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Commodity Market Volatility and Climate Policy Uncertainty: A GARCH-MIDAS Approach

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Abstract: In this study, we employ the GARCH-MIDAS (Generalised Autoregressive Conditional Heteroskedasticity variant of Mixed Data Sampling) model to explore the predictability of commodity return volatility in relation to US climate policy uncertainty (CPU). Our analysis utilizes the 20-day annualized realized commodity volatility returns of nine global commodities (Aluminium, Cocoa, Coffee, Copper, Cotton, Rice, Soybean, Sugar, and Wheat) to construct the GARCH-MIDAS model, with Climate Policy Uncertainty (CPU) serving as the predictive variable. The outcomes of our investigation reveal a consistently positive and statistically significant relationship between CPU and the selected commodities. This implies that CPU effectively serves as a robust predictor of volatility in commodity returns. The implications drawn from our results suggest that climate change policies play a pivotal role in influencing economic activities within the commodity market. This underscores the substantial impact of climate change considerations on investment decisions and further emphasizes the integral role of climate change in shaping economic choices.

Keywords: commodity market; Garch-Midas; climate policy uncertainty

JEL Codes: C53; E44; G15; G17

1.0. Introduction

In general, climate policy uncertainty (CPU) is defined as the risk associated with policies aimed at mitigating climate change and reducing the emission of greenhouse gas in order to ensure a more sustainable future (Gavriilidis, 2021). Climate change is considered as one of the major systematic risks for global society and therefore a key determinant of investment decisions and market dynamics (Fuss et al., 2008; Pastor and Veronesi, 2012; Huang et al., 2018; Salisu et al., 2020; Berkman et al., 2021; Lasisi et al., 2022). Recent studies have shown a high degree of interconnectedness between CPU and commodity markets, for instance, CPU have been found to exert great movements in the energy and agricultural commodity market (Battiston et al., 2017; Fang et al., 2019; Ghadge et al., 2020; Wang et al., 2023). For more than 3 decades, the social and economic implications of global climate change have been the subject of both political and academic debates (see Guyatt, 2011; Clapp et al., 2018; Hunt & Weber, 2019; Bender et al., 2019; Venturini, 2022; among others). Indeed, the literature is replete with studies showing the connection between climate change and energy market (see, Gavriilidis, 2021; Apergis et al., 2023). Numerous studies have been conducted on the cost and benefit of the impacts of potential climate change in order to formulate appropriate policies to mitigate against the risk.

Interestingly, the increasing attention in economic literature to evaluate the connection between climate change and the commodity market is motivated by a number of reasons. First, most commodities, especially agriculturally produced and mined commodities are climate sensitive. More importantly, the effect of climate change phenomenon such El-Nino and La Nina[1] on the commodity market is well documented in the literature. This phenomenon triggers environmentally hazardous events like flooding, hurricane and drought across the globe. Climate extremes as such often affect the global economy negatively and the effect is almost immediate. Second, there is a strong connection between commodity prices and global inflation, numerous studies have attributed global inflation to the rapid rise in global commodity prices. Fasanya and Awodimila (2020), insists that commodity prices are good predictors of inflation and play a major role in the dynamics of every economy which thereby reinforces the need to understand the drivers of commodity price changes.

Consequently, this study addresses the research question of how climate policy in the US affects the global commodity market. Simply put, it seeks to investigate how the debates around climate change and the policy statements around it impacts activities in the commodity market. Specifically, how do firms engaged in primary production such as agriculture and mining receive news of climate change policies given its implication for the future of their business. Similarly, in terms of asset management, investors may seek to hedge their portfolio by de-investing in the market when uncertainties are too high.

