EDHEC RISK INSTITUTE ELECTIVE

Project Report - Time-varying environmental betas and factors of European stocks

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Abstract

This study, based on the STOXX 600 constituents, provides evidence for the existence of an environmental risk premium, implying that the climate risk faced by companies is being reflected in the stock's prices. After selecting and streaming green characteristics reported by the stocks comprising the STOXX 600, we formed lag-portfolios on each of them. Then, to analyse and interpret our large data-set, we used the Principal Component Analysis (PCA). We were able to extract latent factors suggesting that portfolios formed on either brown or green stocks were able to capture a risk premium related to our environmental characteristics. Finally, we compared the characteristics of our non observable portfolios with two ESG ETFs (Refinitiv Eurozone ESG Select Index and MSCI Europe ESG Universal Index). The non observable portfolios outperformed the ETFs under a risk-adjusted basis, indicating that the latent portfolios were able to capture more information embedded in market prices regarding this environmental criteria.

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1 Introduction

1.1 Motivation

Evidence about how the Earth's climate change has been accelerating in the last few decades has been increasing, which has awakened the general consciousness about the role and contribution that every member of the society has played in the process. As a result, a new trend surged in almost every sector of the economy regarding how to diminish its carbon footprint and how to adopt a "greener" stand. In the investment industry these questions have not been easy to respond as the lack of a physical processes could suggest that no negative impact to climate were coming from the financial industry. Nonetheless, in the last years, investors have realized that choosing to which companies and projects to allocate resources may be even more important than some physical processes.

In this regard, a large discussion arose about the trade-off of financing only environmental-friendly companies against losing some potential return from not investing in the companies that were not. Investors then realized that companies faced two principal risk regarding climate change:

- **Physical risks**: associated with the direct impact of climate change on trade models
- **Transition risks**: which comprises reputation risk and negative economic impacts from governmental policies (these risks are mainly faced by "brown" companies).

With that in mind, investors started to pose the question about how well compensated they were being for bearing those risks, especially for the transition ones. Because of this, some investors were convinced that green companies were standing better off regarding those risks and, therefore, going long would lead to an outperforming strategy once the risk were realized. The findings about this last topic have been large and, at some extent, contradictory. But, maybe, one conclusion that lays in common ground in all the papers is that ESG (Environmental, Social and Governance) factors need to be integrated into the investment decision-making process.

1.2 General idea about the study

1.2.1 Goal and Process

In this paper, we will test the existence of an "*environmental risk premium*" by looking for non observable factors based on firms' environmental, social and governance (ESG) characteristics. The goal is to find non observable factors that capture pricing information not contained in the other traditional market factors and to explore how a portfolio based on such new factors would have performed. Our hypothesis is that it is possible to find a risk premium related to such information based on companies' ESG scores.

As most of the papers around this topic are based on US data, we have chosen to focus on European stocks by taking as the investment universe the components of the **STOXX 600** index. The guideline for investing in such "non observable" portfolios will be to first identify the main exposures to some relevant environmental characteristics and then, try to replicate such exposures. Each environmental characteristic will be represented by a long-short portfolio, which weights will be determined by the stock's score on that characteristic.

After having identified a green premium associated to firm-level environmental characteristics, we will try to find a strategy to capture this risk premium. The way in which we try to capture this premium is by partitioning all the compensated risk and concentrate it into a combination of only a few characteristics. We will use the Principal Components Analysis (PCA) to do this. Nonetheless, we do not affirm that the resulting non observable portfolios will actually reflect the pricing of all possible green criteria, as the information vary among different data providers, but it should be a good starting point to explore this approach.

1.2.2 Challenges and Solutions

Having say that, it is important to insist on the challenge posed in obtaining good quality data regarding green criteria performance. Different data providers have different criteria and even different methodologies to give companies' scores for similar criteria. We chose to focus on the data provided by *Reuters DataStream* because it has a broad portfolio of different characteristics and it offers at least 10 years of observations. Given our resources, access to this data base was granted which also allowed us to give some consistency to the data we used. The importance of performing an analysis on the company's profile through time is highly relevant as a categorized "brown" company can turn into a "green" one at some point in time and the contrary, even if it's more uncommon, can also happen.

1.2.3 Description of the portfolios

Taking this into account we created a portfolio for each environmental characteristic observed. The weight for each stock was derived from the reported data. At this point, we differentiated between **Binary** data and **Numerical** data. As a result, we had two types of portfolios. The first one composed by two buckets, the green bucket, and the brown bucket. These portfolios were constructed in such way that the long position in one bucket is exactly offset by the short position in the other bucket. For the second portfolio we ranked all the constituents regarding the quantity reported for each criteria and assigned weights in such a fashion that it will have long exposure to those stocks reporting the highest value and short exposure to the ones with the lowest reporting values, resulting in a zero-investment portfolio. An important feature of these portfolios is that they were re-balanced each month, capturing any changes on the company's profile.

1.2.4 Construction and Advantages of non observable factors

Once having this "green portfolios", we implemented the Principal Component Analysis to a matrix gathering the time series of all the constructed portfolios returns. The main idea of this process was to reduce the dimensionality of the data-set needed to explain the majority of the variance observed in the whole set of variables. This led us to identify five new "non observable" factors that were represented by portfolios formed as linear combinations of the previously constructed portfolios based on the observable characteristics. We explored, then, the performance of such portfolios to test if they were actually successful in capturing a green risk premium. At this point, its important to clarify our stand regarding the green risk premium. We believe that every company faces a "environmental risk", which is divided into the two components mentioned above.

1.3 Results and Further discussion

In this sense, we tested if such a risk premium existed by adding traditional financial risk factors such as the famous Fama-French factors of size and value. If these factors were highly correlated with our “non observable” portfolios, it would have meant that those traditional factors explained much of the variance observed and, therefore, the hypothesis of a green risk premium would have weakened. We will see in our results that this was not the case. Once having evidence about the existence of such green risk premium, we explored if the derived latent portfolios were able to capture the risk premium associated with it.

At this point, we arrived to a crucial breaking point. We observed that portfolios based on this new "green" factors succeeded in outperforming the market, nonetheless the construction suggested that this is achievable by going long on either the "brown" or "green" companies. We will discuss further this matter in the conclusion of our research but at this point we can say that this result lies within our expectations. This statement is based on the idea that riskier assets are required a higher cost of capital to compensate for such risk, which is actually faced by both, "brown" and "green" companies, so they should offer some risk premium related to it.

Finally, we wanted to explore the question about how much additional information does this new “non observable” factors added regarding the existing ESG indexes in the market. To perform this analysis, we compute the performance statistics of the indexes *Refinitiv Eurozone ESG Select Index* and *MSCI Europe ESG Universal Index*. We found that under a risk-adjusted basis, our portfolios did show an out-performance whit relatively low correlation. This meant that our portfolios were actually capturing additional information that this indexes were failing to incorporate.

2 Methodology

2.1 Principal Component Analysis - PCA

We used the asset pricing model suggested in the paper by Kelly, Pruitt and Su, JFE 2019 to estimate betas associated to latent factors related to environmental characteristics, and then we tried to check ex-post if these estimated factors can be interpreted as “environmental risk factors”. The model define the returns as follows:

$$
\begin{aligned}
&r_{(i,t+1)} = \alpha_{(i,t)} + \beta_{(i,t)}\, h_{(t+1)} + \epsilon_{(i,t+1)} \\
&\text{with} \quad \alpha_{(i,t)} = z'_{(i,t)}\Gamma_{\alpha+}\nu_{(\alpha,i,t)} \quad \text{and} \quad \beta_{(i,t)} = z'_{(i,t)}\Gamma_{\beta+}\nu_{(\beta,i,t)}
\end{aligned}
\tag{1}
$$

$r_{(i,t)}$ is the excess return of the stock *i* at time *t*, where *i* = 1, ... , N, with N potentially very large, ideally between 500 and 1000 or more, and t = 1, ... , T, with T sufficiently large, ideally T $\geq$ 60.

h_t is a K × 1 vector containing the realization of K risk factors at time *t*.

$\beta_{i,t}$ is a 1 × K vector containing the time-varying factor loadings of the K factors for stock *i*

$\alpha_{i,t}$ is a scalar (1 × 1) representing a time-varying intercept of the stock *i*

$z_{i,t} = [z_{i,t}^{(1)}, ..., z_{i,t}^{(L)}]$ is a 1 × L vector containing the different L firm-level characteristics (that is stock-specific), aka "instruments", of the company *i* at time *t*. L is potentially large. In order to estimate the K factors $h_t = [h_{1,t}, \ldots, h_{K,t}]'$, it must be that L ≥ K

Γ_β is a L × K matrix mapping the L characteristics to the K risk factors. The estimation of Γ_β leads to find linear combinations of the firm-specific characteristics that describe the latent factor structure.

If $\Gamma_\alpha = 0$, the restricted (simplified) model becomes:

$$r_{(i,t+1)} = z'_{(i,t)}\Gamma_\beta h_{(t+1)} + \epsilon^*_{(i,t+1)}$$

which can then be used to describe the column vector of excess returns as follows:

$$r_{t+1} = Z'_t\Gamma_\beta h_{(t+1)} + \epsilon^*_{t+1}$$

where: $r_{t+1} = [r_{1,t+1}, ..., r_{N,t+1}]$ is a N × 1 vector of individual firms returns, and $Z_{t+1} = [Z_{1,t+1}, ..., Z_{N,t+1}]$ is a N × L matrix stacking the characteristics from all the firms.

h_t and matrix Γ_β can be estimated using the numerical algorithm (IPCA) proposed by KPS, JFE 2019 through the following minimization problem:

$$min_{\Gamma_\beta,H}\left[\sum_{t=1}^{T-1}(r_{(t+1)} - Z_t\Gamma_\beta h_{t+1})'(r_{(t+1)} - Z_t\Gamma_\beta h_{(t+1)})\right]$$

By solving this problem, we will obtain the values of h_t and matrix Γ_β that capture most of the information embedded in the firm-specific characteristics. The values of h_{t+1} and Γ_β that minimize the previous equation and satisfy the first-order conditions are the defined as:

$$\hat{h}_{t+1} = (\widehat{\Gamma}'_\beta Z'_t Z_t \hat{\Gamma}_\beta)^{-1}\widehat{\Gamma}'_\beta Z'_t r_{t+1}, \qquad \forall t$$

And

$$vec\left(\widehat{\Gamma}'_\beta\right) = \left(\sum_{t=1}^{T-1} Z'_t Z_t \bigotimes \hat{h}_{t+1}\widehat{h}'_{t+1}\right)^{-1} \left(\sum_{t=1}^{T-1}[Z_t \bigotimes \widehat{h}'_{t+1}\ ]' r_{t+1}\right)$$

Let N be the number of stocks for which returns and instruments are available at time *t+1* . Consider the $L \times 1$ vector of managed portfolios x_t defined as:

$$x_{t+1} = \frac{Z'_t r_{t+1}}{N_{t+1}} = \frac{1}{N_{t+1}}\left[\sum_{i=1}^{N_{t+1}} z_{i,t}^{(1)} r_{i,t+1}\ , \ \ldots \ , \sum_{i=1}^{N_{t+1}} z_{i,t}^{(L)} r_{i,t+1}\right]'$$

Each component of the column vector x_{t+1} correspond to a observation for a managed portfolio based on each of the L firm-specific characteristics, which is obtained as the weighted average returns of the constituents of each portfolio. We can then define:

$$X = [x_1\ , \ \ldots\ , \ x_t\ , \ldots\ , \ x_T]'$$

X is the T × L matrix with the time series of the returns for each managed portfolios. In this matrix for example, if the first three characteristics are, for example, size, value, and the market factor, then the first three columns of X are time series of returns from the portfolios managed based on each of these.

2.1.1 First method

Assuming that the characteristics are constant (for each stock) over time and that:

$N_t = N$, for all dates *t* = 1,...,T

Then, Γ_β can be estimated (up to a rotation matrix) as the first K-eigenvectors of the sample (uncentered) second moment matrix, which has dimensions L x L.

$$\frac{1}{T}X'X = \frac{1}{T}\sum_{t=1}^{T} x_t {x'}_t \tag{2}$$

Meaning that:

$$\widehat{\Gamma_\beta^{**}} = W_{1:K} \qquad \left(\frac{1}{T}X'X\right).W = W\Omega \qquad W'W = WW' = I_L$$

where Ω is the L x L diagonal matrix collecting the L eigenvalues (in ascending order) of the matrix $\frac{1}{T}X\prime X$ and $W = [W_1, ..., W_K, ..., W_L]$ is the L x L matrix where each column is an eigenvector of the matrix $\frac{1}{T}X\prime X$.

KPS, JFE 2019 state in their Section 2.1.1 that this $\hat{\Gamma}_\beta^{**}$ is an excellent starting point for their IPCA recursive estimator, which implies that $\hat{\Gamma}_\beta^{**}$ it can be substituted into:

$$\hat{h}_{t+1} = (\widehat{\Gamma}'_\beta {Z'}_t Z_t \hat{\Gamma}_\beta)^{-1} \widehat{\Gamma}'_\beta {Z'}_t r_{t+1}, \qquad \forall t$$

$\hat{h}_t + 1$ is K × 1 column vector that compiles the returns at time *t+1* associated with the first K latent factors implied by the reported L firm-specific "green" characteristics until time *t*.

