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Project Title:

Climate risk and Chinese stock volatility forecasting: Evidence from ESG Index

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Abstract

This study utilizes a generalized autoregressive conditional heteroscedasticity mixed data sampling model (GARCH-MIDAS) to investigate the predictive power of Chinese climate uncertainty (CU), Chinese climate policy uncertainty (CEU), Chinese economic policy uncertainty (CEPU), and US climate policy uncertainty (UCPU) in forecasting volatility for both the CSI 300 ESG and SSEC indices. The empirical results indicate that both CU and CEU can serve as effective predictors of CSI 300 ESG Index volatility, outperforming the predictive abilities of CEU and UCPU. As an extension to our study, we then employed the use of machine learning techniques comprising ensemble methods such as Random Forest and Extra Trees Regressors to corroborate our findings.

1. Introduction

In recent years, a growing number of researchers, central banks, and investors have been increasingly wary of the risks associated with climate change (Campiglio et al., 2018; Engle et al., 2020; Chenet et al., 2021; Stroebel and Wurgler, 2021; Ma et al., 2022). Empirical research has shown that climate risk can have an impact on various aspects, including financial system stability (Campiglio et al., 2018), energy price (Liang et al., 2022), stock market (Khalfaoui et al., 2022) and exchange market volatility (Bonato et al., 2022), as well as decision-making by firms and investors (Chen et al., 2022), amongst other factors. The purpose of this study is to offer further insight into the role of Chinese climate uncertainty (CU) and Chinese climate policy uncertainty (CEU) in predicting market volatility as suggested by Lee and Cho (2022).

The extant literature on climate risk assessment can be broadly categorized into three main categories. The first category leverages search volumes from platforms like Google or Baidu to gauge public sentiment and investor attention towards climate change (El Ouadghiri et al., 2021; Chen et al., 2022). The second category utilises climate risk indices such as the Climate Policy Uncertainty (CPU) index introduced by Gavriilidis in 2021, which uses keyword frequency data from leading US newspapers. This index has been widely adopted by researchers across various domains to predict financial sector volatility across studies on stock markets, exchange markets, and renewable energy (Liang et al., 2022; Bonato et al., 2022). The third and final category considers climatic variables such as temperature, precipitation, and wind speed in their assessment of climate risk (Bonato et al., 2022).

A recent study conducted by Lee and Cho (2022) utilized text-mining techniques to glean valuable insights into China's climate landscape from Twitter data. Through strategic keyword analysis, they devised innovative metrics to quantify both Climate Uncertainty (CU) and Climate Policy Uncertainty (CEU) based on Twitter activity. Given the pivotal role of volatility in asset pricing, risk management, and portfolio allocation (Bollerslev et al., 2018), this study delves into the predictive capabilities of CU and CEU within the Chinese stock market context. Building upon extant research that relies on Climate Policy Uncertainty (CPU) to forecast stock volatility, we also consider the impact of the widely recognized Chinese Economic Policy Uncertainty (CEPU) index developed by Davis et al. (2019), as well as the US Climate Policy Uncertainty (UCPU) index created by Gavriilidis (2021). Our investigation aims to determine whether indicators of climate risk can effectively forecast volatility in the Chinese market. Additionally, in assessing stock performance, we extend our analysis beyond the Shanghai Composite Index (SSEC) to include the CSI 300 ESG index. Developed by the China Securities Index Company, the CSI 300 ESG index offers insights into the practices and performance of listed companies in terms of sustainable development. Notably, the computation of the CSI 300 ESG index involves excluding the bottom 20% of securities in the CSI tier-one industry based on ESG scores, with the remaining securities chosen as index samples.

In accordance with the works of Engle and Rangel (2008), Pan et al. (2017), Wang et al. (2020), Ma et al. (2021), and Liang et al. (2022), we assess stock volatility using the well-known generalized autoregressive conditional heteroscedasticity mixed data sampling model (GARCH-MIDES). The findings of our empirical research suggest that the uncertainty index examined in this research has the potential to substantially affect the volatility of the CSI 300 ESG index. Moreover, climate-related uncertainty, which includes uncertainty with respect to Chinese climate and climate policy, is shown to exhibit superior performance when employed as a predictor of future realized volatility as compared to other uncertainties. Upon comparing the forecasting performance of UCPU, CU, CEU, and CEPU, it becomes evident that UCPU and CEPU exhibit a certain degree of efficacy when it comes to predicting the volatility of SSEC. According to our findings, it is also possible to infer that listed companies with high ESG scores may be more significantly impacted by changes in underlying climate risk factors.

2. Methodology

2.1 GARCH-MIDAS and its extension

First and foremost, we introduce the GARCH-MIDAS model, which was initially proposed by Engle et al. (2013) and further developed by Conrad and Loch (2015). This model aims to capture two distinct components of volatility. The short-term component is modelled using a mean-reverting high-frequency daily GARCH process, while the long-term component incorporates low-frequency explanatory variables through Beta weighting schemes.

The representation of the daily log return on the stock market index $r_{i,t}$ at day $i = 1, \dots, N_t$ in a period $t = 1, \dots, T$ (e.g. month) is as follows:

$$r_{i,t} - E_{i-1,t}(r_{i,t}) = \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \tag{1}$$

$$\varepsilon|\varphi_{i-1,t} \sim N(0,1), \tag{2}$$

where $E_{i-1,t}(r_{i,t})$ is the expected value or the mean; the demeaned index return, as shown on the left-hand side, is thus subject to a heteroskedastic process that can be broken down into three components:

1. The secular (long-term) component of conditional volatility τ_t
2. The short-term component of conditional volatility $g_{i,t}$
3. The normally distributed white noise portion $\varepsilon_{i,t}$ conditional on $\varphi_{i-1,t}$ (available information as at the $i-1$ previous business day of month t)

The short-term component of conditional volatility $g_{i,t}$ which accounts for daily fluctuations is governed by the GARCH(1, 1) process as follows:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t}, \tag{3}$$

