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Abstract

In this paper, we first utilize a Dynamic Factor Model with Stochastic Volatility (DFM-SV) to filter out the national factor from the local components of weekly state-level economic conditions indexes of the United States (US) over the period of April 1987 to August 2021. In the second step, we forecast the state-level factors in a panel data set-up based on the information content of corresponding state-level climate risks, as proxied by changes in temperature and its SV. The forecasting experiment depicts statistically significant evidence of out-of-sample predictability over a one-month- to one-year-ahead horizon, with stronger forecasting gains derived for states that do not believe that climate change is happening and are Republican. We also find evidence of national climate risks in accurately forecasting the national factor of economic conditions. Our analyses have important policy implications from a regional perspective.

Keywords: State-Level Economic Conditions, Climate Risks, Dynamic Factor Model with Stochastic Volatility, Panel Predictive Regression, Forecasting.

JEL Classification: C31, C32, C53, E32, E66, Q54.

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Declaration of interest: None

1. Introduction

In light of the growing concern of global warming, recent studies have indicated the importance of local risks associated with climate change, as captured by both first- and second moments of temperature changes, in driving state-level economic activities of the United States (US) (see for example, Colacito et al. (2019), and Sheng et al. (2022a)). Theoretically heightened climate risks is likely to adversely impact economic activity not only through labour productivity and capital quality, but also through the patent obsolescence channel, which in turn, dampens research and development (R&D) expenditure growth (Donadelli et al., 2017, 2021a, b, 2022). In other words, climate risks can negatively impact the economy from both the demand- and supply-sides. Moreover, with such risks also shown to be associated with enhancing regional economic uncertainties (Sheng et al., 2022b), there is likely to be an impact on economic activities of the states through the uncertainty channel as well (Mumtaz, 2018; Mumtaz et al., 2018).

Against this backdrop, our objective is to extend the in-sample based analyses of the impact of temperature changes and its volatility on state-level economic activity into an out-of-sample set-up. This is in light of the well-accepted statistical view that forecasting tends to provide a relatively stronger test of predictability than full-sample analyses (Campbell, 2008). More importantly, accurate forecasting of state-level economic activity based on climate risks is likely to be of more important to policymakers in undertaking appropriate policy decisions in real-time compared to outcomes derived from structural analyses. In addition, unlike the existing studies on the impact of climate change on annual and monthly metrics of state-level economic activity, we predict a measure of economic conditions at the weekly frequency, which in turn is the highest possible frequency available for such indicators, as developed by Baumeister et al. (2022). Again, such high-frequency forecasting should be of more value to policy authorities. Finally, we go beyond looking at annual gross state product or monthly coincident indicators of the states (which involves nonfarm payroll employment, the unemployment rate, average hours worked in manufacturing and wages and salaries) by utilizing Baumeister et al.'s (2022) novel dataset of weekly economic-conditions indexes for the 50 US states that cover multiple dimensions the state economies. The dimensions covered are the following: Mobility measures, labor market indicators, real economic activity, expectations measures, financial indicators, and household indicators.

This is important, since the impact of climate change is not only restricted to the real side of the economy (Giglio et al., 2021).

To achieve our goal econometrically, we undertake a two-step approach. First realizing the evidence that exists in terms of the importance of a common (national) factor in explaining large proportion of the total variability in state-level economic conditions (Gupta et al., 2018), we first estimate a Dynamic Factor Model with Stochastic Volatility (DFM-SV), as in Bhatt et al. (2017), on the state-level weekly economic-conditions indexes of the states. The DFM-SV allows us to separate out the influence of the national factor, and we then forecast the local or state factors, which in turn avoids us from underestimating the predictive effect of state-level climate risks on state-level economic conditions. In the second step, in terms of forecasting the local factors, we utilize a panel predictive regression framework to determine the importance of temperature changes and its volatility over the weekly period of April, 1987 to August, 2021. Note that, in a time series set-up, we also forecast the national factor utilizing the aggregate US temperature changes and volatility, i.e., national climate risks. Finally, we investigate how the predictive power of temperature-related variables for economic conditions changes across different characteristics of different states, such as political party affiliation (Democrats versus Republicans) and belief about climate change (happening versus not happening).

