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How climate change news (do not) influence the market

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Abstract

Climate change is one of the biggest issues of our time and consequently the number of news articles about it is surging. Inspired by the work of the noble prize economist Robert F. Engle, we wanted to study the influence of these news on the stock market. The fundamental idea from which we started our analysis is that, when public is exposed to information about climate change spikes, the so-called green stocks (those of companies with relatively low carbon emissions) should get a temporary boost, while brown stocks (those of companies that emit large quantities of greenhouse gases) should face a fall.

Keywords: Stock Market, Climate Change, News

Contents

Introduction

Climate change has been one of the most debated topics in the past few decades. The news about it are more and more frequent in newspapers and in TV news. Even in the financial word we have seen an increasing number of companies trying to become as *green* as possible. Furthermore there has been a growth in the *ESG* (Environmental, Social and Governance) funds. Nevertheless some people consider all of this just as a trend of the moment, namely as another way to get some profit, using the attention around this situation. But how much all of this hype did really impact the choices of the investors? It is reasonable to assume that, when good news get released, people tend to invest more in *green* companies, having more growth prospective, than in *brown* companies. Moreover these investment trends can be triggered or accentuated by international conferences on climate change (e.g. the 2012 UN Climate Change Conference), international agreements (e.g. the Paris agreements) or new regulatory proposals (e.g. Climate Action Plan). Climate change policies aim to reduce carbon emissions; thus, carbon risk should be included in investment decision making. In fact, recent studies show that investors recognize climate risk (Krueger, Sautner, and Starks 2020) and they require higher returns from firms with higher emission levels (Bolton and Kacperczyk 2021). Additionally, the cost of debt for climate-aware firms is lower compared to firms without carbon disclosure (Jung, Herbohn, and Clarkson 2018). These findings suggest that investors require compensation for holding stocks with higher climate risks.

In this paper, inspired by the work of noble prize economist Robert Engle, we study the effect that climate change news can have (or not) on the returns of various firms, some of which are very environmentally friendly and others which have an opposite attitude; we also study the relation of these news with some commodities.

1 | Literature

As we mentioned before the subject we intend to analyse has attracted in recent years considerable attention. Climate change is a topical and controversial issue with repercussions in a wide range of areas, such as politics, economics and finance.
In order to detect the effects of global warming on the market stocks, many researchers tried in these past years to design a proper index that effectively map climate change trends; the main idea of the academics was to observe the frequency of the appearance of climate change news in major information channels. One of the main difficulties encountered in this process was certainly the narrow range of observations available, given the relatively recent nature of the phenomenon. Moreover, once collected the relevant news, an important decision to be made is how to interpret them; whether to distinguish between positive and negative ones or whether to focus the analysis on a particular sentiment subcategory.
Even after the index has been created, the controversial question of how to select stocks for the future tests arises. Indeed, it is still rather difficult to find an objective criterion to qualify a company as environmentally friendly or not.
Here we try to summarize the most important findings on the subject.
Pastor, Stambaugh, and Taylor (2020) propose a theoretical framework to model the impact of changes in sustainability preferences on asset prices. In the specific case of climate change, their model predicts that green stocks outperform brown stocks when concerns about climate change strengthen unexpectedly. Indeed, the authors posit that first, investors can adjust their expectations about future green vs. brown firms' cash flows. Due to an unexpected increase in climate change concerns, lawmakers are more likely to propose and implement legislation that would harm brown firms' cash flows relative to green firms and so customers are more likely to buy sustainable products. Second, their model assumes that agents care about environmental, social, and governance (*ESG*) criteria and climate change's social impact. Thus, an increase in investors' preferences for green assets because of increasing concerns about climate change increases (decreases) the discount rate of *brown* (*green*) firms leading to a decrease (increase) in stock prices.