In the given model, α and β denote the ARCH and GARCH parameters, respectively. The ARCH portion incorporates the impacts of the secular component τ_t. Moreover, it is necessary for, $\alpha > 0, \beta > 0$, and $(\alpha + \beta) < 1$ in order to satisfy the stability criterion. The secular component, also known as the long-term component of conditional volatility, τ_t is defined as smoothed realized volatility:

$$ln\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{t-k}, \tag{4}$$

where $RV_t = \sum_{i=1}^{N_t} r_{i,t}^2$ indicates the realised volatility at monthly frequency, and K represents the maximum lag order. In this study, the left-hand side of the equation (4) is taken as $ln\tau_t$, the natural logarithm of τ_t , to ensure the positivity of the long-term component of conditional volatility, as stated by Engle et al. (2013). The final form of the GARCH-MIDAS model is as follows:

$$\tau_t = e^{m+\theta \sum_{k=1}^{K} \varphi_k(\omega_1,\omega_2) RV_{t-k}}, \tag{5}$$

where m is a constant and θ is the slope of the weighted effect of the low-frequency variables lagged behind the long-term volatility of the market. Using equation (4) as our benchmark model, we extend the equation to incorporate an additional exogenous variable which gives rise to the GARCH-MIDAS model with exogenous variables, which can be defined as

$$\tau_t = e^{m+\theta_1 \sum_{k=1}^{K} \varphi_k(\omega_1,\omega_2) RV_{t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(\omega_1,\omega_2) U_{t-k}}, \tag{6}$$

where U_{t-k} is the matrix of four exogenous variables. The element τ_t used in our analysis, remains constant over a specified period (e.g. a month). Finally, the total conditional variance can be defined as:

$$\sigma_{it}^2 = \tau_t \cdot g_{i,t}, \tag{7}$$

The weighting scheme used in equation (4), (5), and (6) is described by beta polynomial, as:

$$\varphi_k(\omega_1, \omega_2) = \frac{\left(\frac{k}{K}\right)^{\omega_1 - 1} \left(1 - \frac{k}{K}\right)^{\omega_2 - 1}}{\sum_{j=1}^{K} \left(\frac{j}{K}\right)^{\omega_1 - 1} \left(1 - \frac{j}{K}\right)^{\omega_2 - 1}}, \tag{8}$$

$$\varphi_k(1, \omega_2) = \frac{\left(1 - \frac{k}{K}\right)^{\omega_2 - 1}}{\sum_{j=1}^{K} \left(1 - \frac{j}{K}\right)^{\omega_2 - 1}}, \tag{9}$$

The unrestrictive weighting scheme that generates attenuated and hump weight distributions is represented by equation (8). On the other hand, equation (9) can be derived from equation (8) by applying the constraint $\omega_1 = 1$. To derive the equation (8) for the restricted weight function, the constraint of $\omega_1 = 1$ is imposed on the unrestricted weight function. As determined by the parameters ω_2, the restricted weighting function is solely capable of producing an attenuated weight distribution. This indicates that the decay rate increases with the value of ω_2, and vice versa. Both beta weighting functions are applicable to GARCH-MIDAS model estimation. For the purposes of our study, we adopt the use of the beta restricted weighting scheme as shown in equation (9).

2.2 Evaluation methods

In order to evaluate the predictive accuracy of our four exogenous uncertainty factors, we employ a commonly utilized technique in the domain of volatility forecasting: the out-of-sample R^2 test developed by Campbell and Thompson (2008) and is defined as follows:

$$R_{OOS}^2 = 1 - \frac{\sum_{t=1}^{\delta} (\sigma_t - \widehat{\sigma_t})^2}{\sum_{t=1}^{\delta} \left(\sigma_t - \hat{\sigma}_{t,bench}\right)^2} \tag{10}$$

where $\widehat{\sigma_t}$ is the volatility forecast from competing models, $\hat{\sigma}_{t,bench}$ is the volatility forecast generated by the GARCH-MIDAS model, and δ represents the length of the out-of-sample period. Specifically, σ_t is the daily log return, which is taken as a proxy for the actual volatility in the out-of-sample period. A positive R_{OOS}^2 value indicates that the performance of the contending model surpasses that of the benchmark model. Evidently, R_{OOS}^2 is capable of assessing the percentage of variation in the mean squared predictive error (MSPE) of competing models in comparison to the benchmark.

However, when dealing with a complex model that includes a simpler counterpart, it becomes essential to determine if the complex model demonstrates superior forecasting capabilities. If additional parameters do not enhance the predictive performance of the competing model, the mean squared prediction error (MSPE) of the simpler model should be lower than that of the alternative model. This discrepancy suggests that noise in the forecasting process may inflate the MSPE.

To mitigate the risk of introducing unnecessary noise into the larger model, we adjust the point estimate of the difference between the mean squared prediction errors (MSPEs) of the two models to account for the noise inherent in the larger model's forecast. This adjustment ensures that the adjusted MSPE provides a more accurate assessment during performance testing.

For the benchmark GARCH-MIDAS models, the mean squared predictive error is defined as:

$$MSPE_{bench} = \frac{\sum_{t=1}^{\delta}\left(\sigma_t - \hat{\sigma}_{t,bench}\right)^2}{\delta}. \tag{11}$$

For the competing models, the mean squared predictive error is defined as:

$$MSPE = \frac{\sum_{t=1}^{\delta}(\sigma_t - \hat{\sigma}_t)^2}{\delta}. \tag{12}$$

Based on this, define a term called “adjustment” (“adj.”) as:

$$adj. = \frac{\sum_{t=1}^{\delta}\left(\hat{\sigma}_{t,bench} - \hat{\sigma}_t\right)^2}{\delta}. \tag{13}$$