2.1.2 Second method: D-mean method

An alternative for the previous methodology is to take the RP-PCA estimator of the loadings, denoted by $\hat{\Lambda}_{PCA}$, as the first $\sqrt{T}$ times k-eigenvectors of the sample variance-covariance matrix of returns, which is estimated as follow:

$$\hat{V}\,(r_t) = \; M_{RP}\,(\,\gamma_{RP} = \; -1)\,\frac{1}{T}\sum_{t=1}^{T}\widetilde{r}_t\widetilde{r}'_t$$

Where $\widetilde{r}_t = [r_{1,t} - r_{mean,t}, \ldots, r_{N,t} - r_{mean,t}]'$ is the N × 1 vector of individual demeaned returns at time *t*. We denote the RP-PCA factor returns estimator in this special case as $\widehat{\widehat{h}}_{t,PCA}$:

$$\widehat{\widehat{h}}_{t,PCA} = (\hat{\Lambda}'_{PCA}\hat{\Lambda}_{PCA})^{-1}\hat{\Lambda}'_{PCA}\widetilde{r}_t$$

Where $\widehat{\widehat{h}}_{t,PCA}$ is the K × 1 column vector having the same interpretation as $\hat{h}_t + 1$ found in the previous method. It is important to note that if the characteristics are not constant, we will found different observations for the matrix Γ_β an the matrix $\hat{\Lambda}_{PCA}$ at each point in time. This fact allows to have latent factors with time-varying loadings on the observable L characteristics.

3 Implementation

3.1 Data obtention

All the data used in our study comes from ***Reuters DataStream***. DataStream is a time series data retrieval service that provides significant historical data for a variety of financial markets worldwide. We obtained a number of environmental characteristics, split into three main categories, **Emissions**, **Innovation**, and **Resources**, for a total of **136** characteristics. In those three categories we have three additional sub-categories that specify further the type of the characteristic:

- **Numerical**: The data reported is a quantity
- **Binary**: Two state possible per characteristic *YES* or *NO*
- **Quantitative**: Different state possible by characteristics

We obtained those characteristics for each one of the constituents in the **STOXX 600** index. It is important to note that the stocks chosen in our study reflect the index at a given point in time. The basket of stocks chosen are, therefore, fixed for the entire study. Then, we exported the data for a period of 19 years, from *2001 – 2019* . For each year we had 136 characteristics for each of the 600 stocks. Thus, we processed more than 1 million data.

The Environmental, Social, and Corporate Governance (ESG) concepts are not new as the term appeared in the 60s, but companies did not use to report and disclose this information until recently. Thus, across our sample of stocks and periods we found a fair amount of missing information. Likewise, as we took the index at today's date some stocks were not public or did not existed some years ago, leading to additional missing information. That is why we chose to filter our data according to the next two parameters:

- **Characteristics**: We took the most significant characteristics for our study which were the ones allowing us to get enough data for our analysis
- **Period**: We choose the years in which the highest amount of data were reported while trying to keep a large enough period

The goal was to select the optimal period and basket of characteristics to be able to get meaningful results from our study.

3.2 Determination of the optimal number of characteristics

Before choosing the stocks and the period we were going to use in the next steps, we perform an initial exploratory data analysis. The first step was to observe the trade off between the number of stocks and the number of characteristics once we filtered for only those characteristics that were reported by at least N stocks for a given year. N is a threshold representing the minimum number of stocks that should be reporting a given characteristic. As the threshold diminished, the number of characteristics available went up. In this step, we also controlled for the characteristic's specified types (Numerical, Binary and Quantitative) as we were looking to get at least some Numerical characteristics because they allow for a more detailed differentiation between the stocks in our sample and, thus, provide more relevant information.

We build the graphs (Figures 1 and 2) summarizing the results for two values of N: 200 and 250.

The Figures 1 and 2 emphasized the fact that the larger the period chosen, by incorporating earlier years, the less data we had. From 2010, the number of characteristics reported, specially the Numerical ones, were relevant. Considering the slightly more restrictive threshold of 250 stocks, we decided to start our study with only **71** characteristics (Table 1), out of them we had:

- Binary characteristics: **55**
- Numerical characteristics: **14**
- Quantitative characteristics **2**
  (see *Weighting scheme*)

For the period, we choose two samples, ***2008 – 2019*** and ***2010 – 2019***. The periods were chosen to test if the financial crisis of *2008* could impact the outcome of our study.

Among the Numerical characteristics it is important to define the ones related to CO2 emissions. These emissions are classified in the following three scopes:

- **Scope 1**: Direct emissions
- **Scope 2**: Indirect emissions from the purchase of electricity, steam, heating and cooling consumed by the company
- **Scope 3**: Any other indirect emissions related with the company's activities

In addition to these measures, the carbon intensity was also reported. This characteristic reflect how many CO2 does the company need to emit in order to generate USD 1 of revenue.

3.3 Construction of the portfolios

After having chosen both, the characteristics and the period, we proceeded to form the portfolios. We construct one portfolio by characteristic, which were re-balanced at the end of each month in which we observed a change in the reported characteristics. To form the portfolios, first, we needed to compute the weights for each stock given the value observed for any given characteristic. To do this we created a weighting scheme that created zero investment portfolios, i.e, long-short portfolios in which the sum of the weights added to zero. Then, we computed the monthly returns for every stocks in the sample. Finally, we computed the monthly returns of the portfolios as the weighted average of observed monthly return. In order to prevent a look-ahead bias, we formed lag-portfolios. To do so, we computed the weight for the stocks based on the observed values for a given characteristic at time *t* (month) while using the return from the stocks at time *t+1*.

Before implementing the Principal Component Analysis (PCA) we needed to check for the correlation between the portfolios and remove wisely the characteristics that were highly correlated.

3.3.1 Weighting scheme

In order to form the portfolios for each one of the characteristics, we had to assign weights to each stock. As mentioned above, we had three different characteristics: **Binary**, **Numerical** ,and **Qualitative**, but we decided to disregard the two **Qualitative** ones as we couldn't define a proper and consistent weighting scheme for them. We also decided to disregard two characteristics related to Scope 3 emissions. The reason for this was that this type of emissions are estimated by each data provider using highly subjective and different methodologies, which could make our results highly dependent on the methodology implemented by DataStream. For the rest of them we used the following weighting schemes:

Numerical Characteristics:

- Rank the stocks (descending order) on the value they report for the numerical characteristic
- $weight\ (w)\ =\ \frac{Rank\ of\ the\ stock}{Number\ of\ stocks\ +1}\ -\ 0.5$

The portfolios formed on the numerical characteristics are long-short portfolios with weights ranging between -0.5 and 0.5. With this weighting scheme we go short on the stock with the highest rank (lower rank number) and long on the stock with the lowest rank (higher rank number), where the highest rank were assigned to the stock reporting the lowest reported value.

Binary Characteristics:

- Two possibilities for the classification: *YES* or *NO*
- Weight for *YES*: $w_Y = \frac{1}{Number\ of\ Yes}$
- Weight for *NO*: $w_N = -\frac{1}{Number\ of\ No}$

We go long on the *YES* and short on the *NO*.

Based on these schemes, we computed the weights at each of month of the chosen period. Then, as mentioned before, we computed the return of the lag-portfolio related to each characteristic by multiplying the stock's weight at time *t* by the return of the stock at time *t+1*.

This helped us to construct the time series of returns for each of the 67 characteristics chosen. Nonetheless, we observed that some portfolios were presenting high volatility levels in relation to others. The problem was that the weighting scheme used was assigning high weights to some stocks that observed abnormal returns in a given month. To solve this problem we re-scaled the weights by dividing them by half the number of stocks in each portfolio. This led us to have more conservative weights while preserving the property that the sum of all the weights in a portfolio added to zero for all the months. Thanks to this adjustment we diminished this effect, which added consistency and strength to our analysis.

3.4 Portfolios characteristics

3.4.1 Correlation check

Out of all the characteristics we selected above, we ran a correlation check on the portfolios formed to confirm that there were no high correlation coefficients between any of them. Normally, factors that are highly correlated contain redundant information and this could be problematic when implementing the IPCA methodology. So, to identify these correlations, we computed the variance-covariance matrix and derived from it the correlation coefficients for all the possible pairs of stocks.

The correlation matrix is a L × L symmetric matrix, in which L is the number of characteristics and has as entries the correlation coefficient associated with all the possible pairs of initial variables. We decided to remove those characteristics having a correlation above 0.90.

After having computed the correlation matrix for the two periods, *2008 – 2019* and *2010-2019*, we identified five highly correlated characteristics:

- **CO2 Equivalent Emission Total:** It is a linear combination of “CO2 Equivalents Emission Direct” and “CO2 Equivalents Emission Indirect” *Numerical Characteristic*
- **Direct Energy/Energy Purchase Direct** *Binary Characteristic*
- **Internal Carbon Pricing** *Binary Characteristic*
- **Fossil Fuel Divestment Policy** *Binary Characteristic*
- **Estimated CO2 Equivalents Emission Total** *Numerical Characteristic*

Thus, we ended using only **62** characteristics out of the first 71 selected (Table 2):

- Binary characteristics: **52**
- Numerical characteristics: **10**

For the rest of the study, we will only use the characteristics presented in the table 2.

3.5 Additional Portfolios

After having completed the previous analysis we added to the 62 portfolios three additional portfolios. The first two were constructed based on the stocks’ market capitalization and book-to-market values. We used the methodology previously mentioned to construct the portfolios with Numerical observations. The third one was an equally weighted portfolio that we used as a proxy for the market portfolio and which is our only long only portfolio.

The main motivation to add these portfolios to the ones we constructed previously was to test if any of these three added portfolios were highly correlated with any of our 62 environmental-based portfolios. If this happened it would have meant that those environmental portfolios were not adding any new relevant pricing information as most of the information contained in them was already captured by the traditional factor portfolios. To check this point we computed again the correlation matrix and we did not find any correlation coefficient above 0.90.

After this final check, we had an enough solid base to perform the Instrumented Principal Component Analysis.

3.6 Application of the Principal Component Analysis (PCA)

3.6.1 First five eigenvalues

Based on the methodology previously presented we obtained a matrix containing the time series of "observations" from the latent portfolios. We perform the two variations of the PCA and we found that the results were fairly consistent. We chose to present only the results based on the second method to facilitate the interpretation of the results.

The Principal Component Analysis provided us with a L × L matrix, where L now was 65 (62 environmental portfolios plus the market and traditional factors portfolios: Market Cap, Book To

Market Value and an equally weighted portfolio). To continue with our study we took only the first five non observable portfolios.

Why do we only took the first five eigenvectors? Because they explain most of the variance embedded in the portfolios' time series (i.e contain most of the information). We will explain briefly why this is true.

Let's take $\{X_n\}$, $n = 1,\ 2,\ ...,\ N$ with dimension D

The goal it is to map the data that has dimensionality D onto a space that has a dimensionality M, where M < D. The one-dimensional space vector μ_1 will have to maximize the variance to contain most of the information. To do this is important to recall the formula for projecting any point $x_i \in \{X_n\}_{n=1,\ 2,\ ...,N}$ onto the vector μ_1:

$$Proj_{\mu_1}(x_i) = \mu_1\prime * x_i * \mu$$

$\mu_1\prime * \bar{x} * \mu$ is the mean of the projections and μ is a unit vector

From that expression it is possible to derive the variance of the projection as:

$$\frac{1}{N}\sum_{n=1}^{N}(\mu_1' x_n - \mu_1\bar{x})^2 = \frac{1}{N}\sum_{n=1}^{N}[\mu_1' * (x_n - \bar{x})]^2 = \sum_{n=1}^{N}\mu_1'(x_n - \bar{x})(x_n - \bar{x})\mu_1 = \mu_1' S \mu_1$$

Where S is the variance-covariance matrix of the $\{X_n\}_{n=1,\ 2,\ ...,N}$

What we would want is to maximize $\mu_1'\ S\ \mu_1$, with the constraint that $\mu_1'\mu_1 = 1$ (i.e., μ_1 is a unit vector), so that our projection capture as much information as possible from the original data. To find the local maximum for the function above, we will use the method of the Lagrange multiplier. Thus, we get the following formula:

$$\mathcal{L}(x,\ \lambda) = f(x) - \lambda * g(x) \text{ where } f(x) = x'\ S\ x \text{ and } g(x) = \lambda(1 - x'x)$$

Then, we derive the Lagrange function:

$$\begin{aligned} \tfrac{d}{d\ \mu_1}[\ \mu_1'\ S\ \ \mu_1\ + \lambda(1 -\ \mu_1'\ \mu_1)] &= 0 \\ \text{i.e., } 2S\ \mu_1\ -\ 2\lambda\ \mu_1 &= 0 \\ \text{i.e., } S\ \mu_1 &= \lambda\ \mu_1 \end{aligned}$$

From this result, it is easy to observe that λ is an eigenvector from the variance-covariance matrix we got above.