For this study, we find the Garch-Midas approach appropriate for numerous reasons. One, the approach gives the modeller freedom to use series in their natural form instead of having to manipulate data to conform to lower existing frequencies and often resulting in information loss (Salisu et al., 2022). This approach works best when both the dependent and independent variable are of different frequencies, especially when the dependent variable is of high frequency and the independent variable is of low frequency. Our study falls into this category. The dependent variable, commodity return volatility, is of high frequency (daily) while the independent variable of interest, Climate Policy Uncertainty, is of monthly (relatively lower) frequency for the commodities under consideration. Additionally, since both the dependent and the independent variables are used in their "natural" frequencies, the loss of information associated with averaging the daily volatility to a lower CPU monthly frequency (Clements and Galvão, 2008; Das et al., 2019) is circumvented. Two, traditional GARCH models are single component volatility models which ordinarily do not account for volatility persistence (i.e. long memory volatility), however the Garch-Midas model decomposes the conditional variance into a short-run component and a long-run component allowing to capture long memory property of volatility and to link volatility directly to exogenous explanatory variables (Ding and Granger, 1996, Engle and Lee, 1999; Engle et al., 2013). This has also allowed the model suitable for complex volatility dynamics involving high persistence, the structural changes and the nonstationarities (Wang and Ghysels, 2015; Conrad and Kleen, 2020). Nevertheless, Garch-Midas model does not capture return information in real time and is unable to adapt to quick changes associated with financial and commodity markets. It also fails to properly account for conditional heteroskedasticity of volatility which is important for modelling the dynamics of the volatility process (Wu, Zhao, & Cheng, 2023).

The use of Garch-Midas model has become rather popular in economic literature, researchers using it to analyse different relationships (see, Girardin and Joyeux, 2013, Fang et al., 2018, Salisu et al., 2020; Wang et al., 2020, Ndako et al., 2021; Salisu and Gupta, 2021; Salisu et al., 2022a; Salsiu et al., 2022b, and Salisu et al., 2023 among others). For instance, Salisu et al., 2022 employed this approach to explain the connection between geopolitical risk (GPR) and stock market volatility in emerging economies. In the same vein, Ndako et al. (2021) investigated the predictive content of GPR for Islamic stock return volatility with special interest in Indonesia and Malaysia, the study found that GPR positively impacts return volatility in these countries. Conclusively, Islamic stock return volatility is found to be vulnerable to GPR in the two countries.

Foreshadowing our results, we find that US climate policy uncertainty (CPU) shows a positive and significant relationship with commodity returns volatility. Further analysis involving out-of-

[1] El Niño and La Niña stand out as the primary climate phenomena significantly impacting the global climate system, manifesting in a recurring pattern every four to five years, each episode spanning approximately 9 to 12 months (Nam, 2021).

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sample predictability reveals that CPU has significant predictive contents for out-of-sample commodity market volatility and outperforms traditional benchmark model, Garch-Midas RV in predicting volatility returns. For the sake of robustness, we employ economic policy uncertainty (EPU) index to evaluate the sensitivity of the result to a variable change. Similarly, we observe that all our commodities show positive and significant relationships with the EPU, implying that not only is the EPU able to predict commodity market volatility but it also drives the market in the same direction as itself as in the case of CPU. Hence, CPU and EPU are good predictors of volatility in the commodity market. The remainder of the paper is organised as follows: Section 2 presents the data, Section 3 outlines the methodology, Section 4 discusses the results, and Section 5 concludes.

2.0. Data and Preliminary Analysis

Our dataset consists of futures prices 9 major international commodities obtained from www.investing.com and climate policy uncertainty index developed by Konstantinos Gavriilidis in "Measuring Climate Policy Uncertainty" and US economic policy uncertainty index (EPU) obtained from www.policy uncertainty.com. The CPU index developed by Gavriilidis (2021) employs a news-based approach that focuses on climate policy-related articles from eight leading US newspapers (Lasisi, Omoke and Salisu, 2022). While relying on CPU as the principal predictor in our study, we include another uncertainty measure, the US economic policy uncertainty (EPU) to evaluate the robustness of our result. In general, we have no fixed start date for our daily data and as such they have varying start dates due to data availability but with a uniform end date. Our monthly data, CPU index, starts from January 2000 and ends in August 2022. The eventual data scope is presented in Table 1 below.

In Table 1, we present the summaries of commodity return series and climate policy uncertainty. The data frequencies are stated, along with the start and end dates, which show the interval of time over which data are available.

Table 1. Summary statistics.

