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Climate Risks and Forecastability of US Inflation: Evidence from Dynamic Quantile Model Averaging

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Abstract

This study examines the impact of climate-related risks on the inflation rates of the United States, focusing on the overall Consumer Price Index (CPI) and its significant components, namely food and beverages and housing inflation. Employing quantile regression models and a comprehensive dataset spanning from January 1985 to September 2022, we analyze five specific climate risk factors alongside traditional macroeconomic predictors. Our findings indicate that models incorporating individual climate risks generally outperform those considering only macroeconomic factors. However, models combination strategies that integrate all five climate risk measures consistently deliver superior forecasting performance. Notably, the pronounced effect of climate risks on food inflation significantly contributes to the observed trends in the overall CPI, which is largely driven by this subcomponent. This research highlights the crucial role of climate factors in forecasting inflation, suggesting potential avenues for enhancing economic policy-making in light of evolving climate conditions.

Keywords: Climate risks; US inflation; Dynamic quantile moving averaging; Forecasting

JEL Codes: C21, C22, C53, E31, Q54

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1. Introduction

Theoretically speaking, extreme weather conditions caused by global warming and climate change can impact the inflation of a country through both aggregate demand- and aggregate supply-side channels. On one hand, negative supply shocks, which operate through lower agricultural production, increased food prices, dampened economic activity, reduced labor productivity, and the destruction of transportation infrastructure along with increased distribution costs, are likely to cause an inflationary impact. On the other hand, adverse demand shocks, which tend to raise the risk aversion of economic agents and reduce consumption and investment even after fiscal support and reconstruction, are expected to lead to a reduction in inflation. Understandably, the final effect on inflation depends on the strength of these two shocks and remains an empirical issue. In this regard, the reader is referred to Faccia et al. (2021), Mukherjee and Ouattara (2021), Kabundi et al. (2022), Cevik and Jalles (2023), who report mixed findings at the international level for panels of developed and emerging countries. As far as the United States (US), the focus of our study, is concerned, barring Natoli et al. (2023) who report a decline in prices due to climate-related risks, studies have primarily indicated that such shocks are indeed inflationary due to a relatively stronger supply-side influence, impacting particularly via the food sector (see, for example, Laosuthi and Selover (2007), Cashin et al. (2017), Kim et al. (2022), Liao et al. (2024), Sheng et al. (forthcoming),).

While the importance of these structural in (full)-sample-based predictive analyses cannot be discounted, for design of appropriate monetary policy responses, what policymakers ideally need are out-of-sample forecasts of inflation, especially with the rising prices in the US being a concern since April, 2021 (Boneva and Ferrucci, 2022). Just as globally, damages due to the physical risks of climate change have become more apparent in terms of magnitude, more severe, and more frequent in the US (Mendelsohn et al., 2012; Stott, 2016), and such trends are expected to continue (Fifth National Climate Assessment (NCA5)[1]). Naturally, a question of paramount importance to ask would be: Is there a role of climate risks in forecasting US inflation, over and above its standard predictors?

In the context of forecasting US inflation, Atkeson and Ohanian (2001) demonstrate that even naïve random walk forecasts outperformed those derived from the Phillips curve, as noted by Stock and Watson (1999). Consequently, there emerged a body of literature that estimated models by utilizing the simultaneous or joint information contained in a large number of macroeconomic and financial variables. This was achieved through the extraction of a relatively small number of principal components (PCs), i.e., latent factors, individual predictors-based forecasts, and model combinations (both Bayesian and dynamic averaging), or through Bayesian shrinkage. Examples include works by Stock and Watson (2002, 2009), Wright (2009), Koop and Korobilis (2012), Faust and Wright (2013), Hauzenberger et al. (2023), and Clark et al. (forthcoming), among others cited therein. Simultaneously, to monitor the expected evolution of price dynamics, central banks rely not only on point forecasts but also on predictive densities. These densities help assess the tail risks of inflation, as shown by Kilian and Manganelli (2007) and Andrade et al. (2012), in addition to the uncertainty surrounding the future path of inflation. Given the need to forecast the entire conditional distribution of inflation, the role of quantile regressions has also gained prominence, as evidenced by Manzan and Zerom (2015), Korobilis (2017), Ghysels et al. (2018), Korobilis et al. (2021), and Pfarrhofer (2022).

[1] See: https://nca2023.globalchange.gov/.

Considering these two modeling issues, namely the importance of a large number of predictors and predictive densities, our paper investigates the role of climate-related risks—seasonal, predictable, and abnormal patterns of temperature, precipitation, heating degree days, cooling degree days, and wind speed—in forecasting the conditional distribution of US inflation. This is achieved by controlling for the information content of a large number of predictors (134) from the FRED-MD database (McCracken and Ng, 2016), summarized through 8 PCs. Specifically, for our objective, we utilize Quantile Autoregressive models with exogenous predictors (QAR-X) over the monthly period from January 1985 to September 2022. Moreover, we investigate not only the role of climate risks in forecasting the aggregate US inflation rate but also inflation associated with food and beverages, given its significance in driving overall inflation following extreme weather shocks, as suggested by the in-sample literature cited earlier. This observation should not be surprising, given that abnormal weather patterns would tend to have a major disruptive influence on agricultural production, which would then impact the aggregate CPI, with this sector carrying a weight of 14.4% in the CPI basket (US Bureau of Labor Statistics (BLS)).[2] At the same time, with housing comprising of 45.07% of the overall US CPI (BLS), we also consider the role of climate risks in forecasting inflation associated with this sub-index, which corresponds to the most dominant sector in defining overall inflation. Note that abnormal weather can lead to delays in construction projects, which, in turn, can decrease the supply of new housing in the short term, leading to upward pressure on prices if demand remains constant. Moreover, extreme weather conditions can increase the costs of construction materials and labor. For example, rebuilding efforts after a hurricane or flood can lead to a surge in demand for materials and labor, thus driving

[2] See: https://www.bls.gov/cpi/tables/relative-importance/2023.htm.

up costs. These increased costs can be passed on to buyers, contributing to housing inflation. In areas more prone to extreme weather, the cost of insurance can rise significantly, decreasing the affordability of housing, affecting demand and prices. Additionally, new regulations aimed at making housing more resilient to extreme weather can increase construction costs, which may be passed on to consumers, contributing to inflation. In other words, multiple channels through which climate risks can impact the most dominant component of overall CPI, i.e., housing, require close attention from the perspective of forecasting.

Furthermore, to account for model uncertainty, we employ the Dynamic Model Averaging (DMA) method, following Koop and Korobilis (2012), who employed it in forecasting US inflation rates, as well as five other dynamic model combination approaches (DQMA-I, DQMA-II, DQMA-Gods, DQMA-MSE, DQMA-Eq; which we describe in detail below), recently utilized by Cai et al. (2020) while forecasting quantiles of realized stock market volatility, i.e., Dynamic Quantile Model Averaging (DQMA). One must realize that although a large literature exists on strategies for combining forecasts, the combinations are usually derived under the mean squared error (MSE) loss or Bayesian frameworks designed mainly for mean regression models (see, for example, the survey papers by Chan and Pauwels (2018) and Steel (2020)), with dynamic forecast combination designed specifically for quantile estimators being a rarity. In this regard, while the DMA is non-quantile-specific, using the same weights for each quantile, the other five approaches utilized by us are indeed designed for dealing with our quantiles-based models. Note that the dynamic evolution of model combination weights also allows us to tackle the issue of structural changes in the relationship between the inflation rate and its predictors, as widely acknowledged in the aforementioned inflation forecasting literature, while utilizing time-varying parameter models (Stock and Watson, 2007; Bauwens et al., 2015; Hauzenberger et al., 2022).

The main findings of our paper highlight the critical role of climate-related risks in forecasting US inflation, particularly considering their impact on different subcomponents such as food and beverages and housing. Our results demonstrate that incorporating climate risk metrics generally improves forecasting accuracy across various quantiles of the inflation rate. However, no single model consistently outperforms others, indicating the importance of model combination strategies. Through DMA and five other dynamic model combination approaches (DQMA-I, DQMA-II, DQMA-Gods, DQMA-MSE, DQMA-Eq), we show that integrating diverse model outputs significantly enhances the stability and accuracy of quantile-based forecasting for US inflation rates. Moreover, dynamic model combination approaches highlight the relative significance of different climate risk predictors over time. Overall, our study contributes to the understanding of how climate risks impact inflation forecasting of the US. To the best of our knowledge, this is the first paper to forecast the overall US inflation rate and its two important sub-components based on the information content of climate risks, over and above other standard predictors, using DQMA.[3] In the process, we contribute to the vast existing literature on forecasting inflation from the perspective of the associated role of climate change, in an ever-changing environment, captured through quantiles-based model combination strategies. In this regard, specifically speaking, our study can be considered to build on the somewhat related work of Yeganegi et al. (2023), who produced accurate conditional mean forecasts of the US inflation (over medium- to long-run) based on the information

[3] We must point out that D'Ecclesia et al. (2022) highlighted the role of growth in CO_2 emissions in forecasting annual inflation of the US in a DMA-set-up, over and above other standard predictors used in this literature.

content of the El Niño Southern Oscillation (ENSO), measured by the Equatorial Southern Oscillation Index (EQSOI), using bivariate Singular Spectrum Analysis (SSA).

Our first contribution lies in providing a comprehensive measure of abnormal weather patterns that extend beyond the typical focus on temperature (Faccia et al, 2021, Lucidi et al. 2022). By considering a range of climate risks—including precipitation, heating and cooling degree days, and wind speed—we address a significant gap in the literature which often limits its scope to temperature impacts. This broader perspective on climate factors is crucial for a more accurate prediction of inflation, compared to those considering only traditional macroeconomic predictors (Manzan and Zerom, 2013; Mandalinci, 2017; Cepni and Clements, 2024). Additionally, by employing DQMA, our approach innovatively captures the distributional effects of climate risks on inflation. This methodology allows for dynamic adjustments based on evolving climate and economic conditions, offering a more robust and responsive modeling strategy than traditional methods. The effectiveness of DQMA in handling such complex model dynamics is particularly noted in works by Koop and Korobilis (2012), who underscore the utility of model averaging techniques in managing prediction uncertainty in macroeconomic forecasting.

The structure of the remainder of this paper is as follows: Section 2 details the dataset used in this study. Section 3 describes the econometric models, including the model combination strategies and forecast evaluation metrics. Section 4 presents the empirical results from the forecasting analysis. Finally, Section 5 concludes the paper.

2. Data

In this study, we first gather data on the Consumer Price Index (CPI) for All Urban Consumers: All Items in US City Average, along with data for the two sub-indexes: US CPI Urban Consumers Food & Beverages and US CPI Urban Consumers Housing. These indices are sourced from the FRED database of the Federal Reserve Bank of St. Louis. After collecting the data, we transform it to analyze the month-on-month growth rates. Furthermore, we collect monthly weather data for the US from the Bloomberg terminal, as compiled by the National Climatic Data Center (NCDC). The collected weather data encompasses various meteorological dimensions, such as temperature, precipitation, number of heating degree days (HDD), number of cooling degree days (CDD), and wind speed, as detailed below:

• Temperature ($Temp_t$): The average temperature (usually of the high and low) that was observed between 7am and 7pm local time, recorded in Fahrenheit.

• HDD (HDD_t): This measures the number of degrees that the day's average temperature falls below 65 degrees Fahrenheit, useful for assessing the heating demands of a building.

• CDD (CDD_t): The number of degrees that the day's average temperature exceeds 65 degrees Fahrenheit, used to estimate the cooling requirements of a building.

• Precipitation ($Prec_t$): The total amount of rain, snow, sleet, or hail that falls at a specific location.

• Wind speed ($Wind_t$): The average wind speed, excluding gusts, measured in knots.

Following the approach of Choi et al. (2020), we analyze these weather-related variables by decomposing them down into three components to account for seasonal, predictable, and abnormal patterns. Specifically, for each month t, we compute the monthly weather measure (W_t) for the overall US using the following formula: $W_t = W_t^A + W_t^M + W_t^{Ab}$, where $W_t = \{Temp_t, HDD_t, CDD_t, Prec_t, Wind_t\}$, and the term W_t^A represents the average of W_t for the overall US, calculated over the previous 120 months leading up to t. The term W_t^M denotes the deviation of the W_t from the average for the same calendar month over the last ten years, adjusted for the mean of these deviations. Finally, the variable W_t^{Ab} captures the residual value, representing abnormal deviations in weather conditions, which include extreme variations from typical patterns. In our analysis, we particularly focus on W_t^{Ab} by standardizing these anomalies, commonly referred to as the standardized anomaly. This approach helps highlight significant deviations from normal weather conditions.

In line with the existing literature on forecasting inflation using a large number of predictors, we employ 8 factors extracted from a FRED-MD via the Expectation-Maximization (EM) algorithm and Principal Component Analysis (PCA).[4] The data for the three inflation rates, the five climate risk predictors, and the eight factors are plotted in Figure 1, covering the monthly sample period from January 1985 to September 2022. Descriptive statistics for all variables are presented in Table 1, spanning the same period.

[Insert Table 1 Here]
[Insert Figure 1 Here]

[4] The whole dataset can be downloaded from: https://research.stlouisfed.org/econ/mccracken/fred-databases/.

3. Methodology

In this section, we present our econometric models, including the specifics of the DMA and DQMA approaches used in model combinations.

