1), 17–29.

Piazzesi, M., and Schneider, M. (2016). Housing and Macroeconomics. In Handbook of Macroeconomics, Volume 2, Edited by: John B. Taylor and Harald Uhlig, Chapter 19, 1547–1640, Elsevier, Amsterdam, The Netherlands.

R Core Team (2023). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL: https://www.R-project.org/.

Rossi, B. (2014). Density forecasts in economics and policymaking. Els Opuscles del The Centre de Recerca en Economia Internacional (CREI). Available at: https://www.crei.cat/wp-content/uploads/opuscles/140929110100_ENG_ang_37.pdf.

Shiller, R.J. (2015). Irrational exuberance. Princeton University Press, Princeton, USA.

Shiller, R.J., and Thompson, A.K. (2022). What Have They Been Thinking? Home Buyer Behavior in Hot and Cold Markets: A Ten-Year Retrospect. Brookings Papers on Economic Activity, 2022(1), 307–366.

Figure 1: Aggregate Data

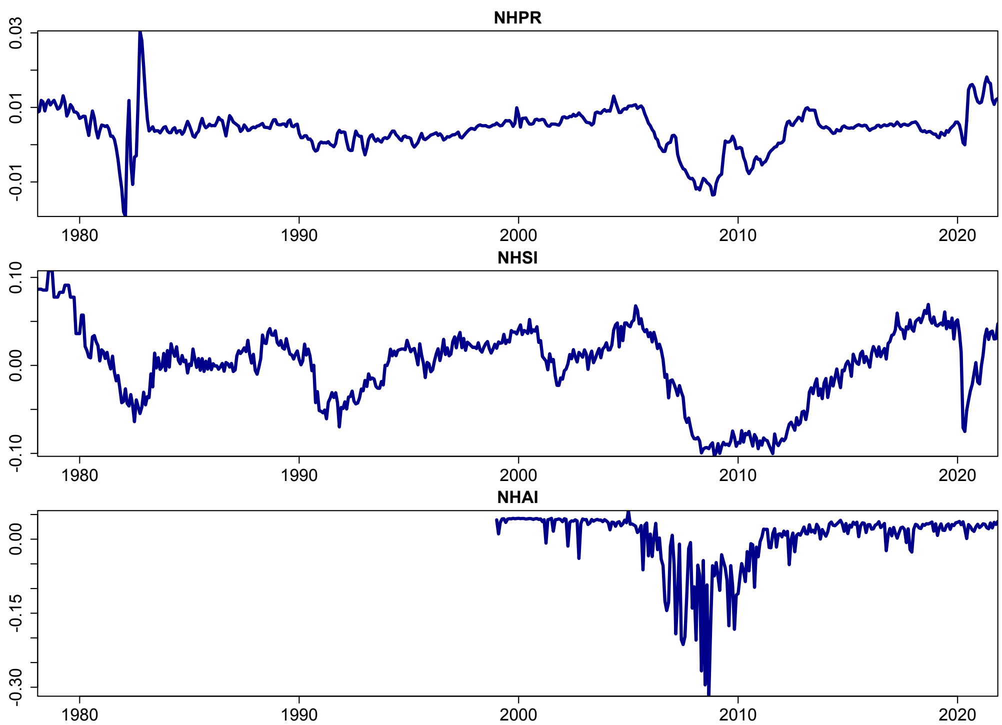

Figure 2: Measures of Economic Activity

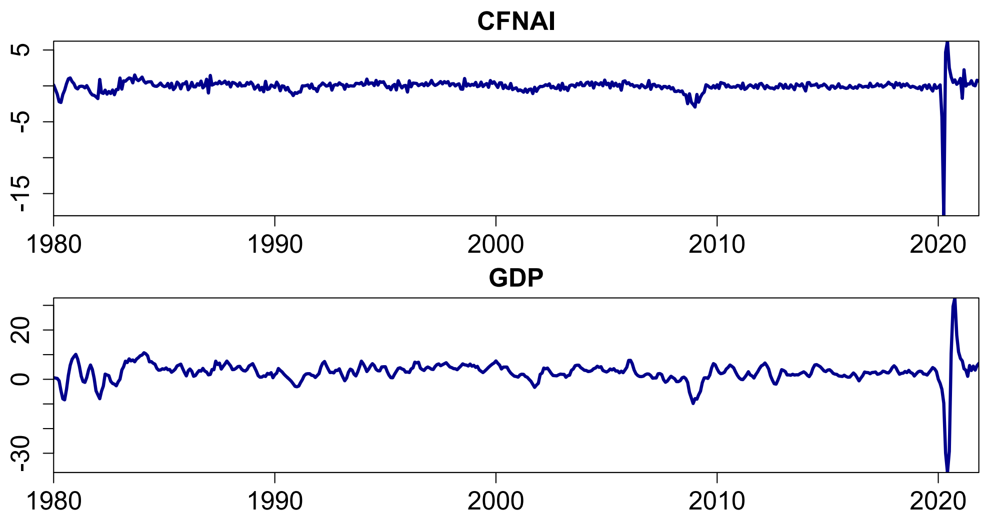

Figure 3: Predictors

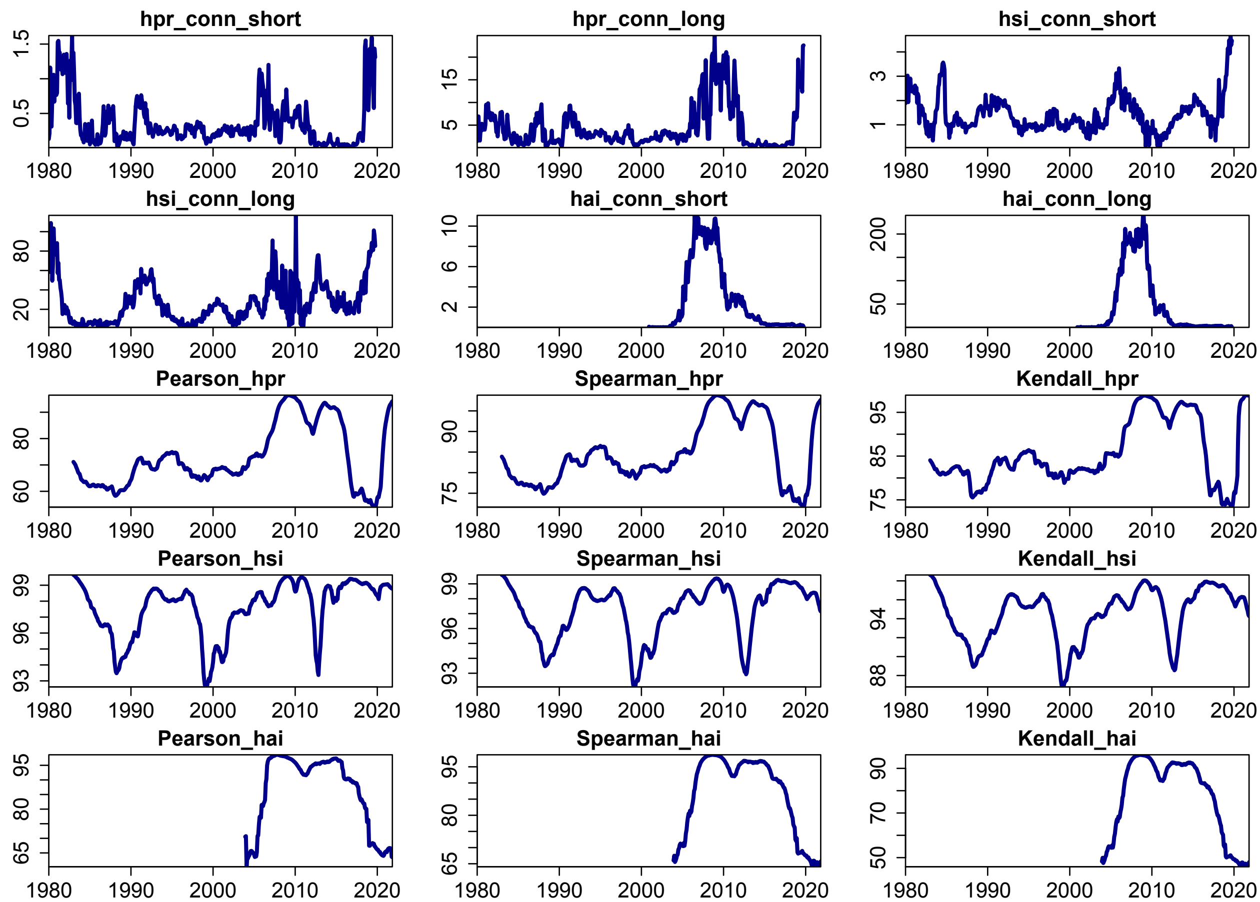

Figure 4: Control Variable

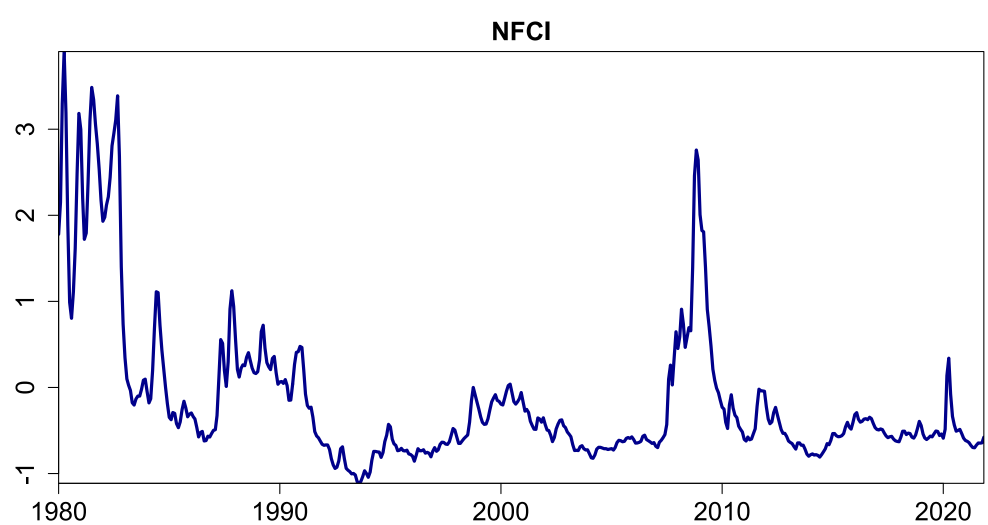

Table 1: Aggregate data (OLS results)

Panel A: CFNAI

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
NHPR vs. NHSI	0.9768	0.9497	0.8426
NHPR vs. NHAI	0.9901	0.9426	0.9045
		L2 ratio	
NHPR vs. NHSI	0.9973	0.9511	0.8429
NHPR vs. NHAI	0.9996	0.9973	0.9637