	Mean	Std. dev.	Skewness	Kurtosis	CV	N	Frequency	Start Date	End Date
				Returns					
Aluminium	0.0510	0.0190	2.1563	9.4074	0.3726	2057	Daily	6/16/2014	31/08/2022
Cocoa	0.0806	0.0274	1.3477	7.6439	0.3401	5680	Daily	1/3/2000	8/31/2022
Coffee	0.0898	0.0291	2.1571	13.6618	0.3234	5715	Daily	1/14/2000	8/31/2022
Copper	0.1090	0.5776	13.0580	172.1375	5.2971	3508	Daily	7/4/2008	31/08/2022
Cotton	0.0676	0.0290	2.0782	10.0833	0.4286	3291	Daily	10/14/2009	31/08/2022
Rice	0.0647	0.0328	3.7798	25.6581	0.5079	3908	Daily	1/19/2007	31/08/2022
Soybean	0.0720	0.0850	12.3465	183.4991	1.1810	5801	Daily	1/3/2000	7/20/2022
Sugar	0.0892	0.0335	1.6476	8.8647	0.3750	5733	Daily	1/3/2000	8/31/2022
Wheat	0.0888	0.0388	2.3120	11.7889	0.4373	5906	Daily	1/1/2000	8/31/2022
				Climate policy uncertainty (CPU)					
CPU	115.3236	62.6616	1.5872	5.8541	0.5434	272	Monthly	Jan - 2000	Aug - 2022

Note: Std. dev. is the standard deviation of the computed mean; CV is the coefficient of variation, which is computed as the percentage ratio of the standard deviation and the mean; and N is the number of observation points.

All the commodity returns have positive means, positive skewness and kurtosis value exceeding the conventional threshold. Also, copper and Aluminium seems to be the most and least volatile members of the group given the standard deviation values. Meanwhile, climate policy uncertainty has a positive and large mean value, positively skewed and slightly above normal kurtosis. On the coefficient of variation in Table 1, all the returns appear to be minimally dispersed around the mean with copper recording the highest level of dispersion. The CPU is also minimally dispersed around the mean. Owing to the mixed nature of our dataset, we have opted for the GARCH-MIDAS framework to examine the predictability of our low frequency independent variable (CPU) for the high frequency dependent variable (commodity returns' volatility). Additionally, our chosen

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framework will also enable us to evaluate the forecast performance of the GARCH–MIDAS model, in comparison with the conventional GARCH (1,1) model.

In our preliminary test, we examine our data for Autoregressive Conditional Heteroscedasticity (ARCH) effect, a formal test for volatility. The result as presented in Table 2, shows that all our selected commodities are volatile. This result is confirmed with 1% statistical significance of the ARCH effect at lags 5, 10, and 20. Although, we observe the weakness of ARCH effect on some commodities like copper, cotton, rice and soybean, the implication of this result remains unchanged, which is that the returns of our commodities are volatile and that the use of GARCH variant modelling is appropriate. Similarly, CPU is also characterised by conditional heteroscedasticity as shown in the very significant values of Arch effect and presence of autocorrelation and higher order autocorrelation, as represented by the Q-statistic and the Q^2 –statistic, respectively.

The preliminary result for Table 2 is presented below. Returns' series for the commodities are presented in the first panel titled, 'Returns', while those for CPU are in the second panel titled, 'Climate policy uncertainty (CPU)'. It consists mainly of the Autoregressive Conditional Heteroscedasticity (ARCH) effect test, which is a formal test for volatility; and the Q-statistic and Q2 –statistic testing for the presence of autocorrelation and higher order autocorrelation, respectively; at lags 5, 10, and 20.

Table 2. Preliminary results.