3.1 Quantile ARX models

Consider the following general quantile regression:

$$y_t = \boldsymbol{\beta}'_\tau \boldsymbol{X}_t + \varepsilon_t, \tag{1}$$

where y_t is the variable of interest; $\boldsymbol{X}_t$ corresponds to the predictors including the intercept, own lags, and explanatory variables; $\boldsymbol{\beta}_\tau$ is a vector of coefficients that varies with the quantile τ, ε_t is the error term. The estimation of this quantile regression relies on the check function $\rho_\tau(x) = x \cdot \big(\tau - I(x < 0)\big)$,

$$\hat{\beta}_\tau = \arg\min \textstyle\sum_{t=1}^{T} \rho_\tau(\varepsilon_t). \tag{2}$$

In our analysis, y_t is the growth inflation rate, and X_t includes the intercept term, lags of y_t, five abnormal weather variables, and eight control variables, i.e., the factors. To assess whether the climate variables enhance the forecasts aggregate and sub-indices of US inflation (denoted by *IN*), we develop seven quantile ARX (auto-regressive with exogenous variables) models that integrate various climate risk-related variables as predictors:

QARX-Temp:

$$IN_{t+h} = \beta_{0,\tau} + \textstyle\sum_{l=1}^{p} \beta_{l,\tau} IN_{t+1-l} + \beta_{Temp,\tau} Temp_t + \boldsymbol{\beta}'_{Control,\tau} \boldsymbol{Contr}\quad_t + \varepsilon_{t+h} \tag{3}$$

QARX-HDD:

$$IN_{t+h} = \beta_{0,\tau} + \textstyle\sum_{l=1}^{p} \beta_{l,\tau} IN_{t+1-l} + \beta_{HDD,\tau} HDD_t + \boldsymbol{\beta}'_{Control,\tau} \boldsymbol{Control}_t + \varepsilon_{t+h} \tag{4}$$

QARX-CDD:

$$IN_{t+h} = \beta_{0,\tau} + \textstyle\sum_{l=1}^{p} \beta_{l,\tau} IN_{t+1-l} + \beta_{CDD,\tau} CDD_t + \boldsymbol{\beta}'_{Control,\tau} \boldsymbol{Control}_t + \varepsilon_{t+h} \tag{5}$$

QARX-Prec:

$$IN_{t+h} = \beta_{0,\tau} + \sum_{l=1}^{p} \beta_{l,\tau} IN_{t+1-l} + \beta_{Prec,\tau} Prec_t + \boldsymbol{\beta}'_{Control,\tau} \boldsymbol{Control}_t + \varepsilon_{t+h} \tag{6}$$

QARX-Wind:

$$IN_{t+h} = \beta_{0,\tau} + \sum_{l=1}^{p} \beta_{l,\tau} IN_{t+1-l} + \beta_{Wind,\tau} Wind_t + \boldsymbol{\beta}'_{Control,\tau} \boldsymbol{Control}_t + \varepsilon_{t+h} \tag{7}$$

QARX-All:

$$IN_{t+h} = \beta_{0,\tau} + \sum_{l=1}^{p} \beta_{l,\tau} IN_{t+1-l} + \beta_{Temp,\tau} Temp_t + \beta_{HDD,\tau} HDD_t + \beta_{CDD,\tau} CDD_t + \beta_{Prec,\tau} Prec_t + \beta_{Wind,\tau} Wind_t + \boldsymbol{\beta}'_{Control,\tau} \boldsymbol{Control}_t + \varepsilon_{t+h} \tag{8}$$

QARX:

$$IN_{t+h} = \beta_{0,\tau} + \sum_{l=1}^{p} \beta_{l,\tau} IN_{t+1-l} + \boldsymbol{\beta}'_{Control,\tau} \boldsymbol{Control}_t + \varepsilon_{t+h} \tag{9}$$

where the dependent variable $IN_t = (P_t - P_{t-1})/P_{t-1}$ denotes the month-on-month inflation rate, and P_t is the overall US CPI, or the corresponding indices for food and beverages or housing. All models include the same control variables, the eight factors extracted from the FRED-MD, denoted by $\boldsymbol{Control}_t$ in all equations. The primary distinction between these models lies in the inclusion of different abnormal weather variables. We consider three forecast horizons, i.e., h =1-, 6-, and 12-month-ahead. For horizons greater than one month, we employ the direct forecast approach, which is known to be more robust to model misspecification compared to the iterated version (Marcellino et al., 2006). The lag length of the model is determined using the Bayesian Information Criterion (BIC), which identifies an optimal lag length of 1 for all three measures of inflation rates across the three forecasting horizons, except in the case of the housing inflation rate at 1-month-ahead, where 2 lags are optimally chosen.

3.2 Model combination strategies

The existing literature highlights the importance of incorporating model combination strategies for macroeconomic forecasting, such as forecasting the US inflation rate (see, Nonejad (2021) for a comprehensive review). For the sake of brevity, we use 1-step-ahead forecasts as an example. Assuming that we have K individual models, the forecasts of the k-th model is denoted as $\hat{y}_{t+1,k}$. The combined forecast is then given by:[5]

$$\hat{y}_{t+1} = \sum_{k=1}^{K} \pi_{t+1|t,k} \hat{y}_{t+1,k}, \tag{10}$$

where $0 \leq \pi_{t+1|t,k} \leq 1$ represents the weight of the k-th model at time t, with the constraint that $\sum_{k=1}^{K} \pi_{t+1|t,k} = 1$. A crucial aspect is determining the weight $\pi_{t+1|t,k}$. In this regard, we initially apply the traditional DMA approach proposed by Raftery et al. (2010) to estimate the model weights as described in equation (10). The weights have the following recursive relationship:

$$\pi_{t+1|t,k} = \frac{\pi_{t|t,k}^{\alpha}}{\sum_{k=1}^{K} \pi_{t|t,k}^{\alpha}}, \tag{11}$$

$$\pi_{t+1|t+1,k} = \frac{\pi_{t+1|t,k} f_k(y_{t+1}|\boldsymbol{X}_{t,k})}{\sum_{k=1}^{K} \pi_{t+1|t,k} f_k(y_{t+1}|\boldsymbol{X}_{t,k})}, \tag{12}$$

where y_{t+1} is the variable of interest, $\boldsymbol{X}_{t,k}$ represents vector of all predictors in the k-th, α is the *forgetting factor*, typically slightly less than one, and $f_k(y_{t+1}|\boldsymbol{X}_{t,k})$ is the predictive density of y_{t+1} conditional on $\boldsymbol{X}_{t,k}$. The function $f_k(y_{t+1}|\boldsymbol{X}_{t,k})$ determines how the weight evolves indicating that different functions lead to different dynamics in the weighting mechanism. Initially, for the quantile forecasting models, we apply the same weights determined by the DMA approach across all quantile levels. Subsequently, following Cai et al. (2020), we also explore five dynamic quantiles-based combination strategies in this paper:

DQMA-I:

According to Koenker and Xiao (2004), the conditional density function can be approximated by:

[5] For ease of notation, the subscript τ is omitted.

$$f_k\left(y_{t+1}\middle|\boldsymbol{X}_{t,k}\right)=\begin{cases}\frac{\tau_{i+1}-\tau_i}{\hat{q}_{t+1,\tau_{i+1},k}-\hat{q}_{t+1,\tau_i,k}},\ if\ \hat{q}_{t+1,\tau_i,k}<y_{t+1}<\hat{q}_{t+1,\tau_{i+1},k}\\ 0,\ else\end{cases}, \tag{13}$$

where $\{\tau_i\}_{i=1}^{n+1}$ is a chosen sequence of τ's, with $0<\tau_1<\tau_2\ldots<\tau_{n+1}<1$ for some large n. $\hat{q}_{t+1,\tau_i,k}$ denotes the τ_i-th conditional quantile estimate of y_{t+1} conditional on $\boldsymbol{X}_{t,k}$. By replacing the predictive density $f_k\left(y_{t+1}\middle|\boldsymbol{X}_{t,k}\right)$ in (12) with (13), we obtain the first combination strategy, named DQMA-I.

DQMA-II:

The previous combination strategy does not depend on τ, as f remains same at different quantiles. Yu and Moyeed (2001) demonstrate that the minimizing the check function is equivalent to maximizing a likelihood function formed by combining independently distributed asymmetric Laplace densities:

$$f_{\tau,k}(u_{t+1,k})=\tau(1-\tau)\exp\left\{-\rho_\tau\left(u_{t+1,\tau,k}\right)\right\}, \tag{14}$$

where ρ_τ denotes the check function, and $u_{t+1,\tau,k}=y_{t+1}-\hat{q}_{t+1,\tau,k}$. By replacing the predictive density $f_k\left(y_{t+1}\middle|\boldsymbol{X}_{t,k}\right)$ in (12) with $f_{\tau,k}(u_{t+1,k})$ in (14), we obtain a combination strategy that depends on τ, called DQMA-II.

DQMA-Gods:

Inspired by the R^2 of classical least squares regression, Koenker and Machado (1999) propose a method to quantify the goodness of fit for quantile regressions as:

$$R^2=1-\frac{\hat{V}}{V_0}, \tag{15}$$

$$\hat{V}=\sum_{t=1}^{T_0}(Y_{t+1}-\hat{q}_{t+1,\tau})\,(\tau-I(Y_{t+1}-\hat{q}_{t+1,\tau}<0)), \tag{16}$$

where V_0 denotes $\hat{V}$ for the where only an intercept is included in the model, and T_0 is the window size. This R^2 is used to determine the dynamic weight of the k-th individual model at quantile τ as:

$$\pi_{t+1|t+1,\tau,k}=\frac{R_{t,\tau,k}^2}{\sum_{k=1}^{K}R_{t,\tau,k}^2}. \tag{17}$$

This combination strategy is depends on τ and is named DQMA-Gods.

DQMA-MSE:

Cai et al. (2020) also employ the following MSE loss function to determine the dynamic weights by defining the MSE for quantile forecasts as:

$$MSE_k = T_0^{-1} \sum_{t=1}^{T_0} \left(y_t - \bar{y}_{t,k}\right)^2, \tag{18}$$

$$\bar{y}_{t+1,k} = \sum_{i=1}^{n} ((\tau_{i+1} - \tau_i) \frac{\hat{q}_{t+1,\tau_i,k} + \hat{q}_{t+1,\tau_{i+1},k}}{2}), \tag{19}$$

where T_0 is the window size, and $0 < \tau_1 < \tau_2 \ldots < \tau_{n+1} < 1$ is a chosen sequence of τ's. The dynamic weight is then obtained by the following equation:

$$\pi_{t+1|t+1,\tau,k} = \frac{MSE_k^{-1}}{\sum_{k=1}^{K} MSE_k^{-1}}. \tag{20}$$

DQMA-Eq:

The *forecast combination puzzle* is a well-known phenomenon associated the forecast combination, where a combination with all individual models having equal weight can perform better than those with complicated weight strategies. Hence, following Cai et al. (2020), we also consider the equal weight combination strategy named DQMA-Eq:

$$\pi = 1/K. \tag{21}$$

Among the previous five combination strategies, only DQMA-II and DQMA-Gods have weights that vary with different τ, while the rest have the same weight across the chosen quantiles.

2.3 Evaluation methods for quantile forecasting models

We consider two types of evaluation approaches for the quantile forecasting models. First, we use the violation rate (Vio_{τ}), a quantile forecasting accuracy evaluation indicator used in Kuester et al. (2005), Gerlach et al (2011), and Lu and Su (2015), expressed as:

$$VioR_\tau = \frac{1}{T_2 - T_1 + 1} \sum_{t=T_1}^{T_2} I(y_t < \hat{y}_{t,\tau}), \tag{22}$$

where T_1 and T_2 are the time-stamps of the first and last out-of-sample forecasts respectively, $\hat{y}_{t,\tau}$ is the forecast of τth quantile, and $I(\cdot)$ denotes the indicator function. The violation rate can be explained as the ratio of the actual values that are smaller than their τ-th forecasting quantiles, with a better model model having a $VioR_\tau$ to close to τ. Second, we employ the out-of-sample R_O^2 for quantile regressions to examine the performance of models as per Campbell and Thompson (2007) and Lu and Su (2015). The out-of-sample R_O^2 is defined as:

$$R_O^2 = 1 - \frac{\sum_{T_1}^{T_2} \rho_\tau(y_t - \hat{y}_{t,\tau})}{\sum_{T_1}^{T_2} \rho_\tau(y_t - \bar{y}_{t,\tau})}, \tag{23}$$

where $\rho_\tau(\cdot)$ is the check function, $\bar{y}_{t,\tau}$ denotes the unconditional τ-th quantile over the sample involving the past window-size. A higher R_O^2 indicates a better model.

To statistically evaluate the hypothesis of equal predictability of the different quantile forecasting models, we adopt the approach proposed by Ge and Lee (2017), which extends the Clark and West (2007, CW) test for models of conditional mean to those associated with conditional quantiles. Specifically, the adjusted check loss-differential is defined by:

$$\widehat{cw} = g(\hat{e}_{0,t})(\hat{e}_{0,t} - \hat{e}_{i,t}), \tag{24}$$

with,

$$\hat{e}_{0,t} = y_t - \hat{y}_{t,\tau}^0,$$

$$\hat{e}_{i,t} = y_t - \hat{y}_{t,\tau}^i,$$

where y_t, $\hat{y}_{t,\tau}^0$ and $\hat{y}_{t,\tau}^i$ denote the actual data and forecasts of the benchmark (0), and i-th model at τ-quantile, respectively, and $g(x) = (\tau - I(x < 0))$. Then we employ the following test statistic:

$$CW = \frac{\overline{cw}}{\hat{\sigma}}, \tag{25}$$

wherein $\overline{cw}$ denotes the mean value of $\widehat{cw}$, and $\hat{\sigma}$ is the heteroscedasticity and autocorrelation consistent (HAC) standard error estimator of the sequence $\widehat{cw}$.

4. Empirical results

4.1. Out-of-sample forecasting results

For the forecasting exercise, we utilize a rolling window of 100 data points to estimate the various models and obtain the associated forecasts of the inflation rates. We adopt the same procedure outlined by Koop and Korobilis (2012) to derive the DMA weights, while the other five DQMA strategies align with Cai et al. (2020). Our chosen sequence of 11 quantiles is: 0.05, 0.1, 0.2,…, 0.9, 0.95.

Tables 2-4 display the quantile forecasting accuracy results, including the violation rate, out-of-sample R^2, and the CW test statistics, respectively, for the overall US inflation rate at the 11 selected quantiles. To determine whether incorporating individual climate risk variables into the benchmark QARX model can enhance forecasting performance, we first compare the results of each model against the benchmark, which does not include weather-related predictors. As evidenced in Tables 1 and 2, models that incorporate climate risk metrics typically outperform at different quantile levels. However, no single model linked to particular extreme weather risks consistently outshines others across all inflation rate quantiles, with some even underperforming compared to the benchmark QARX model that excludes all climate-related variables. This variability makes it impractical to preselect a specific model. Consequently, we now shift our focus to model combination strategies aimed at enhancing the stability of forecasting improvements attributed to climate risks.

Table 2 clearly shows that model combination strategies frequently result in violation rates that more closely match the corresponding τ across all forecast horizons, compared to the QARX model. This suggests that model combinations effectively integrate diverse information, potentially enhancing the stability and accuracy of quantile-based forecasting for US inflation rates. Furthermore, the alternative combination strategies exhibit similar performances, indicating that no single method consistently outperforms the others. This reinforces the utility of combining model outputs as a robust approach to managing the variability inherent in single-model forecasts.

Turning to the findings in Table 3, which presents the out-of-sample R^2, we draw parallels with the conclusions from the violation rates. The model combinations generally deliver improved predictive accuracy, as evidenced by higher R^2 values, which measure the proportion of variability in the inflation rate that the models can explain. Just like with the violation rates, the R^2 results across different models and combination strategies indicate that incorporating multiple predictive approaches can mitigate the limitations of relying on a single model or predictor set. This approach is particularly effective in capturing the dynamics of inflation, which is influenced by a complex interplay of economic factors, including those related to climate risks as shown in the extended model setups.

Table 4 presents the quantile-specific CW test statistics for comparing the forecast accuracy of combined models against the benchmark QARX model. The positive and statistically significant values indicated by asterisks (**) confirm that the combined models generally outperform the QARX model across various quantiles, particularly at the middle to higher end of the distribution (0.3 to 0.9). These results highlight the effectiveness of integrating multiple models, which tends to enhance forecasting accuracy significantly compared to relying on a single model framework. The CW test statistics that are significantly positive across different models and forecast horizons (h=1, h=6, and h=12) underscore that the integration of diverse model outputs can capture a broader range of inflation dynamics, providing a more robust prediction platform. For instance, at a 1-month horizon, the models DQMA-I, DQMA-II, DQMA-Gods, and DQMA-MSE consistently show higher CW test values in the mid to upper quantiles, reinforcing their superior predictive power for inflation forecasts.

