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Parametric portfolio policies with ESG -There is no cost

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Abstract

We propose an investment strategy with the potential for investors to gain a stronger environmental, social, and corporate governance (ESG) profile without a negative impact on performance. Specifically, we study the performance of a parametric portfolio policy when utilizing ESG score and ESG momentum characteristics in addition to value and momentum, in contrast to utilizing value and momentum only. We compare the performance of these two policies using both fixed and dynamic coefficients modelled with generalized autoregressive score (GAS). Our sample covers all S&P 500 constituents over the period Feb 2003 to Jan 2021. We find the "policy with ESG" to perform significantly better in-sample. Out-of-sample results show some tendency for the "policy with ESG" to perform better compared to the "policy without ESG", although the difference in performance is not significant. Additionally, we find the "policy with ESG" to have consistently higher average ESG portfolio scores, suggesting the potential for investors to gain a stronger ESG profile without sacrificing financial returns.

Keywords: Sustainable investment, ESG, Parametric portfolio policy, Generalized autoregressive score (GAS).

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1 INTRODUCTION

Sustainable investing is growing with portfolio managers overseeing over 35 trillion dollars to combine environmental, social and corporate governance (ESG) into their investment strategies (GSI, 2021). However, empirical findings on whether it is possible for ESG strategies to add value are mixed. Some argue that portfolios created based on ESG generate negative performance (Avramov, Cheng, Lioui, and Tarelli, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021), meanwhile others find evidence for ESG to deliver superior or improved performance (Nagy, Kassam, and Lee, 2016; Pollard, Sherwood, and Klobus, 2018). The overall findings also depend notably on the type of ESG strategy used.

Our main contribution of this paper is, in light of previous mixed findings, that we study how ESG can add value to investors using a mean-variance utility optimizing portfolio strategy. In contrast to the more common strategies that either screen or sort portfolios based on certain ESG criteria (see Auer (2016); Giese, Lee, Melas, Nagy, and Nishikawa (2019)). Our research objective is to answer the question “what is the cost of obtaining a stronger ESG profile, for a mean-variance optimizing investor?”, and the simple answer that we find in this paper is that “there is no cost”.

In essence, we study the performance of a parametric portfolio policy (Brandt, Santa-Clara, and Valkanov, 2009) that uses ESG score and ESG momentum asset characteristics alongside with value and momentum. We compare the performance of this policy in contrast to using the asset characteristics value and momentum only. First, we study the performance of the static policies in-sample and out-of-sample. Second, we dive deep into the out-of-sample performance using moving window and alternative rebalancing frequencies. Third, we study the performance of dynamic policies by modelling the parametric policy parameters of each asset characteristic using generalized autoregressive score (GAS) (Creal, Koopman, and Lucas, 2013). Additionally, for robustness, we study the performance of the static policies using two alternative risk aversion profiles and when accounting for transaction costs.

Formally, we provide an answer to the following research questions:

I. Can investors gain a stronger ESG profile and at the same time improve portfolio performance by considering ESG score and ESG momentum in the parametric portfolio policy in addition to value and momentum?

II. Is the potential gain in ESG and improvement in performance also present (i) out-of-sample, (ii) when using dynamic parameters, (iii) considering alternative risk aversion profiles, and (iv) when accounting for transaction cost?

Our findings are four-fold. First, in-sample results show that the parametric policy that uses ESG characteristics performs better compared to the policy without ESG. Both in terms of higher Sharpe ratios and significantly higher abnormal returns. This is true also when applying short-sell restrictions, when considering alternative risk aversion profiles and when allowing for dynamically modelled portfolio weights. These findings are consistent with the ones of Nagy et al. (2016); Pollard et al. (2018) who find that ESG strategies generate superior performance. Second, out-of-sample results show some tendency for the policy with ESG to perform better compared to the policy without ESG. Sharpe ratios and abnormal returns remain higher for the policy with ESG but the differences in abnormal returns are insignificant. These findings are aligned with those of Auer (2016); Halbritter and Dorfleitner (2015), who fail to detect any significant effects of ESG strategies on performance. Third, results show no remarkable differences in performance between the policies with and without ESG after accounting for transaction costs. Forth, and most importantly, the average ESG score of the portfolio increases consistently when considering ESG characteristics in the parametric portfolio. Overall, this suggests that there is a great potential for investors to improve their ESG profile without the cost of sacrificing financial returns.

Our main conclusions of this paper agree with Bruno, Esakia, and Goltz (2022) in the sense that ESG strategies can indeed offer substantial value to investors, and especially so when utilizing the optimizing parametric portfolio policy. However, while there are no additional costs or underperformance in terms of financial returns for gaining a stronger ESG profile, investors who only seek superior financial performance might be looking in the wrong place. Investors should therefore most of all consider this specific type of ESG strategy when considering the unique benefits that a stronger ESG profile can provide. That is, doing good for the environment and society in whole.

The remainder of our paper is structured as follows: *2 Literature Review* presents the theoretical framework and empirical findings related to the parametric portfolio policy, relevant asset characteristics, ESG strategies, and measurements used to evaluate the portfolio performance. *3 Data* describes the data sample used in this paper as well as the main variables used in our analysis. *4 Method* presents the underlying method of the parametric portfolio policy and GAS, as well as the construction of the various portfolios that we use in this paper. *5 Results* present the resulting performance of our various portfolios with the main objective to compare the performance of the policy with ESG to the policy without ESG, followed by a brief discussion regarding our overall findings, limitations, and potential future research opportunities.

2 LITERATURE REVIEW

2.1 Mean variance portfolio optimization

Mean variance portfolio optimization is an important issue to consider, as it paves the way forward to the final asset allocation strategy that we use in this paper. Therefore, we start this literature review with a brief discussion regarding one of the most traditional portfolio optimization models (Markowitz, 1952), followed by the potential advantages of the parametric portfolio policy (Brandt et al., 2009).

Markowitz portfolio optimization

Traditionally, Markowitz (1952) models the optimal mean-variance portfolio weights by minimizing the portfolio's expected conditional variance subject to a certain conditional expected target return. For this approach, however, the optimal weights become heavily dependent on estimates based on historical data of risk and return that are inevitably subject to estimation errors. The mean variance optimization also comes with large computational costs. For finding the optimal asset allocation of a portfolio with N assets, the Markowitz (1952) optimization requires the modelling of N first, and $(N^2 + N)/2$ second moments of returns. Subsequently resulting in exhilarating amounts of separate estimates even for relatively few assets. As the number of assets increases, so does the complexity of the estimation as well as the risks of unstable and suboptimal results (Michaud, 1989). In this paper, we use an alternative asset allocation model that, like Markowitz (1952), focuses on finding asset weights under an optimizing objective while simultaneously avoiding some of the mentioned drawbacks given its simple framework. That is, we use the parametric portfolio policy proposed by Brandt et al. (2009).

Parametric portfolio policy

The parametric portfolio policy chooses asset weights that deviate linearly from its initial benchmark weights using a set of long-short portfolio components of certain asset characteristics, optimized with respect to investor utility. This policy has the advantage compared to the pure Markowitz (1952) model that it requires the modelling of only N portfolio weights, regardless of the joint distribution of asset returns. Hence, there is a clear dimensionality reduction with the potential of escaping statistical issues like imprecise estimates (Brandt et al., 2009). Examples of common asset characteristics used in this policy are: size, value, and momentum (Ammann, Coqueret, and Schade, 2016; Brandt et al., 2009; Dichtl, Drobetz, Lohre, Rother, and Vosskamp, 2019). In this paper, we extend the policy by including ESG scores and ESG momentum together with value and momentum as our four key asset characteristics. The coefficients used to construct the long-short components of each asset characteristic are, in Brandt et al. (2009), obtained by optimizing the investor utility of portfolio returns. For finding each coefficient with respect to value, momentum, ESG score, and ESG momentum, we optimize the mean variance investor utility according to DeMiguel, Martín-Utrera, Nogales, and Uppal (2020); Dichtl et al. (2019); Hjalmarsson and Manchev (2012).

The parametric portfolio policy of Brandt et al. (2009) is arguably easy to extend over arbitrary objective functions as well as additional asset characteristics. The original paper uses investor utility assuming constant relative risk aversion equal to five. This approach has been replicated by Hand and Green (2011); Medeiros, Passos, and Vasconcelos (2014). But other utilities can be used as well, for instance, the quadratic utility function (Ammann et al., 2016) or the mean variance utility function (DeMiguel et al., 2020; Dichtl et al., 2019; Hjalmarsson and Manchev, 2012), which we also use in this paper. Brandt et al. (2009) model asset weights using the traditional selection of size, value, and momentum. Meanwhile, others turn to more extended sets of asset characteristics (Ammann et al., 2016; DeMiguel et al., 2020; Dichtl et al., 2019).

Potential issues worth mentioning, given the optimizing nature of the policy, relate mostly to the policy being relatively leveraged and exposed to transaction costs (Ammann et al., 2016). As a large majority of equity portfolio managers face short-sale restrictions, Brandt et al. (2009) propose extending the policy so that it fits a long-only trading strategy by ensuring non-negative asset weights only. Ammann et al. (2016); Dichtl et al. (2019); Medeiros et al. (2014) highlight the importance of accounting for transaction costs when considering the performance of the policy. Meanwhile, DeMiguel et al. (2020) also argue that transaction costs matter for the cross-sectional dimension as they affect the significance of asset characteristics contribution to the optimal portfolio.

Brandt et al. (2009) find short-sell restrictions to decrease the performance of the parametric portfolio policy as it restricts the policy from exploiting negative relationships between asset characteristics and returns. In the presence of transaction costs, Dichtl et al. (2019) find that the parametric portfolio policy performs worse compared to the equally weighted benchmark in terms of transaction cost adjusted returns. Ammann et al. (2016) suggest that the unstable nature of some asset characteristics leads to higher turnover and consequently higher transaction costs. In this paper, we also consider the effects of both short-sell restrictions and transaction costs, further presented under *Method 4.1*.

2.2 Asset characteristics

Value and momentum

The choice of which asset characteristics to include in the parametric portfolio policy is important. Today, hundreds of factors or characteristics have been proposed to capture various cross-sectional anomalies of stock returns (DeMiguel et al., 2020; Feng, Giglio, and Xiu, 2020; Green, Hand, and Zhang, 2017; C. R. Harvey, Liu, and Zhu, 2016). Fama and French (1992, 2015) promote value as a relevant asset characteristic, predicting a positive relationship between book value and return (Fama and French, 1992). Jegadeesh and Titman (1993) propose the momentum characteristic to predict firms with high returns to continue with high future returns.

Ammann et al. (2016) find evidence for the parametric portfolio policy using the single characteristics of size and value to, respectively, outperform the equally weighted benchmark. However, the authors find no evidence for the single characteristic momentum to outperform on its own. When analysing which characteristics that are significantly different from zero, DeMiguel et al. (2020) find only little significance for value. Furthermore, the characteristics size and momentum are deemed redundant. In contrast, results of Dichtl et al. (2019) show momentum being a relevant asset characteristic. However, the authors find no significant contribution of size or value.

Smith and Timmermann (2021) highlight the importance of assessing the present relevance of any asset characteristic before adding it into investment strategies. Findings that show size associated with risk premia have impacted investors to specialize in investment styles like small caps. However, the authors criticize the attractiveness of such actions as high allocations toward small stocks risk becoming defective if the premia associated with size reduces over time. In fact, for a total of 94 different asset characteristics, Green et al. (2017) only find two asset characteristics being significantly independent determinants of returns in the post-2003 period. For the pre-2003 period, however, the authors recognize at least twelve relevant asset characteristics, including value.

C. R. Harvey et al. (2016); Hou, Xue, and Zhang (2015) claim the asset characteristics of both value and momentum to have a present significant contribution to the portfolio. Although, the impact of size is, again, found to be irrelevant. Smith and Timmermann (2021) similarly argue that the premia associated with size and value have declined systematically over the past decades, being presently insignificant, while the premium associated with momentum remains strong. The significant contribution of momentum is further confirmed by Feng et al. (2020). For brevity and given the combined findings supporting the relevance of value and momentum in contrast to the lesser relevance of size (DeMiguel et al., 2020; Dichtl et al., 2019; Feng et al., 2020; Green et al., 2017; C. R. Harvey et al., 2016; Hou et al., 2015; Smith and Timmermann, 2021), we only include value and momentum as asset characteristics in all our parametric portfolio policies.

ESG score and ESG momentum

Before including ESG score and ESG momentum in the parametric portfolio policy, it is important to consider how ESG could matter for the financial performance of firms. Success and financial performance of firms arises from various strategic and operational, efficiencies as well as challenges. Access to capital and liquidity play a major role for firms' ability to meet financial constraints, invest in new opportunities, and encourage growth prospects (Goddard, Tavakoli, and Wilson, 2005; Khurana, Pereira, and Martin, 2006; Pattitoni, Petracci, and Spisni, 2014). Profitability is likewise driven by operational efficiencies surrounding employer motivation, innovation, and completive advantage (Goddard et al., 2005; Jensen, 1986; Nunes, Serrasqueiro, and Sequeira, 2009).

Dunn, Fitzgibbons, and Pomorski (2018); Kotsantonis, Pinney, and Serafeim (2016) argue that firms with high ESG profiles face less risk by being better positioned toward environmental transitions and regulatory as well as social pressures. For instance, firms with higher levels of emissions, poorly treated employees, or poor governance may be more exposed to risks of future carbon taxes, customer-backlashes, or scandals (Dunn et al., 2018). In connection, El Ghoul, Guedhami, Kwok, and Mishra (2011) argue that improvements of employee relations, environmental policies, and risk management promote reductions in the cost of capital. Chava (2014) suggests that lenders demand higher rates on loans from firms that are involved in environmental controversies. Firms with high ESG profiles and subsequently lower costs of capital, can likewise improve their growth prospects and ability to manage capital constraints without sacrificing profitable investment opportunities (Cheng, Ioannou, and Serafeim, 2014; Khurana et al., 2006).

Actions toward improving ESG scores are, however, commonly associated with higher short-term costs, lower profit margins, and competitive disadvantages (Eccles and Serafeim, 2013; Horvathova, 2012). Horvathova (2012) argues that firms taking environmental actions to reduce emissions are affected by increased short-term costs. Eccles and Serafeim (2013) argue that social improvements of raising wages for low-skilled workers place firms in competitive disadvantages by decreasing firms' profits. However, improving firms ESG profiles can sometimes also be cost-saving, at least in the long-term (Horvathova, 2012; Kotsantonis et al., 2016). Additionally, as argued by Edmans (2011); Pedersen et al. (2021), firms with high ESG profiles can be more profitable compared to their peers if they benefit from cost reductions of waste and material, energy efficiencies or motivated employees. Firms can similarly benefit from avoiding losses related to environmental fines or labour disputes (Nagy et al., 2016). In turn, Gompers, Ishii, and Metrick (2003) suggest that firms with better governance benefit from reduced agency costs and operational efficiencies. Serafeim, Kaiser, and Linder (2015) also points out the potential for firms with high ESG profiles to benefit from regulatory incentives related to emission taxes. As well as accessing broader markets when complying to certain environmental and social requirements.

Moreover, Nagy et al. (2016) argue that improvements in ESG can place firms in a more advantageous position toward future environmental opportunities. Environmental strategies can likewise have a positive impact on firms innovation dynamics, making them better equipped for exploring long term investment opportunities (Porter and Van der Linde, 1995). Forsman (2013) highlights the risk of some environmental innovations to create inefficiency-related competitive disadvantages for firms. Resulting in inferior returns and earnings. Forsman also finds that firms are more likely to profit from environmental innovations if starting from a strong economic and competitive position to begin with.

Given the combined findings suggesting a relationship between profitability and ESG as well as changes in ESG, we choose to study how including ESG score and ESG momentum as asset characteristics can alter the performance of our parametric portfolio policy.

2.3 Portfolio strategies with ESG

Conventional strategies of integrating ESG in portfolios commonly involve screening or sorting: stocks are either included/excluded or portfolio weights are tilted given certain ESG criteria. Auer (2016); Pedersen et al. (2021) use negative screenings to exclude stocks with the lowest ESG scores. Following these strategies, Pedersen et al. (2021) find evidence that a negative screening yields inferior performance. In contrast, Auer (2016) finds no evidence that such screens either add or destroy portfolio value. Ashwin Kumar et al. (2016) only include stocks with the highest ESG scores and find that this strategy delivers superior risk-adjusted returns compared to an equally weighted benchmark. In a different approach, Verheyden, Eccles, and Feiner (2016) screen a portfolio to exclude stock with the lowest ESG scores, but simultaneously keep stocks with positive ESG momentum. Using this strategy, they only little evidence for the screened portfolio to give superior risk-adjusted returns.

Nagy et al. (2016) use a sorting strategy to tilt their portfolio toward stocks with high ESG scores as well as high ESG momentum. The authors find evidence for the portfolio sorted on ESG momentum to have a positive short-term performance. The portfolio sorted on ESG scores is found to yield superior performance compared to a benchmark. Giese et al. (2019) similarly sort stocks based on ESG momentum. The authors find the top ESG momentum portfolio to have a positive performance, which suggests that positive changes in the ESG yield increasing value over time. Pollard et al. (2018), replace the lowest returning stocks in a portfolio with the highest ESG momentum stocks and when comparing this strategy to replacing the stocks with new randomly selected ones, the authors find evidence for the ESG momentum strategy to increase the risk-adjusted performance.

Eccles, Ioannou, and Serafeim (2014) find evidence for portfolios sorted on high ESG scores to significantly outperform the portfolio sorted on low ESG scores. Breedt, Ciliberti, Gualdi, and Seager (2019), however, find no evidence for a portfolio tilted towards high ESG scores to deliver superior risk-adjusted returns. The authors argue that any benefits from including ESG in investments are already fully captured by other well-known equity factors. Avramov et al. (2021) sort stocks according to ESG scores as well as ESG uncertainty, which is measured as the standard deviation of ESG scores between different rating providers. The authors find high ESG ratings to be negatively associated with future performance, but only when the ESG uncentring is low.

Others evaluate various high-minus-low strategies, essentially buying stocks with high ESG scores and shorting stocks with low scores. Kempf and Osthoff (2007) find this strategy to create positive abnormal returns. However, Brammer, Brooks, and Pavelin (2006) find the average returns of this strategy to be mostly negative. Halbritter and Dorfleitner (2015); Lee, Faff, and Rekker (2013) find no significant difference in returns or risk-adjusted performance between high and low ESG portfolios. As a result, investors should no longer expect abnormal returns when trading a high minus low ESG strategy (Halbritter and Dorfleitner, 2015). In turn, De Spiegeleer, Höcht, Jakubowski, Reyners, and Schoutens (2021) combine ESG with the mean variance optimization framework of Markowitz (1952) by minimizing portfolio variance subject to additional constraints based on ESG scores. Constraining the optimization with respect to low ESG scores is found to generate superior results in the early parts of the investment period. Meanwhile, constraints with respect to high ESG scores performs better during the last year. Like De Spiegeleer et al. (2021), we combine the aspects of portfolio optimization and ESG by including ESG into the parametric portfolio policy.

In sum, the overall empirical findings of whether it is possible for portfolio strategies with ESG to add value are mixed. The various findings also depend notably on the type of the investment strategy itself. Some argue that ESG portfolios generate negative performance (Avramov et al., 2021; Pedersen et al., 2021), meanwhile, others find evidence for ESG to deliver superior or improving performance (Nagy et al., 2016; Pollard et al., 2018). Many studies also fail to detect any significant effects of ESG strategies on performance (Auer, 2016; Halbritter and Dorfleitner, 2015).

2.4 Time variation

Inefficiencies and solutions

The parametric portfolio policy of Brandt et al. (2009) assumes that the optimal weights tied to asset characteristics are constant over time. However, the authors acknowledge that there is no obvious evidence for such fixed relationship to exist in the market. Angelidis, Sakkas, and Tessaromatis (2015); Farmer, Schmidt, and Timmermann (2019) both agree that the efficiency in utilizing asset characteristics to create returns anomalies vary over time. This is resulting in constant optimal weights models being inferior compared to time-varying models (Dangl and Halling, 2012). In turn, de Oliveira Souza (2020a, 2020b, 2020c) find evidence for the size, value, and momentum premia to strongly depend on time. For instance, he argues that portfolios exploiting the size characteristics are only efficient if formed in “bade states”. Angelidis et al. (2015) similarly show time-variation for the value and momentum premia, suggesting high return dispersion to coincide with stronger/weaker premiums for value/momentum. Additionally, Bruno, Esakia, and Goltz (2022) also suggest that the potential ESG premium may vary over time, as it depends on investor attention.

Given the potential time-varying nature of the premium associated with asset characteristics, we combine the parametric portfolio policy with the generalized autoregressive score (GAS) framework of Creal et al. (2013) and A. C. Harvey (2013) to model time-varying, or dynamic, optimal weights. GAS can be used for modelling dynamic variables via functions of lagged and predetermined variables. Hence, the framework allows for the possibility of predicting future dynamic variables, using a set of available information. GAS starts with the assumption that the target variable follows a conditional distribution, where the parameters of that distribution are expressed as a GARCH-like equation. The driving variable in GAS is, originally, the lagged score of the log-likelihood function, scaled by the inverse Hessian matrix (Creal et al., 2013). The driving variable used in this paper is a function of the derivative of the mean-variance investor utility.

GAS has been used in various settings, For instance, Creal et al. (2013) demonstrate the potential of using GAS for estimating the dependence of the daily exchange rates. Ayala, Blazsek, and Licht (2022); Bernardi and Catania (2018); Zhao, Stasinakis, Sermpinis, and Fernandes (2019), on the other hand, demonstrate the potential of using GAS in a portfolio optimizing setting. By allowing GAS to capture time-variation in the conditional moments of asset returns, Ayala et al. (2022); Bernardi and Catania (2018) both find evidence for a superior performance compared to static portfolio optimizing strategies. In turn, Zhao et al. (2019) argue that incorporating the asymmetric dependence among returns as well as the asset characteristics value and momentum can substantially increase the diversification benefits for investors. Monache, Petrella, and Venditti (2021) also use GAS to study the time-varying relationship between certain asset characteristics and stock returns.

2.5 Performance evaluation

In this paper, we evaluate the performance of the parametric portfolio policy using Sharpe ratio, abnormal returns, turnover, and transaction costs both in- and out-of-sample. The theoretical background behind these performance measurements is presented as follows:

Defined as the excess portfolio return divided by the portfolio risk, Shape ratio is one of the more frequently used indicators for evaluating risk-adjusted performance. Used, among many others, by Brandt et al. (2009); DeMiguel et al. (2020); Pedersen et al. (2021). Sharpe ratio serves as a useful measurement for indicating which among other competing portfolios that is having the highest risk-adjusted returns.

Another common indicator for evaluating portfolio performance is abnormal returns or alpha. Abnormal returns are typically measured as the intercept in a linear regression of the excess portfolio return and the market, or against extended asset pricing models such as Carhart (1997) four-factor model, Fama and French (2018) six-factor model (Avramov et al., 2021), or the q-factor model of Hou et al. (2015) (DeMiguel et al., 2020).

Measured as the sum of absolute changes in portfolio weights between certain rebalancing periods, Brandt et al. (2009); Dichtl et al. (2019); Pollard et al. (2018) evaluate portfolio performance using turnover. DeMiguel et al. (2020); Dichtl et al. (2019); Hand and Green (2011) also evaluate risk-adjusted portfolio performance net of transaction costs. The transaction costs are typically measured as the turnover times an assumed percentages cost (Brandt et al., 2009).

Last, Brandt et al. (2009); DeMiguel et al. (2020); Medeiros et al. (2014) evaluate performance out-of-sample. Using coefficients that are optimally estimated over a prior sample period to determine the asset weights in the portfolio for the consecutive out-of-sample period. The resulting out-of-sample performance can then be compared with subsequent benchmarks (Brandt et al., 2009; DeMiguel et al., 2020) or competing out-of-sample portfolios (Medeiros et al., 2014).

3 DATA

3.1 Sample overview

Our data sample consists of all constituent stocks of the Standards & Poor's 500 (S&P 500) index over the period from Jan 2001 to Jan 2021. We include all 997 historical constituents. Although, for each month, we only include the stocks being active constituents of the S&P 500. Hence representing a monthly investible universe of approximately 500 individual assets. For each constituent, we collect the following time series data using the Thomson Reuter Refinitiv database (Refinitiv, 2022a): stock price, market equity, price-to-book ratio, and the combined ESG score. We use this data to construct our main variables of interest, namely, returns, value, momentum, ESG score, and ESG momentum. A full description of the collected data and related calculations is presented under appendix (A.1).

