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ESG INTEGRATION: ESG SCORE MOMENTUM FACTOR AS ASSET CHARACTERISTIC AND OPTIMAL PARAMETRIC PORTFOLIO - AN EMPIRICAL RESULT OF THE US STOCK MARKET.

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Abstract

Sustainable finance has become the rising concern of the global markets. The term ESG investment has been discussed in many international forums. The number of ESG investment assets and ESG investment products is increasing continuously. However, the question of integrating ESG information into investment products is being put ahead together with the ESG data challenges. This report investigates the potential of integrating the ESG factor into the investment process using parametric weight allocations. The parametric portfolio is a simple acclaimed approach proposed by Brandt et al. (2009). Based on the US stock market data in the period of 2008 -2020, at the individual stock level, I empirically investigate the performance of investment strategies that consider ESG Score and ESG Score Changes as characteristics. By integrating ESG information as additional characteristics, using the parametric allocations approach with an optimal Sharpe Ratio objective, I found a performance-enhancing effect of the ESG Score Change on portfolio performance in the US market. Even though policy that focuses on the firm's ESG Score improvement might impact the available stocks as available options, the net selective benefits are still positive. I thereby testify an approach for integrating ESG Score Change into the investment process and boost further research on different optimal objectives or different stock markets.

Keywords: Responsible Investment, ESG Factor Investment, Sustainable Investment, ESG Integration, ESG Investment, Sustainability.

Acknowledgment

When writing this master thesis, I have the chance to learn more about empirical asset pricing as well as portfolio management and performance valuation in terms of responsible investment. I have learned to work independently and enhance my self-leadership skill.

However, I have stood on countless experts' and researchers' shoulders to be able to do this. I want to express my deepest gratitude to Professor Erik Hjalmarsson for guidance, instructions, critical reflections, and review of this thesis. I would also like to extend my sincere thanks to the Swedish Institute, who grants me a chance to study master's program in Sweden under the SISGP scholarship. Having said that, omissions and errors are, of course, utterly on my own.

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1. Introduction

Sustainable investment has been a rising issue during the past decades. Many researchers have spent a lot of time finding "good" asset management strategies related to responsible finance. Moreover, ESG (Environment, Social, and Governance) issues have recently climbed up government agendas, and ESG investment guidelines are likely to become mandatory in major markets. Particularly, benefit pension funds in the UK are required to include ESG policies; or listed companies on the Hongkong stock exchange market are required to report actions on improving sustainability. In the US, a draft on ESG funds standards has been developed by the Securities and Exchange Commission (SEC), while a green bond standard is under discussion in the EU markets (Barclays, 2020). Moreover, on 4 Mar 2021, the US SEC announced the establishment of the Climate and ESG Task Force in the Division of Enforcement, which works toward the disclosure and compliance related to the Climate and ESG risk (SEC, 2021). Thus, it is obvious that ESG issues have a growing influence on global financial markets to a broader and broader extent.

Financial Markets have witnessed investments shifting to sustainable finance, in which more and more vendors are joining forces to provide companies ESG data and services. Financial Institutes have been releasing more and more sustainable investment products to attract potential investors. At the end of 2018, the total ESG assets were USD 30.6 trillion; this number is anticipated to reach USD 53 trillion by 2025 (Bloomberg, 2021). It is also documented that ESG scores provide information about firm fundamentals and affect investor preferences (Pedersen, et al., 2020). The Investor Insights report from SustainAbility (2020) shows that 65% of the surveyed investors use ESG ratings at least once a week. As a result of growing attention in sustainable finance and ESG investment is becoming the mainstream of sustainable investing (SustainAbility, 2020), integrating this characteristic into investment products to improve the investment profile and attract more investors is necessary. The key belief of ESG investment is that the investors, society, and environment can benefit from including ESG information in the investment decisions.

It is a fact that different investors have distinct investment approaches. When it comes to sustainable investment, investors can consider ESG integration, which mainly focuses on improving the risk-return characteristics of the portfolio; or maybe using their capital to trigger changes for “E, S, G” purpose (impact investment); or otherwise imposing the investors’ norms or beliefs about responsible finance (Giese, et al., 2019).

This paper is motivated by the fact that most studies argue about the benefits of ESG investment. ESG enterprises should lead to higher returns, lower risk as companies with higher sustainable governance would drive a lower risk profile. Therefore, in this report, I would like to examine the possibility of ESG integration into the investment process by building the portfolios using ESG scores and ESG score changes as the asset's characteristics and other characteristics. Other characteristics include return momentum, size, and enterprise value to sales. Since the US market is considered mature and well-aware of responsible investment, where the initial forms of responsible investment starts (Schueth, 2003), this report targets to inspect the policy's performance on this stock market.

With a focus on sustainable investment policy, this report aims to answer the questions: (1) Which characteristics would an optimal Sharpe Ratio investor value more? (2) Do ESG score changes contribute to higher performance when considered an asset's characteristic in parametric portfolio policies? It is based on the idea of building large-scale portfolios with asset characteristics introduced by Brandt et al. (2009), with the motivation that a company's sustainable performance has a positive impact on stock returns and a lower residual risk. Subsequently, four portfolio schemes are built for further evaluation. An investigation on the magnitude of each characteristic subject to maximizing the risk-adjusted return (Sharpe) ratio will answer the question (1). Based on the comparison-based method, this report also looks into the performance of each policy in terms of model alphas and risk profile to further discover the costs and benefits of sustainable investment using ESG score changes as a characteristic. Question (2) will be answered by going through five sub-questions as follow:

2a. Which portfolio has the highest attainable SR?

2b. Which portfolio has a higher alpha value?

2c. Which portfolio provides higher returns during the Covid period?

2d. What is the risk profile of portfolios (VaR, ES)?

2e. Which portfolio provides better net selective benefits?

The report amplifies the work of Brandt et al. (2009) along different dimensions: Firstly, I use ESG information as additional criteria in the portfolio building process. Secondly, I build different 4 portfolios with a high level of asset number and compare the performances based on diversified performance indicators. Lastly, I look at the risk profile of the portfolios based on current market practices. The Dataset used in this report is in a different period from Brandt et al. (2009)'s.

As a detailed comparison of these strategies' performance in the US stock markets, the report gives an in-depth analysis of how the responsible investment performs to mitigate the risk and recommend investors. This report also seeks to suggest how asset managers can incorporate ESG information and other factors to form portfolio policies for their clients, aiming to reallocate funds towards companies that focus on improving ESG profiles. Moreover, as a rising concern, the suggestion can go further to encourage global corporations to shift focuses on ESG profile improving to fortify their public images about sustainable development on appealing potential responsible investors.

I structure this report as follows: First, I summary scholarly sources in risk factors, ESG investment, and portfolio evaluation in section 2. Then I provide an overview of the Dataset being used in this report in section 3. Next, I describe the report's methodology in section 4. After that, the results are presented in section 5, and finally, the conclusion being made in section 6.

2. Literature review

2.1. Asset characteristic and common risk factors

In the series of comprehensive research on cross-sectional stock returns from 1992 to 2015, Fama & French (1992, 1993, 1995, 2007, 2015) continuously suggest that Market Equity (ME) and Book to Market (BTM) ratio capture much of the cross-section of average stock returns. Fama & French (1992) strongly affirm the role of ME and BTM ratio in proving a simple and powerful characterization of the cross-section of average stock return during the period of 1963-1990. The work in 1995 on the behaviors of earnings toward size and BTM of the two authors has shown that the common factors in returns mirror common factors in earnings. That low BTM stocks are more profitable than high BTM stocks. Fama et al. (1993) report that the three risk factors include market factor, factors related to size (market capitalization), and BTM perform well in explaining the average stock returns. The report is based on Fama & French's (1993) model, using the data of stock on the NYSE (New York Stock Exchange) and the NASD (National Association of Security Dealers) system.

Other than the common factors mentioned, the Sales–Price (S/P) ratio and the debt-to-equity (D/E) ratios have been documented to outperform BTM and ME ratios in explaining stock returns. Using the US stock market data sample from 1979 to 1991, Barbee et al. (1996) investigate the merits of some financial variables, which were proposed to be explanatory factors for future stock returns. The authors propose that alternative variables S/P and D/E have more power in the stock return explanation. They also point out that the S/P ratio may be a more reliable indicator of a firm's relative market valuation than the BTM ratio as sales figures are less affected by company-specific factors than the book equity value. However, it is arguable that the sales revenue figures can be unreliable to a certain extent. While the stock price and market value drop, a company's sales might not drop. It also does not count for the company's debt burdens. A high level of debt would need higher sales to accommodate the debts. The Sale-to-Enterprise Value ratio takes into account the company's long-term debts. It deducts the leftover cash, which is considered as an extension of the Sale to Price ratio in explaining the equity performance.

The return momentum factor was documented by Jegadeesh & Titman (1993), then being captured as a risk factor in Carhart (1997). Return momentum factor recently added to Fama & French's five-factor model, forming the Fama & French's six-factor model. It is also reported that Carhart's (1997) four-factor model performs almost as well as the six-factors model (Fama & French, 2016).

As time goes by, many patterns in average return are being discovered and become potential candidates for inclusion in factor models (Fama & French, 2018). Therefore, the introduction of the ESG factor is documented as a potential risk premium (Pollard et al., 2018) that will be brought into this report in the later part.

2.2. Parametric portfolio weights

The idea of estimating optimal portfolio weights directly by parameterizing the weights as a function of observables quantities and solving the parameters that maximize specific objectives was developed by Brandt & Santa-Clara (2006). In this paper, the authors deal with the market timing problem with parameterized portfolio weights of a single asset as a linear function of state variables. A similar approach was introduced by Brandt et al. (2009) with a high number of assets in the optimal portfolio by modeling portfolio weights in each asset as a function of the asset's characteristics. This function's coefficients are found in their report by optimizing the investor's average utility of the portfolio's return over the sample period. It is claimed to be computationally simple, easy to modify, and can be extended to capture the effect of transaction costs.

Following the results documented by Brandt et al. (2009), Hjalmarsson & Manchev (2012) investigate the optimal mean-variance policy by parameterizing the portfolio weights as proportional to single standardized stock characteristics (i.e., momentum or value). The paper documented better performance of the direct approach to estimate portfolio weights to the regression-based method of estimating the conditional mean. They emphasized the benefits of combining different characteristics were improved rather than employing individual characteristics. The authors also highlighted that a simple equal-weighted characteristic-based policy produced almost similar and sometimes better results than the direct approaches. Hjalmarsson & Manchev (2012) suggest the potential of portfolio choices using characteristic-based policy to achieve much higher Sharpe Ratios than the market's. None of those mentioned papers considers an investor who uses ESG score or ESG score look back as asset characteristics when parameterizing optimal weights allocation.

2.3. ESG integration & investment

Investment strategies that consider a company's non-financial information when making investment decisions started about 35 years ago. The initial forms of responsible investment generated in the US, starting with Jewish directives on ethical investment or the Religious Society such as the Quakers who screened out specific investments out of the moral values of the clients in the 1700s (Schueth, 2003). The anti-Vietnam war and anti-apartheid responsible investments by the late 1970s and early 1980s were recorded as examples of the initial form of responsible investment in many academic papers from 1988 to 1998. Since then, this form of investment has embraced various strategies such as screening for positive or best-in-sector, shareholder activism, targeted investing, and enhanced analytics (Viviers & Eccles, 2012). ESG investment has become more complex and has begun to enter mainstream investment practices (Sparkes & Cowton, 2004). Duuren et al. (2016) reported similar ESG strategies updated as of 2016 include ESG screening (both negative and positive screening), best-in-class investing[1], activism[2], and engagement[3].

By building two ESG strategies: the "ESG tilt" strategy and the "ESG momentum" strategy, Nagy et al. (2016) find that both strategies outperform the MSCI world index as a global benchmark for an eight years trading period. Pollard et al. (2018) documented the existence of an ESG risk premium within global equity portfolios both geographically and longitudinally. The authors suggested including ESG as a blended risk premium within a multi-factor model. Along with other common of risk premia such as value, market, size, profitability, and investment (Fama & French, 2015) or liquidity (Pástor & Stambaugh, 2003) and return momentum (Jegadeesh & Titman, 1993;

[1] Top 25-33%
[2] Filing petitions and voting on annual general meeting of shareholders
[3] Meeting with the board of corporate and trying to convince them to perform better on ESG activities.

Carhart, 1997; Asness et al., 2013). According to Pollard et al. (2018), ESG risk premium provides increased insight into the probability distribution of assets and result in a higher risk-adjusted return. It is suggested to integrate the ESG factor in a quantifiable metric with other proven investment strategies to generate alpha. Following the results, Sherwood & Pollard (2018) quantify the potential on the performance of integrating ESG strategies on emerging market equities using equity indices of this market; the result showed significant outperformance of ESG-based strategies. Furthermore, Giese & Nagy (2018) show that unlike ESG scores, which are historically correlated with quality factors and value factors, ESG scores momentum has historically been uncorrelated to any equity style factors. The authors define ESG momentum as year-on-year changes of MSCI industry-adjusted ESG scores. They also express that companies with positive ESG score momentum outperformed companies with negative ESG score momentum, suggesting that changes in the ESG profile may be useful when analyzing a company's valuation.

Most of the research related to ESG investing so far is based on the equity index level or based on the approaches that screening ESG scores at a specific quantile. There is yet no report based on the parametric approach for the large-scale portfolio which utilizes ESG information, especially ESG Score change as an characteristic. In this report, the ESG information will be integrated into the asset allocations process using the parametric method introduced by Brandt et al. (2009), targeting to maximize Sharpe Ratio.

2.4. Portfolio performance evaluation

It is important that investors acknowledge the relative performance of the investment portfolio for further investment decisions and other related decisions. According to Samarakoon & Hasan (2006), the performance evaluation methods include the conventional and risk-adjusted methods.
Conventional methods refer to benchmark comparison and style-based comparison. Benchmark comparison is a classic way that compares results of investment return in a specific period to the benchmark portfolio. On the other side, style comparison compares returns of the target portfolio to a similar investment style. Both measures suffer from a similar issue of not considering the risk level of the investment. The Risk-adjusted methods take into account the differences in risk levels between the target portfolio and benchmark portfolio. Many methods are being used in practice, such as Sharpe Ratio, Jensen’s alpha, Treynor Ratio, Modigliani and Modigliani, or Treynor Squared. In the bound of this report, I will select to discuss two of the mentioned ratios:

2.4.1. Sharpe Ratio

The Sharpe Ratio (SR) is considered the simplest measure in the risk-adjusted method (Argon & Ferson, 2006). SR measures the risk premium of an investment portfolio per unit of portfolio's risk or also called the "reward to variability" ratio.

$$SR = \frac{E(R_p - R_f)}{\sigma_{R_p}},$$

in which R_p is portfolio return, R_f is the risk-free rate, σ_{R_p} Standard deviation of portfolio return.

As SR measure the excess return investor can get per risk unit, the higher SR, the better portfolio's performance is. In general, SR (annualized) above one is considered good as the excess return compensates for the risk level being exposed. However, it is more informative when compare the SR value with other assets or benchmarks. The limit of SR is that it assumes portfolio returns are normally distributed. It may be inappropriate when returns are highly non-normal. SR can be misleading in the case of the skewed return distribution. However, the skewness of equity returns distribution is mainly driven by surprising drops in stock prices, while standard deviation assumes that it is equally risky for both side movements.

Despite some drawbacks, SR is still a common measure for portfolio performance in practice.

2.4.2. Jensen's alpha

The original version of Jensen's alpha is based on the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966). Jensen's alpha is defined as the intercept in the OLS regression model:

$$r^e_{p,t} = \alpha^J_p + \beta_{Mkt} r^e_{Mkt,t} + \varepsilon_{p,t},$$

where: $r^e_{p,t}$ portfolio excess return

$r^e_{Mkt,t}$ market excess return

Jensen's alpha measures if the average return of a portfolio is higher or lower than that predicted by the CAPM model, given the portfolio's beta and average market excess return. Positive alpha suggests that earning rate of the portfolio is exceeding the expected return given its market risk. Since Jensen's alpha is based on the assumption of the CAPM model with a single market risk factor. One of its disadvantages is that it does not control systematic risk unrelated to firm-specific risk; it also does not take the portfolio volatility into account. The alpha in the Multi-beta

Regression Model is considered as an extension of Jensen's alpha using the same logic as CAPM alpha.

$$r_{p,t}^{e} = \alpha_{p}^{M} + \sum_{i} \beta_{i} F_{i,t} + \varepsilon_{p,t} ,$$

Where F_i is a risk factor "i" in the assumed asset pricing model.

In addition to the traditional methods of portfolio valuation, asset managers have been shifting their attention in the past decades into market risk management with the rise of Basel II and Basel III accords as the frameworks for the financial system. As a result, value at Risk (VaR) and Expected Shortfalls (ES) have become the key quantitative measures of market risk for risk management and regulatory purposes. Financial institutions and professional asset managers use VaR and ES to estimate the maximum potential loss of the investment portfolios in a period for a given confidence level.

2.4.3. Portfolio Risk

VaR is basically defined as the maximum loss expected of an investment at a certain confidence level over a given time period. Expected Shortfalls (ES) is the mean of the losses, given that losses are greater than those under VaR at the same confidence level.

Ho & Lee (2006) document three common methods to estimate the VaR/ES of a portfolio: the parametric (variance-covariance) or delta-normal method, the historical method, and the Monte-Carlo simulation method. (i) The parametric method involves the first moment and standard deviation of portfolio return. This method looks at the investment price movements over a look-back period. It employs probability theory to estimate the maximum portfolio loss with the assumption of normal distribution of the loss. (ii) The historical method: resample data using empirical distributions. It is assumed that the loss is following empirical distribution. In this method, the movement of risk sources is observed through a historical period. A number of random indices are generated to draw data in the data set to simulate return over that period. VaR is calculated based on the change in resampled losses by locating the x-percent percentile of losses. (iii) Monte-Carlo simulation: generate sample realization using random draws and creating several scenarios using a forward-looking estimate of the change in value or volatilities of each scenario; VaR is calculated based on the percentile of simulated losses generated.

Lopez & Walter (2001) examine the performance of different VaR models using a portfolio of foreign exchange rates. The result shows that under standard statistical loss function, the covariance matrix model appears to perform best. The authors also denote that the performance of VaR models depends more on the distributional assumptions than on the covariance matrix specification. Berkowitz & O'Brien (2002) argue that given large-scale trading positions with several risk factors, it is impossible for structural models to accurately measure the joint distribution of all material market risk factors, as well as the relationship between all risk factors and trading positions. The author suggested the potential of using a Generalized Autoregressive Conditional Heteroskedasticity (Garch) VaR forecast. It applies Garch to portfolio returns instead of applying Garch at the risk factor level. In contrast, Santos et al. (2013) compare multivariate and univariate Garch models to forecast portfolio VaR with the conclusion on the outperformance of multivariate models against their univariate counterparts on an out-of-sample basis. The paper also suggests that the dynamic conditional correlation model with Student’s t errors seems to be the most appropriate specification for the VaR estimation in the real portfolios analyzed. Different VaR models might work well under different assumptions. Choosing which model to use should base on the research purposes and the assumptions made.

2.4.4. Portfolio Diversification

In addition, investors might put concern on portfolio diversification. The argument made is based on the fact that the number of available stocks is lower than that of the market-wide level. Moreover, when we apply the short-sale constraint on the policies, the number of long-only positions holding a portfolio will decrease. As fewer stocks are included in the portfolios, it raises the possibility that our targeted strategies could entail an increase in risk through a loss of diversification. However, Hoepner (2010) provides evidence on the significant negative relationship between a firm’s ESG rating and its specific risk by developing a model based on stocks' numbers, correlation of stocks, and average specific risk of stocks. The author’s theory indicates that including ESG criteria is likely to worsen portfolio diversification via the first two drivers while improving portfolio diversification by lowering the average stock’s specific. Verheyden et al. (2016) affirm the result showed by Hoepner (2010) with the conclusion that ESG screening does not lead to large diversification losses, on average. Hoepner (2010) also expresses that stock with high ESG criteria has been found to experience significantly under-proportional specific risk. The use of ESG criteria might be beneficial for portfolio diversification in some situations.

3. Data

3.1. Data Overview

In conducting further analysis of this report, I begin by selecting the Dataset and defining the investment universe. Data are observed from the US stock market from 2008 to 2020, monthly, and at the individual stock level. The stock level data is chosen rather than the equity index level, purposing to deploy the parametric approach on large-scale assets portfolio in a high-dimensional setting with ESG information integration.

The period is picked to facilitate information after the establishment of the United Nations Principles of Responsible Investment (PRI) in 2006; the rising concern of sustainable investment after the global financial crisis in 2008, as well as the release of the ESG Manual for Investors by the Chartered Financial Analyst (CFA) in 2008. Moreover, the desired trading period is set to be ten years, starting from 2010; subsequently, the data on characteristics should contain the two-year look-back figures to serve the investment selection process. The choice of asset characteristics is motivated by the empirical results from previous research papers, especially based on the work of Brandt et al. (2009). However, due to the limit of data on BTM, which appears to show too many negative values (about 45%) of the sample, I use the Sales to Enterprise Value (S/EV) ratio as an alternative.

Data are mainly extracted from the Refinitiv (Thomson Reuters) Platform, one of the dominant platforms globally providing financial market data and infrastructure. In terms of ESG rating, Refinitiv provides ESG scores for 9,000 public companies globally (Refinitiv, 2021), including ESG scores, ESG Controversies Score, and ESG Combined Score. Refinitiv ESG scores are provided in numerical format; therefore, it would be more convenient to use than that of other ESG rating providers such as MSCI, which is in alphabet format. ESG Controversies are updated continuously when the events occur and get picked up by international media. ESG Scores are not updated at a particular date in the year; it depends on the industry and company self-report. Since ESG combined scores (as a combination of ESG Controversies and ESG Scores) are considered more dynamic than ESG scores, I will use ESG combined scores for further analysis. Moreover, as ESG combined score is based on ESG Score – which is updated annually, the latest update of ESG combined scores (2018, 2019) should be available for the following time (2019,2020). For further convenience, the ESG combined score used in this report is called as ESG Score, in general.

The process of investment universe construction begins with identifying all firms which have a positive available ESG Score[4]. Using the screener function of Reuters Eikon, the list of all stocks that have positive ESG scores is created. Based on the available stocks with positive ESG scores with correspondent RIC codes, data on characteristics are downloaded using Refinitiv DataStream. The data includes Market Value (ME), Stock Price, ESG Combined Score, Dividend, Sale to Enterprise Value (S/EV), Book-to-Market (BTM) ratio, and Sales to Price ratio (S/P).

Stocks with less than two years of continuously available return data or ESG scores will be removed from the universe. Moreover, as S/EV is characteristic of interest, to prevent survival bias, stocks with less than one year of S/EV data available provided by Refinitiv are also excluded in this report. The stock price of month t that less than one will be modified to invalid value or not available at that month. Since two factors drive the company's year-over-year ESG scores: the company's relative ranking against its peers and changes in underlying data reported by the company, which lead to false data in metric value, some companies[5] that did not update their ESG report will have drastically dropped in 2020 ESG score (i.e., from above 50% to 1%); moreover, checking on peer vendors data shows no related ESG scandal nor ESG downgrade viewed. Thus, the latest available scores will be applied for the mentioned year. The screening process is performed by VBA. Among 2903 stocks with a positive ESG score as of 31 Dec 2020, 2333 stocks were chosen to form the specified investment universe.

To avoid a low level of ESG scores in the target portfolios, the stock with an ESG score less than the 10^{th} percentiles of the universe at month t will be set as not available. This setting is based on the low threshold recommended by Verheyden et al. (2016) to improve the investment universe's quality without any impact on the diversification potential, even though the investors are entirely uninterested in sustainability by themselves.

As earlier mentioned, risk factors include HML, SMB, WML, RF, Mkt-RF are downloaded from Kenneth French's Data Library. To avoid extreme values and outliers, the bottom and top 10% of characteristics, including BTM, SEV, and SP, are set at the mean level of the correspondent variable. This outlier filtering level is set at 1% for monthly return, subsequently resulting in the neutral effect of those items for such variables. (Histogram on adjusted and un-adjusted variables can be found in Appendix H).

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[4] The process begins with ESG Scores instead of ESG Combined Scores to avoid companies that have negative ESG Score but still have positive ESG Combined Scores (at low level: <1).

[5] These companies included HES.N, DFS.N, CVM.A, MTSC.OQ, JEF.N, AZPN.OQ.

3.2. Descriptive statistics of data

Our Dataset contains 156 months of observations observed from the market from 31Jan2008 to 31Dec2020, of 2333 stocks with positive ESG Scores available at the end of 2020[6]. The total market value of the investment universe as of 31 Dec 2020 was about US$36.90Trillions, account for 72.6% of the US stock market (Total Market value of 50.809Trillions). The biggest company in terms of market value in the investment universe during the observed period is Apple (AAPL.OQ). Technology and Consumer Discretionary are in the top two industries in terms of market capitalization. Utilities and Other industries are the two industries that have the highest ESG scores in our investment universe by 2020 year-end.

Table 3.1: US Data by Industries as of 31 Dec 2020

Industries	Number of Companies	Average of ESG Score	Sum of Cap ($bio)
Basic Materials	93	45.51	608.70
Consumer Discretionary	372	40.98	6,791.19
Consumer Staples	83	48.56	2,026.21
Energy	121	36.02	914.41
Financials	381	37.30	3,515.34
Health Care	364	35.58	4,833.40
Industrials	362	41.44	4,916.56
Others	3	78.43	219.13
Real Estate	179	46.20	1,286.55
Technology	242	41.15	9,464.21
Telecommunications	58	33.70	1,188.11
Utilities	75	51.14	1,138.66
Grand Total	**2333**	**40.41**	**36,902.46**

Source: author's calculation based on Refinitiv Data

Table 3.2: Data Summary

	Mean	Min	Max	Median	Std	Count
Return (monthly)	0.014	-0.975	18.584	0.011	0.145	301,133
SEV	0.819	-1000	1000	0.448	5.039	283,589
ESGS	37.936	0.390	92.660	35.170	17.357	210,445
ESGSL18	7.424	-76.160	87.510	2.970	14.362	208,112
ME(US$bio)	9.444	0.000	2232.280	1.602	36.793	305,186
Adjusted Return	0.013	-0.786	0.992	0.011	0.127	300,802
Adjusted SEV	0.729	-2.933	5.714	0.442	0.829	280,438

Source: author's calculation.