Conversely, where the CW test statistics are negative or not statistically significant (e.g., certain values at the h=12 horizon), it suggests that the model combinations do not markedly outperform the QARX model, often at the extreme ends of the quantile range. This may indicate reduced predictability at these ends or potentially the impact of extreme inflation fluctuations which are harder to predict accurately. In such cases, the performance of the combined models approximates that of the benchmark, highlighting the challenges of forecasting under extreme economic conditions.

In summary, the incorporation of climate risks-based predictors within these combination strategies significantly enhances the accuracy of the forecasts associated with the conditional distribution of inflation. This is particularly evident in the robust performance of model combinations at the core quantiles. However, the predictability at the extreme ends of the distribution remains a challenge, suggesting an area for further model refinement and investigation to achieve more consistent predictive success across the entire range of inflation rates.

[Insert Table 2 Here]
[Insert Table 3 Here]
[Insert Table 4 Here]

4.2. Which models and climate risks predictors matter more?

Figure 2 illustrates the dynamic evolution of model weights across different forecast horizons (h=1, 6, and 12) using DMA and DQMA combination strategies, highlighting how different models are prioritized in forecasting US inflation quantiles under varying conditions.

From the graphs, it is evident that the benchmark QARX model generally receives the lowest weighting across most scenarios. This suggests that, while foundational, the QARX model alone may not fully capture the complexity of the factors influencing inflation, particularly those related to climate risks. Conversely, the QARX-All model, which likely integrates multiple weather-related predictors, tends to receive the highest weight over time. This underscores the value of a more comprehensive approach in capturing the nuanced impacts of various climate-related risks on inflation.

The individual weather-based models (QARX-Temp, QARX-HDD, QARX-CDD, QARX-Preci, QARX-Wind) exhibit weights that fluctuate significantly over time and across forecast horizons. These fluctuations indicate the varying degrees of relevance these specific climate factors have under different economic conditions and times. For instance, during periods where temperature variations are more pronounced due to seasonal changes, the QARX-Temp model may receive a higher weighting. The substantial variance in weights, especially visible in the DQMA combinations at h=6 and h=12, points to the adaptive nature of these forecasting strategies. They recalibrate the importance of different models based on the most current data, which is crucial for managing the inherent uncertainties in economic forecasting and enhancing the reliability of the predictions.

Overall, this dynamic weighting system demonstrates the strategic advantage of model combinations over single-model approaches, particularly in capturing the multifaceted impacts of climate variables on inflation. It highlights the necessity for an adaptive, informed forecasting approach that can integrate and re-weight multiple data sources in response to evolving economic landscapes.

[Insert Figure 2 Here]

Furthermore, we also calculate the posterior inclusion probabilities (PIPs), as described in Koop and Korobilis (2012), of each of the climate risks to detect their respective relative importance in forecasting inflation. The PIP of the i-th predictor at time t in τ-th quantile regression using dynamic combination strategies is defined by:

$$PIP_{t,\tau}^{i} = \sum_{k=1}^{K} \pi_{t|t-1,\tau,k} \times I(X_t^i \in M_k), \tag{26}$$

where $\pi_{t+1|t,\tau,k}$ is the predicting weight of the k-th individual model as described earlier, and $I(X_t^i \in M_k)$ takes a value of 1 if the predictor X_t^i is included in the k-th individual model M_k, and zero otherwise.

[Insert Figure 3 Here]

Figure 3 offers a compelling visualization through heatmaps, detailing the mean values of PIPs for five climate risk predictors across various forecasting horizons (h=1, 6, and 12) and model combination strategies. This visualization serves to underscore the relative significance each climate risk holds within the forecasting models employed. A few trends are immediately noticeable across the heatmaps. Firstly, certain predictors such as precipitation, CDD, HDD, and temperature consistently appear with darker shades, indicating higher mean PIPs. This consistent prominence suggests a significant reliance on these predictors, likely due to their direct impacts on economic activities and consumption patterns, which are closely linked to inflationary trends. In contrast, wind speed, while integral, shows lighter shades in some of the model strategies and forecast horizons. This variance might reflect their indirect or varying influence on specific sectors or inflation components, highlighting a nuanced incorporation into the models based on their perceived impact.

Additionally, the differentiation in shading across the DMA and various DQMA strategies reveals the diversity in how these models process and prioritize climate risk information. Notably, the dynamic DQMA-II approach, especially the quantile-specific variations, demonstrate an adaptive integration strategy. These models adjust the importance of predictors according to the specific demands of the quantile being forecasted, potentially enhancing the model's responsiveness to extreme values or outliers that could differently influence the inflation rate at different quantiles.

4.3. Robustness Checks

In this sub-section, we assess the robustness of our results on two fronts. First, we switch from using month-on-month inflation rate data to year-over-year inflation rate, defined as $IN_t = (P_t - P_{t-12})/P_{t-12}$. Due to the data change, we reselect the lags included in the model based on the Bayesian Information Criterion (BIC), resulting in new optimal lag choices of 2, 1, and 1 for forecast horizons h=1, 6, and 12, respectively. The quantile Clark-West (CW) test results are reported in Table A1 in the Appendix. Second, we implement a new rolling window size of 80 observations, with the results presented in Table A2 in the Appendix.

As observed previously, the results from model combinations, which consider various climate risk predictors simultaneously, continue to show relatively more stable forecasting improvements compared to the benchmark model. Overall, the alternative definition of inflation, i.e., year-on-year growth of US CPI, and a smaller rolling window size do not alter the main conclusions derived from the month-on-month inflation and those from a larger rolling window length.

4.4. Further Analyses

Understanding the differential impact of climate risks on various components of the Consumer Price Index (CPI) is crucial. Sub indices such as food and beverages and housing reflect diverse economic activities with varying sensitivities to climate conditions. Analyzing these indices separately allows for a nuanced understanding of how climate risks affect the economy, facilitating targeted policy responses to mitigate adverse impacts. Therefore, this section further analyzes the impact of climate risks variables on quantile forecasting of food and beverages inflation, as well as housing inflation.

[Insert Table 5 Here]
[Insert Table 6 Here]
[Insert Table 7 Here]

Tables 5, 6, and 7 detail the violation rate, out-of-sample R^2, and CW test statistics for quantile forecasts at h=1, 6, and 12 steps ahead for food and beverages inflation. The results indicate that climate risk variables generally enhance forecast accuracy for this sector. This improvement is most pronounced in the middle to upper quantiles, suggesting that extreme weather events are particularly predictive of higher inflation spikes, likely due to their impact on agricultural outputs. This finding is in line with Niles and Salerno (2018), who documented significant food insecurity linked to climate shocks, impacting agricultural productivity and prices.

[Insert Table 8 Here]
[Insert Table 9 Here]
[Insert Table 10 Here]

For the housing CPI index, as shown in Tables 8, 9, and 10, the influence of climate risks is less pronounced compared to the food sector. Although there is still a notable improvement in forecasting performance, it is less uniform across the quantiles. This may be due to the indirect effects of climate risks on housing, such as changes in construction costs and insurance premiums post-climate events, as discussed by Zhou et al. (2022) in their study on the vulnerability of farm households to poverty due to climate shocks.

The superior forecasting performance for food and beverage inflation likely stems from the direct and immediate impact of weather anomalies on agricultural production, a sector highly sensitive to climatic conditions. In contrast, the housing sector, while also affected by climate risks, reacts in a more buffered and delayed manner due to the nature of construction and real estate markets.

These results illustrate that while climate risks are a significant predictor for both sectors, the immediacy and intensity of the impact vary. The stronger predictive power for food and beverages inflation underscores the vulnerability of agriculture to climate anomalies, necessitating robust strategies for climate adaptation and mitigation in this sector. This aligns with broader findings in the literature, emphasizing the critical role of adaptive capacities to buffer against food insecurity and inflationary pressures due to climate risks.

5. Conclusion

This paper explores the efficacy of incorporating climate risk-related variables into quantile regression models to enhance the forecasting performance of the conditional distribution of US inflation rates. By comparing models that integrate climate risks with a benchmark model that excludes these variables, covering the period from January 1985 to September 2022, we find that although specific weather variables improve inflation forecasts at certain quantiles, there is no universally dominant climate risk factor. However, when employing model combination strategies, including those tailored to specific quantiles, the augmented models consistently outperform the benchmark across virtually the entire conditional distribution of the aggregate US inflation rate. This improvement is particularly notable in forecasts related to the food and beverages sector and, to a lesser extent, housing—which constitutes a significant portion of overall CPI inflation.

From an academic perspective, our findings underscore the value of model combination methods in effectively handling climate risks to predict inflation's conditional distribution more accurately. For policymakers, these results emphasize the necessity of integrating diverse climate risk information rather than focusing on isolated factors. This approach is vital for crafting nuanced monetary policies that can respond adeptly to the inflationary impacts of climate risks. Practically, it is crucial for policymakers to prioritize the stability of food inflation, which significantly influences the overall inflation structure, especially following extreme weather events. Given the direct impact of climate variables on agricultural outputs, enhancing the resilience of this sector to climate shocks should be a focal point. This includes investing in sustainable agricultural practices, improving water management, and promoting technological innovations that can mitigate the adverse effects of extreme weather.

Additionally, the lesser but still significant impact of climate risks on housing inflation suggests a need for policies that encourage building more resilient infrastructure and housing. This may involve revising building codes, promoting energy-efficient and weather-resistant materials, and considering climate risks in urban planning and development strategies.

As part of future research, it would be beneficial to extend this study to other countries, particularly emerging economies, which are more vulnerable to climate change due to their reliance on agriculture. Such studies could provide valuable insights into the global applicability of our findings and support the development of targeted interventions to mitigate the economic impacts of climate variability.

References

Andrade, P., Ghysels, E., & Idier, J. (2012). Tails of Inflation Forecasts and Tales of Monetary Policy. Working paper series, Banque de France, No. 407.

Atkeson, A., & Ohanian, L. E. (2001). Are Phillips curves useful for forecasting inflation?, Quarterly Review, Federal Reserve Bank of Minneapolis, 25(Winter), 2-11.

Bauwens, L., Koop, G., Korobilis, D., & Rombouts, J. (2015). The Contribution of Structural Break Models to Forecasting Macroeconomic Series. Journal of Applied Econometrics, 30(4), 596-620.

Boneva, L., & Ferrucci, G. (2022). Inflation and climate change: the role of climate variables in inflation forecasting and macro modelling. LSE Research Online Documents on Economics 115533, London School of Economics and Political Science, LSE Library.

Cai, Z., Ma, C., & Mi, X. (2020). Realized Volatility Forecasting Based on Dynamic Quantile Model Averaging. Working Papers Series in Theoretical and Applied Economics, No. 202016, University of Kansas, Department of Economics.

Campbell, J. Y., & Thompson, S. B. (2008). Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average? The Review of Financial Studies, 21(4), 1509–1531.

Cashin, P., Mohaddes, K., & Raissi, M. (2017). Fair weather or foul? The macroeconomic effects of El Niño. Journal of International Economics, 106(C), 37-54.

Cepni, O., & Clements, M. P. (2024). How local is the local inflation factor? Evidence from emerging European countries. International Journal of Forecasting, 40(1), 160-183.

Chan, F. & Pauwels, L. L. (2018). Some theoretical results on forecast combinations. International Journal of Forecasting, 34(1), 64-74.

Clark, T. E., Huber, F., Koop, G., & Marcellino, M. (Forthcoming). Forecasting US Inflation using Bayesian Nonparametric Models. Annals of Applied Statistics.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics, 138(1), 291–311.

Cevik, S., & Jalles, J. T. (2023). Eye of the Storm: The Impact of Climate Shocks on Inflation and Growth. International Monetary Fund (IMF), Working Paper No. WP/23/87.

D'Ecclesia, R. L., Morelli, G., &, Scaramagli, V. (2022). Inflation and CO2 emissions. Mimeo, Department of Economics and Finance, LUISS.
Dickey, D. A., & Fuller, W. A. (1979). Distributions of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association, 74(366), 427-431.
Dickey, D. A., & Fuller, W. A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. Econometrica, 49(4), 1057-1072.
Faccia, D., Parker, M., & Stracca, L. (2021). Feeling the heat: extreme temperatures and price stability. ECB Working Paper No. 2021/2626. Available at SSRN: https://ssrn.com/abstract=3981219.
Faust, J., & Wright, J. H. (2013). Forecasting inflation. In Handbook of Economic Forecasting eds. by Elliott, G., & Timmermann, A., 2, Amsterdam, Elsevier, 2-56
Ge, Y., & Lee, T.-H.. Comparing Predictive Accuracy and Model Combination Using Encompassing Test for Nested Quantile Models. Mimeo, University of California, Riverside, available at: https://faculty.ucr.edu/~taelee/paper/ge1.pdf.
Gerlach, R. H., Chen, C. W. S., & Chan, N. Y. C. (2011). Bayesian Time-Varying Quantile Forecasting for Value-at-Risk in Financial Markets. Journal of Business & Economic Statistics, 29(4), 481-492.
Ghysels, E., Iania, L., & Striaukas, J. (2018). Quantile-based Inflation Risk Models. Working Paper Research 349, National Bank of Belgium.
Hauzenberger, N., Huber, F., & Klieber, K (2023). Real-time inflation forecasting using non-linear dimension reduction techniques. International Journal of Forecasting, 39(2), 901-921.
Hauzenberger, N., Huber, F., Koop, G. & Onorante, L. (2022). Fast and flexible Bayesian inference in time-varying parameter regression models. Journal of Business and Economic Statistics, 40(4), 1904-1918.
Kabundi, A., Mlachila, M., & Yao, J. (2022). How Persistent Are Climate-Related Price Shocks? Implications for Monetary Policy. International Monetary Fund (IMF), Working Paper No. WP/22/207.
Kilian, L., & Manganelli, S. (2007). Quantifying the risk of deflation. Journal of Money, Credit and Banking, 39(2/3), 561-590.
Kim, H.S., Matthes, C., & Phan, T. (2022). Severe Weather and the macroeconomy. Federal Reserve Bank of Richmond Working Paper No. 21-14R.

