The Predictive Power of ESG Ratings in Stock Market Returns

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Abstract

Climate change is one of the greatest challenges humanity faces, driving the need for sustainable investment practices. Even though ESG investing has become popular with investors seeking to align their portfolios with sustainability goals, ESG information has yet to be included into modelling the stock market. With this thesis, I aim to study whether ESG ratings can predict stock market returns by complementing the Sum of the Parts model (Ferreira & Santa-Clara, 2011) with an ESG factor that I developed using two different approaches: cross-sectional and time-series. I find that ESG ratings enhance predictive models, with the Time-Series ESG factor demonstrating superior performance compared to the models without ESG integration. Variables, such as book-to-market ratio and dividend yield, benefited more from including an ESG factor, implying that ESG information can complement backward-looking metrics. However, the models did not yield significant improvements in risk-adjusted returns. Furthermore, robustness tests revealed different adaptability of the models to periods of higher market volatility. Overall, my results suggest that ESG ratings capture unique dimensions of stock returns' performance that traditional macroeconomic indicators fail to account for, which shows the potential of integrating ESG considerations into investment strategies.

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Resumo

As alterações climáticas são um dos maiores desafios que a humanidade enfrenta, impulsionando a necessidade de práticas de investimento sustentáveis. Embora o investimento ESG se tenha tornado popular entre os investidores que procuram alinhar as suas carteiras com os seus objetivos de sustentabilidade, a informação ESG ainda não foi incluída na modelação do mercado de ações. Com esta tese, eu pretendo estudar se as classificações ESG podem prever os retornos do mercado de ações, complementando o modelo da Soma das Partes (Ferreira & Santa-Clara, 2011) com um fator ESG que desenvolvi utilizando duas abordagens diferentes: transversal e temporal. Observo que as classificações ESG melhoram os modelos preditivos, sendo que o fator ESG temporal demonstra um desempenho superior em comparação com os modelos sem integração ESG. Variáveis, como o rácio entre o valor de mercado e o valor contabilístico e o rendimento de dividendos, beneficiaram mais da inclusão de um fator ESG, o que implica que a informação ESG pode complementar as métricas retrospetivas. No entanto, os modelos não produziram melhorias significativas nos retornos ajustados ao risco. Adicionalmente, os testes de robustez revelaram que os modelos apresentaram níveis variados de adaptabilidade durante períodos de maior volatilidade do mercado. No geral, os meus resultados sugerem que as classificações ESG captam dimensões únicas do desempenho dos retornos das ações que os indicadores macroeconómicos tradicionais não conseguem ter em conta, o que demonstra o potencial de integração ESG nas estratégias de investimento.

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1. Introduction

> Humanity is just one small blip on the radar. But like the meteor that wiped out the dinosaurs, we’re having an outsized impact. In the case of climate, we are not the dinosaurs. We are the meteor. We are not only in danger. We are the danger. But we are also the solution.

These words were delivered by António Guterres, Secretary-General of the United Nations (Guterres, 2024). They depict the current reality of one of the biggest challenges that humanity has faced: climate change. But how can humanity be both the reason and the solution for this matter?

The main contributor to climate change is the release of man-made greenhouse gas emissions, produced mostly by the energy and transportation sectors. Moreover, deforestation decreases the Earth's ability to absorb carbon dioxide, while individual lifestyle choices also play a significant role in contributing to the climate crisis. This environmental transformation leads to extreme weather conditions, frequent droughts, loss of biodiversity and lack of available food. These eventually lead to severe socioeconomic consequences, such as reducing crops, rising energy and health costs, damaging infrastructure and disrupting ecosystems. If there are no substantial changes in the behaviours that drive climate change, there could be a decline in global GDP by 2% up to 10% by the end of the century (OECD, 2015).

To resolve these issues, there needs to be a major transition to more sustainable practices implemented across every industry and sector worldwide. However, fundamentally changing industries that have been established for years and implementing new technologies to reduce emissions to the atmosphere requires significant financing. Despite public initiatives like the European Green Deal in the European Union and the Inflation Reduction Act in the United States promoting more sustainable business practices, the scale of the challenges we face necessitates intervention that extends beyond the public sector. There is a need for private stakeholders to actively participate in the transition, based on their economic resources and influence across value chains. This is where humanity’s solution can emerge from. The financial sector plays a key role in the economy by allocating resources and, by directing investments towards organizations and projects that prioritize environmental and social goals, it can mobilize the transition to a more sustainable future. This practice, known as sustainable finance, integrates environmental, social and governance (ESG) considerations in investment decisions (European Investment Bank, 2023) to align economic growth with long-term sustainability goals.

One of the most popular concepts in sustainable finance is ESG ratings. These evaluate a company or financial instrument's impact on society and the environment and its exposure to sustainability-related risks (Council of the European Union, 2024). These ratings allow investors to identify risks and opportunities that traditional financial metrics tend to not capture, providing an additional layer for valuing companies and financial instruments more comprehensively. The importance of ESG ratings is underscored by the rapid rise in sustainable investing, with global ESG assets exceeding $30 trillion in 2022 and projected to exceed $40 trillion by 2030 (Bloomberg Intelligence, 2022).

Despite the growing adoption of ESG investing, investors and researchers have only been relying on traditional financial metrics to forecast stock market returns. However, these models often fail to account for non-financial factors such as environmental, social and governance effects which can have an impact on a company's long-term performance and risk management practices. By including ESG information in the form of ESG ratings in predictive models, investors can have a better understanding of a company's profile and its possible long-term value creation, potentially improving the predictability of stock market returns and their decision-making processes.

This study aims to evaluate if ESG ratings can complement and enhance traditional predictive models for stock market returns, leveraging the models created by Ferreira & Santa Clara (2011). Additionally, I aim to analyse how different approaches to modelling ESG information can contribute to the effectiveness of forecasting returns and enable investors to achieve greater economic benefits. Moreover, I analyse how the different methods behave when incorporating ESG factors into them. Lastly, I evaluate which macroeconomic variables, such as inflation and long-term bond returns, benefit the most from including ESG information in predictive models.

This thesis is organized as follows: Section 2 provides the literature review, Section 3 outlines the data and methodology, Section 4 presents and discusses the main results, Section 5 evaluates their robustness and Section 6 concludes with the key findings of the thesis.

2. Literature Review

2.1. Stock Return Predictability

Return predictability has been a central topic in empirical finance for a long time, contributing to important findings for the portfolio management and the corporate finance fields while also contributing to understanding market dynamics. The weak form of the Efficient Market Hypothesis argues that historical price information is fully reflected in current prices and, despite the existence of minor patterns in price changes, these don’t imply that the market is inefficient (Fama, 1970). A small degree of predictability can coexist with rational and weak-form efficient markets, especially when based on superior fundamental analysis, showing that market efficiency and predictability are not mutually exclusive.

Different methodologies have been developed to accurately predict the market. Goyal & Welch (2008) introduced a critique of the previous models used for stock market returns’ predictability, significantly impacting the research field of return predictability. In their paper, the authors evaluate the effectiveness of commonly used financial variables as predictors, including stock market variance, the treasury-bill rate and inflation by using predictive regressions and calculating in-sample and out-of-sample R_2. Their findings show that these typical variables fail to perform in out-of-sample models, highlighting their unreliability in practical applications. Moreover, the authors argue that no financial variable can consistently outperform the use of historical averages when predicting stock market returns. In my thesis, I aim to address this challenge by creating a model that outperforms the historical average in predicting stock market returns.

An alternative method to predict stock market returns was proposed by Ferreira & Santa- Clara (2011): the Sum of the Parts (SOP) method. By decomposing the returns into dividend price, growth in earnings and multiple growth in the price-earnings ratio, and forecasting each component separately, the authors effectively predict the stock market returns compared to using the historical average. In my thesis, I use this model and introduce an additional component to the SOP equation: two ESG factors that I have developed, one based on a cross-sectional approach and the other based on a time-series approach. By adding this ESG factor, I aim to extend the authors’ methodology to include sustainability and test if sustainability information can predict stock market returns and enhance the performance of forecasting models.

Rapach et. al (2010) further support the use of combined forecasts, by arguing that combining return forecasts rather than just relying on single forecasts improves predictability power. This concept aligns with the approach followed in this thesis, as I aim to integrate both traditional financial information and ESG ratings into a combined model. Bianchi et. al (2024) find that merging forecasts from both theoretically grounded models and data-driven methods allows for more accurate and robust predictions, an intuition that I use in the creation of my method.

2.2. Sustainability and the Stock Market

In 2023, climate change indicators including greenhouse gas levels, surface temperatures, ocean heat and acidification and sea level reached record highs, increasing the risk of socio-economic impacts such as food insecurity, population displacement and increased vulnerability for at-risk populations (WMO, 2024). These developments highlight the need for action across all segments of the value chain. To address this need, companies across all sectors must take decisive action to reduce emissions and secure a habitable planet for future generations by adopting both mitigation and adaptation strategies (IPCC, 2023).

