Exploring and Forecasting ESG Index

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Abstract

This study explores ESG's relationship with anti-ESG stocks during crises with the VAR model. Findings, without strong statistical support, imply anti-ESG index profit during financial distress. While ESG index correlates negatively, suggesting a susceptibility to market downturns. Additionally, the study trialed with forecasting models ARIMA and LSTM using ESG index.

Introduction

ESG which stands for Environment, Social and Governance, has been a hot topic for the last decade. We are witnessing increasing numbers of capital inflow into ESG investing and funds as more and more investors, driven by global policy changes, are tilting their values to sustainable growth. ESG investing is one of the investment choices in funds that consider environmental, social and governance issues. In other terminologies, some investors also refer to 'socially responsible investing (SRI)' and 'sustainable investing' (Vanguard, n.d.).

The research Baker et al. (2022) have done reveals that there's a growing financial preference for ESG-focused funds among investors. Specifically, the average investor's willingness to pay a premium for ESG funds has increased significantly, from 9 basis points in 2019 to 28 basis points by 2022. This shift suggests a higher expected return, in both financial and non-financial terms, from ESG investments. Moreover, the study considers various factors, including the overlap between ESG and non-ESG fund holdings and the specific concerns of environmentally-conscious investors. These factors further amplify the perceived value of ESG investments.

Literature Review

Evidence by BlackRock's decision, however, (Hoffman, G., 2023) in dissolving 2 ESG-related mutual funds showed a different story. 'ESG funds generally 'perform poorly.' An important study on self-labeled ESG funds in the U.S. from 2010 to 2018 showed that ESG scores were based on the quantity of voluntary ESG-related disclosure not based on magnitude in ESG in actions. Moreover, the study also indicated that the ESG funds are underperforming financially compared to other funds, charging higher fees (Raghunandan et al, 2022).

Another research (Albuquerque, Koskinen, & Santioni, 2021) found that during the market downturn, all types of funds (ESG and non-ESG funds) that witnessed inflows contributed to market stabilization by increasing their net buying relative to the inflows. This trend was notably more prominent in ESG funds. Furthermore, when facing outflows, non-ESG funds were observed to escalate their net selling of non-ESG stocks proportionate to the outflows, thereby gradually shifting their portfolios in favor of ESG stocks.

Hypothesis and Methodology

1. *ESG indexes and anti-ESG indexes are inversely related, with ESG acting as an investor refuge during market shocks.*

2. *ESG indexes are expected to be more stable, while anti-ESG indexes are predicted to be more volatile during crises.*

To reduce potential multicollinearity issues, anti-ESG index is considered, instead of non-ESG index. The study investigates the relationship between ESG and anti-ESG indices using a Vector AutoRegression (VAR) model, and separately, it explores the potential of a Long Short-Term Memory (LSTM) model to project ESG stock prices. The VAR model is utilized to understand the interplay and influence between ESG-centric investments and their anti-ESG counterparts, capturing the dynamics within multivariate time series data.

In a different analysis, the LSTM model is tested for its ability to handle the complex, anti-linear patterns often present in stock price movements, specifically focusing on ESG stocks. The study's objective is to assess the predictive strength of a neural network approach in financial forecasting for ESG investments, which is a novel attempt alongside the traditional econometric VAR modeling for interrelated market indices.

1. Data Parameters

ESG ETF:

ESGU is an ESG U.S. Stock ETF that tracks the performance of weighted indexes of large, mid and small capitalization stocks. They are screened for certain levels of environmental, social and corporate governance criteria. Companies from industries such as adult entertainment, alcohol and biological weapons are strictly excluded. Companies that do not meet certain labor, human rights, anti-corruption and diversity standards are not considered.

Anti-ESG ETF:

The anti-ESG index went through various considerations. The initial pick was VIX, known as ‘fear index’ and typically captures market volatility or potential crisis. Another consideration is oil and gas related index, however, this result will be more multidimensional in interpretation and there will be other things that greatly influence crude oil and natural gas prices. Therefore for the anti-ESG index, VICE was chosen.

AdvisorShares Vice ETF (VICE) is an actively managed fund that invests in U.S. alcohol, tobacco, food and beverage, and gaming-related activities, where gaming businesses include casinos and lottery services. It is in direct contrast to ESG themes and solely focuses on vice activities.

Crisis Index:

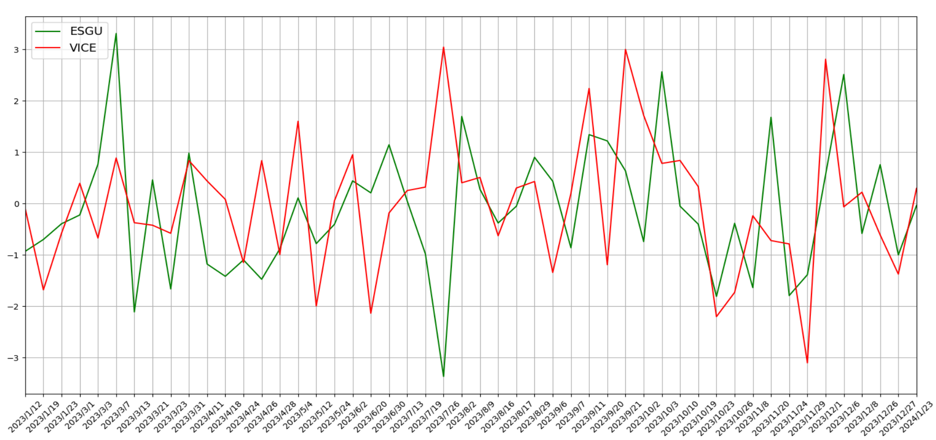
Financial Stress Index(FSI) is a market-based index that measures the degree of financial stress in the global financial markets. It captures 33 financial market variables from yield spreads to interest rates. The region covers the United States, other advanced economies and emerging markets.

