Climate risk and Chinese stock volatility forecasting

Evidence from ESG index

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CONTENT

PART 01

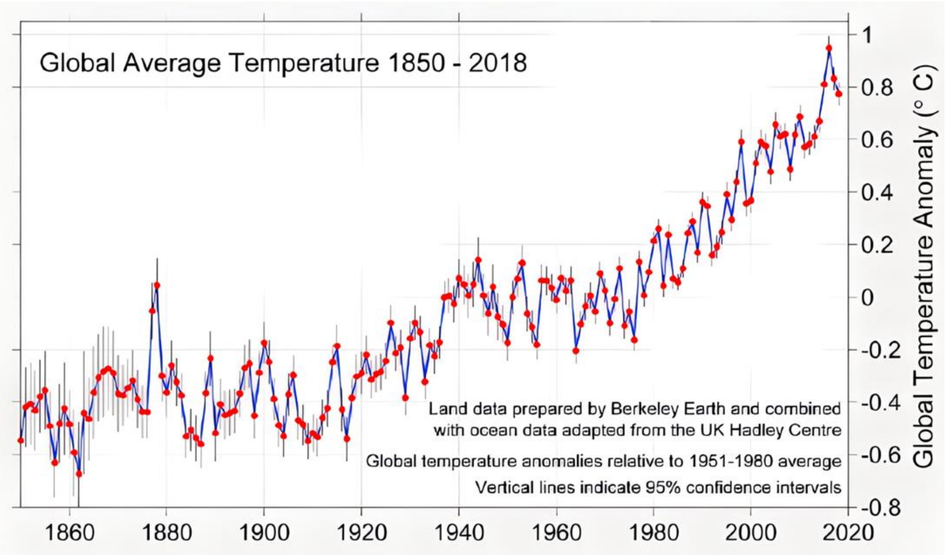
Introduction

01 Introduction

Influence of Climate Change

In recent years, frequent **extreme weather** events have brought a series of **catastrophic consequences**

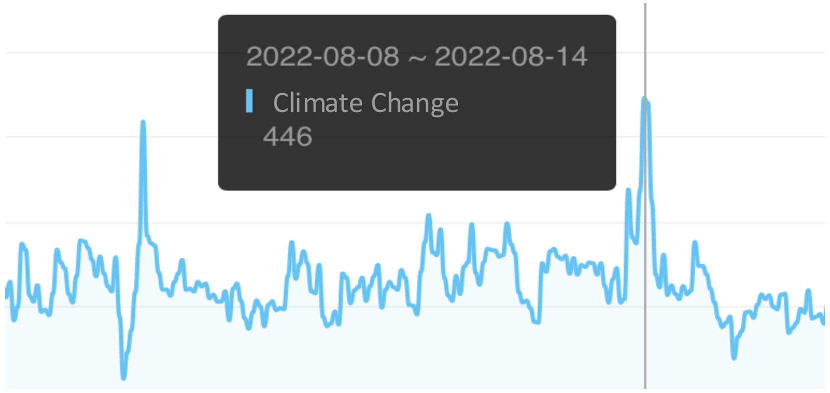
- Energy crisis in Europe - Under the influence of extreme weather



Whether it is gradual climate change or sudden extreme weather, it will pose a serious **threat to economic growth and financial stability**.

Ways to Capture Climate Risk

The search volumes of Google	**Public Sentiment**
Climate policy uncertainty index	
Climate factors (e.g., temperature, precipitation)	



Applying Climate Risk to forecasting

- Examines the forecasting performance of indicators of climate risk;
- Mainly focused on the volatility of the Chinese stock market

PART 02

Data

Index

- Shanghai Stock Exchange Index (SSEC)
- CSI 300 ESG Index

Uncertainty

- Chinese Climate Uncertainty (CU)
- Chinese Climate Policy Uncertainty (CEU)
- Chinese Economic Policy Uncertainty (CEPU)
- US Climate Policy Uncertainty (UCPU)

Formula

$$R(t) = \ln \frac{P_{t+1}}{P_t}$$

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

In-sample data: 3 July 2017 to 18 July 2019 (500 trading days)

Out-of-sample data: 19 July 2019 to 30 June 2022 (715 trading days)

Latest period: 1 July 2022 to 31 January 2023 (141 trading days)

