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Climate policy uncertainty and the forecastability of inflation☆

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ABSTRACT

We investigate the predictive content of climate policy uncertainty (CPU) for forecasting the inflation rate of the United States (US) over the monthly period of 1987:05–2024:11. We evaluate the performance of our proposed CPU-based predictive model, estimated via the Feasible Quasi Generalized Least Squares (FQGLS) approach, against a historical average benchmark model, with the FQGLS technique adopted to account for heteroscedasticity and autocorrelation in the data. We find statistical evidence in favour of a CPU-based model relative to the benchmark, as well as in the case of an extended model involving physical risks of climate change and financial and macroeconomic factors, extracted from a large data set, when CPU is included. The predictive superiority of climate policy-related uncertainties relative to the historical mean remains robust across alternative local and global CPU metrics, as well as in a mixed-frequency setup, given the availability of high-frequency (weekly) CPU data. Moreover, the importance of local- and global-CPUs is also found to hold for forecasting the inflation rates of 11 other advanced and emerging countries, in a statistically significant manner relative to the historical average model. Across all 12 economies, own- and global-CPUs perform equally well in forecasting the respective inflation rates. The general importance of uncertainties surrounding policy decisions to tackle climate change in shaping the future path of inflation, understandably, carries implications for the monetary authority.

1. Introduction

In recent years, the intensification of climate risks has become a critical global concern, with extreme weather events, ranging from heatwaves and heavy precipitation to powerful windstorms, occurring with increasing frequency and severity (AghaKouchak et al., 2020), and hence, imposing a large aggregate risk to the economy (Giglio et al., 2021). Although major economies have pledged to address climate change, uncertainty surrounding the formulation and implementation of climate policies continues to rise and has become an important factor influencing macroeconomic outcomes (Ilhan et al., 2020; Ma et al., 2023).

Against this backdrop, a key yet insufficiently explored question is whether Climate Policy Uncertainty (CPU) provides forward-looking information with incremental value for forecasting future inflation. Huang and Teresa Punzi (2024) develop an environmental DSGE model calibrated to the United States. They show that heightened climate policy uncertainty reduces physical capital by prompting firms to postpone investment, thereby lowering employment, consumption, and output, thereby generating an inflationary effect. These authors also empirically verify the theoretical implications associated with higher inflation following a positive shock to a newspaper-based index of climate policy uncertainty (CPU), as developed by Gavriilidis (2021), for the US using a Bayesian Vector Autoregressive (BVAR) model. Similar inflationary effects of CPU have been documented for the US and other economies around the world by Moessner (2022), Doğan (2023), Chaâbane (2024), and Akshaya and Gopalakrishna (2025). However, this evidence is primarily based on in-sample analyses, whereas monetary policy relies more heavily on out-of-sample forecasting performance. Therefore, determining whether the CPU can enhance inflation forecasts is of considerable importance for central banks and policymakers.

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In light of this requirement, we analyze the role of the CPU index of Gavriilidis (2021), as generally used by the abovementioned in-sample analyses, in predicting the inflation rate of the US, but from the perspective of forecasting, over the monthly period of 1987:05–2024:11. To check for the robustness of our findings, we also utilize an alternative newspapers articles-based CPU index data developed by Ji et al. (2024) and Ma et al. (2024) to perform a forecasting analysis of monthly US inflation covering 2000:01–2023:12.

The advantage of using these two studies is multi-dimensional: Firstly, besides the US, Ji et al. (2024) and Ma et al. (2024), also develops the CPU indexes for 11 other advanced (Australia, Canada, France, Germany, Japan, South Korea, and the United Kingdom (UK)) and emerging (Brazil, China, India, and South Africa) countries, thus allowing us to extend our analysis to a global dimension, and hence, generalize our findings. Secondly, these authors also develop 3 global CPU (GCPU) indexes, as weighted averages of the 12 country-specific CPUs, involving equal weights, and the same based on current prices Gross Domestic Product (GDP), and purchasing power parity (PPP)-adjusted GDP. This enables us to also analyze the role of the global CPU indexes in forecasting the inflation rates of the 12 economies, given evidence of a general trend of rising co-movement of uncertainty involving climate-related policies across major economies of the world post the Paris Climate Agreement in 2015 (Challinor et al., 2017, 2018; Lin and Zhao, 2023) as they try to embark on the path of the so-called "green energy transition" (Bettarelli et al., 2025). Naturally, one would expect the GCPUs, capturing the CPUs of all the countries in our sample, to also indirectly influence local-inflation, as they might contain information of inflation spillovers and connectedness due to trade linkages and alignment of monetary policy decisions (Al-Nassar and Albahouth, 2023), Lastly, in addition to the monthly indexes of CPU, these two papers also makes available daily and weekly values of the same. Given this, and the fact that averaging high-frequency data to low-frequency can result in loss of information (Clements and Galvão, 2008), we utilize the weekly local and global indexes in a Mixed Data Sampling (MIDAS) framework (Ghysels et al., 2007), to check for the degree of robustness of our results for the US derived under the forecasting exercise obtained with the monthly version of these indexes.[1]

Moreover, the theoretical channels through which the CPU affects inflation have become increasingly clear in the literature. First, higher policy uncertainty raises firms' expected volatility regarding future energy policies, carbon taxes, and regulatory costs, prompting them to postpone investment. This slows capital accumulation, constrains supply, and ultimately puts upward pressure on prices (Huang & Punzi, 2024). Second, CPU significantly influences commodity markets—particularly the oil market—by increasing risk premia and amplifying oil price volatility (Guo et al., 2022; Li, 2022). The transmission of higher energy costs then feeds into both producer prices and consumer prices. Third, CPU induces exchange rate volatility (Peng et al., 2023; Afshan et al., 2023), thereby raising imported inflation, with even stronger effects in more open economies.

In summary, this paper makes four key contributions. First, while existing studies primarily focus on structural models or in-sample effects within VAR frameworks, this paper is the first to systematically examine the forward-looking impact of CPU on inflation from an out-of-sample forecasting perspective, covering the United States and 11 major advanced and emerging economies. Second, by employing CPU indices from multiple sources, we document that domestic CPU and global CPU are substitutable for forecasting inflation, providing new empirical evidence on the cross-country synchronization and risk transmission of climate policy uncertainty. Third, we incorporate FQGLS and MIDAS into the climate–inflation forecasting framework, which not only effectively addresses heteroskedasticity and autocorrelation but also fully exploits high-frequency weekly CPU information to forecast monthly inflation. Finally, we construct an extended model by accounting for the effects of extreme weather (Liao et al., 2024; Sheng et al., 2022b; Kim et al., 2025) and a wide set of financial and macroeconomic variables (Stock & Watson, 2002, 2009), augmenting the forecasting specification with physical-risk indicators and eight macro-financial factors extracted via PCA. This allows us to assess whether CPU retains incremental predictive value after controlling for key climate and macroeconomic drivers.

The remainder of the paper is organized as follows: Section 2 outlines the data; Section 3 presents the methodology; Section 4 discusses the results; and Section 5 provides the conclusions.