Which eigenvector? The goal is to maximize the following function $\mu_1\prime\ S\ \mu_1$, thus, maximizing this function is the same as taking the highest possible λ. Thus, we see that taking the first eigenvectors, sorted in ascending order, help to maximize the amount of variance captured. This mean that the first eigenvectors explain the most the variance from the data set. This idea extrapolates directly to our analysis. To get how much of the total variance is explained by the first five eigenvectors, we divided the eigenvalues associated to each eigenvector by the sum of eigenvalues.

In our case, we saw that the first five principal components (PC) explained:

- **58**% of the variance for the data from 2008 – 2019
- **55**% of the variance for the data from 20010 – 2019

3.7 The non observable portfolios and its characteristics

Out of the Principal Component Analysis (PCA), we got the eigenvalues and the eigenvectors associated with them. What is worth noticing is that the eigenvectors' components can be interpreted as weights for the non observable portfolios. Analyzing these non observable portfolios and how they are constructed is paramount to understand what will drive our results. We saw above that the first eigenvectors explained most of the variance from the data, thus, capturing most of the information from the data set. Up until this point we hadn't talk again about the "green" risk premium. We are not quite there yet. But we can start seeing that there is additional information embedded in market prices not being captured by the traditional factors used by investors.

The next step will be to see how this portfolios perform so that we can see if they are actually capturing any risk premium, which should led them to have positive and, hopefully, high Sharpe ratios. For this part it was crucial to understand the strategy behind each of the obtained latent factors.

3.8 Performance of the non observable portfolios

We constructed bar plots showing the size and direction of the components of our five latent factors. The bar plots gave us very important information regarding the strategy of our non observable portfolios. The bar plots represent the non observable portfolios' loadings on the 65 characteristics used originally. We will interpret the results we got for the periods *2008 – 2019* and *2010 – 2019* to better understand the strategy behind our latent portfolios.

3.8.1 Period: 2008 - 2019

We noticed that the first three highest loadings in absolute value were highly important to interpret the direction of the non observable portfolios. For this part we will refer to those companies having positive environmental-friendly scoring as "**green**" companies and to those failing to get a good score as "**brown**" companies.

An important adjustment that we made was to flip the loadings sign whenever the mean returns of the resulting latent portfolios were negative. This adjustment do not change the results in any manner but allow for a more direct interpretation of the results. This is important to bear in mind as a flipped non observable portfolio will point to the opposite direction as the one suggested by its loadings presented in the bar plots. We present the first three characteristics, for the first eigenvector (Figure 5):

1. **Agrochemical 5 % Revenues**
    - Binary characteristic
    - With the weighting scheme we go long on brown and short on green
    - Here the loading is **positive** meaning that we go long on **brown**

2. **Constant**
    - Numerical characteristic
    - Represent the market
3. **Value - Resource Reduction/Policy**
    - Binary characteristic
    - With the weighting scheme we go long on green and short on brown
    - Here the loading is **negative** meaning that we go long on **brown**

Overall, the non observable portfolio is going long on **brown**. The Sharpe ratio (Table 3) is positive and not flipped (N-F), thus, is better to go long on **brown**.

First three characteristics, for the second eigenvalue (Figure 6):

1. **Agrochemical 5 % Revenues**
    - Binary characteristic
    - With the weighting scheme we go long on brown and short on green
    - Here the loading is **positive** meaning that we go long on **brown**
2. **Value - Resource Reduction/Environmental Resource Impact Controversies**
    - Binary characteristic
    - With the weighting scheme we go long on brown and short on green
    - Here the loading is **negative** meaning that we go long on **green**
3. **Resource Efficiency Processes/Policy Energy Efficiency**
    - Binary characteristic
    - With the weighting scheme we go long on green and short on brown
    - Here the loading is **negative** meaning that we go long on **brown**

Overall, the non observable portfolio is going long on **brown**. The Sharpe ratio (Table 3) is positive and not flipped (N-F), thus, is better to go long on **brown**.

First three characteristics, for the third eigenvalue (Figure 7):

1. **Value - Resource Reduction/Policy**
    - Binary characteristic
    - With the weighting scheme we go long on green and short on brown
    - Here the loading is **positive** meaning that we go long on **green**
2. **Agrochemical 5 % Revenues**
    - Binary characteristic
    - With the weighting scheme we go long on brown and short on green
    - Here the loading is **positive** meaning that we go long on **brown**
3. **Constant**
    - Numerical characteristic
    - Represent the market

Overall, the non observable portfolio is going long on **green**. The Sharpe ratio (Table 3) is negative and not flipped (N-F). On a risk-adjusted bias this portfolio fails to get enough excess return to compensate for the risk borne.

First three characteristics, for the fourth eigenvalue (Figure 8):

1. **Emission Reduction Processes/Policy Emissions Reduction**
   - Binary characteristic
   - With the weighting scheme we go long on green and short on brown
   - Here the loading is **negative** meaning that we go long on **brown**
2. **Agrochemical 5 % Revenues**
   - Binary characteristic
   - With the weighting scheme we go long on brown and short on green
   - Here the loading is **negative** meaning that we go long on **green**
3. **Animal Testing Cosmetics**
   - Binary characteristic
   - With the weighting scheme we go long on brown and short on green
   - Here the loading is **positive** meaning that we go long on **brown**

Overall, the portfolio is going long **brown**. The Sharpe ratio (Table 3) is negative, very small, and not flipped (N-F). On a risk-adjusted bias this portfolio fails to get enough excess return to compensate for the risk borne.

First three characteristics, for the fifth eigenvalue (Figure 9):

1. **Animal Testing Cosmetics**
   - Binary characteristic
   - With the weighting scheme we go long on brown and short on green
   - Here the loading is **negative** meaning that we go long on **green**
2. **Equator Principles**
   - Binary characteristic
   - With the weighting scheme we go long on green and short on brown
   - Here the loading is **positive** meaning that we go long on **green**
3. **Value - Resource Reduction/Policy**
   - Binary characteristic
   - With the weighting scheme we go long on green and short on brown
   - Here the loading is **negative** meaning that we go long on **brown**

Overall, the portfolio is going long **green**. The Sharpe ratio (Table 3) is positive but flipped. Meaning that we need to short the latent portfolio, thus, we would actually be going long **brown**.

Conclusion for the 2008 – 2019 period:
Four out the five first non observable portfolios associated with the first eigenvalues capture the information from the data set by going long on **brown**. Nevertheless, only three of them succeeded in capturing a risk premium yielding positive Sharpe ratios .

This results suggests that an environmental risk premium does exist in the market and it is possible to exploit it to improve investors' risk-adjusted returns. The idea that brown companies are the ones capturing this premium is consistent with the fact that those companies are the ones facing most of the risk and, thus, investors require a higher cost of capital. Nevertheless, this results might have been affected by the 2008 financial crisis. We will now analyze the data set after such crisis to see if we obtain consistent results.

3.8.2 Period: 2010 - 2019

First three characteristics, for the first eigenvalue (Figure 10):

1. **Agrochemical 5 % Revenues**
   - Binary characteristic
   - With the weighting scheme we go long on brown and short on green
   - Here the loading is **negative** meaning that we go long on **green**
2. **Value - Resource Reduction/Policy**
   - Binary characteristic
   - With the weighting scheme we go long on green and short on brown
   - Here the loading is **positive** meaning that we go long on **green**
3. **Constant**
   - Numerical characteristic
   - Represent the market

Overall, the non observable portfolio is going long on **green**. The Sharpe ratio is positive but we needed to flip it (Table 4), thus, we should go long on **brown**.

First three characteristics, for the second eigenvalue (Figure 11):

1. **Value - Resource Reduction/Policy**
   - Binary characteristic
   - With the weighting scheme we go long on green and short on brown
   - Here the loading is **positive** meaning that we go long on **green**
2. **Agrochemical 5 % Revenues**
   - Binary characteristic
   - With the weighting scheme we go long on brown and short on green
   - Here the loading is **positive** meaning that we go long on **brown**
3. **Constant**
   - Numerical characteristic
   - Represent the market

Overall, the non observable portfolio is going long on **green**. The Sharpe is positive but we needed to flip it (Table 4), thus, we should go long on **brown**.

First three characteristics, for the third eigenvalue (Figure 12):

1. **Equator Principles**
   - Binary characteristic
   - With the weighting scheme we go long on green and short on brown
   - Here the loading is **negative** meaning that we go long on **brown**
2. **Animal Testing Cosmetics**
   - Binary characteristic
   - With the weighting scheme we go long on brown and short on green
   - Here the loading is **positive** meaning that we go long on **brown**
3. **Organic Products Initiatives**
   - Binary characteristic
   - With the weighting scheme we go long on green and short on brown

- Here the loading is **positive** meaning that we go long on **green**

Overall, the non observable portfolio is going long on **brown**, with a positive Sharpe ratio and it was not necessary to flip it (Table 4).

First three characteristics, for the fourth eigenvalue (Figure 13):

1. **GMO Products**
    - Binary characteristic
    - With the weighting scheme we go long on brown and short on green
    - Here the loading is **positive** meaning that we go long on **brown**
2. **Animal Testing Cosmetics**
    - Binary characteristic
    - With the weighting scheme we go long on brown and short on green
    - Here the loading is **positive** meaning that we go long on **brown**
3. **Organic Products Initiatives**
    - Binary characteristic
    - With the weighting scheme we go long on green and short on brown
    - Here the loading is **positive** meaning that we go long on **green**

Overall, the non observable portfolio is going long **brown**. The Sharpe ratio is **positive but flipped** (Table 4), thus, we should go long on **green**.

First three characteristics, for the fifth eigenvalue (Figure 14):

1. **Value - Resource Reduction/Environmental Resource Impact Controversies**
    - Binary characteristic
    - With the weighting scheme we go long on brown and short on green
    - Here the loading is **negative** meaning that we go long on **green**
2. **GMO Products**
    - Binary characteristic
    - With the weighting scheme we go long on brown and short on green
    - Here the loading is **positive** meaning that we go long on **brown**
3. **Constant**
    - Numerical characteristic
    - Represent the market

Overall, the non observable portfolio is going long **green**. The Sharpe ratio is **positive and not flipped** (Table 4), thus, we should go long on **green**.

Conclusion for the 2010 – 2019 period:
Three out of the five first non observable portfolios are going long on brown and two of them are going long on green, but all of them succeeded in having positive Sharpe ratios. At this point we can see that this analysis do not suggest whether it is more profitable to invest in brown or green companies. The scope of the analysis was to look for the existence of an embedded environmental risk premium. Given the consistency in our study among the two periods used we can affirm that such an environmental risk premium is in fact discounted in market prices

3.9 ESG ETFs

Today, more and more ESG ETFs are being created to respond to the growing investors' demand for this kind of products. Indeed, a growing number of investors want to invest in socially responsible impact investing funds, which are also known as Environmental, Social, and Governance (ESG) funds. The portfolios are formed with stock piking based on a positive screening process on their ESG rating. They also create portfolios based on environmental characteristics but following different methodologies and using data from different data providers, therefore, it is interesting to compare the statistics we get against the ones obtained from other ETFs. However, the craze for ESG ETF is quite recent, thus, there are few ESG ETF providing a sufficiently large data set. In our analysis we will focus on two ESG ETFs:

- Refinitiv Eurozone ESG Select Index
- MSCI Europe ESG Universal Index

Those ETFs provide data from *2009-11-30* to *2019-12-31*.

The Table 5 provides the characteristics of the ETFs for the period mentioned above. Compared to our non observable portfolios, both ETFs present a higher beta and a lower Sharpe ratio. This means that the portfolios constructed trough our approach outperform the ETFs. However, the non observable portfolios are not green portfolios. On the contrary, most of our portfolios go long on the brown stocks and short on the green stocks.

After seeing that our brown stocks portfolios outperform the ESG ETFs on the period 2009 - 2019, we proceeded to look more closely to the correlation. We expected a high correlation between our portfolios and the ETFs, as they should contain similar information regarding environmental risk given that both of them are constructed based on ESG characteristics.

The Table 6 provides the correlation between the ETFs and the first five non observable portfolios for the period 2010 - 2019. The correlation between the ETFs and the latent portfolios is very low indicating that they share very little information. This result suggest that either the ETFs or the latent portfolios are capturing more information that the other. Given the outperformance of our portfolios, we have reasons to believe that the methodology implemented allowed us to capture more information than the one that is currently used by these ETFs.

Where this result can come from?

- The characteristic choice: The ETFs might be basing their construction model on a more limited or different set of environmental characteristics
- The basket of companies: For our study we choose to use the STOXX 600 constituents at a given point in time, while the ETFs considered the companies that existed at every point in time.

4 Conclusion

4.1 Environmental Risk Premium

The results from our study present strong evidence for the existence of an environmental-risk premium embedded in market prices. Furthermore, it suggest that trying to capture this premium could be an important way for investors to improve their portfolios' risk-adjusted performance. This is supported, first, by the fact that none of our 62 original "green" portfolios were highly correlated with the "market" portfolio nor with the traditional factors used in other models, such as the size factor and the value factor. Nevertheless, capturing all that information might be slightly impractical. Using the Principal Components Analysis we found that it is possible to capture more than half of that information by constructing only five latent portfolios.