To the best of our knowledge, this is the first paper to forecast state-level economic conditions due to state-level climate risks, especially in light of the dissimilarity in terms of underlying time series properties of temperature for the overall US from those of the states (Gil-Alana, forthcoming). The remainder of the paper is organized as follows: In Section 2, we introduce our data. In Section 3, we explain the methods utilized in our empirical study. In Section 4, we present our empirical findings. In Section 5, we conclude.

2. Data

The economic-conditions indexes (ECIs) of the 50 US states, on which we apply the DFM-SV, are based on the work of Baumeister et al. (2022). These authors derive the indexes from mixed-frequency dynamic factor models with weekly, monthly, and quarterly variables that cover multiple dimensions of the aggregate and the state economies. Specifically, Baumeister et al. (2022) group variables into six broad categories: mobility measures, labor market indicators, real economic activity, expectations measures, financial indicators, and household indicators. Table 1 in their paper summarize the state-level data that they use in the construction of the weekly ECIs, and also include information on the data frequency, data source, data transformation, seasonal adjustment, and the start date of each series. The indexes are scaled to 4-quarter growth rates of US real GDP and normalized such that a value of zero indicates national long-run growth. As far as the predictors, i.e., national and state-level climate risks data are concerned, weekly data on temperature in degree Fahrenheit are obtained from Bloomberg. We then compute year-on-year changes in the weekly temperature to remove seasonal patterns. As far as volatility is concerned, we estimate a SV model on the year-on-year changes in the weekly temperature to be consistent with the modelling of volatility using a SV approach in the DFM.

Based on data availability, we cover the period of 1st week of April, 1987 to the 4th week of August, 2021.

3. Methodology

3.1. Dynamic factor model with stochastic volatility

Our dynamic factor model with stochastic volatility follows Del Negro and Otrok (2008) and Bhatt et al. (2017) and decomposes each economic conditions index to a common national factor and a idiosyncratic factor as follows:

$$y_{i,t} = \lambda_i g_t + u_{i,t}, \tag{1}$$

where $y_{i,t}$ is the economic conditions index for i-th state at time period t; g_t is the common factor which captures the comovement of the economic conditions indexes of the different states; λ_i is the corresponding factor loading, and; $u_{i,t}$ is the idiosyncratic state factor.

We assume both the common factor and the idiosyncratic factor follows $AR(2)$ processes with stochastic volatility as described below:

$$g_t = \beta_1 g_{t-1} + \beta_2 g_{t-2} + \sqrt{\exp h_t^g}\varepsilon_t,\ \varepsilon_t \sim i.i.d.N(0, Q_g), \tag{2}$$

$$u_{i,t} = \alpha_1^i u_{i,t-1} + \alpha_2^i u_{i,t-2} + \sqrt{\exp h_t^i}e_t^i,\ e_t^i \sim i.i.d.N(0, Q_i). \tag{3}$$

To deal with the stochastic volatilities, we assume random walk processes given by:

$$h_t^g = h_{t-1}^g + \sigma_h^g v_t^g, v_t^g \sim i.i, dN(0,1). \tag{4}$$

$$h_t^i = h_{t-1}^i + \sigma_h^i v_t^i, v_t^i \sim i.i, dN(0,1). \tag{5}$$

Following Del Negro and Otrok (2008), we assume the initial value of the stochastic volatilities to be equal to 0.

