InvestVerte

A Brief description of our framework…

April 2022

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Contents

I. INTRODUCTION

In recent years, Environmental, Social, and governance (hereafter, ESG) ratings have become influential information for Investors relying on assessing corporate ESG performance. Institutional investors aim from corporations to set up ESG processes, manage ESG issues and monitor ESG performance (Dyck et al., 2019). This is due to the additional return expectation in the generally low-interest rate financial environment and the lack of return in a more conventional investment area. The latter lead to growing sustainable investment from mutual funds (Hartzmark and Sussman, 2019). ESG ratings become crucial in financial decisions influencing the financial ratios and corporate performance inducing a general change in corporate policies (Liang and Renneboog, 2007). This led to an increasing number of academic papers on ESG ratings through empirical analysis. (see Liang and Renneboog (2017), Servaes (2013), Hong and Kostovetsky (2012), and Lins et al. (2017).

However, ESG ratings and their providers are not a mature market as the well-known credit rating market and their providers (S&P, Fitch and Moody's). Indeed, where the credit rating has an extremely low spread on their credit assessment and final corporate credit rating, meaning that the consensus is well accepted. ESG providers disclose a high difference in their final rating (Chatterji et al., 2016). From six different providers namely, KLD (MSCI Stats), Sustainalytics, Vigeo Eiris (Moody's), RobecoSAM (S&P Global), Asset4 (Refintiv), and MSCI a recent study assesses the average correlation of 0.54 (F. Berg et al., 2020). These discrepancies between providers can influence badly the financial investment decision or corporate policies. Also, this leads to making even worst the empirical influence of the ESG ratings on stock and bond prices (Fama and French, 2007; Pasto et al., 2020). Also, ESG rating agencies disclose a low level of transparency on their Rating assessment and as the discrepancies are high, we can say that their framework differs substantially. Many different root causes can explain the discrepancies between providers, but we can denote the set of attributes or even if the providers measure the same set of attributes the metrics used may differ and the scorecards and the weights for a given set of attributes may differ and induces the ESG rating differences between providers (F. Berg et al., 2020).

All the reasons lead to biased information for corporate ESG improvement purposes and make ESG influence on Corporate performance difficult to study for academic research purposes. Given the discrepancies, we can argue that each provider masters a piece of the real information about the ESG performance of the firms under assessment. Because the large majority of the ESG rating framework are manuals because the final weights (scorecards) are expert-based and the lack of backtesting and statistical evidence of those frameworks induce a bias on the final ESG rating this paper proposes a manner to converge the different frameworks under a robust statistical method to align and bound the underlying root cause under each ESG rating movement. The latter reduces the information asymmetry between the providers the firms and the evolution of return of stock prices and bonds.

This paper explores how to merge statistically the information from different providers and explores a larger source of attributes that can explain the movement in ESG ratings. the aim is to have an in-house and transparent scorecard and to find the most relevant attributes for ESG ratings for the firms belonging to a certain sector.

Before the weighted average is performed, the target variable namely E, S and G are transformed in gaussian quantile under 100 buckets. The reasons are, first, to make the E, S G ratings from different providers comparable. Second, as it is a biased market, the ESG rating outputs from different providers mays lead to having non-gaussian behaviour. As in credit rating, and thanks to central limit theory, the rating should converge towards a Gaussian distribution. Given the low number of rated companies for each provider, a gaussian transformation should be applied.

This is performed by ranking the companies from 1 to 100 and applying a “probit” transformation.

On this basis, we aim to find a way to merge the E, S and G separately from different providers by a weighted average of the Ratings. We explore two different ways to weigh the ESG ratings from different providers. In the first approach, the number weighted average way counts the number of firms rated by specific providers by sector. Higher is the number of firms rated by one provider within the sector, the higher is the weight. The second method explored is book value-weighted average. Higher is the firms’ values sum rated by one provider within the sector, higher is the weight. The rationale behind the first method is the following: the assumption is we suppose that the more a provider rates a specific sector higher is the knowledge about the firms under assessment within the sector. The rationale behind the second method is the following: the assumption is, given the difficulties to rate many firms within the sector because of manual processes or the frequency required to rate the firm, we suppose that the provider concentrates their effort on the most important firms and have a better knowledge about those firms. Also, the bigger are the firms, the better is the quality of the disclosure of ESG related information easier for the provider to find valuable information.

Methodologically, we explore as far as possible all indicators provided by the different data providers. As our goal is not to reproduce exactly the attributes, we collect the raw attribute definition and data. For example, instead of collecting the ratios of the carbon gas emission as CO_2 to sales, we collect separately the 2 components. On top of ESG related indicators, we explore more traditional financial indicators of the firms. Our assumption is that part of the remaining information should be in the financial performance of the firms as explanatory attributes. Indeed, it is easier for a firm having good financial performance to adopt policies towards the improvement of their internal corporate social responsibility and governance and have a possibility to invest in Environmental solutions. Also, this permits us to investigate at a later stage, the financial impact of the ESG rating movement. The latter depends on the model design we implement.

Our approach explores all possibilities of numerator and denominator and results in a set of more than 4000 attributes in total. To avoid as much as a possible missing effect, we implement an appropriate adjustment imputing in the hierarchy.

In a second step, we explore different attributes transformation namely, (1) linear, (2) exponential, (3) sigmoid, (4) cubic, bucket. For each attribute, the more suitable transformation is selected by the explanatory power as well as the simplicity of the transformation. For instance, if an attribute has the same explanatory power by using linear and cubic, we prefer linear. The explanatory power is measured by the C-statistic. We perform in this step the first variable selection, where a C-static having a value around 50 means it is a random variable. This is a univariate analysis. A threshold is set at 60%, and each attribute having a C- statistic lower than 60% is avoided in the analysis. Each attribute is divided into 100 buckets. This process transforms the attributes into the target variables.

The third step aims to perform a univariate analysis. This step explores one by one, the explanatory power of each attribute separately. This step allows us to select a shortlist of plausible candidate attributes. We define the model design as follows: (A) to explore if ESG performance has an impact on financial performance (Financial statement or Cash flow type of attributes), we performed a univariate analysis as each attribute is designed as a target variable and is explained by the ESG rating from one year before. The purposes of this model design are to select a shortlist of attributes and to assess whether a change in ESG rating has an impact on one of the financial performances visible in the financial statement (long term impact). (B) The second model design is reversely explaining the ESG rating by the financial statement variables at the same reporting date from the shortlist from the model design (A). For this model design, we performed univariate analysis as well as multivariate analysis. The latter is discussed in the following paragraph as it implies variable selection and the final model. (C) The third model design is explaining the current ESG rating by the financial variable from one year before. As for the previous model design (B), univariate and multivariate analyses are performed. The purposes are to assess whether the movement in financial variables discriminates the ESG ratings.

As we explore a large set of synthetical attributes, first, we aim to avoid the multicollinearity effect. Therefore, for model designs (B) and (C) after the first selection, we perform a Variance Inflation factor (hereafter, VIF). Second, we regress each E, S, G rating using a Stepwise regression selection. Thus, model design (B) and (C) after variable selection result in a final quantitative model.

We explore as well qualitative attributes as the framework from provides is mainly qualitative. However, we do not include all qualitative attributes as we think that most of them are redundant or can be summarized in a smaller set of variables. Also, we aim to explore qualitative attributes giving significant added value to the final model as the sector, the region as well as the size and the listed/non-listed type of information. Those qualitative attributes are included in the qualitative specific sub-model and combined with the quantitative sub-model discuss above. This gives the advantage of first, leading with a different number of observations. The latter may lead to an increase in the overall robustness of the final combined model. Second, strong qualitative attributes may hide relevant variables in the selection process such as the stepwise even if a Lasso selection can mitigate this risk. Having a separate qualitative sub-model makes the model easier to explain and to read or combined it into a scorecard form (for model use mainly) for business or professional consideration. Finally, having two different sub-model and combining them through a final logistic regression makes it easier to explain the importance of qualitative and quantitative factors specifically.