	ARCH (5)	ARCH (10)	ARCH (20)	Q (5)	Q (10)	Q (20)	Q^2 (5)	Q^2 (10)	Q^2 (20)
					Returns				
Aluminium	12.2241***	12.3991***	20.7671***	94.17***	143.51***	621.23***	66.882***	147.4***	413.54***
Cocoa	88.7917***	44.3635***	56.8757***	79.057***	83.029***	1285.7***	387.32***	387.8***	977.01***
Coffee	47.6306***	24.6230***	56.5551***	155.45***	176.48***	1397.4***	284.91***	288.79***	1027.4***
Copper	0.0149	0.0146	56.9550***	5.7066***	12.823***	853.85***	0.0754***	0.1497***	873.16***
Cotton	0.0232	0.0148	33.33281***	24.994***	37.001***	770***	0.1164	0.1489	559.32***
Rice	0.0279	0.0197	28.61482***	12.503**	20.466**	822.01***	0.141	0.2009	506.63***
Soybean	0.0153	0.0150	95.4675***	12.879**	19.509**	1376.5***	0.0773	0.153	1449.9***
Sugar	41.34687***	20.64616***	43.41466***	177.59***	182.25***	1363.6***	192.27***	192.39***	775.98***
Wheat	54.18134***	27.1678***	69.9159***	475.86***	498.14***	1797.3***	246.9***	247.58***	1164.6***
					Climate policy uncertainty (CPU)				
CPU	10.50846***	8.6001***	3.2747***	27.256***	38.581***	62.832***	65.387***	110.88***	144.69***

Note: *** and ** & * imply the rejection of the null hypothesis at 1% 5% & 10% levels of significance, respectively. Commodity returns is computed as 100*log (commodity price/commodity price (-1)). Also, the Q^2 (k) statistics are obtained from the Ljung-Box test for serial correlation respectively using the squared residuals of the test regressions where k=5, 10, 20. The ARCH (k) reports the F-statistics of the ARCH-LM test used to test for conditional heteroscedasticity. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM (F-distributed) test is that there is no conditional heteroscedasticity.

3.0 . Methodology

In this study, we employed the GARCH-MIDAS framework to examine the predictability of Climate Policy Uncertainty (CPU) for commodity market volatility. As mentioned earlier, our attraction to this methodology is based on its ability to allow for the use of mixed data frequencies and therefore circumventing the need to limit the variables of interest to the same (low) frequency. Traditionally, whenever a variable is available at a high frequency (commodity returns in this case) and the other variable at a low frequency (CPU in this case), the analysis is restricted to the latter frequency which may lead to information loss and biased outcomes. To avoid this, our methodology accommodates the high and low frequencies observed for the two series in order to ensure that greater variability and more robust information are captured in the estimation process with greater

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potential for improved forecast outcomes (as further demonstrated in the results section which further offers some reasonable basis for considering mixed frequencies for predictability analysis).[2]

Given a 20-day annualised realised commodity volatility returns series RV_t at period t, we construct a GARCH-MIDAS-X model where Climate Policy Uncertainty (CPU), serves as the predictor. The model consists basically of two components, the mean equation and the conditional variance equation. The conditional variance equation is further divided into short run and long run components. The purpose of this is to accommodate the predictor series.

$$RV_t = \mu + \sqrt{\tau_t \times h_{i,t}} \times \varepsilon_{i,t}, \quad \varepsilon_{i,t} \mid \Phi_{i-1,t} \sim N(0,1) \quad \forall \ \text{i} = 1,\ldots, \text{N}_t \tag{1}$$

$$\text{h}_{i,t} = (1-\alpha-\beta) + \alpha \frac{(RV_{i-1,t}-\mu)^2}{\tau_i} + \beta h_{i-1,t} \tag{2}$$

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{k} \phi_k(w_1, w_2) X_{i-k}^{rw} \tag{3}$$

Equation (1) above defines the mean equation, while equations (2) and (3) represent the conditional variance components specified for the short and long run components respectively. The parameters in the system are defined as follows; μ is the unconditional mean of the return series as specified in equation (1); $\text{h}_{i,t}$ is the short run component of a high frequency, and as specified in equation (2), it follows the GARCH (1,1) process, where α and β are the ARCH and GARCH terms, respectively, conditioned to be positive and/or at least zero (α > 0 and β ≥ 0) and sum up to less than unity $(\alpha+\beta<1)$; τ_t describes the long run component that incorporates the exogenous macroeconomic series (or realized volatility where there is no macroeconomic series), and it involves repeating the monthly value throughout the days in that month (see Salisu et al., 2022). The superscript "(rw)" in equation (3) denotes the implementation of a rolling window framework (which allows the secular long-run component to vary daily), while m represents the long-run component intercept. The focus of our analysis is the MIDAS slope coefficient (θ) that indicates the predictability of the incorporated exogenous predictor X_{i-k} where $\phi_k(w_1, w_2)$ ε 0, k = 1,...k is the weighting scheme that must sum to one for the parameters of the model to be identified; and K is chosen based on the log-likelihood statistic for each pair of the predicted and the predictor series in order to filter the secular component of the MIDAS weights.

