Group Assignment Writeup & Analysis

Cesar Anzola | Ahyaan Raghuvanshi

16/03/2022

NOTE: See README.pdf for best readability.

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.8
## v tidyr   1.2.0     v stringr 1.4.0
## v readr   2.1.2     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(dplyr)
library(png)

setwd("/Users/Agha/Documents/GitHub/final-project-bestgrouptoday")
```

1 MORAL MONEY: Introduction to ESG Metrics

In the past decade, financiers have shown increasing interest in transitioning to a sustainable global economy. Money managers are reluctant to associate themselves with carbon-intensive and socially-irresponsible businesses, and have coalesced around the development and application of a standardised metric called ESG (Environmental, Social, and Governance metric).

ESG is a meta indicator of public and private listed companies' impact on the environment, local communities, supply chains, gender diversity, and wealth inequality. Tackling issues erstwhile labelled as 'market externalities' that did not necessarily affect the bottom line, new ESG metrics signal to private and institutional investors not only if their money is protected from risks within new realities of climate change and social justice movements, but also the level of moral good performed by it.

This project will probe two problem with ESG metrics. First, too many ratings agencies use non-transparent methodologies to provide ESG scores (1-100) of companies, which make them not just unreliable but susceptible to be used as a false marketing tool, where highly polluting fossil fuel companies cherry-pick the agency that gives them the highest score. Second, given that the basis for calculating ESG scores is costly bureaucratic self-reported company data, scored end up being biased towards large companies. Both issues thus lead to a situation where the market for environmentally and socially responsible investments gets increasingly captured by highly polluting big companies.

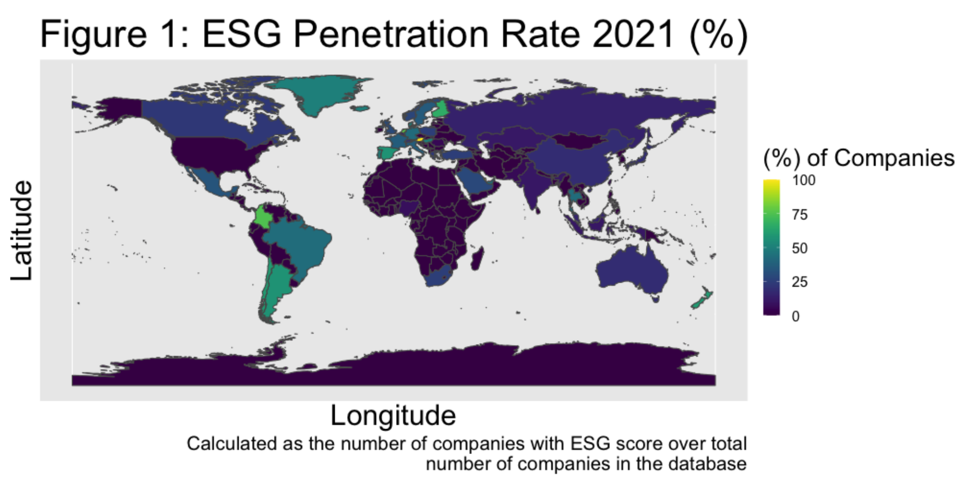
We sample all the energy companies that have received an ESG score by Refinitiv (formerly Thomson Reuters): a British-American financial markets information agency, covering >80% of global market capitalisation. Since their ESG ratings methodology is non-transparent, not unlike other ratings agencies, we look at several variables that could be influencing the ratings. As a broad guide for choosing the variables, we use the World Bank ESG DATA Framework's key sustainable themes of: greenhouse gas emissions, water-use efficiency, gender equality, and CEO-employee pay gaps. We end with a multi-variate regression of these independent variables to the dependent ESG score.

2 Data Pocessing and Plotting

Using Refinitiv's immense data portal (accessible with a UChicago email account https://www.refinitiv.com/en/products/refinitiv-workspace) to pull two dataframes: one with data on all global energy companies, the other with ESG data of energy companies. Both frame are cleaned and merged to form Figure 1.

Figure 1 shows the ESG penetration rate of global energy companies. It is calculated as percentage of publicly listed energy companies which have received an ESG score. The plot shows high penetration in Western and Central Europe, and Latin America. Nearly all energy companies in Austria, Finland, and Colombia have the ESG score. However, we should reiterate that the data doesn't cover all energy companies in every country: the 100% penetration can be deceiving in the case of Colombia, since only 3 energy companies are publicly listed in Refinitiv, all of them receiving the ESG score. There are many more companies not covered by Refinitiv, regardless of the ESG score.

