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Forecasting total energy's CO_2 emissions

Leonardo Iania* Bernardina Algieri† Arturo Leccadito‡

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Abstract

In recent years, the international community has been increasing its efforts to reduce the human footprint on air pollution and global warming. Total CO_2 emissions are a key component of global emission, and as such, they are closely monitored by national and supranational entities. This study evaluates the performance of a broad set of forecasting models and their combinations to predict energy's carbon dioxide releases using an in-sample and out-of-sample analysis. The focus is on the US for the period 1973-2021 using quarterly observations. The results show that economic variables, energy and interannual climate variability indicators help forecast short-/medium- term CO_2 emissions. In addition, a combination of models sharpens quantile predictions.

Keywords: *CO_2 Emissions; Forecasting Models; Quantile Forecast; Economic, Energy and Nature-related drivers; Climate Change; Drought Severity; Interannual Variability*

JEL: *C01; C13; C31; C51; C52; C53; C55; C82; Q43; Q47; Q53; Q59*

1 Introduction

Global warming and climate change are vital challenges that society is currently facing. Over the recent decades, economies worldwide have recognized (at various scales) the importance of

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implementing coordinated policies to reduce the anthropogenic influence on climate and preserve ecosystems, the environment, and human health. More than 190 parties have thus ratified the Paris Agreement and signed the Agenda 2030 to save the planet. The issue of pollutant reductions is very complex but it requires a prompt response, even if the transition towards greener productions is not immediate and needs time. Arguably, as most global economic activities are strongly carbon-based, carbon dioxide (CO_2) emissions are among the pivotal factors linking climate change and human activity (Filimonova et al., 2021; Mi et al., 2019; Meng and Han, 2018; Green and Stern, 2017; Olaizola and Dietzenbacher, 2014). Given the relevance of climate change policies and their link with carbon emissions, empirical science is called upon to deliver theoretical and empirical models that monitor and forecast carbon emissions. We feed the ongoing debate by focusing on energy's CO_2 emissions[1] forecast using a large dataset including measures of anthropogenic activity (arising from economic activity) and local and global interannual variability (IAV) indicators such as oceans/land surface temperature, local extreme weather events, and local drought indicators. While various studies stress the importance of these variables in explaining/forecasting the evolution of atmospheric and/or energy's CO_2 emissions - see Fosten (2019) and Bennedsen et al. (2021) Betts et al. (2016), Luo and Keenan (2022) and Meangbua et al. (2019) among many others - there is the lack of an analysis evaluating the performance of this variety of data sources in predicting energy's CO_2 emissions. Our study fills this gap by focusing the point and quantile forecasting.

We employ direct (linear) forecasting methods, see Marcellino et al. (2006), which overcome the problem of quantiles temporally aggregation, see Ghysels (2014). We perform both an in- and out-of-sample analysis using quarterly data for the period 1973Q1-2021Q3 with the aim of forecasting the total CO_2 emissions for the US. We target forecasting horizons ranging form one quarter to two years. Our explanatory variables are grouped in two categories. The first category links to anthropogenic factors, which include (i) the McCracken and Ng (2020) macroeconomic database, (ii) the University of Michigan's Survey of Consumers and Survey of Professional Forecasts series, and (iii) energy-related indicators such as the Residential Energy Demand Temperature Index, see Heim et al. (2003a). The second category relates to IAV indexes such as the northern/southern

[1] Unless explicitly stated, for the rest of the paper the terms "energy's CO_2 emissions" and "CO_2 emissions" interchangeably.

hemisphere anomalies indexes for land and ocean, the Palmer (1985)'s Drought Index and the year-to-date temperature anomalies around the Arctic region. For each group of variables, we use dimensionality reduction techniques based on the Principal Component Analysis and, for the larger databases, Quantile Factor (QF) Models, see Chen et al. (2021), with the goal of investigating if distribution's indicators of large datasets are linked to CO_2 emissions patterns. For each of these data category we build-up separate model (13 in total) and we assess the forecasting abilities of each of them both separately and in combination.

In a nutshell, our results indicate that macro factors obtained from McCracken and Ng (2020), energy factors, drought indicators and Arctic factors have strong in-sample and out-of sample predicting power for future growth rates of CO_2 emissions. Broadly speaking these results holds for quantile forecasting but with a warning. In order to achieve superior quantiles forecasts it is advisable to combine among data categories. To the best of our knowledge, this set of results is new in the literature. Fosten (2019) and Bennedsen et al. (2021) look at macroeconomic determinant of US CO_2 emissions via wavelet techniques combined with dynamic factor models and structural dynamic factor models, respectively. In contrast to their approaches we use a direct/quantile forecasting setting and we stress the importance of accounting for a broader range of factors for most forecasting horizons. Luo and Keenan (2022) link the global atmospheric CO_2 growth rate variability to extreme droughts conditions in tropical areas while Betts et al. (2016) show that El Nĩno events have contributed to the rise in CO_2 emissions. We show that local (droughts factors) and global (Arctic anomalies) IAV determinants play a key role in forecasting for energy' CO_2 emissions.

In the rest of the paper we present our methodology, Section 2, we describes the data, Section 3, and we discuss our results, Section 4. Section 5 concludes.

2 Methodology

To set notation, we define the quarterly observation of the h-period growth rate of total CO_2 emissions as:

$$g^{CO_2}_{t\to t+h} = \log(E_{t+h}) - \log(E_t), \tag{1}$$

where $\{E_t\}_{t=1,\dots,T}$ is the level of emissions.

With the objective to forecast carbon dioxide releases and to assess the role of a group of potential drivers, we link $g^{CO_2}_{t\to t+h}$ to the last p quarter on quarter growth rates and a set of determinants at time t, X_t:

$$g^{CO_2}_{t\to t+h} = \beta^0 + \sum_{j=1}^{p} \beta_j g^{CO_2}_{t-j\to t+1-j} + \gamma' X_t + \epsilon_t, \quad t = p+1, p+2, \dots, T-h. \tag{2}$$

Model (2) is particularly suited for forecasting purposes, as it allows to directly forecast the growth rate of CO_2 emissions over a h periods horizon, i.e. from time T to time $T+h$, conditional on the information up to time T. The explanatory variables in (2) might be related to anthropogenic determinants and to measures of temperature variations (IAV). We use the same explanatory variables of model (2) to predict the conditional τ-quantile of $g^{CO_2}_{t\to t+h}$:

$$Q_\tau\left(g^{CO_2}_{t\to t+h}\middle| \mathcal{F}_t\right) = \beta^0_\tau + \sum_{j=1}^{p} \beta_{j,\tau} g^{CO_2}_{t-j\to t+1-j} + \gamma'_\tau X_t, \quad t = p+1, p+2, \dots, T-h \tag{3}$$

where $\mathcal{F}_t$ denotes the information available up to time t and $\tau \in (0,1)$. Using a model like the above for conditional quantile of the growth rate over h periods is particularly useful since iterative forecasts (i.e. forecasts obtained from a one-period ahead model, iterated forward for h periods, Marcellino et al., 2006) are not available for quantiles. Indeed, quantiles cannot be easily temporally aggregated, (Ghysels, 2014). We combine the predicted quantiles obtained from (2) to form a robust estimator of the mean of CO_2 emissions growth rates, see Lima et al. (2020), Taylor (2007) and references therein. In particular, we consider the following quantile combinations:

- Trimean

$$\widehat{g^{CO_2}_{T\to T+h}} = 0.25Q_{0.25}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right) + 0.5Q_{0.5}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right) + 0.25Q_{0.75}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right)$$

- Gastwirth:

$$\widehat{g^{CO_2}_{T\to T+h}} = 0.3Q_{1/3}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right) + 0.4Q_{0.5}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right) + 0.3Q_{2/3}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right)$$

- 5-quantile:

$$\begin{aligned}\widehat{g^{CO_2}_{T\to T+h}} = {} & 0.05Q_{0.1}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right) + 0.25Q_{0.25}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right) + 0.4Q_{0.5}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right) \\ & +0.25Q_{0.75}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right) + 0.05Q_{0.9}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right)\end{aligned}$$

- 99-quantile:

$$\widehat{g^{CO_2}_{T\to T+h}} = \frac{1}{99}\sum_{i=1}^{99} Q_{0.01\times i}\left(g^{CO_2}_{T\to T+h}\middle|\mathcal{F}_T\right)$$

Both in the case of mean and quantile predictions, we implement also AIC and BIC model averaging, see Moral-Benito (2015) for an overview on the topic, and Lu and Su (2015) for the case of quantile model averaging. Given $\mathcal{M}$ models and their predictions $\{\hat{y}\}_{m=1,\ldots,\mathcal{M}}$ for the mean or quantiles of CO_2 emissions growth rates, we obtain the prediction from AIC and BIC model averaging as

$$\sum_{m=1}^{\mathcal{M}} w_m \hat{y}_m \tag{4}$$

where the weights are calculated as

$$w_m = \frac{\exp\left(-\frac{1}{2}IC_m\right)}{\sum_{j=1}^{M}\exp\left(-\frac{1}{2}IC_j\right)}$$

and IC can be either AIC or BIC.

In addition to model average, we combine the forecasts from M models using again a weighted average of the forecasts as in (4), but using weights obtained from a training sample. The training sample is used to derive W out-of-sample forecasts, that, in turn, are used in conjunction with the realized values to obtain a loss function L_m. To be more specific, we use the Root Mean Square Error (RMSE),

$$\mathrm{RMSE}_m = \sqrt{\frac{1}{W}\sum_{t=1}^{W}(\hat{y}_{t,m} - y_t)^2}$$

in the case of mean predictions. Here, $\hat{y}_{t,m}$ denotes the predicted mean for t based on model m and y_t the realized value. In the case of quantile predictions, we use the average check function,

$$\bar{\rho}_m = \frac{1}{W}\sum_{t=1}^{W}\rho_\tau(Q_\tau(t,m) - y_t)$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ and $Q_\tau(t,m)$ is the predicion we make for the τ-quantile at time t using model m. The weights in the combination of forecasts (4) are obtained as

$$w_m = \frac{1/L_m}{\sum_{j=1}^{M} 1/L_j}$$

where the loss function L is RMSE or the average check function, $\bar{\rho}$.

For some of the considered models, we reduce the dimension of the explanatory variables using the QFA method. This technique allows us to extract the most relevant common factors from these many variables. We assume that for $\tau \in (0,1)$ the observed explanatory variable $Z_{i,t}$, with $i = 1,\ldots,N$ and $t = 1,\ldots,T$ can be decomposed as

$$Z_{i,t} = \lambda_i'(\tau)f_t(\tau) + e_{i,t}(\tau)$$

where the error term $e_{i,t}(\tau)$ satisfies the quantile restriction

$$P\left(e_{i,t}(\tau) \leq 0 \middle| f_t(\tau)\right) = \tau \quad \text{almost surely},$$

and where for $r(\tau) \ll N$, $f_t(\tau)$ is an $r(\tau) \times 1$ vector of random common factors, and $\lambda_i(\tau)$ is an

$r(\tau) \times 1$ vector of non-random factor loadings. Factors and loadings are estimated by minimizing

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\rho_\tau(Z_{i,t} - \lambda_i'(\tau)f_t(\tau)) \tag{5}$$

under the restrictions

$$\frac{1}{T}\sum_{t=1}^{T} f_t(\tau)f_t'(\tau) = I_{r(\tau)}$$

$$\frac{1}{N}\sum_{i=1}^{N}\lambda_i(\tau)\lambda_i'(\tau) \quad \text{is diagonal with non-increasing diagonal elements.}$$

Here I_s denotes the identity matrix of dimension s. Contrary to PCA, however, it is not possible to obtain in closed form estimators of factors and loadings that minimize (5). For this purpose we therefore follow the computationally efficient algorithm proposed by Chen et al. (2021), i.e. the iterative quantile regression (IQR), that allows to efficiently identify the stationary points of the object function (5). The optimal number of factors, $r^*(\tau)$, is chosen by rank-minimization (see Section 3.2.1. of Chen et al., 2021). Once factors and loadings have been extracted from the set of observed explanatory variables $Z_{i,t}$ via IQR, we use the $r^*(\tau)$ factors $f_t(\tau)$ in models (2) and (3) in place of the explanatory variables X_t.

3 Data

3.1 CO_2 emission rates

Our measure of CO_2 emission, E_t, is the seasonally-adjusted US Total Energy CO_2 Emissions (TETCEUS) retrieved from the US Energy Information Administration and spanning from Q1 1972 to Q3 2021. The seasonal adjustment is performed using the software X-13ARIMA-SEATS of the US Census Bureau[2].

Insert Figure 1

[2]See: https://www.census.gov/data/software/x13as.html

Figure 1 sketches $g^{CO_2}_{t\rightarrow t+h}$ over one quarter (left column), one year (middle column) and two years (right column). To gain some insight into the potential links between CO_2 emissions growth and natural and anthropogenic episodes, Figure 1 reports periods in which severe nature-related and economic events took place. In detail, the shaded areas in the top row of Figure 1 highlight periods of severe drought, defined as episodes that have caused losses of more than $3 billion, according to the Centers for Environmental Information[3]. The middle row reports periods of oil crises, as detected by Hamilton (2011), plus the 2010s oil glut. Finally, the bottom row presents phases of economic recessions in the U.S. as identified by the National Bureau of Economics and Research[4].

The visual inspection of the top rows of Figure 1 suggests that recessions episodes are generally associated with drops in CO_2 emissions, both over short-term (one quarter) and medium-term (two years) horizons. For example, five out of the seven largest drops in yearly CO_2 emissions are associated with recession periods, particularly the early '80s, early '90s, early '00s, 07-08 and Covid-19 recessions. Turning to oil episodes, the subplots in the middle row of Figure 1 show that oil crises (glut) are followed by a decrease (increase) in CO_2 emissions. The intuition behind this pattern might be that major oil crises were often followed by recessions, which in turn cause a decrease in anthropogenic activity and hence in CO_2 emissions. Finally, the bottom-left panel of Figure 1 seems to highlight that drought episodes are linked to an increase in one-quarter growth rate of CO_2 emissions. For example, the CO_2 emission increased around the short-term drought of the '70s, the Northern Plains drought of 1989, the U.S. drought in 1991, the drought and heat wave of 2000, and the U.S. drought and heat wave of 2012. The reason can be ascribed to the fact that when soils dry out due to droughts, plants breathe less and reduce their photosynthesis; hence, they can no longer seize carbon dioxide from the surrounding air, and more CO2 pollutant stagnates[5].

Insert Figure 2

[3]See: https://www.ncei.noaa.gov/access/billions/events/US/1980-2021.

[4]See: https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions.

[5]See ETH Zurich, "Drought increases CO2 concentration in the air" ScienceDaily, 29 August 2018 www.sciencedaily.com/releases/2018/08/180829133214.htm.

To gain further insights on the potential relationship between CO_2 emissions, droughts and economic episodes, Figure 2 reports the time-varying CO_2 growth volatility over one (left column), two (middle column) and four (right column) quarters. Each volatility series has been obtained via a generalized autoregressive conditional heteroskedasticity model, GARCH(1,1)[6]. Focusing on the three plots on the bottom row, where there are severe drought periods, two points are worth noticing. First, volatility episodes seem to spike during most of the drought periods. Second, as drought frequency intensifies, so does the volatility of short-term growth CO_2 emissions. A similar link between the long-term increase in atmospheric CO_2 growth and extreme tropical droughts has been recently pointed out by Luo and Keenan (2022).

Overall, these simple graphical exercises highlight that the growth rate of CO_2 emissions is potentially linked to both antrhopogenic and natural determinants. The next sections layout the dataset we use in our analysis.

3.2 Anthropogenic determinants: Economic data and energy factors

We trace the US-based historical evolution of economic activities via the large-scale dataset of McCracken and Ng (2020), available at the Federal Reserve of Saint Louis website. The dataset consists of 248 quarterly series classified in 14 groups ranging from financial and nominal variables, such as interest rates and prices, to output data, such as industrial production[7]. In our analysis, we work with two types of factors: (i) $X_{M,t}^{70\%}$, i.e. the set of principal components that explain up to 70% of the variation of all the original series, and (ii) $Q_{M,t}^{70\%}$, namely the set of principal components that explain up to 70% of the variation in the 1%, 10% , 90% and 99% quantile factors of all the series.

[6]See Bollerslev (1986).

[7]We use the data and data-transformation proposed by McCracken and Ng (2020) at the Federal Reserve of Saint Louis website: https://research.stlouisfed.org/econ/mccracken/fred-databases/ with two exceptions. First, from this database, we remove the series with ID: 32, 128,129,130,194 as we included them in a larger energy-related database. Second, for nominal prices we use first differences of the log indexes instead of the second; using the proposed transformation by McCracken and Ng (2020) does not alter the results.

Insert Figure 3 and Table 1

Figure 3 and Table 1 report the macro factors extracted over the whole sample period and their correlation with the (volatility of the) growth rate of CO_2 emission over (1, 2, and 4) 1, 2, 4, 6, and 8 quarters, respectively. Several macro factors are correlated with future CO_2 emissions evolution. Quarterly growth rates negatively relate to the first PCs and the quantile factor, see Panel A of Table 1. Figure 3 highlights that these two factors increase during a recession, which intuitively explains their negative correlation with CO_2 emissions evolution. Longer-term CO_2 emission's growth, i.e. over 6 and 8 quarters, correlate with several factors, the strongest link being with factor 4. Figure 3 shows that this factor tends do decrease during a recession, indicating it might be linked to a contraction in economic activity. While the other factors do not have an immediate interpretation, two interesting patterns emerge. First, only recessions-related factors link to short-term growth rate of CO_2 emissions. Second, for longer horizons, CO_2 emissions growth relates to a wider range of economic conditions, which can potentially be important in a forecasting exercise. Panel B of Table 1 while does not reveal any particular pattern in the relationship between CO_2 emission growth's volatility and macro factors, it indicates that most of the correlations are statistically significant (10% level) for short horizons.

Insert Table 2 and Table 3

Next to historical macroeconomic data, we consider (potential) future tendencies on economic activity and consumption by using (i) a set of consumers-spending based surveys indicators, retrieved from the University of Michigan's Survey of Consumers, from which we extracted $X^{70\%}_{MSC,t}$ via PCA, and (ii) the one-year ahead average forecast of real gross domestic product made by survey of professional forecasters (SPF), $X_{SPF,t}$. Table 2 lists the data used and their sources. Our last indicators set of anthropogenic variables are from the energy market. Table 3 shows the 15 energy-related variables we employ, which refer to (i) energy consumption, (ii) energy production, export and import, (iii) energy prices, and (iv) the temperature related measures of energy demand. The latter indicator is given by the Residential Energy Demand Temperature Index (REDTI), see Heim et al. (2003b), which is a population-weighted heating and cooling degree days index tracing residential energy demands via its strong correlation with daily temperatures. From these 15 variables, in our analysis we use $X_{E,t}^{70\%}$, and $Q_{E,t}^{70\%}$, both obtained with the same procedure used for the macro variables.

Insert Figure 4, Table 4

Figure 4 and Table 4 report $X_{MSC,t}^{70\%}$, $X_{SPF,t}$, $X_{E,t}^{70\%}$ and $Q_{E,t}^{70\%}$ and their correlation with the (volatility of the) growth rate of CO_2 emissions over (1, 2, and 4) 1, 2, 4, 6, and 8 quarters, respectively. Focusing first on the surveys data, the top-middle and top-right panels of Figure 4 indicate that the first (second) Michigan surveys factor, $X_{MSC,t}^{1}$ ($X_{MSC,t}^{2}$), negatively (positively) relates with recessions episodes, indicating that its growth might signal an improvement (deterioration) of economic conditions. Following this interpretation, the correlations of surveys factors with emissions' growth rates are in accordance with intuition. Expected improvement in economic conditions, i.e. an increase (decrease) in $X_{SPF,t}$ and $X_{MSC,t}^{1}$ ($X_{MSC,t}^{1}$) positively relate with growth of CO_2 emissions. Turning on the energy factors, Panel A of Table 4 indicates that the first and third factors have the strongest correlations with growth of CO_2 emissions, i.e. $X_{E,t}^{1}$ and $X_{E,t}^{4}$. The middle-left panel (bottom-left) of Figure 4 reveals that $X_{E,t}^{1}$ ($X_{E,t}^{4}$) tend to decrease (increase) during oil crisis periods, while it increases (decreases) during recessions. Such a pattern suggests that changes in $X_{E,t}^{1}$ ($X_{E,t}^{4}$) are associated with economic contractions (expansions), which intuitively explains the sign of the correlations in Panel A of Table 4.

3.3 Interannual variability (IAV) determinants

Our determinants of CO_2 emissions related to nature hinges upon measures of temperature variations, drought and precipitation indicators, and oscillation indexes. The motivation for choosing this this set of variables is threefold. First, as highlighted by Kushnir et al. (2019) and the references therein, atmospheric teleconnection patterns and anomalies related to the surface conditions of ocean and land are crucial determinants of the natural fluctuations of the climate system, which in turn impact CO_2 emissions, see Matthews et al. (2021), Tokarska et al. (2020) and Ray et al. (2020). Second, Ray et al. (2020) and Luo and Keenan (2022), among others, have highlighted that CO_2 emission cycles are linked to vegetated land surface and soil conditions, which in turn are influenced by natural events, such as drought and temperature, and rainfall. Finally, Meangbua et al. (2019) using a panel of household data highlight that temperature is the crucial factor influencing energy and CO2 requirements, with a 1 °C increase in temperature resulting in The temperature is the crucial factor influencing energy and CO2 requirements.