From equation (11) to equation (13), we can write the adjusted MSPE formula based on the principle of adjusting the difference in MSPEs by a consistent estimate of the asymptotic difference between the two models as:

$$adjusted\ MSPE = MSPE_{bench} - [MSPE - adj.]. \tag{14}$$

3. Data

In our study, we extensively analysed and compared the predictive ability of the CU, CEU, CEPU and UCPU indices. The data for CEPU and UCPU are acquired from the economic policy uncertainty website (http://www.policyuncertainty.com/), whereas the data for CU and CEU can be found at https://sites.google.com/view/twitter-chn-epu/home. Furthermore, the Wind database allows us to obtain the SSEC and CSI 300 ESG indices. To mitigate disparities in magnitudes, the logarithmic difference is employed to scale the initial four uncertainty indices as follow:

$$U\_Change\ (t) = \ln\frac{U(t)}{U(t-1)}, \tag{15}$$

The full sample period ranges from 3 July 2017 to 31 January 2023, covering 1356 trading days. The summaries of the returns of the four uncertainty indices and the stock indexes are presented in Table 3-1. R_{ESG} and R_{SSEC} represent the log return of CSI 300 ESG index and SSEC. All-time series are unequivocally stationary, as demonstrated by the ADF test.

Table 3-1 Descriptive Statistics

Variables	Mean	Std. dev	Skewness	Kurtosis	ADF Test
R_{ESG}	0.0102	1.2728	-0.3828	2.9509	-36.6522***
R_{SSEC}	0.0014	1.1056	-0.6461	5.1242	-16.3446***
CU	0.0078	1.0382	0.2689	0.6534	-6.5453***
CEU	0.0120	0.7736	-0.0546	-0.2914	-9.3232***
CEPU	0.0119	0.2627	-0.4281	1.5711	-8.2336***
UCPU	0.0009	0.3537	0.3335	1.3619	-6.5105***

*Notes:***, **, * denote the significance levels of 1%, 5% and 10%, respectively.*

Split the time series dataset into the train set and the test set. The train set contains data from the first 500 trading days (3 July 2017 to 18 July 2019) while the test set from original paper contains data from the rest of 715 trading days (19 July 2019 to 30 June 2022). In this project, we extended the data to 141 more days (until 31 January 2023).

4. Empirical Result

4.1 Out-of-sample results

Table 4-1 Out-of-sample Forecasting Performance

Regressions	R^2_{OOS}	MSPE. Adj
Panel A: CSI 300 ESG index		
GARCH-MIDAS-RV -CU	0.0265	0.0982
GARCH-MIDAS-RV -CEU	0.0079	0.0298
GARCH-MIDAS-RV -CEPU	0.2307	1.0891
GARCH-MIDAS-RV -UCPU	0.1201	0.5209
Panel B: SSEC index		
GARCH-MIDAS-RV -CU	-0.2665	-0.6588
GARCH-MIDAS-RV -CEU	-0.1024	-0.2229
GARCH-MIDAS-RV -CEPU	0.1320	0.4350
GARCH-MIDAS-RV-UCPU	0.4842	1.9830

Due to the positive R^2_{OOS}, models with four examined types of uncertainty outperform the benchmark for the CSI 300 ESG Index, while only models containing CEPU and UCPU outperform the benchmark for the SSEC Index. On the other hand, smaller MSPE. Adj indicates the $\widehat{\sigma_t}$ is closer to the σ_t. As a result, the findings from the data suggest that both CU and CEU have a notable impact on the volatility of CSI 300 ESG, surpassing the performance of CEU and UCPU.

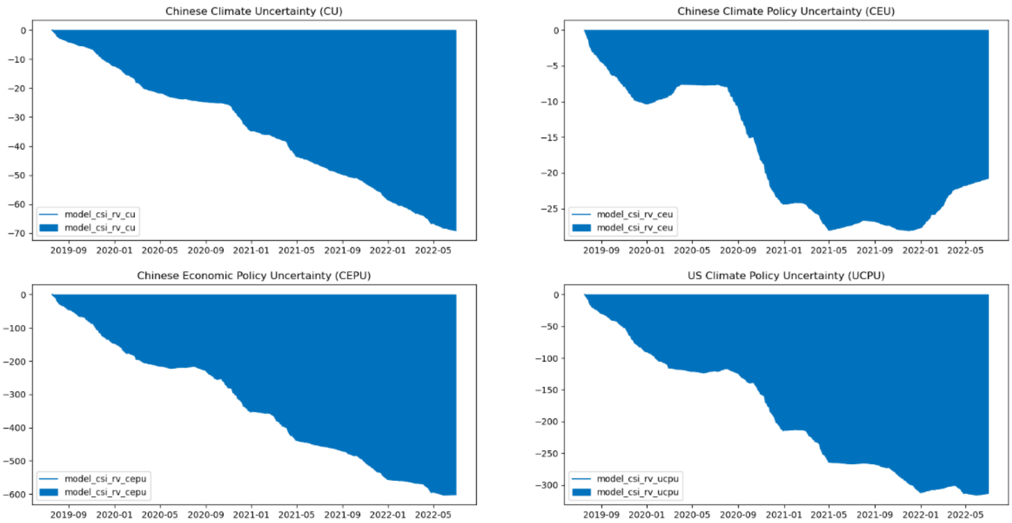

Figure 4-1 CumSFE of the Uncertainty index

$$CumSFE = \sum_{t=1}^{\delta}\left(\left(\hat{\sigma}_{i,model} - \sigma_t\right)^2 - \left(\hat{\sigma}_{t,bench} - \sigma_t\right)^2 \right)$$

The Cumulative Squared Forecast Error (CumSFE) values are consistently negative over the out-of-sample period which suggests that the CU, CEU, CEPU and UCPU models demonstrate superior forecasting performance over the benchmark model. These values align with our findings of the out-of-sample R-squared values which shows us that for the CSI 300 ESG index models are outperforming the benchmark model.

To test whether this model works for a longer period, we extend the test period to the latest period, from 2022-07-01 to 2023-01-31. The results are shown in the table below.

