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## Abstract

There is growing evidence that ESG investments have demonstrated higher resiliency to the COVID-19 pandemic shock. While the performance of mutual funds is largely documented, there is limited evidence on stocks, especially in the European market. In this paper we focus on the environmental dimension of firms and we identify a green cluster among listed companies in the EU using a comprehensive database of environmental information. We let the data speak: we identify three clusters of firms (green, non-green and brown) by using clustering techniques and we evaluate their financial performances (return, risk and liquidity) over the full sample period and around the COVID-19 Crisis. We find that green firms yielded a lower return than non-green firms, especially after the Paris Agreement. However, in March 2020, green firms performed better than the other clusters. We find evidence that the COVID-19 period is not a special case, since green firms perform generally better during market contractions. We then extend standard asset pricing models by including the Green Risk Factor, the difference between the green and brown portfolios' returns and we find that the Factor is significant for a large fraction of firms suggesting that climate risk is priced in stocks.

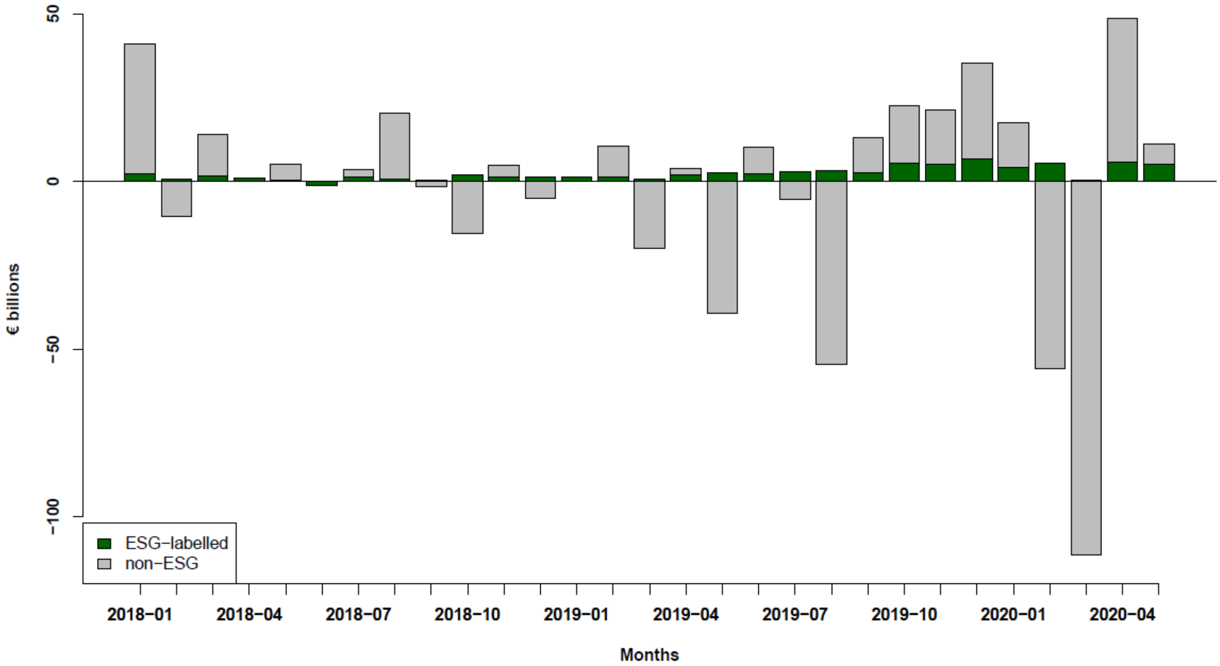
**Keywords:** ESG, CSR, SRI, COVID-19, Market Crash, Sustainable Investing, Unsupervised Learning, Clustering Methods, K-Means Clustering
**JEL:** C38, G01, G11, G12, G14, G23, G32, G41, M14

## 1. Introduction

COVID-19 pandemic forced governments to impose social distancing and lockdown measures leading to a collapse in the price of risky assets and spikes in market volatility in anticipation of the fall in economic activity globally. The drop in equity prices was the fastest ever, while the contraction at the through was half the size of that observed during the Subprime Crisis in 2008-2009 (IMF (2020)). However, there is growing evidence that sustainable and more generally ESG asset classes have been more resilient to the shock. According to Briére (2020), 62% of large-cap ESG funds outperformed MSCI world index in March. According to Ferriani and Natoli (2020), investors have especially demanded low-ESG risk equity funds and, surprisingly, particularly those with low environmental (instead of social or governance) risk. Compositional effects might explain this result. By construction, ESG funds tend to overweight sectors that have been less exposed to the recent shock, such as health care and tech, and underweight those that have been most impacted, such as transport, energy, materials. However, according to their analysis, other confounding factors, such as exposure to sectors or regions hit hardest by the crisis or market size, do not completely explain larger inflows into ESG funds. Pastor and Vorsatz (2020) analyze actively-managed equity mutual funds in the US market during the COVID-19 crisis and they also find that more sustainable funds (according to Morningstar), and particularly those that are more environmentally sustainable and those that employ exclusion criteria in their investment process, received relatively more net inflows than less sustainable funds within the same style group. These findings are not specific to the COVID-19 crisis; Nofsinger and Varma (2014) showed that socially responsible mutual funds outperformed during other market crises at the cost of underperforming during non-crisis periods. In figure 1 we plot monthly net flows of European equity mutual funds from January 2018 to May 2020 for funds classified as ESG/Green or which claim to have investment strategies based on ESG/Green factors and other funds. Over the sample period, ESG/Green funds flows are more stable than traditional funds even if the former have been only recently introduced. This is relevant especially when markets collapse, as during the last quarter of 2018 and after the outbreak of COVID-19. While traditional funds suffered high outflows in February and hit a low in March 2020 (-112 euro billions), ESG labelled funds were not dramatically impacted; indeed, data do not show massive disinvestments from ESG-labelled funds. Albuquerque et al. (2020) focus on stocks' performance rather than fund flows and find that firms with higher Environmental and Social ratings had significantly higher returns, lower return volatility, and higher operating profit margins during the first quarter of 2020. Other explanations for the better performance of sustainable assets during market crisis point towards market segmentation (investors with different characteristics and strategies can invest separately in the ESG and conventional ETF market segments) or loyalty effects (firms invest in ESG policies to create a more loyal customer base and consequently a less price-elastic demand). Albuquerque et al. (2020) find support for the loyalty theory. In this paper we focus on equity performances of green firms. While mutual fund performance during the COVID-19 crisis is largely documented, there is limited evidence on how stocks, and in particular in the European market, behaved. Moreover, identifying green firms is not an easy task because ESG disclosure by firms might be not fully reliable (i.e. green washing)[13]. Many papers rely on environmental scores produced by different data providers to identify green firms. However, Berg et al. (2020) document the large divergence between ESG ratings across agencies. Some papers identify green firms by taking the best performers according to these scores, i.e. by selecting firms whose score is above certain thresholds. However, the choice of the threshold, like specific percentiles of the score distribution (as in Alessi et al. (2020), Görgen et al. (2019), Albuquerque et al. (2020)) can be subjective and impose an a-priori on the size of the green cluster.

[13] see Federal Trade Commission: https://www.ftc.gov/enforcement/rules/rulemaking-regulatory-reform-proceedings/ green-guides

Figure 1: Monthly net flows of European equity mutual funds




Source: Prometeia analysis and estimates on internal database and external data providers. Data as of May 2020.