Table 1.1 Statistical Summary (ESGU, VICE)

	ESGU	VICE
count	277.000000	277.000000
mean	-0.040756	-0.003838
std	1.387706	1.425211
min	-4.143643	-5.469463
25%	-0.784575	-0.769122
50%	0.088942	0.074265
75%	0.762135	0.765051
max	3.941730	4.158383

Each ETF or index's close price was collected from Yahoo Finance with daily frequency from January 29, 2019 to January 26th, 2024. Close price was then calculated into daily return over the last day. The datasets are 'differenced until stationary', and observations left are 277 for each variable. Both indices show a similar range of performance with VICE having a slightly higher extreme loss and gain as well as a bit more volatility. However, the average performance of ESGU was slightly more negative than that of VICE. Both distributions appear to be left-skewed since the mean is less than the median.

Table 1.2 Selected 50 Samples Daily Returns (ESGU, VICE)



2. VAR Model and Impulse Response

Here is the Vector Autoregression (VAR(2)) model with two equations, ESGU and VICE, and a lag order of 2.

Table 2.1 Summary of Regression, Correlation Matrix of Residuals, Granger Causality Test (ESGU & VICE)

```
lag order: 2
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Mon, 29, Jan, 2024
Time:                     20:57:53
--------------------------------------------------------------------
No. of Equations:         2.00000    BIC:                    1.00750
Nobs:                     216.000    HQIC:                  0.914367
Log likelihood:          -694.915    FPE:                    2.34258
AIC:                     0.851236    Det(Omega_mle):         2.23778
--------------------------------------------------------------------
Results for equation ESGU
==========================================================================
             coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------
const           0.108442         0.084981            1.276           0.202
L1.ESGU        -0.244261         0.071420           -3.420           0.001
L1.VICE         0.068379         0.069849            0.979           0.328
L2.ESGU         0.078944         0.071886            1.098           0.272
L2.VICE         0.011438         0.069842            0.164           0.870
==========================================================================

Results for equation VICE
==========================================================================
             coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------
const           0.038413         0.086947            0.442           0.659
L1.ESGU        -0.079625         0.073073           -1.090           0.276
L1.VICE        -0.047250         0.071466           -0.661           0.509
L2.ESGU         0.183046         0.073549            2.489           0.013
L2.VICE        -0.076561         0.071458           -1.071           0.284
==========================================================================

Correlation matrix of residuals
            ESGU      VICE
ESGU    1.000000  0.303585
VICE    0.303585  1.000000


Granger causality F-test. H_0: VICE does not Granger-cause ESGU. Conclusion: fail to reject H_0 at
5% significance level.
==============================================
Test statistic Critical value p-value    df
----------------------------------------------
        0.4835          3.017   0.617 (2, 422)
----------------------------------------------
Granger causality F-test. H_0: ESGU does not Granger-cause VICE. Conclusion: reject H_0 at 5%
significance level.
==============================================
Test statistic Critical value p-value    df
----------------------------------------------
         4.502          3.017   0.012 (2, 422)
```

For equation ESGU:

$$ESGU_t = 0.10_{ESGU} + (-0.24)ESGU_{t-1} + 0.06VICE_{t-1} + 0.07\ ESGU_{t-2} + 0.01VICE_{t-2} + \epsilon_{ESGU,t}$$

The constant (intercept) for ESGU is 0.108442, and it is not statistically significant at the 5% level (p-value = 0.202). The coefficient for L1.ESGU is -0.244261, and it is statistically significant at the 0.1% level (p-value = 0.001). This suggests that the past value of ESGU negatively influences its current value. The coefficient for L1.VICE is 0.068379, but it is not statistically significant (p-value = 0.328). The coefficients for the second lag (L2) of ESGU and VICE are 0.078944 and 0.011438, respectively. None of them is statistically significant.

Granger Causality Test

The Granger causality tests assess whether one variable can predict changes in the other. The test for VICE on ESGU, it fails to reject the null hypothesis (p-value = 0.617), suggesting that VICE does not have a statistically significant predictive power for ESGU.

For equation VICE:

$$VICE_t = 0.038_{VICE} + (-0.079)ESGU_{t-1} + (-0.047)VICE_{t-1} + 0.183ESGU_{t-2} + (-0.076)VICE_{t-2} + \epsilon_{VICE,t}$$

The constant (intercept) for VICE is 0.038413, and it is not statistically significant at the 5% level (p-value = 0.659). The lagged values of ESGU and VICE are used as predictors in the model. The coefficient for L1.ESGU is -0.079625, but it is not statistically significant (p-value = 0.276). The coefficient for L1.VICE is -0.047250, and it is not statistically significant (p-value = 0.509). The coefficient for L2.ESGU is 0.183046, and it is statistically significant at the 1% level (p-value = 0.013). However, the relationships are not very strong. The coefficient for L2.VICE is -0.076561, but it is not statistically significant (p-value = 0.284).

Granger Causality Test

In contrast, the test for "ESGU does not Granger-cause VICE" rejects the null hypothesis at the 5% significance level (p-value = 0.012), indicating that ESGU does Granger-cause VICE, meaning past values of ESGU provide information that helps predict VICE.

Table 2.2 Granger Causality and Correlation Matrix of Residuals

	ESGU_coeff	ESGU_pvalue	VICE_coeff	VICE_pvalue
const	0.108	0.202	0.038	0.659
L1.ESGU	-0.244***	0.001	-0.08	0.276
L1.VICE	0.068	0.328	-0.047	0.509
L2.ESGU	0.079	0.272	0.183**	0.013
L2.VICE	0.011	0.870	-0.077	0.284