An important advantage of choosing such an approach is that loadings are allowed to vary through time, which helps to find the optimal exposures on the original portfolios to capture the environmental risk premium under a time-varying framework. Nonetheless, it is important to insist on the fact that observing that seven out of the ten latent portfolios are long on "brown" companies do not suggest that it is better to invest in those companies. It only suggest that "brown" portfolios, constructed in the way we did, do a very good job in capturing the required excess return to justify bearing the additional risk coming from climate change.

Under the traditional Mean Variance Optimization framework it is clear that it is not possible to compare returns in a straightforward fashion. Investors need rather to think under a risk-adjusted basis. This means that it is necessary to see how much return the investor get for the risk he is bearing. In this regard, it is normal to expect "brown" companies to offer an additional risk premium over the "green" companies. Despite this, its important to notice that the two highest Sharpe ratios were obtained from "green" latent factors. This effect is hard to explain as the time frame is not large enough to look for causal relations within our data set and several one-time events could have affected this result, specially the speculation about "brown" companies looking to acquire smaller "green" companies in order to incorporate its technology to their processes and, therefore, to comply with the increasing regulations.

Regardless this apparent contradictory results, we need to clarify that the scope of this analysis is not to discover which type of firms outperform the other. This study has helped to demonstrate the existence of an environmental risk premium and the importance of incorporating this premium into investors' considerations when constructing their portfolios, even if the investor do not follow necessarily a ESG thematic strategy. A possible complication to do this could be that, to be able to succeed in capturing such a risk premium, several firm-specific environmental characteristics need to be addressed and monitored and that a change in any one of them might not be easy to extrapolate into a price impact on the investors' holdings. We recommend to implement the Principal Components Analysis to facilitate this analysis, even if the overall difficulty may remain elevated.

4.2 Performance

The importance of taking into account this environmental risk premium is evidenced by two principal facts. The first one is that only two out of the ten latent portfolios presented negative Sharpe ratios. Most of the other factors presented a positive and relatively high Sharpe ratios. This suggests that investors that are able to capture this premium could actually being overcompensated for the risk that they have been bearing. We consider this to be a very important result as the pace of change toward green processes within firm's value chains and tighter regulations regarding the negative impact of companies processes on climate is accelerating and this could result in the realization of some of the discounted environmental risks. Thus, being compensated correctly for this kind of risks will be more and more important in the near term.

For those investors following a thematic strategy, it could be important to revise more closely how the ETFs they are investing in are composed and how well do they capture the desired information. The method we used emphasizes in getting the highest amount of information available in market prices and the results suggest that it is worth making the effort. For the time frame considered, almost all of our latent portfolios succeeded to outperform the both ETFs used in our comparison analysis while not incurring in additional systematic risk. Although our "brown" portfolios might not be as comparable to them, the two "green" latent factors, which are the ones offering the highest Sharpe ratios of 3.21 and 3.17, largely outperform the ETFs, which reported Sharpe ratios of 0.26 and 0.18.

Despite the consistency of our results we need to highlight some limitations in our work which could give some insights for further improvement regarding the studies about the implications of the existence of an environmental risk premium.

4.3 Limitations

Throughout the entire work, we encountered a number of circumstances that limited the scope and strength of our results. We will briefly explain the more relevant ones. The first, and probably the most important one, is the implication of choosing to retrieve the data from a specific data provider. As we mentioned above, each data provider has different methodologies and criteria. Using the data provided by only one of them is already limiting. Trying to incorporate all of them might be impractical and could even lead to inconsistent results given the subjectivity implicit in some of the scores. A tremendous effort need to be made jointly by investors, data providers, and governmental agencies around the world to establish a common framework that allows to standardize the data among different data providers. This will have a very big positive impact in the efficiency of the financial markets.

Another important limitation of our work is the important survivorship bias that we have in our sample. As mentioned above, we took as our stock universe the constituents of the STOXX 600 at a given point in time and we kept the sample fixed. This mean that we are not considering the performance of the companies that were acquired or ceased to exist during this time frame. By keeping in the sample the survivor companies, negative results might have been omitted. The STOXX 600 constituents change quarterly, which make highly difficult to control for this changes. Using a broader market index as a reference might be good solution for this but additional work will still need to be done to control for corporate events.

A clear improvement of our analysis would have been to further control for the companies' industry. This could enlighten further the conclusions obtained and allow for further discussion. Normally, the companies within a sector or an industry share some of the main value chain processes. Then, it might be possible to identify which companies are facing more risk relative to others within the same sector so that the required risk for that company can be adjusted accordingly.

Besides the traditional factors used, there exist a number of more recent factors that should also be included in the analysis. The importance for this is to check that those factors do not contain already the information extrapolated in our analysis. A good example would be the factor added in the Carhart four-factors model which tries to capture a risk premium from the momentum observed in some stocks.

A Appendix

A.1 Tables

A.1.1 Table of the characteristics

Characteristics	Type	Category
Agrochemical 5 % Revenues	Binary	Emissions
Biodiversity Impact Reduction	Binary	Emissions
Climate Change Risks/Opportunities	Binary	Emissions
CO2 Equivalents Emission Direct	Numerical	Emissions
CO2 Equivalents Emission Total	Numerical	Emissions
Emission Reduction Objectives/Targets Emissions Reduction	Binary	Emissions
Emission Reduction Processes/Policy Emissions Reduction	Binary	Emissions
Emissions Trading	Binary	Emissions
Environmental Investments Initiatives	Binary	Emissions
Environmental Partnerships	Binary	Emissions
Environmental Restoration Initiatives	Binary	Emissions
Estimated CO2 Equivalents Emission Total	Numerical	Emissions
e-Waste Reduction Initiatives	Binary	Emissions
Internal Carbon Pricing	Binary	Emissions
NOx and SOx Emissions Reduction Initiatives	Binary	Emissions
Particulate Matter Reduction Initiatives	Binary	Emissions
Staff Transport Impact Reduction Initiatives	Binary	Emissions
Total CO2 Equivalent Emissions To Revenues USD in millions	Numerical	Emissions
Total Waste To Revenues USD in millions	Numerical	Emissions
Value - Emission Reduction/Environmental Expenditures	Binary	Emissions
VOC Emissions Reduction Initiatives	Binary	Emissions
Waste Reduction Initiatives	Binary	Emissions
Waste Total	Numerical	Emissions
Agrochemical 5 % Revenues	Binary	Innovation
Animal Testing	Binary	Innovation
Animal Testing Cosmetics	Binary	Innovation
Animal Testing Reduction Initiative	Binary	Innovation
Clean Technology	Binary	Innovation
Eco-Design Products	Binary	Innovation
Environmental Products	Binary	Innovation
Environmental Project Financing	Binary	Innovation
Equator Principles	Binary	Innovation
ESG Screened Asset Under Management	Binary	Innovation
Fossil Fuel Divestment Policy	Binary	Innovation
GMO Products	Binary	Innovation
Hybrid Technology	Binary	Innovation
Labeled Wood	Binary	Innovation
Noise Reduction	Binary	Innovation
Nuclear	Binary	Innovation
Organic Products Initiatives	Binary	Innovation
Product Environmental Responsible Use	Binary	Innovation
Sustainable Building Products	Binary	Innovation

Take-back and Recycling Initiatives	Binary	Innovation
Water Technology	Binary	Innovation
Direct Energy/Energy Purchased Direct	Numerical	Rescource Use
Energy Use Total	Numerical	Rescource Use
Environment Management Team	Binary	Rescource Use
Environment Management Training	Binary	Rescource Use
Environmental Supply Chain Partnership Termination	Binary	Rescource Use
Environmental Supply Chain Selection Management	Binary	Rescource Use
Green Buildings	Binary	Rescource Use
Land Environmental Impact Reduction	Binary	Rescource Use
Materials Sourcing Environmental Criteria	Binary	Rescource Use
Renewable Energy Use	Binary	Rescource Use
Resource Efficiency Objectives/Targets Energy Efficiency	Binary	Rescource Use
Resource Efficiency Objectives/Targets Water Efficiency	Binary	Rescource Use
Resource Efficiency Processes/Policy Energy Efficiency	Binary	Rescource Use
Resource Efficiency Processes/Policy Environmental Supply Chain	Binary	Rescource Use
Resource Efficiency Processes/Policy Sustainable Packaging	Binary	Rescource Use
Resource Efficiency Processes/Policy Water Efficiency	Binary	Rescource Use
Total Energy Use To Revenues USD in millions	Numerical	Rescource Use
Toxic Substances Reduction Initiatives	Binary	Rescource Use
Value - Resource Reduction/Environmental Resource Impact Controversies	Binary	Rescource Use
Value - Resource Reduction/Improvements	Binary	Rescource Use
Value - Resource Reduction/Policy	Binary	Rescource Use
Water Use To Revenues USD in millions	Numerical	Rescource Use
Water Withdrawal Total	Numerical	Rescource Use

Table 1: Characteristics selected before the correlation check

Characteristics	Type	Category
Agrochemical 5 % Revenues	Binary	Emissions
Biodiversity Impact Reduction	Binary	Emissions
Climate Change Risks/Opportunities	Binary	Emissions
CO2 Equivalents Emission Direct	Numerical	Emissions
Emission Reduction Objectives/Targets Emissions Reduction	Binary	Emissions
Emission Reduction Processes/Policy Emissions Reduction	Binary	Emissions
Emissions Trading	Binary	Emissions
Environmental Investments Initiatives	Binary	Emissions
Environmental Partnerships	Binary	Emissions
Environmental Restoration Initiatives	Binary	Emissions
e-Waste Reduction Initiatives	Binary	Emissions
NOx and SOx Emissions Reduction Initiatives	Binary	Emissions
Particulate Matter Reduction Initiatives	Binary	Emissions
Staff Transport Impact Reduction Initiatives	Binary	Emissions
Total CO2 Equivalent Emissions To Revenues USD in millions	Numerical	Emissions
Total Waste To Revenues USD in millions	Numerical	Emissions
Value - Emission Reduction/Environmental Expenditures	Binary	Emissions
VOC Emissions Reduction Initiatives	Binary	Emissions
Waste Reduction Initiatives	Binary	Emissions
Waste Total	Numerical	Emissions
Agrochemical 5 % Revenues	Binary	Innovation
Animal Testing	Binary	Innovation
Animal Testing Cosmetics	Binary	Innovation
Animal Testing Reduction Initiative	Binary	Innovation
Clean Technology	Binary	Innovation
Eco-Design Products	Binary	Innovation
Environmental Products	Binary	Innovation
Environmental Project Financing	Binary	Innovation
Equator Principles	Binary	Innovation
ESG Screened Asset Under Management	Binary	Innovation
GMO Products	Binary	Innovation
Hybrid Technology	Binary	Innovation
Labeled Wood	Binary	Innovation
Noise Reduction	Binary	Innovation
Nuclear	Binary	Innovation
Organic Products Initiatives	Binary	Innovation
Product Environmental Responsible Use	Binary	Innovation
Sustainable Building Products	Binary	Innovation
Take-back and Recycling Initiatives	Binary	Innovation
Water Technology	Binary	Innovation
Energy Use Total	Numerical	Rescource Use
Environment Management Team	Binary	Rescource Use
Environment Management Training	Binary	Rescource Use
Environmental Supply Chain Partnership Termination	Binary	Rescource Use
Environmental Supply Chain Selection Management	Binary	Rescource Use
Green Buildings	Binary	Rescource Use
Land Environmental Impact Reduction	Binary	Rescource Use
Materials Sourcing Environmental Criteria	Binary	Rescource Use
Renewable Energy Use	Binary	Rescource Use

Resource Efficiency Objectives/Targets Energy Efficiency	Binary	Rescource Use
Resource Efficiency Objectives/Targets Water Efficiency	Binary	Rescource Use
Resource Efficiency Processes/Policy Energy Efficiency	Binary	Rescource Use
Resource Efficiency Processes/Policy Environmental Supply Chain	Binary	Rescource Use
Resource Efficiency Processes/Policy Sustainable Packaging	Binary	Rescource Use
Resource Efficiency Processes/Policy Water Efficiency	Binary	Rescource Use
Total Energy Use To Revenues USD in millions	Numerical	Rescource Use
Toxic Substances Reduction Initiatives	Binary	Rescource Use
Value - Resource Reduction/Environmental Resource Impact Controversies	Binary	Rescource Use
Value - Resource Reduction/Improvements	Binary	Rescource Use
Value - Resource Reduction/Policy	Binary	Rescource Use
Water Use To Revenues USD in millions	Numerical	Rescource Use
Water Withdrawal Total	Numerical	Rescource Use