II. DATA

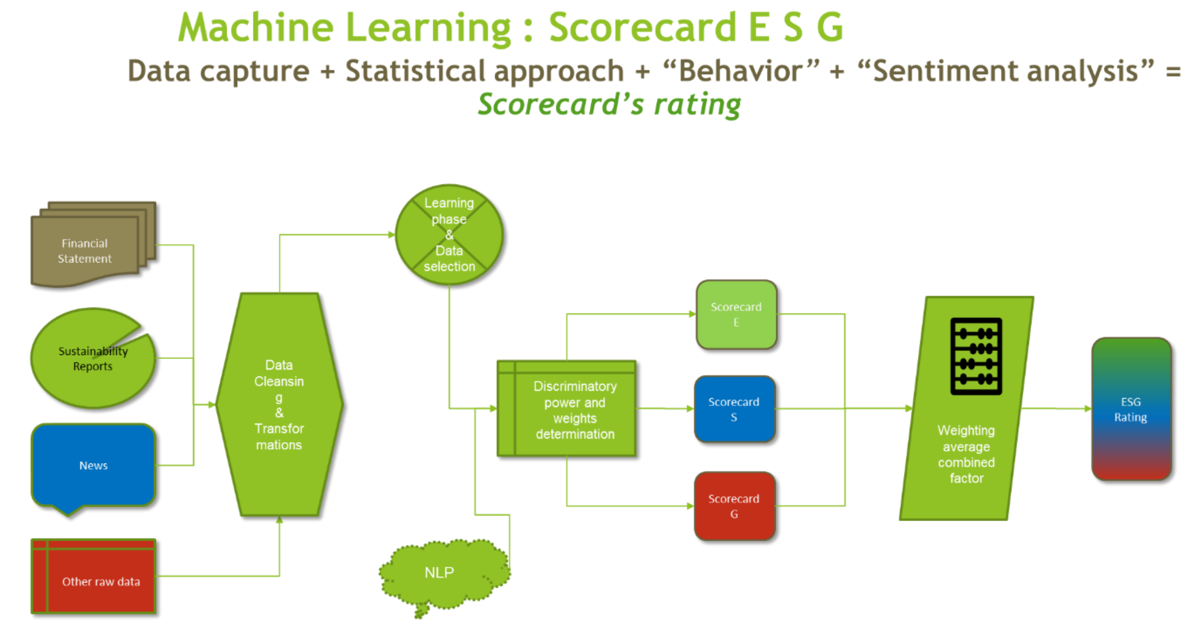

Figure 1:InvestVerte infrastructure, process & data flow

Figure 1 shows the infrastructure and ecosystem for this project/venture. Free or relatively low-price data are mainly used. Each component can bring new factors to be treated as inputs to the Machine Learning tool.

ESG ratings appear in the 1980s to help investors in assessing the company's performance not only on financial ratios but through more qualitative attributes social and environmental related. The very first ESG rating agency named Vigeo Eiris was created in France in 1983. ESG rating agencies use the same outcomes as credit rating agencies in ranking companies but are not related to creditworthiness. Therefore, even if a rating scale gives the analysts a good assessment of the ESG level of the companies the principles driving the outcomes are not clear and even worst; the discrepancy between ESG ratings from different providers for the same company rated can be high. The lack of consensus and the competition on the disclosure report about SRI information is the results of an immature market for ESG rating provider. The lack of consensus is not a synonym of wrong information disclosed but it is more a matter of methodology behind, the way to disclose such information and to what extent a provider is a specialist in assessing ESG information for such sector.

Our study aims to propose a methodology for consensus such as all information available from different public sources can be aggregated and collected.

To combine all ESG rating (after probit transformation) providers we explore two methods. The first method (α) uses a number weighted average ESG rating. The rationale is that the more a provider rates companies in a specific sector and/or region, the more accurate is the rating. The final ESG rating is calculated as follows.

The second method (β) uses a value weighted average ESG rating per sector. The rationale is that the provider may have an incentive to rate a certain size of the firm for a specific sector. This may lead to considering the expert effect of the provider on the average. More a provider is a specialist in one sector higher its weight. Therefore, the weight will be assigned per sector/region.

This ends up with the target variable induced by all information from different providers merged by the consensus process. Table 1 provides the number and the exposure weights per sector. that firm size matters in the provider's ratings frameworks. Moreover, this induces our approach ratio orientated instead of the use of raw attributes as well as including sizes type of attribute. Also, we aim to explore whether the region covered by the provider matters and if we should take also into account the weight of the region also using the total assets. It is indeed interesting that Vigeo covers largely Australia, but this should be due to the low number of firms where one big firm can cause the figure.

In conclusion, the Sector and the Region matter in the way to have a weighted average combined E, S and G score. A more granular weight will be used in our methodology to use Sector and Region segmentation to weight the ratings.

III. RATING METHODOLOGY

In this section, we assess whether financial performance or distress can predict E, S and G ratings using the shadow rating methodology (SRM). Therefore, we seek to map the drivers to ESG ratings. This approach presents an additional statistical and econometric challenge. The ratings are discrete and not continuous. This implies either a transformation of the ratings into a continuous scale to make the standard least-squares techniques possible to use or use a different technique considering a natural ordering to the ratings such as the ordered probit model as proposed in Hausman, Lo and Machkinlay (1992).

The ECB guide to internal models - Credit Risk, Sep 2018 define the SRM as an internal rating approach that selects and weighs the risk drivers to be used for risk differentiation purposes by identifying the main factors that explain external ratings provided by an external credit assessment institution or similar organization, rather than internal directly observed defaults. We derive from SRM to predict ESG ratings with one year lag. This method allows institutions to use internal specific criteria to explain external ratings. The advantage is the ability to rate the full internal portfolio instead of those rated by the external agency companies. Also, to have internally the ability to understand the rating movements.

Those arguments for using a SRM are even more important for ESG ratings. As the consensus is not reached, the rating movement and the scope is not well defined. The different providers can have different views or peace of information to rate a firm related to CSR topics. This makes the rating more likely to be subjective. Also, using pre-selected drivers having an impact on financial performance allows us to differentiate what is good or bad. For example, by scanning the provider's frameworks the scorecards are not always based on criteria screening from bad to good behaviour or position of the firm. It is for instance not obvious that the number of women on board has a good impact or bad impact on the financial performance of the firm. Also, when a criterion becomes normal 50% of the women on the board, the drivers cannot discriminate anymore, and the model will lose performance.

Most current E, S and G frameworks are based on qualitative factors and do not explore the fact that the E, S and G performance are a later consideration from a business perspective when firms are in distress. In other words, investments in CSR are possible when firms are in good condition. Therefore, E, S and G can be partially explained by the financial condition of the firm. We aim to demonstrate the fact that, determinant information is available in the financial performance of the firms. Therefore, considerably less attention has been given to includes not directly ESG related data in the different provider scorecards. We aim to fill in this gap by selecting drivers having impacts on ESG ratings.

IV. MODEL DESIGN

In this section, we will further discuss the model design and modelling steps to come up with the final model.

1. Impact-based approach

Current ESG frameworks are mainly based on direct or indirect indicators without statistical concerns such as correlation for instance. The Carbon gas emission can be in several drivers outputting the E rating. Moreover, the weights are human-based and subject to be biased. We aim to have an impact-based approach where the drivers are statically chosen based on their explanatory power to the changes to the financial ratios or ESG related components. This approach aims to avoid the redundancy of the drivers.