		DM statistic (p-value, L1)	
NHPR vs. NHSI	0.8467	0.7685	0.8336
NHPR vs. NHAI	0.9791	0.9240	0.8298
		DM statistic (p-value, L2)	
NHPR vs. NHSI	0.5811	0.9227	0.9148
NHPR vs. NHAI	0.5607	0.6197	0.8537

Panel A: GDP

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
NHPR vs. NHSI	1.0159	0.9868	0.9256
NHPR vs. NHAI	0.9936	0.9644	0.9605
		L2 ratio	
NHPR vs. NHSI	0.9876	0.9736	0.9033
NHPR vs. NHAI	0.9928	0.9580	0.8840
		DM statistic (p-value, L1)	
NHPR vs. NHSI	0.1727	0.6158	0.7383
NHPR vs. NHAI	0.8605	0.8628	0.7291
		DM statistic (p-value, L2)	
NHPR vs. NHSI	0.8382	0.8619	0.8961
NHPR vs. NHAI	0.9362	0.8534	0.8247

L1: Absolute-forecasts-error loss function. L2: Squared-forecasts-error loss function. L1 ratio and L2 ratio: results for the benchmark model divided by the results for the rival model such that a ratio larger than unity indicates a superior performance of the rival model given the respective loss function. DM statistic: Results of the modified Diebold-Mariano test (p-values) given the respective loss function. The alternative hypothesis is that the rival forecasts are more accurate than the benchmark forecasts. Results are based on ten fixed-estimation windows of varying in length: 0.50, 0.53, 0.56, ,,,, 0.75 of the data are used as training data (beginning at the start of the sample period). Results are averages across the ten fixed-estimation windows. h denotes the forecast horizon.