3.2 Asset characteristics

Value and momentum

For all policy portfolios, we use the value characteristic (Fama and French, 1992), and the momentum characteristic (Jegadeesh and Titman, 1993) for exploiting the book value and return persistency of each constituent stock.

For this purpose, we calculate value as the inverse of the price-to-book ratio:

$$Value_{i,t} = \frac{1}{price-to-book\ ratio_{i,t}}.$$

Additionally, we calculate the one-year momentum following Brandt et al. (2009) as the compounded return from $t-13$ to $t-1$:

$$Mom_{i,t} = \prod_{t-13}^{t-1}(1 + r_{i,t}) - 1.$$

ESG score and ESG momentum

Together with value and momentum, we include ESG score and ESG momentum as additional asset characteristics for a certain subset of the policy portfolios, which we denote as the "policies with ESG". For this purpose, we use the combined ESG score collected from Refinitiv

(2022a) as ESG score and we define ESG momentum as the year-on-year chance in ESG scores following Giese et al. (2019).

The combined ESG score measures firms socially responsible commitment in terms of environmental (E), social (S), and corporate governance (G) performance, in addition to the firm's exposure toward environmental, social, and governance controversies reflected in media. The ESG scores provided by Refinitiv (2022a) are based on various publicly available and auditable data metrics including emissions, human rights, shareholders, and more. The ESG scores are updated, approximately, once a year for each firm and presented on a scale from 0 to 100. With 0 (100) representing a relatively poor (good) ESG performance, respectively (Refinitiv, 2022b).

3.3 Data overview

Descriptive statistics

Using historical data starting from Jan 2001, we require in total 14 months for calculating returns and the one-year momentum. Subsequently, the total sample period used for the analysis in this paper covers the period Mar 2002 to Jan 2021. Descriptive statistics for our main variables of interest are presented in table (3.1).

Tabel 3.1: Descriptive statistics

Statistics	**Mean**	**Standard Deviation**	**95th percentile**	**5th percentile**
Mar 2002 to Jan 2021				
Return	1.17	7.55	12.90	-9.97
Value	0.43	0.64	0.97	0.06
Mom	14.34	32.55	64.34	-25.15
ESG Score	44.52	16.30	71.90	18.821
ESG Mom	1.84	10.24	19.04	-14.21

Tabel 3.1 shows the cross-sectional statistics including: mean, standard deviation, the 95th percentile, and the 5th percentile for stock returns and asset characteristics over the period Mar 2002 to Jan 2021. The asset characteristics include: value, defined as the book-to-market ratio, momentum, defined as the lagged compounded twelve-month return, ESG score, and ESG momentum, defined as the year-on-year chance in ESG scores.

The descriptive statistics in table (3.1) show that the ESG scores in our sample ranges from approximately 19 to 71, with an average equal to 45. ESG momentum ranges from 19 to -14 with an average equal to 2, suggesting the overall ESG scores to increase slightly over time.

Figure 3.1: ESG coverage of S&P 500

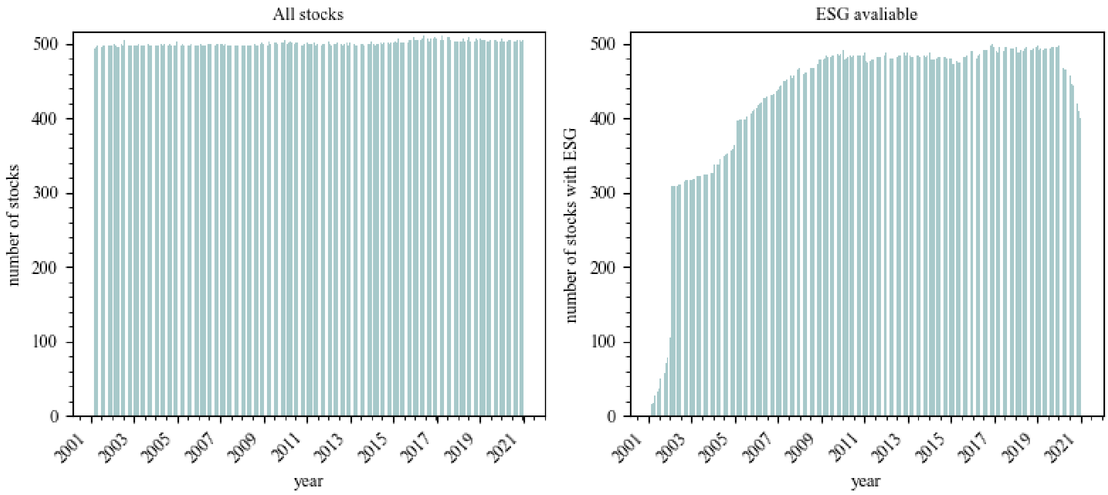

Figure 1.3 displays the monthly number of all stock constituents in S&P 500 over the period Mar 2001 to Jan 2021 on the left side and the monthly number of all constituents in S&P 500 with available ESG data on the right side.

As seen in figure (3.1), the number of stocks with available ESG data is relatively small in the beginning of our sample period. Considering this pattern, we analyse two alternative sample periods. The main sample period: from Jan 2003 to Jan 2021 allows us to study the efficiency in utilizing ESG score and ESG momentum as asset characteristics with a broader coverage of ESG data. This is especially in consideration for the ESG momentum characteristic that requires twelve additional months of historical ESG data. The sub-sample period: Mar 2002 to Jan 2021 uses the longest time horizon available given our data sample. For the sub-sample period, we refer to the results presented in appendix (B) and (C).

The "all stocks" and "ESG available" sample

In this paper, we focus on comparing the performance of a parametric portfolio policy when including ESG score and ESG momentum asset characteristics together with value and momentum, in contrast to including the asset characteristics value and momentum only. However, as can be seen in figure (3.1), available ESG data is missing for parts of our S&P 500 sample. Considering this, we divide our data into two alternative samples when forming the policy portfolios both with and without ESG characteristics. The "all stocks" sample includes all active S&P 500 stock constituents and representing the full investible universe available to investors. For forming the policy portfolios including ESG characteristics using the "all stock" sample, missing ESG scores are set equal to zero. The "ESG available" sample, on the other hand, only includes the active S&P 500 stock constituents that also have available ESG data. Hence, representing a partly limited investible universe that investors considering ESG data are expected to face, if, excluding the potential opportunity for investors to gather proxies for ESG using other external and available data.

3.4 Additional data

For estimating the abnormal returns of the policy portfolios using the asset pricing models presented in *Method 4.5*, we collect the following additional data: The risk-free rate (r_f), excess market return (*MKT*), and returns on the small-minus-big (*SMB*), high-minus-low (*HML*), robust-minus-weak (*RMW*), and conservative-minus-aggressive (*CMA*) portfolios are collected from the Kenneth R. French data library (French, 2022). Returns on the momentum (*UMD*) portfolio are collected from AQR (2022). Returns on the market equity (*ME*), investment (*I/A*), profitability (*ROE*) and expected growth (*EG*) portfolio are collected from Hou, Xue, and Zhang (2022).

4 METHOD

4.1 Static portfolios

The parametric portfolio policy

For the static policy portfolios, we model asset weights following Brandt et al. (2009):

$$w_{i,t} = \frac{1}{N_t} * \left(1 + \hat{x}_{i,t}^T \theta\right), \tag{1.1}$$

where θ is a vector of estimated theta coefficients that nudge the parametric weights away from the initial benchmark weights. For brevity, we assume initial equally weighted, $\frac{1}{N_t}$, benchmark weights. $\hat{x}_{i,t}$ is a matrix containing the asset characteristics of stock i. The asset characteristics in $\hat{x}_{i,t}$ are cross-sectionally standardized to have a zero mean and unit standard deviation across all stocks at time t.

Portfolio returns are modelled as the asset weights times the asset returns:

$$r_{p,t+1} = \sum_{i=1}^{N_t} w_{i,t} r_{i,t+1},$$

where N_t is the number of S&P 500 constituents at time t.

For estimating the optimal values of theta, we optimize the mean variance investor utility function following Hjalmarsson and Manchev (2012):

$$\theta = \max_{\theta} \frac{1}{T} \sum_{t=1}^{T} r_{p,t+1} - \frac{\gamma}{2} Var\left(r_{p,t+1}\right), \tag{1.2}$$

where γ is the risk aversion parameter $\gamma = 5$, if not stated otherwise, and $Var\left(r_{p,t+1}\right)$ is the variance of the portfolio returns.

Short-sell restrictions

For the static portfolio with short sell restrictions, we follow the renormalization following Brandt et al. (2009):

$$w_{i,t}^{+} = \frac{\max\,[0, w_{i,t}]}{\sum_{j=1}^{N_t} \max\,[0, w_{i,t}]}, \tag{1.3}$$

to ensure positive asset weights only.

Transaction costs

When accounting for transaction costs, we first model portfolio turnover at time t:

$$T_t = \sum_{i=1}^{N_t} |w_{i,t} - w_{i,t-1}].$$

Next, we model portfolio return, net transaction costs:

$$r_{p,t+1}^{T} = \sum_{i=1}^{N_t}(w_{i,t}r_{i,t} - c|\, w_{i,t} - w_{i,t-1}|),$$

where c is the proportional transaction cost. We only account for transaction costs in the robustness policy portfolio presented under *Method 4.4.* We set the transaction cost c equal to 50 basis points following the fixed transaction cost used in Brandt et al. (2009).

For estimating the optimal values of theta when accounting for transaction costs, we optimize the mean variance investor utility using the portfolio return, net transaction costs:

$$\max_{\theta} \frac{1}{T}\sum_{t=1}^{T}\left(r_{p,t+1}^{T} - \frac{\gamma}{2}Var\left(r_{p,t+1}^{T}\right)\right). \tag{1.4}$$

4.2 Dynamic portfolios

Generalized autoregressive score (GAS)

For the dynamic policy portfolio, we use generalized autoregressive score (GAS) to model the dynamic values of theta for each asset characteristics i ate time t following Creal et al. (2013):

$$\theta_{i,t} = \omega_i + \beta_i\theta_{i,t-1} + \alpha_i s_{i,t}, \tag{2.1}$$

where ω_i, β_i, and α_i are the estimated parameters for each asset characteristics i, representing the long-run or unconditional mean, the persistence, and the learning rate, respectively. $s_{i,t}$ is the driving variable of the scaled score function:

$$s_{i,t} = S_t \nabla_{i,t,f_t},$$

with $S_t = 1$, i.e., we are assuming “unit scaling”.

For deriving ∇_{i,t,f_t}, we model the conditional criterium function (representing the one-month mean-variance investor utility at time t):

$$u_t = w_{i,t}r_{i,t+1} - \frac{\gamma}{2}\left(w_{i,t}r_{i,t+1}\right)^2,$$

and:

$$\nabla_{i,t,f_t} = \frac{\delta u_t}{\delta \theta_i},$$

where $\left(w_{i,t}r_{i,t+1}\right)^2$ represents the squared portfolio return at time t. We use $\left(w_{i,t}r_{i,t+1}\right)^2$ as a proxy for the one-month variance of portfolio returns to avoid the complexity in estimating the "true" variance given that we only have one data point of portfolio returns per month. ∇_{i,t,f_t} is the partial derivative of the one-month mean-variance investor utility at time t with respect to asset characteristics i. We obtain ∇_{i,t,f_t} computationally using autograd (Maclaurin, Duvenaud, and Johnson (2022).

For finding the optimal parameters of ω_i, β_i, and α_i, we optimize the mean variance investor utility for the whole period:

$$\max_{\omega_i,\beta_i,\alpha_i} \frac{1}{T}\sum_{t=1}^{T}\left(r_{p,t+1} - \frac{\gamma}{2}Var\left(r_{p,t+1}\right)\right). \tag{2.2}$$

The corresponding dynamic asset weights are then modelled:

$$w_{i,t} = \frac{1}{N_t} * \left(1 + \hat{x}_{i,t}^T\theta_t\right), \tag{2.3}$$

where θ_t is a vector of the dynamic theta coefficients for each asset characteristics i at time t.

4.3 Out-of-sample

Splitting the sample period

For the static and dynamic policy portfolios, we study the performance out-of-sample by splitting our sample period into two. We denote the first "portfolio formation period":

$$t_1 \in [1, T - t - 1],$$

and the second "out-of-sample period":

$$t_2 \in [T - t, T].$$

For estimating the optimal or dynamic values of theta, we use the data contained in the "sample formation period" to estimate θ following Eq. (1.2) and ω_i, β_i, α_i following Eq. (2.2). We then use these previously estimated parameters together with data contained in the "out-of-sample" period to model asset weights following Eq. (1.1) and Eq. (2.3), respectively.

Moving window

For the static policy portfolios, we study the performance out-of-sample using a moving window with window sizes equal to 12-, 24-, 36-, and 48-months of historical observations, $s = [12, 24, 36, 48]$. For each month t, we repeat the out-of-sample methods described above by denoting the moving "portfolio formation period":

$$t_1 \in [t, t + s - 1],$$

and the moving "out-of-sample period":

$$t_2 \in [t + s, T].$$

Rebalancing frequency

For the static policy portfolios, we also study the performance out-of-sample using a moving window with 48-months of historical observations, $s = [48]$. Together with a rebalancing frequency from two to twelve months, $b =\in [2, 12]$. For this purpose, we repeat the out-of-sample method described above. However, in contrast to allocating new asset weight for each month as in Eq. (1.1), we continue to hold the same asset weights allocated in time t up to time b.

4.4 Portfolios

We create various policy portfolios that can be divided into three different groups. The first group consists of the benchmark portfolios. The next two groups are the policy portfolios with and without ESG that are based on the parametric portfolio policy of Brandt et al. (2009).

BENCHMARK PORTFOLIOS

Portfolio A: Equally weighted benchmark

For the equally weighted benchmark, we model the asset weights for each asset i at time t:

$$w_{i,t} = \frac{1}{N_t}. \tag{A}$$

where N_t is the number of S&P 500 constituents at time t.

Portfolio B: Value weighted benchmark

For the value weighted benchmark, we model the asset weights by weighting each asset i at time t according to their market capitalization:

$$w_{i,t} = \frac{market\ capitalization_{i,t}}{\sum_{j=1}^{N_t} market\ capitalization_{i,t}}. \tag{B}$$

Portfolio C: ESG screened benchmark

The ESG screened benchmark is constructed following Auer (2016) and only includes stocks with ESG scores that are higher than the 25th percentile of all ESG scores at time t. For calculating the 25th percentile of ESG scores (p_t^{25}), we also exclude stocks with missing ESG data. Formally, we model the weights for each asset i at time t:

$$w_{i,t} = \frac{1}{N_{t,I_{ESG}}} I_{ESG}, \tag{C}$$

and:

$$I_{ESG} = \begin{cases} 1 & if\ ESG_{i,t} > p_t^{25} \\ 0 & if\ ESG_{i,t} > p_t^{25} \end{cases},$$

where I_{ESG} is an indicator function for including stocks based on their ESG score.

STATIC POLICY PORTFOLIOS

Portfolio D: Static policy without ESG

For the static policy without ESG, we model the asset weights following Eq. (1.1):

$$w_{i,t}^{Without} = \frac{1}{N_t} * \left(1 + \hat{x}_{i,t}^T \theta\right), \tag{D}$$

$$\hat{x} = value, mom,$$
$$\theta = \theta_{value}, \theta_{mom}.$$

The policy without ESG uses the asset characteristics value ($value$), and momentum (mom) to allocate asset weights according to its optimal values of theta ($\theta_{value}, \theta_{mom}$). The optimal values of theta are estimated following Eq. (1.2). The policy without ESG is constructed using two different samples. First, using the "all stocks" sample and second, using the "ESG available" sample as described in *Data 3.3.*

The "all stocks" and "ESG available" samples are also used for portfolios (E) to (I) as presented below.

Portfolio E: Static policy with ESG

The static policy with ESG is modelled similar to portfolio (D). However, the policy with ESG also includes ESG score ($ESG\ score$) and ESG momentum ($ESG\ mom$) as additional asset characteristics together with value and momentum. Hence, we model the asset weights following Eq. (1.1):

$$w_{i,t}^{With} = \frac{1}{N_t} * \left(1 + \hat{x}_{i,t}^T \theta\right), \tag{E}$$

$$\hat{x} = value, mom, ESG\ score, ESG\ mom,$$
$$\theta = \theta_{value}, \theta_{mom}, \theta_{ESG\ score}, \theta_{ESG\ mom}.$$

For the policy with ESG, we likewise estimate the optimal values of theta (θ_{value}, $\theta_{mom}, \theta_{ESG\ score}, \theta_{ESG\ mom}$) following Eq. (1.2).

Portfolio F and G: Short-sell restrictions

For the static policy portfolios with and without ESG, we apply short-sell restrictions by first modelling the asset weights as in portfolio (D) and (E). Second, we use the renormalization following Brandt et al. (2009) in Eq. (1.3):

$$w_{i,t}^{Without,+} = \frac{\max\left[0, w_{i,t}^{Without}\right]}{\sum_{j=1}^{N_t} \max\left[0, w_{i,t}^{Without}\right]}, \tag{F}$$

and:

$$w_{i,t}^{With,+} = \frac{\max\left[0, w_{i,t}^{With}\right]}{\sum_{j=1}^{N_t} \max\left[0, w_{i,t}^{With}\right]}, \tag{G}$$

to ensure positive asset weights for the two policies with and without ESG, respectively.

DYNAMIC POLICY PORTFOLIOS

Portfolio H: Dynamic policy without ESG

For the dynamic policy without ESG, we model asset weights following Eq. (2.3):

$$w_{i,t}^{Without} = \frac{1}{N_t} * \left(1 + \hat{x}_{i,t}^{T} \theta_t\right), \tag{H}$$

$$\hat{x} = value, mom,$$
$$\theta_t = \theta_{value,t}, \theta_{mom,t}.$$

The dynamic values of theta ($\theta_{value,t}, \theta_{mom,t}$) are modelled using GAS following Eq. (2.1):

$$\theta_t = \begin{cases} \theta_{value,t} & = \omega_{value} + \beta_{value}\theta_{value,t-1} + \alpha_{value}s_{value,t} \\ \theta_{mom,t} & = \omega_{mom} + \beta_{mom}\theta_{mom,t-1} + \alpha_{mom}s_{mom,t} \end{cases},$$

where the optimal parameters of ω, β, and α are derived for each of the asset characteristics value and momentum following Eq. (2.2).

Portfolio I: Dynamic policy with ESG

The dynamic policy with ESG uses ESG score and ESG momentum as additional asset characteristics together with value and momentum. The policy with ESG is otherwise modelled similar to portfolio (F). Hence, we model the asset weights following Eq. (2.3):

$$w_{i,t}^{With} = \frac{1}{N_t} * \left(1 + \hat{x}_{i,t}^{T} \theta_t\right), \tag{I}$$

$$\hat{x} = value, mom, ESG\ score, ESG\ mom,$$
$$\theta_t = \theta_{value,t}, \theta_{mom,t}, \theta_{ESG\ score,t}, \theta_{ESG\ mom,t},$$

with the dynamic values of theta ($\theta_{value,t}, \theta_{mom,t}, \theta_{ESG\ score,t}, \theta_{ESG\ mom,t}$) being modelled following Eq. (2.1):

$$\theta_t = \begin{cases} \theta_{value,t} & = \omega_{value} + \beta_{value}\theta_{value,t-1} + \alpha_{value}s_{value,t} \\ \theta_{mom,t} & = \omega_{mom} + \beta_{mom}\theta_{mom,t-1} + \alpha_{mom}s_{mom,t} \\ \theta_{ESG\ score,t} & = \omega_{ESG\ score} + \beta_{ESG\ score}\theta_{ESG\ score,t-1} + \alpha_{ESG\ score}s_{ESG\ score,t} \\ \theta_{ESG\ mom,t} & = \omega_{ESG\ mom} + \beta_{ESG\ mom}\theta_{ESG\ mom,t-1} + \alpha_{ESG\ mom}s_{ESG\ mom,t} \end{cases}.$$

The optimal parameters of ω, β, and α are likewise derived for each of the asset characteristics value, momentum, ESG score and ESG momentum following Eq. (2.2).

ROBUSTNESS SCENARIOS

Risk aversion

For each of the static policy with and without ESG, we model asset weights as in portfolio (D) and portfolio (E) respectively. However, for deriving the optimal value of theta following Eq. (1.2) we use two different risk aversion parameters reflecting two alternative risk profiles. First, we use a risk aversion parameter of $\gamma = 2$ for modelling the "less risk averse" portfolio. Second, we use a risk aversion parameter of $\gamma = 10$ for modelling the "more risk averse" portfolio. We choose the alternative risk aversion parameters following Medeiros et al. (2014).

Transaction costs

For each of the static policy with and without ESG, we also model asset weights as in portfolio (D) and portfolio (E) respectively. However, for estimating the optimal values of theta, we account for transaction costs equal to 50 basis point following Eq. (1.4), using the portfolio turnover and the portfolio return, net transaction costs presented in *Method 4.1.* We follow Brandt et al. (2009) in the choice of 50 bp as transaction costs.

4.5 Performance evaluation

Sharpe ratio

We use Sharpe ratio to measure the risk-adjusted return of the policy portfolios in terms of the excess portfolio return divided by portfolio risk. For each policy portfolio, we calculate Sharpe ratio:

$$SR = \frac{r_p - r_f}{\sqrt{Var(r_p)}},$$

where $r_p - r_f$ is the excess portfolio return, calculated as the portfolio return (r_p) minus the risk-free rate (r_f) (French, 2022). $\sqrt{Var(r_p)}$ is the standard deviation of the portfolio.

Abnormal returns of the policy portfolios

We use abnormal returns, or alpha, to measure the risk-adjusted performance of the policy portfolios compared to the market and extended market factors. For modelling the abnormal returns (α), we use the three asset pricing models: Carhart (1997) four factor model, Fama and French (2018) six factor model, and the q-factor model of Hou, Mo, Xue, and Zhang (2021) as presented below.

First, we model abnormal returns using Carhart (1997) four factor regression model. The four-factor model uses (i) the market excess returns (MKT), (ii) the differences in returns between a small and big stock portfolios (SMB), (iii) the difference in returns between a value and growth stock portfolios (HML), and (iv) the returns of a momentum portfolios (UMD):

$$r_{p,t} - r_{f,t} = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \varepsilon_t, \tag{5.1}$$

where MKT, SMB, HML, and UMD are the factor returns, and β_{MKT}, β_{SMB}, β_{HML}, and β_{UMD} are the corresponding factor loadings.

Second, we model abnormal returns using Fama and French (2018) six factor model. The six-factor model adds, in addition to MKT, SMB, HML, and UMD (i) the difference in returns between a robust and weak profitability stock portfolios (RMW), and (ii) the difference in returns between a conservative and aggressive investment stock portfolios (CMA):

$$r_{p,t} - r_{f,t} = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + \beta_{UMD}UMD_t + \varepsilon_t, \tag{5.2}$$

where MKT, SMB, HML, RMW, CMA, and UMD are the factor returns, and β_{MKT}, β_{SMB}, β_{HML}, β_{RMW}, β_{CMA}, and β_{UMD} are the corresponding factor loadings.

Third, we model abnormal returns using the q-factor model with expected growth of Hou et al. (2021). The q-factor model adds, in addition to MKT, (i) the difference in returns between a small and big market equity portfolios (ME), (ii) the difference in returns between a low and high investment stock portfolios (I/A), (iii) the difference in returns between a high and low return on equity stock portfolios (ROE), and (iv) the returns of a expected growth portfolios (EG):

$$r_{p,t} - r_{f,t} = \alpha + \beta_{MKT}MKT_t + \beta_{ME}ME_t + \beta_{I/A}I/A + \beta_{ROE}ROE_t + \beta_{EG}EG_t + \varepsilon_t, \tag{5.3}$$

where MKT, ME, I/A, ROE, and EG are the factor returns, and β_{MKT}, β_{SMB}, $\beta_{I/A}$, β_{ROE}, and β_{EG} are the corresponding factor loadings.