2. Data issues

As far as the inflation data is concerned for the US, as well as the 11 other countries, we utilize the year-on-year first-differences of the natural logarithmic values of the Harmonized Index of Consumer Prices (HICP) expressed in percentages (i.e., multiplied by 100), with the HICP obtained from the Main Economic Indicator (MEI) database of the Organisation for Economic Co-operation and Development (OECD).[2]

In terms of the CPU data for the US associated with the longer sample period of the forecasting exercise, i.e., 1987:05–2024:11, we rely on the index created by Gavriilidis (2021).[3] To construct the CPU index, the author searches for articles in eight leading US newspapers (Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal) which contain at least one keywords in all three categories of: (1) Climate, (2) Policy, and, (3) Uncertainty. Specifically, the terms searched for are: "uncertainty" or "uncertain" and "carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO2" or "emissions" or "global warming" or "climate change" or "green energy" or "renewable energy" or "environmental" and "regulation" or "legislation" or "White House" or "Congress" or "EPA" or "law" or "policy" (including variants such as: "uncertainties", "regulatory", "policies", etc.). For each newspaper, the number of relevant articles per month is scaled with the total number of articles during the same month, with these eight series then standardized to have a unit standard deviation and then averaged across newspapers by month. Finally, the averaged series are normalized to have a mean value of 100 for the period April 1987 to August 2022.

In the papers by Ji et al. (2024) and Ma et al. (2024), the same approach as Gavriilidis (2021) was followed for the US, but restricted to searches of the Wall Street Journal, as in Engle et al. (2020). Though restricted in terms of newspaper coverage, these authors provide daily and weekly versions of the US CPU, which we use to conduct a MIDAS-based forecasting analysis of the corresponding inflation rate, thereby providing an advantage for our analysis. The data coverage for the US in this case runs from 2000:01–2023:12.

In addition, as stated earlier, these two studies also construct (daily, weekly and monthly) indexes of CPU for 11 other advanced and emerging countries, as well as 3 global indexes based on weighted averages of the 12 countries under 3 different weighting schemes: equal weights (GCPU-EQ), current prices GDP (GCPU), and PPP-adjusted GDP (GCPU-GDP).[4] Note that, for the 11 other countries, Ji et al. (2024) and Ma et al. (2024) perform most searches in the native language, if not

[1] Unfortunately, we observed convergence issues in the MIDAS model with the daily CPU data for the US and with both the daily and weekly CPU indexes for the other 11 countries, due to a large number of zeros.

[2] See: https://www.oecd.org/en/publications/serials/main-economic-indicators_g1g11c1c.html.

[3] The data can be downloaded from: https://policyuncertainty.com/climate_uncertainty.html.

[4] Data for the 12 countries at the three frequencies can be accessed from: http://www.cnefn.com/data/download/climate-risk-database/.

available in English, of the specific important newspaper[5] chosen for these economies, by utilizing climate policy white papers from the Intergovernmental Panel on Climate Change (IPCC) and national climate/environmental authorities to construct a vocabulary for terms related to climate, policy and uncertainty.[6]

Given the availability of the CPU of the 11 other countries and the GCPU indexes at the time of writing this paper, while all data ended in 2023:12, the forecasting exercise for inflation covered heterogeneous starting periods of: 2000:01 for Canada, China and the UK; 2001:01 for France; 2005:03 for Brazil; 2007:04 for Korea; 2008:05 for India; 2009:10 for Germany; 2012:12 for Japan, and; 2018:07 for South Africa. As HICP data for Australia are only available at a quarterly frequency, the corresponding analysis covered 2000:Q1–2023:Q4, with monthly values for local and global CPUs averaged over 3 months.

Table 1 provides a detailed summary of the descriptive statistics and preliminary tests for inflation rates and the various CPU indexes. The table is organized into 3 panels, each offering distinct empirical insights that are crucial for selecting the appropriate econometric framework for analyzing the climate-inflation nexus. The first panel captures the inflation dynamics across countries, with Brazil, India, and South Africa (representative emerging economies) exhibiting relatively higher mean inflation rates. The inflation series are predominantly positively skewed and leptokurtic, except for South Africa and South Korea, respectively. Unit root tests, including Augmented Dickey-Fuller (ADF; Dickey and Fuller, 1979) and Phillips-Perron (PP; Phillips and Perron, 1988), largely fail to reject the null hypothesis of a unit root, suggesting that inflation is non-stationary. Additionally, strong evidence of heteroscedasticity and serial correlation implies the need to address these violations to ensure consistent and efficient inference.

In Panels 2 and 3, substantial cross-country heterogeneity is observed in the climate policy uncertainty (CPU) series. Apart from Australia, most countries exhibit CPU indicators with positive skewness and excess kurtosis, indicating non-normality and potential outliers. The stationarity tests uniformly reject the null of non-stationarity at the 1 % level, affirming that these series are stationary. Similarly, the global climate policy uncertainty proxies (GCPU, GCPU-EQ, and GCPU-GDP) show consistent statistical features (right skewness, leptokurtosis, and confirmed stationarity). Across both panels, the presence of conditional heteroscedasticity and serial dependence further substantiates the need for an estimation approach that accommodates non-constant variance and dynamic error structures.

These stylized features (non-normality, conditional heteroscedasticity, and temporal correlation) are common across the dataset. Therefore, the FQGLS estimator is recommended for subsequent modelling (Westerlund and Narayan, 2012; 2015), as it explicitly accounts for heteroscedasticity and serial correlation, thereby improving the efficiency and reliability of parameter estimates in the context of climate transition-inflation analysis. The outline of the methodology is what we turn to next in Section 3.

3. Methodology

Guided by the inherent characteristics of the dataset, we adopt a FQGLS estimation framework that accounts for key data features, notably the presence of heteroscedasticity and autocorrelation of varying lag orders. To mitigate conditional heteroscedasticity, we implement a pre-weighting procedure using the inverse of the standard deviation of residuals obtained from an initial OLS estimation of the same model specification. The resulting FQGLS model is formally represented in Eq. (1) as follows:

$$inf_t = \alpha + \beta\, unc_{t-1} + \delta \Delta unc_t + \varepsilon_t \tag{1}$$

where inf_t is the country-specific inflation rate at time t; unc_t represents the climate policy uncertainty measures (country-specific CPU, GCPU, GCPU-GDP and GCPU-EQ) at time t; α is the constant; β denotes the slope coefficients associated with the incorporated climate policy uncertainty proxy; δ is incorporated to account to any inherent bias associated with the presence of persistence effect in unc_t; while ε_t is the residual term that follows a white noise process. A more detailed derivation is presented in Appendix B.

To formally evaluate the relative forecast performance of our climate policy uncertainty–augmented FQGLS model against a restricted benchmark, the historical average model, we implement the Clark and West (2007); CW) test, which is specifically designed for nested model comparisons. The historical average serves as the conventional benchmark in these pairwise evaluations. The CW test adjusts for the potential overfitting bias inherent in nested model comparisons, providing a robust framework to assess whether our augmented model yields statistically significant improvements in forecast accuracy. The null hypothesis posits no improvement in predictive performance, that is, the expected squared forecast error difference is zero. The CW test statistic is derived from the adjusted mean squared error differential, formally expressed in Eq. (2) below.

$$\widehat{f}_{t+h} = \left(r_{t+h} - \widehat{r}_{1t,t+h}\right)^2 - \left[\left(r_{t+h} - \widehat{r}_{2t,t+h}\right)^2 - \left(\widehat{r}_{1t,t+h} - \widehat{r}_{2t,t+h}\right)^2\right] \tag{2}$$

where h is the forecast period; $\left(r_{t+h} - \widehat{r}_{1t,t+h}\right)^2$ and $\left(r_{t+h} - \widehat{r}_{2t,t+h}\right)^2$ are the squared residuals from the benchmark–historical average model (restricted) and our climate policy uncertainty-based predictive FQGLS model (unrestricted), respectively; while $\left(\widehat{r}_{1t,t+h} - \widehat{r}_{2t,t+h}\right)^2$ is an adjusted squared residual that is peculiar to the Clark and West test and incorporated as a corrective measure for the noisy forecasts of the larger model. The term, $\widehat{f}_{t+h}$ is defined as $MSE_1 - (MSE_2 - adj.)$, where $MSE_1 = P^{-1}\sum\left(r_{t+h} - \widehat{r}_{1t,t+h}\right)^2$, $MSE_2 = P^{-1}\sum\left(r_{t+h} - \widehat{r}_{2t,t+h}\right)^2$, $adj. = P^{-1}\sum\left(\widehat{r}_{1t,t+h} - \widehat{r}_{2t,t+h}\right)^2$ and P represents the number of averaged forecast points. The test is based on the regression of $\widehat{f}_{t+h}$ on a constant and the determination of equality, or otherwise, of paired contending forecast errors using the t-statistic of the estimated constant. A statistically significant t-value indicates that the unrestricted model, augmented with climate policy uncertainty measures, yields superior forecast accuracy compared to the restricted benchmark model (i.e., the historical average). Conversely, an insignificant result implies no measurable improvement in predictive performance, thus failing to reject the null hypothesis of equal forecast accuracy across the competing specifications.

