Green Bond Funds (NAV) and Oil Prices: A Multivariate Analysis of European Union

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Introduction

In recent years, the definition of economic development has changed remarkably. The developed stage in an economy is no longer described by macroeconomic indicators like GDP growth, FDIs and exchange rates alone but by also how efficiently the cost of this development can be managed. One of the major costs thought of here is the pressure on the climate. Sustainable economic development aims at minimizing negative impacts of economic expansion on the climate which can be done by "greening" the economy using instruments like Green Bonds (UNESCO,2011). Green Bonds are fixed-income instruments that are heralded to raise money for projects having a positive environmental impact. They are considered an optimal entry in the portfolio for an environmentally aware investor.

On the other hand, according to the Paris Agreement in 2015, the shift from fossil fuels as the primary source of power generation to myriad renewable sources of energy is a significant effort directed at sustainable development. Switching over to climate friendly energy sources help reduce the level of carbon emissions (Yadav et al., 2022) which is vital for a cleaner ecosystem. As a consequence of this move, the demand for crude oil and therefore its price has been affected reasonably. Hence, it is evident that the rise of green bonds and the use of crude oil as fuel in presence of a cleaner alternative cannot be factored into the same objective.

Objective & Policy Relevance

While discussing Green Bonds and Crude Oil, it is essential to comprehend the theory underlying how these two disparate ideas with opposing goals function together in the current real-world context. Performance of Green Bonds on the other hand can be monitored closely by realizing the performance of some major companies taken together that share the same purpose as the former. These companies invest the majority of their assets into climate heavy projects and green bonds thereby contributing directly to its demand and other related favorability matrices (like prices, returns, etc.). This paper attempts to answer the following research questions in this regard –

1. Do crude oil prices share a relationship with the growth of these climate friendly companies that hold huge investments in green bonds and other climate related projects?

2. How will this growth react to external shocks arising on the oil side?

Paris Agreement (2015) and the United Nations Conference on Trade and Development (UNCTAD, 2014) have set multiple targets and organized schemes that align with the idea of a climate-resilient global development schedule. For instance, as per the UNCTAD estimates, $5 to $7 trillion in annual investments are needed to meet Sustainable Development Goals (SDGs) by 2030 (Tolliver et al., 2019). On the other hand, according to the International Energy Agency, an estimated $53 trillion in energy-oriented investments by 2035 is required to maintain the 2-degree Celsius temperature threshold stated in the Paris Agreement (Tolliver et al., 2019). The Green Climate Fund (GCF) is another climate green finance instrument that channels its investments into curbing GHG emissions in emerging economies that reside on the growth trajectory. All these initiatives emphasize on the importance of environmentally-aware financial decision making that have started to pan out as major determinants while choosing an investment option, amidst many. Green Bonds, thus in this scenario act as a very safe green financing opportunity (Ng and Tao, 2016). Therefore, with green financing being on the radar, it is imperative to work out an incentive for large corporations to invest in climate positive projects and an important way to understand this is by understanding their valuations. Valuations for a large conglomerate help to analyze the profitability, credibility and fundamentals of the company and attract funding from investors funneling growth. Movement of the crude oil prices are used to replicate the event of gradually shifting to renewable alternatives resembling the green outcomes that are actually realized in the economy. Estimating its influence on the valuations of major companies will explain if greener outcomes invite volumes of growth and strengthen the incentives. This would in turn govern if investments in green finance help encourage corporate growth and also if unfolding of greener outcomes would attract green investments in reality. Hence, the research objective highlighted here is instrumental in expressing the motivation behind green financing through a lens that does not capture climate narrative alone. Its relevant to the policies that promote investments in climate positive projects by shedding light on the investors' perspectives that would ultimately welcome money into the system.

