ESG scores and price Momentum are more than compatible

Matúš Padyšák

Abstract

While price momentum is a stable part of financial markets, ESG scores are emerging more and more. However, there is an ongoing debate on the social responsibility of firms and the relationship with the performance. Literature offers mixed results whether the ESG enhances the performance of a stock, does not influence performance at all or even hampers the performance. In this paper, the pure price momentum is combined with ESG scores using a knapsack algorithm. Knapsack algorithm is a well-known mathematical problem of optimization, and in the case of momentum and ESG, can be used to make the momentum portfolios significantly more responsible, with lower volatility and better risk-adjusted return. The second option is to make the ESG portfolio substantially more profitable by using Knapsack algorithm to construct high ESG portfolio with large momentum. The approach resulted in a strategy with high ESG score and compared to pure momentum or momentum-ESG strategy, with significantly reduced volatility. Therefore, the ESG-momentum strategy has the best risk-adjusted return, the lowest drawdown, the lowest volatility and the most consistent returns.

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1. Introduction

Momentum in stocks is not only a key strategy in the many portfolios of practitioners, but it is also an attractive research topic for academics. The original idea behind momentum, is that past winner tend to perform well in the near future, and vice versa, past loser tend to underperform (Jegadeesh and Titman, 2001). Later, the momentum anomaly was found practically everywhere, Moskowitz, Ooi, and Pedersen (2012) identified momentum in an equity index, currency, commodity, and bond futures. Hartley (2020) identified momentum anomaly in global yield curves. Moreover, the momentum factor is also presented in the equity factors, as concluded by Arnott, Clements, Kalesnik and Linnainmaa (2019).

While momentum anomaly is a staple in the financial literature, the theory behind socially responsible investing, and mainly ESG scores is emerging. E score stands for environmental, S for social and G for governance qualities of firms. Aim of the score is to measure quality or responsibility of the firm in each of the categories mentioned above. Vojtko and Padysak (2019) reviewed literature related to the ESG and concluded that ESG scores could be successfully used in practice, utilized in negative screening, level, or momentum strategies. It is no surprise that researchers looked for momentum in ESG scores. Nagy, Kassam and Lee (2016) found momentum also in the ESG scores, concluding that stocks that have improved their ESG scores the most tend to outperform the worst improvers.

The aim of this paper is to study the momentum anomaly and ESG scores in a slightly less traditional way. While it may sound shocking, the relationship between price equity momentum and ESG scores can be compared to a robber in a jewellery store with a knapsack of limited capacity. The ESG scores and momentum anomaly can be related to the famous optimization knapsack problem. One of the most straightforward explanations of the knapsack problem is a robber that has limited capacity in the backpack, and naturally, wants to return from the store with a maximal loot. Therefore, the weight of the loot is limited, and robber wants to maximize his profit by choosing the most valuable combination of items that would fit into his knapsack.

The knapsack problem applied to the equity momentum and ESG scores can form two different scenarios. Firstly, it is possible to make classical momentum more „sustainable" or ESG friendly. In this case, the aim is to pick stocks with the highest momentum, but at the same time, maximize the ESG score of the portfolio. In other words, the momentum represents the weight, the higher the momentum, lower the weight. The limited capacity of the knapsack ensures that only stocks with high momentum (low weight) would be included in a portfolio. The ESG score of each stock represents the value. Therefore, picking stocks with the lowest „weight" and maximizing the „value" creates a more ESG friendly momentum strategy. Secondly, the situation can be reversed, and ESG can represent the „weight" of the stock – higher the ESG, lower the weight. In this case, momentum represents the „value" of the stock. In practice, such an approach chooses portfolio with as highest ESG as possible while maximizing the momentum of the stocks.

The first approach can be used to make the portfolio more attractive in terms of the ESG scores. The average ESG score of stocks in a portfolio can be significantly improved, with only a slight reduction in the performance. The second approach leads to a portfolio that can be without a doubt called as socially responsible according to the ESG scores. Additionally, this approach largely improves the returns of ESG strategies compared to, for example, the ESG level or momentum strategies as shown by Dorfleitner, Utz, and Wimmer (2013) and Nagy, Kassam and Lee (2016). Moreover, compared to the traditional momentum in stocks, both the volatility and maximal drawdowns are substantially improved, leading to a better risk-adjusted return compared to the momentum alone. Paper is divided as follows: section 2 is related to the data, section 3 presents the Knapsack problem, section 4 presents results of portfolio sorts, section 5 sheds light on possible explanations of the performance and risk metrics and finally, section 6 concludes the paper.

