The Shades of Investment Factors

Maxime Sauzet* Jiayi Zhu*

August 7, 2025

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Do investors inadvertently tilt towards certain non-financial characteristics when they follow well-known investment strategies? Using both standard asset pricing factors and a wide range of anomalies, we document that, while factors related to low leverage, low risk, profitability and quality tilt towards green firms, those related to value, size, accruals, seasonality, and short-term reversals invest disproportionately in brown stocks. The underlying firms also vary in their social, and governance scores. However, there is ample variation even within a given investment style so that an investor can reduce their exposure to firms with poor non-financial scores by picking the right characteristics to implement their chosen strategies. In addition, we build trimmed factors by gradually excluding firms with the worst scores from the investment universe, and show that investors can improve the non-financial performance of the majority of them substantially at little to no financial cost. A more engaged investor can also build factors within a subset of highly rated stocks, but at the risk of deviating more in terms of performance. Our findings have implications for the rapid development of smart-beta and other indexing strategies in the context of sustainable finance.

Keywords: Sustainable Finance, ESG, Index Investing, Smart-beta, Investment Factors, Asset Pricing Anomalies. ***JEL codes:*** G11, G12, G23.

*Boston University, Questrom School of Business. Emails: msauzet@bu.edu, jyszhu@bu.edu. We thank participants at various conferences and seminars for helpful discussions that led or contributed to this paper. We are grateful for financial support from the Boston University Impact Measurement and Allocation Program, and Institute for Global Sustainability. All errors are our own. First version: October 17, 2024.

1 Introduction

Since the seminal work of Sharpe (1964) and Fama and French (1993), investment factors have become central to both academic finance research and investment practice. An extensive literature has identified a range of systematic risk factors—including size, value, momentum, and profitability—that aim to explain cross-sectional differences in asset returns (Carhart, 1997, Fama and French, 1996, 2015). In recent decades, this agenda has accelerated significantly, culminating in an explosion ("zoo") of documented asset pricing anomalies, which have both deepened our understanding of return determinants and prompted efforts to evaluate the collective robustness of these findings (Hou et al., 2015, Harvey et al., 2016, Jensen et al., 2023). In parallel, and as a result, the investment industry has attracted substantial (and growing) amounts of capital in passive, index, smart-beta, and other quantitative strategies designed to capture these very factor premia and anomalies.[1]

More recently, sustainable finance has emerged as a rapidly growing area in that context, with a surge of interest in investment strategies that incorporate non-financial characteristics, such as environmental, social, and governance (ESG) considerations. Here again, this development has taken place both in academic research —with a growing body of theoretical and empirical work— and across the industry. Estimates of ESG-related assets under management vary depending on classification and scope, and may sometimes be overstated (Pástor et al., 2025), but many suggest that they have reached several trillions of dollars globally.[2] While growth has slowed and may even reverse in certain jurisdictions due to political pressures or shifting priorities, sustainable investing continues to drive academic research, as well as regulatory agendas and financial innovation. Moreover, some of its tools and approaches may extend beyond ESG-specific contexts.

Bringing these two lines of research together, however, little is known about the non-financial characteristics of popular investment factors and anomalies. This is what we tackle in this paper by asking two broad questions. First, do index and other passive investors

[1]For example, Figure A.1 in the Appendix, based on Morningstar data, shows that assets under management (AUM) for passive strategies (including ETFs and index funds) have exceeded $15 trillion globally. By some measures, passive management may soon surpass active management in scale. Additionally, Figure A.2 highlights that smart-beta ETFs alone have already surpassed $2 trillion in total net assets (TNA).

[2]For instance, from Morgan Stanley Institute for Sustainable Investing, "Sustainable Reality", total AUM in sustainable funds reached $3.56 trillion as of December 31, 2024.

inadvertently tilt toward certain non-financial characteristics when allocating capital based on investment factors? In other words, what are the "shades" of these factors—green, brown, pro-social, or otherwise? Second, if such tilts exist, what is the financial cost of limiting their impacts while still investing according to their preferred factors?

On the first question, we start by focusing on the main seminal asset pricing factors of Fama and French (1993, 1996) and Carhart (1997) —namely, market (MKT_t), value (HML_t), size (SMB_t), profitability (RMW_t), investment (CMA_t), momentum (MOM_t)—, and compute their "shades" based on market-adjusted environmental, social, and governance scores from MSCI,[3] as well as carbon emissions and intensities from S&P Trucost. We document that the size, value, and investment factors tend to tilt towards "brown" firms, while operating profitability and momentum invest disproportionally in "green" firms. This is true based on both MSCI score and carbon intensity.[4] When it comes to the social score instead, except for SMB_t that tends to load strongly on firms with poor performance on that front, the findings are broadly flipped: namely, HML_t and CMA_t invest disproportionally in firms with good social scores, while RMW_t and MOM_t tend to tilt towards firms with poor ones.[5] Lastly, the result on the governance side are a bit more of a mix with the size, profitability, and momentum factors loading more on well-governed firms, while value and investment tilt more towards firms with poorer governance.

We then generalize our analysis to a wide variety of anomalies that have been discussed in the literature, following Jensen et al. (2023). We group the anomalies by investment theme clusters like the authors, and find once again that these clusters tilt significantly towards certain non-financial "shades". For instance, when it comes to environmental performance, accruals, size, seasonality, and to some extent value-style characteristics load more strongly on brown stocks, while profitability, low leverage, low risk, debt issuance, quality, and to

[3]We follow the construction in Pástor et al. (2022) to ensure that the scores are not industry-adjusted, and generalize it to social and governance scores.

[4]The finding for the value and momentum factor can explain why a "green-minus-brown" (GMB_t) portfolio has tended to load negatively on HML_t and positively on MOM_t in the recent decade, as documented in Pástor et al. (2022). The "greenness" of the momentum factor is also consistent with the sizable realized outperformance of green stocks over the same period, due to short-run —potentially transitory— developments such as large demand flows towards green investments on the part of institutional investors.

[5]These flipped results between the E and S dimensions are consistent with the findings in Sauzet and Zhu (2025) who document that a "good-minus-bad" factor based on social scores ($SGMB_t$) has tended to strongly *under*perform in the recent decade, in sharp contract to the *out*performance of a $EGMB_t$ based on environmental scores.

some extent momentum, tend to tilt towards green stocks on average. Their shades also vary when it comes to other aspects, with, e.g., profitability and low risk investing disproportionally in firms with high social scores while size and low leverage anomalies do the opposite, and quality, profitability, accruals, and others, investing more in well-governed firms while value, size, and debt issuance, load more on firms with lower governance scores.

Taken together, these results highlight that well-known investment factors and anomalies do tend to tilt substantially towards certain non-financial characteristics, a finding that is novel to the literature. Investors that have preferences towards some of these characteristics should therefore be mindful when following popular investment strategies, or risk involuntarily financing the very dimensions that they seek to avoid. We emphasize that this is not innocuous given the trillions of dollars in asset under management that are allocated based on index, smart-beta, or other passive strategies.[6]

Given these investment factor shades, and turning to our second question: what is an investor with non-financial preferences to do if they wish to limit their exposure to some of these dimensions while continuing to invest based on their preferred factors? From that perspective, we discuss several approaches, and find that it does not have to be bad news across the board.

First, there is considerable score heterogeneity within investment theme clusters. As a result, an investor with non-financial preferences can maintain their allocation to a desired theme while reducing exposure to certain non-financial characteristics by carefully selecting specific factors or anomalies within that theme. This approach can be highly effective. For instance, within the low leverage or value clusters, environmental performance can range from clearly brown to strongly green depending on the specific anomaly, and this holds for most other investing themes and non-financial metrics.

Second, and this is our main analysis, we propose a trimming approach in which the worst firms along the environmental, social, or governance dimension are progressively excluded before building factors based on the restricted universe (which we dub "E(SG)-trimmed" or "E(SG)-constrained" factors). Although there are interesting nuances across factors and

[6]On a different note, documenting the shades of these seminal investment factors and anomalies is also valuable in that it may help us understand the reasons behind their out/underperformance, especially because these shades are varying over time, as we discuss. These also matter because these factors are used as benchmarks for a large number of investment managers.

dimensions, the main message is that investors can substantially reduce their exposure to the shades that they want to avoid at little to no financial cost, even with high exclusion thresholds.[7] This holds whether performance is measured using realized returns or forward-looking metrics that capture expected returns, such as the implied cost of capital (ICC) or option-based estimates. While some factors may still load relatively more on certain "unappealing" shades, the underlying investment universe becomes progressively better aligned with investors' preferences.[8] As such, this method can serve as a useful compromise for those who wish to remain close to traditional factor investing while limiting the most pronounced aspects of the exposures they seek to avoid.

Lastly, we explore a more engaged approach in which investors rebuild factors *within* a subset of highly rated stocks —for instance, constructing HML_t within the "green bucket". While this method has a stronger and clearer impact on the underlying average shades, this comes at the risk of deviating more in terms of performance. As a result, the tradeoff between financial returns and non-financial preferences that has been widely emphasized (conceptually) in the literature comes back into focus with this more engaged strategy.

We conclude the paper by discussing several additional results —such as long-run and industry-specific aspects, whether our trimmed factors retain their ability to price traditional portfolios (and vice versa), and an alternative approach that rebuild factors by minimizing tracking errors—, as well as various robustness checks —such as the use of alternative measures, and the treatment of missing scores. Some of these analyses remain ongoing.

In summary, our results highlight that well-known investment factors and anomalies often exhibit pronounced tilts with respect to the non-financial characteristics of the firms on which they bet: these are the "shades" of investment factors. Consequently, investors following popular strategies should be mindful of these hidden exposures, or risk inadvertently supporting dimensions that they may wish to avoid. The good news is that there

[7] In more detail, while certain factors experience a modest decline in performance, others see slight improvements, and the impact remains limited in terms of magnitude for the majority of them. As a result, the Sharpe ratio that an index investor can achieve based on the combination of these factors barely changes with trimming.

[8] Interestingly, constraining portfolios using a given non-financial characteristic (e.g., the environmental score) can influence factor shades along other dimensions (e.g., their social or governance scores). This underscores the potential interactions among non-financial dimensions (cf., also, Sauzet and Zhu, 2025), and could mean that jointly restricting all dimensions may come at a higher financial cost, an aspect that we are currently exploring.

exist several methods to mitigate such exposures, with varying impacts on performance depending on the level of investor engagement. These findings have important implications for the ongoing growth of smart-beta and other indexing strategies in the context of sustainable finance, particularly given the substantial amount of capital that they continue to attract.

Related literature This paper contributes to two main strands of research.

First, we add to the large and growing literature on investment factors and anomalies —including, among many others, Sharpe (1964), Fama and French (1993, 1996), Jegadeesh and Titman (1993), Dichev (1998), Abarbanell and Bushee (1998), Pástor and Stambaugh (2003), Richardson et al. (2005), Heston and Sadka (2008), Bali et al. (2011), Kelly and Jiang (2014), Fama and French (2015), Hou et al. (2015), Bali et al. (2016), Stambaugh and Yuan (2017), Asness et al. (2019), and Hou et al. (2021). The recent proliferation of factors has both deepened our understanding of the cross-section of returns and sparked efforts to assess the overall robustness of these sets of findings —see, for instance, Hou et al. (2015), Harvey et al. (2016), Feng et al. (2020), Giglio et al. (2021b) and Jensen et al. (2023), among many others. While factors based on non-financial characteristics —such as "green-minus-brown" portfolios— have begun to emerge (cf. the literature below), our contribution instead is to examine the non-financial characteristics, or "shades", of existing traditional and widely-used factors and anomalies. In addition, we document how the performance and "shades" of these factors evolve as the investment universe is progressively restricted to accommodate non-financial preferences. These findings are, to the best of our knowledge, novel, and they help bridge the gap between the appeal of factor-based investing —grounded in decades of academic finance research— and the growing relevance of sustainable finance (or more generally, of investing that accounts for non-financial criteria, whatever those may be).

Second, we contribute to the vast and rapidly expanding literature on sustainable finance and ESG investing, including Derwall et al. (2005), Chava (2014), Flammer (2015, 2021), In et al. (2019), Engle et al. (2020), Bolton and Kacperczyk (2021), Pedersen et al. (2021), Pástor et al. (2021, 2022, 2025), Alekseev et al. (2022), Zerbib (2022), Aswani et al. (2024), Eskildsen et al. (2024), Sauzet (2024), Sauzet and Zerbib (2024), Berk and Van Binsbergen (2025), Flammer et al. (2025), Zhang (2025), Sauzet and Zhu (2025), among many others. Cf., also, Giglio et al. (2021a), and Pástor et al. (2025), for surveys. Among more closely related papers, including Abis et al. (2024) and Pástor et al. (2025), the focus is

on non-financial tilts in investment *funds*, particularly ESG-oriented ones, using data from holdings or prospectuses. In contrast, we examine the "shades" —that is, the non-financial characteristics— of traditional investment *factors* themselves, which, to our knowledge, has not been explored in the literature. Our perspective therefore offers complementary and distinct insights that could matter: many investors who rely on factor-based or passive strategies may unknowingly introduce such "shades" into their portfolios, even without realizing it. Given the vast amount of capital allocated to these strategies, understanding these unintended exposures is an important consideration. Our point is that investors should at least be aware of these shades, and adjust for them if they wish to do so.

At a high level, our findings that, in some cases, it might be possible to reduce exposure to certain non-financial characteristics at little to no financial cost, are consistent with those of Pedersen et al. (2021) and Lindsey et al. (2024), among others, who report that the cost of "doing good" or implementing ESG-type strategies may not be as large as often perceived. However, these contributions do not address the impact of, or connection with, factor investing and the "shades" of factors that is our focus here. Our results also align with the prevailing view among practitioners, who frequently argue (perhaps due to their institutional context) that strategies focused on firms with strong non-financial characteristics can generate financial value, at least over the long term.

Lastly, in terms of financial performance measures beyond realized returns, we build on Pástor et al. (2022), Eskildsen et al. (2024) and Lee et al. (2021) for the implied cost of capital (ICC), and on Chabi-Yo et al. (2023), Martin and Wagner (2019), Kadan and Tang (2020) for option-based estimates. Our construction of the traditional factors closely follows Fama and French (2015) and the original literature, and we draw on Jensen et al. (2023) to construct our broad range of anomalies.

Outline The remainder of the paper proceeds as follows. Section 2 presents our approach, and documents the "shades" of well-known investment factors and anomalies. In Section 3, we explore several methods to limit the exposure of these factors to certain non-financial characteristics, for varying degree of investor engagement, and discuss their impact on financial performance. Section 4 covers additional results and robustness checks, and Section 5 concludes. Additional material is provided in Appendix.

2 How green, pro-social, and well-governed are investment factors?

This section presents the first main step in our analysis: we compute the average environmental (as well as social and governance) scores across investment factors, and over time. We start by discussing the metrics that we use and factor construction in Section 2.1. Section 2.2 describes our main findings: we document that, while factors related to low leverage, low risk, profitability and quality tilt towards green firms, those related to value, size, accruals, seasonality, and short-term reversals invest disproportionately in brown stocks. The underlying firms also vary in their social, and governance scores. We discuss further results over the longer run, and across industries, in Section 2.3.

2.1 Non-financial performance measures, factor construction, and data sources

We use two main sets of measures to capture the non-financial performance of companies, which we call their "shades" (e.g., green, brown, *etc.*).

First, we build on Pástor et al. (2022) and construct environmental ($e_{i,t}$), social ($s_{i,t}$), and governance ($g_{i,t}$), scores based on industry-unadjusted granular data from MSCI. Specifically, for stock i in month t, we compute raw scores based on both the scores and pillar weights for each category as follows

$$\begin{aligned} E_{i,t} &\equiv -(10 - E_score_{i,t}) \times E_weight_{i,t}/100 \\ S_{i,t} &\equiv -(10 - S_score_{i,t}) \times S_weight_{i,t}/100 \\ G_{i,t} &\equiv -(10 - G_score_{i,t}) \times G_weight_{i,t}/100 \end{aligned} \tag{1}$$

We then subtract the value-weighted market average of each category ($\overline{E}_t, \overline{S}_t, \overline{G}_t$), to obtain

our baseline market-adjusted scores as

$$\begin{aligned} e_{i,t} &\equiv E_{i,t} - \overline{E}_t \\ s_{i,t} &\equiv S_{i,t} - \overline{S}_t \\ g_{i,t} &\equiv G_{i,t} - \overline{G}_t \end{aligned} \tag{2}$$

These measures have the advantage of not being industry adjusted, contrary to the scores of many alternative vendors, so that they capture the true absolute "greenness" (socialness, well-governedness) of each company. In addition, MSCI is one of the world's largest ESG rating providers (Eccles and Stroehle, 2018), and their scores are used by a large number of financial practitioners and have been shown to impact the allocation of ESG-focused funds, among others (Berg et al., 2022). The market adjustment controls for the fact that the average rating in each category evolves over time so that our scores capture, say, greenness relative to the market.[9]

Second, we measure greenness using an alternative measure based on carbon emissions data from S&P Trucost. Specifically, we use both absolute carbon emissions ($CE_{i,t}$), and carbon intensity normalized by revenues ($CI_{i,t}$) for each firm i and month t. We focus on direct and first-tier indirect emissions, which are Trucost's default scopes.[10] Like for scores, we obtain market-adjusted measures, $ce_{i,t}$, $ci_{i,t}$, by subtracting the value-weighted market average in each month. Because emissions have a negative impact on the environment, we often show the additive *inverse* of those measures, $-ce_{i,t}$, $-ci_{i,t}$ (which we refer to as "negated") so as to have a measure of greenness, unless specified otherwise. Finally, following Bolton and Kacperczyk (2021), we winsorize both measures at the 2.5% level to limit the impact of outliers, given that emissions data tend to be noisy.

[9]Because scores change only infrequently, we forward fill our $E_{i,t}, S_{i,t}, G_{i,t}$ measures so that once a firm was rated, it retains those values until they get updated. The market adjustments, $\overline{E}_t, \overline{S}_t, \overline{G}_t$, are updated each period. In ongoing robustness tests, we also find that our results are generally robust to using raw scores. We also plan to perform checks based on the scores of other vendors. Note that the market adjustment has no impact when focusing on value-weighted long-short portfolios, but it does once we discuss other versions (e.g., equal weighted or capped valued weighted), or when it comes to the trimming exercises that we discuss in Section 3.

[10]Trucost defines direct emissions as the GHG Protocol's scope 1 emissions, plus any other emissions derived from a wider range of GHGs relevant to a company's operations. First-tier indirect emissions are defined as GHG Protocol scope 2 emissions, plus the company's first-tier upstream supply chain—their direct suppliers. The goal of is to include some of the company's most relevant upstream scope 3 emissions, while limiting the extent of the double counting of emissions.

When it comes to factor construction, we first focus on the main seminal asset pricing factors —namely, market (MKT), value (HML_t), size (SMB_t), profitability (RMW_t), investment (CMA_t), and momentum (MOM_t)—, which we build as in Fama and French (1993, 2015) and Carhart (1997). We then generalize our analysis to a wide variety of anomalies, based on Jensen et al. (2023), and also use the authors' clustering procedure to organize them. Our construction closely follows the methodology in each set of papers, so that our factors/anomalies are representative of the ones that have been investigated at length in the literature.[11]

In more details, as is standard, factors are calculated as the difference between the value-weighted average of the realized returns, $r_{i,t}$, for all firms i in the long leg(s) for a given factor in a given month, and that of all firms in the short leg(s). The short and long leg(s) are like in the original papers for the main factors, and simply the top and bottom terciles when we focus on the broader set of anomalies. We also report robustness checks based on equal-weighted, and capped value-weighted, averages, when relevant.

Because we are interested not only in the realized returns on those factors, but also (mostly) in their non-financial performance —i.e., their shades—, we repeat the construction by replacing $r_{i,t}$ by the various metrics described previously. This yields our measures of greenness ($e_{j,t}$), socialness ($g_{j,t}$), well-governedness ($g_{j,t}$), and (negated) carbon emissions and intensity ($-ce_{j,t}, -ci_{j,t}$, for each factor or anomaly, j. Except the market whose score is normalized to zero, these are all long-short portfolios so that our measures capture the relative scores of the long minus short leg. Therefore, e.g., a positive $e_{j,t}$ implies that factor j tends to load more on green firms than on brown ones.

Lastly, in Section 3, we are also interested in the *expected* returns on those factors and anomalies. We proxy for them using a measure of implied cost of capital ($ICC_{i,t}$) following Eskildsen et al. (2024),[12] as well one-year-ahead option-based measures based on the generalized lower bound of Chabi-Yo et al. (2023), ($GLB_{i,t}$), and the variance-based bound of

[11] Details are provided on Kenneth French's website, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, as well as on https://jkpfactors.com/. Alternative, but broadly equivalent, sets of anomalies include Hou et al. (2015) and Chen and Zimmermann (2022).

[12] The authors in turn follow Mohanram and Gode (2013), who computed the ICC as an average of four different measures from the accounting literature. We obtained the data of these four separate measures from the website of the authors. An alternative set of implied cost of capital construction would follow Lee et al. (2021).

Kadan and Tang (2020) ($KT_{i,t}$), which is similar to the one proposed by Martin and Wagner (2019) ($MW_{i,t}$).

All together, our main sample covers 8460 firms from January 2007 to March 2023, and we report results based on the whole sample whenever possible. However, coverage varies across measures, and we use the longest sample for which we have enough observations along each. For instance, as shown in Figure B.1 and documented in Pástor et al. (2022), the number of rated firms in MSCI increases dramatically in November 2012 so that we start the analysis at that date when using those measures, unless it does not affect the results.[13] For certain other measures, e.g., when using ICC, the sample has to be shortened some more due to data availability. We specify the exact time period under consideration in each case.

2.2 Main results: the shades of investment factors

Are asset pricing factors "green" or "brown"? Do they load more on pro-social stocks? What about governance? In short, what are the shades of the investment factors that are used extensively by researchers and practitioners? Equipped with our measures, we set out to answer these questions in this section.

Figure 1 starts by providing some answers on average, over the main sample, for the seminal factors that are ubiquitous in the literature. Turning first to their environmental performance, the size (SMB_t), value (HML_t), and investment (CMA_t) factors tend to tilt towards "brown" firms, while operating profitability (RMW_t) and momentum (MOM_t) invest disproportionally in "green" firms. This is true based on both the MSCI E score (first panel), and carbon intensity (second panel). The finding for the value and momentum factor can explain why a "green-minus-brown" (GMB_t) portfolio has tended to load negatively on HML_t and positively on MOM_t in the recent decade, as documented in Pástor et al. (2022). The "greenness" of the momentum factor is also consistent with the sizable realized outperformance of green stocks over the same period, due to short-run —potentially transitory— developments such as large demand flows towards green investments on the part of institu-

[13] For Trucost, Figure B.1 shows that the coverage also increases noticeably, but only in 2017. Because this would lead to too short a sample, and given that there are already around rated 1000 firms before that, we stick to using the full sample for these measures.

tional investors.[14]

When it comes to the social score, except for SMB_t that tends to load strongly on firms with poor performance on that front, the findings are broadly flipped compared to the environmental aspect: namely, HML_t and CMA_t invest disproportionally in firms with good social scores, while RMW_t and MOM_t tend to tilt towards firms with poor ones. These flipped results between the E and S dimensions are consistent with the findings in Sauzet and Zhu (2025) who document that a "good-minus-bad" factor based on social scores ($SGMB_t$) has tended to strongly *under*perform in the recent decade, in sharp contract to the *out*performance of a $EGMB_t$ based on environmental scores.

Lastly, the result on the governance side are a bit more of a mix with the size, profitability, and momentum factors loading more on well-governed firms, while value and investment tilt more towards firms with poorer governance.[15]

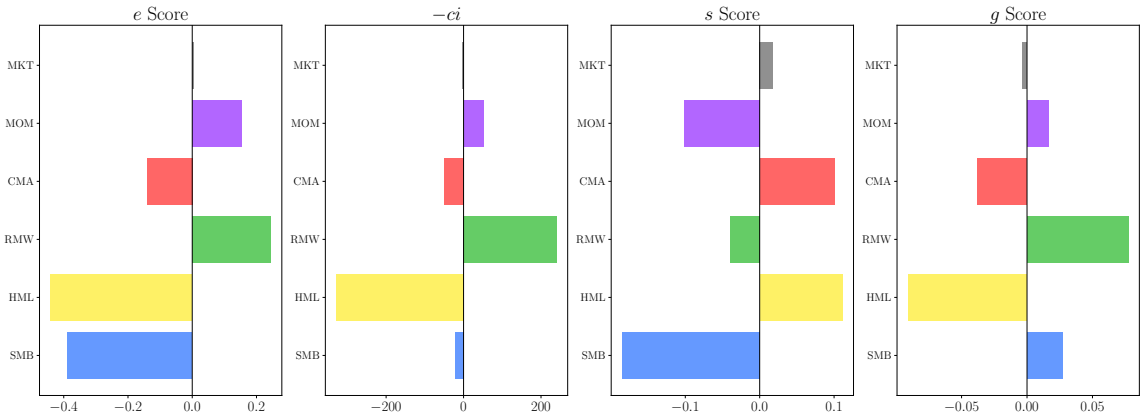
Taken together, these novel results emphasize that investors may inadvertently tilt towards certain non-financial characteristics as they follow well-known investment factors. We note that these tilts towards certain shades are also sizable in terms of magnitude, given that, e.g., the interquartile range for adjusted scores are from around -1 (or more) to $+0.65$.[16] As such, these findings are not innocuous: given the trillions of dollars (and growing) in AUM allocated based on index, smart-beta, or other passive strategies, firms with poor non-financial performances may receive a disproportionate amount of financing without their investors intending to, or at least realizing it. On a different note, documenting the shades of these seminal investment factors is also valuable in that it may help us understand the reasons behind their out/underperformance.

[14] For the size factor, we also note that these findings could be under-statements: small firms tend to be rated less often by score providers, and the ones that are might be more likely to have good non-financial performance and to therefore make the effort of reporting to data providers. We briefly touch upon these issues when we discuss investment factors based on non-rated firms in Section 3.4.

[15] The shades of the market factor are zero by construction, given that we focus on market-adjusted measures. Based on raw (non market-adjusted) measures, Table B.3 show that $e_{MKT,t} = 5.841, s_{MKT,t} = 4.691, g_{MKT,t} = 5.340$. Loosely interpreted, given that the scores range between 0 and 10, this means that the market scores slightly above the mid-score (5) for the environmental and governance dimension, and slightly below for the social score.

[16] In more details, we list the descriptive statistics for e, s, g and $-ci$ of our main sample in Table B.1.

Figure 1: Non-Financial Performance ("Shades") of Seminal Investment Factors



Notes: This figure shows the average non-financial performance of seminal investment factors over the longest available sample, based on MSCI scores (January 2007 to March 2023) and Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness". Details are provided in Section 2.1. Table B.3 in Appendix presents the same results in a tabular format.

To go one step further, and although sample averages are informative already, they do not tell the full story. To see this, Figure 2 plots the environmental score of the factors above over time, and highlights that the shade of investment factors is inherently time-varying.[17] For instance, although the value factor tends to be "brown" throughout the sample, its environmental performance has improved —albeit slowly— closer to being neutral in recent years. Conversely, although profitability (RMW_t) was "green" on average throughout the sample, its e score has in fact deteriorated significantly in recent years, to the point of turning negative, i.e., "brown". Likewise, although it was already negative on average, the pattern for investment (CMA_t) suggests that the deterioration of its environmental performance has been sizable. Lastly, although momentum was tilted towards green stocks on average, its e score has fluctuated a lot and changed signs multiple times, which is perhaps not surprising given the nature of this factor.

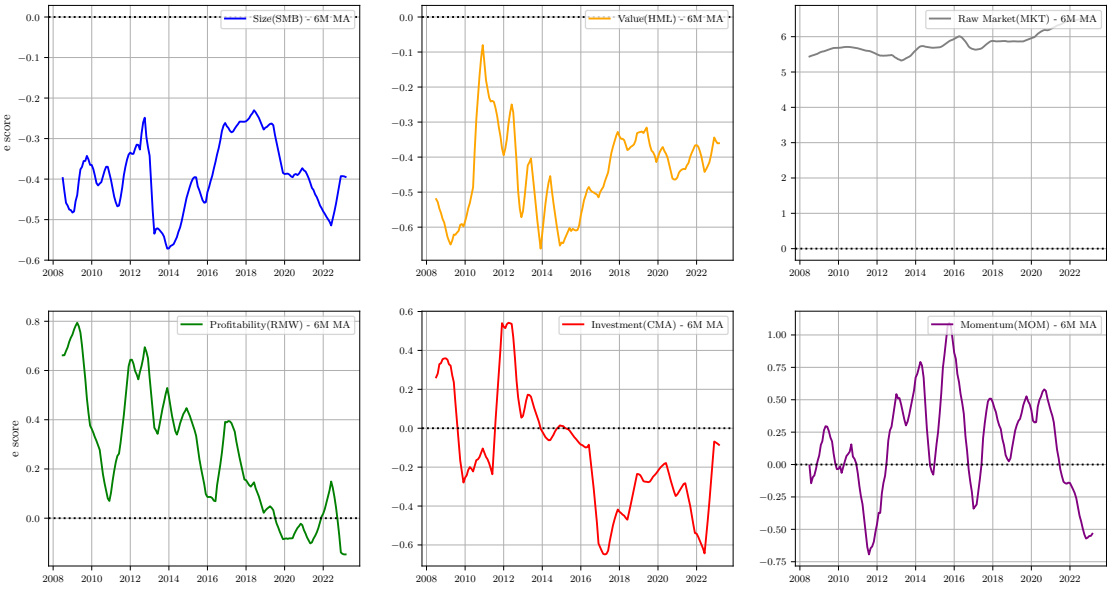
Figures B.2-B.4 in Appendix present similar graphs over time for (minus) carbon intensity ($-ci_{j,t}$), social score ($s_{j,t}$), and governance score ($g_{j,t}$), for each of these factors, j. They

[17] We show 6-month moving averages to smoothen the measures, but the exact window that we use is not consequential for the results.

confirm that for the other non-financial performance measures as well, such time variations are common and the "shades" of the factors often switch sign: for example, the social score for HML_t went from slightly negative to strongly positive to negative again more recently, its governance score has gradually increased from loading more on "badly governed" firms towards better managed ones, and the scores of several other factors switch signs or magnitudes over the sample.

All in all, these time variations do not necessarily have to be a negative, but they highlight that accounting for them requires a inherently dynamic approach. One such approach is the "trimmed factors" that we discuss in Section 3. We also briefly touch upon longer-run evolutions below.

Figure 2: Environmental Score of Seminal Investment Factors over Time ($e_{j,t}$)

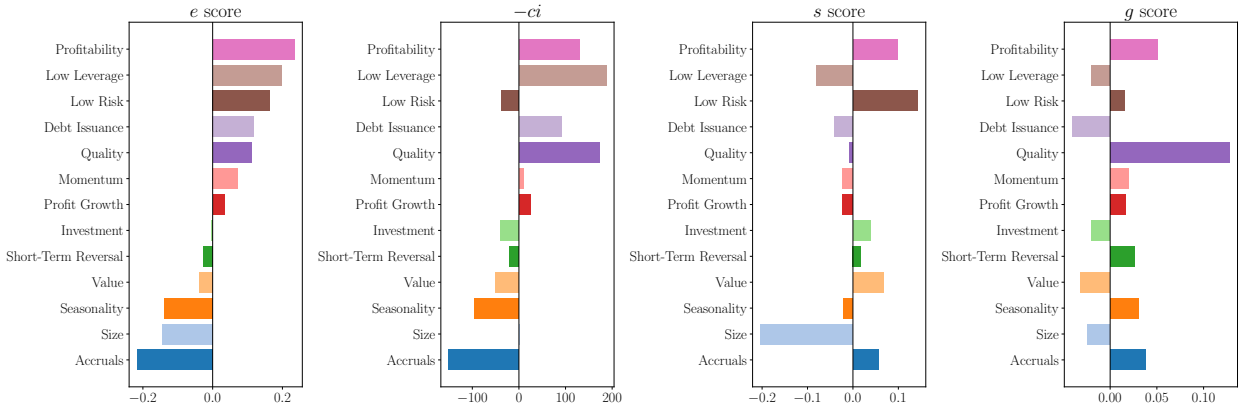


Notes: The figure shows the environmental score ($e_{j,t}$) of seminal investment factors over the longest available sample, based on MSCI data. Details are provided in Section 2.1. Figures B.2-B.4 in Appendix plot the equivalent for (minus) carbon intensity ($-ci_{j,t}$), social score ($s_{j,t}$), and governance score ($g_{j,t}$), respectively.