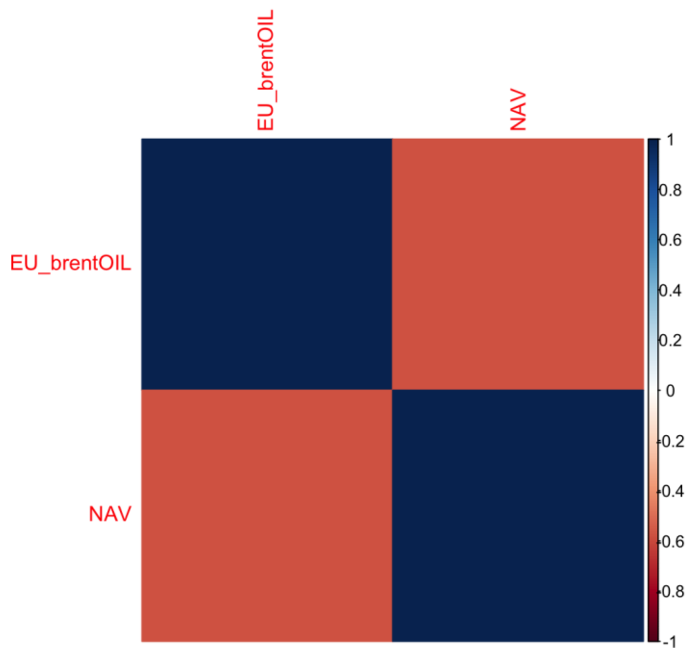
This analysis is done for Europe as it has shown significant interest in support of a climate sensitive paradigm and has been a flagbearer in developing standards and targets to meet the SDG demands of the future.

Literature Review

With the advent of the technology boomerang experienced by the world in the last few decades, the trajectory of economic growth and development as an increasing function of technology has been non-negotiable. However, with pros comes its cons and this technology led growth is coupled with incremental carbon emissions, depletion of ozone layer, rise in Earth's annual temperature, etc. resulting from usage of fossil fuels as primary sources of power generation. Therefore, climate experts around the world have legitimized multiple control targets to combat climate hazards and the Paris Agreement (2015) and United Nations Development Program (UNDP) hosted pioneers for the same. Under the SDG framework, an estimate of $5 to $7 trillion annual investments through 2030 is required to meet the climate-oriented agendas. Similarly, the International Energy Agency (IEA) has said that an approximated energy-related investment of $53 trillion is needed by 2035 to maintain the 2-degree temperature threshold formalized by the Paris Agreement (Tollivar et al., 2019). Governments all over the world are actively promoting mobility in green technology and greener outcomes (Kai-Hua Wang et al., 2022). These climate subjective investments require massive capital inflows led by large private corporations and holdings. Incentives to invest for private sectors on the contrary have been earmarked as low due to green projects having poor yields over the long run combined with unique dangers (Yoshino et al., 2019). As a result, the need for a financial instrument that attracts green investors by projecting long run returns on the projects is strengthened leading to the birth of climate bonds namely – green bonds, water bonds and carbon bonds.

Data

To measure the valuation metric of the major companies, the security chosen is Franklin Euro Green Bond UCITS ETF which primarily trades on London Stock Exchange, Swiss Exchange and Borsa Italiana. It is an exchange traded fund with an aim to maximize total overall returns for 90 holdings. The fund allocates at least 75% of its Net Asset Value to green bonds whereas the remaining is invested in other climate related bonds providing an exposure to the green bond market. Net Asset Value (NAV) represents the net value of an entity which is calculated as the total value of the entity's assets minus the total value of its liabilities. This ETF mirrors the Green Bond Price Index very closely as most of its investments are in fact within green bonds. Majority of the bonds the fund invests in are valued in EUR with an average credit quality A+. The ETF operates across multiple geographies with around 90% operations in Europe. The values used in the analysis are the daily trading data on Net Asset Value (NAV) of this ETF, reported in euros, taken for a period of 4.5 years from 30/04/2019 to 30/10/2023 which is roughly 1,162 observations. Data is collected from Franklin Templeton website and is our time-dependent dependent variable. Independent variable is the daily data on Brent Crude Oil Prices (COPs) denominated in EUR for the same period as mentioned before taken for Europe as a whole. Brent COPs majorly trades on the International Petroleum Exchange in London. The data is picked from Federal Reserve Economic Data.