Table 2: Aggregate data (quantile results)

Panel A: CFNAI

Models	$q = 0.1$	$q = 0.2$	$q = 0.3$	$q = 0.4$	$q = 0.5$	$q = 0.6$	$q = 0.7$	$q = 0.8$	$q = 0.9$
					$h = 1$				
NHPR vs. NHSI	0.9272	0.9298	0.9513	0.9799	0.9881	0.9891	1.0224	1.0585	1.0485
NHPR vs. NHAI	0.9934	1.0059	1.0072	1.0051	0.9980	0.9991	0.9839	0.9759	0.9852
					$h = 6$				
NHPR vs. NHSI	0.9697	0.9268	0.9184	0.9643	0.9967	0.9893	1.0113	1.0002	0.9438
NHPR vs. NHAI	1.0078	1.0001	0.9844	0.9549	0.9367	0.9452	0.9272	0.9148	0.9084
					$h = 12$				
NHPR vs. NHSI	0.9335	0.9341	0.9594	0.9804	0.9606	0.9538	0.9323	0.8656	0.8791
NHPR vs. NHAI	0.9644	0.9055	0.9051	0.9523	0.9430	0.9066	0.8860	0.8633	0.8580

Panel B: GDP

Models	$q = 0.1$	$q = 0.2$	$q = 0.3$	$q = 0.4$	$q = 0.5$	$q = 0.6$	$q = 0.7$	$q = 0.8$	$q = 0.9$
					$h = 1$				
NHPR vs. NHSI	0.9961	0.9881	1.0301	1.0386	1.0274	1.0008	0.9904	0.9874	0.9543
NHPR vs. NHAI	0.9939	0.9937	1.0019	1.0004	1.0043	0.9879	0.9894	1.0010	0.9900
					$h = 6$				
NHPR vs. NHSI	1.0058	1.0312	1.0044	0.9911	0.9931	0.9889	0.9922	0.9806	0.9319
NHPR vs. NHAI	0.9832	1.0234	1.0408	1.0033	0.9753	0.9282	0.9356	0.9442	0.9839
					$h = 12$				
NHPR vs. NHSI	0.9652	0.9660	0.9046	0.9187	0.9582	0.9678	0.9716	0.9648	0.8447
NHPR vs. NHAI	1.0329	0.9833	0.9976	1.0275	0.9221	0.9180	0.8673	0.8543	0.9349

Results are loss ratios for the check function (that is, absolute-forecasts-error loss function). Ratio: results for the benchmark model divided by the results for the rival model such that a ratio larger than unity indicates a superior performance of the rival model given the respective loss function. Results are based on ten fixed-estimation windows of varying in length: 0.50, 0.53, 0.56, ,,,, 0.75 of the data are used as training data (beginning at the start of the sample period). Results are averages across the ten fixed-estimation windows. h denotes the forecast horizon. q quantile.

Table 3: Fixed-estimation window (OLS results)

Panel A: CFNAI

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
Pearson_hpr vs. Pearson_hsi	0.9928	1.0062	1.0979
Pearson_hpr vs. Pearson_hai	1.0216	1.0309	1.0136
Spearman_hpr vs. Spearman_hsi	0.9733	0.9922	1.0773
Spearman_hpr vs. Spearman_hai	1.0237	1.0411	1.0386
Kendall_hpr vs. Kendall_hsi	0.9645	1.0260	1.1929
Kendall_hpr vs. Kendall_hai	1.0316	1.0831	1.1393
		L2 ratio	
Pearson_hpr vs. Pearson_hsi	0.9881	0.9653	0.9607
Pearson_hpr vs. Pearson_hai	1.0011	1.0286	1.0516
Spearman_hpr vs. Spearman_hsi	0.9875	0.9696	0.9653
Spearman_hpr vs. Spearman_hai	1.0018	1.0242	1.0586
Kendall_hpr vs. Kendall_hsi	0.9893	0.9894	1.0202
Kendall_hpr vs. Kendall_hai	1.0029	1.0305	1.1095
		DM statistic (p-value, L1)	
Pearson_hpr vs. Pearson_hsi	0.5654	0.5930	0.5552
Pearson_hpr vs. Pearson_hai	0.0415	0.3023	0.4680
Spearman_hpr vs. Spearman_hsi	0.6478	0.6346	0.5920
Spearman_hpr vs. Spearman_hai	0.0487	0.2333	0.4018
Kendall_hpr vs. Kendall_hsi	0.6423	0.6140	0.2335
Kendall_hpr vs. Kendall_hai	0.0424	0.1175	0.2108
		DM statistic (p-value, L2)	
Pearson_hpr vs. Pearson_hsi	0.7047	0.6240	0.5943
Pearson_hpr vs. Pearson_hai	0.3312	0.0811	0.1855
Spearman_hpr vs. Spearman_hsi	0.7350	0.6165	0.5896
Spearman_hpr vs. Spearman_hai	0.1638	0.0492	0.1508
Kendall_hpr vs. Kendall_hsi	0.6852	0.5152	0.3550
Kendall_hpr vs. Kendall_hai	0.1171	0.0306	0.0929