The number of stocks available in our investment universe is on an upward trend, which means that more and more firms with available sustainable information are provided. As the time

[6] Subsequently, the dataset includes 363,948 firm-month observations, 1,308,468 characteristic-firm-month observations.

gets closer to the 2020 year-end, the more firms we have in our investment universe. The average number of stocks available in our investment universe is 1,300 securities. The mean ESG Combined Scores of our universe is about 37.94 percentage points, with the highest score in the investment universe is 92.66 percentage points. The average score change in the last 18 months is 7.42 percentage points. This suggests that the average level of Sustainable ratings in the US market is just slightly above the median level. As of 2020 year-end, 75% of the stocks in the investment universe were scored under 50 percentage points; only 5% of stocks in the sample have ESG Score higher than 75 percentage points. While the average score is low in general, the average improvement of ESG rating is also not so high; the variance of score changes is quite significant.

Table 3.3: Data breakdown by market capitalization as of 31 Dec 2020

	Penny (<=2bil)	Mid-Cap (2-10bil)	Large Cap (>10bil)	Total
Number of stocks (N)	1,059	760	514	2,333
N/Total stocks	45.39%	32.58%	22.03%	100.00%
Total Cap	862.67	3,504.09	32,535.70	36,902.46
Avg ESG Score	31.61	41.16	57.44	
Max	80.51	92.66	93.20	
Min	0.46	0.95	0.26	

Source: author's calculation.

The breakdown by market capitalization shows that almost a haft number of our investment universe are Penny stocks, which account for only 2.3% of the total value of the investment universe. 22% of the stocks are large-cap companies and account for 88.17% total value of the investment universe. The gap between the average ESG Score of one group to the next group is ten percentage points. Moreover, the min-max values in table 3.3 motivate that small companies do not always have low ESG Scores, and likewise, large companies are not always focusing on a sustainable perspective.

For a better understanding of our Dataset, especially data on ESG information, In the following part, I will describe the data related to S/EV, ESG Score, and ESG Score Changes. Other data definitions are presented in Appendix A.

3.3. Sales to Enterprise Value and ESG Data definitions:

3.3.1. Sale to Enterprise Value ratio (S/EV)

S/EV measures the price of a company's value in terms of its sales. The higher the S/EV ratio, the more attractive investment it is, considering that the company is relatively undervalued. S/EV can be calculated as:

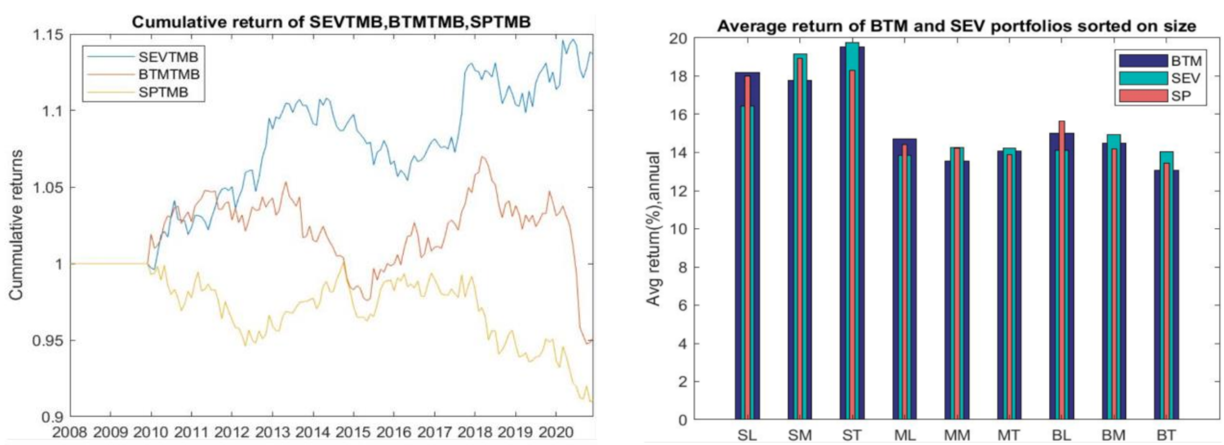
$$\textbf{S/EV} = \frac{\text{Annual Sales/Revenues}}{\text{Market Capitalization} + \text{Debt} - \text{Cash and Cash equivalents}^{7}}$$

S/EV involves both company's equity value and debt loads.

Investigate the performance of the BTM, S/EV, and S/P in our investment universe shows that S/EV well captures the performance pattern of the BTM ratio (see figure 3.1). The left side of Figure 3.1 gives us a visual image of the cumulative return of SEVTMB, BTMTMB, and SPTMB. The three series are created similarly by taking the gap between the top 3 portfolios with a high SEV ratio and the bottom three portfolios having a low SEV ratio.

SEVTMB = 1/3(Small High+Middle High +Big High) – 1/3 (Small Low + Middle Low + Big Low)

Figure 3.1: Performance of SEV, BTM, SP sorted on size



Source: author's calculation.

Therefore, S/EV is used as an alternative characteristic instead of BTM ratio when conduction parametric portfolio building in this report.

---

[7] Cash:

For Insurance Companies: Cash, Banks: Cash and Due from Banks, other industries: Short-Term Investments.

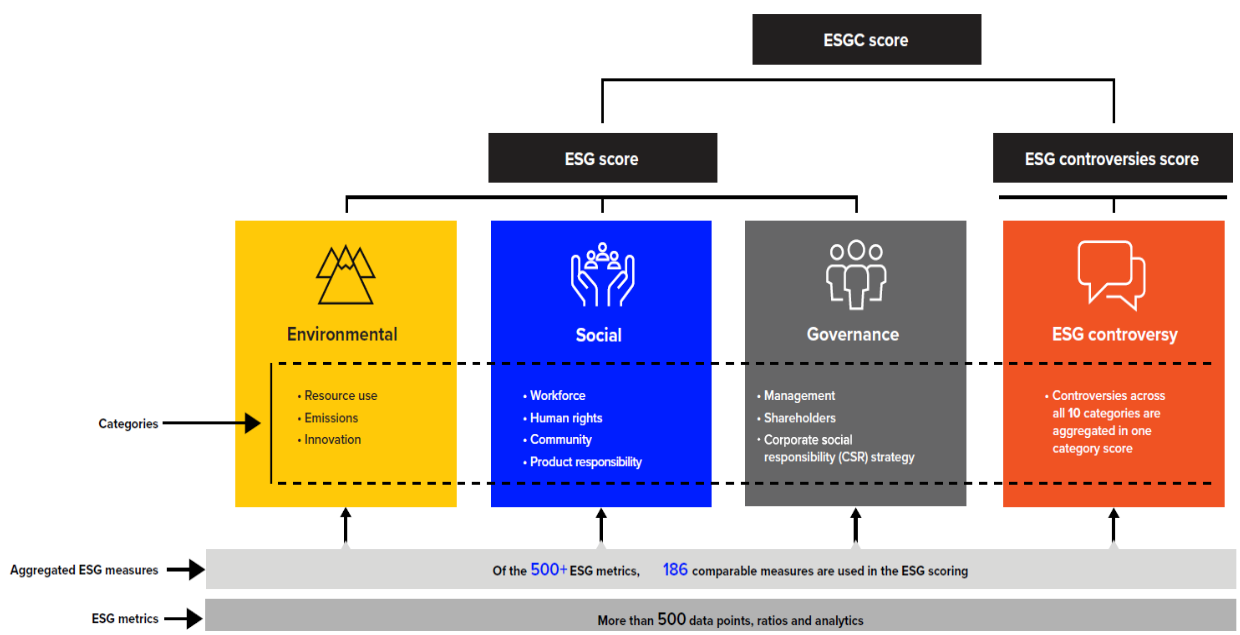
For Multiple-type ordinary shares company: Market Capitalization represents the company's total market value calculated as the total number of common equivalent shares (listed and unlisted) multiplied by the price of the primary issue at fiscal year-end date.

3.3.2. ESG Characteristics*:*

ESG Scores (ESGS)*:* A comprehensive measure of the company's commitment to socially responsible (SRI) and ESG (Environmental (E), Social (S), and Corporate Governance (G)) performance based on verifiable reported data in the public domain. In addition to the three pillars (E, S, and G), the aggregated ESG Score also refer to the ESG controversy score.

Refinitiv captures and calculates over 500 different ESG metrics, in which a sub-set of 186 of the most comparable measures are used in the ESG scoring (Refinitiv, 2021). The score ranges from 0 to 100 percentage points. It is equivalent to 12 panels of grade; the lowest is 0.0 to 8.333 percentage point, equal to D-, the highest is in the range of 91.6666 to 100, equivalent to A+. ESG Scores within the first quartile (0 to 25) indicate poor relative ESG performance and insufficient degree of transparency in reporting material ESG data publicly. The Scores within the second quartile present satisfactory relative ESG performance and a moderate degree of transparency in reporting material ESG data publicly. Scores in the range between 50 to 75 indicate good relative ESG performance and an above-average degree of transparency in reporting material ESG data publicly. A score higher than 75 represents excellent relative ESG performance and a high degree of transparency in reporting material ESG data publicly (Refinitiv, 2021).

Figure 3.2: ESG Score metrics



Source: (Refinitiv, 2021)

ESGSL18: ESGSL18 is created by looking at the ESG Score changes within a specific period. To avoid 1-year unchanged scores (ESG score is updated annually), lag 18-months ESG Score (t-18 to t-1) is used. The idea of ESG score changes was inspired by Giese & Nagy (2018), in which ESG score momentum presents a year-on-year change of ESG scores. Giese & Nagy (2018) argue that excluding zero updated ESG score firms, 12 months ESG Scores looked back is reasonable as the 6-months period provided noisy and almost flat performance while lag 24 months delivered weaker performance signal. Giese & Nagy (2018) suggest that ESG score change gives stable and robust performance results only with a time horizon that used scores changes of at least one year. Employment of score changes between 12 months and 24 months is reasonable. Moreover, it is observed that the ESG profile of most firms in the investment universe was not updated for 2020; a major part was not updated since 2019. To avoid too many stocks with zero ESG updates, a lag of 18 months of ESG score is used in this report.

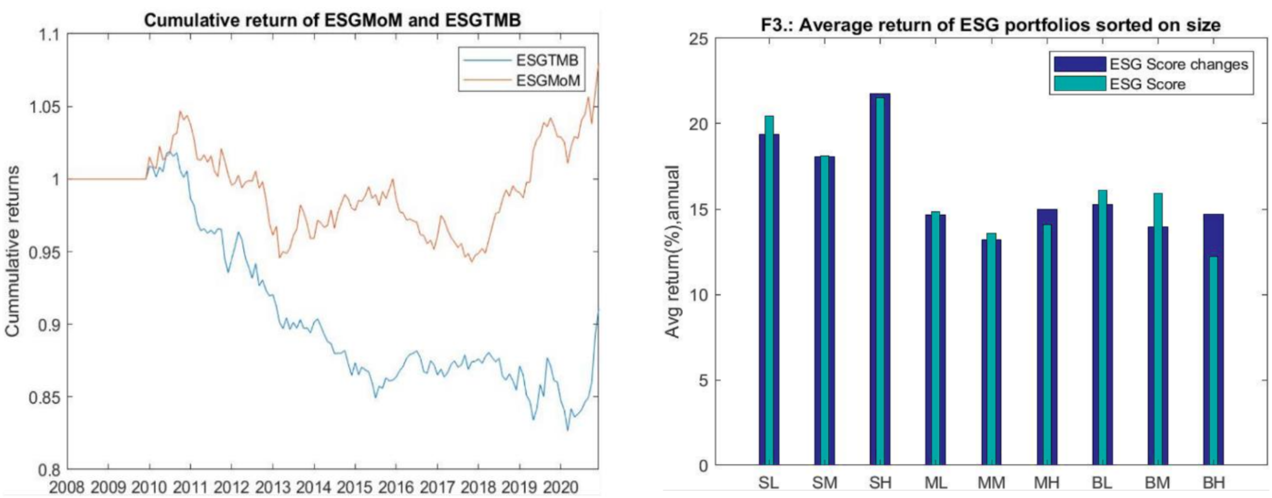
3.3.3. ESG Risk factors:

ESGMoM – ESG Score momentum**:** ESG momentum factor is created based on the same intuitive idea of the return momentum construction process. Accordingly, I create monthly quintile breakpoints based on the calculated ESG score changes in the last 18 months (ESGSL18). The 30th and 70th percentile of calculated ESGSL18 are used as breakpoints for the ESG portfolio construction. For the stock's size classification, the 30th and 70th percentile of market value are used as a breakpoint to sort companies into small, middle-, or big-sized categories. The sorting is executed independently, the intersections between the top (70%) or bottom (30%) ESG score momentum quintile and size classification form ESG momentum portfolios (Small Top (ST), Small Medium (SM), Small Bottom (SB), Big Top (BT), Big Medium (BM), Big Bottom (BB)) which we can use to construct the monthly ESGMoM as follow:

$$\text{ESGMoM} = \frac{1}{3}\ (Small\ Top + Big\ Top + MiddleTop) - \frac{1}{3}\ (Small\ Bottom + Big\ Bottom + Middle\ Top)$$

The same mechanism is applied to calculate ESGTMB based on the breakpoints of ESG Scores and companies' size. The left panel of figure 3.2 shows the cumulative return of ESGMoM and ESGTMB, and the right panel shows the average return (annualized) of ESG scores and ESG score changes portfolios sorted on size. It is suggested that in both cases, growth firms provide higher expected (annual) returns than value firms. It captures the same pattern as the value factor. In terms of ESG scores, small firms with higher scores are likely to have higher average returns than small firms with lower scores. However, big firms with lower scores provide slightly higher returns(average) than big firms in the top ESG Score. The same pattern is most likely applied to the ESG Score changes, that growth firms who focus on improving ESG scores will have higher average returns than small firms with less sustainable profile improvements. In contrast, big firms with lower changes in ESG scores within the last 18 months provide higher average returns than the ones that have higher ESG Score increments. The plot in the right panel of figure 3.3 suggests that the performance of ESG stocks also depends on the company size.

Figure 3.3: Cumulative return of ESGMoM and ESGTMB



Source: author's calculation.

4. Methodology

This study is aiming to explore the possibility of integrating ESG information into parametric portfolio policies. The main idea is to build optimal investment strategies based on asset characteristics, using the approach proposed by Brandt, et al. (2009). Transaction cost and Short-sale constraints are also considered to evaluate the performance of portfolios.

4.1. Brandt et al. (2009) 's approach on parametric portfolio policy:

Brandt et al. (2009) suggested taking into account factors that can predict the future relative performance of different assets by picking θ^T - a vector of coefficients such that the resulting portfolio returns maximize the conditional expected utility of the portfolio return $r_{p,t+1}$

$$\max_{\{w_{i,t}\}_{i=1}^{N_t}} E_t\left[u\left(r_{p,y+1}\right)\right] = E_t[u(\sum_{i=1}^{N_t} w_{i,t} r_{i,t+1})].$$

The optimal portfolio weights are defined as a linear function of the stock's characteristic, which applies to all stocks, instead of estimating one weight for each stock.

$$w_{i,t} = \overline{w}_{i,t} + \frac{1}{N_t}\theta^T \hat{x}_{i,t} ,$$

The return of portfolios is written as: $r_{p,t+1} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1}$,

In which $\overline{w}_{i,t}$ stands for weight allocated to stock i at date t in value-weighted market (benchmark) portfolio, θ is a vector of coefficient parameters to be estimated, and $\hat{x}_{i,t}$ are the cross-sectionally standardized characteristics of stock i (zero mean and unit standard deviation) across all stocks at time t. The market capitalization of the stock (ME), the book to market ratio of the stock (BTM), the lagged 12-month return on the stock (LR12) are specified as asset characteristics in this model.

The key assumptions of these specifications are (1) investors have constant relative risk aversion (CRRA) preference over wealth with relative risk aversion γ =5, and (2) the coefficient parameters are time-invariant. Portfolio weight constraints, time-varying coefficients, and transaction costs were considered as extensions of their policies for further discussions.

4.2. Short-sale constraint

The short-sale constraint is also applied to the targeted strategies to check behavior further when only long positions are applied. The effect of intended and unintended bets on portfolio performance is revealed when comparing the results between these policies. Brandt et al. (2009) introduce the method of truncating the weights in parametric portfolios at zeros. Portfolio weights are then being renormalized to ensure the sum to one of the optimal portfolio weights.

$$w_{i.t}^{+} = \frac{\max[0, w_{i,t}]}{\sum_{j=1}^{N_t} \max[0, w_{i,t}]} .$$

4.3. Transaction cost's presence

We care about transaction costs and turnovers in active trading as they hurt fund performance (Carhart, 1997).

a. Portfolio Turnover

Portfolio turnover is calculated to measure the trading activity (percentage of the portfolio has to be reallocated) to maintain the optimal weights. Suppose we were to rebalance the portfolio at the beginning of each month. The portfolio weights change by the individual stock returns during the previous month. The remaining weights of asset i in portfolio j can be calculated as:

$$\widetilde{w}_{i.t}^{j} = w_{i,t-1}^{j} \frac{1+R_{i,t-1}}{1+\mathrm{R}_{p,t-1}^{j}} \quad , \quad R_{p,t-1}^{j}: \text{return of portfolio j at month t-1.}$$

Turnover of portfolio j at month t:

$$Turnover_t^j = \frac{1}{2} \sum_{i=1}^{N_t} \left| w_{i,t}^j - \widetilde{w}_{i.t}^j \right| .$$

b. Portfolio adjusted returns.

In the presence of transaction cost "trans_cost" the monthly adjusted return of portfolio j is written as:

$$\tilde{R}_{p,t}^{j} = \sum_{i=1}^{N_t} (R_{p,t}^{j} - trans\_cost \left| w_{i,t}^{j} - \widetilde{w}_{i.t}^{j} \right|) ,$$

the objective function in the presence of transaction cost can be rewritten as:

$$\max_{\theta_j{}^T} \frac{E\left[\tilde{R}_p^j\right] - E[RF]}{std(\tilde{R}_p^j)} .$$

Transaction cost will be considered for the given policies to see the trade-off in the presence of the proportional transaction cost of stock i at time t. In addition to the ideal condition where there is no transaction cost. This report tests the performance of different transaction cost levels, including

10bps, 30bps, 50bps, and 100bps. Different transaction cost levels are considered to understand the tendency and tolerance of active trading policies using a parametric approach.

4.4. Portfolio Building

4.4.1. Portfolio policies

According to Brandt, et al. (2009), applying maximum Sharpe Ratio as an objective function provided similar investment exposures to maximizing γ =5 CRRA. This report focuses on the risk-adjusted return level the investors could get when it comes to sustainable investment. Considering the object of interest is to maximize the risk-adjusted return ratio, the optimal weights allocation in this report is created by picking θ^T to maximizing Sharp Ratio (SR) that:

$$\max_{\theta^T} SR = \frac{E[R_p]-E[R_f]}{\sqrt{\mathrm{Var}(R_p)}} \qquad (1),$$

Where:

R_f is the risk-free rate.

$$R_{p,t+1} = \sum_{i=1}^{N_t} w_{i,t} R_{i,t+1},\ and\ w_{i,t} = \bar{w}_{i,t} + \frac{1}{N_t}\theta^T \tilde{x}_{i,t} \qquad (2),$$

N_t as the number of assets allocated at time t.

θ^T is assumed to be time-invariant.

Brandt et al. (2009) consider the set of three characteristics, ME, BTM, and LR12, to be specified in their weight functions. However, due to the BTM data series' availability, as discussed in the data section, this report considers S/EV an alternative characteristic to BTM. Besides, non-financial information includes ESG score (ESGS), and ESG scores 18months look back (ESGSL18), which are considered new characteristics and build the desired portfolios. The portfolio rebalance is performed monthly; only tradeable stocks (available stock prices) with available Market Value are considered to be allocated in the strategies.

While Brandt et al. (2009) build the optimal portfolio based on a parametric approach with three characteristics (ME, BTM, and LR12) and compares it with the value-weighted portfolio as a benchmark portfolio; this report uses the same parametric mechanism to build four policies, in which the equal-weighted portfolio is considered as the benchmark (portfolio 1); the other three portfolios (portfolios 2, 3, and 4) are using the parametric approach with additional characteristics (ESGS, ESGSL18), details as follows:

Portfolio 1: I define a baseline/benchmark portfolio as a portfolio of all available assets in our investment universe with equal-weighted allocation. (P1).

$$w^1{}_{i,t} = \frac{1}{N_t} \quad (3).$$

One possible argument for this benchmark allocation in our investment universe is that equal-weight allocation is more efficient than value-weighted allocation, to the extent that while it requires less information to be collected, a higher average return is recognized. The following graphs on cumulative returns of equal weight policy outperformed the value-weighted portfolio, both with or without transaction cost (100bps).

Figure 4.1.a. Cumulative return of baseline equal-weighted return and value-weighted return – no cost

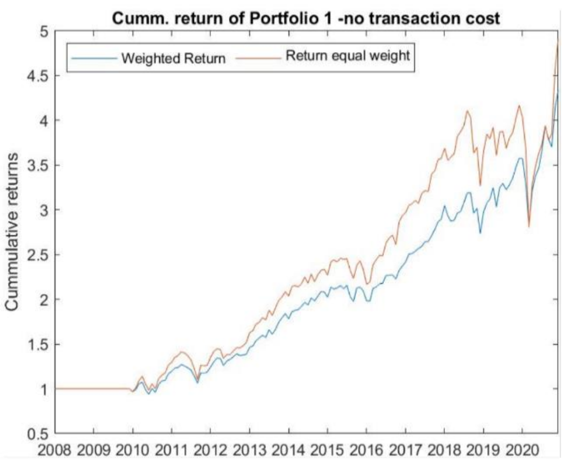
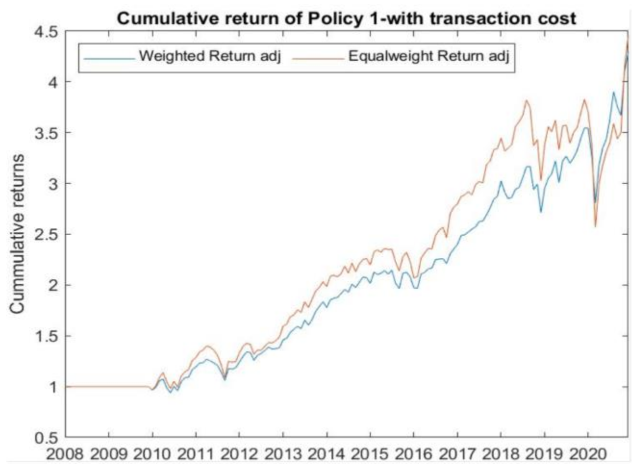


Figure 4.1.b. Cumulative return of baseline equal-weighted return and value-weighted return – 100bps trans_cost



Source: author's calculation

Portfolio 2: The second portfolio is built based on the method described in Brandt et al. (2009). In which the optimal portfolio weights will be parameterized as a function of the stock's characteristics"; As previously described, stocks with ESG score lower than the 10^{th} percentiles of the universe's ESG scores at month t will be sorted out of the investment list of that month. Subsequently, the investment universe is considered as an ESG screened universe. Portfolio 2, hereafter called parametric ESG screened.

$$w^2{}_{i,t} = \overline{w}_{i,t} + \frac{1}{N_t}\theta^T \tilde{x}_{i,t} , \ \tilde{x} = \widetilde{ME}, \widetilde{SEV}, \widetilde{LR12} \quad \text{(P2) ,}$$

$$w^2{}_{i,t} = \frac{1}{N_t}(1 + \theta_1^2 \widetilde{ME}_{i,t} + \theta_2^2 \widetilde{SEV}_{i,t} + \theta_3^2 \widetilde{LR12}_{i,t}) \quad (4),$$

$\tilde{x}$: the cross-sectional standardized version of x, to have a mean of zero and standard deviation of one across all stock in the portfolio at time t. By this setting, it is expected that the total weight of the optimal portfolio is always summed to one. Normalized variables also provide us the possibility to compare the magnitude of optimal parameters directly. Z-score normalization method would also be applied to the variables in the following portfolios:

Portfolio 3: The third portfolio is built in a similar way to Portfolio 2; however, the additional characters will be added into the model, using ESG score as asset characteristic: hereafter called parametric ESG scores:

$$w^3{}_{i,t} = \bar{w}_{i,t} + \frac{1}{N_t}\theta^T\tilde{x}_{i,t} \text{ , } \tilde{x} = \widetilde{ME}, \widetilde{SEV}, \widetilde{LR12}, \widetilde{ESGS} \qquad \text{(P3) ,}$$

$$w^3{}_{i,t} = \frac{1}{N_t}(1 + \theta_1^3\widetilde{ME}_{i,t} + \theta_2^3\widetilde{SEV}_{i,t} + \theta_3^3\widetilde{LR12}_{i,t} + \theta_4^3\widetilde{ESGS}_{i,t}) \qquad \text{(5).}$$

Portfolio 4*:* Lastly, the ESG momentum score will replace the ESG score in Portfolio 3 to establish Portfolio 4. Momentum ESG is calculated by the change of ESG score in the past 18 months: hereafter called parametric ESG momentum.

$$w^4{}_{i,t} = \bar{w}_{i,t} + \frac{1}{N_t}\theta^T\tilde{x}_{i,t}, \ \tilde{x} = \widetilde{ME}, \widetilde{SEV}, \widetilde{LR12}, \widetilde{ESGSL18} \qquad \text{(P4) ,}$$

$$w^4{}_{i,t} = \frac{1}{N_t}(1 + \theta_1^4\widetilde{ME}_{i,t} + \theta_2^4\widetilde{SEV}_{i,t} + \theta_3^4\widetilde{LR12}_{i,t} + \theta_4^4\widetilde{ESGSL18}_{i,t}) \qquad \text{(6),}$$

The part of $\frac{1}{N_t}\theta^T\tilde{x}_{i,t}$ is considered as the deviation part of the weights from the baseline ($\bar{w}_{i,t}=\frac{1}{N_t}$). value of the deviation part at month t depends on the value of the standardized characteristic $\tilde{x}_{i,t}$ and magnitude level of coefficient parameters θ^T. The parameters are found through the optimization process of the following objective. Portfolios are rebalanced monthly to maintain the desired levels of optimal weights.

