Samuel Li, KJ McEachern, and Emily Val Tuliao

STA3180

December 11, 2023

Do ESG Strategies Improve Corporations' Financial Performances?

Abstract

The influences of Environmental, Social, and Governance (ESG) criteria on investment decisions and corporate strategies has become a focus in contemporary business landscapes. ESG is a framework coined by the United Nations (UN), to influence investors based on corporations' efforts towards the UN's 17 SDGs. Our research examines the influence of ESG scores on a corporation's financial performance. Utilizing the *Kroll* dataset, data gathered from Refinitiv and composed of companies from the European Stock market (Euro Stoxx 50). We analyzed significance of ESG Pillar scores with a fixed panel analysis to account for longitudinal data. Of the ESG criteria Governance pillar scores, only Governance revealed a significant positive association with Return on Assets (ROA). Future studies should use a comprehensive list of corporations and potentially exclude stock market data from COVID year 2020 to gather a representative and stable analysis of the stock market.

Introduction

In recent times, Environmental, Social, and Governance (ESG) criteria have come up as an important guideline influencing corporate practices on a global scale. ESG considerations has been the focus of many companies now due to several factors: investors' interest in sustainability due to the impact of climate change (Eccles & Klimenko, 2019), the more socially conscious consumers demanding ethical and responsible conduct from corporations (Tilley, 2019), and stakeholders' increased recognition of the impact of ESG factors on long-term financial performance(Eccles & Klimenko, 2019). Furthermore, with this growing importance of ESG criteria in corporate strategies, there is also a renewed call for sustainability as a whole by the United Nations, as proven by their advocated Sustainable Development Goals. These goals outline a multi-year plan for a more sustainable future by 2030 and they cover goals such as climate action, affordable and clean energy, and responsible consumption and production (UN General Assembly 2015). Similarly, the European Union has announced their commitment to a sustainable future through the proposal of the European Green Deal, where they aim to become climate neutral by 2050 (Fetting, 2020). These global frameworks show the growing urgency of transitioning towards more sustainable objectives. Thus, we look to understand if sustainability efforts measured by ESG scores are affecting the financial performance of corporations.

By checking how the ESG factors could influence financial performance, it allows companies to make decisions that could help them figure out the best way to approach the use of ESG strategies. By understanding the relationship between ESG practices and their financial performance, we can try to identify potential ESG related risks. By discovering these problems early, we could allow companies to protect themselves against the vulnerabilities that may occur from these factors as quickly as possible. Even just the detection of the problems could allow for any vulnerability to be shut down. Additionally, more findings have been revealed showing a positive relationship between both ESG and financial performance factors. Whelan et al. (2021) found that better financial performance resulting from ESG strategies manifest themselves in the long-term and ESG strategies retain diversification characteristics in portfolio management even in times of crisis. Thus, our aim has become to facilitate more investments around the world geared towards transitioning to a climate-neutral, competitive, and inclusive economy. By using our dataset, we hope to offer valuable information into some statistical modeling with integrated ESG factors.

As a measure of a company's financial performance our team decided to use their Return on Assets (ROA) as our primary response variable for analysis. Unlike Return on Equity (ROE) which examines company management of its investments, ROA focuses on the returns generated from the operational efficiency of a business (Birken & Curry, 2021). As stated in Harvard Business Review, ROA stands out as an important measure for industries like manufacturing and industrial sectors, where the emphasis lies in measuring efficiency to create their profits (Gallo, 2016).

In our study, our statistical analysis uses a dataset source from Refinitiv, as it is one of the world's largest providers of financial market data and infrastructure (Refinitiv, n.d.). This dataset covers many variables that hopefully captures the dynamics of 47 companies from the European Stock market from the years of 2015 to 2021. It includes annual ESG metrics and a wide array of financial indicators, broad structure information, and development factors for each of these companies.