Panel B: GDP

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
Pearson_hpr vs. Pearson_hsi	0.9806	0.9594	0.9904
Pearson_hpr vs. Pearson_hai	0.9996	1.0017	0.9511
Spearman_hpr vs. Spearman_hsi	0.9901	0.9642	0.9958
Spearman_hpr vs. Spearman_hai	0.9991	1.0030	0.9544
Kendall_hpr vs. Kendall_hsi	1.0018	0.9678	1.0290
Kendall_hpr vs. Kendall_hai	0.9983	1.0469	1.0356
		L2 ratio	
Pearson_hpr vs. Pearson_hsi	0.9967	0.9819	0.9680
Pearson_hpr vs. Pearson_hai	0.9999	1.0134	1.0076
Spearman_hpr vs. Spearman_hsi	0.9979	0.9830	0.9732
Spearman_hpr vs. Spearman_hai	0.9997	1.0105	1.0102
Kendall_hpr vs. Kendall_hsi	1.0002	0.9903	0.9988
Kendall_hpr vs. Kendall_hai	0.9991	1.0210	1.0611
		DM statistic (p-value, L1)	
Pearson_hpr vs. Pearson_hsi	0.8881	0.6966	0.6185
Pearson_hpr vs. Pearson_hai	0.5498	0.4838	0.6852
Spearman_hpr vs. Spearman_hsi	0.8236	0.7175	0.6240
Spearman_hpr vs. Spearman_hai	0.5850	0.4669	0.6834
Kendall_hpr vs. Kendall_hsi	0.5288	0.7484	0.4603
Kendall_hpr vs. Kendall_hai	0.6578	0.1258	0.3753
		DM statistic (p-value, L2)	
Pearson_hpr vs. Pearson_hsi	0.6484	0.5953	0.6097
Pearson_hpr vs. Pearson_hai	0.5058	0.3402	0.4532
Spearman_hpr vs. Spearman_hsi	0.6203	0.5975	0.5922
Spearman_hpr vs. Spearman_hai	0.5221	0.3307	0.4290
Kendall_hpr vs. Kendall_hsi	0.5093	0.5412	0.4358
Kendall_hpr vs. Kendall_hai	0.6097	0.1878	0.2158

L1: Absolute-forecasts-error loss function. L2: Squared-forecasts-error loss function. L1 ratio and L2 ratio: results for the benchmark model divided by the results for the rival model such that a ratio larger than unity indicates a superior performance of the rival model given the respective loss function. DM statistic: Results of the modified Diebold-Mariano test (p-values) given the respective loss function. The alternative hypothesis is that the rival forecasts are more accurate than the benchmark forecasts. Results are based on ten fixed-estimation windows of varying in length: 0.50, 0.53, 0.56, ,,,, 0.75 of the data are used as training data (beginning at the start of the sample period). Results are averages across the ten fixed-estimation windows. h denotes the forecast horizon.

Table 4: Fixed-estimation window (quantile results)

Panel A: CFNAI

Models	$q = 0.1$	$q = 0.2$	$q = 0.3$	$q = 0.4$	$q = 0.5$	$q = 0.6$	$q = 0.7$	$q = 0.8$	$q = 0.9$
					$h = 1$				
Pearson_hpr vs. Pearson_hsi	1.2260	1.2931	1.2358	1.1119	0.9475	0.8976	0.8690	0.8586	0.9034
Pearson_hpr vs. Pearson_hai	0.9096	0.9871	1.0113	1.0315	1.0122	1.0461	1.0643	1.0627	1.0603
Spearman_hpr vs. Spearman_hsi	1.1542	1.1966	1.1600	1.0620	0.9336	0.9002	0.8905	0.8865	0.9477
Spearman_hpr vs. Spearman_hai	0.9052	0.9927	1.0076	1.0284	1.0078	1.0534	1.0611	1.0626	1.0614
Kendall_hpr vs. Kendall_hsi	1.1438	1.2601	1.1639	1.0274	0.9271	0.9176	0.9686	0.9024	0.9805
Kendall_hpr vs. Kendall_hai	0.9237	1.0115	1.0085	1.0277	1.0256	1.0769	1.0641	1.0595	1.0561
					$h = 6$				
Pearson_hpr vs. Pearson_hsi	1.6232	1.3312	1.2475	1.0983	1.0270	0.9614	0.8251	0.7834	0.8470
Pearson_hpr vs. Pearson_hai	0.9974	1.0020	0.9926	1.0191	1.0553	1.1017	1.1618	1.2511	1.2311
Spearman_hpr vs. Spearman_hsi	1.4629	1.2354	1.1120	1.0678	1.0101	0.9335	0.8555	0.8185	0.8659
Spearman_hpr vs. Spearman_hai	1.0019	1.0069	1.0055	1.0347	1.0676	1.1164	1.1855	1.2729	1.2004
Kendall_hpr vs. Kendall_hsi	1.2258	1.2670	1.1494	1.0568	1.0367	1.0119	0.9597	0.9571	0.9864
Kendall_hpr vs. Kendall_hai	1.0359	1.0390	1.0444	1.0891	1.1002	1.1465	1.2311	1.2506	1.2120
					$h = 12$				
Pearson_hpr vs. Pearson_hsi	1.8177	1.5720	1.5807	1.3517	1.1070	0.9501	0.8956	0.7945	0.7793
Pearson_hpr vs. Pearson_hai	1.1311	1.0541	1.0236	1.0250	1.1110	1.1841	1.2810	1.3364	1.3714
Spearman_hpr vs. Spearman_hsi	1.6290	1.5001	1.4849	1.2573	1.0611	0.9313	0.8980	0.8275	0.8165
Spearman_hpr vs. Spearman_hai	1.1130	1.0390	1.0375	1.0048	1.1306	1.1909	1.2762	1.3267	1.3674
Kendall_hpr vs. Kendall_hsi	1.3563	1.3195	1.2871	1.1840	1.0775	0.9839	1.0336	1.0329	1.0619
Kendall_hpr vs. Kendall_hai	1.1193	1.0609	1.1048	1.1176	1.1418	1.2009	1.2742	1.3244	1.3371