4.4.2. Optimal parameters and statistical inference

As specified earlier, our optimal parameters are solved by maximizing the Sharpe Ratio. The optimal parameters can be found using the numerical method by Matlab function. Moreover, it is essential to set constraints when doing numerical using the “fmincon” function.

The constraint is set as below:

$$w_{i,t} = \frac{1}{N_t} + \frac{1}{N_t}\theta^T \tilde{x}_{i,t} \geq 0 \Leftrightarrow \frac{1}{N_t}\theta^T \tilde{x}_{i,t} \geq -\frac{1}{N_t} \Rightarrow \theta^T \tilde{x}_{i,t} \geq -1,$$

The optimal problem can be written as:

$$\max_{\theta^T} SR = \frac{E[R_p]-E[R_f]}{\sqrt{\mathrm{Var}(R_p)}} = \frac{\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_t}\frac{1}{N_t}(1+\theta^T\tilde{x}_{i,t})(R_{i,t}) - \frac{1}{T}\sum_{t=1}^{T} R_{f,t}}{\sqrt{\sum_{t=1}^{T}(\frac{1}{N_t}(1+\theta^T\tilde{x}_{i,t})R_{i,t} - \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N_t}\frac{1}{N_t}(1+\theta^T\tilde{x}_{i,t})R_{i,t})^2}},$$

w.r.t: $\sum_{i=1}^{N_t}\left(\frac{1}{N_t}\theta^T\tilde{x}_{i,t}\right) = 0$ and $\theta^T\tilde{x}_{i,t} \geq -1$.

The standard error of estimated parameters can be estimated through the bootstrap resampling method. The bootstrap experiments are as follows:

- Number of bootstrap samples to perform: nboot = 1000
- Size bootstrap samples: same size as original data sets, resampling with N assets, and T month of observations.
- For each bootstrap sample, I draw random samples with replacement. Sampling with replacement means that each observation is selected separately as a random from the original data set; this leads to the possibility that a particular observation from the original data set could appear many times in a bootstrap sample. However, it is acknowledged that trading activities happened from month t = 201001 of the data sample. The random index will be drawn for observations from month t-1 to T to avoid unnecessary information.

In addition, as our data sets contain many variables such as asset returns (net returns, cumulative returns), asset characteristics (ME, SEV, LR12, ESGS, ESGSL18), the sampling is performed in parallel from these variables. Random observation's index can be conducted in one variable and a selected sample of all variables in original data sets using that same random index.

- Calculate optimal parameters in exactly the same way as they were in original data sets.
- Standard Error (SE) of estimated parameters can be calculated as the Standard Deviation (SD) of nboot parameters estimated from the bootstrap repetitions).

4.5. Risk profile performance

Portfolio's Value at Risk (VaR) and Expected Shortfall (ES) would be considered for further risk evaluation. In the constraint of data available for ESG score, as our data using for the period from 2008 to 2020, it is acknowledgeable that empirical loss distribution assumption should not be applied due to the sensitivity with time horizon and realized events (worst-case scenario never beyond real cases happened).

The plot of return density and autocorrelation in Appendix I indicates that the t-distribution of portfolio returns fits the density better than the normal distribution assumption. Moreover, it is obvious that the first lag of our portfolio returns is significantly auto-correlated. The loss is assumed to have a t-distribution to accommodate fat tails and larger kurtosis (compared to kurtosis = 3 normal distribution). The probability density (pdf) function for the t-distribution is:

$$f(x) = \frac{\Gamma(\frac{v+1}{2})}{\sqrt{v\pi}\Gamma(\frac{v}{2})}[1+\frac{x^2}{v}]^{-(v+1)/2} = \frac{\Gamma(\frac{v+1}{2})}{\sigma\sqrt{(v-2)\pi}\Gamma(\frac{v}{2})}[1+\frac{1}{v-2}(\frac{x}{\sigma})^2]^{-(v+1)/2},$$

$\sigma = \sqrt{\frac{v}{v-2}}$: standard deviation

v : degrees of freedom ($v > 2$ $for\ variance\ to\ exist$)

μ : sample mean.

Γ : gamma function

VaR and ES at confidence level $\alpha \in (0,1)$ are defined as:

$VaR_\alpha(L) \equiv \inf\{x \in \mathbb{R} : P(L \geq x) \leq \alpha\}$ $0 < \alpha < 1$,

$VaR_\alpha(L) = \inf\{x \in \mathbb{R} : F_L(x) \geq \alpha\} = F_L^{-1}(\alpha)$ $0 < \alpha < 1$ (7),

in which $F_L(x)$ is the cumulative distribution function(cdf) of L, F_L^{-1} is the inverse cdf.

The expected shortfall is the average VaR overall levels $u \geq \alpha$

$$ES_\alpha(L) = \frac{1}{1-\alpha}\int_\alpha^1 VaR_u(L)du \quad (8),$$

$ES_\alpha(L) = E[L \mid L \geq VaR_\alpha(L)]$, (if L is a continuous random variable).

The loss is calculated as: $L_t = -(R_{p,t}) \sim t(v)$.

Allowing for auto correlation and time varying variance, assume portfolio returns with fat tail distribution are described by the following Garch(1,1) model

$R_{p,t} = \mu + \Phi_t$ with $\Phi_t = \sigma_t z_t$, $z_t \sim t(\upsilon)$ → $R_{p,t} \sim t(\upsilon)$, and

$$\sigma_t^2 = \omega + \gamma\, \Phi_{t-1}^2 + \theta \sigma_{t-1}^2 \quad (9).$$

Using the Garch(1,1) above to forecast one period ahead of volatility, we, therefore, can estimate one period ahead of VaR. Since the purpose of this report is to investigate which policies produce higher/lower risk in terms of VaR and ES, rather than study which VaR model works better, I process the estimation of VaR and ES using Monte Carlo simulation under Garch(1,1) model. The simulation process starts by estimating each portfolio's return using Garch(1,1) with the assumption of fat-tail innovation of return variance (t-distribution). The innovations are simulated by a 10^6 random draw from Student's t distribution with υ = 131 (observed months -1) degrees of freedom. One million paths of return are then estimated based on the Garch(1,1) specification. Value-at-Risk and Expected Shortfalls can be estimated based on simulated loss (negative side of return).

4.6. The alpha value of investment policies

Portfolio alpha is inspired by the idea of Jensen's Measure. In this report, I will use the extended version of Jensen's alpha with the Multi-beta model. Portfolio returns are assumed to follow Carhart's (1997) 4-factor model. In this report, I try to do a Linear Regression of portfolio returns on the set of common risk factors (X1) using the Carhart model, then ESGMoM is added as an additional factor (X1+ ESGMoM) to verify the performance of the policy, as well as the ESG score change factor.

Model 1:

$$R_{p,i}^{ej} = \alpha^{1,j} + \beta_{Mkt}^{1,j} Mkt_i^{1,ej} + \beta_{SMB}^{1,j} SMB_i^{1,j} + \beta_{HML}^{1,j} HML_i^{1,j} + \beta_{WML}^{1,j} WML_i^{1,j} \quad (10).$$

Model 2:

$$R_{p,i}^{ej} = \alpha^{2,j} + \beta_{Mkt}^{2,j} Mkt_i^{2,ej} + \beta_{SMB}^{2,j} SMB_i^{2,j} + \beta_{HML}^{2,j} HML_i^{2,j} + \beta_{WML}^{2,j} WML_i^{2,j} + \beta_{ESGMoM}^{2,j} ESGMoM_i^{2,j} \quad (11).$$

Robust multiple linear regression is performed to deal with heteroscedasticity using the "HAC" function in Matlab; briefly report the regression result recorded in panel 4 of the result table with annualized alpha. Acknowledge that Matlab "HAC" produces similar results to Sata "Robust OLS Regression" considering Stata package provides more result properties than HAC with a simple command, the parallel results generated from equation (10) and (11) will be processed by Stata and presented in Appendix F.

4.7. Performance of policy during Covid pandemic

Global economies have witnessed the heavy impact of the covid pandemic throughout industries, especially on the performance of corporations. It is unclear if the pandemic would slow down ESG activities or shed light on ESG characteristics' performance that helps to size up the ESG investment to some extent. This part provides a quick review of the performance of the four strategies during the covid-19 period. A timetable that reports the performance of portfolio policies during Covid time (TCovid) will be created for the year between 31 Dec 2019 and 31 Dec 2020. The evaluation is conducted in the TCovid period to compare policies that should exploit the performance of strategies during this time.

4.8. Diversification and Diversification Effect

Chouefaty & Coignard (2008) defined Portfolio Diversification Ratio (PDR) as the weighted average of asset’s volatilities divided by the portfolio volatility.

$$PDR = \frac{w'\Sigma}{\sqrt{w'Vw}} \qquad (12),$$

$\Sigma = \begin{bmatrix} \sigma_1 \\ \cdots \\ \sigma_N \end{bmatrix}$ is the vector of asset volatilities, V is the covariance matrix of assets in the portfolio.

The diversification ratio of any long-only portfolio will be strictly higher than 1, except the portfolio is equivalent to a mono-asset portfolio, in which the diversification ratio will be equal to 1 (Chouefaty & Coignard, 2008). PDR is also interpreted as a measure of the degree of freedom (Choueifaty, et al., 2013), by this setting, Choueifaty et al. (2013) report PDR^2 as the level of independent risk factors that investor would have been effectively exposed to by deploying a specific investment strategy.

Hoepner (2010) suggests that while reducing the number of assets in a portfolio might higher systemic risk proportion, investors can reduce the proportion of specific risk by adopting different stock selection strategies. Further processes were conducted by Verheyden et al. (2016); based on Fama (1972), the required return to justify specific risk using Diversification Effect (DE) is stated as:

$$\text{DE} = [\frac{\sigma_{Rp}}{\sigma_{Rm}} - \beta] * (r_m - r_f) \qquad (13)\ ,$$

σ_{Rp} : The standard deviation of portfolio return.

σ_{Rm} : The standard deviation of the market return.

β : The beta between the (selective) portfolio excess return and the market (unscreened universe) excess return.

$r_m - r_f$ Market excess return.

The discussion on portfolio diversification in this report will base on the two ratios mentioned above. The net selective benefits are also considered as the gap between portfolio alpha and diversification effect. Positive net selective benefits manifest the performance of the portfolio in consideration of the diversification factor.

5. Results

In the tables below, the estimation of related indicators of each policy is reported. Colum panels 1, 2, 3, 4 refer to portfolio policies P1, P2, P3, P4 in respect order, as described in section 4.1.

Row panel number 1 presents the estimated optimal parameters for each characteristic in each policy with its estimated standard errors.

$\theta_{me\,:}$ coefficient of Market Equity

$\theta_{sev\,:}$ coefficient of Sales to Enterprise Value ratio

$\theta_{lr12\,:}$ coefficient of lag one year return

$\theta_{esgs\,:}$ coefficient of ESG Score

$\theta_{esgsl18:}$ coefficient of ESG Score changes

Row panel number 2 display the set of statistics for portfolio weights. In this panel, the mean level across time of statistics is reported for:

$|w_i| * 100$: average absolute weights of portfolios, in percentage levels.

$\min w_i * 100$: minimum weight in the portfolio, in percentage levels.

$\max w_i * 100$: maximum weight in the portfolio, in percentage levels.

$\sum w_i I(w_i < 0)$: sum of negative weights in the portfolio

$\sum I(w_i \leq 0)/N_t$: Faction of negative or zero holding positions that are in the portfolio.

$(\sum w_i)/1$: the average deviation of total portfolio weight to 1

Row panel number 3 shows the statistics of average portfolio returns ($\bar{r}$), return's standard deviation (σ_r), Sharpe Ratio (SR), the average return in the Covid period ($\bar{r} - TCovid$), Value at

Risk (VaR) and Expected Shortfall (ES) at two confidence levels (95% and 99%), average ESG combined scores for the whole period and at the end of 2020. This information set also provides the data on the mean of used market value (Size) - presents how much fund investor would allocate to specific portfolios, on average; the average number of assets in the trading period, and average Turnover of portfolios.

Row panel number 4 exhibits the estimated parameter from the linear regression of the asset pricing model quoted in equations (10) and (11).
The last row panel (5) shows the average of standardized cross-sectional variables in each portfolio. The weighted characteristic is calculated as:

$$\sum_{i=1}^{N_t} w_{i,t}\widetilde{x_{i,t}}\ ,\ \tilde{x} = \tilde{x} = \widetilde{ME},\ \widetilde{SEV},\ \widetilde{LR12},\ \widetilde{ESGS},\ ES\widetilde{GSL}18\ .$$

All the tables present portfolio performance results have the same structure as described above. The results of portfolio performance in case of no transaction cost are presented in Tables 5.1 and 5.2. The results on different cost levels (10bps, 30bps, 50bps, and 100bps) are reported in Appendix B. All the mentioned tables hereafter are called “the result tables”.

Table 5.1: Estimates of portfolio policies in case of no transaction cost, no constraints.

No Transaction cost, Without Shortsale constraint					
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	3.77227	5.92287	7.10546
		-	(1.9576)	(2.60742)	(2.09575)
	θ_{sev}	-	-0.75051	-0.23840	0.01699
		-	(1.26294)	(1.33271)	(1.33955)
	θ_{lr12}	-	0.80984	0.76380	-0.34379
		-	(0.59712)	(0.61841)	(0.66148)
	θ_{esgs}	-	-	-2.75930	-
		-	-	-1.95161	-
	$\theta_{esgsl18}$	-	-	-	11.28926
		-	-	-	(2.43838)
2	$\lvert w_i \rvert * 100$	0.1003	0.1885	0.3178	0.9315
	$\min w_i * 100$	0.0477	-1.1045	-1.5383	-2.1728
	$\max w_i * 100$	0.1645	8.4819	13.3426	14.6655
	$\sum w_i I(w_i < 0)$	0.0000	-0.4066	-1.0126	-4.0482
	$\sum I(w_i \leq 0)/\mathrm{Nt}$	0.0000	0.3916	0.4302	0.6209
	$(\sum w_i)/1$	1.0000	1.0000	1.0000	1.0000
3	$\bar{r}$(annual)	0.1636	0.1395	0.1630	0.4034
	σ(r) (annual)	0.1851	0.1244	0.1398	0.2110
	SR (annual)	0.8566	1.0808	1.1300	1.8879
	$\bar{r} - TCovid$(annual)	0.2432	0.2252	0.3625	0.2834
	VaR-95%*100/ ES-95%*100	13.01/ 16.81	6.10/ 7.97	7.85/ 10.23	5.89/ 8.19
	VaR-99%*100/ ES-99%*100	19.18/ 22.32	9.15/ 10.70	11.71/ 13.69	9.62/ 11.52
	mean ESGS(wholeperiod)	41.60	41.60	41.60	41.60
	mean ESGS(2020-end)	41.72	41.72	41.72	41.72
	Size(US$mio)	16,087	183,758	255,627	284,996
	Nt	1,300	1,300	1,300	1,300
	Turnover*100	3.85	14.72	19.55	90.01
4	α (annual)	0.0198	-0.0033	0.0065	0.2591
	β_{Mkt}	1.0394	0.8878	0.9325	0.7964
	β_{SMB}	0.4999	-0.2319	-0.0986	0.1279
	β_{HML}	0.2024	-0.0933	-0.1932	-0.2918
	β_{WML}	-0.0778	0.2761	0.2980	0.2848
5	ME	0.0000	3.8561	5.4937	6.2125
	SEV	0.0000	-1.1207	-0.9281	-0.5472
	LR12	0.0000	1.0298	1.0652	0.2860
	ESGS	0.0000	-0.6638	-1.7759	-0.3794
	ESGSL18	0.0000	-0.2612	-0.5125	10.7182

**Standard errors reported in bracket*

Source: author's calculation

Table 5.2: Estimates of portfolio policies in case of no transaction cost, with short-sale constraint

		No transaction cost, Shortsale constraint applied			
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	4.70957	4.47503	2.74151
		-	(0.92988)	(0.92143)	(0.82032)
	θ_{sev}	-	-0.00045	0.00545	-0.03406
		-	(0.02035)	(0.01889)	(0.03504)
	θ_{lr12}	-	-0.00169	-0.00649	0.10764
		-	(0.07132)	(0.07387)	(0.0499)
	θ_{esgs}	-	-	-0.03237	-
		-	-	(0.03627)	-
	$\theta_{esgsl18}$	-	-	-	0.73133
		-	-	-	(0.3744)
2	$\lvert w_i \rvert * 100$	0.1003	0.1003	0.1003	0.1003
	$min\, w_i * 100$	0.0477	0.0000	0.0000	0.0000
	$\max w_i * 100$	0.1645	7.4977	7.4301	5.2330
	$\sum w_i I(w_i < 0)$	-	-	-	-
	$\sum I(w_i \leq 0)$/Nt	-	0.5774	0.5472	0.3359
	$(\sum w_i)/1$	1.0000	1.0000	1.0000	1.0000
3	$\bar{r}$(annual)	0.16360	0.15067	0.15099	0.16666
	σ(r) (annual)	0.12392	0.13966	0.14035	0.15246
	SR (annual)	0.85664	1.04258	1.03973	1.05992
	$\bar{r} - TCovid$(annual)	0.2432	0.2454	0.2508	0.2471
	VaR-95%*100/ ES-95%*100	13.01/ 16.81	8.28/ 10.75	8.64/ 11.19	8.97/ 11.69
	VaR-99%*100/ ES-99%*100	19.18/ 22.32	12.28/ 14.32	12.78/ 14.90	13.38/ 15.63
	mean ESGS(wholeperiod)	41.60	49.78	48.76	44.50
	mean ESGS(2020-end)	41.72	41.74	41.72	41.73
	Size(US$mio)	16,087	176,644	174,138	118,771
	Nt	1,300	595	647	915
	Turnover*100	3.85	1.06	1.10	4.75
4	α (annual)	0.0198	0.0090	0.0093	0.0236
	β_{Mkt}	1.0394	0.9739	0.9752	0.9890
	β_{SMB}	0.4999	(0.1522)	(0.1432)	0.1107
	β_{HML}	0.2024	(0.0032)	(0.0025)	0.0605
	β_{WML}	(0.0778)	(0.0010)	(0.0063)	(0.0006)
5	ME	0.0000	3.6204	3.5732	2.3720
	SEV	0.0000	(0.2487)	(0.2456)	(0.1963)
	LR12	0.0000	0.1332	0.1301	0.1716
	ESGS	0.0000	(0.1684)	0.5361	(0.1317)
	ESGSL18	0.0000	(0.2565)	(0.2565)	0.3966

**Standard errors reported in bracket*

Source: author’s calculation

5.1. Estimated optimal parameters and average standardized characteristics.

The optimal coefficients are estimated and presented in the first panel of tables 5.1, 5.2, and Appendix B. The consolidated results of estimated parameters are presented in the below table for convenient discussion.

Table 5.3: Consolidated result of estimated parameters

	Transaction Cost	N/A			10bps			30bps			50bps			100bps		
	Characteristic	P2	P3	P4	P2	P3	P4	P2	P3	P4	P2	P3	P4	P2	P3	P4
No Constraint	θ_{me}	3.7723	5.9229	7.1055	3.8288	5.7192	6.7746	3.9400	5.3824	6.2241	3.9823	5.0657	5.7798	3.7061	4.2112	4.9027
	θ_{sev}	-0.7505	-0.2384	0.0170	-0.7547	-0.3207	0.0140	-0.6476	-0.3381	-0.0197	-0.4349	-0.2465	-0.0575	-0.0630	-0.0500	-0.0991
	θ_{lr12}	0.8098	0.7638	-0.3438	0.6197	0.5902	-0.1837	0.3222	0.3396	0.0066	0.1589	0.1880	0.0932	0.0422	0.0513	0.1170
	θ_{esgs}	-	-2.7593	-	-	-2.4304	-	-	-1.8211	-	-	-1.2726	-	-	-0.4379	-
	$\theta_{esgsl18}$	-	-	11.2893	-	-	10.1955	-	-	8.3293	-	-	6.7418	-	-	3.3698
Short-sale constraint	θ_{me}	4.7096	4.4750	2.7415	4.7095	4.7173	2.8602	4.7095	4.7173	3.3991	4.7095	4.7173	3.7365	4.7095	4.7173	4.7047
	θ_{sev}	-0.0004	0.0054	-0.0341	-0.0004	-0.0001	-0.0323	-0.0004	-0.0001	-0.0187	-0.0004	-0.0001	-0.0136	-0.0004	-0.0001	-0.0004
	θ_{lr12}	-0.0017	-0.0065	0.1076	-0.0017	-0.0026	0.0972	-0.0017	-0.0026	0.0853	-0.0017	-0.0026	0.0562	-0.0017	-0.0026	-0.0017
	θ_{esgs}	-	-0.0324	-	-	-0.0030	-	-	-0.0030	-	-	-0.0030	-	-	-0.0030	-
	$\theta_{esgsl18}$	-	-	0.7313	-	-	0.7138	-	-	0.6115	-	-	0.5613	-	-	0.0079

Source: author's calculation

In general, the estimated (absolute) value of $\theta_{esgsl18}$ and θ_{me} are higher than other parameters where there is no short-sale constraint. The (absolute) value of θ_{me} and θ_{esgs} tend to reduce when the transaction cost increases. These two parameters (θ_{me}, θ_{esgs}) have the tendency to converge to zero in the long-only policies with higher transaction cost levels. The positive sign of $\theta_{esgsl18}$ though the cases suggests that ESG Score changes add value to the fund allocation in both no constraint and short-sale constraint cases at all specified cost levels.

The result suggests that to optimize SR, investors following each strategy would allocate assets as[8]:

	P2	P3	P4
Long-short Policies	Overweight big companies, past winners, underweight small companies, past losers, companies with high Sales to Enterprise value (S/EV).	Overweight big companies, past winners, underweight small companies, past losers, companies with high ESG Score and Sales to Enterprise value.	Overweight big companies, high ESG Score change. Underweight small companies, low ESG Score changes. Other information depends on transaction cost levels. Mostly underweight past winners and overweight high S/EV ratio if the transaction cost not higher than 0.01% and vice versa.
Long-only Policies	Overweight big companies, past losers, underweight small companies, past	Overweight big companies, underweight past winners, and companies with high ESG Score	Overweight big companies, high ESG Score change, past winners. Underweight small companies, low ESG Score change, past

[8] Interpretation made based on the fact that characteristics are cross-sectional standardized (zeros mean and unit Standard Deviation).

	winners, high (S/EV).	and S/EV.	losers, high S/EV.

It is also noticeable that S/EV provides the least information to the asset allocation process than other characteristics.

The interpretation of estimated parameters delivers an interesting point for further discussion. Investors following our approach applied for this investment universe seem to overweight big companies. This result appears to be opposite to the result shown in Brandt et al. (2009) and common practice where small/ growth companies are overweighted. However, the estimated parameters align with what is expected when forming ESGMoM or ESGTMB, as shown in the data section and figure 3.2. It is seeable that companies with high ESG score change provide a higher return than companies with low ESG score change (on average). In contrast, companies with low ESG Score provide a higher return than companies with high ESG Score (on average). The result leads to a potential explanation that the world is changing so that investors nowadays are not only focusing on the profitability of stock but looking at the behavior of enterprises toward sustainable issues as well.

Table 5.4: Consolidated result of average characteristics (standardized)

	Transaction Cost	N/A			10bps			30bps			50bps			100bps		
	Characteristic	P2	P3	P4	P2	P3	P4	P2	P3	P4	P2	P3	P4	P2	P3	P4
No Constraint	ME	3.8561	5.4937	6.2125	3.9460	5.3959	5.9182	4.0389	5.1544	5.5420	4.0587	4.9173	5.2430	3.7462	4.1793	4.6628
	SEV	-1.1207	-0.9281	-0.5472	-1.0689	-0.9382	-0.5173	-0.9458	-0.8688	-0.5201	-0.7309	-0.7111	-0.5254	-0.3458	-0.3981	-0.4896
	LR12	1.0298	1.0652	0.2860	0.7866	0.8313	0.4713	0.5104	0.5826	0.5548	0.3415	0.4132	0.5610	0.1856	0.2201	0.4289
	ESGS	-0.6638	-1.7759	-0.3794	-0.6486	-1.4481	-0.3580	-0.5791	-0.9014	-0.3550	-0.4561	-0.4063	-0.3544	-0.2325	0.2860	-0.3261
	ESGSL18	-0.2612	-0.5125	10.7182	-0.2779	-0.4705	8.7836	-0.2943	-0.4396	7.1478	-0.3026	-0.4093	5.7461	-0.2865	-0.3329	2.7362
Short-sale constraint	ME	3.6204	3.5732	2.3720	3.6432	3.6467	2.4777	3.6432	3.6467	2.8591	3.6432	3.6467	2.8591	3.6432	3.6467	3.0696
	SEV	-0.2487	-0.2456	-0.1963	-0.2485	-0.2486	-0.1988	-0.2485	-0.2486	-0.2142	-0.2485	-0.2486	-0.2142	-0.2485	-0.2486	-0.2224
	LR12	0.1332	0.1301	0.1716	0.1334	0.1333	0.1638	0.1334	0.1333	0.1607	0.1334	0.1333	0.1607	0.1334	0.1333	0.1489
	ESGS	-0.1684	0.5361	-0.1317	-0.1681	0.5515	-0.1341	-0.1681	0.5515	-0.1452	-0.1681	0.5515	-0.1452	-0.1681	0.5515	-0.1513
	ESGSL18	-0.2565	-0.2565	0.3966	-0.2585	-0.2587	0.3188	-0.2585	-0.2587	0.1768	-0.2585	-0.2587	0.1768	-0.2585	-0.2587	0.1017

In terms of average characteristics, investors following policies number 2 and number 3 would weigh more toward big-winner companies, while investors following strategy number 4 would weigh more toward company capitalization and ESG score changes. In strategy number 3, it is also noticeable that investors would give allocations toward big firms with lower ESG scores and a high return momentum level in the ideal environments with no transaction cost applied. However, investors would shift the allocations to big companies with higher ESG scores when short-sale constraints are applied.