Descriptive Statistics

Confirming our Data Sources

	Mean	Standard Deviation	Skew	Kurtosis
R_{ESG}	0.0174	1.2928	-0.4484	3.0101
R_{SSEC}	0.0052	1.1274	-0.6907	5.2227
CU	0.0476	0.8805	0.8634	1.6477
CEU	0.0648	0.7808	-0.1429	-0.1829
CEPU	0.0270	0.2721	-0.4324	1.4489
UCPU	-0.0011	0.3608	0.3226	1.4047

2017-06-30 to 2023-01-31

Descriptive Statistics

Data to the Latest Period

	Mean	Standard Deviation	Skew	Kurtosis
R_{ESG}	0.0102	1.2728	-0.3828	2.9509
R_{SSEC}	0.0014	1.1056	-0.6461	5.1242
CU	0.0078	1.0382	0.2689	0.6534
CEU	0.0120	0.7736	-0.0546	-0.2914
CEPU	0.0119	0.2627	-0.4281	1.5711
UCPU	0.0009	0.3537	0.3335	1.3619

****2017-06-30 to 2023-01-31***

ADF Test

Variables	***ADF Test***
R_{ESG}	**-36.6522**
R_{SSEC}	**-16.3446**
CU	**-6.5453**
CEU	**-9.3232**
CEPU	**-8.2336**
UCPU	**-6.5105**

Conclusion

Data has no unit root and is stationary

PART 03

Methodology

GARCH-MIDAS and its extension

Volatility Components

- **Short-term**: mean-reverting high-frequency daily GARCH
- **Long-term**: by integrating low-frequency explanatory variables through the Beta weighting schemes

demeaned index return

$$\underbrace{r_{i,t}}_{} - \underbrace{E_{i-1,t}(r_{i,t})}_{\text{mean}} = \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}$$

mean

Daily log return at day $i = 1, \ldots, N_t$ in a period $t = 1, \ldots, T$ (e.g. month)

1. The τ_t secular component exerts an influence on the dynamics of long-term volatility,
2. $g_{i,t}$ is the short-run component of volatility, and
3. $\varepsilon|\varphi_{i-1,t} \sim N(0,1)$

GARCH-MIDAS and its extension

GARCH (1,1)

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

- α and β denote the ARCH and GARCH parameters
- ARCH portion incorporates the impacts of the secular component τ_t
- $\alpha > 0, \beta > 0$ and $(\alpha+\beta) < 1$ in order to satisfy the stability criterion

Smoothed Realized Volatility

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

- RV_t is the realized volatility of t month, calculated by $RV_t = \sum_{i=1}^{N_t} r_{i,t}^2$
- $\varphi_k(\omega_1,\omega_2)$ is weighting function of lag variables; K is the length of lag
- m and θ are parameters in GARCH-MIDAS model

With Exogenous Factors

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

GARCH-MIDAS and its extension

Weight Function

- Unrestrictive weighting scheme

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

- Applying the constraint $\omega_1 = 1.$

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

This indicates that the decay rate increases with the value of ω_2

We used the restrictive weighting scheme in our project

Calculate Volatility

Benchmark Sigma

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

RV is calculated by log return of CSI ESG index/SSEC index

$$\hat{\sigma}_{t,bench} = \sqrt{\tau_{t,bench} * g_{i,t}}$$

Competing model Sigma

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

RV is calculated by log return of CSI ESG index/SSEC index, and U_{t-k} is the logarithmic difference of CU/CEU/CEPU/UCPU

$$\hat{\sigma}_t = \sqrt{\tau_t * g_{i,t}}$$

Actual Sigma

$$\sigma_t = logReturn_t$$

01 Out-of-sample R^2 test

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

02 Mean squared predictive error (MSPE)

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

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

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

03 Cumulative sum of squared forecast error (CumSFE)

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

PART 04

Empirical Results

Out-of-Sample Results

**Test set: 2019-07-19 to 2022-06-30*

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

Results Interpretation

Models with four examined types of uncertainty outperform the benchmark for the **CSI 300 ESG Index**