Abnormal return of the difference portfolios

For the "all stocks" and "ESG available" sample respectively, we calculate the return of a difference portfolio (r_t^{diff}) as the difference in returns between the "policy with ESG" portfolios and the "policy without ESG" portfolios:

$$r_t^{diff} = r_{p,t}^{With} - r_{p,t}^{Without},$$

where $r_{p,t}^{With}$ is the portfolio return of the "policy with ESG" and $r_{p,t}^{Without}$ is the portfolio return of the "policy without ESG". We use the r_t^{diff} to model the abnormal returns of the difference portfolio using the three asset pricing models:

$$r_t^{diff} = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD_t + \varepsilon_t, \tag{5.4}$$

$$r_t^{diff} = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{RMW}RMW_t + \beta_{CMA}CMA_t + \beta_{UMD}UMD_t + \varepsilon_t, \tag{5.5}$$

$$r_t^{diff} = \alpha + \beta_{MKT}MKT_t + \beta_{ME}ME_t + \beta_{I/A}I/A_t + \beta_{ROE}ROE_t + \beta_{EG}EG_t + \varepsilon_t. \tag{5.6}$$

Regression analysis

The abnormal returns of the policy portfolios and difference portfolios are estimated with regressions analysis as modelled in Eq. (5.1) to Eq. (5.6), using Statsmodels (Seabold and Perktold, 2010) together with heteroskedasticity and autocorrelation correcting (HAC) standard errors.

5 RESULTS

Here, we present the performance of the parametric portfolio policy when including ESG score and ESG momentum as asset characteristics together with value and momentum “policy with ESG”, compared to including the asset characteristics value and momentum only “policy without ESG”.

5.1 In-sample

First, we study the performance of the two static parametric portfolio policies with and without ESG in-sample.

Table 5.1: Estimated values of theta

	Panel A: Unrestricted				Panel B: Restricted			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Jan 2003 to Dec 2020								
Value	4.32	4.74	4.51	4.81	1.05	0.92	1.56	1.75
Mom	2.48	2.49	2.63	2.80	0.81	0.71	0.92	0.62
ESG Score	-	1.79	-	1.49	-	0.36	-	0.45
ESG Mom	-	1.17	-	1.02	-	0.24	-	0.02

Table 5.1, Panel A shows the estimated values of theta for the two unrestricted policies without ESG and with ESG as specified in Eq. (D) and (E), using the “All stocks” and “ESG available” sample. The estimated values of theta are derived by optimizing the mean variance investor utility function as in Eq. (1.2) with a risk aversion equal to five over the period Jan 2003 to Dec 2020. Panel B shows the estimated values of theta for the two policies when applying short-sell restrictions as specified in Eq. (F) and (G).

In the static portfolio, estimated values of theta in Eq. (1.2) show that the policy without ESG characteristics puts higher weights on value stocks compared to momentum stocks. This is true across the “all stocks”, “ESG available” sample, and for the sub-period displayed in appendix table (B.2.1), Panel A. The policy with ESG also puts higher weights on value stocks compared to momentum stocks. In turn, ESG scores are weighted more strongly compared to ESG momentum. With short-sell restrictions, optimal values of theta show similar positions, although with a decreasing magnitude of the overall theta coefficients. In turn, the policy with ESG puts substantially less weight on stocks with positive ESG momentum Especially for the “ESG available” sample and for the sub-period displayed in appendix (B.2.1), Panel B, with thetas close to zero. Suggesting the change in ESG score to provide little information when short-sell restrictions are induced.

Table 5.2: Performance

	Panel A: Unrestricted				Panel B: Restricted			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Feb 2003 to Jan 2021								
Avg. ESG	43.48	75.01	43.42	72.23	42.22	47.62	44.99	49.82
$\lvert w_i \rvert$ x 100	0.55	0.70	0.70	0.83	0.20	0.20	0.22	0.22
$\max w_i$ x 100	11.22	12.29	10.26	10.89	2.78	2.45	3.34	3.64
$\min w_i$ x 100	-3.86	-4.71	-3.64	-4.39	0.00	0.00	0.00	0.00
Avg. Pos.	0.65	0.78	0.82	0.93	0.23	0.23	0.29	0.29
Avg. Neg.	-0.43	-0.59	-0.54	-0.70	-	-	-	-
$\sum w_i I(w_i < 0)$	-0.88	-1.26	-1.05	-1.35	-	-	-	-
$\sum I(w_i < 0)/N_t$	0.41	0.42	0.43	0.43	-	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	266.85	332.66	306.04	361.90	63.28	61.87	75.40	73.59
$\bar{r}$	1.66	1.81	1.89	1.99	0.96	0.94	1.07	1.15
σ	6.40	6.57	6.85	6.89	5.03	4.95	5.35	5.55
df	3.53	3.19	3.56	3.60	3.02	2.96	2.73	2.40
SR	25.89	27.53	27.55	28.92	19.04	19.08	20.01	20.65
$\alpha^{Carhart}$	0.72**	0.91***	0.94***	1.08***	-0.00	-0.00	0.11	0.22**
α^{FF6}	0.87***	1.03***	1.11***	1.21***	0.06	0.04	0.19*	0.30**
$\alpha^{Q\ Factor}$	0.53*	0.70**	0.71**	0.84**	-0.00	-0.00	0.09	0.17
$\text{diff}^{Carhart}$	0.20**		0.14*		-0.00		0.11***	
diff^{FF6}	0.16*		0.10		-0.02		0.11***	
$\text{diff}^{Q\ Factor}$	0.17**		0.12*		0.00		0.09***	

Table 5.2, Panel A shows statistics for the two unrestricted policies without ESG and with ESG as specified in Eq. (D) and (E), using the "All stocks" and "ESG available" sample. The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Feb 2003 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics when applying short-sell restrictions as in Eq. (1.3) for the policies without ESG and with ESG as specified in Eq. (F) and (G). Note: ***p<0.01, **p<0.05, *p<0.1.

In-sample results for the static portfolio in Eq. (1.1) show the policy with ESG to take larger and more extreme positions in terms of absolute, maximum, and minimum weights compared to the policy without ESG. The policy with ESG also takes larger short-sell positions in terms of higher sums of negative weights. Resulting in the policy with ESG being more leveraged compared to the policy without ESG. The fractions of negative weights are, however, equally large between the two policies. Additionally, as measured by the turnover, results show the policy with ESG being more exposed to transaction costs. The average portfolio ESG score is also notably higher for the policy with ESG compared to the policy without. Suggesting the policy with ESG having an overall stronger ESG profile.

With short-sell restrictions, the turnover decreases substantially across all policies. Being equally high for the policy with ESG compared to the policy without. Hence, resulting in the two policies being equally exposed to transaction costs. In turn, the average portfolio ESG score decreases notable for the policy with ESG. Now being equally high compared to the policy without ESG.

For the performance, in-sample results show the policy with ESG to have higher returns and, more importantly, higher Sharpe ratios compared to the policy without ESG. The volatility is also higher for the policy with ESG. Both policies gain positive and significant abnormal returns. However, the abnormal returns of the policy with ESG are consistently higher compared to the policy without ESG. The abnormal returns of the difference portfolio, defined as the policy with ESG minus the policy without ESG, are positive and statistically significant on at least the 10% level. The average portfolio ESG score is also notable higher for the policy with ESG compared to the policy without.

With short-sell restrictions, results continue to show the policy with ESG to have higher Sharpe ratios compared to the policy without. The returns are higher for the policy with ESG in the “ESG available” sample, but smaller compared to the policy without out ESG in the “all stocks” sample. The volatility is mostly lower for the policy with ESG compared to the policy without. Expect for the “ESG available” sample displayed in table (5.2), Panel B. Both policies still gain some positive abnormal returns, but them being smaller and less significant compared to the unconstrained portfolio policies. The abnormal returns of the policy with ESG are higher compared to the policy without ESG. Except for the “all stocks” sample displayed in table (5.2), Panel B. The abnormal returns of the difference portfolios are mostly positive, but only significant for the “ESG available” sample.

In turn, in-sample results show the two policies to have higher Sharpe ratios and abnormal returns compared to the equally weighted and value weighted benchmark. As well as compared to the ESG screened benchmark displayed in appendix table (B.1.1) and (B.1.2). This is also true with short-sell restrictions.

In sum, in-sample results show the policy with ESG to perform better compared to the policy without ESG. We find higher Sharpe ratio and higher abnormal returns for the policy with ESG. The abnormal returns of the difference portfolio are positive and significant. Results also hold when inducing short-sell restrictions, although significant for the “ESG available” sample only. Additionally, results show the policy with ESG taking more extreme and leveraged positions compared to the policy without. As well as being more exposed to transaction costs.

5.2 Out-of-sample

In this section, we study the performance of the static policy portfolios out-of-sample as further described under *Method 4.3.* We split our sample period in two. Then, we use the “portfolio formation” period to estimate the values of theta as in Eq. (1.2). We use theses thetas to model the portfolio weights for the "out-of-sample" period, in which we evaluate out-of-sample performance accordingly.

Table 5.3: Estimated values of theta

	Panel A: Unrestricted				Panel B: Restricted			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Jan 2003 to Jan 2012								
Value	3.23	3.73	3.62	4.09	0.59	0.69	0.81	0.92
Mom	1.68	1.67	1.86	1.88	-0.03	0.13	-0.07	0.17
ESG Score	-	2.49	-	2.26	-	0.41	-	0.45
ESG Mom	-	1.60	-	1.53	-	0.22	-	0.26

Table 5.3, Panel A shows the estimated values of theta for the two unrestricted policies without ESG and with ESG as specified in Eq. (D) and (E), using the "All stocks" and "ESG available" sample. The estimated values of theta are derived by optimizing the mean variance investor utility function as in Eq. (1.2) with a risk aversion equal to five over the "portfolio formation" period Jan 2003 to Jan 2012. Panel B shows the estimated values of theta for the two policies when applying short-sell restrictions as specified in Eq. (F) and (G).

In the static portfolio, optimal values of theta in Eq. (1.2), arising from the "portfolio formation" period, show similar positions for the policy without ESG compared to the in-sample results in table (5.1), Panel A. This is true across the "all stocks", "ESG available" sample, and for the sub-period displayed in appendix table (B.2.2), Panel A. In contrast, the policy with ESG now puts relatively higher weights on stocks with high ESG scores compared to momentum stocks. However, for the sub-period displayed in appendix (B.2.2), Panel A, the positions for the policy with ESG are also similar compared to the in-sample results in table (5.1), Panel A.

With short-sell restrictions, optimal values of theta show similar positions compared to the corresponding in-sample results in table (5.1), Panel B. Except for the policy with ESG, putting higher weights on stocks with a positive ESG momentum. The policy without ESG displayed in table (5.3), Panel B, now puts smaller weights on momentum stocks with theta coefficients being negative and close to zero. Suggesting momentum to provide little information for the policy during the "portfolio formation" period when short-sell restrictions are induced.

Table 5.4: Performance

Policy	Panel A: Unrestricted **All Stocks** Without ESG	With ESG	**ESG Available** Without ESG	With ESG	Panel B: Restricted **All Stocks** Without ESG	With ESG	**ESG Available** Without ESG	With ESG
Feb 2012 to Jan 2021								
Avg. ESG	50.38	96.03	52.90	96.37	50.94	57.70	53.18	60.54
$\lvert w_i \rvert$ x 100	0.37	0.67	0.43	0.71	0.20	0.20	0.21	0.21
$\max w_i$ x 100	10.88	12.77	11.66	13.46	2.11	2.46	2.76	3.10
$\min w_i$ x 100	-1.58	-2.93	-1.94	-3.22	0.07	0.00	0.04	0.00
Avg. Pos.	0.43	0.73	0.52	0.78	0.20	0.21	0.21	0.23
Avg. Neg.	-0.24	-0.58	-0.29	-0.62	-	-	-	-
$\sum w_i I(w_i < 0)$	-0.42	-1.19	-0.54	-1.21	-	-	-	-
$\sum I(w_i < 0)/N_t$	0.33	0.40	0.36	0.41	-	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	180.11	322.55	212.74	337.25	23.19	46.49	37.01	56.14
$\bar{r}$	1.41	1.58	1.53	1.70	1.00	1.03	1.01	1.05
σ	4.46	4.88	4.77	5.17	4.51	4.44	4.64	4.52
df	4.80	3.07	5.25	3.70	2.58	2.53	2.70	2.63
SR	31.67	32.43	32.00	32.99	22.10	23.26	21.77	23.31
$\alpha^{Carhart}$	0.13	0.26	0.24	0.37	-0.10	-0.09	-0.07	-0.08
α^{FF6}	0.12	0.25	0.23	0.37	-0.10	-0.09	-0.07	-0.08
$\alpha^{Q\ Factor}$	0.35	0.47**	0.45*	0.58**	-0.12	-0.09	-0.12	-0.08
$\text{diff}^{Carhart}$	0.13		0.14		0.00		-0.00	
diff^{FF6}	0.13		0.14		0.00		-0.00	
$\text{diff}^{Q\ Factor}$	0.12		0.13		0.03		0.04	

Table 5.4, Panel A shows statistics for the two unrestricted policies without ESG and with ESG as specified in Eq. (D) and (E), using the "all stocks" and "ESG available" sample. The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the out-of-sample period Feb 2012 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics when applying short-sell restrictions as in Eq. (1.3) for the policies without ESG and with ESG as specified in Eq. (F) and (G). Note: ***p<0.01, **p<0.05, *p<0.1.

Out-of-sample results for the static portfolio in Eq. (1.1) are similar compared to the in-sample results in table (5.2), Panel A. Results show the policy with ESG taking larger and more leveraged positions compared to the policy without ESG. As well as suffering more from the exposer to transaction costs. In turn, the fractions of negative weights are now larger for the policy with ESG compared to the policy without ESG. The average portfolio ESG score also remains higher for the policy with ESG compared to the policy without. With short-sell restrictions, results are similar compared to the in-sample results in table (5.2), Panel B.

For the performance, out-of-sample results are also similar compared to the in-sample results in table (5.2), Panel A. Except for the sub-period displayed in appendix table (B.3.2), Panel A, with the policy without ESG having a slightly higher volatility compared to the policy with ESG. Both policies gain positive, but mostly insignificant, abnormal returns and the abnormal returns of the policy with ESG are higher compared to the policy without. The abnormal returns of the difference portfolio are positive but insignificant at the 10% level.

With short-sell restrictions, result remain mostly similar compared to the corresponding in-sample results in table (5.2), Panel B. Except for the "all stocks" sample in the sub-period displayed in appendix table (B.3.2), Panel B, with the policy without ESG having a higher Sharpe ratio compared to the policy with ESG. None of the policies gain positive abnormal returns. Although, the abnormal returns of the policy with ESG tend to be slightly less negative compared to the policy without ESG. The anormal returns of the difference portfolio are close to zero and insignificant at the 10% level.

In turn, out-of-sample results show the two unrestricted policies to have higher Sharpe ratios and abnormal returns compared to the benchmark portfolios displayed in appendix table (1.3) and (1.4). However, Sharpe ratios are lower for the two policies compared to the value weighted benchmark when inducing short-sell restrictions.

In sum, out-of-sample results show some tendencies for the policy with ESG to perform better compared to the policy without ESG. We find overall higher Sharpe ratios and higher abnormal returns for the policy with ESG. The abnormal returns of the difference portfolio are mostly positive but insignificant. In turn, out-of-sample results show the policy with ESG to have higher average portfolio ESG scores compared to the policy without. Suggesting the policy with ESG attaining a stronger ESG profile without sacrificing the financial performance.

Figure 5.1: Abnormal returns of difference portfolio (24 months window)

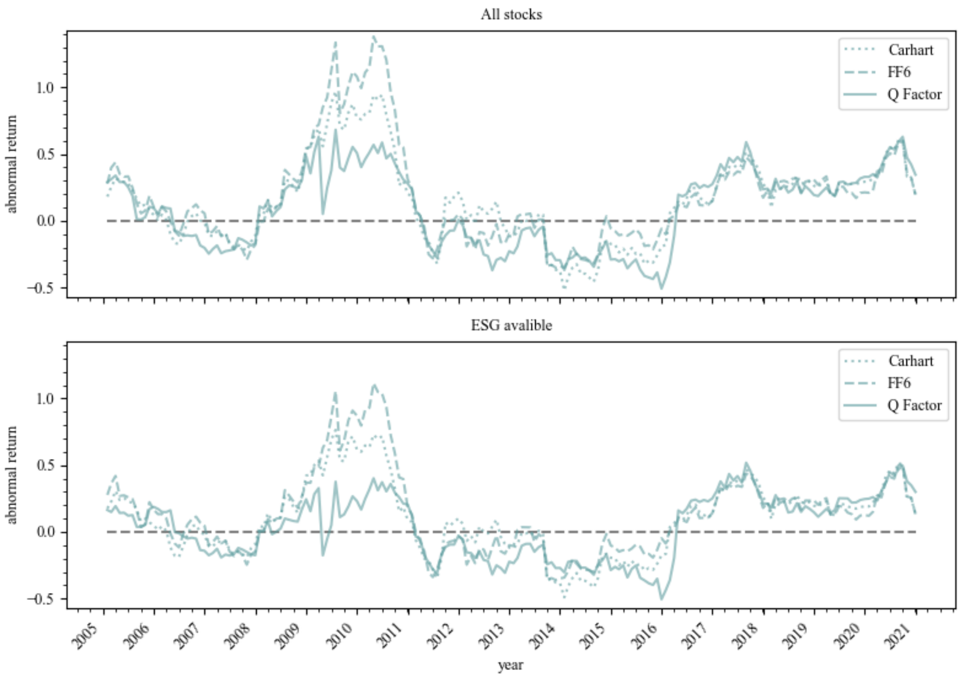

Figure 5.1 displays the abnormal returns of the difference portfolio, defined as the unrestricted policy with ESG minus unrestricted the policy without ESG, for the "all stocks" sample above and for the "ESG available" sample below. The abnormal returns are estimated using a moving window with a window size equal to 24 months over the period Feb 2003 to Jan 2021. The dotted line represents the abnormal returns estimated with Carhart (1997) four-factor model in Eq. (5.4), the dashed line represents the abnormal returns estimated with Fama and French (2016) six-factor model in Eq. (5.5), and the solid line represents the abnormal returns estimated with the q-factor model with expected growth of Hou et al. (2021) in Eq. (5.6).

Additionally, we study the abnormal returns of the difference portfolio using moving window to analyse what the insignificant abnormal returns of the difference portfolio out-of-sample might depend on. Using a window size of 24 months in figure (5.1), we see a notable drop in abnormal returns during 2011, that is, just before the start of our out-of-sample period in Feb 2012. We also see abnormal returns being mostly negative or close to zero during the years 2012 to 2016, in contrast to the abnormal returns being positive since 2016.

This pattern may serve as one explanation for the different significance in abnormal returns of the difference portfolio for the in-sample compared to out-of-sample results. The significant abnormal returns from the in-sample results are driven by the peak during 2009 to 2011, possibly reflecting a raising investor attention to ESG. Meanwhile, the insignificant abnormal returns for the out-of-sample result are driven by a longer period of depressed abnormal returns that amounts to a large part of the total out-of-sample period. Similar patterns can be seen when using a window size of 12 and 36 months as displayed in appendix figure (C.1.1) and (C.1.2). The underlying determinants of what depresses the abnormal returns of the difference portfolios between 2012 to 2016 also serves as an interesting topic for future studies.

5.3 Moving window and rebalancing

In this section, we dive deep into the out-of-sample performance using mowing window and alternative rebalancing frequencies, as further described under *Method 4.3*. In each window, we use 48 months of historical data to estimate the values of theta. We then use these thetas to obtain portfolio weights for each next consecutive month and we evaluate out-of-sample performance accordingly.

Figure 5.2: Estimated values of theta (48 months window)

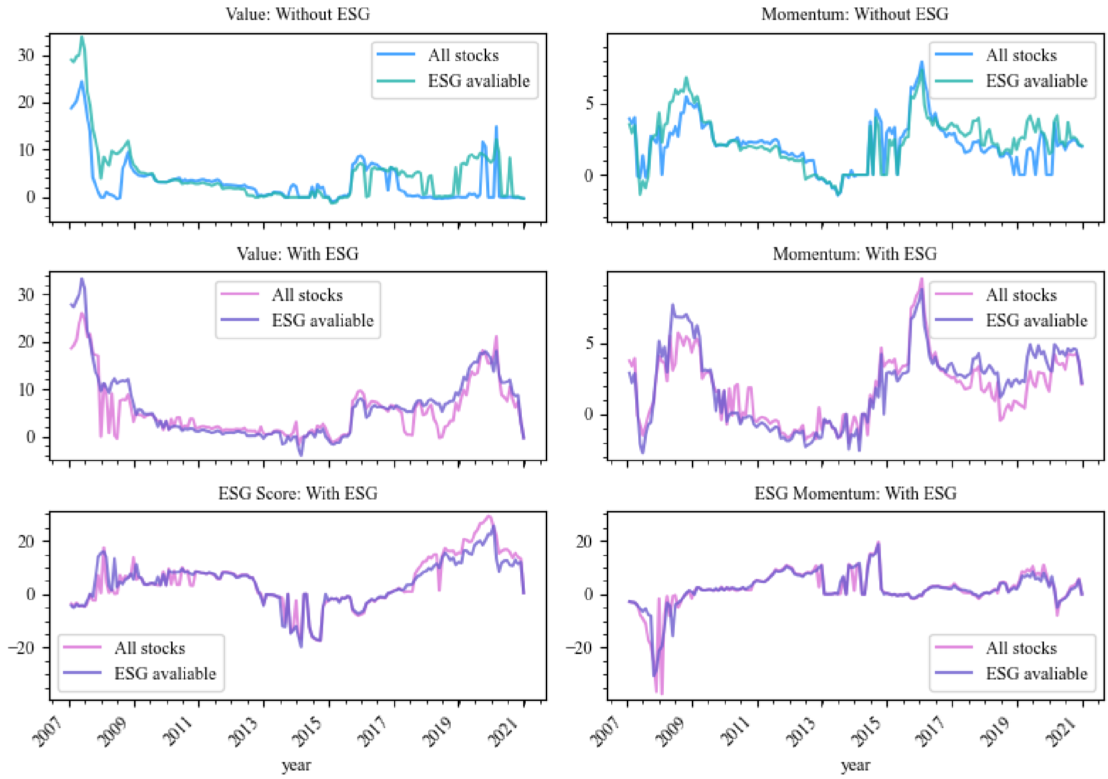

Figure 5.2 displays the estimated values of theta for each month using a moving window of with a window size equal to 48 months over the period Jan 2007 to Dec 2020. The first row shows the estimated values of theta for the policy without ESG for the asset characteristics value on the right and momentum on the left. The second row shows the estimated values of theta for the policy with ESG for value on the right and momentum on the left. The final row shows the estimated values of theta for the policy with ESG for ESG score on the right and ESG momentum on the left. For each month, the estimated values of theta are derived by optimizing the mean variance investor utility function in Eq. (1.2) with a risk aversion equal to five over the moving "portfolio formation" period presented under *Method 4.3.* The blue line represents the policy without ESG using the "all stocks" sample, the turquoise line represents the policy without ESG using the "ESG available" sample, the pink line represents the policy with ESG using the "all stocks" sample, and the purple line represents the policy with ESG using the "ESG available" sample.

For the moving window, estimated values of theta in figure (5.2) show the policy without ESG to put higher weight on value stocks in the beginning of our sample period. While putting higher weights on momentum stocks during the two peaks in 2009 and 2016. This is true across the "all stocks", "ESG available" sample, and for the sub-period displayed in appendix figure (C.1.3). The policy with ESG also puts higher weight on value stocks in the beginning of our sample period as well as during the peak in 2020. The estimated values of theta for momentum stocks are similar for the policy with ESG compared to the policy without ESG. In turn, the estimated values of theta translate into the policy with ESG putting higher weights on stocks with high ESG score in the beginning and end of our sample period. I contrast to the negative peak in 2014. The policy with ESG also puts higher weight on stocks with positive ESG momentum during 2010 to 2019 in contrast to the negative peak in 2008. In addition, the estimated values of theta for the moving window fluctuate substantially compared to the estimated values of that displayed in table (5.1) and (5.3). Especially with respect for the asset characteristics Value, ESG score, and ESG momentum.