Both Engle et al. (2020) and Ardia et al. (2020) empirically test this prediction of Pastor, Stambaugh, and Taylor (2020). However, the challenge in testing the above is that unexpected changes in concerns about climate change is latent and must be proxied. Engle et al. (2020) use news media articles to build two monthly indices to proxy for climate change risk. The first index captures the attention about climate change in the Wall Street Journal. The second index relies on the Crimson Hexagon proprietary sentiment measure to capture the negative attention about climate change. Similarly, Ardia et al. (2020) use media news data but aim at capturing concerns about climate change. To do so, they propose a novel daily "concerns score", called *Media Climate Change Concerns* index (*mccc*), measuring the level of negativity as well as the level of risk and uncertainty discussed in each article. Moreover, they obtain a proxy of unexpected changes in climate change concerns using the prediction error of a first-order autoregressive model calibrated on the *mccc* index, which they refer to as unexpected media climate change concerns (*umc*).

Using these indexes both groups of researchers confirm the initial thesis of Pastor et al. (2020).

2 | Data

2.1. Climate News Indexes

Given the results of Engle and his collegues, we collected the data of the two indexes *wsj* and *chn* in order to keep track of climate change news trends. The first index is based on climate news coverage in The Wall Street Journal. After collecting seventy-four authoritative text documents on the subject of climate change, they create a “Climate Change Vocabulary” which amounts to the list of unique terms concerning the topic appearing in these texts. The index quantifies the similarity between this vocabulary and each daily *wsj* edition, keeping record of the important news related to the theme. However, *wsj* index embeds the view that, when it comes to climate change, no news is good news; in other words there is a risk of inaccurately capturing positive climate news as increases in climate risk.

In order to avoid this problem, they study a second news-based climate risk index that is designed to focus specifically on negative climate news. In particular they use the services of the data analytics vendor Crimson Hexagon, which has collected from May 2008 a massive corpus of over one trillion news articles and social media posts. They calculate the CH Negative Climate Change News Index (*chn*) as the share of all news articles that are both about "climate change" and that have been assigned to the “negative sentiment” category from Crimson Hexagon.

Finally, we use a third index called Media Climate Change Concerns index (*mccc*)[1], based on the researches of D. Ardia, K. Bluteau, K. Boudt, K. Inghelbrecht. This last one aims at capturing concerns about climate change, proposing a novel “concerns score" measuring the level of negativity as well as the level of risk and uncertainty discussed in each article.

[1] https://sentometrics-research.com/download/mccc/

2.2. Green and Brown stocks

To construct our models and verify our hypothesis, we built a portfolio based on both green and brown stocks. In particular we took two different datasets, one for the analysis of the *wsj* and *chn* indexes, and one for the test of the *mccc* index. The first one is composed of monthly data from July 2008 to June 2017; we selected six green stocks (those of companies with relatively low carbon emissions) and six brown stocks (those of companies that emit large quantities of greenhouse gases) and finally we collected the data of some commodities (oil, gas and gold) [1]. For the second dataset, trying to follow the steps of D. Ardia and his collegues, we took as green assets the first eleven *ESG S&P 500* companies, while for brown stocks we collected the data of eleven firms that have negative reputations for their climate impact. Specifically, this latter dataset is composed by daily observations from the 29th of June 2010 to the 29th of June 2018. For both the datasets we then computed the returns of each variable, in order to use them for our inspections.

2.3. Commodities

Commodities often reflects the trends present in the market. To fully understand the phenomenon we investigated, it seamed necessary to analyze the possible influence that climate change news have on this type of assets. We selected three commodities: Crude Oil, Natural Gas and Gold. Moreover we decided to study only the relation with the *wsj* and *chn* indexes; to do so we collected monthly data from July 2008 to June 2017 [2].

[1] https://finance.yahoo.com/
[2] https://fred.stlouisfed.org/

3 | Methodology and models

3.1. Data visualization

After we created the dataset as explained before, we started visualising our climate news indexes.