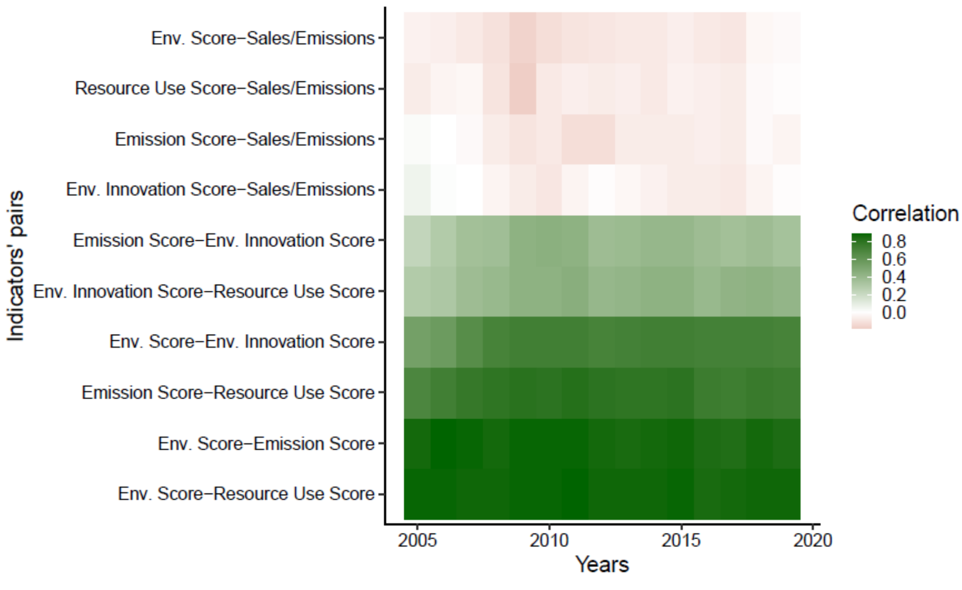
In this paper, for each calendar year we identify a green cluster of firms among EU listed companies using a comprehensive database from January 2005 to July 2020 of environmental information at date/firm level from Refinitiv.
For each firm we collected data on emission intensity (Emission/Total Revenue) and four environmental scores (Environmental Pillar Score, Emission Score, Resource Use Score, Environmental Innovation score) constructed by Refinitiv. Differently from previous studies, our objective is to let the data speak by identifying green firms with clustering techniques, instead of creating an aggregate score and selecting the best performer based on this score.
Clustering techniques seek to partition observations in a dataset into distinct groups so that the observations within each group are quite similar to each other, while observations in different groups are different from each other. This approach has several advantages.
First, we do not need to take a stance on the relative importance of different indicators in selecting green firms as the procedure might assign more relevance to some variables to identify specific clusters. Second, the cluster size might change from year to year according to the distribution of the environmental variables among listed firms. We claim therefore that this approach involves less subjective choices in the identification of green firms.
We find quite a large number of green firms. Moreover, green firms are generally bigger than non-green and brown firms (i.e. firms in sectors with large emission levels), maybe because larger firms have more incentive/resources to disclose environmental data. Moreover, the sectorial distribution of green firms is quite heterogeneous and they are not necessarily concentrated in low emitting sectors.
We then evaluate the financial performance of the three clusters (green, non-green and brown) over the full sample period, from January 2006 to July 2020 and around the COVID-19 crisis. When considering stock performance, we find that green firms offered a lower return to stockholders than non-green firms over the full sample period. As suggested by Bolton and Kacperczyk (2020b), investors have only recently become aware of the urgency of climate change.
Consequently, we also evaluate the financial performance splitting the sample in two sub-periods, before and after the Paris Agreement (before and after 2013), and we find the same result.
This is consistent with the view that green firms offer lower compensation because they are a hedge against climate risk. However, green firms outperformed brown firms over the same period. During the market stress induced by the COVID-19 crisis, green firms performed better than both brown and non-green firms, in line with recent literature (Albuquerque et al. (2020)).
We also investigate the performance in terms of risk-adjusted returns in a rolling window setup. On average, we find superior risk-adjusted performances of green firms over the full sample although after 2013 differences among clusters tend to disappear, except during the COVID-19 crisis when green firms outperformed again.
We also proxy the liquidity of the stocks in our database with their bid-ask spread over the mid-price and find that green firms are more liquid than the other two clusters, and the difference in liquidity increases in March 2020.
To investigate whether green firms perform generally better in periods of market stress (Nofsinger and Varma (2014)), as in Alessi et al. (2020) we calculate a Green Risk Factor as the difference between the returns of the green and the brown portfolio. We find that this factor is negatively correlated with the Fama & French market risk premium and is generally positive during periods of market correction. Moreover, we estimate a standard CAPM and a 3-factor model using the return on the green, non-

green and brown portfolio as dependent variable. Consistently we find that the green portfolio has beta below one (i.e. they are defensive stocks), while the other two groups have beta well above one (cyclical stocks).
To get a better understanding of the evidence that climate risk is priced in stocks, we extend the standard 3-factors model of Fama and French (1993) by including the Green risk factor. We find that this factor is significant for around 30% of the firms at a 10% significance level in line with the other well-established factors in the literature (HML and SMB).
We also find that green firms have generally positive exposure to the green risk factor while the opposite holds for brown firms. However, there are firms whose exposure to the factor is not aligned with cluster identification, suggesting that markets consider these firms greener (or browner) in comparison with the environmental information that the firms produce.
The rest of the paper is organized as follows. Section 2 describes the dataset. Section 3 is devoted to explaining the methodology: the clustering approach identifying green firms, the measure of financial performance we used in our analysis and the extended asset pricing model. Section 4 describes the results of the clustering procedure and the relative performance of the green cluster of firms over the full sample period, during the COVID-19 crisis and pre/post Paris Agreement periods. Section 5 concludes.

## 2. Data

Our sample consists of companies listed on the STOXX Europe Total Market Index in July 2020, with the exclusion of financial and real estate companies, i.e. companies with NACE-1 digit level equal to K or L.
In order to identify green firms, we collect ESG data from Refinitiv; in particular, we focus on an emission intensity measure and various environmental scores: Sales/Emission ratio, Environmental Pillar Score, Emission Score, Resource Use Score, Environmental Innovation score [14].
The inverse of the emission intensity (i.e. Sales/Emission ratio) has been included for two reasons. Firstly, it is an indicator widely used in the literature to identify best performers in terms of emission policy. Secondly, unlike the Refinitiv scores that are industry-specific and measure the relative performance of a firm within its own sector, emission intensity is an absolute measure.[15]
Furthermore, in figure 2 we present the Indicators' correlation Heatmap; it is worth noticing that the sales/emissions indicator is not necessarily correlated with the other environmental indicators and this is true over the years. In table 7 we provide summary statistics for each Environmental indicator, mentioned above.

Figure 2: Environmental Indicators' correlation HeatMap




In this paper brown firms are not identified using our clustering procedure, but as firms that belong to sectors that are more exposed to climate risk, independently from their relative ranking based on the environmental data considered.
Following Alessi et al. (2020), the first step of our analysis consists in selecting, for each year, only the securities that do not belong to the sectors defined as CPRS (Climate policy-relevant sectors) according to their associated NACE-2 digit level.
Based on Eurostat data, in table 1 we identify the CPRS sectors as those which, in descending order by level of GHG emissions, contributed to 85% of total GHG emissions between 2008 and 2018; the firms which operate in CPRS sectors are labelled as "Brown".

[14] See the Appendix A for a detailed description of the scores.
[15] Note that, as explained in the Refinitiv's ESG methodology guide, in order to calculate the environmental category scores, the industry group is used as the benchmark. In addition, some indicators are industry-specific, thus they are not relevant for some sectors; in this case they are excluded from the calculation.

Table 1: European Union Climate Policy Relevant Sectors (CPRS) with their relative contribution to total GHG emission, based on Eurostat data

| NACE-2 digit lvl. | % of total GHG emissions (2008-2018) | Cumulative % |
|---|---|---|
| D35 - Electricity, gas, steam and air conditioning supply | 31.5 | 31.5 |
| A01 - Crop and animal production, hunting and related service activities | 13.4 | 44.9 |
| H49 - Land transport and transport via pipelines | 5.5 | 50.3 |
| C23 - Manufacture of other non-metallic mineral products | 5.5 | 55.8 |
| C24 - Manufacture of basic metals | 4.9 | 60.7 |
| E37-E39 - Sewerage, waste management, remediation activities | 4.6 | 65.3 |
| C20 - Manufacture of chemicals and chemical products | 4.3 | 69.6 |
| H51 - Air transport | 4.0 | 73.6 |
| C19 - Manufacture of coke and refined petroleum products | 4.0 | 77.6 |
| H50 - Water transport | 3.3 | 80.9 |
| B05-B09 - Mining and quarrying | 2.3 | 83.3 |
| F41-F43 - Construction | 1.8 | 85.0 |

In other words, we exclude the possibility that Brown firms are identified as green. While this hypothesis might look very subjective, given that some brown firms are largely investing to diversify their core business and in adaption technologies, it is quite reasonable to assume that these sectors are highly affected by transition risk (i.e. carbon pricing policies). In identifying green firms, a crucial aspect is how to treat missing data. Indeed, a large fraction of firms does not report any environmental information, especially at the beginning of the sample period. Our approach is to penalize non-reporting firms compared to reporting firms. Then, when a firm presents missing data for an indicator, we replace it with the minimum value observed for the indicator in each specific year minus an arbitrary value. Moreover, due to the presence of outliers and indicators with different scales, we standardize the data calculating the rank of each Refinitiv indicator every year, effectively minimizing distortions in the clustering procedure[16]. One of the main contributions of this study is the clustering technique for the identification of green firms, which is described in the next section.