The investment factors above are seminal, in the sense that they are ubiquitous in the literature and used extensively by practitioners both as strategies and performance benchmarks. However, in recent decades, a vast number of additional factors and anomalies —sometimes referred to as the "factor zoo"— have been uncovered. Their shades could

also be relevant because these emerging factors are driving an increasing share of portfolio allocation through the growth of smart-beta and other quantitative approaches. To study these, we extend our analysis to a wide array of 153 anomalies that we build as in Jensen et al. (2023). Figure 3 shows the resulting average shades over the sample, grouped by investment theme clusters.[18] Again, these various anomalies (or "factors", depending on the interpretation) differ significantly in their non-financial performance. When it comes to environmental scores or (minus) carbon intensity for instance, accruals, size, seasonality, and to some extent value-style characteristics load more strongly on brown stocks, while profitability, low leverage, low risk, debt issuance, quality, and to some extent momentum, tend to tilt towards green stocks on average. Their shades also vary when it comes to other aspects, with, e.g., profitability and low risk investing disproportionally in firms with high social scores while size and low leverage anomalies do the opposite, and quality, profitability, accruals, and others, tilting more towards well-governed firms while value, size, and debt issuance, load more on firms with lower g scores.

Figure 3: Non-Financial Performance ("Shades") of Asset Pricing Anomalies, by Theme

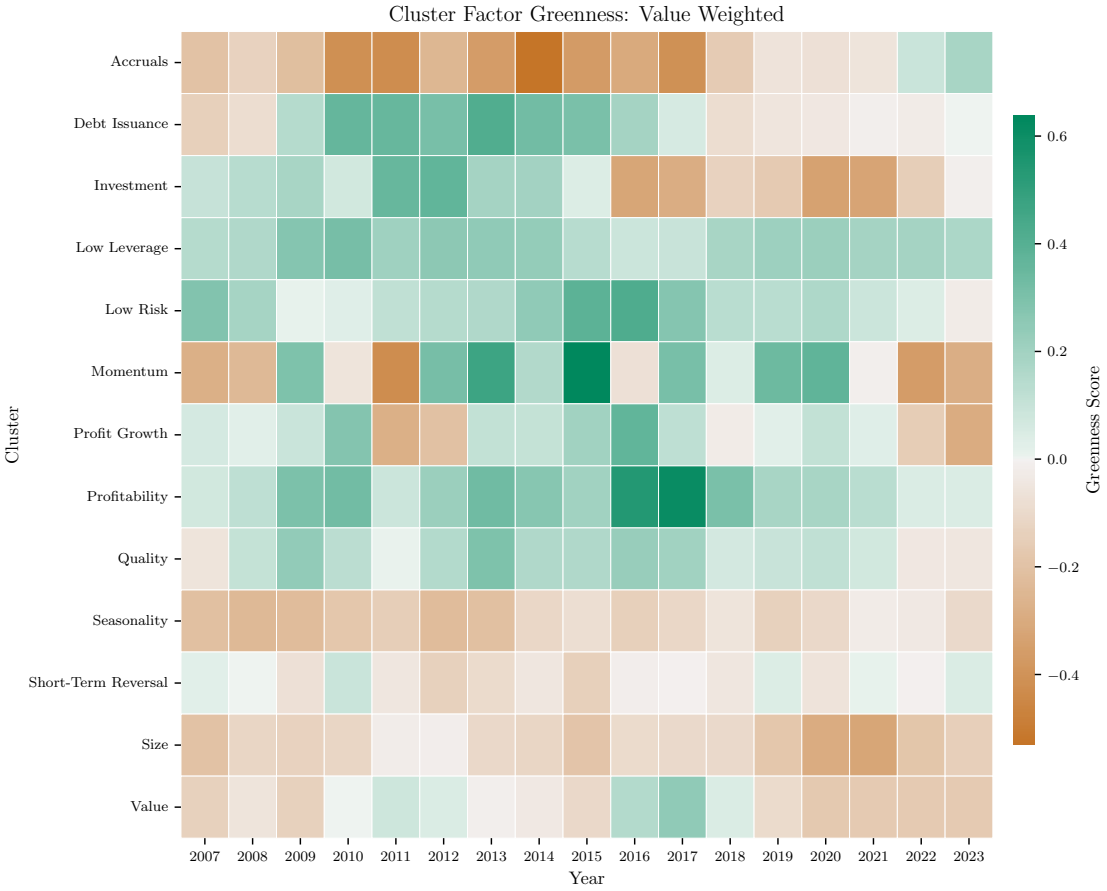


Notes: The figure shows the average non-financial performance of 153 asset pricing anomalies. These anomalies are clustered into 13 themes following Jensen et al. (2023). These anomalies are constructed over the longest available sample, based on MSCI scores (January 2007 to March 2023) and Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness". Details are provided in Section 2.1.

[18] We follow the clustering approach by Jensen et al. (2023). Each "shade" is computed as the value-weighted score of the factors in each cluster. Results for equal-weighted and capped-valued-weighted are broadly similar, and shown in Appendix (Figure B.15 and Figure B.16).

Taken together, these findings can help us elicit the underlying drivers of these anomalies, and we discuss how they relate to *financial* performance, namely returns, in Section 3. Here again, time variations are relevant. For instance, Figure 4 shows a heatmap for the environmental score of each anomaly cluster over time, similar in spirit to Figure 2 for Fama-French factors above, and highlights that debt issuance and investment-type anomalies have turned browner in recent years, although those related to accruals hedged towards greener stocks.

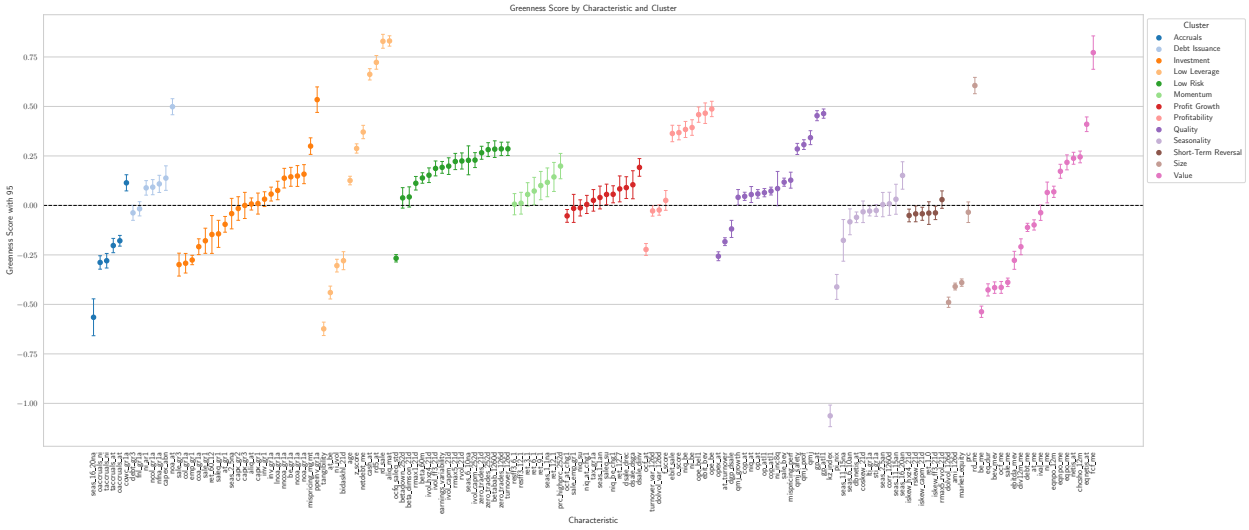
Figure 4: Environmental Scores of Anomalies by Theme Cluster over Time



Notes: This figure shows a heatmap for the environmental score ($e_{j,t}$) of each anomaly cluster over time. These anomalies are constructed over the longest available sample, based on MSCI environmental scores (January 2007 to March 2023). Each cell in the heatmap represents the average "greenness" of the corresponding cluster in that year. Figures B.5-B.7 shows the equivalent for (minus) carbon intensity, social score, and governance score respectively.

Similarly, Figures B.5-B.7 in Appendix show heatmaps for (minus) carbon intensity, social, and governance scores, and reveal, among others, that various anomaly themes — e.g., accruals, debt issuance, and to some extent value— veered towards firms with lower social scores in recent years, although profitability and quality have loaded increasingly more towards high scores. Several clusters also gradually moved towards firms with poorer governance, including, perhaps surprisingly, quality and low leverage-type anomalies.

Figure 5: Average Environmental Score by Anomaly and Theme Cluster



Notes: The figure reports the average environmental score by anomaly and cluster. Each point represents the average score of the anomaly over the longest available sample, reflecting shade heterogeneity within each theme clusters. Figures B.12-B.14 shows the equivalent for (minus) carbon intensity, social score and governance score respectively

In short, these results emphasize that investors that have preferences towards specific non-financial characteristics should be mindful when they follow well-known investment strategies, or risk involuntarily tilting towards certain shades. This does not have to be bad news across the board, however. First, there is considerable score heterogeneity within theme clusters, as illustrated in Figure 5 for the environmental score (and Figures B.12–B.14 in Appendix for other measures). Accordingly, an investor with such preferences can maintain their allocation to a desired investment theme, while reducing exposure to certain non-financial characteristics, by carefully selecting particular anomalies within that theme. This

can be very effective. For instance, within the low leverage theme, the long-short portfolio associated with the asset tangibility (from Hahn and Lee, 2009, denoted *"tangibility"*) characteristic has an average environmental score of -0.6, squarely in brown territory, while the liquidity of market assets (from Ortiz-Molina and Phillips, 2014, denoted *"aliq_mat"*) characteristic implies to strongly tilt towards green stocks, with a score of 0.8. Similarly, within the value theme, the environmental performance can range from brown ($e_{j,t} = -0.5$) to green ($e_{j,t} = +0.75$) depending on the specific anomaly, and this is the case for most other investing themes. Second, the type of trimming approaches that we discuss in Section 3 can also help investors limit their exposure to certain shades substantially at little to no financial cost, as we shall see.

2.3 Long-run sample and industry analysis

We conclude this section by a brief discussion of longer-run evolutions, and industry aspects.

Long-run sample When considering longer-term trends, we note that the non-financial measures that we use cover the longest available periods based on actual data, although they are unfortunately still short. This is because many of these metrics have only been developed recently, in response to the rapidly growing interest in such topics. As a possible —albeit imperfect— approach to study longer-run evolutions, we assign to each underlying firm its average score over the available sample and use this value as the representative "score" for that firm, including for prior months (i.e., we backfill scores for earlier periods). This method is of course imperfect: these scores were not observable by investors at the time and, in practice, they do vary, although somewhat infrequently. Nevertheless, this approach can still provide useful insights into longer-term trends, provided that the results are interpreted with appropriate caution. In particular, changes in the "shades" of each factor are now driven solely by time variations in the market weight of the underlying stock in each bucket.

With these caveats in mind, we use this approach to extend our analysis to the January 1970-March 2023 sample. Table 1 presents the average scores for the seminal factors, and broadly supports our earlier findings. Specifically, regarding environmental performance, the size, value, and investment factors have tilted strongly toward brown stocks in recent decades, while profitability has shown a tendency to load on green stocks. This pattern

is also evident when considering (minus) carbon intensity, although results for SMB_t are somewhat reversed.[19] The findings for the social score are also in line with Section 2.2, and so are those for governance, although the latter are slightly closer to zero (suggesting relative neutrality on that dimension) on average.

Table 1: Long-run Non-Financial Performance ("Shades") of Seminal Investment Factors

Factor (j)	Environmental Score ($e_{j,t}$, MSCI)	$-$Carbon Intensity ($-ci_{j,t}$, Trucost)	Social Score ($s_{j,t}$, MSCI)	Governance Score ($g_{j,t}$, MSCI)
SMB	-0.322	125.398	-0.344	-0.125
HML	-0.733	-540.677	0.240	0.056
RMW	0.365	313.939	-0.038	-0.005
CMA	-0.329	-150.447	0.245	0.035
MOM	0.041	10.260	-0.027	0.004
MKT	-0.001	-3.541	0.012	0.003
MKT (unadj.)	5.589	-478.427	5.511	5.650

Notes: The table shows the average non-financial performance of seminal investment factors over the long-run sample (January 1970-March 2023), based on MSCI and Trucost data. Carbon intensity is negated so as to measure "greenness". The score of each underlying stock is computed as the average score over available data, and is assumed to be constant and known throughout the long-run sample. Details are provided in the main text of Section 2.3.

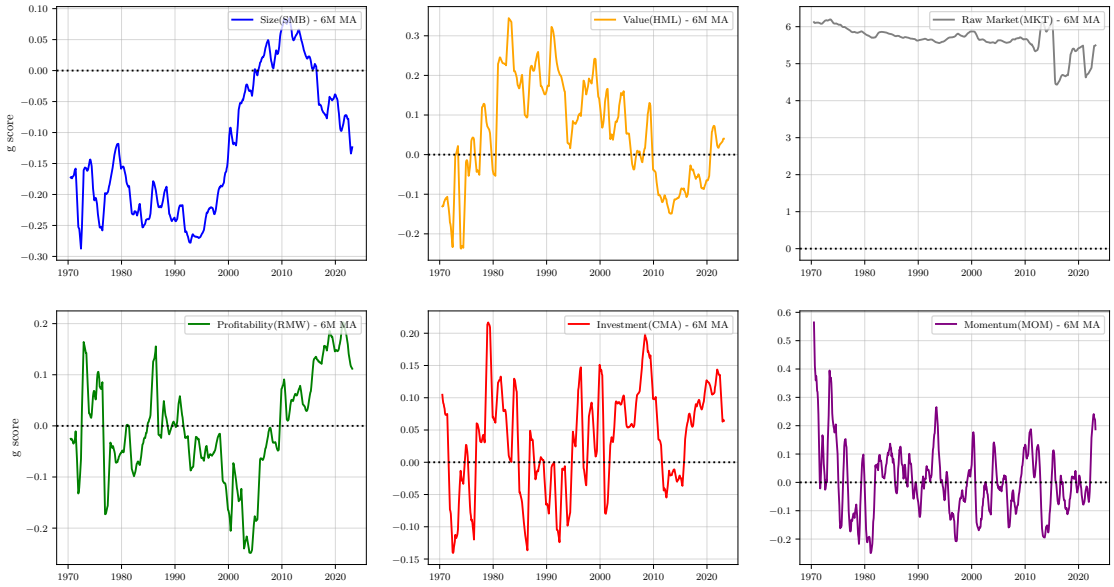
However, these average values mask noteworthy changes over time. For example, Figure 6 shows that the close-to-neutral average governance score conceals substantial variations. HML_t experienced a marked shift toward better-governed firms from the 1970s to the early 1990s, but this trend has reversed since then. On the other hand, profitability displays a broadly opposite pattern, with a shift towards better governance beginning shortly before the 2007–2009 global financial crisis, while the investment factor saw several, albeit milder, reversals over time. Similarly, the momentum factor experienced multiple shifts throughout the sample period.

Figures B.19–B.21 in Appendix plot the equivalent long-run evolutions, for each factor,

[19] Although we plan to examine this finding further, we interpret it with some caution given that small firms are rated less frequently, and that the choice of which firms are rated may not be fully exogenous.

of the environmental score ($e_{j,t}$), (minus) carbon intensity ($-ci_{j,t}$), and social score ($s_{j,t}$), respectively, and illustrate several important trends. For instance, HML_t has gradually become "greener" over the sample, while RMW_t (profitability) shifted from being "very green" to exhibiting an average environmental shade near zero, or potentially even brown in recent years. Likewise, CMA_t (investment) became browner before shifting toward greener firms, then began to move back toward brown firms more recently. Most of the factors also exhibited considerable fluctuations when it comes to the social score of the underlying stocks.

Figure 6: Long-Run Governance Score of Seminal Investment Factors over Time ($g_{j,t}$)



Notes: The figure shows the governance score ($g_{j,t}$) of seminal investment factors over time over the long-run sample (January 1970-March 2023), based on MSCI data. The score of each underlying stock is computed as the average score over available data, and is assumed to be constant and known throughout the long-run sample. Details are provided in Section 2.3. Figures B.19-B.21 in Appendix plot the equivalent for environmental score ($e_{j,t}$), (minus) carbon intensity ($-ci_{j,t}$), and social score ($s_{j,t}$), respectively.

Taken together, these results highlight important slow-moving, underlying trends in the firms comprising each investment theme, and reinforce the case for a dynamic, time-varying approach when accounting for non-financial characteristics, even at lower frequencies.

Industry analysis There is also considerable variation across industries. Table 2 reports the shade for the environmental score —i.e., the "greenness"— for each industry, as well as for the factors reconstructed *within* each industry.[20] As expected, average green scores vary markedly by industry, with firms in mining, utilities, construction, and manufacturing being, on average, much browner than the market. These differences across industries assuredly explain part of the shade patterns we uncovered above.

Table 2: Greenness based on Environmental Scores by Industry and Factor

Industry	Avg	VW Avg	SMB	HML	RMW	CMA	MOM
Mining	-2.186	-2.010	-0.160	-0.283	0.139	0.252	-0.014
Utilities	-2.104	-1.821	-0.321	-0.354	0.437	-0.176	0.072
Construction	-0.414	-0.526	-0.004	-0.075	0.160	-0.187	-0.119
Manufacturing	-0.659	-0.159	-0.643	-0.589	-0.109	-0.095	0.071
Wholesale	-0.634	-0.022	-0.506	-0.069	-0.079	-0.173	0.158
Retail	-0.171	0.232	-0.416	0.038	-0.024	0.145	-0.042
Transportation	0.041	0.530	-0.776	0.287	0.154	0.198	0.156
Services	0.275	0.542	-0.090	0.007	0.205	0.020	0.046
Finance	0.314	0.551	-0.292	-0.295	0.405	0.021	-0.004

Notes: The table shows the average environmental score of firms by industry (first two columns), as well as that of seminal investment factors constructed within industry, over the longest available sample, based on MSCI scores (January 2007 to March 2023) and Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness". Details are provided in Section 2.3. The second column, along which industries are sorted, is the value-weighted average score of firms within each industry, and therefore corresponds to the "market" factor within each..

Interestingly, however, there is also substantial variation in the shades of the factors themselves, both quantitatively (for instance, SMB_t is mostly negative —i.e., brown— but varies considerably in magnitude) and qualitatively (for example, HML_t is brown for mining,

[20]Firms in the sample are categorized into 11 broad industries based on SIC codes: Agriculture, Construction, Finance, Manufacturing, Mining, Public, Retail, Services, Transportation, Utilities, and Wholesale. Table B.6 in the Appendix shows summary statistics for the industries in the sample. Agriculture and Public are excluded from our exercise, however, due to insufficient variation in the factor-sorting variables. Other sectoral classifications, such as MSCI, or Fama-French industries, could be interesting to explore.

utilities, and construction but green for transportation; similarly, CMA_t is brown for utilities and wholesale but green for mining, retail, and other sectors). The shades of factors also vary within industries: e.g., for mining, size, value, and, to some extent, momentum are brown, while profitability and investment are green, and these patterns differ across industries.

Similarly, Tables B.7–B.9 display comparable patterns and variations by factor and industry for the social score, governance score, and (minus) carbon intensity, respectively. The presence of substantial within-industry variation —not just differences across sectors— is consistent with findings in Pástor et al. (2022) for environmental scores themselves (although the authors do not discuss the shades of factors). These measures also fluctuate considerably over time. Overall, there are many interesting nuances, which we are investigating further and extending to our broader set of anomalies.

Taking stock In summary, our analysis so far highlights that both well-known investment factors, and more recently identified anomalies, exhibit distinct "shades" (e.g., brown, green) by tilting toward specific non-financial characteristics. Given the substantial capital flowing into index investing and other smart-beta or quantitative strategies that track these factors recently, we believe that these findings are both novel and important. Investors should, at a minimum, be aware of these patterns, and may wish to take action if they are so inclined. While we have illustrated one possible approach —namely, selecting the appropriate anomaly within a given theme— and have discussed the time variations in these "shades", we now turn to more systematic strategies for limiting exposure to particular non-financial characteristics.

3 E(SG)-trimmed factors: is there a financial cost to greenness, pro-socialness, and good governance?

Given the tendency of investment factors to tilt toward certain non-financial characteristics, investors with specific preferences in this regard may seek to limit their exposure to particular "shades". We now explore several approaches to achieve this. First, we propose a "trimming" strategy, whereby stocks with lower environmental, social, or governance scores are gradually excluded before constructing factors (Sections 3.1 and 3.2). We show that

this method allows investors to substantially enhance the non-financial performance of most factors, with little to no financial cost. Next, we discuss a more engaged approach, in which investors construct factors solely within a subset of highly rated stocks (Section 3.3). While this method yields a more pronounced improvement in non-financial performance, it comes with the risk of larger deviations in terms of financial performance. Finally, we touch upon additional considerations such as the case of non-rated firms in the construction of these factors, alternative potential approach(es), as well as findings related to longer-term dynamics and industry effects (Section 3.4). These various methods provide a menu of options from which investors can select, depending on the strength of their preferences.[21]

3.1 Construction of trimmed factors, and baseline performance

The construction of our E(SG)-trimmed, or E(SG)-constrained, factors proceeds as follows. We begin with the entire investment universe that we used to construct investment factors in Section 2, in line with the literature. The resulting factors in this initial step constitute the original ("trim 0%") set.

Next, we progressively exclude the bottom 5% of stocks in terms of non-financial performance and construct the factors based on this restricted universe, repeating the process iteratively. For each trimmed version, we compute both the factor's updated non-financial scores and its financial performance. For the latter, we consider both realized returns and measures of *expected* returns (namely, implied cost of capital and option-based estimates, as discussed in Section 2.1). While realized returns are standard in empirical asset pricing, they may not always provide an accurate reflection of the expected returns that are theoretically relevant and ultimately of interest for assessing performance. This is because sample periods for the metrics that we use —and for ESG-related topics more broadly— tend to be relatively short, and because large, transitory demand shocks may be particularly relevant in such case because of the large shifts towards (and away from?) sustainable investing in recent years (Pástor et al., 2022). We apply this approach separately for each of our non-financial metrics: environmental score ($e_{i,t}$), (minus) carbon intensity ($-ci_{i,t}$), social score

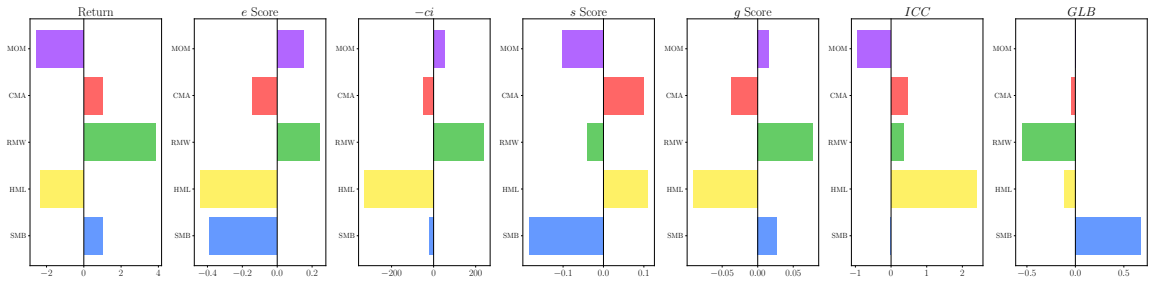
[21] While we focus on trimming the firms with the lowest non-financial performance scores, we note that this could be reversed for investors that are so inclined. These approaches could also be applied to other non-financial characteristics.

$(s_{i,t})$, and governance score $(g_{i,t})$.[22]

Our primary focus is on the seminal factors —namely, market (MKT), value (HML_t), size (SMB_t), profitability (RMW_t), investment (CMA_t), and momentum (MOM_t)—, although we are currently extending the analysis to the broader set of anomalies that we discussed in Section 2. An important note is that when building these trimmed factors, we still retain stocks without available non-financial ratings at each step to ensure that the initial "trim 0%" versions are as closely aligned as possible with factors in the literature. Although including non-rated stocks does not substantially affect our results, we discuss these aspects in some detail in Section 3.4.

Before discussing the impact of progressively excluding stocks, we first present the baseline performance of the untrimmed factors for reference. Figure 7 summaries the "shades" of the seminal factors discussed previously, along with various measures of their financial performance. Similarly, Figure 8 provides the corresponding results for the 153 anomalies, grouped by theme clusters as before. [23]

Figure 7: Financial vs. Non-Financial Performance for Seminal Investment Factors



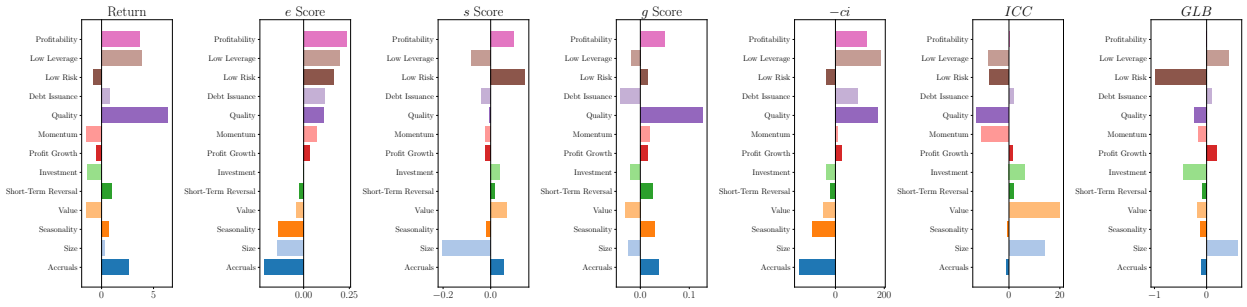
Notes: The figure shows the average non-financial performance of seminal investment factors over the longest available sample, based on MSCI scores (January 2007 to March 2023) and Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness". Details are provided in Section 2.1. Table B.3 in Appendix presents the same results in a tabular format.

[22]It can also be of interest to explore trimming based on carbon *emissions*, rather than intensities. Indeed, Bolton and Kacperczyk (2021), among others, emphasize that total emissions may be the more relevant metric for assessing the impact on climate. Although this approach is less common among practitioners, we are extending our analysis to include this case, which could prove insightful. Preliminary results are broadly consistent with those based on for carbon intensity.

[23]Results for equal-weighted and capped-valued-weighted are shown in Appendix (Figures B.17 and B.18).

At a high level, it is interesting to note that, although these are well-established factors and anomalies that are typically expected to generate positive returns, their realized performance are not positive across the board in our dataset. For example, both value and momentum strategies exhibit negative average realized returns when constructed according to the standard methodologies of Fama and French (1993) and Carhart (1997). Similarly, the low-risk, momentum, profitability, growth, investment, and value clusters display negative realized returns on average when computed from the broader set of 153 anomalies discussed previously. Part of this stems from our relatively short sample period, as the inclusion of data on non-financial characteristics imposes additional data limitations. Moreover, aside from the fact that it sometimes diminishes (or even disappears) post-publication, factor outperformance has been shown to be inherently time-varying. For example, value strategies experienced a prolonged "dry-spell" from the mid-2000s through at least 2020, which is consistent with our results.

Figure 8: Financial vs. Non-Financial Performance for Asset Pricing Anomalies, by Theme



Notes: The figure shows the average financial and non-financial performance of anomalies clusters over the longest available sample, based on MSCI scores, Trucost data, ICC data and GLB data. Carbon intensity is negated so as to measure "greenness". Figures B.17-B.18 shows the results for equal-weighted and capped-value-weighted constructions respectively

From this perspective, alternative performance measures, such as implied cost of capital (ICC) and option-based estimates, can be informative. These metrics indicate that, in expected returns terms, certain factors, such as size, value, and investment, may in fact remain alive and well. On the other hand, they also suggest that some other anomalies may appear less promising when evaluated through that lens. Unsurprisingly, it is challenging to

construct a fully coherent picture using this entire set of metrics over such a short sample period, especially when transitory demand pressures can cause realized and expected returns to diverge markedly (cf., e.g., Pástor et al., 2022, Eskildsen et al., 2024). However, we mention these occurrences —for example, instances of negative outperformance— simply to set a baseline for the discussion that follows. Resolving these discrepancies is not the primary objective of this paper, as they mainly stem from the properties of the underlying metrics themselves.[24] Rather, we use these measures as complementary perspectives on financial performance and focus on how they evolve as we begin to constrain portfolios with respect to non-financial characteristics. We also discuss using alpha measures instead of raw returns, as well as Sharpe ratios, below. They paint a similar picture.

Returning to economic considerations, we observe strong correlations between financial performance and non-financial characteristics for several of these factors. While we do not argue that these relationships are necessarily causal or systematic, it is important to note that, within the context of our approach, trimming portfolios based on non-financial criteria could therefore entail a significant risk of reducing financial performance. And indeed, from a theoretical standpoint, restricting the investment universe or embedding ESG preferences is generally expected to yield lower expected returns, as highlighted in much of the literature. Whether this plays out in practice, and to what extent, is precisely the focus of the analysis that follows.

3.2 Main results: is there a financial cost to greenness, pro-socialness, and good governance?

Let us now turn to our main questions: is there a financial cost associated to greenness, pro-socialness, and good governance, when applied to investment factors? We begin by discussing the results of our trimming approach here, before exploring a more engaged method in the next subsection.

Figure 9 presents the outcomes of our trimming exercise on financial and non-financial

[24] Another example is that ICC and option-based measures tend to yield values that are, on average, lower than realized returns. This pattern is acknowledged in the corresponding literature (e.g., Chabi-Yo et al., 2023 for option-based estimates), and once again, addressing this issue is beyond the scope of our analysis scope and instead relates to the broader literature on these metrics.

performance.[25] This is based on the environmental score, but the key findings are broadly similar when other non-financial characteristics are used and these additional results are shown in Figures C.1–C.3 in Appendix.

With respect to the non-financial performance score itself, Panel (a) highlights a general improvement, as factors tend to move closer to a neutral or green shade. Note that this improvement is not mechanical and does not occur for all factors (apart from the market portfolio). Indeed, although the investment universe becomes progressively restricted, the reconstitution of long-short portfolios does not necessarily guarantee that each factor's shade will improve. In fact, when factors are constrained based on social or governance scores instead, the shade of several factors shifts further away from being more pro-social or well-governed. However, although certain investment factors therefore still load on relatively "unappealing" characteristics, this is less problematic given that the underlying investment universe is becoming progressively better aligned with ESG-type preferences (as reflected by the market score). This approach can thus serve as a useful compromise for investors who wish to remain close to traditional factor investing while limiting the most pronounced aspect of the exposures they seek to avoid. Moreover, even for those with relatively strong preferences, increasing the trimming threshold can provide an even greater alignment with their non-financial objectives.