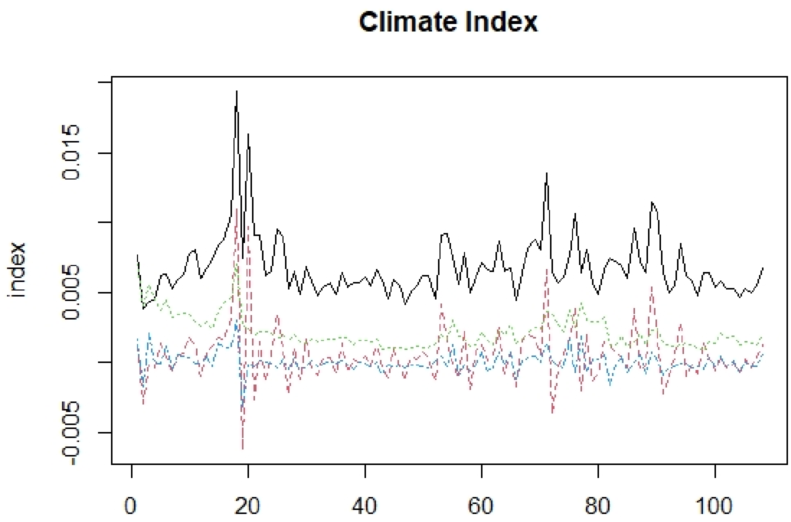

Figure 3.1: Climate Indexes

As we can see from the graph above the peaks of the graph correspond to some significant event concerning climate change, that has been reported by the media. We then tried to visualise the returns of our green and brown stocks, in order to see if there is some evident correlation with the news indexes. This first impression was not so good since we couldn't notice evident similarities, but obviously it is just a first look at our data.

Even the plot of the correlations did not show any significant information for our analysis except for an obvious correlation within green stocks, brown ones and the indexes separately.