Correlation matrix of residuals

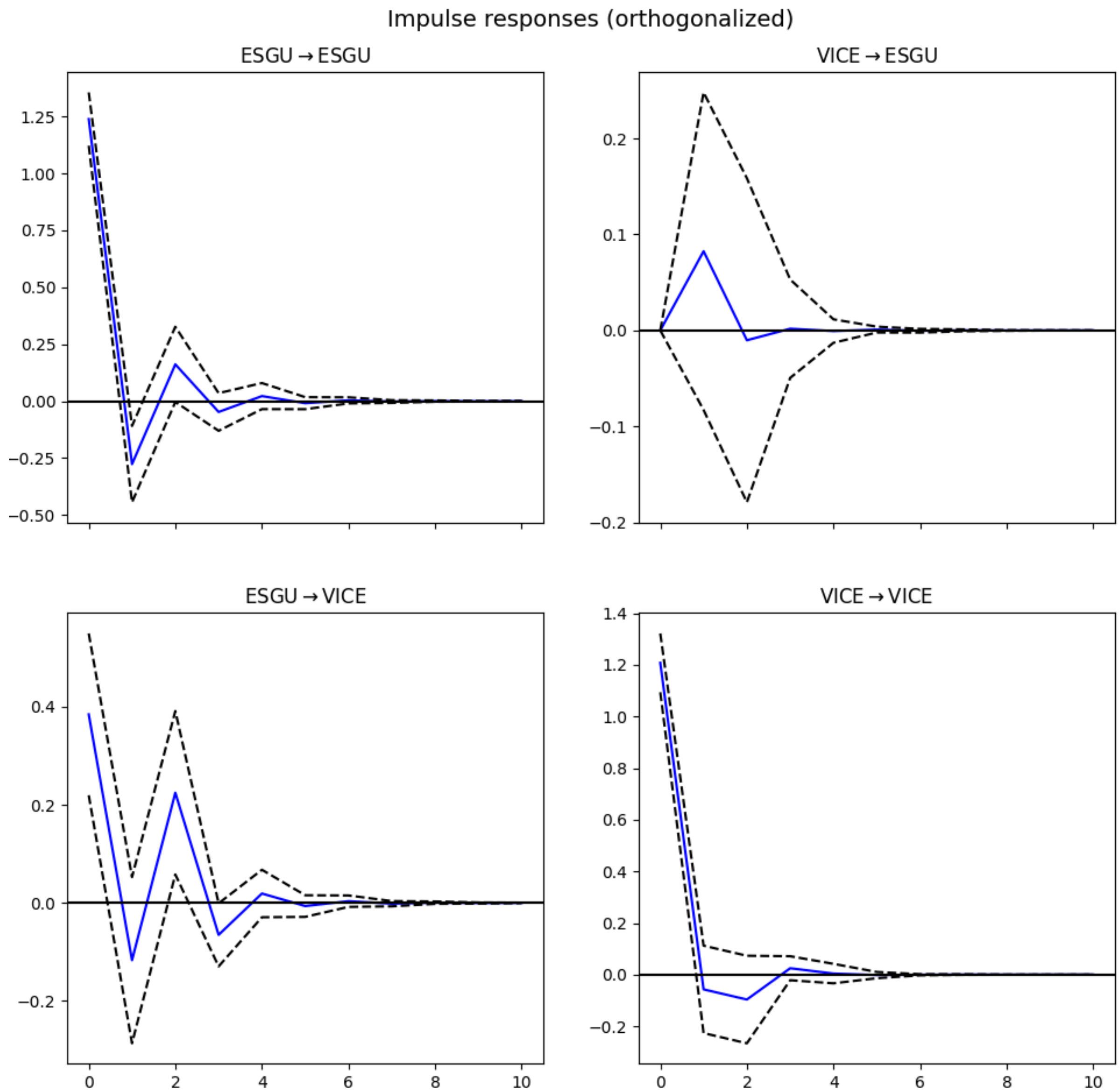
	ESGU	VICE
ESGU	1.000000	0.303585
VICE	0.303585	1.000000

The correlation between the residuals of ESGU and VICE is 0.303585, indicating some degree of correlation between the two variables' unexplained variations. It is potentially due to systemic risks on stock market against bond market especially during economic turning points, where bond market or gold are considered investment alternatives to stocks.

3. Impulse Response and Forecasting

Impulse Pulse Response Analysis evaluates the mechanisms of shock transmission and systemic risk in financial markets. It is the method used to study the propagation effects of shocks in VAR (Vector Autoregression) models, assisting the understanding of the interactions and reactions between different variables in financial markets.

Table 3.1 Impulse Response ESGU and VICE



VICE → ESGU: This shows the ESGU's response to a shock to VICE. The point estimate shows a very small positive response initially at first period, but quickly stabilizes, suggesting that shocks in VICE have little to no lasting impact on ESGU. The confidence level is wide, which might indicate the insignificance of the relationship.

ESGU → VICE: This is the response of VICE to a shock in ESGU, which has more rooms for interpretations. The initial response was positive and turned negative in the first period, then VICE return rose again in the second period. It decreased again in the third period and fluctuated for another three periods before it stabilized. A positive ESG shock may reflect an overall market optimism which might increase investors' risk appetite, leading to a short-term boost in VICE stocks, which is perceived as riskier investments. ESGU includes companies from various companies but mostly concentrated by the 'Magnificent 7' tech firms(iShare, n.d.). A positive shock in ESGU return, could also lead to investors to flood into its underlying composing stocks with higher volatility but potentially greater returns.

The lower bound of the confidence interval crosses 0 at t=2, which aligns with the VAR result. The significant positive coefficient for the second lag of ESGU in VAR(2) model suggests that it takes time for the impact of ESGU to be reflected in VICE return. The delayed effect could be due to the time it takes for the investors to digest ESG news. However, the mixed reaction on ESGU shock might imply that ESGU and VICE are not substitutes for each other, and a shock in one sector would not necessarily lead to investors fleeing into the other fund.

The response could reflect a complex and indirect relationship between ESG and anti-ESG sectors in the financial markets, where factors other than ESG compliance may be driving the performance of VICE stocks. For instance, investors could be using VICE stocks to hedge against ESG stocks, or there could be a rebalancing of portfolios following an ESG shock that temporarily affects VICE stocks.