Knotek, E. S., & Zaman, S. (2023). Real-time density nowcasts of US inflation: A model combination approach. International Journal of Forecasting, 39(4), 1736-1760.
Koenker, R., & Machado, J. A. F. (1999). Goodness of Fit and Related Inference Processes for Quantile Regression. Journal of the American Statistical Association, 94(448), 1296-1310.
Koenker, R., & Xiao, Z. (2004). Unit Root Quantile Autoregression Inference. Journal of the American Statistical Association, 99(467), 775-787.
Koop, G., & Korobilis, D. (2012). Forecasting inflation using dynamic model averaging. International Economic Review, 53(3), 867-886.
Korobilis, D. (2017). Quantile regression forecasts of in
ation under model uncertainty. International Journal of Forecasting, 33, 11-20.
Korobilis, D., Landau, B., Musso, A., & Phella, A. (2021). The time-varying evolution of inflation risks. Working Paper Series 2600, European Central Bank.
Kuester, K., Mittnik, S., & Paolella, M. S. (2006). Value-at-Risk Prediction: A Comparison of Alternative Strategies. Journal of Financial Econometrics, 4(1), 53-89.
Laosuthi, T., & Selover, D. D. (2007). Does El Niño affect Business Cycles? Eastern Economic Journal, 33(1), 21-42.
Liao, W., Sheng, X., Gupta, R., & Karmakar, S. (2024). Extreme Weather Shocks and State-Level Inflation of the United States. Economics Letters, 238, 111714.
Lu, X., & Su, L. (2015). Jackknife model averaging for quantile regressions. Journal of Econometrics, 188(1), 40-58.
Lucidi, F. S., Pisa, M. M., & Tancioni, M. (2022). The Effects of Temperature Shocks on Energy Prices and Inflation in the Euro Area. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4109417.
Mandalinci, Z. (2017). Forecasting inflation in emerging markets: An evaluation of alternative models. International Journal of Forecasting, 33(4), 1082-1104.
Manzan, S., & Zerom, D. (2013). Are macroeconomic variables useful for forecasting the distribution of US inflation?. International Journal of Forecasting, 29(3), 469-478.
Manzan, S. & Zerom, D. (2015). Asymmetric Quantile Persistence and Predictability: the Case of US Inflation. Oxford Bulletin of Economics and Statistics, 77(2), 297-318.
Marcellino, M., Stock, J. H., & Watson, M. W. (2006). A comparison of direct and iterated multistep ARX methods for forecasting macroeconomic time series. Journal of Econometrics, 135(1), 499-526.

McCracken, M. W. & Ng, S. (2016). FRED-MD: A Monthly Database for Macroeconomic Research. Journal of Business & Economic Statistics, 34(4), 574-589.

Mendelsohn, R., Emanuel, K., Chonabayashi, S., & Bakkensen, L. (2012). The impact of climate change on global tropical cyclone damage. Nature Climate Change, 2(3), 205-209.

Mukherjee, K., & Ouattara, B. (2021). Climate and monetary policy: do temperature shocks lead to inflationary pressures? Climatic Change, 167, 32.

Natoli, F. (2023). The macroeconomic effects of temperature surprise shocks. Bank of Italy (Banca d'Italia), Working Papers (Temi di discussione) No. 1407.

Niles, M. T., & Salerno, J. D. (2018). A cross-country analysis of climate shocks and smallholder food insecurity. PloS one, 13(2), e0192928.

Nonejad, N. (2021). An Overview Of Dynamic Model Averaging Techniques In Time□Series Econometrics. Journal of Economic Surveys, 35(2), 566-614.

Pfarrhofer, M. (2022). Modeling tail risks of inflation using unobserved component quantile regressions. Journal of Economic Dynamics and Control, 143, 104493.

Raftery, A. E., Kárný, M., & Ettler, P. (2010). Online Prediction Under Model Uncertainty via Dynamic Model Averaging: Application to a Cold Rolling Mill. Technometrics, 52(1), 52-66.

Sheng, X., Gupta, R., & Cepni, O. (Forthcoming). Time-Varying Effects of Extreme Weather Shocks on Output Growth of the United States. Sustainable Futures.

Steel, M. F. J. (2020). Model averaging and its use in economics. Journal of Economic Literature, 58(3), 644-719.

Stock, J. H., & Watson, M. W. (1999). Forecasting inflation. Journal of Monetary Economics, 44(2), 293-335.

Stock, J. H., & Watson, M. W. (2002). Macroeconomic forecasting using di usion indexes. Journal of Business & Economic Statistics, 20(2), 147-162.

Stock, J. H., & Watson, M.W. (2007). Why Has U.S. In
ation Become Harder to Forecast?, Journal of Money, Credit and Banking, 39(1), 3-33.

Stock J. H., & Watson M. W. (2009). Phillips Curve Inflation Forecasts. In Understanding Inflation and the Implications for Monetary Policy eds by Fuhrer, J., Kodrzycki, Y., Little, J., & Olivei, G. Cambridge: MIT Press, 99-202.

Stott, P. (2016). How climate change affects extreme weather events. Science, 352(6293), 1517-1518.

Wright, J. H. (2009). Forecasting US inflation by Bayesian model averaging. Journal of Forecasting, 28(2), 131-144.

Yeganegi, M.R., Hassani, H., & Gupta, R. (2023). The ENSO Cycle and Forecastability of Global Inflation and Output Growth: Evidence from Standard and Mixed-Frequency Multivariate Singular Spectrum. Journal of Forecasting, 42(7), 1690-1707.

Yu, K., & Moyeed, R. A. (2001). Bayesian quantile regression. Statistics & Probability Letters, 54(4), 437-447.

Zhou, Z., Yu, Z., & Wu, H. (2022). Climate shocks, household resource allocation, and vulnerability to poverty. Agriculture, 12(7), 971.

Table 1: Summary statistics

	Mean	SD	Skew	Kurt	JB statistics	Ljung-Box Q(5)	Ljung-Box Q(10)	Ljung-Box Q(20)	ADF
Inflation	0.002	0.003	-0.82	11.79	1508.26***	121.14***	146.46***	183.65***	-12.65***
Temperature	1.053	2.420	0.78	5.17	134.69***	261.23***	426.54***	651.73***	-13.48***
HDD	-0.892	2.303	-1.18	6.33	315.45***	267.36***	414.46***	709.09***	-12.47***
CDD	0.302	0.842	1.54	7.64	583.86***	160.96***	186.54***	278.20***	-12.20***
Precipitation	0.208	2.972	0.45	4.17	41.00***	553.33***	973.09***	1812.85***	-11.56***
Wind Speed	-0.078	0.379	0.23	4.35	38.44***	125.23***	189.06***	309.79***	-16.50***
F1	-1.368	20.466	0.20	6.69	260.32***	34.36***	68.14***	118.25***	-25.65***
F2	-5.676	0.516	-0.76	7.79	475.74***	55.87***	92.89***	122.52***	-20.09***
F3	0.054	0.677	1.65	7.68	617.92***	942.70***	1322.33***	1621.30***	-6.84***
F4	-0.089	0.274	-0.08	3.04	0.57	582.50***	959.93***	1149.94***	-11.49***
F5	0.048	0.312	0.11	3.79	12.47***	5.58	19.24***	36.19***	-20.53***
F6	0.028	0.087	0.31	2.48	12.51***	1569.57***	2704.15***	4532.72***	-4.40***
F7	-0.005	0.071	0.44	2.72	15.77***	1699.08***	2992.19***	4686.81***	-4.13***
F8	0.003	0.069	0.34	8.64	608.80***	23.88***	33.36***	43.59***	-19.33***

Note: SD: standard deviation; Skew: skewness; Kurt: kurtosis; ADF: Augmented Dickey and Fuller (1979, 1981) unit root test; *** denotes significance at the 1% level.

Figure 1: Data plots

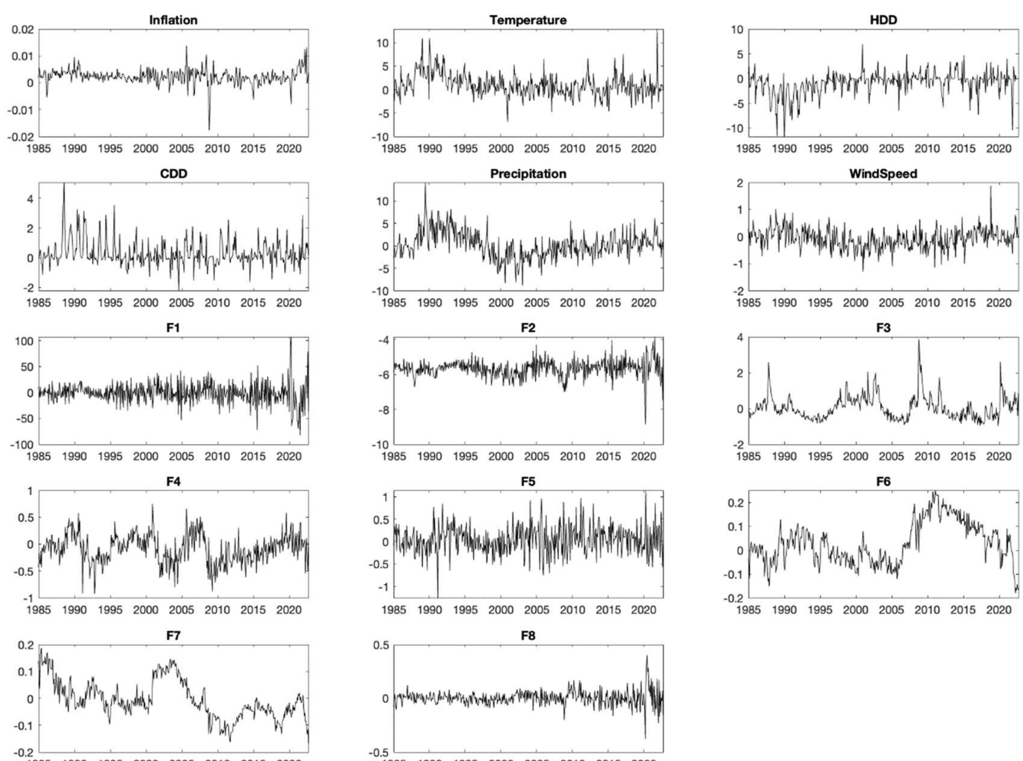


Table 2: Violation rate results for aggregate US inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
	QARX-Temp	0.0652	0.1105	0.2153	0.3343	0.4079	0.4901	0.5949	0.6827	0.8045	**0.8980**	0.9462
	QARX-HDD	0.0850	0.1190	0.2380	0.3173	0.4136	**0.5014**	0.5949	**0.6912**	0.8159	0.8895	0.9348
	QARX-CDD	**0.0595**	0.1048	0.2181	0.3144	0.4306	**0.5014**	0.6091	0.6799	0.7847	0.8924	0.9433
	QARX-Prec	0.0623	**0.0992**	0.2153	0.3201	**0.3938**	0.4844	0.5864	0.6799	0.8017	**0.8980**	**0.9490**
	QARX-Wind	**0.0595**	**0.0992**	0.1955	0.2720	0.4193	0.5099	0.5921	0.6884	0.7932	0.8895	0.9462
	QARX-All	0.0737	0.1190	**0.1983**	**0.2890**	0.3711	0.4561	0.5779	0.6459	0.7592	0.8867	0.9263
h=1	QARX	0.0680	0.1190	0.2181	0.3229	0.4164	0.4929	**0.5977**	0.6856	**0.7989**	0.8952	**0.9490**
	DMA	0.0595	0.1161	0.2096	0.3144	0.4136	0.4986	0.5921	0.6912	0.7960	0.9008	0.9462
	DQMA-I	0.0595	0.1048	0.1955	0.3003	0.4136	0.4958	0.5949	0.6941	0.7989	0.8952	0.9377
	DQMA-II	0.0538	0.1105	0.1983	0.3088	0.4023	0.4986	0.5977	0.6856	0.7875	0.9008	0.9462
	DQMA-Gods	0.0567	0.1133	0.2011	0.3003	0.4023	0.4958	0.5949	0.6856	0.7904	0.8980	0.9462
	DQMA-MSE	0.0595	0.1105	0.2011	0.3059	0.3994	0.4986	0.5949	0.6856	0.7904	0.9008	0.9462
	DQMA-Eq	0.0538	0.1105	0.1983	0.3088	0.4023	0.4986	0.5977	0.6856	0.7875	0.9008	0.9462
	QARX-Temp	0.0833	**0.1092**	0.2155	**0.2989**	0.3764	0.4626	0.5489	0.6063	0.6753	0.8046	0.8736
	QARX-HDD	**0.0776**	0.1236	0.2098	0.3017	0.3678	0.4655	0.5431	0.6092	0.6753	0.8103	**0.8879**
	QARX-CDD	0.0833	0.1236	**0.2040**	0.3046	0.3851	0.4713	0.5517	**0.6236**	0.7040	0.8046	0.8563
	QARX-Prec	0.0862	0.1178	0.2069	0.2874	**0.4080**	0.4770	**0.5575**	0.6121	0.6954	0.8161	0.8592
	QARX-Wind	0.0833	0.1494	0.2069	0.2816	0.3764	0.4770	0.5460	0.6092	**0.7098**	**0.8247**	0.8822
	QARX-All	0.0891	0.1207	0.1897	0.2787	0.3707	0.4713	0.5345	0.6063	0.6724	0.7902	0.8477
h=6	QARX	0.0833	0.1322	0.2270	0.2816	0.3822	**0.4799**	0.5402	0.6178	**0.7098**	0.8046	0.8822
	DMA	0.0805	0.1236	0.2213	0.2960	0.3736	0.4770	0.5517	0.6121	0.7040	0.7989	0.8707
	DQMA-I	0.0891	0.1351	0.2011	0.2960	0.3937	0.4770	0.5489	0.5977	0.6925	0.8132	0.8707
	DQMA-II	0.0862	0.1178	0.2069	0.2931	0.3649	0.4655	0.5460	0.6149	0.7069	0.8075	0.8793
	DQMA-Gods	0.0862	0.1178	0.1983	0.2989	0.3678	0.4799	0.5517	0.6121	0.7069	0.8075	0.8736
	DQMA-MSE	0.0862	0.1178	0.2040	0.2931	0.3649	0.4655	0.5460	0.6121	0.7069	0.8075	0.8793
	DQMA-Eq	0.0862	0.1178	0.2069	0.2931	0.3649	0.4655	0.5460	0.6149	0.7069	0.8075	0.8793
	QARX-Temp	0.1930	0.2515	0.3626	0.4444	0.5351	0.5731	0.6374	0.7047	0.7690	0.8567	0.8947
	QARX-HDD	**0.1842**	**0.2485**	0.3801	0.4444	0.5058	0.5673	0.6228	0.7076	0.7690	**0.8772**	0.8977
	QARX-CDD	0.2018	0.2749	0.4035	0.4708	0.5088	0.5819	0.6433	**0.7018**	0.7924	0.8713	**0.9181**
	QARX-Prec	0.2135	0.2661	0.3977	0.4620	0.5117	0.5789	0.6257	0.7047	0.7865	0.8626	0.9094
	QARX-Wind	0.1959	0.2602	0.3947	0.4649	0.5351	0.5702	0.6316	0.6930	0.7924	0.8713	0.9094
	QARX-All	0.2018	0.2573	**0.3567**	**0.4240**	**0.4883**	**0.5351**	**0.5789**	0.6696	0.7427	0.8304	0.8509
h=12	QARX	0.2018	0.2544	0.3830	0.4561	0.5205	0.5643	0.6287	**0.7018**	**0.7953**	0.8713	0.9006
	DMA	0.2047	0.2661	0.3713	0.4503	0.5205	0.5877	0.6228	0.6988	0.7924	0.8713	0.8977
	DQMA-I	0.2018	0.2602	0.3918	0.4649	0.5146	0.5702	0.6170	0.6901	0.7749	0.8509	0.8947
	DQMA-II	0.2076	0.2661	0.3772	0.4415	0.5146	0.5789	0.6257	0.6930	0.7865	0.8713	0.9006
	DQMA-Gods	0.2047	0.2690	0.3684	0.4298	0.5088	0.5789	0.6257	0.6901	0.7836	0.8684	0.9006
	DQMA-MSE	0.2076	0.2661	0.3743	0.4357	0.5146	0.5789	0.6257	0.6930	0.7865	0.8713	0.9006
	DQMA-Eq	0.2076	0.2661	0.3772	0.4415	0.5146	0.5789	0.6228	0.6930	0.7865	0.8713	0.9006

Note: The number in bold represents the best model among all individual models; numbers in shade depict the combined model that performs better than the benchmark QARX model.