Following these developments, shareholders are increasingly demanding that companies take responsibility by actively adopting and integrating sustainable practices, even holding them accountable for their negative impacts. Recent surveys suggest that sustainability aspects are a significant consideration for investment decision-makers. In fact, approximately 85% of Chief Investment Officers (CIOs) recognise ESG as an important factor in their investment decisions, while 60% of the CIOs evaluate their entire portfolio for ESG aspects (McKinsey & Company, 2023). This importance of sustainability is further reflected in investors' behaviours, as supported by Hartzmark & Sussman (2019), who investigated how investors value sustainability based on their reactions to mutual funds' sustainability rankings. The authors found that funds categorized with higher sustainability scores tend to attract larger inflows of capital. Additionally, they found that when a fund is classified with a lower sustainability ranking, it faces greater outflows.

The importance of sustainability and its effects on a company's strategy has been increasing in the past decade, particularly regarding how it can increase a company's long-term value. In fact, Ferrell et. al (2016) show that firms with strong governance that engage in Corporate Social Responsibility (CSR) initiatives can be both socially responsible and maximize shareholder value. These findings demonstrate that sustainability is not only an ethical aspect that businesses need to pay attention to but also a strategic factor that can increase financial performance.

Similarly, Shanaev & Ghimire (2022) find that the impact of ESG rating changes on abnormal returns is significant in the U.S., with increased shocks on rating downgrades of ESG leaders. The authors also find that the effects of ESG rating levels on investors' risk-adjusted returns are modest, with the ESG laggards underperforming. This aligns with my intuition that ESG ratings influence stock market returns and are correlated with investors' decisions.

Pedersen et. al (2021) study how ESG measures can influence portfolio construction, by predicting firms' fundamental information and influencing investors' preferences. By extending the Markowitz mean-variance optimization model to include ESG scores, they are able to account for investors' preferences of achieving the highest sustainability level. They propose an ESG efficient frontier, which shows investors' trade-offs between financial returns and ESG scores. Their findings demonstrate the double impact of ESG ratings on expected returns. On one hand, higher ESG scores can increase demand since they attract ESG-conscious investors and, therefore, lower expected returns due to investors paying a premium for sustainability. On the other hand, higher ESG scores can also signal better future profitability or stronger fundamentals that the market has not yet fully priced in. If the market doesn't react to this signal, the stock can yield higher returns than initially expected. These forces highlight how ESG scores can influence stock prices and returns.

While many studies demonstrate the impact of ESG on stock performance, Shackleton et. al. (2022) find an opposing view: sustainability is not the driving force of stock market performance, rather it is the consequence of financial performance. Specifically, the authors find that if a company has poor stock market performance, it will often proceed with increased efforts in both Environmental and Social factors. They argue that sustainability is a reactive outcome, driven by financial performance, rather than a proactive indicator of future financial success. Both the authors' and my thesis's views can coexist as I defend that ESG factors (including Governance) can be a driver of returns to predict future ones, while the authors view them as a response to past stock performance.

2.3. Stock Return Predictability and Sustainability

Khan (2019) integrates corporate governance and ES factors into stock returns, by creating a score based on industry-specific materiality. The author uses multivariate regression analyses with control variables for size, momentum, value, profitability and investment and with time and industry fixed effects. Despite using a different methodology from the one used in this thesis, the author finds that ESG metrics can predict stock market returns, laying the foundation for my analysis.

The ESG Index proposed by Chu et. al (2020) based on thirty-eight singular ESG measures can predict the stock market returns, both in-sample and out-of-sample. The authors use Partial Least Square (PLS) to aggregate the ESG measures and remove their market component, to isolate the effect of ESG. By using a predictive regression with only the ESG index as the predictor variable, the authors show that their index has strong predictive power in predicting the stock market returns. They also find that their ESG index provides unique predictive understandings for the stock market, which cannot be explained by the traditional economic fundamentals or growth indicators. This supports the strength of my model, since it is based on economic theory and is enhanced by adding an ESG-based component. Additionally, although I use two different methods to create the ESG factor, without using PLS, I follow the same intuition of isolating the ESG effect by subtracting the stock market return from the created factors. Finally, despite distinctive methods, their findings support my thesis that ESG ratings have strong predictive power in predicting stock market returns out-of-sample, reinforcing the accuracy of my model.

3. Data and Methodology

3.1. Data

This thesis aims to predict stock market returns using two distinct ESG factors by applying three different methods. The data used in this thesis consists of monthly stock returns and annual ESG scores spanning the period between 2005 and 2023.

The S&P 500 is used as the market proxy in this thesis. This index tracks the performance of the 500 largest publicly traded U.S. companies by market capitalization. Due to this and to the fact that it includes companies from the eleven biggest industries, it is widely recognized as a benchmark that represents the overall performance of the United States stock market. The index is rebalanced quarterly each year.

The stock return and macroeconomic data was retrieved from the dataset constructed by Goyal & Welch, which was originally constructed up until 2005, but has since been updated up until 2023. This dataset starts in 1870 and includes different measures of the economic environment. A summary of the variables included can be found in Appendix A.

To be able to analyse the ESG performance of the stock market, I retrieved the monthly list of constituents of the S&P 500, their returns and ESG scores using Refinitiv Datastream. The ESG score provided by Refinitiv is a company's relative ESG performance displayed as a percentage. It represents the percentile rank within its industry group, defined by Refinitv. The score is based on more than 600 measures which can be presented as a number or a Yes/No. These measures are grouped into 10 categories, which are then weighted based on the company's industry or group. Finally, the category scores are grouped into one of the three pillar scores: Environmental, Social or Governance. These scores are also weighted based on the company's industry. This comprises the ESG score attributed to each company.

The ESG data was only retrieved since 2005 due to the lack of previously available data. Overall, the data includes information regarding approximately 500 companies across 19 years.

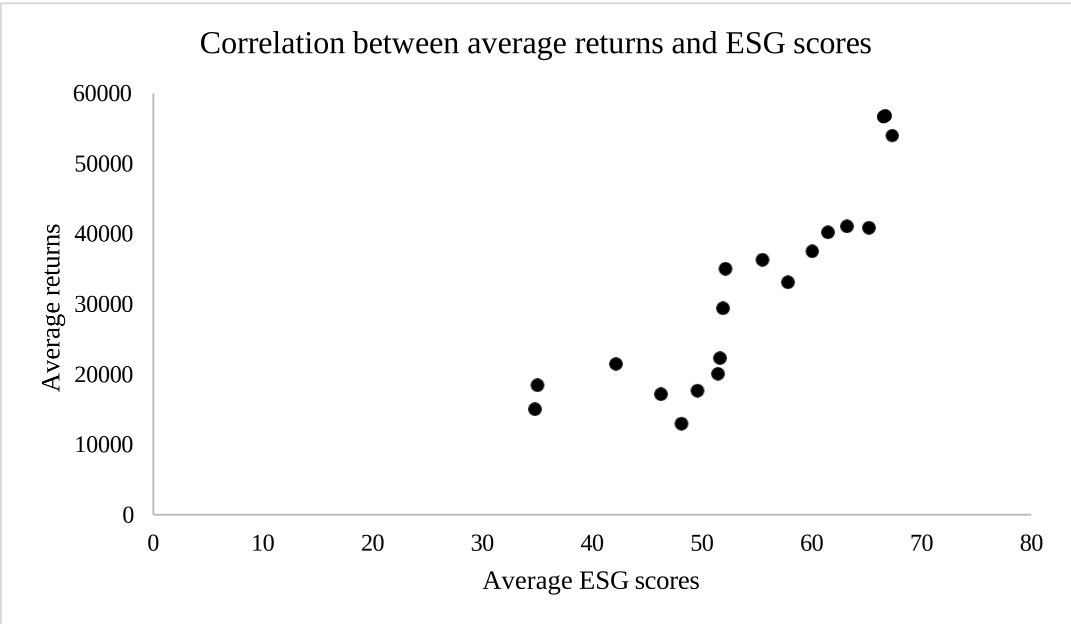
Due to the lack of ESG scores for some companies, I cleaned the data. For the missing information, VBA was used to input either the closest (in time) ESG score or the last available score. Companies with no available ESG data were excluded from the sample. This resulted in twelve companies being removed.

Table 1 exhibits the summary statistics of the ESG scores retrieved for the analysis. Throughout the sample period, both the maximum and minimum ESG scores increased which showcases how ESG standards have become progressively more important for companies to adopt. The distribution appears to be slightly right skewed throughout the sample period, demonstrating how a few companies with exceptionally high scores contributed to raising the average ESG score in the stock market. Figure 1 demonstrates the positive relationship between the stock market returns and the ESG scores, which suggests that companies with higher ESG scores tend to, on average, experience higher returns. This can suggest that investors value companies with higher ESG scores, due to perceived lower risk and potential for long-term success. The relationship can also be interpreted as a non-linear one, which might imply that ESG improvements lead to stronger returns or that high ESG scores only become a differentiator for investors once a certain threshold is passed.