3.2. ***Out-of-sample forecasting using a predictive panel data model***

We employ a panel predictive regression model to investigate the importance of temperature changes and its volatility for forecasting the state level local factors obtained via utilizing of DFM-SV model. In particular, we utilize the following predictive panel data model:

$$u_{it+h} = \alpha + \beta temp_{it} + \delta temp\_sv_{it} + \epsilon_{it+h} \tag{6}$$

where $temp_{it}$ represent the year-on-year changes in the weekly temperature in state i at time t. Similarly, $temp\_sv_{it}$ denotes the temperature volatility computed using the SV model on the year-on-year changes in the weekly temperature. u_{it+h} is the idiosyncratic state factor for given state i at time t. estimated in Section 3.1. We consider six different forecast horizons: h = 4, 8, 12, 24, 36, 52-weeks-ahead. When evaluating the forecast accuracy, we compare the root mean square forecast error (RMSE) of the panel data model predictions with a "naïve" forecast where the last observation of the in-sample period is used as a direct forecast for the out-of-sample observations. We utilize the 25% of the sample period to evaluate out-of-sample forecast performance, giving us 449-h weekly observations. In particular, we estimate the model parameters using 75% of the sample and then use the resulting parameters to predict the idiosyncratic state factors recursively.

4. Empirical results

Figure 1 shows the estimated national factor with 90 percent confidence bands. The shaded areas are NBER recession periods. During recessions, the national factor decreases dramatically, especially during the COVID-19 episode. Figure 2 shows the estimated state factors with 90 percent confidence bands, and is indicative of their dissimilarities. Table 1 shows the average percentage contribution of the national factor for the economic conditions of the different states, which in turn ranges between 9.43% (Alaska) and 87.84% (Kentucky). As far as the cross-sectional average is concerned, this value is at 61.01%, highlighting the importance of the national factor, and the need to filter it out from the economic conditions of the states, before forecasting the local factor due to information contained in climate risks.

– Insert Figures 1 and 2 about here. –

– Insert Table 1 about here. –

Table 2 summarizes the out-of-sample forecast results compared to the naive predictions, where each entry denotes the ratio of RMSE of the panel data model to the RMSE of the naive forecasts. A closer inspection of the first row of Table 2 indicates that all the entries at $h = 4$, 8, 12, 24, 36, and 52, are smaller than one, implying that the panel predictive regression augmented with the temperature changes and its volatility yields superior forecasting performance compared to the naive benchmark model. However, the accuracy gains from utilizing the temperature-related variables decrease with the forecast horizon, which is in line with observations drawn generally with forecasting exercises involving predictors, i.e., the predictive influence of the climate risks variables (in our case) declines for economic conditions as we move from short- to long-run. For instance, the average the RMSE of the panel data predictions is 9% lower than those associated with the naive benchmark forecasts for a one-month-ahead forecast horizon, which falls to 5% a year out. More importantly, significant $MSE–F$ statistics of McCracken (2007) in Table 2, suited for nested models, indicate that predictions of the panel data model are statistically superior to those of the naive model at the 1% level for $h = 4$, 8, 12, 24, and 36, and at the 5% level for $h = 52$. In other words, temperature changes and its volatility contain valuable information for predicting the future path of the idiosyncratic state factor.

– Insert Table 2 about here. –

Several studies investigate whether variations in perceptions regarding the impacts of climate change influence residential real estate values (Baldauf et al., 2020; Bakkensen and Barrage, 2022). Borrowing from these studies, and given the importance of housing price movements for shaping state-level economic activities (Emirmahmuroglu et al., 2016),[1] we examine whether the predictive power of temperature-related variables for idiosyncratic state factors reflects the belief differences about climate change. We use the Yale Climate Opinion Maps 2021 survey to measure the beliefs about climate change. In particular, we focus on the answers to the survey question: "Do you believe that climate change is happening?". We classify the states into two groups (happening versus not happening) based on the median value of the fraction of the population in a state adopting a climate change belief. Results in Table 2 show that the predictive power of temperature-related variables is relatively more substantial in states where a lower fraction of the population believes climate change is happening (i.e., under the not happening case). This conclusion holds for all forecast horizons since temperature-related variables consistently yield considerably higher forecast improvement than naive forecasts in the so-called non-believer states, possibly due to corresponding lack of action to mitigate climate risks. But, under both the happening and not happening cases, the $MSE-F$ statistics are always statistically significant at least at the 5% level for all the forecast horizons considered by us.