2. Data

The OWL Analytics kindly provided unfiltered ESG data. Each month, the data consisted from 5000 stocks at the beginning up to almost 30 000 companies at the end. For each company, data includes ISIN, shareClassFIGI, region, and over 200 detailed parameters for the E, S, and G score and the total ESG score. In this paper, a scaled total ESG score, that is between zero and one, is in the scope of interest. Stocks were filtered to be from the US region. Later, through their ISIN, were paired with their ticker and price for each month. Small firms and firms without the ticker or price were omitted. The dataset contains 691 stocks and spans from 31.3.2010 to 31.10.2019. Factor portfolios were obtained from Kenneth R. French`s data library.

3. The Knapsack problem

Consider two paired vectors of features of objects. The weight of objects is denoted as $\boldsymbol{w} = \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix}$, and the value (or prices) of objects as $\boldsymbol{p} = \begin{pmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{pmatrix}$, where n denotes the number of objects. Then the knapsack problem consists of finding the combination of objects $S = \{1,2,3, \dots, n\}$ that maximize the value, given the condition of the maximal weight W.

The problem can be denoted as follows:

$$max \sum_{i \in S} p_i \text{ s.t. } \sum_{i \in S} w_i \leq W. \tag{1}$$

The complexity of the knapsack problem raises with the rising number of objects. For the lower number of objects, the direct search might be comfortably fast. However, for the task of portfolio construction, direct search method is impossible. For example, there are 120 $(5!)$ possibilities if we have five objects. If we have ten objects, there are 3,628,800 $(10!)$ possibilities. Clearly, searching directly between $(500!)$ (or even more, if objects are stocks) is impossible.

Complex problems can be usually solved by using methods of stochastic optimization that are deeply connected with probability. For the knapsack problem, for example, the simple greedy algorithms such as hill climbing can be used. However, a large number of objects favours more complex algorithms such as Simulated annealing, Differential evolution or Particle swarm optimization.

In this paper, we utilize a modified approach of Simulated annealing that does not rely only on the annealing and the convergence to the optima but remembers the best solution. Therefore, it is possible to utilize the ability of annealing to jump from local optimum, and yet similar to other algorithms, remember the best solution so far.

If we have a possible solution X, Y is a new candidate solution and R is a uniformly distributed random variable on the interval $(0,1)$, then we accept Y as a new solution on the i-th step if: $R < \exp\left\{\frac{X-Y}{\frac{tau}{t \times i}}\right\}$, where tau can be characterized as an initial temperature and $t \times i$ ensures that temperature is decreasing with each step. Decreasing temperature causes the probability of accepting a new solution is falling with the rising number of iterations. Therefore, we are less prone to accept candidate solutions that are not better than our solution. Additionally, we remember the best solution so far; therefore, we do not rely only on the convergence of annealing to the optimum. We consider the best solution of all iterations as our solution and not the solution given by the last step of the algorithm. For the more complex theory behind the Simulated annealing see the Bélisle (1992).

The implementation of the Knapsack problem used for a portfolio construction was made in R.

4. Portfolio sorts

In this section, various portfolio sorts are considered. Firstly, portfolios that pick stocks with the highest momentum while maximizing ESG score of the portfolios. Secondly, a reversed situation, portfolios that picks stocks with the highest ESG score while maximizing momentum of the stocks. These sorts are made by transforming the stock-picking to the Knapsack problem. In the first case, the weight is represented by the momentum (higher the momentum, lower the weight). Therefore the maximal weight ensures that the portfolio would be formed of stocks with high momentum. Given the maximal „weight“, we want to maximize total value, which is represented by the ESG scores. Approach, as mentioned earlier results in a MOM-ESG portfolio.