Table 1 - Summary statistics of ESG scores

Year	Max	Min	Median	Average	Std. Dev.
2005	86.52	3.21	31.52	34.78	16.59
2006	87.63	2.02	31.96	34.99	17.26
2007	92.27	2.06	40.54	42.16	17.96
2008	91.29	1.80	45.04	46.26	18.70
2009	94.93	1.40	47.06	48.13	19.91
2010	95.16	2.81	50.02	49.57	19.68
2011	92.54	2.96	52.51	51.47	19.28
2012	91.31	1.90	51.61	51.63	18.72
2013	92.28	2.49	51.40	51.90	18.61
2014	92.39	2.46	52.97	52.13	17.72
2015	92.84	5.81	55.55	55.49	17.07
2016	91.29	10.87	59.42	57.83	16.55
2017	92.00	10.30	61.98	60.04	16.06
2018	93.01	14.47	63.36	61.47	15.81
2019	92.84	18.17	65.40	63.21	15.21
2020	93.24	19.61	67.32	65.21	14.51
2021	92.69	21.77	68.43	66.55	13.37
2022	91.81	20.89	69.36	67.32	12.49
2023	91.81	20.89	69.10	67.41	12.24

Figure 1 - Correlation between average returns and average ESG scores



3.2. Methodology

3.2.1. Sum of the Parts (SOP)

3.2.1.1. Simple Sum of the Parts with ESG factor

The method described below is based on Ferreira & Santa-Clara (2007). I extend this research by adding an ESG factor which represents the ESG scores attributed to the stocks of the underlying proxy of the overall stock market, the S&P 500 in this thesis.

The method is based on how stock returns in period t+1 can be decomposed into the dividend yield and capital gains:

$$1 + R_{t+1} = 1 + Capital\ Gains_{t+1} + Dividend\ Yield_{t+1} = \frac{P_{t+1}}{P_t} + \frac{D_{t+1}}{P_t} \quad (1)$$

Where P_t and P_{t+1} represent the stock price at time t and at time t+1, respectively. The dividend paid by each share throughout the return period is represented by D_{t+1}.

Furthermore, capital gains can be decomposed into the change in value of the price-earnings ratio and the growth in earnings as we can observe in the following formula:

$$1 + Capital\ Gains_{t+1} = \frac{P_{t+1}}{P_t} = \frac{\frac{P_{t+1}}{E_{t+1}}}{\frac{P_t}{E_t}} \frac{E_{t+1}}{E_t} = \frac{M_{t+1}}{M_t} \frac{E_{t+1}}{E_t} = (1 + GM_{t+1})(1 + GE_{t+1}) \quad (2)$$

Where the earnings per share at time t are represented by E_t, the price-earnings multiple is represented by M_{t+1}, the price-earnings growth multiple is represented by GM_{t+1} and the growth rate of earnings is represented by GE_{t+1}.

The dividend yield can also be decomposed:

$$Dividend\ Yield_{t+1} = \frac{D_{t+1}}{P_t} = \frac{D_{t+1}}{P_{t+1}} \frac{P_{t+1}}{P_t} = DP_{t+1}(1 + GM_{t+1})(1 + GE_{t+1}) \quad (3)$$

Where DP_{t+1} is the dividend-price ratio.

If we include these in the initial equation, we get:

$$1 + R_{t+1} = (1 + GM_{t+1})(1 + GE_{t+1}) + DP_{t+1}(1 + GM_{t+1})(1 + GE_{t+1})$$
$$= (1 + GM_{t+1})(1 + GE_{t+1})(1 + DP_{t+1}) \quad (4)$$

To make this expression an additive one, making it easier to interpret, we apply the logarithm. By doing this, we end up with the final decomposition of the returns:

$$r_{t+1} = \log(1 + R_{t+1}) = gm_{t+1} + ge_{t+1} + dp_{t+1} \quad (5)$$

Since ESG information is material to stock returns, a component representing it is also included in the formula. Finally, we arrive at the final formula representing stock returns:

$$r_{t+1} = gm_{t+1} + ge_{t+1} + dp_{t+1} + esg_{t+1} \quad (6)$$

Based on this, I propose forecasting the stock market returns using the following formula:

$$\hat{u}_t = \hat{\mu}_s^{dp} + \hat{\mu}_s^{ge} + \hat{\mu}_s^{gm} + \hat{\mu}_s^{ESG} \quad (7)$$

The expected earnings growth is estimated by using a 20-year moving average of the growth in the earnings per share up to time s. This relies on the assumption that the earnings growth is close to being unpredictable. The expected dividend-price ratio is forecasted by taking the logarithm of the current dividend-price ratio, which assumes that this component follows a Random Walk hypothesis. Because of this, the price-earnings growth multiple is assumed to be 0. This assumption will be challenged in the following sub-section.

The ESG factor forecast will be calculated using an out-of-sample 60-month window. This means that, for example, the ESG component included in the forecast of the stock return of January 2010 will be based on the ESG factor calculated in January 2005. I choose a 5-year window since the response of the stock market to ESG rating changes tends to take place over a longer period, rather than immediately (Giese et. al, 2019). This window allows for a gradual adjustment of the returns to the ESG ratings, while still ensuring the robustness of the model, given that the sample only consists of 19 years.

To assess the power of the method in predicting the stock returns, the R_2 proposed by Goyal & Welch (2008) is used. This measure compares the Sum of the Parts plus the ESG factor method against simply using the historical mean.

$$R^2 = 1 - \frac{MSE_P}{MSE_M} \quad (8)$$

With MSE_M being the Mean-Squared Error of the historical sample average, where the $\bar{r}$ is the historical mean of the stock returns, using a 5-year moving window.

$$MSE_M = \frac{1}{T-s_0} \sum_{s=s_0}^{T-1} (r_{s+1} - \bar{r}_s)^2 \quad (9)$$

MSE_P is the Mean Squared Error of the predictions from the Sum of the Parts plus ESG factor method.

$$MSE_P = \frac{1}{T-s_0} \sum_{s=s_0}^{T-1} (r_{s+1} - \hat{\mu}_s)^2 \quad (10)$$

3.2.1.2. Sum of the Parts Extensions

Assuming that the price-earnings growth multiple is equal to "0" can produce misleading errors in the model. Because of this, I follow the extensions of the method proposed by Ferreira & Santa-Clara (2011).

The first extension, SOP with Multiple Growth, is based on the price-earnings growth multiple being predicted by economic conditions. Indeed, these factors can severely influence businesses. For instance, in periods of lower interest rates companies can finance their expansion into new business opportunities and, consequently, increase their earnings. Additionally, equities are more attractive compared to fixed-income assets in low-interest rate environments, increasing stock prices. Subsequently, I perform a predictive regression to predict the price-earnings growth multiple by using the traditional macroeconomic variables as predictors.

$$gm_{t+1} = \alpha + \beta x_t \tag{11}$$

The second extension, SOP with Multiple Reversion, follows a similar logic. It assumes that the price-earnings ratio tends to converge to its expected value, which is influenced by the current economic conditions. As a result, I first regress, using a contemporaneous regression and starting from January 2005 using an expanding window, the price-earnings ratio on the previously used macroeconomic variables, excluding the ones that are directly influenced by changes in the stock market index price: the book-to-market ratio (BM), the dividend yield (DY), the dividend price (DP), the earnings price (EP) and the smooth earnings price (SEP).

$$log \frac{P_t}{E_t} = m_t = \alpha + \beta x_t \tag{12}$$

Where m_t is the observed growth multiple of the price-earnings ratio, given the macroeconomic environment.

This regression indicates what growth multiple of the price-earnings ratio prevailed during economic periods characterized by specific levels of the macroeconomic variable being used. If we observe discrepancies when comparing the expected value with the real value, we can deduce what the implicit growth multiple will be. For example, if the value observed is higher than the expected one, we can anticipate that the price-earnings ratio will decrease to reach the expected one.

Consequently, the residual estimation from the regression provides a forecast of the expected price-earnings growth multiple:

$$-\hat{u}_s = \hat{m}_s - m_t = \hat{\mu}_s^{gm} \tag{13}$$

Since the reversion to the mean of the price-earnings growth is gradual and occurs over multiple periods, a second regression is performed. The predictive regression regresses the lagged error terms obtained in the previous formula to forecast the price-earnings growth multiple, by using a 5-year expanding window. This window is chosen among other options such as using 2.5 years and 4 years, experimenting with both moving and expanding windows. This specific window was chosen as it yields less negative and more consistent results, while still analysing a significantly longer period. This also allows for consistency when comparing with and adding to the simple SOP method, since this last one also uses a 5-year predictive window.

$$gm_{t+1} = c + d(-\hat{u}_s). \tag{14}$$

3.2.2. ESG factor

The following two subsections will describe the two different methods used to calculate the ESG factor used for predicting the stock market returns. Both methods were chosen to assess which yields the best results. The methods aim to translate the ESG data, in this case ESG scores, into stock return components.

3.2.2.1. Cross-Sectional ESG Factor

The ESG factor created with a cross-sectional approach is based on tracking a portfolio, a reference portfolio, and its returns and ESG scores over time. The reference portfolio is the first one in the sample, the constituents of the S&P 500 in January of 2005. I then track the performance and ESG scores of the constituents of this reference portfolio throughout the sample period. For each month, I calculate the total portfolio returns, weighted on the ESG scores. To isolate the effect of the ESG ratings on the overall performance, I subtract from each month's performance the S&P 500's monthly performance. With this, I get the excess returns and can assess how the ESG scores added value over the market performance.