Most importantly, and this constitutes one of our central findings: trimming has very little impact on financial performance. Interestingly, this holds whether we consider realized returns (Panel (b)), or expected return measures such as implied cost of capital (Panel (c)), or option-based estimates (Panel (d)). In short, investors can exclude the worst firms from a non-financial perspective —even many of them— without materially sacrificing financial outcomes. This is not to say that there is no effect whatsoever; for example, CMA_t and SMB_t perform slightly worse for the first couple of trimming levels based on the environmental score, HML_t becomes more negative when constrained based on carbon intensity in realized returns (though it was already negative), and several factors show deterioration (most mild, some slightly more marked) when performance is measured via option-based metrics or at a higher level of trimming based on carbon intensity. However, these impacts are generally

[25] Tables C.1 and C.2 in Appendix provide the corresponding results in tabular format, together with additional details such as the impact on standard deviations.

modest, and for a number of factors, financial performance even improves (e.g., when trimming based on social and governance scores) —though the latter may at least partly reflect outperformance in terms of realized returns due to short-term demand fluctuations towards highly rated stocks.

Table 3: Sharpe Ratios Across Models and Environmental Trim Levels

		Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Factors	MKT-RF	✓	✓	✓	✓	✓
	SMB		✓	✓	✓	✓
	HML		✓	✓	✓	✓
	RMW			✓		✓
	CMA			✓		✓
	MOM				✓	✓
Trim level				**Sharpe Ratio**		
0%		0.65	0.73	1.21	0.75	1.22
5%		0.66	0.76	1.20	0.77	1.21
10%		0.67	0.76	1.16	0.77	1.16
15%		0.68	0.76	1.13	0.76	1.13
20%		0.69	0.76	1.12	0.77	1.12
25%		0.71	0.77	1.13	0.79	1.13
30%		0.71	0.77	1.13	0.79	1.13
35%		0.70	0.75	1.10	0.77	1.10
40%		0.69	0.75	1.08	0.77	1.08
45%		0.69	0.72	1.08	0.75	1.08
50%		0.67	0.71	1.13	0.74	1.13

Notes: This table shows the maximum in-sample (realized) Sharpe ratios that can be obtained by combining various investment factors, for different trim levels of the environmental score of the underlying stocks. Scores are from MSCI data, and the sample spans January 2007 to March 2023.

Another way to summarize these results is to compute the maximum Sharpe ratio achievable by an investor allocating capital using these sets of factors (both original, and trimmed), as shown in Table 3.[26] In short, although specific factors may under- or outperform as the

[26]These results are based on trimming using the environmental score, but the findings are similar when applying other non-financial metrics.

universe is constrained based on non-financial scores, as we mentioned, the overall impact is minimal: the Sharpe ratio remains largely unchanged and, in some cases, even improves, as we restrict the investment universe.[27] This is not to say that theoretical predictions are conceptually not relevant, but rather that, in practice, the negative impact on financial performance appears to be limited.

Here are a few final remarks for completeness.

First, constraining portfolios using a given non-financial characteristic can influence factor shades along other dimensions. For example, Figure C.9 shows that both social and governance scores tend to *de*crease for most factors as we trim based on the environmental performance.[28] This underscores the potential interactions among non-financial dimensions (cf., also, Sauzet and Zhu, 2025), and could mean that jointly restricting all dimensions may come at a higher financial cost, an aspect that we are currently exploring.

Second, there is some variation over time as to when these constraints have the most bite. Environmental scores, for instance, fluctuate more around key events such as the Paris Agreement, so that trimmed factors diverge more in terms of their green scores during these periods (Figures C.12-C.15). The effects on returns also vary over time, although these are generally more modest (Figure C.4-C.8).

Third, we reiterate that our analysis in this section is based on restricting the investment universe according to non-financial scores, while still retaining all stocks for which ratings are unavailable. Our goal is to remain as close as possible to the construction of the original factors. However, the main finding of a limited financial impact of trimming persists even focusing exclusively on rated firms, a point to which we briefly return in Section 3.4.

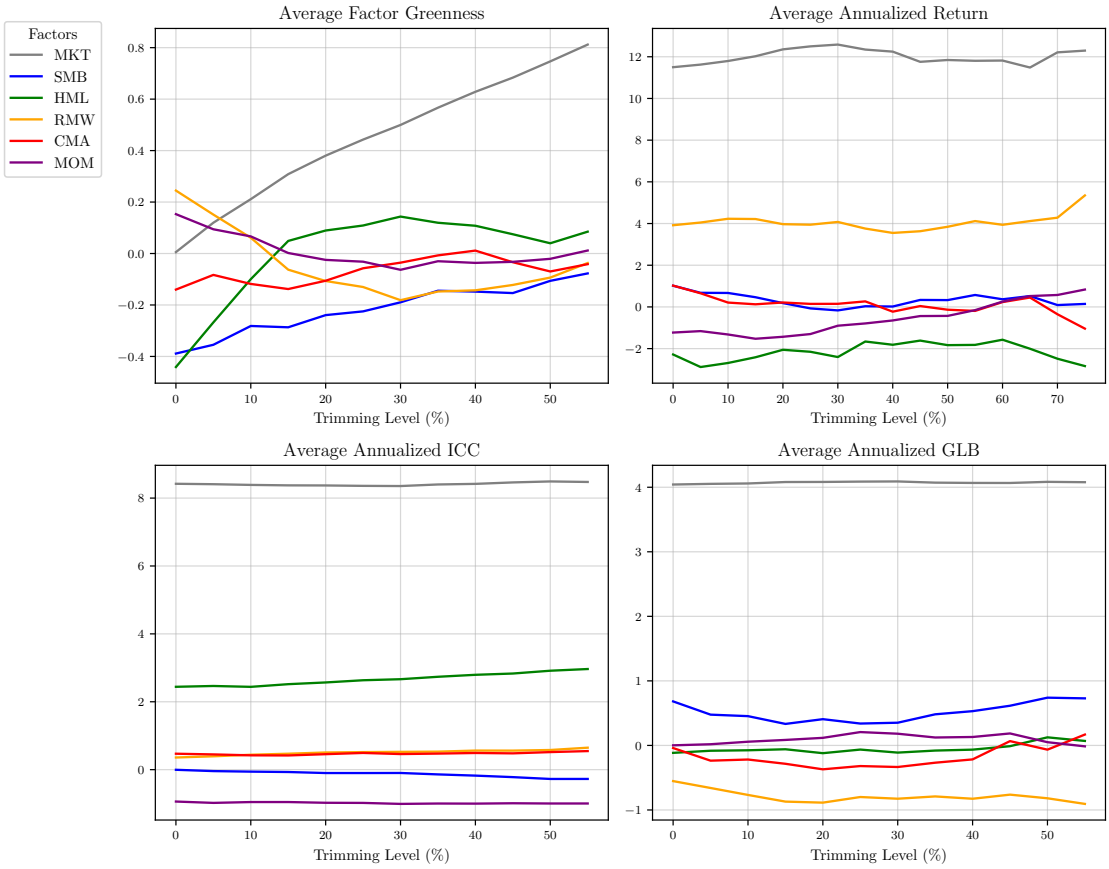
Finally, while our primary focus has been on carbon intensity, given its prevalence among practitioners, trimming based on carbon emissions may also be relevant. Indeed, emissions could provide a more accurate measure of a firm's actual impact on climate, as noted by Bolton and Kacperczyk (2021). Preliminary results suggest that, although the effects vary

[27] This occurs because average (realized) returns generally change little —and sometimes improve—, as discussed above. Moreover, changes in standard deviation and correlation are typically modest (Table C.1 in Appendix), and, overall, optimal factor combination helps to offset these effects. On another note, we compute the Sharpe ratio in-sample. While out-of-sample estimation could be of interest, it is besides the focus of this paper and our intention here is simply to provide a summary of overall performance.

[28] Similarly, Figure C.10 suggests that, as we trim on social, the environmental scores of certain factors tend to decrease (although governance scores differ across factors), and Figure C.11 highlights that environmental scores decrease (while social scores are little changed or mildly increase), as we trim on governance.

across factors —with some benefiting while others suffer slightly (cf. Tables C.3-C.4 for a comparison between the two)— the central finding that financial performance is relatively unaffected remains broadly robust. We are currently extending our analysis to further investigate the use of carbon emissions.

Figure 9: Financial Performance (%) and "Shade" of Investment Factors Trimmed based on Environmental Score



Notes: This figure shows how the average "shade" and financial performance of seminal investment factors evolve as the underlying investment universe is progressively restricted by trimming stocks with the worst environmental scores. The "shade" is measured using the environmental score, while financial performance is captured by realized returns and two measures of expected returns: the implied cost of capital (ICC) and option-based estimates (GLB).

In summary, although there are interesting nuances across factors and metrics, we broadly conclude that factor investors who are so inclined may be able to significantly reducle their exposure to certain non-financial characteristics at little to no financial cost using this trimming strategy, even with high exclusion thresholds. While some factors may still load relatively more on certain "unappealing" shades, the underlying investment universe becomes progressively better aligned with investors' preferences. As such, this method can serve as a useful compromise for those who wish to remain close to traditional factor investing while limiting the most pronounced aspects of the exposures they seek to avoid. At a high level, these findings are consistent with those of Pedersen et al. (2021) and Lindsey et al. (2024), who report that the cost of "doing good" or implementing ESG-type strategies may not be as large as often perceived, although these contributions do not address the impact of, or connection with, factor investing and the "shades" of factors that is our focus here. Our results also align with the prevailing view among practitioners, who frequently argue (perhaps due to their institutional context) that strategies focused on firms with strong non-financial characteristics can generate financial value, at least over the long term.

3.3 Factors within score buckets: a more engaged approach

What if the trimming strategy above does not quite cut it for certain investors, particularly those seeking stronger alignment with their non-financial preferences? In this section, we explore a more engaged approach, where factor portfolios are reconstructed within score buckets —-typically among highly rated stocks, but applicable to any preference.

Table 4 reports the average realized returns for the canonical asset pricing factors, computed within score terciles for environmental, social, and governance metrics.[29] This exercise highlights that the impact on financial performance can become more pronounced under this more engaged approach.

[29]We are currently extending this analysis to other measures of expected performance, namely ICC and option-based estimates, as well as to carbon emissions/intensities data and the broader set of anomalies. On another note, this exercise requires ratings for all underlying stocks, making its results more comparable to the "inner merge" version of the trimming analysis, which focuses exclusively on rated firms. We briefly discuss this version in Section 3.4. As mentioned earlier, it does not materially affect the results presented in the previous section. An alternative for the within-bucket exercise here could be to include non-rated firms as part of the medium-, or low-rated, group.

Table 4: Average Annual Realized Returns of Factors Constructed Within Different Buckets

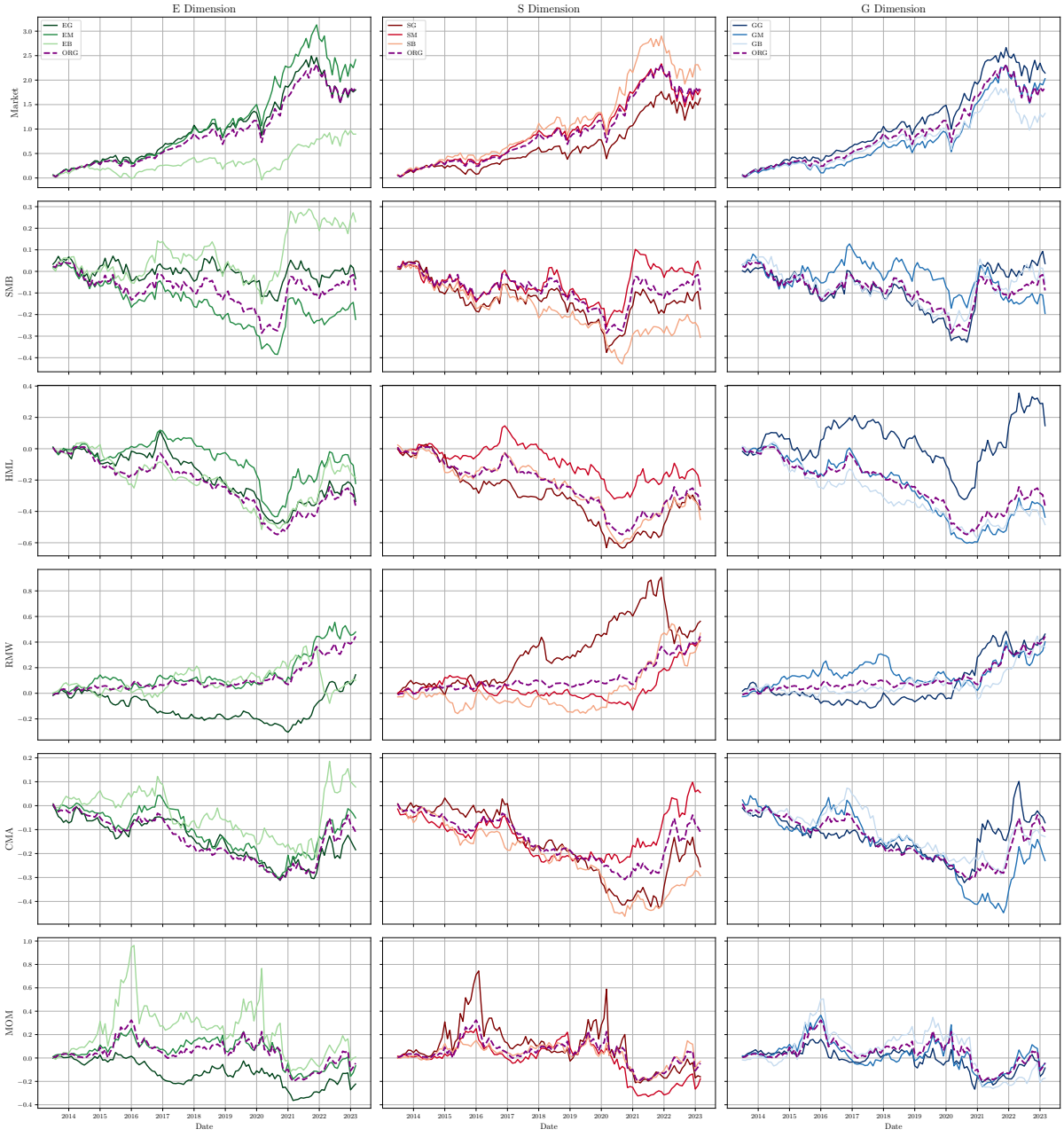
Factors	Non-Financial Characteristic Buckets								
	EG	EM	EB	SG	SM	SB	GG	GM	GB
MKT	12.441	12.335	7.167	9.867	10.543	13.641	11.076	12.421	9.890
SMB	1.246	1.776	4.154	1.343	2.702	-0.580	4.264	-0.347	0.897
HML	-1.730	-1.983	1.348	-3.375	-0.736	-3.475	-0.545	-1.495	-4.290
RMW	2.859	4.334	-0.200	2.817	3.171	4.435	4.334	2.863	4.069
CMA	-2.307	2.178	3.108	-0.343	2.201	-2.579	1.260	1.124	2.155
MOM	-4.553	-3.316	-5.314	-4.087	-5.456	-3.906	-4.206	-5.857	-3.946
Observations	99532	130345	99365	99015	131157	99209	101087	129013	99142

Notes: The tables reports the average annual realized returns (in %) of common asset pricing factors across different buckets formed using MSCI scores from November 2012 to March 2023. Within each of the E, S, and G dimensions, firms are sorted into three buckets based on their adjusted scores ($e_{i,t}, s_{i,t}$ and $g_{i,t}$), with the top tier placed in the "EG", "SG" and "GG" buckets, while the bottom tier fall into the corresponding "EB", "SB" and "GB" buckets.

For example, even simply for the market portfolio, restricting the universe to certain "shades" can significantly alter performance. While there are cases where performance improves —such as the market doing particularly well within the green bucket, or within high-governance groups—, this might have more to do with the well-documented short-run (realized) outperformance of green stocks in recent decades (In et al., 2019, Pástor et al., 2022). Moreover, there are also clear drawbacks: e.g., average market returns are nearly 4 percentage points lower among firms with high social scores compared to those with low scores.[30] Importantly, this tradeoff extends beyond the market factor. Investors would have achieved significantly better performance, often by several percentage points per year, by reconstructing the size, value, and investment factors within "brown-painted" buckets, profitability within the low-social-score group, or investment within firms with weak governance. At the same time, not all of this is negative: some factors still perform well, or even better, within high- or mid-rated groups —for instance, SMB_t and RMW_t within firms with high or neutral social scores, and RMW_t within the mid- to high-governance group.

[30]This specific result, and related patterns, are the focus of Sauzet and Zhu (2025).

Figure 10: Cumulative Realized Returns of Factors Constructed Within Different Buckets over Time



Notes: The figure presents the financial performance of common asset pricing factors within different buckets that are formed using MSCI scores from November 2012 to March 2023. Each column corresponds to the non-financial dimension used to construct the buckets. "ORG" refers to the original factors constructed using the full sample over the same period and serves as a benchmark. These original factors were constructed following the same method outlined in Section 2.1, using all firms with available return data.

Overall, therefore, these findings show that while this more engaged strategy offers stronger alignment with investor preferences —by construction, all stocks belong to the desired score range— it can also lead to weaker or more variable financial performance, sometimes strongly so. As such, the tradeoff between financial returns and non-financial preferences that has been widely emphasized (conceptually) in the literature comes back into focus with this more engaged strategy. The tradeoff can be even more acute once we focus not only on average returns, but also consider their fluctuations over time (Figure 10). In short, investors following such approaches must be willing to accept this potential sacrifice in terms of performance, in exchange for stronger alignment with their values, whatever those may be.

3.4 Additional considerations

We wrap up this section with a brief mention of some additional considerations that we are currently exploring.

Alternative approach(es) There are several alternative approaches to limiting exposure to certain non-financial characteristics while investing based on factors. One approach we are currently exploring involves trimming firms based on their scores, as before, but then constructing factors by minimizing tracking errors to closely replicate the return patterns of the original factors. This method may appeal to investors who prioritize maintaining factor returns and risk profiles. In contrast, our current approach aligns more closely with investors focused on preserving an investment *style* or *thesis* —based on the sorting variables underlying the factors— rather than strictly matching returns. These approaches are complementary, and the tracking error minimization method could be particularly relevant in the industry because closely tracking benchmarks is often important for practitioners. We also expect this alternative approach to result in even smaller performance differences.

Another, relatively different approach —somewhat outside the main focus of this paper but worth mentioning— would be to maintain benchmark and portfolio weights but to act on non-financial preferences through shareholder engagement, such as voting. This method embodies a truly more "engaged" strategy in the traditional sense of shareholder activism. A

notable example in practice is the VOTE ETF, launched by Hedge Fund Engine No. 1 in June 2021. However, the future of such approaches remains uncertain, especially as shareholder engagement faces increasing scrutiny, complexity, and limitations in today's regulatory and political environment.[31]

There may also be alternative approaches, and we look forward to exploring those further.

The case of missing scores In most of our analysis so far, particularly in the trimming approach, we have also retained firms without ESG ratings to remain as close as possible to the original factor constructions.[32] However, investors with preferences for non-financial characteristics may be reluctant to include non-rated firms, as the absence of a rating might signal a lack of effort or even an attempt to hide negative information by firms. In other words, the lack of ratings may not be truly exogenous. While we are not overly concerned about this —except perhaps for smaller firms that lack resources to produce non-financial information—, we rerun the trimming analysis restricting only to the subset of rated firms in the sample, which we call the "inner merge" version. Table C.6 presents these results, and in short, excluding non-rated firms does not substantially change the findings. We could also consider alternative approaches, such as imputing scores for non-rated firms based on other characteristics.

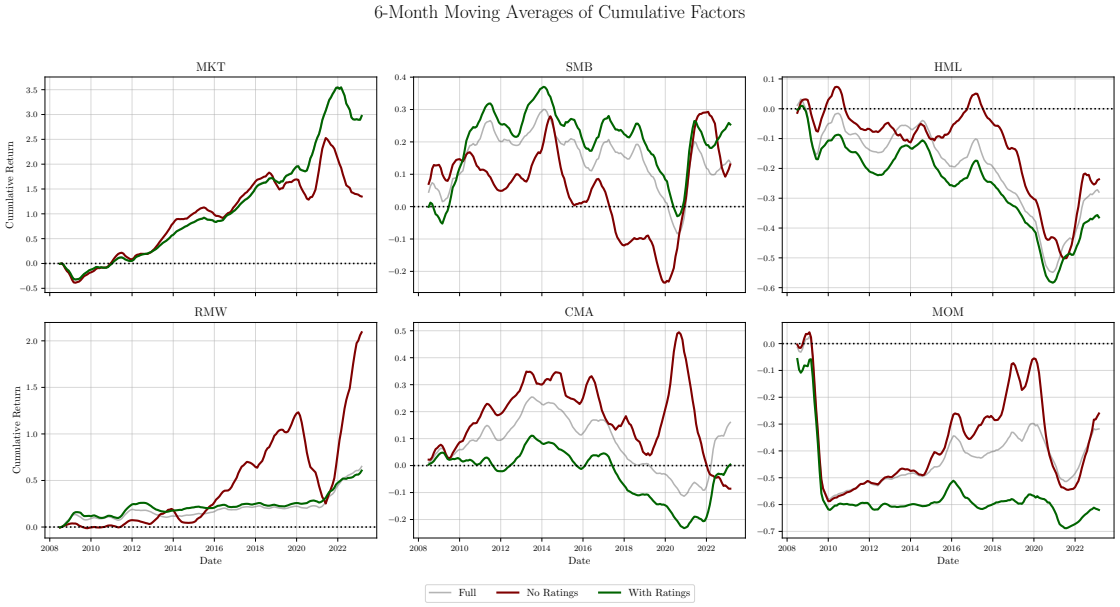
Interestingly, still, non-rated firms exhibit meaningful different patterns to rated firms in terms of factor returns (see Figure 11). However, because non-rated firms tend to be smaller in terms of market capitalization, their impact on value-weighted portfolios is limited. Nonetheless, this remains an interesting avenue for further exploration (e.g., the patterns for CMA_t and MOM_t).

Long-run sample and industry analysis Here again, we plan to conduct additional analyses focusing on a longer-run sample and industry-specific aspects, which we believe could provide valuable insights and add further richness to our findings.

[31] As of 2025, the VOTE ETF remains active but with modest assets under management. Engine No. 1, the activist hedge fund behind the ETF's launch, has since shifted focus and is not as prominently engaged in shareholder activism on ESG issues as during the initial launch period.

[32] By contrast, the within-bucket analysis inherently requires firms to have ratings. As an alternative, non-rated firms could be grouped into the middle or low-score buckets, and we plan to try that approach as a robustness check.

Figure 11: Comparison of Factors Returns between the Non-Rated and Rated Group



Taking stock To conclude this section, although popular investment factors and anomalies exhibit strong tilts toward certain non-financial characteristics, we have proposed several approaches to reduce these exposures, including selecting specific factors within an investment style, building "ESG-trimmed" factors, and reconstructing factors within subsets of highly rated stocks. While the impact varies somewhat across factors, the first two approaches generally allow investors to substantially reduce exposure to certain "shades" with little to no financial cost. The last approach offers stronger alignment with investor preferences but comes with the risk of deviating more in terms of performance. Taken together, these methods provide a menu of options from which factor investors can choose depending on the strength of their preferences.

4 Additional results and robustness checks

This section discusses various additional results and robustness checks that we are currently working on, in complement to the the alternative approaches and considerations outlined in Section 3.4 above.

Regressions and trimmed portfolios We are currently running various factor regressions similar to those in Equations (3) and (4) below. The first regression aims to further test our results using alpha as a measure of outperformance, as opposed to relying solely on realized returns and expected returns (such as implied cost of capital and option-based estimates). Preliminary results (Table D.1), suggest that the findings are broadly consistent.

$$\begin{gathered} F_{i,t} = \alpha_i + \sum_{j \neq i} \beta_{i,j} F_{j,t} + \epsilon_{i,t} \\ F_i, F_j \in \mathcal{A} \equiv \{MKT - RF_t, SMB_t, HML_t, RMW_t, CMA_t, MOM_t\} \end{gathered} \tag{3}$$

The second regression (Equation 2) tests whether ESG-trimmed factors can effectively price the standard Fama-French type portfolios constructed from various sorts—up to 196 portfolios in total.

$$\begin{gathered} R_{i,t} = \alpha_i + \sum_{k} \beta_{i,k} F_{k,t} + \epsilon_{i,t} \\ F_k \in \mathcal{A} \equiv \{MKT - RF_t, SMB_t, HML_t, RMW_t, CMA_t, MOM_t\} \end{gathered} \tag{4}$$

Representative results are displayed in Figure D.1, which presents the average coefficients and t-statistics across these portfolios within size buckets. In summary, the ESG-trimmed factors perform well in pricing many of these common portfolios, with alphas close to zero (statistically indistinguishable from zero) and strong, significant factor loadings. We also construct trimmed portfolios and show summary statistics over time in Figure D.2, as well as regression results based on original Fama-French fractors in D.3. Testing whether ESG-trimmed factors can price these portfolios yields consistent results, as expected given their performance on the standard portfolios. We are currently exploring these analyses in much greater detail.

Other scores and measures We are in the process of testing our results using various other non-financial characteristics, including raw (non-market-adjusted) scores. Preliminary findings on these suggest broadly similar patterns. We also plan to try additional metrics from other vendors such as Refinitiv and others. In terms of financial performance, we may also explore other measures.

Other robustness checks We are planning and conducting a range of additional robustness checks to further validate our findings.

5 Conclusion

This paper provides novel insights into the non-financial characteristics embedded in widely used investment factors and anomalies. Our findings highlight that popular factor-based and passive strategies can carry significant exposures toward particular "shades" (e.g., green, brown, *etc.*) along the environmental, social, and governance dimensions. Consequently, many investors relying on these strategies may inadvertently introduce such "shades" into their portfolios without realizing it. We argue that investors should at least be aware of these hidden exposures, and adjust for them if doing so aligns with their non-financial preferences.

We propose several approaches to reduce these exposures, including selecting specific factors within an investment style, applying a trimming method that progressively excludes low-rated firms from the investment universe to construct "ESG-trimmed" factors, and reconstructing factors within subsets of highly rated stocks. While the effect varies slightly across factors, the first two approaches generally allow investors to substantially reduce exposure to certain "shades" with little to no financial cost. The last approach —rebuilding factors within score buckets— offers stronger alignment with investor preferences, as all stocks belong to the desired score range by construction, but carries the risk of greater deviations in financial performance. Taken together, these methods provide a menu of options from which factor investors can select depending on the strength of their preferences.

Given the vast and growing amount of capital that they continue to attract, these findings have important implications for the rise of passive and smart-beta strategies in the context of sustainable finance. Investors following popular index-based approaches should be mindful of hidden ESG exposures, or risk inadvertently supporting the very dimensions they may wish to avoid. Future research could further explore how these implicit tilts interact with evolving investor preferences or regulatory changes, and some of the approaches that we propose could also drive financial innovation —particularly with the rapid development of so-called direct indexing.

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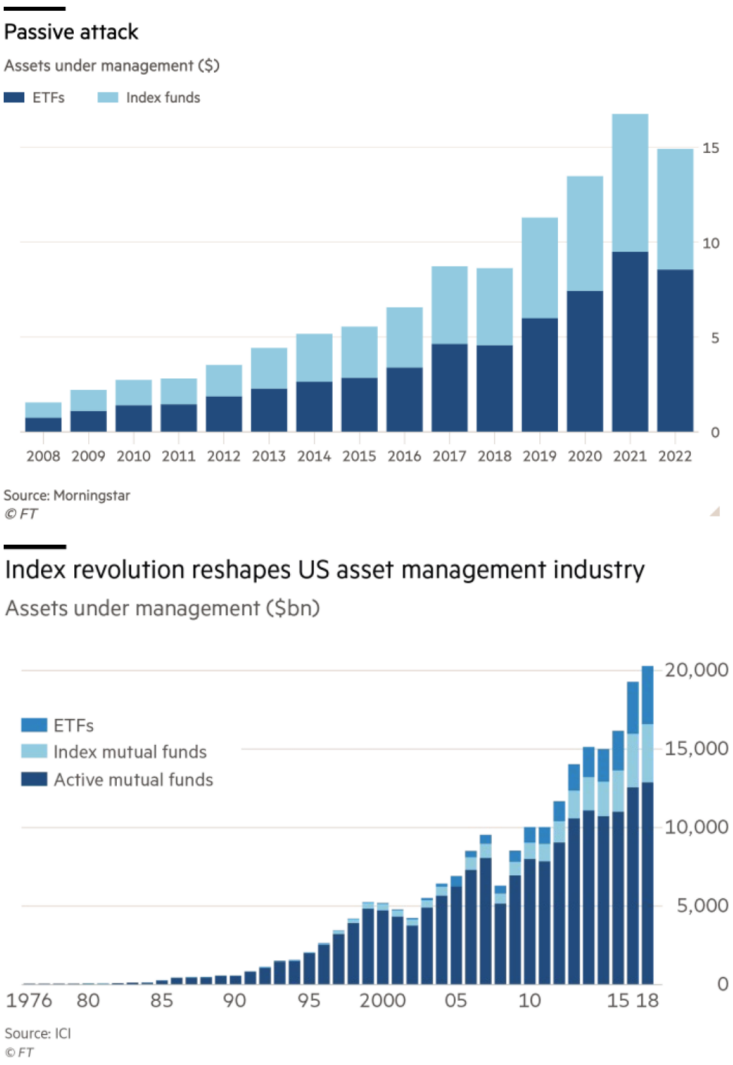
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Appendix

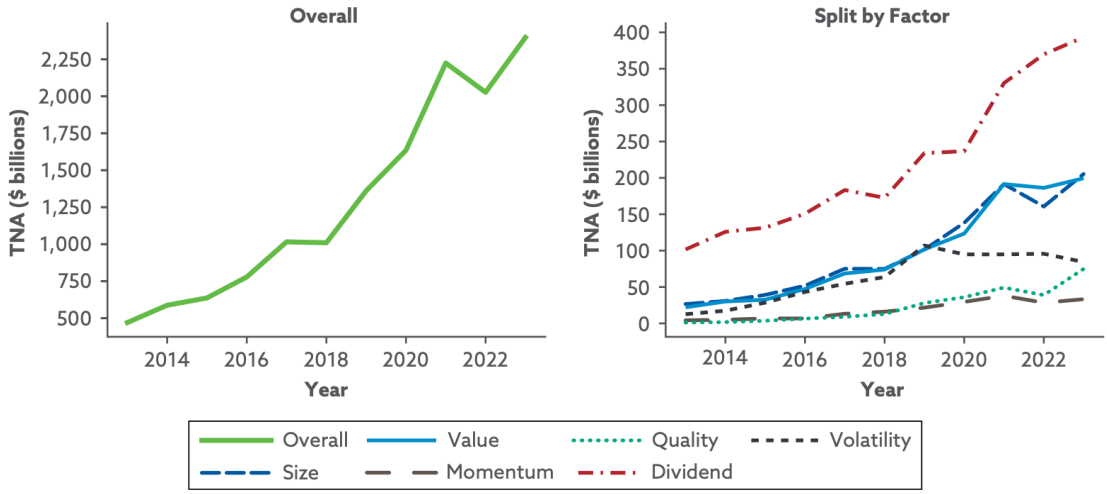
A Additional figures for the introduction

Figure A.1: Passive strategies Asset Under Management (AUM)



Notes:The figure shows global assets under management (AUM) for passive strategies (including ETFs and index funds) have exceeded $15 trillion based on Morningstar data.