Methods

Our chosen data is called *Kroll*. Data that was used in this research was collected from the companies within the European Stock market and gathered by Refinitiv for analytical purposes of explaining the relationship between Correspond Governance ("G" in "ESG") and "financial performance" (using stock price growth rate as a measurement). Environmental ("E" in "ESG") and Social ("S" in "ESG") pillars are also included within the data set to provide further analysis that could present results regarding the financial performance.

Within this analysis, we cleaned the overall data set by eliminating any variable that was identified as a string or character variable since it might have negative impacts on our further analysis, which was stored inside of the *cleandata* variable as a new data frame. Looking at our dataset, there were many scale differences between variables, that the units and magnitudes of many of our potential predictor variables were not comparable. Thus, using the built-in R function, scale(), we standardized our values to conduct analysis. In order to gain an initial comprehensive understanding of our dataset, we conducted an exploratory data analysis focusing on the trends of ROA over time. This would allow us to know some of the trends and outliers that might appear for those variables with a visual representation (Patil, 2022). Additionally, we created a correlation matrix between all of the variables in the dataset with a R package called corrplot() to observe any initial correlations between all of the variables of the entire dataset.

After our cleaning and preliminary assessment of the data, we split our data into two different data frames: training (training_data) and testing (testing_data). The testing data frame contains the data associated with the year 2021 for each of the companies, while the training data model consists of the rest of the data, from 2015-2020. From here, we will use the training data to conduct any further analysis.

The next step is to find any highly correlated values within the training data set using the correlation matrix and the heatmap from corrplot(). We would extract those values with their combinations of correlated variables into an independent table for later usage on models to determine their significance. The heatmap would be the best visual illustration of our desired outputs. Using this matrix, we were able to identify pairs of variables that had highly correlated values ($r \geq 0.8$), which we addressed by creating interaction effects in our models. We started off by creating an initial model with all of the possible variables and interaction terms. We wanted to find the best combination of variables to develop a model with the best significance. In order to do this, we decided to use backwards selection to manually find the combination of variables with the greatest significance using the Radj-squared as our guide.

After the development of a model with the greatest model fit, we used our testing data set to test the accuracy of our model's predictive ability. We visually assessed the observed values from the testing data frame and the predicted values using residual plots and a Normal Q-Q Plot.