To include these excess returns in the SOP method, I apply several transformations to the data to transform the preliminary ESG factor into a lower scale. Building on the findings of Shanaev & Ghimire (2022) on the impact of ESG score changes on stock returns, I divide the portfolio returns to quantify their changes over time. Additionally, I use the natural logarithm to make this component additive to the other elements of the SOP formula. Finally, to adjust the returns to the scale of the components and make them additive, I divide the results by 100. The following formula represents the ESG factor computed using a cross-sectional approach:

$$\hat{\mu}_s^{ESG^{CS}} = ln \frac{Rp_{s+1}}{Rp_s} * \frac{1}{100} \tag{15}$$

3.2.2.2. Time-Series ESG factor

The ESG factor based on the time-series approach is calculated by focusing on stocks that are top and bottom performing in ESG scores for each period. For each month, I use a 20% threshold to assess the top and bottom ESG-performing stocks. The threshold was chosen to capture the extreme stocks, to ensure that the stocks with the most impact are being assessed. Additionally, 20% was the threshold that provided the least extremely negative outcomes, compared with a 10%, a 30% and a 50% threshold.

Based on the top and bottom 20% of ESG-rated stocks, I created a portfolio that goes long on the best-rated stocks and shorts the worst-rated stocks. A portfolio where I long the worst-scored stocks and short the best-scored stocks was also done but the predictive power did not increase. Afterwards, I calculate the monthly returns for each portfolio.

I also remove the market returns from the portfolio's returns following the same rationale as before, to isolate the effect of the ESG scores in the returns.

Lastly, I normalized the data to be able to add this component to the other components of the SOP method. First, I followed the same logic explained in the previous section and calculated the relative change of returns to account for the growth rate. Then I apply the logarithm to reflect continuous growth and to make this component additive. Furthermore, I divide this component by 1000 to scale it to match the other SOP components, as the returns produced by this method are of a higher scale. Following this approach, I end up with the following formula for the ESG factor computed with a time-series approach, which accounts for the negative portfolio returns inherent in the creation of this method:

$$\hat{\mu}_s^{ESG^{TS}} = \begin{cases} ln \frac{Rp_{s+1}}{Rp_s} * \frac{1}{1000}, if \ \frac{Rp_{s+1}}{Rp_s} > 0 \\ 0, if \ \frac{Rp_{s+1}}{Rp_s} = 0 \\ -ln \left| \frac{Rp_{s+1}}{Rp_s} \right| * \frac{1}{1000}, if \ \frac{Rp_{s+1}}{Rp_s} < 0 \end{cases} \tag{16}$$

3.2.3. Shrinkage

When dealing with regressions, the probability of over-fitting is high. This means that the regressions can capture the random fluctuations, instead of the inherent patterns in the data. Shrinkage reduces this problem, by reducing the intensity of the coefficients and making them closer to its mean value. I will follow the approach of Connor (1997), which proposes a specific method to shrink the forecasted returns by applying it directly to the forecasting model.

The method starts with evaluating the forecasting power, ρ, of the methods used:

$$\rho = E\left(\frac{R^2}{1-R^2}\right) \approx E(R^2) \tag{17}$$

Additionally, the shrinkage intensity, i, can also be seen as the weight given to the initial belief of no predictability, which is the same as attributing a value below 1% to ρ:

$$i = \frac{1}{\rho} \tag{18}$$

The author suggests that using return forecasts without a shrinkage factor may lead a mean-variance optimization investor to incorrectly maximize errors in the portfolio. This happens because positive forecasts are biased upwards, while negative forecasts are biased downwards since the investor neglects to include, in the forecasts, the prior knowledge that predictable return changes generally trend around zero over time. As a result, the optimal portfolio created by using these forecasts would exhibit extreme overweighting and underweighting of the risky assets, making the model impractical for real-world application.

To address this issue, the shrinkage factors will push the coefficients derived from the different models toward zero, which is the prior expected value of the true, non-observable coefficient. I applied the Solver in Excel to identify the shrinkage intensity, i, could be that would maximize the portfolio Sharpe Ratio gains. Interestingly, this initial analysis suggested an i of zero, reaffirming the need for shrinkage to align with real-life asset allocation requirements.

When determining the optimal i, I aimed to maximize the Sharpe Ratio gains from both SOP with Multiple Growth and SOP with Multiple Reversion methods, ensuring a positive balance for all variables used (i.e., more positive than negative gains). I considered the expected R_2 of the simple SOP method as an indicator of forecasting power, ρ, remarking that the Cross-Sectional ESG factor yielded a lower R_2. This suggests a correspondingly lower forecasting power in the shrinkage-adjusted model.

My objective was to maintain theoretically correct and higher results, while also ensuring consistency across both ESG factors. During testing, I found that even a minor difference in shrinkage intensity (e.g., a change of 50) impacted results significantly. Specifically, in the Cross-Sectional ESG factor, the R_2 improved from the SOP with Multiple Growth to the SOP with Multiple Reversion models but in the Time-Series ESG factor it decreased substantially.

After carefully balancing these considerations, I established a shrinkage intensity factor of i = 500 for the models where the Cross-Sectional ESG factor is used and i = 450 for the models where the Time-Series ESG factor is used. These values were chosen to meet theoretical expectations and to keep practical consistencies.

The SOP with Multiple Growth and SOP with Multiple Reversion methods use regressions with different intuitions therefore I apply different shrinkage methods to both.

For the SOP with Multiple Growth method, I use the following formulas to transform the coefficients of the Equation (11):

$$\beta^* = \frac{s}{s+i}\beta \tag{19}$$

and

$$\alpha^* = -\beta^* \bar{x}_s \tag{20}$$

where $\bar{x}_s$ is the historical mean of the predictor used up to time s.

For the SOP with the Multiple Reversion method, I apply the following formulas to the coefficients of Equation (14):

$$d^* = \frac{s}{s+i}d \tag{21}$$

and

$$c^* = d^* * \bar{\bar{\hat{u}}}_s \tag{22}$$

Where $\bar{\bar{\hat{u}}}_s$ is the average of the regression residuals up to time s.

3.2.4. Significance Tests

The statistical significance of the results will be evaluated using the MSE-F statistic proposed by McCracken (2007). This statistic allows the evaluation of forecasting results produced using out-of-sample tests, by assessing if adding more predictors increases the predictability power of a model. The following formula is used to calculate the statistic:

$$MSE_F = (T - S_0)\left(\frac{MSE_M - MSE_P}{MSE_P}\right) \tag{23}$$

Where T and S_0 are the total time periods in the sample and the window size, respectively.

To be able to determine the percentiles of the out-of-sample statistics, the following parameters need to be calculated:

$$\pi = \frac{P}{R} \tag{24}$$

and

$$k_2 = K_U - K_R \tag{25}$$

Where P is the number of out-of-sample observations, R is the number of in-sample observations, K_U is the number of parameters in the unrestricted model, which in the context of this thesis are the different SOP models, and K_R is the number of parameters in the restricted model, in this thesis this is the model which uses the historical average as the only predictor. Since in the context of this thesis I only use a 5 year window to predict stock market returns out-of-sample, I assume that P is the out-of-sample window size (60 months) and R is the total number of observations in the full sample, given that if I would have done in-sample forecasting tests I would have used the total number of observations.

The critical values to assess the significance of each result which depend on the π and k_2 can be observed in Appendix B. The critical values which were not directly provided in McCracken (2007), were derived by using linear interpolation:

$$x_t = x_1 + \left(\frac{\pi_t - \pi_1}{\pi_2 - \pi_1}\right)(x_2 - x_1) \tag{26}$$

Where π_t corresponds to the π calculated using Equation (24), π_1 and π_2 are the observable π in the table provided by McCracken (2007) and x_1 and x_2 are their corresponding critical values.

3.2.5. Asset Allocation

One of the main purposes of predicting the market is to be able to profit from it. In this section, I will conduct two asset allocation exercises for all the methods used to predict the returns, to assess if the investors can indeed yield higher returns by using the proposed forecasting methods.

3.2.5.1. Sharpe Ratio

In the first asset allocation exercise, I use the Sharpe Ratio which allows investors to assess how much additional return they can earn for each extra unit of volatility of holding a risky asset.

I perform a 5-year window out-of-sample exercise for each period, where I calculate the optimal weights for the risky asset (holding the stock market in this thesis) and for the risk-free asset, by following the Markowitz mean-variance optimization weight formula:

$$w_s = \frac{\hat{u} - rf_{s+1}}{\gamma \hat{\sigma}^2_s} \quad (27)$$

$\hat{\sigma}_s^2$ is the historical variance from the realized stock market returns with an expanding window up to time s, the rf_{s+1} refers to the risk-free returns from the time s to s+1, γ is the risk-aversion metric. I choose a risk aversion of 2 as it is a moderate level of risk aversion. Other values for the risk aversion coefficient were assessed and the corresponding results can be found in Appendix C and Appendix D. As observed, the Sharpe Ratio gains decrease as the investor becomes more risk averse in the three SOP methods for the two ESG factors.

Restrictions on the weights were applied to prevent shorting stocks ($w_s \geq 0\%$) and to avoid leverage ($w_s \leq 100\%$). These constraints ensured there were no extreme weights for both assets and led to the best results in this asset allocation exercise.