Table 4-2 Out-of-sample (latest period) Forecasting Performance

Regressions	R^2_{OOS}	**MSPE. Adj**
Panel A: CSI 300 ESG index		
GARCH-MIDAS-RV -CU	0.0265	0.0903
GARCH-MIDAS-RV -CEU	0.0058	0.0195
GARCH-MIDAS-RV -CEPU	0.1824	0.8201
GARCH-MIDAS-RV -UCPU	0.0827	0.3425
Panel B: SSEC index		
GARCH-MIDAS-RV -CU	-0.3117	-0.7056
GARCH-MIDAS-RV -CEU	-0.0633	-0.1231
GARCH-MIDAS-RV -CEPU	0.1140	0.3655
GARCH-MIDAS-RV-UCPU	0.4515	1.6076

The same results could be obtained as above, indicating the GARCH-MIDAS prediction models with climate risk indices have certain feasibility.

5. Extension

5.1 Rolling window for out-of-sample forecasting

In the financial market, data changes rapidly with the passage of time. Therefore, the use of a rolling window forecast method could generate better predictions. For the train set and the test set of our empirical research, we illustrate the following flow to demonstrate how the rolling window works.

Algorithm Rolling Window in Forecasting

procedure: N = 1215 [Number of Trading Days]

  Train = 500; Test = 715 [Split the whole dataset]

  for i from 0 to Test **do**

    Window $\in [i,\ i + Train]$

    Index of dataset $\in Window$

    Simulate parameters by using GARCH-MIDAS model (K = 9)

    Forecast 1 day ahead → obtain the predicted data with index $(i + Train + 1)$

    $i = i + 1$

  end for

  return 715 forecasting data

  Compare with real data in test set

end procedure

Comparing the fitted Sigma with the actual Sigma, we found that the prediction model with the rolling window method can capture most of the changes in the CSI ESG Index. Citing GARCH-MIDAS-RV-CU for the CSI 300 ESG Index as an instance, the forecasting results are shown in the graph below.

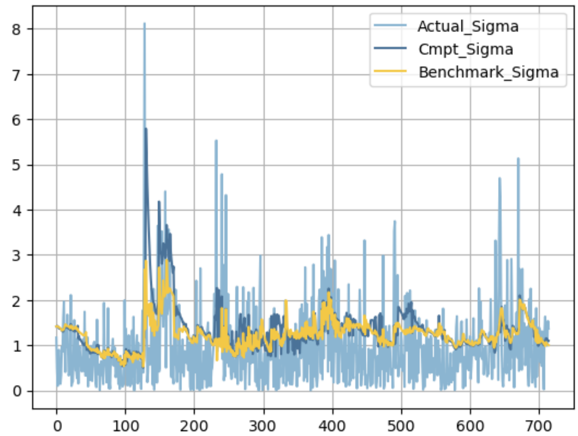

Figure 5-1 Volatility forecasting by rolling window method

In conclusion, if investors have abundant computing power, the rolling prediction model can effectively assist them in forecasting the volatility in the stock market. Besides, from the line graph above, we can identify that the competing model performs better in forecasting some extreme fluctuations than the benchmark model, which also demonstrates that the climate risk factors play an important role in predicting the volatility of the CSI ESG Index.

5.2 Machine Learning Ensemble Methods

Preamble

As an extension to our study, we integrate machine learning techniques comprising ensemble methods to corroborate our earlier findings. In fact, the application of machine learning in predicting realized volatility is a well-established approach as evidenced by the work of Carr et al. (2020). Thus, we have curated a selection of bootstrap aggregation (commonly referred to as "bagging") and boosting algorithms to assess the ability of the CU, CEU, CEPU and UCPU indices in forecasting Chinese stock market volatility. Specifically, we leverage the following ensemble methods: Random Forest Regressor ("RFR"), Extra Trees Regressor ("ETR"), Adaptive Boosting Regressor ("ABR") and Gradient Boosting Regressor ("GBR").

Data Wrangling and Pre-processing

Train Test Split

Given the inherent characteristics of machine learning, we have adopted an 80-20 train-test-split approach for our data which differs from the in-sample and out-of-sample test periods used in the aforementioned GARCH-MIDAS model. For the purposes of our machine learning study, we define the in-sample train and out-of-sample test periods as follows:

- In-Sample Training Period: 3 Jan 2018 – 19 Jan 2022
- Out-of-Sample Testing Period: 20 Jan 2022 – 31 Jan 2023

Cubic Spline Interpolation

Further, while the mixed data sampling algorithm in R adeptly manages the varying frequencies of the dependent variable and the exogenous variable which are observed at daily and monthly intervals respectively, we will have to preprocess this data prior to deployment in our machine learning model. To this end, we apply a cubic spline interpolation method to transform and smooth not only the monthly CU, CEU, CEPU and UCPU index data, but also the monthly realised volatility to a daily frequency to ensure better results (Fig. 5-2).

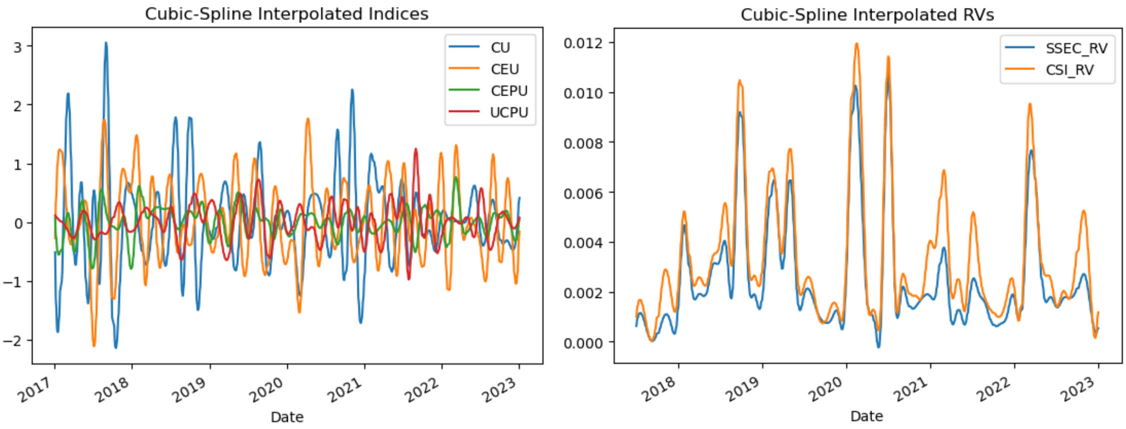

Figure 5-2 Cubic spline interpolation of monthly data

Methodology

We implemented K-Fold cross-validation in accordance with established best practices to ensure robustness and reliability in our analysis. In this process, we fitted models for each machine learning algorithm and assessed their predictive performance based on mean squared error (MSE) as shown in Figure 5-3. The full K-Fold cross validation results are presented in Appendix 1 of this paper.