In our out-of-sample forecast evaluation, we compare the forecasts of our proposed GARCH-MIDAS predictive model (involving CPU), i.e. GARCH-MIDAS-X with that of the conventional GARCH-MIDAS specifications that include realized volatility (GARCH-MIDAS-RV). The out-of-sample forecast performance is evaluated in a rolling window setting for three forecast horizons that correspond to short- and long-run predictability (h = 30, 60, 180). Given that the contending models are not nested, we employ the modified version of the Diebold and Mariano (1995) (DM) test as per Harvey, Leybourne, and Newbold (1997) test which calculates the p-value and addresses the issue with the assumption of zero covariance at 'unobserved' lags to formally ascertain whether the forecast errors associated with the contending models differ significantly. The test statistic is usually formulated as:

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

[2] The technical details and computational advantages of using the MIDAS regressions are well documented in Engle et al. (2013).

where $\overline{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the mean of the loss differential $d_t \equiv l(\varepsilon_{xt}) - l(\varepsilon_{rvt})$; $l(\varepsilon_{xt})$ and $l(\varepsilon_{rvt})$ are loss functions of the forecast errors (ε_{xt} and ε_{rvt}, respectively) that are associated with the GARCH-MIDAS-X and GARCH-MIDAS-RV, respectively; and $\mathrm{v(d}_t)$ is the unconditional variance of the loss differential d_t. The modified DM test statistic as per Harvey, Leybourne, and Newbold (1997) is given as:

$$DM^* = \left(\sqrt{\frac{T+1-2h+T^{-1}h(h-1)}{T}}\right)DM \tag{5}$$

where DM* denotes the modified DM statistic and h represents the forecast horizon. We test the null hypothesis that the accuracy of the two series of forecasts is the same, that is, $\mathrm{H}_0 : E(d_t) = 0$, against the alternative $(\mathrm{H}_1 : E(d_t) \neq 0)$ that the proposed model (that is, the GARCH-MIDAS-RV model). Based on the modified DM test by Harvey, Leybourne, and Newbold (1997), a statistically significant negative statistic implies the adoption of the GARCH-MIDAS-X model while the benchmark (GARCH-MIDAS-RV) model is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical.

4.0. Results and Discussion

4.1. Commodity Market Volatility and Climate Policy Uncertainty (CPU)

In this section, we present the results of predictability of climate policy uncertainty (CPU) and commodity returns' volatility and the forecast performance of GARCH-MIDAS-X model vis-à-vis the benchmark model which is the conventional GARCH-MIDAS model with realised volatility (GARCH-MIDAS-RV). Overall, we make 3 contributions to the literature. One, we provide evidence for the predictive content of CPU for commodity returns' volatility. Two, we examine the out-of-sample predictive power of CPU in returns' volatility of commodities. Three, we employ a novel methodology, GARCH-MIDAS, that accommodates mixed data frequency thereby circumventing information loss or any associated bias. Our parameter estimates are as follows; the unconditional mean stock returns (μ), the ARCH term (α), the GARCH term (β), the slope coefficient (θ), the adjusted beta polynomial weight (ω) and the long run constant term (m). We consider the 30-day out-of-sample forecast (h=30) as the short run forecast, 60-day ahead forecast (h=60) as the medium-term forecast and 180-day ahead (h=180) forecast as the long term out-of-sample forecast.

Table 3 shows predictability results for 9 commodities. This result illustrates the GARCH-MIDAS-X model with CPU. These results show that across the commodities, the impact of CPU shock is transient given that the sum of ARCH and GARCH coefficients is less than one. Although it may persist for a longer period of time given the closeness of the values to one, it will eventually return to its mean. In essence, we find evidence for high but mean reverting volatility persistence. estimates obtained for the adjusted beta weight for all commodities are greater than one and statistically significant indicating that the weighting scheme assigns higher weight to immediate past observations than those distinctly far apart. The result for slope coefficient (β) which examines the impact of CPU on commodity returns' volatility shows that all the selected commodities have a positive and significant relationship with CPU. The null hypothesis here is that the slope coefficient is not significantly different from zero and hence no predictability. From our result, we infer that CPU is a good predictor of commodity return' volatility. The positive relationship found in all commodities implies that higher CPU values in the current month have the tendency to raise commodity market volatility in the following month. This result implies climate change policies are a great determinant of economic activities in the commodity market which further underlines the