Table 5.5: Performance

Policy	All Stocks Without ESG	With ESG	ESG Available Without ESG	With ESG
Feb 2007 to Jan 2021				
Avg. ESG	48.36	130.63	49.44	126.36
$\lvert w_i \rvert$ x 100	0.57	1.89	0.76	1.99
max w_i x 100	7.24	17.72	10.75	20.33
min w_i x 100	-2.45	-7.74	-4.13	-8.83
Avg. Pos.	0.64	1.97	0.86	2.12
Avg. Neg.	-0.49	-1.83	-0.66	-1.90
$\sum w_i I(w_i < 0)$	-0.92	-4.24	-1.28	-4.25
$\sum I(w_i < 0)/N_t$	0.31	0.44	0.33	0.45
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	297.51	953.76	360.80	963.22
$\bar{r}$	0.26	-0.08	0.52	0.79
σ	7.58	9.92	9.02	10.66
df	2.24	2.74	2.06	2.37
SR	3.44	-0.81	5.79	7.38
$\alpha^{Carhart}$	-0.56	-0.67	-0.08	0.48
α^{FF6}	-0.40	-0.47	0.07	0.73
$\alpha^{Q\ Factor}$	-0.75	-0.63	-0.64	0.32
$diff^{Carhart}$	-0.11		0.56	
$diff^{FF6}$	-0.07		0.65	
$diff^{Q\ Factor}$	0.12		0.96**	

Table 5.5 shows statistics for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the "all stocks" and "ESG available" sample. The portfolio weights for each policy are modelled with the thetas estimated using moving window as displayed in figure (5.2). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Feb 2007 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Note: ***p<0.01, **p<0.05, *p<0.1.

Moving window results are similar compared to the out-of-sample results in table (5.4), Panel A. Although, the turnover does increase substantially for the policy with ESG, making the policy even more exposed to transaction costs.

In addition, moving window results show some interesting differences in performance between the "all stocks" and "ESG available" sample. Results from the "all stocks" sample show the policy with ESG characteristics to have lower returns as well as lower Sharpe ratios compared to the policy without ESG characteristics. In contrast to the "ESG available" sample, where returns and Sharpe ratios are both higher for the policy with ESG compared to the policy without. This is also true for the sub-period displayed in appendix table (B.3.3). For the "all stocks" sample, none of the policies gain positive abnormal returns. The abnormal returns are mostly more negative for the policy with ESG. Resulting in negative but insignificant abnormal returns of the difference portfolio. For the "ESG available" sample however, both policies gain some positive abnormal returns. With abnormal returns of the policy with ESG being higher compared to the policy without and abnormal returns of the difference portfolio being positive and significant at the 5% level.

In turn, moving window results show both policies to deliver substantially lower Sharpe ratios compared to all benchmark portfolios displayed in appendix tale (B.1.5) and (B.1.6). Abnormal returns for the two policies are also lower compared to the benchmarks portfolios in the "all stocks" sample, but higher compared to the benchmarks in the "ESG available" sample.

Figure 5.3: One to twelve months rebalancing

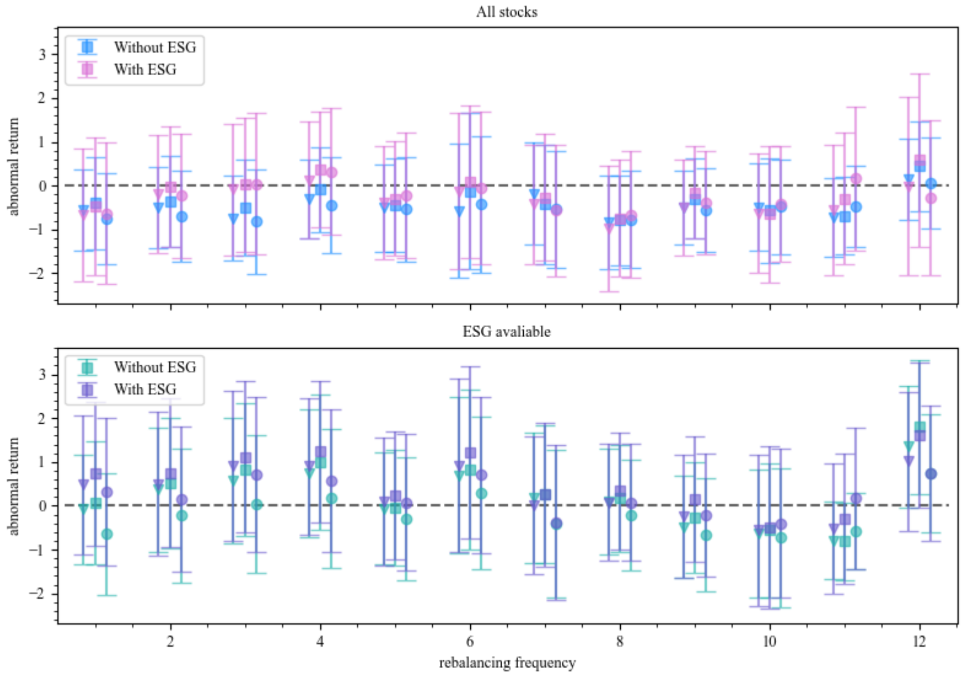

Figure 5.3 displays the abnormal returns and 95% confidence intervals of the two policies with and without ESG for the "all stocks" sample above and the "ESG available" sample below. The policy portfolios are estimated using moving window with a window equal to 48 months and with rebalancing frequencies ranging from one to twelve months over the period Feb 2007 to Jan 2021. The triangular markers represent the abnormal returns estimated with Carhart (1997) four factor model in Eq. (5.1), the squared markers represent the abnormal returns estimated with Fama and French (2016) six factor model in Eq. (5.2), and the circular markers represent the abnormal returns estimated with the q-factor model with expected growth of Hou et al. (2021) in Eq. (5.3). The colour-scheme for the policy portfolios and samples is as follows: Blue represents the policy without ESG using the "all stocks" sample, turquoise represents the policy without ESG using the "ESG available" sample, pink represents the policy with ESG using the "all stocks" sample, and purple represents the policy with ESG using the "ESG available" sample.

Figure 5.4: One to twelve months rebalancing

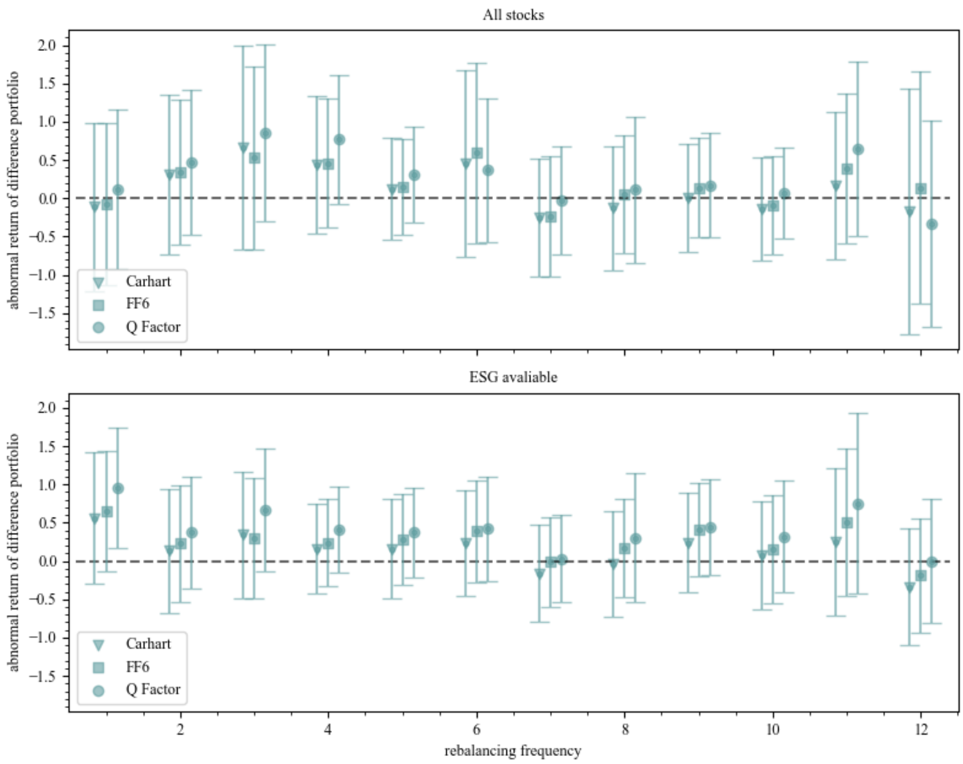

Figure 5.4 displays the abnormal returns and 95% confidence intervals of the difference portfolios, defined as the policy with ESG minus the policy without ESG for the "all stocks" sample above and the "ESG available" sample below. The policy portfolios are estimated using moving window with a window equal to 48 months and with rebalancing frequencies ranging from one to twelve months over the period Feb 2007 to Jan 2021. The triangular markers represent the abnormal returns estimated with Carhart (1997) four factor model in Eq. (5.4), the squared markers represent the abnormal returns estimated with Fama and French (2016) six factor model in Eq. (5.5), and the circular markers represent the abnormal returns estimated with the q-factor model with expected growth of Hou et al. (2021) in Eq. (5.6).

Figure (5.3) and (5.4) display the anormal returns of the individual policies as well as for the difference portfolio. Arising from the moving window when using a rebalancing frequency from one to twelve months. From figure (5.4), we see positive abnormal returns of the difference portfolio for a rebalancing frequency up to six months. Suggesting the policy with ESG to perform better compared to the policy without ESG within these rebalancing frequencies. As indicated by the confidence intervals however, abnormal returns of the difference portfolio are not significant at the 5% level. For a rebalancing frequency of seven to twelve months, abnormal returns of the difference portfolio are mostly negative or close to zero. Suggesting the policy with ESG to perform worse or equal compared to the policy without ESG. Except for the rebalancing frequency of elven months, with the abnormal return of the difference portfolio being positive but insignificant at the 5% level.

In sum, moving window results show the policy with ESG to perform worse compared to the policy without ESG for the "all stocks" sample. While the policy with ESG performs better compared of the policy without ESG for the "ESG available" sample. Results from using different rebalancing frequencies show the policy with ESG to mostly perform better compared to the policy without ESG under shorter rebalancing frequencies up to six months. In turn, the estimated values of theta using mowing window are generally more extreme compared to the thetas displayed in table (5.1) and (5.3). Resulting in the two policies having highly risky returns and lower Sharpe ratios compared to the benchmark portfolios.

5.4 Dynamic policies

In this section, we study the performance of the dynamic policies. With the values of theta being modelled by using generalized autoregressive score (GAS) as further described under *Method 4.2*.

Figure 5.5: Dynamic values of theta

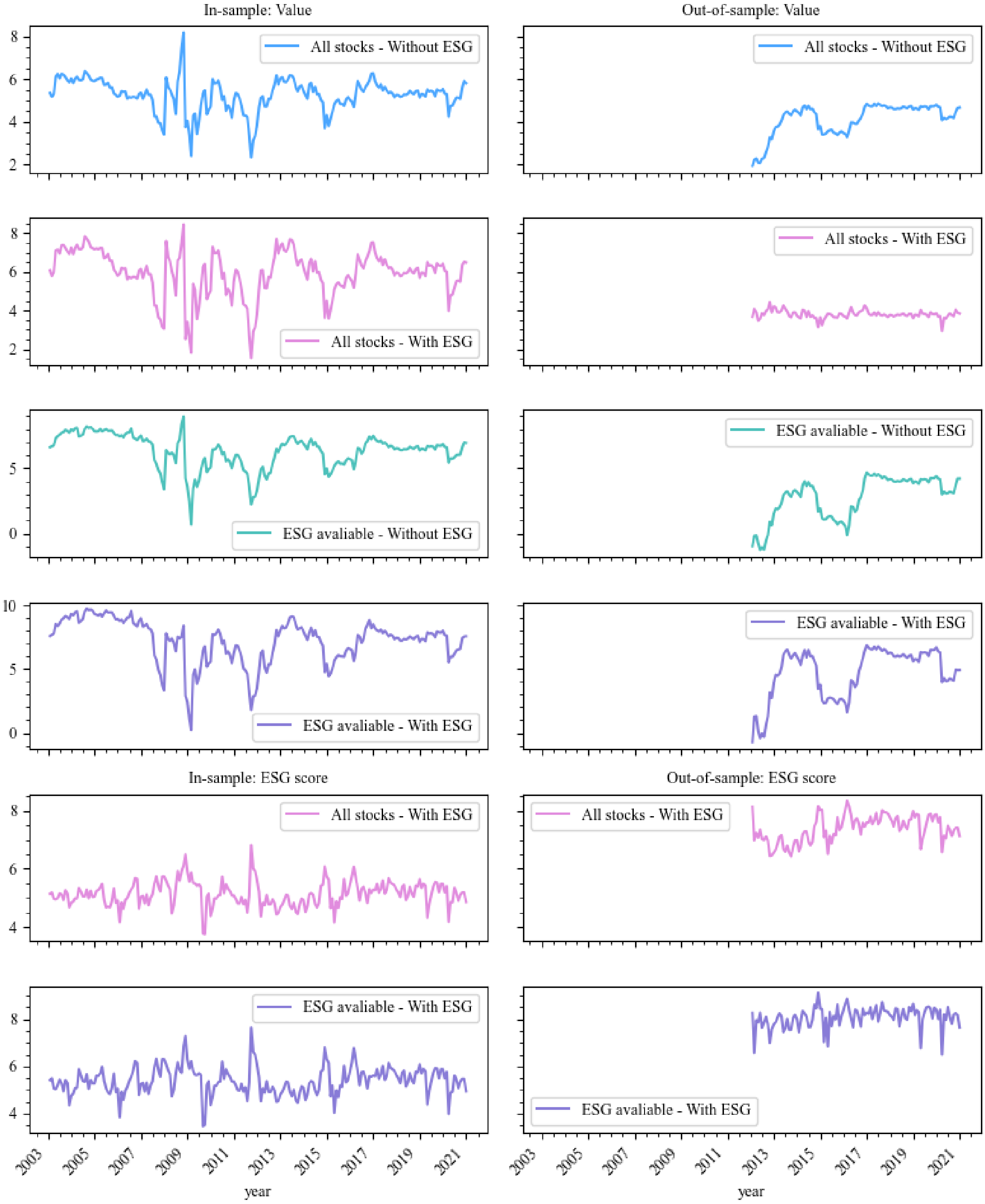

Figure 5.5 displays the dynamic values of theta for the two policies with ESG and without ESG as specified in Eq. (H) and (I). The first four rows display the dynamic values of theta for value and the two las rows display the dynamic value for ESG score. The dynamic values of theta are modelled with GAS as in Eq. (2.1) for the in-sample period Jan 2003 to Dec 2020 on the left and the out-of-sample period Jan 2012 to Dec 2002 on the right. The blue line represents the policy without ESG using the “all stocks” sample, the turquoise line represents the policy without ESG using the “ESG available” sample, the pink line represents the policy with ESG using the “all stocks” sample, and the purple line represents the policy with ESG using the “ESG available” sample.

Figure 5.6: Dynamic values of theta

Figure 5.6 displays the dynamic values of theta for the two policies with ESG and without ESG as specified in Eq. (H) and (I). The first four rows display the dynamic values of theta for momentum and the two las rows display the dynamic value for ESG momentum. The dynamic valued of theta are modelled with GAS as in Eq. (2.1) for the in-sample period Jan 2003 to Dec 2020 on the left and the out-of-sample period Jan 2012 to Dec 2002 on the right. The blue line represents the policy without ESG using the "all stocks" sample, the turquoise line represents the policy without ESG using the "ESG available" sample, the pink line represents the policy with ESG using the "all stocks" sample, and the purple line represents the policy with ESG using the "ESG available" sample.

From figure (5.5) and (5.6), we see the monthly dynamic values of theta to fluctuate less extreme compared to the values of theta estimated using moving window as displayed in figure (5.2). This pattern is partly explained by the estimated persistency parameter (β) and the learning rate parameter (α) displayed in appendix table (B.2.3). When comparing the time series of the dynamic thetas to the thetas estimated using a 12 to 48 months mowing window as displayed in appendix figure (C.1.4), (C.1.5), and (C.1.6), we recognize some similar movements. First, the dynamic and mowing window thetas for value stocks both have a negative peak in 2008, to increase again then gradually in 2009. Second, the dynamic and mowing window thetas for momentum stocks both peak in 2009. Third, the dynamic and mowing window thetas for ESG score both have negative peaks around 2009 to 20011 and 2014 to 2015. Forth, the dynamic and mowing window thetas for ESG momentum both have a double headed peak in 2009 to then gradually decrease in 2010.

Table 5.6: Performance

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Feb 2003 to Jan 2021					*Feb 2012 to Jan 2021*			
Avg. ESG	43.86	133.22	42.64	144.45	50.53	178.26	53.57	207.97
$\lvert w_i \rvert$ x 100	0.63	1.27	0.93	1.69	0.43	1.46	0.47	1.93
max w_i x 100	13.44	15.39	13.81	15.90	13.92	13.89	10.33	18.08
min w_i x 100	-4.79	-7.13	-4.97	-7.71	-1.93	-5.57	-1.84	-7.61
Avg. Pos	0.74	1.37	1.11	1.79	0.51	1.50	0.54	1.97
Avg. Neg	-0.50	-1.16	-0.74	-1.57	-0.30	-1.41	-0.35	-1.88
$\sum w_i I(w_i < 0)$	-1.09	-2.68	-1.54	-3.26	-0.58	-3.18	-0.63	-4.15
$\sum I(w_i < 0)/N_t$	0.42	0.46	0.45	0.46	0.36	0.45	0.37	0.46
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	308.41	597.10	401.30	714.12	216.84	700.01	234.58	900.75
$\bar{r}$	1.78	2.07	2.22	2.64	1.43	1.42	1.22	1.59
σ	6.66	6.94	7.50	7.89	4.63	5.48	4.41	6.81
df	3.63	3.92	4.64	5.41	4.58	4.33	5.25	3.95
SR	26.71	29.86	29.57	33.50	30.99	26.01	27.74	23.29
$\alpha^{Carhart}$	0.90***	1.36***	1.37***	2.00***	0.17	0.36	-0.16	0.32
α^{FF6}	1.06***	1.37***	1.53***	1.97***	0.15	0.32	-0.15	0.32
$\alpha^{Q\ Factor}$	0.68**	1.09***	1.08***	1.65***	0.40	0.55	0.20	0.61
$diff^{Carhart}$	0.47**		0.63**		0.19		0.48	
$diff^{FF6}$	0.31		0.44*		0.16		0.47	
$diff^{Q\ Factor}$	0.41**		0.56**		0.15		0.41	

Table 5.6, Panel A shows statistics for the two policy portfolios without ESG and with ESG as specified in Eq. (H) and (I), using the “all stocks” and “ESG available” sample for the in-sample period Feb 2003 to Jan 2021. Each policy is modelled with the dynamic values of theta estimated using GAS as in Eq. (2.1) and as displayed in figure (5.5) and (5.6). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across time. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics for the out-of-sample period Feb 2012 to Jan 2021. Note: ***p<0.01, **p<0.05, *p<0.1.

In-sample results for the dynamic policy portfolio in Eq. (2.3) are similar compared to the static in-sample results in table (5.2), Panel A. Results show the policy with ESG characteristics to take larger, more extreme, and more leveraged positions as well as being more exposed to transaction costs compared to the policy without ESG characteristics. Out-of-sample results for the dynamic portfolio are likewise similar compared to the static out-of-sample results in table (5.4), Panel A. This is true across the “all stocks”, “ESG available” sample, and for the sub-period displayed in appendix table (B.3.6), Panel B.

For the performance, in-sample results for the dynamic portfolio also remain similar compared to the static in-sample results in table (5.2), Panel A. Both policies gain positive abnormal returns that are significant on at least the 1% level. The abnormal returns of the policy with ESG are higher compared to the policy without. The abnormal returns of the difference portfolio are positive and significant on at least the 5% level.

Out-of-sample results for the dynamic portfolio are mostly similar compared to the static out-of-sample results in table (5.4), Panel A. Expect for the policy with ESG having lower Sharpe ratio compared to the policy without ESG across both samples displayed in table (5.6), Panel B. However, Sharpe ratio do remain higher for the policy with ESG for the sub-period displayed in appendix (B.3.6), Panel B. Both policies gain some positive abnormal returns, but them being significant for the policy with ESG in the sub-period displayed in appendix (B.3.6), Panel B only. The abnormal returns remain higher for the policy with ESG compared to the policy without. In turn, the abnormal returns of the difference portfolio are positive but mostly insignificant. Except for the “ESG available” sample for the sub-period displayed in appendix (B.3.6), Panel B, with the abnormal return being positive and significant at the 10% level.

In sum, results continue to show some tendencies for the policy with ESG to perform better compared to the policy without ESG, also when using dynamic values of theta. Again, we find overall higher Sharpe ratios and higher abnormal returns for the policy with ESG. The abnormal returns of the difference portfolio are positive but generally only significant in-sample.

When comparing the results of the dynamic portfolio to the corresponding results of the static portfolio, we observe some notable differences. First, the average portfolio ESG score increases substantially for the dynamic policy with ESG compared to when using static values of theta. This is true across in-sample results as well as out-of-sample results. Suggesting a potential for the dynamic policy with ESG to successfully gain a stronger ESG profile, again without sacrificing financial return. Second, the abnormal returns of the dynamic portfolios are mostly higher compared to the anormal returns of the static ones. Suggesting improved performance when modelling asset weights using dynamic values of theta. Third, dynamic values of theta fluctuate notably less extremely compared to thetas estimated using moving window. Resulting into the dynamic portfolio also being less risky and having higher Sharpes ratio as well as abnormal returns compared to the mowing window portfolio.

5.5 Robustness Results

Risk Aversion

In this section, we study the performance of the static policy portfolios using two different risk aversion profiles. For each of the static policy with and without ESG, we model asset weights as in portfolio (D) and portfolio (E) respectively. However, for deriving the optimal value of theta following Eq. (1.2) we use two different risk aversion parameters reflecting two alternative risk profiles. First, we use a risk aversion parameter of $\gamma = 2$ for modelling the "less risk averse" portfolio. Second, we use a risk aversion parameter of $\gamma = 10$ for modelling the "more risk averse" portfolio.

Table 5.7: Estimated values of theta

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Jan 2003 to Dec 2020					*Jan 2003 to Jan 2012*			
$\boldsymbol{\gamma = 2}$								
Value	11.83	12.59	12.53	13.34	9.25	9.78	10.53	11.06
Mom	4.88	4.96	5.37	5.53	3.21	3.02	3.91	3.80
ESG Score	-	2.48	-	2.11	-	3.02	-	2.49
ESG Mom	-	3.46	-	3.43	-	3.23	-	3.19
$\boldsymbol{\gamma = 10}$								
Value	1.81	2.22	1.86	2.27	1.20	1.03	1.31	1.28
Mom	1.68	1.76	1.68	1.78	1.15	0.44	1.17	0.64
ESG Score	-	1.67	-	1.60	-	4.95	-	4.28
ESG Mom	-	0.41	-	0.38	-	1.81	-	1.64

Table 5.7, Panel A shows the estimated values of theta for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the "All stocks" and "ESG available" sample. The estimated values of theta are derived by optimizing the mean variance investor utility function as in Eq. (1.2) with a risk aversion equal to two above and ten below, both over the "in-sample" period Jan 2003 to Dec 2020. Panel B shows the estimated values of theta, also using a risk aversion equal to two above and ten below, over the "portfolio formation" period Jan 2003 to Jan 2012.

In the static, "less risk averse" portfolio, optimal values of theta arising from the in-sample period show the policy without ESG puts substantially higher weights on value stocks compared to momentum stocks. This is true across the "all stocks", "ESG available" sample, and for the-sub period displayed in appendix table (B.2.5), Panel A. The policy with ESG also puts higher weights on value stocks compared to momentum stocks and ESG momentum is weighted more strongly compared to ESG scores. In the "more risk averse" portfolio, optimal values of theta show the policy without ESG puts smaller more balanced weights on both value and momentum stocks. The policy with ESG also show more balanced positions. With ESG scores being weighted more strongly compared to ESG momentum.