To select the preferable variables to enter in the final model based on the univariate analysis we aim to rank the predictive power of each candidates' ratios. This is performed by quantifying the goodness of fit using the likelihood function. This can be performed by the Akaike information criterion (AIC). We choose this criterion because this allows us to lead with the risk of overfitting and underfitting at the same time by measuring the amount of information lost by the model. This is important because it is a univariate analysis, and one to one relationship may result in both effects (overfitting/underfitting).

2. E, S and G model design quantitative module

As ESG frameworks are largely qualitative based models, we argue that financial situation and size have a role in the ability of a firm to invest in CSR topics or to increase CSR transparency. Therefore, we aim to isolate the two types of model components in one quantitative sub-model component and one qualitative model component. This allows us to not exclude valuable financial information during the final variable selection process. This approach allows us to lead with a potential scarcity of qualitative drivers. From the 2 model components, we aim to output a specific score, one for quantitative and qualitative scores. The two scores will be joined by a combined model where the target variable is the ESG ratings, and the explanatory variables are the scores. The final relative weights give us the allocation and importance to assign to each model component. This will be discussed further in a late stage. In this section, we will discuss the quantitative model component.

Once we preselect the candidate quantitative variables, we aim to explain ESG rating by synthetical financial ratios from one year before in a continuous linear model as well as an ordinal cumulative logistic model. The continuous linear model allows us to control the model for multicollinearity effect after controlling the candidate variables for correlation between them. For correlation control, we used the Spearman correlation as it measures the rank ordering correlation between 2 variables. If two variables are highly correlated (above 80%) we select the variable having the highest predictive power.

To avoid the multicollinearity effect, we perform a Variance Inflation Factor (VIF) in an ordinary least square regression analysis. This gives us an index that quantifies how much the variance of an estimated regression is increased by the collinearity effect.

However, rating scales are by nature discrete scales where the ordering matters. Therefore, it is a classification or segmentation issue to solve. Also, the probability to be in a higher rating is conditionally defined to do not being in the rating just below. The latter includes a condition or cumulative probability to be solved. The best model design to perform such an issue is using an ordinal cumulative logistic regression. We start from the continuous scale and apply an integer function resulting in a scale between 1 and 100.

As 100 buckets are a very big number and make it difficult to differentiate between different levels of rating grades, we combine them into 7 buckets. The rationale behind this is to have homogeneity of the observation within the grades and heterogeneity of the observations across grades (for differentiation purposes). In credit risk rating, the homogeneity and heterogeneity of grades are measured with the default rate. Indeed, the default rate should be statistically different across grades and statistically close within grades. For ESG ratings we did not have such metrics to confront the homogeneity and heterogeneity. However, in further study, an impact-based approach can lead to having such metrics. For instance, the number of controversies for Social and Governance components as well as Climate direct impact risks such as several floods or environmental disasters caused by an oil company can be explored. Also, to align the credit risk to ESG risk, those controversial reasons can be seen as default triggers or additional unlikely to pay reasons in a conservative manner to enhance the firm consideration of CSR concerns this approach can be further discussed in a new study measuring the ESG impact on credit risk.

The ordinal logistic regression (OLR) model formulation is an extension of the binary logistic regression formulation used by Ohlson for bankruptcy prediction (1980). When considering the bucketed ESG rating scale, the target variable is an ordinal categorical variable with 7 or 20 categories: [1,2,…,7] or [1,2,…,20]. The regression problem can be considered as a multi-class categorization problem where the categories are ordered from good to bad. As in the first model design, ordinary least squares regression can also be used, however, it can yield a worse generalization performance t. Van Gestel, B. Baesens, J. Garcia, P. Van Dujcke (2003).

The model performance and the choice of the best model during the stepwise procedure will be measured in three ways:

- First, the p-value of the corresponding coefficient must be sufficiently low: a p-value below 5% is frequently used, but as the number of observations is relatively high the p-value below 1% will be considered.
- A second criterion is that each variable yields a significant improvement in the deviance of the model (adding value to the model
- the estimated coefficient should be stable with respect to the sample within a reasonable range i.e., the estimated coefficient should not vary too much and/or the resulting predictability should remain constant. This will be measured using a cross-validation technic assessing the stability of the predictive power through the C-static (Area under ROC curve) for the logistic type of model.

3. E, S and G model design qualitative module

In the section above we explain the methodology and the rationale behind using financial information to find relevant determinants to ESG ratings. We aim to prove that financial distress is one of the key components for a firm to be able to invest and disclose ESG type of information.

However, selected qualitative drivers can also play a significant role in the ESG rating determination. We aim to demonstrate that ESG providers capture or are biased in their assessment of the firm in the local regulatory environment and the sector. For instance, we do think that the S rating for a firm in France is greater than in the USA because of the local regulatory environment and state social protection. Therefore, we aim to include the geographical area in the qualitative module.

This regulatory environment can also affect a specific sector, such as the recent regulatory limitation for carbon gas emission for cars, imposing in Europe a drastic change of the type of engine possible to purchase, the diesel fuel becoming less attractive to sell and making electric more suitable. Mercedes Benz has decided to do not to sell fossil fuel-based engines from 2035[1].

Therefore, we aim to include the sector in the qualitative module.

Small and medium companies will require more resources and are less visible to have the incentive to disclose ESG type of information. Instead of big companies having internal resources and being visible enough to disclose ESG type of information. The quality of the information discloses as well plays a role here. Big firms have the resource to disclose good quality information where it can be difficult to make the information readable in the report. So, we used Total Asset as a size variable, and we design it in 3 quantiles for small, medium, and big firms as one of the qualitative components.

Finally, we do think that Listed and non-listed firms' status plays an important role in the ESG rating determination. Indeed, listed firms have more incentive to disclose CSR information than non-listed firms. Therefore, we created a flag set of 0 for non-listed and 1 for listed firms.

4. Combined model

The model scorecard provides an intuitive way of reading the model. It involves the rescaling of the model coefficients and variables so that the final model outcome is translated into a score between 0 (worst) and 100 (best). Given that, the final model combines the quantitative and qualitative sub-models.

However, the score is not very readable as each variable has a different range and the coefficients cannot be compared as such. Consequently, a rescaling is performed to obtain a more interpretable score function between 0% and 100%. A value of 0% is obtained when all the ratios have the worst values. This corresponds to the lowest value for a ratio when the sign of the coefficient is positive or, vice versa, the highest value, when the sign of the corresponding

The coefficient is negative. Likewise, a value of 100% can be achieved when all ratios have their best value.

The final model is a joint model which combines the quantitative model and the qualitative model. Both models produce a score function which is obtained by multiplying each variable with its coefficient and summing these terms in a logistic regression function. A rescaling is done so that each score is between 0 and 100 (the so-called z-score). We denote the z-score for the quantitative model as Z_{Quant} and for the qualitative model as Z_{Qual}. To construct the final model, the quantitative model and qualitative are joined using the multiple ordinal logistic regression with the quantitative and qualitative z-scores as inputs. Only the common observations between quantitative and qualitative datasets can be used. It is generally the case that one of the 2 components has more observation making the estimators and the final z-score more robust in one of the components.

V. ALPHA – ESG Score Vs Expected Return

In this section, we will further discuss the model output and stock return. The dataset is a combination of ESG score from InvestVerte solution and stock return from the US market. Stock return was composed of the US-listed stocks which are major index constituents such as Dow Jones, S&P and the 100th biggest NASDAQ capitalization.