The correlation between NAV and COP as indicated by the heat map is -0.5 which is really strong and is a good precursor to begin the analysis with.

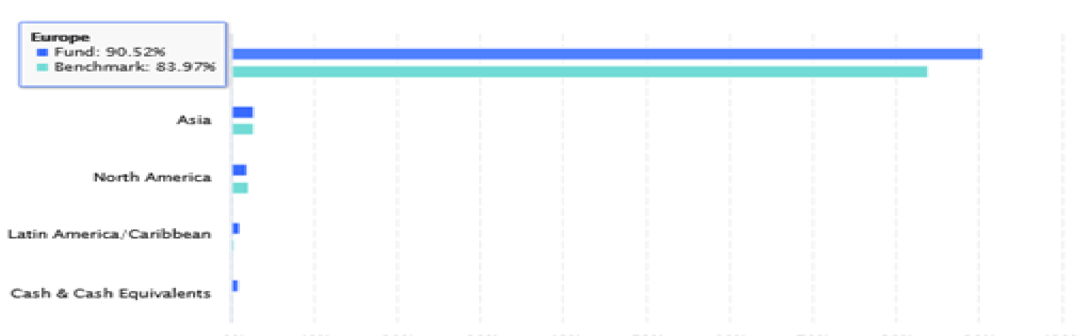
Portfolio Statistics

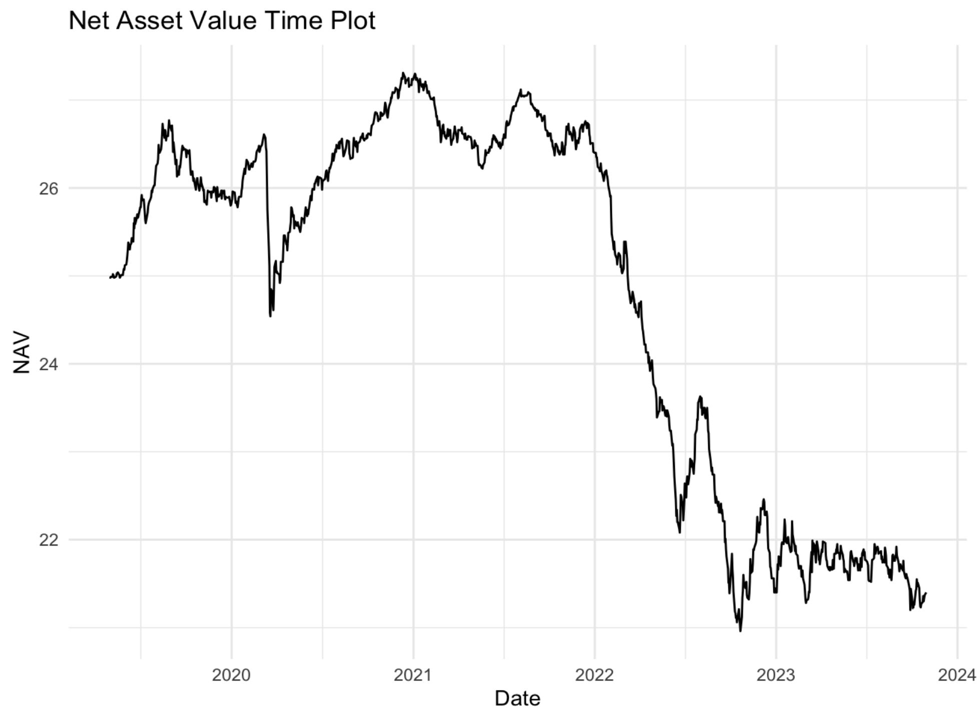
As of 01/11/2023 Updated Daily

	Fund	Benchmark
Option Adjusted Spread	113.45 Yrs	110.86 Yrs
Average Credit Quality [5]	A+	A+
Average Weighted Maturity	8.76 Yrs	8.04 Yrs
Yield to Maturity [6]	4.00%	3.94%
Effective Duration	7.50 Yrs	7.02 Yrs
Yield to Worst	3.96%	3.94%