Table 2: Characteristics selected after the correlation check

A.1.2 Table with the characteristics of the unobservable portfolios

Unobservable Portfolios: 2008 - 2019 with lag					
	1	**2**	**3**	**4**	**5**
Observations	139	139	139	139	139
Min	-0.030	-0.036	-0.021	-0.035	-0.016
Max	0.051	0.019	0.025	0.034	0.013
Mean	1.71E-06	2.85E-04	2.33E-04	2.51E-04	-9.42E-04
Variance	7.74E-05	4.58E-05	3.70E-05	3.35E-05	2.03E-05
Skewness	1.563	-1.923	0.300	-0.022	-0.441
Kurtosis	9.638	10.258	2.618	18.295	1.588
Sharpe ratio	0.336	1.261	-1.768	-0.096	0.386
Flip	N-F	N-F	N-F	N-F	F
Beta	-0.05434	0.013302	0.003932	0.046974	-0.00137

Table 3: Characteristics of the unobservable portfolios for 2008 - 2019

Unobservable Portfolios: 2010 - 2019 with lag					
	1	**2**	**3**	**4**	**5**
Observations	120	120	120	120	120
Min	-0.02716	-0.01433	-0.00854	-0.01763	-0.01046
Max	0.016195	0.012086	0.014989	0.008287	0.014805
Mean	-5.7E-06	-2.9E-05	0.001077	-2.7E-05	0.000739
Variance	4.39E-05	2.98E-05	1.71E-05	1.48E-05	1.28E-05
Skewness	-0.47583	-0.4379	0.204167	-0.84098	0.4051
Kurtosis	2.481632	0.072832	0.351009	2.934775	2.534263
Sharpe ratio	0.830282	2.085199	1.991694	3.209958	3.169882
Flip	F	F	N-F	F	N-F
Beta	0.034035	0.012665	0.003912	0.002709	0.002261

Table 4: Characteristics of the unobservable portfolios for 2010 - 2019

A.1.3 ESG ETFs Characteristics

	RF CRI EUROPE ESG E	MSCI EUROPE LRG CAP ESG UNIVERSAL
Observations	121	121
Min	-0.09847	-0.0947
Max	0.063575	0.060939
Mean	0.007672	0.007027
Variance	0.000797	0.00073
Skewness	-0.87543	-0.8334
Kurtosis	1.857761	1.683293
Sharpe ratio	0.913222	0.871372
Beta	0.264963	0.177785

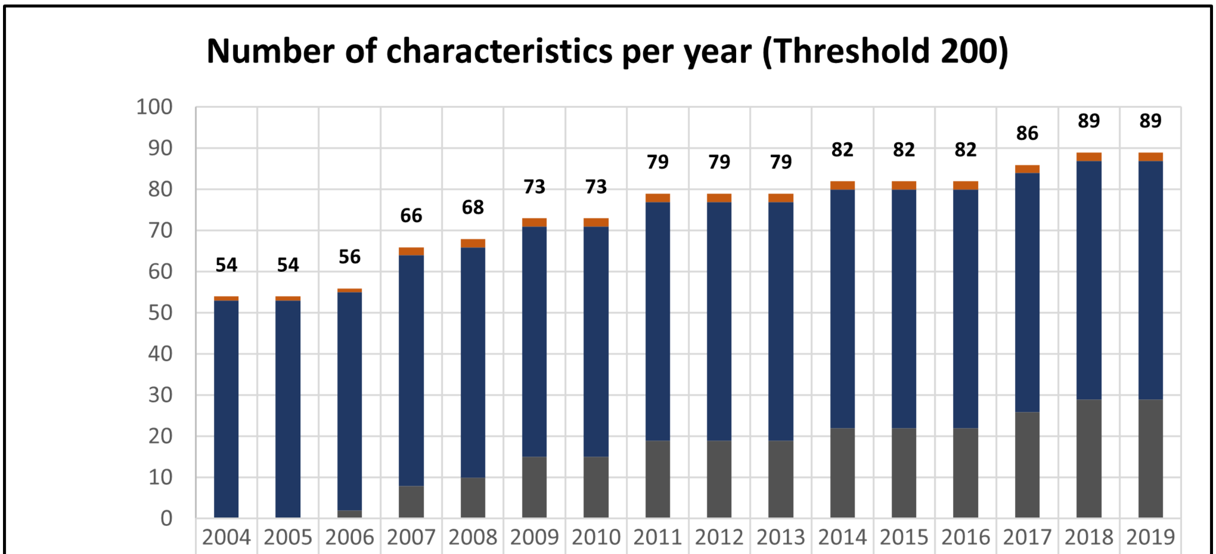
Table 5: Characteristics of the ESG ETFs

	RF CRI EUROPE ESG E	MSCI EUROPE LRG CAP ESG UNIVERSAL
1	0.021	0.019
2	0.204	0.194
3	-0.072	0.005
4	-0.162	-0.141
5	0.081	0.035

Table 6: Correlation between ETF and the unobservable portfolios 2010 – 2019

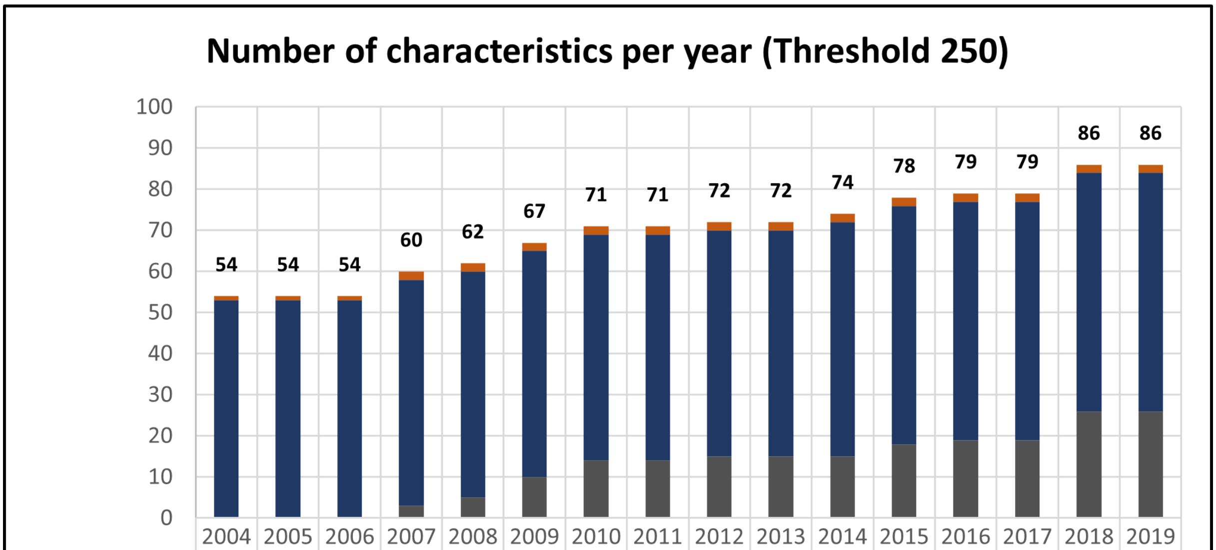
A.2 Figures

A.2.1 Number of characteristics per year



	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Qualitative	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2
Binary	53	53	53	56	56	56	56	58	58	58	58	58	58	58	58	58
Numerical	0	0	2	8	10	15	15	19	19	19	22	22	22	26	29	29
Total	54	54	56	66	68	73	73	79	79	79	82	82	82	86	89	89

Figure 1: Number and type of characteristics available each year for a minimum of 200 stocks.



	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Qualitative	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2
Binary	53	53	53	55	55	55	55	55	55	55	57	58	58	58	58	58
Numerical	0	0	0	3	5	10	14	14	15	15	15	18	19	19	26	26
Total	54	54	54	60	62	67	71	71	72	72	74	78	79	79	86	86

Figure 2: Number and type of characteristics available each year for a minimum of 250 stocks.

A.2.2 Graph of the variance explained by the first five PC

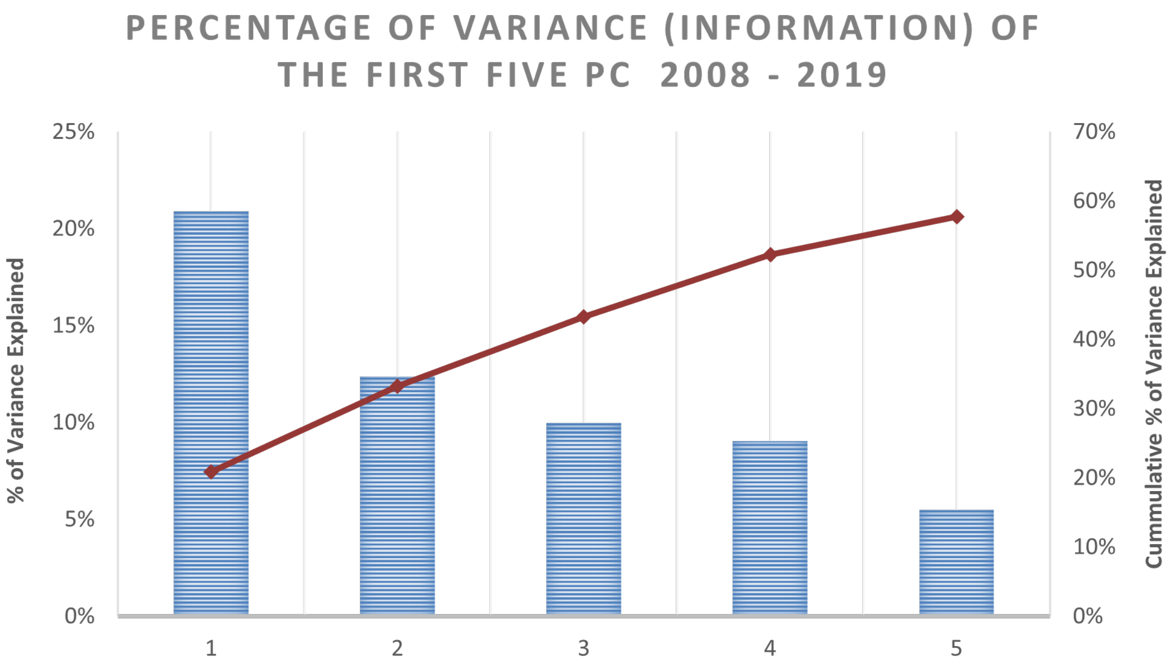


Figure 3: Variance explained by the first five PC and the cumulative percentage for 2008 - 2019

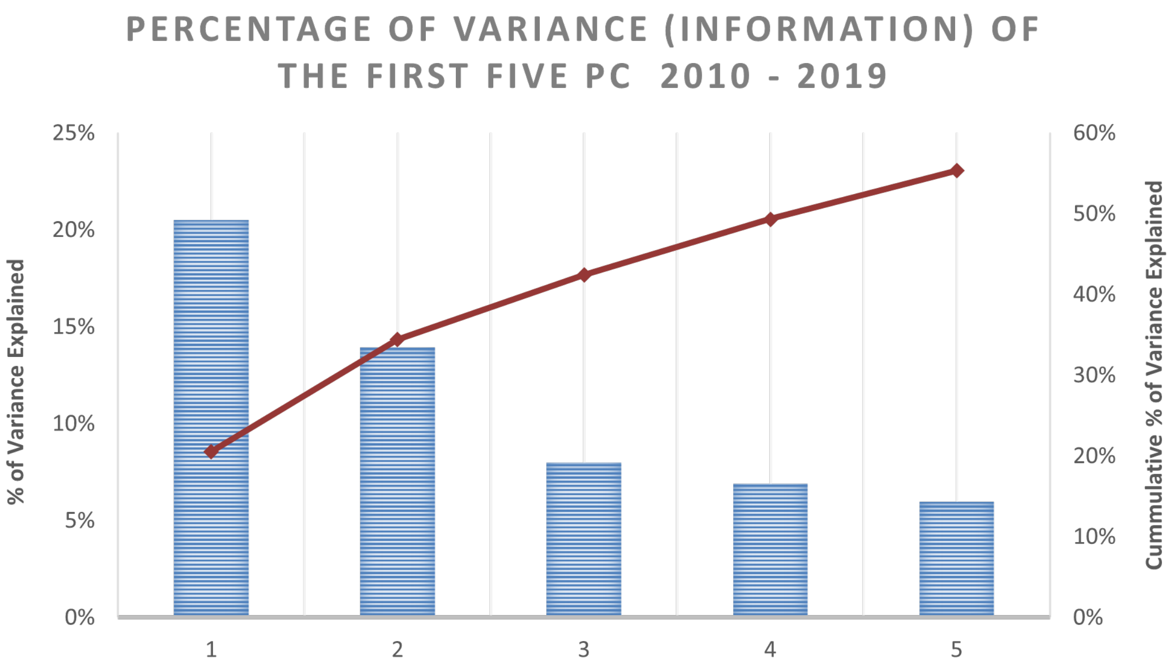


Figure 4: Variance explained by the first five PC and the cumulative percentage for 2010 - 2019