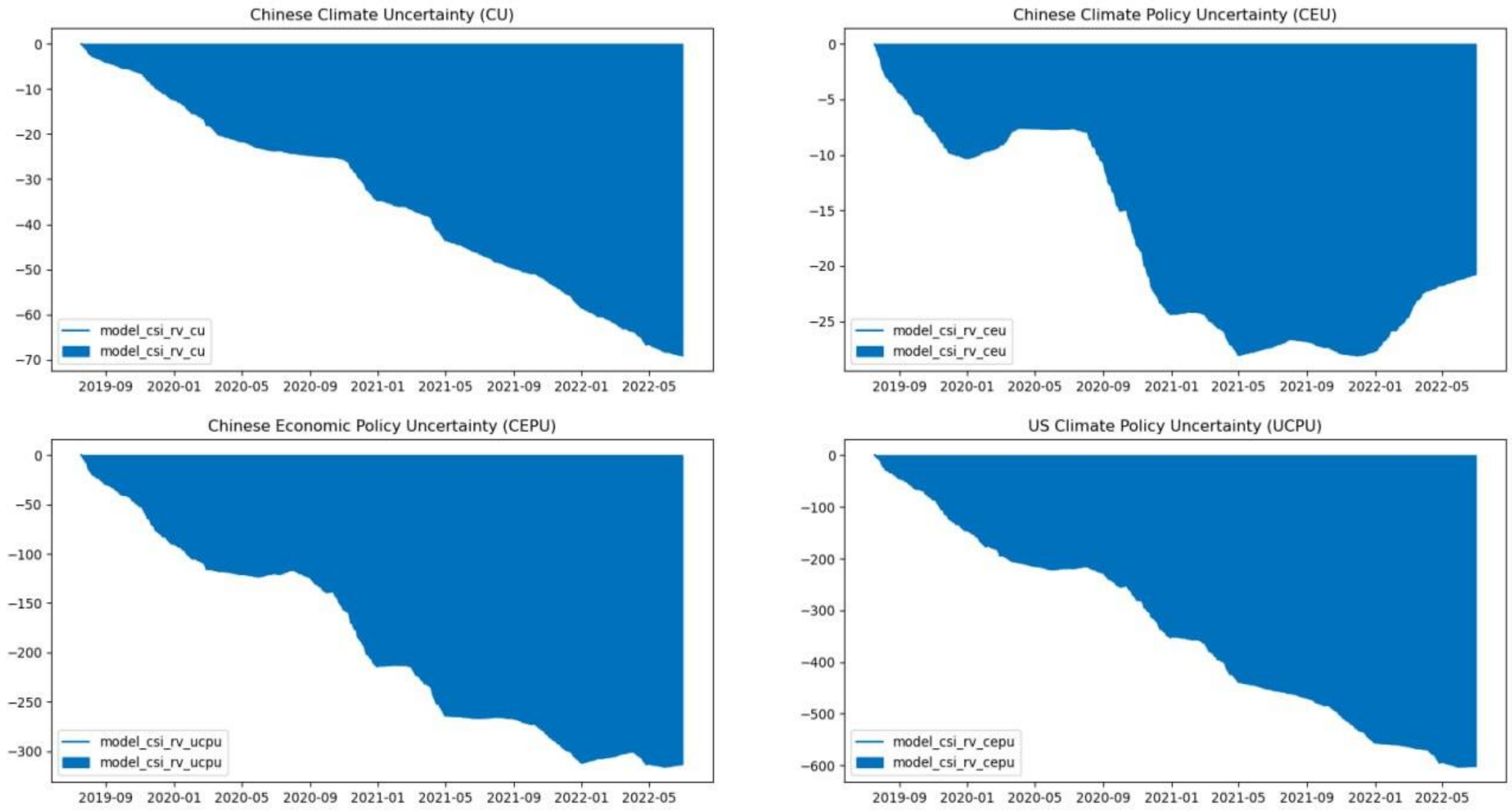
Only models containing CEPU and UCPU outperform the benchmark for the **SSEC Index**

$R^2_{OOS} > 0$: Competing model performs better;
Smaller MSPE.Adj: Forecasting results of models with CU/CEU are more accurate

Out-of-Sample Results

**Test set: 2019-07-19 to 2022-06-30*

CumSFE of the Uncertainty index



Results Interpretation

Consistently negative CSFE, suggesting superior forecasting performance of the CU, CEU, CEPU and UCPU

Results are consistent with the out-of-sample R^2 test, confirming the robustness of our empirical findings

Out-of-Sample Results (latest period)