Geographic Exposure

As of 01/11/2023 Notional Exposure % of Total Updated Daily





Methodology

To capture the impact of fluctuations in COPs on the overall value-based growth experienced the following equation was stated -

$$NAV \ = f\ (NAV, Crude\ Oil\ price) \ - \ equation\ (1)$$

Where , NAV = Net Asset Value (in EUR) = Total Value of Assets - Total Value of Liabilities
Crude Oil Price = Daily Close Prices of Brent Crude Oil traded on the NYMEX

DIAGNOSTIC CHECKS

The precondition for any time series analysis usually starts with exercising a stationarity check (Burange et al., 2019) that identifies the presence of a unit root in the model. Augmented- Dickey Fuller test is used to check the stationarity of both the time series variables separately with null hypothesis stating non stationarity and alternative stating stationarity. On identifying non-stationarity in both the variables, we proceed to integrate them into differenced series resulting in the choice variables becoming I (1). Therefore, independent and dependent variables get transformed into Return on Crude Oil Prices and NAV Change (expressed as %) respectively.

Since both the variables are I(1) , in order to understand the short run and long run dynamics between them, it is necessary to check for a cointegrating relationship using Johansen Juselius Cointegration Test. Cointegration Analysis attempts to establish if a linear combination between two time series variables is stationary in nature, i.e., if the two series are moving together during shorter and longer time intervals. Having a single cointegrating factor suggests the presence of a long-term trend between the variables. Presence of cointegration supports the usage of VECM representation of VAR over Structural/Reduced VAR.

EMPIRICAL ANALYSIS

Initially the analysis is approached through Vector Auto Regression as a means to explain the underperformance of that model while explaining both the long and short run trends. VAR is used to regress the dependent variable NAV Change (%) on its own past terms and on the current and the past terms of our independent variable COP Returns. The inclusion of current value for COP returns might lead to a presence of contemporaneous as there might exist a bidirectional causality between the two and COP return at current time period might not remain entirely exogenous. This would disturb the model known as Structural VAR. Thereby, we need to convert it into a Reduced form VAR to combat this issue of endogeneity and will deem COP returns exogenous by excluding just the current value of the same. VAR uses Ordinary Least Squares method for estimation.

Impulse Response Function is realized on VAR to understand the behavior of NAV Change (%) when one standard deviation unit shock is given to COP Returns. Furthermore, the Variance Decomposition Analysis explains how the variance of the variables can be decomposed into smaller components each of which is contributed by the respective variances of the factors present on the explanatory side.

STABILITY

Granger's Causality is used to validate the presence of causality between two-time variables, i.e., if the independent variables actually cause the dependent variables or not. Null hypothesis is that the past values of COP Returns cause changes in the present value of NAV Change (%). The alternative hypothesis is the negation of the null statement. Granger's causality is also used to test the stability of the VAR Model.

Durbin - Watson Test is exercised on the residuals of VAR models to trace the presence of autocorrelation (if any) for the error terms. The null hypothesis is no autocorrelation between errors. Jarque-Bera Test is used to check if the residual errors are normally distributed or not. Null hypothesis for the same is that the errors are normally distributed. All of these acts as stability checks to understand the fitting of the respective models.

