Yuan Lee

05/15/2024

CFRM 509

How Do Energy-related Commodities Influence ESG ETFs

This project aims to analyze how energy-related commodities influence various ESG ETFs managed by different financial institutions. The paper will assess whether these ETFs genuinely track the ESG indicators or if they merely capitalize on trending topics to attract investors. Additionally, it will investigate whether the prices of commodities impact the prices of ESG ETFs. Therefore, the focus will be on examining the calculations and measurements of several ESG ETFs to determine if they truly pursue the goals of ESG. This includes measuring the correlation, covariance and linear regression between these ETFs and commodities, thereby providing a comprehensive analysis of their interactions.

The term "ESG" stands for environmental, social, and governance, and it represents a group of metrics that assess an organization's impact on environmental and social factors. While the term was first introduced in 2004 by the United Nations Global Compact, the underlying concept of evaluating companies based on their broader societal impacts has been influential in the investor community for many years prior, playing a critical role in investment decision-making.

Since the concept of ESG was introduced these decades, ESG ETFs have become increasingly popular in recent years. People are more motivated to get involved and invest in ESG-related financial products, making ESG ETFs indicators of how investors feel about investing in ESG. By analyzing the relationship between energy-related commodities and ESG

ETFs, we can determine whether investing in ESG ETFs encourages companies to focus more on ESG initiatives and reduce the use of non-renewable energy sources, such as oil and natural gas.

We selected the largest ETFs, each managing assets exceeding three billion dollars, as samples to assess whether ESG ETFs genuinely invest in ESG principles or merely capitalize on the trend to generate revenue. Utilizing filters provided by Charles Schwab, a financial services company that offers ETF data to its clients, we identified seven ETFs managing assets above the three-billion-dollar threshold (refer to Table 1). These ETFs are predominantly administered by BlackRock and Vanguard.

Table 1

Symbol	Description	Fund Type	ESG Fund	Total Assets
ESGU	iShares ESG Aware MSCI USA ETF	ETF	Yes	$12B
ESGD	iShares ESG Aware MSCI EAFE ETF	ETF	Yes	$8B
ESGV	Vanguard ESG U.S. Stock ETF	ETF	Yes	$8B
DSI	iShares MSCI KLD 400 Social ETF	ETF	Yes	$4B
ESGE	iShares ESG Aware MSCI EM ETF	ETF	Yes	$4B
VSGX	Vanguard ESG International Stock ETF	ETF	Yes	$4B
SUSA	iShares MSCI USA ESG Select ETF	ETF	Yes	$3B

Upon reviewing the Summary Prospectuses of these ETFs, it is evident that they all adhere to established indices rather than formulating their own ESG scores for portfolio weighting. Specifically, BlackRock's ETFs track ESG indices from MSCI, an American agency that develops ratings and indices. Conversely, Vanguard's ETFs follow ESG indices from FTSE Russell, a UK-based agency known for similar services.

All the indices followed by these ESG ETFs explicitly exclude companies involved with Vice Products (such as Adult Entertainment, Alcohol, Gambling, and Tobacco), Non-Renewable Energy (including Nuclear Power and Fossil Fuels), and Weapons (encompassing Civilian Firearms, Controversial Military Weapons, and Conventional Military Weapons). This approach highlights the commitment of these ETFs to uphold ESG standards by avoiding investment in these sectors.

To examine the influence of energy-related commodities on ESG performance, conducting covariance analysis, correlation studies, and linear regression provides a comprehensive overview of how these commodities relate to ESG ETFs. The selected energy-related commodities include oil, which is significantly linked to global warming, natural gas, also highly associated with global warming, and copper, a crucial component in batteries and electrical cables.

The results of the correlation and covariance analyses (refer to Tables 2 and 3) demonstrate that most of the ETFs are related to oil prices, as indicated by a comparison with Exxon Mobil (XOM), where most correlations are not far away from 0.7. This suggests that oil prices still influence these ETFs, despite the indices they follow excluding companies involved with non-renewable energy. This enduring impact may be attributable to the fact that completely eliminating oil costs from business operations is impractical, given the heavy reliance on oil for transportation. In contrast, the ETFs exhibit low correlation with natural gas prices, indicating that natural gas prices have minimal impact on these ETFs. Lastly, all ETFs show a strong correlation with copper prices, possibly due to a significant representation of tech companies within these ETFs or because they hold a substantial weight in large market cap companies, which are predominantly tech firms that consume considerable amounts of copper in product development and manufacturing.

