Forecasting National Recessions of the United States with State-Level Climate Risks: Evidence from Model Averaging in Markov-Switching Models[#]

Oguzhan Cepni[*], Christina Christou[**] and Rangan Gupta[***]

Highlights

- We forecast business cycle turning points of the United States (US) with state-level climate risks data.
- We use Bayesian model averaging (BMA) and dynamic model averaging (DMA) incorporated into Markov-switching (MS) models.
- Results show that forecasts obtained from the DMA combination scheme provide timely updates of US business cycles.

Abstract

This paper utilizes Bayesian (static) model averaging (BMA) and dynamic model averaging (DMA) incorporated into Markov-switching (MS) models to forecast business cycle turning points of the United States (US) with state-level climate risks data, proxied by temperature changes and their (realized) volatility. We find that forecasts obtained from the DMA combination scheme provide timely updates of US business cycles based on the information content of metrics of state-level climate risks, particularly the volatility of temperature, relative to the corresponding small-scale MS benchmarks that use national-level values of climate change-related predictors.

JEL Codes: C22, C53, E32, E37, Q54
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[*] Copenhagen Business School, Department of Economics, Porcelænshaven 16A, Frederiksberg DK-2000, Denmark; Central Bank of the Republic of Türkiye, Haci Bayram Mah. Istiklal Cad. No:10 06050, Ankara, Türkiye. Email address: oce.eco@cbs.dk.
[**] Corresponding Author. School of Economics and Management, Open University of Cyprus, 2252, Latsia, Cyprus. Email address: christina.christou@ouc.ac.cy.
[***] Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa. Email address: rangan.gupta@up.ac.za.

1. Introduction

A growing literature tends to highlight the role of regional variables in driving aggregate-level business cycles in the United States (US; see Beraja et al. (2019) for a detailed review). In light of the growing role of global warming, recent studies have also indicated the importance of risks associated with climate change, as captured by both first- and second moments of temperature changes, in driving state-level economic variables of the US (Colacito et al., 2019; Sheng et al., 2022a), as well as its associated uncertainties (Sheng et al., 2022b), which is likely to feed back again into the regional predictors (Mumtaz, 2018; Mumtaz et al., 2018). Against this backdrop, we aim to compare the ability of temperature changes and its volatility of the aggregate US, with the corresponding values of the same at the state-level, in forecasting national-level US recessions.[1] Since state-level employment growth has already been shown to outperform commonly used set of national predictors in forecasting recessionary periods of the overall US (Owyang et al., 2015; Guérin and Leiva-León; 2017), we expect that state-level climate risks will also serve to be more informative than those measured for the aggregate US in forecasting national recessions. This presumption is driven by the recent evidence of heterogeneity detected in the underlying property of persistence in temperature across the US states (Gil-Alana, 2022), which in turn is likely to capture better the non-synchronous state-level business cycles (Owyang et al., 2005; Hamilton and Owyang, 2012).

In other words, given that climate risks are known to drive state-level economic variables and associated uncertainties, and that the data generating processes for temperature are heterogeneous across US states, we hypothesize that regional climate risks are more likely to predict national recessions accurately than national-level climate risks. This hypothesis is

[1] Theoretically, heightened climate risks are likely to cause a recession by adversely affecting not only labor productivity and capital quality, but also through the patent obsolescence channel. This, in turn, dampens research and development (R&D) expenditure growth (Donadelli et al., 2017, 2021a, b, 2022). In other words, climate risks can negatively influence the economy from both the demand and supply sides of the economy.

motivated by existing evidence that regional employment growth is more closely linked to capturing US recessions than national employment growth, and with climate risks known to lead economic aggregates; we can formalize this hypothesis in light of the underlying climate-economy nexus.

As far as the econometric framework is concerned, we follow Guérin and Leiva-León (2017) and utilize the Markov-switching framework with Dynamic Model Averaging (MS-DMA), which provides a time-varying flexible framework that evaluates the performance of different Markov-switching models to infer the regimes of a target variable. Comparisons are also made with Bayesian (static) Model Averaging (BMA). Guérin and Leiva-León (2017) used this framework successfully in forecasting national recession with state-level non-farm employment growth. Our aim is to conduct, for the first time, an analysis of the role of state-level climate risks, specifically temperature changes and their volatility, over the period of January 1971 to March 2022.