1. All universe

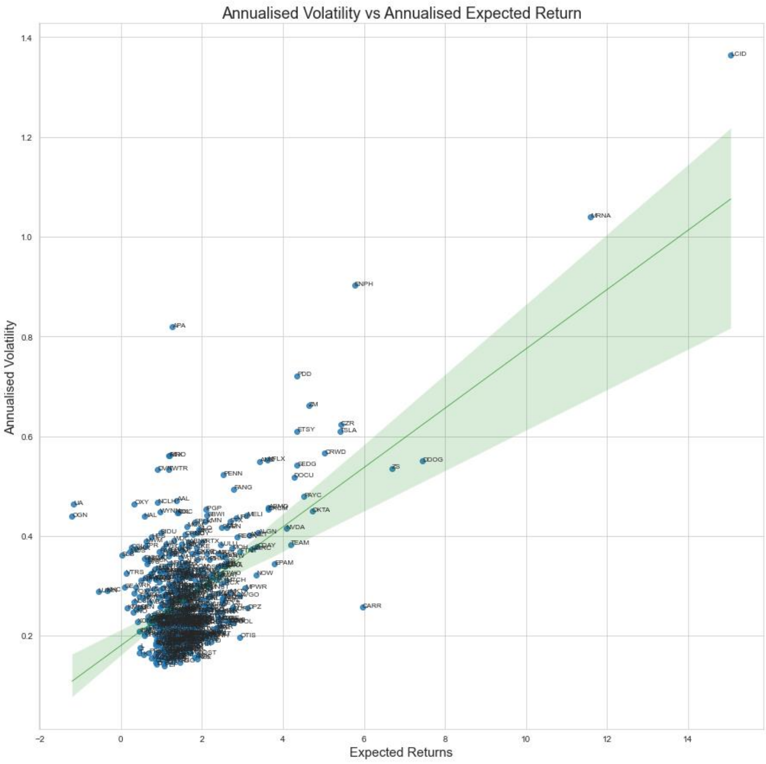

Figure 2: Annualized Volatility Vs Stock returns - 10 years

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.400
Model:                            OLS   Adj. R-squared:                  0.399
Method:                 Least Squares   F-statistic:                     348.2
Date:                Sun, 03 Apr 2022   Prob (F-statistic):           6.54e-60
Time:                        19:29:11   Log-Likelihood:                 524.35
No. Observations:                 524   AIC:                            -1045.
Df Residuals:                     522   BIC:                            -1036.
                    Df Model:                           1
                    Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1720      0.007     24.401      0.000       0.158       0.186
0              0.0629      0.003     18.659      0.000       0.056       0.070
==============================================================================
Omnibus:                      150.400   Durbin-Watson:                   1.951
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              462.038
Skew:                           1.352   Prob(JB):                   4.67e-101
Kurtosis:                       6.721   Cond. No.                         4.42
==============================================================================
```

Removing extreme data points, regarding stock return and annualised volatility, has an impact on the correlation output by decreasing R^2 but we have a better idea of the universe shown in Figure 3.

Figure 3: Annualized Volatility Vs Stock returns - 10 years without extreme data points

2. Period analysis

InvestVerte cover around 7,000 listed companies and those companies have been reviewed on a yearly basis with regard to the Financial Statement and Sustainability Report. The distribution in Figure 4 shows 10 years of ESG rating per company, country, sector and industry.

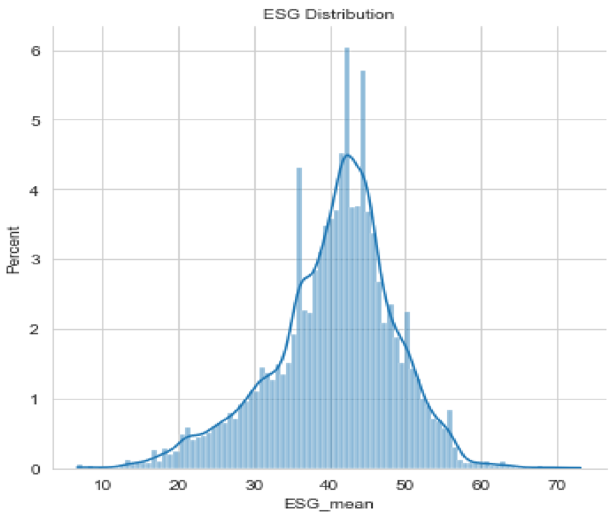

Figure 4: Average ESG score distribution - 10 years

Through the cycle point of view, some sectors have a better ESG over the time, however sub-sector is more important regarding ESG scoring processes which have been implemented in our solutions. Financial ratios have been too volatile within the same sector and correlations between companies is not necessarily high, industry level has been picked through Machine Learning processes. The sector's average ESG score is shown in Figure 5.

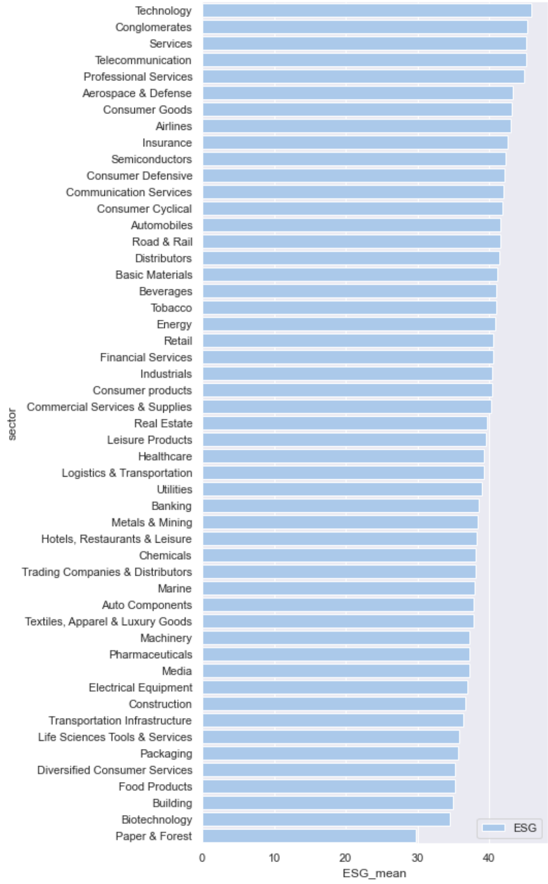

Figure 5: Average ESG score per sector through time

3. ESG Impact - Point-In-Time

Some years could be visited and the stock return period in Figure 6, ESG score as of 2015 has been set up in a cohort which has been crossed to those constituent's stock return.

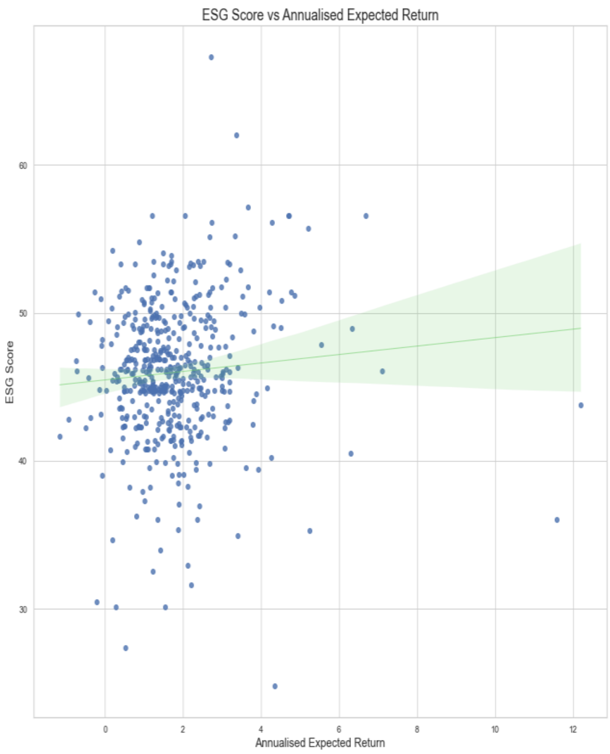

Figure 6: 2015 - ESG score vs Annualized Expected Return

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    ESG   R-squared:                       0.006
Model:                            OLS   Adj. R-squared:                  0.004
Method:                 Least Squares   F-statistic:                     3.165
Date:                Sun, 03 Apr 2022   Prob (F-statistic):             0.0758
Time:                        19:04:08   Log-Likelihood:                -1491.9
No. Observations:                 505   AIC:                             2988.
Df Residuals:                     503   BIC:                             2996.
                     Df Model:                       1
==============================================================================
         coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         45.4765      0.349    130.383      0.000      44.791      46.162
Return         0.2858      0.161      1.779      0.076      -0.030       0.601
==============================================================================
Omnibus:                       48.290   Durbin-Watson:                   0.859
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              154.655
Skew:                          -0.402   Prob(JB):                     2.61e-34
Kurtosis:                       5.589   Cond. No.                         4.20
==============================================================================
```