Once I retrieve the optimal weights for each asset I calculate the portfolio returns:

$$rp_{s+1} = w_s r_{s+1} + (1 - w_s) rf_{s+1} \quad (28)$$

I compute this process until the end of the sample to get a time series of portfolio returns for the different methods for the two ESG factors. I compute the Sharpe Ratio of each portfolio for all months in the sample:

$$Sharpe\ Ratio_s = \frac{\hat{u} - rf_{s+1}}{\hat{\sigma}_s} \quad (29)$$

To have a better understanding of the benefits that investors can have when using different methods compared to using the historical average, I use a measure based on the R_2 proposed by Goyal & Welch (2008). I compare the Sharpe Ratio of using each strategy compared with the Sharpe Ratio of using the historical average:

$$Sharpe\ Ratio\ Gains = \sum \frac{SR_P - SR_M}{n} \tag{30}$$

3.2.5.2. Certainty Equivalent Return

In this asset allocation exercise, I will obtain the Certainty Equivalent Return by using the forecasted returns obtained from the different methods. This measure evaluates the equivalent risk-free return that a mean-variance investor would consider equivalent to investing in this strategy. This means that, for an investor to invest in a risky portfolio, the Certainty Equivalent Return would have to be higher than the current risk-free rate. Furthermore, this measure can also be interpreted as the fee an investor would be willing to pay to acquire the information provided by each forecasting model.

This exercise starts by calculating the Markowitz mean-variance optimization weight by using Equation (27) and obtaining the total portfolio returns such as in Equation (28). The same constraints were applied to maintain consistency in the results, as well as a risk aversion coefficient, γ, of 2, which will be also applied in Equation (31).

Finally, the Certainty Equivalent Return is obtained by following the formula:

$$Certainty\ Equivalent\ Return = \bar{r}\bar{\bar{p}} - \frac{\gamma}{2}\sigma^2{}_{rp} \tag{31}$$

4. Results

4.1. Forecasts of the stock market

Table 2 displays the results of the three forecasting methods incorporating the two ESG factors. The forecasting period is from February 2010 to December 2023, using a 5-year expanding window. These results summarise how each method performs in terms of predicting the stock market returns out-of-sample, by using the R_2 proposed by Goyal & Welch (2008).

Overall, the three forecasting methods demonstrate a consistent ability to predict stock market returns, with R_2 values over 1% and statistically significant for most variables, which is consistent with the existing literature. Among these, the simple SOP method achieves slightly higher R_2 values overall, achieving 2.15% and 2.46% when using the Cross-Sectional ESG factor and the Time-Series ESG factor, respectively. This suggests that ESG information can predict stock market returns effectively even when modelled in different ways.

However, the SOP extension models benefit from ESG information only in specific variables, such as BM, DP and DY. BM describes how the overall stock market values a company relative to its book value, which is backward-looking and does not account for future risks, such as climate risks that ESG information can provide information on. For example, a company with a high BM ratio might seem undervalued, but its ESG rating might provide insights on poor environmental or governance practices. DP and DY are predominantly driven by past earnings and market prices, which might overlook non-financial factors that might be observed in a company's ESG rating. For example, firms with higher sustainability efforts perform better financially (Chen et. al, 2023, Pedersen et. al, 2021, Velte, 2017, Ferrell et. al, 2016) and are more stable (Bax et. al, 2024) which could be better sustained to face sustainability-related liabilities, and therefore be able to increase the dividends. In sum, these variables mainly reflect the financial aspects of firm valuation, based on past information. The improvement in the predictive ability of these variables demonstrates the value that ESG information can provide in stock return predictability.

In contrast, certain variables show limitations in their predictive performance. Specifically, SEP in the SOP with Multiple Growth and ROE within the SOP with Multiple Reversion demonstrate extremely negative R_2 values, suggesting that these variables have no predictive power in these modelling contexts. This might be due to SEP not benefitting from the short period analysed in this thesis. Additionally, the behaviour of ROE in the SOP with Multiple Reversion might be due to the conflict between the variable and the methodology. SOP with

Multiple Reversion relies on the mean reversion of the price-earnings ratio, driven by economic fundamentals. ROE follows a non-linear mean-reverting process, with its speed depending on the current profitability level (Fama & French, 2000). Based on this, the current profitability level might be close to the mean, resulting in a slower reversion that may not fully correct within the short span of 5 years used in the methodology of this thesis.

Some variables, such as SVAR, LTR and NTIS, exhibit enhanced forecasting power in the SOP with Multiple Reversion method, suggesting this model better describes the impact of these variables in the price-earnings growth multiple. Furthermore, SVAR benefits significantly from the transition from the SOP with Multiple Growth to the SOP with Multiple Reversion, particularly when using the Time-Series ESG factor.

The methods were also assessed without taking into consideration ESG information, which can be seen in Panel C of Table 2. Note that the shrinkage factor applied on this model was adjusted to $i = 475$ based on the explanation previously given in Section 3.2.3. I find that incorporating ESG data into predictive models generally enhances their predictive power, though the traditional financial variables remain the primary drivers of return predictability. I also observe that the Time-Series ESG factor demonstrates the greatest predictive power, with R_2 values higher than the ones of the models using the Cross-Sectional ESG factor and the models that do not include the ESG factors. While traditional variables remain the primary drivers, the ESG factors provide complimentary insights that improve predictive models.

4.2. Asset allocation

Table 3 displays the average Sharpe Ratio gains achieved using the different forecasting methods using both the Cross-Sectional and Time-Series ESG factors. The Simple SOP, the SOP with Multiple Growth and the SOP with Multiple Reversion methodologies were applied to assess their impact on an investor's portfolio, measured by Sharpe Ratio gains compared to using the historical average of the stock returns as a predictor.

I find that, overall, Sharpe Ratio gains are modest across the three models, with a few variables showing consistent improvement over the historical average. The SOP with Multiple Reversion yields the most positive Sharpe Ratio gains for the two ESG factors, which suggests that this method might slightly enhance the portfolio's performance.

Table 2 - Forecasts of the stock market returns. The forecasts were obtained by applying the different SOP models using the Cross-Sectional and the Time-Series ESG factors. All the results are in percentage. The asterisks represent the significance of the out-of-sample tests by using the MSE-F statistic (McCracken, 2007). ***, ** and * display significance at the 1%, 5% and 10% levels, respectively.

		Out-of-sample R^2		
Variable	Description	Simple SOP	SOP with Multiple Growth	SOP with Multiple Reversion
Panel A: Monthly return forecasts using the Cross-Sectional ESG Factor				
		2.15***		
SVAR	Stock Variance		1.75**	2.12**
DFR	Default Return Spread		2.20***	2.02**
LTY	Long-term Bond Yield		2.82***	1.66**
LTR	Long-term Bond Return		1.09*	2.08**
INFL	Inflation		2.27***	2.08**
TMS	Term Spread		2.11**	0.15
TBL	T-bill Rate		1.60**	-0.22
DFY	Default Yield Spread		0.91*	-0.47
NTIS	Net Equity Expansion		1.35**	1.89**
ROE	Return on Equity		1.44**	-4.18
DE	Dividend Payout		2.10**	2.19**
EP	Earnings Price		2.06**	-
SEP	Smooth Earnings Price		-4.88	-
DP	Dividend Price		3.56***	-
DY	Dividend Yield		2.78***	-
BM	Book-to-Market		2.16**	-
Panel B: Monthly return forecasts using the Time-Series ESG Factor				
		2.46***		
SVAR	Stock Variance		1.34**	2.41**
DFR	Default Return Spread		2.52***	2.33**
LTY	Long-term Bond Yield		3.14***	1.92**
LTR	Long-term Bond Return		1.25**	2.39**
INFL	Inflation		2.38***	2.39**
TMS	Term Spread		2.38***	0.18
TBL	T-bill Rate		1.86**	-0.21
DFY	Default Yield Spread		0.88*	-0.71
NTIS	Net Equity Expansion		1.60**	2.19**
ROE	Return on Equity		1.70**	-4.69
DE	Dividend Payout		2.41***	1.93**
EP	Earnings Price		2.35***	-
SEP	Smooth Earnings Price		-5.56	-

DP	Dividend Price	3.64***	-
DY	Dividend Yield	2.99***	-
BM	Book-to-Market	2.46***	-

Panel C: Monthly return forecasts without using any ESG factor

2.29***

SVAR	Stock Variance	1.46**	2.27**
DFR	Default Return Spread	2.34***	2.16**
LTY	Long-term Bond Yield	2.98***	1.76**
LTR	Long-term Bond Return	1.13**	2.22**
INFL	Inflation	2.32***	2.22**
TMS	Term Spread	2.22***	0.09
TBL	T-bill Rate	1.70**	-0.29
DFY	Default Yield Spread	0.85*	-0.57
NTIS	Net Equity Expansion	1.46**	2.01**
ROE	Return on Equity	1.56**	-4.56
DE	Dividend Payout	2.24***	2.01**
EP	Earnings Price	2.20***	-
SEP	Smooth Earnings Price	-5.26	-
DP	Dividend Price	3.53***	-
DY	Dividend Yield	2.82***	-
BM	Book-to-Market	2.28***	-

More specifically, variables such as SVAR, LTR and DFY show small but positive Sharpe Ratio gains when applying the SOP with Multiple Reversion model with the two ESG factors.