Table 3: Out-of-sample R^2 results for aggregate US inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
	QARX-Temp	0.2576	0.2120	0.2178	0.2242	0.2191	0.2435	0.2654	0.2709	0.3139	0.3239	0.3210
	QARX-HDD	0.2725	0.2136	0.2208	0.2182	0.2133	0.2303	0.2491	0.2613	0.2900	0.2994	0.2622
	QARX-CDD	0.2810	**0.2947**	0.2097	0.2201	0.2151	0.2145	0.2489	0.2659	0.3070	**0.3575**	**0.3823**
	QARX-Prec	0.2920	0.1990	0.2204	**0.2436**	0.2314	**0.2541**	0.2647	0.2913	**0.3331**	0.3395	0.3279
	QARX-Wind	**0.3180**	0.2332	**0.2304**	0.2375	**0.2389**	0.2346	**0.2728**	**0.3110**	0.3218	0.3287	0.3789
	QARX-All	0.2077	0.1651	0.1961	0.1874	0.1985	0.2060	0.2228	0.2414	0.2831	0.3407	0.3387
h=1	QARX	0.2786	0.2041	0.2184	0.2207	0.2325	0.2498	0.2715	0.3082	0.3312	0.3350	0.3698
	DMA	0.2929	0.2298	0.2401	0.2354	0.2297	0.2416	0.2720	0.2954	0.3291	0.3576	0.3759
	DQMA-I	0.2658	0.2301	0.2233	0.2496	0.2395	0.2399	0.2626	0.2770	0.3068	0.3566	0.3363
	DQMA-II	0.3051	0.2407	0.2442	0.2442	0.2420	0.2501	0.2777	0.2998	0.3355	0.3588	0.3795
	DQMA-Gods	0.3014	0.2283	0.2402	0.2407	0.2398	0.2496	0.2757	0.2981	0.3362	0.3594	0.3760
	DQMA-MSE	0.3037	0.2403	0.2439	0.2439	0.2420	0.2499	0.2774	0.2994	0.3357	0.3597	0.3806
	DQMA-Eq	0.3051	0.2407	0.2442	0.2442	0.2420	0.2501	0.2777	0.2998	0.3355	0.3587	0.3795
	QARX-Temp	-0.0049	0.0049	-0.0537	-0.0377	-0.0544	-0.0496	-0.0224	-0.0192	0.0620	0.0708	0.0070
	QARX-HDD	**0.1175**	0.0237	-0.0435	-0.0423	-0.0571	-0.0262	-0.0268	-0.0078	0.0443	0.1139	**0.1646**
	QARX-CDD	0.0820	-0.0341	-0.0389	-0.0315	-0.0549	-0.0218	-0.0009	0.0285	0.0900	0.0923	0.0418
	QARX-Prec	0.0475	0.0074	**-0.0309**	-0.0508	**-0.0411**	-0.0418	0.0041	0.0199	0.0868	0.0888	0.0999
	QARX-Wind	0.1165	**0.0320**	-0.0777	-0.0452	-0.0587	**-0.0124**	0.0011	0.0166	0.0783	**0.1141**	0.1154
	QARX-All	-0.0377	-0.0756	-0.0464	**-0.0274**	-0.0474	-0.0378	-0.0278	-0.0099	-0.0097	-0.0479	-0.0413
h=6	QARX	0.0907	0.0094	-0.0586	-0.0369	-0.0505	-0.0307	**0.0063**	**0.0312**	**0.1392**	0.0942	0.1082
	DMA	0.1197	0.0215	-0.0344	-0.0287	-0.0345	-0.0165	0.0017	0.0146	0.0903	0.0899	0.1261
	DQMA-I	0.0517	-0.0041	-0.0393	-0.0394	-0.0425	-0.0299	-0.0082	0.0108	0.0769	0.0868	0.0993
	DQMA-II	0.1104	0.0200	-0.0338	-0.0265	-0.0338	-0.0147	0.0047	0.0228	0.0935	0.1122	0.1525
	DQMA-Gods	0.1113	0.0109	-0.0370	-0.0264	-0.0350	-0.0146	0.0002	0.0168	0.1049	0.1021	0.1660
	DQMA-MSE	0.1101	0.0194	-0.0336	-0.0262	-0.0336	-0.0148	0.0044	0.0224	0.0926	0.1107	0.1510
	DQMA-Eq	0.1104	0.0200	-0.0338	-0.0265	-0.0338	-0.0147	0.0048	0.0228	0.0935	0.1123	0.1525
	QARX-Temp	-0.6266	**-0.4595**	-0.4000	**-0.2931**	**-0.2272**	-0.1835	-0.1329	-0.1015	-0.0292	0.0458	0.0757
	QARX-HDD	**-0.5845**	-0.4794	-0.3796	-0.2997	-0.2327	-0.1770	-0.1378	-0.1131	-0.0418	0.0301	0.0776
	QARX-CDD	-0.6448	-0.5391	-0.4550	-0.3176	-0.2528	-0.1711	**-0.1168**	-0.1055	**-0.0170**	**0.0693**	0.0570
	QARX-Prec	-0.6029	-0.5321	-0.4267	-0.3336	-0.2680	-0.2063	-0.1558	-0.1137	-0.0289	0.0475	**0.1375**
	QARX-Wind	-0.7958	-0.5549	-0.4166	-0.3438	-0.2524	-0.1839	-0.1248	-0.0951	-0.0244	0.0213	0.0606
	QARX-All	-0.6997	-0.5719	-0.4081	-0.3009	-0.2499	-0.1978	-0.1374	-0.1176	-0.0570	-0.0088	-0.0053
h=12	QARX	-0.6344	-0.5258	**-0.3712**	-0.3255	-0.2503	**-0.1700**	-0.1325	**-0.0877**	-0.0309	0.0675	0.1339
	DMA	-0.6035	-0.4838	-0.4008	-0.3094	-0.2397	-0.1835	-0.1365	-0.0957	-0.0254	0.0542	0.1257
	DQMA-I	-0.7168	-0.5535	-0.4048	-0.3139	-0.2544	-0.1844	-0.1413	-0.1194	-0.0150	0.0209	0.0566
	DQMA-II	-0.6026	-0.4844	-0.3912	-0.3007	-0.2320	-0.1728	-0.1241	-0.0901	-0.0147	0.0644	0.1205
	DQMA-Gods	-0.6116	-0.4922	-0.3959	-0.2986	-0.2315	-0.1721	-0.1237	-0.0910	-0.0103	0.0679	0.1255
	DQMA-MSE	-0.6026	-0.4861	-0.3912	-0.3001	-0.2315	-0.1722	-0.1239	-0.0894	-0.0140	0.0654	0.1210
	DQMA-Eq	-0.6025	-0.4844	-0.3912	-0.3007	-0.2320	-0.1728	-0.1241	-0.0901	-0.0148	0.0643	0.1205

Note: The number in bold represents the best model among all individual models; numbers in shade depict the combined model that performs better than the benchmark QARX model.

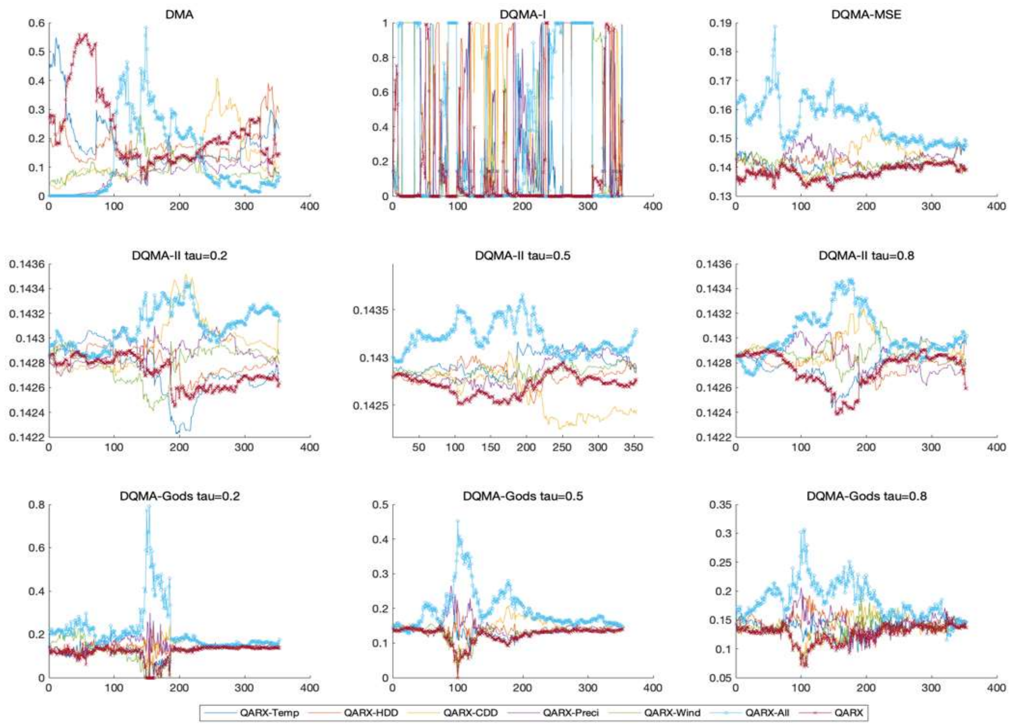
Table 4: Quantile CW test results for aggregate US inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
h=1	DMA	1.386	1.804**	2.472**	2.357**	0.723	0.397	1.358	0.152	1.424	2.533**	1.236
	DQMA-I	1.399	1.569	2.646**	4.479**	2.469**	1.404	1.574	0.764	0.741	2.363**	1.414
	DQMA-II	1.728**	1.876**	2.645**	3.538**	2.026**	1.368	1.808**	0.598	1.695**	2.631**	1.487
	DQMA-Gods	1.676**	1.688**	2.390**	3.213**	1.873**	1.291	1.818**	0.565	1.918**	2.735**	1.422
	DQMA-MSE	1.705**	1.866**	2.667**	3.496**	2.034**	1.364	1.829**	0.599	1.754**	2.683**	1.527
	DQMA-Eq	1.728**	1.876**	2.644**	3.539**	2.026**	1.367	1.807**	0.599	1.694**	2.629**	1.486
h=6	DMA	1.360	1.147	2.617**	1.592	1.965**	2.320**	0.767	-0.025	-2.173**	0.557	2.612**
	DQMA-I	1.041	1.007	2.447**	1.025	1.652**	1.582	0.867	0.356	-1.244	0.999	3.072**
	DQMA-II	1.530	1.268	2.976**	2.073**	2.052**	2.664**	1.223	0.697	-1.463	1.729**	2.921**
	DQMA-Gods	1.601	1.096	2.509**	2.098**	2.061**	2.627**	1.082	0.503	-0.461	1.382	2.632**
	DQMA-MSE	1.524	1.256	2.974**	2.082**	2.059**	2.646**	1.212	0.673	-1.494	1.660**	2.912**
	DQMA-Eq	1.530	1.268	2.975**	2.073**	2.051**	2.665**	1.223	0.698	-1.462	1.729**	2.921**
h=12	DMA	1.030	1.863**	-1.043	2.182**	1.588	-0.758	0.127	-0.324	2.227**	0.707	0.426
	DQMA-I	0.778	0.565	-0.199	2.093**	1.544	1.128	1.292	-0.213	4.263**	0.978	0.439
	DQMA-II	1.173	2.069**	-0.463	2.921**	2.654**	0.524	1.655**	0.290	3.330**	1.266	0.413
	DQMA-Gods	1.062	1.892**	-0.401	2.945**	2.665**	0.562	1.759**	0.309	3.784**	1.552	0.701
	DQMA-MSE	1.181	2.010**	-0.421	2.953**	2.679**	0.583	1.686**	0.353	3.398**	1.341	0.427
	DQMA-Eq	1.176	2.069**	-0.465	2.920**	2.652**	0.522	1.653**	0.289	3.329**	1.265	0.412

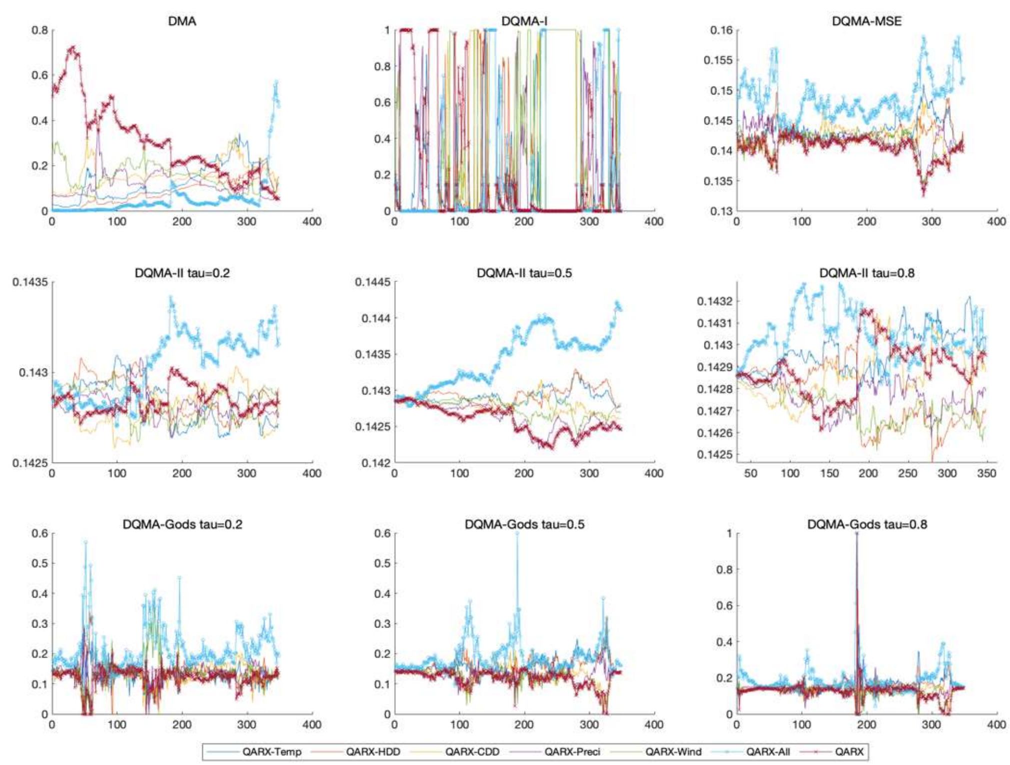
Note: The table reports the quantile CW test statistics for the null hypothesis of equal predictive ability between the combination models versus the QARX model; positive values indicate the combination models outpeform the QARX model and vice versa, ** indicates significance at the 5% level.