4. ESG and Financial Distress

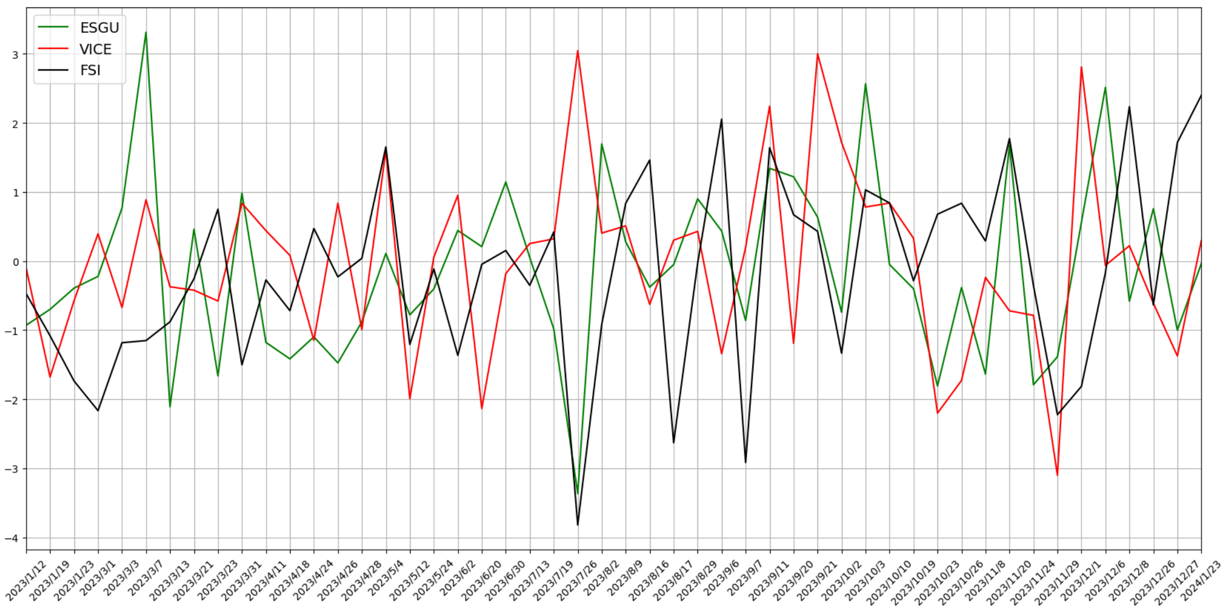
Understanding how ESG and anti-ESG indices react to market distress is another way to interpret their relationship. Therefore, this section uses 3 variables to do the VAR model.

Table 4.1 Statistical Summary (ESGU, VICE, FSI)

	ESGU	VICE	FSI
count	277.000000	277.000000	277.000000
mean	-0.040756	-0.003838	0.067432
std	1.387706	1.425211	1.377704
min	-4.143643	-5.469463	-4.532599
25%	-0.784575	-0.769122	-0.714425
50%	0.088942	0.074265	0.000000
75%	0.762135	0.765051	0.834226
max	3.941730	4.158383	6.216606

This statistical summary reveals VICE is more volatile compared to ESGU in both downside and upside.

Table 4.2 Last 50 Observations Daily Returns (ESGU, VICE, FSI)



In *Table 4.4*, the lack of significant p-values for the lagged terms of ESGU, FSI, and VICE showed that these do not have strong linear predictive relationships. The significant constant for FSI suggests a trend within the FSI itself, and the significant lag of FSI in its own equation indicates some predictability of the FSI based on its own lagged values.

Table 4.3 Granger Causality and Table of Coefficients

```
Granger causality F-test. H_0: ['ESGU', 'FSI'] do not Granger-cause VICE. Conclusion: fail to
reject H_0 at 5% significance level.
=============================================
Test statistic Critical value p-value    df
---------------------------------------------
        0.7350          3.010   0.480 (2, 648)
---------------------------------------------
Granger causality F-test. H_0: ['VICE', 'FSI'] do not Granger-cause ESGU. Conclusion: fail to
reject H_0 at 5% significance level.
=============================================
Test statistic Critical value p-value    df
---------------------------------------------
         1.330          3.010   0.265 (2, 648)
---------------------------------------------
Granger causality F-test. H_0: ['ESGU', 'VICE'] do not Granger-cause FSI. Conclusion: fail to
reject H_0 at 5% significance level.
=============================================
Test statistic Critical value p-value    df
---------------------------------------------
        0.8616          3.010   0.423 (2, 648)
---------------------------------------------
```

	ESGU_coeff	ESGU_pvalue	VICE_coeff	VICE_pvalue	FSI_coeff	FSI_pvalue
const	-0.044	0.634	-0.051	0.605	0.168*	0.065
L1.ESGU	-0.21***	0.003	-0.082	0.266	-0.056	0.414
L1.VICE	-0.1	0.145	-0.081	0.261	-0.052	0.438
L1.FSI	-0.033	0.645	0.05	0.500	-0.199***	0.004

The positive correlations in the residuals suggest that there may be unmodeled factors or omitted variables that are influencing the indices similarly. Potentially, it could be the broader economic or market factors affecting both ESGU and VICE that are not captured by the models. However compared to the ESGU and VICE in *Table 2.2*, having FSI have lowered the values, implying FSI is capturing the systematic turmoil that is influencing the stock market.