I also conclude that the Time-Series ESG factor and the Cross-Sectional ESG factor provide similar benefits, with some differences in individual variables. For example, SVAR and ROE show improvements with the Time-Series ESG factor transitioning from the SOP with Multiple Growth to the SOP with Multiple Reversion. Interestingly, ROE demonstrates negative predictive power in this exact model setting. This might stem from the high dispersion of the returns it generates, which, despite making it difficult to establish consistent patterns and hence resulting in a negative R_2, occasionally might capture extreme positive returns. These occurrences positively influence the Sharpe Ratio gains, while compensating for the increased volatility.

In contrast, variables with higher predictive power such as DY, DP and BM produce more stable return predictions, offering consistent performance and reduced volatility. However, this stability limits the potential for superior Sharpe Ratio gains since these eliminate the possibility of capturing outlier events.

Table 4 shows the Certainty Equivalent Returns an investor can achieve using the different forecasting methods while using the two ESG factors.

The results show that, in general, the Certainty Equivalent Returns are relatively consistent across both ESG factors and forecasting methods, with some slight variations in individual variables. The SOP with Multiple Reversion generally provides higher Certainty Equivalent Returns for variables such as SVAR and DFY. The Cross-Sectional ESG factor yields slightly higher Certainty Equivalent Returns overall, which is evident in variables such as SVAR, DFR and BM, where gains are higher when incorporating this type of ESG factor.

Table 3 - Asset allocation: Sharpe Ratio Gains.

		Out-of-sample R_2		
Variable	Description	Simple SOP	SOP with Multiple Growth	SOP with Multiple Reversion
Panel A: Average Sharpe Ratio Gains using the Cross-Sectional ESG Factor				
		0.00		
SVAR	Stock Variance		-0.05	0.07
DFR	Default Return Spread		0.01	0.00
LTY	Long-term Bond Yield		0.07	0.00
LTR	Long-term Bond Return		0.00	0.01
INFL	Inflation		0.00	0.01
TMS	Term Spread		0.02	0.01
TBL	T-bill Rate		-0.02	0.00
DFY	Default Yield Spread		-0.07	0.03
NTIS	Net Equity Expansion		0.04	-0.01
ROE	Return on Equity		0.02	0.01
DE	Dividend Payout		0.00	-0.01
EP	Earnings Price		0.01	-
SEP	Smooth Earnings Price		0.06	-
DP	Dividend Price		-0.05	-
DY	Dividend Yield		-0.05	-
BM	Book-to-Market		-0.02	-
Panel B: Average Sharpe Ratio Gains using the Time-Series ESG Factor				
		0.00		
SVAR	Stock Variance		-0.05	0.04
DFR	Default Return Spread		0.01	0.00
LTY	Long-term Bond Yield		0.07	0.00
LTR	Long-term Bond Return		0.00	0.01
INFL	Inflation		0.00	0.00
TMS	Term Spread		0.02	0.01
TBL	T-bill Rate		-0.02	0.00
DFY	Default Yield Spread		-0.07	0.03
NTIS	Net Equity Expansion		0.04	-0.01
ROE	Return on Equity		0.01	0.02
DE	Dividend Payout		0.00	0.00
EP	Earnings Price		0.01	-
SEP	Smooth Earnings Price		0.06	-
DP	Dividend Price		-0.06	-
DY	Dividend Yield		-0.05	-
BM	Book-to-Market		-0.02	-

Table 4 - Asset allocation: Certainty Equivalent Returns. All the results are in percentage.

		Out-of-sample R_2		
Variable	Description	Simple SOP	SOP with Multiple Growth	SOP with Multiple Reversion
Panel A: Certainty Equivalent Returns using the Cross-Sectional ESG Factor				
		0.70		
SVAR	Stock Variance		0.47	1.00
DFR	Default Return Spread		0.75	0.71
LTY	Long-term Bond Yield		0.99	0.68
LTR	Long-term Bond Return		0.68	0.73
INFL	Inflation		0.70	0.73
TMS	Term Spread		0.77	0.73
TBL	T-bill rate		0.62	0.68
DFY	Default Yield Spread		0.38	0.84
NTIS	Net Equity Expansion		0.87	0.66
ROE	Return on Equity		0.76	0.73
DE	Dividend Payout		0.71	0.69
EP	Earnings Price		0.73	-
SEP	Smooth Earnings Price		0.91	-
DP	Dividend Price		0.46	-
DY	Dividend Yield		0.49	-
BM	Book-to-Market		0.62	-
Panel B: Certainty Equivalent Returns using the Time-Series ESG Factor				
		0.70		
SVAR	Stock Variance		0.47	0.90
DFR	Default Return Spread		0.74	0.70
LTY	Long-term Bond Yield		1.00	0.67
LTR	Long-term Bond Return		0.68	0.73
INFL	Inflation		0.70	0.72
TMS	Term Spread		0.77	0.73
TBL	T-bill Rate		0.60	0.69
DFY	Default Yield Spread		0.38	0.86
NTIS	Net Equity Expansion		0.88	0.65
ROE	Return on Equity		0.76	0.74
DE	Dividend Payout		0.70	0.71
EP	Earnings Price		0.73	-
SEP	Smooth Earnings Price		0.93	-
DP	Dividend Price		0.45	-
DY	Dividend Yield		0.48	-
BM	Book-to-Market		0.60	-

5. Robustness Tests

In this section, I perform robustness tests to ensure that the models I created using both ESG factors are reliable and stable. To test the results, I divided the sample into two equal sub-samples: one sub-sample where I forecast from February 2010 up until December 2016 and another sub-sample where I forecast from January 2017 to December 2023. This split was chosen to keep the same 5-year out-of-sample forecasting window. All the results were also tested for their statistical significance.

The results of this test can be observed in Table 5. This test reveals varying predictive power of different variables across the models and periods. In the earlier sub-sample (February 2010 to December 2016), the three models generally show positive and significant out-of-sample R_2 values, especially for variables such as EP, DP and DY when using both ESG factors. The SOP with Multiple Growth and SOP with Multiple Reversion models also show constant R_2 values, with DE presenting the highest predictive power.

In contrast, the results for the later sub-sample (January 2017 to December 2023) demonstrate a decrease in predictive power. Most variables in both the Cross-Sectional and Time-Series ESG factor models show negative or almost-zero R_2 values, showing a reduced predictive performance in this period. These findings suggest that the model's predictive power is sensitive to the period used.

It is also important to note that SVAR shows a different behaviour when comparing the two sub-samples and its performance in the SOP with Multiple Growth with the SOP with Multiple Reversion. The first sub-sample includes one of the most volatile periods in financial history, most likely driven by events such as the 2008 Global Financial Crisis. The negative performance of this variable in this period allows us to deduce that the SOP with Multiple Growth model struggles to outperform in highly volatile periods. In contrast, the SOP with Multiple Reversion model demonstrates a greater adaptability to such volatile conditions, suggesting it may be better suited to be used during periods of significant market fluctuations.

The incorporation of ESG information into the different models also indicates its potential added value in predicting stock returns. In the second subsample, where results are negative when including macroeconomic variables, using only ESG information in the simple SOP method still demonstrated a modest degree of predictive power, outperforming the use of the historical average as a baseline.

I also tested the results by using a 36-month out-of-sample predictive window, the results of which can be seen in Appendix E. In general, this alternative test does not corroborate the methodology proposed in this thesis. Even though the shrinkage factor was adapted to these results based on the intuition explained before in Section 3.2.3, the results remained extremely negative. This further highlights the importance of selecting the period and determining the correct number of months to include in the forecasting window.

Table 5 - Robustness Test: Subsamples. The asterisks represent the significance of the out-of-sample tests by using the MSE-F statistic (McCracken, 2007). ***, ** and * display significance at the 1%, 5% and 10% levels, respectively.