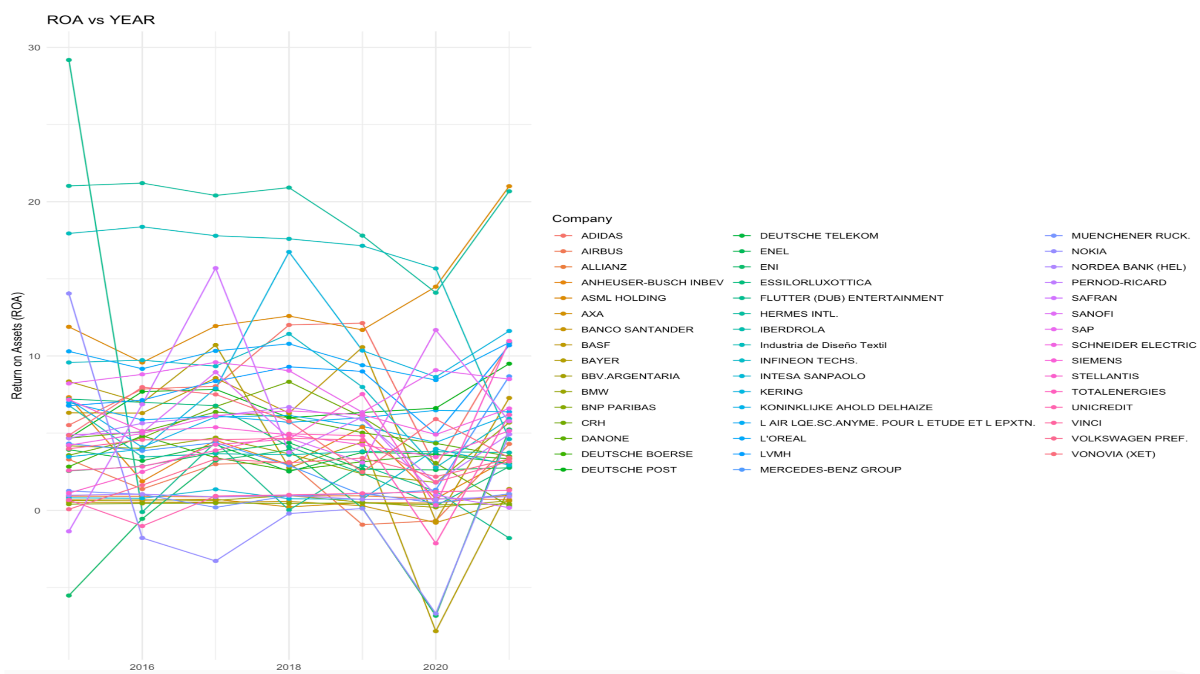
<u>Results</u>

We performed some preliminary exploratory data analysis to observe any trends with the companies in our dataset. We wanted to become familiar with and examine any potential trend or potential outliers that might have occurred during the seven-year period in the Kroll dataset.. Based on the graph from **Figure 1**, most of the companies have consistent changes between 2015 and 2019. However, there were many drops observed in companies' data in 2020.

Other than the observed trend in 2020, some companies stood out from the rest, FLUTTER (DUB) ENTERTAINMENT and Industria de Diseño Textil. The former had a much higher ROA value in 2015, contributing about 29 on their ROA, compared to most other companies who had ROAs of less than 20. Industria de Diseño Textil's ROA, unlike the other companies that had an increase in ROA after 2020, continued to drop drastically. With these observations, we noticed the appearance of these outliers and made more thoughtful considerations on manipulating these companies' data and the interpretation of our overall analysis.

Figure 1.

ROA Trends vs Year for each Company



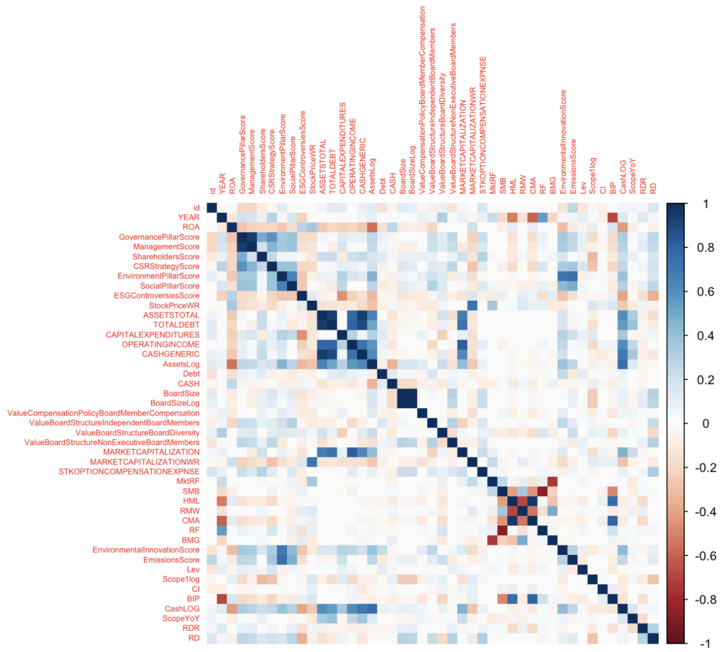
Note. The figure presents a plot of our dataset illustrating the trends of Return on Assets (ROA) across multiple companies from the year 2015 to 2021. Each line represents a distinct company, providing a visual overlay of their respective ROA trajectories over the seven-year time period. The x-axis is the years and the y-axis is the ROA values.