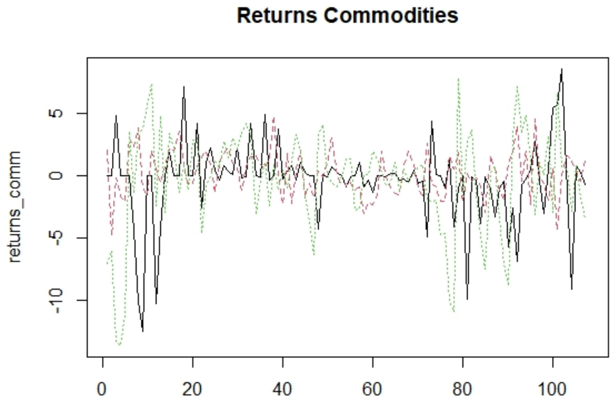

Figure 3.2: Commodities returns

Figure 3.3: Green stocks returns

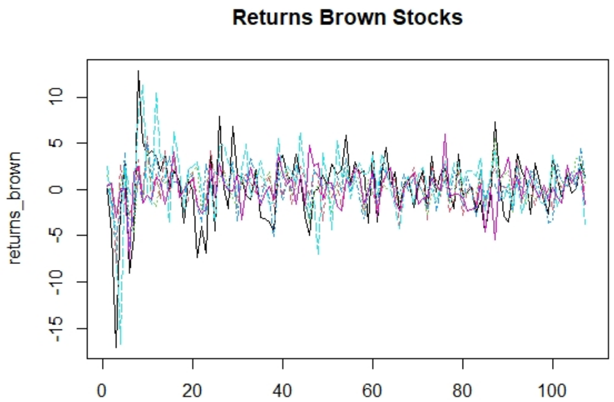

Figure 3.4: Brown stocks returns

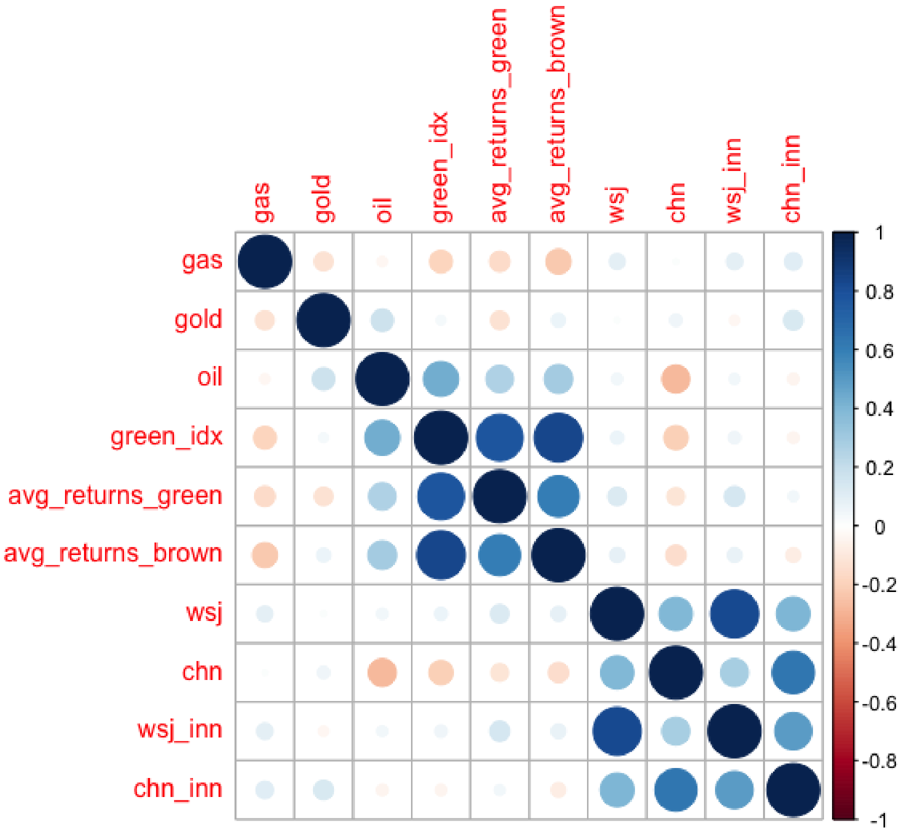

Figure 3.5: Corr Plot between assets

3.2. Linear Regression Lag Models

We have however tried to create models to look for a relationship between our data. We decided to use lag models and not simply linear models because we wanted to capture also the dependence trough time of our observations and indexes. In fact, a piece of news may not have an immediate effect on the market but have an influence at a later date.
As we can observe from the summary of **R** of these analysis, performed via the function *dynlm*, there is no correlation between the *wsj* index and the average returns of our green portfolio, the avarage returns of the brown ones and the commodities. We have tried the same analysis also with different time lags and the *chn* index, but we couldn't find any better result. We have chosen to report only the outputs below as representation of our bad results.

3.2.1. Green

```
Call:
dynlm(formula = avg_returns_green ~ wsj + L(wsj, 1) + L(wsj,
    2) + L(wsj, 3) + L(wsj, 4))

Residuals:
     Min       1Q   Median       3Q      Max
-13.9745  -3.5120  -0.1801   3.6689  10.3386

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.2422     2.1666   0.112    0.911
wsj          194.7112   231.3849   0.842    0.402
L(wsj, 1)   -275.9151   236.8130  -1.165    0.247
L(wsj, 2)   -128.5452   244.3283  -0.526    0.600
L(wsj, 3)    190.5226   235.2870   0.810    0.420
L(wsj, 4)    -13.1812   228.6701  -0.058    0.954

Residual standard error: 4.765 on 97 degrees of freedom
  (0 observations deleted due to missingness)
Multiple R-squared:  0.0224,Adjusted R-squared:  -0.028
F-statistic: 0.4444 on 5 and 97 DF,  p-value: 0.8164
```