5.2. Portfolio Performance

5.2.1. Return and Sharpe Ratio

Information on portfolio return and Sharpe ratio are presented in panel 3 of the results tables. The plot on portfolio average returns and Sharpe Ratios (annualized) in figure 5.1 shows that portfolio 4 provides a higher average return and Sharpe Ratio in most cases. Portfolio 2 and portfolio 3 deliver lower returns than the benchmark but provide a higher Sharpe Ratio. The cumulative return of portfolios in figure 5.2 and Appendix C show that portfolio 4 brings an outstanding return for investors following this strategy; a dollar invested in 2010 would bring 62 dollars (6200%) for investors at the end of 2020, without transaction cost and short-sale constraint. The cumulative return down-graded when transaction cost climbs up or when the short-sale constraint is applied.

Figure 5.1: Plot of portfolio return and Sharpe Ratio.

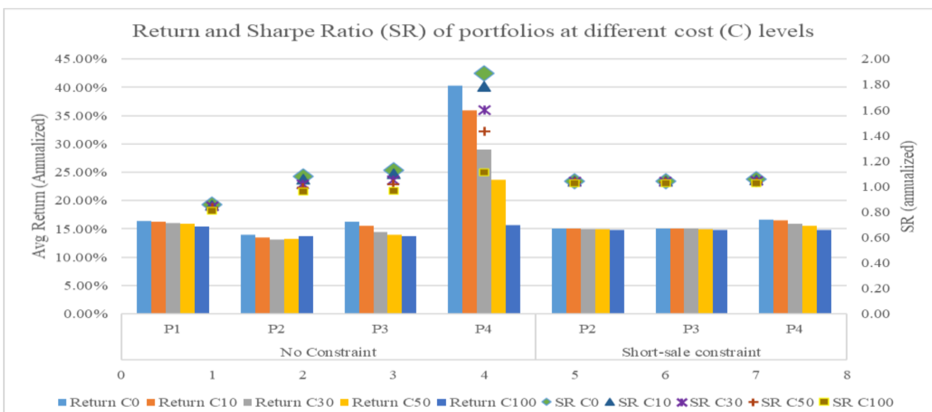
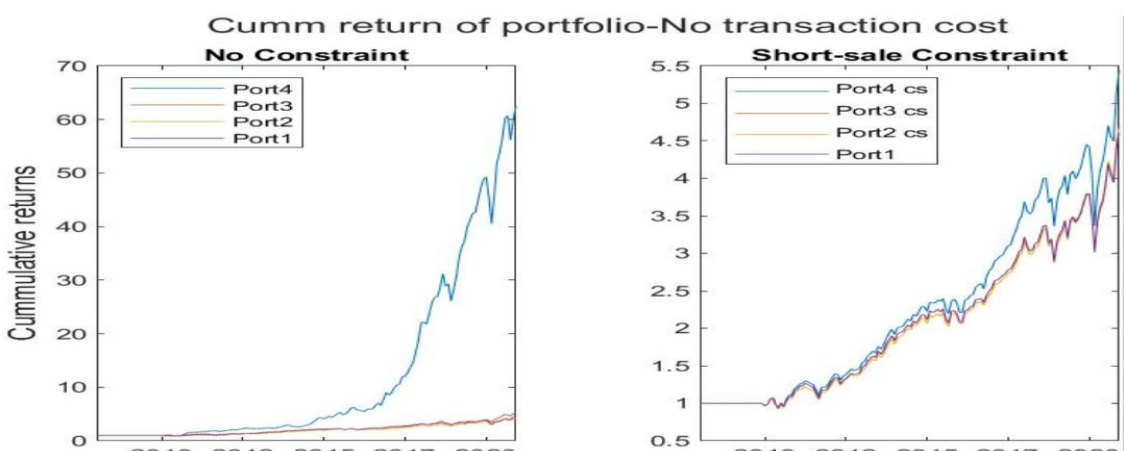


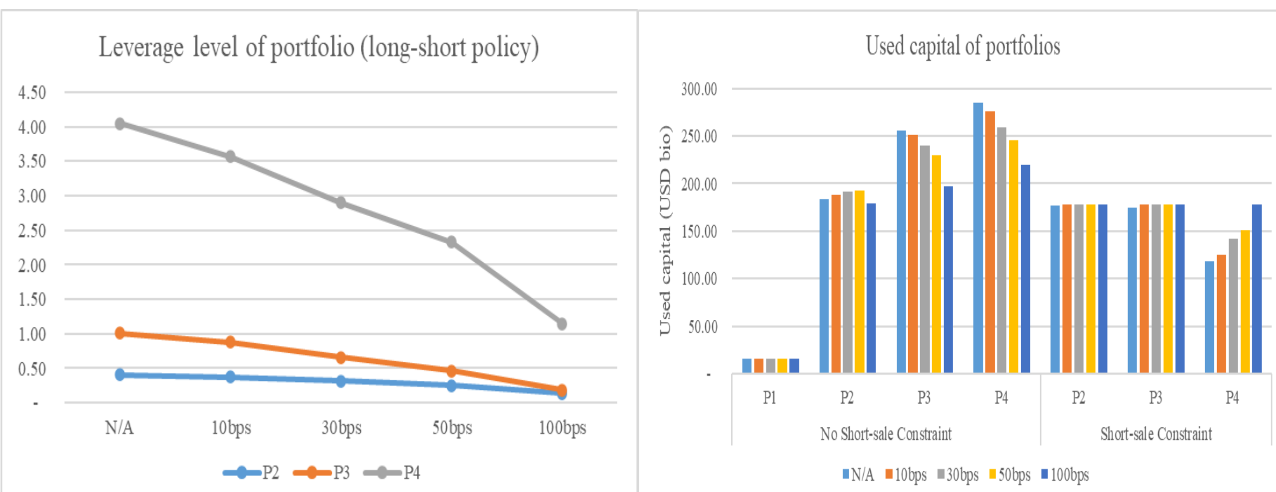
Figure 5.2: Cumulative return in case of no transaction cost.



Source: author's calculation.

Furthermore, the cumulative return of portfolio 4 sharply falls from 6200% (long-short, no cost) to 550% (long-only, no cost) (for ten years investment period). One potential explanation is that investors employing strategy 4 use high leverage and short on small companies with low ESG Score improvements. The statistic of weight allocation present in panel 2 of result tables (5.1, 5.2, B1-B8 Appendix B) provides information on the selective allocation toward each strategy. The deviation from the benchmark weights tends to be bigger in long-short policies, especially for policies 3 and 4. The deviation level is lower when the short-sale constraint is conducted, or the transaction cost is higher. While the allocation to an individual stock is not extreme, it is also considered quite a large exposure; under the fact that portfolio includes a large-scale number of assets (maximum allocation is 15% in long-short policy, no transaction cost, about 100 times of the based case of equal weights). The total negative position reported in panel 2 is interpreted as the leverage ratio that investors should use for the optimal objective purpose. The leverage level used in portfolios 2, 3, and 4 presented in the left panel of figure 5.3. Investors following strategy 4 use higher leverage than portfolios 3 and 2. Especially when there is no constraint and no transaction cost, the leverage is about 4.

Figure 5.3: The used capital and portfolio leverage ratio



Source: author's calculation

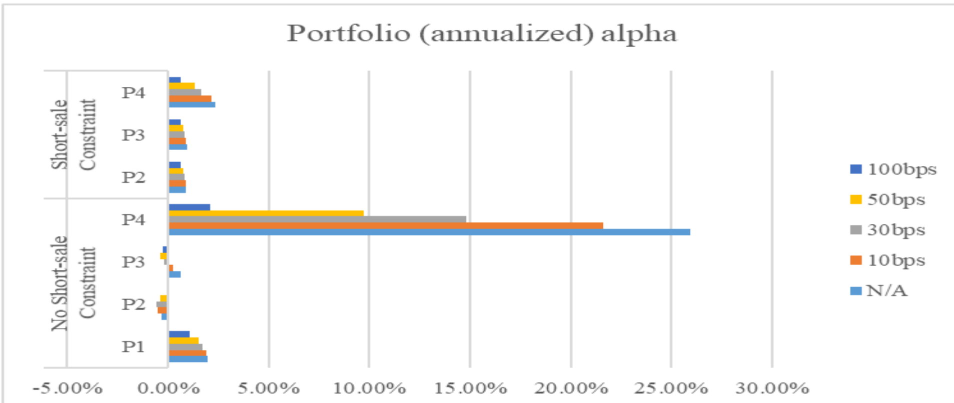
The turnover ratio shown in panel 3 of the result tables indicates that the portfolio value that investors need to rebalance is much higher in portfolio 4 than in other portfolios, especially in the long-short policy. As a result, investors employing portfolio 4 should be more active in trading than investors following other strategies. In addition, the sensitiveness to market information of portfolio

4 leads to the fact that this strategy is more sensitive to transaction cost level or constraint policy than others.

5.2.2. Portfolio's Alpha

Alpha of the portfolios is reported as an annualized number for better comparison. Alpha reported in panel 4 of the result tables is estimated under model (1), equation (10).

Figure 5.4: Plot of portfolio alpha



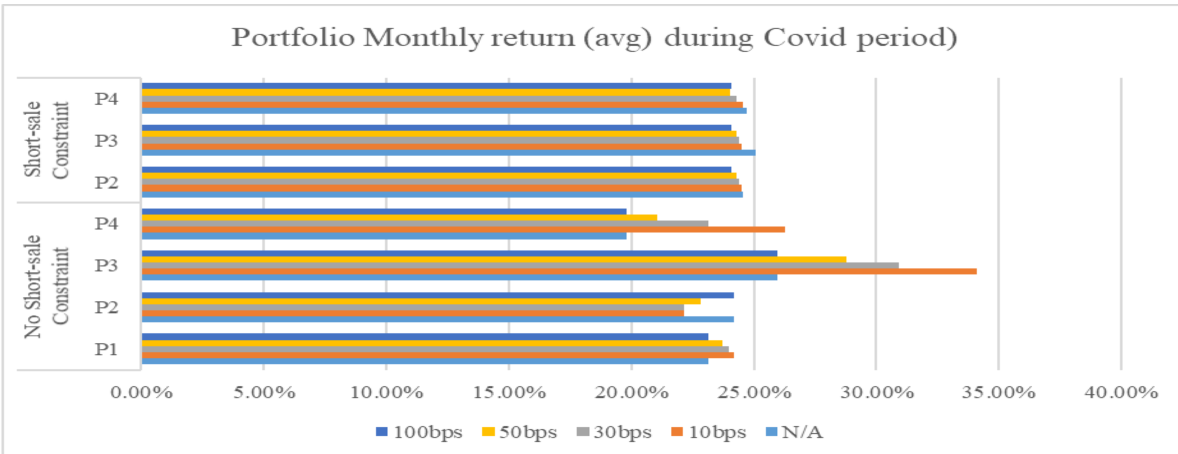
Source: author's calculation

The plot of alpha in figure 5.4 shows that portfolio 4 produces higher alpha than other portfolios if there is no short-sale constraint, at all specified cost levels. However, then short-sale constraint applied, alpha value of portfolio 4 is dropped, this strategy still beat the general market (positive alpha) when there is a transaction cost. The fact is that portfolio 4 seems less efficient than the benchmark portfolio if transaction cost is above 0.01%. It suggests that active traders employing this strategy should carefully consider the Turnover (reported in panel 2 of result tables) and transaction cost level. Portfolios 2 and 3 beat the market with positive alpha in long-only policies but not in long-short policies. The alpha of these two portfolios is lower than the benchmark policy.

5.2.3. Portfolio performance in Covid-period

The average (annualized) returns in the T-covid period reported in tables 5.1, 5.2, and tables B1-B8, Appendix B. Details on monthly average returns of the portfolio are reported in Appendix F. The portfolio's monthly average returns plot recommends that during the covid-19 pandemic, investment policy focuses on the company ESG score seems to have a higher return (on average) than other strategies. Portfolio 4 that focuses on ESG Score changes does not prove efficiency during the pandemic in 2020. Look at the monthly average return table in Appendix F; apparently, investors following policy 4 get more losses than policy 3 during the first wave (the first quarter of 2020) or the second wave (Sep – Oct 2020) of the virus. However, when the cost increases or short-sale constraint is applied, the losses of the two strategies are practically at a similar level.

Figure 5.5: Plot of portfolio monthly average return during Covid period

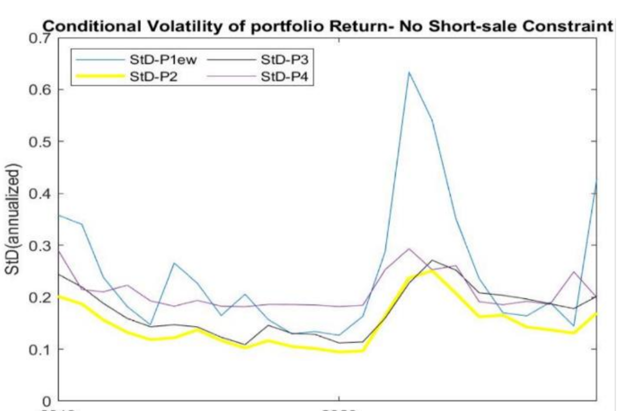


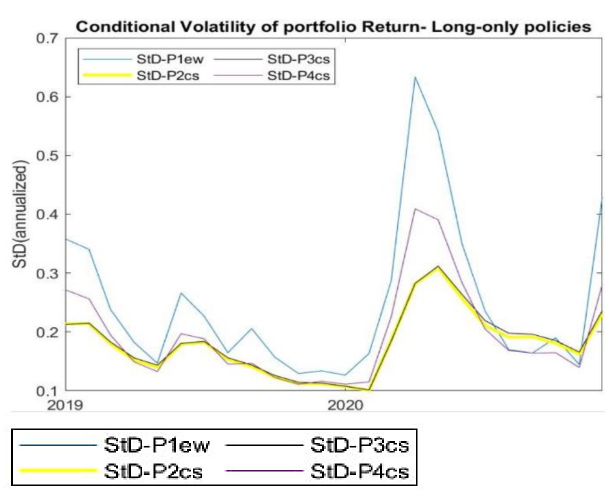
Source: author's calculation

5.3. Value at Risk and Expected Shortfalls.

As described in the previous part, this report employs the Garch(1,1) VaR model using Monte Carlo simulation to create 1 million paths of return under the t-distribution assumption. Instead of using static volatility, the return volatility stated in equation (9) is calculated based on a fixed part, one lag of variance, and random noise. Monte Carlo simulation is employed to simulate the t-distribution random noises.

Figure 5.6: Conditional volatility (standard deviation – annualized) of portfolios by time





Source: author's calculation.

Based on this model, the portfolio volatility next month will heavily depend on the value of the variance at month T (i.e., Dec 2020). Unlike the static number, volatility in this model is allowed to change over time. The plot on volatility (Standard Deviation) of the four portfolios in the period of 2019-2020 showed in figure 5.6 and Appendix E. Note that as of Dec 2020, portfolio 4 has the lowest conditional volatility among long-short policies while portfolio 1 stays as the highest one. Portfolio 3 has higher conditional volatility than Portfolio 2. With long-only strategies, portfolio 1 remains as the highest conditional variance, followed by portfolio 4, and after that is Portfolios 2 and 3. With this estimation, it is expected to have forecasted VaR ranked in the same order. Consequently, the VaR estimated in this model will generate results with different ranking orders as if we use analytical VaR with t-distribution assumption (see Appendix D for analytical VaR). Similar pattern advents are shown in the cases of different transaction costs. (see the plot in Appendix E).

The result on Garch VaR and ES are reported in panel 3 of the result tables. Consolidated results as shown in table 5.5. VaR and ES have been estimated at 95% and 99% confidence intervals. The result denotes that portfolio 4 derives lower 1-month relative VaR/ES in general. It seems that VaR/ES increases when the transaction cost increases or when the short-sale constraint is applied. At the high level of transaction cost, portfolios 2, 3, and 4 tend to derive similar relative VaR/ES when the long-only strategy is deployed.

Table 5.5: Consolidated result of VaR and ES

		No Short-sale Constraint					Short-sale Constraint				
	Portfolio/ Trans_cost	N/A	10bps	30bps	50bps	100bps	N/A	10bps	30bps	50bps	100bps
VaR/ES-95%	P1	12.99/ 16.79	13.02/ 16.82	13.08/ 16.87	13.05/ 16.86	13.16/ 16.97	12.99/ 16.79	13.02/ 16.82	13.08/ 16.87	13.05/ 16.86	13.16/ 16.97
	P2	6.09/ 7.97	6.33/ 8.26	6.90/ 8.96	7.65/ 9.91	9.59/ 12.35	8.27/ 10.74	8.28/ 10.75	8.30/ 10.76	8.27/ 10.72	8.29/ 10.74
	P3	7.84/ 10.22	7.90/ 10.28	8.11/ 10.49	8.32/ 10.76	9.35/ 12.04	8.62/ 11.18	8.28/ 10.74	8.30/ 10.75	8.26/ 10.72	8.29/ 10.74
	P4	5.88/ 8.18	5.76/ 7.94	5.63/ 7.62	5.55/ 7.43	6.05/ 7.93	8.96/ 11.68	8.97/ 11.68	8.79/ 11.41	8.64/ 11.22	8.29/ 10.75
VaR/ES-99%	P1	19.16/ 22.30	19.20/ 22.34	19.24/ 22.38	19.22/ 22.40	19.33/ 22.52	19.16/ 22.30	19.20/ 22.34	19.24/ 22.38	19.22/ 22.40	19.33/ 22.52
	P2	9.14/ 10.69	9.47/ 11.06	10.24/ 11.94	11.32/ 13.20	14.07/ 16.38	12.27/ 14.31	12.28/ 14.32	12.29/ 14.32	12.25/ 14.31	12.27/ 14.32
	P3	11.70/ 13.68	11.76/ 13.73	11.98/ 13.96	12.28/ 14.32	13.72/ 15.98	12.77/ 14.89	12.28/ 14.32	12.28/ 14.32	12.25/ 14.30	12.26/ 14.32
	P4	9.61/ 11.51	9.29/ 11.09	8.87/ 10.52	8.61/ 10.19	9.09/ 10.67	13.37/ 15.62	13.37/ 15.62	13.05/ 15.22	12.83/ 14.98	12.27/ 14.33

The result also suggests that the investment mandate that focuses on ESG score change in the fund allocation process would lower relative risk within the next month. A strategy that focuses on ESG score produces higher relative (1-month) risk than portfolio 4. Both portfolios 3 and 4 have more of a sound risk profile than the benchmark portfolio.

5.4. The Diversification

The summary result table in Appendix B showed that when there is no constraint applied, the average number of stocks are the same for the four portfolios, driven by the fact that the weight allocations in the other three portfolios deviate from the baseline portfolio. Thus, it should not be different in terms of diversification risk-related issues among the four portfolios. However, it also depends on the correlation among selected assets and the weighted variance of each asset in the portfolios. By using equation (12), the Diversification Ratios (PDR) of portfolios are reported in table 5.1 below:

Table 5.6: Diversification Ratio (average) of Portfolios

Diversification Ratio	No Short-sale Constraint				Short-sale Constraint		
Transaction Cost	P1	P2	P3	P4	P2	P3	P4
N/A	1.7721	1.6805	1.8085	1.1609	1.7425	1.7402	1.8049
10bps	1.7697	1.6837	1.8043	1.2371	1.7413	1.7413	1.8003
30bps	1.7704	1.6786	1.7823	1.3591	1.7415	1.7415	1.7850
50bps	1.7710	1.6679	1.7444	1.4697	1.7418	1.7418	1.7736
100bps	1.7726	1.6745	1.6971	1.6778	1.7424	1.7424	1.7423

Source: author's calculation.

Results show that, when there is no short-sale constraint, portfolio 4 has the lowest PDR while the other three portfolios got almost similar level and have little changes when the transaction cost to climb. Higher transaction cost implied higher PDR for portfolio 4. It almost reaches the PDR level of the other three portfolios when the transaction cost is 100bps. The increase may be derived from higher weights on the volatility of individual assets or lower covariance levels between assets in the portfolio. It also can be interpreted that portfolio four has been exposed to a lower level of independent risk factors than other policies when there is no short-sale constraint.

The Effect of Diversification Risk following equation (13) is considered based on table 5.7 below. Positive signs signal the compensation to diversification risk, while negative signs are considered benefits, compared to the general market.

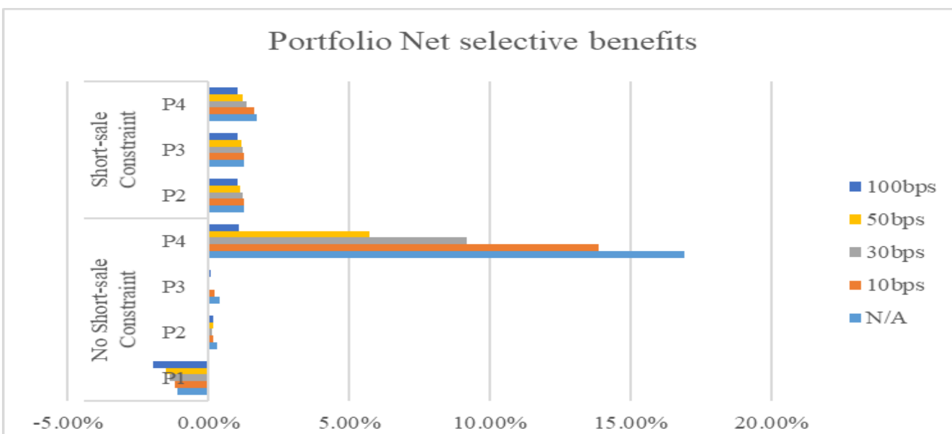
Table 5.7: Diversification Effect of Portfolios

Diversification Effect (annualized)	No Short-sale Constraint				Short-sale Constraint		
Transaction Cost	P1	P2	P3	P4	P2	P3	P4
N/A	3.05%	-0.63%	0.22%	8.99%	-0.38%	-0.33%	0.63%
10bps	3.05%	-0.68%	0.02%	7.71%	-0.38%	-0.38%	0.57%
30bps	3.05%	-0.68%	-0.26%	5.65%	-0.38%	-0.38%	0.24%
50bps	3.05%	-0.59%	-0.41%	3.99%	-0.38%	-0.38%	0.08%
100bps	3.05%	-0.25%	-0.32%	0.98%	-0.38%	-0.38%	-0.38%

Source: author's calculation.

The diversification effect shows that investors employing policies 1 and 4 will need to compensate for holding the selected stocks. In contrast, the ones following strategies 2 and 3 might benefit compared to the general market. The cost is higher for portfolio 4 if there are no restrictions or the transaction cost is lower. The compensation of diversification effect can be explained by high volatility of portfolio return (see σ_r in panel 3 of result tables) or low responsiveness of the asset to the change of overall stock market (low β_{mkt} see in panel 4 of the result table).

Figure 5.7: Plot of portfolio net selective benefits



Source: author's calculation.

Net selective benefits calculated as the gap between alpha and diversification effect, the plot on net selective effect displayed in figure 5.7. Investors who deploy strategy 4, including ESG Score change as asset characteristics, gain positive net selective benefits from this strategy. Moreover, the net selective benefit of portfolio 4 outnumbers the other policies in both long-short policies and long-only policies at any cost level. Portfolios 2 and 3 deliver positive net selective benefits, while negative selective benefits are recorded for portfolio 1.

5.5. The performance of ESGMoM

In this part, I define ESGMoM as an additional risk factor to see if adding ESGMoM in the multi-beta model would increase the alpha value in our regression model. Two set of regression based on model 1 (equation (10)) and model 2 (equation (11)) are executed. The results are reported in Appendix G for both constraint and no constraint cases at different cost levels. The alpha value will be compared between the two models to see if ESGMoM is adding the value(of alpha).

Regression results in table G1- G10 in Appendix G show that: when adding ESGMoM as an additional risk factor along with other factors in the Carhart (1997) model, it seems only to add a small value to the Carhart model's (1997) alpha. Furthermore, the model's Adjusted R-squared is not improved in most cases. Practically we can say ESGMoM adds up alpha value but not at a high level. However, this is initially aligned with the previous assumption that the ESG Score Momentum will add the alpha value. The low level of value-adding might be driven by the fact that the ESGMoM constructed in this report is based on the investment universe[9] but not the market-wide level. It may also be driven by noise or unexplainable economic factors. The other possible thinking is that ESG Scores were not fully updated for the year 2020, which makes ESGSL18 did not fully capture the changes; subsequently, ESGMoM was not fully reflected.

The reason to add ESGMoM over those in Carhart's (1997) model, as shown in Appendix G, is also to show that there is a potential risk factor in our universe in addition to the four common factors mentioned. Different markets may have different behavior, so it is worthy of looking at the performance of this factor on the other markets such as the European market and Emerging Market. Moreover, the result from 2 sets of regression provides quite similar intercepts and adjusted r-squared; practically, we can say that model 2 (Carhart + ESGMoM) performs almost as well as Carhart 4 factor model.

[9] Some stocks have been excluded under the condition quoted when building the investment universe.

6. Discussion and Conclusion

This paper investigates the performance of different portfolio policies using financial (Market capitalization, Sales to Enterprise Value, lagged one-year return) and non-financial information (ESG Score - ESGS and lagged 18 months ESG Score - ESGSL18) as asset characteristics. I define the weights allocated to assets as a linear function of asset characteristics and find optimal coefficient parameters by maximizing the Sharpe Ratio. The result shows that investors overweight size and ESG Score changes while underweight ESG Score in general. S/EV and return momentum provide less information to the weight allocation than the other characteristics (ME, ESGS, ESGSL18).

Is there any trade-off between risk and return for investors when integrating ESG into the asset allocation process? Adding ESG Score change as an asset characteristic higher the portfolio performance while reducing the market risk. Strategies that include ESG Score change in the weight allocation process outperform other strategies, especially when there is no short-sale constraint. The result affirms the higher alpha signal of the ESG Momentum portfolio compared to MSCI World Index reported by Nagy et al. (2016).

Interestingly, the increase of transaction cost or applying short-sale constraints lowers the performance of portfolios. Thus, the source of outperformance may be due to the bets on stocks with increasing ESG score, and high leverage ratio applied. Moreover, the used capital of portfolios that involve ESGS or ESGSL18 requires investors to prepare more funds than the benchmark (see the right panel of figure 5.3).