We completed an additional screen of our available variables by doing a complete correlation matrix to understand any potential combinations of variables that we would have to look into. We would extract those combinations independently and form interaction terms into models in the later analysis after the separation of our data into training and testing data. We used the correlation matrix of the Kroll data set's training data and plotted the heatmap graph in **Figure 2**. Within this graph, we can observe most of the highly correlated values were around the two blue clusters at the upper left and one red cluster at the lower right of the heatmap graph. We would think most of the highly correlated values might come from those three clusters based on the graph only.

To make the analysis more concrete and statistically significant, it was necessary to sort those highly correlated values based on a specific threshold with the correlation matrix. In this study, we selected values that have absolute values over 0.8 as the cutoff point. After operating the logic using programming codes, we created **Table 1** which contains all combinations of variables that have highly correlated values. We have BoardSizeLog & BoardSize, HML & CMA, ManagementScore & GovernancePillarScore, CASHGENERIC & ASSETSTOTAL, TOTALDEBT & ASSETSTOTAL, CASHGENRIC & TOTALDEBT, OPERATINGINCOME & MARKETCAPITALIZATION, and CMA & BIP with a descending order based on the correlation values. BoardSizeLog & BoardSize had the highest correlation value of 0.9908344 and CMA & BIP had the lowest correlation value of 0.8004869. These combinations of variables would be used as the interaction terms in the following analysis to find the best model for us to predict on the Kroll data set.

Figure 2

Correlation Heatmap of All Variables in Training Dataset



Note. The figure presents a correlation heatmap depicting the relationships among all of the continuous variables in the dataset. The color intensity indicates the strength and the direction of the correlation. Red represents negative correlations, while blue presents positive correlations.

Table 1

Pairs of Highly Correlated Variables

Variable 1	Variable 2	Correlation
BoardSizeLog	BoardSize	0.9908344
HML	CMA	0.953063
ManagementScore	GovernancePillarScore	0.9458834
CASHGENERIC	ASSETSTOTAL	0.9446365
TOTALDEBT	ASSETSTOTAL	0.9427537
CASHGENERIC	TOTALDEBT	0.8984615
OPERATINGINCOME	MARKETCAPITALIZATION	0.8246015
CMA	BIP	0.8004869

Note. This table provides an overview of variables within the dataset that exhibited a high degree of correlation, with a threshold set at 0.80.

With this list of highly correlated variables, we created interaction terms to also include with our fixed effects model. First, we created panel data using the IDs of companies and setting the time factor as YEAR. For our first model we included every single variable from our data set and the interaction terms. However, the result of this model was not very significant with a R-squared value of 0.55124 and an adjusted R-squared value of 0.3363 from **Figure 3**. We believed that backwards stepwise selection could potentially help improve the fit of our data.

Figure 3

Initial Model of All Variables with Interaction and the Model's Overall Significance

```
plm(formula = ROA ~ GovernancePillarScore + ManagementScore +
    ShareholdersScore + CSRStrategyScore + EnvironmentPillarScore +
    SocialPillarScore + ESGControversiesScore + StockPriceWR +
    ASSETSTOTAL + TOTALDEBT + CAPITALEXPENDITURES + OPERATINGINCOME +
    CASHGENERIC + AssetsLog + Debt + CASH + BoardSize + BoardSizeLog +
    ValueCompensationPolicyBoardMemberCompensation + ValueBoardStructureIndependentBoardMembers +
    ValueBoardStructureBoardDiversity + ValueBoardStructureNonExecutiveBoardMembers +
    MARKETCAPITALIZATION + MARKETCAPITALIZATIONWR + STKOPTIONCOMPENSATIONEXPNSE +
    MktRF + SMB + HML + RMW + CMA + RF + BMG + EnvironmentalInnovationScore +
    EmissionsScore + Lev + Scope1log + CI + BIP + CashLOG + ScopeYoY +
    RDR + RD + ManagementScore * GovernancePillarScore + TOTALDEBT *
    ASSETSTOTAL + CASHGENERIC * TOTALDEBT + ASSETSTOTAL * CASHGENERIC +
    MARKETCAPITALIZATION * OPERATINGINCOME + BoardSizeLog * BoardSize +
    CMA * HML + BIP * CMA, data = pdata_panel, model = "within")

Total Sum of Squares:    2127.9
Residual Sum of Squares: 954.94
R-Squared:      0.55124
Adj. R-Squared: 0.3363
F-statistic: 5.18635 on 45 and 190 DF, p-value: 4.3621e-16
```