## 3. Methodology

### Clustering Methodology

As mentioned in the introduction, to avoid bias in the choice of the green firms we adopt a data-driven approach. In this work, we propose an innovative approach that identifies a time-varying number of green firms using unsupervised learning clustering techniques. In particular, we apply the K-means algorithm with squared Euclidean distance as a dissimilarity measure in order to find homogenous groups of firms, according to the environmental indicators mentioned before. Therefore, we want to solve this optimization problem

$$\min_{C_{1,t}\dots C_{1,t}} \left( \sum_{k=1}^{K} W(C_{k,t}) \right) \tag{1}$$

with

$$W(C_{k,t}) = \frac{1}{|C_{k,t}|} \sum_{i,i' \in C_{k,t}} \sum_{j=1}^{p} (x_{i,j,t} - x_{i',j,t})^2 \tag{2}$$

where $x_{i,j,t}$ is firm $i$ rank on feature $j$ at time $t$. $W(C_{k,t})$ is a measure of dissimilarity between the observations within the $k$th cluster (i.e. within-cluster variation), defined as the summation of all of the $k$th pairwise squared Euclidean distances between the observations, divided by the $k$th total number of observations. The K-means algorithm allows us to solve this problem such that the total within-cluster variation $\sum_{k=1}^{K} W(C_{k,t})$ is minimized.

This type of algorithm requires the number of clusters that we expect in the data as input; given that the main aim of this procedure is to avoid arbitrary choices, the optimal number of clusters is estimated from the data. The identification problem of the optimal number of clusters is not an easy task: as a matter of fact, a vast number of tests have been introduced in the literature to solve this problem but there is no consensus about which is the most appropriate to use. For this reason, we decide not to rely on a specific test but instead consider the results of different tests, as implemented in Malika et al. (2014). Finally, to aggregate the results of different tests we take the median reported number of clusters in each year. As a result, we find an optimal number of clusters, constant over time, equal to three. In order to assign different labels to the clusters obtained for each year, we assume that the one with the highest average of the medians of each ranked Refinitiv indicator should be labelled “green” and the other two clusters form a unique one called “not green”. This classification allows us to build three different market-value weighted portfolios (green - not green- brown) for each month, based on the previous year classification. This is because, as environmental information is collected and disclosed yearly, we assume that during any given year an investor can only consider the previous year information. We then define the “Green Risk Factor” as the difference between the monthly returns on the green and the brown portfolio.

[16] Since data are standardized using the rank function, the choice of arbitrary value *does* not affect the clustering results.

### Financial performance indicators

For each portfolio, we calculate monthly US dollars returns from January 2006 to June 2020, a risk adjusted score and the bid-ask spread over the mid-price

$$BDSKPM_{i,t} = 100 \times \frac{P_{i,t}^A - P_{i,t}^B}{\frac{P_{i,t}^A + P_{i,t}^B}{2}} \tag{3}$$

Then we evaluate the performance of the portfolios, based on these indicators, considering two different time spans, the full-sample period and the COVID-19 months.

The risk-adjusted score, which brings together various risk-adjusted measures in a single indicator, allows an immediate comparison between portfolios by assessing the overall risk-return profile more completely. For each listed company we consider risk and return indicators calculated on a rolling window of 260 days. Risk indicators include the Sharpe Ratio (Sharpe (1994)), Information Ratio (Goodwin (1998)), Appraisal Ratio (Treynor and Black (1973)), K3 (Kaplan and Knowles (2004)), Sortino Ratio (Sortino and Price (1994)) and Treynor Ratio (Treynor (1965)). For each firm, we determine an aggregate score by averaging the rank of the firm according to each indicator. The score values range from 0 (minimum performance) to 100 (maximum performance). Finally, for each portfolio we calculate the overall score as the market-value weighted average.

### Asset pricing with the Green Risk Factor

We then study the role of climate risk in equity prices by extending the standard asset pricing model by including the Green risk factor as in Alessi et al. (2020) and Görgen et al. (2019). In particular, for each firm we estimate the following regression

$$R_{i,t} = \alpha_i + \beta_i^M MRP_t + \beta_i^H HML_t + \beta_i^S SMB_t + \beta_i^G GRF_t + \epsilon_{i,t} \tag{4}$$

where $R_{i,t}$ represents the monthly excess return of firm *i*, while $MRP_t$, $SMB_t$ and $HML_t$ are respectively the market risk premium and the two factors introduced[17] by Fama and French (1993), while $GRF_t$ is the green risk factor.

The panel data of firms' returns is unbalanced and some firms have a relatively short history of data that might produce inaccurate results. For this reason, when computing summary statistics of the exposure across groups of firms we underweight firms whose estimation results might be less reliable. We follow the approach proposed in Gagliardini et al. (2016), where the weights are used in the second step of the procedure for risk premia estimation. In short, giving weights increase the statistical precision of the estimation of the beta and overcomes the issue of the small sample size relative to the full sample.

## 4. Results

### Clustering Results

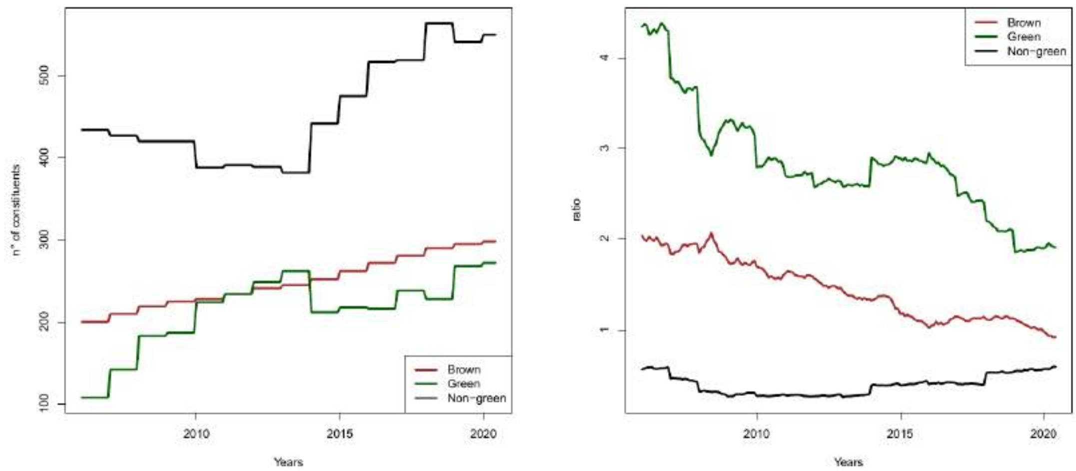
Figure 8 shows the boxplot of the indicators' rank divided into groups. The first thing to notice is that our methodology produces three clusters with different characteristics. In the initial period green firms have higher scores in all indicators than non-green firms, while firms with missing values (non-transparent firms) are cat the bottom of the graph. However, over the rest of the period, the positive correlation between green firms and the sales-to-emission ratio disappears: we find more homogeneity in emission intensity between green and non-green firms. Indeed, starting from 2017 non-green firms show a higher value in the sales-to-emission ratio, while all the other indicators are higher for green firms. Figure 9 shows the sectorial distribution of green, non-green (included non-transparent) and brown portfolios. In the graph we show the most relevant sectors in terms of market value, ordered counter clockwise according to their emission level (the sector in the north part of the radar corresponds to the highest emitting sector). We find that green firms do not necessarily belong to sectors with relatively lower emissions. In figure 3a we present the evolution of the number of firms included in each cluster. First, it can be noticed that the number of green firms increases over time, along with increasing environmental disclosure by firms. Second, the green and brown portfolios have, on average in the sample considered, a similar number of constituents. It should be noted that despite our procedure does not allow for an a-priori classification and therefore there is no guarantee about the stability of the number of firms in each cluster, our green cluster is stable over time, presenting an average turnover of around 88%. As already mentioned, a widely adopted approach in the literature is to identify green firms by selecting those above a certain threshold. The choice of the threshold, like specific percentiles of the distribution, can be subjective, and impose an a-priori on the size of the green cluster. Our approach shows that it is difficult to identify ex ante a unique suitable threshold, since the number of green companies in our sample varies over time. In particular, the share of green firms spans from 9.6% to 24.2% in the sample considered. In figure 3b we show the evolution of the average market value in each cluster over the average market value among all firms. Values above (below) one for a specific cluster/year tell that on average firms in this cluster are bigger (smaller) compared to the entire market in the year considered. It is clear that green firms are generally bigger than non-green and brown firms. This could be also explained by the fact that larger firms are better at disclosing a large amount of non-financial information and therefore receive higher scores.