Figure A.2: Smart-beta ETFs Total Net Assets (TNA)



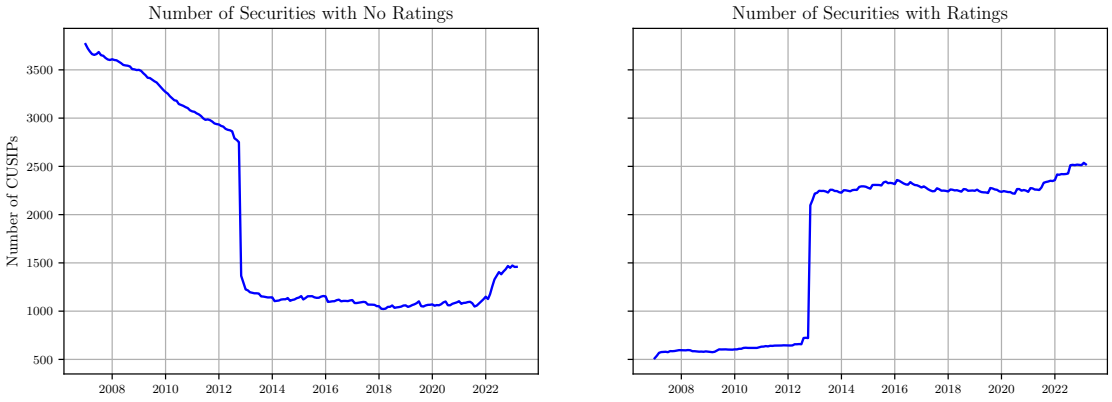
Notes: This figure, presented in the report by CFA Institute Research & Policy Center shows the total net asset (TNA) for smart beta ETFs alone surpassed $2 trillion.

B Additional results on the shades of investment factors

B.1 Non-financial performance measures, factor construction, and data sources

Figure B.1: Coverage of Non-Financial Performance Measures

(a) MSCI Coverage



(b) Trucost Coverage

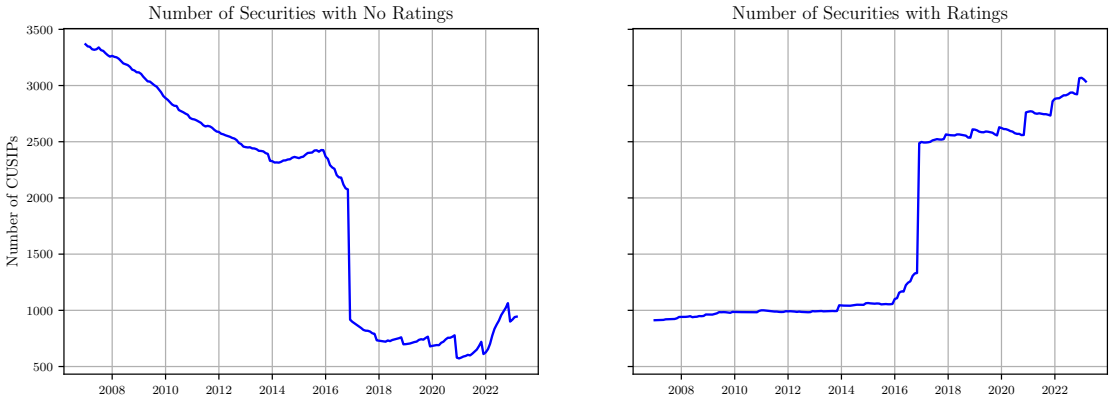


Table B.1: Summary Statistics of Non-financial Performance Measures: Main Sample

Measure	min	$1st$	$10th$	$25th$	$50th$	$75th$	$90th$	$99th$	max	mean
Environmental Score ($e_{i,t}$, MSCI)	-7.00	-3.911	-2.230	-1.034	-0.122	0.643	0.988	1.481	1.919	-0.359
-Carbon Intensity ($-ci_{i,t}$, Trucost)	-4138.836	-3383.065	-296.803	47.559	135.457	187.796	233.877	308.099	346.905	-31.506
Social Score ($s_{i,t}$, MSCI)	-5.41	-2.848	-1.570	-0.953	-0.092	0.910	1.551	2.271	3.013	-0.060
Governance Score ($g_{i,t}$, MSCI)	-4.46	-2.101	-0.862	-0.303	0.253	0.663	0.910	1.244	2.058	0.114

Table B.2: Summary Statistics of Non-financial Performance Measures: Long-run Sample

Measure	min	$1st$	$10th$	$25th$	$50th$	$75th$	$90th$	$99th$	max	mean
Environmental Score ($e_{i,t}$, MSCI)	-6.416	-3.442	-2.121	-0.969	-0.044	0.660	1.045	1.334	1.719	-0.289
-Carbon Intensity ($-ci_{i,t}$, Trucost)	-3825.261	-3438.616	-310.369	87.168	186.800	248.610	324.705	449.775	509.825	16.739
Social Score ($s_{i,t}$, MSCI)	-5.488	-2.765	-1.617	-1.070	-0.224	0.671	1.183	1.766	2.357	-0.231
Governance Score ($g_{i,t}$, MSCI)	-3.406	-1.845	-0.869	-0.407	0.069	0.412	0.669	1.188	1.396	-0.029

Notes: Summary statistics of non-financial measures of main sample and long-run sample

B.2 Main results: the shades of investment factors

Table B.3: Non-Financial Performance ("Shades") of Seminal Investment Factors

Factor (j)	Environmental Score ($e_{j,t}$, MSCI)	$-$Carbon Intensity ($-ci_{j,t}$, Trucost)	Social Score ($s_{j,t}$, MSCI)	Governance Score ($g_{j,t}$, MSCI)
SMB_t	-0.388	-21.974	-0.185	0.027
HML	-0.443	-328.459	0.113	-0.091
RMW	0.246	240.388	-0.041	0.077
CMA	-0.141	-50.489	0.101	-0.038
MOM	0.156	51.396	-0.103	0.016
MKT	0.006	-3.821	0.018	-0.004
MKT (unadj.)	5.841	-244.551	4.691	5.340

Notes: The table shows the average non-financial performance of seminal investment factors over the longest available sample, based on MSCI scores (January 2007 to March 2023) and Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness". Details are provided in Section 2.1. Figure 1 in Section 2.2 presents the same results in a graphical format.

Table B.4: Summary Statistics of Shades of Seminal Investment Factors

Factor (j)	min	$1st$	$10th$	$25th$	$50th$	$75th$	$90th$	$99th$	max	mean
Environmental Score ($e_{j,t}$), MSCI										
SMB	-0.604	-0.581	-0.524	-0.457	-0.387	-0.312	-0.257	-0.175	-0.100	-0.389
HML	-0.696	-0.688	-0.647	-0.533	-0.433	-0.356	-0.271	-0.071	0.057	-0.441
RMW	-0.159	-0.150	-0.088	0.029	0.247	0.407	0.662	0.814	0.850	0.245
CMA	-0.710	-0.680	-0.556	-0.313	-0.168	-0.002	0.291	0.627	0.669	-0.140
MOM	-0.899	-0.771	-0.460	-0.156	0.171	0.463	0.673	1.161	1.205	0.153
MKT	-0.047	-0.028	-0.012	-0.003	0.006	0.013	0.023	0.048	0.049	0.006
MKT (raw)	5.281	5.302	5.471	5.623	5.724	5.964	6.436	6.562	6.578	5.841
-Carbon Intensity ($-ci_{j,t}$), Trucost										
SMB	103.103	97.110	52.953	39.024	-26.351	-74.190	-103.970	-161.280	-174.396	-21.974
HML	-149.278	-160.850	-201.950	-218.599	-283.745	-442.669	-481.082	-550.719	-596.002	-328.459
RMW	479.910	438.847	374.167	335.310	269.385	118.928	89.901	74.488	66.702	240.388
CMA	303.033	298.272	56.129	6.868	-73.910	-115.708	-171.526	-230.552	-242.754	-50.489
MOM	589.839	466.530	301.543	171.295	55.953	-80.131	-206.133	-380.600	-489.152	51.396
MKT	16.755	8.033	1.952	-0.543	-3.646	-7.357	-9.846	-16.301	-20.170	-3.821
MKT (raw)	-139.006	-143.466	-171.285	-199.410	-247.961	-283.433	-320.508	-340.452	-371.820	-244.551
Social Score ($s_{j,t}$), MSCI										
SMB	-0.664	-0.641	-0.550	-0.279	-0.128	-0.062	-0.020	0.219	0.258	-0.185
HML	-0.318	-0.251	-0.184	-0.043	0.080	0.318	0.391	0.496	0.545	0.111
RMW	-0.558	-0.539	-0.338	-0.235	-0.047	0.146	0.244	0.364	0.376	-0.040
CMA	-0.874	-0.813	-0.458	-0.049	0.134	0.355	0.570	0.678	0.706	0.101
MOM	-1.169	-1.111	-0.524	-0.269	-0.092	0.118	0.318	0.563	0.614	-0.102
MKT	-0.017	-0.012	-0.001	0.006	0.017	0.028	0.044	0.058	0.063	0.018
MKT (raw)	3.918	3.939	4.018	4.157	4.576	5.108	5.698	5.819	5.832	4.691
Governance Score ($g_{j,t}$), MSCI										
SMB	-0.445	-0.424	-0.275	-0.171	0.093	0.146	0.257	0.320	0.354	0.027
HML	-0.482	-0.455	-0.330	-0.231	-0.092	0.040	0.154	0.201	0.229	-0.091
RMW	-0.143	-0.097	-0.041	0.004	0.088	0.159	0.193	0.228	0.260	0.077
CMA	-0.349	-0.316	-0.243	-0.141	-0.015	0.060	0.124	0.236	0.240	-0.038
MOM	-0.325	-0.269	-0.136	-0.072	0.006	0.092	0.189	0.368	0.441	0.016
MKT	-0.024	-0.023	-0.013	-0.009	-0.003	0.002	0.006	0.013	0.014	-0.004
MKT (raw)	4.332	4.406	4.610	4.744	5.432	5.714	6.031	6.250	6.340	5.340

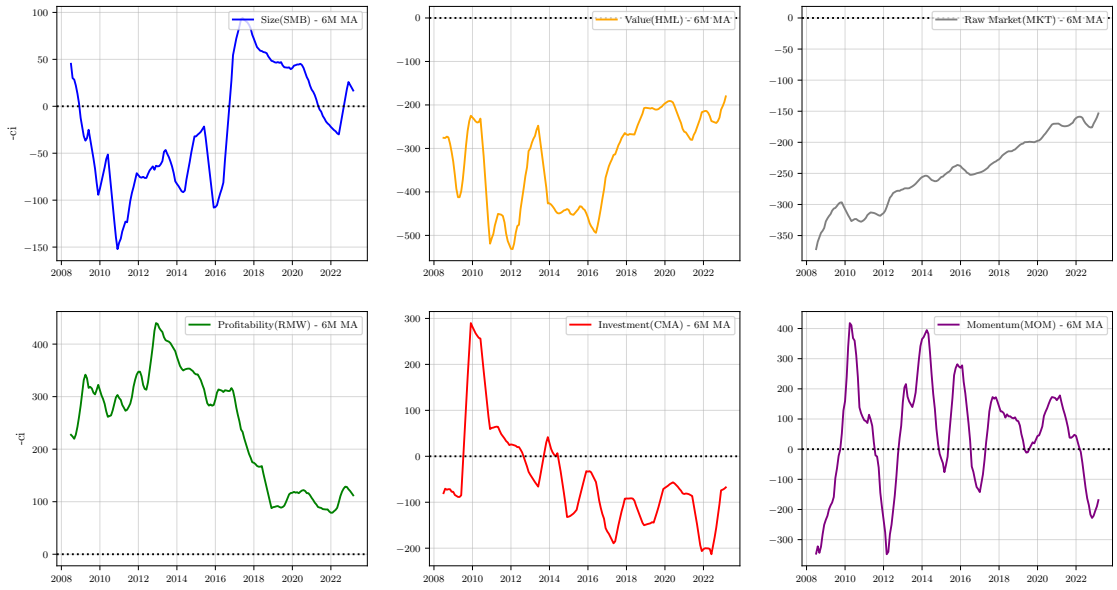
Notes: The table shows the descriptive statistics of non-financial performance of seminal investment factors over the main sample, based on MSCI scores (January 2007 to March 2023) and Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness".

Table B.5: Summary Statistics of Long-run Shades of Seminal Investment Factors

Factor (j)	min	$1th$	$10th$	$25th$	$50th$	$75th$	$90th$	$99th$	max	mean
Environmental Score ($e_{j,t}$), MSCI										
SMB	-0.696	-0.679	-0.472	-0.404	-0.308	-0.220	-0.168	-0.117	-0.090	-0.322
HML	-1.401	-1.363	-1.184	-0.941	-0.740	-0.531	-0.355	-0.082	0.016	-0.733
RMW	-0.121	-0.082	0.008	0.209	0.356	0.550	0.714	0.934	0.977	0.365
CMA	-1.205	-1.145	-0.726	-0.447	-0.307	-0.150	-0.008	0.242	0.263	-0.329
MOM	-1.411	-0.970	-0.556	-0.287	0.053	0.369	0.576	1.005	1.197	0.041
MKT	-0.060	-0.040	-0.018	-0.010	0.000	0.008	0.015	0.032	0.048	-0.001
MKT (raw)	5.098	5.122	5.214	5.305	5.483	5.836	6.109	6.528	6.577	5.589
-Carbon Intensity ($-ci_{j,t}$), Trucost										
SMB	353.545	341.711	239.310	187.498	115.482	54.005	22.472	-39.653	-56.307	125.398
HML	-184.873	-208.129	-259.540	-353.281	-541.719	-669.123	-874.804	-1057.110	-1147.071	-540.677
RMW	868.295	764.967	546.817	418.794	285.609	177.041	128.213	70.891	48.555	313.939
CMA	330.833	312.023	43.895	-51.228	-155.669	-246.121	-367.396	-529.595	-544.368	-150.447
MOM	882.269	624.219	301.443	135.466	12.026	-130.387	-278.017	-478.226	-670.927	10.260
MKT	30.432	17.193	6.086	1.378	-3.440	-8.446	-13.307	-23.608	-30.091	-3.541
MkT (raw)	-139.006	-158.975	-224.197	-299.151	-465.091	-684.318	-728.380	-774.279	-781.564	-478.427
Social Score ($s_{j,t}$), MSCI										
SMB	-0.663	-0.540	-0.463	-0.395	-0.332	-0.286	-0.248	-0.176	-0.159	-0.344
HML	-0.547	-0.471	-0.048	0.085	0.226	0.440	0.552	0.787	0.830	0.240
RMW	-0.525	-0.502	-0.312	-0.205	-0.051	0.099	0.234	0.641	0.725	-0.038
CMA	-0.358	-0.348	-0.027	0.051	0.225	0.396	0.593	0.883	0.923	0.245
MOM	-0.993	-0.822	-0.483	-0.296	-0.046	0.216	0.463	1.027	1.292	-0.027
MKT	-0.029	-0.019	-0.005	0.003	0.011	0.021	0.031	0.044	0.062	0.012
MKT (raw)	3.918	3.962	4.376	5.487	5.729	5.917	6.099	6.249	6.270	5.511
Governance Score ($g_{j,t}$), MSCI										
SMB	-0.311	-0.281	-0.255	-0.222	-0.156	-0.036	0.037	0.084	0.092	-0.125
HML	-0.273	-0.240	-0.109	-0.047	0.054	0.167	0.228	0.340	0.354	0.056
RMW	-0.254	-0.247	-0.143	-0.066	-0.017	0.067	0.144	0.192	0.213	-0.005
CMA	-0.193	-0.138	-0.087	-0.021	0.043	0.096	0.134	0.214	0.222	0.035
MOM	-0.339	-0.261	-0.157	-0.093	0.000	0.083	0.178	0.370	0.564	0.004
MKT	-0.019	-0.008	-0.004	-0.001	0.002	0.005	0.009	0.028	0.035	0.003
MKT (raw)	4.338	4.495	5.327	5.579	5.690	5.843	6.069	6.201	6.335	5.650

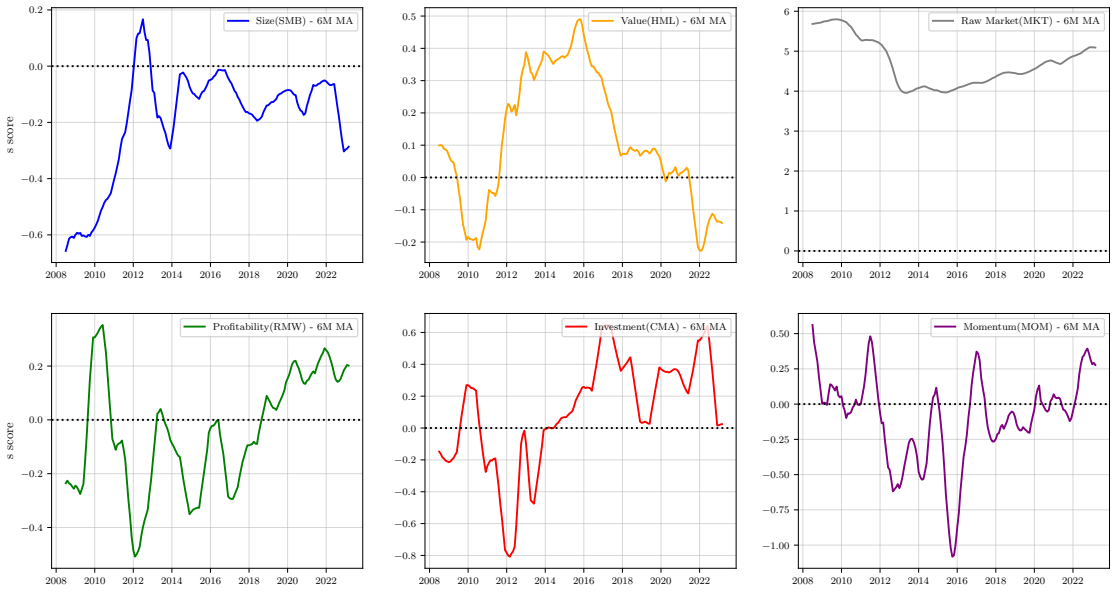
Notes: The table shows the descriptive statistics of non-financial performance of seminal investment factors over the long-run sample, based on MSCI scores and Trucost data. Carbon intensity is negated so as to measure "greenness".

Figure B.2: (Minus) Carbon Intensity of Seminal Investment Factors over Time ($-ci_{j,t}$)



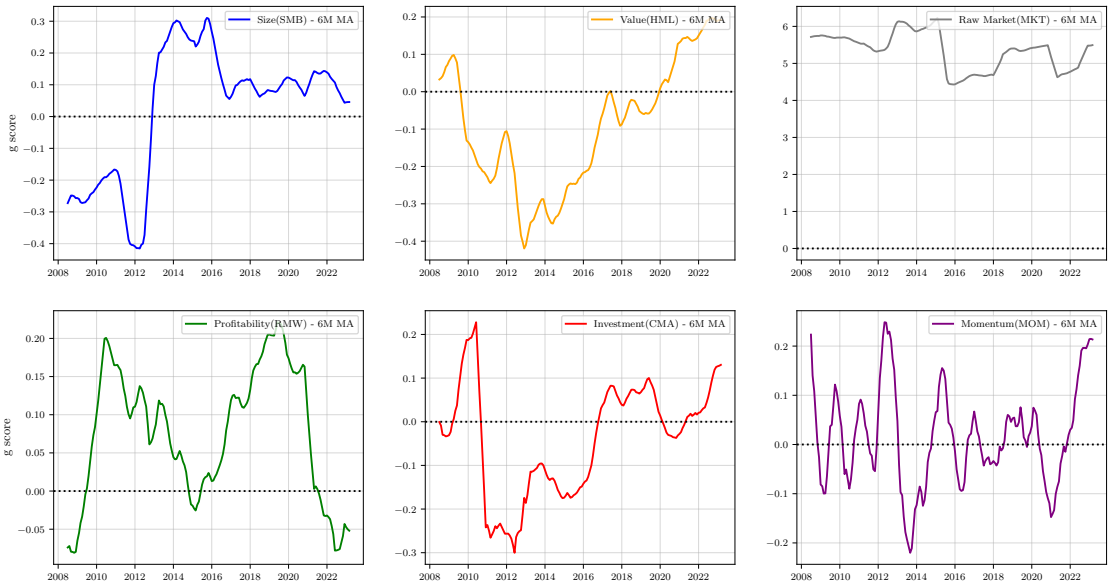
Notes: The figure shows the carbon intensity ($-ci_{j,t}$) of seminal investment factors over the longest available sample, based on Trucost data. It is negated so as to measure "greenness". Details are provided in Section 2.1. Figures 2 in the main text, and B.3-B.4 in Appendix, plot the equivalent for environmental score ($e_{j,t}$), social score ($s_{j,t}$), and governance score ($g_{j,t}$), respectively.

Figure B.3: Social Score of Seminal Investment Factors over Time ($s_{j,t}$)



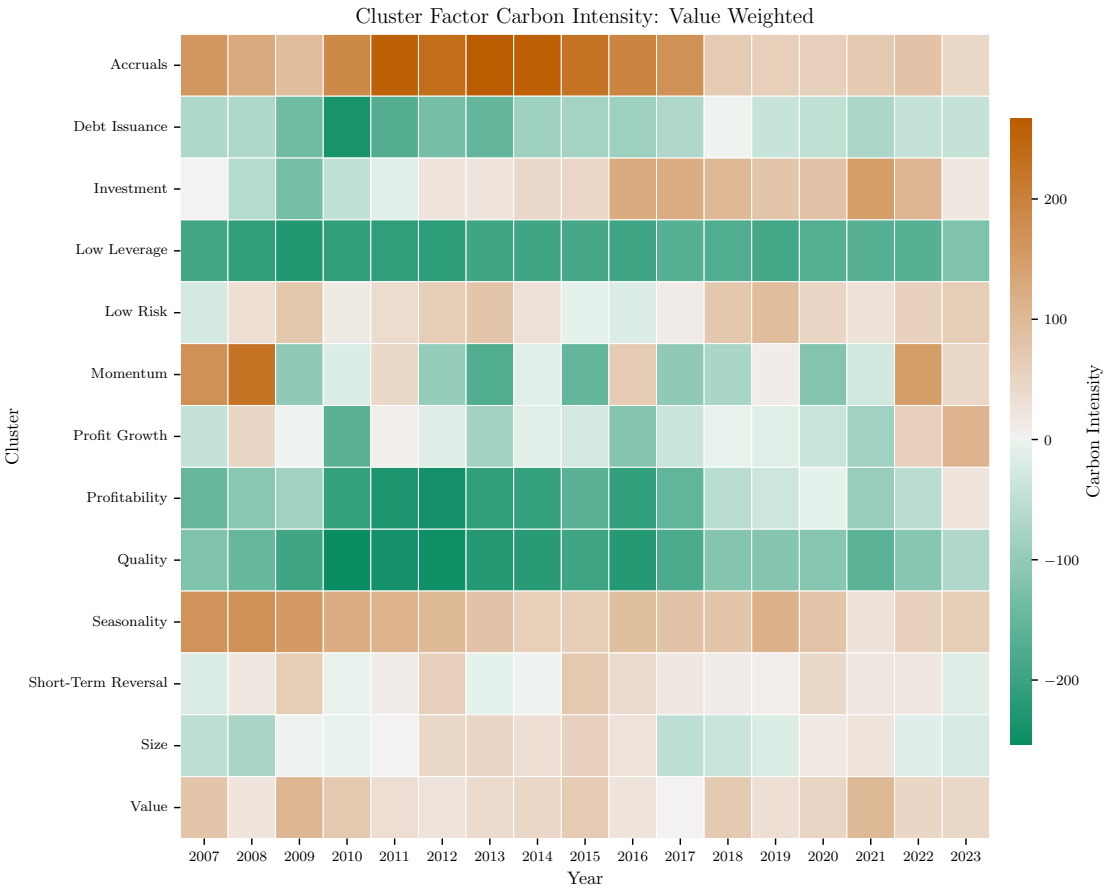
Notes: The figure shows the environmental score ($e_{j,t}$) of seminal investment factors over the longest available sample, based on MSCI data. Details are provided in Section 2.1. Figures 2 in the main text, and B.2-B.4 in Appendix, plot the equivalent for environmental score ($e_{j,t}$), (minus) carbon intensity ($-ci_{j,t}$), and governance score ($g_{j,t}$), respectively.

Figure B.4: Governance Score of Seminal Investment Factors over Time ($g_{j,t}$)



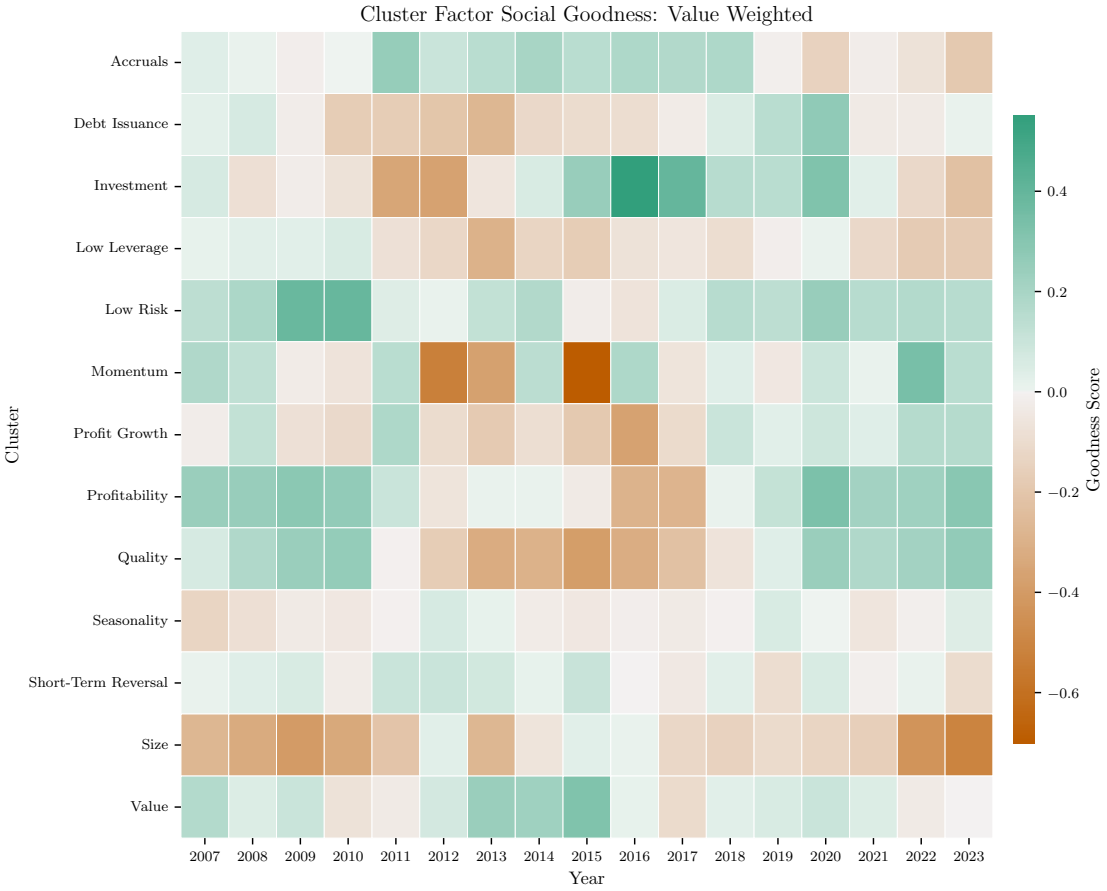
Notes: The figure shows the environmental score ($e_{j,t}$) of seminal investment factors over the longest available sample, based on MSCI data. Details are provided in Section 2.1. Figures 2 in the main text, and B.2-B.3 in Appendix, plot the equivalent for environmental score ($e_{j,t}$), (minus) carbon intensity ($-ci_{j,t}$), and social score ($s_{j,t}$), respectively.

Figure B.5: (Minus) Carbon Intensity of Anomalies by Theme Cluster over Time



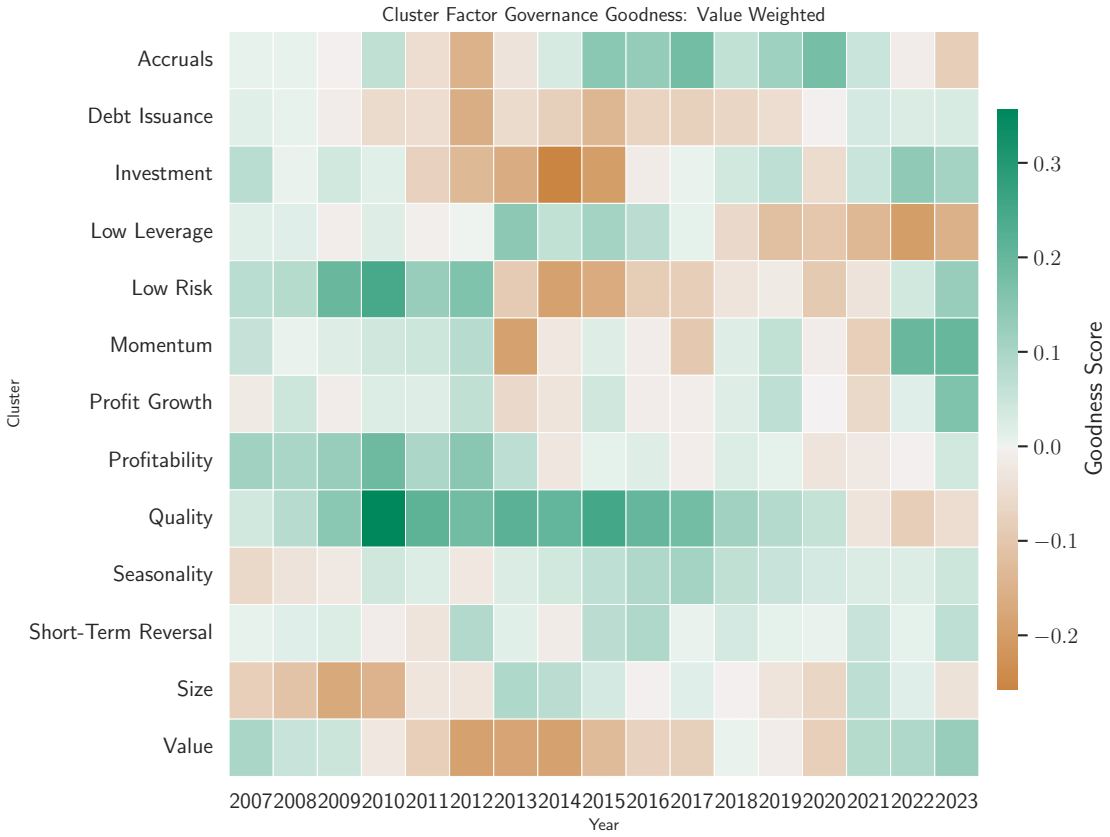
Notes: This figure shows a heatmap for (negated) carbon intensity ($-ci_{j,t}$) of each anomaly cluster over time. These anomalies are constructed over the longest available sample, based on Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness". Each cell in the heatmap represents the average "greenness" of the corresponding cluster in that year.