In the static, "less risk averse" portfolio, optimal values of theta arising from the "portfolio formation" period show similar positions compared to the corresponding in-sample results in table (5.7), Panel A. Except for the policy with ESG in the "all stocks" sample displayed in table (5.7), Panel B. Putting equal weights on momentum stocks and stocks with high ESG scores. In the "more risk averse" portfolio, optimal values of theta arising from the "portfolio formation" period also show similar positions for the policy without ESG compared to the in-sample results in table (5.7), Panel A. In contrast, the policy with ESG puts higher weights on stocks with high ESG scores as well as stocks with positive ESG momentum compared to value and momentum stocks. However, for the sub-period displayed in appendix (B.2.5), Panel B, positions for the policy with ESG are also similar compared to the in-sample results in table (5.7), Panel A.

Tabel 5.8: Performance

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Feb 2003 to Jan 2021					*Feb 2012 to Jan 2021*			
$\gamma = 2$								
Avg. ESG	44.95	97.32	39.12	89.82	49.19	110.15	52.22	107.21
$\lvert w_i \rvert$ x 100	1.32	1.59	1.76	2.04	0.83	1.19	1.06	1.36
max w_i x 100	30.04	31.98	27.87	29.59	30.62	32.65	33.53	35.62
min w_i x 100	-10.41	-11.99	-9.86	-11.44	-4.32	-6.15	-5.52	-7.16
Avg. Pos.	1.55	1.78	2.07	2.29	1.01	1.32	1.29	1.55
Avg. Neg.	-1.10	-1.41	-1.48	-1.80	-0.63	-1.04	-0.84	-1.18
$\sum w_i I(w_i < 0)$	-2.80	-3.49	-3.39	-4.02	-1.57	-2.49	-2.05	-2.79
$\sum I(w_i < 0)/N_t$	0.50	0.49	0.51	0.50	0.48	0.47	0.49	0.48
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	642.35	768.81	768.01	889.20	431.04	600.45	545.82	683.85
$\bar{r}$	3.32	3.64	4.01	4.36	2.21	2.46	2.60	2.87
σ	12.55	13.12	13.97	14.55	6.68	7.26	8.04	8.52
df	3.06	3.18	3.42	3.63	6.50	3.76	5.80	5.41
SR	26.47	27.71	28.70	29.94	33.08	33.95	32.34	33.70
$\alpha^{Carhart}$	2.46***	2.80***	3.16***	3.52***	0.89*	1.07**	1.26*	1.44**
α^{FF6}	2.85***	3.11***	3.60***	3.90***	0.83*	1.01**	1.22**	1.41**
$\alpha^{Q\ Factor}$	1.86**	2.19***	2.43***	2.79***	1.20**	1.35**	1.59**	1.75**
$\text{diff}^{Carhart}$	0.34*		0.36**		0.18		0.18	
diff^{FF6}	0.27		0.30*		0.18		0.19	
$\text{diff}^{Q\ Factor}$	0.33**		0.36**		0.15		0.17	
$\gamma = 10$								
Avg. ESG	42.99	69.26	44.85	72.13	50.78	135.58	53.11	129.91
$\lvert w_i \rvert$ x 100	0.33	0.46	0.38	0.53	0.25	0.92	0.26	0.88
max w_i x 100	5.02	6.06	4.56	5.42	4.25	4.80	4.40	5.36
min w_i x 100	-1.70	-2.47	-1.59	-2.38	-0.67	-3.11	-0.77	-2.94
Avg. Pos.	0.38	0.52	0.44	0.59	0.27	0.96	0.30	0.94
Avg. Neg.	-0.22	-0.36	-0.25	-0.43	-0.12	-0.87	-0.13	-0.80
$\sum w_i I(w_i < 0)$	-0.32	-0.65	-0.35	-0.69	-0.12	-1.82	-0.13	-1.62
$\sum I(w_i < 0)/N_t$	0.29	0.36	0.31	0.36	0.19	0.42	0.20	0.42
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	146.93	207.00	156.91	219.53	99.78	413.07	106.50	378.97
$\bar{r}$	1.10	1.22	1.19	1.31	1.14	1.23	1.17	1.27
σ	4.94	4.95	5.11	5.12	4.01	4.94	4.12	4.87
df	3.91	3.51	3.93	3.48	3.59	2.94	3.65	2.71
SR	22.34	24.61	23.31	25.63	28.45	24.90	28.37	26.11
$\alpha^{Carhart}$	0.14	0.31*	0.22	0.40**	-0.12	0.03	-0.11	0.04
α^{FF6}	0.21	0.36*	0.29*	0.45**	-0.12	0.03	-0.10	0.04
$\alpha^{Q\ Factor}$	0.09	0.22	0.16	0.30	0.06	0.06	0.08	0.10
$\text{diff}^{Carhart}$	0.17**		0.18**		0.15		0.15	
diff^{FF6}	0.15**		0.16**		0.15		0.14	
$\text{diff}^{Q\ Factor}$	0.13**		0.14**		0.00		0.03	

Table 5.8, Panel A shows statistics for the two policy portfolios without ESG and with ESG as specified in Eq. (D) and (E), using the "all stocks" and "ESG available" sample for the in-sample period Feb 2003 to Jan 2021. Each policy is modelled with a risk-aversion equal to two above and ten below. The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across time. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative

weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics for the out-of-sample period Feb 2012 to Jan 2021. Note: ***p<0.01, **p<0.05, *p<0.1.

In-sample results for the static, "less risk averse" portfolio show the policy with ESG to take larger and more extreme positions compared to the policy without ESG. As well as larger short-sell positions in terms of higher sums of negative weights. The turnover is also higher for the policy with ESG compared to the policy without. Resulting in the policy with ESG being more exposed to transaction costs. In the "more risk averse" portfolio, the turnover decreases substantially across all policies. Resulting in the two policies being less exposed to transaction costs. However, the turnover remains notably higher for the policy with ESG compared to the policy without. Out-of-sample results for the "less risk averse" and "more risk averse" portfolios are both similar compared to the corresponding in-sample results in table (5.8), Panel A.

For the performance, in-sample results for the static, "less risk averse" portfolio, show the policy with ESG to have higher returns and, more importantly, higher Sharpe ratios compared to the policy without ESG. The volatility is also higher for the policy with ESG. Both policies gain positive and significant abnormal returns. The abnormal returns are higher for the policy with ESG compared to the policy without and the abnormal returns of the difference portfolio are positive and statistically significant on at least the 5% level.

In-sample results for the "more risk averse" portfolio also show the policy with ESG to have higher returns and Sharpe ratios compared to the policy without. The volatility is higher for the policy with ESG across both samples for the results displayed in table (5.8), Panel A, but equally volatile compared to the policy without ESG for the sub-period displayed in appendix table (B.3.7), Panel A. Both policies continue to gain positive abnormal returns. The abnormal returns are higher for the policy with ESG compared to the policy without and the abnormal returns of the difference portfolio are also positive and significant on at least the 5% level.

Out-of-sample results for the static "less risk averse" portfolios are similar compared to the in-sample results in table (5.8), Panel A. Except for the policy without ESG having a higher volatility compared to the policy with ESG for the sub-period displayed in appendix (B.3.7), Panel B. Both policies gain positive and significant abnormal returns and the abnormal returns of the policy with ESG are higher compared to the policy without. The abnormal returns of the difference portfolio are positive but insignificant even at the 10% level.

Out-of-sample results for the "more risk averse" portfolios are mostly similar compared to the in-sample results in table (5.8), Panel A. Except for the policy with ESG having lower Sharpe ratios compared to the portfolio without ESG across both samples displayed in table (5.8), Panel B. However, Sharpe ratio remain higher for the policy with ESG compared to the policy without for the sub-period displayed in appendix (B.3.7), Panel B. Both policies gain some positive but insignificant abnormal returns. With the abnormal return of the policy with ESG being higher compared to the policy without. The abnormal returns of the difference portfolio are positive but insignificant. Except for the "ESG available" sample in the sub-period displayed in appendix (B.3.7), Panel B, with the abnormal return of the difference portfolio being positive and significant at the 10% level.

In turn, results from the "less risk averse" and "more risk averse" portfolios show both policies to have higher Sharpe ratios and higher abnormal returns compared to the benchmarks portfolios displayed in appendix table (B.1.1) to (B.1.4). This is also true for the out-of-sample results. Except for the "more risk averse" portfolio in the "all stocks" sample displayed in table (5.9), Panel B. With the policy with ESG having a lower Sharpe ratio compared to the value weighted benchmark displayed in appendix (B.1.3).

Transaction Costs

In this section, we study the performance of the static policy portfolios when accounting for transaction costs. For each of the static policy with and without ESG, we also model asset weights as in portfolio (D) and portfolio (E) respectively. However, for estimating the optimal values of theta, we account for transaction costs equal to 50 basis points following Eq. (1.4), as presented under presented in *Method 4.1.* We then use the new estimated values of theta to evaluate the performance, net of transaction costs.

Tabel 5.9: Estimated values of theta

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Jan 2003 to Dec 2020					*Jan 2003 to Jan 2012*			
$c = 50\ bp$								
Value	0.0000	0.0009	0.0051	0.0058	0.0015	0.0039	0.0062	0.0086
Mom	0.0000	0.0002	0.0027	0.0031	-0.0011	-0.0007	0.0000	0.0003
ESG Score	-	-0.0000	-	0.0018	-	0.0012	-	0.0024
ESG Mom	-	-0.0026	-	0.0010	-	0.0004	-	0.0010

Table 5.9, Panel A shows the estimated values of theta for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the "All stocks" and "ESG available" sample. The estimated values of theta are derived by optimizing the mean variance investor utility function when accounting for transaction costs equal to 50 basis points as in Eq. (1.4) with a risk aversion equal five over the "in-sample" period Jan 2003 to Dec 2020. Panel B shows the estimated values of theta, also when accounting for transaction costs, over the "portfolio formation" period Jan 2003 to Jan 2012.

For the portfolio accounting for transaction costs in Eq. (1.4), estimated values of theta arising from the in-sample period show the policy without ESG to put weights close to zero on both value and momentum stocks. Value stocks are weighed slightly stronger compared to momentum stocks. Except for the "all stocks" sample displayed in table (5.9), Panel A, with thetas equal to zero on both value and momentum. The policy with ESG also puts weights close to zero on both value and momentum stocks as well as on stocks with high ESG score and positive ESG momentum. Value stocks are weighted slightly higher compared to momentum stocks. Except for the "all stocks" sample in the sub-period displayed in appendix table (B.2.6), Panel A. ESG scores are weighted higher compared to ESG momentum.

Estimated values of theta arising from the "portfolio formation" period show similar positions for the policy without ESG compared to the in-sample results in table (5.9), Panel A. This is true across the "all stocks", "ESG available" sample, and for the sub-period displayed in appendix (B.2.6), Panel B. The policy with ESG also show similar positions compared to the in-sample results in table (5.9), Panel A. Except for ESG momentum being weighted higher compared to momentum across both samples displayed in table (5.9), Panel B.

Table 5.10: Performance

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Feb 2003 to Jan 2021					*Feb 2012 to Jan 2021*			
$c = 50\ bp$								
Avg. ESG	42.54	42.54	46.00	46.04	51.08	51.10	53.31	53.35
$\lvert w_i \rvert$ x 100	0.20	0.20	0.22	0.22	0.20	0.20	0.21	0.21
max w_i x 100	0.20	0.20	0.23	0.24	0.20	0.21	0.23	0.23
min w_i x 100	0.20	0.20	0.22	0.22	0.20	0.20	0.20	0.20
Avg. Pos.	0.20	0.20	0.22	0.22	0.20	0.20	0.21	0.21
Avg. Neg.	-	-	-	-	-	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-	-	-	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-	-	-	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.61	0.62	1.31	1.36	0.76	0.81	1.29	1.40
$\bar{r}$	0.81	0.81	0.80	0.80	0.93	0.93	0.90	0.90
σ	4.91	4.91	4.92	4.92	4.33	4.33	4.35	4.35
df	2.99	2.99	2.94	2.94	2.62	2.62	2.65	2.65
SR	16.50	16.51	16.29	16.29	21.38	21.38	20.78	20.78
$\alpha^{Carhart}$	-0.11*	-0.11*	-0.12**	-0.12**	-0.20**	-0.20**	-0.23***	-0.23***
α^{FF6}	-0.11*	-0.11*	-0.12**	-0.12**	-0.19***	-0.19***	-0.22***	-0.22***
$\alpha^{Q\ Factor}$	-0.09	-0.09	-0.11	-0.11	-0.19**	-0.19**	-0.23***	-0.23***
$diff^{Carhart}$	0.00**		-0.00		0.00		-0.00	
$diff^{FF6}$	0.00***		-0.00		0.00		-0.00	
$diff^{Q\ Factor}$	0.00		-0.00		0.00		-0.00	

Table 5.10, Panel A shows statistics for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the "all stocks" and "ESG available" sample for the in-sample period Feb 2003 to Jan 2021. Each policy is modelled by accounting for transactions costs equal to 50 basis points. The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across time. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics, net transaction costs: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics for the out-of-sample period Feb 2012 to Jan 2021. Note: ***p<0.01, **p<0.05, *p<0.1.

In-sample results for the static portfolio in Eq. (1.1), accounting for transactions costs, show the policies with and without ESG take equally large positions in terms absolute, maximum, and minimum weights. A consequence of both policies having estimated values of thetas close to zero. Hence, converging to the equally weighted benchmark. In turn, none of the polices take short-sell positions and, when accounting for transaction costs, the turnover also becomes equally low for the policy with ESG compared to the policy without. Resulting in the two policies being equally exposed to transaction costs. Out-of-sample results are similar compared to the in-sample results in table (5.10), Panel A. Except for the policy with ESG now having a slightly higher turnover compared to the policy without ESG. This is especially true for the sub-period displayed in appendix table (B.3.8), Panel B.

For the performance, in-sample results for the static portfolio show the policy with ESG to have equally high returns and Sharpe ratios compared to the policy without ESG. The volatility is also equally high for the policy with ESG compared to the policy without. When accounting for transaction costs, none of the policies gain positive abnormal returns and the abnormal returns are equally negative for the policy with ESG compared to the policy without. Resulting in the abnormal returns of the difference portfolio being very close to zero.

Out-of-sample results also remain similar compared to the in-sample results in table (5.10), Panel A. Except for the sub period displayed in appendix (B.3.8), Panel B, with Sharpe ratios being slightly lower for the policy with ESG compared to the policy without ESG. None of the policies gain positive abnormal returns and the abnormal returns are mostly equally negative for the policy with ESG compared to the policy without. The abnormal returns of the difference portfolio are very close to zero. Except for the "ESG available" sample in the sub-period displayed in appendix (B.3.8), Panel (B), with abnormal returns of the difference portfolio being negative and significant at the 1% level.

When accounting for transaction costs, none of the policies deliver Sharpe ratios or abnormal returns being higher compared to the equally weighted or ESG screened benchmark portfolio displayed in appendix table (B.1.8) and (B.1.9). For the "all stocks" sample, both policies have Sharpe ratios and abnormal returns similar compared to the equally weighted benchmark. For the "ESG available" sample, both policies underperformed compared to the equally weighted benchmark. The two policies also underperform compared to the 25th percentile screened ESG benchmark. This is true across both samples in-sample, and for the "ESG available" sample out-of-sample.

In sum, robustness results show the policy with ESG to perform better compared to the policy without ESG for both the "less risk averse" and "more risk averse" policies. This is, like our main results, recognised by the policy with ESG having higher Sharpe ratios and higher abnormal returns. For the two risk aversion profiles, abnormal returns of the difference portfolio remain positive but only significant in-sample. In contrast, when account for transaction cost equal to 50 basis points, the is no notable difference between to policy with ESG compared to the policy without. Both policies have estimated values of theta being close to zero. Hence converging to the equally weighted benchmark portfolio.

5.6 Conclusion

In this paper, we study performance of various parametric portfolio polices that exploit ESG score and ESG momentum as asset characteristics together with value and momentum “with ESG” in contrast to exploiting the asset characteristics value and momentum only “without ESG”. We implement both static and dynamic policy portfolios. First, we study the performance of the static policies in-sample as well as out-of-sample respectively. Second, we deep dive into the out-of-sample performance using mowing window and alternative rebalancing frequencies. Third, we study the performance of the dynamic policies by modelling the corresponding theta coefficient of each asset characteristic using generalized autoregressive score (GAS). Additionally, as robustness, we study the performance of the static policies using two different risk aversion profiles and by accounting for transaction costs.

Our main purpose of this paper was to answer the research question “what is the cost of obtaining a stronger ESG profile?”. Our findings provide the simple answer: There is no cost. When extending the parametric portfolio policy by using ESG score and ESG momentum as additional asset characteristics, we find it possible for investors to improve the average ESG portfolio score notably without sacrificing financial performance. In fact, we even find some evidence for the “policy with ESG” to perform better compared to the “policy without ESG”. We find higher Sharpe ratios and higher abnormal returns for the policy with ESG. Furthermore, we also find positive abnormal returns of the difference portfolio, defined as the policy with ESG minus the policy without ESG.

These findings remain consistent across both the static and dynamic policies, as well as over different risk aversion profiles. The evidence for better performance is strongest in-sample, with the abnormal returns of the different portfolio being positive and statistically significant. Out-of-sample results also show a tendency for the policy with ESG to perform better. Here, we also find higher Sharpe ratios and higher abnormal returns for the policy with ESG. Although, the positive abnormal returns of the difference portfolio are mostly insignificant.

Adding short-sell restriction to the policies somewhat reduces the gap in performance between the two policies. When accounting for transaction costs, no notable difference in performance between the two policies is observed. Our overall results are also quantitatively similar for both the “all stocks” and “ESG available” samples, reflecting two alternative investable universes with respect to ESG data.

Potential limitations of this paper are firstly related to the single source of ESG scores from Refinitiv (2022a). Scores measuring environmental, social and governance criteria differ notably among different ESG rating providers (Dorfleitner, Halbritter, and Nguyen, 2015).

Hence, there is no guarantee for the overall findings in this paper to hold when accounting for ESG data provided by alternative sources. An important topic for future research would therefore be to extend our analysis using ESG scores from multiple rating providers. An additional interesting extension would also be to account for the overall disagreement in ESG scores between different provides as an additional asset characteristic in the parametric portfolio policy. Like, for instance, Avramov et al. (2021) using the standard deviation of ESG scores between multiple provides.

A second limitation relates to the uncertainty in knowing whether the documented relationship between ESG and financial performance found is this paper will also hold in the future. Our findings related to how the abnormal returns of the difference portfolio evolve over time suggests that the performance of the policy with ESG is partly inflated by a peaking investor attention to ESG between 2008 to 2011. How investor attention to ESG may change in the future and how this in turn will affect the performance of the policy with ESG are therefore also considered as an interesting subject for future research.

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APPENDICIES

Appendix A

A.1 VARIABLE DESCRIPTIONS

Appendix table A.1.1: Variable descriptions

Variable	***Description***	***Source***
Price	The close price of each S&P 500 stock constituent.	Refinitiv DataStream, code: P
Market Equity	The close price times the number of shares outstanding.	Refinitiv DataStream, code: MV
PTBV	The price-to-book ratio defined as the stock price divided by the book value per share.	Refinitiv DataStream, code: PTBV
$Value$	The book-to-market ratio defined as the inverse of the price-to-book ratio: $\frac{1}{price-to-book\ ratio}$.	Author's calculation
Mom	The one-year momentum defined as the compounded return from $t-13$ to $t-1$: $\prod_{t-13}^{t-1}(1+r_{i,t})-1$.	Author's calculation
$ESG\ score$	The combined ESG score based on information in the Environmental, Social, and Corporate Governance pillars plus ESG controversies.	Refinitiv DataStream, code: TRESGCS
$ESG\ Mom$	ESG momentum defined as the year-on-year change in ESG scores.	Author's calculation
r_f	The risk-free rate of return.	Kenneth R. French Data Library
MKT	The market excess return.	Kenneth R. French Data Library
SMB	The small-minus-big return factor.	Kenneth R. French Data Library
HML	The high-minus-low return factor.	Kenneth R. French Data Library
UMD	The momentum factor.	
RMW	The robust-minus-weak profitability factor.	Kenneth R. French Data Library
CMA	The conservative-minus-aggressive investment factor.	Kenneth R. French Data Library
ME	The market equity factor.	Hou-Xue-Zhang q-factors data library
I/A	The investment factor.	Hou-Xue-Zhang q-factors data library
ROE	The return on equity factor.	Hou-Xue-Zhang q-factors data library
EG	The expected growth factor.	Hou-Xue-Zhang q-factors data library
r_i	Stock return defined as the change in stock price between $t-1$ and t: $\frac{Price_t}{Price_{t-1}}-1$.	Author's calculation

Appendix B

B.1 BENCHMARKS

Appendix table B.1.1

	Market Benchmark		ESG Benchmark
Portfolio	EW	VW	25%
Feb 2003 to Jan 2021			
Avg. ESG	42.54	45.23	52.65
$\lvert w_i \rvert$ x 100	0.20	0.20	0.30
max w_i x 100	0.20	3.60	0.30
min w_i x 100	0.20	0.01	0.30
Avg. Pos.	0.20	0.20	0.30
Avg. Neg.	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.61	67.54	1.42
$\bar{r}$	0.81	0.67	0.82
σ	4.91	4.10	4.85
df	2.99	3.42	2.85
SR	16.57	16.30	16.93
$\alpha^{Carhart}$	-0.11*	-0.19***	-0.08
α^{FF6}	-0.11*	-0.20***	-0.09
$\alpha^{Q\ Factor}$	-0.09	-0.22***	-0.08

Appendix table B.1.1 shows statistics for the equally weighted, value weighted, and ESG screened benchmark portfolios as specified in Eq. (A), (B), and (C). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Feb 2003 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). Statistics of these benchmark portfolios corresponds to the in-sample performance of the policy portfolios displayed in table (5.2). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.1.2

	Market Benchmark		ESG Benchmark
Portfolio	EW	VW	25%
Apr 2002 to Jan 2021			
Avg. ESG	41.44	44.37	51.79
$\lvert w_i \rvert$ x 100	0.20	0.20	0.30
max w_i x 100	0.20	3.58	0.30
min w_i x 100	0.20	0.01	0.30
Avg. Pos.	0.20	0.20	0.30
Avg. Neg.	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.62	67.66	1.39
$\bar{r}$	0.66	0.52	0.67
σ	5.07	4.29	4.98
df	3.10	3.67	3.01
SR	13.01	12.11	13.52
$\alpha^{Carhart}$	-0.09	-0.19***	-0.06
α^{FF6}	-0.09	-0.19***	-0.07
$\alpha^{Q\ Factor}$	-0.07	-0.22***	-0.06

Appendix table B.1.2 shows statistics for the equally weighted, value weighted, and ESG screened benchmark portfolios as specified in Eq. (A), (B), and (C). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Apr 2002 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). Statistics of these benchmark portfolios corresponds to the in-sample performance of the policy portfolios displayed in appendix table (B.3.1). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.1.3

	Market Benchmark		**ESG Benchmark**
Portfolio	EW	VW	25%
Feb 2012 to Jan 2021			
Avg. ESG	51.08	50.37	60.28
$\lvert w_i \rvert$ x 100	0.20	0.20	0.28
$\max w_i$ x 100	0.20	3.82	0.28
$\min w_i$ x 100	0.20	0.01	0.28
Avg. Pos.	0.20	0.20	0.28
Avg. Neg.	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.72	69.93	1.64
$\bar{r}$	0.93	0.99	0.92
σ	4.33	3.80	4.37
df	2.62	3.23	2.53
SR	21.47	26.07	21.05
$\alpha^{Carhart}$	-0.19**	-0.19***	-0.21***
α^{FF6}	-0.18**	-0.20***	-0.20***
$\alpha^{Q\ Factor}$	-0.19**	-0.22***	-0.22**

Appendix table B.1.3 shows statistics for the equally weighted, value weighted, and ESG screened benchmark portfolios as specified in Eq. (A), (B), and (C). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Feb 2012 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). Statistics of these benchmark portfolios corresponds to the out-of-sample performance of the policy portfolios displayed in table (5.4). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.1.4

	Market Benchmark		**ESG Benchmark**
Portfolio	EW	VW	25%
Aug 2011 to Jan 2021			
Avg. ESG	50.83	50.30	60.02
$\lvert w_i \rvert$ x 100	0.20	0.20	0.28
$\max w_i$ x 100	0.20	3.79	0.28
$\min w_i$ x 100	0.20	0.01	0.28
Avg. Pos.	0.20	0.20	0.28
Avg. Neg.	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.72	69.30	1.61
$\bar{r}$	0.97	1.02	0.96
σ	4.52	3.92	4.54
df	2.50	3.14	2.43
SR	21.38	26.02	21.23
$\alpha^{Carhart}$	-0.21***	-0.19***	-0.22***
α^{FF6}	-0.21***	-0.20***	-0.22***
$\alpha^{Q\ Factor}$	-0.19**	-0.22***	-0.22***