Figure 2: Weight evolution of all individual models using DMA and DQMA methods

2(a). h=1



2(b). h=6



2(c). h=12

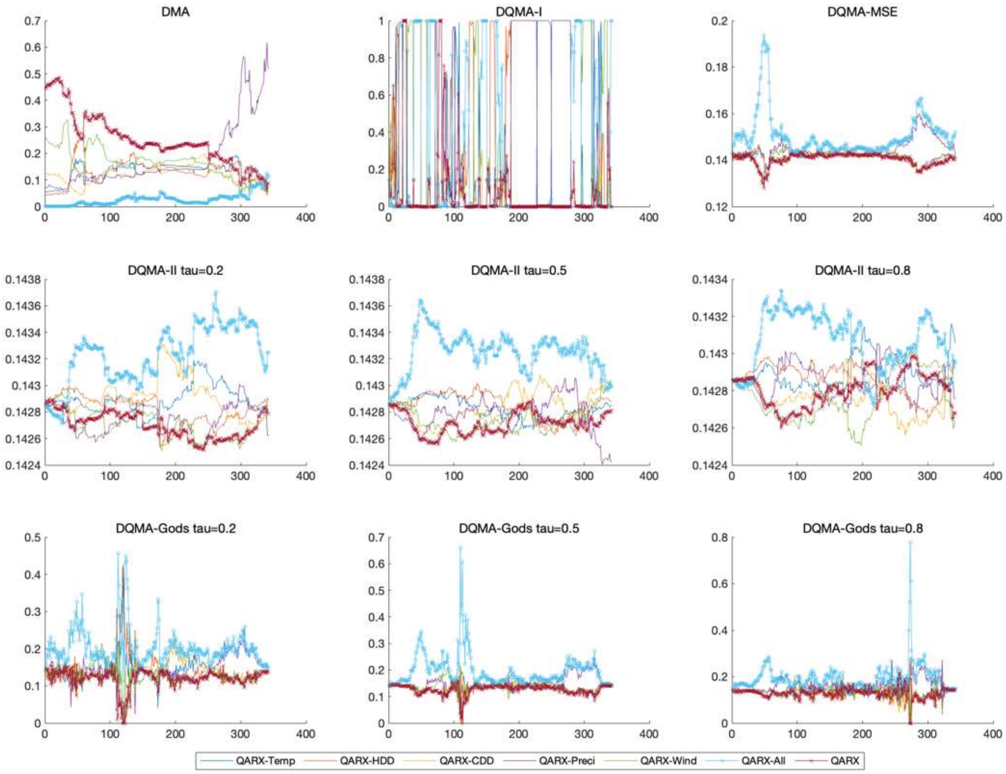
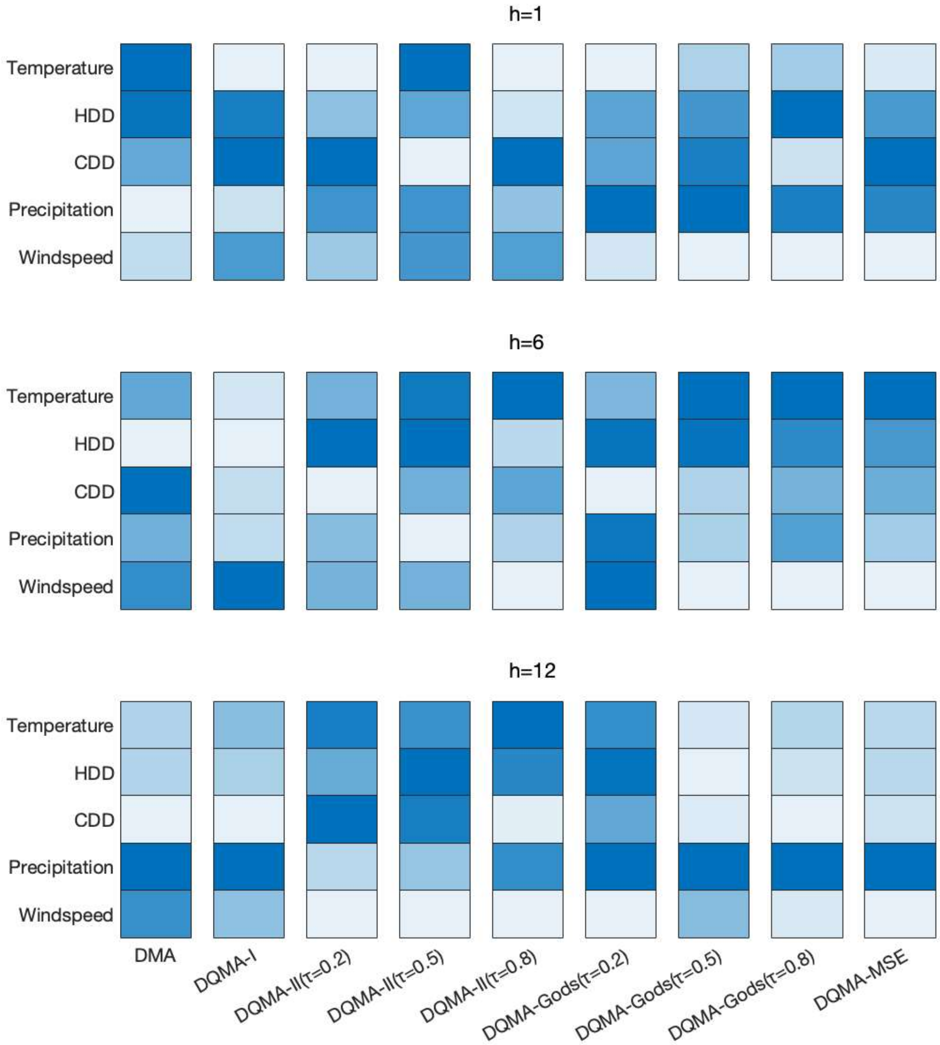

DMA
DQMA-I
DQMA-MSE
DQMA-II tau=0.2
DQMA-II tau=0.5
DQMA-II tau=0.8
DQMA-Gods tau=0.2
DQMA-Gods tau=0.5
DQMA-Gods tau=0.8
QARX-Temp
QARX-HDD
QARX-CDD
QARX-Preci
QARX-Wind
QARX-All
QARX

Figure 3: Heatmaps based on the mean value for the PIPs of the 5 climate risks predictors



Note: The color pattern within each column denote the hightest mean PIP in dark blue to the lowest mean PIP in white.

Table 5: Violation rate results for US Food & Beverages inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
	QARX-Temp	0.0737	0.1161	**0.2238**	0.3966	0.4759	0.5666	0.6997	0.7819	0.8414	0.9178	**0.9462**
	QARX-HDD	0.0737	0.1105	0.2266	0.3626	0.4844	0.5637	0.6771	0.7620	0.8470	**0.9150**	0.9547
	QARX-CDD	0.0652	**0.1048**	0.2493	**0.3484**	0.4646	0.5751	0.6686	**0.7450**	0.8555	0.9263	0.9433
	QARX-Prec	0.0907	0.1275	0.2266	0.3598	0.4816	0.5921	0.6856	0.7564	0.8527	0.9292	**0.9462**
	QARX-Wind	**0.0595**	0.1133	0.2521	0.3626	**0.4504**	**0.5467**	**0.6516**	0.7564	**0.8272**	**0.9150**	0.9348
	QARX-All	0.0793	0.1501	0.2465	0.3626	0.4731	**0.5467**	0.6629	0.7479	0.8300	0.9207	0.9405
h=1	QARX	0.0680	0.1133	0.2493	0.3654	0.4703	0.5722	0.6742	0.7592	0.8527	0.9178	0.9405
	DMA	0.0652	0.1105	0.2323	0.3654	0.4816	0.5751	0.6827	0.7677	0.8555	0.9207	0.9490
	DQMA-I	0.0765	0.1190	0.2436	0.3654	0.4589	0.5496	0.6516	0.7535	0.8414	0.9178	0.9405
	DQMA-II	0.0652	0.1076	0.2295	0.3796	0.4816	0.5666	0.6771	0.7677	0.8470	0.9263	0.9462
	DQMA-Gods	0.0652	0.1133	0.2295	0.3824	0.4788	0.5637	0.6771	0.7677	0.8499	0.9235	0.9433
	DQMA-MSE	0.0623	0.1076	0.2295	0.3796	0.4816	0.5637	0.6771	0.7677	0.8470	0.9263	0.9462
	DQMA-Eq	0.0652	0.1076	0.2295	0.3796	0.4816	0.5666	0.6771	0.7677	0.8470	0.9263	0.9462
	QARX-Temp	0.0718	0.1178	0.2529	0.3391	0.4138	0.4770	0.5776	0.6580	**0.7299**	0.8161	0.8879
	QARX-HDD	0.0747	0.1408	0.2529	0.3305	0.4109	0.4914	0.5833	**0.6782**	**0.7299**	0.8046	0.8908
	QARX-CDD	0.0747	**0.1149**	0.2241	0.3276	**0.4052**	0.4885	0.5431	0.6523	0.7040	**0.8305**	0.8678
	QARX-Prec	0.0776	0.1207	0.2356	0.3075	**0.4052**	0.4856	0.5546	0.6408	0.7069	0.8046	0.8649
	QARX-Wind	**0.0690**	0.1322	0.2241	**0.3046**	0.3908	0.4598	0.5489	0.6264	**0.7299**	0.8161	**0.8966**
	QARX-All	0.0891	0.1322	**0.2098**	0.2874	0.3649	0.4626	0.5431	0.6034	0.7069	0.7989	0.8477
h=6	QARX	0.0776	0.1408	0.2328	0.3190	0.4167	**0.5029**	**0.5862**	0.6523	0.7126	0.8218	0.8793
	DMA	0.0718	0.1322	0.2241	0.3046	0.4023	0.4684	0.5575	0.6494	0.7213	0.8218	0.8822
	DQMA-I	0.0776	0.1322	0.2443	0.3103	0.3879	0.4655	0.5603	0.6437	0.7213	0.8132	0.8736
	DQMA-II	0.0603	0.1264	0.2328	0.3103	0.3994	0.4713	0.5546	0.6580	0.7241	0.8161	0.8966
	DQMA-Gods	0.0632	0.1264	0.2299	0.3103	0.3994	0.4713	0.5546	0.6523	0.7184	0.8161	0.8908
	DQMA-MSE	0.0603	0.1264	0.2299	0.3075	0.3994	0.4713	0.5546	0.6552	0.7184	0.8161	0.8966
	DQMA-Eq	0.0603	0.1264	0.2328	0.3103	0.3994	0.4713	0.5546	0.6580	0.7241	0.8161	0.8966
	QARX-Temp	0.0819	**0.1111**	0.1842	0.2602	0.3333	0.3977	0.4825	0.5702	0.6462	0.7544	0.8363
	QARX-HDD	**0.0789**	0.1228	**0.1959**	0.2632	0.3333	0.3772	0.4620	0.5585	0.6228	**0.7719**	0.8275
	QARX-CDD	0.0906	0.1316	0.2164	0.2573	0.3450	**0.4269**	0.4912	0.5585	0.6345	0.7515	0.8158
	QARX-Prec	0.0965	0.1404	0.2105	0.2778	0.3509	**0.4269**	**0.5058**	**0.5760**	**0.6491**	0.7485	0.8304
	QARX-Wind	0.0906	0.1374	0.2076	**0.2924**	0.3333	0.4181	0.4825	0.5468	0.6316	0.7602	0.8304
	QARX-All	0.1170	0.1608	0.2164	0.2602	0.3392	0.3772	0.4795	0.5731	0.6404	0.7164	0.8129
h=12	QARX	0.0906	0.1345	0.2105	0.2807	**0.3626**	0.4181	0.5029	0.5468	0.6257	**0.7719**	**0.8392**
	DMA	0.0906	0.1228	0.1959	0.2573	0.3480	0.3918	0.4883	0.5614	0.6374	0.7719	0.8421
	DQMA-I	0.0906	0.1316	0.1871	0.2719	0.3392	0.4064	0.4854	0.5614	0.6491	0.7749	0.8421
	DQMA-II	0.0848	0.1404	0.2076	0.2719	0.3392	0.4035	0.4795	0.5526	0.6374	0.7602	0.8363
	DQMA-Gods	0.0877	0.1433	0.2018	0.2690	0.3392	0.4035	0.4737	0.5614	0.6404	0.7573	0.8333
	DQMA-MSE	0.0877	0.1433	0.2076	0.2719	0.3392	0.4035	0.4766	0.5497	0.6374	0.7602	0.8363
	DQMA-Eq	0.0848	0.1404	0.2076	0.2719	0.3392	0.4035	0.4795	0.5526	0.6374	0.7602	0.8363

Note: The number in bold represents the best model among all individual models; numbers in shade depict the combined model that performs better than the benchmark QARX model.