A.2.3 Bar-plot for the unobservable portfolios: 2008 - 2019

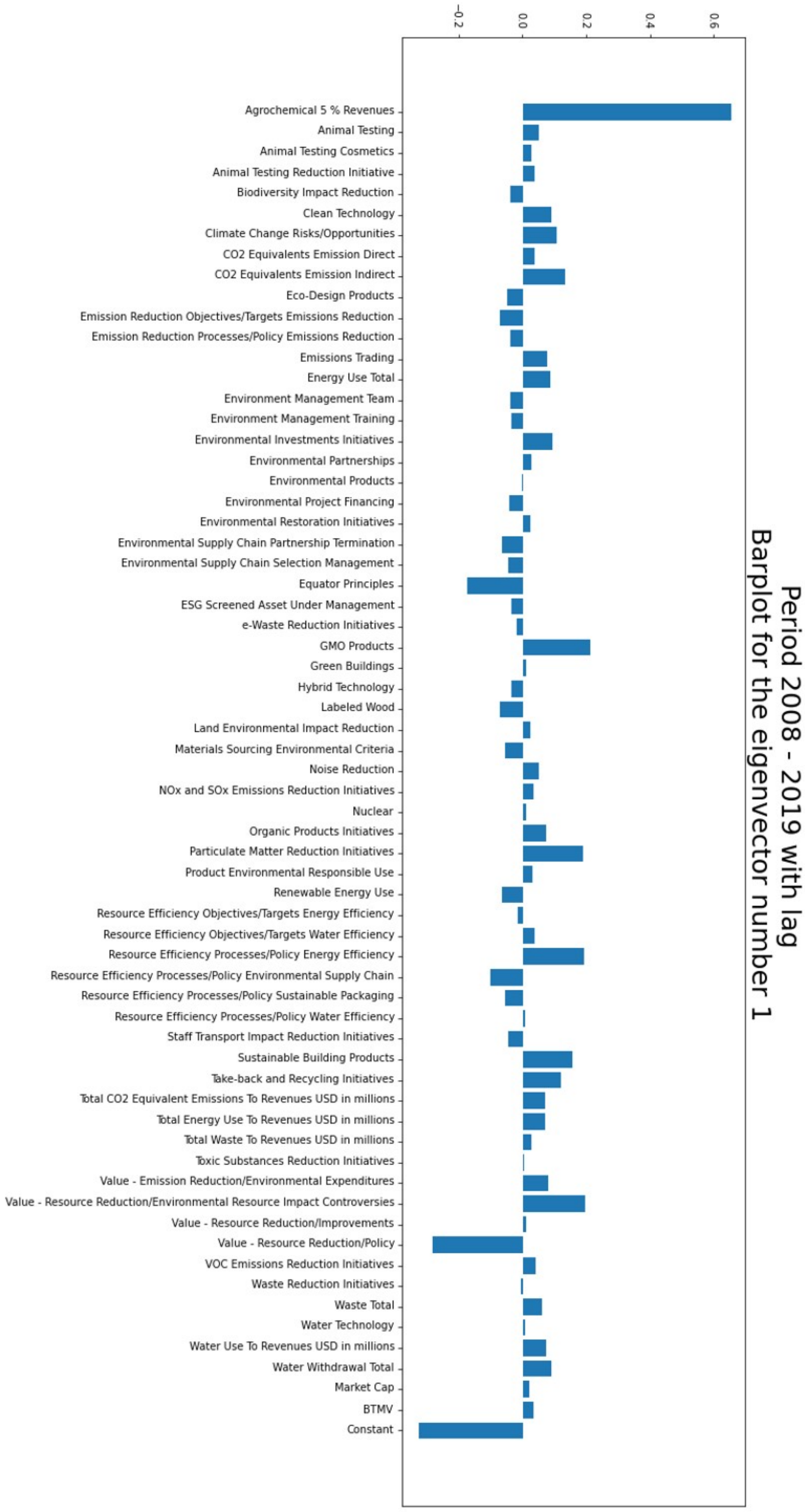


Figure 5: Bar-plot of the first eigenvector for 2008 - 2019

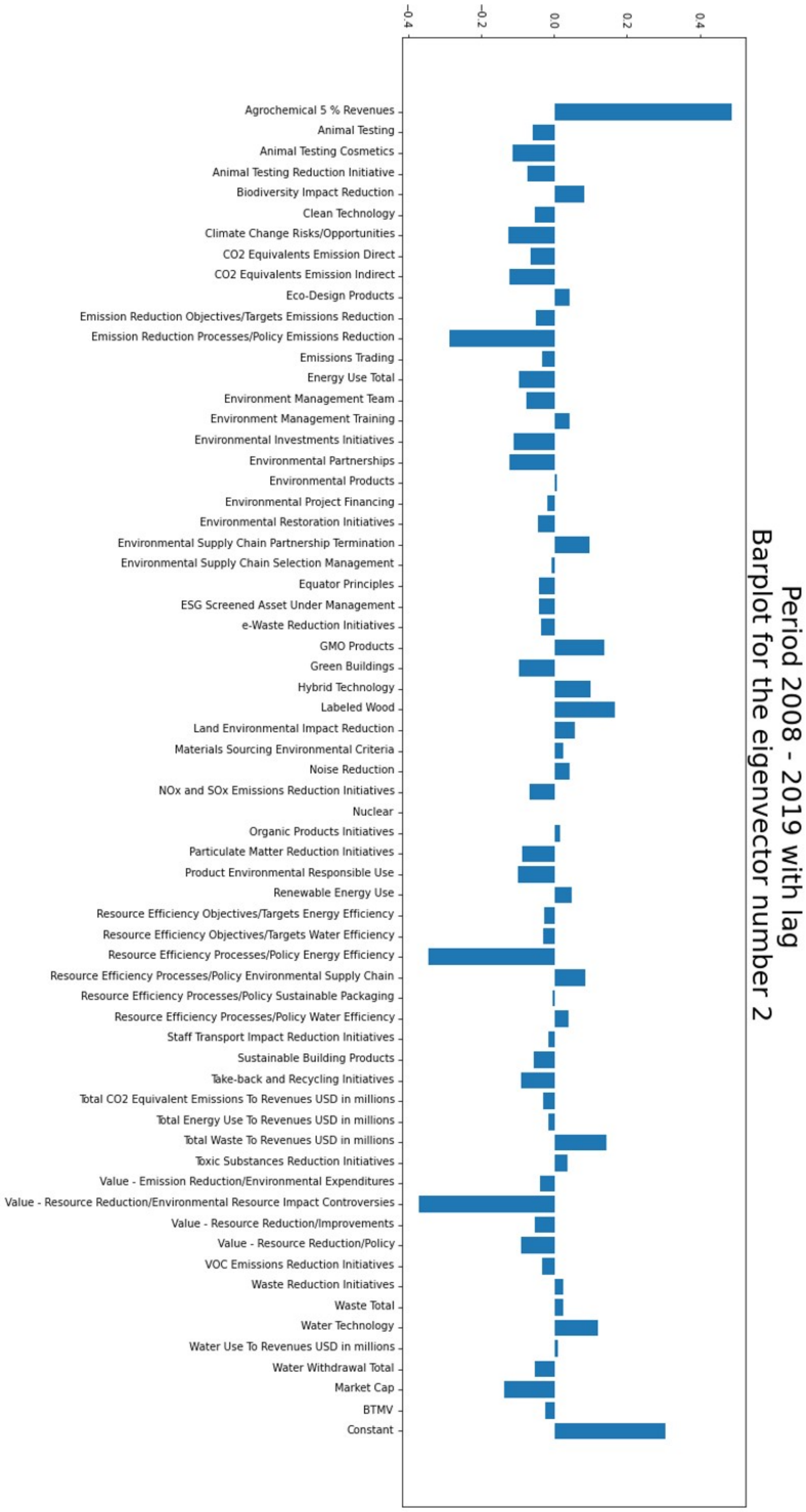


Figure 6: Bar-plot of the second eigenvector for 2008 - 2019

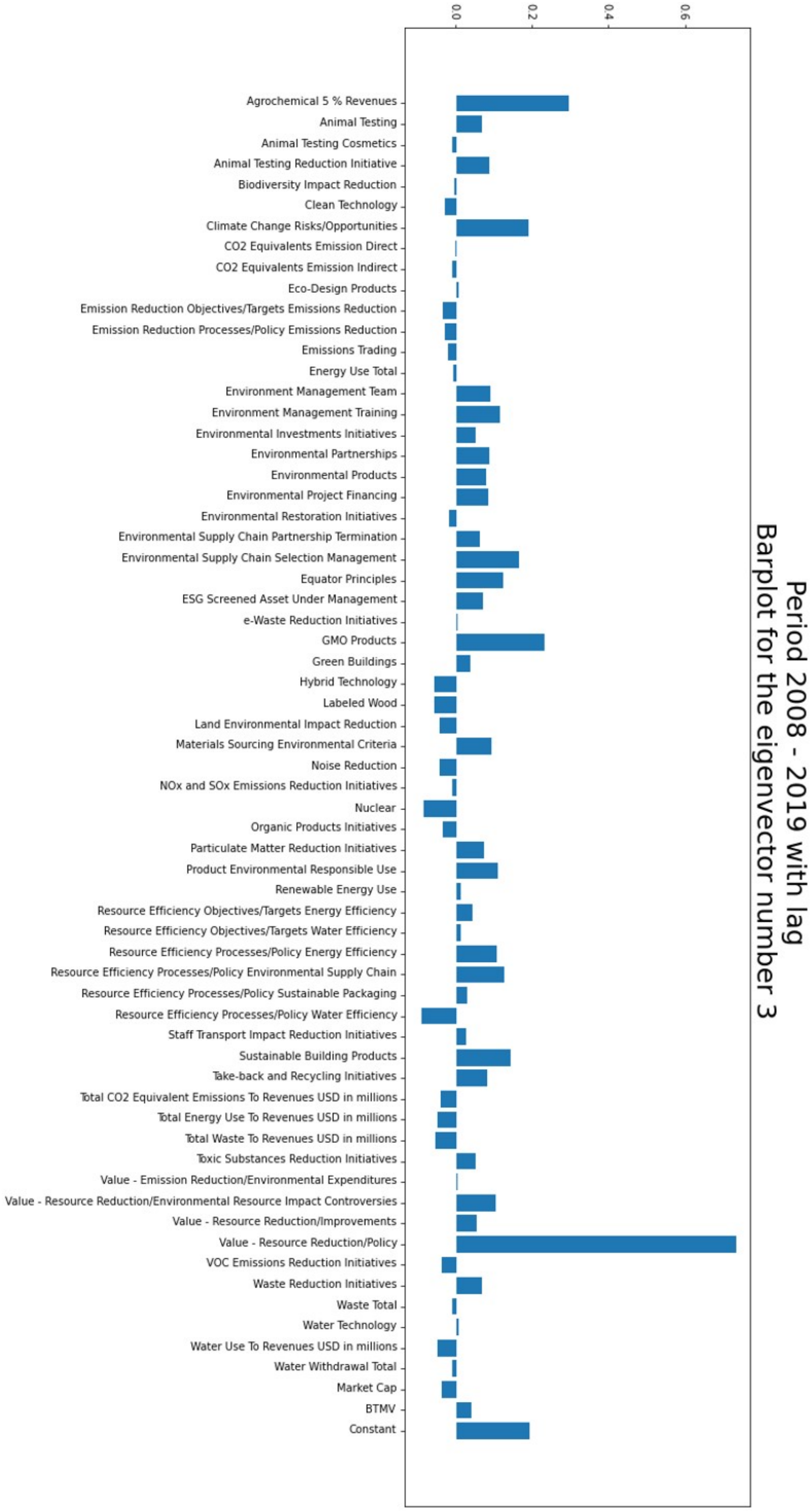


Figure 7: Bar-plot of the third eigenvector for 2008 - 2019

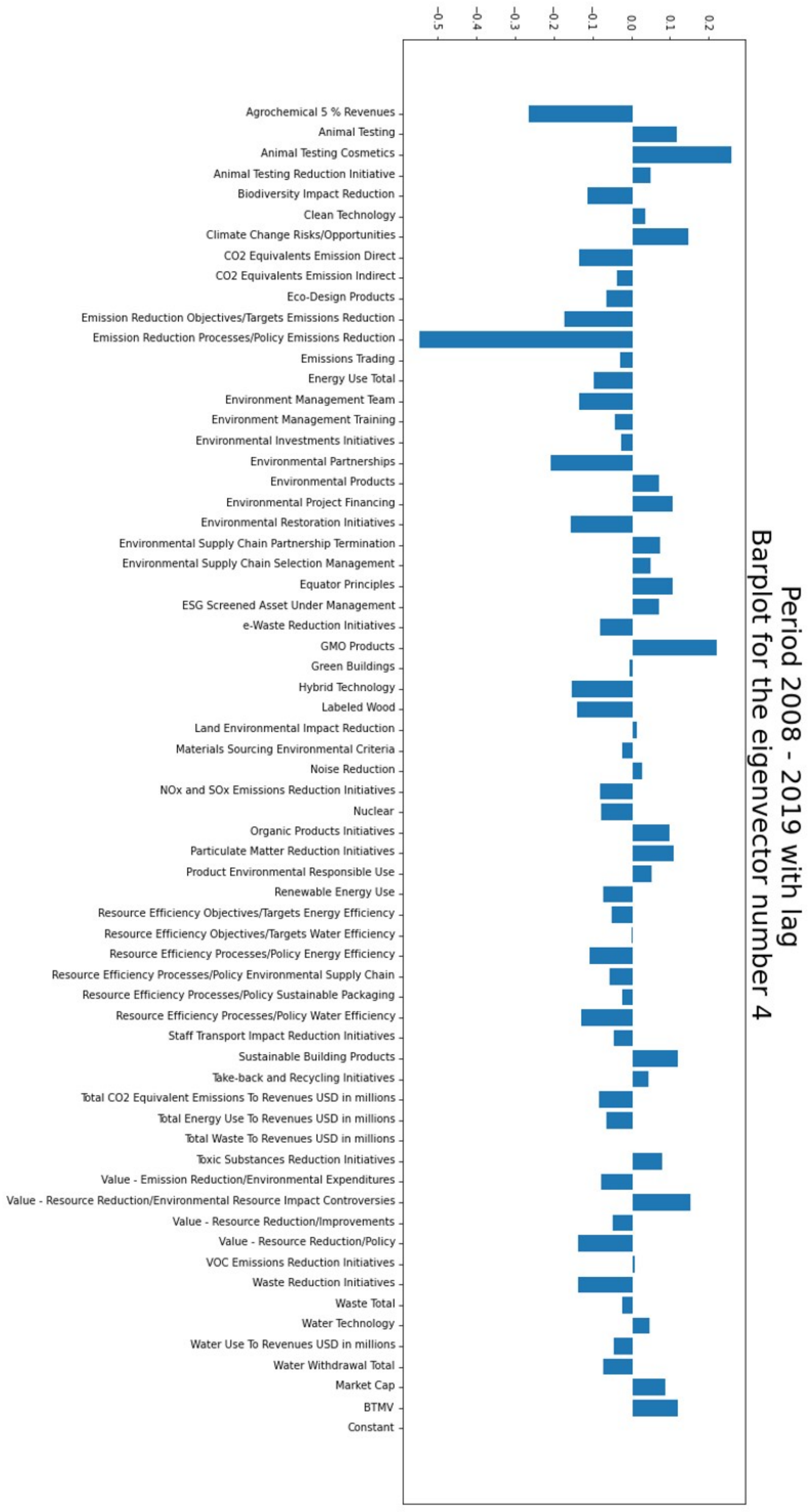