We use three types of temperature/precipitation-based data: (i) The northern/southern hemisphere anomalies indexes for land and ocean, from which we extracted $X^{70\%}_{WAI,t}$. (ii) The year-to-date temperature anomalies around the arctic region, i.e. the area within the 25$^{\text{th}}$ and 50$^{\text{th}}$ latitude. We proceeded in two steps. First, we gridded the area by varying the latitude and the longitude by one degree and collected the year-to-date temperature anomalies of each gridded location. Subsequently, via standard principal component analysis, we extracted $X^{70\%}_{A,t}$, and $Q^{70\%}_{A,t}$ $X^{70\%}_{A,t}$. (iii) Measures of extreme weather conditions, namely the average of the maximum and minimum contiguous US temperature extremes, the average and the difference of the contiguous US maximum and minimum temperature anomalies, and the contiguous US extremes in 1-day precipitation. For these three set of series, in our analysis we use $X^{70\%}_{Extr,t}$. The drought conditions' measures are obtained from the first principal component of the Palmer (1985)'s Drought Index, PDI, for each of the US Lower 48 States (the so-called conterminous US). From the resulting 48 PDI indicators, in our analysis we use $X^{70\%}_{PDI,t}$ and $Q^{70\%}_{PDI,t}$. Finally, as oscillation indexes, we select measures covering vast global areas, namely: the Arctic Oscillation (AO), the Pacific-North America (PNA) pattern, the Pacific Decadal Oscillation (PDO), the North Atlantic Oscillation (NAO) index, the Southern Oscillation Index (SOI), and the Oceanic Niño Index (ONI). As with with the other set of data, of the six oscillation indexes, in our analysis we use $X^{70\%}_{OSCI,t}$ The group of nature-related variables are reported in Table 5.

Insert Table 5 and Figure 5 and Table 6

Figure 5 and Table 6 depict the set of IAV determinants and their correlation with the (volatility of the) growth rate of CO_2 emission over (1, 2, and 4) 1, 2, 4, 6, and 8 quarters, respectively. Panel A of Table 6 points out that extreme temperature/precipitation indicators, $X^1_{Extr,t}$, drought indicators, $X^3_{PDI,t}$ and $X^4_{PDI,t}$, and arctic temperature anomalies, $X^2_{A,t}$, exhibit the largest correlations with growth rate of CO_2 emissions. Panel B of Table 6 indicates that, in line with the intuition outlined in Section 3.1, drought factors correlate with CO_2 volatility. For example, an increase in the quantile factor $Q^1_{PDI,t}$ which peaks during drought episodes, is associated with an increase in quarterly and biannual CO_2 volatility. Similarly, $X^1_{WAI,t}$ ($X^1_{OSCI,t}$), which capture most of the variability in northern/southern hemisphere anomalies indexes (oscillation indexes), positively (negatively) links to CO_2 volatility, even if it is uncorrelated to the growth of CO_2 emissions.

4 Results

4.1 In-Sample Analysis

4.1.1 Setting

We compare the competing models to the baseline setting based on a direct forecasting framework with four lags of quarterly growth rates, $p = 4$:

$$g^{CO_2}_{t\to t+h} = \beta^0 + \sum_{j=1}^{p} \beta_j g^{CO_2}_{t-j\to t+1-j} + \epsilon_t. \tag{6}$$

Note that (6) can be obtained as a particular case of eq. (2) by setting $\gamma = 0$.

We choose four lags for two reasons. First, controlling for the past-year growth rates allows to parsimoniously take into account of the potential medium-term correlation structure in multi-period CO_2 growth rates. Second, from a more formal standpoint, we compare the adjusted R-squared of four forecasting regressions based on equation (6) with $p = 1, 2, 3,$ and 4. We estimate the four models for $h = 1, 2, 4, 6,$ and 8 and over rolling samples of 25 years fixed-window.

Insert Figure 6

Figure 6 reports the evolution of the adjusted R-squared for each model and for the five forecasting growth periods. With just a few exceptions, the adjusted R-squared of the model with four lags (blue line), which we label "baseline" is consistently equal or higher than those of the other models. In this in-sample exercise, each of our alternative models, which augment the baseline with one set of the control factors listed in Table 8, is compared to baseline setting by testing the null $H_0 : \gamma = 0$ in model (2). We perform the in-sample evaluations over the whole sample and, inspired by Luo and Keenan (2022), via rolling estimations based on 25 years fixed windows. The choice of the window size averages out the window sizes of the macro-based study Chen et al. (2021), i.e. 30 years, and of the IAV-based study of Luo and Keenan (2022), i.e. 20 years.

Insert Table 8

Figure 7 (8) reports the ratio between the adjusted coefficient of determination of the benchmark model over that of the competing models for the whole sample (rolling windows) estimation. Therefore, models for which the ratio is less than one (red scale) have a better in-sample goodness of fit than the benchmark model (green scale). For the rolling window analysis, we estimate equation (2) for the models described in Table 8 and test null $H_0 : \gamma = 0$ on every window. For each model, we then employ the resulting p-values to derive the combined p-value using the method of Benjamini and Hochberg (1995) that controls for the family-wise error rate.

Insert Figure 7 and Figure 8

4.1.2 Discussion

Comparing Figure 7 and Figure 8, two points stand out. First, macro (M1), energy (M5), drought (M8) and Arctic (M11) factors have strong in-sample predicting power for future growth rates of CO_2 emissions. For these models the gains in adjusted R-squared relative to the benchmark setting are mostly above 30% and the null hypothesis on the coefficient γ is rejected with a p-value lower than 1%. These result holds both in the static and rolling setting, indicating that this in-sample predicting power is potentially robust to time variation and structural breaks. To a lesser extent, i.e. with lower gains in adjusted R-squared relative to the benchmark model, these findings hold also for the Michigan Surveys (M3) and Arctic Quantiles (M12) factors. Second, the relationship between growth rates of CO_2 emissions and Surveys of Professional Forecasters (M2), Macro quantiles (M4), Energy quantiles (M6), US extreme events (M7), and World Anomalies Indexes (M10) factors appears to be time dependent. Specifically, while the predicting power of M2 and M7 decreases in the sub sample exercises, the reverse is true for M4 and M10.

To the best of our knowledge, this set of results is new in the literature. Fosten (2019) and Bennedsen et al. (2021) look at macroeconomic determinant of US CO_2 emissions via wavelet techniques combined with dynamic factor models and structural dynamic factor models, respectively. In contrast to their approaches, next to employing a broader dataset, we use a direct forecasting setting and we stress the importance of macroeconomic (energy) factors for all forecasting horizons (mainly for forecasting horizons above one quarter). Furthermore, we find that consumer surveys and quantile factors might contain relevant information for predicting CO_2 emissions. Luo and Keenan (2022) link the global atmospheric CO_2 growth rate variability to extreme droughts conditions in tropical areas while Betts et al. (2016) show that El Nĩno events have contributed to the rise in CO_2 emissions, likely due to the warming and drying effects on tropical lands and the induced mortality of trees for droughts and natural fires. We find that local (droughts factors) and global (Arctic anomalies) interannual variability determinants play a role in forecasting for energy' CO_2 emissions. Furthermore, we show that the forecasting power of oscillation and northern/southern hemisphere anomalies is mostly concentrated for longer-term horizons.

4.2 Out-of-Sample Analysis

4.2.1 Setting

The out-of-sample analysis builds on the recursive in-sample setting in terms of rolling window size, i.e. 25 years, and forecasting horizons, i.e. h = 1, 2, 4, 6, and 8 quarters. To this setting we introduce: (i) the conditional quantiles forecasting based on equation (3); for the baseline, quantile predictions model reads

$$Q_\tau \left(g^{CO_2}_{t\to t+h} \middle| \mathcal{F}_t \right) = \beta^0_\tau + \sum_{j=1}^{4} \beta_{j,\tau} g^{CO_2}_{t-j\to t+1-j}; \tag{7}$$

(ii) two naïve benchmark models: one for the point forecast, i.e. the random walk which predicts that $g^{CO_2}_{T\to T+h} = g^{CO_2}_{T-h\to T}$, and one for the conditional quantiles forecast, i.e. the empirical distribution which predicts that $Q_\tau \left(g^{CO_2}_{T\to T+h} \middle| \mathcal{F}_T \right) = \text{Percentile}\left(\{g^{CO_2}_{t\to t+h}\}_{t=1}^{T-h}; 100\times\tau \right)$; (iii) A new family of alternative models, which combine all (or a part of) the original thirteen models using weights obtained via the AIC, the BIC, and the out-of-sample RMSE procedures outlined in section 2. The new models are labelled MAICX, MBICX, and MOOSX, respectively, where X $= 1, ..., 6$ refer to six combinations of the original model, see Table 8.

Model comparison is carried out using the following average loss function: the RMSE for mean predictions for the point forecast and the average check function for quantile predictions. Each loss functions is divided by the loss function of the benchmark model to obtain the Score Ratio (SR)

$$SR^h_j = \begin{cases} \dfrac{\sqrt{\sum_{T=1}^{T_h} (\hat{y}_{T+h,j} - y_{T+h})^2}}{\sqrt{\sum_{T=1}^{T_h} (\hat{y}_{T+h,\text{benchmark}} - y_{T+h})^2}} & \text{for mean predictions} \\ \dfrac{\sum_{T=1}^{T_h} \rho_\tau (Q_\tau(T+h,j) - y_{T+h})}{\sum_{T=1}^{T_h} \rho_\tau (Q_\tau(T+h,\text{benchmark}) - y_{T+h})} & \text{for quantile predictions} \end{cases} \tag{8}$$

Here $\hat{y}_{T+h,j}$ is the growth rate from T to $T+h$ predicted by model j, $Q_\tau(T+h,j)$ is its predicted τ-quantile, y_{T+h} the realized value, and T_h the number of out-of-sample predictions. The measure (8) can be used to test if a model outperforms (underperforms) its benchmark, i.e. SR<1 (SR$>$1), via the statistics proposed by Clark and West (2007) (point forecast) and by Ge and Lee (2014) (quantile predictions). We report p-values for the null hypothesis of equal predictability, denoted 'CW pval' for the Clark and West (2007) statistics and 'GeLee pval' for the Ge and Lee (2014) one.

Insert Figure 9 and Figure 12

4.2.2 Discussion

Figures 9–11 report the heatmaps based on the SR. In each figure/heatmap cell, ***, **, and *, denote SR's significance at the 1%, 5% and 10% levels. Focusing on point forecasts, Figures 9 highlights the poor performance of the naïve benchmark models. This finding is in line with intuition. Since the CO_2 growth series are not persistent, see Figure 1, their current values have little information about their future evolution, see for example Chapter 8 of Elliott and Timmermann (2016). Turing with the comparison with the baseline model, see Figure 10, we observe that, with a few exceptions, the in-sample predicting power of macro (M1), energy (M5), drought (M8) and Arctic (M11) factors extend out of sample. The result is robust on how the point forecast is obtained, see Section 2. While the forecasting power of macroeconomic factors is line with the results of Bennedsen et al. (2021), a few points are worth noticing. First, in contrast with their results, we show that the forecasting power of macroeconomic factors extends for longer forecasting horizon. Second, Bennedsen et al. (2021) compare their results to a the constant growth model, whereby the point forecast is the historical mean of the CO_2 growth rate up until the time of the forecast. However, our approach is a more conservative one as we use a more performing baseline model, which outperform the historical mean model with a SR of 1.03, 1.00, 0.98, 0.97, and 0.95 for h = 1, 2, 4, 6, and 8. The out-of-sample performance of energy factors and local and global IAV (PDI index and Arctic) is, to the best of our knowledge a novel result. It indicates that augmenting the forecasting model by these type of indicators might result in substantial gain in forecasting power. For short-term forecasting horizons (below one year), our results suggest to employ local IAV factors, while for longer horizons (over one year) it is important to account for teleconnection patters among vast global geographical areas. Finally, Figure 10 highlights that there might be forecasting power gains by combining models/factors, especially the IAV factors, see models MAIC5 to MOOS6. Forecast combination appears to be crucial for quantile forecasting. By inspecting Figure 12 and Figure 11 three points stand out. First, with a few exceptions, for short-term horizons, the empirical quantiles are extremely performing with respect to macro factors. For horizons over one year, energy (M5), surveys (M2-3) and to a lesser extend macro factors (M1) seem to have relevant information for the future distribution of CO_2 growth rate. Second, IAV factors have, especially drought indicators, are more informative about CO_2 growth rate's quantiles. Finally, model combinations is crucial in forecasting quantiles, especially by using those based out-of-sample training samples. This indicates that more refined combination methods for our dataset might results in good quantile-forecasting models.

5 Conclusions

We perform point and conditional quantiles predictions of short-term, i.e. up to 2-year, U.S. energy' CO_2 emissions using direct forecasting methods. Our predictors include the principal components and quantile factors large-scale series of anthropogenic and local/global interannual variability (IAV) indicators. Using quarterly data spanning from 1970Q1 to 2021Q3, we assess the in- and out-of-sample forecasting power of naïve (Random walk / empirical distribution) and baseline (with only past quarterly CO_2 growth rates) models against alternative ones which augment the baseline setting with our predictors. The results show that augmented models outperform the naïve and baseline settings, thus revealing the importance of anthropogenic and IAV factors in predicting carbon dioxide emissions. In particular, factors extracted from macro economics data, energy series, drought indexes and Arctic temperature anomalies have in-sample and out-of-sample predicting power in terms of point forecasting. Conditional quantiles predictions require model combinations in order to outperform forecasts based on empirical distributions.

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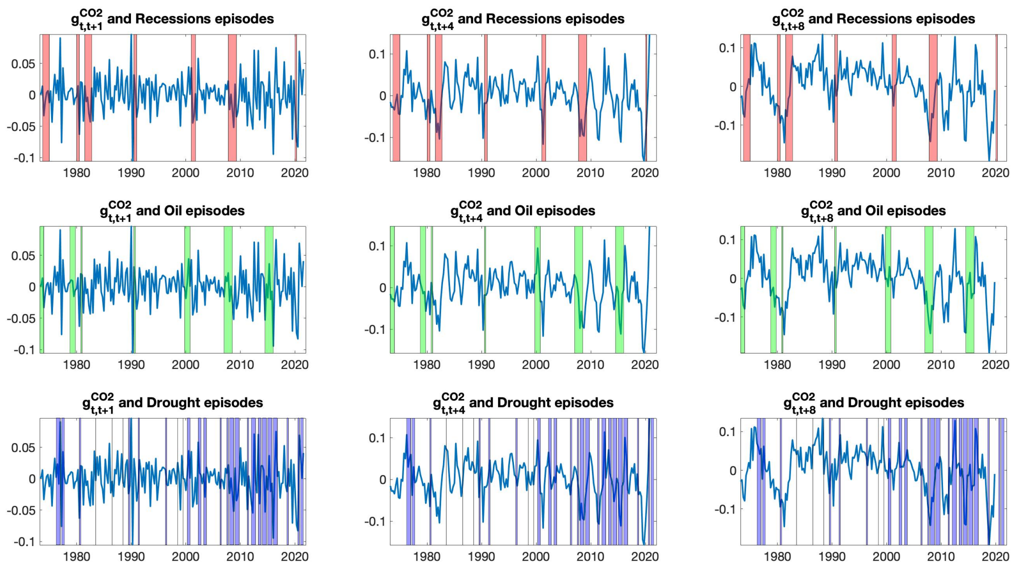
6 Tables and Figures

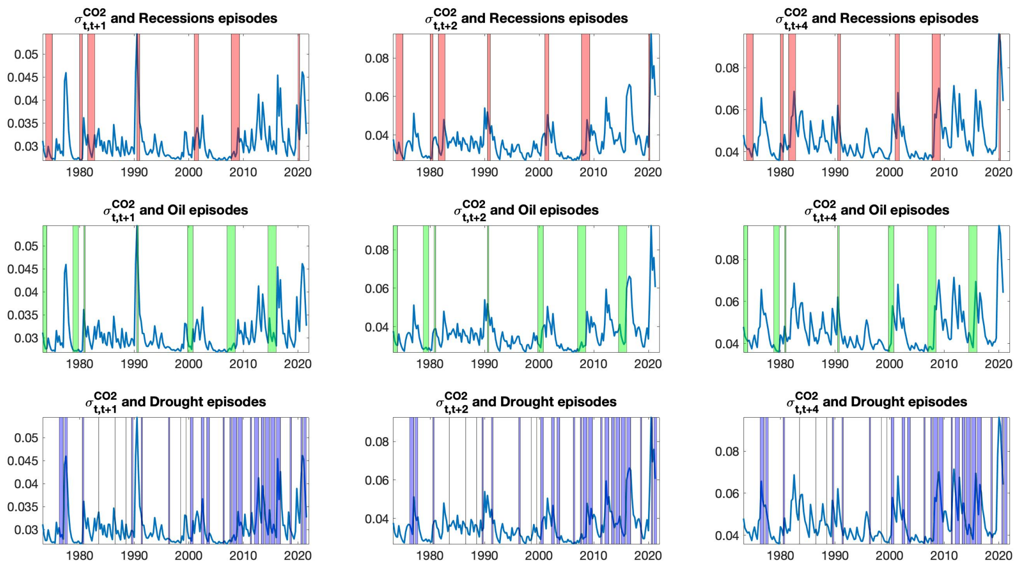
6.1 Figures

Figure 1: Growth rates of total Energy' CO_2 emissions



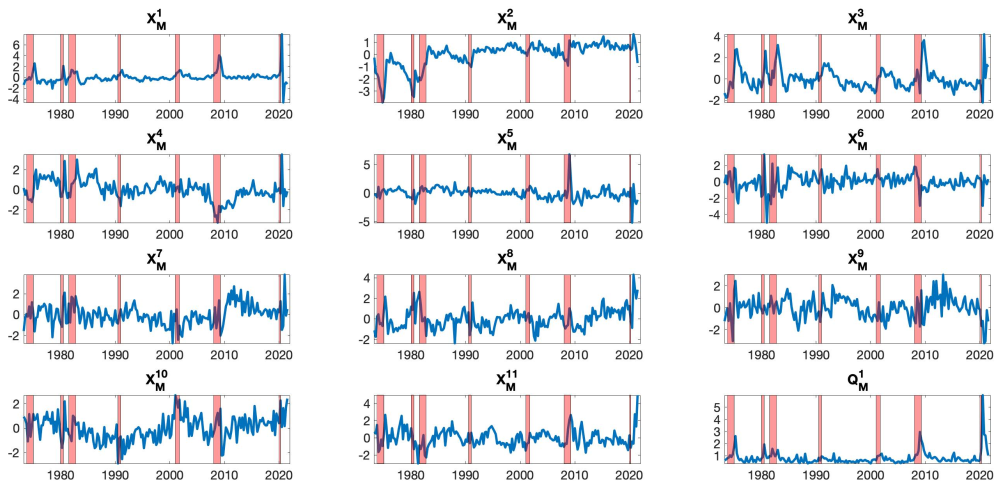
Note: CO_2 emissions are seasonally adjusted using the X-13ARIMA-SEATS filter. The Figure plots the growth of CO_2 emissions over one quarter (left column), one year (middle column) and two years (right column). The shaded areas refer to US recessions (top row), oil crisis (middle row) and sever drought periods (bottom row). The US recessions dates are from the National Bureau of Economics and Research, the oil episodes periods are from Hamilton (2011), with the addition of the 2010s oil glut, and the sever drought periods are those that according to the National Centers for Environmental Information have caused more than 3 billions dollars damages.

Figure 2: Volatility of growth rates of total Energy' CO_2 emissions



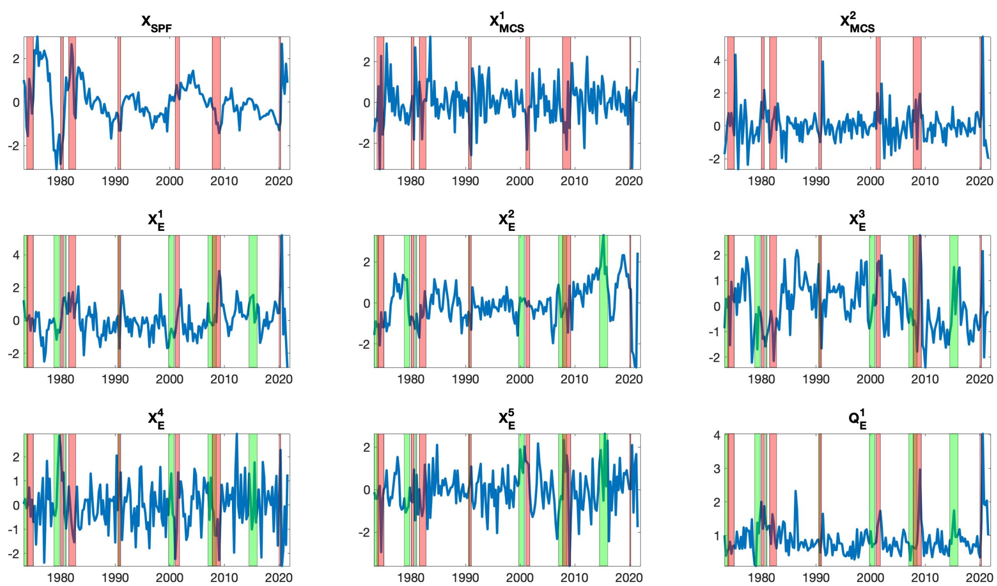
Note: CO_2 emissions are seasonally adjusted using the X-13ARIMA-SEATS filter. The Figure plots the volatility of the growth of CO_2 emissions over one, (left column), (middle column) quarter, and one year (right column). Each volatility series has been extracted by a simple GARCH(1,1) model, see Bollerslev (1986). The shaded areas refer to US recessions (top row), oil crisis (middle row) and sever drought periods (bottom row). The US recessions dates are from the National Bureau of Economics and Research, the oil episodes periods are from Hamilton (2011), with the addition of the 2010s oil glut, and the sever drought periods are those that according to the National Centers for Environmental Information have caused more than 3 billions dollars damages.