In the second case, weight and value are reversed, and the aim is to construct a portfolio with the highest ESG scores and maximizing the momentum at the same time. Such an approach leads to an ESG-MOM portfolio. Because of the Knapsack formulation as in (1), in this application, ESG scores are reversed, to ensure that weight cap is correct for picking high ESG stocks. Both strategies have the weight set in a way that the resulting portfolio would on average represent either top momentum quintile or top ESG quintile. The algorithm may and probably would not choose the exact number of stocks that represent 10% of the investment universe. Aim of the algorithm is to find the best combination, that can be formed of a lower number of stocks. Since the task is to examine whether momentum portfolios can be more socially responsible, portfolios are long-only. Additionally, since the Knapsack algorithm and the Simulated annealing brings randomness into portfolio creation, I consider ten portfolio sorts for both MOM-ESG and ESG-MOM and present an average portfolio. Given the higher computational time and low dispersion among portfolios, I assume that ten different portfolios are sufficient.

For comparison, I consider traditional cross-sectional equally-weighted momentum portfolios (MOM) formed of stocks of equal quintiles used to construct knapsack portfolios. To directly compare the performance to the ESG portfolios, the momentum is a long-only.

Table 1 Portfolio sorts: annualized returns and volatilities. Risk-adjusted return is return divided by the volatility. N is the average number of stocks in the portfolio. Best values are in bold.

Panel A: Top 10% of stocks						
	Return	**Volatility**	**Maximal drawdown**	**Risk adjusted return**	**ESG**	**N**
MOM	**21.25%**	21.78%	-25%	0.97	0.39	68
MOM-ESG	19.71%	18.48%	-25%	1.07	0.52	45
ESG-MOM	17,47%	**13.49%**	**-18%**	**1.29**	**0.90**	52
Panel B: Top 15% of stocks						
	Return	**Volatility**	**Maximal drawdown**	**Risk adjusted return**	**ESG**	**N**
MOM	18.02%	19.6%	-25%	0.92	0.41	103
MOM-ESG	**18.64%**	16.5%	-23%	1.13	0.76	65
ESG-MOM	17.44%	**13.47%**	**-17%**	**1.29**	**0.85**	74

Figure 1 Comparision of portfolios consisting of “Top 10%” stocks

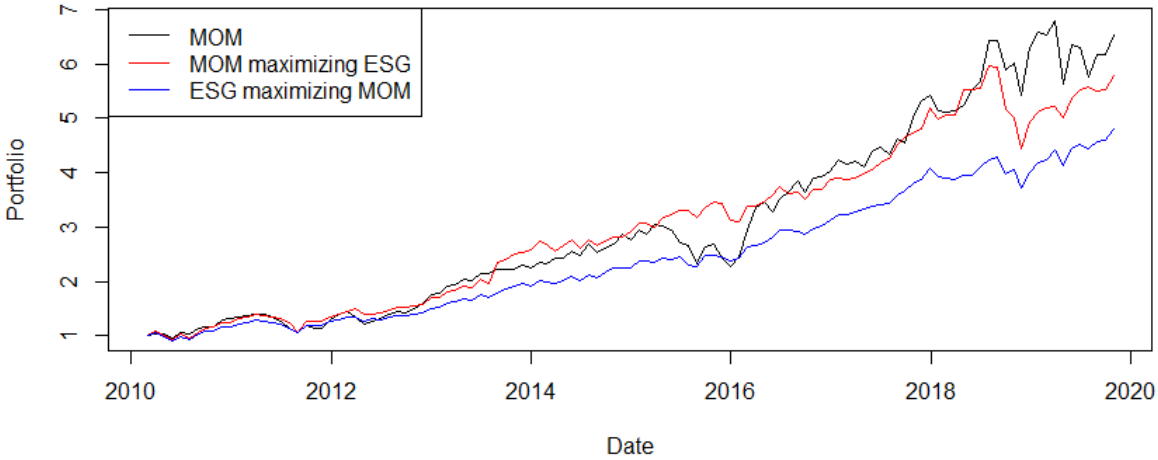
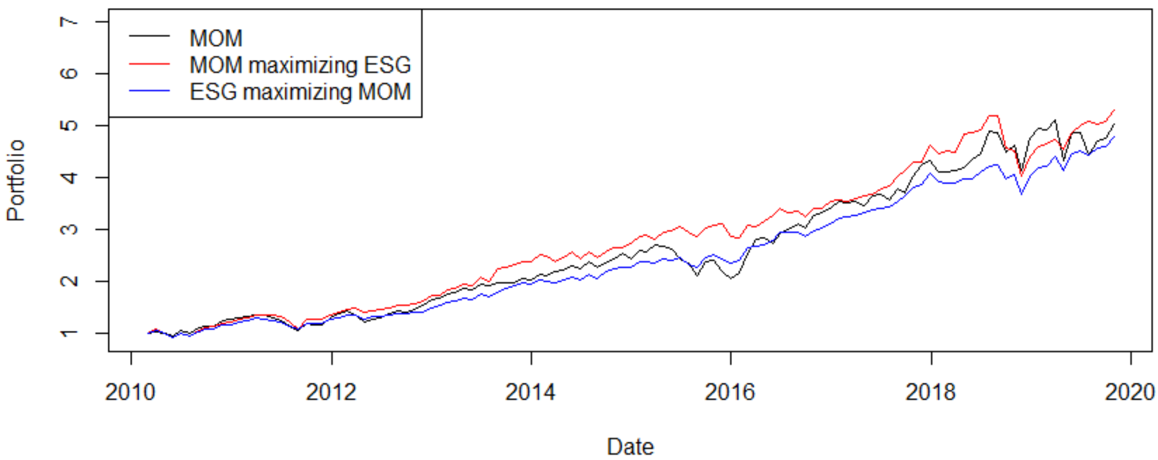