Figure 8: Bar-plot of the fourth eigenvector for 2008 - 2019

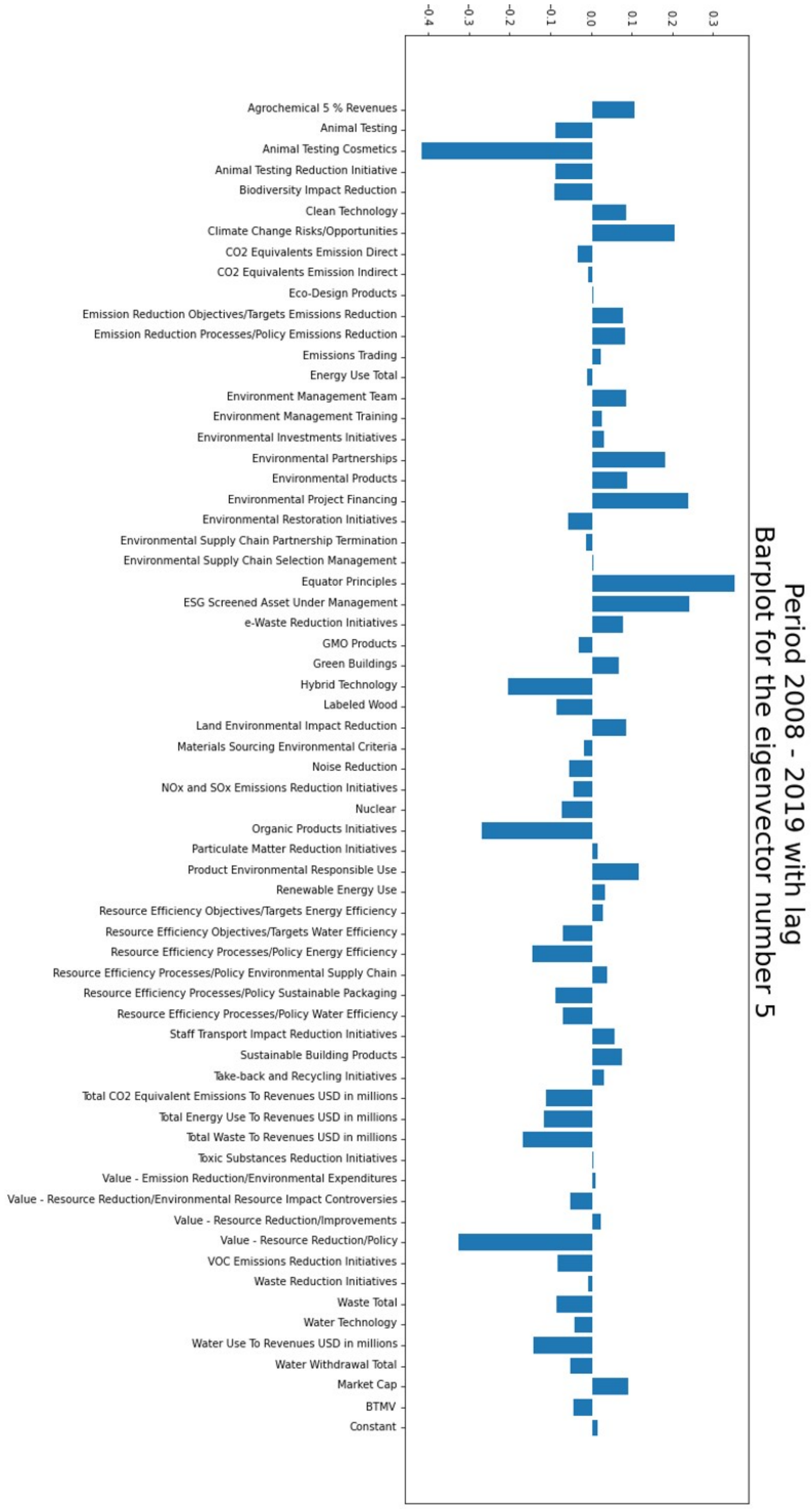


Figure 9: Bar-plot of the fifth eigenvector for 2008 - 2019

A.2.4 Bar-plot for the unobservable portfolios: 2010 - 2019

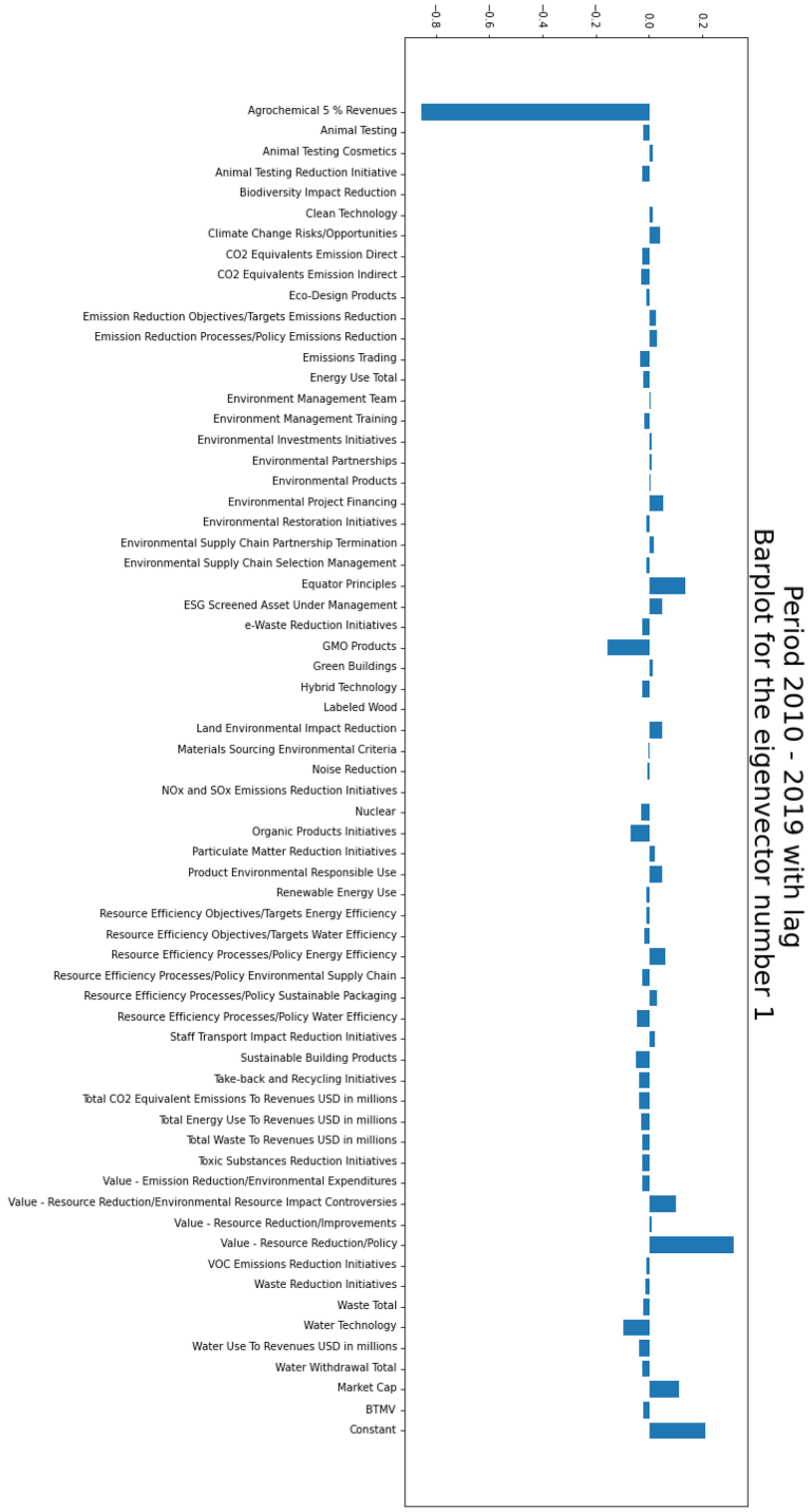


Figure 10: Bar-plot of the first eigenvector for 2010 - 2019

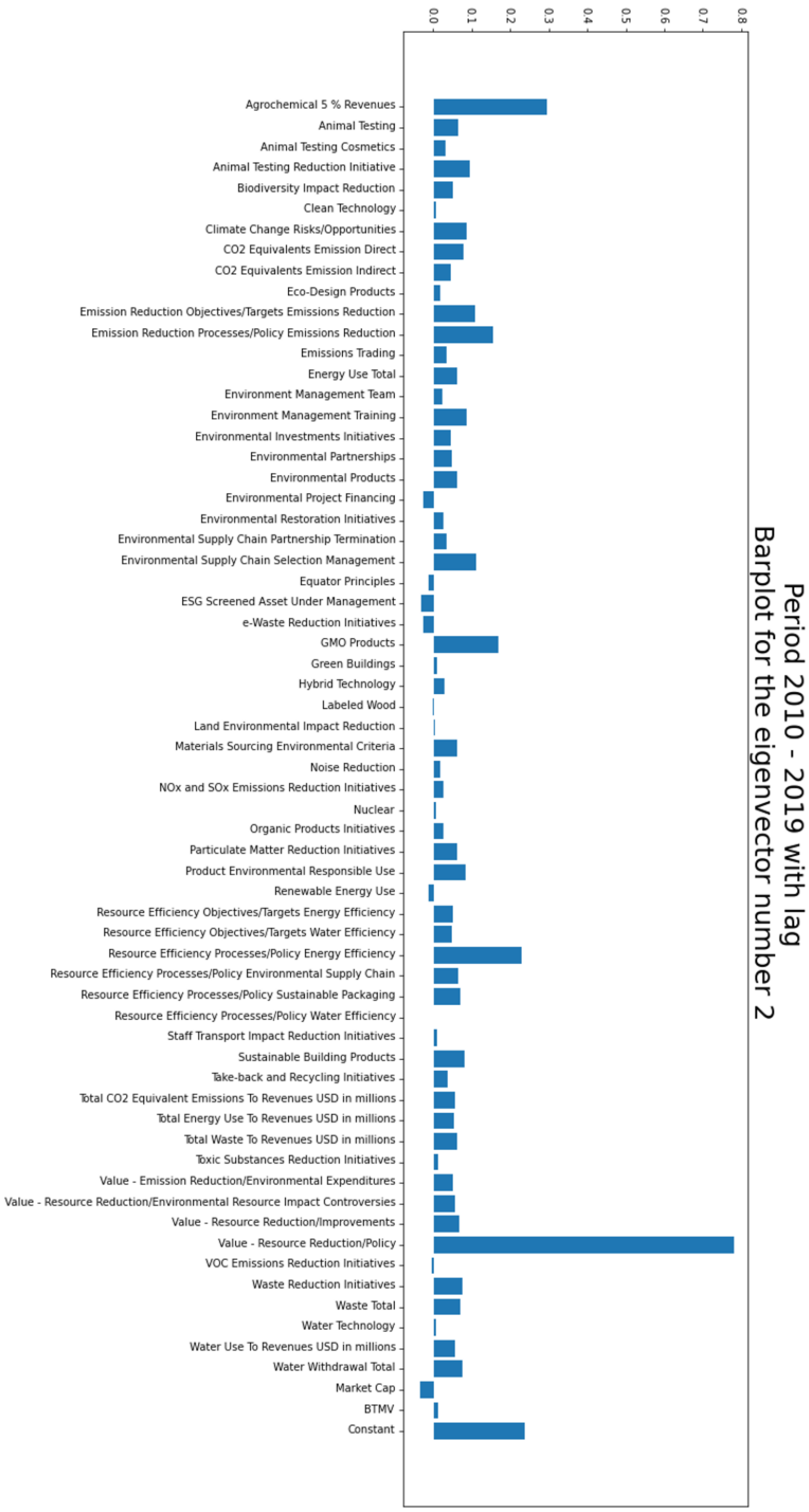


Figure 11: Bar-plot of the second eigenvector for 2010 - 2019