Appendix table B.1.4 shows statistics for the equally weighted, value weighted, and ESG screened benchmark portfolios as specified in Eq. (A), (B), and (C). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Aug 2011 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). Statistics of these benchmark portfolios corresponds to the out-of-sample performance of the policy portfolios displayed in appendix table (B.3.2). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.1.5

	Market Benchmark		ESG Benchmark
Portfolio	EW	VW	25%
Feb 2007 to Jan 2021			
Avg. ESG	47.60	48.58	56.73
$\lvert w_i \rvert$ x 100	0.20	0.20	0.28
max w_i x 100	0.20	3.73	0.28
min w_i x 100	0.20	0.01	0.28
Avg. Pos.	0.20	0.20	0.28
Avg. Neg.	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.69	71.15	1.43
$\bar{r}$	0.66	0.60	0.67
σ	5.30	4.47	5.26
df	2.92	4.11	2.85
SR	12.54	13.49	12.67
$\alpha^{Carhart}$	-0.14**	-0.19***	-0.12*
α^{FF6}	-0.15**	-0.20***	-0.14**
$\alpha^{Q\ Factor}$	-0.14*	-0.23***	-0.14*

Appendix table B.1.5 shows statistics for the equally weighted, value weighted, and ESG screened benchmark portfolios as specified in Eq. (A), (B), and (C). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Feb 2007 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). Statistics of these benchmark portfolios corresponds to the 48-months moving window performance of the policy portfolios displayed in table (5.5). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.1.6

	Market Benchmark		ESG Benchmark
Portfolio	EW	VW	25%
Aug 2006 to Jan 2021			
Avg. ESG	46.65	38.09	55.89
$\lvert w_i \rvert$ x 100	0.20	0.20	0.28
max w_i x 100	0.20	3.70	0.28
min w_i x 100	0.20	0.01	0.28
Avg. Pos.	0.20	0.20	0.28
Avg. Neg.	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.67	71.07	1.41
$\bar{r}$	0.66	0.60	0.66
σ	5.17	4.36	5.13
df	2.81	3.59	2.72
SR	12.75	13.86	12.92
$\alpha^{Carhart}$	-0.15**	-0.19***	-0.13**
α^{FF6}	-0.15**	-0.20***	-0.14**
$\alpha^{Q\ Factor}$	-0.13*	-0.23***	-0.14*

Appendix table B.1.6 shows statistics for the equally weighted, value weighted, and ESG screened benchmark portfolios as specified in Eq. (A), (B), and (C). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Aug 2006 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). Statistics of these benchmark portfolios corresponds to the 48-months moving window performance of the policy portfolios displayed in appendix table (B.3.3). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.1.7

Portfolio	Market Benchmark EW	VW	ESG Benchmark 25%	Market Benchmark EW	VW	ESG Benchmark 25%
	12-month window			**24-month window**		
Feb 2004 to Jan 2021				*Feb 2005 to Jan 2021*		
Avg. ESG	43.93	46.35	53.72	45.28	47.35	54.75
$\lvert w_i \rvert$ x 100	0.20	0.20	0.29	0.20	0.20	0.28
max w_i x 100	0.20	3.64	0.29	0.20	3.67	0.28
min w_i x 100	0.20	0.01	0.20	0.20	0.01	0.28
Avg. Pos.	0.20	0.20	0.29	0.20	0.20	0.28
Avg. Neg.	-	-	-	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.63	69.29	1.44	0.63	68.89	1.37
$\bar{r}$	0.67	0.57	0.69	0.67	0.59	0.68
σ	4.92	4.14	4.88	5.03	4.23	4.98
df	2.93	3.45	2.78	2.85	3.47	2.72
SR	13.60	13.69	14.15	13.35	13.89	13.66
$\alpha^{Carhart}$	-0.12*	-0.20***	-0.08	-0.13**	-0.20***	-0.11*
α^{FF6}	-0.12**	-0.21***	-0.10*	-0.14**	-0.21***	-0.12**
$\alpha^{Q\ Factor}$	-0.10	-0.23***	-0.08	-0.12*	-0.23***	-0.12
	36-month window			**48-month window**		
Feb 2006 to Jan 2021				*Feb 2007 to Jan 2021*		
Avg. ESG	46.45	47.98	55.72	47.60	48.58	56.73
$\lvert w_i \rvert$ x 100	0.20	0.20	0.28	0.20	0.20	0.28
max w_i x 100	0.20	3.69	0.28	0.20	3.73	0.28
min w_i x 100	0.20	0.01	0.28	0.20	0.01	0.28
Avg. Pos.	0.20	0.20	0.28	0.20	0.20	0.28
Avg. Neg.	-	-	-	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.67	70.89	1.40	0.69	71.15	1.43
$\bar{r}$	0.66	0.60	0.66	0.66	0.60	0.67
σ	5.14	4.34	5.11	5.30	4.47	5.26
df	2.75	3.47	2.66	2.92	4.11	2.85
SR	12.78	13.81	12.93	12.54	13.49	12.67
$\alpha^{Carhart}$	-0.15**	-0.19***	-0.13**	-0.14**	-0.19***	-0.12*
α^{FF6}	-0.16**	-0.20***	-0.15**	-0.15**	-0.20***	-0.14**
$\alpha^{Q\ Factor}$	-0.14*	-0.23***	-0.14*	-0.14*	-0.23***	-0.14*

Appendix table B.1.7 shows statistics for the equally weighted, value weighted, and ESG screened benchmark portfolios as specified in Eq. (A), (B), and (C). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the periods Feb 2004 to Jan 2021, Feb 2005 to Jan 2021, Feb 2006 to Jan 2021, and Feb 2007 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). Statistics of these benchmark portfolios corresponds to the 12, 24, 36, and 48-months moving window performance of the policy portfolios displayed in appendix table (B.3.4). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.1.8

Portfolio	Market Benchmark EW	VW	ESG Benchmark 25%	Market Benchmark EW	VW	ESG Benchmark 25%
Feb 2003 to Jan 2021				*Feb 2012 to Jan 2021*		
$\boldsymbol{c = 50\ bp}$						
Avg. ESG	42.54	45.23	52.65	51.08	50.37	60.28
$\lvert w_i \rvert$ x 100	0.20	0.20	0.30	0.20	0.20	0.28
max w_i x 100	0.20	3.60	0.30	0.20	3.82	0.28
min w_i x 100	0.20	0.01	0.30	0.20	0.01	0.28
Avg. Pos.	0.20	0.20	0.30	0.20	0.20	0.28
Avg. Neg.	-	-	-	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.61	67.54	1.42	0.72	69.93	1.64

$\bar{r}$	0.81	0.33	0.81	0.93	0.64	0.91
σ	4.91	4.11	4.85	4.33	3.80	4.37
df	2.99	3.36	2.85	2.62	3.23	2.52
SR	16.50	8.07	16.78	21.37	16.86	20.87
$\alpha^{Carhart}$	-0.11*	-0.53***	-0.09	-0.20**	-0.54***	-0.22***
α^{FF6}	-0.11*	-0.53***	-0.09*	-0.19***	-0.54***	-0.21***
$\alpha^{Q\ Factor}$	-0.09	-0.56***	-0.09	-0.19**	-0.57***	-0.23**

Appendix table B.1.8 shows statistics for the equally weighted, value weighted, and ESG screened benchmark portfolios as specified in Eq. (A), (B), and (C). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the periods Feb 2003 to Jan 2021 and Feb 2012 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics, net transaction cost equal to 50 basis points: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). Statistics of these benchmark portfolios corresponds to the in-sample and out-of-sample performance of the policy portfolios, after accounting for transaction costs, displayed in table (5.10). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.1.9

	Market Benchmark		**ESG Benchmark**	**Market Benchmark**		**ESG Benchmark**
Portfolio	EW	VW	25%	EW	VW	25%
Apr 2002 to Jan 2021				*Aug 2011 to Jan 2021*		
$\boldsymbol{c = 50\ bp}$						
Avg. ESG	41.44	44.37	51.79	50.83	50.30	60.02
$\lvert w_i \rvert$ x 100	0.20	0.20	0.30	0.20	0.20	0.28
$\max w_i$ x 100	0.20	3.58	0.30	0.20	3.79	0.28
$\min w_i$ x 100	0.20	0.01	0.30	0.20	0.01	0.28
Avg. Pos.	0.20	0.20	0.30	0.20	0.20	0.28
Avg. Neg.	-	-	-	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.62	67.66	1.39	0.72	69.30	1.61
$\bar{r}$	0.66	0.18	0.67	0.96	0.67	0.96
σ	5.07	4.29	4.98	4.52	3.92	4.54
df	3.10	3.53	3.01	2.50	3.08	2.42
SR	12.95	4.21	13.38	21.30	17.16	21.03
$\alpha^{Carhart}$	-0.09	-0.53***	-0.07	-0.22***	-0.54***	-0.23***
α^{FF6}	-0.09	-0.53***	-0.08	-0.21***	-0.55***	-0.23***
$\alpha^{Q\ Factor}$	-0.08	-0.56***	-0.07	-0.20**	-0.57***	-0.23***

Appendix table B.1.9 shows statistics for the equally weighted, value weighted, and ESG screened benchmark portfolios as specified in Eq. (A), (B), and (C). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the periods Apr 2002 to Jan 2021 and Aug 2012 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics, net transaction cost equal to 50 basis points: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). Statistics of these benchmark portfolios corresponds to the in-sample and out-of-sample performance of the policy portfolios, after accounting for transaction costs, displayed in appendix table (B.3.8). Note: ***p<0.01, **p<0.05, *p<0.1.

B.2 ESTIMATED VALUES OF THETA AND GAS

Appendix table B.2.1: Estimated values of theta. In-sample.

	Panel A: Unrestricted				Panel B: Restricted			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Mar 2002 to Dec 2020								
Value	4.42	4.77	4.43	4.79	1.23	1.25	1.31	1.33
Mom	2.52	2.51	2.59	2.57	0.63	0.59	0.68	0.61
ESG Score	-	1.62	-	1.66	-	0.44	-	0.30
ESG Mom	-	0.96	-	0.98	-	0.04	-	0.06

Appendix table B.2.1, Panel A shows the estimated values of theta for the two unrestricted policies without ESG and with ESG as specified in Eq. (D) and (E), using the "All stocks" and "ESG available" sample. The estimated values of theta are derived by optimizing the mean variance investor utility function as in Eq. (1.2) with a risk aversion equal to five over the period Mar 2002 to Dec 2020. Panel B shows the estimated values of theta for the two policies when applying short-sell restrictions as specified in Eq. (F) and (G).

Appendix table B.2.2: Estimated values of theta. Out-of-sample.

	Panel A: Unrestricted				Panel B: Restricted			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Mar 2002 to Jul 2011								
Value	4.22	4.32	4.38	4.46	0.66	0.56	1.03	0.94
Mom	2.41	2.26	2.26	2.30	0.60	0.51	0.54	0.49
ESG Score	-	1.47	-	1.56	-	0.23	-	0.33
ESG Mom	-	0.89	-	0.87	-	0.13	-	0.19

Appendix table B.2.2, Panel A shows the estimated values of theta for the two unrestricted policies without ESG and with ESG as specified in Eq. (D) and (E), using the "All stocks" and "ESG available" sample. The estimated values of theta are derived by optimizing the mean variance investor utility function as in Eq. (1.2) with a risk aversion equal to five over the "portfolio formation" period Mar 2002 to Jul 2011. Panel B shows the estimated values of theta for the two policies when applying short-sell restrictions as specified in Eq. (F) and (G).

Appendix table B.2.3: GAS parameters.

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Jan 2003 to Dec 2020					*Jan 2003 to Jan 2012*			
ω^{Value}	5.35	6.07	6.61	7.60	4.78	3.77	13.22	17.88
ω^{Mom}	2.60	2.68	2.78	2.90	1.92	1.54	2.50	2.51
$\omega^{ESG\ Score}$	-	5.14	-	5.42	-	7.46	-	8.15
$\omega^{ESG\ Mom}$	-	3.03	-	3.21	-	3.16	-	5.41
β^{Value}	0.75	0.79	0.88	0.88	0.00	0.40	1.00	1.00
β^{Mom}	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.15
$\beta^{ESG\ Score}$	-	0.56	-	0.58	-	0.74	-	0.22
$\beta^{ESG\ Mom}$	-	0.35	-	0.38	-	0.70	-	0.78
α^{Value}	52.75	85.82	56.74	82.91	29.35	32.78	59.78	86.90
α^{Mom}	8.97	35.56	15.90	36.88	6.88	56.66	19.46	59.90
$\alpha^{ESG\ Score}$	-	79.39	-	100.00	-	77.07	-	96.72
$\alpha^{ESG\ Mom}$	-	25.97	-	15.08	-	98.76	-	99.89

Appendix table B.2.3, Panel A shows the estimated GAS parameters for the two policy portfolios without ESG and with ESG as specified in Eq. (H) and (I), using the "all stocks" and "ESG available" sample for the "in-sample" period Jan 2003 to Dec 2020. The parameters of each policy are modelled as in Eq. (2.2) by optimizing the mean-variance investor utility function with a risk aversion equal to five. The first set of rows show the long-run unconditional mean with respect to each asset characteristic, the second set of rows show the persistency, and the last set of rows show the learning rate. Panel B shows the same estimated GAS parameters for the "portfolio formation" period Jan 2003 to Jan 2012.

Appendix table B.2.4: GAS parameters.

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Mar 2002 to Dec 2020					*Mar 2002 to Jul 2011*			
ω^{Value}	5.15	5.33	5.51	6.13	4.87	4.92	5.36	6.33
ω^{Mom}	2.75	2.89	2.77	2.78	3.37	3.14	2.75	2.71
$\omega^{ESG\ Score}$	-	4.94	-	4.66	-	4.05	-	3.40
$\omega^{ESG\ Mom}$	-	3.32	-	3.73	-	2.59	-	4.04
β^{Value}	0.37	0.09	0.57	0.63	0.30	0.00	0.43	0.63
β^{Mom}	0.00	0.01	0.00	0.00	0.00	0.02	0.02	0.01

$\beta^{ESG\ Score}$	-	0.43	-	0.24	-	0.62	-	0.09
$\beta^{ESG\ Mom}$	-	0.62	-	0.41	-	0.74	-	0.48
α^{Value}	41.74	65.60	45.25	83.16	5.00	47.29	33.80	72.71
α^{Mom}	5.00	32.45	6.91	25.49	34.46	43.05	5.70	24.45
$\alpha^{ESG\ Score}$	-	99.83	-	100.00	-	99.50	-	99.13
$\alpha^{ESG\ Mom}$	-	27.63	-	50.43	-	99.27	-	99.54

Appendix table B.2.4, Panel A shows the estimated GAS parameters for the two policy portfolios without ESG and with ESG as specified in Eq. (H) and (I), using the "all stocks" and "ESG available" sample for the "in-sample" period Mar 2002 to Dec 2020. The parameters of each policy are modelled as in Eq. (2.2) by optimizing the mean-variance investor utility function with a risk aversion equal to five. The first set of rows show the long-run unconditional mean with respect to each asset characteristic, the second set of rows show the persistency, and the last set of rows show the learning rate. Panel B shows the same estimated GAS parameters for the "portfolio formation" period Mar 2002 to Jul 2011.

Appendix table B.2.5: Estimated values of theta. Risk aversion.

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Mar 2002 to Dec 2020					*Mar 2002 to Jul 2011*			
$\boldsymbol{\gamma = 2}$								
Value	11.93	12.58	12.13	12.84	10.98	11.07	11.61	11.71
Mom	4.79	4.84	5.12	5.21	4.40	4.16	4.84	4.55
ESG Score	-	2.30	-	2.31	-	1.72	-	1.90
ESG Mom	-	2.91	-	2.98	-	2.07	-	2.25
$\boldsymbol{\gamma = 10}$								
Value	1.92	2.26	1.87	2.22	1.96	2.16	1.91	2.13
Mom	1.76	1.79	1.74	1.77	1.75	1.69	1.72	1.64
ESG Score	-	1.48	-	1.54	-	1.46	-	1.65
ESG Mom	-	0.32	-	0.32	-	0.52	-	0.56

Appendix table B.2.5, Panel A shows the estimated values of theta for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the "All stocks" and "ESG available" sample. The estimated values of theta are derived by optimizing the mean variance investor utility function as in Eq. (1.2) with a risk aversion equal to two above and ten below, both over the "in-sample" period Mar 2002 to Dec 2020. Panel B shows the estimated values of theta, also using a risk aversion equal to two above and ten below, over the "portfolio formation" period Mar 2002 to Jul 2011.

Appendix table B.2.6: Estimated values of theta. Transaction costs.

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Mar 2002 to Dec 2020					*Mar 2002 to Jul 2011*			
$\boldsymbol{c = 50\ bp}$								
Value	0.0041	0.0044	0.0049	0.0053	0.0051	0.0089	0.0227	0.0925
Mom	0.0040	0.0048	0.0040	0.0043	0.0035	0.0060	0.0110	0.0431
ESG Score	-	0.0013	-	0.0020	-	0.0033	-	0.0249
ESG Mom	-	0.0001	-	0.0008	-	0.0014	-	0.0038

Appendix table B.2.6, Panel A shows the estimated values of theta for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the "All stocks" and "ESG available" sample. The estimated values of theta are derived by optimizing the mean variance investor utility function when accounting for transaction costs equal to 50 basis points as in Eq. (1.4) with a risk aversion equal five over the "in-sample" period Mar 2002 to Dec 2020. Panel B shows the estimated values of theta, also when accounting for transaction costs, over the "portfolio formation" period Mar 2002 to Jul 2011.

B.3 PERFOMANCE

Appendix table B.3.1: Performance. In-sample.

	Panel A: Unrestricted				Panel B: Restricted			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Apr 2002 to Jan 2021								
Avg. ESG	42.64	70.20	42.45	73.41	41.19	46.40	44.28	49.27
$\|w_i\|$ x 100	0.57	0.68	0.71	0.84	0.20	0.20	0.23	0.23
$\max w_i$ x 100	11.40	12.28	10.01	10.71	3.16	3.14	2.93	2.90
$\min w_i$ x 100	-4.07	-4.78	-3.69	-4.47	0.00	0.00	0.00	0.00
Mean positive	0.66	0.76	0.83	0.94	0.23	0.24	0.27	0.28
Mean negative	-0.44	-0.57	-0.55	-0.71	-	-	-	-
$\sum w_i I(w_i < 0)$	-0.91	-1.20	-1.03	-1.34	-	-	-	-
$\sum I(w_i < 0)/N_t$	0.41	0.42	0.43	0.43	-	-	-	-
$\sum\|w_{i,t} - w_{i,t-1}\|$	273.05	323.06	299.69	353.94	60.57	62.01	67.40	67.20
$\bar{r}$	1.58	1.71	1.78	1.93	0.89	0.89	0.93	0.94
σ	6.48	6.61	6.90	7.04	5.31	5.27	5.43	5.40
df	3.86	3.52	3.72	3.58	2.87	2.77	2.71	2.59
SR	24.44	25.94	25.79	27.44	16.72	16.94	17.20	17.45
$\alpha^{Carhart}$	0.80**	0.97***	0.99***	1.19***	0.12	0.14	0.17	0.19*
α^{FF6}	0.86**	0.99***	1.05***	1.21***	0.17	0.17*	0.21*	0.23**
$\alpha^{Q\ Factor}$	0.55*	0.69**	0.72**	0.89**	0.09	0.10	0.13	0.15
$diff^{Carhart}$	0.17**		0.20**		0.02		0.02*	
$diff^{FF6}$	0.13*		0.15*		0.00		0.02	
$diff^{Q\ Factor}$	0.14**		0.16**		0.01		0.02	

Appendix table B.3.1, Panel A shows statistics for the two unrestricted policies without ESG and with ESG as specified in Eq. (D) and (E), using the “All stocks” and “ESG available” sample. The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Apr 2002 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics when applying short-sell restrictions as in Eq. (1.3) for the policies without ESG and with ESG as specified in Eq. (F) and (G). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.3.2: Performance. Out-of-sample.

	Panel A: Unrestricted				Panel B: Restricted			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Aug 2011 to Jan 2021								
Avg. ESG	49.55	76.39	52.07	81.37	50.46	54.43	52.66	58.13
$\|w_i\|$ x 100	0.49	0.58	0.52	0.63	0.20	0.20	0.21	0.21
$\max w_i$ x 100	13.82	14.27	13.77	14.21	2.32	2.03	3.35	3.06
$\min w_i$ x 100	-2.25	-2.82	-2.45	-3.12	0.00	0.00	0.00	0.00
Mean positive	0.58	0.65	0.62	0.72	0.21	0.21	0.22	0.23
Mean negative	-0.35	-0.47	-0.37	-0.52	-	-	-	-
$\sum w_i I(w_i < 0)$	-0.72	-0.95	-0.74	-1.03	-	-	-	-
$\sum I(w_i < 0)/N_t$	0.39	0.40	0.40	0.41	-	-	-	-
$\sum\|w_{i,t} - w_{i,t-1}\|$	246.70	284.90	256.67	307.02	49.72	47.33	55.93	57.72
$\bar{r}$	1.55	1.63	1.63	1.72	1.06	1.05	1.10	1.10
σ	5.38	5.37	5.69	5.65	4.42	4.42	4.62	4.60
df	3.88	3.39	3.67	3.47	2.57	2.52	2.64	2.56
SR	28.73	30.39	28.60	30.46	23.93	23.84	23.81	23.85
$\alpha^{Carhart}$	0.03	0.14	0.15	0.25	-0.21**	-0.19**	-0.16*	-0.15*
α^{FF6}	0.03	0.14	0.16	0.26	-0.20**	-0.19**	-0.15*	-0.14*
$\alpha^{Q\ Factor}$	0.39	0.46	0.45	0.53*	-0.09	-0.10	-0.08	-0.08
$diff^{Carhart}$	0.11		0.10		0.01		0.00	

diff^{FF6}	0.11	0.09	0.01	0.00
$\mathrm{diff}^{Q\ Factor}$	0.06	0.08	-0.00	-0.00

Appendix table B.3.2, Panel A shows statistics for the two unrestricted policies without ESG and with ESG as specified in Eq. (D) and (E), using the "all stocks" and "ESG available" sample. The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the out-of-sample period Aug 2011 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics when applying short-sell restrictions as in Eq. (1.3) for the policies without ESG and with ESG as specified in Eq. (F) and (G). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.3.3: Performance. 48 months moving-window.

	All Stocks		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG
Aug 2006 to Jan 2021				
Avg. ESG	47.88	122.64	47.20	117.36
$\lvert w_i \rvert$ x 100	0.63	1.89	0.91	2.08
$\max w_i$ x 100	9.99	19.88	11.03	20.09
$\min w_i$ x 100	-4.07	-9.06	-4.75	-9.19
Avg. Pos.	0.71	1.97	1.04	2.23
Avg. Neg.	-0.55	-1.82	-0.82	-1.98
$\sum w_i I(w_i < 0)$	-1.07	-4.23	-1.61	-4.42
$\sum I(w_i < 0)/N_t$	0.32	0.44	0.35	0.45
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	327.15	952.76	419.76	989.02
$\bar{r}$	0.06	-0.30	0.64	0.85
σ	7.59	9.84	9.22	10.76
df	2.38	2.94	2.02	2.40
SR	0.81	-3.07	6.97	7.93
$\alpha^{Carhart}$	-0.76	-0.91	0.11	0.62
α^{FF6}	-0.58	-0.67	0.29	0.90
$\alpha^{Q\ Factor}$	-0.90*	-0.82	-0.38	0.51
$\mathrm{diff}^{Carhart}$	-0.14		0.51	
diff^{FF6}	-0.10		0.61	
$\mathrm{diff}^{Q\ Factor}$	0.09		0.89**	

Appendix table B.3.3 shows statistics for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the "all stocks" and "ESG available" sample. The portfolio weights for each policy are modelled with the thetas estimated using moving window as displayed in appendix figure (xx). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the period Aug 2006 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.3.4: Performance. Multiple moving-windows.