ESG score calculated for as of the year 2018 and stock’s return from 2018 to 2022 are shown in Figure 7.

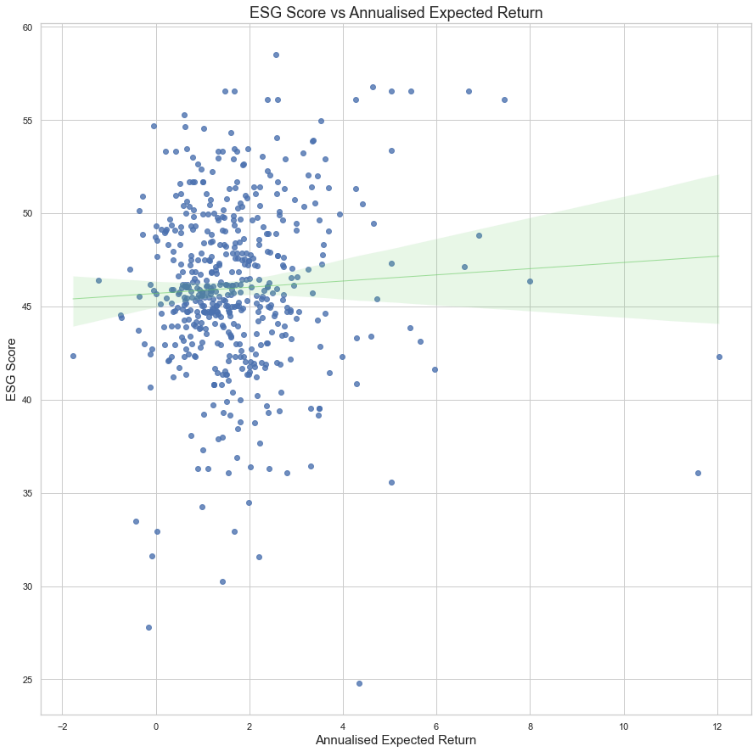

Figure 7: 2018 - ESG score vs Annualized Expected Return

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    ESG   R-squared:                       0.003
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     1.324
Date:                Sun, 03 Apr 2022   Prob (F-statistic):              0.250
Time:                        19:12:18   Log-Likelihood:                -1521.6
No. Observations:                 520   AIC:                             3047.
Df Residuals:                     518   BIC:                             3056.
                    Df Model:                           1
==============================================================================
         coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         45.7029      0.316    144.419      0.000      45.081      46.325
Return         0.1658      0.144      1.151      0.250      -0.117       0.449
==============================================================================
Omnibus:                       45.172   Durbin-Watson:                   0.793
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               90.408
Skew:                          -0.518   Prob(JB):                     2.33e-20
Kurtosis:                       4.761   Cond. No.                         3.98
==============================================================================
```

Based on the latter explanation about the Machine Learning technics used, correlations between ESG score and stock return are stable across the different points in the time period.

4. Best in class strategy

R^2 is weak regarding the entire universe but with a best-in-class per sector could increase this correlation and build a strong portfolio's opportunities.

2018 ESG score and three quartiles have been extracted and analysed in Figure 8.

Figure 8: 3rd quartile - ESG score 2018

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    ESG   R-squared:                       0.070
Model:                            OLS   Adj. R-squared:                  0.068
Method:                 Least Squares   F-statistic:                     28.88
Date:                Sun, 03 Apr 2022   Prob (F-statistic):           1.34e-07
Time:                        19:43:25   Log-Likelihood:                -990.80
No. Observations:                 385   AIC:                             1986.
Df Residuals:                     383   BIC:                             1994.
                     Df Model:                            1
==============================================================================
         coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         46.5772      0.271    171.632      0.000      46.044      47.111
Return         0.7191      0.134      5.374      0.000       0.456       0.982
==============================================================================
Omnibus:                       15.371   Durbin-Watson:                   0.594
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               16.467
Skew:                           0.507   Prob(JB):                     0.000266
Kurtosis:                       2.998   Cond. No.                         3.97
==============================================================================
```

2018 ESG score and two quartiles have been extracted and analysed in Figure 9.

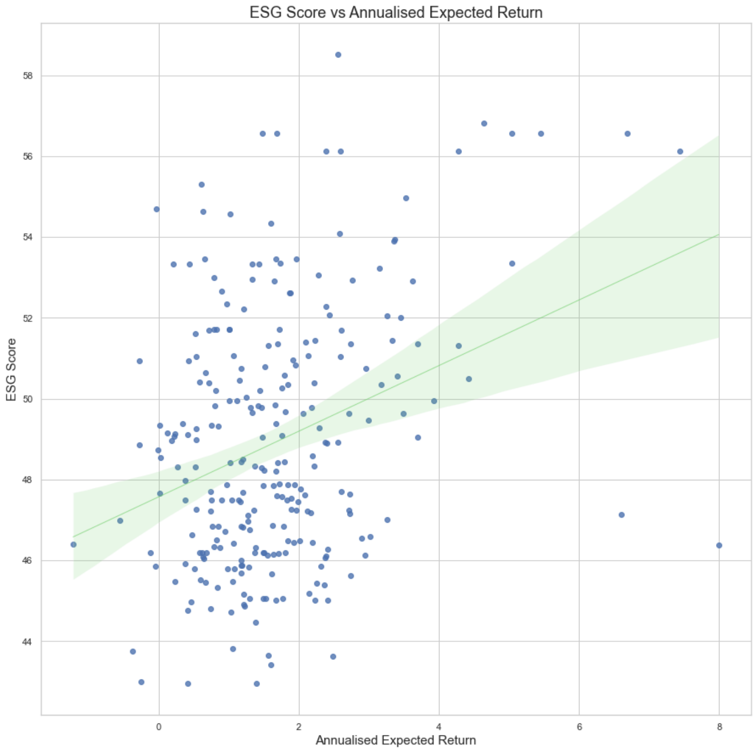

Figure 9: 2nd quartile - ESG score 2018

OLS Regression Results

Dep. Variable:	ESG	R-squared:	0.103
Model:	OLS	Adj. R-squared:	0.100
Method:	Least Squares	F-statistic:	29.55
Date:	Sun, 03 Apr 2022	Prob (F-statistic):	1.27e-07
Time:	19:43:41	Log-Likelihood:	-648.97
No. Observations:	258	AIC:	1302.
Df Residuals:	256	BIC:	1309.
Df Model:	1		

	coef	std err	t	P>|t|	[0.025	0.975]
const	47.5725	0.310	153.251	0.000	46.961	48.184
Return	0.8114	0.149	5.436	0.000	0.517	1.105