Table 2

Symbol	Correlation_with_Oil	Correlation_with_Natural_Gas	Correlation_with_Copper
ESGU	0.647	0.410	0.899
ESGD	0.517	0.177	0.869
ESGV	0.610	0.383	0.895
DSI	0.656	0.403	0.892
ESGE	0.118	0.059	0.633
VSGX	0.388	0.169	0.841
SUSA	0.637	0.415	0.905
XOM	0.722	0.349	0.415

Table 3

Symbol	Covariance_with_Oil	Covariance_with_Natural_Gas	Covariance_with_Copper
ESGU	202.184	11.396	9.688
ESGD	81.839	2.491	4.738
ESGV	156.769	8.740	7.924
DSI	179.184	9.770	8.396
ESGE	10.826	0.479	2.005
VSGX	47.497	1.833	3.546
SUSA	200.003	11.568	9.798
XOM	381.374	16.369	7.549

The linear regression results, detailed in Tables 4, 5, and 6, reveal that oil prices have a significant and positive effect on the prices of the ETFs analyzed. Additionally, all coefficients are positive, indicating that higher oil, natural gas, and copper prices contribute to an increase in ETF prices. This finding reinforces the implications drawn from the correlation and covariance analyses, suggesting a direct relationship between the increase in commodity prices and the corresponding rise in ETF values.

Table 4

Symbol	R_squared_of_Oil	R_squared_of_Natural_Gas	R_squared_of_Copper
ESGU	0.418	0.168	0.808
ESGD	0.267	0.031	0.754
ESGV	0.372	0.146	0.801
DSI	0.430	0.162	0.796
ESGE	0.013	0.003	0.400
VSGX	0.150	0.028	0.708
SUSA	0.405	0.171	0.820
XOM	0.521	0.121	0.171

Table 5

Symbol	Coefficient_of_Oil	Coefficient_of_Natural_Gas	Coefficient_of_Copper
ESGU	0.475	3.397	19.176
ESGD	0.192	0.743	9.379
ESGV	0.369	2.606	15.684
DSI	0.421	2.913	16.620
ESGE	0.025	0.143	3.968
VSGX	0.112	0.546	7.019
SUSA	0.470	3.449	19.394
XOM	0.897	4.880	14.943

Table 6

Symbol	P_value_of_Oil	P_value_of_Natural_Gas	P_value_of_Copper
ESGU	0.000	0.000	0.000
ESGD	0.000	0.000	0.000
ESGV	0.000	0.000	0.000
DSI	0.000	0.000	0.000
ESGE	0.000	0.037	0.000
VSGX	0.000	0.000	0.000
SUSA	0.000	0.000	0.000
XOM	0.000	0.000	0.000

From the analysis presented, it can be concluded that ETFs remain significantly influenced by oil prices, which may reflect the demand for oil, as rising oil prices are typically associated with increased demand. This suggests that ETFs may not substantially reduce companies' reliance on non-renewable energy sources, given their strong and positive correlation with oil prices. However, an alternative interpretation could be considered: the correlation might indicate that the U.S. stock market (^GSPC) is partly responsive to fluctuations in oil prices, as referenced in Table 7. Additionally, the global economic environment might significantly impact the prices of these ETFs, a relationship that can be observed through the Beta values provided in Table 8. Beta values measure the correlation between ETFs and stock market. This interplay underscores the complexity of factors influencing ETF performance, extending beyond mere commodity price movements to economic dynamics.

Table 7

Symbol	Correlation_with_Oil	Correlation_with_Natural_Gas	Correlation_with_Copper
^GSPC	0.671	0.416	0.898

Table 8

Symbol	Beta	Symbol	Beta
ESGD	1.07	VSGX	1.03
ESGV	1.05	SUSA	1.07
DSI	1.05	ESGU	1.02
ESGE	1	^GSPC	1

In conclusion, this comprehensive analysis demonstrates the influence of oil prices on ESG ETFs, suggesting that despite the ethical mandates to exclude non-renewable energy sources, these ETFs remain significantly affected by fossil fuel markets. This connection is evident in the high correlation and positive coefficients with oil prices, reflecting broader market dependencies and perhaps the practical challenges in completely divorcing operational aspects from oil. Additionally, the strong correlation with copper prices indicates that ETF prices interact with various commodities, influenced by sector-specific demands, particularly from technology firms that most of ETFs hold.