Figure B.6: Social Scores of Anomalies by Theme Cluster over Time



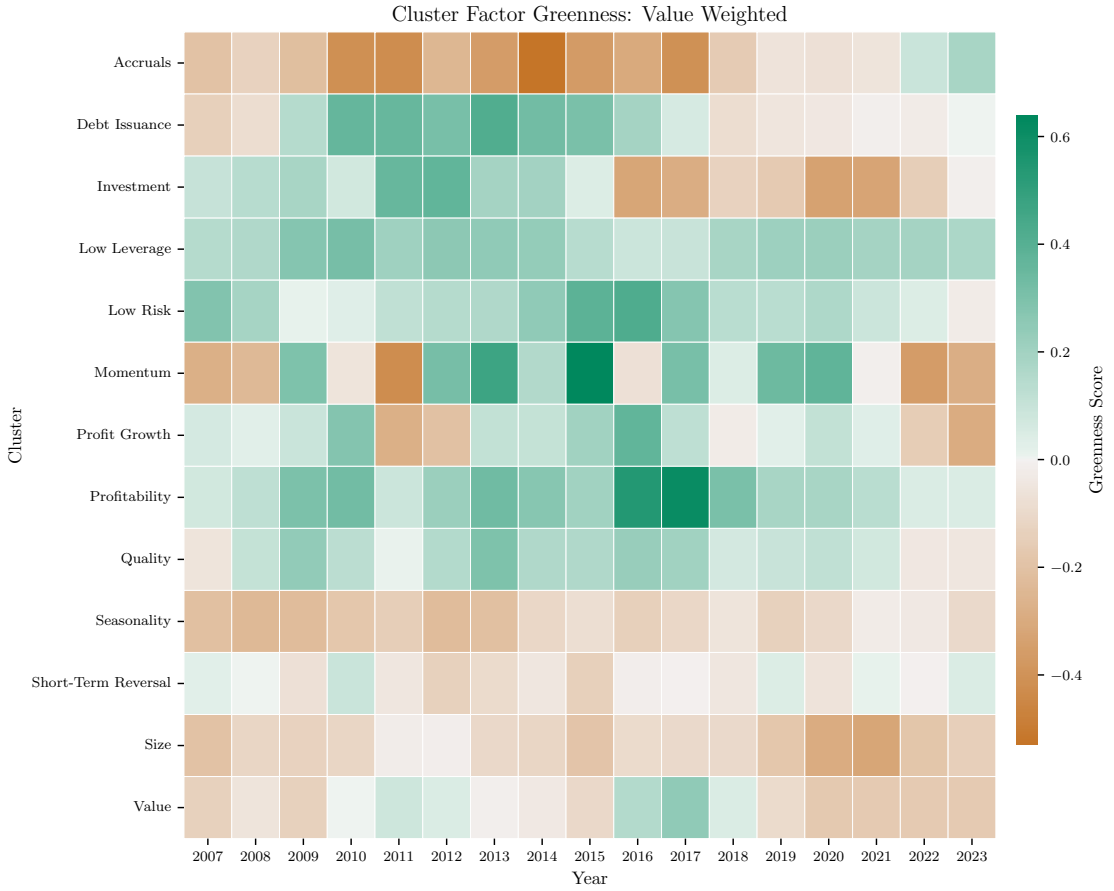
Notes: This figure shows a heatmap for the social score ($s_{j,t}$) of each anomaly cluster over time. These anomalies are constructed over the longest available sample, based on MSCI social scores (January 2007 to March 2023). Each cell in the heatmap represents the average level of socialness of the corresponding cluster in that year.

Figure B.7: Governance Scores of Anomalies by Theme Cluster over Time



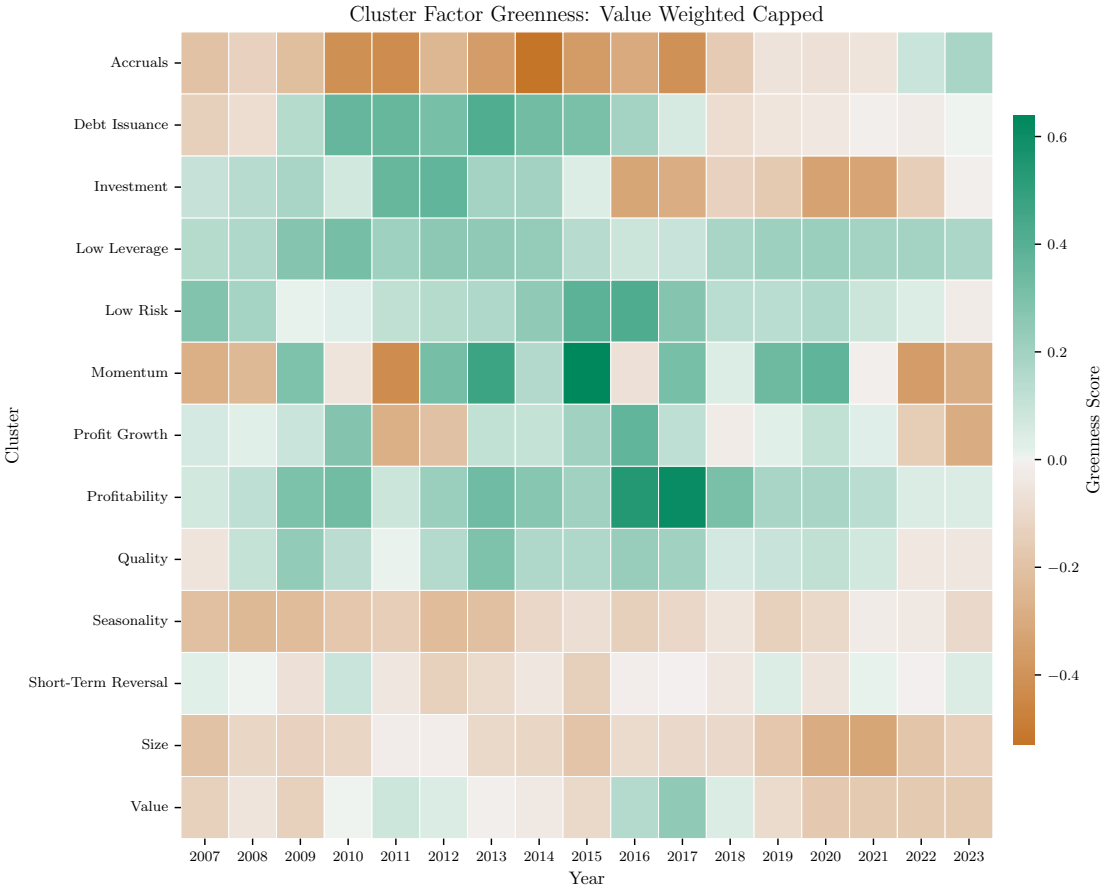
Notes: This figure shows a heatmap for the governance score ($g_{j,t}$) of each anomaly cluster over time. These anomalies are constructed over the longest available sample, based on MSCI governance scores (January 2007 to March 2023). Each cell in the heatmap represents the average level of governedness of the corresponding cluster in that year.

Figure B.8: Environmental Scores of Anomalies by Theme Cluster over Time (Value-Weighted)



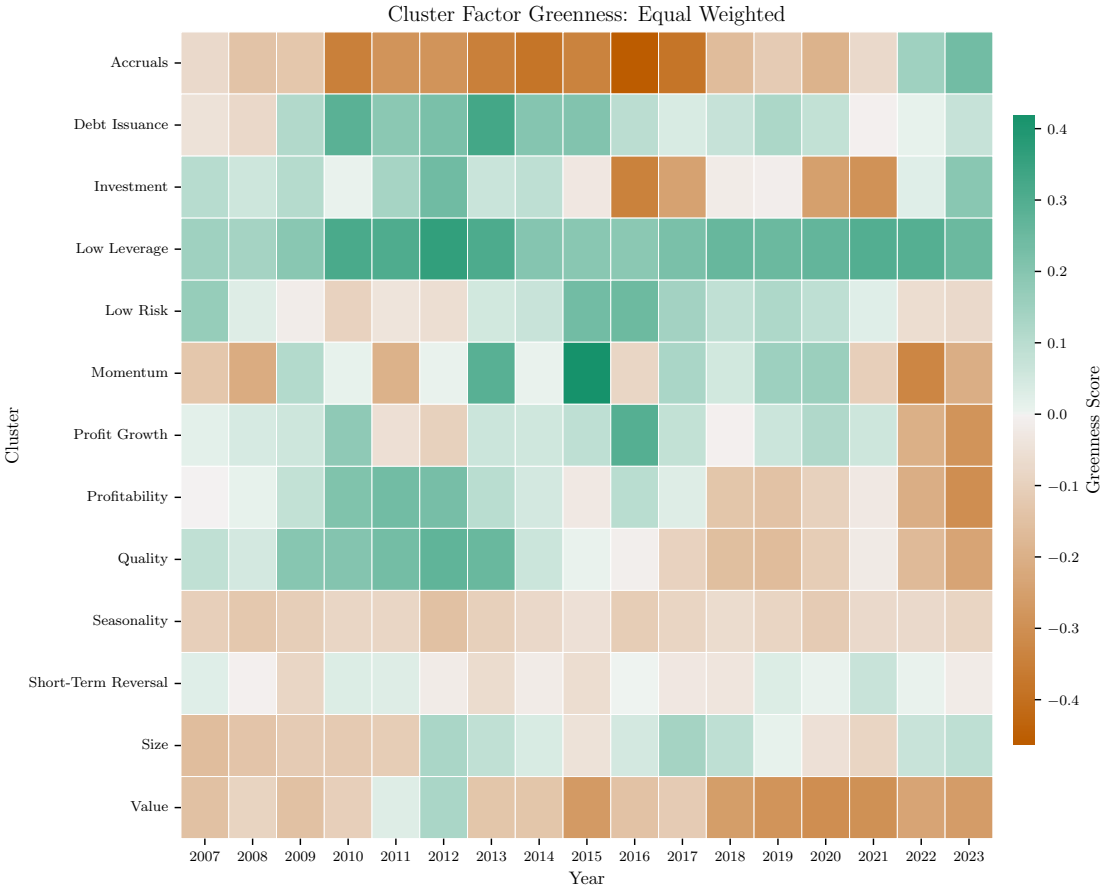
Notes: This heatmap is identical to Figure 4 in the main text, and for comparison to capped-valued-weighted (Figure B.9), and equal-weighted (Figure B.10), versions below.

Figure B.9: Environmental Scores of Anomalies by Theme Cluster over Time (Capped Value-Weighted)



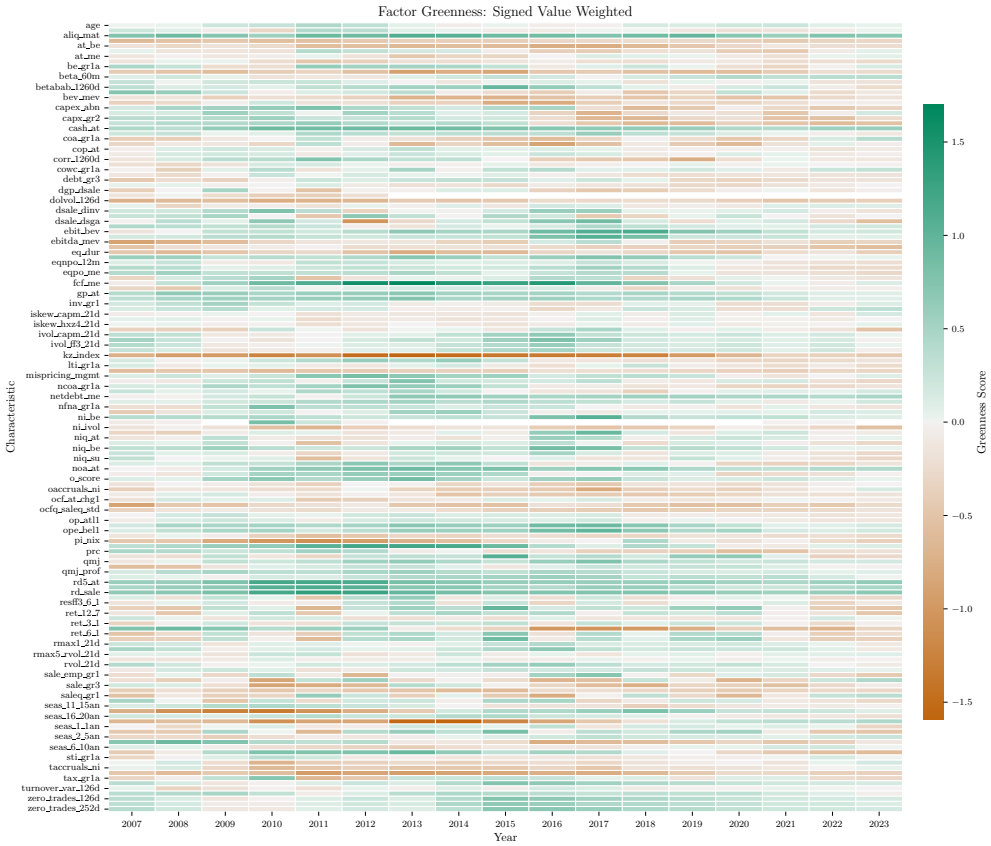
Notes: This is similar to Figure 4 in the main text (replicated in Figure B.8 for comparison), except that it is based on capped-valued-weighted averages. Figure B.10 shows the equal-weighted version.

Figure B.10: Environmental Scores of Anomalies by Theme Cluster over Time (Equal-Weighted)



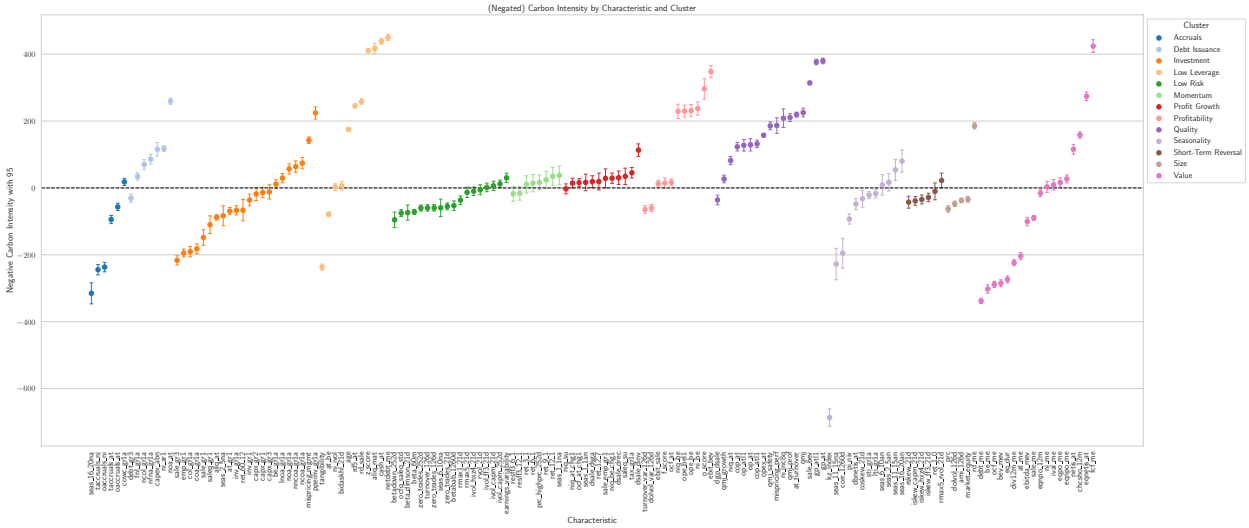
Notes: This is similar to Figure 4 in the main text (replicated in Figure B.8 for comparison), except that it is based on equal-weighted averages. Figure B.9 shows the capped-value-weighted version.

Figure B.11: Environmental Scores of All Anomalies over Time (Value-Weighted)



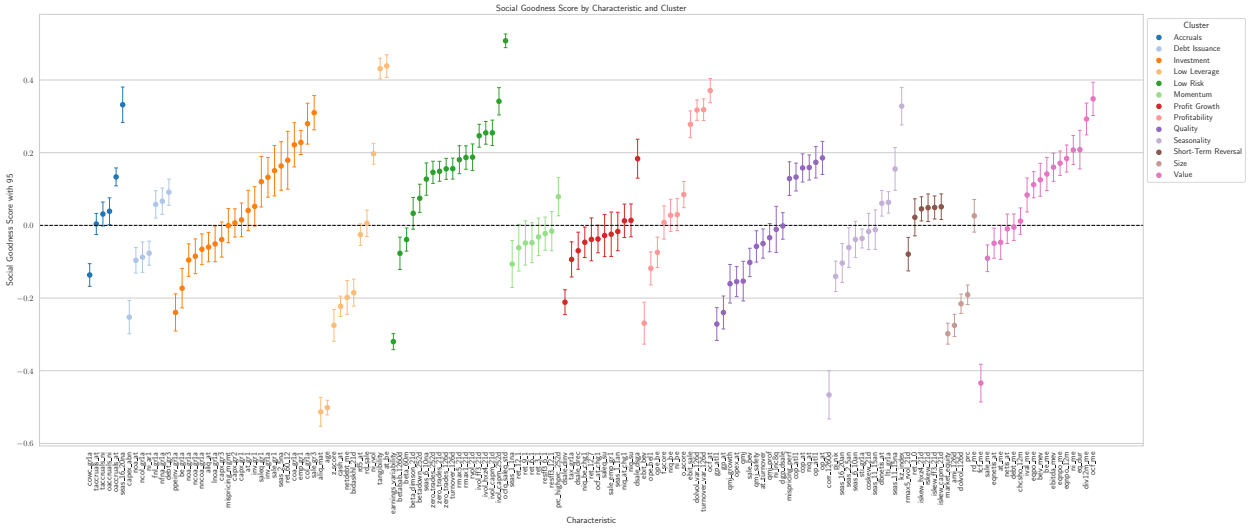
Notes: This heatmap is similar to Figure 4 in the main text, but shows the environmental scores of all underlying anomalies, as opposed to them being grouped by theme clusters.

Figure B.12: Average (Minus) Carbon Intensity by Anomaly and Theme Cluster



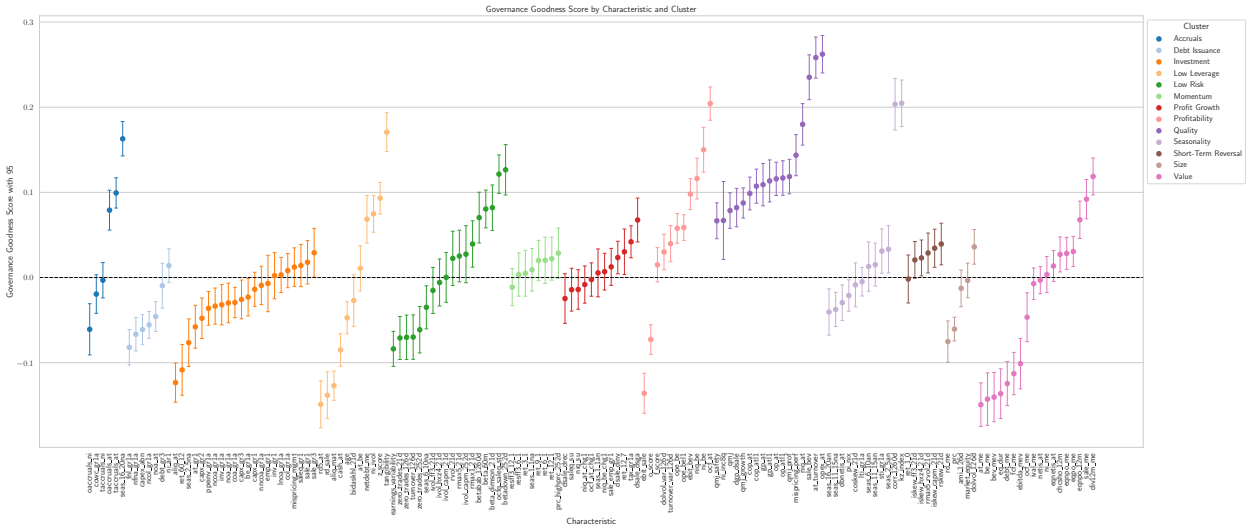
Notes: The figure reports the average (minus) carbon intensity ($-ci_{j,t}$) by anomaly and cluster. Carbon intensity is negated to better measure "greenness". Each point represents the average "greenness" of the anomaly over the longest available sample based on Trucost data, reflecting shade heterogeneity within each theme clusters.

Figure B.13: Average Social Score by Anomaly and Theme Cluster



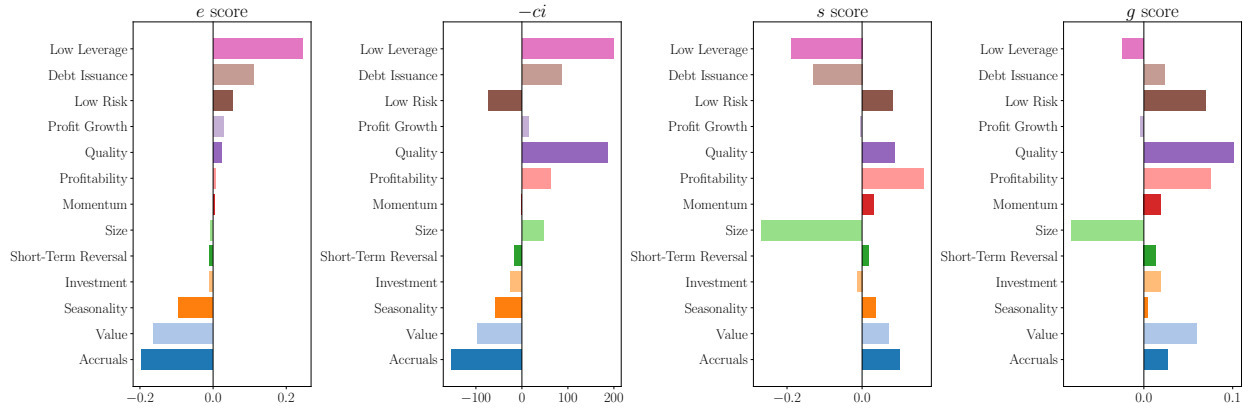
Notes: The figure reports the average social score ($s_{j,t}$) by anomaly and cluster. Each point represents the average "socialness" of the anomaly over the longest available sample based on MSCI scores, reflecting shade heterogeneity within each theme clusters.

Figure B.14: Average Governance Score by Anomaly and Theme Cluster



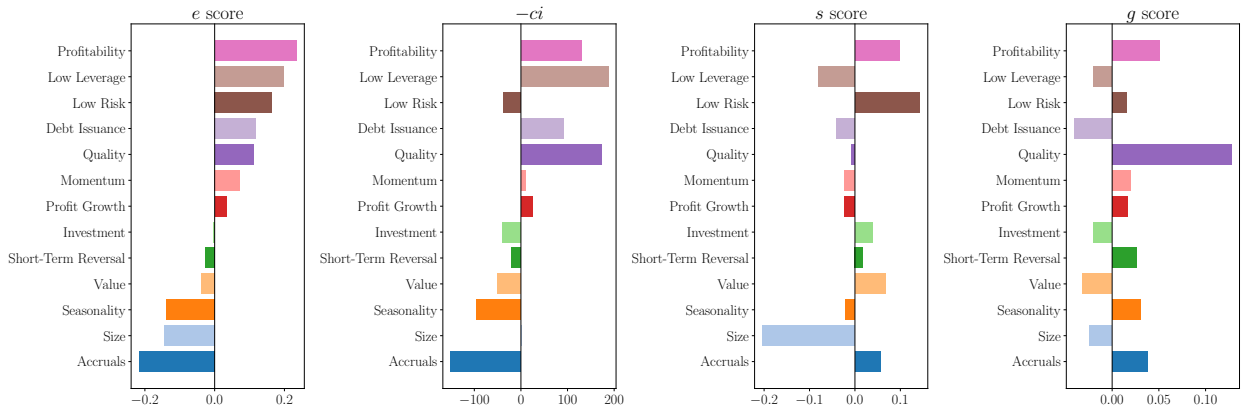
Notes: The figure reports the average governance score ($g_{j,t}$) by anomaly and cluster. Each point represents the average "governedness" of the anomaly over the longest available sample based on MSCI scores, reflecting shade heterogeneity within each theme clusters.

Figure B.15: Non-Financial Performance for Asset Pricing Anomalies, by Theme (Equal Weighted)



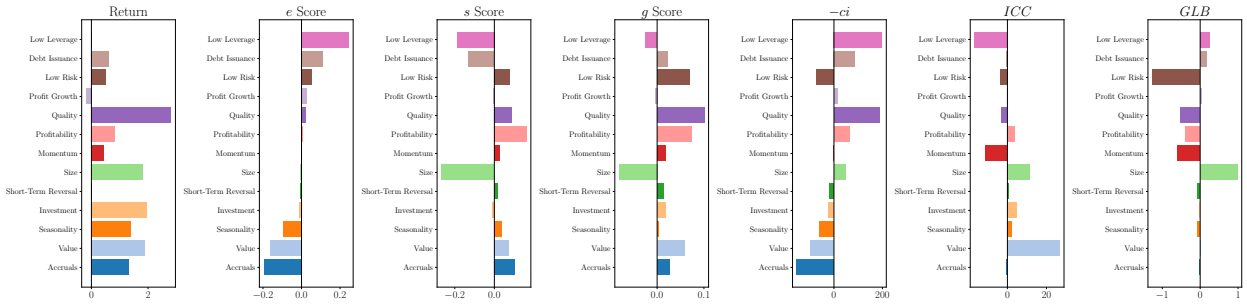
Notes: This is similar to Figure 3 in the main text, except that it is based on equal-weighted averages. Figure B.15 shows the equal-weighted version

Figure B.16: Non-Financial Performance for Asset Pricing Anomalies, by Theme (Value Weighted Capped)



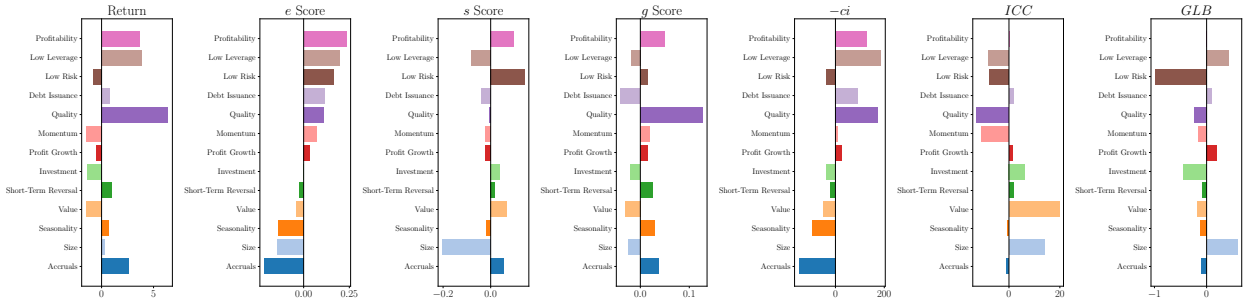
Notes: This is similar to Figure 3 in the main text, except that it is based on capped-value-weighted averages. Figure B.16 shows the capped-value-weighted version

Figure B.17: Financial vs. Non-Financial Performance for Asset Pricing Anomalies, by Theme (Equal Weighted)



Notes: This is similar to Figure 8 in the main text, except that it is based on equal-weighted averages. Figure B.18 shows the capped-value-weighted version

Figure B.18: Financial vs. Non-Financial Performance for Asset Pricing Anomalies, by Theme (Value Weighted Capped)

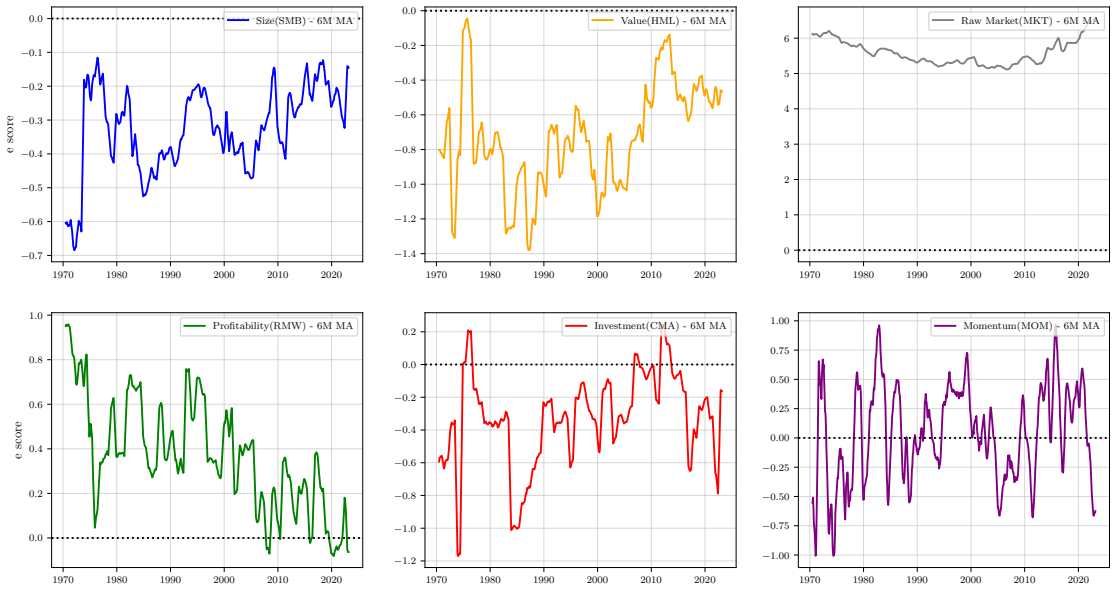


Notes: This is similar to Figure 8 in the main text, except that it is based on capped-weighted averages. Figure B.18 shows the capped-value-weighted version

B.3 Long-run sample and industry analysis

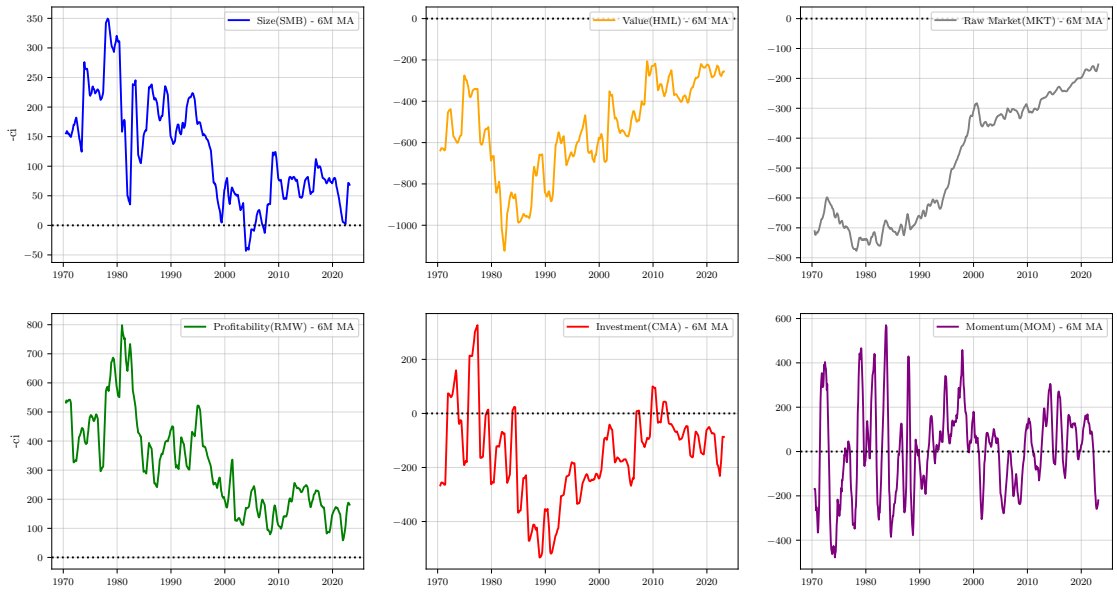
B.3.1 Long-run sample

Figure B.19: Long-Run Environmental Score of Seminal Investment Factors over Time ($e_{j,t}$)



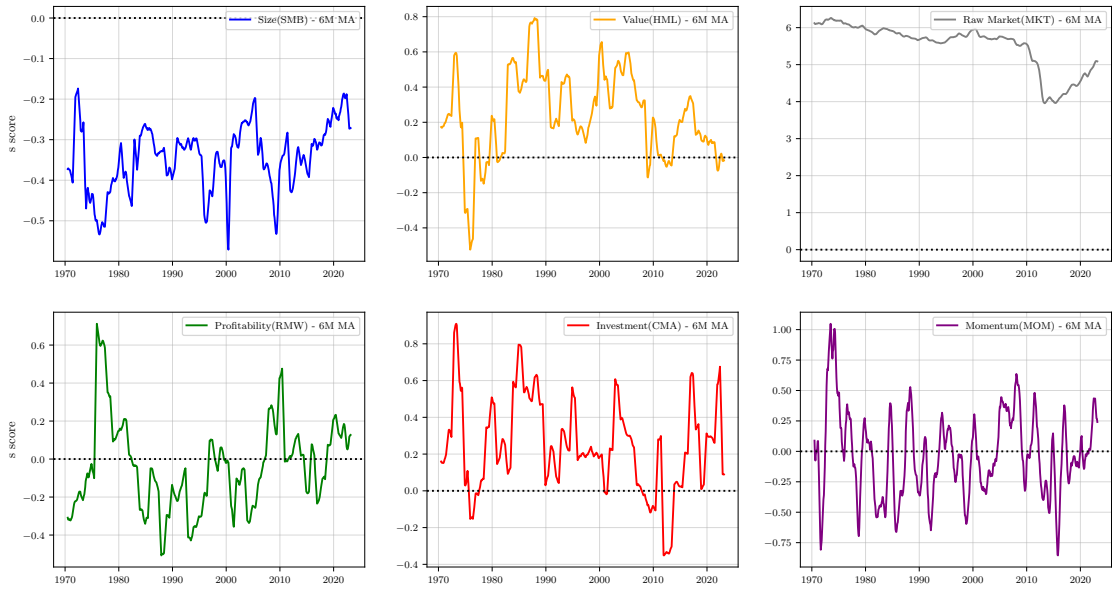
Notes: The figure shows the environmental score ($e_{j,t}$) of seminal investment factors over time over the long-run sample (January 1970-March 2023), based on MSCI data. The score of each underlying stock is computed as the average score over available data, and is assumed to be constant and known throughout the long-run sample. Details are provided in Section 2.3. Figures B.19 in the main text, and B.20-B.21 plot the equivalent for governance score ($e_{j,t}$), (minus) carbon intensity ($-ci_{j,t}$), and social score ($s_{j,t}$), respectively.