Omnibus:	7.543	Durbin-Watson:	0.673
Prob(Omnibus):	0.023	Jarque-Bera (JB):	7.770
Skew:	0.406	Prob(JB):	0.0205
Kurtosis:	2.748	Cond. No.	4.00

2018 ESG score and the first quartile have been extracted and analysed in Figure 10.

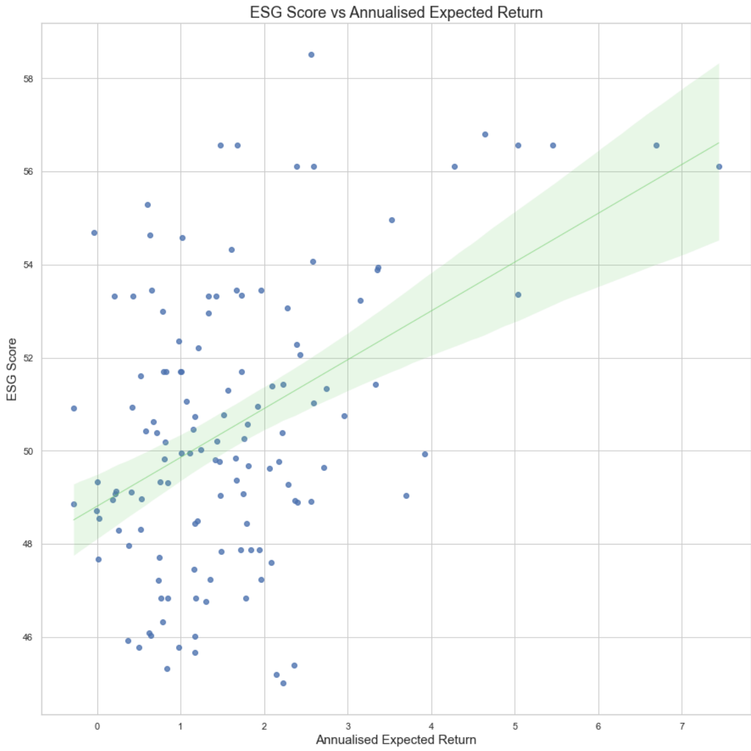

Figure 10: 1st quartile - ESG score 2018

OLS Regression Results

Dep. Variable:	ESG	R-squared:	0.201
Model:	OLS	Adj. R-squared:	0.195
Method:	Least Squares	F-statistic:	32.18
Date:	Sun, 03 Apr 2022	Prob (F-statistic):	8.92e-08
Time:	19:43:41	Log-Likelihood:	-314.26
No. Observations:	130	AIC:	632.5
Df Residuals:	128	BIC:	638.2
Df Model:	1		

	coef	std err	t	P>|t|	[0.025	0.975]
const	48.8095	0.386	126.401	0.000	48.045	49.574
Return	1.0485	0.185	5.673	0.000	0.683	1.414

Omnibus:	1.429	Durbin-Watson:	0.790
Prob(Omnibus):	0.489	Jarque-Bera (JB):	1.508
Skew:	0.232	Prob(JB):	0.471
Kurtosis:	2.750	Cond. No.	3.88