Table 6: Out-of-sample R^2 results for US Food & Beverages inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
	QARX-Temp	0.0657	0.1707	**0.2085**	0.2338	0.2546	0.2972	**0.3129**	0.3225	**0.3684**	0.3561	0.4031
	QARX-HDD	0.0985	0.1583	0.2008	**0.2506**	0.2468	0.2937	0.3074	**0.3264**	0.3621	0.3845	**0.4113**
	QARX-CDD	**0.1753**	**0.1915**	0.1871	0.2286	**0.2679**	0.2983	0.3019	0.3139	0.3668	0.3684	0.3782
	QARX-Prec	0.0502	0.1635	0.2072	0.2334	0.2513	**0.3054**	0.3125	0.3107	0.3650	**0.3920**	0.3946
	QARX-Wind	0.0912	0.1334	0.1877	0.2043	0.2388	0.2656	0.2882	0.3192	0.3366	0.3849	0.3877
	QARX-All	0.1094	0.1593	0.1661	0.1928	0.2049	0.2399	0.2647	0.3108	0.3456	0.3644	0.3353
h=1	QARX	0.1414	0.1886	0.1913	0.2178	0.2518	0.2998	0.3027	0.3138	0.3588	0.3663	0.4050
	DMA	0.1802	0.1985	0.2133	0.2369	0.2610	0.3009	0.3111	0.3244	0.3661	0.3876	0.4137
	DQMA-I	0.0917	0.1713	0.1781	0.2112	0.2444	0.2738	0.3066	0.3242	0.3558	0.3903	0.3810
	DQMA-II	0.1950	0.2031	0.2096	0.2370	0.2590	0.2972	0.3111	0.3251	0.3675	0.3892	0.4152
	DQMA-Gods	0.1895	0.1964	0.2093	0.2368	0.2564	0.2947	0.3095	0.3275	0.3669	0.3903	0.4153
	DQMA-MSE	0.1942	0.2026	0.2092	0.2368	0.2586	0.2968	0.3107	0.3252	0.3674	0.3894	0.4157
	DQMA-Eq	0.1950	0.2031	0.2096	0.2370	0.2590	0.2972	0.3111	0.3251	0.3675	0.3892	0.4152
	QARX-Temp	0.0244	0.0272	0.0082	0.0361	**0.0698**	0.0970	0.1372	0.1864	0.1830	0.1888	0.1419
	QARX-HDD	0.0254	-0.0337	0.0105	0.0353	0.0603	0.0994	0.1347	0.1812	0.2051	0.1780	**0.1912**
	QARX-CDD	**0.0562**	**0.0348**	0.0249	0.0255	0.0694	0.1024	0.1335	**0.1968**	0.2037	0.1625	0.1548
	QARX-Prec	-0.0289	-0.0056	0.0034	0.0212	0.0604	0.0961	0.1341	0.1859	0.1767	0.1800	0.1180
	QARX-Wind	-0.1061	-0.0182	**0.0309**	**0.0497**	0.0659	0.0967	0.1319	0.1611	**0.2311**	**0.1970**	0.1390
	QARX-All	-0.0787	-0.0877	-0.0241	0.0090	0.0290	0.0552	0.1033	0.1469	0.1450	0.1430	0.0619
h=6	QARX	0.0084	-0.0027	0.0173	0.0422	0.0666	**0.1063**	**0.1477**	0.1882	0.2010	0.1963	0.1015
	DMA	0.0144	0.0084	0.0247	0.0394	0.0640	0.1039	0.1412	0.1951	0.2130	0.2048	0.1983
	DQMA-I	-0.0037	-0.0091	0.0031	0.0281	0.0635	0.1011	0.1348	0.2041	0.2159	0.1783	0.1283
	DQMA-II	0.0559	0.0277	0.0378	0.0451	0.0723	0.1091	0.1527	0.1970	0.2092	0.2020	0.2007
	DQMA-Gods	0.0392	0.0198	0.0389	0.0458	0.0721	0.1077	0.1541	0.1997	0.2111	0.2049	0.2008
	DQMA-MSE	0.0555	0.0270	0.0382	0.0454	0.0724	0.1089	0.1527	0.1973	0.2093	0.2018	0.2015
	DQMA-Eq	0.0559	0.0277	0.0378	0.0451	0.0723	0.1091	0.1527	0.1970	0.2092	0.2020	0.2006
	QARX-Temp	-0.1183	**-0.0905**	**-0.1118**	**-0.1270**	**-0.1185**	-0.1199	-0.1062	**-0.0978**	-0.1214	**-0.1025**	**-0.0831**
	QARX-HDD	**-0.1073**	-0.1191	-0.1134	-0.1358	-0.1202	**-0.1119**	**-0.1016**	-0.1035	-0.1609	-0.1115	-0.1170
	QARX-CDD	-0.1657	-0.1570	-0.1573	-0.1539	-0.1371	-0.1398	-0.1034	-0.1042	-0.1161	-0.1747	-0.2220
	QARX-Prec	-0.1844	-0.1642	-0.1810	-0.1605	-0.1442	-0.1494	-0.1161	-0.1057	-0.1174	-0.1142	-0.1614
	QARX-Wind	-0.1762	-0.1459	-0.1485	-0.1641	-0.1203	-0.1177	-0.1096	-0.1022	-0.1517	-0.1465	-0.1675
	QARX-All	-0.2608	-0.2149	-0.1376	-0.1655	-0.1648	-0.1400	-0.1448	-0.1397	-0.2042	-0.2636	-0.2516
h=12	QARX	-0.1272	-0.1446	-0.1503	-0.1706	-0.1392	-0.1246	-0.1086	-0.1160	**-0.1136**	-0.1242	-0.1332
	DMA	-0.1249	-0.1328	-0.1449	-0.1629	-0.1339	-0.1253	-0.1079	-0.1151	-0.1473	-0.1293	-0.1372
	DQMA-I	-0.1222	-0.1338	-0.1083	-0.1486	-0.1123	-0.0961	-0.0989	-0.1035	-0.1263	-0.0989	-0.0965
	DQMA-II	-0.1012	-0.1080	-0.1196	-0.1311	-0.1205	-0.1125	-0.0943	-0.0905	-0.1197	-0.1061	-0.1016
	DQMA-Gods	-0.1046	-0.1054	-0.1117	-0.1284	-0.1225	-0.1160	-0.0973	-0.0935	-0.1241	-0.1159	-0.1074
	DQMA-MSE	-0.1006	-0.1073	-0.1187	-0.1313	-0.1205	-0.1120	-0.0945	-0.0907	-0.1203	-0.1077	-0.1026
	DQMA-Eq	-0.1012	-0.1080	-0.1197	-0.1311	-0.1205	-0.1126	-0.0943	-0.0905	-0.1197	-0.1061	-0.1016

Note: The number in bold represents the best model among all individual models; numbers in shade depict the combined model that performs better than the benchmark QARX model.

Table 7: Quantile CW test results for US Food & Beverages inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
h=1	DMA	1.894**	2.579**	2.979**	3.285**	2.420**	1.237	2.359**	2.494**	1.299	2.671**	1.999**
	DQMA-I	1.757**	2.632**	1.080	1.384	1.820**	0.200	1.677**	1.528	0.287	2.438**	1.144
	DQMA-II	2.431**	3.130**	2.541**	2.976**	2.121**	0.868	2.006**	2.293**	1.296	2.585**	2.224**
	DQMA-Gods	2.520**	3.053**	2.188**	2.779**	1.899**	0.712	1.833**	2.291**	1.339	2.594**	2.243**
	DQMA-MSE	2.442**	3.143**	2.481**	2.907**	2.085**	0.824	1.951**	2.287**	1.304	2.591**	2.247**
	DQMA-Eq	2.430**	3.130**	2.542**	2.977**	2.122**	0.869	2.006**	2.293**	1.295	2.585**	2.224**
h=6	DMA	1.706**	1.799**	1.840**	1.318	0.915	1.373	0.790	2.471**	1.163	1.637	4.018**
	DQMA-I	1.575	1.644	0.921	0.763	1.345	1.034	1.248	3.380**	1.404	0.810	2.572**
	DQMA-II	2.237**	2.168**	2.524**	1.705**	1.767**	2.191**	1.540	1.996**	0.936	1.561	3.996**
	DQMA-Gods	2.047**	2.108**	2.524**	1.748**	1.734**	2.089**	1.907**	2.298**	1.086	1.809**	4.205**
	DQMA-MSE	2.252**	2.173**	2.527**	1.719**	1.759**	2.166**	1.599	2.039**	0.943	1.588	4.048**
	DQMA-Eq	2.237**	2.168**	2.524**	1.705**	1.768**	2.192**	1.541	1.996**	0.936	1.560	3.995**
h=12	DMA	1.460	1.334	1.980**	1.828**	1.607	1.525	1.393	1.730**	-0.109	2.170**	0.700
	DQMA-I	2.073**	1.262	3.017**	3.498**	2.574**	2.869**	1.847**	2.028**	0.802	4.451**	2.161**
	DQMA-II	1.372	2.065**	3.037**	4.146**	2.688**	1.880**	2.027**	2.886**	0.044	3.140**	1.848**
	DQMA-Gods	1.328	2.130**	3.240**	4.300**	2.487**	1.716**	1.885**	2.664**	-0.060	2.980**	1.681**
	DQMA-MSE	1.400	2.055**	3.036**	4.102**	2.666**	1.900**	2.001**	2.827**	0.027	3.107**	1.806**
	DQMA-Eq	1.371	2.065**	3.036**	4.146**	2.688**	1.881**	2.029**	2.888**	0.044	3.140**	1.847**

Note: The table reports the quantile CW test statistics for the null hypothesis of equal predictive ability between the combination models versus the QARX model; positive values indicate the combination models outpeform the QARX model and vice versa, ** indicates significance at the 5% level.

Table 8: Violation rate results for US Housing inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
	QARX-Temp	0.0881	0.1392	0.2443	0.3381	0.4148	0.4972	0.6023	0.6903	0.7869	0.8722	0.9233
	QARX-HDD	0.0852	0.1364	0.2131	0.3295	**0.4006**	0.4915	0.5938	0.6932	0.7898	0.8722	**0.9261**
	QARX-CDD	0.0966	0.1563	0.2301	0.3295	0.4261	0.5028	0.5852	0.6932	0.7784	0.8835	**0.9261**
	QARX-Prec	0.0966	0.1392	**0.2102**	**0.2983**	0.3722	0.4744	0.5795	0.6960	**0.7926**	0.8665	0.9091
	QARX-Wind	0.0682	**0.1307**	0.2244	0.3153	0.3920	0.4972	0.5824	0.6761	0.7841	0.8835	0.9176
	QARX-All	0.1051	0.1477	0.2472	0.3381	0.4261	**0.5000**	0.5909	0.6619	0.7443	0.8608	0.9034
h=1	QARX	**0.0653**	0.1364	0.2244	0.2841	**0.4006**	0.4943	**0.5994**	**0.6989**	0.7756	**0.8864**	0.9148
	DMA	0.0739	0.1477	0.2273	0.3210	0.4176	0.5085	0.5966	0.6875	0.7926	0.8807	0.9261
	DQMA-I	0.0938	0.1392	0.2386	0.3352	0.4119	0.5000	0.5852	0.6903	0.7727	0.8722	0.9290
	DQMA-II	0.0739	0.1335	0.2131	0.3125	0.4034	0.5057	0.5966	0.6847	0.7926	0.8778	0.9176
	DQMA-Gods	0.0824	0.1364	0.2188	0.3125	0.4034	0.5057	0.5938	0.6818	0.7898	0.8778	0.9233
	DQMA-MSE	0.0739	0.1335	0.2131	0.3125	0.4034	0.5057	0.5966	0.6847	0.7898	0.8778	0.9176
	DQMA-Eq	0.0739	0.1335	0.2131	0.3125	0.4034	0.5057	0.5966	0.6847	0.7926	0.8778	0.9176
	QARX-Temp	0.0517	0.0862	0.1724	0.2529	0.3477	0.4282	0.5115	0.6207	0.7241	0.8506	0.9167
	QARX-HDD	0.0546	0.0776	0.1667	0.2615	0.3678	0.4483	0.5029	0.6092	0.7299	0.8477	0.8966
	QARX-CDD	0.0460	0.0805	**0.1868**	**0.2672**	0.3678	**0.4626**	0.5345	0.6408	0.7385	0.8592	0.9109
	QARX-Prec	0.0431	0.0833	0.1523	0.2356	0.3362	0.4310	0.5259	**0.6667**	0.7471	0.8477	0.9109
	QARX-Wind	**0.0489**	0.0891	0.1724	0.2529	**0.3793**	0.4483	**0.5374**	0.6466	0.7299	**0.8621**	**0.9253**
	QARX-All	**0.0489**	0.0718	**0.1868**	0.2414	0.3305	0.4224	0.5115	0.6236	0.7184	0.8276	0.9052
h=6	QARX	0.0517	**0.0948**	0.1724	0.2586	0.3621	**0.4626**	0.5345	0.6437	**0.7500**	0.8477	**0.9253**
	DMA	0.0460	0.0776	0.1609	0.2586	0.3534	0.4425	0.5144	0.6322	0.7270	0.8592	0.9195
	DQMA-I	0.0460	0.0690	0.1753	0.2471	0.3534	0.4282	0.4971	0.6236	0.7098	0.8333	0.8937
	DQMA-II	0.0460	0.0833	0.1638	0.2586	0.3592	0.4397	0.5144	0.6379	0.7356	0.8678	0.9195
	DQMA-Gods	0.0460	0.0776	0.1638	0.2529	0.3534	0.4454	0.5115	0.6379	0.7385	0.8678	0.9167
	DQMA-MSE	0.0460	0.0833	0.1667	0.2586	0.3592	0.4397	0.5144	0.6379	0.7356	0.8649	0.9195
	DQMA-Eq	0.0460	0.0833	0.1638	0.2586	0.3592	0.4397	0.5144	0.6379	0.7356	0.8678	0.9195
	QARX-Temp	0.1462	**0.2076**	0.3216	0.3947	0.4678	0.5322	**0.6053**	0.6871	0.7398	**0.8538**	**0.8626**
	QARX-HDD	**0.1433**	0.2135	0.3275	0.3860	0.4766	0.5439	0.6170	0.6784	0.7398	0.8421	0.8596
	QARX-CDD	**0.1433**	0.2105	0.3187	0.4035	**0.4444**	0.5409	0.6374	0.6813	0.7368	0.8304	0.8596
	QARX-Prec	**0.1433**	0.2222	**0.2982**	0.3830	0.4474	**0.5263**	0.6111	0.6754	0.7544	0.8480	0.8596
	QARX-Wind	0.1550	0.2193	0.3187	0.3947	0.4825	0.5556	0.6404	0.6842	**0.7602**	**0.8538**	0.8596
	QARX-All	0.1608	0.2251	0.3363	0.4152	0.4737	0.5468	0.5877	0.6579	0.7398	0.8099	0.8421
h=12	QARX	0.1608	0.2193	0.3129	**0.3801**	0.4678	0.5556	0.6228	**0.6901**	0.7485	0.8509	0.8480
	DMA	0.1316	0.1988	0.3041	0.3801	0.4678	0.5380	0.6199	0.6871	0.7456	0.8480	0.8567
	DQMA-I	0.1374	0.2164	0.3246	0.4006	0.4737	0.5351	0.6053	0.6754	0.7485	0.8129	0.8480
	DQMA-II	0.1345	0.2105	0.3041	0.3743	0.4737	0.5497	0.6170	0.6842	0.7456	0.8450	0.8596
	DQMA-Gods	0.1404	0.2105	0.3099	0.3772	0.4649	0.5497	0.6140	0.6813	0.7485	0.8421	0.8596
	DQMA-MSE	0.1345	0.2105	0.3070	0.3743	0.4737	0.5526	0.6170	0.6842	0.7427	0.8450	0.8596
	DQMA-Eq	0.1345	0.2105	0.3041	0.3743	0.4737	0.5497	0.6170	0.6842	0.7456	0.8450	0.8596

Note: The number in bold represents the best model among all individual models; numbers in shade depict the combined model that performs better than the benchmark QARX model.