Figure 3: Macro factors and quantiles.



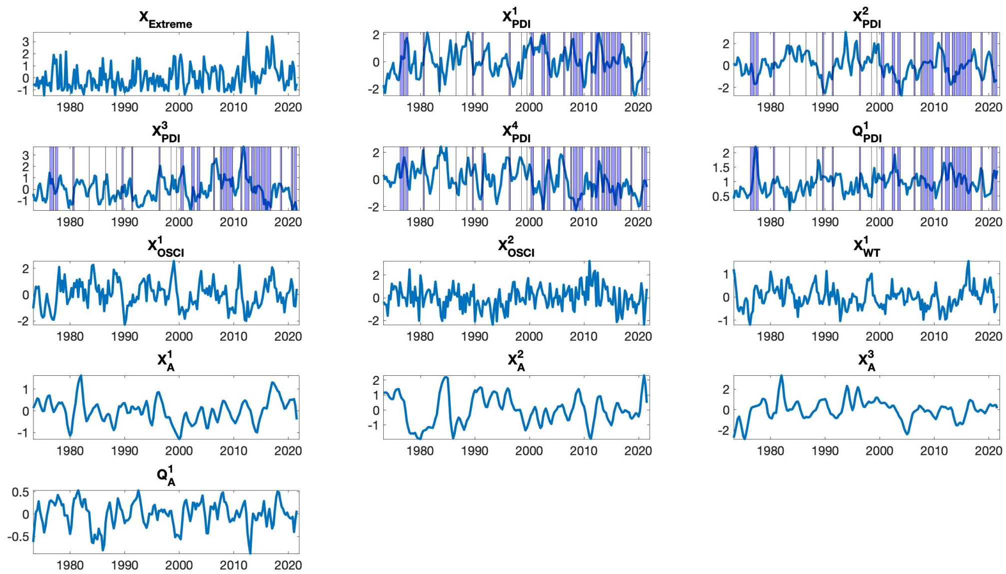
Note: Shaded areas refer to the US recession periods, as indicated by the National Bureau of Economics and Research. The Figure plots the first eleven principal components of the McCracken and Ng (2020) quarterly series, which explain 70% of the variation of the whole series. The bottom right plot report the first principal component of the 1%, 10% , 90% and 99% quantile factors of the same dataset. The PCs and quantile factors are computed over the whole period, Q1 1972 to Q3 2021.

Figure 4: Surveys and energy factors



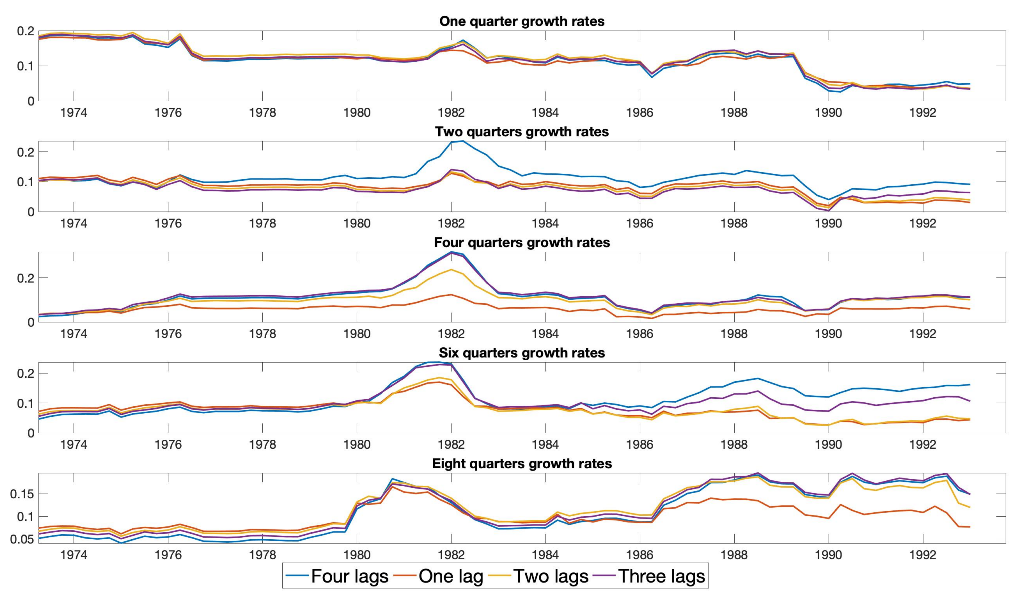
Note: Light-red shaded areas refer to the US recession periods, as indicated by the National Bureau of Economics and Research, while light-green shaded areas indicate oil episodes, which are from Hamilton (2011), with the addition of the 2010s oil glut. The Figure plots the SPF surveys, top-left panel, the first two principal components of the Michigan surveys, top-middle and top-right panels, the first five principal components of the energy dataset, all other panels except the bottom-right, and the first first principal component of the 1%, 10% , 90% and 99% quantile factors of the energy dataset, bottom-right panel. All PCs are selected to explain 70% of the variation of the original series. The PCs and quantile factors are computed over the whole period, Q1 1972 to Q3 2021.

Figure 5: IAV factors



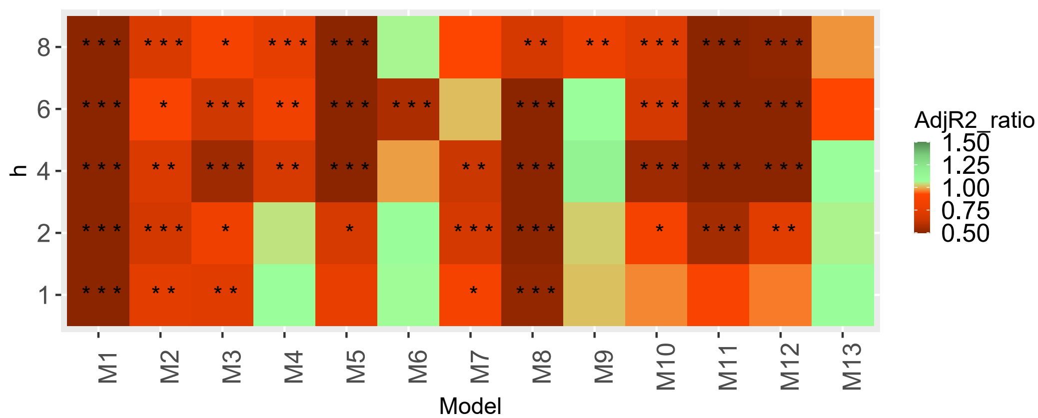
Note: Shaded areas refer to US drought periods

Figure 6: Rolling estimates of Adjusted R-squared



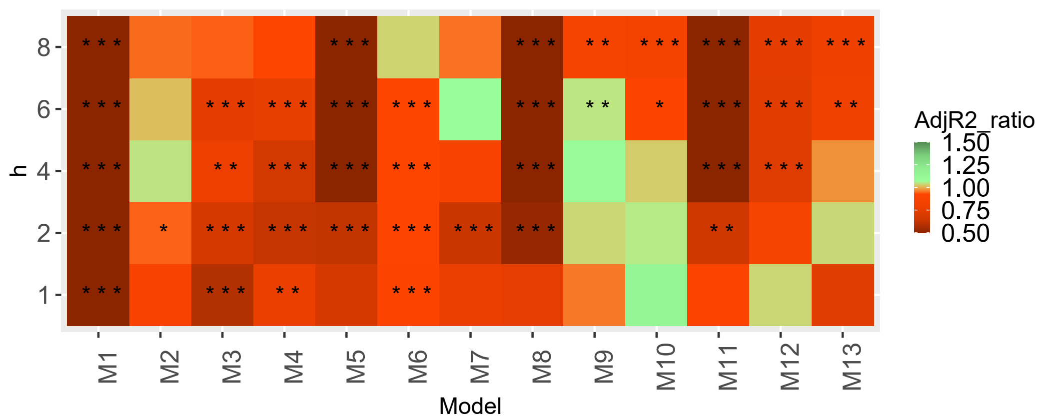
Note: Comparison of adjusted R-squared. The dates on the horizontal axis represent the beginning of the sample period of the 25 years window used to obtain the adjusted R-squared.

Figure 7: Heatmap for the ratio Adjusted$R^2(Baseline)$/Adjusted$R^2(i)$, whole sample.



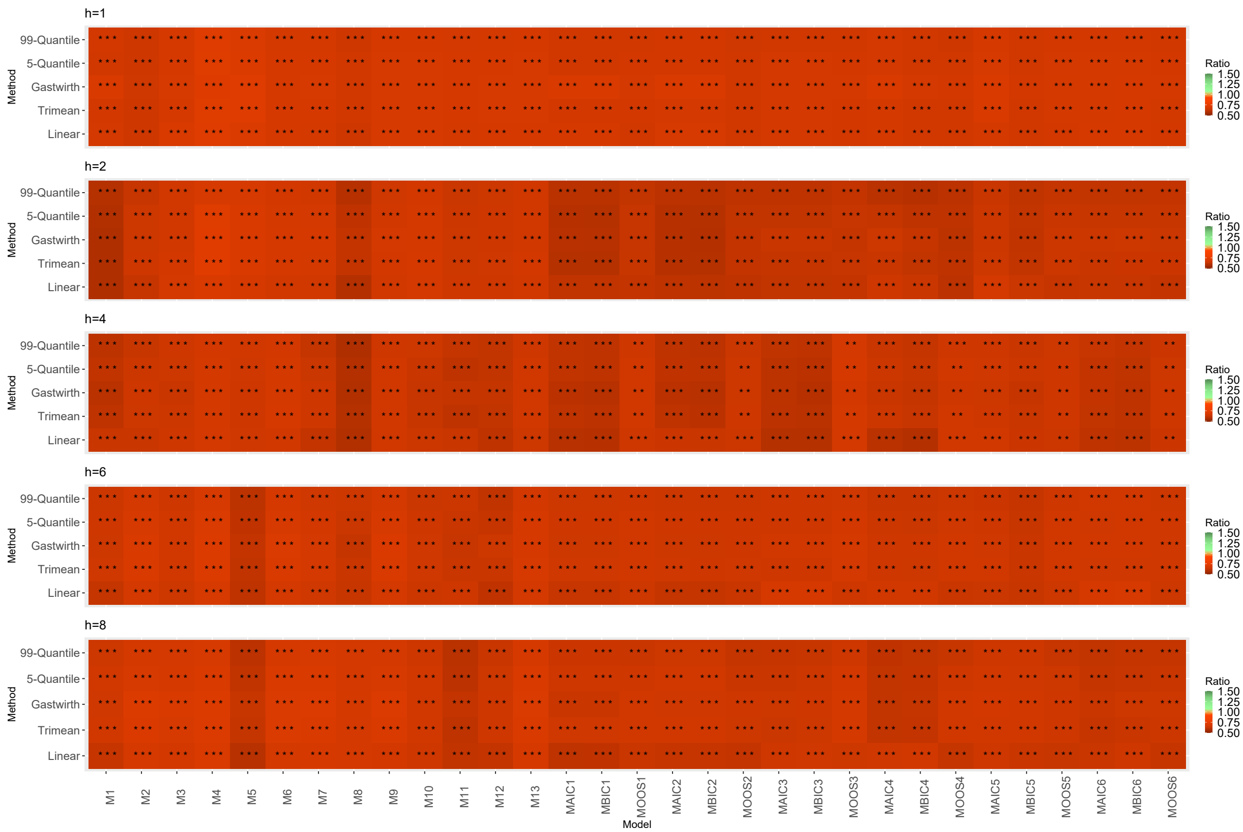
Note: Adjusted$R^2(Baseline)$ is the Adjusted R^2 of model (6). Adjusted$R^2(i)$ is the Adjusted R^2 of model i. The stars in each cell are related to the p-values for the test with null $H_0 : \gamma = 0$ in eq. (2). ***, **, and *, denote significance at the 1%, 5% and 10% levels, respectively.

Figure 8: Heatmap for the average Adjusted$R^2(Baseline)$/Adjusted$R^2(i)$, rolling windows.



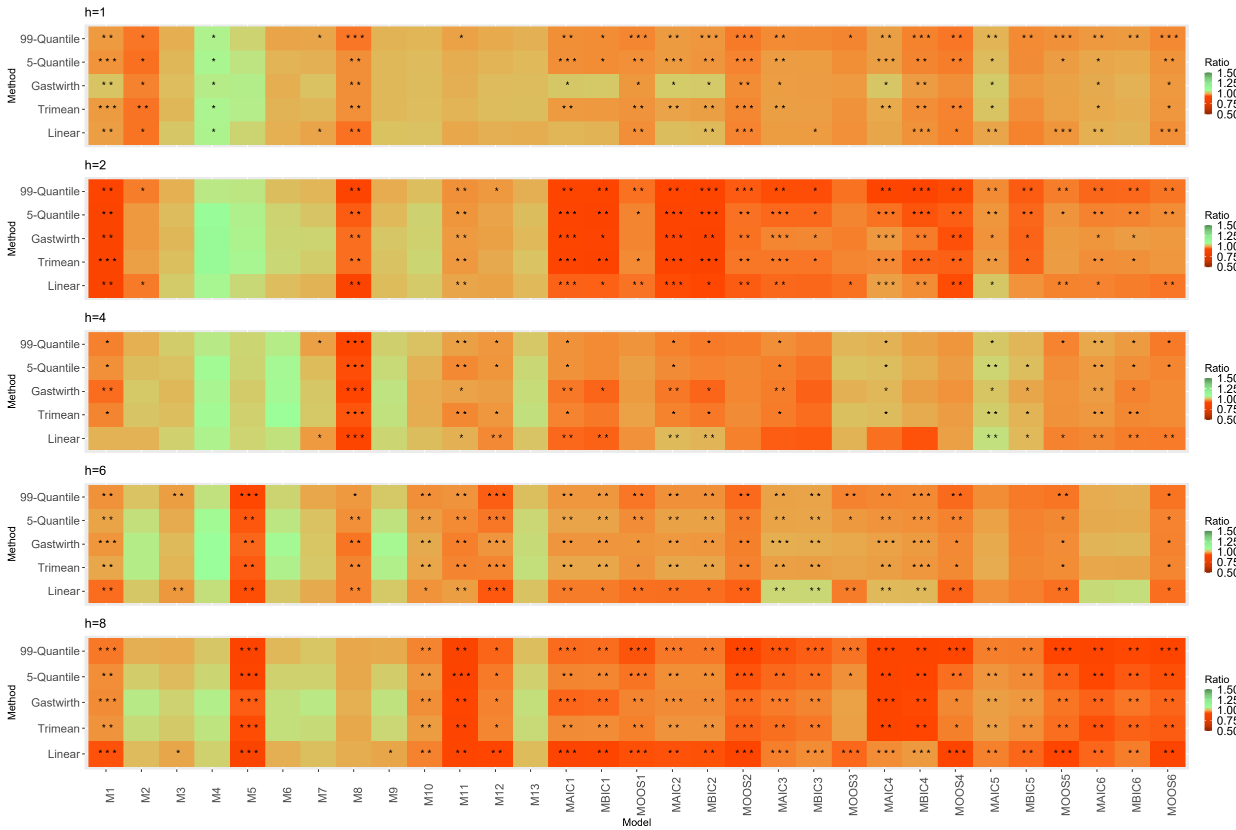
Note: Adjusted$R^2(Baseline)$ is the Adjusted R^2 of model (6). Adjusted$R^2(i)$ is the Adjusted R^2 of model i. The stars in each cell are related to the p-value for the combined test (Benjamini and Hochberg, 1995) of the null hypothesis that no p-value is significant. The combined p-values are for the test with null $H_0 : \gamma = 0$ in eq. (2) in all the possible windows. ***, **, and *, denote significance of γ at the 1%, 5% and 10% levels, respectively.

Figure 9: Mean Predictions: Heatmap for SR, eq. (8). Naïve benchmark.



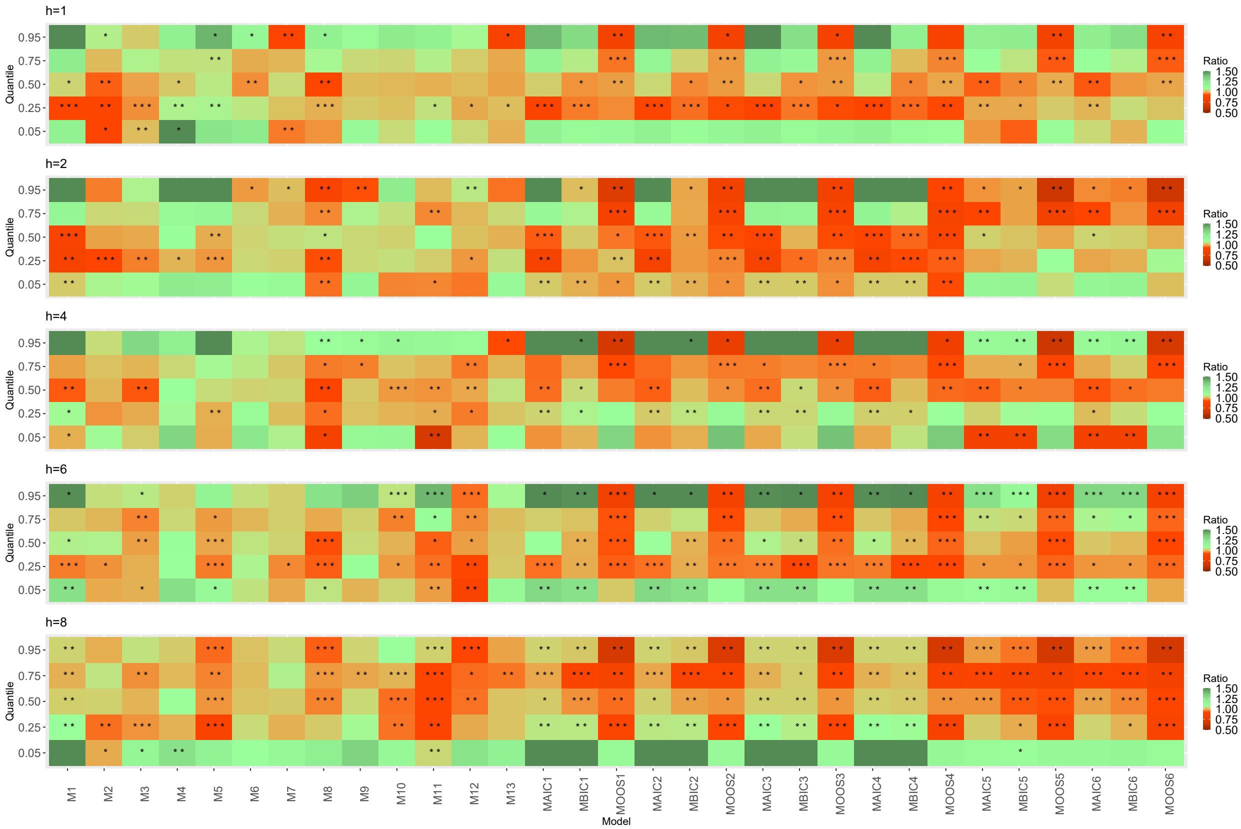
Note: SR is the ratio between the RMSE of a given model and the one of the benchmark model (Random Walk). The stars in each cell are related to the p-values for the null hypothesis of equal predictability (test of Clark and West, 2007). ***, **, and *, denote significance at the 1%, 5% and 10% levels, respectively.

Figure 10: Mean Predictions: Heatmap for SR, eq. (8). Benchmark: baseline model.