Having said that, we note that a portfolio that looks at company ESG score provides a higher average return during covid-19. In contrast, portfolio policy that focuses on ESG score change brings the lowest average return in this period. One potential explanation of this situation is that portfolio 4 has long positions on some industries that do not perform well during the pandemic despite the high ESG score changes such as Energy or Materials, while short on industries that benefit from the pandemic like Technology or Telecommunication (Morningstar, 2021), especially during the first and second waves of coronavirus. Of course, the lockdown has impacted the whole market heavily, but the performance also depends on each industry. Even so, one can argue that covid-19 has shed critical light on the performance of the non-information characteristic such as ESG scores and ESG score changes when applying parametric portfolio policies.

It is claimed that ESG investing is an approach that the ESG investment strategies seek to incorporate forward-looking financially material information into the expectation of returns and risks, which can help generate superior long-term returns (Boffo & Patalano, 2020). To the true extent that ESG Score-based strategies are more on long-term investment, the ESG Score momentum-based policies are considered a more short-term strategy in nature. Investors who target on company's long-term financial performance and sustainable investment tend to buy stocks with high ESG Scores rather than ESG Score changes. At the same time, investors who seek a more short-term value with a potential contribution in sustainable activities in the long run would shift the focus on ESG score change.

This report shows that integrating company information on the sustainable profile, especially the improvement of ESG score, into asset allocation strategy using a parametric portfolio approach enhances the performance of investment strategies. This is considered simple and easy to apply, especially when investors want to switch between the objective functions. As encourage investors to higher the fund allocations on companies that tend to improve the ESG profile, this investment policy benefits the investors and urges the company to focus on ESG profile improvement. This does not explicitly aim to raise the ex-post ESG profile of the targeted portfolio since stocks with the highest improvement of ESG scores are not necessarily the best-rated stocks at the time (Nagy, et al., 2016). However, encouraging companies to shift their focus on ESG activities actively will raise the market-wide concern level and gradually increase the ex-ante ESG profile in the long run. Subsequently, society will gain benefits.

The results are important to the financial market in general and sustainable investment in specific, for the reasons that:

- It shows the potential of integrating ESG score momentum into the asset allocation process with a parametric approach and boosting the portfolio performance.
- Shifting the focus on ESG profile improvement lifts the spirits of companies that have poor ESG performance to make progress in their ESG activities. Eventually, the ESG performance of the market increase, on average.
- Parametric approach is a clear and easy approach for not only institutional investors but also individual investors. It implies that with accessible ESG data, investors can build their own strategies based on the characteristics. Therefore, in the long run, not only the ESG trusted funds or ESG asset management agencies are specialized in ESG investing but also individual investors or mutual funds[10].

[10] Mutual funds that invest in common stocks.

This report is built with the expectation to recommend a sophisticated but easy to conduct method in integrating ESG information into the asset allocation process. However, in the constraints of this thesis, it is anticipated that some enhancements or further investigation could be made:

- As more ESG data available in the future, other researchers might want to conduct further studies to verify the results presented in this report, especially for Emerging Markets.
- Industry effect is not considered in this report; the ESG profile improvement might differ in each industry. This might lead to industry tilts in the optimal policy, which is not dug deeper into in this report. Further research might look at the industry bias of the policy or break out into the single item of E, S, G for further analysis.
- Taxes and other fees that are not considered in this report might derive some changes in the function's coefficients to investigate more to improve the results.
- Different investors will have different preferences and different investment methods. Therefore, one might want to choose other maximizing objectives when conducting the optimal weight allocations. For example, the objectives can be ratio-based objectives (Treynor ratio, Sortino ratio) or preference-based objectives (conditionally expected utility function, mean-variance, mean-variance with a penalty for loss probability).
- Fat tail risk factors are considered beyond the scope and were not discussed in this report when calculating for VaR and ES; other researchers might want to see the difference of risk profiles accounting for the distribution of risk factors.

The contribution of adding tracking errors of ESG momentum, as a risk factor, along with other common risk factors in the asset pricing models, might differ between the markets since the regulations on ESG activities are not the same, and investors' awareness is also different. Therefore, I let the readers conclude and open the question to research this factor for different equity markets further.

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Appendix A: Variable Definitions

Variables	Formula /Description	Sources
ME Market Equity (size)	The close price times shares outstanding at the end of the month.	Refinitiv Datastream, Series code: MV
BTM Book-to-Market ratio	The BTM ratio is defined as book equity (BE) divided by market equity (ME). BE is the book value of stockholder' equity, including balance-sheet deferred taxes and investment tax responsible (if available), deducting preferred stock's book value. The BTM ratio is calculated as the inverse of the Price to Book ratio provided by the Reuter Eikon data stream. PTBV is the share price divided by the book value (BV) per share. Book Value Per Share is determined by the BV (proportioned common equity divided by outstanding shares) (non-US companies: at the fiscal year-end, US companies: at the last calendar quarter)[12].	Refinitiv Datastream Series code: PTBV (inverse values)
$\mathbf{P_t}$ Price	The official closing price. This is a historically adjusted price for subsequent capital actions such as dividends/splits to make data directly comparable to current market practice	Refinitiv Datastream, Series code: P
$\mathbf{D_t}$ Dividend	Represents the unadjusted individual cash income dividend payment per share upon dividend date. If there are two or more payments that fall on the same day, the dividend is added up. Dividends paid in different currencies will be converted into local currency using the exchange rate of the previous two working days	Refinitiv Datastream, Series code: UDD
$\mathbf{r_t}$ Return	Stock returns are calculated as the change in the total value of an investment in a security time t divided by stock price at time t-1: $r_t = (\frac{P_t+D_t}{P_{t-1}} - 1)$. The stock price is the closed price at time t.	Calculated from Price and Dividend data

[12] Preference stock has been included in equity and the calculation of book value per share where it participates with common/ordinary shares in the profits of the company. It is excluded in all other cases, deducted at liquidation value for US companies and at par value for all others. (*For US corporations, common equivalent and fully diluted book values are shown, when available.).*
For companies with more than one type of common/ordinary share, the book value is based on combined shares adjusted for the par value of the specified share type.

	Return is calculated monthly, not compounded daily returns, and not annualized. Returns in this report are set as missing in cases: invalid current price (time t), but no valid previous price(t-1); no trading at time t or missing price at time t or outside the stock' price range.	
S/P Sales to Price ratio	S/P measures a company's market capitalization in terms of its sales; it shows how much the market values each unit of the company sales. S/P also can be calculated by dividing Sales per Share to stock Price	Refinitiv Datastream, Series code: FTSPS
ESGS ***ESG Scores***	1. ESG Score is an overall score determined by company self-reported information in the environmental, social, and corporate governance pillars. 2. ESG Controversies Score measures a company's exposure to environmental, social, and governance controversies and adverse events reflected in global media. ESG news 3. ESG Combined Score: overall Score built using both self-reported information in the Environmental, Social, and Corporate Governance pillars (ESG Score) and ESG Controversies Score.	Refinitiv Datastream, Series code: 1. TRESGS 2. TRESGCCS 3. TRESGCS* * This series is used in this report.
RF	Monthly risk-free rate on US market.	Kenneth F. French Library
Mkt-RF Market excess return	Defined by the value-weighted return of all the US CRSP (Center for Research in Security Prices) firms.	Kenneth F. French Library
SMB Small Minus Big	Fama-French factor was constructed by forming six value-weight portfolios based on size and book to market ratio. SMB is the gap between the three small portfolios' average return and three big portfolios' average return.	Kenneth F. French Library
HML High Minus Low	Fama-French factor was constructed by forming six value-weight portfolios based on size and book to market ratio. HML is defined by deducting the average return of two value portfolios from the average return of two growth portfolios (the difference between the returns on high and low BTM stocks).	Kenneth F. French Library
WML Return Momentum	Measures the differences between the average of high prior return portfolios and the average of the low prior return portfolios.	Kenneth F. French Library

*Note: Details on the construction of SMB, HML, and WML can be found in Kenneth R. French's Data Library***.**

Appendix B: Portfolio performance results in the presence of the transaction cost

B.1 No Short-sale Constraint

Table B1: Estimates of portfolio policies in case of 10bps transaction cost, no constraint

10bps transaction cost, Without Shortsale constraint					
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	3.82877	5.71919	6.77455
		-	(1.6796)	(2.01432)	(1.7719)
	θ_{sev}	-	-0.75471	-0.32074	0.01398
		-	(1.0266)	(1.0527)	(1.08481)
	θ_{lr12}	-	0.61966	0.59022	-0.18371
		-	(0.47503)	(0.49534)	(0.53147)
	θ_{esgs}	-	-	-2.43036	-
		-	-	(0.99923)	-
	$\theta_{esgsl18}$	-	-	-	10.19549
		-	-	-	(1.23794)
2	$\lvert w_i \rvert * 100$	0.1012	0.1824	0.2923	0.8385
	$\min w_i * 100$	0.0078	-1.4253	-1.8595	-2.5553
	$\max w_i * 100$	0.2857	9.6919	14.4479	15.7090
	$\sum w_i I(w_i < 0)$	0.0000	-0.3772	-0.8824	-3.5643
	$\sum I(w_i \leq 0)$/Nt	0.0084	0.3924	0.4323	0.6199
	$(\sum w_i)/1$	1.0000	1.0000	1.0000	1.0000
3	$\bar{r}$(annual)	0.1627	0.1353	0.1548	0.3596
	σ(r) (annual)	0.1850	0.1235	0.1363	0.1983
	SR (annual)	0.8518	1.0550	1.0992	1.7876
	$\bar{r} - TCovid$(annual)	0.2420	0.2214	0.3411	0.2630
	VaR-95%*100/ ES-95%*100	13.02/ 16.82	6.33/ 8.26	7.90/ 10.28	5.76/ 7.94
	VaR-99%*100, ES-99%*100	19.20/ 22.34	9.47/ 11.06	11.76/ 13.73	9.29/ 11.09
	mean ESGS(wholeperiod)	41.60	41.60	41.60	41.60
	mean ESGS(2020-end)	41.72	41.72	41.72	41.72
	Size(US$mio)	16,087	187,681	251,171	275,704
	Nt	1300	1300	1300	1300
	Turnover*100	3.8513	12.1827	16.6041	80.5229
4	α (annual)	0.0189	-0.0050	0.0025	0.2161
	β_{Mkt}	1.0392	0.8855	0.9226	0.8003
	β_{SMB}	0.4998	-0.2468	-0.1293	0.1122
	β_{HML}	0.2029	-0.0946	-0.1841	-0.2685
	β_{WML}	-0.0774	0.2135	0.2375	0.2855
5	ME	-	3.9460	5.3959	5.9182
	SEV	-	-1.0689	-0.9382	-0.5173
	LR12	-	0.7866	0.8313	0.4713
	ESGS	-	-0.6486	-1.4481	-0.3580
	ESGSL18	-	-0.2779	-0.4705	8.7836

**Standard errors reported in bracket*

Source: author's calculation

Table B2: Estimates of portfolio policies in case of 30bps transaction cost, no constraint

30bps transaction cost, Without Shortsale constraint					
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	3.94002	5.38241	6.22411
		-	(1.33914)	(1.49916)	(1.3526)
	θ_{sev}	-	-0.64761	-0.33807	-0.01969
		-	(0.71343)	(0.70704)	(0.7315)
	θ_{lr12}	-	0.32218	0.33960	0.00664
		-	(0.28796)	(0.29282)	(0.29879)
	θ_{esgs}	-	-	-1.82109	-
		-	-	(0.27776)	-
	$\theta_{esgsl18}$	-	-	-	8.32931
		-	-	-	(0.15747)
2	$\lvert w_i \rvert * 100$	0.1012	0.1707	0.2466	0.7015
	$min\, w_i * 100$	0.0078	-1.1253	-1.4318	-2.1502
	$\max w_i * 100$	0.2857	9.7838	13.4341	14.5814
	$\sum w_i I(w_i < 0)$	0.0000	-0.3132	-0.6596	-2.8952
	$\sum I(w_i \leq 0)$/Nt	0.0084	0.3980	0.4299	0.6143
	$(\sum w_i)/1$	1.0000	1.0000	1.0000	1.0000
3	$\bar{r}$(annual)	0.1608	0.1317	0.1442	0.2895
	σ(r) (annual)	0.1850	0.1246	0.1326	0.1778
	SR (annual)	0.8421	1.0165	1.0496	1.5997
	$\bar{r} - TCovid$(annual)	0.2396	0.2214	0.3094	0.2316
	VaR-95%*100/ ES-95%*100	13.08/ 16.87	6.90/ 8.96	8.11/ 10.49	5.63/ 7.62
	VaR-99%*100, ES-99%*100	19.24/ 22.38	10.24/ 11.94	11.98/ 13.96	8.87/ 10.52
	mean ESGS(wholeperiod)	41.60	41.60	41.60	41.60
	mean ESGS(2020-end)	41.72	41.72	41.72	41.72
	Size(US$mio)	16,086.75	191,569.35	240,424.04	259,033.95
	Nt	1,300	1,300	1,300	1,300
	Turnover*100	3.85	8.05	11.86	65.10
4	α (annual)	0.0171	-0.0054	-0.0021	0.1482
	β_{Mkt}	1.0387	0.8928	0.9176	0.8070
	β_{SMB}	0.4997	-0.2683	-0.1850	0.0762
	β_{HML}	0.2039	-0.0868	-0.1575	-0.2308
	β_{WML}	-0.0767	0.1077	0.1397	0.2637
5	ME	-	4.0389	5.1544	5.5420
	SEV	-	-0.9458	-0.8688	-0.5201
	LR12	-	0.5104	0.5826	0.5548
	ESGS	-	-0.5791	-0.9014	-0.3550
	ESGSL18	-	-0.2943	-0.4396	7.1478

**Standard errors reported in bracket*

Source: author's calculation

Table B3: Estimates of portfolio policies in case of 50bps transaction cost, no constraint

50bps transaction cost, Without Shortsale constraint					
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	3.98234	5.06573	5.77976
		-	(1.04214)	(1.15329)	(1.04217)
	θ_{sev}	-	-0.43495	-0.24654	-0.05752
		-	(0.42407)	(0.4099)	(0.43222)
	θ_{lr12}	-	0.15886	0.18797	0.09321
		-	(0.18018)	(0.18011)	(0.18299)
	θ_{esgs}	-	-	-1.27256	-
		-	-	(0.12676)	-
	$\theta_{esgsl18}$	-	-	-	6.74176
		-	-	-	(0.04031)
2	$\lvert w_i \rvert * 100$	0.1012	0.1595	0.2064	0.5859
	$min\, w_i * 100$	0.0078	-0.7541	-1.0464	-1.7885
	$\max w_i * 100$	0.2857	9.7645	12.5084	13.6433
	$\sum w_i I(w_i < 0)$	0.0000	-0.2498	-0.4644	-2.3297
	$\sum I(w_i \leq 0)$/Nt	0.0084	0.4227	0.4316	0.6082
	$(\sum w_i)/1$	1.0000	1.0000	1.0000	1.0000
3	$\bar{r}$(annual)	0.15898	0.13243	0.13908	0.23658
	σ(r) (annual)	0.18489	0.12844	0.13215	0.16187
	SR (annual)	0.83243	0.99164	1.01415	1.43023
	$\bar{r} - TCovid$(annual)	0.2373	0.2284	0.2878	0.2107
	VaR-95%*100/ ES-95%*100	13.05/ 16.86	7.65/ 9.91	8.32/ 10.76	5.55/ 7.43
	VaR-99%*100, ES-99%*100	19.22/ 22.40	11.32/ 13.20	12.28/ 14.32	8.61/ 10.19
	mean ESGS(wholeperiod)	41.60	41.60	41.60	41.60
	mean ESGS(2020-end)	41.72	41.72	41.72	41.72
	Size(US$mio)	16,087	192,342	229,922	245,741
	Nt	1,300	1,300	1,300	1,300
	Turnover*100	3.85	5.41	8.24	52.53
4	α (annual)	0.01535	-0.00408	-0.00367	0.09744
	β_{Mkt}	1.03832	0.91250	0.92498	0.81573
	β_{SMB}	0.49956	-0.26814	-0.22531	0.03429
	β_{HML}	0.20485	-0.06679	-0.12351	-0.19905
	β_{WML}	-0.07599	0.03833	0.06853	0.22442
5	ME	-	4.0587	4.9173	5.2430
	SEV	-	-0.7309	-0.7111	-0.5254
	LR12	-	0.3415	0.4132	0.5610
	ESGS	-	-0.4561	-0.4063	-0.3544
	ESGSL18	-	-0.3026	-0.4093	5.7461

**Standard errors reported in bracket*

Source: author's calculation

Table B4: Estimates of portfolio policies in case of 100bps transaction cost, without short-sale constraint

100bps transaction cost, Without Shortsale constraint					
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	3.70613	4.21115	4.90270
		-	(0.31344)	(0.33527)	(0.31354)
	θ_{sev}	-	-0.06298	-0.05000	-0.09911
		-	(0.03739)	(0.03665)	(0.0374)
	θ_{lr12}	-	0.04220	0.05127	0.11704
		-	(0.03171)	(0.03175)	(0.03222)
	θ_{esgs}	-	-	-0.43793	-
		-	-	(0.03275)	-
	$\theta_{esgsl18}$	-	-	-	3.36977
		-	-	-	(0.00715)
2	$\lvert w_i \rvert * 100$	0.1012	0.1370	0.1489	0.3457
	$\min w_i * 100$	0.0078	-0.2451	-0.4421	-1.0004
	$\max w_i * 100$	0.2857	8.9834	10.2498	11.7240
	$\sum w_i I(w_i < 0)$	0.0000	-0.1357	-0.1875	-1.1491
	$\sum I(w_i \leq 0)/\mathrm{Nt}$	0.0084	0.4168	0.4359	0.5781
	$(\sum w_i)/1$	1.0000	1.0000	1.0000	1.0000
3	$\bar{r}$(annual)	0.1544	0.1375	0.1373	0.1568
	σ(r) (annual)	0.1847	0.1382	0.1369	0.1368
	SR (annual)	0.8082	0.9584	0.9658	1.1090
	$\bar{r} - TCovid$(annual)	0.2313	0.2421	0.2595	0.1982
	VaR-95%*100/ ES-95%*100	13.16/ 16.97	9.59/ 12.35	9.35/ 12.04	6.05/ 7.93
	VaR-99%*100, ES-99%*100	19.33/ 22.52	14.07/ 16.38	13.72/ 15.98	9.09/ 10.67
	mean ESGS(wholeperiod)	41.60	41.60	41.60	41.60
	mean ESGS(2020-end)	41.72	41.72	41.72	41.72
	Size(US$mio)	16,087	178,709	197,617	219,831
	Nt	1,300	1,300	1,300	1,300
	Turnover*100	3.8513	2.7312	3.7398	26.6541
4	α (annual)	0.01095	-0.00054	-0.00230	0.02092
	β_{Mkt}	1.03727	0.95453	0.95062	0.85871
	β_{SMB}	0.49923	-0.19844	-0.21160	-0.09188
	β_{HML}	0.20724	-0.01389	-0.04607	-0.12496
	β_{WML}	-0.07421	-0.02925	-0.01489	0.10211
5	ME	-	3.7462	4.1793	4.6628
	SEV	-	-0.3458	-0.3981	-0.4896
	LR12	-	0.1856	0.2201	0.4289
	ESGS	-	-0.2325	0.2860	-0.3261
	ESGSL18	-	-0.2865	-0.3329	2.7362

**Standard errors reported in bracket*

Source: author's calculation

B.2. Short-sale constraint applied

Table B5: Estimates of portfolio policies in case of 10bps transaction cost, short-sale constraint

10bps transaction cost, Shortsale constraint applied					
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	4.70954	4.71730	2.86022
		-	(0.72355)	(0.43028)	(0.55234)
	θ_{sev}	-	-0.00044	-0.00010	-0.03233
		-	(0.01316)	(0.02271)	(0.02044)
	θ_{lr12}	-	-0.00169	-0.00257	0.09724
		-	(0.03453)	(0.04907)	(0.03655)
	θ_{esgs}	-	-	-0.00301	-
		-	-	(0.03524)	-
	$\theta_{esgsl18}$	-	-	-	0.71379
		-	-	-	(0.1515)
2	$\|w_i\| * 100$	0.1012	0.2675	0.2679	0.1686
	$\min w_i * 100$	0.0078	0.0000	0.0000	0.0000
	$\max w_i * 100$	0.2857	8.2604	8.2680	5.9877
	$\sum w_i I(w_i < 0)$	-	-	-	-
	$\sum I(w_i \leq 0)/\mathrm{Nt}$	0.0084	0.5854	0.5861	0.3550
	$(\sum w_i)/1$	1.0000	1.0000	1.0000	1.0000
3	$\bar{r}$(annual)	0.16267	0.15042	0.15043	0.16463
	σ(r) (annual)	0.18503	0.13965	0.13964	0.15153
	SR (annual)	0.85180	1.04082	1.04103	1.05304
	$\bar{r} - TCovid$(annual)	0.2420	0.2450	0.2451	0.2456
	VaR-95%*100/ ES-95%*100	13.02/ 16.82	8.28/ 10.75	8.28/ 10.74	8.97/ 11.68
	VaR-99%*100, ES-99%*100	19.20/ 22.34	12.28/ 14.32	12.28/ 14.32	13.37/ 15.62
	mean ESGS(wholeperiod)	41.60	49.98	49.95	44.79
	mean ESGS(2020-end)	41.72	41.72	41.72	41.72
	Size(US$mio)	16,087	177,694	177,858	124,960
	Nt	1,300	580	579	889
	Turnover*100	3.85	1.06	1.07	4.52
4	α (annual)	0.0189	0.0088	0.0088	0.0218
	β_{Mkt}	1.0392	0.9738	0.9738	0.9876
	β_{SMB}	0.4998	-0.1522	-0.1525	0.0936
	β_{HML}	0.2029	-0.0031	-0.0033	0.0567
	β_{WML}	-0.0774	-0.0009	-0.0009	-0.0023
5	ME	-	3.6432	3.6467	2.4777
	SEV	-	-0.2485	-0.2486	-0.1988
	LR12	-	0.1334	0.1333	0.1638
	ESGS	-	-0.1681	0.5515	-0.1341
	ESGSL18	-	-0.2585	-0.2587	0.3188

**Standard errors reported in bracket*

Source: author's calculation

Table B6: Estimates of portfolio policies in case of 30bps transaction cost, short-sale constraint

30bps transaction cost, Shortsale constraint applied					
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	4.70953	4.71730	3.39912
		-	(0.7527)	(0.61485)	(0.51147)
	θ_{sev}	-	-0.00044	-0.00010	-0.01875
		-	(0.01403)	(0.01713)	(0.02216)
	θ_{lr12}	-	-0.00169	-0.00257	0.08530
		-	(0.0291)	(0.02892)	(0.03313)
	θ_{esgs}	-	-	-0.00301	-
		-	-	(0.02775)	-
	$\theta_{esgsl18}$	-	-	-	0.61146
		-	-	-	(0.03456)
2	$\lvert w_i \rvert * 100$	0.1012	0.2675	0.2679	0.1840
	$\min w_i * 100$	0.0078	0.0000	0.0000	0.0000
	$\max w_i * 100$	0.2857	8.2604	8.2680	6.7489
	$\sum w_i I(w_i < 0)$	-	-	-	-
	$\sum I(w_i \leq 0)/\text{Nt}$	0.0084	0.5854	0.5861	0.4014
	$(\sum w_i)/1$	1.0000	1.0000	1.0000	1.0000
3	$\bar{r}$(annual)	0.16082	0.14991	0.14992	0.15871
	σ(r) (annual)	0.18496	0.13963	0.13962	0.14757
	SR (annual)	0.84213	1.03731	1.03752	1.04116
	$\bar{r} - TCovid$(annual)	0.2396	0.2440	0.2441	0.2430
	VaR-95%*100/ ES-95%*100	13.08/ 16.87	8.30/ 10.76	8.30/ 10.75	8.79/ 11.41
	VaR-99%*100, ES-99%*100	19.24/ 22.38	12.29/ 14.32	12.28/ 14.32	13.05/ 15.22
	mean ESGS(wholeperiod)	41.6012	49.9793	49.9505	45.4895
	mean ESGS(2020-end)	41.7244	41.7181	41.7181	41.7181
	Size(US$mio)	16,087	177,694	177,858	141,825
	Nt	1,300	580	579	831
	Turnover*100	3.85	1.06	1.07	3.57
4	α (annual)	0.0171	0.0083	0.0083	0.0162
	β_{Mkt}	1.0387	0.9737	0.9737	0.9838
	β_{SMB}	0.4997	-0.1523	-0.1526	0.0163
	β_{HML}	0.2039	-0.0029	-0.0032	0.0385
	β_{WML}	-0.0767	-0.0008	-0.0007	-0.0018
5	ME	-	3.6432	3.6467	2.8591
	SEV	-	-0.2485	-0.2486	-0.2142
	LR12	-	0.1334	0.1333	0.1607
	ESGS	-	-0.1681	0.5515	-0.1452
	ESGSL18	-	-0.2585	-0.2587	0.1768

**Standard errors reported in bracket*

Source: author's calculation

Table B7: Estimates of portfolio policies in case of 50bps transaction cost, short-sale constraint