The Rstudio programming language did not provide any sufficient built-in functions for backward selection on fixed effects models with panel data, applying backward selection manually was the only way for this study to create a model with the greatest significance. Through careful elimination, **Figure 4** was the final model for this study. Although its significance improved slightly compared to the previous model with all variables and interaction terms, it is less likely to conclude it is statistically significant with an R-squared value of 0.53728 and an adjusted R-squared value of 0.38378. Nonetheless, this is the best model we could approach using backward selection manually and this model will be used to compare with observed data from the testing data.

Figure 4

Final Model and Output After Backward Step Regression

```
plm(formula = ROA ~ GovernancePillarScore + ManagementScore +
    ShareholdersScore + CSRStrategyScore + EnvironmentPillarScore +
    StockPriceWR + ASSETSTOTAL + OPERATINGINCOME + AssetsLog +
    BoardSize + BoardSizeLog + ValueBoardStructureNonExecutiveBoardMembers +
    MARKETCAPITALIZATION + SMB + RMW + CMA + EnvironmentalInnovationScore +
    EmissionsScore + Lev + CI + BIP + RDR + RD + MARKETCAPITALIZATION *
    OPERATINGINCOME, data = pdata_panel, model = "within")

Coefficients:
                                             Estimate Std. Error t-value  Pr(>|t|)
GovernancePillarScore                        13.78737    4.25578  3.2397 0.0013902 **
ManagementScore                             -10.60136    3.47540 -3.0504 0.0025784 **
ShareholdersScore                            -4.25959    1.22806 -3.4685 0.0006342 ***
CSRStrategyScore                             -2.37830    0.62238 -3.8213 0.0001747 ***
EnvironmentPillarScore                        0.85238    0.65365  1.3040 0.1936435
StockPriceWR                                  0.24529    0.18003  1.3625 0.1745051
ASSETSTOTAL                                   6.44437    3.22033  2.0012 0.0466571 *
OPERATINGINCOME                               0.65270    0.56845  1.1482 0.2521815
AssetsLog                                    -7.79221    0.82851 -9.4051 < 2.2e-16 ***
BoardSize                                     3.72540    2.15092  1.7320 0.0847346 .
BoardSizeLog                                 -3.52328    2.02880 -1.7366 0.0839118 .
ValueBoardStructureNonExecutiveBoardMembers   0.59395    0.43076  1.3789 0.1693986
MARKETCAPITALIZATION                          1.37318    0.56779  2.4185 0.0164343 *
SMB                                          -0.39446    0.19148 -2.0601 0.0406147 *
RMW                                          -0.81710    0.25388 -3.2185 0.0014919 **
CMA                                          -1.28377    0.36405 -3.5263 0.0005168 ***
EnvironmentalInnovationScore                 -0.77323    0.77095 -1.0030 0.3170311
EmissionsScore                               -0.66133    0.40282 -1.6418 0.1021281
Lev                                           0.34226    0.15315  2.2347 0.0264827 *
CI                                           -0.14100    0.13706 -1.0287 0.3047841
BIP                                           1.11702    0.37753  2.9588 0.0034411 **
RDR                                          -0.25914    0.16406 -1.5796 0.1157046
RD                                           -5.64703    0.85949 -6.5702 3.859e-10 ***
OPERATINGINCOME:MARKETCAPITALIZATION         -0.32066    0.15764 -2.0341 0.0431883 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    2127.9
Residual Sum of Squares: 984.64
R-Squared:      0.53728
Adj. R-Squared: 0.38378
F-statistic: 10.2084 on 24 and 211 DF, p-value: < 2.22e-16
```

Note. The final model consists of 24 variables, all of which improve the overall fit of the model, despite some of their not significant p-values.