3.2.2. Brown

```
Call:
dynlm(formula = avg_returns_brown ~ wsj + L(wsj, 1) + L(wsj,
    2) + L(wsj, 3) + L(wsj, 4))

Residuals:
    Min      1Q  Median      3Q     Max
-5.3917 -0.8773  0.0229  0.9600  4.3380

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.9706     0.7210   1.346    0.181
```

```
wsj           28.2871    76.9963   0.367    0.714
L(wsj, 1)    -48.2390    78.8025  -0.612    0.542
L(wsj, 2)     20.3740    81.3034   0.251    0.803
L(wsj, 3)      1.9257    78.2948   0.025    0.980
L(wsj, 4)    -75.9512    76.0929  -0.998    0.321

Residual standard error: 1.585 on 97 degrees of freedom
  (0 observations deleted due to missingness)
Multiple R-squared:  0.01628,Adjusted R-squared:  -0.03443
F-statistic: 0.3211 on 5 and 97 DF,  p-value: 0.8992
```

3.2.3. Commodities

```
Call:
dynlm(formula = oil ~ wsj + L(wsj, 1) + L(wsj, 2) + L(wsj, 3) +
    L(wsj, 3) + L(wsj, 4))

Residuals:
     Min       1Q   Median       3Q      Max
-10.8128  -1.9463   0.5095   2.4702   7.5143

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.8379     1.6525   0.507   0.6133
wsj            2.0754   176.4833   0.012   0.9906
L(wsj, 1)   -155.6979   180.6235  -0.862   0.3908
L(wsj, 2)   -114.8349   186.3556  -0.616   0.5392
L(wsj, 3)    310.0663   179.4595   1.728   0.0872 .
L(wsj, 4)   -169.6636   174.4126  -0.973   0.3331
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.634 on 97 degrees of freedom
  (0 observations deleted due to missingness)
Multiple R-squared:  0.04115,Adjusted R-squared:  -0.008271
F-statistic: 0.8327 on 5 and 97 DF,  p-value: 0.5296
```

3.2.4. Autoregression

We then ask ourselves if the indexes at our disposal could be explained via an autoregressive-model. The only one that had a quite significant R^2 *adjusted* is the AR(2) model for the *chn* index:

$$Chn_t = \alpha Chn_{t-1} + \beta Chn_{t-1} + \epsilon_t$$

```
Call:
dynlm(formula = chn ~ L(chn, 1) + L(chn, 2))

Residuals:
       Min         1Q     Median         3Q        Max
-2.616e-03 -3.217e-04 -9.007e-05  2.917e-04  3.039e-03

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0004216  0.0001560   2.703 0.008049 **
L(chn, 1)   0.4538354  0.0899298   5.047 1.94e-06 ***
L(chn, 2)   0.3342113  0.0826788   4.042 0.000102 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0006938 on 103 degrees of freedom
Multiple R-squared:  0.5928,Adjusted R-squared:  0.5849
F-statistic: 74.96 on 2 and 103 DF,  p-value: < 2.2e-16
```

From the summary of **R** above, we can see the estimated coefficients are $\hat{\alpha} = 0.454$ and $\hat{\beta} = 0.334$. We also see that the R^2_{adj} is equal to 0.585, so a quite significant result. This means that this index can be explained for a big part from an autoregressive model of order 2. We did not expect to get an higher R^2_{adj} since the hype on the news is obviously determined by the news on climate change, which cannot possibly be explained by an AR model. Nevertheless we were satisfy and happy with this result, and we would use it in the section **3.5**.

3.3. PCA On Indexes

3.3.1. PCA

Given previous failures, we tried to merge our two indexes (*wsj* and *chn*, with their two different versions each being basically the same as the original, but zero-centred) into a single one using PCA. As expected, just with the first principal component we are able to explain the 80% of the volatility; this component, looking at the plots of the loadings, can simply be interpreted as the mean of all the values.