[17] The three factors for the European market in US dollars together with the risk free rate are taken from Fama&French website

Figure 3

(a) *Number of firms included in each cluster*

(b) *Average market value in each cluster over the average market value among all firms*



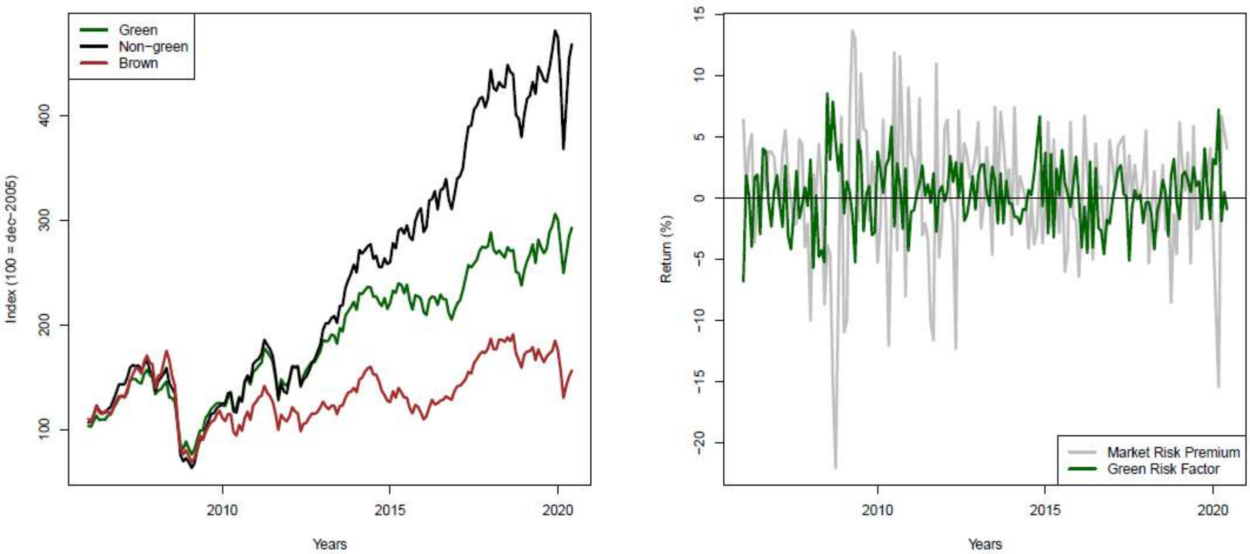

## Performance Results

In figure 4a we present the monthly cumulative returns of the green, non-green and brown portfolio starting from 2006. The three portfolios diverge from 2010, with the brown portfolio that under-performs the other two. Moreover, the green portfolio underperforms the non-green portfolio from 2013, in anticipation of the Paris Agreement, in which occurred in 2015. The underperformance of green firms with respect to non-green firms is in line with the main findings in the literature (Alessi et al. (2020), Bolton and Kacperczyk (2020a), Bolton and Kacperczyk (2020b), Görgen et al. (2019)).
The intuition behind this finding is that investors are already demanding compensation for their exposure to climate risk. However, this interpretation appears in contrast with the finding that green firms outperform CPRS firms, that are supposed to be more exposed to climate risk. According to Görgen et al. (2019), if firms surprise markets by performing relatively worse on environmental issues, by becoming browner, investors discount these firms. Pastor et al. (2019) model ESG preferences and their impact on asset prices.

Figure 4

(a) *Monthly cumulative returns of the green, non green and brown portfolios*

(b) *Green Risk Factor and Market Risk premium*




Note: The brown portfolio is composed by firms belonging to Climate Policy Relevant Sectors in July 2020 and each company is weighted in the index according to market size. The green portfolio composition changes every year according to the selection of firms from clustering procedure and according to their market capitalization.

Note: The "Green risk factor" is the difference between the green and the brown portfolio return, while Market Risk Premium is taken from Fama&French website.

Investors vary in their ESG preference and invest in a long short green-brown portfolio. In their model the greener the asset, the lower the returns. They also introduce an ESG factor that represents a shift in investor demand, and they show that positive realizations increase green-asset prices even though brown assets earn higher expected returns. Our result is consistent with this view, with increasing environmental awareness green firms are those that performed relatively better than brown firms that are "stuck" in more climate intensive sectors. Moreover, according to our data, green firms are becoming relatively greener over time since the average rank of the indicators increased in the full sample. In table 2 we present summary statistics of returns over the full sample period and pre/post Paris agreement. The over-performance of non-green versus both green and brown portfolios is especially evident in the post Paris agreement period.
To investigate the performance of green firms compared to brown firms during COVID-19 Crisis and before then we calculate a "Green risk factor" as in Alessi et al. (2020) as the difference between the green and brown portfolios (figure 4b). Our result is that in March 2020 this factor is positive (7%), implying green firms performed better than brown firms.

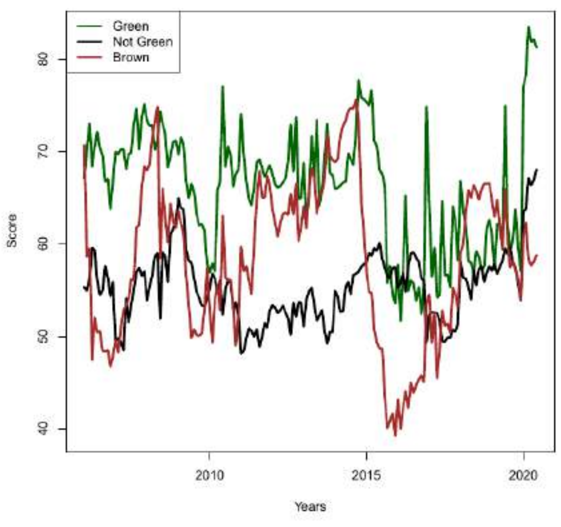
Table 2: Summary Statistics of returns in the full sample and pre/post Paris agreement

| Portfolio Excess Return | Pre-2013 | | | Post-2013 | | | 2006-2020 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | t-stat | Mean | Std. Dev. | t-stat | Mean | Std. Dev. | t-stat |
| Green | 10.29 | 28.62 | 0.95 | 8.87 | 16.74 | 1.40 | 9.58 | 22.54 | 1.59 |
| Brown | 6.34 | 33.95 | 0.49 | 7.10 | 15.18 | 1.24 | 6.72 | 25.27 | 1.00 |
| Non-green | 12.08 | 41.10 | 0.78 | 14.88 | 15.96 | 2.47 | 13.48 | 29.99 | 1.68 |