To answer the question of whether global metrics of CPUs matter more than the country-specific variant for the forecasting of the inflation rates of the 12 countries under consideration, we adopt the modified-Diebold-Mariano test proposed by Harvey et al. (1997); DM*), as specified in Eq. (3). This test extends the conventional Diebold and Mariano (1995); DM) framework, formulated in Eq. (4), making it more suitable for comparing paired non-nested models. The statistical formulations for these tests are provided in Eqs. (3) and (4).

$$DM^* = \left(\sqrt{\frac{T + 1 - 2h + T^{-1}h(h-1)}{T}}\right) DM \tag{3}$$

$$DM = \frac{\overline{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{4}$$

where DM^* denotes the modified DM statistic; T represents the number of the out-of-sample periods of the forecast errors and h represents the forecast horizon; $\overline{d} = 1/T\left[\sum_{t=1}^{T} d_t\right]$ indicates the average of the loss differential, $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$; $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$ are loss functions (squares of the forecast errors (ε_{it} and ε_{jt}, respectively) from the paired

[5] See Table A1 of Ma et al. (2024).

[6] The interested reader is referred to Table A2 in Ma et al. (2024).

Table 1
Summary statistics and preliminary analyses.

Country	Descriptive Statistics					Unit Root Tests		Heteroscedasticity Test		Serial Correlation	
	Mean	Standard Deviation	Skewness	Kurtosis	Nobs	ADF	PP	$ARCH(6)$	$ARCH(12)$	$Q(6)$	$Q(12)$
Panel 1: Country-Specific Inflation Rate											
Australia	2.86	1.53	1.20	4.40	96	-2.83^{*a}	-3.10^{**a}	0.04	9.03***	2.48	19.10***
Brazil	6.13	2.56	1.33	5.52	288	-3.04^{b}	-3.18^{*b}	13.38***	10.64***	169.98***	233.58***
Canada	2.19	1.37	1.41	6.32	288	-2.20^{b}	-3.24^{*b}	0.70	3.21***	11.59*	80.40***
China	2.06	1.88	0.80	3.97	288	-2.96^{**a}	-3.55^{***a}	1.15	4.94***	12.90**	105.00***
France	1.67	1.28	1.37	5.59	288	-1.60^{b}	-2.35^{b}	3.32***	4.01***	18.48***	62.20***
Germany	1.86	1.62	2.13	8.36	288	-3.57^{**b}	-2.65^{b}	23.76***	13.81***	18.05***	71.63***
India	6.05	2.57	0.88	3.56	288	-1.85^{a}	-2.64^{a}	1.32	2.75***	26.12***	84.34***
Japan	0.31	1.24	1.06	4.00	288	-2.92^{b}	-3.07^{b}	0.42	4.93***	11.74*	80.09***
South Korea	2.47	1.34	0.28	2.53	288	-2.26^{b}	-2.83^{b}	1.14	3.55***	11.76*	70.60***
South Africa	5.13	2.44	-0.08	4.64	288	-2.60^{a}	-3.45^{**a}	13.16***	14.41***	124.65***	212.78***
UK	2.39	1.73	2.13	7.85	288	-2.83^{b}	-2.65^{b}	15.24***	12.25***	61.67***	99.57***
US1	2.52	1.74	1.00	5.11	288	-3.07^{b}	-2.98^{b}	5.01***	7.48***	55.84***	86.82***
US2	2.77	1.57	0.73	4.84	451	-3.45^{**b}	-3.43^{**b}	8.05***	13.08***	79.96***	196.13***
Panel 2: Country-Specific Climate Policy Uncertainty											
Australia	1.57	0.81	0.58	2.85	96	-4.01^{**b}	-7.46^{***b}	3.24**	1.61	10.29***	12.43**
Brazil	1.26	1.00	1.57	6.37	226	-2.85^{*a}	-10.47^{***b}	1.06	1.81**	31.22***	51.70***
Canada	1.12	1.00	1.54	5.57	288	-3.61^{**b}	-12.91^{***b}	11.19***	6.10***	63.10***	81.39***
China	1.23	1.00	1.54	5.94	288	-6.88^{***a}	-11.24^{***b}	5.89***	5.10***	30.54***	44.32***
France	1.36	1.00	1.42	4.10	276	-2.20^{b}	-8.51^{***b}	11.82***	6.80***	40.14***	47.36***
Germany	1.49	1.00	1.11	3.65	171	-3.54^{**b}	-10.77^{***b}	2.43**	1.57	42.23***	50.90***
India	1.48	1.00	1.37	6.89	188	-11.368^{**b}	-11.68^{***a}	8.95***	5.10***	25.12^{***c}	28.20^{***c}
Japan	0.63	1.00	1.47	4.13	133	-11.68^{***b}	-11.71^{***a}	2.75**	1.65*	10.36	21.64**
South Korea	1.05	1.00	1.85	6.72	201	-6.35^{***b}	-10.61^{***b}	4.54***	4.01***	23.28***	48.86***
South Africa	1.82	1.00	0.81	3.21	66	-6.03^{***b}	-5.91^{***b}	1.55	1.03	15.04**	25.02**
UK	2.12	1.00	0.81	3.42	288	-12.03^{***b}	-12.02^{***b}	1.28	1.95**	18.16***	42.65***
US1	1.59	1.00	0.94	4.79	288	-6.61^{***b}	-11.42^{***b}	11.55***	7.03***	23.84***	39.38***
US2	107.31	62.47	1.75	6.54	451	-5.24^{***b}	-12.23^{***b}	14.23***	8.91***	44.97***	75.00***
Panel 3: Predictors - Global Climate Policy Uncertainty Proxies											
GCPU	100.00	43.87	0.96	3.68	288	-5.82^{***b}	-9.57^{***b}	6.39***	3.53***	26.96***	39.08***
GCPU-EQ	100.00	42.83	0.81	3.19	288	-6.38^{***b}	-9.87^{***b}	2.94***	1.78*	26.41***	42.27***
GCPU-GDP	100.00	43.39	0.98	3.66	288	-5.97^{***b}	-9.94^{***b}	4.74***	2.65***	27.56***	39.80***

Note: The table includes summary statistics (mean, standard deviation, skewness, and kurtosis) and preliminary analysis (unit root tests, heteroscedasticity tests, and tests for first- and higher-order serial correlation). The null hypothesis for the ADF and PP tests is a unit root; hence, rejecting the null for either test implies that the series is stationary. The superscripts "a" and "b" denote the models with constant-only and constant-and-trend, respectively. On the heteroscedasticity test, the null hypothesis asserts homoscedasticity, and as such, rejection of the null hypothesis would imply the presence of heteroscedasticity at the specified lags. The null hypothesis for the serial correlation test is that there is no serial correlation; thus, rejecting the null hypothesis would imply the presence of serial correlation. Al, the superscript "c" attached to some of the serial correlation test values indicates that a higher-order, rather than a first-order, serial correlation was observed at the specified lags. *, ** and *** indicate statistical significance of the corresponding test at 10 %, 5 % and 1 %, respectively and implies rejection of the stated null. In Panel 2, US1 indicates the CPU for the US from Gavriilidis (2021), and US2 indicates the CPU based on Ji et al. (2024) and Ma et al. (2024).

competing models); while $V(d_t)$ is the unconditional variance of the loss differential d_t. The DM^* test null hypothesis asserts equality in the forecast precision of the paired non-nested contending models ($H_0 : d = 0$) against a mutually exclusive alternative, ($H_1 : d \neq 0$). The null hypothesis is retained when both models exhibit statistically indistinguishable forecast accuracy, whereas its rejection implies a significant difference in their predictive performances. The direction of the DM^* statistic informs model preference: a negative value favours the FQGLS specification incorporating global CPU variants, while a positive value supports the country-specific CPU-based model.

