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Climate Policy Uncertainty and Stock Market Volatility

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We examine the relationship between climate policy uncertainty (*CPU*) and stock market volatility using the GARCH-MIDAS framework to accommodate the variables in their available frequencies thereby circumventing information loss associated with data aggregation or splicing. We find that stock market volatility significantly responds to *CPU* and we further document improved forecast and economic gains of observing *CPU* relative to ignoring it.

I. Introduction

In this short communication, we examine the implication of climate policy uncertainty (*CPU*) for stock market volatility. We tease out information on this nexus using new datasets on *CPU* developed by Gavrilidis (2021). The novelty of this contribution is marked by a number of reasons. First, we acknowledge that although the literature is replete with studies establishing the relationship between different uncertainty measures and the stock market,¹ our study employs a new dataset on climate policy uncertainty, which provides new information to evaluate this relationship. Second, we manage this information by using an information-efficient analytical technique, GARCH-MIDAS, to examine the nexus. The GARCH-MIDAS preserves information by accommodating the available “natural frequencies” of the series. Third, we enhance the information provided by our predictor variable (*CPU*) by blending it with another important uncertainty measure – uncertainty due to pandemics and epidemics (*UPE*) – to get a better forecast. Fourth, we extend the predictive information provided in our results to include out-of-sample forecast performance of each of the proposed models, which gives investors a sense of the expected portfolio returns.

Our interest in this nexus is underlined by several reasons. First is the recent surge in policies addressing the adversities of climate change and the increased yearning for a reduction of greenhouse emission and adoption of alternative cleaner energy sources. Second, there is the presence of an existential threat that the governments of advanced economies, especially the US and UK, will place a federal price on carbon emission, which will consequently impact cost of production and, by extension, the global economy.

In essence, the high tendency of a future climate policy imposes a risk on investment decisions taking note of the consideration of the usefulness of the fossil fuel energy in the production of goods and services. Third is the recent attention in the literature (e.g., Apergis et al., 2021; Bretschger & Soretz, 2021; Fried et al., 2021; Lemoine, 2017; Lemoine & Traeger, 2014; van der Ploeg & Rezai, 2020) focusing on climate policy uncertainty risk and its impact on national and global macroeconomic variables. The present paper contributes to this evolving strand of literature by testing the hypothesis that an increase in climate policy uncertainty may result in an increased stock return volatility such that higher risks emerging from climate policy pronouncements will tend to create fluctuations of future investments in risky assets. Since the pronouncements may discourage investment in certain assets or perhaps increase the cost of production in others, investors may engage in panic selling of stocks, which may further heighten the uncertainty and increase market volatility.

Our proposed predictability model shows strong evidence for the predictability of stock market volatility using *CPU* – and greater predictability when *UPE* is blended with *CPU*. Our results confirm our suspicion about the combined effect of *CPU* and *UPE* on stock market volatility. We further extend our results to include possible economic gains that can be derived from observing *CPU* when forecasting stock market volatility. All these results further advance the empirical literature on the significant role of climate risk in the valuation of conventional stocks.

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¹ Examples include Baker et al. (2020), Phan & Narayan (2020), Salisu & Sikiru (2020), and Sharma (2020).

II. Data and Methodology

A. Data

The datasets employed for this study cover three major variables, namely the daily stock market indices for the US and UK based on the Standard and Poor's (S&P) 500 and the FTSE 100 respectively, with both obtained from investing.com and a measure of the Climate Policy Uncertainty index which is obtained from https://www.policyuncertainty.com/climate_uncertainty.html. The CPU index developed by Gavrilidis (2021) employs a news-based approach that focuses on climate policy-related articles from eight leading US newspapers. While relying on CPU index as the main predictor, we adopt principal component analysis (PCA) to include another measure of uncertainty associated with pandemics and epidemics (UPE) developed by Baker et al. (2020) and obtained from the FRED database of the Federal Reserve Bank of St. Louis. The PCA-based index serves as a form of additional analysis in order to test the interaction effect of both CPU and UPE on stock market volatility. Our daily data covers the period of January 03, 2000 to December 31, 2021 for US stocks and January 04, 2001 to December 12, 2021 for UK stocks based on data availability and the necessity of having the same start and end dates for the series employed in the study while monthly data is between January 2000 and December 2021.