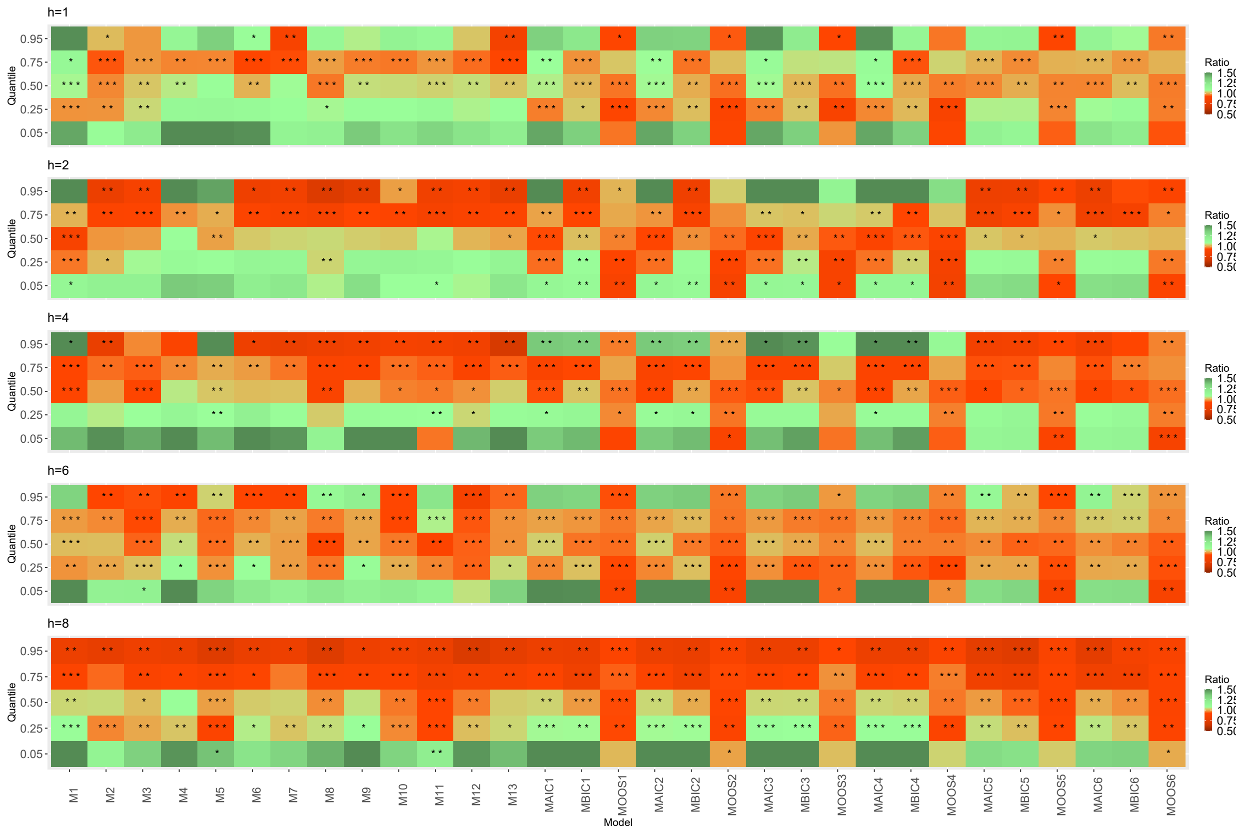
Note: SR is the ratio between the RMSE of a given model and the one of the benchmark model (baseline model). The baseline model is given in eq. (6). The stars in each cell are related to the p-values for the null hypothesis of equal predictability (test of Clark and West, 2007). ***, **, and *, denote significance at the 1%, 5% and 10% levels, respectively.

Figure 11: Quantile Predictions: Heatmap for SR, eq. (8), Naïve benchmark.



Note: SR is the ratio between the average check function of a given model and the one of the benchmark model (Empirical quantile). The stars in each cell are related to the p-values for the null hypothesis of equal predictability (test of Ge and Lee, 2014). ***, **, and *, denote significance at the 1%, 5% and 10% levels, respectively.

Figure 12: Quantile Predictions: Heatmap for SR, eq. (8). Benchmark: baseline model.



Note: SR is the ratio between the average check function of a given model and the one of the benchmark model (baseline model). The baseline model is given in eq. (7). The stars in each cell are related to the p-values for the null hypothesis of equal predictability (test of Ge and Lee, 2014). ***, **, and *, denote significance at the 1%, 5% and 10% levels, respectively.

6.2 Tables

Table 1: Correlation tables: macro factors.

Panel A: Correlation with the growth of CO_2 emissions												
$H(Q)$	X_M^1	X_M^2	X_M^3	X_M^4	X_M^5	X_M^6	X_M^7	X_M^8	X_M^9	X_M^{10}	X_M^{12}	Q_M^1
1	-0.33^{***}	0.09	0.03	0.00	0.05	-0.05	-0.02	0.01	-0.05	-0.04	0.12^{*}	-0.20^{***}
2	-0.32^{**}	0.17^{**}	0.11	0.15^{**}	-0.05	-0.05	-0.08	-0.01	-0.07	-0.17^{**}	0.05	-0.11
4	-0.25^{***}	0.23^{***}	0.22^{***}	0.24^{***}	0.01	-0.09	-0.17^{**}	-0.10	-0.08	-0.20^{***}	0.12^{*}	-0.07
6	-0.15^{**}	0.22^{***}	0.23^{***}	0.32^{***}	0.13^{*}	-0.05	-0.11	-0.27^{***}	-0.03	-0.18^{**}	0.16^{**}	-0.12^{*}
8	-0.05	0.18^{***}	0.24^{***}	0.34^{***}	0.24^{***}	0.01	-0.12^{*}	-0.23^{***}	0.01	-0.16^{**}	0.20^{***}	-0.07

Panel B: Correlation with the volatility of growth of CO_2 emissions												
$H(Q)$	X_M^1	X_M^2	X_M^3	X_M^4	X_M^5	X_M^6	X_M^7	X_M^8	X_M^9	X_M^{10}	X_M^{12}	Q_M^1
1	-0.00	0.15^{**}	0.15^{**}	-0.01	0.05	-0.12^{*}	0.12^{*}	0.12^{*}	-0.12	0.13^{*}	0.03	0.24^{***}
2	0.19^{***}	0.08	0.03	0.02	0.04	0.00	0.17^{**}	0.10	0.03	0.16^{**}	-0.15^{**}	0.13^{*}
4	-0.07	0.06	0.01	-0.08	-0.04	-0.20^{***}	0.13^{*}	0.14^{**}	0.08	0.01	-0.14^{*}	-0.04

Note: The table reports the correlation between the macro factors/quantile and (i) Panel A: the growth rated of CO_2 emissions over 1, 2, 4, 6 and 8 quarters and (ii) Panel B: the volatility of the growth rated of CO_2 emissions over 1, 2, and 4 quarters. Each volatility series has been extracted by a simple GARCH(1,1) model, see Bollerslev (1986). **Notation**: H(Q) stands for the quarters while ***, **, and * indicate 1, 5 and 10% significance levels, respectively.

Table 2: Surveys of consumers and professional forecasters

Label	**University of Michigan's Survey of Consumers**
Table 6	Current Financial Situation Compared with a Year Ago
Table 8	Expected Change in Financial Situation in a Year
Table 9	Annual Trend in Past and Expected Household Financial Situation
Table 23	News Heard of Recent Changes in Business Conditions
Table 25	Current Business Conditions Compared with a Year Ago
Table 26	Expected Change in Business Conditions in a Year
Table 28	Business Conditions Expected During the Next Year
Table 29	Business Conditions Expected During the Next 5 Years
Table 30	Expected Change in Unemployment During the Next Year
Table 31	Expected Change in Interest Rates During the Next Year
Table 35	Buying Conditions for Large Household Durables Vehicles Buying conditions
Table 37	Buying Conditions for Vehicles

	Surveys of Professional Forecasters
RGDP	Real Gross National Product/Gross Domestic Product

Note: The surveys of consumers are retrieved from the University of Michigan website, where a full description of each series is available: https://data.sca.isr.umich.edu/tables.php. The surveys of professional forecasters are from the Philadelphia Federal Reserve website, where a full description of each series is available: https://www.philadelphiafed.org/surveys-and-data/data-files.

Table 3: Energy related variables

Number	**Variable name**	Tranformation
1	Total Petroleum Consumed by the Residential Sector	1
2	Total Petroleum Consumed by the Commercial Sector	1
3	Total Petroleum Consumed by the Industrial Sector	1
4	Total Petroleum Consumed by the Transportation Sector	1
5	Fraction of gasoline on total for Transportation Sector	1
6	Total Petroleum Field Production	1
7	Total Renewable Energy Consumption	1
8	Petroleum Imports	1
9	Petroleum Exports	1
10	Petroleum Stock Change	0
11	IP: Consumer energy products (Index 2012=100)	2
12	PPI by CFRPP: Natural Gas (1982=100)	2
13	PPI by CFRPP (Domestic Production) (1982=100)	2
14	Real Crude Oil Prices: WTI-CO (2012 $/b), Core PCE deflated	2
15	REDTI: Residential Energy Demand Temperature Index	0

Note: **PPI by CFRPP** = Producer Price Index by Commodity for Fuels and Related Products and Power. **WTI-CO** = West Texas Intermediate (WTI) - Cushing, Oklahoma. **Transformation**: 0 = no transformation, 1 = year on year growth rate, 2 = quarter on quarter growth rate. **Sources**: series 1 to 10 are from https://www.eia.gov/totalenergy/data/monthly/, series 11 to 14 are form https://research.stlouisfed.org/econ/mccracken/sel/, and series 15 is available at https://www.ncdc.noaa.gov/societal-impacts/redti/overview.

Table 4: Correlation tables: surveys and energy factors.

Panel A: Correlation with the growth of CO_2 emissions

$H(Q)$	X_{SPF}	X^1_{MSC}	X^2_{MSC}	X^1_E	X^2_E	X^3_E	X^4_E	X^5_E	Q^1_E
1	0.03	0.07	-0.29^{***}	-0.33^{***}	0.06	-0.08	-0.24^{***}	-0.17^{**}	-0.20^{***}
2	0.16^{**}	0.19^{***}	-0.18^{***}	-0.22^{***}	-0.05	0.05	-0.11	-0.18^{***}	-0.07
4	0.17^{**}	0.25^{***}	-0.12^{*}	-0.17^{**}	-0.09	0.09	-0.08	-0.13^{*}	-0.09
6	0.19^{***}	0.25^{***}	-0.12	-0.14^{**}	-0.11	0.28^{***}	-0.03	-0.13^{*}	-0.07
8	0.21^{***}	0.21^{***}	-0.03	-0.16^{**}	-0.13^{*}	0.39^{***}	-0.13^{*}	-0.09	-0.02

Panel B: Correlation with the volatility of growth of CO_2 emissions

$H(Q)$	X_{SPF}	X^1_{MSC}	X^2_{MSC}	X^1_E	X^2_E	X^3_E	X^4_E	X^5_E	Q^1_E
1	0.10	0.01	-0.09	0.10	-0.09	0.04	-0.05	0.00	0.27^{***}
2	-0.04	-0.07	0.16^{**}	0.13^{*}	0.13^{*}	0.03^{*}	0.01	0.14^{**}	0.13^{*}
4	-0.04	0.09	-0.06	0.12^{*}	0.27^{***}	-0.13^{*}	-0.04	0.13^{*}	-0.06

Note: The table reports the correlation between the surveys/energy factors/quantile and (i) Panel A: the growth rated of CO_2 emissions over 1, 2, 4, 6 and 8 quarters and (ii) Panel B: the volatility of the growth rated of CO_2 emissions over 1, 2, and 4 quarters. Each volatility series has been extracted by a simple GARCH(1,1) model, see Bollerslev (1986). **Notation**: H(Q) stands for the quarters while ***, **, and * indicate 1, 5 and 10% significance levels, respectively.

Table 5: Nature-related Determinants

Label	**Temperature**
NHLTA	Northern hemisphere land temperature anomalies
NHOTA	Northern hemisphere ocean temperature anomalies
SHLTA	Southern hemisphere land temperature anomalies
SHOTA	Southern hemisphere ocean temperature anomalies
M-ARTIC	Average Arctic temperatures anomalies
RA-ARTIC	Cross sectional robust asymmetry measure of Arctic temperatures anomalies
M-US	Average US temperatures anomalies
RA-US	Cross sectional robust asymmetry measure of US temperatures anomalies
M-US-Extreme	Average US maximum and minimum temperature extremes
M-US-Anomalies	Average US maximum and minimum temperature anomalies
D-US-Anomalies	Difference of maximum and minimum US temperature anomalies
	Drought and precipitations
PDI	First principal component of the PDIs for US Lower 48 Divisions
EP	U.S. extremes in 1-day precipitation
	Oscillation indexes
AO	Arctic Oscillation index
PNA	Pacific-North America pattern
PDO	Pacific Decadal Oscillation
NAO	North Atlantic Oscillation index
SOI	Southern Oscillation Index
ONI	Oceanic Niño Index

Note: All the data on natural determinants are from the National Centers for Environmental Information: https://www.ncei.noaa.gov/access/monitoring/products/. The average and the robust asymmetry measures for the US and the Arctic regions were obtained by collecting data each 5 latitudes/longitudes.

Table 6: Correlation tables: IAV.

Panel A: Correlation with the growth of CO_2 emissions

$H(Q)$	X^1_{Extr}	X^1_{PDI}	X^2_{PDI}	X^3_{PDI}	X^4_{PDI}	Q^1_{PDI}	X^1_{OSCI}	X^2_{OSCI}	X^1_{WAI}	X^1_A	X^2_A	X^3_A	Q^1_A
1	0.09	0.07	−0.07	−0.07	0.12^{**}	0.03	0.02	0.00	−0.03	−0.06	0.05	0.01	−0.03
2	0.19^{***}	0.08	−0.10	-0.18^{***}	0.20^{***}	0.02	0.01	−0.06	−0.04	−0.10	0.11	0.00	−0.06
4	0.25^{***}	0.14^{**}	−0.03	-0.18^{***}	0.26^{***}	0.05	−0.01	0.05	0.04	-0.17^{**}	0.16^{**}	−0.02	−0.11
6	0.19^{***}	0.14^{*}	0.01	-0.16^{**}	0.26^{***}	0.04	−0.01	0.03	−0.03	-0.18^{***}	0.19^{***}	−0.02	-0.15^{**}
8	0.18^{**}	0.08	0.10	−0.10	0.12^{*}	−0.03	0.01	−0.02	−0.04	−0.09	0.22^{***}	0.03	-0.17^{**}

Panel B: Correlation with the volatility of growth of CO_2 emissions

$H(Q)$	X^1_{Extr}	X^1_{PDI}	X^2_{PDI}	X^3_{PDI}	X^4_{PDI}	Q^1_{PDI}	X^1_{OSCI}	X^2_{OSCI}	X^1_{WAI}	X^1_A	X^2_A	X^3_A	Q^1_A
1	0.09	0.14^{**}	-0.15^{**}	-0.16^{**}	-0.13^{*}	0.21^{***}	-0.13^{*}	−0.09	0.15^{**}	0.12^{*}	0.18^{***}	0.12^{*}	−0.09
2	0.17^{**}	0.09	-0.17^{**}	-0.21^{***}	−0.04	0.20^{***}	-0.19^{***}	−0.11	0.22^{***}	0.10	0.18^{***}	0.14^{*}	−0.11
4	0.01	−0.08	-0.17^{**}	−0.04	−0.06	0.09	-0.27^{***}	0.01	0.07	0.11	0.13^{*}	0.12^{*}	−0.06

Note: The table reports the correlation between the IAV factors/quantile and (i) Panel A: the growth rated of CO_2 emissions over 1, 2, 4, 6 and 8 quarters and (ii) Panel B: the volatility of the growth rated of CO_2 emissions over 1, 2, and 4 quarters. Each volatility series has been extracted by a simple GARCH(1,1) model, see Bollerslev (1986). **Notation**: H(Q) stands for the quarters while ***, **, and * indicate 1, 5 and 10% significance levels, respectively.

Table 7: In-sample analysis: list of models

Benchmark name	Direct forecasting equation	
Baseline	$\beta^0 + \sum_{j=1}^{p} \beta_j g_{t-j \to t+1-j}^{CO_2}$	
Model name	**Direct forecasting equation**	**Type of control variables**
M1	Baseline + $\gamma X_{M,t}^{70\%}$	All Macro, except Oil
M2	Baseline + $\gamma X_{SPF,t}$	Survey of professional forecasters GDP growth
M3	Baseline + $\gamma X_{MSC,t}^{70\%}$	Michigan surveys
M4	Baseline + $\gamma Q_{M,t}^{70\%}$	Quantiles factors of all Macro, except Oil
M5	Baseline + $\gamma X_{E,t}^{70\%}$	Energy series
M6	Baseline + $\gamma Q_{E,t}^{70\%}$	Quantiles factors of Energy series
M7	Baseline + $\gamma X_{Extr,t}^{70\%}$	US extreme events
M8	Baseline + $\gamma X_{PDI,t}^{70\%}$	Palmer Drought Index
M9	Baseline + $\gamma X_{OSCI,t}^{70\%}$	OSCI variables
M10	Baseline + $\gamma X_{WAI,t}^{70\%}$	World Anomalies Indexes
M11	Baseline + $\gamma X_{A,t}^{70\%}$	Arctic temperatures
M12	Baseline + $\gamma Q_{A,t}^{70\%}$	Quantiles factors of Arctic temperatures
M13	Baseline + $\gamma Q_{PDI,t}^{70\%}$	Quantiles factors of Palmer Drought Index

Note: $X_V^{70\%}$ denotes the set of principal components that explain up to 70% of the variation of the series V. $Q_V^{70\%}$ is the set of principal components that explain up to 70% of the variation in the 1%, 10% , 90% and 99% quantile factors of the series V.

Table 8: Out-of-sample analysis: list of models

Benchmark name	Direct forecasting equation
Baseline	$\beta^0 + \sum_{j=1}^{p} \beta_j g_{t-j\to t+1-j}^{CO_2}$
Naïve (point forecast)	$g_{T-h\to T}^{CO_2}$
Naïve (quantile forecast)	Percentile $\left(\{g_{t\to t+h}^{CO_2}\}_{t=1}^{T-h}; 100\times\tau\right)$

Model name	Direct forecasting equation	Description
M1-M13	See Table 7	See Table 7
MXYZ1	$\sum_{m=1}^{\mathcal{M}} w_m \hat{y}_m$	Combination of all factors
MXYZ2	$\sum_{m=1}^{\mathcal{M}} w_m \hat{y}_m$	Combination of all factors less quantiles
MXYZ3	$\sum_{m=1}^{\mathcal{M}} w_m \hat{y}_m$	Combination of macro factors (M1 to M6)
MXYZ4	$\sum_{m=1}^{\mathcal{M}} w_m \hat{y}_m$	Combination of macro factors less quantiles
MXYZ5	$\sum_{m=1}^{\mathcal{M}} w_m \hat{y}_m$	Combination of IAV factors (M7 to M13)
MXYZ6	$\sum_{m=1}^{\mathcal{M}} w_m \hat{y}_m$	Combination of IAV factors less quantiles

Note: The string XYZ can be: i) 'AIC', for the case when the combination is via AIC; ii) 'BIC', for the case when the combination is via BIC; or iii) 'OOS', for the case when the combination is via out of sample training. $\{\hat{y}\}_{m=1,\ldots,\mathcal{M}}$ are the predictions for the mean or quantiles of CO_2 emissions growth rates from $\mathcal{M}$ models and w_m are the weights derived based on information criteria or RMSE (or average check function) calculated on the training sample.