By way of robustness of our findings for the US, we also consider the CPU-inflation predictive nexus from a MIDAS model framework, whereby the monthly inflation rate is forecasted using weekly local and global CPUs. We specify a MIDAS regression model using the Exponential Almon lag polynomial. The model is given in Eq. (6) as:

$$inf_t^{mnt} = \alpha + \beta \sum_{j=0}^{k-1} exp\left(j\theta_1 + j^2\theta_2\right) \cdot unc_{t-\tau/f}^{wk} \ + \varepsilon_t \tag{5}$$

where inf_t^{mnt} is the monthly inflation rate at time t, and $unc_{t-\tau/S}^{wk}$ represents the specific weekly CPU at lag j, with f indicating the number of weeks per month. The term $\sum_{j=0}^{k-1} exp\left(j\theta_1 + j^2\theta_2\right)$ defines the exponential Almon weighting scheme, where the parameters θ_1 and θ_2 flexibly control the shape and decay of the lag weights across k weekly lags, ensuring positivity and interpretability. The scalar β captures the marginal effect of the weighted US- or global-CPU on inflation, while ε_t is a mean-zero error term. This specification avoids arbitrary aggregation of high-frequency data and effectively models persistence or delayed effects of CPU shocks. The exponential Almon lag is parsimonious and reduces overfitting, while preserving essential dynamics, making it ideal for mixed-frequency macroeconomic forecasting. The MIDAS model was pre-weighted with the inverse of the standard deviation, in a manner similar to the FQGLS approach. As with the same frequency framework, the CW test statistic is utilized to check whether the local- and global-CPU based MIDAS models outperforms the historical average model.

For forecast evaluation, the dataset is partitioned into a 75:25 ratio—where 75 % supports in-sample estimation, and 25 % is reserved for out-of-sample forecasts over 3-, 6-, and 12-month horizons.

Table 2
Out-of-sample forecast evaluation results for the US using the Clark-West Test.

Model	$h = 3$	$h = 6$	$h = 12$
Panel A: Benchmark model is Historical Average			
CPU	3.2067***	3.2755***	3.3267***
	[0.2792]	[0.2796]	[0.2757]
Panel B: Benchmark model is DACI+ 8 Factors-based Model			
DACI+ 8 Factors+CPU	2.61E-03*	2.66E-03*	2.57E-03*
	[1.41E-03]	[1.40E-03]	[1.38E-03]

Note: The figures in the table represent the Clark-West (CW) test statistics, along with the corresponding standard errors in square brackets. Statistical significance is denoted at 1 % and 10 % levels, respectively, by *** and *. Significantly positive statistics indicate that the US CPU-based predictive FQGLS model outperforms the panel-named models (the historical average model in Panel A and the DACI+8 factors-based FQGLS model in Panel B), which serve as the benchmark. The forecast evaluation is performed for three forecast horizons (h): 3-, 6-, and 12-month ahead.

Table 3
Out-of-sample forecast evaluation results for the US using Clark-West Test (Benchmark model: Historical Average).

Horizon	CPU	GCPU	GCPU-GDP	GCPU-EQ
$h = 3$	2.77E+ 00***	2.79E+ 00***	2.77E+ 00***	2.77E+ 00***
	[2.83E-01]	[2.84E-01]	[2.85E-01]	[2.83E-01]
$h = 6$	2.73E+ 00***	2.76E+ 00***	2.74E+ 00***	2.73E+ 00***
	[2.80E-01]	[2.81E-01]	[2.81E-01]	[2.80E-01]
$h = 12$	2.67E+ 00***	2.69E+ 00***	2.67E+ 00***	2.67E+ 00***
	[2.74E-01]	[2.75E-01]	[2.75E-01]	[2.74E-01]

Note: The figures in the table represent the Clark-West (CW) test statistics, along with the corresponding standard errors in square brackets. Statistical significance is denoted at 1 % level by ***. Significantly positive statistics indicate that the US CPU-based predictive FQGLS model outperforms the historical average model, which serves as the benchmark. The forecast evaluation is performed for three forecast horizons (h): 3-, 6-, and 12-month ahead.

4. Empirical results

In this section, we first provide the same- and mixed-frequency results for the US, before turning to the findings for the 11 other countries.

4.1. Main findings for the US

Table 2 compares the forecasting accuracy of the CPU-based FQGLS model with the historical average model (Panel A) and the FQGLS model that includes a measure of physical risks of climate change and 8 financial and macroeconomic factors extracted from a large data set of 134 monthly economic indicators of the US, relative to the nested model that excludes the CPU.

Note that, in line with the existing literature, here the CPU refers to the index of Gavriilidis (2021). As for the metric for physical risks, we use the Actuaries Climate Index (ACI), developed by the Actuarial Society of the US.[7] The ACI is an aggregate indicator of the frequency of severe weather (high and low temperatures, heavy rainfall, drought (consecutive dry days), and high wind, with all based on gridded data at the resolution of 2.5 by 2.5 ° latitude and longitude), and the extent of sea level rise (using tidal gauge station data). The non-stationarity of this index, implies that we work with the first-difference of this variable (*daci*). PCA analysis is used to extract 8 factors (f) from the FRED-MD database (McCracken and Ng, 2016), wherein we ensure that we exclude the CPI data.[8] Note that, the FRED-MD database includes industrial production, weekly hours, personal inventories, monetary aggregates, interest rates and interest-rate spreads, stock prices, and consumer expectations, and hence, includes both demand- and supply-side predictors, widely used in the forecasting literature. So formally, the extended model, relative to Eq. (1), with *daci* and 8 f_is over and above the CPU can be written as follows:

$$inf_t = \alpha + \beta\, unc_{t-1} + \delta \Delta unc_t + \phi daci_{t-1} + \sum_{i=1}^{8} \gamma_i f_{i,t-1} + \varepsilon_t \tag{6}$$

All the definitions for the parameters, variables and the error structure as in the original model in Eq. (1) remain.