		Out-of-sample R_2		
Variable	Description	Simple SOP	SOP with Multiple Growth	SOP with Multiple Reversion
Panel A: Monthly return forecasts using the Cross-Sectional ESG Factor (February 2010 - December 2016)				
		5.73***		
SVAR	Stock Variance		-4.47	5.68***
DFR	Default Return Spread		6.04***	5.70***
LTY	Long-term Bond Yield		5.47***	4.12**
LTR	Long-term Bond Return		3.94**	6.00***
INFL	Inflation		3.76**	5.95***
TMS	Term Spread		5.42***	-0.92
TBL	T-bill Rate		4.44**	-1.54
DFY	Default Yield Spread		1.73*	2.40*
NTIS	Net Equity Expansion		3.27**	5.00**
ROE	Return on Equity		6.17***	-6.97
DE	Dividend Payout		5.70***	11.76***
EP	Earnings Price		6.45***	-
SEP	Smooth Earnings Price		-13.34	-
DP	Dividend Price		10.42***	-
DY	Dividend Yield		8.33***	-
BM	Book-to-Market		5.32***	-
Panel B: Monthly return forecasts using the Time-Series ESG Factor (February 2010 - December 2016)				
		6.36***		
SVAR	Stock Variance		-4.83	6.27***
DFR	Default Return Spread		6.67***	6.32***
LTY	Long-term Bond Yield		5.96***	4.59**
LTR	Long-term Bond Return		4.28**	6.64***
INFL	Inflation		3.98**	6.58***
TMS	Term Spread		5.94***	-1.17
TBL	T-bill Rate		4.93**	-1.84
DFY	Default Yield Spread		1.71*	2.13*
NTIS	Net Equity Expansion		3.64**	5.56***
ROE	Return on Equity		6.80***	-8.16
DE	Dividend Payout		6.32***	12.27***
EP	Earnings Price		7.11***	-
SEP	Smooth Earnings Price		-15.43	-

DP	Dividend Price		11.23***	-
DY	Dividend Yield		9.08***	-
BM	Book-to-Market		5.91***	-
Panel C: Monthly return forecasts using the Cross-Sectional ESG Factor (January 2017 - December 2023)				
		0.08		
SVAR	Stock Variance		3.25**	-1.98
DFR	Default Return Spread		-1.70	-2.05
LTY	Long-term Bond Yield		0.57	-1.53
LTR	Long-term Bond Return		-2.73	-2.15
INFL	Inflation		-1.75	-2.11
TMS	Term Spread		0.08	0.05
TBL	T-bill Rate		-1.63	-0.42
DFY	Default Yield Spread		-3.55	-5.50
NTIS	Net Equity Expansion		-0.06	-1.77
ROE	Return on Equity		-2.37	-1.62
DE	Dividend Payout		-1.84	-10.69
EP	Earnings Price		-2.70	-
SEP	Smooth Earnings Price		-2.90	-
DP	Dividend Price		-7.34	-
DY	Dividend Yield		-5.98	-
BM	Book-to-Market		-2.55	-
Panel D: Monthly return forecasts using the Time-Series ESG Factor (January 2017 - December 2023)				
		0.22		
SVAR	Stock Variance		2.73**	-2.03
DFR	Default Return Spread		-1.70	-2.07
LTY	Long-term Bond Yield		0.70	-1.51
LTR	Long-term Bond Return		-2.85	-2.18
INFL	Inflation		-1.87	-2.14
TMS	Term Spread		0.18	0.16
TBL	T-bill Rate		-1.63	-0.34
DFY	Default Yield Spread		-3.80	-5.91
NTIS	Net Equity Expansion		0.03	-1.77
ROE	Return on Equity		-2.42	-1.72
DE	Dividend Payout		-1.84	-11.84
EP	Earnings Price		-2.78	-
SEP	Smooth Earnings Price		-3.03	-
DP	Dividend Price		-8.13	-
DY	Dividend Yield		-6.50	-
BM	Book-to-Market		-2.62	-

6. Conclusion

This thesis studies the effectiveness of using ESG scores to predict stock market returns. I use the Sum of the Parts method and its extensions (Ferreira & Santa-Clara, 2011) and complete the method by adding an ESG factor. Two different types of factors were created: the Cross-Sectional ESG factor, which tracks a portfolio's ESG scores throughout the sample, and the Time-Series ESG factor, which focuses on the best and worst ESG performers in each period.

This study was subject to some restrictions. ESG scores provided by Refinitiv are only updated annually, which limited my ability to capture more frequent changes in ESG scores combined with changes in returns. Additionally, the lack of data might not allow me to capture long-term trends, since I relied on a short sample of only 228 months. Finally, each data provider has its own method to calculate ESG scores which might introduce some variability into my analysis.

Despite these limitations, this study provides valuable understanding of how investors can leverage ESG ratings and other sustainability-focused information to enhance their market and company modelling, potentially achieving superior returns. By demonstrating that ESG information captures dimensions of performance that are not accounted for by the traditional macroeconomic indicators, this thesis highlights the importance of incorporating ESG factors into investment decision making.

The results demonstrate that ESG scores, combined with different macroeconomic indicators, improve the predictability of stock market returns compared to only using historical averages. Among the three SOP methods, the simple SOP model performed best overall. The SOP extensions (SOP with Multiple Growth and SOP with Multiple Reversion) did not provide significant improvements, except for variables such as BM, DP and DY, which benefited due to their backward-looking nature. On the contrary, variables like SEP and ROE did not perform better under the models with extensions.

When comparing the two ESG factors created, both effectively improved stock return predictability, but the Time-Series ESG factor proved to be superior, by achieving higher R_2 values than the models without applying ESG factors. Still, the Cross-Sectional ESG factor yielded slightly higher Certainty Equivalent Returns, which highlights how both factors can differently contribute to improving stock return predictability and to improving investor returns.

However, the SOP methods did not demonstrate significant Sharpe Ratio gains for a risk-adjusted investor. The SOP with Multiple Reversion yielded the highest Sharpe Ratio gains, highlighted by variables such as SVAR, LTR and DFY. The Certainty Equivalent Returns were consistent across ESG factors and SOP methods, with the SOP with Multiple Reversion method and the Cross-Sectional ESG factor slightly outperforming.

All methods demonstrated robustness when the sample was divided into two subsamples, although the earlier sample (February 2010 – December 2016) appeared to drive most of the predictive power. The results also highlight the adaptability of the SOP with Multiple Reversion model, which performed better during the volatile period, suggesting its potential value in forecasting stock returns in periods of high market uncertainty. Interestingly, while predictive power decreased in the later subsample (January 2017 – December 2023), both ESG factors showed resilience by outperforming the traditional macroeconomic variables due to the relatively higher R_2 values in the simple SOP method. Furthermore, changing the size of the out-of-sample window from 60 months (5 years) to 36 months completely offsets the results, indicating that a 5-year window is more suitable for this study.

This study emphasizes the importance of incorporating ESG factors into investment strategies. Investors should combine ESG ratings and other sustainability information with traditional macroeconomic variables to enhance their ability to model stock market returns. Additionally, investors should adjust the choice of the model used based on market conditions. For instance, in turbulent markets, SOP with Multiple Reversion is more effective, while in stable markets, the simple SOP model performs well. Investors should also prioritize combining ESG factors with variables that may not capture all the information that might influence valuation such as book-to-market ratio, dividend price and dividend yield. Moreover, even though the risk-adjusted returns and Certainty Equivalent Returns were modest, ESG integration is still crucial for investors focused on long-term gains and value investing, where accurately assessing a company's fundamental value is essential. Finally, I believe that investors should explore this methodology using different ESG data sources to reduce bias and should extend this analysis to regional and sector-specific contexts to explore additional variations, influenced by diverse market dynamics, legislations and cultural influences.

Sustainable finance not only plays a crucial role in mitigating climate change, but it also aids investors to better predict stock market returns. This dual impact demonstrates the potential of integrating ESG considerations into financial decisions, serving as both a catalyst for addressing climate challenges and an instrument for capturing economic opportunities.

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Appendix A - List of variables.

Name	Definition	Source
SVAR	Sum of squared daily stock market returns on the S&P 500.	Goyal & Welch
DFR	Difference between long-term corporate bond and long-term government bond returns.	Goyal & Welch
LTY	Long-term government bond yields.	Goyal & Welch
LTR	Long-term Rate of Return.	Goyal & Welch
INFL	Consumer Price Index.	Goyal &Welch
TMS	Difference between the long-term yield on government bonds and the Treasury Bill.	Goyal & Welch
TBL	Treasury Bills.	Goyal & Welch
DFY	Difference between BAA and AAA-rated corporate bond yields.	Goyal &Welch
NTIS	Ratio of 12-month moving sums of net issues by NYSE listed stocks, divided by the total end-of-year market capitalization of NYSE Stocks.	Goyal & Welch
ROE	Ratio of 12-month moving sums of earnings to book value of equity for the S&P 500.	Goyal & Welch
DE	Difference between the log of dividends and the log of earnings.	Goyal & Welch
EP	Difference between the log of earnings and the log of prices.	Goyal & Welch
SEP	Five-year moving average of earnings-price ratio.	Goyal & Welch
DP	Difference between the log of dividends and the log of prices.	Goyal &Welch
DY	Difference between the log of dividends and the log of lagged prices.	Goyal &Welch
BM	Ratio of book to market value for the Dow Jones Industrial Average.	Goyal &Welch

Appendix B - Critical values of OOS-F statistic.