Figure 2 Comparision of portfolios consisting of “Top 15%” stocks



Drawdown charts are presented in Appendix A.

Furthermore, coefficients of asset pricing models: CAPM, Fama and French three-factor model and Fama and French five-factor model are presented in the following tables. Overall, strategies have both economically, and statistically, significant alphas and common market factors cannot explain the performance. Strategies are unrelated to common equity risk factors.

Table 2 CAPM model (Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '...' 0.1)

Panel A: Top 10% of stocks		
	$\boldsymbol{\alpha}$	$\boldsymbol{\beta_{Mkt-Rf}}$
MOM	2.11^{***}	-0.19
MOM-ESG	1.81^{***}	-0.14
ESG-MOM	1.62^{***}	$-0.18^{...}$
Panel B: Top 15% of stocks		
	$\boldsymbol{\alpha}$	$\boldsymbol{\beta_{Mkt-Rf}}$
MOM	1.86^{***}	-0.28^{*}
MOM-ESG	1.7^{***}	-0.13
ESG-MOM	1.62^{***}	$-0.18^{...}$

Table 3 Fama and French three factor model (Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '...' 0.1)

Panel A: Top 10% of stocks				
	$\boldsymbol{\alpha}$	$\boldsymbol{\beta_{Mkt-Rf}}$	$\boldsymbol{\beta_{SMB}}$	$\boldsymbol{\beta_{HML}}$
MOM	2.12^{***}	-0.19	0.02	-0.004
MOM-ESG	1.79^{***}	-0.13	-0.02	-0.04
ESG-MOM	1.58^{***}	-0.15	-0.08	-0.06
Panel B: Top 15% of stocks				
	$\boldsymbol{\alpha}$	$\boldsymbol{\beta_{Mkt-Rf}}$	$\boldsymbol{\beta_{SMB}}$	$\boldsymbol{\beta_{HML}}$
MOM	1.80^{***}	-0.24	-0.14	-0.03
MOM-ESG	1.69^{***}	-0.13	-0.02	-0.01
ESG-MOM	1.58^{***}	-0.16	-0.06	-0.06

Table 4 Fama and French five factor model (Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '...' 0.1)