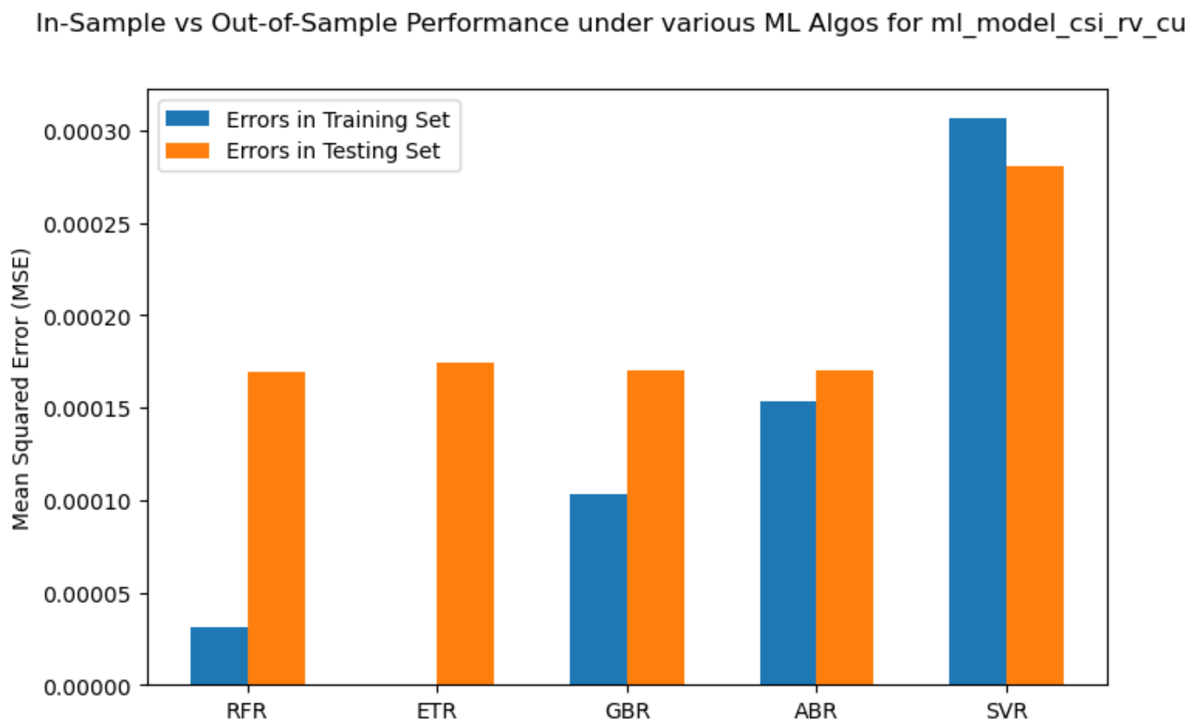

Figure 5-3 Illustrative example of K-Fold cross validation results under various ML algorithms

Subsequently, we also used the fitted models to generate predictions of the dependent variable over the out-of-sample test period and evaluated them against the benchmark model using the out-of-sample R-squared R^2_{OOS}, MSPE-adjusted as well as cumulative squared forecast error (CumSFE). The results for

R^2_{OOS} and MSPE-adjusted under all 4 ensemble methods are summarised in Table 5-1 while selected results for CumSFE pertaining to the better performing Random Forest ("RFR") and Extra Trees Regressor ("ETR") models applied to CSI ESG 300 index are shown in Figure 5-5 and Figure 5-6.