Figure B.20: Long-Run (Minus) Carbon Intensity of Seminal Investment Factors over Time ($-ci_{j,t}$)



Notes: The figure shows the carbon intensity ($-ci_{j,t}$) of seminal investment factors over time over the long-run sample (January 1970-March 2023), based on MSCI data. It is negated so as to measure "greenness". The score of each underlying stock is computed as the average score over available data, and is assumed to be constant and known throughout the long-run sample. Details are provided in Section 2.3. Figures B.19 in the main text, and B.20-B.21 plot the equivalent for governance score ($e_{j,t}$), environmental score ($e_{j,t}$), and social score ($s_{j,t}$), respectively.

Figure B.21: Long-Run Social Score of Seminal Investment Factors over Time ($s_{j,t}$)



Notes: The figure shows the social score ($s_{j,t}$) of seminal investment factors over time over the long-run sample (January 1970-March 2023), based on MSCI data. The score of each underlying stock is computed as the average score over available data, and is assumed to be constant and known throughout the long-run sample. Details are provided in Section 2.3. Figures B.19 in the main text, and B.19-B.21 plot the equivalent for governance score ($e_{j,t}$), environmental score ($e_{j,t}$), and (minus) carbon intensity ($-ci_{j,t}$), respectively.

B.3.2 Industry analysis

Table B.6: Industry distribution in the MSCI sample

Industry	**Count**	**Percentage (%)**
Manufacturing	240,487	34.30
Finance	127,200	18.14
Services	109,320	15.59
Public	75,817	10.81
Retail	37,433	5.34
Transportation	30,095	4.29
Mining	29,378	4.19
Wholesale	21,329	3.04
Utilities	20,057	2.86
Construction	7,837	1.12
Agriculture	1,513	0.22
Missing	763	0.11

Table B.7: Pro-socialness based on Social Scores by Industry and Factor

Industry	Avg	VW Avg	SMB	HML	RMW	CMA	MOM
Retail	-0.685	-1.059	0.539	-0.140	0.325	-0.067	-0.101
Finance	-0.940	-0.606	-0.372	0.092	-0.298	0.065	0.033
Transportation	-0.247	-0.340	0.036	0.074	-0.144	-0.108	0.054
Services	-0.340	-0.099	-0.551	-0.107	0.347	-0.065	0.110
Construction	0.346	-0.025	0.344	0.048	0.353	-0.037	-0.107
Manufacturing	0.280	0.301	-0.017	0.206	0.206	-0.002	-0.088
Wholesale	0.340	0.119	0.032	-0.263	0.165	-0.007	-0.111
Mining	1.126	1.148	-0.204	0.131	0.031	0.148	-0.017
Utilities	1.434	1.534	-0.345	0.349	-0.421	-0.089	-0.038

Notes: The table shows the average social score of firms by industry (first two columns), as well as that of seminal investment factors constructed within industry, over the longest available sample, based on MSCI scores (January 2007 to March 2023) and Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness". Details are provided in Section 2.3. The second column, along which industries are sorted, is the value-weighted average score of firms within each industry, and therefore corresponds to the "market" factor within each..

Table B.8: Well-governedness based on Governance Scores by Industry and Factor

Industry	Avg	VW Avg	SMB	HML	RMW	CMA	MOM
Transportation	-0.278	-0.399	0.205	-0.572	0.073	-0.166	-0.033
Construction	-0.560	-0.329	-0.228	-0.095	-0.611	0.104	0.146
Finance	0.101	-0.262	0.267	-0.118	-0.116	-0.115	0.075
Wholesale	0.180	-0.133	0.322	0.160	0.054	0.060	-0.185
Mining	-0.086	-0.081	-0.042	0.097	-0.072	-0.024	0.003
Services	0.014	-0.022	-0.334	-0.470	0.075	-0.021	0.106
Manufacturing	0.140	0.031	-0.001	-0.044	0.132	0.003	-0.064
Retail	0.457	0.414	-0.224	-0.146	0.108	-0.086	0.057
Utilities	0.603	0.610	-0.116	0.090	-0.101	0.019	0.001

Notes: The table shows the average governance score of firms by industry (first two columns), as well as that of seminal investment factors constructed within industry, over the longest available sample, based on MSCI scores (January 2007 to March 2023) and Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness". Details are provided in Section 2.3. The second column, along which industries are sorted, is the value-weighted average score of firms within each industry, and therefore corresponds to the "market" factor within each..

Table B.9: Greenness based on (minus) Carbon Intensity by Industry and Factor

Industry	Avg	VW Avg	SMB	HML	RMW	CMA	MOM
Utilities	-1672.078	-1967.244	434.632	-1050.611	718.467	-431.821	59.888
Mining	-446.590	-432.917	19.758	-50.931	-43.840	-173.383	41.184
Transportation	-57.543	33.296	-219.953	-78.262	161.740	101.547	11.595
Manufacturing	-18.723	40.091	-70.967	-191.520	23.885	-77.207	48.990
Wholesale	61.776	127.557	7.451	-58.152	43.283	-0.846	-13.725
Construction	128.965	154.941	-16.703	-6.346	19.246	-14.819	-8.900
Retail	149.783	174.160	-30.831	15.383	26.259	-10.076	-5.063
Services	171.577	198.577	-17.835	-26.244	0.321	-19.220	14.066
Finance	198.959	206.345	16.115	-28.236	32.207	10.622	4.718

Notes: The table shows the average (minus) carbon intensity of firms by industry (first two columns), as well as that of seminal investment factors constructed within industry, over the longest available sample, based on MSCI scores (January 2007 to March 2023) and Trucost data (January 2002 to January 2024). Carbon intensity is negated so as to measure "greenness". Details are provided in Section 2.3. The second column, along which industries are sorted, is the value-weighted average score of firms within each industry, and therefore corresponds to the "market" factor within each..

C Additional results on the financial cost to greenness, pro-socialness, and good governance

C.1 Trimmed factors: baseline

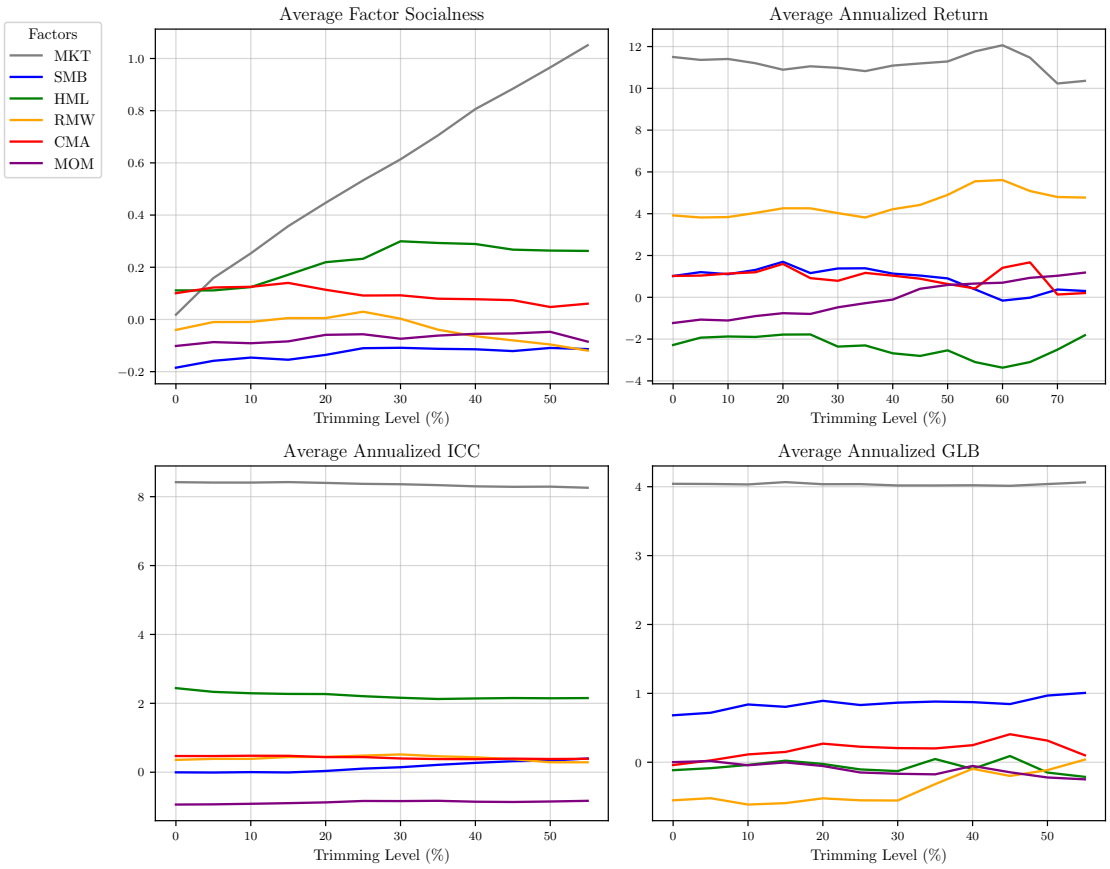
Table C.1: Average Annualized Return of Factors across Trimming Level

Factors	Trimmed Datasets															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
								Returns								
MKT	11.499	11.624	11.797	12.025	12.355	12.499	12.585	12.345	12.246	11.757	11.845	11.807	11.818	11.483	12.211	12.295
SMB	1.017	0.677	0.669	0.465	0.184	-0.071	-0.167	0.032	0.019	0.335	0.327	0.573	0.367	0.520	0.089	0.143
HML	-2.282	-2.884	-2.689	-2.415	-2.057	-2.152	-2.404	-1.660	-1.816	-1.615	-1.833	-1.822	-1.574	-2.006	-2.485	-2.838
RMW	3.919	4.049	4.229	4.216	3.969	3.944	4.076	3.758	3.549	3.631	3.845	4.118	3.939	4.118	4.280	5.348
CMA	1.022	0.654	0.208	0.126	0.212	0.145	0.148	0.266	-0.228	0.042	-0.134	-0.191	0.233	0.450	-0.352	-1.041
MOM	-1.230	-1.160	-1.323	-1.527	-1.433	-1.302	-0.901	-0.792	-0.649	-0.439	-0.431	-0.155	0.255	0.521	0.573	0.834
								Standard Deviations								
MKT	16.674	16.699	16.783	16.618	16.591	16.796	16.934	17.043	16.694	16.682	16.736	16.749	16.735	16.817	16.767	16.734
SMB	9.830	10.055	9.994	10.149	10.348	9.911	9.770	9.666	9.781	9.874	9.992	9.980	9.902	9.878	9.858	9.976
HML	11.515	12.164	12.385	12.474	12.257	11.667	11.681	11.156	11.318	11.299	11.256	11.551	11.771	11.935	12.135	12.106
RMW	6.737	8.542	8.868	8.968	9.237	9.362	9.314	8.818	7.034	7.178	7.510	7.689	7.876	8.007	8.188	8.410
CMA	6.946	7.080	7.189	7.238	7.251	7.193	7.549	7.341	6.719	6.702	6.565	6.599	6.591	6.591	6.692	6.938
MOM	16.477	15.890	15.922	15.973	16.076	16.309	16.521	16.642	16.161	15.976	15.880	15.837	15.885	15.929	15.902	15.943
Trimming Level	0%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%	60%	65%	70%	75%
Observations	701229	684795	668281	651854	635446	619037	602663	586269	569795	553258	536942	520545	503898	487504	471519	454885

Table C.2: Average Value of Factors under Different Measures across Trimming Levels

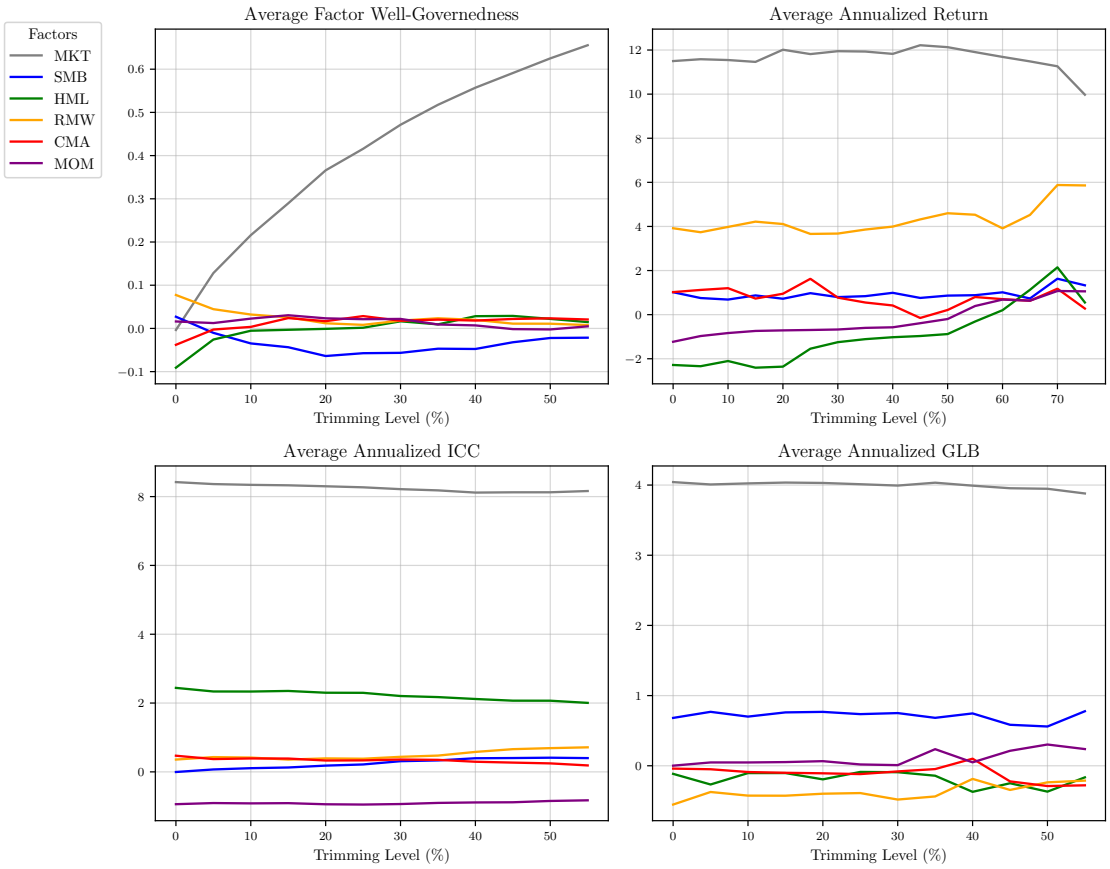
Factors	Measure	Trimmed Datasets											
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Score	0.006	0.120	0.211	0.308	0.380	0.443	0.500	0.567	0.628	0.684	0.747	0.812
	Return	11.499	11.624	11.797	12.025	12.355	12.499	12.585	12.345	12.246	11.757	11.845	11.807
MKT	ICC	8.421	8.409	8.388	8.375	8.372	8.360	8.355	8.401	8.419	8.462	8.490	8.475
	Options (GLB)	4.042	4.052	4.059	4.081	4.082	4.087	4.090	4.071	4.067	4.066	4.084	4.078
	Options (KT)	6.451	6.423	6.360	6.383	6.381	6.350	6.338	6.257	6.245	6.186	6.175	6.124
	Score	-0.389	-0.355	-0.282	-0.287	-0.239	-0.225	-0.190	-0.145	-0.148	-0.154	-0.106	-0.077
	Return	1.017	0.677	0.669	0.465	0.184	-0.071	-0.167	0.032	0.019	0.335	0.327	0.573
SMB	ICC	-0.004	-0.042	-0.058	-0.069	-0.099	-0.100	-0.098	-0.140	-0.176	-0.220	-0.274	-0.273
	Options (GLB)	0.682	0.477	0.454	0.333	0.407	0.339	0.352	0.482	0.531	0.615	0.740	0.729
	Options (KT)	16.122	15.751	15.252	13.827	13.820	14.533	15.255	15.326	15.009	16.345	15.701	16.930
	Score	-0.441	-0.268	-0.100	0.049	0.089	0.109	0.144	0.120	0.108	0.075	0.040	0.085
	Return	-2.282	-2.884	-2.689	-2.415	-2.057	-2.152	-2.404	-1.660	-1.816	-1.615	-1.833	-1.822
HML	ICC	2.441	2.465	2.439	2.518	2.569	2.634	2.665	2.736	2.794	2.832	2.914	2.964
	Options (GLB)	-0.115	-0.082	-0.075	-0.059	-0.120	-0.064	-0.111	-0.080	-0.065	-0.012	0.125	0.070
	Options (KT)	2.087	1.236	0.533	0.857	0.649	-0.946	-0.570	-0.917	-0.902	-0.559	-2.473	-2.364
	Score	0.245	0.151	0.061	-0.063	-0.107	-0.130	-0.181	-0.148	-0.143	-0.122	-0.094	-0.037
	Return	3.919	4.049	4.229	4.216	3.969	3.944	4.076	3.758	3.549	3.631	3.845	4.118
RMW	ICC	0.358	0.393	0.440	0.470	0.506	0.517	0.525	0.531	0.562	0.561	0.579	0.647
	Options (GLB)	-0.553	-0.659	-0.767	-0.870	-0.886	-0.799	-0.826	-0.790	-0.826	-0.763	-0.819	-0.906
	Options (KT)	-2.301	-2.696	-2.869	-1.873	-2.000	-2.221	-2.007	-2.129	-2.293	-1.928	-1.136	-1.282
	Score	-0.140	-0.083	-0.118	-0.138	-0.106	-0.057	-0.036	-0.007	0.011	-0.034	-0.070	-0.041
	Return	1.022	0.654	0.208	0.126	0.212	0.145	0.148	0.266	-0.228	0.042	-0.134	-0.191
CMA	ICC	0.470	0.449	0.422	0.418	0.456	0.493	0.460	0.473	0.491	0.480	0.517	0.547
	Options (GLB)	-0.040	-0.236	-0.218	-0.284	-0.370	-0.320	-0.334	-0.268	-0.217	0.067	-0.066	0.169
	Options (KT)	0.441	0.336	-0.448	2.203	2.332	0.562	0.265	1.108	0.583	2.360	0.783	3.004
	Score	0.153	0.094	0.067	0.002	-0.025	-0.032	-0.063	-0.030	-0.036	-0.032	-0.021	0.012
	Return	-1.230	-1.160	-1.323	-1.527	-1.433	-1.302	-0.901	-0.792	-0.649	-0.439	-0.431	-0.155
MOM	ICC	-0.939	-0.979	-0.954	-0.954	-0.976	-0.980	-1.009	-0.998	-1.001	-0.990	-0.997	-0.997
	Options (GLB)	0.002	0.018	0.057	0.085	0.117	0.207	0.181	0.123	0.131	0.186	0.050	-0.014
	Options (KT)	-2.740	-2.548	-2.172	-2.491	-2.253	-2.486	-2.555	-2.668	-2.734	-3.255	-3.423	-3.523

Figure C.1: Financial Performance (%) and "Shade" of Investment Factors Trimmed based on Social Score



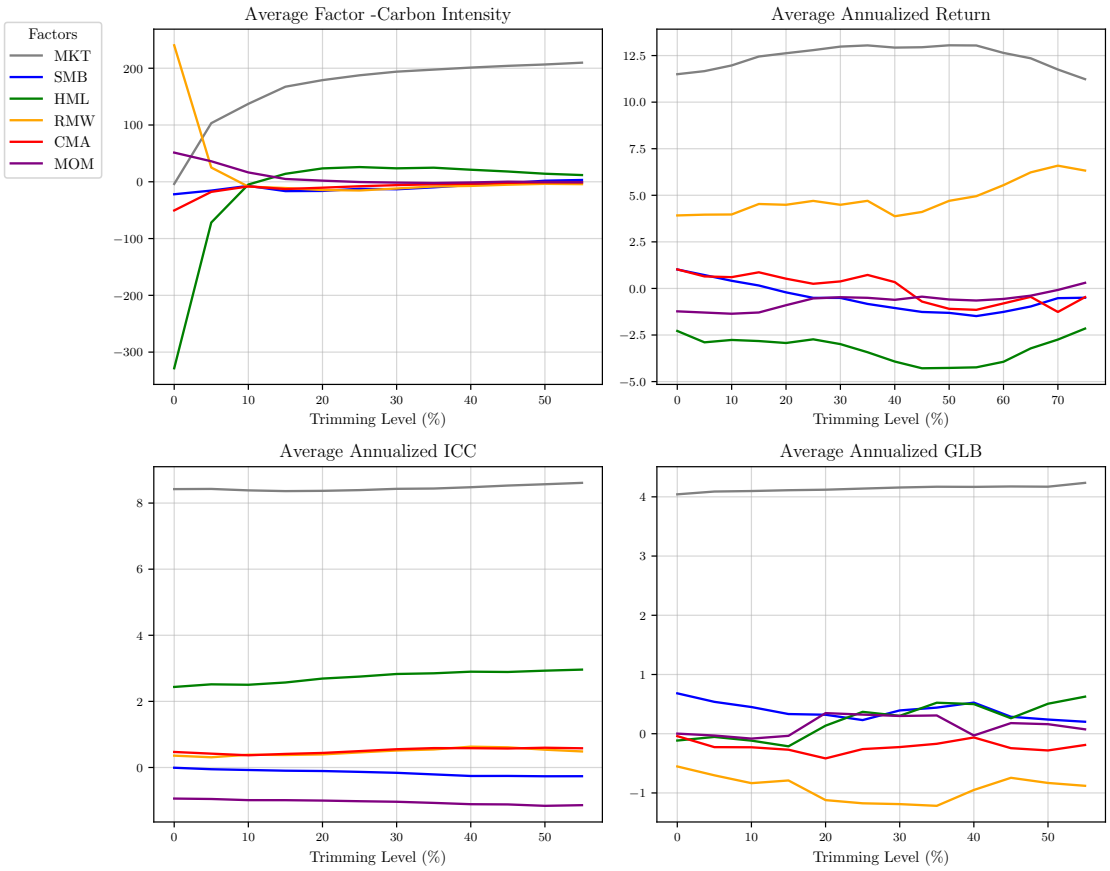
Notes: This figure shows how the average "shade" and financial performance of seminal investment factors evolve as the underlying investment universe is progressively restricted by trimming stocks with the worst social scores. The "shade" is measured using the social score, while financial performance is captured by realized returns and two measures of expected returns: the implied cost of capital (ICC) and option-based estimates (GLB).

Figure C.2: Financial Performance (%) and "Shade" of Investment Factors Trimmed based on Governance Score



Notes: This figure shows how the average "shade" and financial performance of seminal investment factors evolve as the underlying investment universe is progressively restricted by trimming stocks with the worst governance scores. The "shade" is measured using the governance score, while financial performance is captured by realized returns and two measures of expected returns: implied cost of capital (ICC) and option-based estimates (GLB).

Figure C.3: Financial Performance (%) and "Shade" of Investment Factors Trimmed based on (Minus) Carbon Intensity



Notes: This figure shows how the average "shade" and financial performance of seminal investment factors evolve as the underlying investment universe is progressively restricted by trimming stocks with the worst carbon intensities. The "shade" is measured using (minus) the carbon intensity so as to measure "greenness", while financial performance is captured by realized returns and two measures of expected returns: the implied cost of capital (ICC) and option-based estimates (GLB).

C.2 Trimmed factors: Trucost

Table C.3: Average Annualized Return of Factors across Trimming Level (Trucost Intensity)

Factors	Trimmed Datasets															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
MKT_Excess	11.499	11.664	11.970	12.449	12.625	12.791	12.981	13.045	12.927	12.947	13.051	13.042	12.642	12.354	11.751	11.233
SMB	1.017	0.718	0.411	0.158	-0.211	-0.505	-0.509	-0.832	-1.051	-1.262	-1.312	-1.484	-1.259	-0.968	-0.522	-0.499
HML	-2.282	-2.893	-2.765	-2.824	-2.929	-2.732	-2.989	-3.425	-3.924	-4.285	-4.266	-4.235	-3.936	-3.218	-2.745	-2.155
RMW	3.919	3.960	3.970	4.533	4.490	4.699	4.490	4.703	3.875	4.105	4.702	4.953	5.544	6.230	6.590	6.327
CMA	1.022	0.645	0.606	0.867	0.523	0.250	0.378	0.725	0.340	-0.704	-1.094	-1.149	-0.803	-0.452	-1.263	-0.466
MOM	-1.230	-1.294	-1.358	-1.291	-0.900	-0.536	-0.471	-0.504	-0.611	-0.441	-0.593	-0.648	-0.564	-0.388	-0.081	0.301
Observations	701229	684795	668281	651854	635446	619037	602663	586269	569795	553258	536942	520545	503898	487504	471519	454885

Table C.4: Average Annualized Return of Factors across Trimming Level (Trucost Emission)

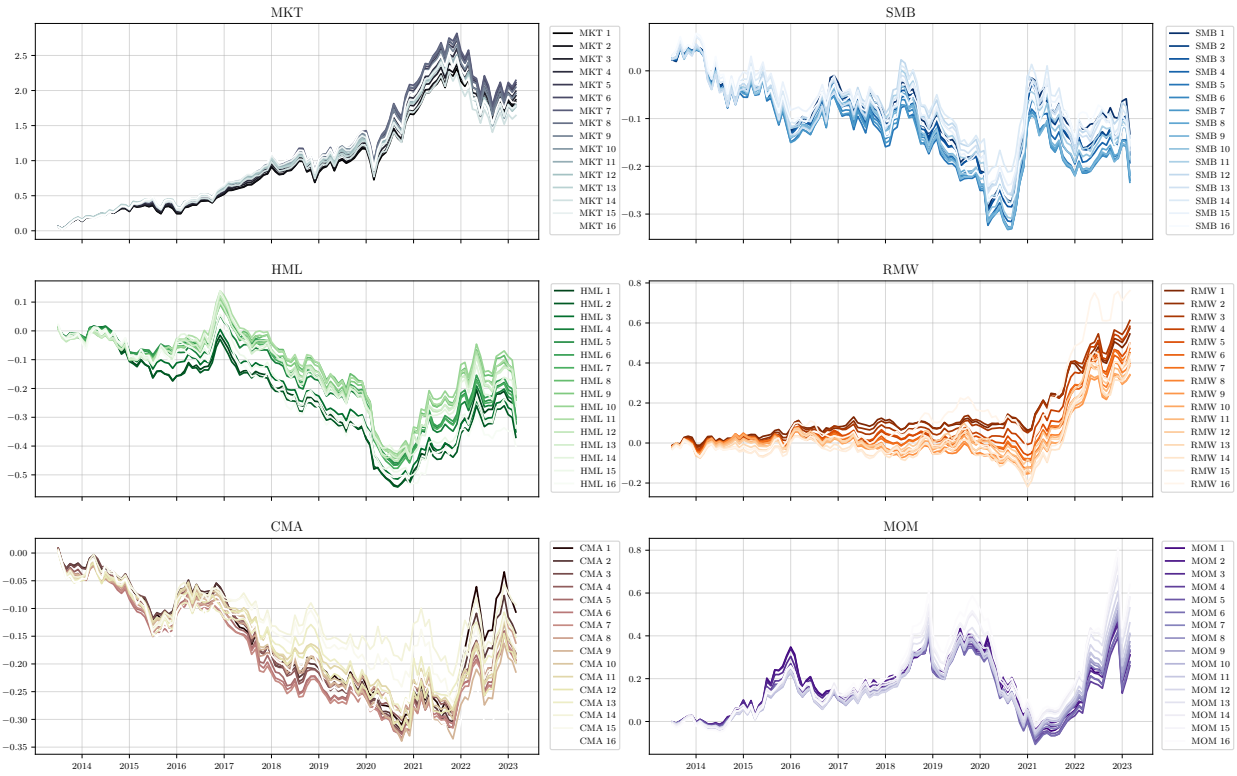
Factors	Trimmed Datasets															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
MKT_Excess	11.499	11.660	11.904	11.870	11.689	12.103	12.058	11.867	11.218	10.584	10.231	10.127	9.982	9.139	8.504	7.443
SMB	1.017	0.710	0.253	-0.040	-0.134	-0.537	-0.850	-0.544	-0.356	-0.034	0.347	0.658	0.541	0.972	1.268	1.769
HML	-2.282	-1.889	-1.500	-1.589	-1.924	-1.301	-2.341	-2.202	-1.960	-1.265	-1.478	-1.769	-1.826	-0.119	-0.052	1.284
RMW	3.919	3.822	4.282	3.826	3.915	3.562	3.518	4.175	4.288	5.007	3.690	4.161	4.370	4.866	3.905	4.054
CMA	1.022	0.537	1.135	0.933	0.693	-0.174	0.034	0.190	1.146	1.597	1.174	1.607	1.846	2.303	2.895	4.565
MOM	-1.230	-1.170	-1.154	-1.056	-1.365	-1.127	-0.809	-0.603	-0.393	-0.215	-0.006	0.186	0.218	-0.227	-0.526	0.083
Observations	701229	684969	668818	652662	636522	620372	604189	588033	571892	555722	539602	523392	507256	491085	474933	458793

Table C.5: Average Value of Factors under Different Measures across Trimming Level (Trucost)