2015 ESG score and three quartiles have been extracted and analysed in Figure 11.

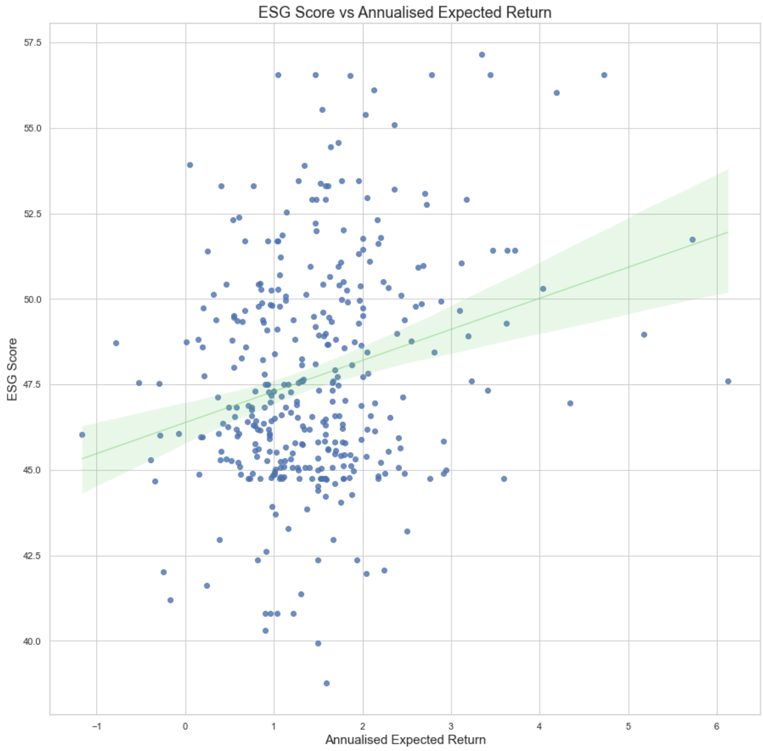

Figure 11: 3rd quartile - ESG score 2015

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    ESG   R-squared:                       0.012
Model:                            OLS   Adj. R-squared:                  0.010
Method:                 Least Squares   F-statistic:                     5.889
Date:                Sun, 03 Apr 2022   Prob (F-statistic):             0.0156
Time:                        20:08:59   Log-Likelihood:                -1419.2
No. Observations:                 489   AIC:                             2842.
Df Residuals:                     487   BIC:                             2851.
                    Df Model:                           1
==============================================================================
        coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          45.2499      0.374    120.915      0.000      44.515      45.985
Return          0.5163      0.213      2.427      0.016       0.098       0.934
==============================================================================
Omnibus:                       37.397   Durbin-Watson:                   0.832
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               59.603
Skew:                          -0.532   Prob(JB):                     1.14e-13
Kurtosis:                       4.339   Cond. No.                         4.12
==============================================================================
```

2015 ESG score and two quartiles have been extracted and analysed in Figure 12.

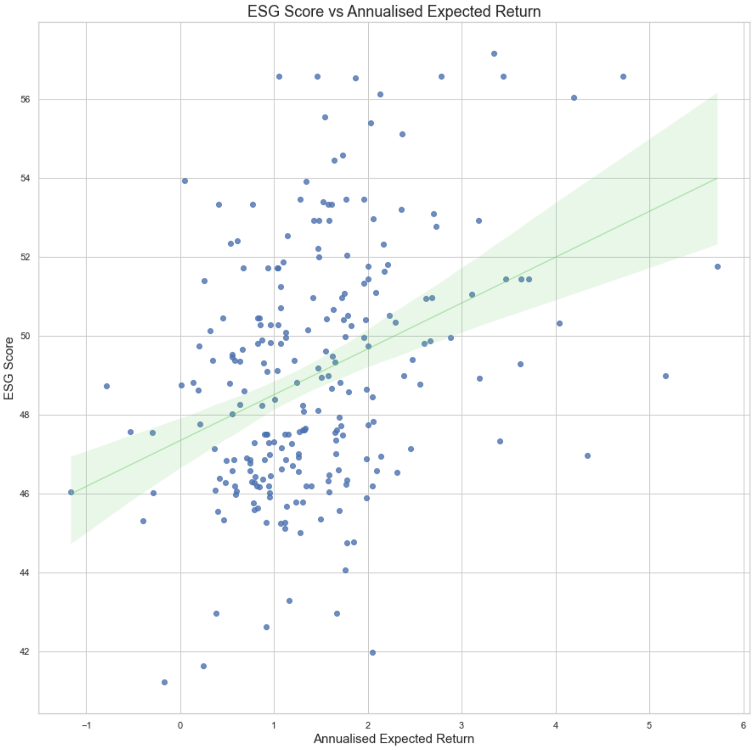

Figure 12: 2nd quartile - ESG score 2015

OLS Regression Results

Dep. Variable:	ESG	R-squared:	0.132
Model:	OLS	Adj. R-squared:	0.129
Method:	Least Squares	F-statistic:	35.82
Date:	Sun, 03 Apr 2022	Prob (F-statistic):	8.01e-09
Time:	20:09:07	Log-Likelihood:	-585.90
No. Observations:	237	AIC:	1176.
Df Residuals:	235	BIC:	1183.
Df Model:	1		

	coef	std err	t	P>|t|	[0.025	0.975]
const	47.3346	0.336	141.022	0.000	46.673	47.996
Return	1.1622	0.194	5.985	0.000	0.780	1.545

Omnibus:	3.942	Durbin-Watson:	0.718
Prob(Omnibus):	0.139	Jarque-Bera (JB):	3.972
Skew:	0.313	Prob(JB):	0.137
Kurtosis:	2.895	Cond. No.	3.88

2015 ESG score and the first quartile have been extracted and analysed in Figure 13.

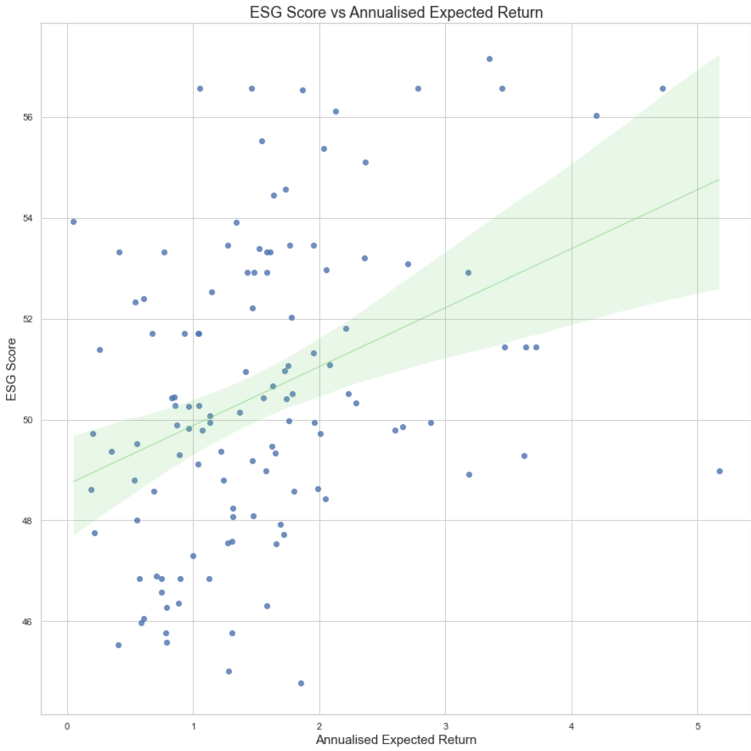

Figure 13: 1st quartile - ESG score 2015

OLS Regression Results

Dep. Variable:	ESG	R-squared:	0.138
Model:	OLS	Adj. R-squared:	0.131
Method:	Least Squares	F-statistic:	19.11
Date:	Sun, 03 Apr 2022	Prob (F-statistic):	2.65e-05
Time:	20:09:07	Log-Likelihood:	-293.57
No. Observations:	121	AIC:	591.1
Df Residuals:	119	BIC:	596.7
Df Model:	1		

	coef	std err	t	P>|t|	[0.025	0.975]
const	48.7116	0.488	99.912	0.000	47.746	49.677
Return	1.1691	0.267	4.372	0.000	0.640	1.699