	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	Without ESG
	12-month window				**24-month window**			
Feb 2004 to Jan 2021					*Feb 2005 to Jan 2021*			
Avg. ESG	62.43	-68.67	36.17	-116.97	51.57	84.69	40.76	83.91
$\lvert w_i \rvert$ x 100	2.69	9.22	3.29	11.08	1.38	3.30	1.95	4.04
$\max w_i$ x 100	28.11	62.38	23.83	61.34	24.17	35.54	16.96	25.21
$\min w_i$ x 100	-32.95	-67.19	-21.31	-57.49	-14.83	-22.62	-10.02	-17.36
Avg. Pos.	2.97	9.30	3.70	11.19	1.55	3.43	2.21	4.29
Avg. Neg.	-2.57	-9.24	-3.04	-11.13	-1.33	-3.24	-1.86	-3.83
$\sum w_i I(w_i < 0)$	-6.21	-22.58	-6.49	-24.36	-2.95	-7.77	-3.82	-8.86
$\sum I(w_i < 0)/N_t$	0.42	0.47	0.43	0.47	0.38	0.45	0.38	0.47
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	1386.69	5351.29	1426.43	5888.27	662.59	1691.61	827.32	1891.49

$\bar{r}$	4.50	7.29	3.91	7.70	0.71	0.26	1.65	1.28
σ	24.25	58.59	25.31	77.37	12.40	16.65	12.73	17.28
df	1.52	1.16	1.57	1.10	1.99	1.86	1.92	1.87
SR	18.56	12.44	15.46	9.95	5.76	1.59	12.94	7.42
$\alpha^{Carhart}$	4.16**	6.94	3.39**	7.90	-0.42	-0.96	1.00	0.68
α^{FF6}	4.30**	6.52	3.63**	7.45	-0.20	-0.40	1.11	1.09
$\alpha^{\mathrm{Q\ Factor}}$	3.30	8.47**	2.18	8.92	-0.86	-0.43	0.32	0.83
$\mathrm{diff}^{Carhart}$	2.77		4.51		-0.54		-0.32	
$\mathrm{diff}^{\mathrm{FF6}}$	2.22		3.82		-0.21		-0.02	
$\mathrm{diff}^{\mathrm{Q\ Factor}}$	5.46		6.74		0.43		0.52	
	36-month window				**48-month window**			
Feb 2006 to Jan 2021					*Feb 2007 to Jan 2021*			
Avg. ESG	49.51	130.00	45.77	118.43	48.36	130.63	49.44	126.36
$\lvert w_i \rvert$ x 100	0.81	2.43	1.21	2.82	0.57	1.89	0.76	1.99
$\max w_i$ x 100	15.50	27.48	12.85	21.86	7.24	17.72	10.75	20.33
$\min w_i$ x 100	-6.30	-12.51	-5.32	-11.05	-2.45	-7.74	-4.13	-8.83
Avg. Pos.	0.91	2.54	1.37	3.02	0.64	1.97	0.86	2.12
Avg. Neg.	-0.78	-2.42	-1.12	-2.70	-0.49	-1.83	-0.66	-1.90
$\sum w_i I(w_i < 0)$	-1.53	-5.59	-2.25	-6.13	-0.92	-4.24	-1.28	-4.25
$\sum I(w_i < 0)/N_t$	0.32	0.44	0.36	0.46	0.31	0.44	0.33	0.45
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	406.97	1246.35	552.16	1339.80	297.51	953.76	360.80	963.22
$\bar{r}$	-0.50	-0.52	0.27	0.24	0.26	-0.08	0.52	0.26
σ	9.02	13.00	10.36	13.28	7.58	9.92	9.02	7.58
df	2.53	2.36	1.98	2.09	2.24	2.74	2.06	2.24
SR	-5.54	-4.01	2.58	1.77	3.44	-0.81	5.79	3.44
$\alpha^{Carhart}$	-1.67***	-1.51	-0.41	-0.11	-0.56	-0.67	-0.08	-0.56
α^{FF6}	-1.34**	-1.08	-0.23	0.27	-0.40	-0.47	0.07	-0.40
$\alpha^{\mathrm{Q\ Factor}}$	-1.76***	-1.15	-0.86	-0.18	-0.75	-0.63	-0.64	-0.75
$\mathrm{diff}^{Carhart}$	0.16		0.30		-0.11		0.56	
$\mathrm{diff}^{\mathrm{FF6}}$	0.25		0.50		-0.07		0.65	
$\mathrm{diff}^{\mathrm{Q\ Factor}}$	0.61		0.68		0.12		0.96**	

Appendix table B.3.4 shows statistics for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the "all stocks" and "ESG available" sample. The portfolio weights for each policy are modelled with the thetas estimated using moving window with a window size equal to 12, 24, 36, and 48 months as displayed in appendix figure (xx). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across the periods Feb 2004 to Jan 2021, Feb 2005 to Jan 2021, Feb 2006 to Jan 2021, and Feb 2007 to Jan 2021. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.3.5: Performance. One to twelve months rebalancing.

	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Feb 2007 to Jan 2021								
Rebalancing = 1 months					***Rebalancing = 2 months***			
Avg. ESG	48.36	130.63	49.44	126.36	48.21	110.53	49.34	112.00
$\bar{r}$	0.26	-0.08	0.52	0.79	0.34	0.19	0.87	0.77
σ	7.58	9.92	9.02	10.66	7.50	9.43	9.30	10.52
Df	2.24	2.74	2.06	2.37	2.59	3.12	2.02	2.61
SR	3.44	-0.81	5.79	7.38	4.49	2.03	9.36	7.30
$\alpha^{Carhart}$	-0.56	-0.67	-0.08	0.48	-0.50	-0.20	0.37	0.50
α^{FF6}	-0.40	-0.47	0.07	0.73	-0.37	-0.03	0.52	0.75
$\alpha^{Q\ Factor}$	-0.75	-0.63	-0.64	0.32	-0.70	-0.23	-0.22	0.15
$\mathrm{diff}^{Carhart}$	-0.11		0.56		0.31		0.13	
$\mathrm{diff}^{\mathrm{FF6}}$	-0.07		0.65		0.34		0.23	
$\mathrm{diff}^{Q\ Factor}$	0.12		0.96**		0.47		0.37	
Rebalancing = 3 months					***Rebalancing = 4 months***			
Avg. ESG	48.79	114.91	49.00	119.77	47.28	94.08	48.10	98.64

$\bar{r}$	0.24	0.41	1.04	1.26	0.52	0.68	1.20	1.24
σ	8.16	10.35	9.47	11.50	7.39	9.25	9.11	9.91
df	1.99	2.34	1.93	2.28	2.84	3.16	3.32	2.78
SR	2.95	3.98	10.93	10.93	7.05	7.31	13.17	12.47
$\alpha^{Carhart}$	-0.74	-0.09	0.57	0.91	-0.31	0.13	0.74	0.90
α^{FF6}	-0.50	0.03	0.82	1.12	-0.09	0.37	1.00	1.24
$\alpha^{Q\ Factor}$	-0.82	0.04	0.04	0.71	-0.44	0.32	0.17	0.58
$\mathrm{diff}^{Carhart}$	0.66		0.34		0.44		0.16	
$\mathrm{diff}^{\mathrm{FF6}}$	0.53		0.30		0.46		0.24	
$\mathrm{diff}^{Q\ Factor}$	0.85		0.67		0.77*		0.41	
Rebalancing = 5 months					***Rebalancing = 6 months***			
Avg. ESG	49.35	86.09	48.64	96.03	49.04	98.46	48.05	105.32
$\bar{r}$	0.31	0.16	0.54	0.46	0.14	0.18	0.99	1.08
σ	7.25	8.80	8.09	9.05	8.71	11.04	10.11	11.50
df	3.11	3.51	2.26	2.72	1.82	2.43	1.48	2.22
SR	4.30	1.84	6.70	5.03	1.62	1.67	9.75	9.43
$\alpha^{Carhart}$	-0.51	-0.39	-0.06	0.10	-0.58	-0.13	0.69	0.92
α^{FF6}	-0.44	-0.29	-0.04	0.24	-0.51	0.08	0.83	1.22
$\alpha^{Q\ Factor}$	-0.54	-0.22	-0.29	0.08	-0.43	-0.06	0.30	0.71
$\mathrm{diff}^{Carhart}$	0.12		0.16		0.45		0.23	
$\mathrm{diff}^{\mathrm{FF6}}$	0.15		0.28		0.59		0.39	
$\mathrm{diff}^{Q\ Factor}$	0.31		0.37		0.37		0.42	
Rebalancing = 7 months					***Rebalancing = 8 months***			
Avg. ESG	49.33	89.20	48.15	90.11	49.43	70.95	46.88	77.91
$\bar{r}$	0.57	0.12	0.69	0.27	-0.10	-0.36	0.61	0.51
σ	9.02	10.14	10.90	11.23	7.81	9.64	8.58	9.20
df	2.13	3.26	1.86	2.50	2.20	2.24	2.01	2.65
SR	6.30	1.14	6.36	2.37	-1.29	-3.78	7.08	5.52
$\alpha^{Carhart}$	-0.18	-0.43	0.18	0.02	-0.84	-0.97	0.10	0.07
α^{FF6}	-0.03	-0.27	0.27	0.26	-0.79	-0.74	0.17	0.34
$\alpha^{Q\ Factor}$	-0.54	-0.57	-0.42	-0.39	-0.77	-0.66	-0.21	0.08
$\mathrm{diff}^{Carhart}$	-0.25		-0.16		-0.13		-0.04	
$\mathrm{diff}^{\mathrm{FF6}}$	-0.24		-0.01		0.05		0.17	
$\mathrm{diff}^{Q\ Factor}$	-0.03		0.03		0.11		0.30	
Rebalancing = 9 months					***Rebalancing = 10 months***			
Avg. ESG	46.92	61.90	45.85	65.65	49.96	77.02	47.56	90.49
$\bar{r}$	0.46	0.30	0.29	0.29	0.28	-0.06	0.04	-0.09
σ	7.25	8.06	8.48	9.13	7.66	9.15	9.92	10.95
df	2.38	4.51	2.48	4.19	2.03	2.54	1.56	2.08
SR	6.41	3.71	3.44	3.13	3.64	-0.68	0.41	-0.86
$\alpha^{Carhart}$	-0.50	-0.51	-0.48	-0.24	-0.49	-0.63	-0.63	-0.56
α^{FF6}	-0.29	-0.15	-0.27	0.14	-0.56	-0.65	-0.56	-0.49
$\alpha^{Q\ Factor}$	-0.56	-0.39	-0.65	-0.21	-0.48	-0.41	-0.72	-0.40
$\mathrm{diff}^{Carhart}$	-0.00		0.24		-0.14		0.07	
$\mathrm{diff}^{\mathrm{FF6}}$	0.14		0.41		-0.09		0.16	
$\mathrm{diff}^{Q\ Factor}$	0.17		0.44		0.07		0.32	
Rebalancing = 11 months					***Rebalancing = 12 months***			
Avg. ESG	51.51	93.95	48.73	85.77	49.52	66.70	46.78	81.92
$\bar{r}$	0.40	0.34	0.26	0.35	1.03	0.47	1.93	1.53
σ	6.83	9.48	6.73	9.40	7.39	12.90	9.41	10.84
df	2.52	2.10	2.79	2.05	2.65	1.71	1.94	2.83
SR	5.87	3.58	3.93	3.73	13.94	3.63	20.49	14.12
$\alpha^{Carhart}$	-0.72	-0.55	-0.79*	-0.53	0.15	-0.01	1.35*	1.01
α^{FF6}	-0.69	-0.29	-0.81*	-0.30	0.44	0.58	1.80**	1.61*
$\alpha^{Q\ Factor}$	-0.47	0.16	-0.58	0.17	0.05	-0.27	0.74	0.74
$\mathrm{diff}^{Carhart}$	0.17		0.25		-0.17		-0.34	
$\mathrm{diff}^{\mathrm{FF6}}$	0.39		0.51		0.14		-0.19	
$\mathrm{diff}^{Q\ Factor}$	0.64		0.75		-0.33		-0.00	

Appendix table B.3.5 shows statistics for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the “all stocks” and “ESG available” sample. The portfolio weights for each policy are modelled using moving window with a window size equal to 48-months and rebalanced using rebalancing frequencies ranging from one to twelve months over the period Feb 2007 to Jan 2021. The first row shows the average portfolio ESG score. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.3.6: Performance. GAS.

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Apr 2002 to Jan 2021					*Aug 2011 to Jan 2021*			
Avg. ESG	42.87	128.64	41.96	133.86	49.33	124.30	51.89	125.90
$\lvert w_i \rvert$ x 100	0.63	1.23	0.83	1.54	0.62	1.07	0.62	1.23
max w_i x 100	13.12	13.96	12.03	13.58	16.01	16.60	16.73	19.97
min w_i x 100	-4.78	-6.60	-4.50	-6.90	-2.84	-4.70	-3.03	-5.72
Avg. Pos	0.74	1.32	0.99	1.64	0.72	1.13	0.74	1.31
Avg. Neg	-0.50	-1.12	-0.66	-1.43	-0.48	-0.99	-0.47	-1.13
$\sum w_i I(w_i < 0)$	-1.09	-2.58	-1.31	-2.89	-1.05	-2.19	-1.00	-2.46
$\sum I(w_i < 0)/N_t$	0.43	0.46	0.45	0.46	0.42	0.44	0.43	0.45
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	309.65	582.79	354.91	645.20	324.81	532.40	315.74	601.34
$\bar{r}$	1.68	2.01	1.99	2.40	1.54	1.64	1.77	2.05
σ	6.65	6.94	7.27	7.67	5.71	5.58	6.08	6.53
df	4.26	3.95	4.43	4.64	3.82	4.07	3.86	3.85
SR	25.20	28.96	27.33	31.33	27.04	29.36	29.15	31.39
$\alpha^{Carhart}$	0.92***	1.39***	1.24***	1.81***	-0.00	0.24	0.28	0.68*
α^{FF6}	0.98***	1.30***	1.30***	1.69***	-0.02	0.21	0.29	0.67*
$\alpha^{Q\ Factor}$	0.63*	1.08***	0.93**	1.45***	0.51	0.69*	0.63	0.99**
$diff^{Carhart}$	0.47**		0.57**		0.24		0.39*	
$diff^{FF6}$	0.31		0.39*		0.23		0.38*	
$diff^{Q\ Factor}$	0.45*		0.53**		0.18		0.36*	

Appendix table B.3.6, Panel A shows statistics for the two policy portfolios without ESG and with ESG as specified in Eq. (H) and (I), using the “all stocks” and “ESG available” sample for the in-sample period Apr 2002 to Jan 2021. Each policy is modelled with the dynamic values of theta estimated using GAS as in Eq. (2.1) and as displayed in appendix figure (xx) and (xx). The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across time. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics for the out-of-sample period Aug 2011 to Jan 2021. Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.3.7: Performance. Risk aversion.

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Apr 2002 to Jan 2021					*Aug 2011 to Jan 2021*			
$\boldsymbol{\gamma = 2}$								
Avg. ESG	44.23	90.46	37.97	88.74	47.73	83.79	50.62	92.01
$\lvert w_i \rvert$ x 100	1.33	1.54	1.75	1.99	1.04	1.16	1.22	1.35
max w_i x 100	30.11	31.75	26.82	28.25	35.55	36.02	36.18	36.80
min w_i x 100	-10.80	-12.13	-9.80	-11.25	-5.52	-6.28	-6.55	-7.28
Avg. Pos.	1.56	1.73	2.06	2.25	1.26	1.34	1.47	1.56
Avg. Neg.	-1.11	-1.35	-1.46	-1.76	-0.84	-0.98	-0.99	-1.15
$\sum w_i I(w_i < 0)$	-2.82	-3.36	-3.28	-3.84	-2.13	-2.40	-2.45	-2.76
$\sum I(w_i < 0)/N_t$	0.50	0.49	0.51	0.50	0.49	0.48	0.50	0.49
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	644.15	742.11	738.34	843.58	541.54	589.97	623.19	677.39
$\bar{r}$	3.32	3.60	3.91	4.24	2.41	2.55	2.70	2.86
σ	12.79	13.28	14.03	14.57	8.62	8.54	9.77	9.64
df	3.07	3.13	3.55	3.71	3.77	3.79	3.61	4.02

SR	25.97	27.10	27.88	29.10	27.90	29.87	27.59	29.69
$\alpha^{Carhart}$	2.64***	2.94***	3.23***	3.59***	0.66	0.81	0.94	1.12
α^{FF6}	2.82***	3.04***	3.44***	3.70***	0.64	0.79	0.96	1.14*
$\alpha^{Q\ Factor}$	1.89**	2.16***	2.43***	2.75***	1.21*	1.31**	1.48*	1.60**
$\mathrm{diff}^{Carhart}$	0.30**		0.36**		0.15		0.18	
diff^{FF6}	0.22		0.27*		0.15		0.18	
$\mathrm{diff}^{Q\ Factor}$	0.27**		0.32**		0.10		0.11	
$\boldsymbol{\gamma = 10}$								
Avg. ESG	42.04	64.67	43.95	69.76	50.16	75.19	52.52	81.78
$\lvert w_i \rvert$ x 100	0.34	0.44	0.40	0.54	0.32	0.43	0.34	0.47
max w_i x 100	5.25	6.10	4.55	5.25	6.60	7.37	6.15	7.03
min w_i x 100	-1.85	-2.49	-1.68	-2.38	-1.18	-1.78	-1.23	-1.95
Avg. Pos.	0.39	0.50	0.46	0.59	0.37	0.48	0.39	0.53
Avg. Neg.	-0.23	-0.34	-0.26	-0.42	-0.21	-0.33	-0.21	-0.38
$\sum w_i I(w_i < 0)$	-0.36	-0.61	-0.37	-0.66	-0.31	-0.58	-0.31	-0.64
$\sum I(w_i < 0)/N_t$	0.30	0.35	0.31	0.36	0.29	0.34	0.29	0.35
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	155.09	200.45	159.77	212.07	153.27	199.87	154.37	213.18
$\bar{r}$	1.00	1.11	1.07	1.12	1.26	1.34	1.28	1.37
σ	4.96	4.96	5.12	5.12	4.57	4.59	4.66	4.70
df	4.55	4.15	4.06	3.70	3.48	3.02	3.43	2.97
SR	20.25	22.30	20.85	23.18	27.60	29.22	27.38	29.20
$\alpha^{Carhart}$	0.18	0.33*	0.24	0.41**	-0.18	-0.07	-0.16	-0.03
α^{FF6}	0.21	0.33*	0.26	0.40**	-0.17	-0.07	-0.15	-0.02
$\alpha^{Q\ Factor}$	0.10	0.21	0.16	0.28	0.12	0.19	0.12	0.20
$\mathrm{diff}^{Carhart}$	015**		0.18***		0.11		0.13	
diff^{FF6}	0.12**		0.14**		0.10		0.13*	
$\mathrm{diff}^{Q\ Factor}$	0.11**		0.13**		0.07		0.08	

Appendix table B.3.7, Panel A shows statistics for the two policy portfolios without ESG and with ESG as specified in Eq. (D) and (E), using the "all stocks" and "ESG available" sample for the in-sample period Apr 2002 to Jan 2021. Each policy is modelled with a risk-aversion equal to two above and ten below. The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across time. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics for the out-of-sample period Aug 2011 to Jan 2021. Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix table B.3.8: Performance. Transaction costs.

	Panel A: In-sample				Panel B: Out-of-sample			
	All Stocks		**ESG Available**		**All Stocks**		**ESG Available**	
Policy	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG	Without ESG	With ESG
Apr 2002 to Jan 2021					*Aug 2011 to Jan 2021*			
$\boldsymbol{c = 50\ bp}$								
Avg. ESG	41.44	41.46	45.21	45.25	50.83	50.88	53.02	53.43
$\lvert w_i \rvert$ x 100	0.20	0.20	0.23	0.23	0.20	0.20	0.21	0.21
max w_i x 100	0.21	0.21	0.24	0.24	0.22	0.23	0.28	0.50
min w_i x 100	0.20	0.19	0.22	0.22	0.20	0.19	0.19	0.14
Avg. Pos.	0.20	0.20	0.23	0.23	0.20	0.20	0.21	0.21
Avg. Neg.	-	-	-	-	-	-	-	-
$\sum w_i I(w_i < 0)$	-	-	-	-	-	-	-	-
$\sum I(w_i < 0)/N_t$	-	-	-	-	-	-	-	-
$\sum \lvert w_{i,t} - w_{i,t-1} \rvert$	0.80	0.85	1.32	1.36	0.89	1.14	2.09	6.20
$\bar{r}$	0.66	0.66	0.65	0.65	0.96	0.96	0.94	0.93
σ	5.06	5.06	5.07	5.07	4.52	4.52	4.54	4.54
df	3.10	3.10	3.10	3.09	2.50	2.50	2.53	2.52
SR	12.95	12.95	12.88	12.88	21.30	21.29	20.73	20.52
$\alpha^{Carhart}$	-0.09	-0.09	-0.10*	-0.10*	-0.22***	-0.22***	-0.25***	-0.26***
α^{FF6}	-0.09	-0.09	-0.10*	-0.10*	-0.21***	-0.21***	-0.24***	-0.26***
$\alpha^{Q\ Factor}$	-0.08	-0.08	-0.09	-0.09	-0.20**	-0.20**	-0.23***	-0.24***
$\mathrm{diff}^{Carhart}$	-0.00***		-0.00		-0.00***		-0.01***	

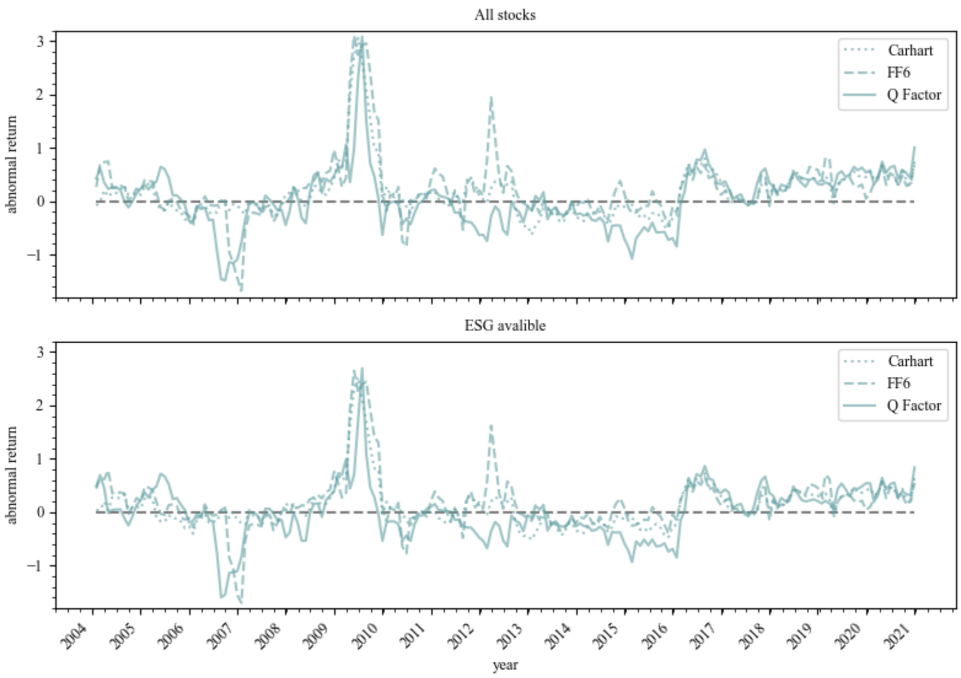
diff^{FF6}	-0.00***	-0.00	-0.00***	-0.01***
$\text{diff}^{Q\ Factor}$	-0.00***	-0.00	-0.00*	-0.00*

Appendix table B.3.8, Panel A shows statistics for the two policies without ESG and with ESG as specified in Eq. (D) and (E), using the "all stocks" and "ESG available" sample for the in-sample period Apr 2002 to Jan 2021. Each policy is modelled by accounting for transactions costs equal to 50 basis points. The first set of rows show the average portfolio ESG score, and statistics of the portfolio weights averaged across time. These statistics include the average absolute portfolio weight, the average maximum and minimum portfolio weights, the average positive and negative portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio, and the turnover. The second set of rows show the average portfolio return statistics, net transaction costs: average excess return, volatility, degrees of freedom of returns, Sharpe ratio of returns and the abnormal returns estimated with the three asset pricing models as specified in Eq. (5.1), (5.2), and (5.3). The final set of rows show the abnormal return of the difference portfolio, defined as the policy with ESG minus the policy without ESG, estimated using the asset pricing models as specified in Eq. (5.4), (5.5), and (5.6). Panel B shows the same corresponding statistics for the out-of-sample period Aug 2011 to Jan 2021. Note: ***p<0.01, **p<0.05, *p<0.1.