Panel B: GDP

Models	$q = 0.1$	$q = 0.2$	$q = 0.3$	$q = 0.4$	$q = 0.5$	$q = 0.6$	$q = 0.7$	$q = 0.8$	$q = 0.9$
					$h = 1$				
Pearson_hpr vs. Pearson_hsi	1.0085	1.0657	1.0695	1.0615	0.9920	0.9614	0.9859	0.9809	0.9425
Pearson_hpr vs. Pearson_hai	1.0039	0.9993	0.9945	0.9984	1.0007	0.9809	1.0181	0.9674	0.9481
Spearman_hpr vs. Spearman_hsi	1.0082	1.0267	1.0456	1.0460	0.9932	0.9678	1.0031	1.0027	0.9661
Spearman_hpr vs. Spearman_hai	1.0083	0.9990	0.9933	0.9967	0.9989	0.9889	1.0085	0.9790	0.9557
Kendall_hpr vs. Kendall_hsi	1.0416	1.1931	1.0376	1.0180	0.9904	0.9607	1.0472	1.0587	1.0665
Kendall_hpr vs. Kendall_hai	1.0040	1.0011	0.9951	0.9969	0.9986	0.9930	1.0097	0.9895	0.9650
					$h = 6$				
Pearson_hpr vs. Pearson_hsi	1.4094	1.3318	1.2292	1.0806	0.9962	0.9298	0.8906	0.8608	1.0708
Pearson_hpr vs. Pearson_hai	1.1401	1.0900	1.0256	1.0251	1.0788	1.0621	1.0549	1.0468	0.9728
Spearman_hpr vs. Spearman_hsi	1.2485	1.1980	1.1122	1.0444	0.9899	0.9485	0.9163	0.8978	1.0910
Spearman_hpr vs. Spearman_hai	1.1529	1.0922	1.0200	1.0432	1.0719	1.0676	1.0575	1.0664	1.0611
Kendall_hpr vs. Kendall_hsi	1.1999	1.1999	1.1611	1.0275	0.9681	0.9429	0.9157	0.9098	1.1660
Kendall_hpr vs. Kendall_hai	1.1736	1.0816	1.0347	1.0823	1.0847	1.0726	1.0806	1.0661	1.0864
					$h = 12$				
Pearson_hpr vs. Pearson_hsi	1.6199	1.4594	1.3136	1.1924	1.0360	0.9705	0.9073	0.8802	0.8558
Pearson_hpr vs. Pearson_hai	1.2924	1.1556	1.0668	1.0953	1.2031	1.2022	1.1582	1.1259	1.0953
Spearman_hpr vs. Spearman_hsi	1.4520	1.2212	1.2467	1.1439	1.0445	0.9854	0.9271	0.9119	0.8836
Spearman_hpr vs. Spearman_hai	1.2821	1.1302	1.0547	1.1160	1.2155	1.2387	1.1547	1.1113	1.0728
Kendall_hpr vs. Kendall_hsi	1.1735	1.0986	1.2135	1.1306	1.0915	1.0148	0.9379	0.9072	0.9537
Kendall_hpr vs. Kendall_hai	1.2707	1.1380	1.0976	1.1660	1.2238	1.2380	1.1789	1.0941	1.0843

Results are loss ratios for the check function (that is, bsolute-forecasts-error loss function). Ratio: results for the benchmark model divided by the results for the rival model such that a ratio larger than unity indicates a superior performance of the rival model given the respective loss function. Results are based on ten fixed-estimation windows of varying in length: 0.50, 0.53, 0.56, ,,,, 0.75 of the data are used as training data (beginning at the start of the sample period). Results are averages across the ten fixed-estimation windows. h denotes the forecast horizon. q quantile.

Table 5: Fixed-estimation window (DM results for quantiles)

Panel A: CFNAI

Models	$q = 0.1$	$q = 0.2$	$q = 0.3$	$q = 0.4$	$q = 0.5$	$q = 0.6$	$q = 0.7$	$q = 0.8$	$q = 0.9$
					$h = 1$				
Pearson_hpr vs. Pearson_hsi	0.0131	0.0025	0.0074	0.1613	0.6706	0.7965	0.9024	0.9714	0.9946
Pearson_hpr vs. Pearson_hai	0.9680	0.6666	0.3285	0.0697	0.3573	0.0943	0.0110	0.0127	0.0876
Spearman_hpr vs. Spearman_hsi	0.0277	0.0304	0.0609	0.2172	0.7159	0.7793	0.8920	0.9669	0.8596
Spearman_hpr vs. Spearman_hai	0.9389	0.5835	0.4013	0.1119	0.4003	0.0655	0.0060	0.0046	0.0400
Kendall_hpr vs. Kendall_hsi	0.0354	0.0075	0.0882	0.3301	0.7182	0.7867	0.6598	0.9824	0.5596
Kendall_hpr vs. Kendall_hai	0.8544	0.3109	0.2034	0.0713	0.2064	0.0192	0.0030	0.0007	0.0527
					$h = 6$				
Pearson_hpr vs. Pearson_hsi	0.0290	0.0554	0.1532	0.4044	0.5603	0.6913	0.8570	0.9880	0.9498
Pearson_hpr vs. Pearson_hai	0.5196	0.5048	0.5305	0.4186	0.2012	0.0506	0.0079	0.0001	0.0002
Spearman_hpr vs. Spearman_hsi	0.0205	0.1034	0.3475	0.4909	0.6295	0.7621	0.8673	0.9853	0.9207
Spearman_hpr vs. Spearman_hai	0.4993	0.4772	0.4879	0.3514	0.1525	0.0498	0.0013	0.0001	0.0172
Kendall_hpr vs. Kendall_hsi	0.0275	0.0764	0.2908	0.5194	0.5651	0.4477	0.6303	0.5376	0.5209
Kendall_hpr vs. Kendall_hai	0.3489	0.3501	0.3514	0.1986	0.1208	0.0163	0.0005	0.0003	0.0007
					$h = 12$				
Pearson_hpr vs. Pearson_hsi	0.0355	0.0493	0.0927	0.2225	0.5731	0.7442	0.7770	0.9305	0.9897
Pearson_hpr vs. Pearson_hai	0.4005	0.4598	0.4705	0.4475	0.2091	0.0594	0.0093	0.0008	0.0008
Spearman_hpr vs. Spearman_hsi	0.0405	0.0637	0.1188	0.3327	0.6097	0.7643	0.8064	0.9350	0.9826
Spearman_hpr vs. Spearman_hai	0.3982	0.4804	0.4545	0.4962	0.1442	0.0190	0.0042	0.0006	0.0014
Kendall_hpr vs. Kendall_hsi	0.1149	0.1720	0.4854	0.5991	0.6841	0.7310	0.4141	0.4630	0.4751
Kendall_hpr vs. Kendall_hai	0.3647	0.4113	0.3162	0.2153	0.1267	0.0295	0.0062	0.0015	0.0011