Results

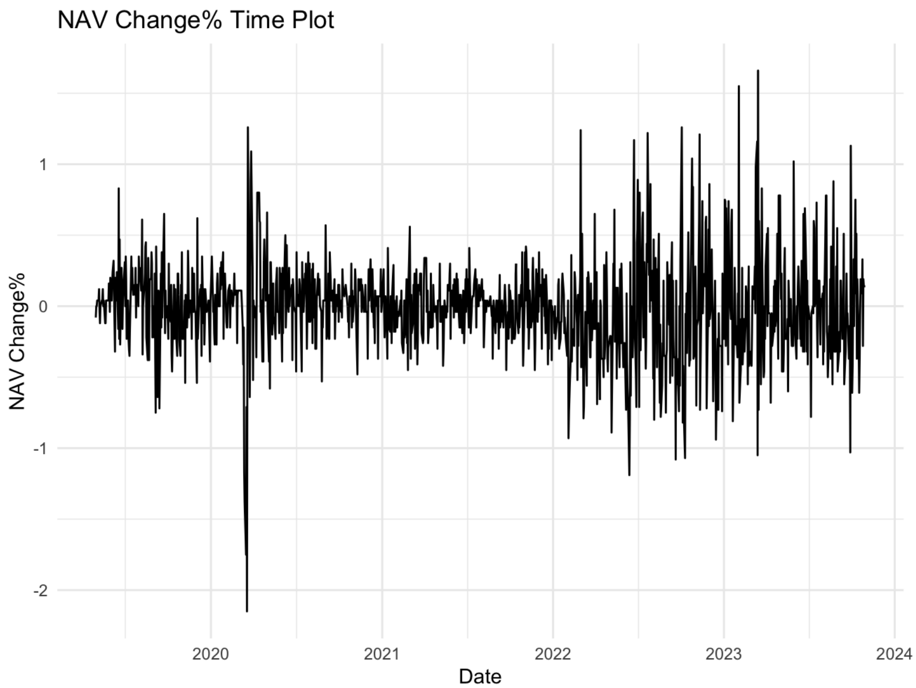
Augmented Dickey-Fuller Test

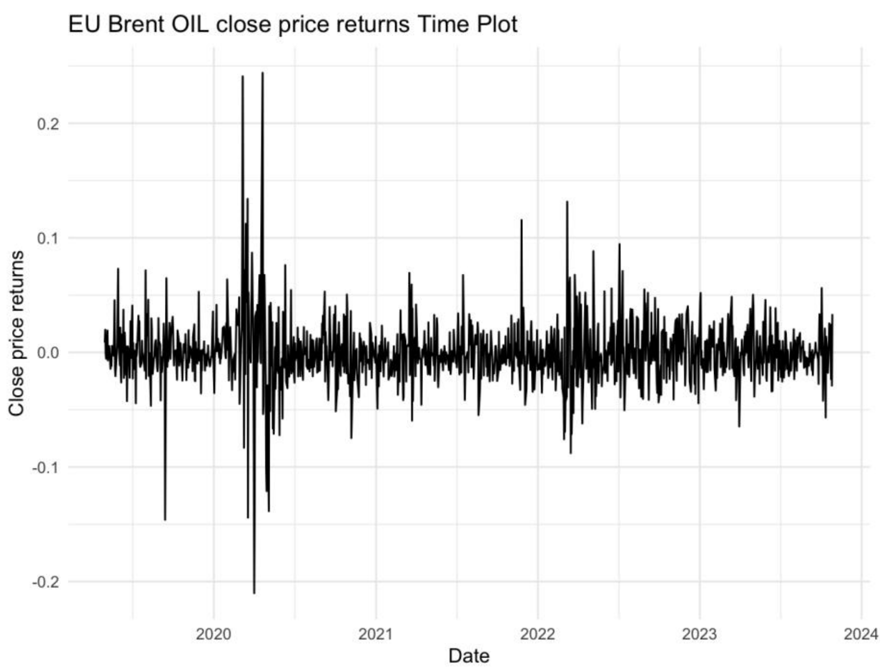
Parent series of NAV and Crude Oil Close Prices are non-stationary and have unit root . Therefore, to make the series stationary the choice variables are transformed into 1st differenced series which are tweaked further to give more economically meaningful terms. This first order difference augmented series is stationary and conforms to the stationarity hypothesis of the ADF test. The final equation is given below-