```
fig1 <- readPNG("images/esg_penetration_map.png")
grid::grid.raster(fig1)
```



3 Plotting: Shiny

see: https://cesaranzola945.shinyapps.io/Final_project_DataandProg/

You will find three time-series plots in the economist theme.

First Plot Choose any 'Country'and a 'WDI ESG Metric' to see plot of the country's past four years of CO2 emissions, unemployment, female labour force participation, and female/male ratio. This data is from the World Bank, and is the third dataset merged for this project.

Second plot (choose 'Company ESG Metric') Company level ESG metrics and polynomial regression of its trend in time

Third Plot (choose 'Company ESG Metric') Scatter plot between the metrics and their ESG score that is used by financial markets to target companies with sustainable vision

Taking a quick look, the third plot shows, quite alarmingly, that higher emissions are positively coorelated with high ESG score, and overall female to male employee ratio is slightly negatively coorelated with ESG score! However, percentage of women on company board is positively coorelated.

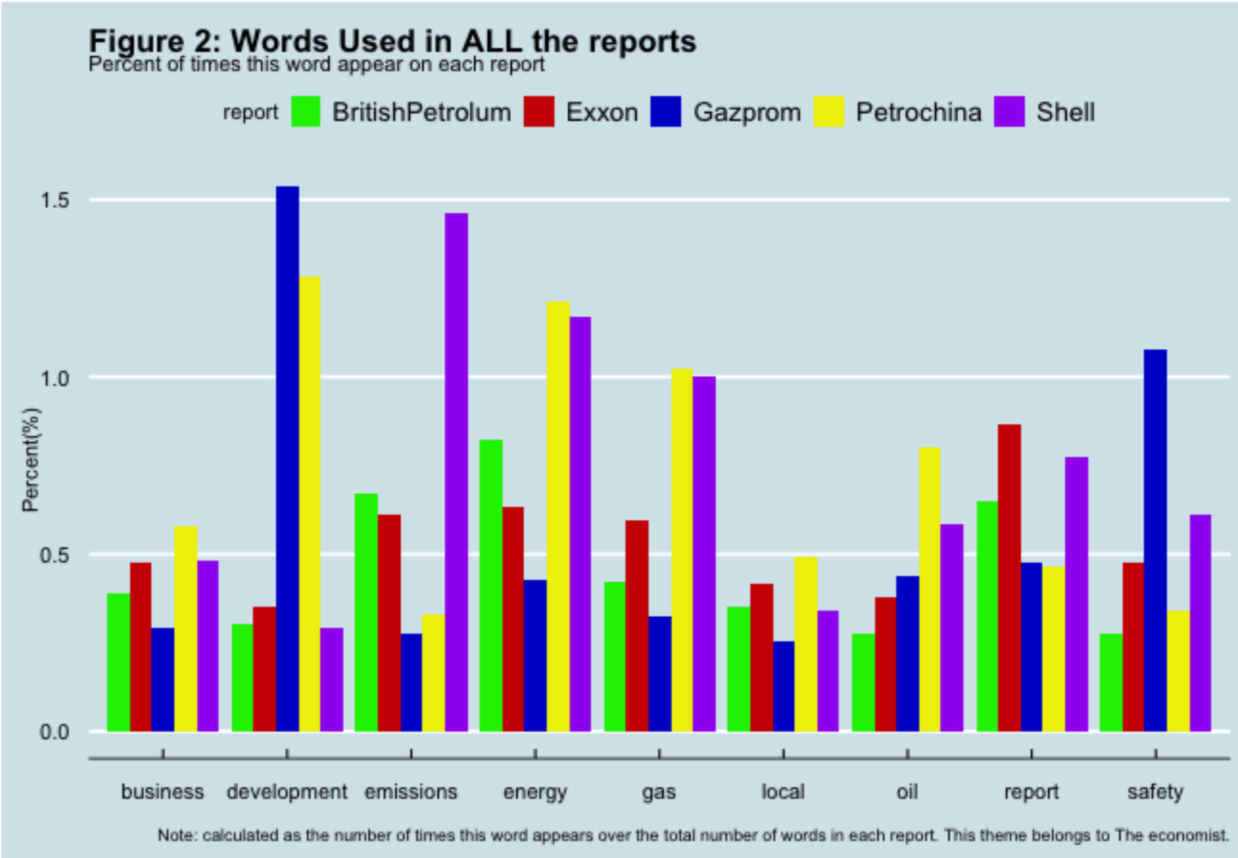
4 Text Processing

To complement our analysis, we take the sustainability/ESG reports of five of the ten biggest energy companies by market cap. These are: Exxon (US), PetroChina (China), British Petroleum (UK), Shell (UK), and Gazprom (Russia).

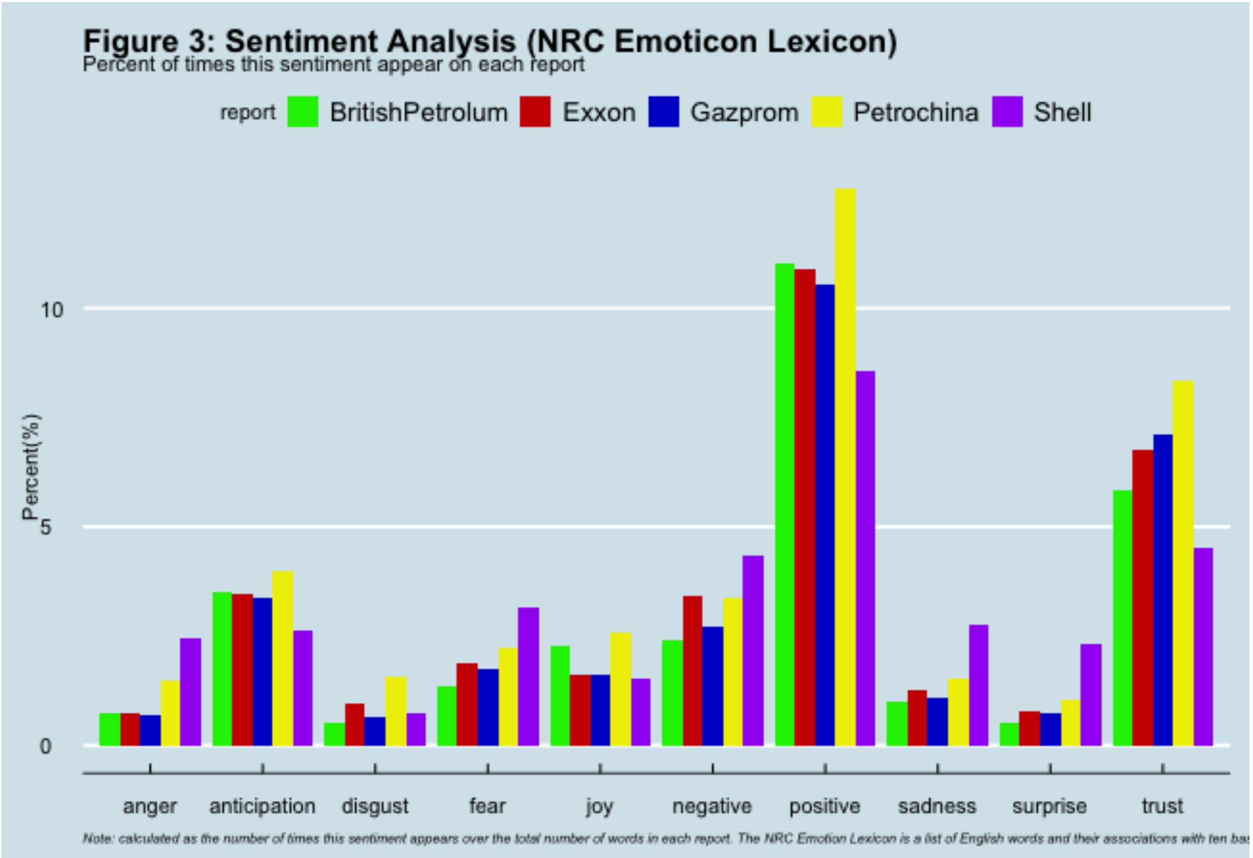
Figure 2: We find that emerging markets like Russia and China show foremost concern with the issue of development, and least concern with emissions. The opposite is true for Shell. All five companies share least concern with thr words 'business' and 'local'. 'Safety' ranks much higher for Gazprom than for its competitors.

Figure 3: Sentiment analysis shows largely shared trends, dominated by 'positive' (about 10%) and 'trust'(about 4-8%). 'Disgust', 'surprise', and 'anger' feature the least.