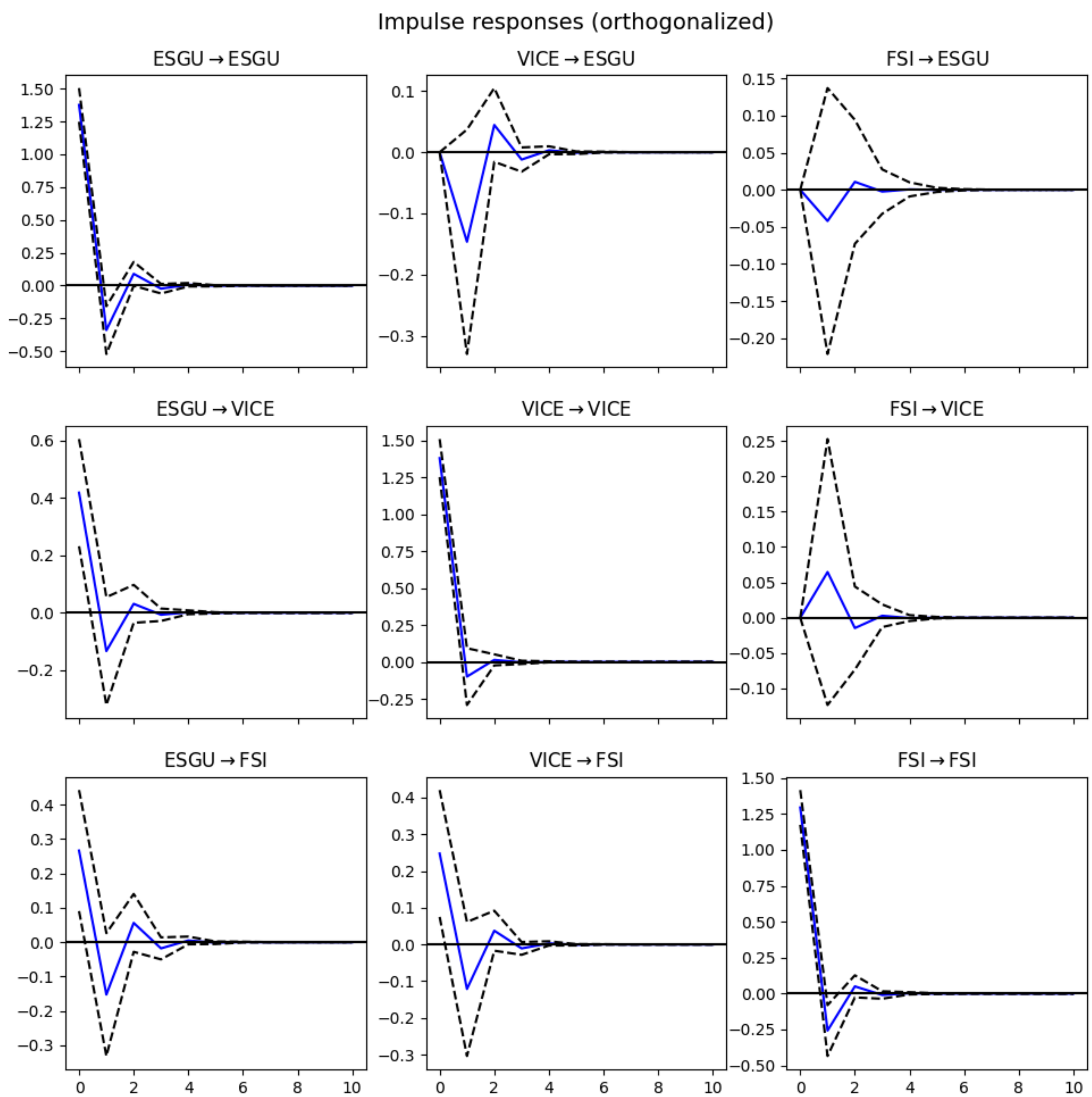
Table 4.4 Summary of Regression Results, Correlation Matrix of Residuals

```
lag order: 1
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Mon, 29, Jan, 2024
Time:                     23:55:22
--------------------------------------------------------------------
No. of Equations:         3.00000    BIC:                    2.03658
Nobs:                     220.000    HQIC:                   1.92623
Log likelihood:          -1128.16    FPE:                    6.36928
AIC:                      1.85148    Det(Omega_mle):         6.03413
--------------------------------------------------------------------
Results for equation ESGU
==========================================================================
             coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------
const          -0.044461         0.093386           -0.476           0.634
L1.ESGU        -0.209679         0.070397           -2.979           0.003
L1.VICE        -0.100281         0.068740           -1.459           0.145
L1.FSI         -0.032521         0.070620           -0.461           0.645
==========================================================================

Results for equation VICE
==========================================================================
             coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------
const          -0.050669         0.097867           -0.518           0.605
L1.ESGU        -0.081991         0.073775           -1.111           0.266
L1.VICE        -0.080978         0.072038           -1.124           0.261
L1.FSI          0.049871         0.074008            0.674           0.500
==========================================================================

Results for equation FSI
==========================================================================
             coefficient       std. error           t-stat            prob
--------------------------------------------------------------------------
const           0.168371         0.091337            1.843           0.065
L1.ESGU        -0.056277         0.068852           -0.817           0.414
L1.VICE        -0.052158         0.067231           -0.776           0.438
L1.FSI         -0.198761         0.069070           -2.878           0.004
==========================================================================

Correlation matrix of residuals
            ESGU      VICE       FSI
ESGU    1.000000  0.289880  0.198200
VICE    0.289880  1.000000  0.233676
FSI     0.198200  0.233676  1.000000
```

Granger Causality Test results with the regression models showed again there are no strong relationships between ESGU, VICE and FSI. Adding FSI, notably, made ESGU(t-2) no longer significant to VICE(t). FSI does not improve the VAR(2) ESGU and VICE model fit, and changes are statistically insignificant.

5. Impulse Response and Forecasting

Table 5.1 Impulse Response (ESGU, VICE, FSI)



VICE → ESGU: Adding FSI into the model, ESGU perceives the shock in VICE in the negative reactions, which is different from the previous VAR(2) VICE model, where they moved in the same direction.

FSI → ESGU: ESGU responds to a FSI shock in a negative direction as well. One interpretation could be that under a rising financial distress environment, some investors sell ESGU. The response was short-lived, where it quickly stabilized after the 2nd period.

FSI → VICE: Compared to FSI → ESGU, the graph is intriguingly different, which affirms their relationship under financial stress periods. During financial stress times(index goes up), the return for VICE goes up as well, indicating the market may favor vice industries over ESG investments.