**Test set: 2022-07-01 to 2023-01-31*

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

Results Interpretation

Models with four examined types of uncertainty outperform the benchmark for the **CSI 300 ESG Index**

Only models CEPU and UCPU outperform the benchmark for the **SSEC Index**

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PART 05

Extension

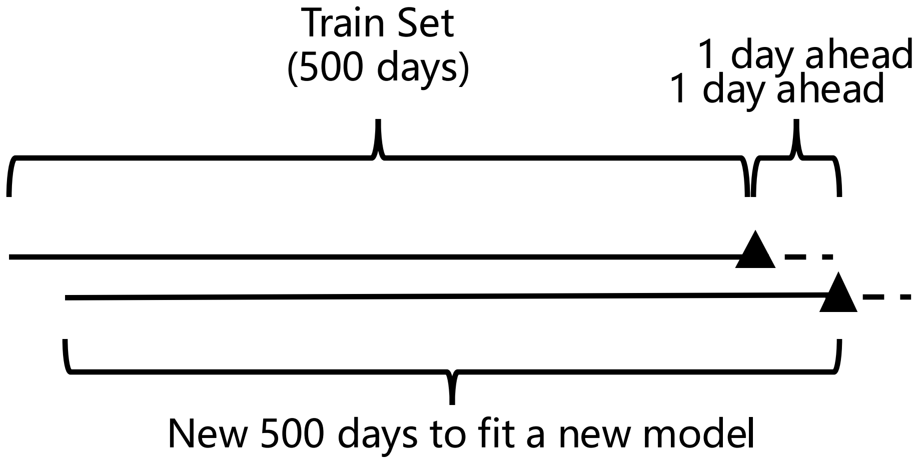
05 Extension

Rolling Window

Algorithm of rolling window

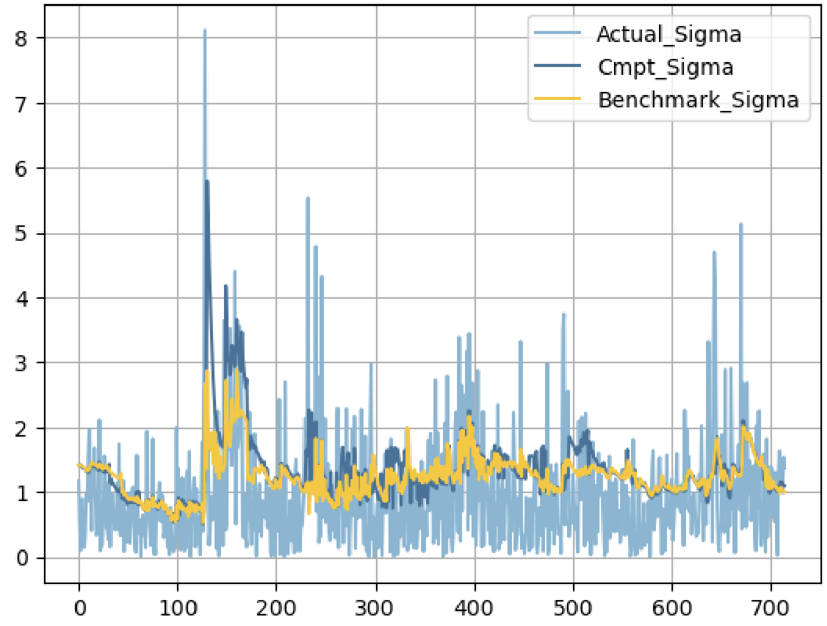
Algorithm Rolling Window in Forecasting

```
procedure: N = 1215 [Number of Trading Days]
    Train = 500; Test = 715 [Split the whole dataset]
    for i from 0 to Test do
        Window ∈ [i, i + Train]
        Index of dataset ∈ 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
```



Algorithm of rolling window

**Citing GARCH-MIDAS-RV-CU for CSI ESG Index as an instance*



- Both $\hat{\sigma}_{t,bench}$ and $\hat{\sigma}_t$ fit σ_t well
- Competing model performs better in forecasting some **extreme fluctuations**