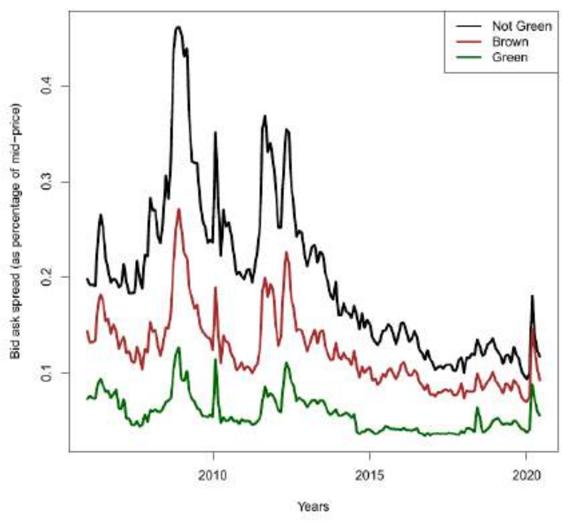
Actually, green firms performed better than the market as well in the same period (6%). Moreover, we check whether green firms perform generally better in period of market stress (Nofsinger and Varma (2014)) and find that the green risk factor is on average positive (4.5%). Finally, the factor is negatively correlated with the Fama & French Market risk premium (-0.36).
When considering risk adjusted performance we find that the green portfolio yields a better risk-adjusted average score than the non-green and brown portfolios especially before 2013. As we show in figure 5a the gap is clear from 2005 to 2013, and in particular in 2009 and 2011, when Europe experienced the effects of the sub-prime and sovereign debt crises, and then it becomes a bit fuzzier. The gap increases in 2015, when the score of the brown portfolio drops because of the 2014-16 oil glut. Then, the performance of the brown portfolios starts to improve until the COVID-19 crisis, which is characterized by the better performance of the green firms.

Figure 5

(a) *Market-value weighted Risk-Adjusted Score*




(b) *Bid ask spread (as a percentage of the mid-price)*




Furthermore, we verify whether green firms are more liquid than brown firms. To this end, we use the bid ask spread over the mid-price (*BDSKPM*) as our liquidity measure (see Sarr and Lybek (2002)). Figure 5b indicates that there is a clear gap between our three clusters, indeed the bid-ask spread of green firms is lower than that of brown and non-green firms throughout the whole sample period. In line with previous results, we find that *BDSKPM* of all the three clusters increased in crisis periods (i.e. the subprime crisis, the sovereign debt crisis and the COVID-19 crisis). However, the magnitude of the increase of the *BDSKPM* of green firms was lower than the other two clusters. In particular during the COVID-19 crisis, the *BDSKPM* of brown and non-green firms jumped from, respectively, 0.76 and 0.9 in February 2020, to 0.15 and 0.18 in March 2020; meanwhile for the green firms it increased from 0.04 in February 2020 to 0.08 in March 2020. In other words, during the COVID-19 crisis the liquidity gap between green firms and the others has further increased. This evidence supports the hypothesis that the demand for green securities increased during the crisis relatively to the other clusters.
Our preliminary results suggest that the green portfolio is more resilient than the non-green and brown portfolios. In tables 5-6 we show the betas of the excess return of those portfolios, estimated using a standard CAPM and a 3-factor model. First, we

find a statistical significance for the market risk premium for all portfolios in both models. We also find that the green portfolio has a beta lower than one, with respect to the market (defensive stocks), and lower than non-green and brown portfolios, which have beta well above one (cyclical stocks). This implies that green firms have lower exposure to systematic risk than brown and non-green firms, leading to better performance during market collapses.

## Asset pricing with Green Risk Factor

In Figure 6 we show the histogram with the frequency distribution of $\beta_i^G$, the exposure to the Green Risk Factor (GRF). As shown in table 5, we find that the Green Risk Factor (GRF) is highly significant. More specifically, it is significant for 25% (32%) of the firms in the sample, at a 5% (10%) significance level, not far from the other well-established factors in the literature (HML and SMB). Firms with positive (negative) $\beta^G$ should have larger (smaller) returns when the GRF increases, meaning that they benefit (lose) when climate risk deteriorates. According to our estimates exposures to GRF are quite heterogeneous.
Moreover, the results are line with the sectorial classification. In Figure 7 we represent the sectorial (NACE2 level) weighted average of the exposure to the green risk factor across firms. In particular in the left panel we represent the top 14 sectors according to the weighted average beta and on the right panel the bottom 14 sectors. We find that high emitting sectors exhibit negative Beta's, while low emitters have generally positive Betas. Confirmation of this is shown in Table 6, which represents clustered Betas: the weighted mean is positive for the stable-green cluster[18], while it is around zero and negative for the non-green and brown clusters, respectively. This means that on average stable green firms are benefiting from increasing climate risk, measured by the GRF, while the opposite holds for brown firms. However not all green firms have positive beta (around 76% in the stable-green cluster), and there are brown firms that have positive exposure (approximately 35%). This might suggest that markets identify potential environmental weakness/strengths of firms that are not correctly measured by the environmental data and KPI considered in this analysis.

Table 3: CAPM estimates on different portfolio excess returns

| | *Dependent variable:* | | |
|---|---|---|---|
| | Green | Brown | Non-green |
| MRP | 0.905*** | 1.086*** | 1.065*** |
| | (0.020) | (0.029) | (0.027) |
| Constant | 0.380*** | 0.013 | 0.646*** |
| | (0.107) | (0.159) | (0.145) |
| Observations | 174 | 174 | 174 |
| $R^2$ | 0.925 | 0.890 | 0.904 |
| Adjusted $R^2$ | 0.925 | 0.890 | 0.903 |
| Residual Std. Error (df = 172) | 1.412 | 2.088 | 1.907 |
| F Statistic (df = 1; 172) | 2,122.159*** | 1,397.150*** | 1,611.612*** |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 4: Fama-French three-factor model estimates on different portfolio excess returns

| | *Dependent variable:* | | |
|---|---|---|---|
| | Green | Brown | Non-green |
| MRP | 0.984*** | 1.095*** | 1.123*** |
| | (0.019) | (0.033) | (0.023) |
| SMB | −0.116** | 0.161* | 0.592*** |
| | (0.049) | (0.085) | (0.057) |
| HML | −0.355*** | −0.052 | −0.297*** |
| | (0.044) | (0.076) | (0.051) |
| Constant | 0.272*** | −0.019 | 0.496*** |
| | (0.092) | (0.160) | (0.108) |
| Observations | 174 | 174 | 174 |
| $R^2$ | 0.947 | 0.893 | 0.949 |
| Adjusted $R^2$ | 0.946 | 0.891 | 0.948 |
| Residual Std. Error (df = 170) | 1.196 | 2.075 | 1.401 |
| F Statistic (df = 3; 170) | 1,008.113*** | 473.244*** | 1,044.288*** |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

[18] We define as "stable-green" the firms that, considering only the time span where they were effectively listed, are labelled green in more than 50% of the years.

Table 5: Percentage of companies that present significant risk factors for different levels of significance

| | alpha = 5% | alpha = 10% |
|---|---|---|
| const | 4.8 | 13.8 |
| MRP | 99.6 | 99.7 |
| SMB | 53.9 | 60.6 |
| HML | 43.4 | 50.9 |
| GRF | 25.4 | 32.4 |

Figure 6: Frequency distribution of the Beta green risk factor

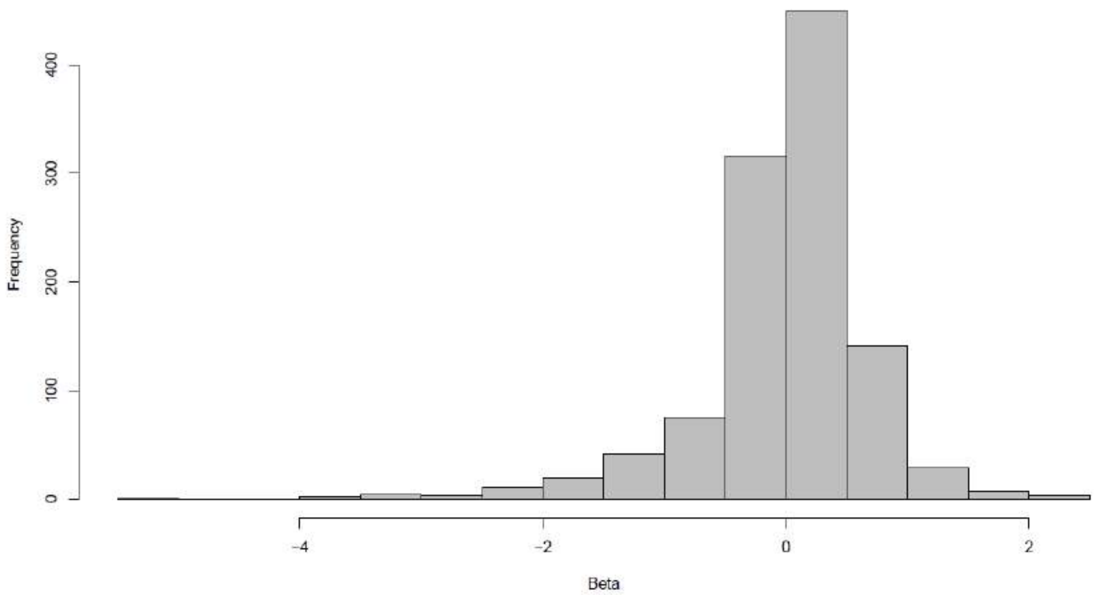



Table 6: Statistics of Green Risk Factor's Betas in different clusters

| | Mean | Std.Dev. | % significant | % positive |
|---|---|---|---|---|
| Brown | -0.27 | 0.56 | 42.61 | 34.64 |
| Non-green | 0.09 | 0.35 | 17.08 | 62.60 |
| Stable green* | 0.18 | 0.24 | 36.97 | 75.77 |