The forecast evaluation results across all three forecast horizons reveal that the CW test statistics are consistently positive and statistically significant at the 1 % and 10 % levels, respectively (see results in Panels A and B in Table 2). This indicates that the US CPU-based FQGLS model, without controls and when augmented with control variables, consistently outperforms both benchmark models: historical average and FQGLS with DACI and financial and macroeconomic factors, in forecasting accuracy, thus enforcing the robust predictive strength of the CPU across various horizons in forecasting inflation. Overall, the findings provide strong statistical evidence that the CPU carries important forward-looking signals for predicting US inflation.[9] This result can be used to argue for integrating climate risk indicators into mainstream inflation forecasting frameworks, as they offer meaningful improvements in forecast precision across prediction horizons, especially in the context of monetary policy decisions. This is more so given that the full-sample estimates of CPU in the two models considered above were positive (0.0058 and 0.0050) and statistically significant at the 1 % level.[10]

4.2. Additional results for the US: Same- and mixed-frequency

In Table 3 and Table 4, we present our findings using the alternative narrower CPU index of Ji et al. (2024) and Ma et al. (2024) as a matter of robustness, and also analyze the performance of the 3 GCPUs, with the benchmark models of historical average and the own-country CPU, respectively.

The following outcomes are evident: i) Based on the CW tests statistics, the proposed FQGLS model is superior to the historical across all the forecast horizons, regardless of whether own- or global-CPU is considered; imperatively, as depicted in Table 3, CPU indexes contain valuable forward-looking information for US inflation forecasts, emphasizing again the need to include of climate risk variables in the US inflation modelling framework. ii) Drawing on the modified Diebold-Mariano (*DM**) test results reported in Table 4, the forecasting performance for inflation involving the 3 GCPUs cannot significantly outperform the same using the country-specific CPU across the different

[7] The data can be downloaded from: https://actuariesclimateindex.org/data/.

[8] The whole dataset is available at: https://research.stlouisfed.org/econ/mccracken/freddatabases/.

[9] As CPU is likely to be capturing the transition risks component of climate change, as an additional analysis, we conducted a forecasting exercise for the US using the four indicators associated with Global Warming (GW), Natural Disasters, US Climate Policy (USCP), and international Summits (IS), as derived from textual and narrative analysis of Reuters climate-change news by Faccini et al. (2023). GW and ND represent physical risks, while USCP and IS capture transition risks. Based on data over the period of 2001:01–2025:01, the results presented in Table A1 in the Appendix of the paper provides statistically significant (at the 1 % level under the CW test statistics) evidence of forecastability of inflation, relative to the benchmark of historical average, emanating from GW, ND, USCP and IS, suggesting the important role of both types of climate risks in shaping the future path of inflation rate in the US. Note that the daily climate risk indicators of Faccini et al. (2023), which we average to a monthly frequency for our estimations, are available at: https://sites.google.com/site/econrenatofaccini/home/research?authuser=0.

[10] *daci* also carried a positive coefficient of 0.7430, which was significant at the 5 % level, highlighting, in line with the literature, that physical risks is also inflationary.

Table 4
Out-of-sample forecast evaluation results using modified Diebold-Mariano Test (Benchmark model: US CPU-based model).

Horizons	GCPU	GCPU-GDP	GCPU-EQ
$h = 3$	0.6098	-0.4313	-0.5687
$h = 6$	0.5206	-0.5227	-0.5855
$h = 12$	0.4399	-0.5861	-0.6105

Note: The figures in each cell are the modified Diebold-Mariano (*DM**) test statistics. The null hypothesis asserts that the forecast precision of our global climate policy uncertainty model is equal to that of the country-specific variant (benchmark) models. The sign associated with the *DM** statistics determines the direction of out-performance. A positive result indicates that the US CPU-based FQGLS model outperforms the global variants-based FQGLS models, while a significantly negative result indicates the converse. Non-significance, as in this case, indicates that there is no significant difference between the US and global CPU measures. The forecast evaluation is performed for three forecast horizons (h): 3-, 6-, and 12-month ahead.

Table 5
Out-of-sample forecast evaluation results for the US using the Clark-West Test in the MIDAS model (Benchmark model: Historical Average).

Predictors	$h = 3$	$h = 6$	$h = 12$
US CPU	1.08E-02** [4.92E-03]	1.07E-02** [4.87E-03]	1.15E-02** [4.81E-03]
GCPU	1.44E-02*** [5.20E-03]	1.53E-02*** [5.19E-03]	1.52E-02*** [5.09E-03]
GCPU-EQ	4.01E-03* [2.17E-03]	4.21E-03* [2.15E-03]	3.68E-03* [2.13E-03]
GCPU-GDP	1.36E-02** [5.45E-03]	1.50E-02*** [5.48E-03]	1.40E-02** [5.40E-03]

Note: The figures in each cell represent the estimated Clark-West (CW) test statistics, along with their standard errors in square brackets, and statistical significance at 1 %, 5 %, and 10 % levels, denoted by ***, **, and *, respectively. Significantly positive CW statistics indicate that models incorporating the row predictors are preferred to the historical-average model, serving as the benchmark; while significantly negative CW statistics imply the converse. Non-significance would imply that the predictor-based MIDAS models do not differ markedly from the historical average model in forecast precision. The forecast evaluation is performed for three forecast horizons (h): 3-, 6-, and 12-month ahead.

horizons ($h = 3$-, 6- and 12-month-ahead). This finding tends to suggest that the information content of the global-level climate policies-related uncertainties is already contained in the US CPU, thus resulting in insignificant forecasting gains across the local versus global comparisons. In other words, both the US-based CPU and the 3 global CPUs perform equally well in forecasting the inflation rate, and serve as substitutable predictors.

Next, we turn our focus to robustness based on the mixed-frequency analysis, to ensure that temporal aggregation of high-frequency, i.e., weekly, values of the local and global CPUs to corresponding monthly values does not impact the forecasting results for US inflation. Table 5 presents the forecast evaluation using the CW test for MIDAS models, with the historical average serving as the benchmark. Across all the 3 forecast horizons, significantly positive CW statistics are found for both the US and global CPUs serving as predictors for the inflation rate, thus confirming that the uncertainty-based models consistently outperform the benchmark. Notably, the FQGLS-type adjusted MIDAS models incorporating higher-frequency climate uncertainty proxies, such as CPU, GCPU, and GCPU-GDP, exhibit strong and statistically significant gains in forecast accuracy, particularly with GCPU and GCPU-GDP having the highest CW values at the 1 % significance level, while for CPU, significance holds at the 5 % level. The GCPU-EQ-based MIDAS model improves forecast precision, although the improvement is weakly significant at the 10 % level. These results confirm that incorporating high-frequency measures of climate-related uncertainty into inflation forecasting frameworks yields significant predictive advantages over traditional models based on historical averages. This supports the relevance of climate risk indicators as forward-looking inputs and highlights the value of frequency-aligned FQGLS-type adjusted MIDAS models in enhancing the reliability of inflation forecasts. At the same time, we show that aggregating the CPU metric to lower frequencies does not affect its forecasting performance for the US inflation rate.

In addition, we assessed the robustness of our results by examining how the predictive framework responds when we juxtapose the performance of the FQGLS estimator with that of the conventional OLS specification. This exercise reinforces the central conclusion that our preferred model consistently outperforming the OLS alternative that fails to accommodate salient inherent data features. As reported in Table A4, our adopted model's structure and its explicit treatment of salient statistical features confer both stability and methodological superiority over competing estimators.

4.3. International evidence

Having provided robust evidence of the role of own- and global CPUs in forecasting the US inflation rate, we now extend the analysis to an international context involving 11 other countries for the sake of generalization of our findings.

Across the 7 advanced countries and horizons, the CW test statistics are positive and significant at the 1 % level, affirming that the climate-uncertainty-based FQGLS model consistently outperforms the benchmark in terms of forecast precision, as shown in Table 6. This observation is evident across all four predictors: CPU, GCPU, GCPU-GDP, and GCPU-EQ, i.e., both local and global CPUs, as in the case of the US. A similar pattern holds for the 4 examined emerging economies, all of which show highly significant and positive CW test statistics across the specified horizons and predictors. Importantly, CPU, both domestic and global, contains valuable forward-looking information for inflation forecasts across both advanced and emerging economies.[11] This statistical analysis supports the inclusion of climate risk variables in global inflation modelling frameworks.