Regarding our analysis into the role of ESG as a potential factor in the assessment of ROA, the only ESG factor to not be included in this model is the SocialPillarScore. Both the “E” and the “G” aspects of ESG are present in this model. Our analysis shows a noteworthy finding regarding the “G” of the ESG factors that we were interested in.

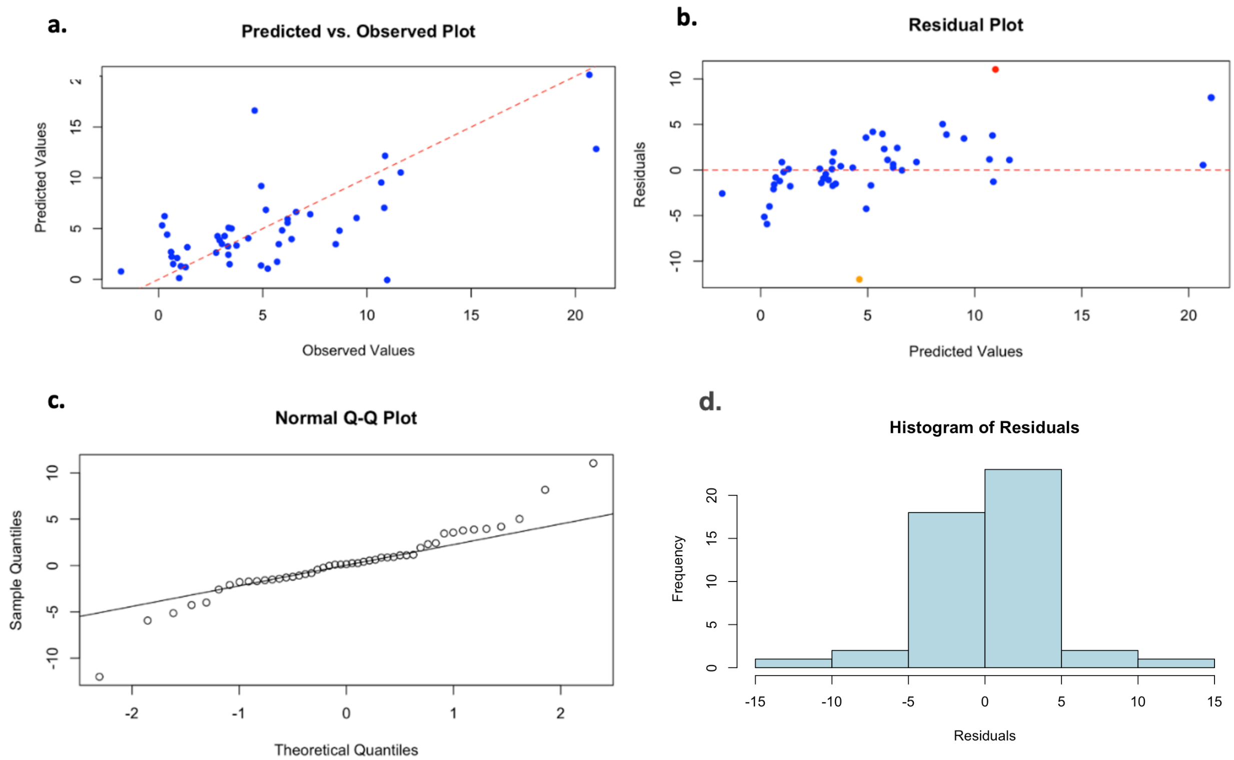
The GovernancePillarScore has a positive coefficient of 13.78738, signifying that an increase in Governance is associated with a corresponding increase in ROA. This positive relationship is statistically significant at a significance level of 0.05, as indicated by its p-value of 0.0013902. This is interesting because it appears to contradict the governance related variables: ManagementScore, ShareholdersScore, and the CSRStrategyScore; which all present a significant negative relationship with ROA.