Panel A: Top 10% of stocks						
	α	β_{Mkt-Rf}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}
MOM	2.24***	-0.22	-0.10	0.002	-0.53	-0.03
MOM-ESG	1.90***	-0.17	-0.13	-0.01	-0.45	-0.08
ESG-MOM	1.56***	-0.14	-0.13	-0.19	-0.18	0.36
Panel B: Top 15% of stocks						
	α	β_{Mkt-Rf}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}
MOM	1.64**	-0.19	-0.14	-0.40	0.05	0.96*
MOM-ESG	1.78***	-0.15	-0.13	-0.04	-0.47	0.06
ESG-MOM	1.56***	-0.15	-0.11	-0.21	-0.20	0.40

5. Risk, Volatility and Drawdowns and ESG

Across the financial literature, there is a consent that high ESG stocks bear a lower „risk". According to Ashwin Kumar et al. (2016), the integration of Environmental, Social and Fair Governance practices makes a company less vulnerable to reputation, political and regulatory risk and thus leading to lower volatility of cash flows and profitability. Authors have also found that across every industry, the annualized volatility is lower for the high ESG stocks. Socially responsible behaviour makes firms less vulnerable to expensive government-imposed fines (Freedman and Stagliano, 1991). In many cases, this effect can be directly observed and utilized, as shown by Taehyun and Yongjun (2020). Corporate Environmental Responsibility actions significantly affect firm value and proxied by reduction of toxic chemical emissions can be directly used for a portfolio sorting, where firms that have reduced the emissions the most outperform those that have reduced the emissions least. Additionally, as shown by

Godfrey (2005), socially responsible behaviour aids firms to minimize exposure to risk. Results of Dorfleitner, Utz, and Wimmer (2013) show that a high corporate social performance today can save money and yield high (unexpected by the market) cash flows in future periods. Therefore, lower volatility and drawdowns of ESG-MOM and MOM-ESG portfolios are largely in line with a majority of literature. As a result, the MOM-ESG and mainly, the ESG-MOM portfolios should be accompanied by lower volatility and drawdowns. This can be directly observed by looking at Figures 1 and 2. A similar effect was found by Varma and Nofsinger (2012), responsible mutual funds outperform other mutual funds during bear markets. However, according to paper, the dampening of downside risk has its price. Responsible funds tend to underperform during non-crisis periods. Paper argues that the outperformance in crisis periods is driven by the focus on shareholder advocacy and environmental, social, and governance issues. However, the combined knapsack portfolios naturally do not have such problems with underperformance. After all, there are two criteria, one momentum-based and one representing social responsibility.

For data in this study, linear models can be used to examine the relationship between ESG scores and volatility and maximal drawdown. Natural expectation would be that higher the ESG, lower the volatility. For the maximal drawdowns, higher ESG should lead to more „positive“ drawdowns.

The models can be formed as:

$$volatility_{t,i} = \beta_{0,vol} + \beta_{ESG,vol} \times ESG_{t,i} + \varepsilon_{t,i}, \tag{2}$$

$$drawdown_{t,i} = \beta_{0,dd} + \beta_{dd,ESG} \times ESG_{t,i} + \varepsilon_{t,i}, \tag{3}$$

Where $ESG_{t,i}$ is the average ESG score of the stock i for two years, $volatility_{t,i}$ is two-year volatility and $drawdown_{t,i}$ is a maximal drawdown of each stock i during two years. $\varepsilon_{t,i}$ are random errors. Therefore, for both measures of risk, we obtain rolling regressions. Since the residuals are not normally distributed, parameters are found by a more robust method – Theil´s regression (for the slope coefficient, Theil´s regression uses a median of all slopes, instead of traditional OLS approach, for which can be shown that it is a weighted average of all slopes). Moreover, the OLS regression is not that robust and is vulnerable to outliers.

Table 5 Regression for volatility and drawdowns

Panel A: Volatility		
Year	$\beta_{0,vol}$	$\beta_{ESG,vol}$
2010-2012	10.28***	-3.12***
2012-2014	8.46***	-1.73***
2014-2016	6.33***	-0.50***
2016-2018	7.48***	-1.14***
2018-2020	8.03***	-1.52***
Panel B: Drawdown		
Year	$\beta_{0,dd}$	$\beta_{ESG,dd}$
2010-2012	-14.22***	4.42***
2012-2014	-15.74***	3.84***
2014-2016	-11.71***	1.87***
2016-2018	-12.81***	2.77***
2018-2020	-15.36***	2.08***

In conclusion, results are in line with the previous literature, and high ESG stocks bear a lower risk, either represented by the drawdowns or volatility.