Panel B: GDP

Models	$q = 0.1$	$q = 0.2$	$q = 0.3$	$q = 0.4$	$q = 0.5$	$q = 0.6$	$q = 0.7$	$q = 0.8$	$q = 0.9$
					$h = 1$				
Pearson_hpr vs. Pearson_hsi	0.3148	0.0686	0.1130	0.0693	0.6810	0.9166	0.6664	0.8387	0.9777
Pearson_hpr vs. Pearson_hai	0.4435	0.5605	0.5378	0.6223	0.4910	0.9273	0.1554	0.8874	0.9790
Spearman_hpr vs. Spearman_hsi	0.3141	0.1253	0.1439	0.0817	0.7025	0.9003	0.6239	0.4980	0.7969
Spearman_hpr vs. Spearman_hai	0.4281	0.5336	0.6246	0.7392	0.5672	0.8760	0.2257	0.8696	0.9766
Kendall_hpr vs. Kendall_hsi	0.1275	0.0280	0.0446	0.2003	0.8331	0.9640	0.5148	0.4082	0.4590
Kendall_hpr vs. Kendall_hai	0.3886	0.4289	0.6064	0.7259	0.5841	0.7924	0.2482	0.7317	0.9483
					$h = 6$				
Pearson_hpr vs. Pearson_hsi	0.1413	0.0506	0.1098	0.2398	0.5632	0.7666	0.9006	0.9319	0.4924
Pearson_hpr vs. Pearson_hai	0.1085	0.2140	0.3663	0.3605	0.1482	0.1643	0.1857	0.1870	0.5458
Spearman_hpr vs. Spearman_hsi	0.1229	0.0904	0.1444	0.3318	0.5943	0.7525	0.9022	0.8775	0.4720
Spearman_hpr vs. Spearman_hai	0.1378	0.2037	0.4156	0.2906	0.1449	0.1383	0.1387	0.1270	0.2794
Kendall_hpr vs. Kendall_hsi	0.1264	0.0646	0.1340	0.4158	0.6928	0.7777	0.9056	0.8246	0.4857
Kendall_hpr vs. Kendall_hai	0.0912	0.2446	0.3620	0.1628	0.0764	0.0427	0.0412	0.0654	0.1753
					$h = 12$				
Pearson_hpr vs. Pearson_hsi	0.1510	0.1170	0.1152	0.3033	0.6290	0.7588	0.8196	0.9199	0.9887
Pearson_hpr vs. Pearson_hai	0.1495	0.1834	0.3355	0.2714	0.0838	0.0401	0.0190	0.0577	0.1146
Spearman_hpr vs. Spearman_hsi	0.1625	0.1897	0.1424	0.3428	0.6129	0.7412	0.8206	0.9087	0.9772
Spearman_hpr vs. Spearman_hai	0.1978	0.2371	0.4051	0.2239	0.0926	0.0034	0.0086	0.0575	0.1943
Kendall_hpr vs. Kendall_hsi	0.2064	0.2954	0.1884	0.4339	0.4539	0.5355	0.8219	0.9348	0.7439
Kendall_hpr vs. Kendall_hai	0.1504	0.2937	0.3777	0.1643	0.0731	0.0030	0.0036	0.0639	0.0467

DM statistic: Results of the modified Diebold-Mariano test (p-values) given the respective loss function. The alternative hypothesis is that the rival forecasts are more accurate than the benchmark forecasts. Results are loss ratios for the check function (that is, bsolute-forecasts-error loss function). Results are based on ten fixed-estimation windows of varying in length: 0.50, 0.53, 0.56, ,,,, 0.75 of the data are used as training data (beginning at the start of the sample period). Results are averages across the ten fixed-estimation windows. h denotes the forecast horizon. q quantile.

Appendix

A1 Additional Results

Table A1: Aggregate data (recursive-estimation window)

Panel A: CFNAI

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
NHPR vs. NHSI	0.9759	0.9381	0.9316
NHPR vs. NHAI	0.9971	0.9927	1.0351
		L2 ratio	
NHPR vs. NHSI	0.9847	0.9319	0.8564
NHPR vs. NHAI	0.9995	0.9930	0.9917
		DM statistic (p-value, L1)	
NHPR vs. NHSI	0.9560	0.8631	0.7466
NHPR vs. NHAI	0.8182	0.5589	0.4342
		DM statistic (p-value, L2)	
NHPR vs. NHSI	0.9170	0.9135	0.911
NHPR vs. NHAI	0.6756	0.8843	0.558

Panel A: GDP

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
NHPR vs. NHSI	1.0159	0.9868	0.9256
NHPR vs. NHAI	0.9936	0.9644	0.9605
		L2 ratio	
NHPR vs. NHSI	0.9876	0.9736	0.9033
NHPR vs. NHAI	0.9928	0.9580	0.8840
		DM statistic (p-value, L1)	
NHPR vs. NHSI	0.1727	0.6158	0.7383
NHPR vs. NHAI	0.8605	0.8628	0.7291
		DM statistic (p-value, L2)	
NHPR vs. NHSI	0.8382	0.8619	0.8961
NHPR vs. NHAI	0.9362	0.8534	0.8247

L1: Absolute-forecasts-error loss function. L2: Squared-forecasts-error loss function. L1 ratio and L2 ratio: results for the benchmark model divided by the results for the rival model such that a ratio larger than unity indicates a superior performance of the rival model given the respective loss function. DM statistic: Results of the modified Diebold-Mariano test (p-values) given the respective loss function. The alternative hypothesis is that the rival forecasts are more accurate than the benchmark forecasts. The first 0.50 of the data are used as training data (beginning at the start of the sample period). h denotes the forecast horizon.