Retrieved from McCracken, 2007.

k_2	%-ile	π 0.0	0.1	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
1	0.99	5.902	1.608	2.129	2.768	3.179	3.459	3.584	3.771	3.589	3.838	3.882	3.951
	0.95	3.270	0.850	1.038	1.298	1.554	1.567	1.548	1.583	1.623	1.599	1.553	1.518
	0.90	2.210	0.530	0.659	0.814	0.796	0.798	0.751	0.759	0.698	0.685	0.687	0.616
2	0.99	7.910	1.996	2.691	3.426	3.907	4.129	4.200	4.362	4.304	4.309	4.278	4.25
	0.95	4.826	1.184	1.453	1.733	1.891	1.820	1.802	1.819	1.752	1.734	1.692	1.706
	0.90	3.324	0.794	0.912	1.029	1.077	1.008	0.880	0.785	0.697	0.666	0.587	0.506
3	0.99	9.230	2.418	3.092	4.080	4.136	4.322	4.341	4.337	4.192	4.089	4.365	4.184
	0.95	5.946	1.434	1.710	2.062	2.073	1.978	1.909	1.930	1.795	1.715	1.710	1.612
	0.90	4.216	0.970	1.064	1.117	1.121	0.960	0.857	0.691	0.599	0.386	0.276	0.127
4	0.99	10.472	2.714	3.440	4.541	4.609	4.378	4.202	4.586	4.477	4.337	4.247	4.096
	0.95	6.712	1.566	1.964	2.246	2.194	1.900	1.809	1.578	1.376	1.256	1.122	1.029
	0.90	5.048	1.060	1.225	1.313	1.184	0.829	0.545	0.354	0.197	-0.058	-0.234	-0.456
5	0.99	11.398	2.902	3.673	4.466	4.434	4.249	4.351	4.349	4.187	3.945	3.783	3.783
	0.95	7.404	1.688	2.082	2.235	2.242	1.773	1.449	1.316	1.045	0.718	0.502	0.459
	0.90	5.568	1.130	1.277	1.228	0.958	0.614	0.241	-0.099	-0.361	-0.656	-0.820	-1.072
6	0.99	12.434	3.212	3.846	4.545	4.676	4.637	4.703	4.286	4.144	3.981	3.525	3.321
	0.95	8.164	1.829	2.124	2.217	2.121	1.660	1.360	1.181	0.761	0.413	0.299	-0.109
	0.90	6.216	1.22	1.313	1.164	0.890	0.419	-0.044	-0.405	-0.776	-1.072	-1.395	-1.644
7	0.99	13.212	3.450	4.098	4.508	4.419	4.271	4.312	4.150	3.677	3.155	3.090	2.880
	0.95	8.930	2.000	2.239	2.424	2.057	1.604	1.282	0.928	0.378	-0.008	-0.199	-0.591
	0.90	6.584	1.272	1.333	1.118	0.799	0.242	-0.363	-0.728	-1.194	-1.657	-2.033	-2.507
8	0.99	13.886	3.408	4.130	4.645	4.625	4.202	4.147	3.912	3.185	2.933	2.952	2.484
	0.95	9.346	2.136	2.312	2.373	1.895	1.390	0.943	0.587	0.131	-0.372	-0.680	-1.140
	0.90	7.014	1.338	1.369	1.058	0.552	0.014	-0.632	-1.076	-1.633	-2.174	-2.731	-3.160
9	0.99	15.010	3.540	4.388	4.703	4.873	4.122	4.066	3.753	3.027	2.925	2.802	2.186
	0.95	9.946	2.168	2.440	2.219	1.714	1.286	0.631	0.198	-0.356	-0.851	-1.241	-1.696
	0.90	7.480	1.354	1.432	0.920	0.393	-0.327	-1.007	-1.595	-2.229	-2.666	-3.250	-3.794
10	0.99	15.586	3.646	4.433	4.813	4.718	3.944	3.645	3.194	2.578	2.282	2.152	1.436
	0.95	10.414	2.202	2.489	2.157	1.536	1.055	0.205	-0.431	-1.071	-1.459	-1.988	-2.378
	0.90	7.862	1.458	1.401	0.884	0.155	-0.600	-1.341	-2.008	-2.782	-3.348	-3.839	-4.437

Appendix C - Sharpe Ratio Gains using a risk-aversion coefficient of 3.

		Out-of-sample R_2		
		Simple SOP	SOP with Multiple Growth	SOP with Multiple Reversion
Variable	Description			
Panel A: Average Sharpe Ratio Gains using the Cross-Sectional ESG Factor				
		0.00		
SVAR	Stock Variance		-0.05	0.07
DFR	Default Return Spread		0.01	0.00
LTY	Long-term Bond Yield		0.07	0.00
LTR	Long-term Bond Return		-0.01	0.01
INFL	Inflation		0.00	0.00
TMS	Term Spread		0.02	0.01
TBL	T-bill Rate		-0.02	0.00
DFY	Default Yield Spread		-0.07	0.03
NTIS	Net Equity Expansion		0.04	-0.01
ROE	Return on Equity		0.01	0.01
DE	Dividend Payout		0.00	-0.01
EP	Earnings Price		0.00	-
SEP	Smooth Earnings Price		0.05	-
DP	Dividend Price		-0.06	-
DY	Dividend Yield		-0.05	-
BM	Book-to-Market		-0.02	-
Panel B: Average Sharpe Ratio Gains using the Time-Series ESG Factor				
		0.00		
SVAR	Stock Variance		-0.05	0.04
DFR	Default Return Spread		0.01	0.00
LTY	Long-term Bond Yield		0.07	-0.01
LTR	Long-term Bond Return		-0.01	0.00
INFL	Inflation		0.00	0.00
TMS	Term Spread		0.02	0.01
TBL	T-bill Rate		-0.02	0.00
DFY	Default Yield Spread		-0.07	0.03
NTIS	Net Equity Expansion		0.05	-0.02
ROE	Return on Equity		0.01	0.01
DE	Dividend Payout		0.00	0.00
EP	Earnings Price		0.00	-
SEP	Smooth Earnings Price		0.06	-
DP	Dividend Price		-0.06	-
DY	Dividend Yield		-0.05	-
BM	Book-to-Market		-0.03	-

Appendix D - Sharpe Ratio Gains using a risk-aversion coefficient of 5.

		Out-of-sample R_2		
Variable	Description	Simple SOP	SOP with Multiple Growth	SOP with Multiple Reversion
Panel A: Average Sharpe Ratio Gains using the Cross-Sectional ESG Factor				
		-0.03		
SVAR	Stock Variance		-0.05	0.07
DFR	Default Return Spread		-0.01	-0.02
LTY	Long-term Bond Yield		0.07	-0.03
LTR	Long-term Bond Return		-0.01	-0.01
INFL	Inflation		0.00	-0.02
TMS	Term Spread		0.01	0.00
TBL	T-bill Rate		-0.05	-0.01
DFY	Default Yield Spread		-0.07	0.03
NTIS	Net Equity Expansion		0.03	-0.04
ROE	Return on Equity		0.00	0.01
DE	Dividend Payout		-0.03	0.00
EP	Earnings Price		-0.01	-
SEP	Smooth Earnings Price		0.05	-
DP	Dividend Price		-0.06	-
DY	Dividend Yield		-0.06	-
BM	Book-to-Market		-0.05	-
Panel B: Average Sharpe Ratio Gains using the Time-Series ESG Factor				
		-0.03		
SVAR	Stock Variance		-0.04	0.04
DFR	Default Return Spread		-0.01	-0.03
LTY	Long-term Bond Yield		0.07	-0.03
LTR	Long-term Bond Return		-0.01	-0.01
INFL	Inflation		0.00	-0.02
TMS	Term Spread		0.01	0.00
TBL	T-bill Rate		-0.05	-0.01
DFY	Default Yield Spread		-0.07	0.03
NTIS	Net Equity Expansion		0.03	-0.04
ROE	Return on Equity		0.00	0.01
DE	Dividend Payout		-0.03	0.00
EP	Earnings Price		-0.01	-
SEP	Smooth Earnings Price		0.06	-
DP	Dividend Price		-0.06	-
DY	Dividend Yield		-0.06	-
BM	Book-to-Market		-0.05	-

Appendix E - Robustness Test: Using a 36-month expanding window.

		Out-of-sample R_2		
Variable	Description	Simple SOP	SOP with Multiple Growth	SOP with Multiple Reversion
Panel A: Monthly return forecasts using the Cross-Sectional ESG Factor				
		-4.10		
SVAR	Stock Variance		-2.52	-4.01
DFR	Default Return Spread		-0.83	-6.02
LTY	Long-term Bond Yield		0.03	-4.46
LTR	Long-term Bond Return		-0.66	-5.55
INFL	Inflation		-1.22	-5.64
TMS	Term Spread		0.09	-8.10
TBL	T-bill Rate		-0.33	-3.87
DFY	Default Yield Spread		-3.22	-2.74
NTIS	Net Equity Expansion		-6.91	-4.49
ROE	Return on Equity		-0.03	-5.22
DE	Dividend Payout		-1.59	-2.93
EP	Earnings Price		-0.86	-
SEP	Smooth Earnings Price		-2.19	-
DP	Dividend Price		-1.14	-
DY	Dividend Yield		-1.28	-
BM	Book-to-Market		1.06	-
Panel B: Monthly return forecasts using the Time-Series ESG Factor				
		-3.39		
SVAR	Stock Variance		-6.42	-3.52
DFR	Default Return Spread		-2.20	-6.19
LTY	Long-term Bond Yield		-2.95	-4.07
LTR	Long-term Bond Return		-3.66	-5.48
INFL	Inflation		-4.54	-5.60
TMS	Term Spread		-2.85	-8.75
TBL	T-bill Rate		-3.39	-6.92
DFY	Default Yield Spread		-7.36	-2.63
NTIS	Net Equity Expansion		-12.03	-4.04
ROE	Return on Equity		-3.15	-5.13
DE	Dividend Payout		-5.26	-2.17
EP	Earnings Price		-4.29	-
SEP	Smooth Earnings Price		-4.16	-
DP	Dividend Price		-4.78	-
DY	Dividend Yield		-4.92	-
BM	Book-to-Market		-1.66	-