50bps transaction cost,Shortsale constraint applied					
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	4.70954	4.71726	3.73647
		-	(0.76117)	(0.43616)	(0.49078)
	θ_{sev}	-	-0.00044	-0.00010	-0.01359
		-	(0.01712)	(0.0221)	(0.02206)
	θ_{lr12}	-	-0.00169	-0.00256	0.05617
		-	(0.02605)	(0.03084)	(0.02728)
	θ_{esgs}	-	-	-0.00301	-
		-	-	(0.03175)	-
	$\theta_{esgsl18}$	-	-	-	0.56128
		-	-	-	(0.01777)
2	$\lvert w_i \rvert * 100$	0.1012	0.2675	0.2679	0.1950
	$\min w_i * 100$	0.0078	0.0000	0.0000	0.0000
	$\max w_i * 100$	0.2857	8.2604	8.2680	7.1501
	$\sum w_i I(w_i < 0)$	-	-	-	-
	$\sum I(w_i \leq 0)/\mathrm{Nt}$	0.0084	0.5854	0.5861	0.4327
	$(\sum w_i)/1$	1.0000	1.0000	1.0000	1.0000
3	$\bar{r}$(annual)	0.15898	0.14939	0.14941	0.15525
	σ(r) (annual)	0.18489	0.13961	0.13960	0.14564
	SR (annual)	0.83243	1.03380	1.03400	1.03115
	$\bar{r} - TCovid$(annual)	0.2373	0.2431	0.2432	0.2403
	VaR-95%*100/ ES-95%*100	13.05/ 16.86	8.27/ 10.72	8.26/ 10.72	8.64/ 11.22
	VaR-99%*100, ES-99%*100	19.22/ 22.40	12.25/ 14.31	12.25/ 14.30	12.83/ 14.98
	mean ESGS(wholeperiod)	41.60	49.98	49.95	45.98
	mean ESGS(2020-end)	41.72	41.72	41.72	41.72
	Size(US$mio)	16,087	177,694	177,858	151,204
	Nt	1,300	580	579	790
	Turnover*100	3.85	1.06	1.07	3.02
4	α (annual)	0.0154	0.0078	0.0078	0.0131
	β_{Mkt}	1.0383	0.9736	0.9736	0.9817
	β_{SMB}	0.4996	-0.1524	-0.1527	-0.0262
	β_{HML}	0.2048	-0.0028	-0.0030	0.0287
	β_{WML}	-0.0760	-0.0007	-0.0006	-0.0044
5	ME	-	3.6432	3.6467	3.0696
	SEV	-	-0.2485	-0.2486	-0.2224
	LR12	-	0.1334	0.1333	0.1489
	ESGS	-	-0.1681	0.5515	-0.1513
	ESGSL18	-	-0.2585	-0.2587	0.1017

**Standard errors reported in bracket*

Source: author's calculation

Table B8: Estimates of portfolio policies in case of 100bps transaction cost, short-sale constraint

	100bps transaction cost, Shortsale constraint applied				
	Policies	#1	#2	#3	#4
Panel	Variable	Equal weighted	3 characteristic: ME,SEV, LR12,	4 characteristic: ME,SEV, LR12,ESGS	4 characteristic: ME,SEV, LR12,ESGSL18
1	θ_{me}	-	4.70950	4.71729	4.70473
		-	(0.65603)	(0.4184)	(0.46031)
	θ_{sev}	-	-0.00044	-0.00008	-0.00044
		-	(0.0202)	(0.02141)	(0.0216)
	θ_{lr12}	-	-0.00169	-0.00256	-0.00168
		-	(0.02093)	(0.02239)	(0.02112)
	θ_{esgs}	-	-	-0.00299	-
		-	-	(0.03542)	-
	$\theta_{esgsl18}$	-	-	-	0.00794
		-	-	-	(0.0102)
2	$\lvert w_i \rvert * 100$	0.1012	0.2675	0.2679	0.2673
	$\min w_i * 100$	0.0078	0.0000	0.0000	0.0000
	$\max w_i * 100$	0.2857	8.2604	8.2680	8.2581
	$\sum w_i I(w_i < 0)$	0	0	0	0
	$\sum I(w_i \leq 0)/\mathrm{Nt}$	0.0084	0.5854	0.5861	0.5849
	$(\sum w_i)/1$	1	1	1	1
3	$\bar{r}$(annual)	0.15435	0.14812	0.14813	0.14813
	σ(r) (annual)	0.18473	0.13956	0.13955	0.13957
	SR (annual)	0.80815	1.02501	1.02520	1.02503
	$\bar{r} - TCovid$(annual)	0.2313	0.2407	0.2408	0.2408
	VaR-95%*100/ ES-95%*100	13.16/ 16.97	8.29/ 10.74	8.29/ 10.74	8.29/ 10.75
	VaR-99%*100, ES-99%*100	19.33/ 22.52	12.27/ 14.32	12.26/ 14.32	12.27/ 14.33
	mean ESGS(wholeperiod)	41.60	49.98	49.95	49.98
	mean ESGS(2020-end)	41.72	41.72	41.72	41.72
	Size(US$mio)	16,087	177,694	177,858	177,605
	Nt	1,300	580	579	581
	Turnover*100	3.8513	1.0646	1.0657	1.0665
4	α (annual)	0.0109	0.0066	0.0066	0.0066
	β_{Mkt}	1.0373	0.9732	0.9732	0.9733
	β_{SMB}	0.4992	-0.1527	-0.1530	-0.1526
	β_{HML}	0.2072	-0.0024	-0.0026	-0.0024
	β_{WML}	-0.0742	-0.0004	-0.0003	-0.0004
5	ME	-	3.6432	3.6467	3.6432
	SEV	-	-0.2485	-0.2486	-0.2485
	LR12	-	0.1334	0.1333	0.1334
	ESGS	-	-0.1681	0.5515	-0.1682
	ESGSL18	-	-0.2585	-0.2587	-0.2565

**Standard errors reported in bracket*

Source: author's calculation

Appendix C: Cumulative Returns of Portfolios with different cost level

Figure C.1: Cumulative return in the presence of transaction cost - no short-sale constraint

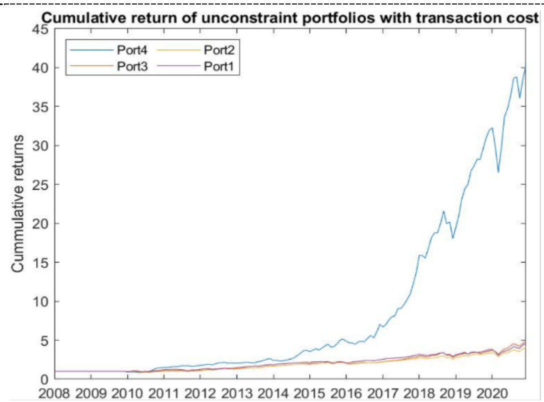
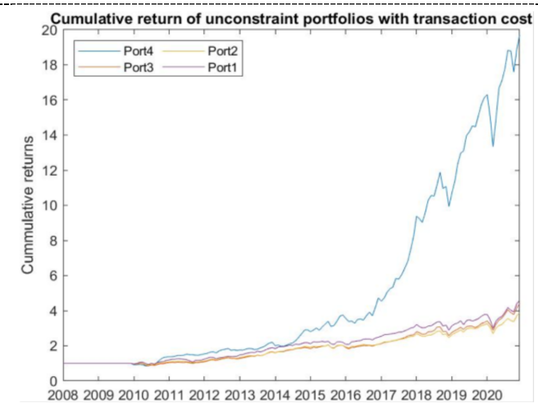
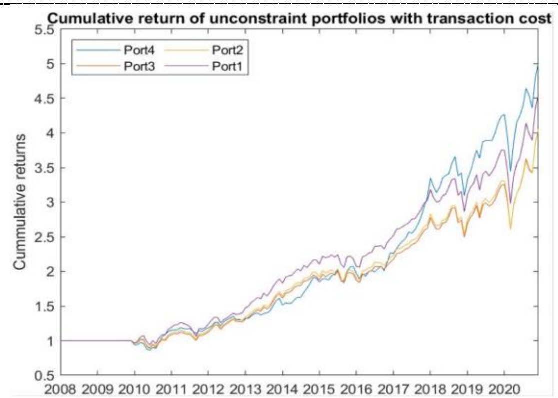
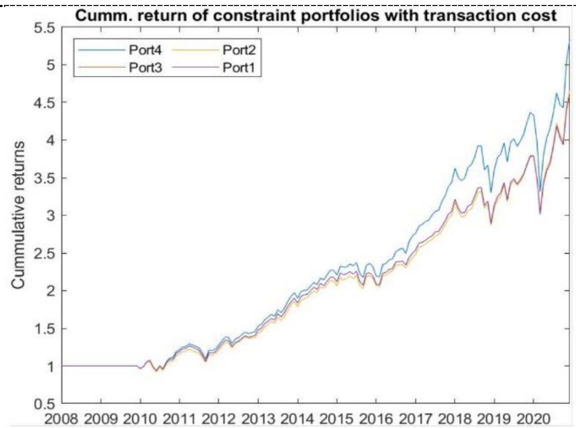
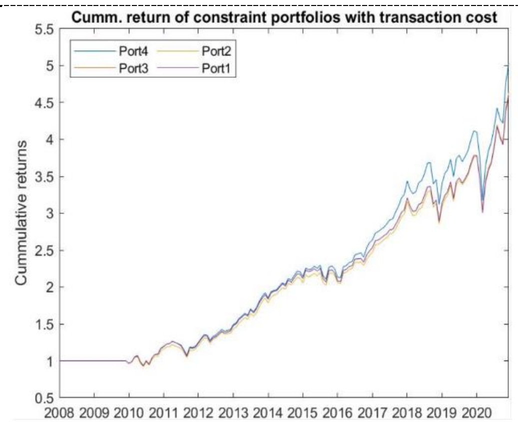
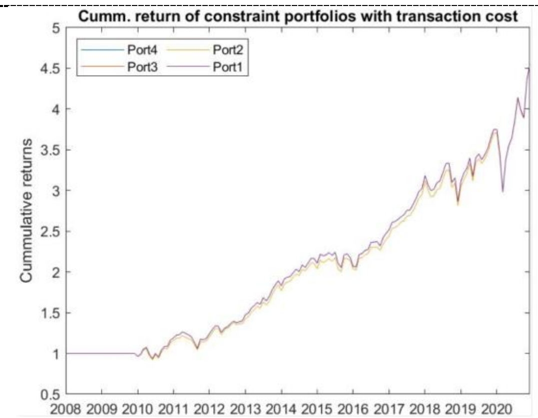
10bps	30bps	100bps
		

Figure C.2: Cumulative return in the presence of transaction cost - in the presence of short-sale constraint

10 bps	30bps	100bps
		

Source: author's calculation

Appendix D: Analytical VaR of Portfolios

Figure D1: Analytical VaR of Portfolios under the assumption that loss has t-distribution.

		No Short-sale Constraint					Short-sale Constraint				
	Portfolio/ Trans_cost	N/A	10bps	30bps	50bps	100bps	N/A	10bps	30bps	50bps	100bps
VaR-95%	P1	7.56	7.57	7.58	7.59	7.62	7.56	7.57	7.58	7.59	7.62
	P2	6.15	4.94	5.00	5.16	5.50	5.42	5.42	5.42	5.43	5.44
	P3	5.75	5.49	5.29	5.25	5.42	5.42	5.42	5.42	5.46	5.43
	P4	6.08	5.99	5.81	5.62	5.24	6.05	5.97	5.83	5.73	5.60
VaR-99%	P1	11.33	11.33	11.34	11.36	11.38	11.33	11.33	11.34	11.36	11.38
	P2	8.75	7.51	7.58	7.81	8.30	8.23	8.24	8.24	8.24	8.25
	P3	8.80	8.38	8.04	7.96	8.20	8.23	8.23	8.24	8.29	8.25
	P4	10.12	9.86	9.37	8.92	8.05	9.21	9.09	8.87	8.70	8.49

Source: author's calculation

Appendix E: Plot of Conditional volatilities of portfolio return

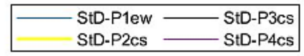
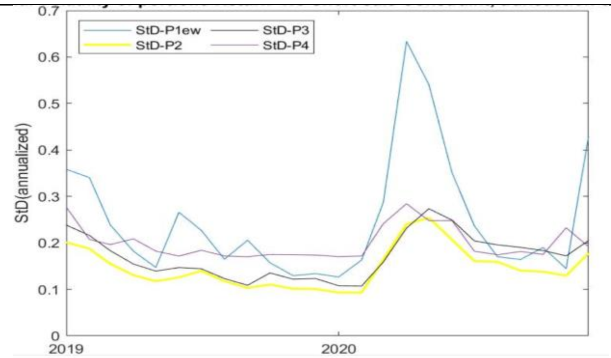
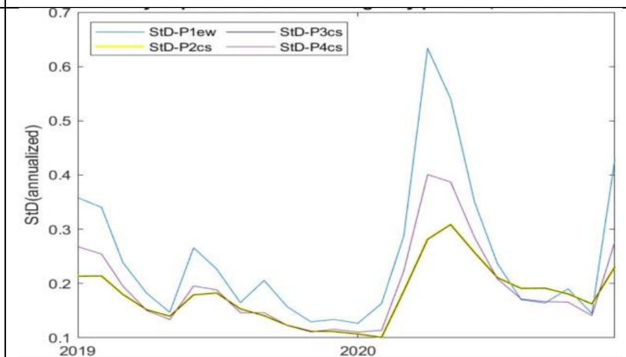
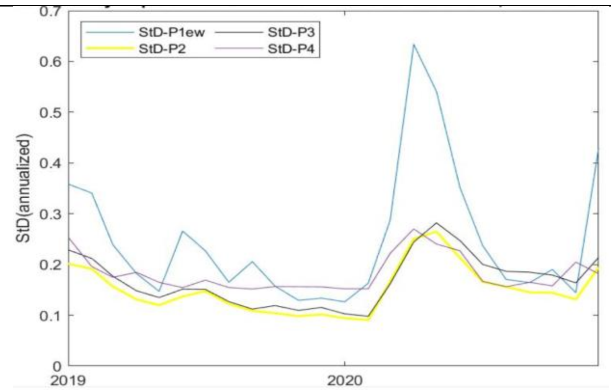
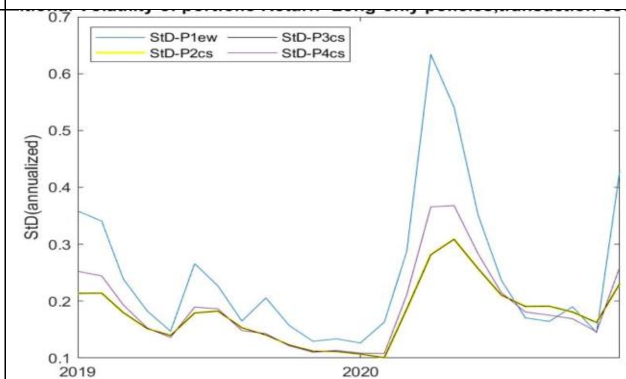
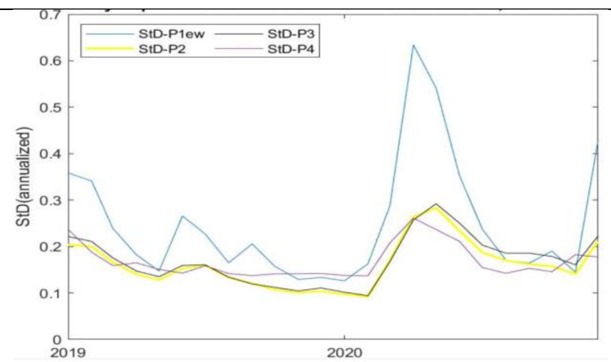
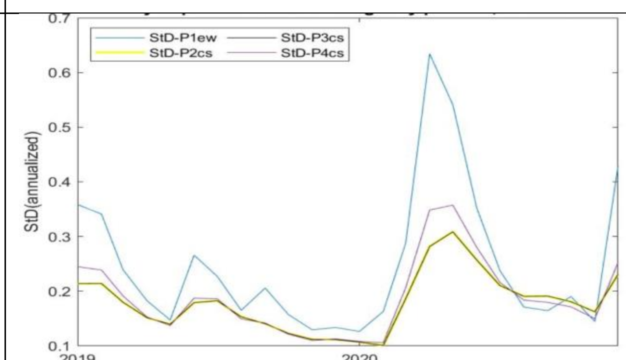
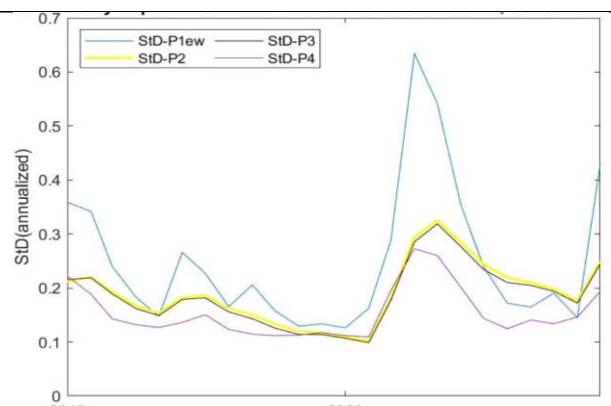
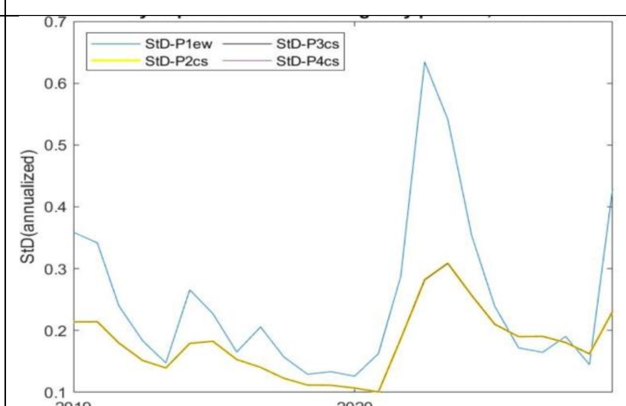


Figure E1: Conditional volatilities (StD) of Portfolio Return by time (2019-2020)

Cost	No Short-sale Constraint	Short-Sale Constraint
10bps		
30bps		
50bps		
100bps		

Appendix F**: Portfolios' Returns during Covid period**

Table F1: Monthly return of the portfolios from Jan2020 – Dec2020

Return during covid period : Jan2020 - Dec2020														
Cost	Month	202001	202002	202003	202004	202005	202006	202007	202008	202009	202010	202011	202012	Remark
NA	R_P1e	-0.0308	-0.0887	-0.2313	0.1701	0.0587	0.0421	0.0295	0.0544	-0.0398	0.0203	0.1844	0.0742	Port 1, equal weight, no constraint
	R_P2	0.0322	-0.0653	-0.0982	0.1072	0.0534	0.0106	0.0669	0.0387	-0.0273	-0.0233	0.0830	0.0473	Port 2, no constraint
	R_P3	0.0426	-0.0540	-0.0864	0.1211	0.0809	0.0349	0.0734	0.0689	-0.0380	-0.0341	0.0878	0.0654	Port 3, no constraint
	R_P4	0.0092	-0.0785	-0.1074	0.1272	0.1385	0.0343	0.0497	0.0675	0.0072	-0.0747	0.0665	0.0438	Port 4, no constraint
	R_P2cs	0.0029	-0.0808	-0.1242	0.1330	0.0503	0.0261	0.0574	0.0734	-0.0373	-0.0211	0.1192	0.0466	Port 2, shortsale constraint
	R_P3cs	0.0025	-0.0811	-0.1265	0.1344	0.0510	0.0270	0.0559	0.0728	-0.0376	-0.0189	0.1230	0.0483	Port 3, shortsale constraint
	R_P4cs	-0.0086	-0.0829	-0.1682	0.1481	0.0600	0.0331	0.0474	0.0614	-0.0338	-0.0073	0.1395	0.0584	Port 4,shortsale constraint
10bps	R_P1eadj	-0.0308	-0.0888	-0.2314	0.1699	0.0586	0.0420	0.0295	0.0543	-0.0399	0.0202	0.1844	0.0741	Port 1, equal weight, no constraint
	R_P2adj	0.0275	-0.0663	-0.1014	0.1089	0.0523	0.0125	0.0623	0.0419	-0.0302	-0.0222	0.0889	0.0472	Port 2, no constraint
	R_P3adj	0.0372	-0.0560	-0.0903	0.1204	0.0766	0.0336	0.0681	0.0679	-0.0396	-0.0319	0.0922	0.0629	Port 3, no constraint
	R_P4adj	0.0104	-0.0791	-0.1086	0.1247	0.1295	0.0310	0.0454	0.0645	0.0042	-0.0709	0.0679	0.0439	Port 4, no constraint
	R_P2csadj	0.0028	-0.0808	-0.1242	0.1329	0.0503	0.0261	0.0574	0.0733	-0.0374	-0.0212	0.1192	0.0465	Port 2, shortsale constraint
	R_P3csadj	0.0029	-0.0808	-0.1241	0.1329	0.0503	0.0261	0.0574	0.0734	-0.0374	-0.0212	0.1191	0.0465	Port 3, shortsale constraint
	R_P4csadj	-0.0082	-0.0829	-0.1659	0.1472	0.0595	0.0328	0.0473	0.0620	-0.0340	-0.0083	0.1383	0.0577	Port 4,shortsale constraint
30bps	R_P1eadj	-0.0310	-0.0889	-0.2315	0.1695	0.0584	0.0418	0.0293	0.0541	-0.0401	0.0201	0.1842	0.0739	Port 1, equal weight, no constraint
	R_P2adj	0.0186	-0.0697	-0.1093	0.1147	0.0510	0.0168	0.0560	0.0497	-0.0345	-0.0202	0.1007	0.0474	Port 2, no constraint
	R_P3adj	0.0274	-0.0615	-0.0990	0.1219	0.0692	0.0317	0.0613	0.0682	-0.0411	-0.0282	0.1009	0.0587	Port 3, no constraint
	R_P4adj	0.0112	-0.0797	-0.1111	0.1212	0.1141	0.0264	0.0379	0.0605	-0.0021	-0.0636	0.0726	0.0442	Port 4, no constraint
	R_P2csadj	0.0028	-0.0809	-0.1242	0.1328	0.0502	0.0261	0.0572	0.0733	-0.0375	-0.0213	0.1191	0.0465	Port 2, shortsale constraint
	R_P3csadj	0.0028	-0.0809	-0.1241	0.1328	0.0502	0.0261	0.0572	0.0733	-0.0375	-0.0214	0.1191	0.0464	Port 3, shortsale constraint
	R_P4csadj	-0.0053	-0.0823	-0.1552	0.1435	0.0576	0.0313	0.0497	0.0647	-0.0345	-0.0127	0.1318	0.0544	Port 4,shortsale constraint
50bps	R_P1eadj	-0.0311	-0.0891	-0.2317	0.1691	0.0581	0.0416	0.0291	0.0540	-0.0403	0.0199	0.1840	0.0736	Port 1, equal weight, no constraint
	R_P2adj	0.0112	-0.0742	-0.1188	0.1224	0.0507	0.0210	0.0536	0.0574	-0.0366	-0.0183	0.1116	0.0483	Port 2, no constraint
	R_P3adj	0.0187	-0.0678	-0.1087	0.1256	0.0632	0.0306	0.0579	0.0696	-0.0411	-0.0249	0.1092	0.0555	Port 3, no constraint
	R_P4adj	0.0106	-0.0801	-0.1139	0.1196	0.1011	0.0237	0.0325	0.0586	-0.0084	-0.0566	0.0789	0.0447	Port 4, no constraint
	R_P2csadj	0.0028	-0.0809	-0.1243	0.1327	0.0502	0.0261	0.0571	0.0732	-0.0377	-0.0214	0.1191	0.0464	Port 2, shortsale constraint
	R_P3csadj	0.0028	-0.0809	-0.1241	0.1327	0.0502	0.0261	0.0571	0.0732	-0.0377	-0.0215	0.1190	0.0463	Port 3, shortsale constraint
	R_P4csadj	-0.0040	-0.0822	-0.1492	0.1414	0.0564	0.0305	0.0504	0.0666	-0.0350	-0.0154	0.1284	0.0523	Port 4,shortsale constraint
100bps	R_P1eadj	-0.0314	-0.0896	-0.2321	0.1681	0.0576	0.0411	0.0287	0.0535	-0.0407	0.0195	0.1835	0.0731	Port 1, equal weight, no constraint
	R_P2adj	-0.0001	-0.0817	-0.1397	0.1366	0.0516	0.0277	0.0515	0.0667	-0.0380	-0.0134	0.1294	0.0516	Port 2, no constraint
	R_P3adj	0.0043	-0.0785	-0.1315	0.1350	0.0554	0.0298	0.0532	0.0702	-0.0397	-0.0172	0.1254	0.0530	Port 3, no constraint
	R_P4adj	0.0068	-0.0809	-0.1219	0.1221	0.0746	0.0223	0.0316	0.0601	-0.0232	-0.0387	0.0988	0.0465	Port 4, no constraint
	R_P2csadj	0.0027	-0.0811	-0.1243	0.1324	0.0500	0.0260	0.0567	0.0730	-0.0380	-0.0217	0.1189	0.0461	Port 2, shortsale constraint
	R_P3csadj	0.0027	-0.0810	-0.1242	0.1324	0.0500	0.0260	0.0567	0.0730	-0.0380	-0.0217	0.1189	0.0461	Port 3, shortsale constraint
	R_P4csadj	0.0027	-0.0811	-0.1244	0.1324	0.0500	0.0260	0.0567	0.0729	-0.0380	-0.0217	0.1190	0.0462	Port 4,shortsale constraint

Source: author's calculation

Appendix G: Regression result of Multi-Beta model

No Short-sale constraint

Table G1: Regression result of excess return on risk factors - 0 transaction cost-No Constraint

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	RP1_0Cncs	RP1_0Cncs	RP2_0Cncs	RP2_0Cncs	RP3_0Cncs	RP3_0Cncs	RP4_0Cncs	RP4_0Cncs
ER_Mkt	1.039***	1.035***	0.888***	0.873***	0.933***	0.920***	0.796***	0.790***
	(0.0240)	(0.0221)	(0.0328)	(0.0317)	(0.0425)	(0.0428)	(0.133)	(0.131)
SMB	0.500***	0.499***	-0.232***	-0.236***	-0.0986	-0.102	0.128	0.126
	(0.0319)	(0.0324)	(0.0417)	(0.0418)	(0.0737)	(0.0737)	(0.218)	(0.219)
HML	0.202***	0.207***	-0.0933*	-0.0772	-0.193***	-0.180**	-0.292	-0.285
	(0.0532)	(0.0558)	(0.0551)	(0.0532)	(0.0703)	(0.0698)	(0.239)	(0.244)
WML	-0.0778***	-0.0791***	0.276***	0.272***	0.298***	0.294***	0.285**	0.283**
	(0.0253)	(0.0253)	(0.0367)	(0.0356)	(0.0528)	(0.0522)	(0.124)	(0.126)
ESGMoM		0.0761		0.252*		0.207		0.106
		(0.0935)		(0.130)		(0.201)		(0.600)
Constant	0.00165**	0.00168**	-0.000273	-0.000160	0.000540	0.000633	0.0216***	0.0216***
	(0.000668)	(0.000663)	(0.00107)	(0.00107)	(0.00162)	(0.00163)	(0.00502)	(0.00508)
Observations	132	132	132	132	132	132	132	132
R-squared	0.979	0.980	0.905	0.908	0.829	0.831	0.301	0.301
Adjusted r-squared	0.979	0.979	0.902	0.904	0.824	0.824	0.279	0.274