Table A2: Recursive-estimation window (OLS results)

Panel A: CFNAI

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
Pearson_hpr vs. Pearson_hsi	1.0031	0.9935	1.0640
Pearson_hpr vs. Pearson_hai	0.9972	0.9546	0.9505
Spearman_hpr vs. Spearman_hsi	1.0009	1.0007	1.0682
Spearman_hpr vs. Spearman_hai	0.9947	0.9452	0.9384
Kendall_hpr vs. Kendall_hsi	1.0001	1.0188	1.1291
Kendall_hpr vs. Kendall_hai	0.9888	0.9438	0.9692
		L2 ratio	
Pearson_hpr vs. Pearson_hsi	1.0191	0.9576	0.9484
Pearson_hpr vs. Pearson_hai	0.9982	0.9960	1.0093
Spearman_hpr vs. Spearman_hsi	1.0188	0.9637	0.9563
Spearman_hpr vs. Spearman_hai	1.0006	0.9938	0.9910
Kendall_hpr vs. Kendall_hsi	1.0167	0.9718	0.9877
Kendall_hpr vs. Kendall_hai	1.0002	0.9933	1.0015
		DM statistic (p-value, L1)	
Pearson_hpr vs. Pearson_hsi	0.4446	0.5234	0.3836
Pearson_hpr vs. Pearson_hai	0.6881	0.8817	0.6620
Spearman_hpr vs. Spearman_hsi	0.4827	0.4971	0.3575
Spearman_hpr vs. Spearman_hai	0.7955	0.9441	0.7405
Kendall_hpr vs. Kendall_hsi	0.4984	0.4078	0.1861
Kendall_hpr vs. Kendall_hai	0.9152	0.9415	0.6452
		DM statistic (p-value, L2)	
Pearson_hpr vs. Pearson_hsi	0.1315	0.8049	0.6532
Pearson_hpr vs. Pearson_hai	0.9454	0.8183	0.3665
Spearman_hpr vs. Spearman_hsi	0.1304	0.7987	0.6500
Spearman_hpr vs. Spearman_hai	0.3964	0.9358	0.6856
Kendall_hpr vs. Kendall_hsi	0.1296	0.7775	0.5567
Kendall_hpr vs. Kendall_hai	0.4553	0.9110	0.4577

Panel B: GDP

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
Pearson_hpr vs. Pearson_hsi	0.9888	0.9540	0.9929
Pearson_hpr vs. Pearson_hai	1.0073	0.9552	0.9236
Spearman_hpr vs. Spearman_hsi	0.9925	0.9580	1.0082
Spearman_hpr vs. Spearman_hai	1.0061	0.9517	0.9070
Kendall_hpr vs. Kendall_hsi	0.9953	0.9577	1.0265
Kendall_hpr vs. Kendall_hai	1.0086	0.9522	0.9214
		L2 ratio	
Pearson_hpr vs. Pearson_hsi	1.0033	0.9835	0.9664
Pearson_hpr vs. Pearson_hai	0.9923	0.9757	0.9764
Spearman_hpr vs. Spearman_hsi	1.0036	0.9875	0.9729
Spearman_hpr vs. Spearman_hai	0.9925	0.9751	0.9686
Kendall_hpr vs. Kendall_hsi	1.0026	0.9883	0.9821
Kendall_hpr vs. Kendall_hai	0.9868	0.9736	0.9777
		DM statistic (p-value, L1)	
Pearson_hpr vs. Pearson_hsi	0.8702	0.7539	0.5174
Pearson_hpr vs. Pearson_hai	0.1878	0.9221	0.8886
Spearman_hpr vs. Spearman_hsi	0.8161	0.7608	0.4754
Spearman_hpr vs. Spearman_hai	0.2199	0.9505	0.9591
Kendall_hpr vs. Kendall_hsi	0.7174	0.7659	0.4127
Kendall_hpr vs. Kendall_hai	0.2562	0.9211	0.9657
		DM statistic (p-value, L2)	
Pearson_hpr vs. Pearson_hsi	0.2354	0.7229	0.6309
Pearson_hpr vs. Pearson_hai	0.9249	0.9225	0.7035
Spearman_hpr vs. Spearman_hsi	0.2063	0.7030	0.6262
Spearman_hpr vs. Spearman_hai	0.9173	0.9312	0.8167
Kendall_hpr vs. Kendall_hsi	0.2336	0.7004	0.5929
Kendall_hpr vs. Kendall_hai	0.9116	0.9273	0.8398

L1: Absolute-forecasts-error loss function. L2: Squared-forecasts-error loss function. L1 ratio and L2 ratio: results for the benchmark model divided by the results for the rival model such that a ratio larger than unity indicates a superior performance of the rival model given the respective loss function. DM statistic: Results of the modified Diebold-Mariano test (p-values) given the respective loss function. The alternative hypothesis is that the rival forecasts are more accurate than the benchmark forecasts. The first 0.50 of the data are used as training data (beginning at the start of the sample period). h denotes the forecast horizon.

Table A3: Additional OLS results (fixed-estimation window)

Panel A: CFNAI

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
hpr_conn_short vs. hsi_conn_short	0.9958	1.0870	1.1431
hpr_conn_long vs. hsi_conn_long	1.0180	1.1758	1.2714
hpr_conn_short vs. hai_conn_short	1.0210	1.0939	1.1227
hpr_conn_long vs. hai_conn_long	1.0320	1.0744	1.0003
		L2 ratio	
hpr_conn_short vs. hsi_conn_short	0.9973	1.0577	1.1791
hpr_conn_long vs. hsi_conn_long	0.9952	1.0349	1.1739
hpr_conn_short vs. hai_conn_short	1.0194	1.0337	1.0748
hpr_conn_long vs. hai_conn_long	1.0437	1.0335	0.9926
		DM statistic (p-value, L1)	
hpr_conn_short vs. hsi_conn_short	0.7513	0.1674	0.2432
hpr_conn_long vs. hsi_conn_long	0.2886	0.0237	0.0430
hpr_conn_short vs. hai_conn_short	0.1667	0.1171	0.2827
hpr_conn_long vs. hai_conn_long	0.1067	0.2165	0.4977
		DM statistic (p-value, L2)	
hpr_conn_short vs. hsi_conn_short	0.7176	0.2027	0.1980
hpr_conn_long vs. hsi_conn_long	0.6767	0.2338	0.0787
hpr_conn_short vs. hai_conn_short	0.1632	0.1097	0.1403
hpr_conn_long vs. hai_conn_long	0.0536	0.1424	0.5548