```
fig2 <- readPNG("images/words_in_common.png")
grid::grid.raster(fig2)
```




```
fig3 <- readPNG("images/reports_sentiment_NRC.png")
grid::grid.raster(fig3)
```



4.1 Text Processing: Word Clouds

Now we take stalk of the most common words used in their sustainability/ESG reports

The most common words in the reports for Shell, Exxonmobil, and Gazprom were self-referential. For PetroChina they were 'management development' and 'energy'; for British Petroleum it was, overwhelmingly, 'sustainability'. In Shell's report, there is no prominence given to 'employees', unlike the other four companies.

```
fig4_exxon <- readPNG("images/worldCloudExxon.png")
grid::grid.raster(fig4_exxon)
```


```r
fig5_petrochina <- readPNG("images/worldCloudPetrochina.png")
grid::grid.raster(fig5_petrochina)
```


```r
fig6_bp <- readPNG("images/worldCloudBritishPetrolum.png")
grid::grid.raster(fig6_bp)
```


```r
fig7_shell <- readPNG("images/worldCloudShell.png")
grid::grid.raster(fig7_shell)
```


```
fig8_gazprom <- readPNG("images/worldCloudGazprom.png")
grid::grid.raster(fig8_gazprom)
```

5 Analysis

Contrary to our presumption, the market capitalisation has very small effect on the dependent variable ESG score. However, it is not statistically significant. Furthermore, while the coefficient is small and negative, there are no statistically significant results here. P-value = 0.1 is larger than the threshold 0.05.

This tells us that more research needs to be done on what exactly is driving companies' ESG scores. Some difficulties we encountered during the research are related to completeness of data, lack of industry standards to identify most scientificically valid variables, However, we think that overall lack of clarity around ESG scores and how they are calculated could precisely be the driverd of their explosive popularity in the market. It is no wonder that these scores are accused of 'greenwashing', and have plenty of whistleblowers to vouch for the fact that they are primarily a marketing tool, not meant to make the world a bettter place.

```
load("Data/data_refinitiv.Rda")


# First we take the first difference in all our independent variables.
# These are: market_cap, emissions_total, water_to_revenue, women_overall_pct, women_board_pct, and sal

refinitiv_diff <-
  data_fin %>%
  arrange(id, year) %>%
  group_by(id)%>%
  mutate(diff_marketcap = market_cap - lag(market_cap), .after = market_cap) %>%
  mutate(diff_emissionstotal = emissions_total - lag(emissions_total), .after = emissions_total) %>%
```

```r
  mutate(diff_water_revenue = water_to_revenue - lag(water_to_revenue), .after = water_to_revenue) %>%
  mutate(diff_womenoverall = women_overall_pct - lag(women_overall_pct), .after = women_overall_pct) %>%
  mutate(diff_womenboard = women_board_pct - lag(women_board_pct), .after = women_board_pct) %>%
  mutate(diff_salarygap = salary_gap - lag(salary_gap), .after = salary_gap)


#new data frame dropping all unnecessary columns.
refinitiv_diff <-
  subset(refinitiv_diff, select = c(id, name, indst_name, country, year, esg_score,
                                    diff_marketcap, diff_emissionstotal, diff_water_revenue,
                                    diff_womenoverall, diff_womenboard, diff_salarygap))

#Select one year
refinitiv_diff <- subset(refinitiv_diff, year == "2021")


# Fitting into OLS model
model <- lm(esg_score ~ diff_marketcap + diff_emissionstotal + diff_water_revenue +
              diff_womenoverall + diff_womenboard + diff_salarygap,
            data = refinitiv_diff)

summary(model)
```

```
##
## Call:
## lm(formula = esg_score ~ diff_marketcap + diff_emissionstotal +
##     diff_water_revenue + diff_womenoverall + diff_womenboard +
##     diff_salarygap, data = refinitiv_diff)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -38.612 -10.406   0.084  11.248  30.035
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          6.028e+01  1.523e+00  39.573   <2e-16 ***
## diff_marketcap       2.784e-10  1.703e-10   1.634   0.1056
## diff_emissionstotal  2.273e-08  2.046e-07   0.111   0.9118
## diff_water_revenue  -4.507e-06  5.284e-06  -0.853   0.3959
## diff_womenoverall   -7.372e-01  7.834e-01  -0.941   0.3492
## diff_womenboard     -3.824e-01  2.208e-01  -1.732   0.0866 .
## diff_salarygap      -5.435e-04  1.664e-03  -0.327   0.7447
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 14.57 on 93 degrees of freedom
##   (429 observations deleted due to missingness)
## Multiple R-squared:  0.07129,    Adjusted R-squared:  0.01137
## F-statistic:  1.19 on 6 and 93 DF,  p-value: 0.3186
```