B. Methodology

For the empirical analysis, we use a daily stock return series compiled as the logarithmic stock return where $r_{i,t} = \ln(p_{i,t}) - \ln(p_{i-1,t})$, $p_{i,t}$ represents the price for day i in month t , with $t = 1, 2, 3, \dots, T$ and $i = 1, 2, 3, \dots, N_t$ denoting monthly and daily frequencies, respectively, and N_t is the number of days in a given month t . Given this, it has become necessary to construct an empirical model that allows for the combination of data in different frequencies; hence, we define our GARCH-MIDAS-X model as:

$$r_{i,t} = \varpi + \sqrt{\ell_t} \times s_{i,j}, \varepsilon_{i,j} \mid \phi_{i-1,t} \sim N(0, 1), \quad (1)$$

$$\forall i = 1, 2, 3, \dots, N_t$$

$$s_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \varpi)^2}{\ell_t} + \beta s_{i-1,t} \quad (2)$$

$$\ell_t^{(rw)} = \lambda^{(rw)} + \rho^{(rw)} \sum_{k=1}^k \partial_k(w_1, w_2) \Upsilon_{i-k}^{(rw)} \quad (3)$$

where equation (1) depicts the mean equation, and equations (2) and (3) express the conditional variance components specified for short- and long-run components respectively. In terms of the parameter definitions, where α and β are the ARCH and GARCH terms respectively, conditioned to be positive and/or at least zero and the summation yields less than unity; and $(\alpha > 0$ and $\beta \geq 0)$ and the summation yields less than unity $(\alpha + \beta < 1)$ captures the long-run component that incorporates the exogenous macroeconomic series (or realized volatility when there is no macroeconomic series) and involves repeating the monthly

value throughout the days in that month. The (rw) as in equation (3) denotes the implementation of a rolling-window framework (which allows the secular long-run component to vary daily), while λ represents the long-run component intercept. The focus of our analysis is the MIDAS slope coefficient (ρ), which indicates the predictability of the incorporated exogenous predictor Υ_{i-k} while $\partial_k(w_1, w_2) \geq 0$ is the weighting scheme that must sum up to one of the parameters of the model to be identified and $k = 1, 2, 3, \dots, K$, where K is chosen based on the log-likelihood statistic for each predicted-predictor series pair, to filter the secular component of the MIDAS weights.

In the final set-up, we compare the out-of-sample forecast performance of the CPU-based GARCH-MIDAS (GARCH-MIDAS-CPU) model with that of the benchmark model involving realized volatility (GARCH-MIDAS-RV). Consequently, we consider multiple forecast horizons ($h = 30, 60, 120$) all in days, and employ the modified version of the Diebold–Mariano (1995) test, as per Harvey et al. (1997) to formally ascertain significant differences in the forecast errors associated with the contending models.

III. MAIN FINDINGS

In this section, we begin the discussion of results with the predictability of stock market volatility for both the US and UK. Our findings, as contained in Table 1 Panel A, show that CPU is a good predictor of stock market volatility in both countries considered. The significantly positive slope coefficient (ρ) suggests that higher values of CPU have the tendency to heighten stock market volatility in both countries. The higher magnitude of the slope coefficient for the US relative to that of the UK is not unexpected given the fact that the newspapers used in the construction of the CPU are US-based. Therefore, investors in the country's stock market are likely to respond more to the uncertainty associated with climate change than investors in other economies. Additionally, we also find that stock market volatility in these two countries is highly persistent, given their high β values and mean reverting ($\alpha + \beta < 1$) implying that shocks from CPU have no permanent effect on any of the markets albeit with a longer time horizon for the shock effect to fizzle out since $\alpha + \beta$ is close to unity. Other previous studies have also established volatility persistence in the stock market, given that economic shocks tend to aggravate stock market volatility in some countries (see, Salisu & Adediran, 2020; Salisu & Gupta, 2021). For completeness, we also conduct an out-of-sample forecast analysis by evaluating the relative forecast performance of two competing GARCH-MIDAS models, that is, the GARCH-MIDAS model with CPU and the other with realized volatility (which excludes the CPU predictor). Based on the modified Diebold–Mariano (1995) test, we find that our proposed model that accounts for CPU data is consistently favored for all the forecast horizons.

Going further to validate our results, we conduct similar out-of-sample analyses using a different index, namely,

CPU_UPE, derived by a hybridization of *CPU* and another index, the uncertainty due to pandemics and epidemics (*UPE*) using principal component approach.² Our out-of-sample results show that the inclusion of *CPU_UPE* improves our model and provides for a better forecast. We suspect that this improved performance is largely due to the impact of the COVID-19 pandemic on stock returns and therefore any model accounting for a combined effect of these two uncertainty indices is likely to possess more explanatory power than one excluding them. Furthermore, we note that our model will be most effective for a short-term forecast rather than long-term, as the result is more significant when our forecast horizon is short.

We perform additional analysis to establish the economic significance of the forecast outcomes. Following the approach of Campbell and Thompson (2008), we calculate the unconditional average excess stock returns by deducting the returns of a 3-month U.S. Treasury bill (riskless asset) from simple stock returns. The resulting series is then introduced into our model and used against our predictor series (*CPU* and *CPU_UPE*). The intuition here is to enable us to compare the obtained R^2 with the squared Sharpe ratio S^2 in a mean-variance relationship, which serves as a better judge of the magnitude of R^2 in our out-of-sample forecast evaluation. We conduct this evaluation over three forecast horizons ($h = 30\text{days}, 60\text{ days and }120\text{days}$). The model with the highest mean-variance ratio represents the model with the largest portfolio return for an investor. Our result is quite informative as it shows somewhat improvements in the portfolio returns across the different forecast horizons when an investor observes *CPU* singly or with any other predictor (*UPE* in this case). It also shows the importance of blending an index like *UPE* with *CPU*. Across all the horizon considered for both countries, the model that accounts for *CPU_UPE* consistently offers the highest economic gains. This finding further amplifies our Diebold and Mariano out-of-sample prediction that *CPU_UPE* is an important factor when predicting future stock returns. In more specific terms, investors seem to care more about uncertainty associated with both climate change and pandemics. Recent evidence on the stock market reaction to pandemics including the COVID-19 pandemic is well documented in the literature (see Baker et al. (2020), Phan and Narayan (2020), Salisu and Sikiru (2020), and Sharma (2020), among others) and our conclusion further advances the literature on the need to include climate risk to improve stock return predictability.