But as in the case of the US, one can observe from the modified Diebold-Mariano (*DM**) test results reported in Table 7, the forecasting

[11] As in the case of the US, in Table A1 in the Appendix of the paper, a forecasting analysis based on the Physical Risks Index (PRI) and Transition Risks Index (TRI), as developed by Bua et al. (2024) by using textual analysis of Reuters climate-change news, confirms that both types of risks matter statistically (at the 1 % level of significance of the CW test statistics) in forecasting the inflation rate of the European Union (EU) over the period of 2005:01–2023:12. The HICP of EU is again sourced from the MEI database of the OECD to compute the year-on-year inflation rate, while the daily PRI and TRI data, converted to monthly data by averaging for our purpose, is available for download from: https://sites.google.com/view/lavinia-rognone-library/research-impact-data?authuser=0.

Table 6
International out-of-sample forecast evaluation results using Clark-West Test (Benchmark model: Historical Average).

	Horizon	CPU	GCPU	GCPU_GDP	GCPU_EQ
Panel A: Advanced Economies					
Australia	$h=3$	1.28E+ 00*** [3.15E-01]	1.60E+ 00*** [4.21E-01]	1.46E+ 00*** [3.66E-01]	1.22E+ 00*** [3.03E-01]
	$h=6$	1.29E+ 00*** [3.11E-01]	1.60E+ 00*** [4.15E-01]	1.46E+ 00*** [3.61E-01]	1.22E+ 00*** [2.98E-01]
	$h=12$	1.31E+ 00*** [3.03E-01]	1.61E+ 00*** [4.04E-01]	1.47E+ 00*** [3.52E-01]	1.24E+ 00*** [2.91E-01]
Canada	$h=3$	1.21E+ 00*** [1.35E-01]	1.22E+ 00*** [1.36E-01]	1.22E+ 00*** [1.36E-01]	1.20E+ 00*** [1.34E-01]
	$h=6$	1.20E+ 00*** [1.34E-01]	1.21E+ 00*** [1.34E-01]	1.21E+ 00*** [1.35E-01]	1.19E+ 00*** [1.32E-01]
	$h=12$	1.18E+ 00*** [1.30E-01]	1.19E+ 00*** [1.31E-01]	1.19E+ 00*** [1.32E-01]	1.17E+ 00*** [1.29E-01]
France	$h=3$	1.31E+ 00*** [1.11E-01]	1.31E+ 00*** [1.11E-01]	1.31E+ 00*** [1.11E-01]	1.32E+ 00*** [1.11E-01]
	$h=6$	1.31E+ 00*** [1.09E-01]	1.30E+ 00*** [1.10E-01]	1.30E+ 00*** [1.10E-01]	1.31E+ 00*** [1.10E-01]
	$h=12$	1.28E+ 00*** [1.07E-01]	1.27E+ 00*** [1.08E-01]	1.27E+ 00*** [1.07E-01]	1.28E+ 00*** [1.07E-01]
Germany	$h=3$	6.98E-01*** [8.11E-02]	7.08E-01*** [8.09E-02]	7.32E-01*** [8.39E-02]	6.82E-01*** [7.87E-02]
	$h=6$	7.84E-01*** [9.40E-02]	7.93E-01*** [9.39E-02]	8.20E-01*** [9.74E-02]	7.65E-01*** [9.14E-02]
	$h=12$	7.91E-01*** [9.20E-02]	7.98E-01*** [9.15E-02]	8.26E-01*** [9.50E-02]	7.72E-01*** [8.94E-02]
Japan	$h=3$	1.99E+ 00*** [3.25E-01]	1.99E+ 00*** [3.27E-01]	2.00E+ 00*** [3.29E-01]	2.04E+ 00*** [3.33E-01]
	$h=6$	1.98E+ 00*** [3.16E-01]	1.98E+ 00*** [3.18E-01]	1.99E+ 00*** [3.20E-01]	2.03E+ 00*** [3.23E-01]
	$h=12$	1.90E+ 00*** [3.01E-01]	1.89E+ 00*** [3.03E-01]	1.90E+ 00*** [3.05E-01]	1.94E+ 00*** [3.08E-01]
South Korea	$h=3$	3.22E+ 00*** [3.20E-01]	3.14E+ 00*** [3.07E-01]	3.15E+ 00*** [3.09E-01]	3.24E+ 00*** [3.21E-01]
	$h=6$	3.27E+ 00*** [3.15E-01]	3.18E+ 00*** [3.03E-01]	3.19E+ 00*** [3.04E-01]	3.28E+ 00*** [3.16E-01]
	$h=12$	3.35E+ 00*** [3.06E-01]	3.27E+ 00*** [2.95E-01]	3.28E+ 00*** [2.96E-01]	3.36E+ 00*** [3.07E-01]
UK	$h=3$	1.49E+ 00*** [1.39E-01]	1.50E+ 00*** [1.41E-01]	1.52E+ 00*** [1.42E-01]	1.50E+ 00*** [1.40E-01]
	$h=6$	1.47E+ 00*** [1.38E-01]	1.48E+ 00*** [1.39E-01]	1.51E+ 00*** [1.41E-01]	1.48E+ 00*** [1.39E-01]
	$h=12$	1.43E+ 00*** [1.35E-01]	1.45E+ 00*** [1.36E-01]	1.47E+ 00*** [1.38E-01]	1.45E+ 00*** [1.36E-01]
Panel B: Emerging Economies					
Brazil	$h=3$	5.86E+ 00*** [6.54E-01]	5.85E+ 00*** [6.54E-01]	5.85E+ 00*** [6.54E-01]	5.87E+ 00*** [6.56E-01]
	$h=6$	5.95E+ 00*** [6.45E-01]	5.93E+ 00*** [6.45E-01]	5.94E+ 00*** [6.45E-01]	5.95E+ 00*** [6.46E-01]
	$h=12$	6.29E+ 00*** [6.29E-01]	6.27E+ 00*** [6.29E-01]	6.28E+ 00*** [6.29E-01]	6.29E+ 00*** [6.30E-01]
China	$h=3$	7.68E+ 00*** [8.36E-01]	7.71E+ 00*** [8.38E-01]	7.63E+ 00*** [8.27E-01]	7.61E+ 00*** [8.23E-01]
	$h=6$	7.58E+ 00*** [8.27E-01]	7.61E+ 00*** [8.28E-01]	7.53E+ 00*** [8.17E-01]	7.51E+ 00*** [8.14E-01]
	$h=12$	7.38E+ 00*** [8.09E-01]	7.41E+ 00*** [8.11E-01]	7.33E+ 00*** [8.00E-01]	7.31E+ 00*** [7.96E-01]
India	$h=3$	1.49E+ 01*** [1.59E+ 00]	1.49E+ 01*** [1.59E+ 00]	1.49E+ 01*** [1.58E+ 00]	1.49E+ 01*** [1.59E+ 00]
	$h=6$	1.48E+ 01*** [1.56E+ 00]	1.47E+ 01*** [1.56E+ 00]	1.47E+ 01*** [1.55E+ 00]	1.48E+ 01*** [1.56E+ 00]
	$h=12$	1.47E+ 01*** [1.50E+ 00]	1.47E+ 01*** [1.50E+ 00]	1.46E+ 01*** [1.49E+ 00]	1.47E+ 01*** [1.50E+ 00]
South Africa	$h=3$	3.48E+ 00*** [7.26E-01]	3.54E+ 00*** [7.39E-01]	3.54E+ 00*** [7.39E-01]	3.56E+ 00*** [7.46E-01]
	$h=6$	4.06E+ 00*** [7.63E-01]	4.14E+ 00*** [7.77E-01]	4.13E+ 00*** [7.77E-01]	4.17E+ 00*** [7.86E-01]
	$h=12$	4.22E+ 00*** [7.13E-01]	4.30E+ 00*** [7.27E-01]	4.29E+ 00*** [7.27E-01]	4.34E+ 00*** [7.36E-01]