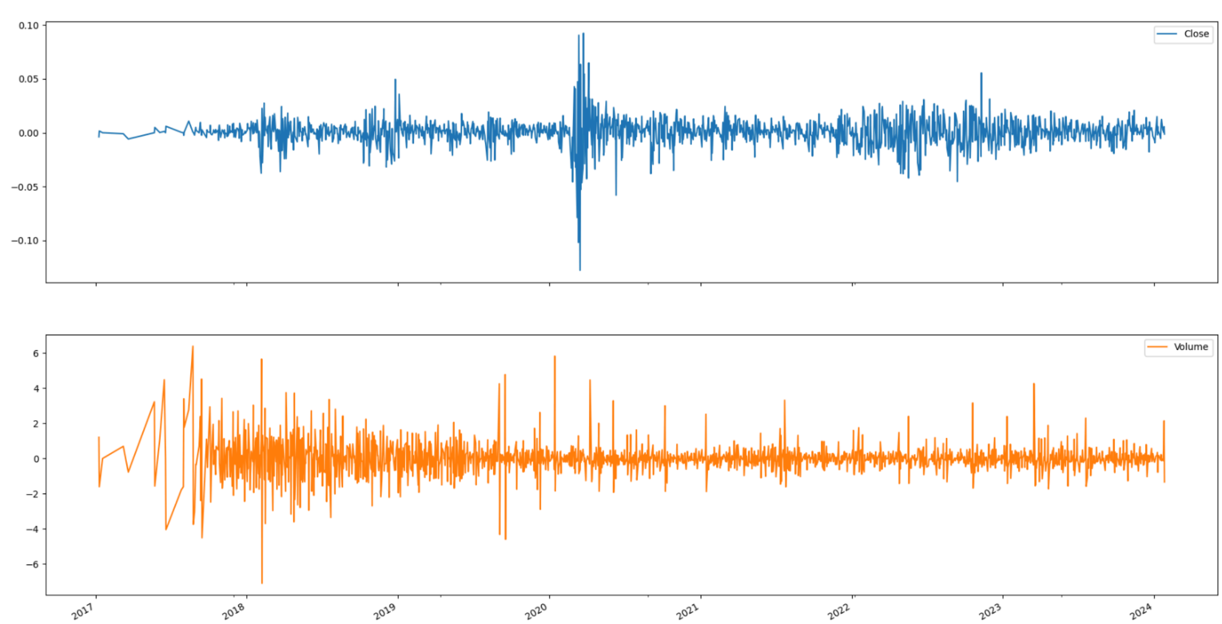
ESGU's negative response during an upward trend of FSI could be explained by investors' prioritizing liquidity and short-term gains over long-term benefits of ESG investing. This does not necessarily indicate a migration away from ESG-focused markets; rather, it could imply that the VICE index, representative of sectors less aligned with ESG principles, exhibits relative resilience during periods of financial turbulence.

Conversely, when FSI goes down, typically characteristic of economic expansion and heightened consumer confidence, it implies ESGU's better performance. However, the statistical insignificance within the model's results tempers the reliability of such interpretations. To enhance the analysis, it would be prudent to incorporate additional indicators reflective of robust economic growth.

The current models provide insufficient evidence to testify Hypothesis 2, which posits that ESG indices would demonstrate less volatility compared to anti-ESG indices during financial stress periods. In fact, the opposite appears plausible, with anti-ESG indices like VICE seemingly benefiting during times of financial duress. This challenges and prompts a re-evaluation of Hypothesis 2, inviting new perspectives on the dynamics at play.

6. ARIMA in Forecasting ESGU

Table 6.1 Stationary Stock Return and Trading Volume



The stock price was stationary using the ADF test. Thus it differenced until stationary for the ARIMA model. (ADF Statistic: -0.8451, p-value: 0.8054)

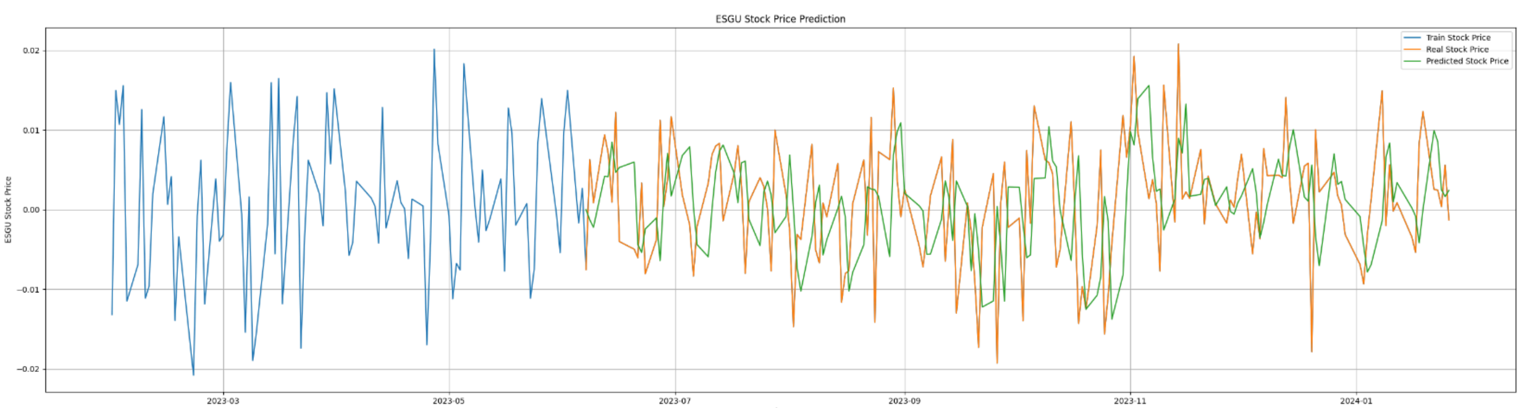
Table 6.2 Error Summary

Error Metric	In-Sample	Out-of-Sample
MSE	0.0002591633951895605	7.655894820925744e-05
MAE	0.01070345899224046	0.007142917208708879
RMSE	0.0160985525805757	0.008749797038175083

It is unusual to see the Out-of-Sample error terms lower than the In-Sample numbers, suggesting the model is better at predicting unseened data compared to the data it was trained with. The stock market often goes through dynamic changes. If the test period happens to coincide with a more stable regime, the prediction might seem more accurate. And for stock return, factors not included in the model, such as macroeconomic indicators or global events, can influence stock prices. If such factors had a more significant impact during the training period than the testing period, they might contribute to higher in-sample errors.