Additionally, in recent times, the focus of the researchers was aimed at momentum crashes or periods where the momentum performed with large drawdowns and periods of persistent negative returns. The literature recognizes momentum crashes, and there are a few possible solutions. According to Fan et al. (2020), stocks with high returns are often highly volatile over the formation period, and as a result, the probability of stock to be included in the portfolio is related to it´s realized volatility. High volatility assets result in momentum portfolios with high volatility or in other words, portfolios with momentum-specific risks. Aforementioned would mean that momentum risks are a result of signal construction and ranking process. A possible solution is to scale returns by some moment of the standard deviations, to obtain risk-adjusted momentum signal. As a result, the strategy would prefer lower volatility stocks, that are more favourable to be utilized in a momentum strategy. Inclusion of ESG into MOM portfolios is indirectly doing the same, as mentioned before, ESG lowers volatility, which enhances the MOM strategy. Moreover, such addition leads to an attractive and modern, socially responsible portfolios.

6. Conclusion

No doubt, ESG is becoming a part of the financial world. While many pure ESG strategies may seem to bring low profits, the profits can be significantly enhanced when ESG is only a part of the portfolio. As shown in this paper, momentum can be an ideal combination to be used with ESG scoring system. Momentum strategies that are both popular and profitable are vulnerable to momentum crashes. ESG stocks tend to be less volatile, a characteristic that is vital in momentum portfolios.

As a result, considering the combination of ESG/MOM as a knapsack problem, can significantly improve ESG score of the MOM portfolio, and make the investment more socially responsible without sacrificing returns. Moreover, volatility is reduced. Therefore, such combination can be an interesting modification of pure momentum strategy, to make it more modern, attractive, responsible and less volatile.

In a reversed situation, where the objective is to improve the MOM of ESG portfolio, the algorithm chooses high ESG stocks that are less volatile and at the same time, have a large momentum. On a risk-adjusted basis, ESG-MOM portfolios outperform both MOM and MOM-ESG portfolios. The strategy based on the knapsack algorithm leads to more consistent returns, lower volatility and drawdowns. Overall, the results are in line with literature about ESG and the connection of momentum and volatility. Results are also supported by rolling regressions that estimate the relationship between ESG scores and volatility or maximal drawdown.

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Zoltán Nagy, Altaf Kassam, Linda-Eling Lee: Can ESG Add Alpha? *An Analysis of ESG Tilt and Momentum Strategies*. The Journal of Investing May 2016, 25 (2) 113-124; DOI: 10.3905/joi.2016.25.2.113