Appendix A Full Set of Results

Table 9: RMSE Ratios, Naïve benchmark

	$h = 1$		$h = 2$		$h = 4$		$h = 6$		$h = 8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
M1,Linear	0.668	**0.000**	0.581	**0.000**	0.634	**0.000**	0.624	**0.000**	0.628	**0.000**
M1,Trimean	0.667	**0.000**	0.582	**0.000**	0.612	**0.000**	0.652	**0.000**	0.657	**0.001**
M1,Gastwirth	0.690	**0.000**	0.581	**0.000**	0.601	**0.000**	0.643	**0.000**	0.652	**0.000**
M1,5-Quantile	0.662	**0.000**	0.585	**0.000**	0.617	**0.000**	0.650	**0.000**	0.654	**0.001**
M1,99-Quantile	0.666	**0.000**	0.595	**0.000**	0.610	**0.000**	0.641	**0.000**	0.643	**0.001**
M2,Linear	0.647	**0.000**	0.628	**0.001**	0.634	**0.001**	0.669	**0.000**	0.679	**0.001**
M2,Trimean	0.647	**0.000**	0.647	**0.001**	0.645	**0.001**	0.692	**0.000**	0.698	**0.001**
M2,Gastwirth	0.654	**0.000**	0.643	**0.001**	0.646	**0.001**	0.692	**0.000**	0.707	**0.001**
M2,5-Quantile	0.645	**0.000**	0.643	**0.001**	0.640	**0.001**	0.684	**0.000**	0.688	**0.001**
M2,99-Quantile	0.648	**0.000**	0.630	**0.001**	0.633	**0.001**	0.667	**0.000**	0.672	**0.001**
M3,Linear	0.691	**0.000**	0.671	**0.000**	0.651	**0.000**	0.644	**0.000**	0.667	**0.001**
M3,Trimean	0.682	**0.000**	0.664	**0.000**	0.641	**0.000**	0.660	**0.000**	0.687	**0.001**
M3,Gastwirth	0.686	**0.000**	0.659	**0.000**	0.638	**0.000**	0.662	**0.000**	0.692	**0.001**
M3,5-Quantile	0.682	**0.000**	0.662	**0.000**	0.643	**0.000**	0.654	**0.000**	0.679	**0.001**
M3,99-Quantile	0.677	**0.000**	0.655	**0.000**	0.648	**0.000**	0.647	**0.000**	0.670	**0.001**
M4,Linear	0.719	**0.000**	0.696	**0.000**	0.670	**0.000**	0.684	**0.000**	0.692	**0.001**
M4,Trimean	0.719	**0.000**	0.728	**0.000**	0.675	**0.001**	0.708	**0.000**	0.703	**0.001**
M4,Gastwirth	0.714	**0.000**	0.727	**0.000**	0.672	**0.001**	0.707	**0.000**	0.710	**0.001**
M4,5-Quantile	0.720	**0.000**	0.720	**0.000**	0.675	**0.001**	0.700	**0.000**	0.695	**0.001**
M4,99-Quantile	0.717	**0.000**	0.688	**0.000**	0.666	**0.001**	0.685	**0.000**	0.685	**0.001**
M5,Linear	0.700	**0.000**	0.678	**0.000**	0.653	**0.000**	0.612	**0.000**	0.599	**0.000**
M5,Trimean	0.715	**0.000**	0.696	**0.000**	0.651	**0.000**	0.617	**0.000**	0.626	**0.000**
M5,Gastwirth	0.715	**0.000**	0.694	**0.000**	0.648	**0.000**	0.621	**0.000**	0.632	**0.000**
M5,5-Quantile	0.710	**0.000**	0.692	**0.000**	0.653	**0.000**	0.615	**0.000**	0.618	**0.000**
M5,99-Quantile	0.699	**0.000**	0.686	**0.000**	0.654	**0.000**	0.610	**0.000**	0.607	**0.000**
M6,Linear	0.678	**0.000**	0.662	**0.000**	0.660	**0.001**	0.670	**0.000**	0.672	**0.001**
M6,Trimean	0.680	**0.000**	0.678	**0.000**	0.677	**0.000**	0.694	**0.000**	0.700	**0.001**
M6,Gastwirth	0.677	**0.000**	0.677	**0.000**	0.675	**0.000**	0.699	**0.000**	0.700	**0.001**
M6,5-Quantile	0.681	**0.000**	0.675	**0.000**	0.674	**0.000**	0.688	**0.000**	0.691	**0.001**
M6,99-Quantile	0.672	**0.000**	0.663	**0.000**	0.667	**0.000**	0.677	**0.000**	0.677	**0.001**
M7,Linear	0.672	**0.000**	0.657	**0.000**	0.622	**0.000**	0.654	**0.000**	0.681	**0.001**
M7,Trimean	0.682	**0.000**	0.671	**0.001**	0.646	**0.001**	0.670	**0.000**	0.697	**0.001**
M7,Gastwirth	0.688	**0.000**	0.676	**0.000**	0.646	**0.001**	0.668	**0.000**	0.705	**0.001**
M7,5-Quantile	0.679	**0.000**	0.667	**0.000**	0.640	**0.001**	0.666	**0.000**	0.691	**0.001**
M7,99-Quantile	0.672	**0.000**	0.659	**0.000**	0.625	**0.000**	0.652	**0.000**	0.684	**0.001**

Table 9: RMSE Ratios, Naïve benchmark *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
M8,Linear	0.646	**0.000**	0.590	**0.000**	0.585	**0.000**	0.633	**0.000**	0.670	**0.001**
M8,Trimean	0.661	**0.000**	0.622	**0.000**	0.593	**0.001**	0.634	**0.000**	0.668	**0.001**
M8,Gastwirth	0.660	**0.000**	0.623	**0.000**	0.587	**0.000**	0.627	**0.000**	0.672	**0.001**
M8,5-Quantile	0.660	**0.000**	0.615	**0.000**	0.590	**0.000**	0.640	**0.000**	0.668	**0.001**
M8,99-Quantile	0.648	**0.000**	0.597	**0.000**	0.580	**0.000**	0.644	**0.000**	0.667	**0.001**
M9,Linear	0.689	**0.000**	0.662	**0.000**	0.654	**0.001**	0.670	**0.000**	0.667	**0.001**
M9,Trimean	0.683	**0.000**	0.665	**0.000**	0.661	**0.001**	0.693	**0.000**	0.695	**0.002**
M9,Gastwirth	0.683	**0.000**	0.667	**0.000**	0.662	**0.001**	0.698	**0.000**	0.702	**0.002**
M9,5-Quantile	0.683	**0.000**	0.660	**0.000**	0.657	**0.001**	0.686	**0.000**	0.688	**0.001**
M9,99-Quantile	0.680	**0.000**	0.653	**0.000**	0.650	**0.000**	0.670	**0.000**	0.669	**0.001**
M10,Linear	0.688	**0.000**	0.670	**0.000**	0.640	**0.000**	0.641	**0.000**	0.648	**0.000**
M10,Trimean	0.686	**0.000**	0.677	**0.000**	0.632	**0.000**	0.651	**0.000**	0.662	**0.000**
M10,Gastwirth	0.685	**0.000**	0.674	**0.000**	0.631	**0.001**	0.653	**0.000**	0.655	**0.000**
M10,5-Quantile	0.685	**0.000**	0.674	**0.000**	0.634	**0.000**	0.646	**0.000**	0.658	**0.000**
M10,99-Quantile	0.682	**0.000**	0.663	**0.000**	0.642	**0.000**	0.639	**0.000**	0.649	**0.000**
M11,Linear	0.673	**0.000**	0.649	**0.000**	0.634	**0.000**	0.647	**0.000**	0.618	**0.000**
M11,Trimean	0.680	**0.000**	0.643	**0.000**	0.613	**0.000**	0.634	**0.000**	0.611	**0.000**
M11,Gastwirth	0.678	**0.000**	0.644	**0.000**	0.627	**0.000**	0.631	**0.000**	0.621	**0.000**
M11,5-Quantile	0.677	**0.000**	0.641	**0.000**	0.614	**0.000**	0.637	**0.000**	0.607	**0.000**
M11,99-Quantile	0.670	**0.000**	0.639	**0.000**	0.626	**0.000**	0.642	**0.000**	0.603	**0.000**
M12,Linear	0.678	**0.000**	0.648	**0.000**	0.614	**0.000**	0.615	**0.000**	0.622	**0.001**
M12,Trimean	0.686	**0.000**	0.651	**0.000**	0.620	**0.000**	0.635	**0.000**	0.650	**0.000**
M12,Gastwirth	0.685	**0.000**	0.647	**0.000**	0.624	**0.001**	0.642	**0.000**	0.648	**0.000**
M12,5-Quantile	0.680	**0.000**	0.648	**0.000**	0.620	**0.000**	0.628	**0.000**	0.644	**0.001**
M12,99-Quantile	0.675	**0.000**	0.642	**0.000**	0.620	**0.000**	0.618	**0.000**	0.635	**0.001**
M13,Linear	0.677	**0.000**	0.660	**0.000**	0.644	**0.000**	0.667	**0.000**	0.679	**0.001**
M13,Trimean	0.686	**0.000**	0.666	**0.000**	0.660	**0.001**	0.684	**0.000**	0.697	**0.001**
M13,Gastwirth	0.686	**0.000**	0.660	**0.000**	0.658	**0.001**	0.681	**0.000**	0.700	**0.001**
M13,5-Quantile	0.684	**0.000**	0.663	**0.000**	0.655	**0.001**	0.679	**0.000**	0.691	**0.001**
M13,99-Quantile	0.679	**0.000**	0.655	**0.000**	0.646	**0.000**	0.665	**0.000**	0.680	**0.001**
MAIC1,Linear	0.682	**0.000**	0.618	**0.000**	0.599	**0.000**	0.630	**0.000**	0.612	**0.000**
MAIC1,Trimean	0.666	**0.000**	0.595	**0.001**	0.611	**0.000**	0.652	**0.000**	0.652	**0.001**
MAIC1,Gastwirth	0.692	**0.000**	0.600	**0.001**	0.606	**0.000**	0.642	**0.000**	0.636	**0.000**
MAIC1,5-Quantile	0.660	**0.000**	0.596	**0.000**	0.618	**0.000**	0.650	**0.000**	0.650	**0.001**
MAIC1,99-Quantile	0.660	**0.000**	0.603	**0.000**	0.618	**0.000**	0.643	**0.000**	0.638	**0.000**
MBIC1,Linear	0.680	**0.000**	0.617	**0.000**	0.597	**0.000**	0.630	**0.000**	0.615	**0.000**

Table 9: RMSE Ratios, Naïve benchmark *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
MBIC1,Trimean	0.665	**0.000**	0.592	**0.000**	0.606	**0.000**	0.652	**0.000**	0.653	**0.000**
MBIC1,Gastwirth	0.692	**0.000**	0.598	**0.000**	0.598	**0.000**	0.642	**0.000**	0.637	**0.000**
MBIC1,5-Quantile	0.659	**0.000**	0.593	**0.000**	0.614	**0.000**	0.650	**0.000**	0.650	**0.000**
MBIC1,99-Quantile	0.659	**0.000**	0.601	**0.000**	0.614	**0.000**	0.643	**0.000**	0.639	**0.000**
MOOS1,Linear	0.662	**0.000**	0.622	**0.005**	0.649	**0.009**	0.643	**0.001**	0.635	**0.005**
MOOS1,Trimean	0.665	**0.000**	0.632	**0.007**	0.657	**0.013**	0.661	**0.001**	0.656	**0.006**
MOOS1,Gastwirth	0.667	**0.000**	0.630	**0.007**	0.654	**0.014**	0.662	**0.001**	0.658	**0.006**
MOOS1,5-Quantile	0.663	**0.000**	0.630	**0.006**	0.656	**0.012**	0.657	**0.001**	0.650	**0.006**
MOOS1,99-Quantile	0.658	**0.000**	0.621	**0.005**	0.650	**0.010**	0.646	**0.001**	0.637	**0.005**
MAIC2,Linear	0.686	**0.000**	0.610	**0.000**	0.639	**0.000**	0.624	**0.000**	0.628	**0.000**
MAIC2,Trimean	0.671	**0.000**	0.595	**0.001**	0.611	**0.000**	0.651	**0.000**	0.657	**0.001**
MAIC2,Gastwirth	0.694	**0.000**	0.595	**0.001**	0.606	**0.000**	0.644	**0.000**	0.652	**0.000**
MAIC2,5-Quantile	0.667	**0.000**	0.597	**0.000**	0.615	**0.000**	0.649	**0.000**	0.654	**0.001**
MAIC2,99-Quantile	0.666	**0.000**	0.608	**0.000**	0.611	**0.000**	0.640	**0.000**	0.643	**0.000**
MBIC2,Linear	0.684	**0.000**	0.609	**0.000**	0.636	**0.000**	0.624	**0.000**	0.628	**0.000**
MBIC2,Trimean	0.669	**0.000**	0.593	**0.001**	0.606	**0.000**	0.651	**0.000**	0.657	**0.000**
MBIC2,Gastwirth	0.694	**0.000**	0.592	**0.001**	0.598	**0.000**	0.643	**0.000**	0.652	**0.000**
MBIC2,5-Quantile	0.664	**0.000**	0.595	**0.001**	0.611	**0.000**	0.649	**0.000**	0.654	**0.000**
MBIC2,99-Quantile	0.665	**0.000**	0.604	**0.001**	0.607	**0.000**	0.640	**0.000**	0.643	**0.000**
MOOS2,Linear	0.657	**0.000**	0.612	**0.004**	0.641	**0.008**	0.637	**0.000**	0.623	**0.004**
MOOS2,Trimean	0.659	**0.000**	0.623	**0.006**	0.646	**0.012**	0.652	**0.001**	0.643	**0.005**
MOOS2,Gastwirth	0.661	**0.000**	0.621	**0.006**	0.644	**0.012**	0.651	**0.001**	0.646	**0.005**
MOOS2,5-Quantile	0.657	**0.000**	0.621	**0.006**	0.645	**0.011**	0.649	**0.001**	0.637	**0.005**
MOOS2,99-Quantile	0.652	**0.000**	0.612	**0.005**	0.639	**0.010**	0.640	**0.000**	0.624	**0.004**
MAIC3,Linear	0.668	**0.000**	0.620	**0.000**	0.595	**0.000**	0.679	**0.000**	0.647	**0.000**
MAIC3,Trimean	0.669	**0.000**	0.626	**0.000**	0.608	**0.000**	0.648	**0.000**	0.639	**0.001**
MAIC3,Gastwirth	0.668	**0.000**	0.633	**0.000**	0.608	**0.000**	0.656	**0.000**	0.645	**0.000**
MAIC3,5-Quantile	0.668	**0.000**	0.620	**0.000**	0.610	**0.000**	0.650	**0.000**	0.636	**0.001**
MAIC3,99-Quantile	0.658	**0.000**	0.610	**0.000**	0.617	**0.000**	0.649	**0.000**	0.629	**0.001**
MBIC3,Linear	0.667	**0.000**	0.620	**0.000**	0.594	**0.000**	0.679	**0.000**	0.654	**0.000**
MBIC3,Trimean	0.669	**0.000**	0.626	**0.000**	0.601	**0.000**	0.647	**0.000**	0.643	**0.001**
MBIC3,Gastwirth	0.668	**0.000**	0.634	**0.000**	0.597	**0.000**	0.655	**0.000**	0.649	**0.001**
MBIC3,5-Quantile	0.668	**0.000**	0.620	**0.000**	0.604	**0.000**	0.651	**0.000**	0.640	**0.001**
MBIC3,99-Quantile	0.658	**0.000**	0.611	**0.000**	0.611	**0.000**	0.650	**0.000**	0.633	**0.001**
MOOS3,Linear	0.663	**0.000**	0.621	**0.004**	0.667	**0.008**	0.649	**0.001**	0.645	**0.006**
MOOS3,Trimean	0.664	**0.000**	0.630	**0.005**	0.675	**0.012**	0.669	**0.001**	0.672	**0.009**
MOOS3,Gastwirth	0.668	**0.000**	0.627	**0.005**	0.666	**0.013**	0.671	**0.001**	0.673	**0.008**

Table 9: RMSE Ratios, Naïve benchmark *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
MOOS3,5-Quantile	0.663	**0.000**	0.630	**0.005**	0.676	**0.011**	0.663	**0.001**	0.664	**0.008**
MOOS3,99-Quantile	0.658	**0.000**	0.621	**0.004**	0.669	**0.010**	0.651	**0.001**	0.649	**0.007**
MAIC4,Linear	0.673	**0.000**	0.646	**0.000**	0.603	**0.000**	0.661	**0.000**	0.654	**0.000**
MAIC4,Trimean	0.675	**0.000**	0.635	**0.000**	0.640	**0.000**	0.647	**0.000**	0.620	**0.001**
MAIC4,Gastwirth	0.691	**0.000**	0.643	**0.000**	0.637	**0.000**	0.648	**0.000**	0.621	**0.000**
MAIC4,5-Quantile	0.669	**0.000**	0.624	**0.000**	0.641	**0.000**	0.642	**0.000**	0.619	**0.001**
MAIC4,99-Quantile	0.669	**0.000**	0.602	**0.000**	0.634	**0.000**	0.635	**0.000**	0.615	**0.001**
MBIC4,Linear	0.662	**0.000**	0.636	**0.000**	0.591	**0.000**	0.661	**0.000**	0.660	**0.000**
MBIC4,Trimean	0.660	**0.000**	0.619	**0.000**	0.631	**0.000**	0.643	**0.000**	0.622	**0.001**
MBIC4,Gastwirth	0.667	**0.000**	0.629	**0.001**	0.624	**0.000**	0.645	**0.000**	0.625	**0.000**
MBIC4,5-Quantile	0.655	**0.000**	0.613	**0.000**	0.632	**0.000**	0.639	**0.000**	0.622	**0.001**
MBIC4,99-Quantile	0.654	**0.000**	0.597	**0.000**	0.626	**0.000**	0.636	**0.000**	0.620	**0.001**
MOOS4,Linear	0.657	**0.000**	0.607	**0.003**	0.657	**0.007**	0.637	**0.000**	0.626	**0.005**
MOOS4,Trimean	0.657	**0.000**	0.614	**0.005**	0.655	**0.011**	0.656	**0.001**	0.655	**0.007**
MOOS4,Gastwirth	0.663	**0.000**	0.608	**0.004**	0.650	**0.012**	0.655	**0.001**	0.659	**0.007**
MOOS4,5-Quantile	0.655	**0.000**	0.613	**0.004**	0.655	**0.010**	0.651	**0.001**	0.647	**0.007**
MOOS4,99-Quantile	0.651	**0.000**	0.607	**0.004**	0.651	**0.009**	0.641	**0.000**	0.633	**0.006**
MAIC5,Linear	0.672	**0.000**	0.668	**0.000**	0.660	**0.000**	0.639	**0.000**	0.648	**0.000**
MAIC5,Trimean	0.690	**0.000**	0.643	**0.000**	0.649	**0.001**	0.654	**0.000**	0.663	**0.000**
MAIC5,Gastwirth	0.694	**0.000**	0.640	**0.000**	0.645	**0.001**	0.653	**0.000**	0.663	**0.000**
MAIC5,5-Quantile	0.685	**0.000**	0.641	**0.000**	0.653	**0.001**	0.648	**0.000**	0.658	**0.000**
MAIC5,99-Quantile	0.680	**0.000**	0.636	**0.000**	0.646	**0.000**	0.638	**0.000**	0.646	**0.000**
MBIC5,Linear	0.654	**0.000**	0.640	**0.001**	0.638	**0.001**	0.632	**0.000**	0.636	**0.000**
MBIC5,Trimean	0.660	**0.000**	0.620	**0.000**	0.635	**0.001**	0.636	**0.000**	0.655	**0.000**
MBIC5,Gastwirth	0.665	**0.000**	0.619	**0.000**	0.628	**0.001**	0.634	**0.000**	0.660	**0.000**
MBIC5,5-Quantile	0.658	**0.000**	0.620	**0.000**	0.641	**0.001**	0.633	**0.000**	0.653	**0.000**
MBIC5,99-Quantile	0.658	**0.000**	0.616	**0.000**	0.637	**0.001**	0.629	**0.000**	0.646	**0.000**
MOOS5,Linear	0.666	**0.000**	0.629	**0.006**	0.641	**0.011**	0.643	**0.001**	0.631	**0.004**
MOOS5,Trimean	0.672	**0.001**	0.642	**0.009**	0.650	**0.014**	0.657	**0.001**	0.647	**0.005**
MOOS5,Gastwirth	0.673	**0.000**	0.641	**0.009**	0.650	**0.014**	0.657	**0.001**	0.650	**0.005**
MOOS5,5-Quantile	0.670	**0.000**	0.637	**0.008**	0.647	**0.013**	0.654	**0.001**	0.642	**0.005**
MOOS5,99-Quantile	0.664	**0.000**	0.626	**0.006**	0.642	**0.011**	0.645	**0.001**	0.630	**0.004**
MAIC6,Linear	0.678	**0.000**	0.632	**0.000**	0.613	**0.000**	0.681	**0.000**	0.636	**0.000**
MAIC6,Trimean	0.675	**0.000**	0.638	**0.000**	0.621	**0.001**	0.652	**0.000**	0.627	**0.000**
MAIC6,Gastwirth	0.675	**0.000**	0.641	**0.000**	0.623	**0.001**	0.659	**0.000**	0.635	**0.000**
MAIC6,5-Quantile	0.673	**0.000**	0.631	**0.000**	0.623	**0.001**	0.654	**0.000**	0.624	**0.000**
MAIC6,99-Quantile	0.666	**0.000**	0.620	**0.000**	0.629	**0.000**	0.654	**0.000**	0.619	**0.000**

Table 9: RMSE Ratios, Naïve benchmark *(continued)*

	$h = 1$		$h = 2$		$h = 4$		$h = 6$		$h = 8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
MBIC6,Linear	0.680	**0.000**	0.630	**0.000**	0.609	**0.001**	0.683	**0.000**	0.646	**0.000**
MBIC6,Trimean	0.677	**0.000**	0.639	**0.000**	0.613	**0.001**	0.651	**0.000**	0.634	**0.000**
MBIC6,Gastwirth	0.679	**0.000**	0.645	**0.000**	0.610	**0.001**	0.661	**0.000**	0.642	**0.000**
MBIC6,5-Quantile	0.675	**0.000**	0.632	**0.000**	0.616	**0.001**	0.655	**0.000**	0.631	**0.000**
MBIC6,99-Quantile	0.666	**0.000**	0.620	**0.000**	0.622	**0.000**	0.656	**0.000**	0.625	**0.000**
MOOS6,Linear	0.663	**0.000**	0.623	**0.005**	0.638	**0.010**	0.642	**0.001**	0.628	**0.004**
MOOS6,Trimean	0.667	**0.000**	0.638	**0.009**	0.646	**0.013**	0.653	**0.001**	0.640	**0.004**
MOOS6,Gastwirth	0.668	**0.000**	0.639	**0.009**	0.646	**0.013**	0.652	**0.001**	0.644	**0.004**
MOOS6,5-Quantile	0.665	**0.000**	0.633	**0.008**	0.644	**0.012**	0.652	**0.001**	0.635	**0.004**
MOOS6,99-Quantile	0.660	**0.000**	0.622	**0.006**	0.638	**0.011**	0.645	**0.001**	0.624	**0.004**

Table 10: RMSE Ratios, benchmark: Baseline Model, eq. (6)