Combined forecasts generated from multiple predictors and/or forecasting models have been shown to produce better forecasts, on average, than those obtained from the best ex-ante individual forecasting model. While there is a large body of literature on model averaging for linear models (Nonejad, 2021), model-averaging schemes for nonlinear frameworks, such as MS models traditionally used for recession analyses, are rare. In this regard, Guérin and Leiva-León (2017) made a valuable contribution by introducing new weighting schemes to combine discrete forecasts from competing MS models. Given that our aim is to forecast national recessions using state-level climate risks, the utilization of the MS-DMA framework is an obvious choice for this empirical contribution, which is the first of its kind.

The remainder of the paper is organized as follows: Section 2 outlines the econometric model, with Section 3 presenting the data and results, and Section 4 concluding the paper.

2. Econometric framework

Guérin and Leiva-León (2017) develop a flexible framework that evaluates the performance of different MS models at every period of time, enabling the inference of regimes for a target variable. The authors also introduced new weighting schemes for model averaging when the variable to forecast is a discrete outcome, such as US recessions in our case. Specifically, Guérin and Leiva-León (2017) propose weights for each model that depend on its past predictive ability to estimate discrete outcomes, since a model that performs well for continuous forecasts may not perform as well for discrete forecasts. Therefore, standard weighting schemes that rely exclusively on likelihood as a measure of model fit may not be appropriate for forecasting recessions. Regarding the weights of the new models, Guérin and Leiva-León (2017) considered two classes of combination schemes: constant weights, or BMA, and time-varying weights, known as DMA. While DMA is more general than BMA, it involves more intensive computation due to its time-variation.

Following Guérin and Leiva-León (2017), we first consider the following univariate regime-switching model:

$$y_t = \mu_0^k + \mu_1^k S_t^k + \beta^k x_t^k + u_t^k, \tag{1}$$

where the dependent variable y_t is the U.S. industrial production, the regressor x_t^k denotes the temperature indicator of state k $(k = 1,2, \dots K)$, the error term is assumed to be normally distributed $u_t^k \sim N(0, \sigma_k^t)$, and S_t^k is a standard Markov chain with a constant transition probability $\pi_{ij}^k = P\left(S_{t+1}^k = j | S_t^k = i\right)$, $\sum_{j=1}^2 \pi_{ij}^k, \forall\, i$. That is, we have K different models $M_k, k = 1,2, \dots K,$ with each one of them attempting to explain the U.S. national indicator y_t.

2.1. Bayesian model averaging

Since we are interested in comparing different models, we use Bayes' rule to calculate the posterior model probability as the degree of support of model k:

$$f(M_k / y_t) = \frac{f(y_t / M_k) f(M_k)}{\sum_{j=1}^{K} f(y_t / M_j) f(M_j)}, k = 1,2, \dots, K. \tag{2}$$

Guerin and Leon (2017) refer to $f(M_k / y_t)$ in Eq. (2) as the likelihood-based static weighting scheme. Given that the goal of the econometric analysis is to predict the discrete variable S_t, Guérin and Leiva-León (2017) use Bayes' rule to derive a probability statement about the most appropriate model M_k to explain the regimes S_t as follows:

$$f(M_k / y_t, S_t) = \frac{f(S_t / y_t, M_k) f(y_t, M_k) f(M_k)}{\sum_{j=1}^{K} f(S_t / y_t, M_j) f(y_t / M_j) f(M_j)} = \frac{QPS_k^{-1} f(y_t, M_k) f(M_k)}{\sum_{j=1}^{K} QPS_j^{-1} f(y_t / M_j) f(M_j)}, \tag{3}$$

where the inverse quadratic probability score QPS is used to evaluate the term $f(S_t / y_t, M_k)$ which expresses model's k ability to fit S_t. The QPS of model k is defined as follows:

$$QPS_k = \frac{2}{T} \sum_{t=1}^{T} \left(P\left(S_t^k = 1/\theta_t\right) - S_t \right)^2,$$

where the lower the QPS, the better the ability of model k to fit S_t. Guérin and Leiva-León (2017) call $f(M_k / y_t, S_t)$ in Eq. (3) the combination-based static weighting scheme.

Lastly, Guérin and Leiva-León (2017) argue that since one is interested only in assessing the ability of the model M_k to predict the regimes S_t, conditioning on y_t could be avoided. Then, the posterior probability model can be written as:

$$f(M_k / S_t) = \frac{QPS_k^{-1} f(M_k)}{\sum_{j=1}^{K} QPS_j^{-1} f(M_j)}, \tag{4}$$

which defines the QPS-based weighting scheme.