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importance of climate change in investment choices. Hence, investors can use insight from our result to make informed decisions. That is, as the uncertainty around the US climate policy increases, the volatility in the commodity market also increases and this might not be the best time to invest, as investors view the future profits and dividend streams to be less than before the crisis caused by geopolitical risk (see also, Homan, 2006). Hoque and Zaidi (2020) and Smales (2021) obtained similar results although with different market, methodology and data scope. Our findings also conform with that of Salisu et al. (2022) using geopolitical risk uncertainty to predict the stock market volatility in 11 countries with the Garch-Midas model.

Table 3. Predictability of Commodity return' volatility with CPU.

	In-sample predictability					
In-Sample	**μ**	**α**	**β**	**θ**	**w**	**m**
Aluminium	0.0005***	0.0503	0.9006***	0.0225***	5***	-0.0370***
	[6.37e-05]	[0.1169]	[0.1486]	[3.71e-06]	[0.7125]	[6.44e-06]
Cocoa	0.0013***	0.0946***	0.9005***	0.0568***	4.5007***	-0.0353***
	[0.0002]	[0.0226]	[0.0237]	[0.0028]	[0.0812]	[0.0017]
Coffee	0.0009	0.0501	0.9003***	0.0575***	5***	-0.0356***
	[0.0008]	[0.0830]	[0.1575]	[0.0131]	[0.1707]	[0.0081]
Copper	0.0011***	0.0503***	0.9006***	0.0297***	5***	-0.0409***
	[9.68e-05]	[0.0042]	[0.0065]	[0.0003]	[0.0636]	[0.0004]
Cotton	0.0006	0.0503	0.9006**	0.0287***	5	-0.0404***
	[0.0008]	[0.1554]	[0.4674]	[6.32e-05]	[5.0332]	[9.64e-05]
Rice	0.0006***	0.0503	0.9006***	0.0309***	5***	-0.0414***
	[0.0002]	[0.1232]	[0.2665]	[0.0002]	[0.3272]	[0.0002]
Soybean	0.0007***	0.0503***	0.9006***	0.0364**	5***	-0.0433**
	[0.0018]	[0.0855]	[0.1977]	[0.0085]	[1.3165]	[0.0101]
Sugar	0.0008***	0.0503***	0.9006***	0.0380**	5***	-0.0437**
	[0.0011]	[0.0991]	[0.1965]	[0.0003]	[0.0092]	[0.0003]
Wheat	0.0008***	0.0503***	0.9006***	0.0380**	5***	-0.0437**
	[0.0010]	[0.1505]	[0.3717]	[0.0007]	[1.9517]	[0.0007]

Note: In Panel A, α represents ARCH term, β represents GARCH term, ρ denotes slope coefficient. The figures in square brackets are the standard errors of the parameter estimates.

Furthermore, we examine the out-of-sample forecast performance of our proposed CPU-based GARCH-MIDAS-X model by comparing the model with the benchmark (GARCH-MIDAS) model that excludes the CPU measure using the modified Diebold and Mariano test. The result is presented in Table 4. This test is executed as per Harvey, Leybourne, and Newbold (1997) to circumvent the assumption of zero covariance at 'unobserved' lags. Thus, we report both the test statistics and the corresponding p-values. The decision criteria for our forecast performance is that if the statistic is negative and significant, the GARCH-MIDAS-X is favoured while the GARCH-MIDAS is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical. We conduct this evaluation over three forecast horizons (h = 30 days, 60 days and 180 days).