Appendix A

Figure 1A Drawdown chart of MOM 10%

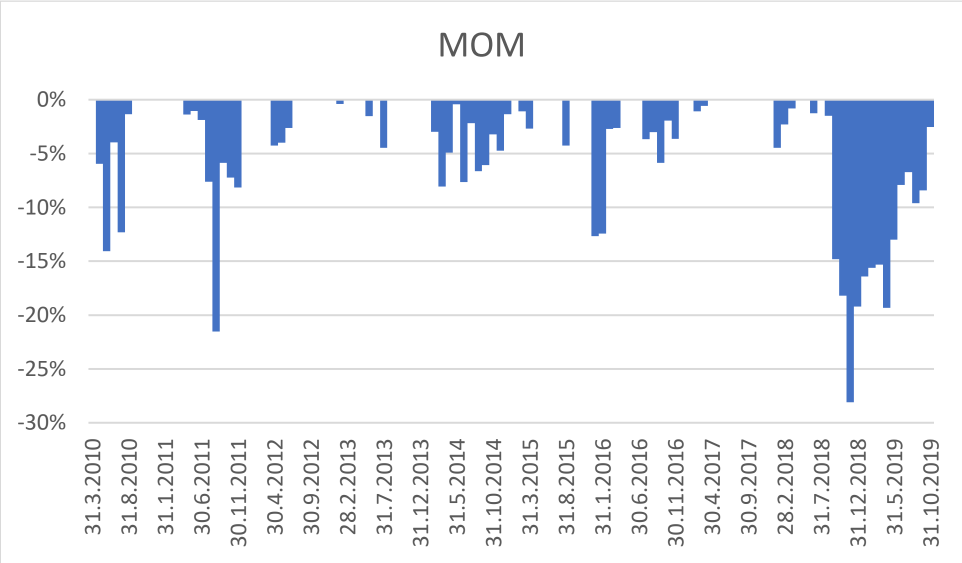

Figure 2A Drawdown chart of MOM-ESG 10%

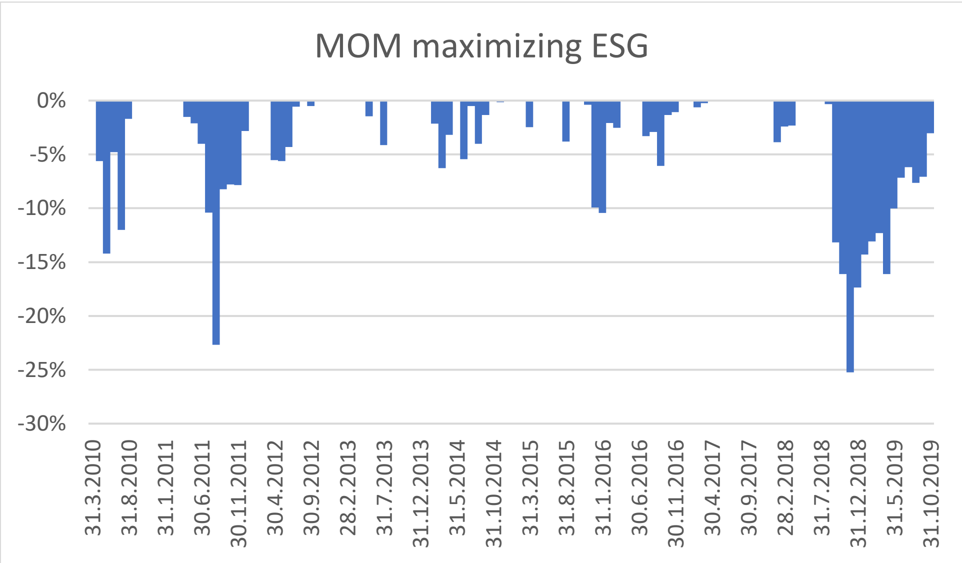

Figure 3A Drawdown chart of ESG-MOM 10%