NAV Change (%) = f (NAV Change (%), Crude Oil Price Returns) - equation (2)

Table 1: Augmented Dickey-Fuller Test Results

Data	Dickey-Fuller	Lag Order	P-value
GB_OIL_data‘$NAVChange\%$	-9.0564	10	0.01
GB_OIL_data$EU_brentOIL_returns[-1]$	-10.858	10	0.01
GB_OIL_data$EU_brentOIL$	-1.2886	10	0.8795
GB_OIL_dataNAV	-0.73761	10	0.9672





Johansen Juselius Cointegration Test

There is one cointegrating relationship between NAV Change (%) and COP returns which asserts the presence of a long run relationship between the former and the latter. The rank of the trace statistic (r<=1) is significant with confirmed the student's t-test. Conflicting results are observed under rank of trace statistics and maximum eigenvalue statistic under the cointegration outputs. The rank of trace statistic is chosen that shows that there is no cointegrating factor indicating no long run association between the two variables. The model of choice in this case is Structural / Reduced VAR.

```
Test type: trace statistic , with linear trend

Eigenvalues (lambda):
[1] 0.009613728 0.002688504

Values of teststatistic and critical values of test:

          test 10pct  5pct  1pct
r <= 1 |  3.12  6.50  8.18 11.65
r = 0  | 14.33 15.66 17.95 23.52

Eigenvectors, normalised to first column:
(These are the cointegration relations)

                  NAV.l1 EU_brentOIL.l1
NAV.l1         1.0000000     1.00000000
EU_brentOIL.l1 0.2535273     0.02384047

Weights W:
(This is the loading matrix)

                    NAV.l1 EU_brentOIL.l1
NAV.d          0.001417326    -0.00136516
EU_brentOIL.d -0.027332260    -0.04153522
```

VAR Model

The optimal lag selection in the VAR model is done using AIC, BIC and HQIC Criterion and it comes out to be (1,1). The cross coefficients in the VAR model for equation (2) are mostly insignificant. This means the past values of COP returns are unable to explain or affect the variations in NAV changes as the dependent variable. Trivially enough, the past values of NAV (especially 1st lag term) is able to explain the variations in its own present values. Checking for misspecification of lags and using lags of higher order still render the coefficients insignificant. Results are in line with our expectations as the parent series are both I (1) and VAR is expected to deliver underperformed outputs.

$$NAV\ Change\ (\%)\ =\ f\ (NAV\ Change\ (\%), COP\ Returns)\quad -\ equation\ (2)$$
$$COP\ Return\ =\ f\ (\ COP\ Returns, NAV\ Change\ (\%))\qquad -\ equation\ (3)$$

Similarly, to accommodate for any of the probable bidirectional dependence, if the dependent and independent variables are interchanged, then also the cross coefficients are insignificant. Regressing COP returns on NAV change (%) and obtaining insignificant coefficients further confirms that the causation between the two is mired. To understand the robustness of this model we can apply the Durbin Watson Test and Jarque-Bera Test on the residuals.

```
Estimation results for equation NAV.Change.:
============================================
NAV.Change. = NAV.Change..l1 + EU_brentOIL_returns.l1 + const

                       Estimate Std. Error t value Pr(>|t|)
NAV.Change..l1          0.11629    0.02917   3.986 7.14e-05 ***
EU_brentOIL_returns.l1 -0.50265    0.35159  -1.430    0.153
const                  -0.01124    0.01016  -1.106    0.269
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.3456 on 1157 degrees of freedom
Multiple R-Squared: 0.01523,    Adjusted R-squared: 0.01352
F-statistic: 8.945 on 2 and 1157 DF,  p-value: 0.0001397
```

```
Estimation results for equation EU_brentOIL_returns:
====================================================
EU_brentOIL_returns = NAV.Change..l1 + EU_brentOIL_returns.l1 + const

                        Estimate Std. Error t value Pr(>|t|)
NAV.Change..l1          0.0037778  0.0024296   1.555   0.1202
EU_brentOIL_returns.l1  0.0688372  0.0292821   2.351   0.0189 *
const                  -0.0005250  0.0008458  -0.621   0.5349
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.02878 on 1157 degrees of freedom
Multiple R-Squared: 0.006843,   Adjusted R-squared: 0.005127
F-statistic: 3.986 on 2 and 1157 DF,  p-value: 0.01883
```

```
VAR Estimation Results:
=======================

Estimated coefficients for equation NAV.Change.:
================================================
Call:
NAV.Change. = NAV.Change..l1 + EU_brentOIL_returns.l1 + const

        NAV.Change..l1 EU_brentOIL_returns.l1                  const
            0.11628651            -0.50264827            -0.01123555


Estimated coefficients for equation EU_brentOIL_returns:
========================================================
Call:
EU_brentOIL_returns = NAV.Change..l1 + EU_brentOIL_returns.l1 + const

        NAV.Change..l1 EU_brentOIL_returns.l1                  const
          0.0037778274           0.0688371653          -0.0005249981
```