2.2. Dynamic model averaging

Guérin and Leiva-León (2017) introduce an algorithm that utilizes dynamic model averaging to combine forecasts from K different Markov-switching models. The algorithm assigns weights based on past predictive ability to estimate discrete outcomes, making it more general than the static Bayesian model averaging (BMA). The algorithm consists of four steps carried out at any given time period t, as follows:

Step 1: Calculate the predicted regime probabilities for any model k ($k = 1,2,\dots,K$):

$$P\left(S_t^k = j/\,\theta_{t-1}\right) = \sum_{S_{t-1}^k} P\left(S_t^k = j, S_{t-1}^k = i/\,\theta_{t-1}\right)$$

$$= \sum_{S_{t-1}^k} P\left(S_t^k = j/S_{t-1}^k = i\right) P\left(S_{t-1}^k = i/\theta_{t-1}\right) \tag{5}$$

Step 2: Use the forgetting factor α as in Raftery et al. (2010) to calculate the predicted probability associated with the kth model:

$$P(M_k/\,\theta_{t-1}) = \frac{P(M_{t-1} = k/\,\theta_{t-1})^\alpha}{\sum_{M_{t-1}} P(M_{t-1} = j/\,\theta_{t-1})^\alpha}. \tag{6}$$

Step 3: Calculate the updated regime probabilities of any model k

$$P\left(S_t^k = j/\,\theta_t\right) = \sum_{S_{t-1}^k} P\left(S_t^k = j, S_{t-1}^k = i/\,\theta_t\right), \tag{7}$$

where,

$$P\left(S_t^k = j, S_{t-1}^k = i/\,\theta_t\right) = \frac{f_k\left(y_t/S_t^k = j, S_{t-1}^k = i, \theta_{t-1}\right) P\left(S_t^k = j, S_{t-1}^k = i/\,\theta_{t-1}\right)}{f_k(y_t/\theta_{t-1})},$$

$f_k\left(y_t/S_t^k = j, S_{t-1}^k = i, \theta_{t-1}\right)$ is the conditional likelihood from the corresponding model and $f_k(y_t/\theta_{t-1})$ is the predictive likelihood.

Step 4: Calculate the predictive likelihood:

$$P(M_t = k/\ \theta_t) = \frac{P(M_t = k/\theta_{t-1}) f_k(y_t/\theta_{t-1})}{\sum_{M_t} P(M_t = j/\theta_{t-1}) f_j(y_t/\theta_{t-1})}. \tag{8}$$

Lastly, repeat the four steps for each model k, where $k = 1,2, \dots, K$, at each period of time $t = 1,2, \dots, T$.

Guérin and Leiva-León (2017) refer to $f(M_k = k/\theta_t)$ in Eq. (8) as the likelihood-based dynamic weighting scheme.

In line with the BMA approach described in section 2.1, Guérin and Leiva-León (2017) introduce two more dynamic weighting schemes by updating Eq. (8); the combination-based and the QPS-based. For the combination-based dynamic averaging scheme, Eq. (8) is replaced by:

$$P(M_t = k/\ \theta_t) = \frac{P(M_t = k/\theta_{t-1}) f_k(y_t/\theta_{t-1}) Q_{t/t,k}^{-1}}{\sum_{M_t} P(M_t = j/\theta_{t-1}) f_j(y_t/\theta_{t-1})\ Q_{t/t,k}^{-1}}, \tag{9}$$

While for the QPS-based dynamic averaging scheme, Eq. (8) is replaced by:

$$P(M_t = k/\ \theta_t) = \frac{P(M_t = k/\theta_{t-1}) Q_{t/t,k}^{-1}}{\sum_{M_t} P(M_t = j/\theta_{t-1})\ Q_{t/t,k}^{-1}}. \tag{10}$$

3. Data and empirical results

We now turn our attention to the main focus of the paper, i.e., the comparative analysis of national- and state-level climate risks for out-of-sample forecasting of US business cycle turning points over January, 1971 to March, 2022. For our analysis, the national level data involves the seasonally-adjusted industrial production index and the National Bureau of Economic Research (NBER) recession dummy, both derived from the FRED database of the Federal Reserve Bank of St. Louis. Regarding the national and state-level climate risks data, daily data on the temperature in degrees Fahrenheit are obtained from Bloomberg. We then compute year-on-year changes in the daily temperature to remove seasonal patterns and then average over a month to get the measure for changes in monthly temperature. As far as volatility is concerned, we sum the square of year-on-year changes in the daily temperature over a month, in line with the idea of realized volatility of Andersen and Bollerslev (1998).