Factors	Measure	Trimmed Datasets											
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Score	3.821	-103.232	-137.289	-167.442	-179.036	-187.551	-193.962	-197.580	-201.138	-204.193	-206.592	-209.773
	Return	11.499	11.664	11.970	12.449	12.625	12.791	12.981	13.045	12.927	12.947	13.051	13.042
MKT	ICC	8.422	8.428	8.384	8.362	8.370	8.392	8.431	8.440	8.480	8.530	8.569	8.611
	Options (GLB)	4.042	4.090	4.098	4.112	4.120	4.139	4.158	4.171	4.168	4.175	4.171	4.236
	Options (KT)	6.451	6.489	6.409	6.470	6.474	6.549	6.601	6.597	6.571	6.567	6.554	6.586
	Score	21.974	15.503	7.219	16.448	16.141	12.340	13.191	9.792	5.740	2.503	-1.920	-3.198
	Return	1.017	0.718	0.411	0.158	-0.211	-0.505	-0.509	-0.832	-1.051	-1.262	-1.312	-1.484
SMB	ICC	-0.008	-0.053	-0.076	-0.097	-0.107	-0.133	-0.161	-0.209	-0.257	-0.256	-0.266	-0.264
	Options (GLB)	0.682	0.538	0.451	0.332	0.320	0.230	0.393	0.441	0.525	0.286	0.239	0.202
	Options (KT)	16.122	14.664	14.180	14.745	14.502	14.407	15.391	15.722	16.397	17.053	16.788	17.450
	Score	328.459	71.765	4.802	-14.056	-23.573	-25.927	-23.700	-24.816	-21.229	-18.096	-14.178	-11.840
	Return	-2.282	-2.893	-2.765	-2.824	-2.929	-2.732	-2.989	-3.425	-3.924	-4.285	-4.266	-4.235
HML	ICC	2.437	2.516	2.503	2.572	2.690	2.750	2.829	2.850	2.898	2.890	2.929	2.961
	Options (GLB)	-0.115	-0.054	-0.117	-0.213	0.136	0.369	0.302	0.524	0.500	0.261	0.506	0.626
	Options (KT)	2.087	2.397	1.354	2.983	3.204	3.169	2.668	2.837	1.252	-0.396	0.325	1.084
	Score	-240.388	-25.086	8.484	10.993	14.525	15.333	11.802	8.267	7.298	5.162	3.632	4.180
	Return	3.919	3.960	3.970	4.533	4.490	4.699	4.490	4.703	3.875	4.105	4.702	4.953
RMW	ICC	0.358	0.309	0.386	0.378	0.396	0.456	0.514	0.545	0.630	0.610	0.538	0.485
	Options (GLB)	-0.553	-0.702	-0.835	-0.789	-1.121	-1.175	-1.189	-1.218	-0.950	-0.744	-0.831	-0.880
	Options (KT)	-2.301	-2.136	-1.183	-1.279	-1.199	-1.216	-0.572	-0.269	0.080	1.546	0.286	-0.771
	Score	50.489	17.775	8.132	12.777	10.408	7.857	5.903	4.323	3.536	1.851	1.054	1.122
	Return	1.022	0.645	0.606	0.867	0.523	0.250	0.378	0.725	0.340	-0.704	-1.094	-1.149
CMA	ICC	0.470	0.419	0.369	0.411	0.440	0.496	0.552	0.587	0.584	0.574	0.598	0.581
	Options (GLB)	-0.040	-0.227	-0.229	-0.270	-0.417	-0.259	-0.225	-0.170	-0.063	-0.244	-0.282	-0.190
	Option (KT)	0.441	2.309	2.209	2.281	2.964	3.201	4.429	5.433	2.618	2.353	2.215	2.215
	Score	-51.396	-36.130	-16.473	-4.928	-2.005	0.426	1.458	2.099	1.187	-0.224	0.296	0.683
	Return	-1.230	-1.294	-1.358	-1.291	-0.900	-0.536	-0.471	-0.504	-0.611	-0.441	-0.593	-0.648
MOM	ICC	-0.940	-0.953	-0.988	-0.989	-1.001	-1.021	-1.037	-1.071	-1.111	-1.118	-1.160	-1.140
	Options (GLB)	0.002	-0.031	-0.082	-0.036	0.348	0.323	0.300	0.308	-0.030	0.179	0.161	0.074
	Options (KT)	-2.734	-3.303	-2.858	-2.671	-1.932	-2.126	-2.389	-2.733	-3.445	-4.885	-5.334	-5.139

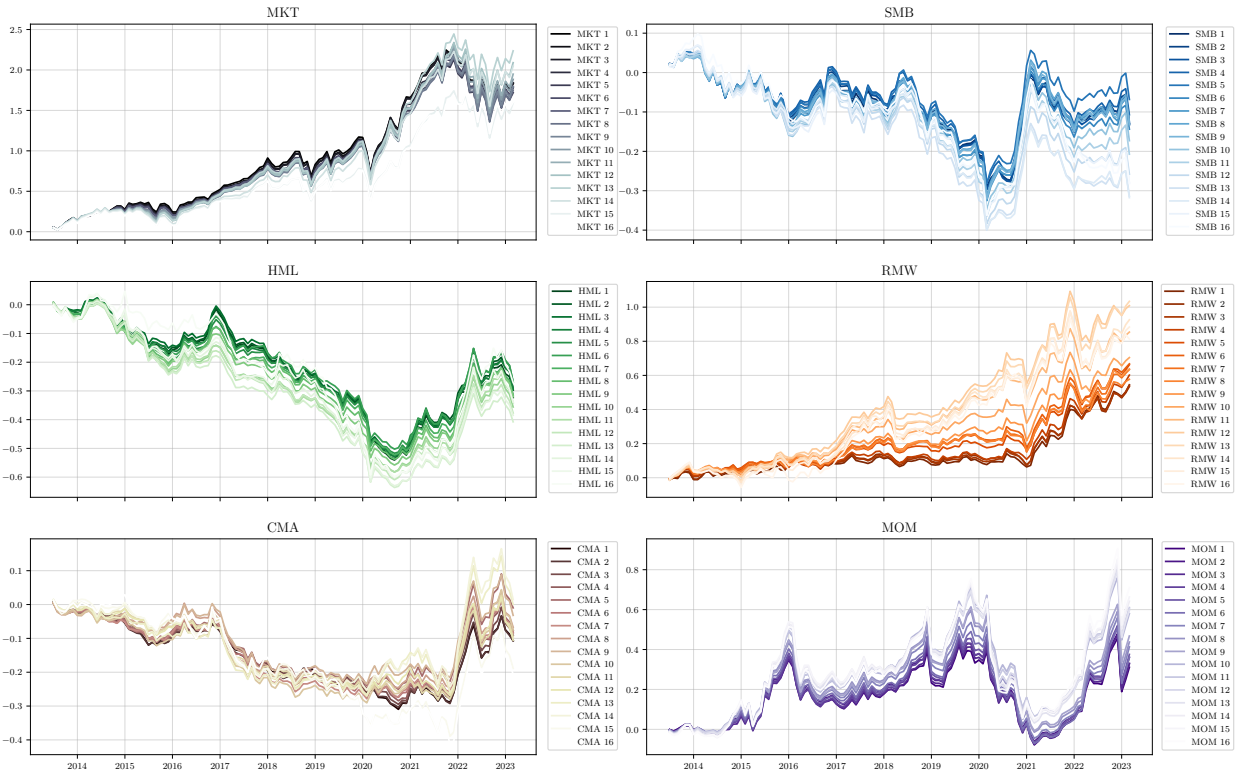
C.3 Trimmed factors over time

Figure C.4: Cumulative Returns of Seminal Factors Trimmed Based on Environmental Score



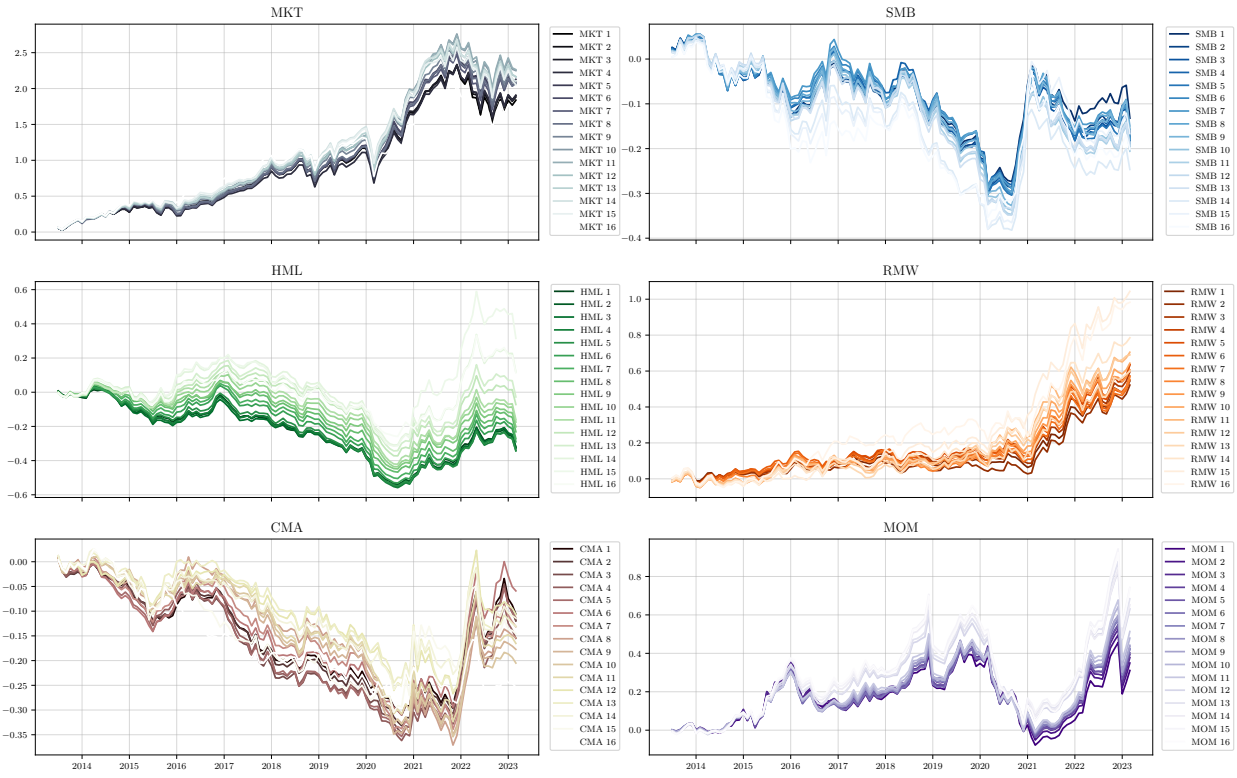
Notes: The figure shows how the cumulative realized returns of each factor evolve as we gradually trim off the firms with lowest MSCI environmental score.

Figure C.5: Cumulative Returns of Seminal Factors Trimmed Based on Social Score



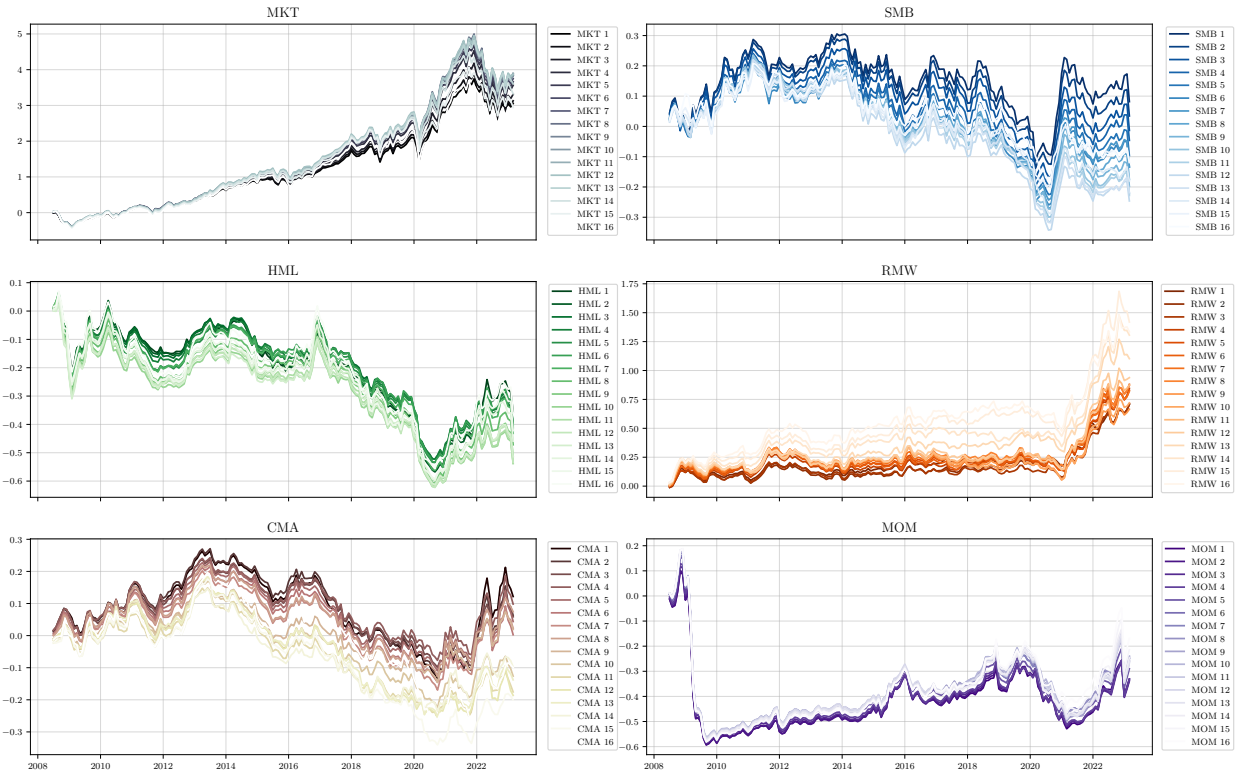
Notes: The figure shows how the cumulative realized returns of each factor evolve as we gradually trim off the firms with lowest MSCI social score.

Figure C.6: Cumulative Returns of Seminal Factors Trimmed Based on Governance Score



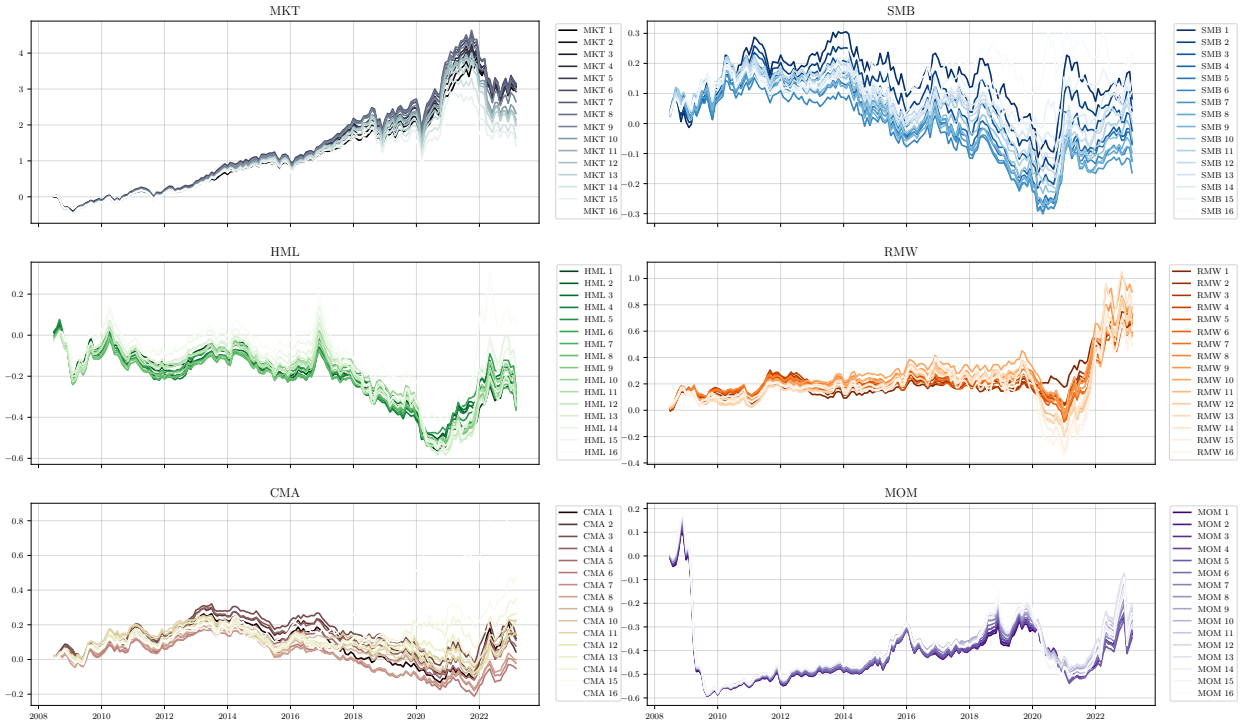
Notes: The figure shows how the cumulative realized returns of each factor evolve as we gradually trim off the firms with lowest MSCI governance score.

Figure C.7: Cumulative Returns of Seminal Factors Trimmed Based on Carbon Intensity



Notes: The figure shows how the cumulative realized returns of each factor evolve as we gradually trim off the firms with highest Trucost carbon intensity.

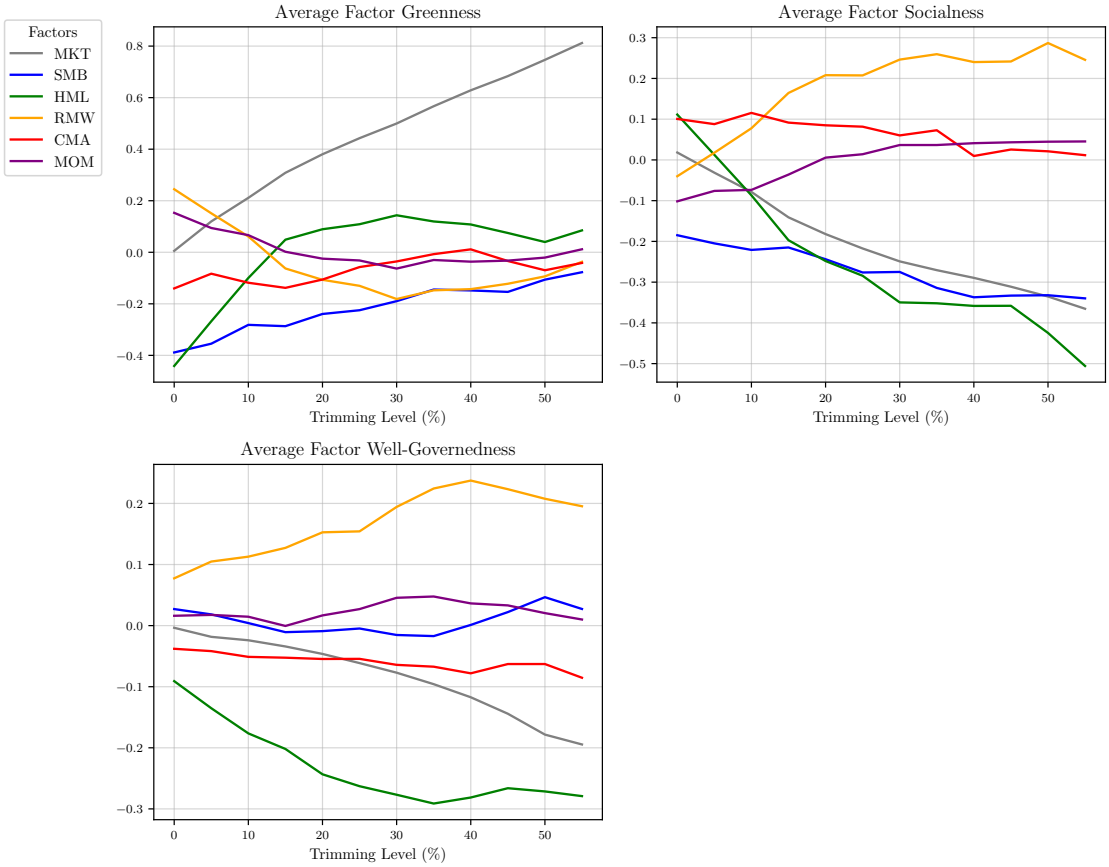
Figure C.8: Cumulative Returns over time of Seminal Factors Trimmed Based on Carbon Emission



*Notes:*The figure shows how the cumulative realized returns of each factor evolve as we gradually trim off the firms with highest Trucost carbon emission.

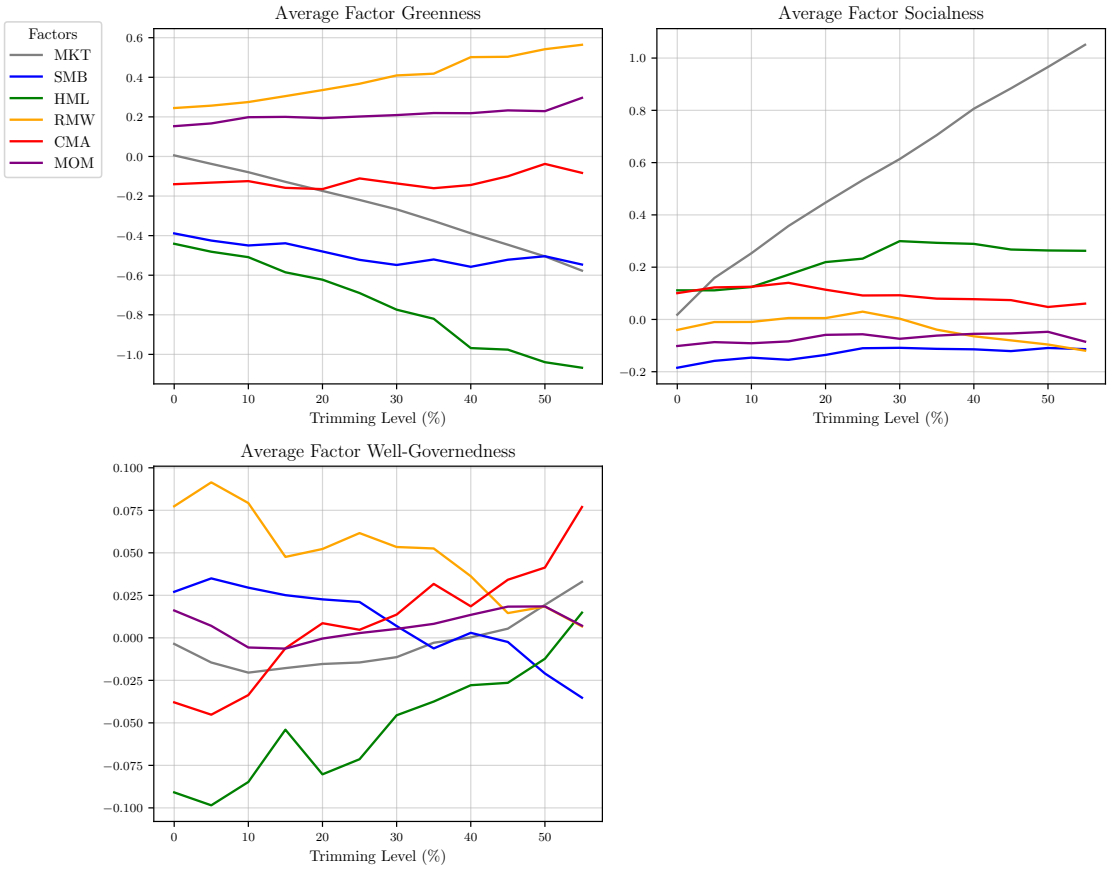
C.4 Interactions across measures: "shades" of factors trimmed based on various (other) measures

Figure C.9: "Shades" of Investment Factors Trimmed based on Environmental Score



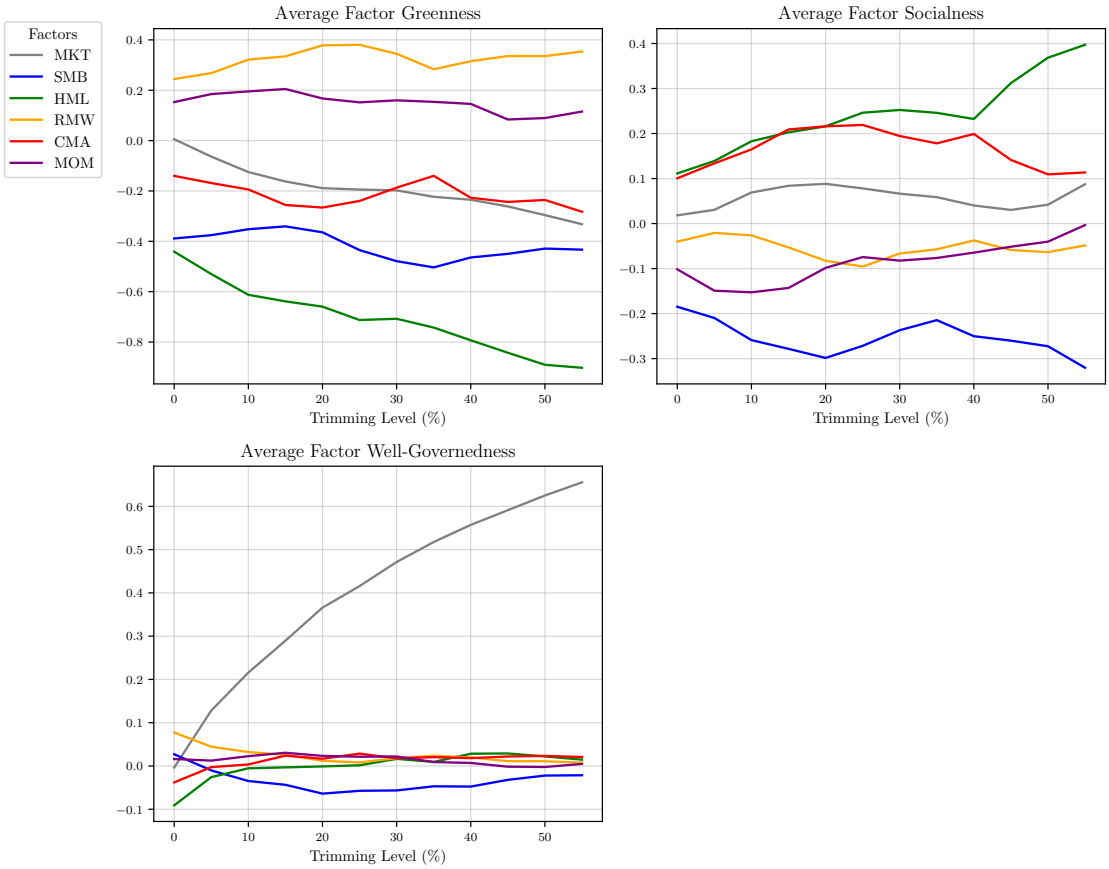
Notes: This figure shows how the average "shades" of seminal investment factors evolve as the underlying investment universe is progressively restricted by trimming stocks with the worst environmental scores. The "shade" is measured using the environmental, social, and governance scores.

Figure C.10: "Shades" of Investment Factors Trimmed based on Social Score



Notes: This figure shows how the average "shades" of seminal investment factors evolve as the underlying investment universe is progressively restricted by trimming stocks with the worst social scores. The "shade" is measured using the environmental, social, and governance scores.

Figure C.11: "Shades" of Investment Factors Trimmed based on Governance Score



Notes: This figure shows how the average "shades" of seminal investment factors evolve as the underlying investment universe is progressively restricted by trimming stocks with the worst governance scores. The "shade" is measured using the environmental, social, and governance scores.

Figure C.12: Environmental Score over Time of Factors Trimmed based on Environmental Score

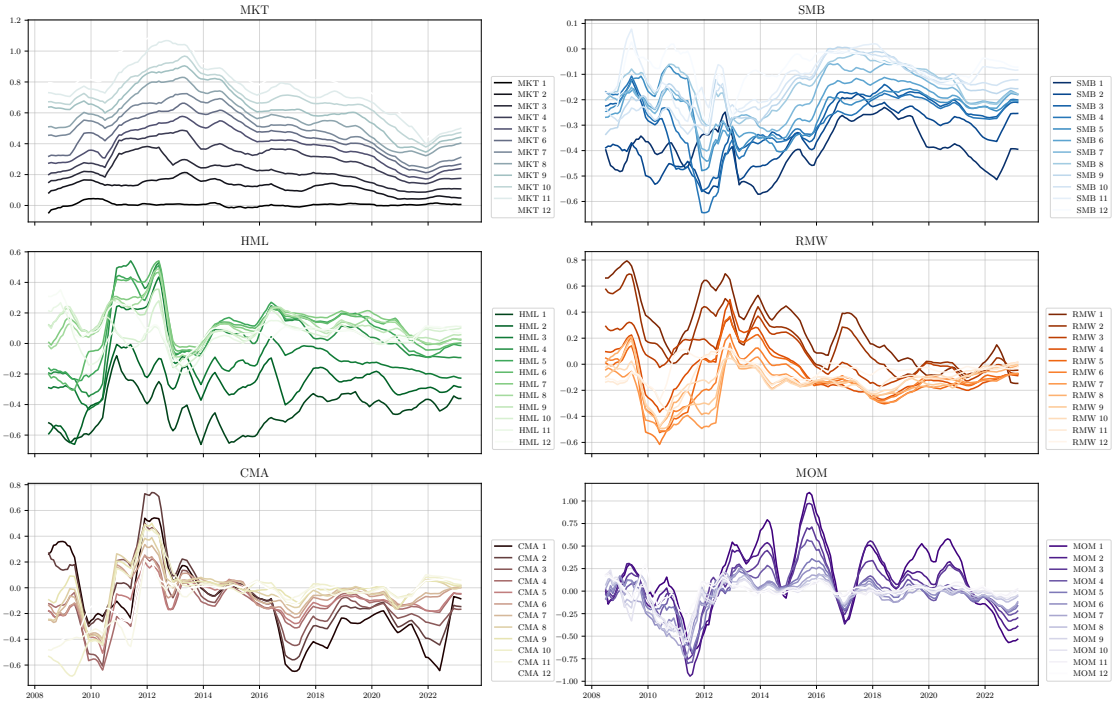


Figure C.13: (Minus) Carbon Intensity over Time of Factors Trimmed based on Environmental Score

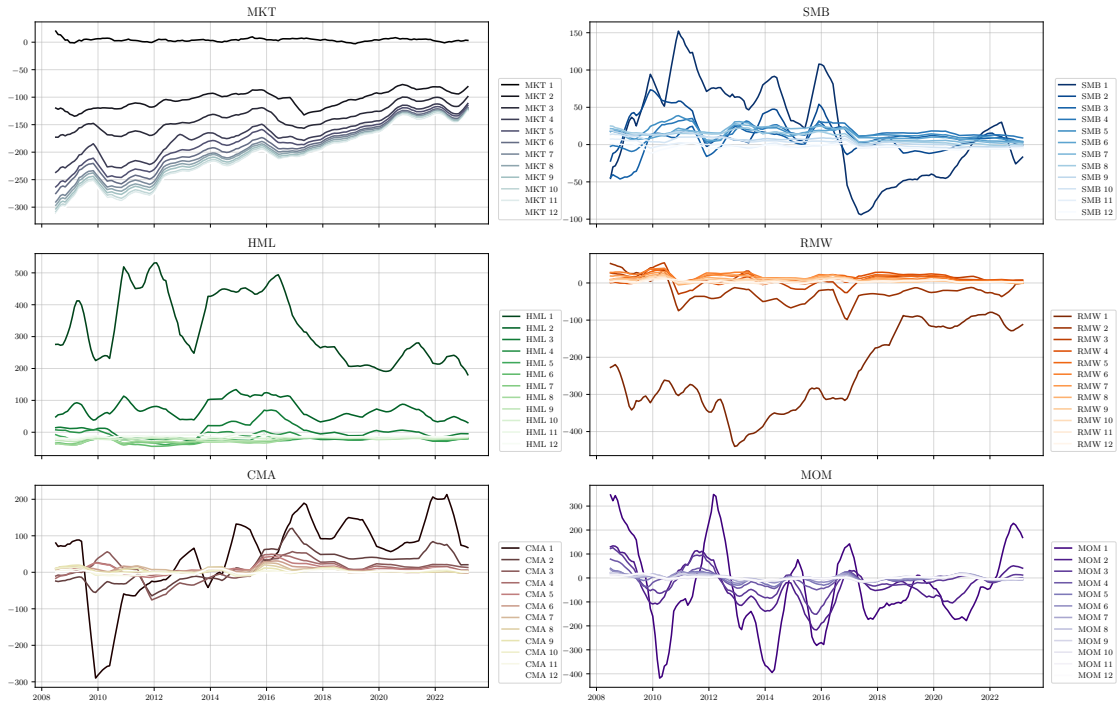


Figure C.14: Social Score over Time of Factors Trimmed based on Environmental Scores