Table 4. Out-of-sample forecast using the Diebold and Mariano test [GARCH-MIDAS vs. GARCH-MIDAS-X].

	h=30	**h=60**	**h=180**
Aluminium	-3.2323***	-2.2949**	-1.3587
Cocoa	-5.3955***	-3.8027***	-2.1944**
Coffee	-6.5554***	-4.6424***	-2.7787***

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Copper	-6.1255***	-4.3010***	-2.4433***
Cotton	-5.5502***	-3.9083***	-2.2318**
Rice	-7.2238***	-5.3363***	-3.6483***
Soybean	-0.6370	-0.4713	-0.3183
Sugar	-5.8622***	-4.1612***	-2.4579***
Wheat	0.2311	0.16717	0.1110

Note: In Table 4, we report the modified DM test statistics as per Harvey, Leybourne, and Newbold (1997). If the statistic is negative and significant, the GARCH-MIDAS-X is favoured while the GARCH-MIDAS-RV is chosen if the test statistic is positive and significant. However, if the test statistic is insignificant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

From our result in Table 4, we find that CPU is a better out-of-sample predictor of market volatility in at least 7 of the 9 commodities under consideration. Another quite notable insight from this result is that as the forecast horizon increases, predictability drops for some of the commodities while others remain strong. This result is consistent across the alternative forecast horizons ranging from short term, medium term to long term. This result further amplifies earlier findings that market volatility responds to CPU. Similar findings showing the impact of climate policy on the market is well documented in the literature (see Lasisi et al. (2022), Baker et al. (2020), Phan and Narayan (2020), Salisu and Sikiru (2020), and Sharma (2020), among others.

4.2. *Additional Result with US Economic Policy Uncertainty (EPU) Index*

For the sake of robustness, we conduct a similar test using economic policy uncertainty (EPU) index developed by Baker et al., (2016). The EPU is an index of policy-related uncertainty developed based on newspaper coverage frequency. The index captures concerns about economic policies like "who" will make economic policy decisions, "what" economic policy actions will be undertaken, "when" will this be taken and the consequences of these economic policy actions. The index captures both near and long-term policy concerns as reflected on the pages of popular newspapers. Our intuition for this is to verify the consistency of our results in the face of a different variable. We seek to know whether our results are index sensitive or not. Consequently, we conduct both in-sample and out-of-sample predictability analysis using the EPU. Our result shows consistency with the earlier observed pattern for CPU. We observe that all our commodities show positive and significant relationships with the EPU, implying that not only is the EPU able to predict commodity market volatility but it also drives the market in the same direction as itself as in the case of CPU. Hence, CPU and EPU are good predictors of volatility in the commodity market. Further implication of the result is that as activities that drive economic policy-concerns in the US such as general elections, foreign policy, military actions, fiscal and monetary policies among others increase, there is likelihood of a surge in volatility in the commodity market through panic trading.

Table 5. Predictability of Commodity return' volatility with US EPU.

Panel A: In-sample predictability						
In-Sample	**μ**	**α**	**β**	**θ**	**w**	**m**
Aluminium	0.0005***	0.0503***	0.9007***	0.0144***	5***	-0.0305***
	[1.93e-05]	[0.0201]	[0.0420]	[5.1196e-07]	[0.1887]	[1.08e-06]
Cocoa	0.0008	0.0501	0.9003***	0.0528***	5***	-0.0345***
	[0.0005]	[0.0766]	[0.1522]	[5.87e-05]	[0.1529]	[5.51e-05]

Coffee	0.0009***	0.0501	0.9003***	0.0527***	5***	-0.0344***
	[0.0002]	[0.0761]	[0.1511]	[0.0022]	[0.1578]	[0.0014]
Copper	0.0011***	0.0503***	0.9007***	0.0196***	5***	-0.0350***
	[9.29e-05]	[0.0042]	[0.0064]	[1.45e-05]	[0.0932]	[2.60e-05]
Cotton	0.0006***	0.0503	0.9007***	0.1867***	5***	-0.0343***
	[0.0001]	[0.0899]	[0.1867]	[0.0187]	[0.0903]	[2.26e-05]
Rice	0.0006	0.0503***	0.9006***	0.0215**	5***	-0.0364**
	[0.0003]	[0.1159]	[0.2268]	[1.52e-05]	[0.0292]	[2.54e-05]
Soybean	0.0007	0.0503***	0.9006***	0.0286**	5***	-0.0403**
	[0.0020]	[0.1195]	[0.2682]	[3.83e-05]	[1.2504]	[0.0001]
Sugar	0.0008	0.0503	0.9006***	0.0283***	5***	-0.0402***
	[0.0012]	[0.0965]	[0.2399]	[2.11e-05]	[1.7427]	[0.0001]
Wheat	0.0008	0.0503***	0.9006***	0.0283**	5***	-0.0402**
	[0.0011]	[0.1212]	[0.2397]	[0.0005]	[0.0091]	[0.0007]

Note: In Panel A, α represents ARCH term, β represents GARCH term, ρ denotes slope coefficient. The figures in square brackets are the standard errors of the parameter estimates.