- Depend on computing power

05 Extension

Machine Learning

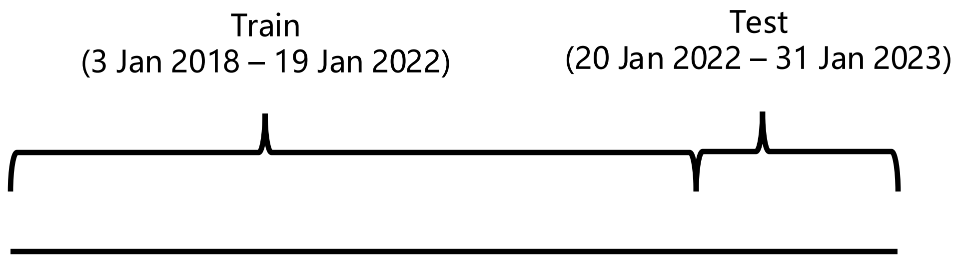
Methodology

Bootstrap Aggregation (“Bagging”) and Boosting Algorithms employed to assess ability of CU, CEU, CEPU, and UCPU indices in forecasting Chinese Stock Market Volatility

Ensemble Methods

- Random Forest Regressor (RFR)
- Extra Trees Regressor (ETR)
- Adaptive Boosting Regressor (ABR)
- Gradient Boosting Regressor (GBR)