According to a Gallup survey in 2018, 89% of Democrats think that global warming is caused by human activity, whereas just 42% of Republicans had the same belief. In other words, Republicans are less inclined than Democrats to believe in climate change. Hence, using the outcomes of the last five general elections in the US, we divide the states into two groups: Democrats vs. Republicans. Then, we examine whether the political affiliation of the states affect the predictive power of temperature-related variables on the economic conditions of the states, i.e., the idiosyncratic local factors. Our findings in Table 2 imply that the temperature-related variables provide relatively better forecasts in states governed by Republicans across all forecast horizons, with the $MSE - F$ test being statistically significant at the 1% level consistently. As far as the Democratic states are concerned, the $MSE - F$ test is also significant at least at the 5% level under the various forecasting horizons. The likely reason, in line withe the happening versus non happening case reported above, is that Democrats are more likely than Republicans to support government actions to mitigate the effect of climate change on economic activity, and hence feel lesser impact

[1] Note that, state-level (quarterly) real home price index is included under the data category of households in the construction of the ECIs.

of climate risks on the underlying economic conditions of the states.

Finally, replacing the idiosyncratic factor with the national factor in equation (6), we also forecast the same using the aggregate US temperature changes and its volatility, i.e., with national climate risks. We present the time series regression results in the last row of Table 2 as well, which in turn, demonstrates that temperature-related variables statistically improves the forecast performance at the 1% level of the $MSE-F$ test (with the accuracy gains being stable across different forecast horizons).

5. Conclusion

This paper examines the role of state-level climate risks, as captured by temperature changes and its stochastic volatility, in forecasting corresponding state-level economic conditions indexes in a panel data set-up over the weekly period of April 1987 to August 2021. To prevent an underestimation of the predictive impact in line with the importance of a national factor in driving local economic conditions, we utilize a DFM-SV model to decompose the overall economic conditions into a common factor and idiosyncratic state-factors, with the latter used for forecasting based on climate risks. Our results reveal statistically significant evidence of out-of-sample predictability of the filtered state-level economic conditions over a one-month- to one-year-ahead horizon, with more substantial forecasting gains for states that do not believe climate change is happening and are Republican, possibly due to lower emphasis on the mitigation of climate risks. We also find evidence of national climate risks in accurately forecasting the national factor of economic conditions.

Our results imply that, while climate change is indeed a national-level problem in defining the economic conditions of the overall US, state-level climate change-related policies are required to mitigate the associated risks on local economic conditions, in light of the evidence of accurate forecastability of the latter due to the movements in the first- and second-moment of local temperature changes. With our analysis conducted at a high-frequency, it has the advantage of informing the policymakers in a timely manner to undertake appropriate policy responses.

As part of future research, though high-frequency analysis is less likely due to data constraints, a similar out-of-sample forecasting exercise should be conducted at the country-level involving a panel of developed and emerging economies.

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Figure 1: Estimated National (Common) Factor