The ARIMA model is ARIMA(1,1,0), where autoregressive order is 1, order of differencing is 1 and moving average order is 0.

Table 6.3 ARIMA Forecast



From *Table 6.3*, the predicted stock price (green line) follows fairly closely with the real stock price (orange line) in the latter part. that the ARIMA model has forecasted the test set with a reasonable degree of accuracy. In addition, the prediction exhibits a slight lag and tends to have a smaller magnitude compared to the actual returns.

7. LSTM in Forecasting ESGU

This section is to extend on the models, and to trial with multivariate Long Short-Term Memory (LSTM) models to project ESGU Close price for the next 14 trading days. Usually 2 weeks should be 10 days of trading days, however for simplicity, 14 days is used to forecast. The previous models used *Log(Return)* values, here for LSTM, *Close* prices are used.

Table 7.1 Data Parameters

	Date	Open	High	Low	Close	Adj Close	Volume
0	2016-12-06	48.259998	48.259998	48.259998	48.259998	43.278954	100
1	2016-12-07	48.259998	48.259998	48.259998	48.259998	43.278954	0
2	2016-12-08	48.259998	48.259998	48.259998	48.259998	43.278954	0
3	2016-12-09	48.259998	48.259998	48.259998	48.259998	43.278954	0
4	2016-12-12	48.259998	48.259998	48.259998	48.259998	43.278954	0

Table 7.2 Stock Price Trend

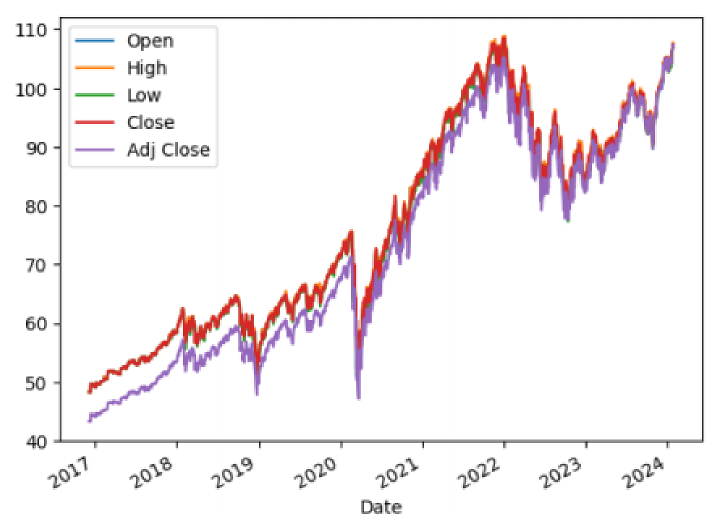
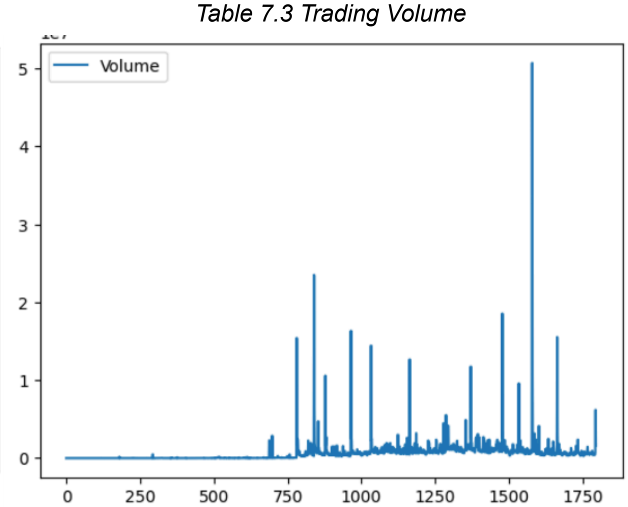