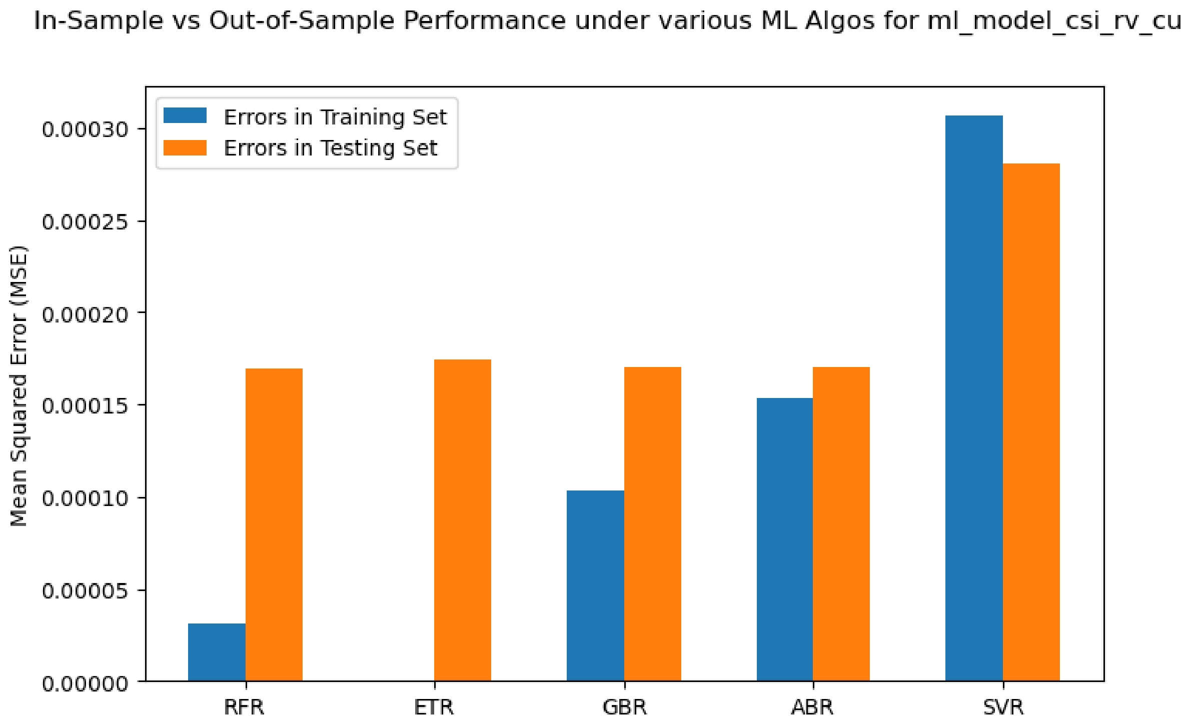
Train-Test Split



80 – 20 Train Test Split

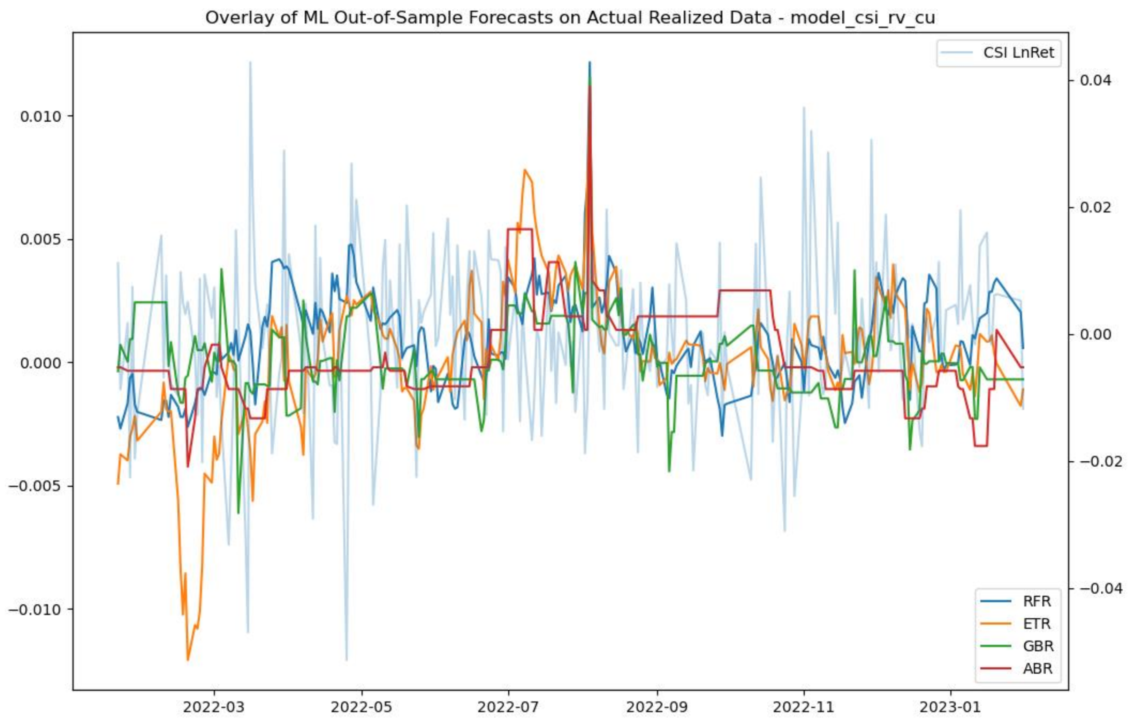
K-Fold Cross Validation: to ensure robustness and reliability of results

K-Fold Cross Validation Results



The use of Support Vector Machine was subsequently discontinued due to the relatively weaker performance for this use case

Generating predictions using fitted ML models



The ETR and RFR methods were able to generate relatively better forecasts as compared to the other ML algos

Machine Learning

CSI Performance Indicators

Models	Metrics	RFR	ETR	GBR	ABR
RV_CU	R^2_{OOS}	0.08387	0.03000	0.02306	0.01632
	MSPE. Adj	0.00002	0.00002	0.00001	0.00001
RV_CEU	R^2_{OOS}	-0.00259	0.04732	-0.02291	-0.04355
	MSPE. Adj	0.00002	0.00002	0.00000	0.00000
RV_CEPU	R^2_{OOS}	0.00353	0.04960	-0.08904	0.02344
	MSPE. Adj	0.00001	0.00002	0.00000	0.00001
RV_UCPU	R^2_{OOS}	-0.95854	0.00398	-1.04125	-1.01001
	MSPE. Adj	0.00003	0.00001	0.00002	0.00003

SSEC Performance Indicators

Models	Metrics	RFR	ETR	GBR	ABR
RV_CU	R^2_{OOS}	0.03472	0.06218	0.02896	0.03136
	MSPE. Adj	0.00001	0.00002	0.00001	0.00001
RV_CEU	R^2_{OOS}	-0.01200	0.06950	-0.02074	-0.04237
	MSPE. Adj	0.00001	0.00002	0.00000	0.00000
RV_CEPU	R^2_{OOS}	-0.03246	0.03470	-0.13366	-0.01548
	MSPE. Adj	0.00001	0.00002	0.00000	0.00001
RV_UCPU	R^2_{OOS}	-1.06827	-0.00600	-1.78133	-1.13290
	MSPE. Adj	-0.00001	0.00002	0.00000	0.00001

PART 06

Conclusion