## 5. Conclusions

We identify green firms among listed companies in the European Union using a comprehensive database of environmental information at time/firm level. Unlike other studies based on subjective criteria for the choice of green firms, we propose an innovative approach that identifies a time-varying number of green firms using unsupervised learning techniques. This is the main contribution of our study to the existing literature. We then defined a pricing factor related to climate risk, calculated as the difference between the return on a portfolio of green and brown firms.

In line with recent studies, we find that green firms have under-performed non-green firms, i.e. investors are willing to buy green securities even if they yield lower returns (although they have higher returns than brown firms). However, focusing on the COVID-19 crisis period, we find that green firms outperformed the whole market, since they had higher returns than both brown and non-green firms. In addition, we also find that during the COVID-19 crisis green firms also had higher risk-adjusted return. Finally, we find that green firms are more liquid than brown and non-green firms and this gap increased during COVID-19 crisis. Overall, our results are consistent with recent contributions suggesting that green firms perform generally better in periods of market stress, in particular during the COVID-19 market collapse.

We then study the role of climate risk in equity prices by estimating an extended standard asset pricing model on single stocks by including the Green risk factor. For the EU stock market, our findings confirm that this factor is relevant when introduced in standard asset pricing models. Indeed, it has significance levels not far from other well-known factors in the literature (HML and SMB). We also find that generally green firms have positive exposure to the green risk factor (they benefit when the market concern on climate risk increases) while the opposite holds for brown firms. However, we also find that there is a significant fraction of firms whose exposure to the green risk factor is not consistent with cluster classification. This suggests that market prices might incorporate additional information on climate exposure of firms that are not correctly measured by the environmental data used to identify the clusters of firms.

More can be done to extend this approach and refine these results. Firstly, in this paper we clustered firms using only five different indicators, and by relying heavily on the environmental scores produced by Refinitiv. An alternative approach could be to cluster firms directly using the KPI used in the analysis, thus considering a larger set of information and without relying on the aggregation method used by the data providers in creating the scores. Secondly, we find that green firms are usually bigger (in terms of market value) than non-green and brown firms. This might be explained by the fact that big firms are better equipped to disclose large amount of information and therefore they receive higher scores. To account for this bias a potential solution could be to apply clustering techniques to separate green firms in two separate groups of firms: large cap and small-mid cap firms and take the union of these two sets. Another potential criticism is related to the definition of brown firms, which are identified as firms that belong to Climate Policy Relevant Sectors.

However, not all brown firms are the same. Brown activities are still needed in the transition to a greener economy and some of these firms could have started investment plans to reduce their emissions or to diversify their activity. A way to overcome this criticism would be to apply the clustering procedure to CPRS firms and identify “truly brown” firms as the worst performers among the clusters identified by the algorithm. Finally, we find that not all green firms have positive exposure to the green risk factor (and similarly for brown firms) suggesting that market prices might incorporate additional information on climate exposure that is not incorporated in our data. Integrating this information in our procedure would require to run clustering techniques in two steps by integrating exposure to the green risk factor for each firm in the database.

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Figure 7: Sectorial (NACE2 level) weighted average of the exposure to the green risk factor across firms