Panel B: GDP

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
hpr_conn_short vs. hsi_conn_short	1.0228	1.0619	1.1259
hpr_conn_long vs. hsi_conn_long	1.0492	1.1827	1.2555
hpr_conn_short vs. hai_conn_short	0.9963	0.9507	0.9115
hpr_conn_long vs. hai_conn_long	0.9967	0.9330	0.9156
		L2 ratio	
hpr_conn_short vs. hsi_conn_short	1.0169	1.0712	1.1894
hpr_conn_long vs. hsi_conn_long	1.0665	1.1680	1.2147
hpr_conn_short vs. hai_conn_short	0.9976	0.9464	0.9258
hpr_conn_long vs. hai_conn_long	0.9978	0.9353	0.9424
		DM statistic (p-value, L1)	
hpr_conn_short vs. hsi_conn_short	0.1821	0.2126	0.1942
hpr_conn_long vs. hsi_conn_long	0.0469	0.0317	0.0091
hpr_conn_short vs. hai_conn_short	0.6079	0.8048	0.7362
hpr_conn_long vs. hai_conn_long	0.6944	0.8079	0.6894
		DM statistic (p-value, L2)	
hpr_conn_short vs. hsi_conn_short	0.2049	0.1371	0.1608
hpr_conn_long vs. hsi_conn_long	0.0875	0.0661	0.0573
hpr_conn_short vs. hai_conn_short	0.5915	0.8505	0.8560
hpr_conn_long vs. hai_conn_long	0.6650	0.8402	0.8565

L1: Absolute-forecasts-error loss function. L2: Squared-forecasts-error loss function. L1 ratio and L2 ratio: results for the benchmark model divided by the results for the rival model such that a ratio larger than unity indicates a superior performance of the rival model given the respective loss function. DM statistic: Results of the modified Diebold-Mariano test (p-values) given the respective loss function. The alternative hypothesis is that the rival forecasts are more accurate than the benchmark forecasts. Results are based on ten fixed-estimation windows of varying in length: 0.50, 0.53, 0.56, ,,,, 0.75 of the data are used as training data (beginning at the start of the sample period). Results are averages across the ten fixed-estimation windows. h denotes the forecast horizon.

Table A4: Additional OLS results (recursive-estimation window)

Panel A: CFNAI

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
hpr_conn_short vs. hsi_conn_short	0.9940	1.0345	1.0589
hpr_conn_long vs. hsi_conn_long	1.0052	1.1197	1.1511
hpr_conn_short vs. hai_conn_short	1.0125	1.0101	1.0674
hpr_conn_long vs. hai_conn_long	1.0335	1.0548	1.0078
		L2 ratio	
hpr_conn_short vs. hsi_conn_short	0.9990	1.0008	1.0815
hpr_conn_long vs. hsi_conn_long	0.9763	1.0164	1.0797
hpr_conn_short vs. hai_conn_short	1.0033	1.0079	1.0159
hpr_conn_long vs. hai_conn_long	1.0199	1.0471	0.9941
		DM statistic (p-value, L1)	
hpr_conn_short vs. hsi_conn_short	0.8288	0.2394	0.3066
hpr_conn_long vs. hsi_conn_long	0.4065	0.0507	0.0739
hpr_conn_short vs. hai_conn_short	0.1410	0.4239	0.3365
hpr_conn_long vs. hai_conn_long	0.0172	0.2305	0.4800
		DM statistic (p-value, L2)	
hpr_conn_short vs. hsi_conn_short	0.6179	0.4862	0.2173
hpr_conn_long vs. hsi_conn_long	0.8080	0.4066	0.0514
hpr_conn_short vs. hai_conn_short	0.3359	0.4176	0.3283
hpr_conn_long vs. hai_conn_long	0.0566	0.1627	0.5573

Panel B: GDP

Models	$h = 1$	$h = 6$	$h = 12$
		L1 ratio	
hpr_conn_short vs. hsi_conn_short	1.0086	1.0277	1.0971
hpr_conn_long vs. hsi_conn_long	1.0245	1.1080	1.1653
hpr_conn_short vs. hai_conn_short	0.9967	0.9952	0.9593
hpr_conn_long vs. hai_conn_long	0.9987	0.9792	0.9387
		L2 ratio	
hpr_conn_short vs. hsi_conn_short	1.0050	1.0224	1.1271
hpr_conn_long vs. hsi_conn_long	1.0150	1.0588	1.1247
hpr_conn_short vs. hai_conn_short	1.0019	0.9944	0.9577
hpr_conn_long vs. hai_conn_long	1.0012	0.9799	0.9681
		DM statistic (p-value, L1)	
hpr_conn_short vs. hsi_conn_short	0.2919	0.2320	0.1549
hpr_conn_long vs. hsi_conn_long	0.0163	0.0482	0.0337
hpr_conn_short vs. hai_conn_short	0.6256	0.5445	0.6376
hpr_conn_long vs. hai_conn_long	0.6231	0.6543	0.6615
		DM statistic (p-value, L2)	
hpr_conn_short vs. hsi_conn_short	0.3527	0.2126	0.1391
hpr_conn_long vs. hsi_conn_long	0.1105	0.2019	0.0328
hpr_conn_short vs. hai_conn_short	0.3974	0.5810	0.8367
hpr_conn_long vs. hai_conn_long	0.3849	0.6648	0.8266

L1: Absolute-forecasts-error loss function. L2: Squared-forecasts-error loss function. L1 ratio and L2 ratio: results for the benchmark model divided by the results for the rival model such that a ratio larger than unity indicates a superior performance of the rival model given the respective loss function. DM statistic: Results of the modified Diebold-Mariano test (p-values) given the respective loss function. The first 0.50 of the data are used as training data (beginning at the start of the sample period). h denotes the forecast horizon.