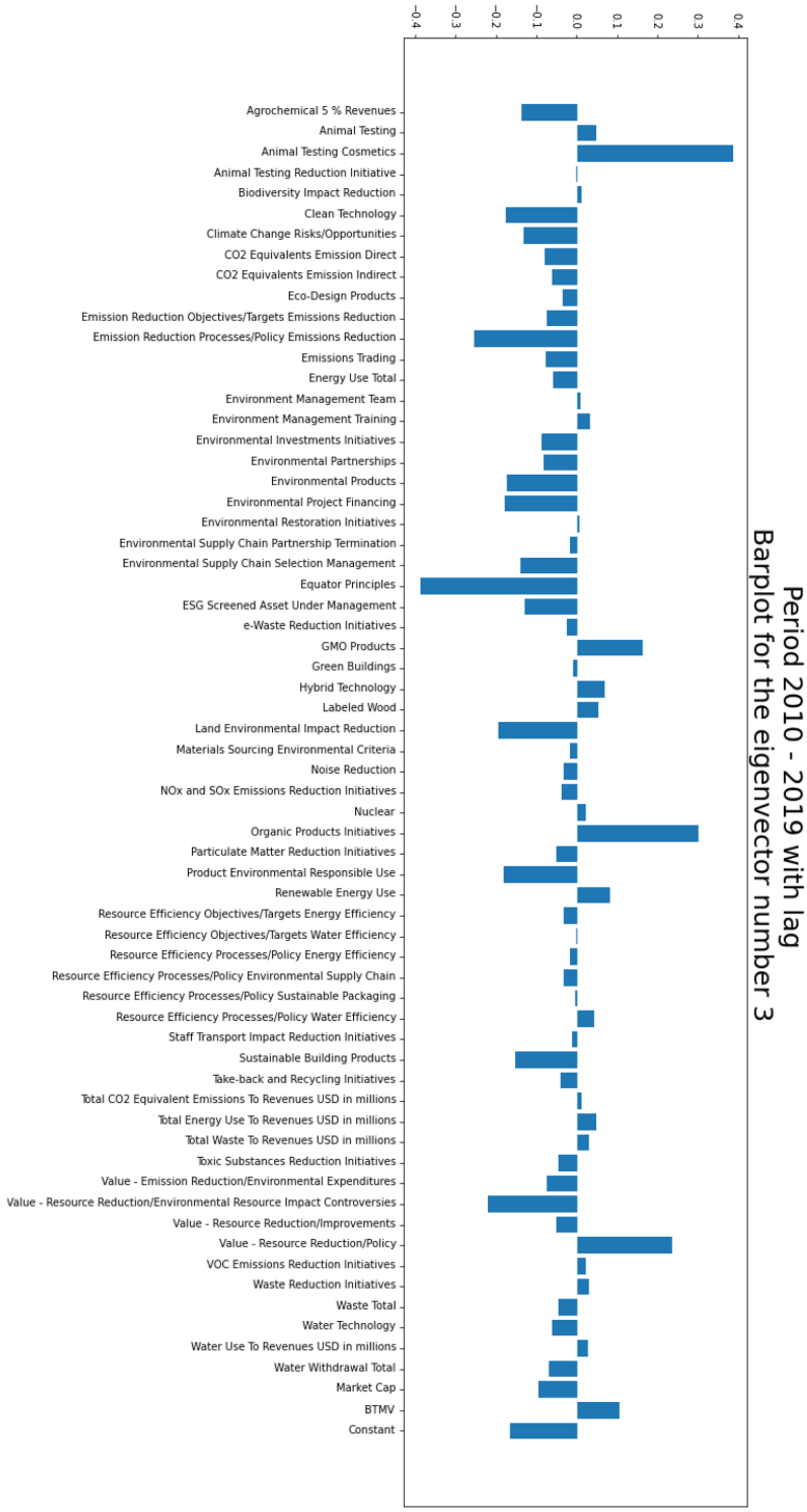


Figure 12: Bar-plot of the third eigenvector for 2010 - 2019

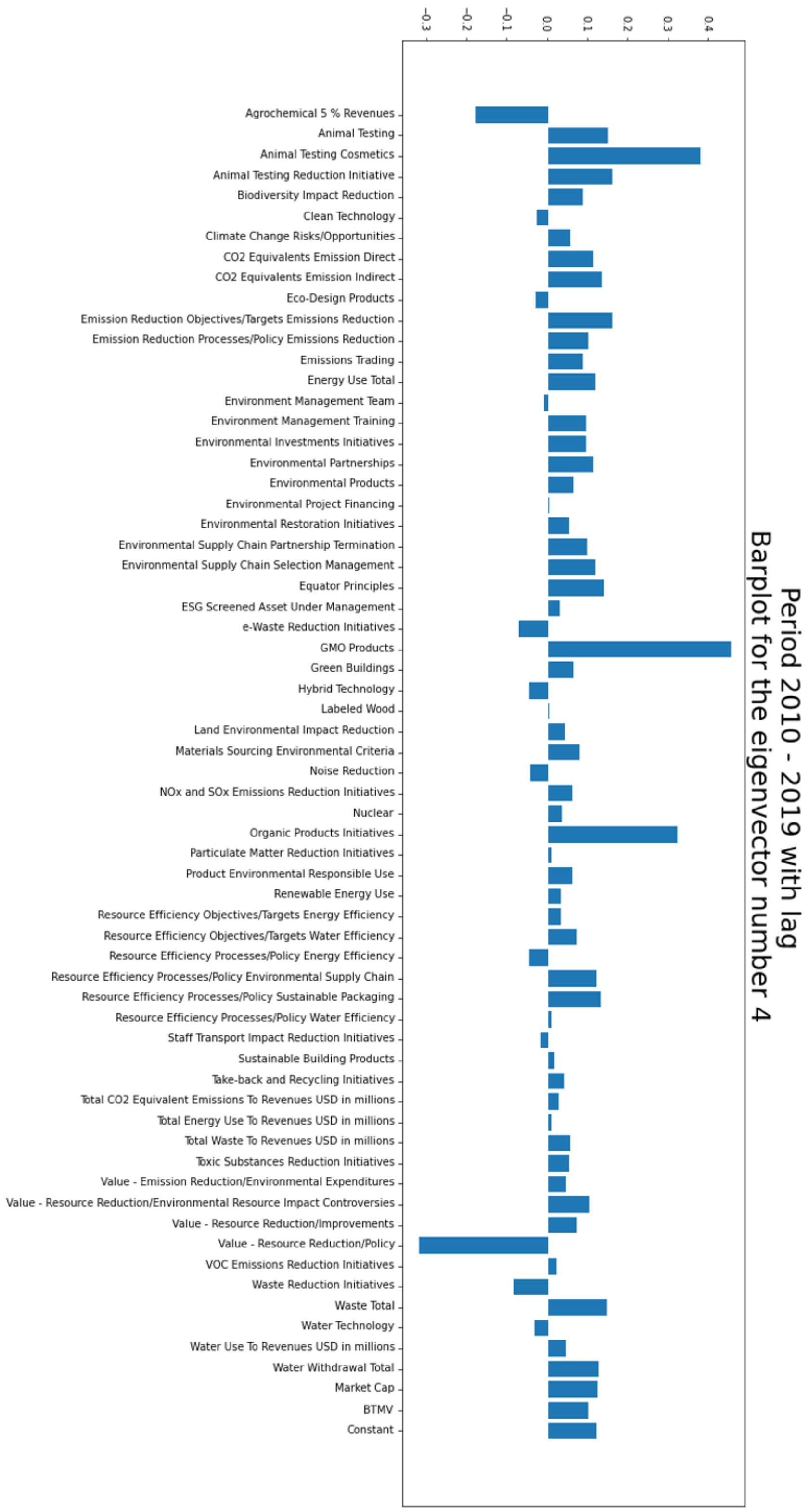


Figure 13: Bar-plot of the fourth eigenvector for 2010 - 2019

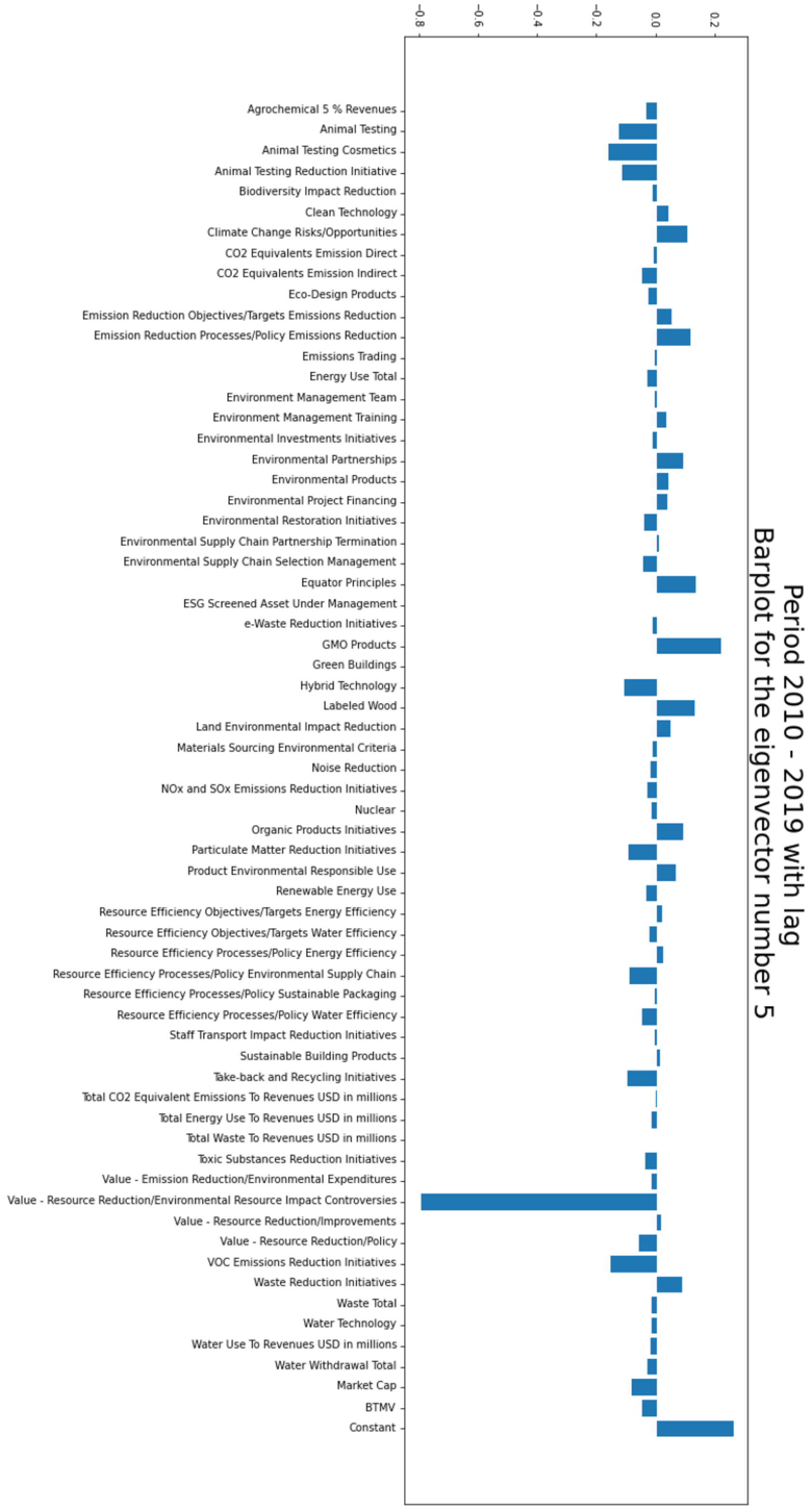


Figure 14: Bar-plot of the fifth eigenvector for 2010 - 2019

References

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