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table G2: Regression result of excess return on risk factors - 10bps transaction cost - No Constraint

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	RP1_10Cncs	RP1_10Cncs	RP2_10Cncs	RP2_10Cncs	RP3_10Cncs	RP3_10Cncs	RP4_10Cncs	RP4_10Cncs
ER_Mkt	1.039***	1.035***	0.885***	0.872***	0.923***	0.911***	0.800***	0.793***
	(0.0240)	(0.0221)	(0.0313)	(0.0301)	(0.0398)	(0.0399)	(0.122)	(0.120)
SMB	0.500***	0.499***	-0.247***	-0.250***	-0.129*	-0.132*	0.112	0.110
	(0.0319)	(0.0324)	(0.0400)	(0.0401)	(0.0675)	(0.0675)	(0.199)	(0.199)
HML	0.203***	0.208***	-0.0946*	-0.0797	-0.184***	-0.172***	-0.269	-0.261
	(0.0532)	(0.0558)	(0.0528)	(0.0510)	(0.0657)	(0.0650)	(0.219)	(0.224)
WML	-0.0774***	-0.0787***	0.214***	0.210***	0.237***	0.234***	0.286**	0.283**
	(0.0253)	(0.0253)	(0.0350)	(0.0340)	(0.0494)	(0.0487)	(0.115)	(0.116)
ESGMoM		0.0761		0.233*		0.196		0.121
		(0.0934)		(0.127)		(0.189)		(0.547)
Constant	0.00157**	0.00161**	-0.000413	-0.000308	0.000211	0.000300	0.0180***	0.0181***
	(0.000668)	(0.000662)	(0.00103)	(0.00103)	(0.00150)	(0.00151)	(0.00457)	(0.00463)
Observations	132	132	132	132	132	132	132	132
R-squared	0.979	0.980	0.913	0.915	0.845	0.847	0.340	0.340
Adjusted r-squared	0.979	0.979	0.910	0.912	0.840	0.840	0.319	0.314

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table G3: Regression result of excess return on risk factors - 30bps transaction cost - No Constraint

VARIABLES	(1) RP1_30Cncs	(2) RP1_30Cncs	(3) RP2_30Cncs	(4) RP2_30Cncs	(5) RP3_30Cncs	(6) RP3_30Cncs	(7) RP4_30Cncs	(8) RP4_30Cncs
ER_Mkt	1.039***	1.034***	0.893***	0.882***	0.918***	0.908***	0.807***	0.799***
	(0.0241)	(0.0221)	(0.0282)	(0.0270)	(0.0348)	(0.0345)	(0.103)	(0.101)
SMB	0.500***	0.498***	-0.268***	-0.271***	-0.185***	-0.188***	0.0762	0.0740
	(0.0319)	(0.0324)	(0.0370)	(0.0371)	(0.0566)	(0.0566)	(0.166)	(0.166)
HML	0.204***	0.209***	-0.0868*	-0.0748	-0.158***	-0.147**	-0.231	-0.222
	(0.0533)	(0.0558)	(0.0485)	(0.0471)	(0.0573)	(0.0564)	(0.185)	(0.188)
WML	-0.0767***	-0.0780***	0.108***	0.104***	0.140***	0.137***	0.264***	0.261***
	(0.0253)	(0.0253)	(0.0322)	(0.0313)	(0.0432)	(0.0425)	(0.0988)	(0.0998)
ESGMoM		0.0760		0.189		0.168		0.140
		(0.0934)		(0.121)		(0.166)		(0.458)
Constant	0.00143**	0.00146**	-0.000454	-0.000369	-0.000175	-9.92e-05	0.0123***	0.0124***
	(0.000668)	(0.000662)	(0.000935)	(0.000937)	(0.00129)	(0.00129)	(0.00382)	(0.00386)
Observations	132	132	132	132	132	132	132	132
R-squared	0.979	0.979	0.930	0.931	0.879	0.880	0.418	0.419
Adjusted r-squared	0.979	0.979	0.928	0.929	0.875	0.875	0.400	0.396

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table G4: Regression result of excess return on risk factors - 50bps transaction cost - No Constraint

VARIABLES	(1) RP1_30Cncs	(2) RP1_30Cncs	(3) RP2_30Cncs	(4) RP2_30Cncs	(5) RP3_30Cncs	(6) RP3_30Cncs	(7) RP4_30Cncs	(8) RP4_30Cncs
ER_Mkt	1.038***	1.034***	0.912***	0.904***	0.925***	0.917***	0.816***	0.807***
	(0.0241)	(0.0221)	(0.0256)	(0.0242)	(0.0303)	(0.0298)	(0.0876)	(0.0855)
SMB	0.500***	0.498***	-0.268***	-0.270***	-0.225***	-0.227***	0.0343	0.0319
	(0.0319)	(0.0324)	(0.0345)	(0.0347)	(0.0476)	(0.0476)	(0.138)	(0.138)
HML	0.205***	0.210***	-0.0668	-0.0574	-0.124**	-0.115**	-0.199	-0.190
	(0.0533)	(0.0558)	(0.0450)	(0.0441)	(0.0503)	(0.0495)	(0.155)	(0.158)
WML	-0.0760***	-0.0773***	0.0383	0.0358	0.0685*	0.0662*	0.224***	0.222**
	(0.0253)	(0.0253)	(0.0302)	(0.0294)	(0.0379)	(0.0373)	(0.0855)	(0.0862)
ESGMoM		0.0759		0.146		0.137		0.148
		(0.0933)		(0.115)		(0.147)		(0.384)
Constant	0.00128*	0.00131**	-0.000340	-0.000274	-0.000305	-0.000244	0.00812**	0.00819**
	(0.000667)	(0.000662)	(0.000852)	(0.000856)	(0.00110)	(0.00110)	(0.00318)	(0.00321)
Observations	132	132	132	132	132	132	132	132
R-squared	0.979	0.979	0.945	0.946	0.911	0.912	0.503	0.504
Adjusted r-squared	0.979	0.979	0.944	0.944	0.908	0.908	0.487	0.484

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table G5: Regression result of excess return on risk factors - 100bps transaction cost-No Constraint

VARIABLES	(1) RP1_100Cncs	(2) RP1_100Cncs	(3) RP2_100Cncs	(4) RP2_100Cncs	(5) RP3_100Cncs	(6) RP3_100Cncs	(7) RP4_100Cncs	(8) RP4_100Cncs
ER_Mkt	1.037***	1.033***	0.955***	0.949***	0.951***	0.945***	0.859***	0.851***
	(0.0241)	(0.0221)	(0.0221)	(0.0207)	(0.0238)	(0.0227)	(0.0534)	(0.0517)
SMB	0.499***	0.498***	-0.198***	-0.200***	-0.212***	-0.213***	-0.0919	-0.0940
	(0.0319)	(0.0324)	(0.0312)	(0.0314)	(0.0352)	(0.0353)	(0.0775)	(0.0779)
HML	0.207***	0.212***	-0.0139	-0.00816	-0.0461	-0.0401	-0.125	-0.116
	(0.0534)	(0.0560)	(0.0414)	(0.0414)	(0.0423)	(0.0421)	(0.0926)	(0.0941)
WML	-0.0742***	-0.0755***	-0.0292	-0.0308	-0.0149	-0.0165	0.102*	0.0998*
	(0.0254)	(0.0254)	(0.0274)	(0.0271)	(0.0300)	(0.0296)	(0.0557)	(0.0558)
ESGMoM		0.0757		0.0896		0.0928		0.136
		(0.0933)		(0.103)		(0.115)		(0.230)
Constant	0.000912	0.000947	-4.52e-05	-4.85e-06	-0.000192	-0.000150	0.00174	0.00180
	(0.000668)	(0.000661)	(0.000728)	(0.000731)	(0.000813)	(0.000817)	(0.00183)	(0.00185)
Observations	132	132	132	132	132	132	132	132
R-squared	0.979	0.979	0.965	0.965	0.954	0.955	0.757	0.758
Adjusted r-squared	0.979	0.978	0.964	0.964	0.953	0.953	0.749	0.748

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Short-sale constraint applied

Table G6: Regression result of excess return on risk factors - 0 transaction cost- Long-only

VARIABLES	(1) RP2_0Ccs	(2) RP2_0Ccs	(3) RP3_0Ccs	(4) RP3_0Ccs	(5) RP4_0Ccs	(6) RP4_0Ccs
ER_Mkt	0.974***	0.972***	0.975***	0.973***	0.989***	0.985***
	(0.00984)	(0.0101)	(0.0104)	(0.0105)	(0.0180)	(0.0168)
SMB	-0.152***	-0.153***	-0.143***	-0.144***	0.111***	0.110***
	(0.0156)	(0.0156)	(0.0165)	(0.0166)	(0.0236)	(0.0238)
HML	-0.00318	-0.00150	-0.00247	-0.000268	0.0605	0.0649
	(0.0160)	(0.0154)	(0.0171)	(0.0164)	(0.0396)	(0.0409)
WML	-0.000954	-0.00140	-0.00628	-0.00687	-0.000596	-0.00178
	(0.0125)	(0.0125)	(0.0136)	(0.0136)	(0.0183)	(0.0182)
ESGMoM		0.0263		0.0345		0.0697
		(0.0490)		(0.0522)		(0.0745)
Constant	0.000752*	0.000764*	0.000774*	0.000789*	0.00197***	0.00200***
	(0.000393)	(0.000393)	(0.000404)	(0.000405)	(0.000532)	(0.000532)
Observations	132	132	132	132	132	132
R-squared	0.990	0.990	0.990	0.990	0.983	0.984
Adjusted r-squared	0.990	0.990	0.989	0.989	0.983	0.983

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table G7: Regression result of excess return on risk factors - 10bps transaction cost- Long-only

VARIABLES	(1) RP2_10Ccs	(2) RP2_10Ccs	(3) RP3_10Ccs	(4) RP3_10Ccs	(5) RP4_10Ccs	(6) RP4_10Ccs
ER_Mkt	0.974***	0.972***	0.974***	0.972***	0.988***	0.984***
	(0.00984)	(0.0101)	(0.00983)	(0.0101)	(0.0176)	(0.0164)
SMB	-0.152***	-0.153***	-0.153***	-0.153***	0.0936***	0.0925***
	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0231)	(0.0233)
HML	-0.00310	-0.00142	-0.00332	-0.00166	0.0567	0.0610
	(0.0160)	(0.0154)	(0.0159)	(0.0153)	(0.0383)	(0.0395)
WML	-0.000897	-0.00134	-0.000854	-0.00130	-0.00231	-0.00345
	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0180)	(0.0179)
ESGMoM		0.0263		0.0261		0.0676
		(0.0490)		(0.0490)		(0.0727)
Constant	0.000732*	0.000744*	0.000733*	0.000744*	0.00182***	0.00185***
	(0.000393)	(0.000393)	(0.000393)	(0.000393)	(0.000522)	(0.000522)
Observations	132	132	132	132	132	132
R-squared	0.990	0.990	0.990	0.990	0.984	0.984
Adjusted r-squared	0.990	0.990	0.990	0.990	0.983	0.983

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table G8: Regression result of excess return on risk factors - 30bps transaction cost- Long-only

VARIABLES	(1) RP2_30Ccs	(2) RP2_30Ccs	(3) RP3_30Ccs	(4) RP3_30Ccs	(5) RP4_30Ccs	(6) RP4_30Ccs
ER_Mkt	0.974***	0.972***	0.974***	0.972***	0.984***	0.980***
	(0.00985)	(0.0101)	(0.00984)	(0.0101)	(0.0155)	(0.0146)
SMB	-0.152***	-0.153***	-0.153***	-0.153***	0.0163	0.0153
	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0208)	(0.0210)
HML	-0.00294	-0.00127	-0.00316	-0.00150	0.0385	0.0423
	(0.0160)	(0.0154)	(0.0159)	(0.0153)	(0.0326)	(0.0334)
WML	-0.000779	-0.00122	-0.000737	-0.00118	-0.00178	-0.00279
	(0.0125)	(0.0125)	(0.0125)	(0.0125)	(0.0164)	(0.0163)
ESGMoM		0.0261		0.0259		0.0594
		(0.0490)		(0.0490)		(0.0651)
Constant	0.000692*	0.000703*	0.000692*	0.000704*	0.00135***	0.00138***
	(0.000393)	(0.000393)	(0.000393)	(0.000393)	(0.000479)	(0.000479)
Observations	132	132	132	132	132	132
R-squared	0.990	0.990	0.990	0.990	0.986	0.986
Adjusted r-squared	0.990	0.990	0.990	0.990	0.986	0.986

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table G9: Regression result of excess return on risk factors - 50bps transaction cost- Long-only

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	RP2_50Ccs	RP2_50Ccs	RP3_50Ccs	RP3_50Ccs	RP4_50Ccs	RP4_50Ccs
ER_Mkt	0.974***	0.972***	0.974***	0.972***	0.982***	0.979***
	(0.00986)	(0.0101)	(0.00985)	(0.0101)	(0.0143)	(0.0136)
SMB	-0.152***	-0.153***	-0.153***	-0.153***	-0.0262	-0.0270
	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0197)	(0.0198)
HML	-0.00277	-0.00111	-0.00299	-0.00135	0.0287	0.0320
	(0.0160)	(0.0154)	(0.0159)	(0.0154)	(0.0291)	(0.0297)
WML	-0.000661	-0.00110	-0.000619	-0.00106	-0.00440	-0.00529
	(0.0125)	(0.0126)	(0.0125)	(0.0126)	(0.0156)	(0.0154)
ESGMoM		0.0260		0.0258		0.0526
		(0.0490)		(0.0490)		(0.0609)
Constant	0.000651	0.000663*	0.000651	0.000663*	0.00109**	0.00111**
	(0.000394)	(0.000394)	(0.000394)	(0.000393)	(0.000458)	(0.000458)
Observations	132	132	132	132	132	132
R-squared	0.990	0.990	0.990	0.990	0.987	0.987
Adjusted r-squared	0.990	0.990	0.990	0.990	0.987	0.987

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table G10: Regression result of excess return on risk factors - 100bps transaction cost- Long-only

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	RP2_100Ccs	RP2_100Ccs	RP3_100Ccs	RP3_100Ccs	RP4_100Ccs	RP4_100Ccs
ER_Mkt	0.973***	0.972***	0.973***	0.972***	0.973***	0.972***
	(0.00989)	(0.0101)	(0.00988)	(0.0101)	(0.00990)	(0.0101)
SMB	-0.153***	-0.153***	-0.153***	-0.153***	-0.153***	-0.153***
	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)	(0.0156)
HML	-0.00236	-0.000723	-0.00258	-0.000958	-0.00239	-0.000739
	(0.0160)	(0.0154)	(0.0160)	(0.0154)	(0.0160)	(0.0154)
WML	-0.000365	-0.000801	-0.000326	-0.000758	-0.000403	-0.000844
	(0.0126)	(0.0127)	(0.0126)	(0.0126)	(0.0126)	(0.0127)
ESGMoM		0.0256		0.0254		0.0259
		(0.0491)		(0.0490)		(0.0491)
Constant	0.000550	0.000561	0.000550	0.000561	0.000550	0.000562
	(0.000394)	(0.000394)	(0.000394)	(0.000394)	(0.000394)	(0.000394)
Observations	132	132	132	132	132	132
R-squared	0.990	0.990	0.990	0.990	0.990	0.990
Adjusted r-squared	0.990	0.990	0.990	0.990	0.990	0.990

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: author's calculation

Appendix H: Histogram of data variables

Figure H1: Histogram of return before and after adjustments

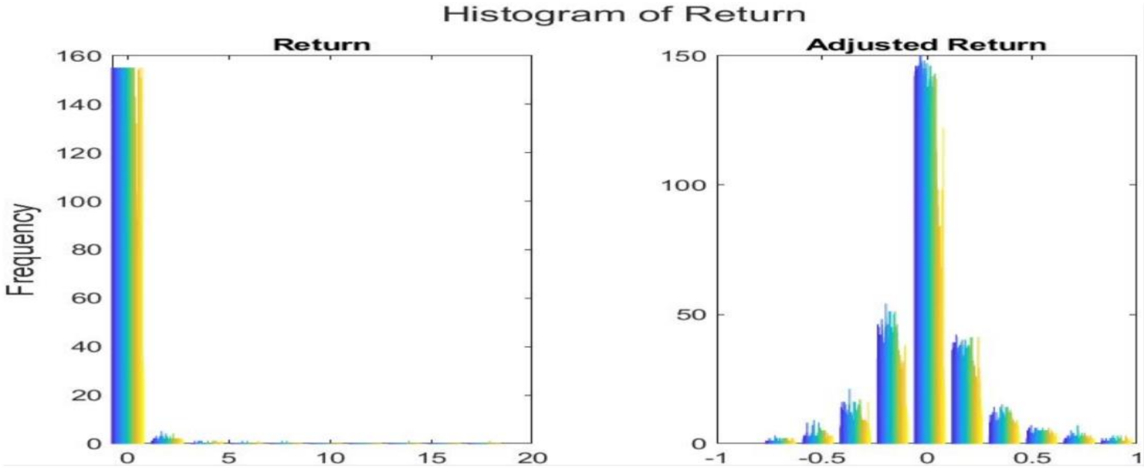
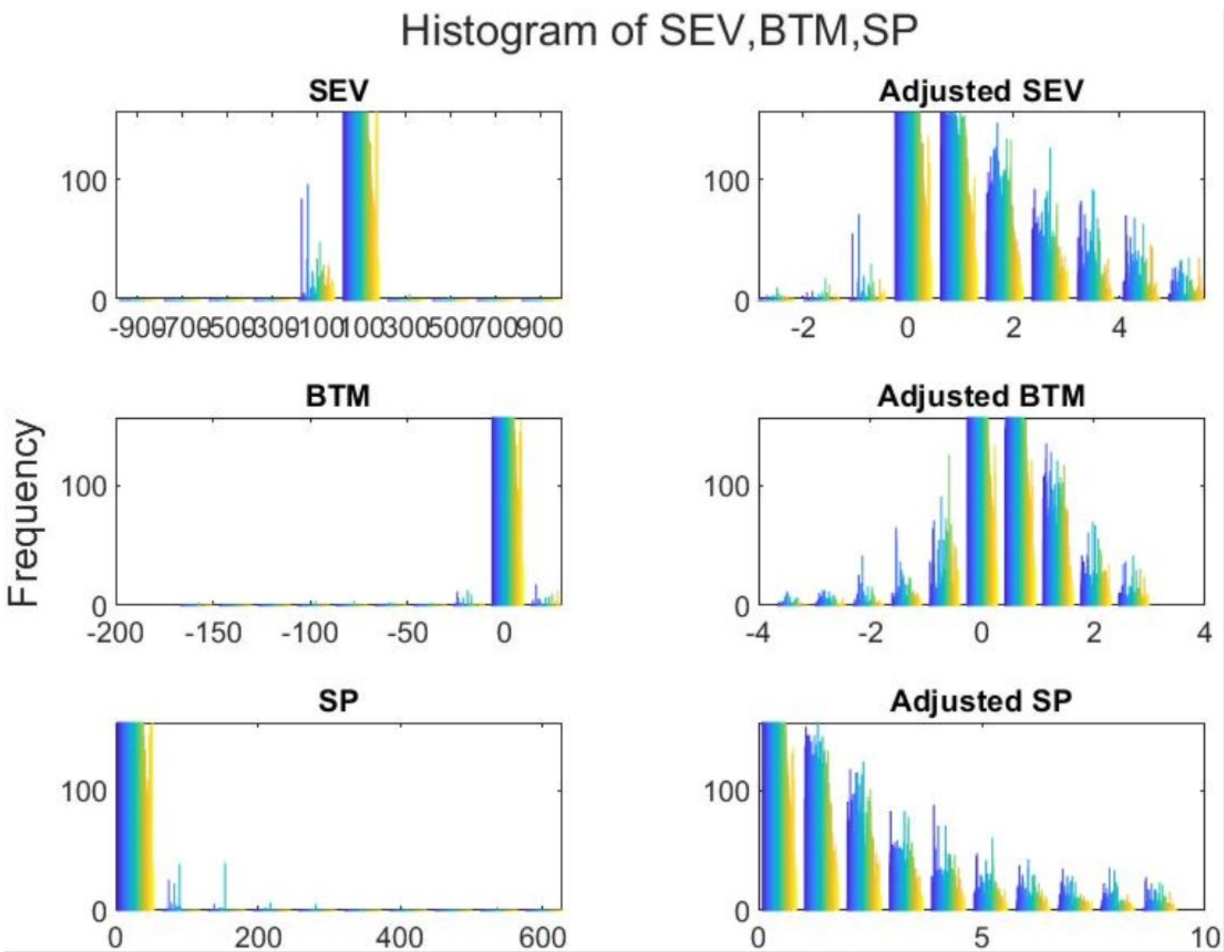


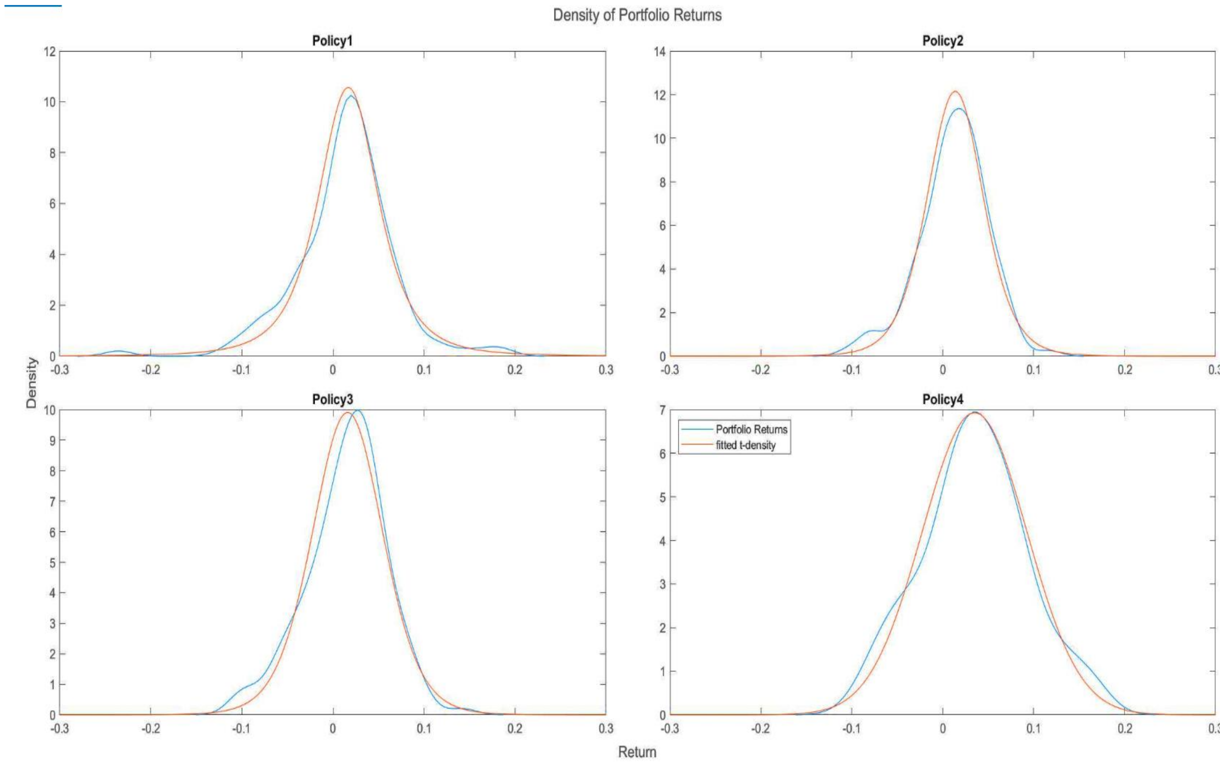
Figure H2: Histogram of SEV, BTM, SP before and after adjustments.