As far as the forecast design is concerned, the first estimation sample extends from January, 1971 to December, 1995, i.e., 50% of in- and out-of-sample splits, and it is recursively expanded, i.e., until the end of the sample is reached (March, 2022). In other words, the models are re-estimated, with new parameter estimates obtained for every month over the pseudo out-of-sample to capture the inflow of new information available to the forecaster. The 50% split is standard in forecasting literature (see Narayan and Gupta, 2015) as it does not bias estimation of the models based on the size of the in- and out-of-samples while providing ample observation for precise non-spurious estimations of regimes. Moreover, with the entire sample period involving seven recessions,[2] our out-of-sample includes the three most important and deep recessions in US history associated with the burst of the dot-com bubble, the Global Financial Crisis and the "Great Recession" thereafter, and of course the one following the outbreak of the COVID-19 pandemic. Moreover, average temperatures have risen more quickly since the late 1970s (0.32 to 0.55°F per decade since 1979), with nine of the top 10 warmest years on record for the US states to have occurred since 1998 (2012 and 2016 were the two warmest years on record).[3] Naturally, with our 50% split, we can cover the relatively riskier period associated with climate during the out-of-sample period.

Forecasts are generated for horizons $h = 0, 1,2,3, 4,5,6$. To compare the out-of-sample forecasting ability, this study focuses on the quadratic probability score (QPS). Guérin and Leiva-León (2017) define the out-of-sample QPS (QPS^{OOS}) as follows:

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[2] See: https://www.nber.org/research/business-cycle-dating.

[3] The reader is referred to: https://www.epa.gov/climate-indicators/climate-change-indicators-us-and-global-temperature.

$$QPS^{OOS} = \frac{2}{T - T_0 + 1} \sum_{t=T_0}^{T} \left(P\left(S_{t+h}^{k} = 0/\theta_t\right) - NBER_{t+h}\right)^2, \tag{11}$$

where $T - T_0 + 1$ is the size of the evaluation sample, $NBER_{t+h}$ is the recession dummy which takes on a value of 1 if the US economy is in recession in period $t + h$ and 0 otherwise. The predicted probabilities of being in regime j from model k are calculated as follows:

$$P\left(S_{t+h}^{k} = j|\theta_t\right) = \sum_{j=1}^{2} \pi_{ij}^{k}\, P\left(S_{t+h-1}^{k} = j|\theta_t\right), \tag{12}$$

Where π_{ij}^{k} is the transition probability. Since we want to examine whether state data indicators outperform national indicator in forecasting U.S. business cycle turning points, we use the following MS as a benchmark model:

$$y_t = \mu_0 + \mu_1 S_t X_t + u_t, \tag{13}$$

where X_t is the US national temperature indicator. Moreover, we evaluate the statistical significance of our results using Diebold-Mariano-West test (Diebold and Mariano; 1995; West; 1996).

The forecasting results are presented in Tables 1 and 2. Table 1 reports the results for temperature returns. It is evident that BMA and Equal Weighting models fail to beat the benchmark. On the other hand, DMA models perform much better relative to the benchmark. Specifically, DMA combined- and QPS-based weighting schemes outperform in a statistically significant way than the MS benchmark. Table 2 reports the results for temperature volatility. Results suggest that all models outperform the MS benchmark in forecasting US business cycle turning points. The results show that DMA combined- and all QPS-based weighting schemes outperform the MS benchmark at the 1% critical level while the rest of the models beat the benchmark at the 5% level.

Table 1: Out-of-sample Quadratic Probability Score (QPS) for forecasting US business cycle turning points from data on national and state-level temperature changes

	Horizon						
	0	1	2	3	4	5	6
Panel A: Dynamic model averaging (DMA) with α=0.95							
Likelihood-based	0.400	0.409	0.427	0.442	0.457	0.457	0.468
QPS-based	0.238**	0.217**	0.209**	0.205**	0.204**	0.205**	0.207**
Combined-based	0.231**	0.219**	0.213**	0.208**	0.206**	0.206**	0.205**
Panel B: Dynamic model averaging (DMA) with α=0.99							
Likelihood-based	0.475	0.494	0.528	0.554	0.579	0.598	0.613
QPS-based	0.233**	0.208**	0.199**	0.192**	0.189**	0.190**	0.192**
Combined-based	0.251*	0.229**	0.216**	0.205**	0.200**	0.196**	0.194**
Panel C: Baysian model averaging (BMA)							
Likelihood-based	0.587	0.590	0.599	0.594	0.588	0.576	0.543
QPS-based	0.598	0.503	0.475	0.474	0.482	0.491	0.499
Combined-based	0.477	0.492	0.559	0.574	0.582	0.583	0.533
Panel D:							
Equal Weighting	0.362	0.342	0.338	0.339	0.342	0.345	0.348
MS	0.329	0.319	0.316	0.316	0.318	0.318	0.318