Appendix C

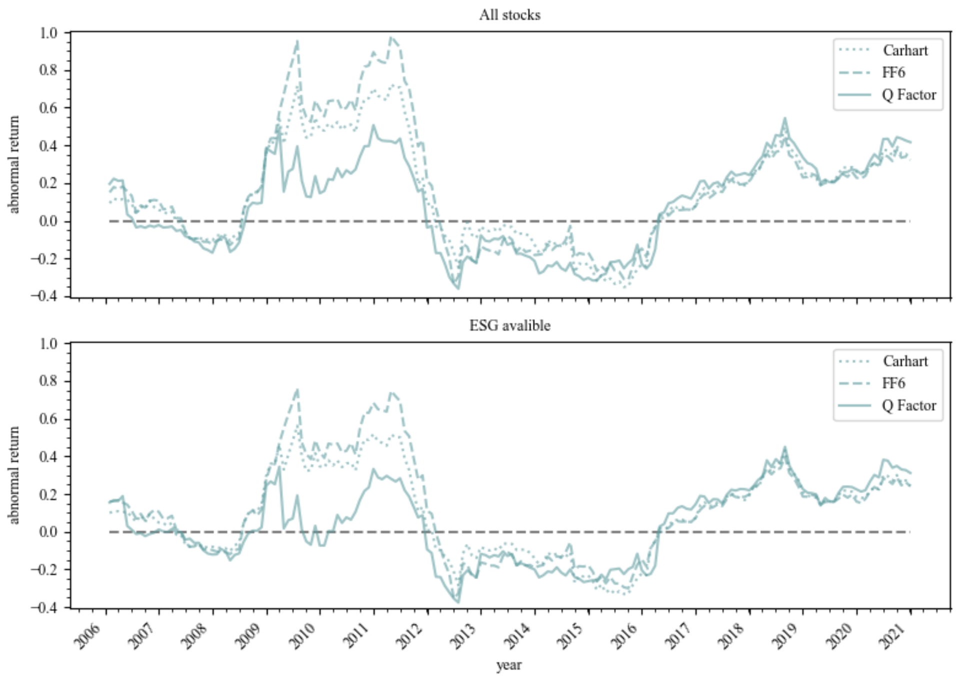
C.1 FIGURES

Appendix figure C.1.1: Abnormal returns of difference portfolio (12 months window)



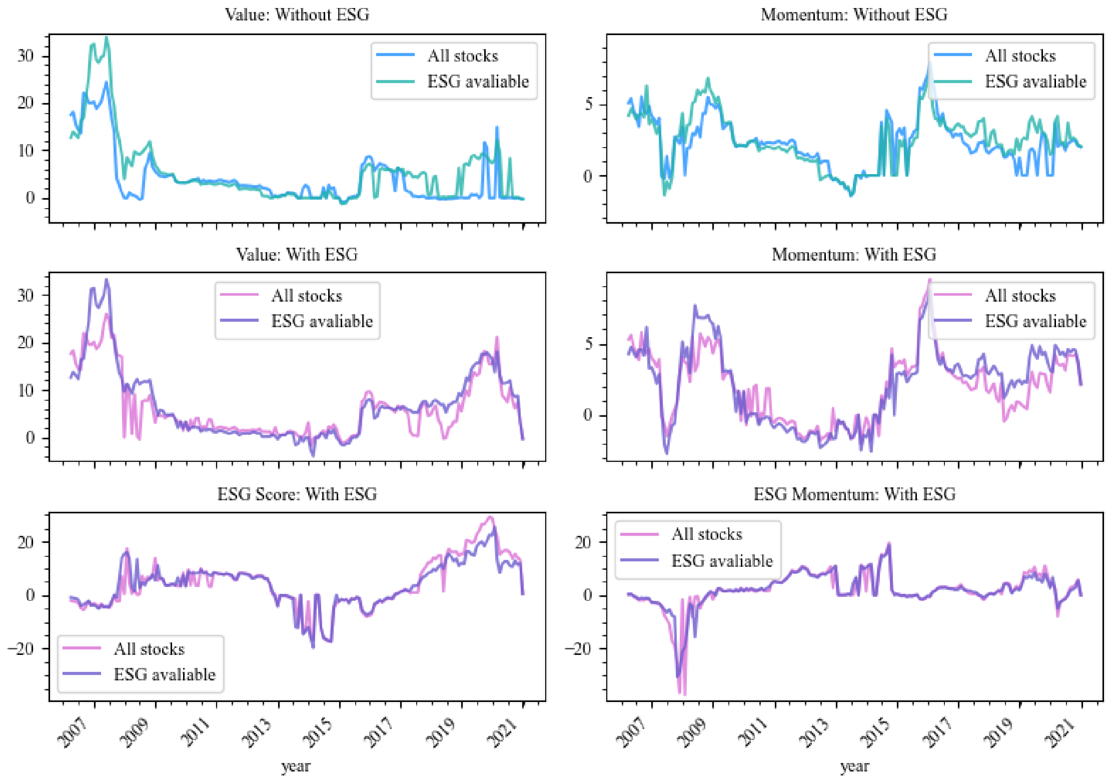
Appendix figure C.1.1 displays the abnormal returns of the difference portfolio, defined as the policy with ESG minus the policy without ESG, for the "all stocks" sample above and for the "ESG available" sample below. The abnormal returns are estimated using a moving window with a window size equal to 12 months over the period Feb 2003 to Jan 2021. The dotted line represents the abnormal returns estimated with Carhart (1997) four-factor model in Eq. (5.4), the dashed line represents the abnormal returns estimated with Fama and French (2016) six-factor model in Eq. (5.5), and the solid line represents the abnormal returns estimated with the q-factor model with expected growth of Hou et al. (2021) in Eq. (5.6).

Appendix figure C.1.2: Abnormal returns of difference portfolio (36 months window)



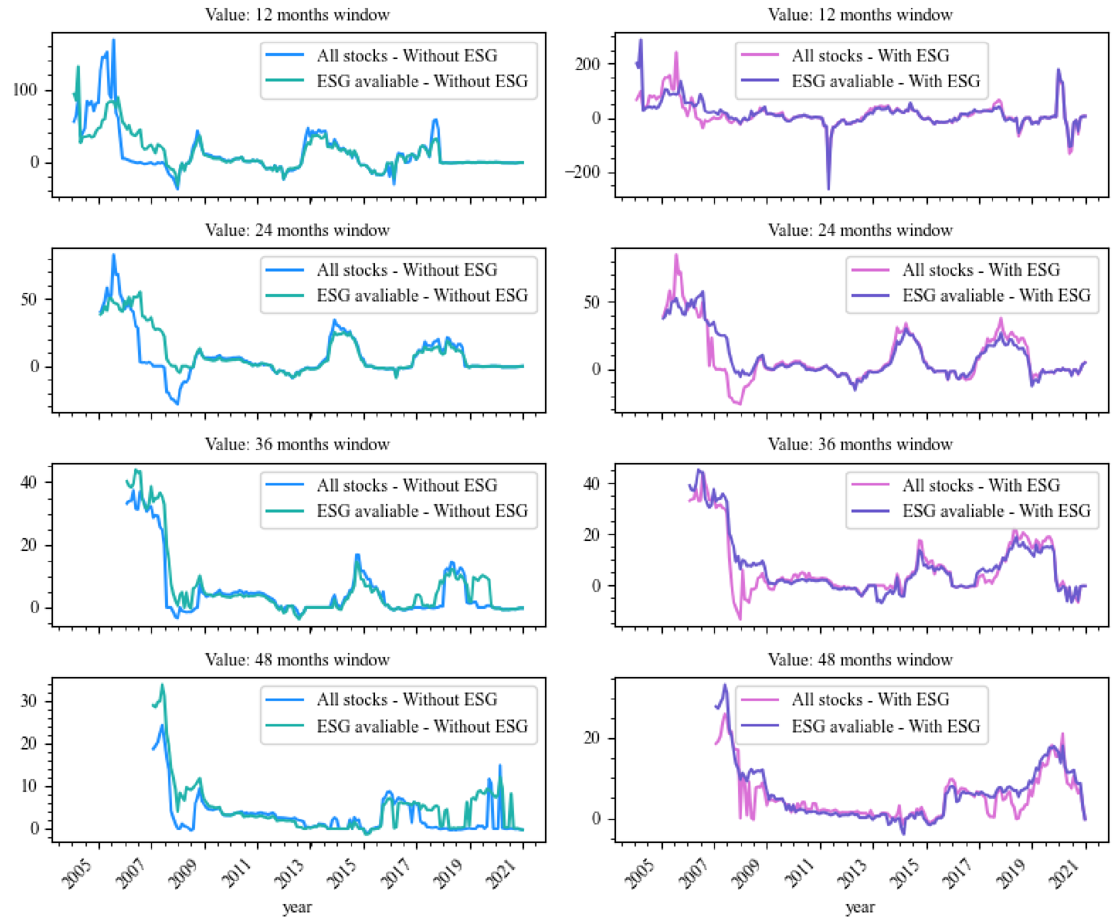
Appendix figure C.1.2 displays the abnormal returns of the difference portfolio, defined as the policy with ESG minus the policy without ESG, for the "all stocks" sample above and for the "ESG available" sample below. The abnormal returns are estimated using a moving window with a window size equal to 36 months over the period Feb 2003 to Jan 2021. The dotted line represents the abnormal returns estimated with Carhart (1997) four-factor model in Eq. (5.4), the dashed line represents the abnormal returns estimated with Fama and French (2016) six-factor model in Eq. (5.5), and the solid line represents the abnormal returns estimated with the q-factor model with expected growth of Hou et al. (2021) in Eq. (5.6).

Appendix figure C.1.3: Estimated values of theta (48 months window)



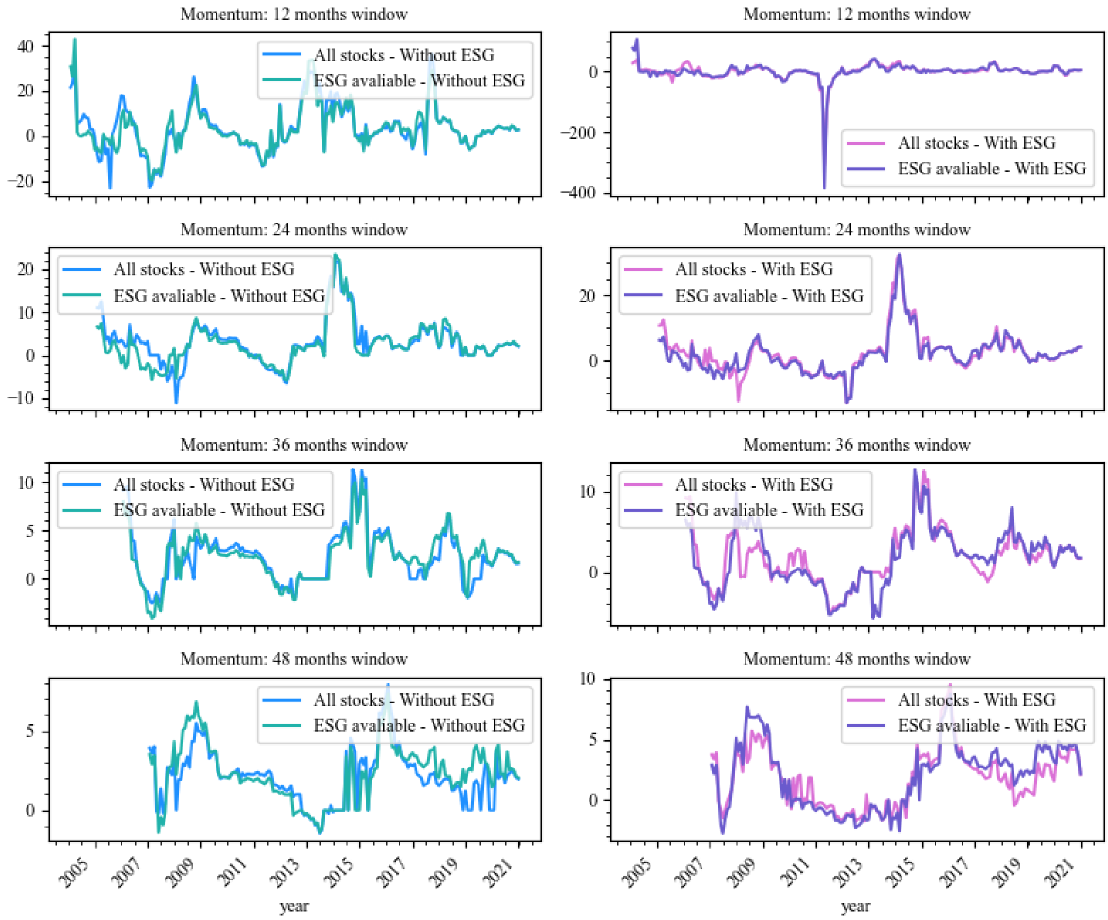
Appendix figure C.1.3 displays the estimated values of theta for each month using a moving window of with a window size equal to 48 months over the period Jul 2006 to Dec 2020. The first row shows the estimated values of theta for the policy without ESG for the asset characteristics value on the right and momentum on the left. The second row shows the estimated values of theta for the policy with ESG for value on the right and momentum on the left. The final row shows the estimated values of theta for the policy with ESG for ESG score on the right and ESG momentum on the left. For each month, the estimated values of theta are derived by optimizing the mean variance investor utility function in Eq. (1.2) with a risk aversion equal to five over the moving "portfolio formation" period presented under *Method 4.3.* The blue line represents the policy without ESG using the "all stocks" sample, the turquoise line represents the policy without ESG using the "ESG available" sample, the pink line represents the policy with ESG using the "all stocks" sample, and the purple line represents the policy with ESG using the "ESG available" sample.

Appendix figure C.1.4: Multiple moving windows

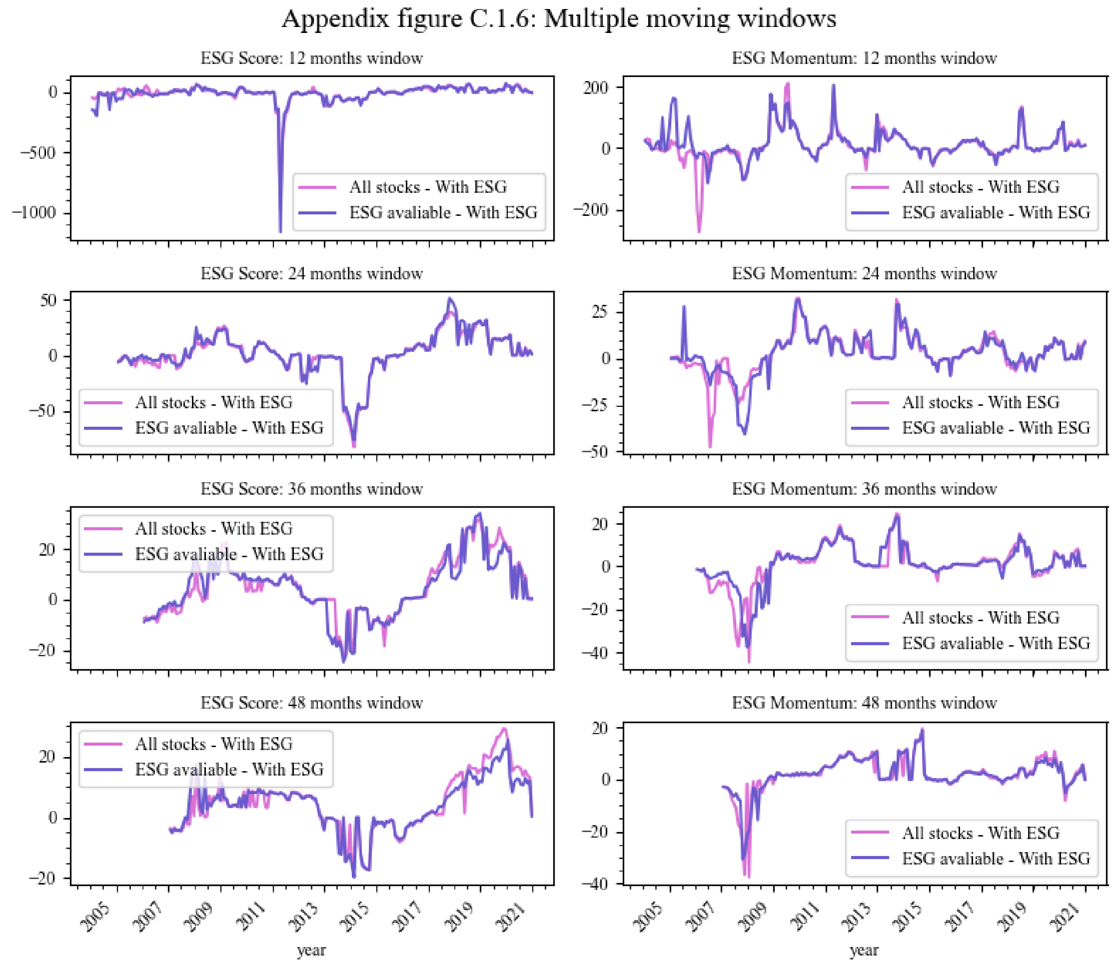


Appendix figure C.1.4 displays the monthly estimated values of theta for the value characteristic using a moving window of with a window size equal to 12, 24, 36 and 48 months. For each month, the estimated values of theta are derived by optimizing the mean variance investor utility function in Eq. (1.2) with a risk aversion equal to five over the moving "portfolio formation" period presented under *Method 4.3.* The blue line represents the policy without ESG using the "all stocks" sample, the turquoise line represents the policy without ESG using the "ESG available" sample, the pink line represents the policy with ESG using the "all stocks" sample, and the purple line represents the policy with ESG using the "ESG available" sample.

Appendix figure C.1.5: Multiple moving windows

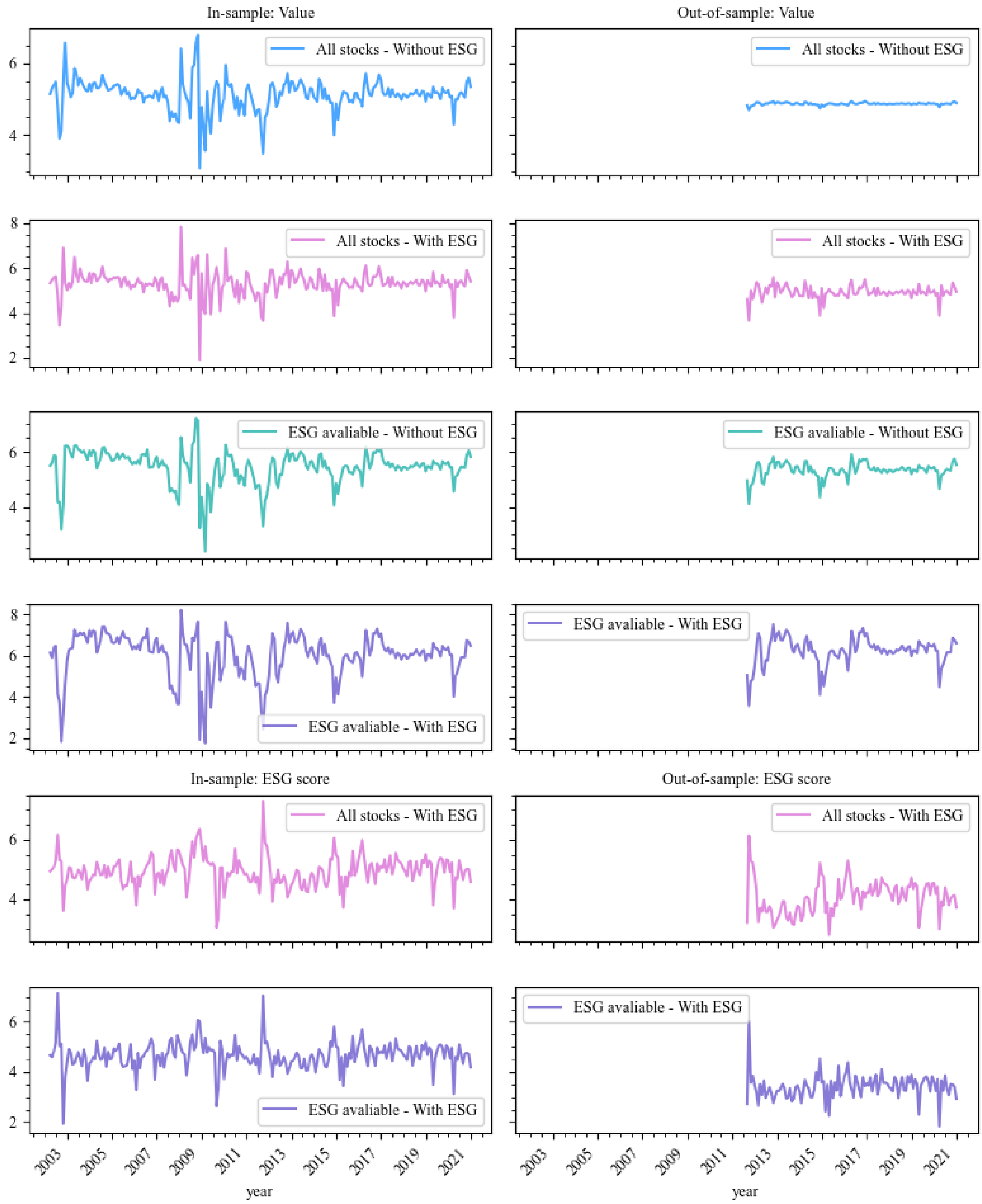


Appendix figure C.1.5 displays the monthly estimated values of theta for the momentum characteristic using a moving window of with a window size equal to 12, 24, 36 and 48 months. For each month, the estimated values of theta are derived by optimizing the mean variance investor utility function in Eq. (1.2) with a risk aversion equal to five over the moving "portfolio formation" period presented under *Method 4.3.* The blue line represents the policy without ESG using the "all stocks" sample, the turquoise line represents the policy without ESG using the "ESG available" sample, the pink line represents the policy with ESG using the "all stocks" sample, and the purple line represents the policy with ESG using the "ESG available" sample.



Appendix figure C.1.6 displays the monthly estimated values of theta for the ESG score characteristic on the left and ESG momentum on the right using a moving window of with a window size equal to 12, 24, 36 and 48 months. For each month, the estimated values of theta are derived by optimizing the mean variance investor utility function in Eq. (1.2) with a risk aversion equal to five over the moving "portfolio formation" period presented under *Method 4.3.* The pink line represents the policy with ESG using the "all stocks" sample, and the purple line represents the policy with ESG using the "ESG available" sample.

Appendix figure C.1.7: Dynamic values of theta



Appendix figure C.1.7 displays the dynamic values of theta for the two policies with ESG and without ESG as specified in Eq. (H) and (I). The first four rows display the dynamic values of theta for value and the two las rows display the dynamic value for ESG score. The dynamic values of theta are modelled with GAS as in Eq. (2.1) for the in-sample period Mar 2002 to Dec 2020 on the left and the out-of-sample period Jul 2011 to Dec 2002 on the right. The blue line represents the policy without ESG using the "all stocks" sample, the turquoise line represents the policy without ESG using the "ESG available" sample, the pink line represents the policy with ESG using the "all stocks" sample, and the purple line represents the policy with ESG using the "ESG available" sample.

Appendix figure C.1.8: Dynamic values of theta

Appendix figure C.1.8 displays the dynamic values of theta for the two policies with ESG and without ESG as specified in Eq. (H) and (I). The first four rows display the dynamic values of theta for momentum and the two las rows display the dynamic value for ESG momentum. The dynamic valued of theta are modelled with GAS as in Eq. (2.1) for the in-sample period Mar 2002 to Dec 2020 on the left and the out-of-sample period Jul 2011 to Dec 2002 on the right. The blue line represents the policy without ESG using the "all stocks" sample, the turquoise line represents the policy without ESG using the "ESG available" sample, the pink line represents the policy with ESG using the "all stocks" sample, and the purple line represents the policy with ESG using the "ESG available" sample.