In regards to the “E” factors of ESG, EnvironmentPillarScore, EnvironmentalInnovationScore, and the EmissionsScore are all included in the model because they help to improve the overall fit, but none of them are significant at any significance level in this model.

Another highlight worth noting is the high significance level of AssetsLog to ROA, but that may be contributed to the possible correlation between them as they are both a means to measure the company’s assets along with ASSETSTOTAL, which is only significant at the significance level of 0.05.

Figure 5

Diagnostic Plots of the Final Model using 2021 Testing Data



Note. Figure 5a depicts a Predicted vs. Observed plot. Figure 5b depicts a Residual vs. Predicted plot with the non-blue points representing outliers that standardized residual larger than 3 (orange representing Industria de Diseño Textil, red representing

STELLANTIS). Figure 5c depicts a Normal Q-Q plot. Figure 5d depicts a histogram of the residuals.

Figure 5 depicts the comparison of the observed values within the testing data frame and the predictions created by the trained model. The residuals vs the predicted values show some curvilinear pattern, indicating that the linearity assumption is not met for this dataset. Two points on the residual vs predicted plot were found to be outliers, additional analysis would have to be done to see if the removal of these points will improve the overall fit of the model.

To examine the normality of the residuals through the use of a histogram and a Q-Q plot. The histogram shows a lack of skew, indicating that the equal variance assumption may be met, but the Q-Q plot curves off in the extremities. This indicates that the data may have more extreme values than it would be expected, which is supported by the presence of the two aforementioned outliers.

Discussion

Although the analysis used most of the variables from the data set with appropriate analytic strategies, there might be a few concerns we might need to be aware of within this study. Removing all string columns (for example, CEOBoardMember_A, ValueBoardStructurePolicy, etc.) from the data set might lead to biased results in this study. A possible solution for some of them might be to use dummy variables based on their data inputs. We can assign 1 or 0 for binary string inputs and add those variables within the study to find a potential significance that variable might have. We also eliminated variables Return on Equity (ROE) and Stock Price (StockPrice) to reduce their impacts on our dependent variable ROA. These procedures would change the results of our study. Those eliminated data might include essential impacts on the results of the study. Additionally, some consideration was made towards the randomization of the selection of training and testing data, however, we were unsure of the impact random missing years would have on the creation of panel data for a fixed effect model. Furthermore, as mentioned before, some data points specifically those associated with the year 2020 were thought to potentially impact the results of the data, thus the inclusion or possible exclusion of it also deterred us from that route.

In the interpretation of our findings, it is important to also acknowledge the fact that the time period of our data set is a bit unique. The inclusion of the year 2020, which is typically remarked as the height of the COVID-19 pandemic (CDC, 2023), introduces a new slew of context that may have influenced the financial landscape of the companies that we have in our Kroll dataset. Our preliminary exploratory data analysis shows some evidence of a similar change in ROA for this year for many of these companies, highlighting the possibility of other external factors, maybe COVID, on the financial performance of companies. This may impact the generalizability of our findings beyond this time period. Additionally, while our fixed effects panel was done to omit variable bias, our dataset is still limited to only the 47 companies. Thus, some caution is also advised regarding the use of our findings to estimate other companies' financial performances based off their ESG factors.

The significance of our models is relatively low due to the restrictions on the statistical techniques we used within this study. The programming language R only allows users to make forward and backward selections on regular linear models. Panel data is not allowed by most of the built-in functions. In this case, we have to complete such a statistical procedure manually, which increases the overall complexity of the study with more than 50 variables. It is almost impossible for this study to find all possible combinations of models and compare their significance scores efficiently. Even if we tried to use iterations to find all possible models, it is time-consuming and liable to error.