Note: The figures in the table represent the Clark and West statistics, along with the corresponding standard errors in square brackets. Statistical significance is denoted at the 1 % level by ***. Significantly positive results indicate that our climate policy-uncertainty-based predictive FQGLS model outperforms the historical-average benchmark model. The forecast evaluation is performed for three different forecast horizons: 3, 6, and 12 months ahead.

performance for inflation involving the 3 GCPUs perform equally as well compared to the country-specific CPUs across the different horizons ($h =$ 3-, 6- and 12-month-ahead), barring the case of Germany at $h = 12$, where global-level uncertainties related to climate policy do tend to matter more. In sum, the information content of local and global CPUs is equally important for forecasting the inflation rates of 11 other economies, consistent with the evidence for the US.[12]

[12] As additional analyses over the period of 2001:01–2023:12, we also analyzed the ability of combined information from provincial- and city-level CPU data for China, obtained using PCA on the CPUs of 31 provinces and 293 cities respectively, on the national inflation rate. In this regard, we first use the CW test statistics to compare the predictive ability of an alternative national-level CPU of China, as well as the PCA-based provincial and city-level CPU indices, all of which are developed by Ma et al. (2023) using deep learning on Chinese news data, in forecasting inflation relative to the benchmark model of historical average. As shown in Table A2 in the Appendix, the CPU-based models consistently outperform the historical average at the 1 % level of significance, suggesting the importance of information on the uncertainty surrounding climate policies at the aggregate and regional levels for Chinese inflation. However, as with the comparison between local- and global-CPUs for the 12 economies, the *DM** test results in Table A3 in the Appendix depict equal performance of national, provincial, and city-level CPUs in forecasting the overall inflation rate of China. Note that the CPU indexes of Ma et al. (2023) are available at http://www.cnefn.com/data/download/climate-risk-database/ and are based on 6 newspapers instead of 1, as in Ji et al. (2024) and Ma et al. (2024). In the process, we also provide robustness for the results of China reported in Table 6, using a broader national-level CPU.

5. Conclusion

This study examines the usefulness of CPU in forecasting the rate of inflation in the US over the monthly period of 1987:05–2024:11. We use FQGLS to estimate single- and multiple-factor models, with the latter also controlling for physical risks and the information of a large number of financial and macroeconomic variables summarized through PCA, for the CPU-inflation predictability nexus in the US. Our findings reveal that the CPU-based predictive regression model outperformed the historical mean benchmark in a statistically significant manner at the 1 % level, with a significant forecasting gain observed at the 10 % level when CPU was added to the multi-factor benchmark. The predictive superiority of CPU, at the 1 % level of significance, relative to the historical mean continues to be robust across alternative local and global metrics of climate policy-related uncertainties, as well as in a mixed-frequency setup that used weekly CPU data to forecast monthly US inflation. Moreover, the importance of local- and global-CPUs is also found to be statistically significant at the 1 % level relative to the historical mean model when forecasting inflation rates for 11 other advanced and emerging countries. We further find that own-country and global CPUs performed equally well, in the sense of insignificant test statistics of forecast comparison, for forecasting inflation. In other words, local and global CPUs are perfectly substitutable as predictors of forecast country-level inflation across the 12 economies considered.

This study finds that CPU significantly improves inflation forecasting accuracy across various models and country settings, indicating that CPU has become an important forward-looking signal for inflation. Therefore, when a positive CPU shock occurs, monetary authorities need to adopt a contractionary policy stance in the short run to prevent future

Table 7
Out-of-sample forecast evaluation results using modified Diebold-Mariano Test (Benchmark model: Country-specific CPU-based model).

Countries	Horizons	GCPU	GCPU_GDP	GCPU_EQ
Advanced Economies				
Australia	$h = 3$	0.5929	-0.0549	0.1574
	$h = 6$	0.5685	-0.0532	0.0351
	$h = 12$	0.5274	-0.0533	0.0003
Canada	$h = 3$	0.1654	-0.0505	-0.3637
	$h = 6$	0.0024	-0.1574	-0.5883
	$h = 12$	-0.0893	-0.2074	-0.6604
France	$h = 3$	0.1307	-0.0303	0.6035
	$h = 6$	0.4552	0.2882	1.0826
	$h = 12$	-0.0909	-0.2241	0.0957
Germany	$h = 3$	0.6344	0.3460	1.7409*
	$h = 6$	0.5915	-0.2565	2.0478**
	$h = 12$	0.7891	-0.1364	1.9932**
Japan	$h = 3$	-0.1123	0.0811	0.2131
	$h = 6$	-0.1430	0.0232	0.1924
	$h = 12$	0.4112	0.4650	0.0305
South Korea	$h = 3$	-1.1758	-1.2962	-0.3513
	$h = 6$	-1.0664	-1.1497	-0.1238
	$h = 12$	-1.2573	-1.3631	-0.6246
UK	$h = 3$	-1.0108	-0.8783	-1.8913
	$h = 6$	-0.9848	-0.8701	-1.8277
	$h = 12$	-0.9865	-0.8635	-1.7956
US	$h = 3$	0.6098	-0.4313	-0.5687
	$h = 6$	0.5206	-0.5227	-0.5855
	$h = 12$	0.4399	-0.5861	-0.6105
Emerging Economies				
Brazil	$h = 3$	-0.0894	-0.4779	0.5561
	$h = 6$	0.4773	-0.0257	0.3743
	$h = 12$	-0.3000	-0.2613	1.1430
China	$h = 3$	0.0536	0.0974	0.8773
	$h = 6$	0.1602	0.1525	0.7955
	$h = 12$	-0.1832	-0.1324	0.6718
India	$h = 3$	-0.7466	-0.6410	-0.8644
	$h = 6$	-0.6524	-0.5051	-0.6551
	$h = 12$	-0.3794	-0.2007	-0.5427
South Africa	$h = 3$	0.0238	0.3783	0.0983
	$h = 6$	-0.0071	0.3102	0.1378
	$h = 12$	0.4077	0.6080	0.6901

Note: The figures in each cell are the modified Diebold-Mariano (*DM**) test statistics. The null hypothesis asserts that the forecast precision of our global climate policy uncertainty model is equal to that of the country-specific variant (benchmark) models. Statistical significance is denoted at the 5 % and 10 % levels by ** and *, respectively. The sign associated with the *DM** statistics determines the direction of outperformance. A positive result indicates that the country-specific CPU-based FQGLS model outperforms the global variants-based FQGLS models, while a significantly negative result indicates the converse. Non-significance, as in this case, indicates that there is no significant difference between the country-specific and global CPU measures. The forecast evaluation is performed for three forecast horizons (h): 3-, 6-, and 12-month ahead.

inflationary pressures. But increases in CPU, accompanied by economic contraction, imply that a firm and clear climate policy stance is desired from the ruling government in the first place to reduce the uncertainty and its adverse macroeconomic impacts (Cepni et al., 2025). Central banks should incorporate CPU into their inflation monitoring and forecasting frameworks, using scenario analysis and expanded indicator sets to improve the identification of future price dynamics. Meanwhile, given the substitutability between domestic and global CPU in forecasting performance, countries should enhance the transparency and stability of their climate policies to reduce the inflationary pressures arising from cross-border uncertainty spillovers. For emerging economies in particular, strengthening energy diversification and exchange rate stabilization mechanisms can help mitigate the impact of global CPU fluctuations on domestic price levels.