	$h = 1$		$h = 2$		$h = 4$		$h = 6$		$h = 8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
M1,Linear	0.986	**0.025**	0.887	**0.014**	1.002	0.131	0.950	**0.010**	0.934	**0.002**
M1,Trimean	0.983	**0.007**	0.889	**0.009**	0.966	**0.081**	0.993	**0.029**	0.978	**0.014**
M1,Gastwirth	1.018	**0.014**	0.887	**0.012**	0.950	**0.041**	0.980	**0.006**	0.971	**0.006**
M1,5-Quantile	0.977	**0.009**	0.893	**0.012**	0.974	0.100	0.990	**0.039**	0.973	**0.014**
M1,99-Quantile	0.982	**0.017**	0.908	**0.024**	0.963	**0.084**	0.976	**0.019**	0.957	**0.010**
M2,Linear	0.954	**0.059**	0.959	**0.090**	1.002	0.502	1.020	0.894	1.010	0.804
M2,Trimean	0.954	**0.046**	0.987	0.165	1.019	0.584	1.054	0.938	1.038	0.948
M2,Gastwirth	0.964	**0.072**	0.982	0.112	1.021	0.557	1.054	0.914	1.052	0.889
M2,5-Quantile	0.952	**0.052**	0.981	0.138	1.012	0.496	1.042	0.936	1.024	0.912
M2,99-Quantile	0.956	**0.074**	0.962	**0.087**	1.001	0.334	1.017	0.865	1.000	0.240
M3,Linear	1.019	0.293	1.024	0.380	1.028	0.512	0.981	**0.021**	0.992	**0.088**
M3,Trimean	1.006	0.212	1.013	0.342	1.013	0.358	1.005	0.201	1.022	0.576
M3,Gastwirth	1.011	0.175	1.006	0.235	1.007	0.291	1.009	0.223	1.030	0.613
M3,5-Quantile	1.007	0.220	1.011	0.320	1.015	0.396	0.996	0.125	1.010	0.434
M3,99-Quantile	0.998	0.138	1.000	0.195	1.024	0.496	0.985	**0.044**	0.997	0.166
M4,Linear	1.060	**0.064**	1.063	0.162	1.059	0.743	1.042	0.723	1.029	0.580
M4,Trimean	1.061	**0.087**	1.112	0.404	1.066	0.561	1.078	0.860	1.046	0.757
M4,Gastwirth	1.054	**0.064**	1.109	0.345	1.062	0.412	1.077	0.827	1.056	0.783
M4,5-Quantile	1.062	**0.089**	1.099	0.350	1.067	0.591	1.066	0.831	1.034	0.663
M4,99-Quantile	1.058	**0.073**	1.050	0.178	1.052	0.463	1.044	0.689	1.020	0.409
M5,Linear	1.032	0.278	1.036	0.238	1.032	0.188	0.932	**0.013**	0.892	**0.001**

Table 10: RMSE Ratios, benchmark: Baseline Model, eq. (6) *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
M5,Trimean	1.055	0.483	1.063	0.293	1.028	0.201	0.940	**0.013**	0.931	**0.003**
M5,Gastwirth	1.055	0.528	1.060	0.238	1.024	0.187	0.947	**0.016**	0.940	**0.002**
M5,5-Quantile	1.047	0.405	1.057	0.304	1.032	0.215	0.937	**0.011**	0.919	**0.002**
M5,99-Quantile	1.031	0.258	1.048	0.304	1.033	0.221	0.930	**0.007**	0.903	**0.001**
M6,Linear	1.000	0.226	1.011	0.449	1.043	0.956	1.020	0.752	1.000	0.288
M6,Trimean	1.003	0.217	1.035	0.601	1.070	0.922	1.057	0.935	1.041	0.955
M6,Gastwirth	0.999	0.176	1.034	0.540	1.066	0.891	1.066	0.925	1.042	0.911
M6,5-Quantile	1.004	0.221	1.031	0.613	1.065	0.934	1.048	0.934	1.028	0.913
M6,99-Quantile	0.991	0.113	1.012	0.447	1.053	0.973	1.032	0.825	1.007	0.448
M7,Linear	0.991	**0.054**	1.003	0.139	0.982	**0.053**	0.996	0.219	1.013	0.562
M7,Trimean	1.006	0.160	1.025	0.290	1.021	0.775	1.021	0.602	1.038	0.749
M7,Gastwirth	1.015	0.213	1.032	0.369	1.020	0.719	1.018	0.475	1.050	0.803
M7,5-Quantile	1.001	0.111	1.019	0.235	1.011	0.513	1.015	0.599	1.029	0.713
M7,99-Quantile	0.991	**0.054**	1.006	0.154	0.987	**0.060**	0.993	0.119	1.018	0.712
M8,Linear	0.953	**0.026**	0.901	**0.015**	0.924	**0.005**	0.965	**0.025**	0.998	0.163
M8,Trimean	0.975	**0.021**	0.951	**0.019**	0.936	**0.008**	0.966	**0.027**	0.994	0.119
M8,Gastwirth	0.974	**0.027**	0.951	**0.019**	0.927	**0.008**	0.955	**0.033**	1.000	0.179
M8,5-Quantile	0.974	**0.020**	0.940	**0.017**	0.932	**0.007**	0.975	**0.034**	0.994	0.122
M8,99-Quantile	0.956	**0.010**	0.912	**0.016**	0.917	**0.006**	0.981	**0.058**	0.993	0.158
M9,Linear	1.015	0.672	1.010	0.585	1.033	0.924	1.022	0.714	0.992	**0.088**
M9,Trimean	1.007	0.275	1.016	0.462	1.044	0.791	1.056	0.851	1.035	0.550
M9,Gastwirth	1.007	0.278	1.019	0.461	1.046	0.759	1.064	0.859	1.045	0.566
M9,5-Quantile	1.007	0.300	1.008	0.398	1.037	0.809	1.044	0.826	1.024	0.453
M9,99-Quantile	1.003	0.282	0.997	0.302	1.027	0.878	1.021	0.663	0.995	0.121
M10,Linear	1.015	0.905	1.023	0.910	1.012	0.660	0.977	**0.050**	0.964	**0.024**
M10,Trimean	1.011	0.480	1.034	0.881	0.998	0.153	0.992	**0.041**	0.984	**0.025**
M10,Gastwirth	1.011	0.355	1.029	0.712	0.997	0.158	0.996	**0.040**	0.974	**0.015**
M10,5-Quantile	1.010	0.540	1.030	0.946	1.002	0.291	0.984	**0.033**	0.980	**0.026**
M10,99-Quantile	1.005	0.577	1.013	0.731	1.015	0.669	0.974	**0.043**	0.965	**0.025**
M11,Linear	0.993	0.103	0.991	**0.045**	1.001	**0.056**	0.985	**0.038**	0.920	**0.013**
M11,Trimean	1.004	0.197	0.981	**0.027**	0.969	**0.040**	0.965	**0.042**	0.909	**0.011**
M11,Gastwirth	1.000	0.169	0.983	**0.029**	0.990	**0.056**	0.962	**0.038**	0.925	**0.015**
M11,5-Quantile	0.998	0.137	0.979	**0.025**	0.969	**0.038**	0.970	**0.042**	0.903	**0.010**
M11,99-Quantile	0.988	**0.079**	0.976	**0.030**	0.988	**0.046**	0.978	**0.039**	0.897	**0.010**
M12,Linear	1.000	0.321	0.989	0.137	0.970	**0.035**	0.938	**0.007**	0.925	**0.019**
M12,Trimean	1.011	0.547	0.995	0.166	0.980	**0.088**	0.967	**0.003**	0.967	**0.070**
M12,Gastwirth	1.010	0.474	0.988	0.111	0.986	0.114	0.979	**0.006**	0.964	**0.050**

Table 10: RMSE Ratios, benchmark: Baseline Model, eq. (6) *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
M12,5-Quantile	1.004	0.368	0.990	0.111	0.979	**0.080**	0.957	**0.005**	0.959	**0.062**
M12,99-Quantile	0.995	0.176	0.981	**0.074**	0.980	**0.070**	0.941	**0.010**	0.945	**0.059**
M13,Linear	0.998	0.271	1.008	0.869	1.018	0.909	1.016	0.709	1.011	0.500
M13,Trimean	1.012	0.492	1.016	0.569	1.043	0.810	1.042	0.846	1.037	0.749
M13,Gastwirth	1.011	0.465	1.008	0.305	1.039	0.772	1.038	0.808	1.042	0.746
M13,5-Quantile	1.008	0.475	1.012	0.569	1.036	0.804	1.034	0.827	1.028	0.695
M13,99-Quantile	1.002	0.315	1.000	0.327	1.021	0.769	1.013	0.635	1.012	0.504
MAIC1,Linear	1.005	0.131	0.943	**0.009**	0.947	**0.043**	0.960	**0.019**	0.910	**0.008**
MAIC1,Trimean	0.983	**0.015**	0.908	**0.006**	0.965	**0.068**	0.993	**0.031**	0.971	**0.011**
MAIC1,Gastwirth	1.021	**0.092**	0.916	**0.006**	0.957	**0.040**	0.979	**0.012**	0.946	**0.003**
MAIC1,5-Quantile	0.974	**0.009**	0.909	**0.008**	0.976	**0.098**	0.991	**0.038**	0.967	**0.012**
MAIC1,99-Quantile	0.973	**0.013**	0.921	**0.018**	0.976	**0.096**	0.980	**0.023**	0.949	**0.009**
MBIC1,Linear	1.003	0.103	0.943	**0.097**	0.943	**0.018**	0.960	**0.093**	0.916	**0.030**
MBIC1,Trimean	0.981	0.125	0.904	**0.047**	0.958	0.111	0.993	**0.041**	0.972	**0.015**
MBIC1,Gastwirth	1.021	0.312	0.914	**0.060**	0.945	**0.087**	0.979	**0.037**	0.948	**0.012**
MBIC1,5-Quantile	0.972	**0.067**	0.906	**0.030**	0.970	0.127	0.991	**0.035**	0.967	**0.014**
MBIC1,99-Quantile	0.972	**0.064**	0.918	**0.015**	0.971	0.108	0.980	**0.026**	0.950	**0.016**
MOOS1,Linear	0.973	**0.020**	0.955	**0.032**	0.975	0.187	0.952	**0.021**	0.933	**0.003**
MOOS1,Trimean	0.978	**0.024**	0.970	**0.098**	0.988	0.339	0.978	**0.064**	0.964	**0.012**
MOOS1,Gastwirth	0.980	**0.052**	0.967	0.101	0.984	0.275	0.979	**0.095**	0.967	**0.013**
MOOS1,5-Quantile	0.975	**0.011**	0.967	**0.068**	0.986	0.316	0.972	**0.031**	0.954	**0.006**
MOOS1,99-Quantile	0.967	**0.002**	0.953	**0.025**	0.977	0.206	0.956	**0.022**	0.935	**0.003**
MAIC2,Linear	1.012	0.112	0.932	**0.002**	1.009	**0.044**	0.951	**0.019**	0.934	**0.010**
MAIC2,Trimean	0.990	**0.011**	0.909	**0.006**	0.965	**0.073**	0.992	**0.031**	0.978	**0.012**
MAIC2,Gastwirth	1.023	**0.082**	0.909	**0.005**	0.957	**0.049**	0.981	**0.013**	0.971	**0.004**
MAIC2,5-Quantile	0.983	**0.007**	0.912	**0.008**	0.971	**0.099**	0.989	**0.039**	0.974	**0.013**
MAIC2,99-Quantile	0.983	**0.011**	0.928	**0.017**	0.965	**0.096**	0.976	**0.023**	0.957	**0.010**
MBIC2,Linear	1.009	**0.021**	0.929	**0.090**	1.005	**0.013**	0.950	**0.090**	0.934	**0.038**
MBIC2,Trimean	0.987	**0.023**	0.905	**0.009**	0.957	**0.093**	0.991	**0.040**	0.978	**0.016**
MBIC2,Gastwirth	1.023	**0.069**	0.904	**0.024**	0.945	**0.062**	0.980	**0.035**	0.971	**0.015**
MBIC2,5-Quantile	0.979	**0.011**	0.908	**0.007**	0.965	0.112	0.989	**0.038**	0.974	**0.017**
MBIC2,99-Quantile	0.980	**0.006**	0.922	**0.005**	0.959	0.100	0.976	**0.035**	0.957	**0.021**
MOOS2,Linear	0.965	**0.003**	0.940	**0.011**	0.963	0.130	0.943	**0.019**	0.915	**0.003**
MOOS2,Trimean	0.968	**0.004**	0.957	**0.019**	0.971	0.159	0.965	**0.036**	0.944	**0.006**
MOOS2,Gastwirth	0.972	**0.015**	0.953	**0.023**	0.968	0.134	0.963	**0.036**	0.949	**0.006**
MOOS2,5-Quantile	0.965	**0.002**	0.953	**0.012**	0.969	0.147	0.961	**0.028**	0.935	**0.004**
MOOS2,99-Quantile	0.958	**0.000**	0.939	**0.009**	0.961	0.101	0.948	**0.023**	0.917	**0.003**

Table 10: RMSE Ratios, benchmark: Baseline Model, eq. (6) *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
MAIC3,Linear	0.984	0.145	0.947	**0.015**	0.940	0.136	1.034	**0.011**	0.962	**0.002**
MAIC3,Trimean	0.987	**0.020**	0.956	**0.005**	0.960	**0.073**	0.987	**0.024**	0.951	**0.014**
MAIC3,Gastwirth	0.985	**0.086**	0.967	**0.005**	0.961	**0.042**	0.999	**0.006**	0.959	**0.006**
MAIC3,5-Quantile	0.985	**0.016**	0.947	**0.008**	0.963	**0.092**	0.990	**0.034**	0.947	**0.014**
MAIC3,99-Quantile	0.970	**0.019**	0.932	**0.019**	0.974	**0.081**	0.989	**0.018**	0.936	**0.010**
MBIC3,Linear	0.984	**0.077**	0.946	0.210	0.939	0.269	1.035	**0.034**	0.972	**0.007**
MBIC3,Trimean	0.986	0.278	0.956	**0.079**	0.949	0.164	0.986	**0.027**	0.957	**0.016**
MBIC3,Gastwirth	0.985	0.299	0.968	**0.063**	0.943	0.135	0.998	**0.020**	0.966	**0.013**
MBIC3,5-Quantile	0.984	0.225	0.947	**0.077**	0.954	0.189	0.991	**0.022**	0.952	**0.012**
MBIC3,99-Quantile	0.970	0.139	0.932	**0.068**	0.966	0.154	0.990	**0.011**	0.941	**0.009**
MOOS3,Linear	0.975	0.145	0.954	**0.099**	1.003	0.529	0.960	**0.023**	0.947	**0.003**
MOOS3,Trimean	0.976	0.127	0.967	0.198	1.014	0.630	0.990	0.258	0.987	0.180
MOOS3,Gastwirth	0.982	0.228	0.962	0.183	1.001	0.514	0.994	0.367	0.988	0.192
MOOS3,5-Quantile	0.974	0.100	0.966	0.190	1.016	0.641	0.982	**0.097**	0.975	**0.053**
MOOS3,99-Quantile	0.966	**0.056**	0.953	0.103	1.006	0.557	0.964	**0.020**	0.954	**0.007**
MAIC4,Linear	0.992	0.119	0.987	**0.001**	0.952	0.133	1.008	**0.011**	0.972	**0.002**
MAIC4,Trimean	0.995	**0.013**	0.970	**0.004**	1.011	**0.074**	0.986	**0.024**	0.922	**0.014**
MAIC4,Gastwirth	1.019	**0.072**	0.982	**0.004**	1.007	**0.051**	0.988	**0.006**	0.923	**0.006**
MAIC4,5-Quantile	0.986	**0.010**	0.954	**0.007**	1.013	**0.091**	0.978	**0.033**	0.921	**0.014**
MAIC4,99-Quantile	0.987	**0.014**	0.919	**0.017**	1.002	**0.081**	0.968	**0.018**	0.915	**0.010**
MBIC4,Linear	0.976	**0.007**	0.972	**0.033**	0.934	0.145	1.007	**0.018**	0.982	**0.005**
MBIC4,Trimean	0.973	**0.019**	0.945	**0.008**	0.996	0.166	0.980	**0.005**	0.926	**0.011**
MBIC4,Gastwirth	0.984	**0.048**	0.960	**0.010**	0.987	0.130	0.983	**0.004**	0.930	**0.011**
MBIC4,5-Quantile	0.967	**0.012**	0.936	**0.006**	0.999	0.190	0.974	**0.005**	0.926	**0.012**
MBIC4,99-Quantile	0.965	**0.009**	0.912	**0.009**	0.989	0.160	0.969	**0.006**	0.923	**0.014**
MOOS4,Linear	0.965	**0.055**	0.932	**0.013**	0.987	0.399	0.943	**0.023**	0.919	**0.003**
MOOS4,Trimean	0.965	**0.038**	0.942	**0.029**	0.984	0.358	0.970	**0.069**	0.963	**0.073**
MOOS4,Gastwirth	0.974	0.136	0.934	**0.025**	0.977	0.291	0.970	**0.087**	0.968	**0.080**
MOOS4,5-Quantile	0.962	**0.024**	0.941	**0.025**	0.985	0.365	0.964	**0.037**	0.951	**0.035**
MOOS4,99-Quantile	0.956	**0.015**	0.931	**0.018**	0.978	0.312	0.948	**0.018**	0.929	**0.009**
MAIC5,Linear	0.991	**0.019**	1.020	**0.073**	1.043	**0.028**	0.974	0.130	0.964	**0.031**
MAIC5,Trimean	1.018	**0.091**	0.982	**0.043**	1.025	**0.042**	0.997	0.108	0.986	**0.038**
MAIC5,Gastwirth	1.024	**0.091**	0.977	**0.053**	1.019	**0.065**	0.996	0.131	0.986	**0.037**
MAIC5,5-Quantile	1.011	**0.080**	0.979	**0.034**	1.032	**0.047**	0.988	0.111	0.979	**0.036**
MAIC5,99-Quantile	1.004	**0.016**	0.971	**0.033**	1.021	**0.064**	0.972	0.102	0.962	**0.027**
MBIC5,Linear	0.965	0.356	0.977	0.117	1.008	**0.054**	0.963	0.141	0.946	**0.022**

Table 10: RMSE Ratios, benchmark: Baseline Model, eq. (6) *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval	Ratio	CW pval
MBIC5,Trimean	0.973	0.189	0.946	**0.050**	1.004	**0.084**	0.968	0.113	0.974	**0.026**
MBIC5,Gastwirth	0.981	0.188	0.945	**0.056**	0.992	0.100	0.966	0.147	0.981	**0.028**
MBIC5,5-Quantile	0.971	0.160	0.946	**0.036**	1.013	**0.092**	0.964	0.115	0.971	**0.025**
MBIC5,99-Quantile	0.970	**0.019**	0.940	**0.035**	1.006	0.105	0.959	0.109	0.961	**0.021**
MOOS5,Linear	0.979	**0.004**	0.965	**0.024**	0.964	**0.054**	0.952	**0.046**	0.928	**0.010**
MOOS5,Trimean	0.988	0.172	0.985	0.169	0.977	0.150	0.972	**0.065**	0.951	**0.017**
MOOS5,Gastwirth	0.989	0.198	0.983	0.187	0.977	0.135	0.972	**0.062**	0.955	**0.019**
MOOS5,5-Quantile	0.984	**0.089**	0.978	**0.064**	0.973	0.119	0.968	**0.053**	0.943	**0.011**
MOOS5,99-Quantile	0.976	**0.006**	0.961	**0.021**	0.965	**0.084**	0.955	**0.045**	0.926	**0.007**
MAIC6,Linear	1.000	**0.017**	0.965	**0.068**	0.969	**0.028**	1.038	0.130	0.946	**0.038**
MAIC6,Trimean	0.995	**0.083**	0.973	**0.042**	0.981	**0.023**	0.993	0.105	0.934	**0.041**
MAIC6,Gastwirth	0.996	**0.086**	0.979	**0.055**	0.984	**0.031**	1.005	0.128	0.945	**0.043**
MAIC6,5-Quantile	0.993	**0.072**	0.964	**0.034**	0.984	**0.031**	0.996	0.111	0.929	**0.038**
MAIC6,99-Quantile	0.982	**0.018**	0.946	**0.033**	0.994	**0.049**	0.997	0.104	0.921	**0.031**
MBIC6,Linear	1.003	0.320	0.961	0.102	0.962	**0.046**	1.041	0.147	0.962	**0.034**
MBIC6,Trimean	0.998	0.218	0.976	**0.056**	0.969	**0.044**	0.992	0.109	0.943	**0.030**
MBIC6,Gastwirth	1.002	0.279	0.985	**0.084**	0.964	**0.051**	1.007	0.146	0.956	**0.034**
MBIC6,5-Quantile	0.995	0.168	0.965	**0.038**	0.974	**0.058**	0.997	0.115	0.938	**0.029**
MBIC6,99-Quantile	0.983	**0.025**	0.947	**0.036**	0.983	**0.077**	1.000	0.113	0.930	**0.026**
MOOS6,Linear	0.974	**0.003**	0.956	**0.022**	0.959	**0.048**	0.951	**0.050**	0.922	**0.015**
MOOS6,Trimean	0.980	**0.070**	0.980	0.110	0.971	0.105	0.967	**0.071**	0.940	**0.016**
MOOS6,Gastwirth	0.982	**0.095**	0.981	0.159	0.970	0.100	0.964	**0.062**	0.945	**0.020**
MOOS6,5-Quantile	0.977	**0.036**	0.972	**0.042**	0.967	**0.089**	0.965	**0.064**	0.933	**0.012**
MOOS6,99-Quantile	0.969	**0.006**	0.955	**0.022**	0.959	**0.073**	0.954	**0.057**	0.917	**0.009**