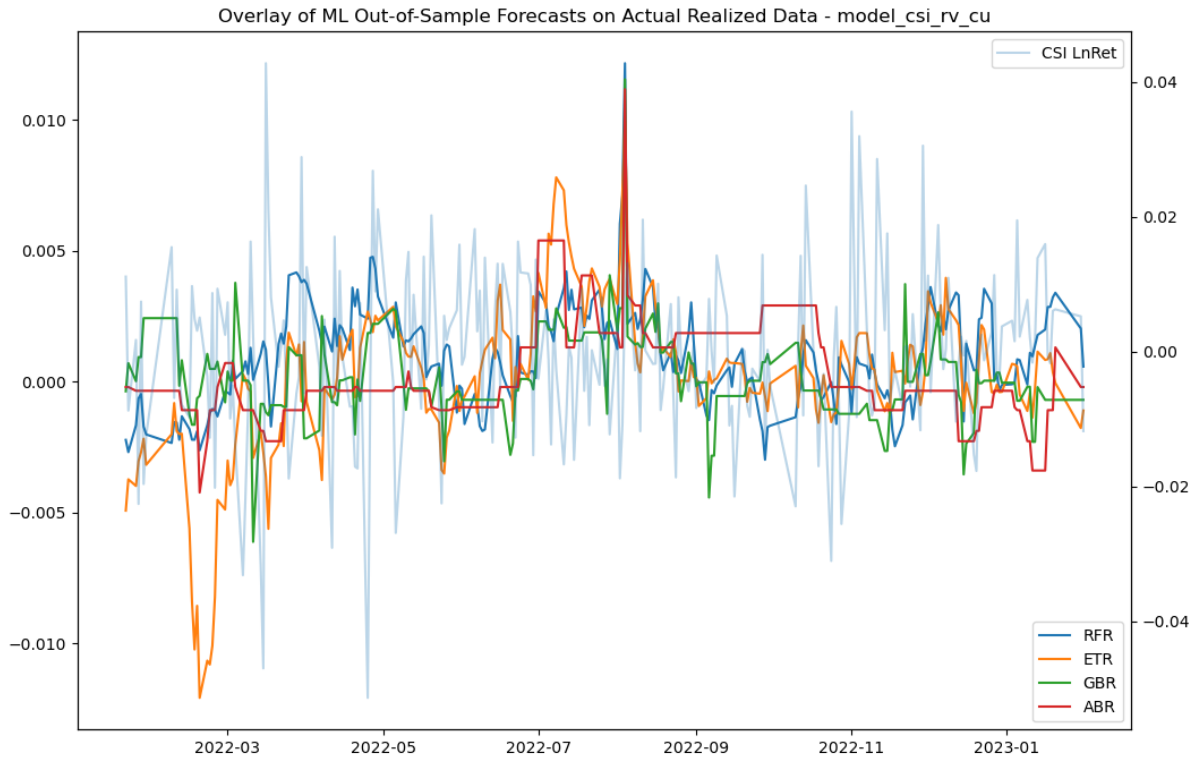

Figure 5-4 Out-of-sample forecasts under various ML algorithms against actual observations

Table 5-1 Out-of-sample Forecasting Performance

Models	Metrics	RFR	ETR	GBR	ABR
Model_csi_rv_cu	R^2_{OOS}	0.08387	0.03000	0.02306	0.01632
	MSPE. Adj	0.00002	0.00002	0.00001	0.00001
Model_csi_rv_ceu	R^2_{OOS}	-0.00259	0.04732	-0.02291	-0.04355
	MSPE. Adj	0.00002	0.00002	0.00000	0.00000
Model_csi_rv_cepu	R^2_{OOS}	0.00353	0.04960	-0.08904	0.02344
	MSPE. Adj	0.00001	0.00002	0.00000	0.00001
Model_csi_rv_ucpu	R^2_{OOS}	-0.95854	0.00398	-1.04125	-1.01001
	MSPE. Adj	0.00003	0.00001	0.00002	0.00003
Model_ssec_rv_cu	R^2_{OOS}	0.03472	0.06218	0.02896	0.03136
	MSPE. Adj	0.00001	0.00002	0.00001	0.00001
Model_ssec_rv_ceu	R^2_{OOS}	-0.01200	0.06950	-0.02074	-0.04237
	MSPE. Adj	0.00001	0.00002	0.00000	0.00000
Model_ssec_rv_cepu	R^2_{OOS}	-0.03246	0.03470	-0.13366	-0.01548
	MSPE. Adj	0.00001	0.00002	0.00000	0.00001
Model_ssec_rv_ucpu	R^2_{OOS}	-1.06827	-0.00600	-1.78133	-1.13290
	MSPE. Adj	-0.00001	0.00002	0.00000	0.00001

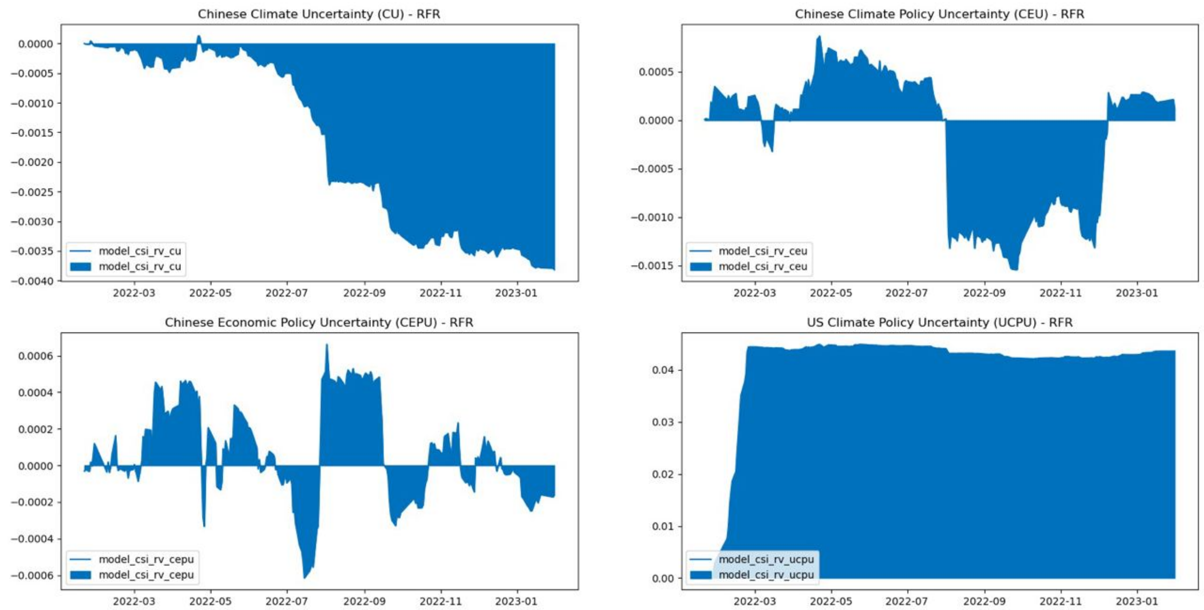

Figure 5-5 Cumulative Squared Forecast Error on CSI models under Random Forest Regressor