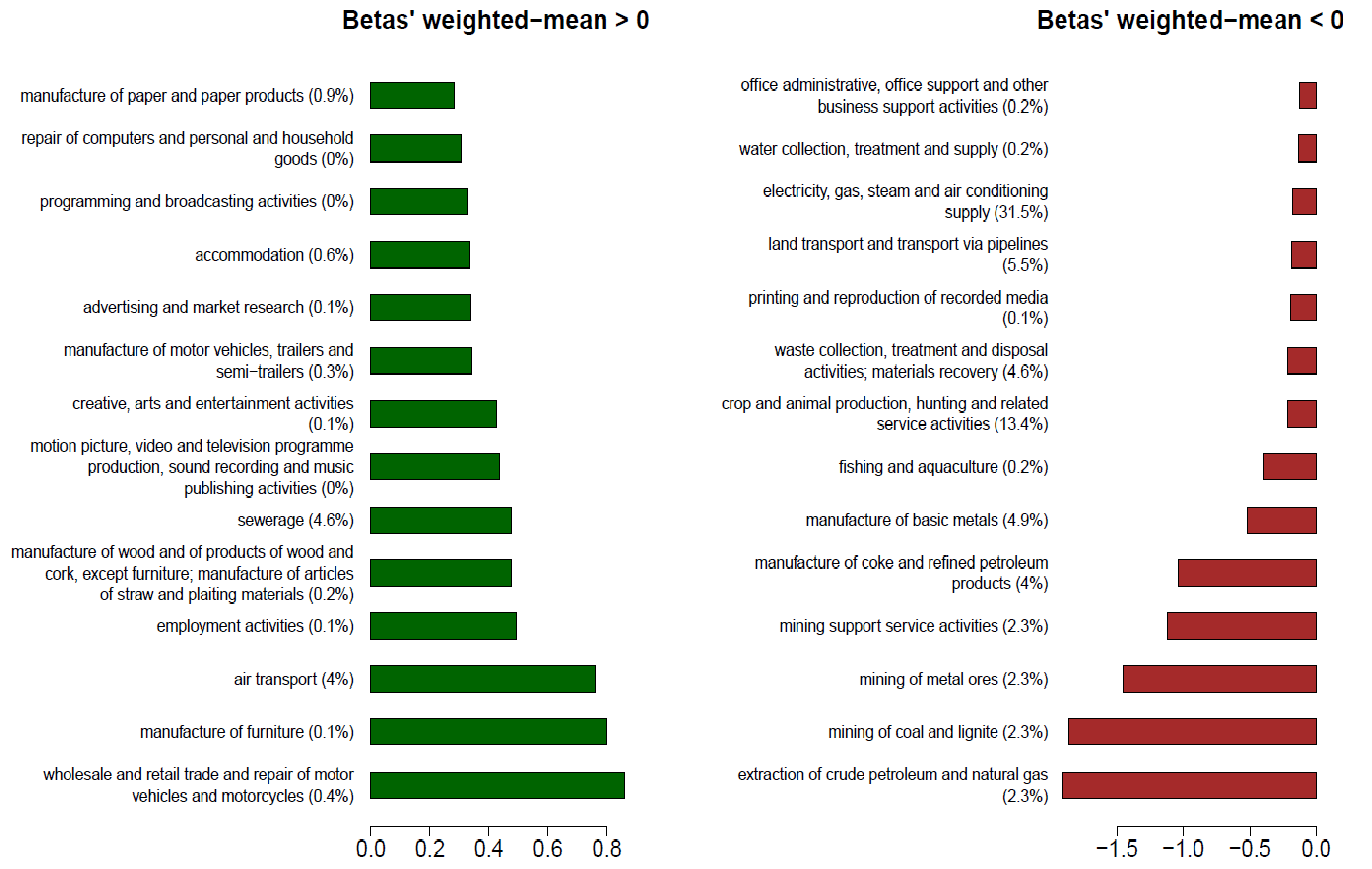
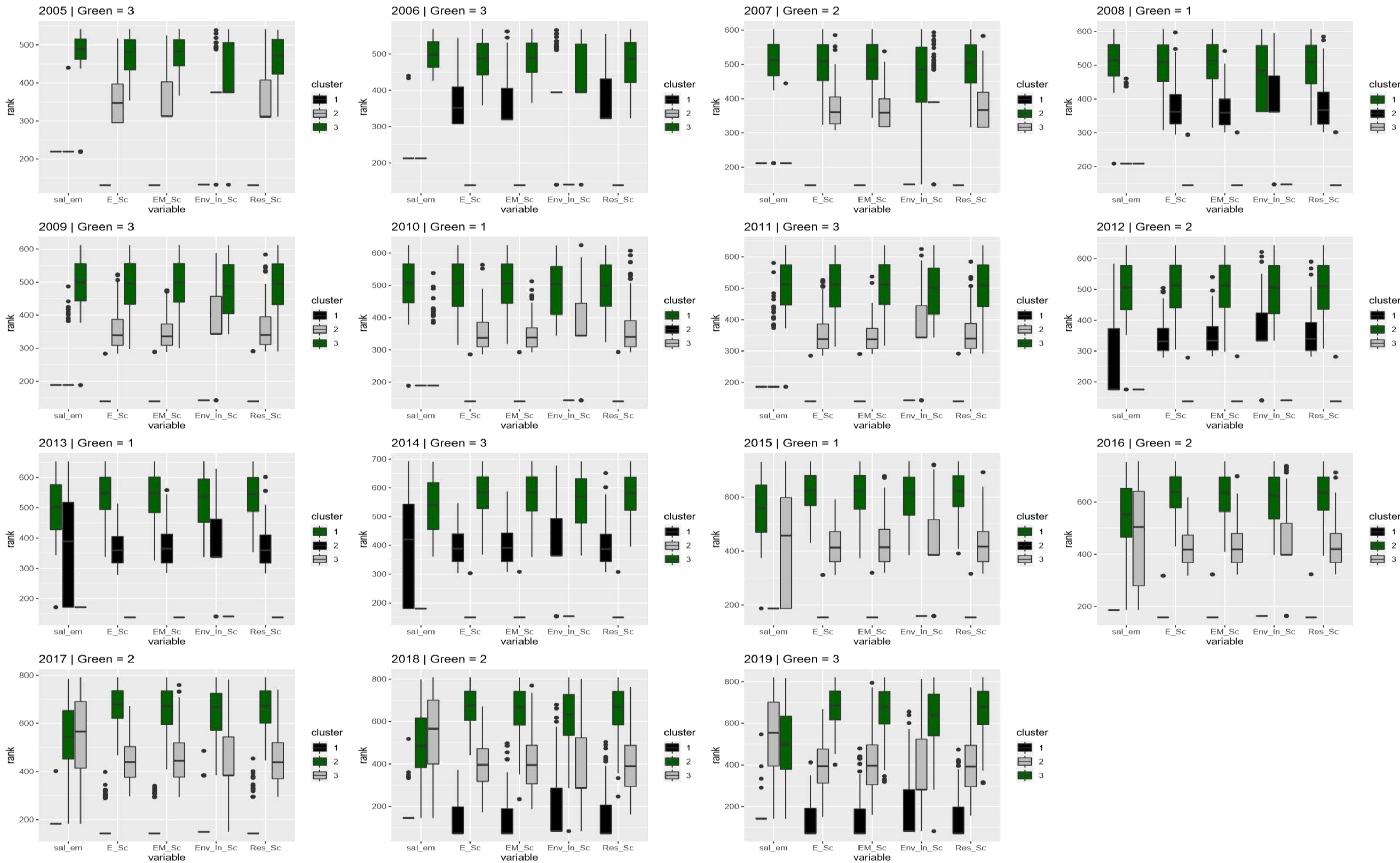
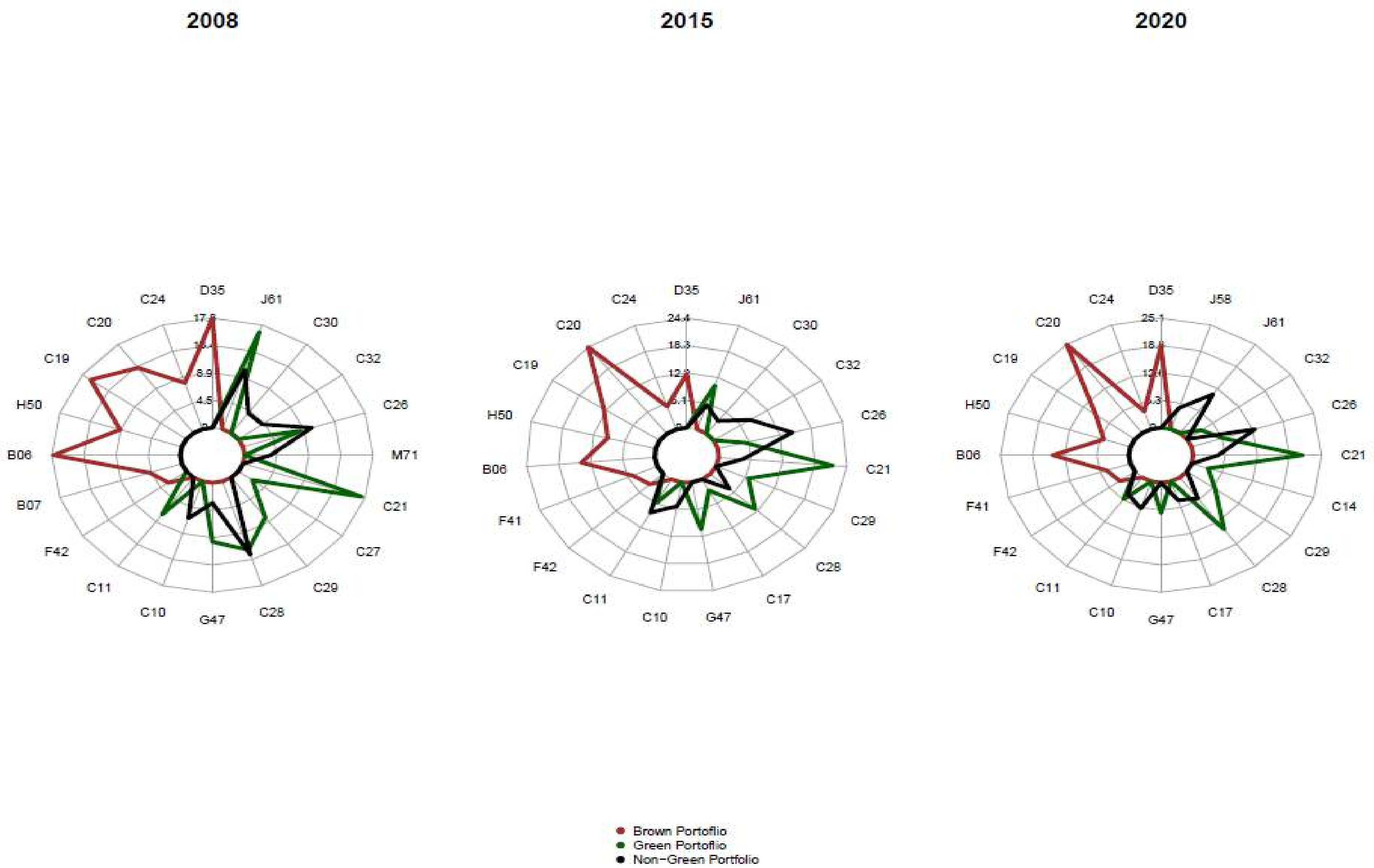


Figure 8: Boxplot of the Environmental Indicators' rank, divided in clusters




Note: sal_em corresponds to the sales/emission ratio, E_Sc to the Environmental Pillar Score, EM_Sc to the Emission Score, Env_In_Sc to the Environmental Innovation Score and lastly Res_Sc stands for Resource Use Score .

Figure 9: Sectorial distribution of Green, Non-green (included non-transparent) and Brown portfolios. For each portfolio are considered the four largest sectors, in terms of market value, ordered counterclockwise in terms of emission level (the sector in the north part of the radar corresponds to the highest emitting sector).