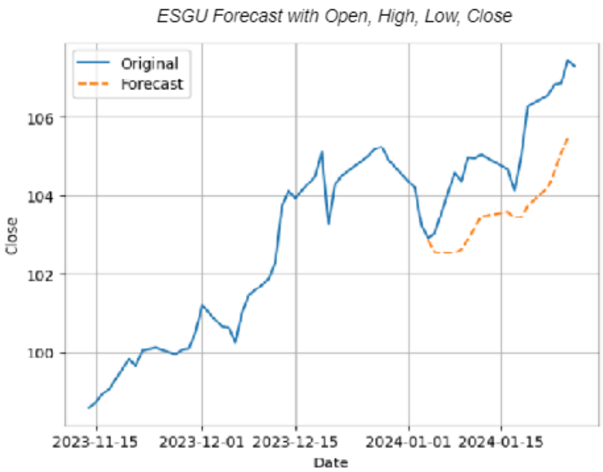
Table 7.3 Trading Volume

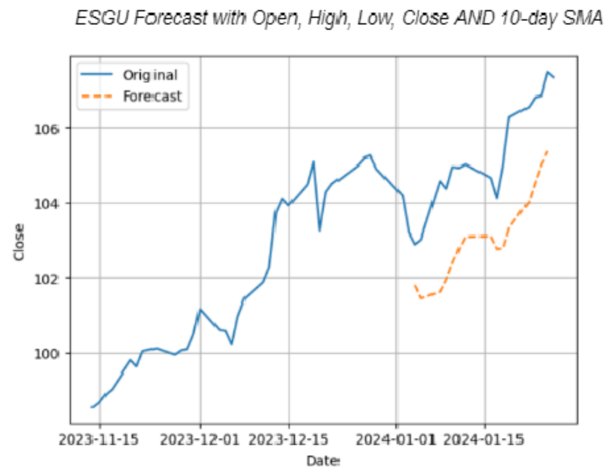


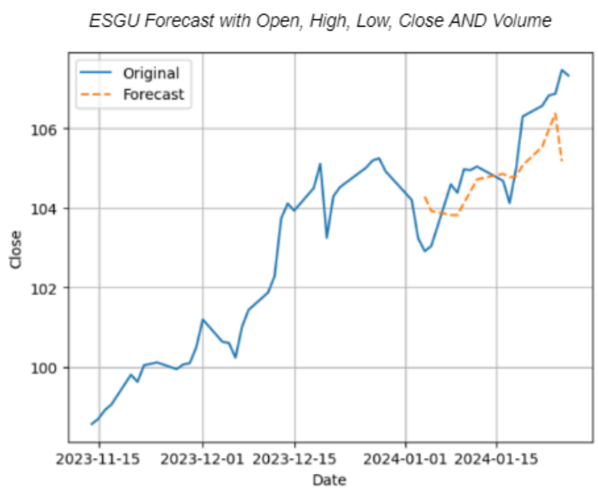
The parameters are constantly adjusted to test whether adding or removing *Volume* improves the model accuracy or not. Data from December 6th, 2016 to January 26th, 2024 are retrieved from Yahoo Finance. The parameter sets aside 10% of the training data for validation. And *Epoch*, the iterations are 10 for every model.

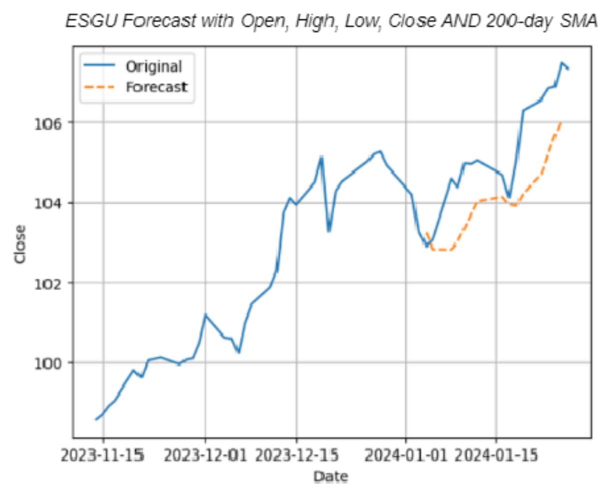
Other parameters are also considered, for example Simple Moving Averages(SMA) (10-day, 20-day, 50-day, 100-day, and 200-day) and Volume Weighted Average Price(VWAP). 10-day SMA, for example, is adding up the closing prices of the stock for the last 10 days then divided by 10 days. Therefore, observations for 10-day SMA add-on are 10 observations less. VWAP, due to lack of source to retrieve the data, was not modeled.

Table 7.4 Table Results









index	**MAE**	**MSE**	**RMSE**	**MAPE**
without adds	56.246786	3164.483622	56.253743	114.453098
with Volume	53.292216	2840.38281	53.295242	108.44703
with 10-day SMA	53.63412169	2877.88733	53.6459442	108.4858732
with 50-day SMA	51.131458	2614.822678	51.135337	99.546461
with 100-day SMA	51.359501	2638.271017	51.364102	98.002213
with 200-day SMA	48.878002	2389.496003	48.882471	88.587597

If interpretation is solely based on the error stats. Without additional features, the model's performance is the least efficient, showing the high errors across all metrics. Adding 200-day SMA as a feature slightly improves the model's accuracy, as indicated by lower error metrics. Incorporating SMAs further refines the predictions. 50-day and 100-day SMAs show progressively better performance, with the 50-day SMA yielding significantly lower errors, suggesting a more accurate model. The 200-day SMA model exhibits the best performance among the variations, with the lowest errors across all metrics, indicating the highest predictive accuracy and efficiency.

From forecast figures in *Table 6.4*, adding volume seems to remove some magnitude (i.e. 2024.01.15 forecast point) and is smoother. 10-day SMA produced lower forecast prices in general than the actual prices. In general, adding these features do not seem to change much for the LSTM model.

Conclusion

This study employed VAR to assess the interplay between ESG and anti-ESG indices and ARIMA as well as LSTM to forecast ESG stock return/price. The first VAR(2) model, testified with Granger Causality test, revealed how 2 period lagged ESGU return is statistically significant to current VICE return, signaling a delayed response by anti-ESG investors to ESG-related news. The second VAR model, even though flawful, revealed potential inverse relationship between ESG and anti-ESG stocks during financial distress. Anti-ESG showed its resilience while the ESG index struggled in the U.S. market.

For ESGU forecasting, the ARIMA model displayed unusual predictive accuracy, with out-of-sample errors being lower than in-sample errors. This anomaly, while positive, calls for careful scrutiny. It might reflect a stable period in the test data or less impactful macroeconomic influences. The LSTM model, tested for its capability to project ESGU prices, suggested that additional features such as SMAs might not significantly alter LSTM's predictive power, although incorporating ‘200-day SMA’ yielded better predictions.

The U.S. 's market has high financial market turnovers(liquidity) and high efficiency, where there’s less likely to have asymmetrical information. Therefore, market reactions are easier to be captured than in other markets. However, while researching the subject on ESG, the U.S. market is typically considered the shareholder-oriented market, where the E.U. market favors stakeholders. Therefore, in the U.S., until most investors favor ESG-investing, the companies are not incentivized to change. Bril *et al*(2022) in their book discussed how prioritizing ESG issues are often tied with investors’ age, wealth, and geographic parameters. Cases by BlackRock investment in fossil fuel and removal of sustainability departments as well as uncredible ESG standards in the U.S. market are examples of investors' sentiments to some extent.

Until the next institutional change, ESG might only gradually influence investors’ preferences and decisions. The EU countries are significantly more supportive, where numerous policies and regulations are in place to promote ESG-related issues(Bril *et al*, 2022). Other countries constantly used the EU’s environmental tariffs and green-bond standards as benchmarks(Bril *et al*, 2022). The study on ESG should be extended towards consolidating the subject of ESG in the EU's market, relative to the U.S. market.

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