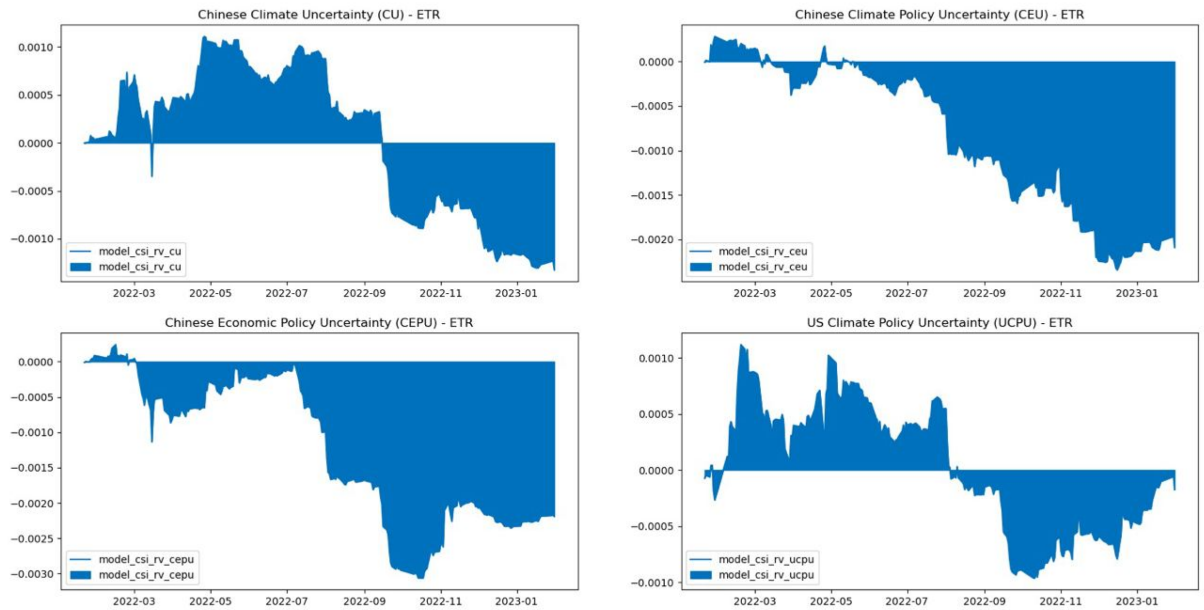

Figure 5-6 Cumulative Squared Forecast Error on CSI models under Extra Trees Regressor

Key Findings

Based on the out-of-sample forecasting performance of machine learning methods, we find that the Random Forest Regressor ("RFR") and Extra Trees Regressor ("ETR") are reasonable methods to forecast the logarithm return of the CSI ESG Index in most models. Specifically, RFR has advantages in predicting when we consider Chinese Climate Uncertainty (CU) as one of the input variables compared with the benchmark model, whereas ETR performs well in models with the input variables as Chinese Climate Policy Uncertainty (CEU) and Chinese Economic Policy Uncertainty (CEPU).

However, US Climate Policy Uncertainty (UCPU) is not a good feature in the machine learning model because of the negative R^2_{OOS}.

Given that our GARCH-MIDAS models that took in the CPU indices as an exogenous variable while using CSI 300 Index realised volatility outperformed the benchmark model, it shows that the CPU indices as an exogenous variable has an impact in predicting volatility especially in the CSI 300 Index.

When we attempted to use a rolling window method to tune the parameters of our GARCH-MIDAS model for each day we were forecasting volatility, this did not yield better results in forecasting volatility as compared to our base model.

Based on the CumSFE and the out-of-sample R-squared values, the GARCH-MIDAS-INDEX models have shown to perform better at forecasting volatility as compared to the Machine Learning Ensemble methods that we have implemented.

6. Challenges

During our efforts to replicate the findings of the paper, we encountered several discrepancies within the original study. First and foremost, the authors omitted to clarify whether the returns of the variables R_{ESG} and R_{SSEC} are logarithmic. The writers also erroneously stated the descriptive statistics results of R_{ESG} and R_{SSEC}, with the labels for R_{ESG} and R_{SSEC} being mistakenly interchanged. For avoidance of doubt, this means that the descriptive statistics for R_{ESG} as shown in the original paper are in fact attributable to R_{SSEC}. Additionally, they scaled "R_{SSEC}" by 100, effectively expressing the data in percentage points, but did not apply the same treatment to "R_{ESG}". Further discrepancies were found in the CEPU data and its accompanying descriptive statistics, which did not align with the information provided by the cited source.

Of greater concern was the writers' negligence to specify critical information such as the number of lags K (in months) which they have applied to the exogenous variables in their GARCH-MIDAS models. This has necessitated extensive experimentation with varying orders of lags in an attempt to closely replicate the paper's results.

Finally, the authors failed to provide any details regarding the methodology employed to transition from the GARCH-MIDAS model to the Markov Switching (MS)-GARCH-MIDAS model in their extension to their study which considers the effect of regime switching. Therefore, the aforementioned factors may inevitably affect our ability to closely replicate the results.

7. Conclusion

Given that our GARCH-MIDAS models that took in the CPU indices as an exogenous variable while using CSI 300 Index realised volatility outperformed the benchmark model, it shows that the CPU indices as an exogenous variable has an impact in predicting volatility especially in the CSI 300 Index.

When we attempted to use a rolling window method to tune the parameters of our GARCH-MIDAS model for each day we were forecasting volatility, this did not yield better results in forecasting volatility as compared to our base model.

Based on the CumSFE and the out-of-sample R-squared values, the GARCH-MIDAS-INDEX models have shown to perform better at forecasting volatility as compared to the Machine Learning Ensemble methods that we have implemented.