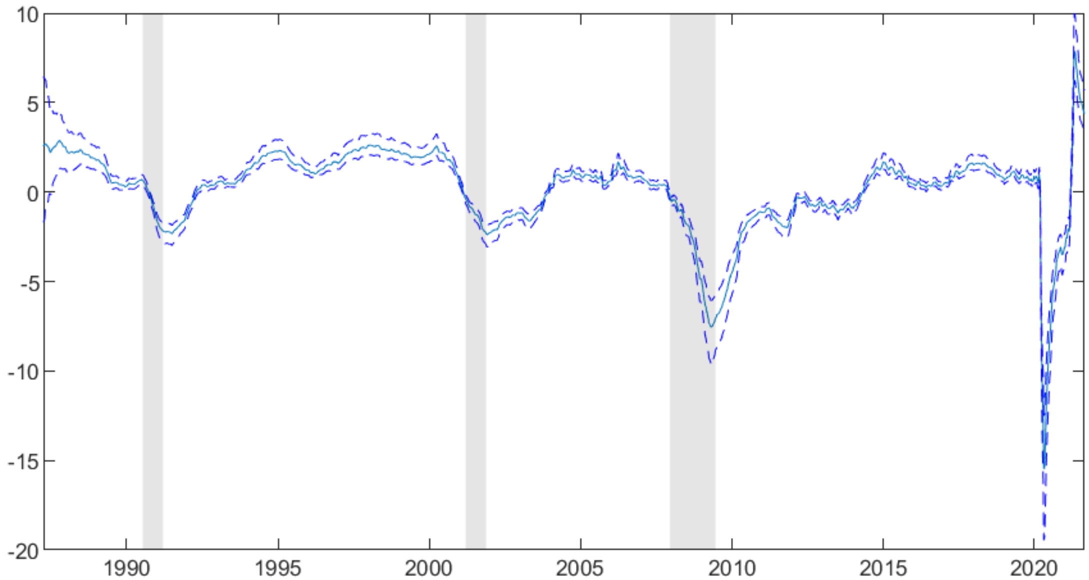

Figure 2: Estimated State-Level (Local) Idiosyncratic Factors

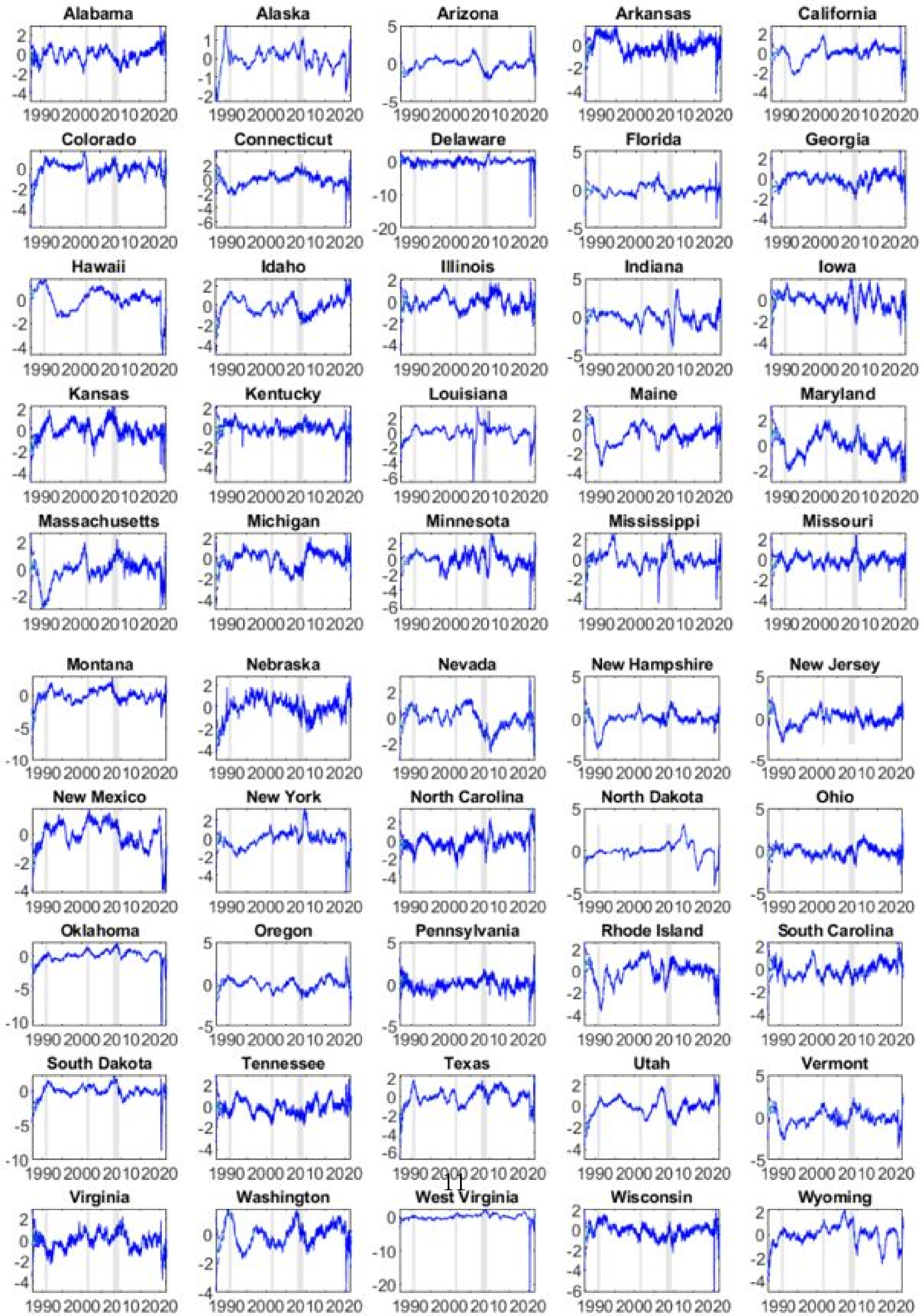

Table 1: Variance Decomposition of the State-Level Economic Conditions Indexes due to the National Factor

State	Average Contribution	State	Average Contribution
Alabama	71.64%	Montana	54.71%
Alaska	9.43%	Nebraska	55.95%
Arizona	68.79%	Nevada	61.39%
Arkansas	72.07%	New Hampshire	63.74%
California	53.49%	New Jersey	58.97%
Colorado	74.06%	New Mexico	41.87%
Connecticut	65.99%	New York	58.88%
Delaware	64.12%	North Carolina	70.77%
Florida	74.96%	North Dakota	14.22%
Georgia	81.18%	Ohio	80.37%
Hawaii	22.11%	Oklahoma	58.36%
Idaho	52.84%	Oregon	70.12%
Illinois	76.70%	Pennsylvania	79.41%
Indiana	66.34%	Rhode Island	46.06%
Iowa	76.75%	South Carolina	71.33%
Kansas	71.06%	South Dakota	64.72%
Kentucky	87.84%	Tennessee	75.12%
Louisiana	34.30%	Texas	62.47%
Maine	45.72%	Utah	51.60%
Maryland	59.00%	Vermont	66.05%
Massachusetts	58.85%	Virginia	72.74%
Michigan	70.39%	Washington	57.80%
Minnesota	64.23%	West Virginia	45.48%
Mississippi	58.31%	Wisconsin	82.03%
Missouri	86.63%	Wyoming	19.55%

Table 2: Out-of-Sample Forecasting Results across Different Horizons (h)

	h=4	h=8	h=12	h=24	h=36	h=52
All States	0.911***	0.915***	0.919***	0.928***	0.938***	0.950**
Happening	0.923***	0.928***	0.932**	0.943**	0.955**	0.968**
Not happening	0.901***	0.905***	0.909***	0.918***	0.927***	0.941**
Democrats	0.919***	0.925***	0.929***	0.941***	0.954**	0.971**
Republicans	0.905***	0.908***	0.911***	0.919***	0.927***	0.937***
National	0.919***	0.921***	0.922***	0.922***	0.920***	0.923***

Notes: This table shows the out-of-sample forecasting results from the panel data model including both temeprature changes and its stochastic volatility relative to the naive predictions, where each entry denotes the ratio of the RMSE from the panel data model to the RMSE of the naive forecasts. Hence, entries that are smaller than one imply that the panel predictive regression augmented with the climate risks variables yield superior forecasting performance compared to the naive benchmark forecasts. *** and ** denote 1% and 5% levels of significance of the $MSE - F$ test of McCracken (2007), respectively.