The result for the out-of-sample forecast performance based on the modified Diebold and Mariano test is presented in Table 6. The result shows that the out-of-sample forecast performance of economic policy uncertainty (EPU) is not different from that of the climate policy uncertainty (CPU). The result shows that the GARCH-MIDAS model with EPU outperforms the conventional GARCH-MIDAS with the realized volatility in predicting commodity market volatility. This result gives further credence to the need to account for systematic risks associated with commodity market volatility in making investment decisions. This result is consistent across the alternative forecast horizons ranging from short term, medium term to long term.

Table 6. Out-of-sample forecast using the Diebold and Mariano test [GARCH-MIDAS vs. GARCH-MIDAS-X].

	h=30	h=60	h=180
Aluminium	-3.2309***	-2.2939**	-1.3582
Cocoa	-5.3909***	-3.7997***	-2.1931**
Coffee	-0.8286	-0.5935	-0.3819
Copper	-6.4837***	-4.6242***	-2.7881***
Cotton	-4.0136***	-2.8357***	-1.6426
Rice	-3.1006***	-2.2559**	-1.4635
Soybean	-2.9278***	-2.0932**	-1.2733
Sugar	-3.9514***	-2.8028***	-1.6511*
Wheat	-2.2602**	-1.6394	-1.1096

Note: In Table 4, we report the modified DM test statistics as per Harvey, Leybourne, and Newbold (1997). If the statistic is negative and significant, the GARCH-MIDAS-X is favoured while the GARCH-MIDAS-RV is chosen if the test statistic is positive and significant. However, if the test statistic is insignificant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical. ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

5.0 . Conclusion

In this study, we examine the predictability of climate policy uncertainty for commodity return volatility in 9 global commodities using the GARCH-MIDAS approach. We contribute to the extant literature in three ways. One, we provide evidence for the predictive content of CPU for commodity returns' volatility. Two, we examine the out-of-sample predictive power of CPU in returns' volatility of commodities. Three, we employ a novel methodology, GARCH-MIDAS, that accommodates mixed data frequency thereby circumventing information loss or any associated bias. By utilising data that cover major global commodities, we offer empirical evidence on commodity returns volatility's predictability by climate policy uncertainty (CPU). We further test the sensitivity of our result to variable change by using economic policy uncertainty (EPU) to predict commodity returns volatility.

Our findings show that all the selected commodities have a positive and significant relationship with CPU. From our result, we infer that CPU is a good predictor of commodity return' volatility for both in- and out-of-sample predictability. The implication of the positive relationship found in all commodities is that higher CPU values in the current month have the tendency to raise commodity market volatility in the following month. Similarly, we observe that all our commodities show positive and significant relationships with the EPU, implying that not only is the EPU able to predict commodity market volatility but it also drives the market in the same direction as itself as in the case of CPU. Hence, CPU and EPU are good predictors of volatility in the commodity market.

On policy, this result implies climate change policies are a great determinant of economic activities in the commodity market which further underlines the importance of climate change in investment choices. Hence, investors can use insight from our result to make informed decisions. That is, as the uncertainty around the US climate policy increases, the volatility in the commodity market also increases and this might not be the best time to invest, as investors view the future profits and dividend streams to be less than before the crisis caused by geopolitical risk (see also, Homan, 2006). Further implication of the result is that as activities that drive economic policy-concerns in the US such as general elections, foreign policy, military actions, fiscal and monetary policies among others increase, there is likelihood of a surge in volatility in the commodity market through panic trading.

For future research, it would be interesting to extend this analysis to include other commodities using country-specific data of climate policy uncertainty and economic policy uncertainty.

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