Overall, efficient techniques for converting data types and limited technical support for a data set having more than 50 independent variables are the limitations of this study to have a deeper understanding of the Kroll data set. With the support from better computational techniques, finding methods to include more possible string variables within this study might present more insights into how variables impact the ROA. These two aspects should be the focus of later studies to improve the overall exploration of the data set Kroll on the economic impacts on individual companies in Europe.

Conclusion

Our study delved into the relationship between Corporate Governance (G in ESG) and financial performance among European stock market companies using the Kroll dataset. We aimed to understand trends, correlations, and predictive models associated with Return on Assets (ROA) over a seven-year period (2015-2021). The rising global emphasis on sustainability, which is driven by investors' increasing interest in ethical practices and consumers' demand for corporate responsibility, proves the analysis of ESG scores is important to predict the financial health of our economy. When developing our model, the “E” and “G”components of ESG resulted in the best fit of our model.

The Governance Pillar Score revealed a positive, moderately significant effect on ROA. Governance Pillar Score yielded a positive coefficient of 13.78738, indicating that an increase in Governance correlates with an increase in ROA. This relationship is moderately significant at the 0.05 significance level, reflected in its p-value of 0.0013902. Notably, the subcategories within the Governance, Management and Shareholder, resulting in a significant negative effect on ROA. The Environmental Pillar and subcategories were included in our model to strengthen the fit. However, none of the Environmental elements were proven significant in the model. Additionally, despite our efforts to construct a model using backward step regression and test accuracy, the final model was robust. Our final model included 24 variables with a R-squared value of 0.53728 and an adjusted R-squared value of 0.38378.

Governance and Environmental Pillar Scores, in addition to market specific elements, explained 38.38% of variation in ROA. The Governance Pillar Score showed a moderately significant positive impact on financial performance, suggesting that firms with stronger governance structures tend to exhibit better financial outcomes. Noted limitations are due to Rstudio programming statistical constraints, complexity of variables, and small sample size resulting in constraints on the strength of our model.

Bibliography

Centers for Disease Control and Prevention. (2023). CDC COVID-19 Timeline. Centers for Disease Control and Prevention. https://www.cdc.gov/museum/timeline/covid19.html

Eccles, R. G., & Klimenko, S. (n.d.). *Shareholders are getting serious about sustainability*. Harvard Business Review. https://hbr.org/2019/05/the-investor-revolution

Fetting, C. (2020). “The European Green Deal”, ESDN Report, December 2020, ESDN Office, Vienna.

Dartmouth. (2023). *Fama/French Factors*. Kenneth R. French - data library. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Gallo, A. (2016). A Refresher on Return on Assets and Return on Equity. *Harvard Business Review*. https://hbr.org/2016/04/a-refresher-on-return-on-assets-and-return-on-equity?registration=success

Guy Birken, E., & Curry, B. (2021, October 28). Understanding Return On Assets (ROA). *Forbes Advisor*. https://www.forbes.com/advisor/investing/roa-return-on-assets/

Patil, P. (2022, May 30). *What is exploratory data analysis?*. Medium. https://towardsdatascience.com/exploratory-data-analysis-8fc1cb20fd15

Refinitiv. (n.d.). [World Economic Forum]. Retrieved December 9, 2023, from https://www.weforum.org/organizations/refinitiv/

Refinitiv. (2023). Kroll-dataset19thOct2023. [Data set]. *Refinitiv*

Tilley, M. (n.d.). *The Increasingly Socially Conscious Consumer*. December 2, 2023, https://www.vericast.com/insights/blog/the-increasingly-socially-conscious-consumer/#:~:text=Fifty%2Dfour%20percent%20of%20consumers,%2C%20with%2072%25%20saying%20so.

UN General Assembly, *Transforming our world : the 2030 Agenda for Sustainable Development*, (2015, October 15), A/RES/70/1, available at: https://www.refworld.org/docid/57b6e3e44.html [accessed 3 December 2023]