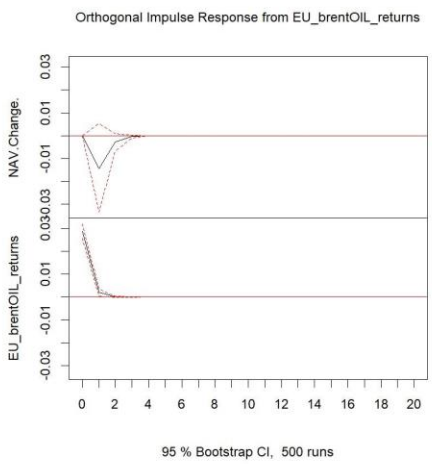
Granger's Causality Test

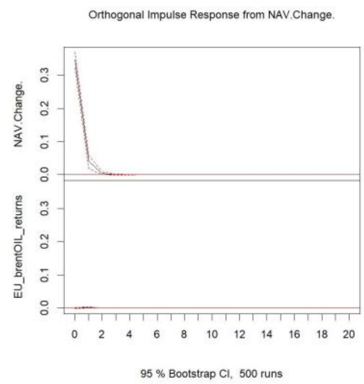
To check the stability of the VAR Model and the credibility of the implied causation, Granger's causality test is applied on the VAR (1,1) Model. This exercise checks for bidirectional causality separately for the two-time variables. As is evident from the results, there is no bidirectional and unidirectional causality between NAV Change (%) and COP returns, i.e., they do not 'Granger Cause' each other. Hence, it is realized that the VAR model above is not stable.

```
$Granger

        Granger causality H0: NAV.Change. do not Granger-cause EU_brentOIL_returns

data:  VAR object var_model
F-Test = 2.4177, df1 = 1, df2 = 2314, p-value = 0.1201


$Instant

        H0: No instantaneous causality between: NAV.Change. and EU_brentOIL_returns

data:  VAR object var_model
Chi-squared = 0.00096926, df = 1, p-value = 0.9752
```

```
$Granger

        Granger causality H0: EU_brentOIL_returns do not Granger-cause NAV.Change.

data:  VAR object var_model
F-Test = 2.0438, df1 = 1, df2 = 2314, p-value = 0.153


$Instant

        H0: No instantaneous causality between: EU_brentOIL_returns and NAV.Change.

data:  VAR object var_model
Chi-squared = 0.00096926, df = 1, p-value = 0.9752
```