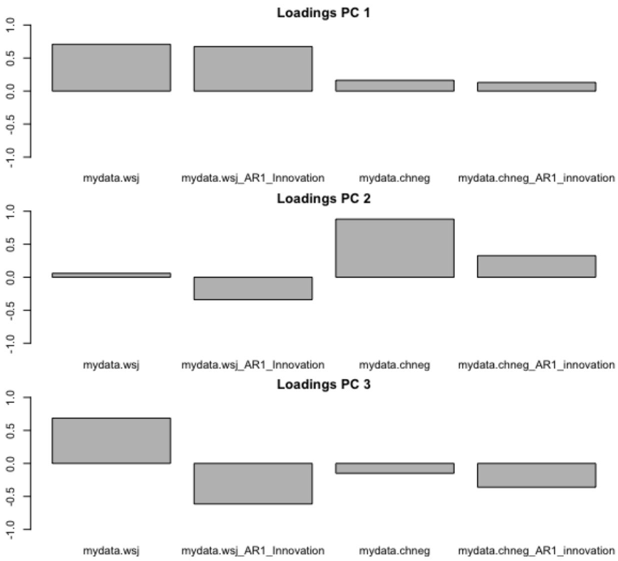

Figure 3.6: PCA Loadings

3.3.2. Regression With First Component

However, using this first component as our new index for lag models with stocks and commodities, hoping that it could capture more information with respect to the single ones separately, nothing new or meaningful came from our inspections. Models continued to be not statistically significant.

3.4. Regression On Portfolio

Inspired by the paper *Climate change concerns and the performance of green versus brown stocks* [4] we wanted to study the relation between our climate change indexes and the performance of the green stocks vs. brown stocks.

3.4.1. Construction and Regression

In order to do so we simply constructed a portfolio that is long in the green stocks and short in the brown ones, in this way we were able to analyze the difference in the return of green vs. brown. In other words we were able to determine the influence of climate change indexes on the event: the green stocks overperform the brown stocks. Regrettably, even when looking at these influences between green and brown, the results did not improve and we could not find evidence that the indices created by the researchers are actually descriptive of market trends.

3.5. Unexpected News Index

3.5.1. Construction

In addition, we created a proxy of unexpected changes in climate change concerns using the prediction error of an autoregressive model calibrated on the *wsj* index, which we refer to as unexpected wsj climate change (*un_ wsj*). Indeed, we used the observation window from January 1984 to June 2008 to construct the AR model, while we used the observation period of our dataset (from July 2008 to June 2017) to calculate the prediction error.

3.5.2. Regression With Unexpected News Index

Overall, we first analyzed the contemporaneous relationship between *un_ wsj* and the daily return of a green-minus-brown portfolio that is long in green firms and short in brown firms. However, we could not find a significant positive relationship, which should suggest that green stocks can outperform brown stocks when there are unexpected increases in climate change concerns. Then, we tried looking at the *green* (*brown*) portfolio returns individually, expecting a positive (negative) and significant relationship with *un_ wsj*, but not finding it this time either. Indeed, we tried unsuccessfully to demonstrate that, when there is an unexpected increase in climate change concerns, investors tend to penalize brown firms and to reward green firms.

3.6. MCCC index

At this point we tried to perform the same analysis done before with our second dataset (with the *mccc* index).