Note: B06 - Extraction of crude petroleum and natural gas; C10 - Manufacture of food products; C11 - Manufacture of beverages; C19 - Manufacture of coke and refined petroleum products; C20 - Manufacture of chemicals and chemical products; C21 - Manufacture of basic pharmaceutical products and pharmaceutical preparations; C26 - Manufacture of computer, electronic and optical products; C28 - Manufacture of machinery and equipment n.e.c.; C29 - Manufacture of motor vehicles, trailers and semi-trailers; C32 - Other manufacturing; D35 - Electricity, gas, steam and air conditioning supply; G47 - Retail trade, except of motor vehicles and motorcycles; J61 - Telecommunications.

## Table 7: Summary Statistics of Refinitiv's Environmental Indicators

| | Sales/Emission Ratio | | | | | | Environmental Pillar Score | | | | | | Emission Score | | | | | | Resource Use Score | | | | | | Environmental Innovation Score | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max |
| 2005 | 0 | 2.4 | 15.8 | 127 | 42.5 | 3001.6 | 0 | 4 | 23.5 | 29.5 | 50.7 | 91.9 | 0 | 0 | 29.2 | 37.7 | 72.4 | 99.3 | 0 | 0 | 31.7 | 36.8 | 69.2 | 99.3 | 0 | 0 | 0 | 11.2 | 0 | 99.3 |
| 2006 | 0.1 | 3.2 | 16.6 | 109.6 | 47.8 | 2957.1 | 0 | 5 | 26.7 | 31.1 | 52.7 | 95 | 0 | 0 | 42.1 | 42 | 76.3 | 99.3 | 0 | 0 | 32.1 | 37.9 | 70.8 | 98.9 | 0 | 0 | 0 | 10.9 | 0 | 97.9 |
| 2007 | 0 | 3.7 | 20.2 | 98.8 | 50.1 | 3460.2 | 0 | 18.1 | 40.2 | 40.6 | 61.4 | 96.9 | 0 | 19.2 | 55.1 | 50.4 | 80.5 | 99.4 | 0 | 20.1 | 50 | 49.2 | 79.2 | 99.4 | 0 | 0 | 0 | 19.9 | 37.5 | 98.1 |
| 2008 | 0 | 3.3 | 19.1 | 106.7 | 50.6 | 4673.5 | 0 | 27.2 | 49.6 | 48.7 | 73.3 | 96.7 | 0 | 30.3 | 61 | 55.8 | 85.3 | 99.6 | 0 | 30.1 | 62.2 | 55.9 | 83 | 99.6 | 0 | 0 | 24 | 31.2 | 61.5 | 99.3 |
| 2009 | 0.1 | 3.8 | 19.1 | 113.8 | 54.4 | 4229.8 | 0 | 29.7 | 54.6 | 51.5 | 75 | 96.9 | 0 | 36.5 | 63.5 | 58.6 | 85.9 | 99.5 | 0 | 34.9 | 63.8 | 58.2 | 86.5 | 99.7 | 0 | 0 | 27.5 | 34.5 | 66.7 | 99.2 |
| 2010 | 0 | 4.6 | 20.2 | 100.3 | 56.4 | 4274.9 | 0 | 32.3 | 56.2 | 52.9 | 75.6 | 96.9 | 0 | 39.7 | 66.3 | 60 | 87 | 99.7 | 0 | 40.2 | 65.3 | 59.9 | 85.4 | 99.6 | 0 | 0 | 28.9 | 35.2 | 66.7 | 99.2 |
| 2011 | 0 | 4.7 | 21 | 104.1 | 58.9 | 5168.4 | 0 | 33.2 | 57 | 53.3 | 75.7 | 98.3 | 0 | 39.4 | 66.9 | 59.9 | 85.6 | 99.7 | 0 | 40.4 | 65.8 | 60.7 | 87.5 | 99.7 | 0 | 0 | 26.2 | 35.4 | 70.3 | 99.5 |
| 2012 | 0 | 5.3 | 23.7 | 103.6 | 67.8 | 4333.1 | 0 | 35.8 | 56.9 | 54.4 | 74.6 | 98.5 | 0 | 40.1 | 66.2 | 60.7 | 84.9 | 99.8 | 0 | 41.1 | 67.1 | 61.7 | 87.3 | 99.7 | 0 | 0 | 32.3 | 37.4 | 69 | 99.5 |
| 2013 | 0 | 5.3 | 22.8 | 103.5 | 63.8 | 3243.6 | 0 | 36.3 | 57.7 | 54.7 | 75.6 | 97.9 | 0 | 41.2 | 68 | 61.7 | 85.3 | 99.8 | 0 | 40.6 | 67.1 | 61.4 | 86.9 | 99.7 | 0 | 0 | 32.1 | 37.3 | 68.7 | 99.5 |
| 2014 | 0 | 6.1 | 25.2 | 133.1 | 81.2 | 10304.3 | 0 | 34.8 | 56.7 | 54.1 | 75.9 | 98.3 | 0 | 39.3 | 66.9 | 60.6 | 85.6 | 99.8 | 0 | 40.5 | 65.8 | 60.8 | 86 | 99.7 | 0 | 0 | 35 | 37.9 | 68.1 | 99.5 |
| 2015 | 0 | 6.7 | 23.8 | 141.2 | 91 | 13677.4 | 0 | 36.4 | 58.2 | 54.4 | 76.1 | 97.7 | 0 | 40.6 | 66.3 | 60.6 | 86.5 | 99.7 | 0 | 41.8 | 67.1 | 61.1 | 86.3 | 99.8 | 0 | 0 | 36.4 | 37.9 | 65 | 99.7 |
| 2016 | 0 | 6.6 | 26.9 | 303.8 | 94.8 | 76302.3 | 0 | 38 | 58.9 | 55.8 | 76.6 | 98 | 0 | 43.8 | 68.2 | 62.9 | 87.5 | 99.8 | 0 | 45.7 | 68.6 | 62.7 | 86.1 | 99.8 | 0 | 0 | 37.9 | 38.3 | 64.9 | 99.8 |
| 2017 | 0.1 | 6.8 | 30.2 | 312.2 | 111.1 | 58156.9 | 0 | 36.3 | 56.7 | 54.8 | 75.3 | 98.4 | 0 | 42.3 | 65.5 | 61.9 | 86.7 | 99.8 | 0 | 43.3 | 68.2 | 62.3 | 87.3 | 99.8 | 0 | 0 | 36.3 | 37.3 | 64.3 | 99.8 |
| 2018 | 0 | 9 | 33.3 | 378.8 | 129.6 | 45150 | 0 | 31.2 | 53.2 | 51.3 | 74.1 | 98.4 | 0 | 36.3 | 61.6 | 57.6 | 84.4 | 99.6 | 0 | 34.2 | 63.8 | 58.4 | 85.9 | 99.8 | 0 | 0 | 30.5 | 35.3 | 62.6 | 99.8 |
| 2019 | 0 | 9.9 | 38.3 | 510.1 | 146 | 55874.5 | 0 | 33.2 | 56 | 53.1 | 74.8 | 98.2 | 0 | 40.5 | 64.9 | 60.2 | 85.5 | 99.8 | 0 | 36.8 | 66.3 | 60.4 | 86.7 | 99.8 | 0 | 0 | 34.2 | 36.3 | 63.2 | 99.8 |

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## Appendix A

Refinitiv Environmental Indicators' definition, as defined by Refinitiv:

- **Sales/Emission Ratio**: Net sales or revenue in US dollars divided by Total CO2 and CO2 equivalents emission in tonnes.
- **Environmental Pillar Score**: The environmental pillar measures a company's impact on living and non-living natural systems, including the air, land and water, as well as complete ecosystems. It reflects how well a company uses best management practices to avoid environmental risks and capitalize on environmental opportunities in order to generate long term shareholder value.
- **Emission Score**: Emission category score measures a company's commitment and effectiveness towards reducing environmental emission in the production and operational processes
- **Resource Use Score**: Resource use category score reflects a company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management.
- **Environmental Innovation score**: Environmental innovation category score reflects a company's capacity to reduce the environmental costs and burdens for its customers, and thereby creating new market opportunities through new environmental technologies and processes or eco-designed products.

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