As part of future research, contingent on data availability, it would be interesting to analyze the role of state-level CPUs within the US (and other countries, if possible), given the heterogeneity in climate-related policies across the states (Trachtman, 2020), and lack of convergence in price levels (Christou et al., 2019), in forecasting their corresponding inflation rates.

CRediT authorship contribution statement

Yunhan Zhang: Writing – review & editing, Resources. **Rangan Gupta:** Writing – review & editing, Supervision, Conceptualization. **Ahamuefula E. Ogbonna:** Writing – review & editing, Methodology, Investigation. **Afees A. Salisu:** Writing – original draft, Software, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Out-of-Sample Forecast Evaluation Results using Clark-West Test (Benchmark model: Historical Average)

Predictors	Out-of-Sample Forecast		
	$h = 3$	$h = 6$	$h = 12$
	European Union (EU)		
PRI	2.13E+ 00*** [1.92E-01]	2.09E+ 00*** [1.89E-01]	2.10E+ 00*** [1.84E-01]
TRI	2.08E+ 00*** [1.87E-01]	2.04E+ 00*** [1.85E-01]	2.04E+ 00*** [1.79E-01]
	US		
GW	2.67E+ 00*** [2.72E-01]	2.64E+ 00*** [2.69E-01]	2.58E+ 00*** [2.63E-01]
IS	2.66E+ 00*** [2.72E-01]	2.63E+ 00*** [2.69E-01]	2.57E+ 00*** [2.64E-01]
ND	2.65E+ 00*** [2.73E-01]	2.62E+ 00*** [2.70E-01]	2.56E+ 00*** [2.64E-01]
USCP	2.66E+ 00*** [2.73E-01]	2.63E+ 00*** [2.70E-01]	2.57E+ 00*** [2.64E-01]

Note: PRI: Physical Risks Index; TRI: Transition Risks Index; GW: Global Warming; IS: International Summits; ND: Natural Disasters; USCP: US Climate Policies. The figures in the table represent the Clark-West statistics, along with the corresponding standard errors in square brackets. Statistical significance is denoted at the 1 % level by ***. Significantly positive results indicate that our climate policy-uncertainty-based predictive FQGLS model outperforms the historical-average benchmark model. The forecast evaluation is performed for three different forecast horizons: 3, 6, and 12 months ahead.

Table A2
Out-of-Sample Forecast Evaluation Results for China using Clark-West Test (Benchmark model: Historical Average)

Predictors	Out-of-Sample Forecast		
	$h = 3$	$h = 6$	$h = 12$
CPU	7.69E+ 00*** [8.40E-01]	7.59E+ 00*** [8.31E-01]	7.39E+ 00*** [8.12E-01]
City-CPU	7.61E+ 00*** [8.31E-01]	7.51E+ 00*** [8.21E-01]	7.31E+ 00*** [8.04E-01]
Province-CPU	7.63E+ 00*** [8.32E-01]	7.53E+ 00*** [8.23E-01]	7.33E+ 00*** [8.05E-01]

Note: CPU: National Chinese CPU; City-CPU: PCA of 293 CPU of Chinese cities CPU; Province-CPU: PCA of 31 CPU of Chinese provinces. The figures in the table represent the Clark-West test statistics, along with the corresponding standard errors in square brackets. Statistical significance is denoted at the 1 % level by ***. Significantly positive results indicate that our climate policy-uncertainty-based predictive FQGLS model outperforms the historical-average benchmark model. The forecast evaluation is performed for three different forecast horizons: 3, 6, and 12 months ahead.

Table A3
Out-of-Sample Forecast Evaluation Results for China using Modified Diebold-Mariano Test

Horizons	Panel A: Benchmark (CPU-based model)		Panel B: Benchmark (City CPU-based model)
	City-CPU vs CPU	Province-CPU vs CPU	Province-CPU vs City-CPU
$h = 3$	0.4042	0.1781	-0.4159
$h = 6$	0.4271	0.2645	-0.3117
$h = 12$	0.3178	0.0788	-0.4288

Note: See Notes to Table A2. The figures in each cell are the modified Diebold-Mariano (*DM**) test statistics. The null hypothesis asserts that the forecast precision of our Chinese City- and Province-based CPU model is equal to that of the national CPU variant (benchmark) model in Panel A; and that the forecast precision of our Chinese Province-CPU model is equal to that of the Chinese City-CPU variant (benchmark) model. The sign associated with the *DM** statistics determines the direction of outperformance. A positive result indicates that the benchmark CPU-based FQGLS model outperforms the contending variants-based FQGLS models, while a significantly negative result indicates the converse. Non-significance, as is the case here, denotes that there is no distinctive precision between the contending model variants. The forecast evaluation is performed for three forecast horizons (h): 3-, 6-, and 12-month ahead.

Table A4
Out-of-Sample Forecast Evaluation Results using Clark and West Test (Benchmark model: OLS-based model)

Horizons	CPU	GCPU	GCPU-GDP	GCPU-EQ
$h = 3$	2.6632***	2.7108***	2.7613***	2.6782***
$h = 6$	2.6299***	2.6778***	2.7290***	2.6590***
$h = 12$	2.5644***	2.6103***	2.6611***	2.6129***

Note: The figures in each cell are the Clark and West test statistics. The null hypothesis asserts that the forecast precision of the variants of our climate policy uncertainty model (FQGLS) is equal to that of the alternative model (OLS) that ignores the inherent salient features (the benchmark). The sign associated with the Clark-West statistics determines the direction of outperformance. Significantly positive statistics indicate that the US CPU-based predictive FQGLS model outperforms the OLS-based alternative model, which serves as the benchmark. The forecast evaluation is performed for three forecast horizons (h): 3-, 6-, and 12-month ahead.

Appendix B. On the Feasible-Quasi Generalized Least Squares Estimator

Suppose that the original predictive model is defined as follows:

$$inf_t = \mu + \beta unc_{t-1} + \nu_t; \quad \nu_t \sim N(0, \sigma_\nu^2) \tag{B1}$$

where inf_t and unc_{t-1} are as previously defined. Let's assume that the uncertainty measure exhibits some degree of persistence; which implies that any shock to the uncertainty measure tends to persist (Usman et al., 2023):

$$unc_t = \phi + \rho\, unc_{t-1} + \xi_t; \quad \xi_t \sim N\left(0, \sigma_\xi^2\right) \tag{B2}$$

Premised on the assumption of persistence in (B2), it is expected that the two disturbances (ν_t and ξ_t) will be correlated, and therefore, the issue of endogeneity bias becomes relevant. To capture any inherent endogeneity bias as well as persistence implied in Eq. (B2), the equation relating the two disturbances is defined as:

$$\nu_t = \gamma \xi_t + \varepsilon_t \tag{B3}$$

Note that $\nu_t = inf_t - \mu - \beta unc_{t-1}$ from Eq. (B1) and $\xi_t = unc_t - \phi - \rho\, unc_{t-1}$ from Eq. (B2). By way of substitution and rearrangement, I can rewrite Eq. (B3) as:

$$inf_t = \alpha + \beta unc_{t-1} + \gamma(unc_t - \rho\, unc_{t-1}) + \varepsilon_t \tag{B4}$$

where $\alpha = \mu - \phi\gamma$. Eq. (B4) is the same as Eq. (1) in the main text. The additional term in (B4) relative to (B1) captures the inherent endogeneity bias as well persistence effect in the predictive model.

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