Table 11: Average Check Function Ratios, Naïve benchmark

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
M1,0.05	1.183	0.435	1.023	**0.047**	1.000	**0.098**	1.274	**0.032**	1.951	0.662
M1,0.25	0.919	**0.005**	0.864	**0.040**	1.067	**0.078**	0.962	**0.003**	1.073	**0.043**
M1,0.50	1.033	**0.050**	0.880	**0.001**	0.939	**0.011**	1.057	**0.056**	1.026	**0.049**
M1,0.75	1.223	0.728	1.144	0.177	0.989	0.166	1.020	0.166	1.001	**0.011**
M1,0.95	1.561	0.563	3.318	0.480	2.229	0.245	1.492	**0.063**	1.031	**0.023**
M2,0.05	0.904	**0.064**	1.061	0.344	1.068	0.712	0.995	0.402	0.996	**0.072**
M2,0.25	0.919	**0.014**	0.911	**0.002**	0.978	0.134	0.976	**0.069**	0.952	**0.045**
M2,0.50	0.941	**0.019**	0.989	0.298	1.005	0.176	1.058	0.946	1.029	0.897

Table 11: Average Check Function Ratios, Naïve benchmark *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
M2,0.75	1.010	0.623	1.035	0.954	1.015	0.431	1.006	0.353	1.046	0.933
M2,0.95	1.056	**0.095**	0.962	0.135	1.039	0.340	1.041	0.777	0.999	0.463
M3,0.05	1.011	**0.037**	1.067	0.446	1.024	0.465	1.002	**0.075**	1.144	**0.094**
M3,0.25	0.974	**0.002**	0.963	**0.013**	0.996	0.219	0.999	0.175	0.978	**0.007**
M3,0.50	0.990	0.159	0.994	0.179	0.937	**0.011**	0.987	**0.026**	1.003	0.328
M3,0.75	1.058	0.223	1.037	0.707	1.004	0.368	0.965	**0.018**	0.976	**0.043**
M3,0.95	1.024	0.192	1.060	0.492	1.309	0.263	1.051	**0.074**	1.044	0.861
M4,0.05	1.653	**0.064**	1.226	0.135	1.316	0.464	1.279	0.118	1.266	**0.036**
M4,0.25	1.058	**0.048**	1.005	**0.064**	1.067	0.346	1.078	0.476	1.002	0.158
M4,0.50	1.021	**0.059**	1.087	0.752	1.071	0.128	1.087	0.599	1.070	0.932
M4,0.75	1.043	0.110	1.113	0.758	1.035	0.127	1.035	0.476	1.008	0.358
M4,0.95	1.199	0.172	2.078	0.530	1.209	0.215	1.029	0.262	1.024	0.828
M5,0.05	1.258	0.306	1.213	0.150	0.998	0.114	1.121	**0.079**	1.178	0.113
M5,0.25	1.062	**0.016**	0.980	**0.006**	0.999	**0.017**	0.960	**0.004**	0.885	**0.004**
M5,0.50	1.050	0.431	0.998	**0.049**	1.039	0.170	0.992	**0.002**	0.979	**0.000**
M5,0.75	1.044	**0.025**	1.139	0.416	1.065	0.441	0.983	**0.090**	0.965	**0.018**
M5,0.95	1.406	**0.083**	1.795	0.910	2.020	0.730	1.160	0.125	0.948	**0.004**
M6,0.05	1.225	0.948	1.087	0.714	1.239	0.828	1.045	0.414	1.076	0.506
M6,0.25	1.048	0.239	1.034	0.509	1.101	0.958	1.061	0.769	1.038	0.829
M6,0.50	0.973	**0.011**	1.031	0.575	1.030	0.393	1.046	0.735	1.016	0.351
M6,0.75	0.997	0.408	1.036	0.334	1.051	0.812	1.005	0.299	1.010	0.344
M6,0.95	1.135	**0.057**	0.983	**0.082**	1.061	0.821	1.041	0.586	1.015	0.573
M7,0.05	0.959	**0.045**	1.115	0.546	1.057	0.129	0.995	0.168	1.132	0.579
M7,0.25	1.016	0.471	1.028	0.216	1.012	0.533	0.970	**0.051**	1.001	0.158
M7,0.50	1.038	0.313	1.041	0.461	1.033	0.533	1.030	0.639	1.022	0.693
M7,0.75	1.006	0.483	1.001	0.398	1.020	0.356	1.026	0.937	1.058	0.865
M7,0.95	0.908	**0.033**	1.013	**0.062**	1.046	0.106	1.026	0.690	1.038	0.498
M8,0.05	0.977	0.232	0.952	**0.047**	0.841	**0.058**	1.047	**0.055**	1.208	0.148
M8,0.25	1.000	**0.002**	0.932	**0.029**	0.951	**0.054**	0.941	**0.004**	1.023	0.138
M8,0.50	0.929	**0.021**	1.046	**0.091**	0.905	**0.019**	0.932	**0.006**	0.965	**0.007**
M8,0.75	1.064	0.510	0.969	**0.029**	0.960	**0.068**	0.995	0.187	0.981	**0.001**
M8,0.95	1.179	**0.056**	0.882	**0.040**	1.075	**0.044**	1.265	0.515	0.941	**0.001**
M9,0.05	1.119	0.772	1.150	0.486	1.125	0.975	1.003	0.161	1.331	0.915
M9,0.25	1.021	0.247	1.036	0.767	1.015	0.613	1.079	0.582	1.066	0.544
M9,0.50	1.010	0.386	1.036	0.724	1.021	0.394	1.037	0.404	1.036	0.205
M9,0.75	1.037	0.581	1.059	0.798	0.963	**0.088**	1.029	0.262	0.992	**0.022**
M9,0.95	1.104	0.210	0.933	**0.020**	1.105	**0.085**	1.349	0.407	1.031	0.107

Table 11: Average Check Function Ratios, Naïve benchmark *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
M10,0.05	1.038	0.351	0.966	0.291	1.140	0.880	1.032	0.339	1.133	0.288
M10,0.25	1.014	0.341	1.042	0.774	1.004	0.434	0.983	**0.072**	0.955	**0.047**
M10,0.50	1.007	0.301	1.029	0.846	0.982	**0.008**	1.002	0.152	0.951	**0.004**
M10,0.75	1.033	0.943	1.042	0.782	1.016	0.480	0.964	**0.019**	1.004	**0.003**
M10,0.95	1.229	0.211	1.223	0.301	1.148	**0.085**	1.046	**0.000**	1.072	0.619
M11,0.05	1.085	0.447	0.968	**0.059**	0.685	**0.010**	0.986	**0.011**	1.036	**0.042**
M11,0.25	1.044	**0.095**	1.026	0.151	0.998	**0.061**	0.952	**0.033**	0.913	**0.034**
M11,0.50	1.000	0.134	1.072	0.417	0.977	**0.038**	0.942	**0.071**	0.918	**0.003**
M11,0.75	1.056	0.182	0.969	**0.043**	1.006	0.161	1.098	**0.062**	0.919	**0.001**
M11,0.95	1.179	0.663	1.009	0.109	1.131	0.512	1.404	**0.000**	1.028	**0.008**
M12,0.05	1.035	0.630	0.956	0.123	1.004	0.462	0.883	**0.012**	1.261	0.535
M12,0.25	0.996	**0.076**	0.981	**0.063**	0.960	**0.052**	0.929	**0.015**	0.996	0.130
M12,0.50	1.009	0.549	1.014	0.436	0.993	**0.021**	0.986	**0.055**	0.953	**0.036**
M12,0.75	1.024	0.876	1.008	0.347	0.957	**0.027**	0.972	**0.013**	0.948	**0.052**
M12,0.95	1.065	0.338	1.050	**0.018**	1.106	0.394	0.949	**0.000**	0.925	**0.000**
M13,0.05	1.001	0.503	1.120	0.657	1.086	0.713	1.125	0.478	1.190	0.392
M13,0.25	1.011	**0.097**	1.043	0.381	1.018	0.638	1.021	0.794	1.017	0.448
M13,0.50	0.989	0.136	1.001	0.205	1.046	0.985	1.019	0.578	1.017	0.204
M13,0.75	0.994	0.311	1.035	0.870	1.004	0.433	1.012	0.374	0.955	**0.014**
M13,0.95	0.873	**0.062**	0.953	0.266	0.930	0.100	1.065	0.812	0.989	0.125
MAIC1,0.05	1.183	0.435	1.023	**0.047**	0.976	0.103	1.300	**0.031**	1.951	0.662
MAIC1,0.25	0.904	**0.003**	0.858	**0.042**	1.031	**0.039**	0.953	**0.002**	1.049	**0.033**
MAIC1,0.50	1.025	0.163	0.939	**0.001**	0.951	**0.011**	1.074	0.117	1.023	**0.051**
MAIC1,0.75	1.160	0.855	1.129	0.465	0.948	0.110	1.026	0.193	0.993	**0.006**
MAIC1,0.95	1.399	0.435	3.168	0.527	1.843	0.162	1.506	**0.063**	1.031	**0.023**
MBIC1,0.05	1.105	0.513	1.000	**0.037**	1.002	0.109	1.264	**0.019**	1.725	0.152
MBIC1,0.25	0.960	**0.006**	0.979	0.162	1.059	**0.050**	0.998	**0.046**	1.050	**0.044**
MBIC1,0.50	0.977	**0.068**	1.023	0.244	1.037	**0.080**	0.998	**0.043**	0.975	**0.008**
MBIC1,0.75	1.053	0.628	1.059	0.558	0.992	0.189	1.016	0.217	0.887	**0.001**
MBIC1,0.95	1.297	0.318	1.012	**0.089**	1.826	**0.085**	1.485	**0.031**	1.020	**0.020**
MOOS1,0.05	1.118	0.876	0.980	**0.072**	1.316	0.826	1.022	0.193	1.115	0.224
MOOS1,0.25	0.970	0.132	1.016	**0.034**	1.084	0.486	0.942	**0.001**	0.895	**0.001**
MOOS1,0.50	0.986	**0.027**	0.956	**0.061**	0.961	0.131	0.934	**0.005**	0.949	**0.017**
MOOS1,0.75	0.955	**0.003**	0.843	**0.002**	0.929	**0.003**	0.935	**0.010**	0.858	**0.026**
MOOS1,0.95	0.835	**0.045**	0.717	**0.011**	0.681	**0.028**	0.815	**0.004**	0.686	**0.031**
MAIC2,0.05	1.183	0.435	1.023	**0.047**	0.976	0.103	1.300	**0.031**	1.951	0.662

Table 11: Average Check Function Ratios, Naïve benchmark *(continued)*

	$h = 1$		$h = 2$		$h = 4$		$h = 6$		$h = 8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
MAIC2,0.25	0.911	**0.003**	0.859	**0.043**	1.023	**0.032**	0.953	**0.002**	1.049	**0.033**
MAIC2,0.50	1.035	0.178	0.936	**0.001**	0.942	**0.011**	1.076	0.121	1.027	**0.056**
MAIC2,0.75	1.155	0.852	1.117	0.389	0.948	0.109	1.029	0.201	0.993	**0.006**
MAIC2,0.95	1.399	0.435	3.174	0.527	1.843	0.162	1.506	**0.063**	1.031	**0.023**
MBIC2,0.05	1.100	0.491	1.001	**0.037**	0.998	0.106	1.270	**0.023**	1.872	0.395
MBIC2,0.25	0.951	**0.002**	0.981	0.197	1.046	**0.043**	0.998	**0.045**	1.051	**0.045**
MBIC2,0.50	0.969	**0.080**	0.983	**0.036**	1.012	0.101	1.002	**0.048**	0.988	**0.014**
MBIC2,0.75	1.030	0.798	0.993	0.240	0.979	0.184	1.045	0.254	0.892	**0.001**
MBIC2,0.95	1.392	0.479	0.992	**0.068**	1.826	**0.085**	1.531	**0.052**	1.020	**0.020**
MOOS2,0.05	1.145	0.830	0.975	**0.071**	1.379	0.872	1.082	0.225	1.121	0.198
MOOS2,0.25	0.931	**0.053**	0.966	**0.002**	1.110	0.627	0.956	**0.001**	0.909	**0.002**
MOOS2,0.50	0.983	**0.033**	0.931	**0.015**	0.973	**0.097**	0.952	**0.011**	0.978	**0.061**
MOOS2,0.75	0.981	**0.006**	0.877	**0.003**	0.960	**0.007**	0.932	**0.012**	0.888	**0.046**
MOOS2,0.95	0.841	**0.066**	0.831	**0.016**	0.768	**0.058**	0.857	**0.017**	0.704	**0.043**
MAIC3,0.05	1.183	0.435	1.023	**0.047**	0.994	0.100	1.274	**0.032**	1.951	0.662
MAIC3,0.25	0.904	**0.003**	0.860	**0.037**	1.035	**0.048**	0.960	**0.002**	1.073	**0.043**
MAIC3,0.50	1.036	0.192	0.922	**0.000**	0.951	**0.011**	1.058	**0.057**	1.026	**0.049**
MAIC3,0.75	1.191	0.856	1.162	0.321	0.961	**0.097**	1.019	0.166	1.001	**0.011**
MAIC3,0.95	1.552	0.479	3.312	0.472	2.224	0.235	1.493	**0.048**	1.031	**0.023**
MBIC3,0.05	1.106	0.516	1.023	**0.047**	1.041	0.164	1.273	**0.032**	1.877	0.623
MBIC3,0.25	0.957	**0.005**	0.950	**0.078**	1.036	**0.035**	0.922	**0.000**	1.055	**0.022**
MBIC3,0.50	0.977	**0.059**	1.004	0.196	1.037	**0.093**	1.040	**0.052**	1.027	**0.047**
MBIC3,0.75	1.126	0.236	1.157	0.700	0.968	0.110	0.996	0.211	1.025	**0.059**
MBIC3,0.95	1.279	0.436	2.785	0.165	2.003	0.109	1.531	**0.098**	1.031	**0.023**
MOOS3,0.05	1.145	0.830	0.975	**0.071**	1.379	0.872	1.082	0.225	1.121	0.198
MOOS3,0.25	0.931	**0.053**	0.966	**0.002**	1.110	0.627	0.956	**0.001**	0.909	**0.002**
MOOS3,0.50	0.983	**0.033**	0.931	**0.015**	0.973	**0.097**	0.952	**0.011**	0.978	**0.061**
MOOS3,0.75	0.981	**0.006**	0.877	**0.003**	0.960	**0.007**	0.932	**0.012**	0.888	**0.046**
MOOS3,0.95	0.841	**0.066**	0.831	**0.016**	0.768	**0.058**	0.857	**0.017**	0.704	**0.043**
MAIC4,0.05	1.183	0.435	1.023	**0.047**	0.994	0.100	1.274	**0.032**	1.951	0.662
MAIC4,0.25	0.911	**0.003**	0.862	**0.038**	1.027	**0.042**	0.960	**0.002**	1.073	**0.043**
MAIC4,0.50	1.052	0.217	0.912	**0.000**	0.941	**0.011**	1.057	**0.056**	1.026	**0.049**
MAIC4,0.75	1.183	0.858	1.167	0.312	0.961	**0.096**	1.019	0.166	1.001	**0.011**
MAIC4,0.95	1.553	0.481	3.316	0.477	2.224	0.235	1.493	**0.048**	1.031	**0.023**
MBIC4,0.05	1.101	0.494	1.023	**0.047**	1.044	0.169	1.273	**0.032**	1.978	0.733
MBIC4,0.25	0.947	**0.001**	0.930	**0.003**	1.026	**0.054**	0.923	**0.000**	1.069	**0.032**
MBIC4,0.50	0.967	**0.055**	0.946	**0.004**	1.011	0.162	1.005	**0.015**	1.021	**0.041**

Table 11: Average Check Function Ratios, Naïve benchmark *(continued)*

	$h = 1$		$h = 2$		$h = 4$		$h = 6$		$h = 8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
MBIC4,0.75	1.009	0.414	1.057	0.520	0.966	0.116	0.996	0.181	1.014	**0.035**
MBIC4,0.95	1.200	0.445	3.018	0.325	2.060	0.110	1.531	**0.098**	1.031	**0.023**
MOOS4,0.05	1.071	0.684	0.931	**0.026**	1.361	0.828	1.115	0.262	1.141	0.180
MOOS4,0.25	0.930	**0.015**	0.941	**0.001**	1.077	0.406	0.925	**0.000**	0.873	**0.002**
MOOS4,0.50	0.992	**0.039**	0.899	**0.003**	0.948	**0.041**	0.945	**0.006**	0.976	**0.034**
MOOS4,0.75	0.966	**0.003**	0.863	**0.004**	0.930	**0.003**	0.925	**0.008**	0.875	**0.029**
MOOS4,0.95	0.867	0.122	0.918	**0.046**	0.795	**0.061**	0.843	**0.011**	0.678	**0.032**
MAIC5,0.05	0.980	0.289	1.148	0.347	0.820	**0.044**	1.085	**0.033**	1.104	0.107
MAIC5,0.25	0.994	**0.020**	0.992	0.338	1.029	0.182	0.978	**0.065**	1.024	0.116
MAIC5,0.50	0.941	**0.044**	1.029	**0.091**	0.944	**0.042**	1.015	0.176	0.976	**0.006**
MAIC5,0.75	1.083	0.800	0.924	**0.017**	0.997	0.136	1.042	**0.047**	0.891	**0.000**
MAIC5,0.95	1.206	0.154	0.977	**0.080**	1.115	**0.030**	1.269	**0.000**	0.984	**0.000**
MBIC5,0.05	0.941	0.170	1.164	0.369	0.832	**0.049**	1.113	**0.042**	1.085	**0.084**
MBIC5,0.25	0.994	**0.067**	1.002	0.388	1.067	0.330	0.977	**0.065**	0.997	**0.083**
MBIC5,0.50	0.969	**0.059**	1.017	0.180	0.963	**0.062**	0.986	0.150	0.937	**0.003**
MBIC5,0.75	1.048	0.927	0.989	0.279	0.998	**0.077**	1.037	**0.065**	0.872	**0.000**
MBIC5,0.95	1.218	0.187	0.989	**0.087**	1.129	**0.020**	1.131	**0.000**	0.955	**0.001**
MOOS5,0.05	1.103	0.867	1.039	0.206	1.291	0.765	1.011	0.184	1.133	0.259
MOOS5,0.25	1.023	0.362	1.072	0.235	1.071	0.374	0.944	**0.002**	0.893	**0.002**
MOOS5,0.50	0.997	**0.034**	0.994	0.187	0.963	0.168	0.931	**0.005**	0.932	**0.008**
MOOS5,0.75	0.938	**0.005**	0.827	**0.002**	0.908	**0.004**	0.945	**0.009**	0.836	**0.016**
MOOS5,0.95	0.833	**0.037**	0.651	**0.013**	0.644	**0.017**	0.812	**0.001**	0.672	**0.025**
MAIC6,0.05	1.036	0.435	1.149	0.350	0.820	**0.044**	1.080	**0.031**	1.133	0.128
MAIC6,0.25	1.004	**0.037**	0.992	0.338	1.010	**0.099**	0.978	**0.065**	1.032	0.127
MAIC6,0.50	0.938	**0.044**	1.032	**0.099**	0.935	**0.033**	1.020	0.182	0.989	**0.006**
MAIC6,0.75	1.084	0.784	0.923	**0.015**	0.996	0.127	1.061	**0.065**	0.896	**0.000**
MAIC6,0.95	1.217	0.169	0.970	**0.072**	1.114	**0.029**	1.312	**0.000**	0.982	**0.001**
MBIC6,0.05	1.003	0.329	1.161	0.379	0.832	**0.049**	1.090	**0.027**	1.143	0.119
MBIC6,0.25	1.039	0.412	1.000	0.376	1.040	0.190	0.980	**0.065**	1.004	**0.092**
MBIC6,0.50	0.982	0.149	1.027	0.232	0.952	**0.055**	1.008	0.186	0.967	**0.010**
MBIC6,0.75	1.057	0.892	0.978	0.184	1.026	0.245	1.065	**0.073**	0.900	**0.000**
MBIC6,0.95	1.281	0.319	0.963	**0.064**	1.146	**0.022**	1.306	**0.000**	0.954	**0.002**
MOOS6,0.05	1.094	0.781	1.014	0.159	1.249	0.698	0.995	0.180	1.103	0.192
MOOS6,0.25	1.017	0.312	1.065	0.197	1.074	0.357	0.946	**0.002**	0.877	**0.001**
MOOS6,0.50	0.991	**0.027**	0.999	0.224	0.958	0.151	0.925	**0.003**	0.924	**0.006**
MOOS6,0.75	0.940	**0.004**	0.817	**0.001**	0.914	**0.004**	0.946	**0.007**	0.832	**0.013**
MOOS6,0.95	0.870	**0.038**	0.645	**0.011**	0.684	**0.014**	0.854	**0.001**	0.667	**0.024**

Table 11: Average Check Function Ratios, Naïve benchmark *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval

Table 12: Average Check Function Ratios, benchmark: Baseline Model, eq. (7)