These findings illustrate a complex dynamic where ESG ETFs are affected not only by direct commodity price movements but also by broader economic and market trends. This is exemplified by the responsiveness of the U.S. stock market to oil price fluctuations and the significant impact of global economic conditions on ETF pricing, as observed through various metrics including Beta values. This interplay underscores the reality that ESG ETFs, despite their sustainable focus, are not isolated from the broader financial system. They are part of a complex financial ecosystem where ethical investment considerations must be balanced against the dynamics of traditional markets and economic forces.

Appendix

```
#Prices
library(quantmod)

## Loading required package: xts

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: TTR

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

symbols <- c("ESGU", "ESGD", "ESGV", "DSI", "ESGE", "VSGX", "SUSA", "XOM", "C
L=F", "NG=F", "HG=F")
prices <- list()
for (symbol in symbols) {
  price <- getSymbols(symbol, from="2019-01-01",to="2023-12-31", auto.assign=
FALSE,periodicity = 'daily')
  prices[[symbol]]<-price[,6]
}

model<-lm(prices$ESGU~prices$`CL=F`[1:1258])
modelsummary<-summary(model)
modelsummary$adj.r.squared

## [1] 0.4176872

modelsummary$coefficients[2]

## [1] 0.4754136

#Crude Oil
oil_corr<-list()
oil_cov<-list()
oil_r2<-list()
oil_pvalue<-list()
oil_coef<-list()

for (symbol in symbols[1:8]){
  oil_cov[[symbol]]<-cov(prices[[symbol]],prices$`CL=F`[1:length(prices[[symb
ol]])])
  oil_corr[[symbol]]<-cor(prices[[symbol]],prices$`CL=F`[1:length(prices[[sym
```

```
bol]])])
  model<-lm(prices[[symbol]]~prices$`CL=F`[1:length(prices[[symbol]])])
  modelsummary<-summary(model)
  oil_r2[[symbol]]<-modelsummary$adj.r.squared
  oil_coef[[symbol]]<-modelsummary$coefficients[2]
  oil_pvalue[[symbol]]<-modelsummary$coefficients[8]

}

#Natural Gas
gas_corr<-list()
gas_cov<-list()
gas_r2<-list()
gas_pvalue<-list()
gas_coef<- list()

for (symbol in symbols[1:8]){
  gas_cov[[symbol]]<-cov(prices[[symbol]],prices$`NG=F`[1:length(prices[[symb
ol]])])
  gas_corr[[symbol]]<-cor(prices[[symbol]],prices$`NG=F`[1:length(prices[[sym
bol]])])
  model<-lm(prices[[symbol]]~prices$`NG=F`[1:length(prices[[symbol]])])
  modelsummary<-summary(model)
  gas_r2[[symbol]]<-modelsummary$adj.r.squared
  gas_coef[[symbol]]<-modelsummary$coefficients[2]
  gas_pvalue[[symbol]]<-modelsummary$coefficients[8]
}

#Copper
copper_corr<-list()
copper_cov<-list()
copper_r2<-list()
copper_pvalue<-list()
copper_coef<-list()
for (symbol in symbols[1:8]){
  copper_cov[[symbol]]<-cov(prices[[symbol]],prices$`HG=F`[1:length(prices[[s
ymbol]])])
  copper_corr[[symbol]]<-cor(prices[[symbol]],prices$`HG=F`[1:length(prices[[
symbol]])])
  model<-lm(prices[[symbol]]~prices$`HG=F`[1:length(prices[[symbol]])])
  modelsummary<-summary(model)
  copper_r2[[symbol]]<-modelsummary$adj.r.squared
  copper_coef[[symbol]]<-modelsummary$coefficients[2]
  copper_pvalue[[symbol]]<-modelsummary$coefficients[8]
}

#Correlation Table
corr_df <- data.frame(
  Correlation_with_Oil = unlist(oil_corr),
  Correlation_with_Natural_Gas = unlist(gas_corr),
```

```r
  Correlation_with_Copper = unlist(copper_corr),
  stringsAsFactors = FALSE
)
corr_df
```

```
##      Correlation_with_Oil Correlation_with_Natural_Gas Correlation_with_Co
pper
## ESGU            0.6466456                   0.41039808                0.898
9832
## ESGD            0.5170227                   0.17718004                0.868
5504
## ESGV            0.6102911                   0.38312386                0.894
9718
## DSI             0.6561315                   0.40282325                0.892
0387
## ESGE            0.1177817                   0.05870972                0.632
8349