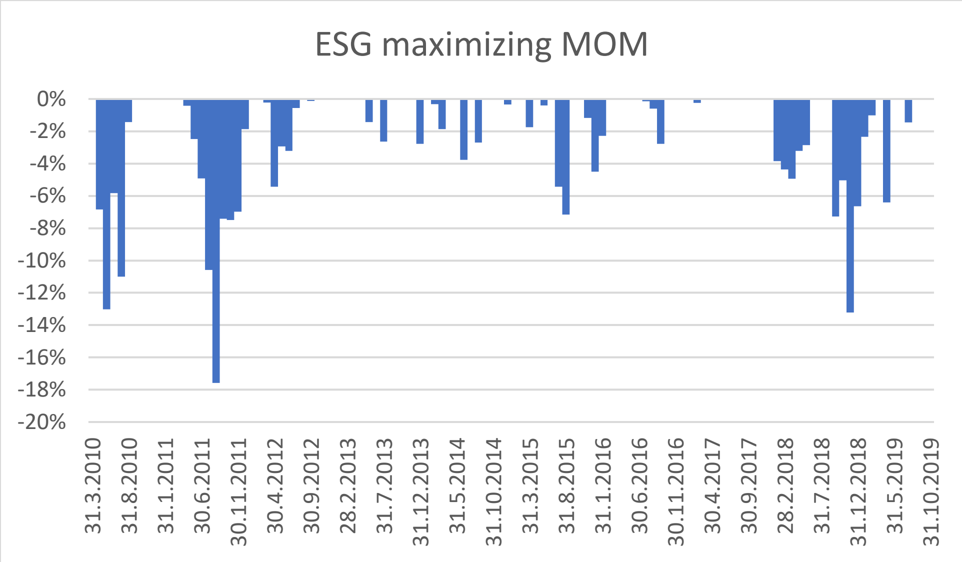

Figure 4A Drawdown chart of MOM 15%

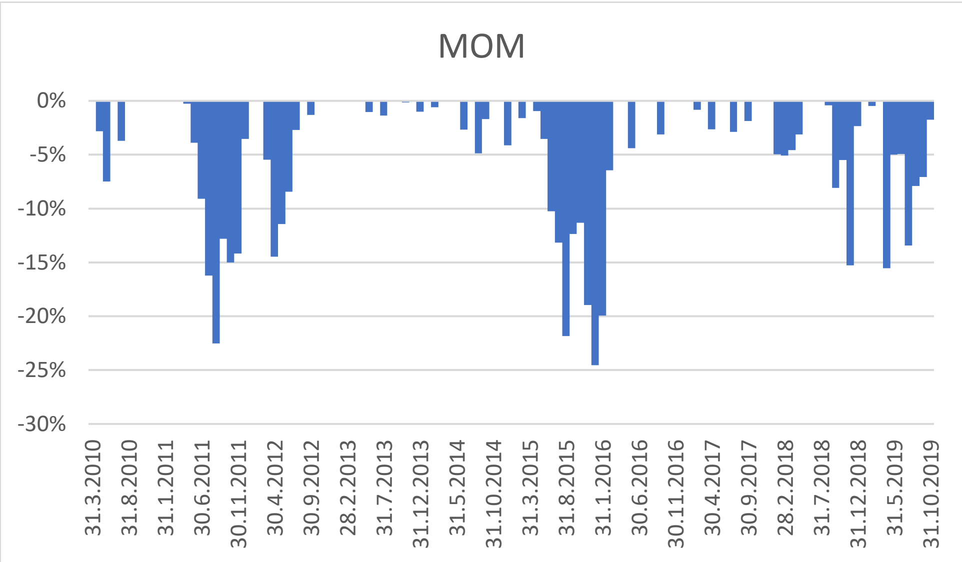

Figure 5A Drawdown chart of MOM-ESG 15%

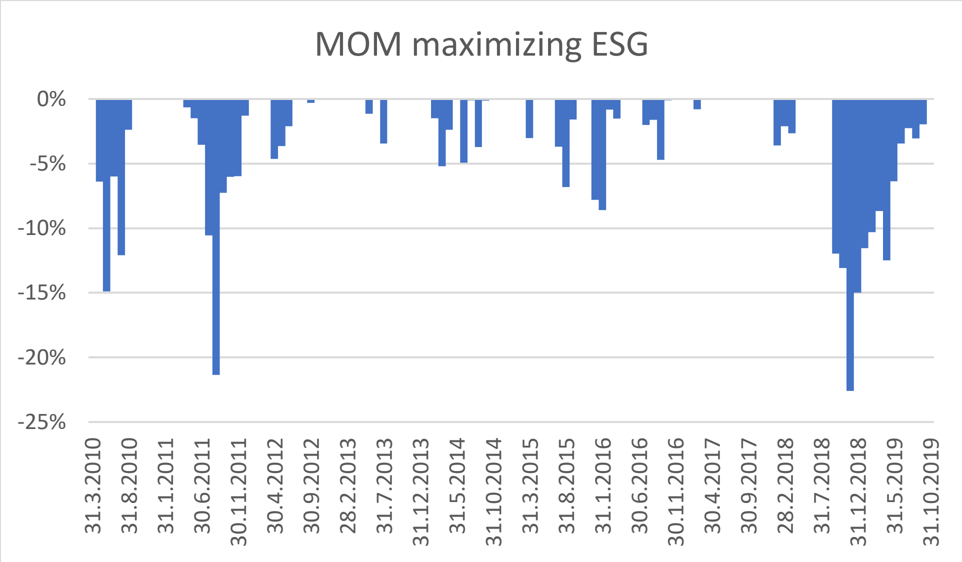

Figure 6A Drawdown chart of ESG-MOM 15%