Table 9: Out-of-sample R^2 results for US Housing inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
	QARX-Temp	-0.0262	0.0469	0.0926	0.1210	0.1456	0.1838	0.1731	0.1928	**0.2292**	0.2319	0.2067
	QARX-HDD	-0.0200	**0.0657**	0.1143	0.1380	0.1610	0.1907	0.1875	0.1900	0.2284	0.2304	0.2153
	QARX-CDD	-0.0462	-0.0085	**0.1603**	0.1560	0.1771	0.1972	0.1924	0.1766	0.1967	0.2111	**0.2403**
	QARX-Prec	-0.0742	0.0419	0.1461	0.1698	0.1777	0.1991	0.2058	0.1847	0.2165	0.2235	0.1869
	QARX-Wind	0.0042	0.0340	0.1391	0.1637	**0.1928**	**0.2243**	**0.2214**	**0.2262**	0.2256	**0.2451**	0.2028
	QARX-All	-0.0616	0.0615	0.1100	0.1344	0.1466	0.1699	0.1556	0.1717	0.2123	0.2196	0.1562
h=1	QARX	**0.0336**	0.0505	0.1467	**0.1868**	0.1742	0.2182	0.2074	0.2118	0.2224	0.2423	0.1634
	DMA	0.0442	0.0703	0.1542	0.1725	0.1781	0.2101	0.2018	0.2042	0.2296	0.2485	0.2397
	DQMA-I	-0.0151	0.0790	0.1888	0.1548	0.1923	0.2095	0.2010	0.1923	0.2128	0.2270	0.2409
	DQMA-II	0.0366	0.0749	0.1562	0.1734	0.1838	0.2134	0.2047	0.2105	0.2380	0.2538	0.2430
	DQMA-Gods	0.0293	0.0774	0.1445	0.1740	0.1847	0.2133	0.2043	0.2111	0.2392	0.2541	0.2406
	DQMA-MSE	0.0372	0.0757	0.1556	0.1731	0.1835	0.2126	0.2040	0.2104	0.2382	0.2539	0.2432
	DQMA-Eq	0.0366	0.0749	0.1562	0.1734	0.1838	0.2134	0.2047	0.2105	0.2380	0.2538	0.2430
	QARX-Temp	0.1995	0.2111	0.2431	0.2236	0.2010	0.1827	0.2399	0.2595	0.2863	0.3297	0.3686
	QARX-HDD	0.1918	0.2071	0.2384	0.2107	0.2109	0.1806	0.2353	0.2573	0.2835	0.3464	0.3709
	QARX-CDD	**0.2129**	**0.2309**	0.2050	0.1926	0.1904	0.1943	0.2359	0.2669	0.2918	**0.3492**	**0.3909**
	QARX-Prec	0.1887	0.2275	0.2227	0.2306	0.2235	0.2045	**0.2574**	**0.2827**	**0.3188**	0.3117	0.3514
	QARX-Wind	0.2101	0.2241	**0.2498**	**0.2433**	**0.2308**	0.2011	0.2566	0.2805	0.2949	0.3220	0.3720
	QARX-All	0.1253	0.1889	0.2107	0.2250	0.2070	**0.2172**	0.2452	0.2762	0.2721	0.3034	0.3829
h=6	QARX	0.1416	0.2005	0.2430	0.2137	0.2169	0.1955	0.2237	0.2503	0.3107	0.3373	0.3723
	DMA	0.2189	0.2364	0.2619	0.2369	0.2270	0.2034	0.2496	0.2742	0.3125	0.3485	0.4045
	DQMA-I	0.1609	0.1988	0.2147	0.2233	0.2275	0.1972	0.2396	0.2664	0.2749	0.3088	0.3961
	DQMA-II	0.2304	0.2422	0.2575	0.2363	0.2258	0.2090	0.2578	0.2846	0.3175	0.3485	0.4150
	DQMA-Gods	0.2325	0.2408	0.2554	0.2367	0.2293	0.2119	0.2605	0.2856	0.3172	0.3479	0.4198
	DQMA-MSE	0.2310	0.2423	0.2577	0.2367	0.2261	0.2093	0.2581	0.2847	0.3174	0.3481	0.4150
	DQMA-Eq	0.2304	0.2422	0.2575	0.2363	0.2258	0.2090	0.2578	0.2846	0.3175	0.3485	0.4150
	QARX-Temp	-0.4811	-0.2060	-0.0828	-0.0611	-0.0347	-0.0236	0.0032	0.0525	0.0713	0.1268	-0.1754
	QARX-HDD	-0.4550	**-0.1509**	-0.0874	-0.0560	-0.0549	-0.0339	0.0011	**0.0780**	0.0804	0.1150	-0.0720
	QARX-CDD	-0.4418	-0.2017	-0.0805	-0.0764	-0.0515	-0.0174	-0.0162	0.0338	0.0681	0.1232	-0.0371
	QARX-Prec	**-0.4198**	-0.2349	**-0.0429**	-0.0685	-0.0261	**0.0001**	**0.0253**	0.0640	**0.0881**	0.1493	-0.0634
	QARX-Wind	-0.5086	-0.2595	-0.0821	-0.0537	-0.0293	-0.0170	0.0037	0.0477	0.0877	0.1074	-0.0948
	QARX-All	-0.5833	-0.2995	-0.1486	-0.1298	-0.1173	-0.0789	-0.0387	0.0002	0.0626	0.0427	**-0.0102**
h=12	QARX	-0.4737	-0.1956	-0.0776	**-0.0378**	**-0.0199**	-0.0132	0.0049	0.0664	0.0827	**0.1587**	-0.0348
	DMA	-0.4246	-0.1649	-0.0617	-0.0475	-0.0263	-0.0094	0.0102	0.0623	0.0846	0.1388	-0.0335
	DQMA-I	-0.4979	-0.2269	-0.0962	-0.0840	-0.0618	-0.0424	-0.0241	0.0126	0.0553	0.1131	0.0079
	DQMA-II	-0.4376	-0.1647	-0.0653	-0.0527	-0.0310	-0.0146	0.0069	0.0615	0.0911	0.1347	-0.0330
	DQMA-Gods	-0.4402	-0.1678	-0.0658	-0.0539	-0.0342	-0.0167	0.0038	0.0612	0.0922	0.1325	-0.0340
	DQMA-MSE	-0.4386	-0.1649	-0.0653	-0.0530	-0.0313	-0.0147	0.0070	0.0616	0.0912	0.1342	-0.0328
	DQMA-Eq	-0.4376	-0.1647	-0.0653	-0.0527	-0.0310	-0.0146	0.0069	0.0615	0.0911	0.1347	-0.0330

Note: The number in bold represents the best model among all individual models; numbers in shade depict the combined model that performs better than the benchmark QARX model.

Table 10: Quantile CW test results for US Housing inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
h=1	DMA	0.675	1.687**	1.269	0.514	1.970**	1.631	1.043	1.251	1.866**	1.931**	2.763**
	DQMA-I	0.489	2.796**	3.144**	0.303	3.120**	1.799**	1.561	1.060	1.691**	1.673**	2.905**
	DQMA-II	0.615	1.802**	1.514	0.256	2.106**	1.115	1.311	1.778**	2.740**	2.408**	2.789**
	DQMA-Gods	0.664	1.968**	0.915	0.572	2.137**	1.208	1.385	1.918**	2.807**	2.374**	2.676**
	DQMA-MSE	0.632	1.819**	1.482	0.283	2.064**	1.098	1.281	1.799**	2.760**	2.398**	2.776**
	DQMA-Eq	0.614	1.802**	1.514	0.255	2.106**	1.114	1.310	1.778**	2.739**	2.407**	2.789**
h=6	DMA	2.429**	3.148**	2.425**	2.943**	2.237**	2.065**	4.490**	3.986**	1.677**	2.466**	2.326**
	DQMA-I	1.997**	1.934**	0.900	2.762**	2.085**	1.988**	2.630**	2.698**	0.763	1.219	3.149**
	DQMA-II	2.481**	3.119**	2.175**	3.066**	1.909**	2.745**	5.277**	4.807**	1.786**	2.630**	2.502**
	DQMA-Gods	2.565**	3.090**	1.876**	3.047**	2.098**	3.003**	5.464**	4.944**	1.784**	2.687**	2.585**
	DQMA-MSE	2.496**	3.129**	2.180**	3.093**	1.942**	2.782**	5.258**	4.796**	1.801**	2.619**	2.503**
	DQMA-Eq	2.482**	3.119**	2.174**	3.065**	1.908**	2.744**	5.277**	4.807**	1.785**	2.629**	2.502**
h=12	DMA	2.689**	2.062**	2.020**	-0.271	0.471	1.345	1.345	0.315	1.396	-0.886	0.495
	DQMA-I	1.772**	1.418	0.099	-1.420	-0.721	-0.668	-0.604	-1.476	0.084	-0.551	1.609
	DQMA-II	2.405**	2.012**	1.767**	-0.436	0.465	0.600	0.985	0.509	2.202**	-1.035	0.659
	DQMA-Gods	2.205**	1.878**	2.104**	-0.502	0.412	0.426	1.049	0.615	2.339**	-1.111	0.673
	DQMA-MSE	2.395**	1.999**	1.759**	-0.446	0.461	0.600	1.035	0.543	2.206**	-1.053	0.665
	DQMA-Eq	2.405**	2.012**	1.767**	-0.435	0.466	0.600	0.984	0.509	2.202**	-1.034	0.660

Note: The table reports the quantile CW test statistics for the null hypothesis of equal predictive ability between the combination models versus the QARX model; positive values indicate the combination models outpeform the QARX model and vice versa, ** indicates significance at the 5% level.

Appendix

Table A1: Quantile CW test results for aggregate US year-on-year inflation forecasts

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
h=1	DMA	2.532**	3.148**	2.145**	2.065**	3.424**	2.240**	1.796**	1.395	0.696	2.673**	1.728**
	DQMA-I	2.606**	1.785**	1.870**	2.770**	3.522**	1.907**	2.055**	2.398**	0.624	1.611	2.454**
	DQMA-II	2.822**	2.893**	2.582**	3.048**	4.782**	3.221**	2.891**	2.323**	1.677**	2.928**	2.186**
	DQMA-Gods	2.817**	2.893**	2.592**	3.045**	4.781**	3.238**	2.902**	2.330**	1.686**	2.932**	2.194**
	DQMA-MSE	2.830**	2.902**	2.586**	3.054**	4.784**	3.234**	2.896**	2.343**	1.686**	2.922**	2.190**
	DQMA-Eq	2.821**	2.894**	2.584**	3.049**	4.785**	3.222**	2.891**	2.320**	1.675**	2.928**	2.186**
h=6	DMA	1.749**	1.538	2.582**	3.771**	2.556**	2.426**	1.278	-0.234	0.410	0.899	0.885
	DQMA-I	1.990**	2.582**	1.822**	2.228**	2.325**	2.775**	1.768**	0.555	0.069	0.754	2.234**
	DQMA-II	2.016**	1.990**	2.646**	3.800**	3.333**	2.703**	1.397	-0.133	0.564	1.367	1.875**
	DQMA-Gods	1.991**	1.957**	2.598**	3.789**	3.334**	2.714**	1.397	-0.079	0.567	1.355	1.753**
	DQMA-MSE	2.028**	2.017**	2.662**	3.806**	3.338**	2.710**	1.420	-0.098	0.553	1.387	1.891**
	DQMA-Eq	2.016**	1.988**	2.645**	3.795**	3.333**	2.695**	1.385	-0.135	0.563	1.366	1.878**
h=12	DMA	0.029	3.260**	3.244**	1.416	2.525**	2.705**	1.493	1.696**	0.812	0.010	1.765**
	DQMA-I	1.582	2.726**	3.902**	1.145	0.695	2.072**	2.154**	1.858**	0.920	1.567	1.798**
	DQMA-II	0.512	3.339**	4.558**	1.786**	1.939**	3.368**	2.970**	2.756**	1.036	0.958	2.178**
	DQMA-Gods	0.891	3.602**	4.658**	1.932**	2.056**	3.151**	2.964**	2.778**	1.069	0.937	2.187**
	DQMA-MSE	0.590	3.429**	4.631**	1.874**	2.018**	3.394**	3.000**	2.748**	1.056	0.951	2.161**
	DQMA-Eq	0.511	3.329**	4.549**	1.773**	1.920**	3.370**	2.967**	2.755**	1.031	0.960	2.181**

Note: The table reports the quantile CW test statistics for the null hypothesis of equal predictive ability between the combination models versus the QARX model; positive values indicate the combination models outpeform the QARX model and vice versa, ** indicates significance at the 5% level.

Table A2: Quantile CW test results for aggregate US inflation forecasts when window size = 80

		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
h=1	DMA	1.971**	3.062**	2.515**	1.925**	1.091	1.158	1.358	2.769**	2.845**	4.054**	2.275**
	DQMA-I	2.482**	2.807**	1.777**	2.454**	0.992	1.366	0.808	2.364**	2.412**	3.258**	1.900**
	DQMA-II	2.506**	3.469**	2.622**	2.936**	1.792**	2.134**	2.009**	2.867**	3.161**	4.060**	2.266**
	DQMA-Gods	2.419**	3.267**	2.612**	2.514**	1.664**	1.946**	1.779**	2.886**	3.244**	4.058**	2.286**
	DQMA-MSE	2.481**	3.430**	2.654**	2.871**	1.799**	2.112**	2.003**	2.910**	3.211**	4.095**	2.276**
	DQMA-Eq	2.506**	3.468**	2.620**	2.937**	1.791**	2.137**	2.011**	2.867**	3.161**	4.059**	2.266**
h=6	DMA	1.928**	2.656**	1.311	1.125	1.189	0.390	-0.439	-0.042	0.282	-0.989	1.597
	DQMA-I	0.711	1.553	1.913**	0.665	0.205	-0.478	-0.694	-0.129	-0.058	-0.923	0.855
	DQMA-II	1.875**	2.738**	1.600	1.361	1.527	0.915	-0.333	0.396	0.801	-0.611	2.090**
	DQMA-Gods	1.888**	2.772**	1.897**	1.432	1.788**	0.992	0.368	1.137	1.319	-0.682	1.998**
	DQMA-MSE	1.881**	2.746**	1.626	1.370	1.520	0.896	-0.354	0.354	0.715	-0.636	2.016**
	DQMA-Eq	1.874**	2.737**	1.600	1.361	1.527	0.915	-0.335	0.396	0.802	-0.611	2.089**
h=12	DMA	2.548**	2.376**	2.514**	1.256	0.542	1.589	1.038	0.822	2.095**	1.182	2.734**
	DQMA-I	2.425**	2.080**	3.031**	2.322**	1.240	1.074	1.709**	0.955	2.821**	1.624	2.689**
	DQMA-II	3.146**	2.782**	3.648**	2.462**	0.964	1.618	1.680**	1.622	2.514**	1.222	2.764**
	DQMA-Gods	2.878**	2.361**	3.330**	2.646**	1.241	1.459	1.830**	1.784**	2.924**	1.400	2.860**
	DQMA-MSE	3.147**	2.794**	3.656**	2.503**	1.023	1.640	1.703**	1.671**	2.544**	1.235	2.775**
	DQMA-Eq	3.146**	2.783**	3.649**	2.461**	0.961	1.618	1.679**	1.620	2.512**	1.222	2.764**

Note: The table reports the quantile CW test statistics for the null hypothesis of equal predictive ability between the combination models versus the QARX model; positive values indicate the combination models outpeform the QARX model and vice versa, ** indicates significance at the 5% level.