## VSGX            0.3883643                   0.16876219                0.841
2908
## SUSA            0.6369935                   0.41485549                0.905
3680
## XOM             0.7221742                   0.34902051                0.414
7717
```

```r
#Covariance Table
cov_df <- data.frame(
  Covariance_with_Oil = unlist(oil_cov),
  Covariance_with_Natural_Gas = unlist(gas_cov),
  Covariance_with_Copper = unlist(copper_cov),
  stringsAsFactors = FALSE
)
cov_df
```

```
##      Covariance_with_Oil Covariance_with_Natural_Gas Covariance_with_Coppe
r
## ESGU           202.18440                  11.3962139               9.68782
9
## ESGD            81.83876                   2.4907958               4.73846
9
## ESGV           156.76851                   8.7404725               7.92363
9
## DSI            179.18427                   9.7700644               8.39626
7
## ESGE            10.82559                   0.4792449               2.00473
8
## VSGX            47.49658                   1.8330410               3.54619
7
## SUSA           200.00263                  11.5683506               9.79759
3
```

```
## XOM           381.37427                    16.3694579               7.54939
5

#R^2 Table
r2_df <- data.frame(
  R_squared_of_Oil = unlist(oil_r2),
  R_squared_of_Natural_Gas = unlist(gas_r2),
  R_squared_of_Copper = unlist(copper_r2),
  stringsAsFactors = FALSE
)
r2_df

##      R_squared_of_Oil R_squared_of_Natural_Gas R_squared_of_Copper
## ESGU        0.4176872              0.167764506           0.8080180
## ESGD        0.2667291              0.030621582           0.7541843
## ESGV        0.3719556              0.146104581           0.8008160
## DSI         0.4300551              0.161599588           0.7955704
## ESGE        0.0130874              0.002653397           0.4000027
## VSGX        0.1501507              0.027707174           0.7075376
## SUSA        0.4052877              0.171445928           0.8195476
## XOM         0.5211546              0.121116125           0.1713764

#Coefficient Table
pvalue_df <- data.frame(
  Coefficient_of_Oil = unlist(oil_coef),
  Coefficient_of_Natural_Gas = unlist(gas_coef),
  Coefficient_of_Copper = unlist(copper_coef),
  stringsAsFactors = FALSE
)
pvalue_df

##      Coefficient_of_Oil Coefficient_of_Natural_Gas Coefficient_of_Copper
## ESGU         0.47541364                  3.3973223             19.176234
## ESGD         0.19243454                  0.7425305              9.379396
## ESGV         0.36862335                  2.6056199             15.684170
## DSI          0.42133144                  2.9125513             16.619697
## ESGE         0.02545514                  0.1428676              3.968209
## VSGX         0.11168282                  0.5464474              7.019395
## SUSA         0.47028346                  3.4486379             19.393502
## XOM          0.89675825                  4.8798947             14.943386

#P Value Table
pvalue_df <- data.frame(
  P_value_of_Oil = unlist(oil_pvalue),
  P_value_of_Natural_Gas = unlist(gas_pvalue),
  P_value_of_Copper = unlist(copper_pvalue),
  stringsAsFactors = FALSE
)
pvalue_df
```

```
##      P_value_of_Oil P_value_of_Natural_Gas P_value_of_Copper
## ESGU  6.955392e-150           2.722949e-52      0.000000e+00
## ESGD   6.410864e-87           2.481062e-10      0.000000e+00
## ESGV  3.069811e-129           2.965623e-45      0.000000e+00
## DSI   9.569134e-156           2.857265e-50      0.000000e+00
## ESGE   2.814867e-05           3.733702e-02     1.026211e-141
## VSGX   1.482045e-46           1.712067e-09      0.000000e+00
## SUSA  3.939352e-144           1.664385e-53      0.000000e+00
## XOM   2.747886e-203           2.393166e-37      1.754799e-53
```