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
M1,0.05	1.437	0.480	1.136	**0.051**	1.395	0.455	1.507	0.758	2.281	0.599
M1,0.25	0.977	**0.005**	0.956	**0.001**	1.149	0.164	0.977	**0.010**	1.090	**0.008**
M1,0.50	1.064	**0.003**	0.872	**0.000**	0.921	**0.001**	1.011	**0.002**	1.034	**0.017**
M1,0.75	1.133	**0.062**	1.003	**0.024**	0.926	**0.000**	0.983	**0.002**	0.907	**0.007**
M1,0.95	1.494	0.325	2.675	0.723	1.650	**0.095**	1.325	0.306	0.783	**0.025**
M2,0.05	1.099	0.483	1.178	0.190	1.490	0.899	1.177	0.133	1.165	0.109
M2,0.25	0.978	**0.045**	1.009	**0.088**	1.053	0.293	0.992	**0.007**	0.967	**0.003**
M2,0.50	0.969	**0.008**	0.979	0.128	0.986	0.136	1.012	0.108	1.037	0.369
M2,0.75	0.936	**0.004**	0.907	**0.032**	0.951	**0.015**	0.970	**0.021**	0.948	0.120
M2,0.95	1.010	**0.095**	0.775	**0.029**	0.769	**0.022**	0.925	**0.048**	0.759	**0.050**
M3,0.05	1.229	0.249	1.185	0.220	1.429	0.908	1.184	**0.086**	1.338	0.319
M3,0.25	1.036	**0.035**	1.066	0.145	1.073	0.453	1.015	**0.005**	0.994	**0.013**
M3,0.50	1.019	**0.043**	0.985	0.131	0.919	**0.003**	0.944	**0.002**	1.011	**0.074**
M3,0.75	0.981	**0.003**	0.909	**0.007**	0.940	**0.004**	0.930	**0.007**	0.884	**0.018**
M3,0.95	0.980	0.101	0.854	**0.032**	0.969	0.154	0.933	**0.026**	0.793	**0.044**
M4,0.05	2.009	0.159	1.361	0.280	1.835	0.805	1.513	0.770	1.480	0.450
M4,0.25	1.126	0.324	1.112	0.132	1.149	0.398	1.095	**0.052**	1.019	**0.019**
M4,0.50	1.051	**0.024**	1.077	0.120	1.051	0.130	1.040	**0.097**	1.079	0.593
M4,0.75	0.967	**0.012**	0.976	**0.030**	0.969	**0.018**	0.998	**0.043**	0.913	**0.069**
M4,0.95	1.147	0.565	1.675	0.545	0.895	0.112	0.914	**0.028**	0.778	**0.052**
M5,0.05	1.530	0.582	1.347	0.274	1.391	0.500	1.326	0.253	1.378	**0.079**
M5,0.25	1.129	0.452	1.086	0.255	1.076	**0.036**	0.975	**0.000**	0.900	**0.002**
M5,0.50	1.081	0.318	0.988	**0.021**	1.019	**0.017**	0.949	**0.000**	0.986	**0.004**
M5,0.75	0.967	**0.002**	0.998	**0.059**	0.997	**0.029**	0.947	**0.002**	0.875	**0.001**
M5,0.95	1.345	0.653	1.447	0.904	1.496	0.688	1.030	**0.032**	0.720	**0.002**
M6,0.05	1.489	0.963	1.207	0.835	1.728	0.967	1.235	0.247	1.258	0.223
M6,0.25	1.115	0.515	1.145	0.257	1.186	0.783	1.078	**0.097**	1.055	**0.065**
M6,0.50	1.002	**0.013**	1.022	0.146	1.011	0.223	1.001	**0.032**	1.024	0.152
M6,0.75	0.924	**0.004**	0.908	**0.015**	0.984	**0.014**	0.969	**0.011**	0.915	**0.055**
M6,0.95	1.086	**0.052**	0.792	**0.072**	0.785	**0.077**	0.924	**0.004**	0.771	**0.036**
M7,0.05	1.165	0.358	1.238	0.646	1.475	0.698	1.176	0.188	1.323	0.465

Table 12: Average Check Function Ratios, benchmark: Baseline Modeleq. (7) *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
M7,0.25	1.080	0.447	1.138	0.342	1.090	0.395	0.985	**0.006**	1.017	**0.019**
M7,0.50	1.069	0.231	1.032	0.294	1.014	0.205	0.985	**0.008**	1.030	0.328
M7,0.75	0.932	**0.004**	0.877	**0.004**	0.956	**0.021**	0.989	**0.030**	0.958	0.133
M7,0.95	0.869	**0.011**	0.816	**0.026**	0.775	**0.042**	0.911	**0.024**	0.789	**0.073**
M8,0.05	1.187	0.366	1.057	0.110	1.173	0.522	1.238	0.354	1.412	0.675
M8,0.25	1.064	**0.073**	1.033	**0.030**	1.024	0.162	0.956	**0.000**	1.040	**0.023**
M8,0.50	0.957	**0.001**	1.036	0.115	0.888	**0.020**	0.892	**0.000**	0.972	**0.034**
M8,0.75	0.986	**0.007**	0.849	**0.006**	0.899	**0.001**	0.960	**0.012**	0.889	**0.006**
M8,0.95	1.129	0.170	0.711	**0.030**	0.796	**0.005**	1.124	**0.010**	0.715	**0.020**
M9,0.05	1.361	0.886	1.277	0.568	1.569	0.928	1.186	0.195	1.556	0.249
M9,0.25	1.086	0.513	1.148	0.407	1.093	0.518	1.096	**0.099**	1.083	**0.099**
M9,0.50	1.041	**0.036**	1.026	0.264	1.002	0.147	0.991	**0.032**	1.045	0.151
M9,0.75	0.961	**0.001**	0.928	**0.015**	0.902	**0.012**	0.992	**0.010**	0.899	**0.040**
M9,0.95	1.056	0.134	0.752	**0.014**	0.818	**0.015**	1.198	**0.067**	0.784	**0.059**
M10,0.05	1.262	0.447	1.072	0.237	1.590	0.888	1.220	0.198	1.325	0.205
M10,0.25	1.079	0.547	1.154	0.525	1.081	0.398	0.998	**0.007**	0.970	**0.007**
M10,0.50	1.037	0.123	1.019	0.264	0.964	**0.061**	0.958	**0.002**	0.958	**0.017**
M10,0.75	0.957	**0.009**	0.913	**0.018**	0.952	**0.003**	0.929	**0.000**	0.910	**0.007**
M10,0.95	1.176	0.242	0.986	**0.052**	0.850	**0.032**	0.929	**0.006**	0.814	**0.007**
M11,0.05	1.319	0.827	1.074	**0.071**	0.955	0.117	1.166	0.117	1.211	**0.049**
M11,0.25	1.110	0.381	1.136	0.175	1.075	**0.044**	0.967	**0.019**	0.928	**0.007**
M11,0.50	1.030	**0.005**	1.062	0.144	0.959	**0.052**	0.901	**0.012**	0.925	**0.005**
M11,0.75	0.978	**0.001**	0.849	**0.000**	0.942	**0.000**	1.058	**0.001**	0.833	**0.002**
M11,0.95	1.128	0.197	0.814	**0.019**	0.837	**0.036**	1.247	0.145	0.781	**0.003**
M12,0.05	1.258	0.885	1.062	0.402	1.401	0.867	1.044	0.180	1.474	0.452
M12,0.25	1.059	0.526	1.086	0.290	1.034	**0.057**	0.944	**0.002**	1.012	**0.037**
M12,0.50	1.040	**0.043**	1.004	0.151	0.975	**0.067**	0.943	**0.010**	0.960	**0.015**
M12,0.75	0.949	**0.005**	0.883	**0.010**	0.897	**0.003**	0.936	**0.002**	0.859	**0.013**
M12,0.95	1.019	0.176	0.846	**0.010**	0.819	**0.023**	0.843	**0.000**	0.703	**0.013**
M13,0.05	1.216	0.821	1.243	0.721	1.515	0.919	1.330	0.205	1.392	0.618
M13,0.25	1.076	0.539	1.155	0.486	1.097	0.679	1.037	**0.054**	1.033	**0.084**
M13,0.50	1.018	**0.030**	0.991	**0.089**	1.026	0.209	0.974	**0.011**	1.025	0.150
M13,0.75	0.921	**0.003**	0.907	**0.023**	0.941	**0.006**	0.975	**0.017**	0.866	**0.023**
M13,0.95	0.835	**0.027**	0.769	**0.046**	0.688	**0.031**	0.946	**0.020**	0.752	**0.028**
MAIC1,0.05	1.437	0.480	1.136	**0.051**	1.361	0.470	1.537	0.754	2.281	0.599
MAIC1,0.25	0.962	**0.004**	0.950	**0.001**	1.111	**0.092**	0.968	**0.009**	1.066	**0.009**
MAIC1,0.50	1.056	**0.006**	0.931	**0.001**	0.933	**0.002**	1.027	**0.003**	1.031	**0.016**

Table 12: Average Check Function Ratios, benchmark: Baseline Modeleq. (7) *(continued)*

	$h=1$		$h=2$		$h=4$		$h=6$		$h=8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
MAIC1,0.75	1.075	**0.027**	0.990	**0.035**	0.888	**0.000**	0.989	**0.002**	0.900	**0.006**
MAIC1,0.95	1.339	0.344	2.554	0.748	1.364	**0.044**	1.338	0.306	0.783	**0.025**
MBIC1,0.05	1.343	0.493	1.110	**0.050**	1.398	0.595	1.495	0.736	2.016	0.231
MBIC1,0.25	1.021	**0.055**	1.084	**0.038**	1.141	0.124	1.014	**0.008**	1.067	**0.010**
MBIC1,0.50	1.006	**0.006**	1.014	**0.049**	1.018	**0.043**	0.955	**0.002**	0.983	**0.006**
MBIC1,0.75	0.976	**0.003**	0.928	**0.006**	0.929	**0.000**	0.979	**0.004**	0.804	**0.000**
MBIC1,0.95	1.241	0.538	0.816	**0.038**	1.351	**0.039**	1.319	0.213	0.775	**0.023**
MOOS1,0.05	0.955	0.202	0.874	**0.043**	0.910	0.136	0.892	**0.018**	1.007	0.135
MOOS1,0.25	0.917	**0.003**	0.914	**0.024**	0.970	**0.061**	0.930	**0.000**	0.930	**0.026**
MOOS1,0.50	0.955	**0.007**	0.963	**0.046**	0.954	**0.006**	0.950	**0.003**	0.931	**0.000**
MOOS1,0.75	1.019	0.259	0.994	0.333	0.991	0.326	0.959	**0.005**	0.942	**0.000**
MOOS1,0.95	0.920	**0.063**	1.004	**0.095**	0.961	**0.006**	0.933	**0.004**	0.905	**0.002**
MAIC2,0.05	1.437	0.480	1.136	**0.051**	1.361	0.470	1.537	0.754	2.281	0.599
MAIC2,0.25	0.969	**0.005**	0.952	**0.001**	1.102	**0.076**	0.968	**0.009**	1.066	**0.009**
MAIC2,0.50	1.066	**0.009**	0.928	**0.000**	0.924	**0.002**	1.029	**0.002**	1.035	**0.018**
MAIC2,0.75	1.070	**0.023**	0.979	**0.028**	0.888	**0.000**	0.991	**0.003**	0.900	**0.006**
MAIC2,0.95	1.339	0.344	2.559	0.747	1.364	**0.044**	1.338	0.306	0.783	**0.025**
MBIC2,0.05	1.337	0.483	1.111	**0.050**	1.393	0.584	1.502	0.741	2.188	0.398
MBIC2,0.25	1.012	**0.026**	1.086	0.126	1.127	**0.091**	1.013	**0.008**	1.069	**0.009**
MBIC2,0.50	0.998	**0.013**	0.974	**0.025**	0.993	**0.033**	0.958	**0.001**	0.996	**0.010**
MBIC2,0.75	0.954	**0.003**	0.871	**0.004**	0.917	**0.000**	1.007	**0.003**	0.809	**0.000**
MBIC2,0.95	1.332	0.650	0.800	**0.026**	1.351	**0.039**	1.360	0.247	0.775	**0.023**
MOOS2,0.05	0.915	0.118	0.860	**0.016**	0.888	**0.080**	0.884	**0.020**	0.989	**0.083**
MOOS2,0.25	0.906	**0.001**	0.905	**0.006**	0.955	**0.017**	0.918	**0.000**	0.900	**0.014**
MOOS2,0.50	0.951	**0.009**	0.949	**0.024**	0.939	**0.001**	0.941	**0.003**	0.920	**0.000**
MOOS2,0.75	1.013	0.190	0.974	0.160	0.979	0.212	0.955	**0.012**	0.930	**0.000**
MOOS2,0.95	0.938	**0.064**	1.026	0.147	0.992	**0.001**	0.957	**0.001**	0.882	**0.003**
MAIC3,0.05	1.437	0.480	1.136	**0.051**	1.387	0.464	1.507	0.758	2.281	0.599
MAIC3,0.25	0.961	**0.004**	0.953	**0.001**	1.115	0.105	0.975	**0.006**	1.090	**0.008**
MAIC3,0.50	1.067	**0.003**	0.913	**0.000**	0.933	**0.002**	1.012	**0.003**	1.034	**0.017**
MAIC3,0.75	1.104	**0.081**	1.018	**0.033**	0.900	**0.000**	0.982	**0.002**	0.908	**0.007**
MAIC3,0.95	1.485	0.350	2.670	0.720	1.646	**0.094**	1.326	0.284	0.783	**0.025**
MBIC3,0.05	1.345	0.494	1.135	**0.051**	1.452	0.578	1.505	0.755	2.194	0.463
MBIC3,0.25	1.018	**0.049**	1.052	**0.014**	1.116	0.140	0.937	**0.000**	1.073	**0.009**
MBIC3,0.50	1.006	**0.005**	0.994	**0.037**	1.018	**0.014**	0.995	**0.008**	1.035	**0.022**
MBIC3,0.75	1.043	0.116	1.014	**0.062**	0.906	**0.000**	0.960	**0.004**	0.929	**0.018**
MBIC3,0.95	1.224	0.365	2.245	0.738	1.483	**0.039**	1.360	0.344	0.783	**0.025**

Table 12: Average Check Function Ratios, benchmark: Baseline Modeleq. (7) *(continued)*

	$h = 1$		$h = 2$		$h = 4$		$h = 6$		$h = 8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
MOOS3,0.05	0.978	0.378	0.869	**0.091**	0.954	0.267	0.945	**0.055**	1.013	0.308
MOOS3,0.25	0.880	**0.011**	0.868	**0.039**	0.993	0.316	0.944	**0.002**	0.944	**0.049**
MOOS3,0.50	0.952	**0.032**	0.938	**0.028**	0.967	**0.063**	0.967	**0.013**	0.959	**0.015**
MOOS3,0.75	1.047	0.200	1.034	0.583	1.024	0.555	0.955	**0.000**	0.976	**0.013**
MOOS3,0.95	0.927	**0.098**	1.164	0.427	1.084	0.306	0.981	**0.099**	0.928	**0.054**
MAIC4,0.05	1.437	0.480	1.136	**0.051**	1.387	0.464	1.507	0.758	2.281	0.599
MAIC4,0.25	0.969	**0.005**	0.954	**0.001**	1.107	**0.089**	0.975	**0.006**	1.090	**0.008**
MAIC4,0.50	1.084	**0.006**	0.903	**0.000**	0.923	**0.001**	1.011	**0.002**	1.034	**0.017**
MAIC4,0.75	1.096	**0.063**	1.023	**0.036**	0.900	**0.000**	0.982	**0.002**	0.908	**0.007**
MAIC4,0.95	1.486	0.352	2.673	0.722	1.646	**0.094**	1.326	0.284	0.783	**0.025**
MBIC4,0.05	1.338	0.485	1.136	**0.051**	1.457	0.588	1.505	0.755	2.312	0.599
MBIC4,0.25	1.008	**0.023**	1.030	**0.030**	1.106	0.120	0.937	**0.000**	1.086	**0.008**
MBIC4,0.50	0.996	**0.009**	0.937	**0.004**	0.992	**0.018**	0.962	**0.002**	1.029	**0.017**
MBIC4,0.75	0.935	**0.001**	0.926	**0.033**	0.904	**0.001**	0.960	**0.003**	0.919	**0.014**
MBIC4,0.95	1.148	0.382	2.433	0.802	1.525	**0.039**	1.360	0.345	0.783	**0.025**
MOOS4,0.05	0.915	0.140	0.831	**0.047**	0.941	0.269	0.973	**0.067**	1.031	0.230
MOOS4,0.25	0.880	**0.002**	0.846	**0.008**	0.963	**0.038**	0.913	**0.001**	0.907	**0.012**
MOOS4,0.50	0.961	**0.030**	0.905	**0.006**	0.941	**0.008**	0.961	**0.010**	0.957	**0.018**
MOOS4,0.75	1.031	0.131	1.018	0.448	0.992	0.348	0.948	**0.003**	0.961	**0.005**
MOOS4,0.95	0.956	0.114	1.285	0.863	1.122	0.353	0.965	**0.049**	0.894	**0.023**
MAIC5,0.05	1.192	0.707	1.274	0.441	1.144	0.549	1.283	0.157	1.291	0.219
MAIC5,0.25	1.057	0.277	1.098	0.226	1.109	0.216	0.994	**0.024**	1.040	**0.030**
MAIC5,0.50	0.969	**0.002**	1.020	**0.066**	0.926	**0.066**	0.971	**0.027**	0.983	**0.021**
MAIC5,0.75	1.003	**0.009**	0.810	**0.003**	0.934	**0.001**	1.004	**0.001**	0.808	**0.000**
MAIC5,0.95	1.154	0.500	0.788	**0.029**	0.825	**0.005**	1.127	**0.019**	0.747	**0.002**
MBIC5,0.05	1.144	0.512	1.292	0.457	1.160	0.568	1.316	0.204	1.269	0.157
MBIC5,0.25	1.058	0.503	1.109	0.285	1.150	0.289	0.993	**0.034**	1.013	**0.020**
MBIC5,0.50	0.998	**0.016**	1.008	**0.090**	0.945	**0.092**	0.943	**0.024**	0.944	**0.009**
MBIC5,0.75	0.971	**0.006**	0.866	**0.003**	0.935	**0.001**	0.999	**0.002**	0.790	**0.000**
MBIC5,0.95	1.166	0.556	0.797	**0.034**	0.836	**0.008**	1.005	**0.018**	0.726	**0.004**
MOOS5,0.05	0.942	0.246	0.926	**0.058**	0.893	**0.028**	0.882	**0.012**	1.024	0.120
MOOS5,0.25	0.967	**0.007**	0.964	**0.013**	0.957	**0.029**	0.932	**0.001**	0.927	**0.039**
MOOS5,0.50	0.966	**0.011**	1.002	0.332	0.956	**0.003**	0.947	**0.020**	0.914	**0.000**
MOOS5,0.75	1.001	0.430	0.975	**0.085**	0.969	0.105	0.969	**0.039**	0.918	**0.000**
MOOS5,0.95	0.918	**0.032**	0.911	**0.023**	0.909	**0.025**	0.929	**0.000**	0.887	**0.000**
MAIC6,0.05	1.259	0.646	1.276	0.444	1.144	0.549	1.277	0.153	1.324	0.220

Table 12: Average Check Function Ratios, benchmark: Baseline Modeleq. (7) *(continued)*

	$h = 1$		$h = 2$		$h = 4$		$h = 6$		$h = 8$	
Models	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval	Ratio	GeLee pval
MAIC6,0.25	1.068	0.301	1.098	0.226	1.088	0.181	0.994	**0.024**	1.048	**0.029**
MAIC6,0.50	0.966	**0.002**	1.022	**0.068**	0.918	**0.054**	0.975	**0.028**	0.997	**0.024**
MAIC6,0.75	1.004	**0.009**	0.809	**0.003**	0.933	**0.001**	1.022	**0.001**	0.812	**0.001**
MAIC6,0.95	1.164	0.523	0.782	**0.024**	0.825	**0.005**	1.166	**0.018**	0.746	**0.002**
MBIC6,0.05	1.219	0.552	1.289	0.467	1.160	0.568	1.289	0.166	1.336	0.160
MBIC6,0.25	1.105	0.592	1.107	0.271	1.120	0.229	0.996	**0.034**	1.020	**0.017**
MBIC6,0.50	1.011	**0.022**	1.017	0.104	0.934	**0.075**	0.964	**0.026**	0.975	**0.023**
MBIC6,0.75	0.980	**0.006**	0.857	**0.002**	0.961	**0.002**	1.027	**0.001**	0.816	**0.001**
MBIC6,0.95	1.067	0.303	0.931	0.156	0.926	0.137	1.031	**-0.022**	0.847	**-0.004**
MOOS6,0.05	0.935	0.216	0.904	**0.047**	0.864	**0.008**	0.869	**0.019**	0.996	**0.070**
MOOS6,0.25	0.961	**0.011**	0.958	**0.013**	0.961	**0.045**	0.934	**0.002**	0.911	**0.039**
MOOS6,0.50	0.960	**0.009**	1.007	0.408	0.952	**0.003**	0.940	**0.024**	0.906	**0.000**
MOOS6,0.75	1.003	0.381	0.964	**0.050**	0.975	0.194	0.970	**0.052**	0.914	**0.000**
MOOS6,0.95	0.958	**0.029**	0.904	**0.019**	0.965	**0.016**	0.978	**0.000**	0.880	**0.000**