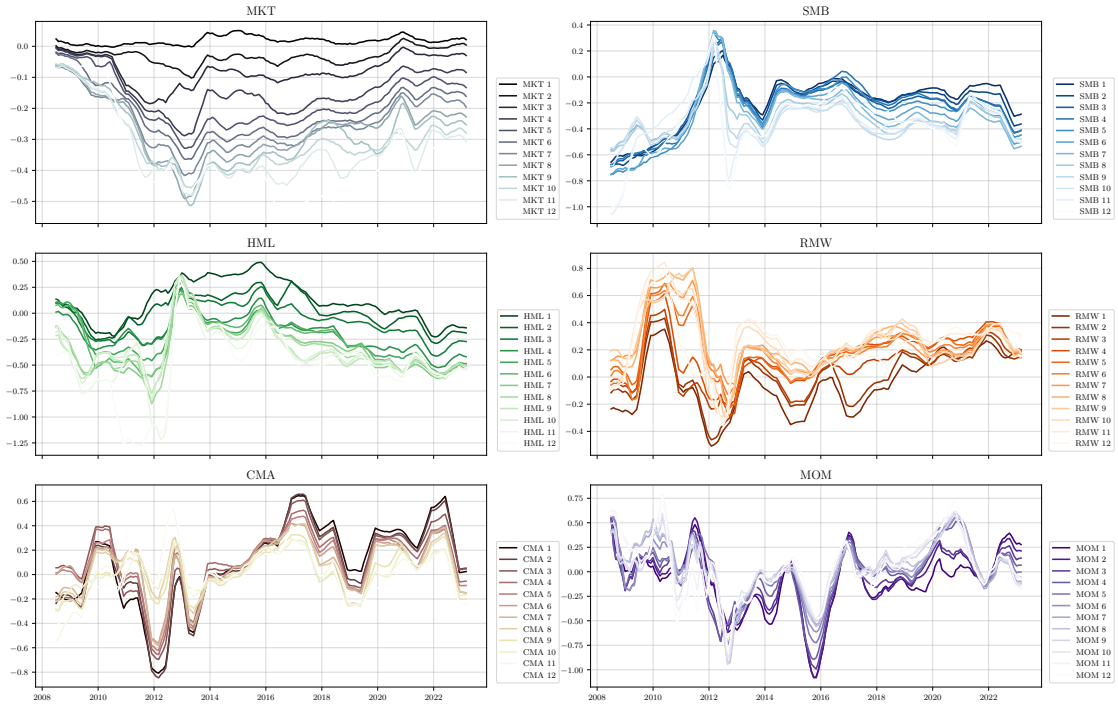
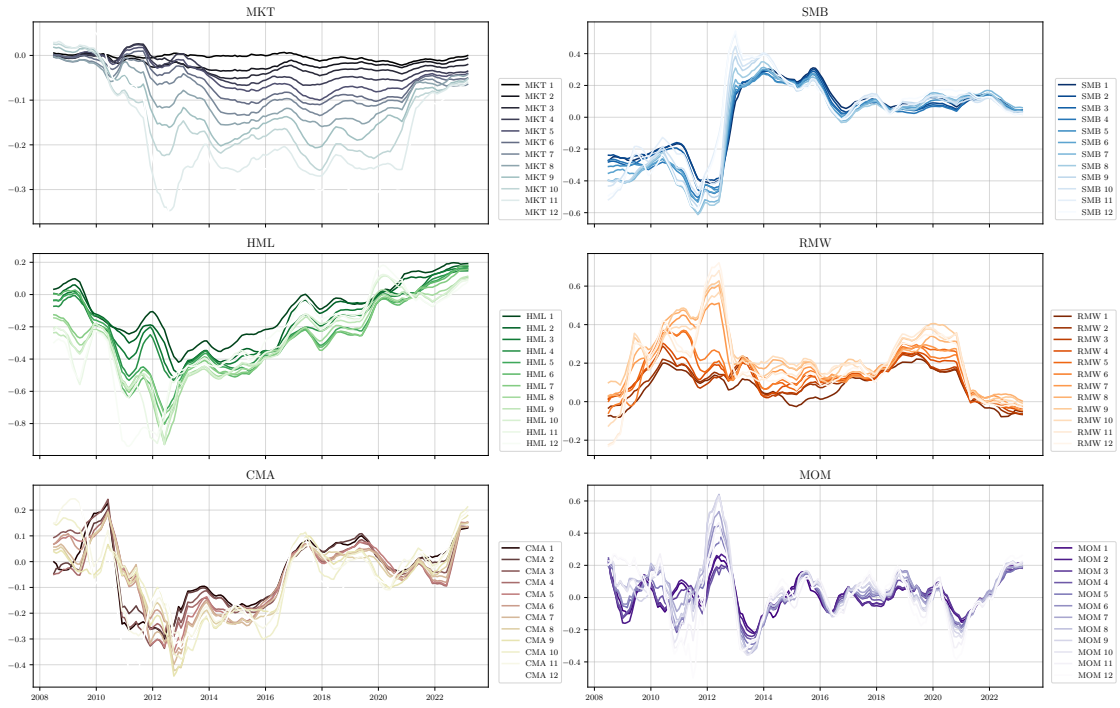


Figure C.15: Governance Score over Time of Factors Trimmed based on Environmental Scores



C.5 Inner merge version: restricting to stocks with ratings only

Table C.6: Average Annualized Return of Factors across Trimming Level - Inner Merge

Factors	Trimmed Datasets															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
								Returns								
MKT	11.447	11.584	11.743	11.977	12.325	12.484	12.587	12.352	12.299	11.800	11.868	11.859	11.865	11.554	12.437	12.550
SMB	1.716	1.380	1.445	1.315	0.999	1.111	1.246	1.347	1.377	1.338	1.571	1.471	1.635	2.017	1.179	1.643
HML	-3.213	-3.701	-3.733	-3.381	-3.279	-3.180	-3.441	-3.139	-3.298	-2.267	-2.541	-2.261	-2.106	-1.620	-1.857	-1.803
RMW	3.806	3.952	4.123	3.734	3.860	3.648	3.874	3.405	3.253	3.605	3.941	3.527	3.116	3.267	3.092	2.653
CMA	0.130	-0.254	-0.781	-0.646	-0.582	-0.618	-0.243	-0.505	-0.890	-0.646	-0.693	-0.749	-1.266	-0.969	-2.412	-2.779
MOM	-4.652	-4.266	-4.429	-4.733	-4.670	-4.254	-3.439	-3.402	-2.966	-2.571	-3.205	-2.933	-2.771	-3.331	-4.172	-4.629
								Standard Deviations								
MKT	16.414	16.346	16.431	16.193	16.129	16.305	16.349	16.464	16.429	16.407	16.452	16.459	16.431	16.513	16.461	16.395
SMB	9.538	9.530	9.375	9.393	9.352	9.021	9.291	8.965	9.589	9.915	9.879	9.699	9.559	9.497	9.607	9.527
HML	11.289	12.921	13.369	13.101	13.142	13.419	13.431	12.671	11.259	11.310	11.284	11.863	12.021	12.224	12.332	12.777
RMW	6.802	8.631	9.014	8.819	9.109	9.358	9.387	9.351	7.159	7.359	7.659	7.767	7.793	7.962	8.158	8.353
CMA	6.938	7.328	7.297	7.349	7.560	7.668	8.582	8.742	6.808	6.727	6.502	6.651	6.806	6.807	6.988	7.282
MOM	18.399	15.539	15.402	15.230	15.579	15.786	15.835	16.476	17.624	17.544	17.131	17.069	16.901	16.841	16.685	16.658
Trimming Level	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%	60%	65%	70%	75%	80%
Observations	334673	318239	301725	285298	268890	252481	236107	219713	203239	186702	170386	153989	137342	120948	104963	88328

D Additional results and robustness checks

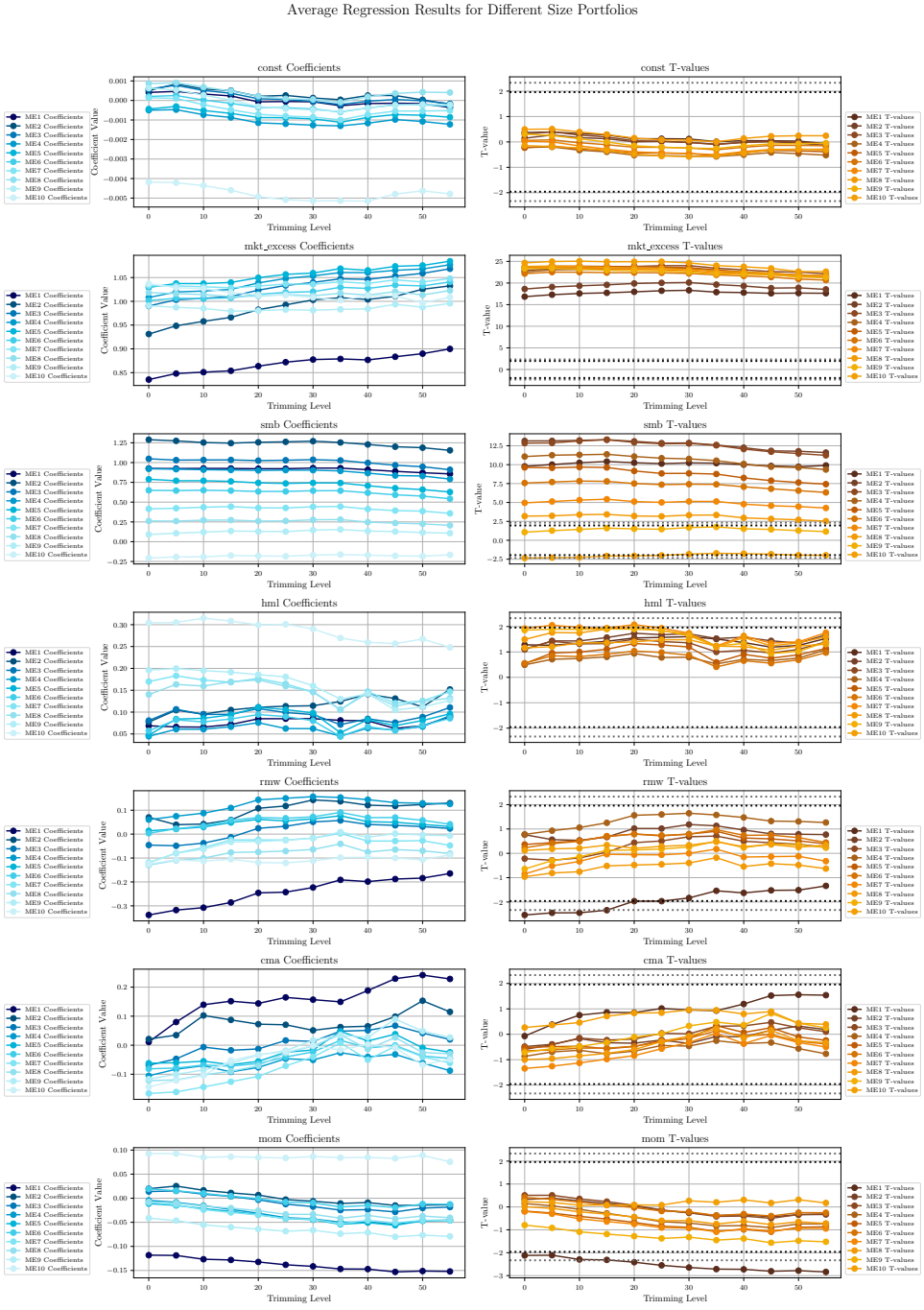
D.1 Alpha Regression

Table D.1: Regression for Trimmed Market Factor

set	const	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{MOM}	R^2
1	0.01	0.45	0.20	0.04	-0.52	-0.26	0.253
	(2.83)	(3.22)	(1.53)	(0.23)	(-2.44)	(-3.38)	
2	0.01	0.45	0.20	0.03	-0.53	-0.26	0.251
	(2.87)	(3.17)	(1.51)	(0.19)	(-2.51)	(-3.36)	
3	0.01	0.45	0.20	0.03	-0.54	-0.26	0.249
	(2.91)	(3.16)	(1.46)	(0.20)	(-2.57)	(-3.32)	
4	0.01	0.44	0.19	0.03	-0.57	-0.26	0.247
	(2.97)	(3.12)	(1.41)	(0.18)	(-2.70)	(-3.29)	
5	0.01	0.44	0.18	0.03	-0.58	-0.25	0.246
	(3.04)	(3.13)	(1.36)	(0.16)	(-2.72)	(-3.25)	
6	0.01	0.44	0.18	0.02	-0.58	-0.25	0.244
	(3.09)	(3.11)	(1.33)	(0.11)	(-2.72)	(-3.22)	
7	0.01	0.43	0.18	0.00	-0.60	-0.26	0.248
	(3.12)	(3.04)	(1.34)	(0.02)	(-2.80)	(-3.31)	
8	0.01	0.43	0.19	-0.01	-0.60	-0.26	0.250
	(3.10)	(3.02)	(1.45)	(-0.05)	(-2.82)	(-3.28)	
9	0.01	0.42	0.19	-0.02	-0.60	-0.26	0.251
	(3.09)	(3.00)	(1.45)	(-0.09)	(-2.83)	(-3.31)	
10	0.01	0.42	0.21	-0.03	-0.61	-0.26	0.259
	(3.03)	(3.03)	(1.57)	(-0.19)	(-2.90)	(-3.32)	
11	0.01	0.43	0.21	-0.06	-0.59	-0.27	0.267
	(3.06)	(3.07)	(1.57)	(-0.33)	(-2.79)	(-3.46)	
12	0.01	0.43	0.20	-0.07	-0.56	-0.26	0.262
	(3.07)	(3.11)	(1.52)	(-0.39)	(-2.67)	(-3.39)	
13	0.01	0.43	0.18	-0.07	-0.51	-0.26	0.250
	(3.03)	(3.08)	(1.36)	(-0.42)	(-2.43)	(-3.32)	
14	0.01	0.45	0.20	-0.06	-0.52	-0.26	0.263
	(2.93)	(3.21)	(1.52)	(-0.32)	(-2.48)	(-3.42)	
15	0.01	0.47	0.22	-0.06	-0.54	-0.26	0.267
	(3.09)	(3.33)	(1.61)	(-0.34)	(-2.53)	(-3.31)	
16	0.01	0.50	0.22	-0.03	-0.50	-0.25	0.267
	(3.04)	(3.54)	(1.63)	(-0.16)	(-2.32)	(-3.22)	

D.2 Original Fama-French Portfolios on ESG-Trimmed Factors

Figure D.1: Average Regression Results for Different Size Portfolios



D.3 ESG-Trimmed Portfolios: Summary Statistics

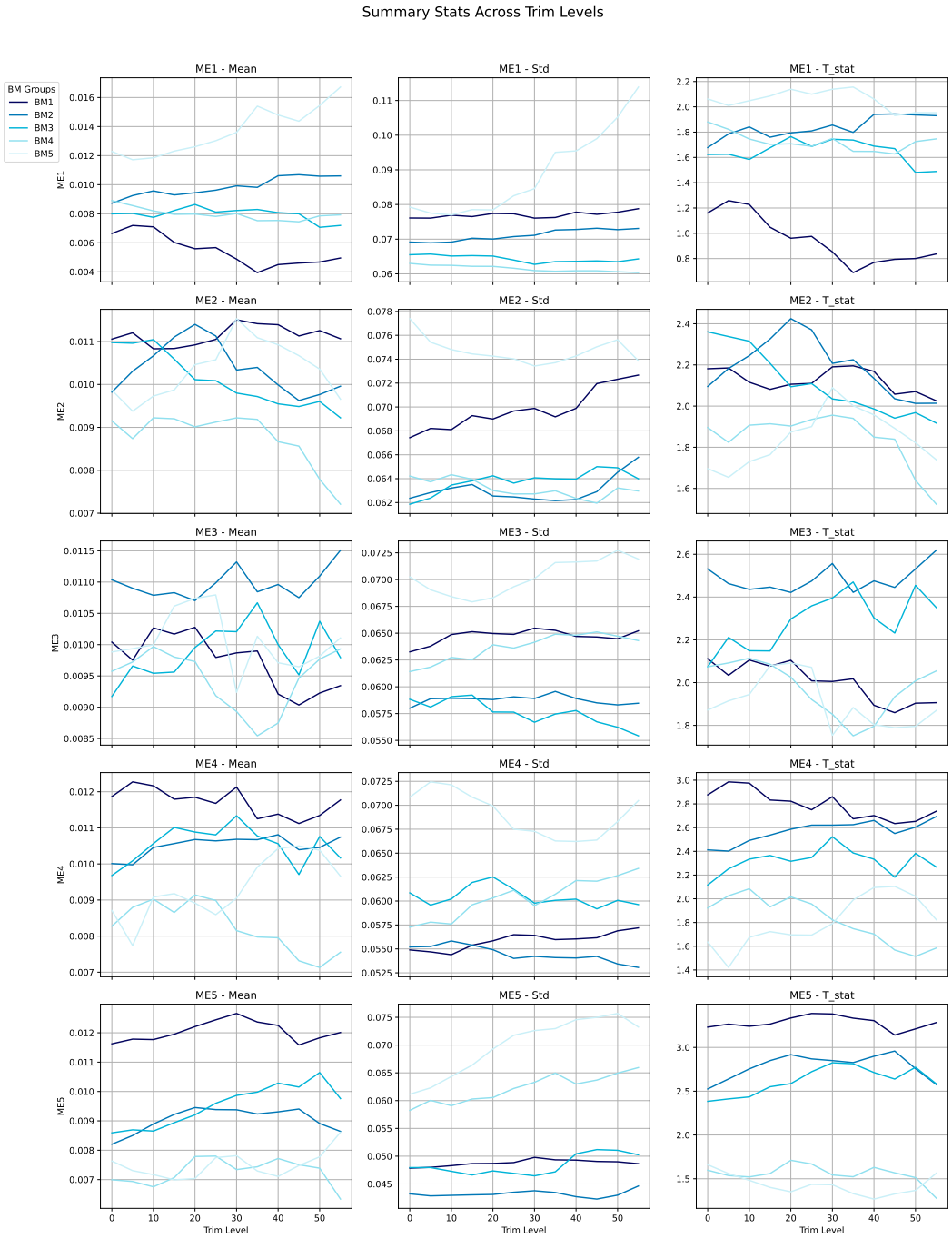


Figure D.2: Summary Statistics Across Trim Levels

D.4 ESG-Trimmed Portfolios on Original Fama-French Factors

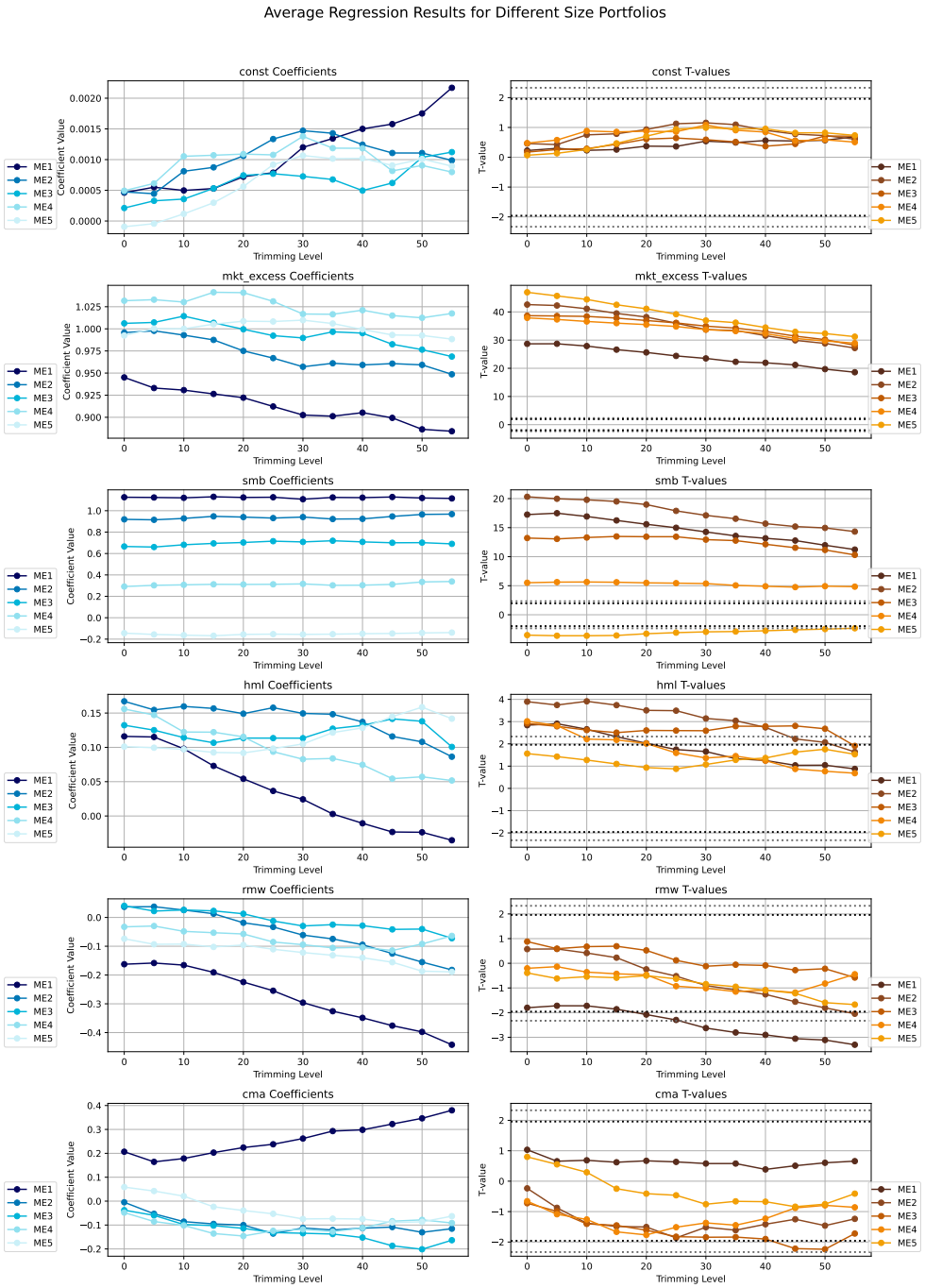


Figure D.3: Average Regression Results for Different Size Portfolios

Table D.2: Average Regression Coefficients and t-values for Different Portfolio Sets

Portfolio Set	β_0	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{MOM}	t_0	t_{MKT}	t_{SMB}	t_{HML}	t_{RMW}	t_{CMA}	t_{MOM}
Bivariate Portfolios Formed on Size and Book-to-Market														
1	0.00	0.99	0.57	0.17	-0.07	0.03	0.00	0.15	36.97	10.57	2.99	-0.64	0.05	-0.07
2	0.00	0.99	0.57	0.17	-0.08	0.00	-0.01	0.23	36.52	10.47	2.97	-0.71	-0.31	-0.08
3	0.00	0.99	0.58	0.16	-0.08	-0.03	0.00	0.35	36.12	10.42	2.83	-0.75	-0.59	0.10
4	0.00	0.99	0.59	0.16	-0.10	-0.05	0.00	0.43	34.95	10.22	2.69	-0.86	-0.83	0.16
5	0.00	0.99	0.59	0.16	-0.11	-0.06	0.01	0.59	33.84	10.01	2.57	-0.96	-0.96	0.34
6	0.00	0.98	0.60	0.16	-0.13	-0.07	0.01	0.68	32.61	9.77	2.50	-1.21	-1.11	0.46
7	0.00	0.98	0.59	0.16	-0.15	-0.07	0.01	0.76	31.24	9.41	2.39	-1.47	-1.09	0.42
8	0.00	0.98	0.59	0.16	-0.16	-0.06	0.01	0.66	30.60	9.08	2.35	-1.60	-1.09	0.37
9	0.00	0.98	0.59	0.15	-0.17	-0.06	0.01	0.62	29.60	8.75	2.26	-1.67	-1.07	0.23
10	0.00	0.97	0.60	0.15	-0.19	-0.06	0.01	0.53	28.43	8.48	2.10	-1.80	-1.06	0.20
11	0.00	0.97	0.60	0.15	-0.20	-0.05	0.01	0.62	27.43	8.26	2.02	-1.88	-1.05	0.20
12	0.00	0.97	0.61	0.12	-0.21	-0.03	0.01	0.54	26.10	7.89	1.70	-2.00	-0.81	0.26
Bivariate Portfolios Formed on Size and Operating Profitability														
1	0.00	1.00	0.58	0.12	-0.02	0.01	0.00	0.31	37.90	10.15	2.68	0.18	-0.30	0.12
2	0.00	1.00	0.58	0.12	-0.02	-0.02	0.00	0.42	37.51	10.14	2.56	0.15	-0.73	0.11
3	0.00	1.00	0.59	0.11	-0.03	-0.04	0.01	0.56	36.45	10.01	2.42	0.11	-1.01	0.32
4	0.00	1.00	0.60	0.10	-0.04	-0.05	0.01	0.64	35.45	9.90	2.27	0.05	-1.26	0.42
5	0.00	1.00	0.60	0.09	-0.06	-0.06	0.02	0.76	34.59	9.78	2.19	-0.12	-1.35	0.55
6	0.00	1.00	0.60	0.09	-0.08	-0.07	0.02	0.88	33.15	9.44	2.06	-0.48	-1.43	0.67
7	0.00	0.99	0.61	0.09	-0.11	-0.06	0.02	0.97	31.63	9.07	2.02	-0.71	-1.46	0.61
8	0.00	0.99	0.60	0.09	-0.12	-0.06	0.02	0.87	30.63	8.65	2.00	-0.83	-1.46	0.52
9	0.00	0.99	0.61	0.08	-0.13	-0.05	0.02	0.78	29.51	8.28	1.88	-0.87	-1.36	0.48
10	0.00	0.98	0.61	0.08	-0.15	-0.04	0.02	0.70	28.00	8.00	1.76	-1.01	-1.28	0.46
11	0.00	0.98	0.62	0.08	-0.16	-0.05	0.02	0.75	26.98	7.84	1.79	-1.02	-1.29	0.44
12	0.00	0.97	0.62	0.07	-0.17	-0.04	0.03	0.75	25.75	7.41	1.48	-1.09	-1.07	0.49
Bivariate Portfolios Formed on Size and Investment														
1	0.00	0.99	0.56	0.11	-0.03	0.06	0.00	0.38	38.70	10.90	2.52	-0.08	0.33	0.16
2	0.00	0.99	0.56	0.10	-0.03	0.03	0.00	0.38	38.28	10.88	2.36	-0.20	-0.03	0.16
3	0.00	0.99	0.56	0.09	-0.04	0.00	0.01	0.55	37.53	10.86	2.27	-0.21	-0.39	0.35
4	0.00	0.99	0.57	0.09	-0.04	-0.01	0.01	0.64	36.30	10.75	2.17	-0.28	-0.64	0.45
5	0.00	0.98	0.57	0.09	-0.06	-0.02	0.01	0.78	35.48	10.54	2.10	-0.48	-0.76	0.58
6	0.00	0.98	0.57	0.08	-0.08	-0.03	0.02	0.84	34.22	10.23	1.99	-0.73	-0.86	0.74
7	0.00	0.97	0.57	0.07	-0.10	-0.02	0.02	0.93	32.56	9.76	1.81	-1.00	-0.75	0.68
8	0.00	0.97	0.56	0.08	-0.11	-0.02	0.02	0.88	32.03	9.45	1.83	-1.09	-0.73	0.64
9	0.00	0.97	0.56	0.07	-0.12	-0.02	0.01	0.81	30.53	8.94	1.64	-1.23	-0.69	0.51
10	0.00	0.96	0.56	0.06	-0.15	-0.02	0.01	0.68	28.88	8.57	1.42	-1.48	-0.67	0.48
11	0.00	0.96	0.57	0.06	-0.16	-0.02	0.02	0.70	27.76	8.26	1.31	-1.55	-0.64	0.48
12	0.00	0.95	0.57	0.04	-0.17	-0.01	0.02	0.68	26.47	7.76	1.03	-1.65	-0.51	0.51

Table D.3: Average Regression Coefficients and t-values for Different Portfolio Sets

Portfolio Set	β_0	β_{MKT}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{MOM}	t_0	t_{MKT}	t_{SMB}	t_{HML}	t_{RMW}	t_{CMA}	t_{MOM}
Bivariate Portfolios Formed on Value and Operating Profitability														
1	0.00	1.03	0.20	0.16	-0.14	0.06	-0.03	0.00	25.35	1.69	2.07	-0.90	0.31	-0.34
2	0.00	1.03	0.19	0.14	-0.17	0.05	-0.03	0.02	24.96	1.56	1.92	-1.10	0.19	-0.37
3	0.00	1.03	0.20	0.13	-0.17	0.03	-0.03	0.18	24.39	1.55	1.71	-1.08	0.00	-0.27
4	0.00	1.02	0.20	0.13	-0.16	-0.01	-0.01	0.26	24.28	1.56	1.67	-1.19	-0.35	-0.15
5	0.00	1.03	0.20	0.15	-0.15	-0.06	-0.01	0.41	23.50	1.61	1.79	-1.13	-0.60	-0.06
6	0.00	1.03	0.20	0.16	-0.15	-0.08	0.00	0.55	22.53	1.60	1.79	-1.18	-0.69	0.10
7	0.00	1.03	0.21	0.15	-0.16	-0.09	-0.01	0.59	21.68	1.57	1.67	-1.33	-0.77	-0.03
8	0.00	1.03	0.21	0.16	-0.17	-0.10	-0.01	0.55	20.87	1.55	1.71	-1.35	-0.79	0.02
9	0.00	1.03	0.21	0.17	-0.19	-0.11	-0.01	0.61	20.23	1.53	1.77	-1.39	-0.78	-0.08
10	0.00	1.02	0.22	0.16	-0.20	-0.09	-0.01	0.49	19.37	1.60	1.71	-1.36	-0.70	-0.06
11	0.00	1.03	0.24	0.15	-0.23	-0.06	-0.01	0.56	18.90	1.63	1.56	-1.53	-0.53	-0.15
12	0.00	1.02	0.25	0.11	-0.21	-0.01	0.00	0.55	18.58	1.71	1.21	-1.42	-0.30	-0.06
Bivariate Portfolios Formed on Value and Investment														
1	0.00	0.99	0.08	0.22	-0.04	0.10	-0.02	0.03	26.25	1.03	2.63	-0.14	0.84	-0.37
2	0.00	0.99	0.08	0.22	-0.06	0.08	-0.02	0.10	25.80	0.91	2.43	-0.36	0.63	-0.39
3	0.00	0.99	0.08	0.21	-0.06	0.06	-0.02	0.14	25.38	0.94	2.23	-0.29	0.47	-0.32
4	0.00	1.00	0.08	0.21	-0.07	0.02	-0.01	0.30	24.76	0.91	2.23	-0.35	0.14	-0.22
5	0.00	1.00	0.10	0.21	-0.06	0.02	-0.01	0.39	24.09	0.97	2.20	-0.29	0.07	-0.14
6	0.00	0.99	0.10	0.22	-0.07	0.00	-0.01	0.51	23.43	1.03	2.20	-0.36	-0.03	-0.07
7	0.00	0.99	0.10	0.21	-0.08	0.00	-0.01	0.53	22.70	0.98	2.10	-0.46	-0.05	-0.08
8	0.00	0.99	0.11	0.22	-0.09	0.01	-0.01	0.53	22.37	0.97	2.13	-0.57	-0.01	-0.04
9	0.00	0.99	0.10	0.22	-0.10	0.02	-0.01	0.54	21.72	0.95	2.21	-0.68	-0.01	-0.18
10	0.00	0.99	0.11	0.22	-0.12	0.02	-0.02	0.43	20.46	0.96	2.08	-0.79	0.00	-0.24
11	0.00	0.99	0.12	0.22	-0.14	0.04	-0.02	0.45	19.83	1.03	1.94	-0.96	0.14	-0.32
12	0.00	0.99	0.12	0.19	-0.15	0.06	-0.02	0.40	19.44	0.99	1.60	-1.05	0.26	-0.27