IV. CONCLUSION

In this study, we examine the role of climate policy uncertainty (*CPU*) in the predictability of stock market volatility. We utilize the new *CPU* dataset by Gavrilidis (2021) and employ the GARCH-MIDAS framework which accom-

modates mixed data frequencies of the relevant series thereby circumventing possible information loss from data aggregation. We find that the information content of *CPU* can be utilised to improve both the in-sample and out-of-sample forecasts of stock market volatility. In addition, we demonstrate how profit-maximizing investors that observe the uncertainty associated with climate change can derive increased portfolio returns relative to those who do not observe it. Consequently, we believe that our findings would have far-reaching implications for future investments especially in large open economies whose economic activities significantly impact climate change. Finally, studies that extend the predictability of *CPU* to include important commodities like oil and gold would further enrich the extant literature.

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² The technical details as well as the results of the PCA are suppressed for want of space but can be made available upon request from the authors.

Table 1. In-Sample Predictability and Out-of-Sample Forecasts

Panel A: In-sample predictability						
In-Sample	ω	α	β	ρ	ω	λ
US S&P 500	0.0002*** [0.0000]	0.1179*** [0.0056]	0.8820*** [0.0056]	0.1086** [0.0484]	9.1202*** [1.6853]	-0.0259** [0.0117]
UK FTSE 100	-6.63e-05 [4.69e-05]	0.2517*** [0.0117]	0.7481*** [0.0117]	0.0989** [0.0445]	4.9568*** [0.3318]	0.0063** [0.0030]
Panel B: Out-of-sample forecast using the Diebold and Mariano test [GARCH-MIDAS vs. GARCH-MIDAS-X]						
		$h = 30$	$h = 60$	$h = 180$		
US S&P 500	CPU	-2.2069**	-1.9994**	-1.6562*		
	CPU_UPE	-2.6059***	-2.3822**	-1.9324*		
UK FTSE 100	CPU	-2.8726***	-2.3311***	-1.8133*		
	CPU_UPE	-6.5108***	-4.8455***	-3.5393***		

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. In Panel B, 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.

Table 2. Excess return predictability

Daily	Forecast horizon (h)	RV				CPU				CPU_UPE			
		Sharp Ratio (S)	S^2	R^2	Mean-Variance ratio $\left(\frac{R^2}{S^2}\right)\%$	Sharp Ratio (S)	S^2	R^2	Mean-Variance ratio $\left(\frac{R^2}{S^2}\right)\%$	Sharp Ratio (S)	S^2	R^2	Mean-Variance ratio $\left(\frac{R^2}{S^2}\right)\%$
US S&P 500	30												
		0.5495	0.3020	0.2539	84.0867	0.5521	0.3048	0.2569	84.2808	0.5313	0.2823	0.2511	88.9543
	60	0.5309	0.2819	0.2465	87.4564	0.5331	0.2842	0.2495	87.7916	0.5116	0.2617	0.2435	93.0332
	120	0.4907	0.2408	0.2293	95.2296	0.4928	0.2429	0.2330	95.9433	0.4718	0.2226	0.2269	101.9339
UK FTSE 100	30	1.1200	1.2544	0.3340	26.6263	1.1200	1.2544	0.3410	27.1843	1.1100	1.2321	0.3420	27.7575
	60	1.0600	1.1236	0.3180	28.3019	1.0500	1.1025	0.3270	29.6599	1.0400	1.0816	0.3270	30.2330
	120	1.1700	1.3689	0.3410	24.9105	1.1600	1.3456	0.3510	26.0850	1.1600	1.3456	0.3510	26.0850

Note: This table presents out-of-sample stock returns performance under different conditions of uncertainty for US and UK. RV denotes realized volatility, CPU is climate policy uncertainty and CPU_UPE represents a blend of CPU and uncertainty due to pandemics and epidemics (UPE) using the principal component analysis. Sharpe Ratio (s) = $\frac{\mu}{\sigma_e + \sigma_e^2}$ where μ is the fitted average or mean, σ_e^2 is the variance of the predictor series (i.e., RV, CPU and CPU_UPE), σ_e^2 is the variance of the residual. Out of sample R2 statistics is computed as $\frac{\sigma_e^2}{\sigma_e^2 + \sigma_e^2}$.



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