Omnibus:	3.602	Durbin-Watson:	0.861
Prob(Omnibus):	0.165	Jarque-Bera (JB):	2.651
Skew:	0.212	Prob(JB):	0.266
Kurtosis:	2.412	Cond. No.	4.38

R^2 is massively increasing when the best-in-class approach when is applied. ESG score year of calculation is following the trend as well. 2018 and 2015 have been picked up randomly.

5. Portfolio cumulative return

This analysis would like to highlight alpha which would be created by using the best-in-class methodology in order to pick up per sector the most relevant shares. Figure 14 and Figure 15 are shown first quartile and combined first and second quartile portfolio against S&P 500.

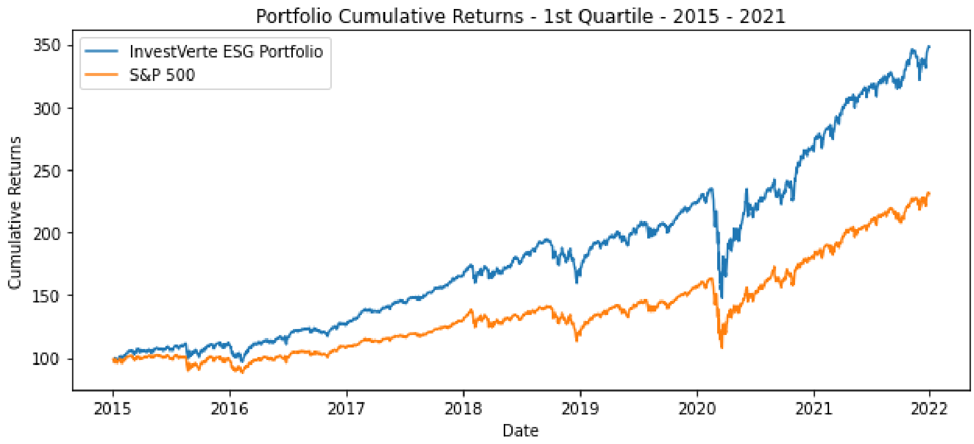

Figure 14: ESG Portfolio Q1 - S&P 500 cumulative return - 2015 – 2021

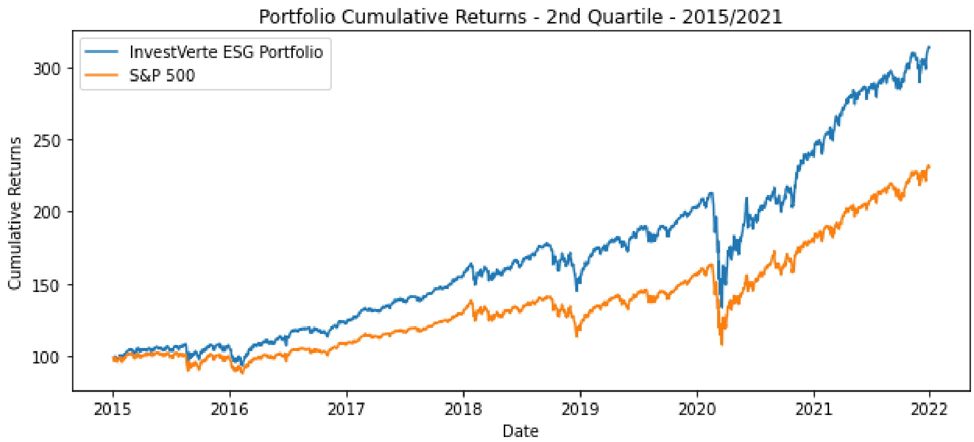

Figure 15 : ESG Portfolio Q1Q2 - S&P 500 cumulative return - 2015 - 2021

Cumulative return between Portfolio and benchmark are shown in Table 1.

Table 1: Cumulative Return – 2015/2021 - Portfolio & Benchmark

Year	Quartile	Portfolio cohort	Portfolio	Benchmark	Relative
2015 - 2021	1st	121	347%	230%	147%
2015 - 2021	1st – 2nd	237	313%	230%	83%

Year 2018 have been captured in Figure 16 and Figure 17 which are describing cumulative return portfolio built on the first quartile and by combining the first and second quartile against S&P 500 cumulative return.

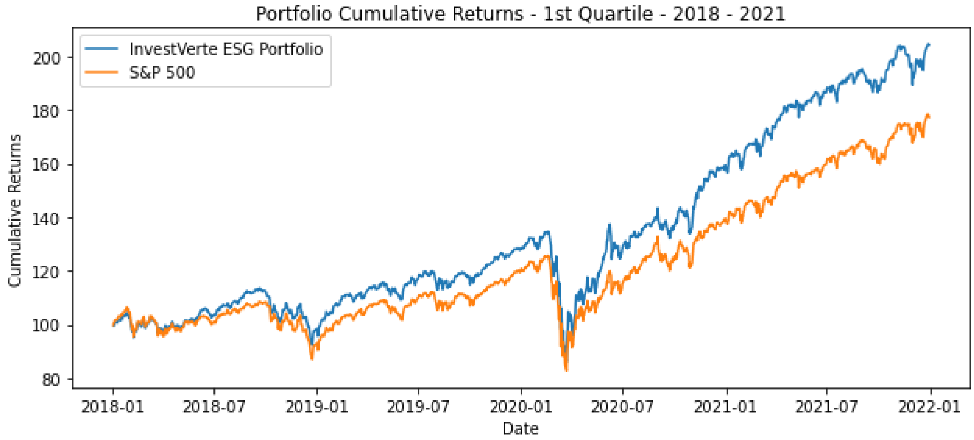

Figure 16: 2018 ESG Portfolio Q1 - S&P 500 cumulative return - 2018 - 2021

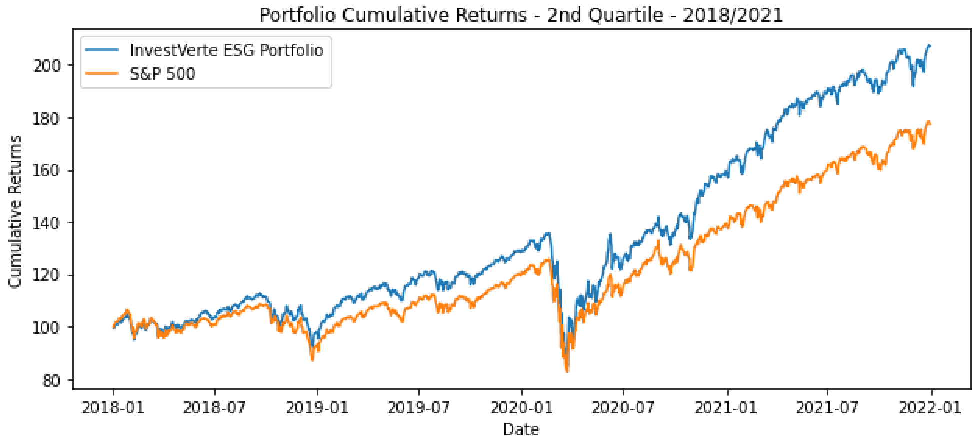

Figure 17: 2018 ESG Portfolio Q1Q2 - S&P 500 cumulative return - 2018 - 2021

Cumulative return between Portfolio and benchmark are shown in Table 2.

Table 2: Cumulative Return – 2018/2021 - Portfolio & Benchmark

Year	Quartile	Portfolio cohort	Portfolio	Benchmark	Relative
2018 - 2021	1st	127	213%	177%	36%
2018 - 2021	1st – 2nd	251	207%	177%	30%

Year 2020 have been captured in Figure 18 and Figure 19 which are describing cumulative return portfolio built on the first quartile and by combining the first and second quartile against S&P 500 cumulative return.

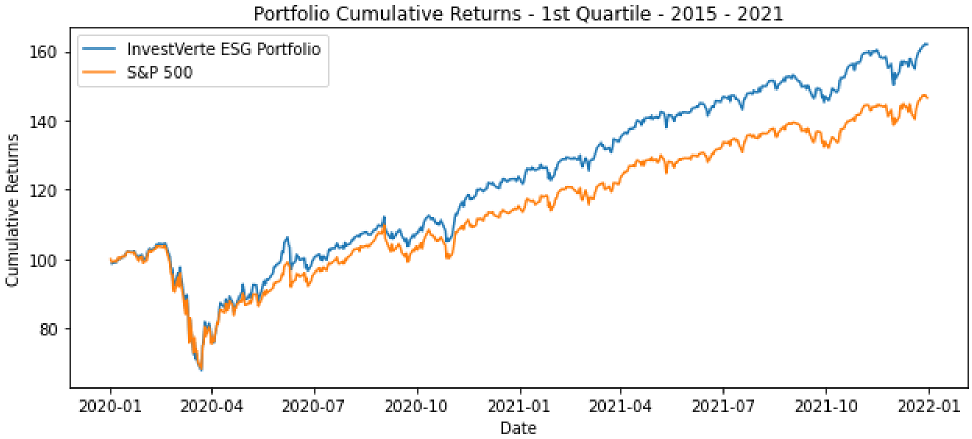

Figure 18: 2020 ESG Portfolio Q1 - S&P 500 cumulative return - 2020 – 2021

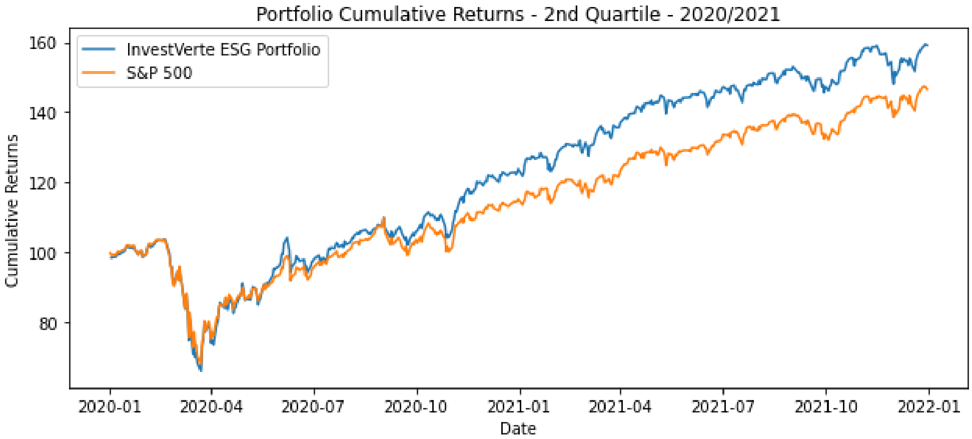

Figure 19: 2020 ESG Portfolio Q1Q2 - S&P 500 cumulative return - 2020 - 2021

Cumulative return between Portfolio and benchmark are shown in Table 3.

Table 3: Cumulative Return - 2020/2021 - Portfolio & Benchmark

Year	Quartile	Portfolio cohort	Portfolio	Benchmark	Relative
2020 - 2021	1st	124	162%	146%	16%
2020 - 2021	1st – 2nd	250	159%	146%	13%

Regarding this brief analysis, it appears that ESG scores have a clear impact on the share's return. Our solution based on ESG impact embedded financials would create alpha based on a distributed score approach stated above and highlighted with a simple stock picking methodology.

VI. Table of Figures