Notes: The first estimation sample extends from January 1971 to December 1995, and it is recursively expanded until the end of the sample is reached (March 2022). Statistically significant reductions in QPS according to the Diebold-Mariano-West test are marked using ** (5% significance level), and * (10% significance level). The benchmark model is Markov-Switching model (MS), which includes a national-level measure of climate risks.

Table 2: Out-of-sample Quadratic Probability Score (QPS) for forecasting US business cycle turning points from data on national and state-level (realized) volatility of temperature changes

	Horizon						
	0	1	2	3	4	5	6
Panel A: Dynamic model averaging (DMA) with α=0.95							
Likelihood-based	0.354**	0.348**	0.345**	0.344**	0.344**	0.347**	0.351**
QPS-based	0.150***	0.149***	0.153***	0.158***	0.163***	0.165***	0.168***
Combined-based	0.149***	0.147***	0.151***	0.156***	0.162***	0.164***	0.167***
Panel B: Dynamic model averaging (DMA) with α=0.99							
Likelihood-based	0.360**	0.355**	0.352**	0.351**	0.353**	0.354**	0.359**
QPS-based	0.159***	0.153***	0.154***	0.158***	0.162***	0.164***	0.167***
Combined-based	0.161***	0.154***	0.154***	0.157***	0.162***	0.164***	0.167***
Panel C: Baysian model averaging (BMA)							
Likelihood-based	0.387**	0.390**	0.399**	0.394**	0.388**	0.376**	0.343**
QPS-based	0.209***	0.206***	0.207***	0.209***	0.212***	0.213***	0.215***
Combined-based	0.377**	0.392**	0.359**	0.374**	0.382**	0.383**	0.343**
Panel D:							
Equal Weighting	0.379**	0.372**	0.369**	0.366**	0.364**	0.362**	0.360**
MS	0.597	0.599	0.609	0.609	0.612	0.624	0.625

Notes: The first estimation sample extends from January 1971 to December 1995, and it is recursively expanded until the end of the sample is reached (March 2022). Statistically significant reductions in QPS according to the Diebold-Mariano-West test are marked using *** (1% significance level), and ** (5% significance level). The benchmark model is Markov-Switching model (MS), which includes a national-level measure of climate risks.

In sum, our results highlight the importance of state-level data associated with climate risks, as proxied by temperature changes and its realized volatility,[4] in forecasting US business cycle turning points.

[4] Based on the suggestion of an anonymous referee, we also conducted our forecasting analyses based on daily precipitation data in millimeters (also obtained from Bloomberg). The results reported in Tables A1 and A2 in the

4. Conclusion

The role of state-level economic factors in driving national business cycles of the US and the associated growing importance of climate change-related risks at both aggregate- and local-level due to global warming are now well-established facts. Moreover, given the strong relationship between regional economic activity and climate risks, this paper compares the ability of state-level temperature changes and its (realized) volatility with the corresponding national values of the same in forecasting recessions of the overall US. In this regard, to combine the information contained in state-level climate risks in Markov-switching models, we utilize Bayesian Model Averaging (BMA) and Dynamic Model Averaging (DMA) approaches. We find that forecasts obtained from the DMA combination scheme provide accurate forecasts of the US business cycles based on state-level measures of climate risks, particularly the volatility of temperature, relative to the corresponding small-scale Markov-switching benchmark models that use national-level values of the climate change-related predictors.

Our results highlight that policymakers should utilize the information contained in state-level measures of climate risks, instead of corresponding national-level values, to forecast overall US recessions accurately, and design appropriate policy responses. However, to best utilize the combined role of local climate risks, which leads to a wide-array of state-level metrics of economic activities, policy authorities should rely on a dynamic rather than a static forecast combination approach. The strong performance of the DMA over the BMA in the large-scale Markov-switching models is, understandably, a depiction that the relative importance of state-level temperature changes and its volatility has been evolving over time.