Impulse Response Function



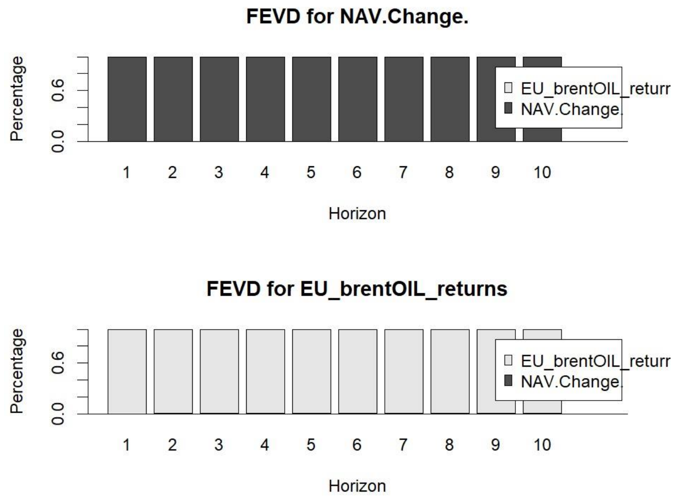


The impulse response graph captures the impact of 1 standard deviation shock of COP returns on the NAV Change (%) for time periods 2 to 10. It is evident from the graph that a positive shock in the COP returns would result in a negative response to NAV Change (%). Obviously, positive shock to COP returns would mean crude oil, which is a non-renewable source of energy, has become increasingly favorable relative to a renewable and therefore greener source. With green energy's demand decreasing due to decreasing popularity, green projects would become less profitable over time and investing in those would not be advantageous. Companies investing at least 75% of their asset values in green finance and bonds would not benefit significantly, rather will lose out as it will be a loss-making allocation of funds. Therefore, their valuations would experience a negative growth as the ETF as whole is composed of all the major climate sensitive institutions. The effect of the shock is maximum at time point 2, where the NAV change declines by an average of 0.03%. The effect then gradually stabilizes over time.

With one-unit standard deviation external positive shock given to NAV Change (%), there is almost no impact on COP Returns because the renewable energy market is relatively small and the crude oil market is substantially large. Several other macroeconomic and geopolitical factors affect COP returns on a larger scale and act as stronger determinants, for instance - Russia Ukraine War led to negative supply shock to the crude oil market resulting in an abnormal price hike. However, the green energy market was unscathed.

Variance Decomposition Analysis

1. External shocks to NAV Change (%) explain majority of the forecast error variance.
2. Shocks to COP returns variable have a small but significant impact on NAV Change variable.



Residual Analysis

Table 5: Post VAR Residual Tests

Test Type	Test Statistic	df (Degrees of Freedom)	p-value
Durbin-Watson for NAV % Change	2.018434		
Durbin-Watson for EU_brentOIL_returns	1.994234		
Jarque-Bera for NAV % Change	638.23	2	$< 2.2e-16$
Jarque-Bera for EU_brentOIL_returns	10379	2	$< 2.2e-16$

Jarque-Bera Test for Normality: Extremely low p values express a departure from normality of the residuals.
Durbin-Watson Test for Autocorrelation: For both the variables are very close to 2 validating the absence of any auto correlation between the residual error terms.

These tests are evidence that the VAR model is underperforming in our case which is intuitively correct. The % change in NAV cannot be explained by COP returns alone and other macroeconomic variables need to be accounted for. Log transformation of the variables might help in making the error terms normal and a functional form misspecification might be precedent in our model.

Conclusion

As per the analysis carried out so far, the COP Returns are not a strong determinant in explaining the % changes in NAV, i.e., the performance of the crude oil price market is not a solid indicator to understand the profitability of the ETF. Since the fund is composed of companies investing in climate projects and bonds, their asset valuations and hence the credibility and profitability depends on the growth of the green market. Through the IRF, it is evident that a negative relationship, strictly short run, exists between the two where growth on the non-renewable side does hit the investments on the renewable side. However, this is a mild hunch and inclusion of other financial factors and macroeconomic variables will strengthen the model. Overall, we stand by our idea that renewable and non-renewable energy markets act in opposite directions and impact investors investing in any particular side of the market. Green financing is beneficial from an investment perspective as green outcomes and a greener market to manifest better returns and depict prospects.

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