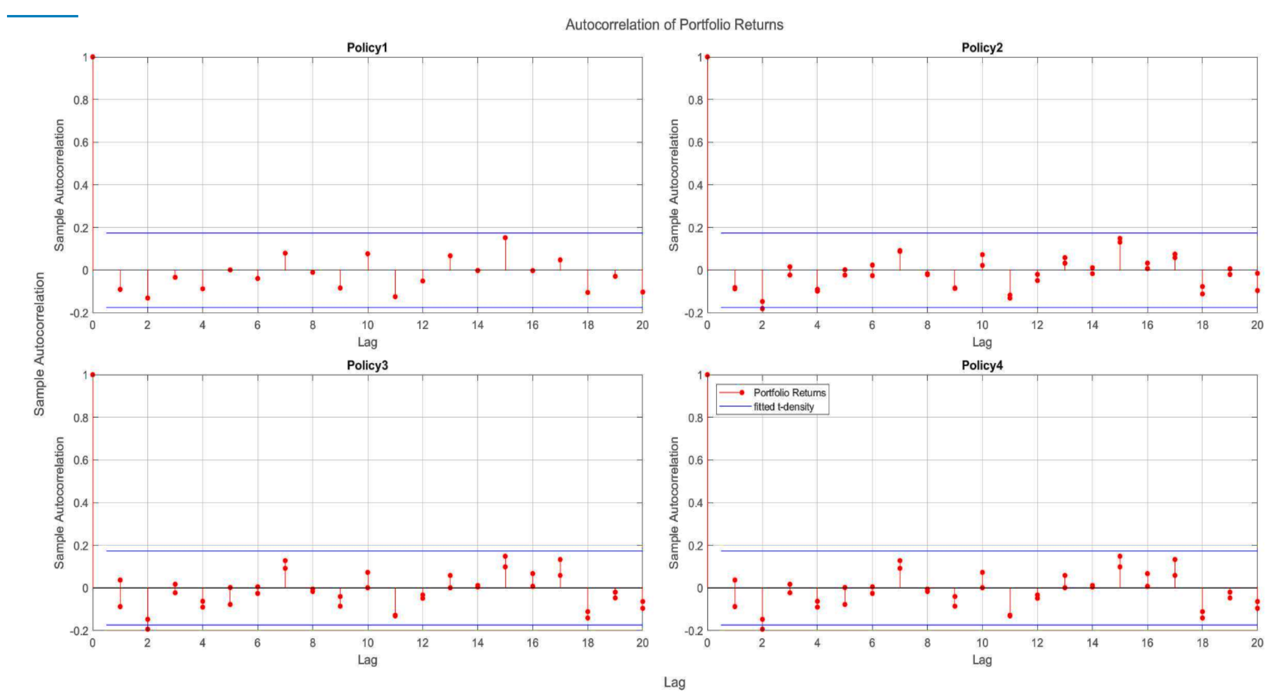


Source: author's calculation

Appendix I: Plot of Return's density and Autocorrelation

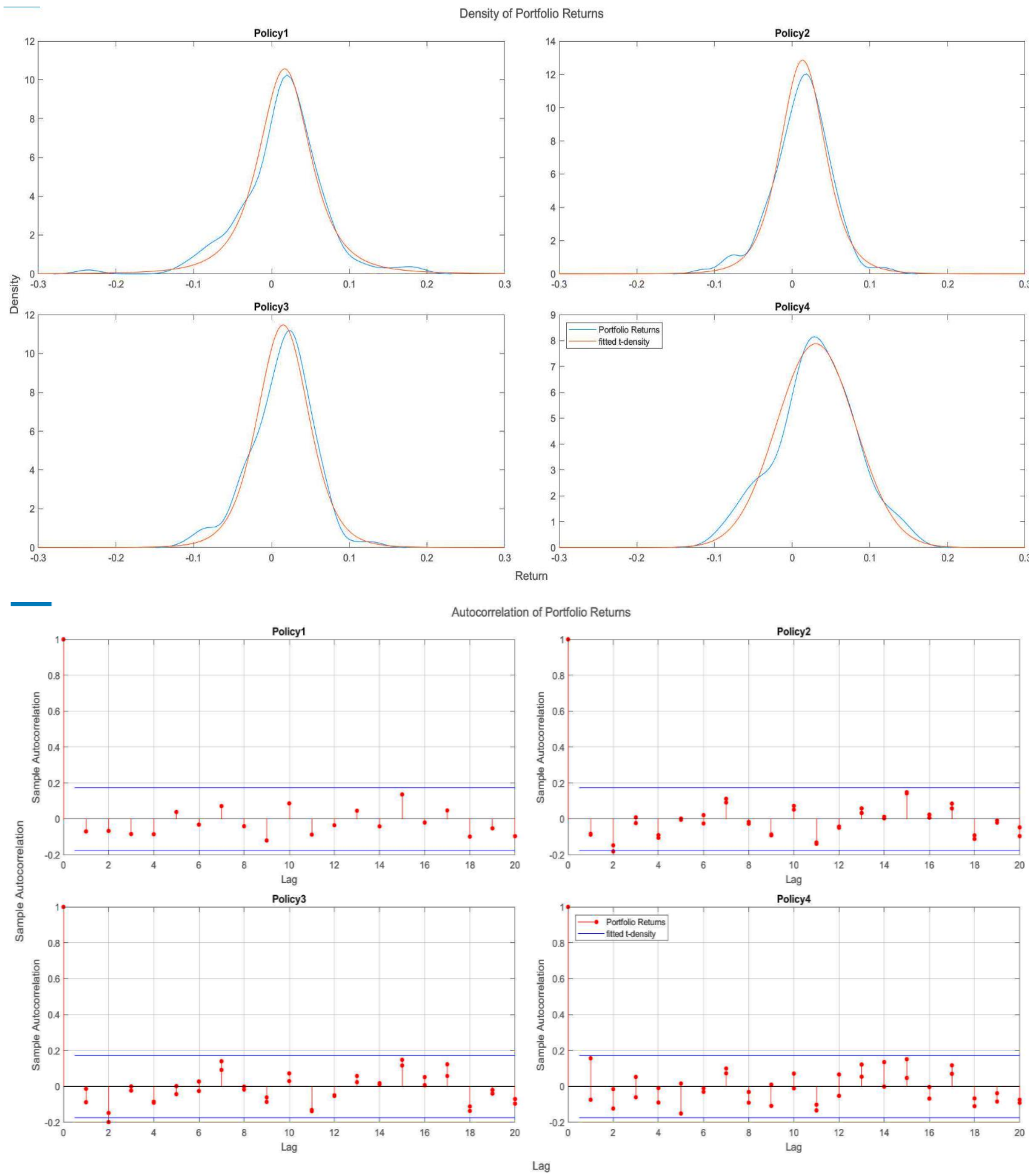
Figure I1: Return density and autocorrelation: No Transaction Cost





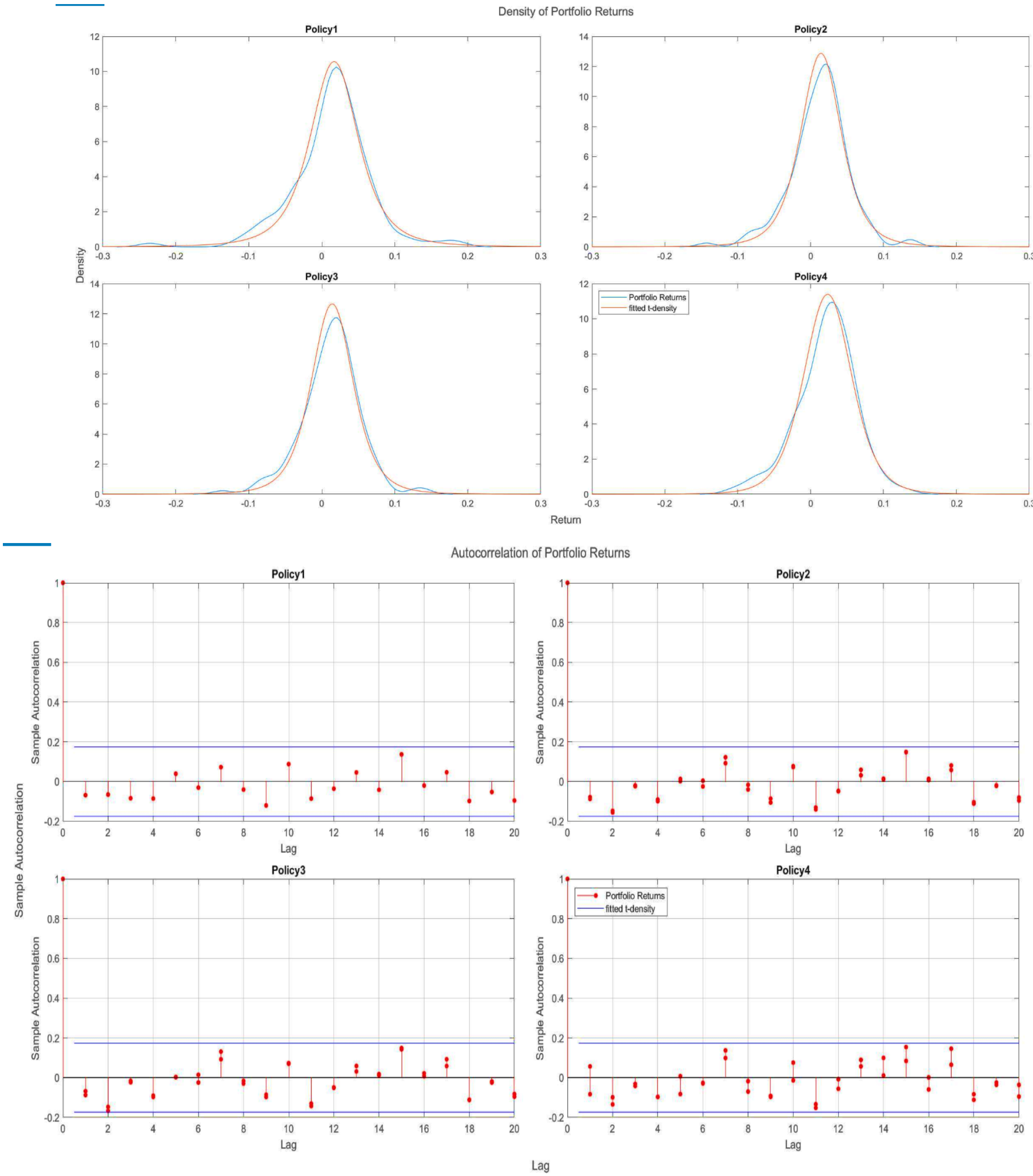
Source: author's calculation

Figure I2: Return density and autocorrelation: 30bps Transaction Cost



Source: author's calculation

Figure I3: Return density and autocorrelation: 100bps Transaction Cost



Source: author's calculation

Appendix K: Plot on the sequence of weights

Figure K1: Sequence of weight in case of no-cost, no constraint policies

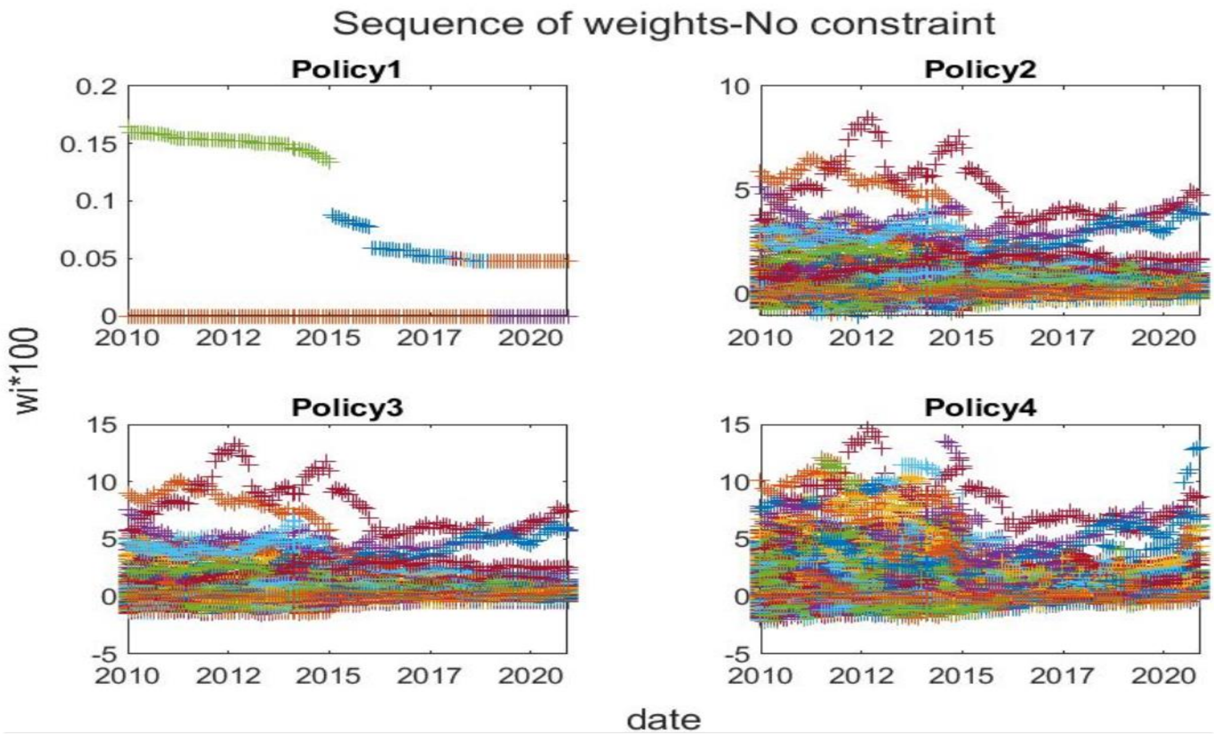
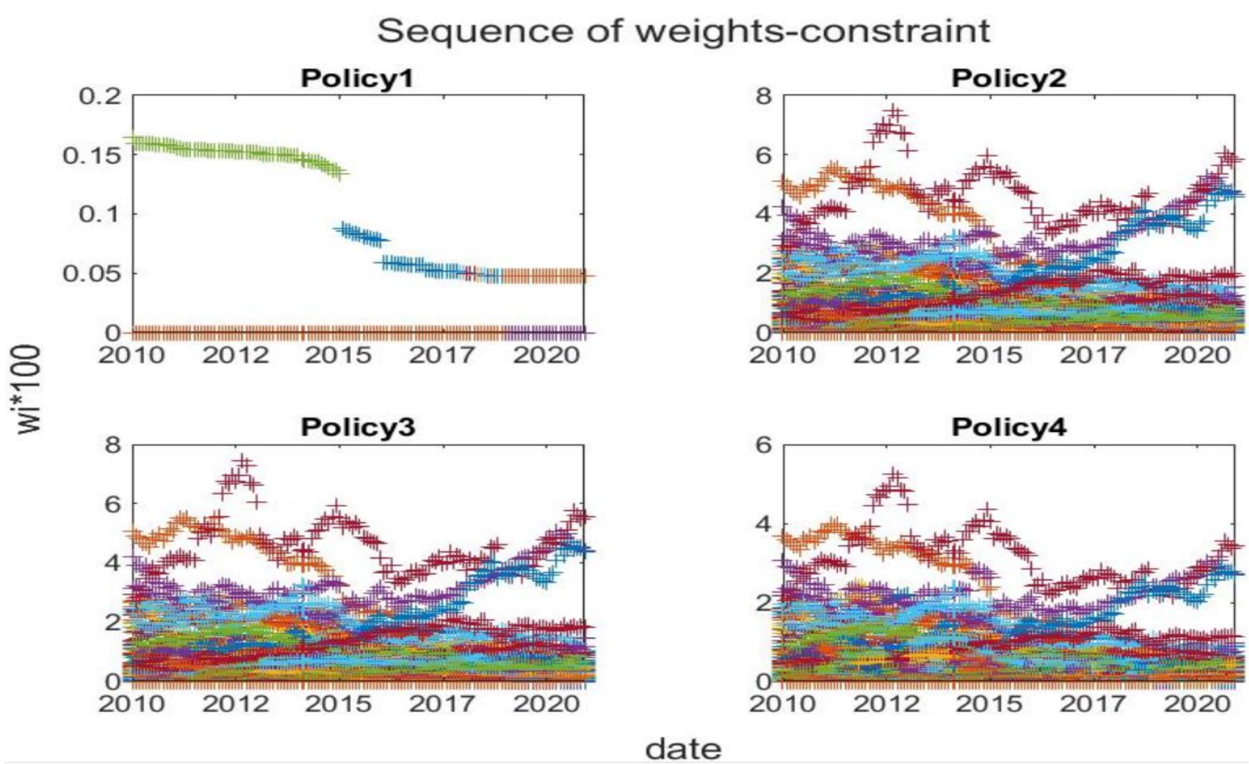


Figure K2: Sequence of weight in case of no-cost, with constraint policies



Source: author's calculation

Figure K3: Sequence of weight, 30bps transaction cost, no constraint policies

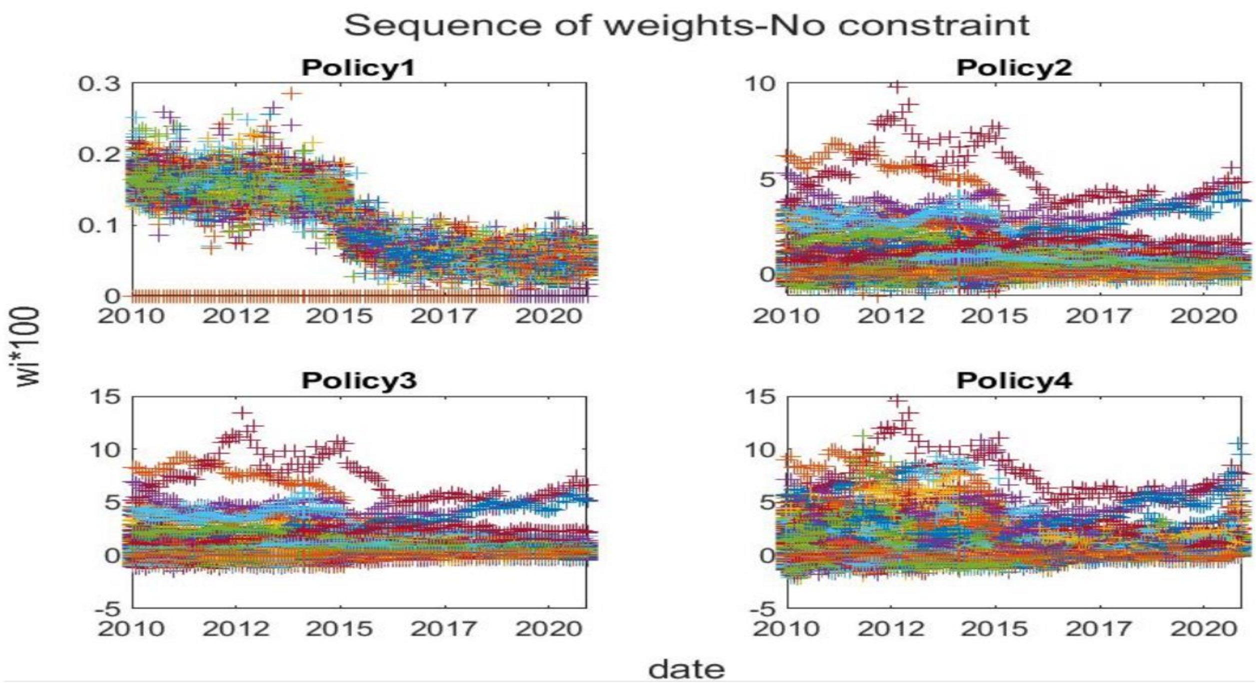
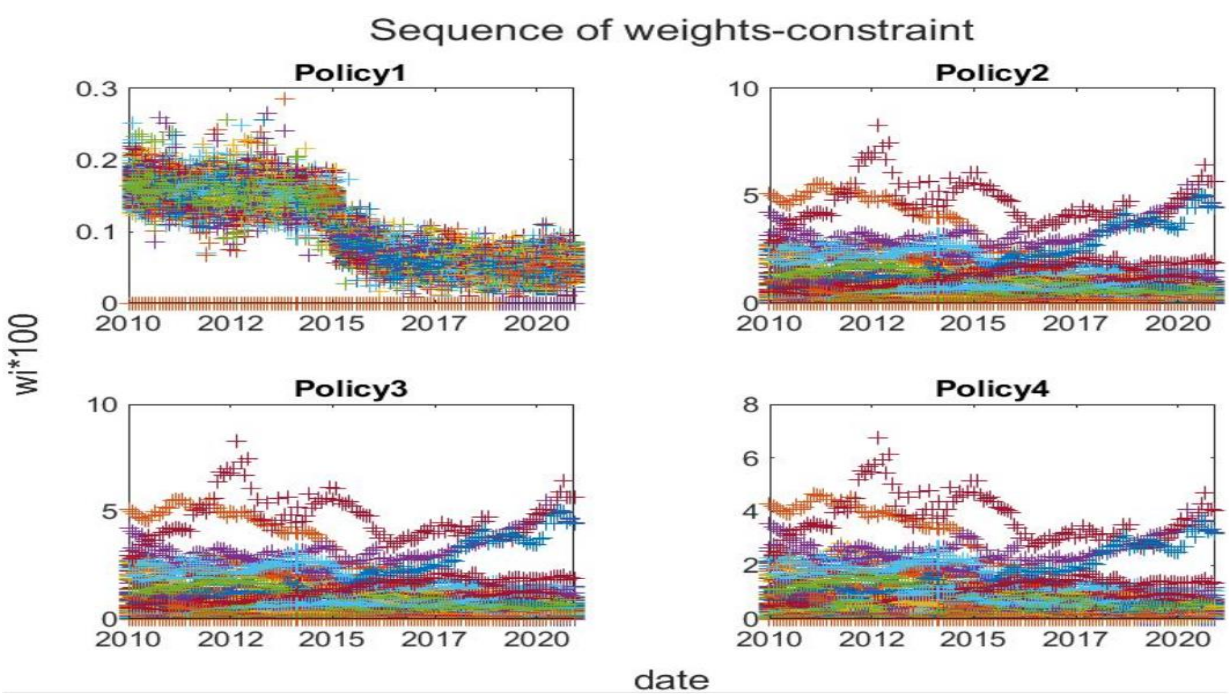


Figure K4: Sequence of weight, 30bps transaction cost, with constraint policies



Source: author's calculation

Figure K5: Sequence of weight, 100bps transaction cost, no constraint policies

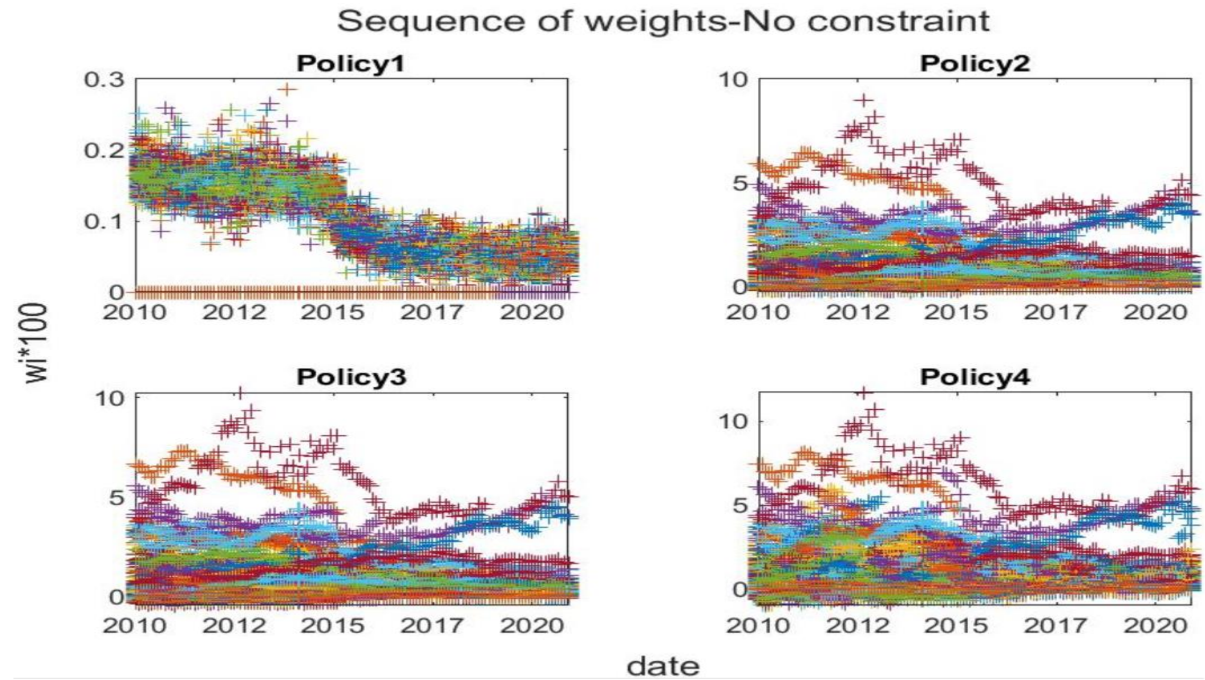
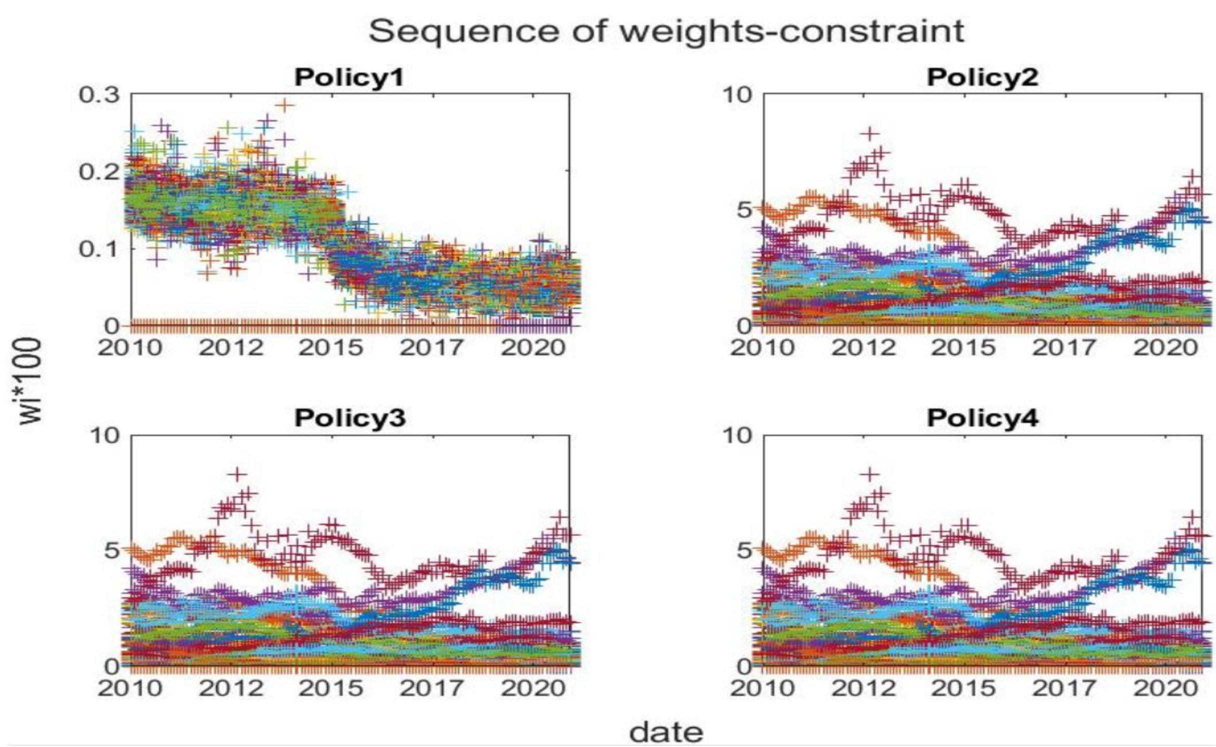


Figure K6: Sequence of weight, 100bps transaction cost, with constraint policies



Source: author's calculation

**Note: The graphs in Appendix I and K are given for the case of no transaction cost and two levels of transaction cost (30bps and 100bps) intentionally. It is to avoid a long report, acknowledge the same patterns saw.*