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appendix of the paper show a similar picture. However, evidence of the forecastability of US recessions is now relatively less apparent under precipitation changes compared to their realized volatility.

As part of future research, it would be interesting to perform such an analysis for other developed and emerging economies, contingent on the availability of regional-level data on climate risks. It is important to point out one issue before we conclude, climate change involves both physical and transition risks. By utilizing changes in temperature and its volatility, we focus on the former, although overall climate risks are likely driven primarily by the physical component, given that the transition to green technologies is a more recent phenomenon. In this regard, it may be possible to compare the roles of physical and transition climate risks in predicting US recessions once we can obtain (or generate) a long-span metric for the latter type of risk (see, for example, discussions in Bua et al. (2021) and Faccini et al. (2021)) at regional and aggregate levels.

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APPENDIX:

Table A1: Out-of-sample Quadratic Probability Score (QPS) for forecasting US business cycle turning points from data on national and state-level precipitation changes

	Horizon						
	0	1	2	3	4	5	6
Panel A: Dynamic model averaging (DMA) with α=0.95							
Likelihood-based	0.359	0.351	0.347	0.343	0.338	0.332	0.327
QPS-based	0.153	0.151	0.154*	0.158*	0.163*	0.166*	0.169*
Combined-based	0.156	0.154	0.157*	0.160*	0.165*	0.166*	0.169*
Panel B: Dynamic model averaging (DMA) with α=0.99							
Likelihood-based	0.348	0.374	0.367	0.361	0.354	0.346	0.339
QPS-based	0.159	0.152	0.153*	0.157*	0.161*	0.163*	0.166*
Combined-based	0.158	0.152	0.153*	0.157*	0.161*	0.162*	0.165*
Panel C: Baysian model averaging (BMA)							
Likelihood-based	0.462	0.473	0.475	0.471	0.478	0.473	0.473
QPS-based	0.217	0.212	0.212	0.215	0.218	0.219	0.220
Combined-based	0.353	0360	0.359	0.364	0.378	0.380	0.380
Panel D:							
Equal Weighting	0.356	0.347	0.342	0.340	0.338	0.336	0.334
MS	0.159	0.169	0.173	0.179	0.182	0.185	0.189

Notes: The first estimation sample extends from January 1971 to December 1995, and it is recursively expanded until the end of the sample is reached (March 2022). Statistically significant reductions in QPS according to the Diebold-Mariano-West test are marked using ** (5% significance level), and * (10% significance level). The benchmark model is Markov-Switching model (MS), which includes a national-level measure of climate risks.

Table A2: Out-of-sample Quadratic Probability Score (QPS) for forecasting US business cycle turning points from data on national and state-level (realized) volatility of precipitation changes

	Horizon						
	0	1	2	3	4	5	6
Panel A2: Dynamic model averaging (DMA) with α=0.95							
Likelihood-based	0.302***	0.297***	0.295***	0.295***	0.296***	0.295***	0.295***
QPS-based	0.153***	0.152***	0.156***	0.161***	0.166***	0.168***	0.171***
Combined-based	0.156***	0.155***	0.158***	0.162***	0.167***	0.169***	0.171***
Panel B: Dynamic model averaging (DMA) with α=0.99							
Likelihood-based	0.286***	0.281***	0.279***	0.279***	0.279***	0.277***	0.277***
QPS-based	0.152***	0.152***	0.156***	0.161***	0.160***	0.168***	0.171***
Combined-based	0.157***	0.152***	0.153***	0.157***	0.162***	0.164***	0.167***
Panel C: Baysian model averaging (BMA)							
Likelihood-based	0.306***	0.299***	0.319***	0.317***	0.315***	0.311***	0.307***
QPS-based	0.192***	0.191***	0.194***	0.197***	0.202***	0.203***	0.205***
Combined-based	0.298***	0.301***	0.301***	0.308***	0.311***	0.311***	0.303***
Panel D:							
Equal Weighting	0.348***	0.343***	0.341***	0.341***	0.342***	0.341***	0.342***
MS	0.838	0.818	0.812	0.822	0.831	0.839	0.860

Notes: The first estimation sample extends from January 1971 to December 1995, and it is recursively expanded until the end of the sample is reached (March 2022). Statistically significant reductions in QPS according to the Diebold-Mariano-West test are marked using *** (1% significance level), and ** (5% significance level). The benchmark model is Markov-Switching model (MS), which includes a national-level measure of climate risks.