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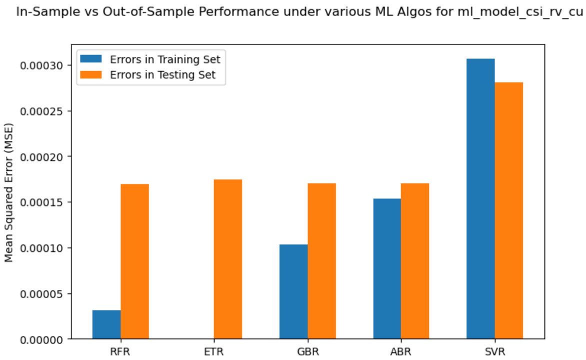
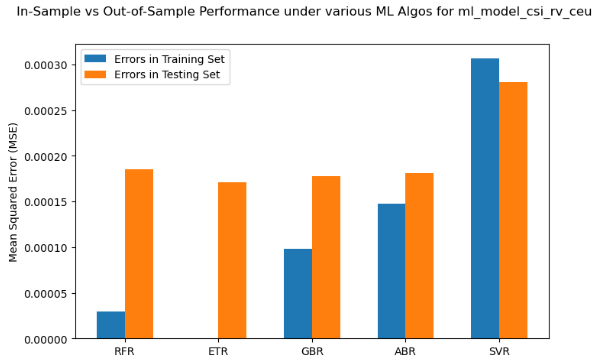
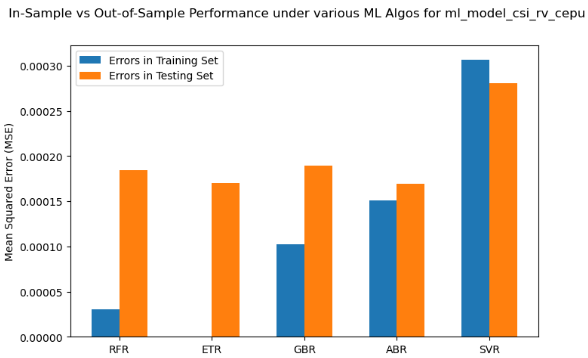
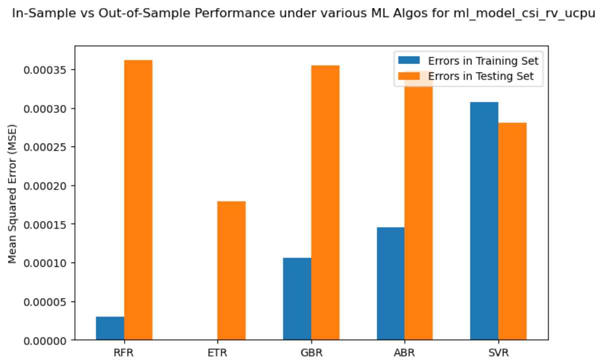
Appendix

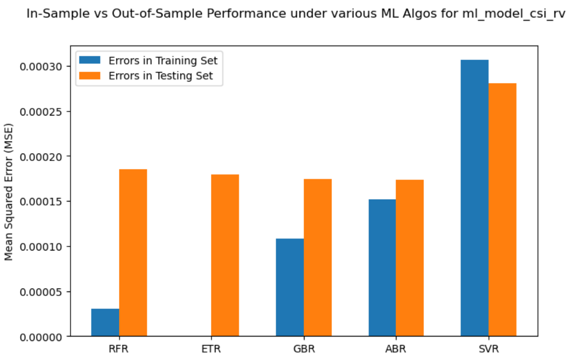
K-Fold Cross Validation Results for CSI 300 ESG Index models





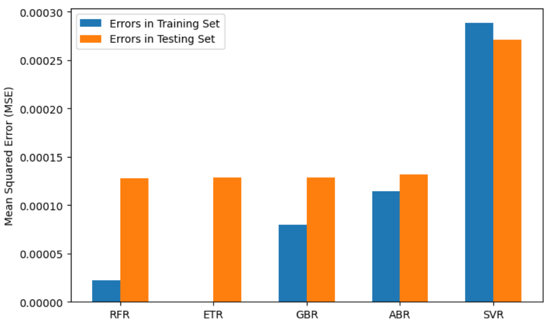




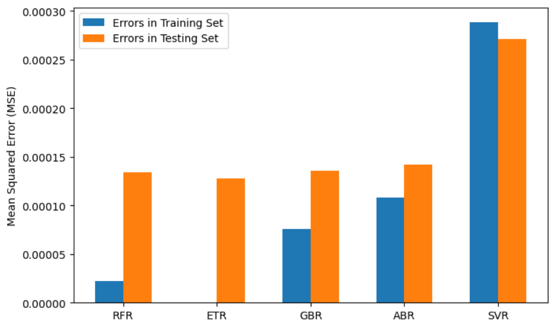


K-Fold Cross Validation Results for SSEC Index models

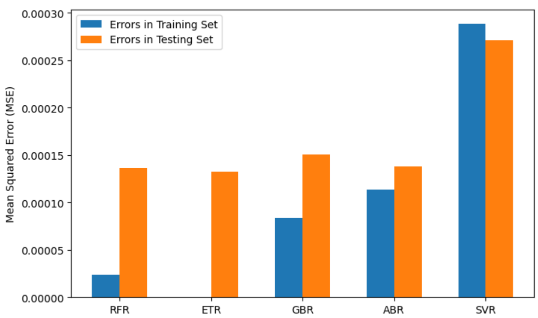
In-Sample vs Out-of-Sample Performance under various ML Algos for ml_model_ssec_rv_cu



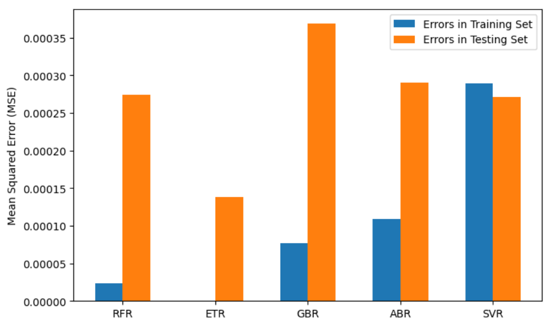
In-Sample vs Out-of-Sample Performance under various ML Algos for ml_model_ssec_rv_ceu



In-Sample vs Out-of-Sample Performance under various ML Algos for ml_model_ssec_rv_cepu



In-Sample vs Out-of-Sample Performance under various ML Algos for ml_model_ssec_rv_ucpu



In-Sample vs Out-of-Sample Performance under various ML Algos for ml_model_ssec_rv