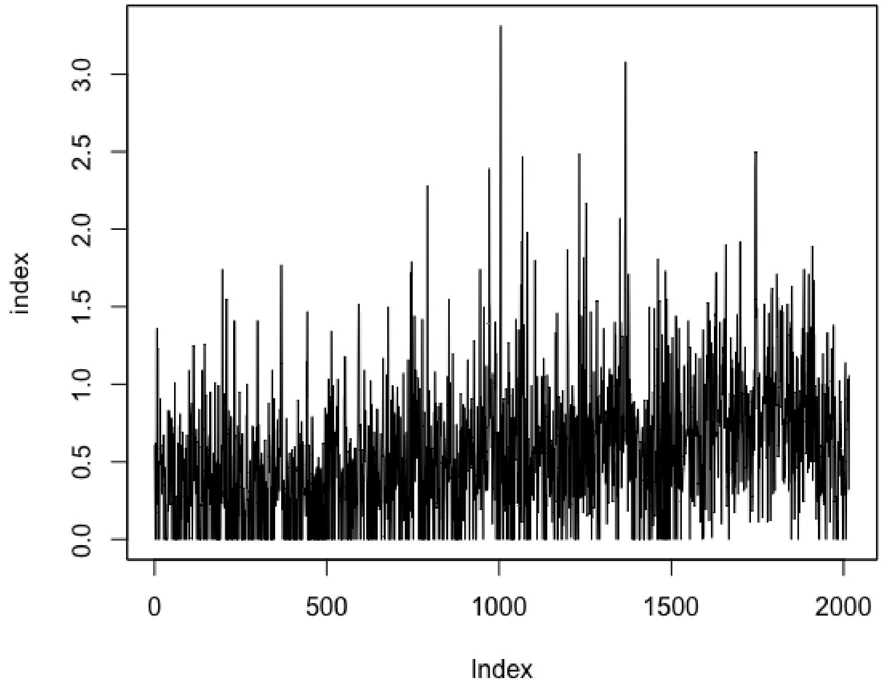

Figure 3.7: *mccc* Index

Nevertheless, as it's evident from the plots, even this time we couldn't find anything truly relevant.
As a final attempt to solve the problem we tried to perform a PCA on the stocks and to apply a correction on our stock returns, as we explain briefly in the next chapters.

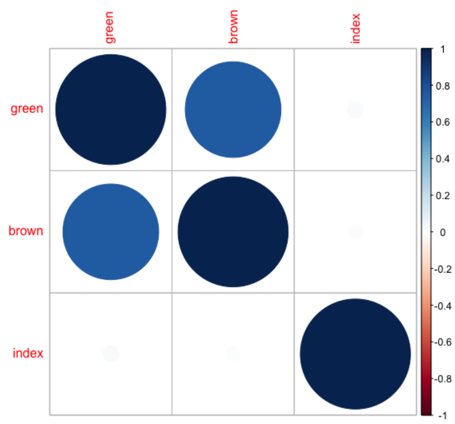

Figure 3.8: Corr Plot between assets

3.7. PCA On Stocks

3.7.1. PCA

In an effort to ignore the systematic volatility that is intrinsically associated with the markets movement, we performed the PCA on the stocks that compose our portfolio. We hoped that the first component of the PCA would carry all the market systematic volatility, and that we could explain the movements of the second component of the PCA with the climate change indexes. Hence, we performed the PCA on the portfolio composed by our daily data. We computed two separate implementations for green and brown stocks to be able to analyze them individually. Finally we extrapolated the second principal component to proceed with our study.

3.7.2. Regression On Second Component

Unfortunately even this time nothing relevant came from our inspections and the influence of the index on the market trends seems absent.

3.8. Fama & French Correction

Again, in an effort to ignore the systematic volatility that is intrinsically associated with the markets movement we performed a correction on the returns of our portfolios. We exploited the Fama & French factor model to try to exclude from our data the systematic volatility, studying in this way the returns dynamics without the movements associated with the market.

3.8.1. Construction and Regression

In order to implement the correction described above we collected the data of the Fama & French three factor model through the database of PhD. French[1]. Then we subtracted the index to the return of our portfolios to obtain our corrected returns. As expected, given previous failures, even this last attempt turned out badly.

[1]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

4 | Conclusions and future developments

In conclusion, even if we tried to follow the steps of the researchers who created the indexes that we analysed, we couldn't find any particular and statistically significant relationships with the market trends. We believe, however, that a way can be found to explain their connection with the climate change. The fundamental impact it is having and will have on the future of the world economy is there for all to see. It is likely that with the development of a society that pays more and more attention to these topics, to transparency regarding the choices of companies in green areas and to more conscious consumption by customers, it will also be easier to understand with more certainty which companies are truly environmentally friendly and which are not. In this way, we will have more reliable and less subjective analyses. Furthermore, as time goes on, we will also have a wider window of observation that will allow for more in-depth analyses. So finally, thanks to these factors and the possibility of always developing new indices, which can best describe the trend of climate change news and its influence, research in this area is open to continuous development and improvement, which we hope will be achieved in the near future.

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