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The Carbon Premium: Quantitative Assessment of Multiple Carbon Risk Factors in the European Equity Market

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Abstract

This thesis undertakes a quantitative evaluation of various carbon risk factors and their impact on asset pricing in the European financial markets. Focusing on data from the STOXX 600 index from 2010 to 2021, the study analyzes four principal metrics: Environmental Pillar Score, Environmental Pillar Momentum Score, Brown-Minus-Green (BMG), and Carbon Futures Dependency Score. Through factor regression analysis, our research demonstrates that carbon risk factors significantly influence stock returns, with a notable increase in their impact post-2015. However, we suggest caution in treating carbon risk as a universal risk factor due to its potential transitory nature during the transition to a green economy. By providing a nuanced view of how carbon risk is integrated into asset pricing, this research offers valuable insights for investors and policymakers on incorporating sustainability considerations into investment decisions.

Diese Masterarbeit bewertet quantitativ die Einflüsse von Kohlenstoffrisikofaktoren auf die Preisentwicklung von Vermögenswerten innerhalb der europäischen Finanzmärkte. Unter Verwendung des STOXX 600 Index, der den Zeitraum von 2010 bis 2021 abdeckt, wurden vier Metriken analysiert: der Environmental Pillar Score, der Environmental Pillar Momentum Score, der Brown-Minus-Green (BMG) Score und der Carbon Futures Dependency Score. Die Ergebnisse einer Faktor-Regressionsanalyse zeigen, dass Kohlenstoffrisikofaktoren signifikante Auswirkungen auf die Aktienrenditen haben, wobei der Einfluss seit 2015 merklich gestiegen ist. Allerdings sollte der Kohlenstoffrisiko-Faktor nicht als universeller Risikoindikator angesehen werden, da seine Bedeutung im Zuge des Übergangs zu einer grüneren Wirtschaft vorübergehender Natur sein könnte. Diese Studie liefert wichtige Erkenntnisse für Investoren und politische Entscheidungsträger über die Integration von Nachhaltigkeitsaspekten in Anlagestrategien.

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[1] written by Julian Strasser

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1. Introduction

“Climate risk is investment risk” (Larry Fink, 2020).

Public discussions frequently involve intense debates about the challenges and benefits of moving from a traditional, fossil-fuel-based economy to a sustainable, environmentally friendly one. However, this issue is less controversial among academics and investors. Blackrock, the world's largest asset manager, identifies the shift towards a low-carbon economy as one of the key megatrends shaping investment landscapes now and into the future (*Blackrock, 2024*). While this, very prominent, player is just one of many market participants, its perspective reflects a widespread consensus among investors. Asked about threats, which companies are most pressingly exposed to in the following 12 and 60 months, investors ranked climate change as number five in the short and number four in the long term. Only fears of rising inflation, the volatile macroeconomic environment, geopolitical- and cyber threats are viewed as even more urgent. Investors not only are concerned about this topic but expect companies to actively manage climate risks. 44% of respondents in *PwC’s Global Investor Survey (2022)* placed reducing greenhouse gas emissions among their top five priorities they want companies to tackle. There is an apparent belief among investors that the global economy and individual companies are vulnerable to the impacts of climate change. Certainly, it's important to distinguish between investor sentiment and actual reallocations, the former is not necessarily leading the latter and sentiment can change significantly over time.

But in this case, there is indeed some evidence of investors changing their investment behavior as a result of the heightened risk awareness. Morningstar reports in their Global Sustainable Fund Flows—Q4 2023 report that assets under management of sustainable funds have almost doubled from Q1 2021 to Q4 2023. This is remarkable since the broader market of open-end funds has seen net redemptions. On top of that, more than 120 new sustainable funds were launched in the fourth quarter of 2023 alone. The lion's share of this net new money for sustainable funds is sourced from Europe but almost all regions worldwide have reported net inflows into this category of funds (*Morningstar, 2024*).

Both investors and asset managers have become increasingly aware of the risks that climate change poses to their portfolios, leading to a shift in investment sentiment. This shift has influenced their allocation decisions, resulting in a significant flow of capital into sustainable funds, which are now outperforming broader market open-end funds in terms of inflows. What do investors expect from their sustainable investments, and how do they believe these allocations will affect their portfolio's risk/reward profile? According to a survey by PwC, 46% of respondents are unwilling to accept a lower rate of return when investing in a company undertaking activities with a beneficial impact on society or the environment. Moreover, almost two-thirds of respondents think that increasing investment returns is a major factor driving interest in sustainable investments (*PwC’s Global Investor Survey, 2022*). Overall, investors acknowledge the risks associated with climate change and are reallocating to more sustainable investments, with the predominant expectation that they will be rewarded—or at least not penalized—for these shifts.

This thesis wants to challenge this expectation and, drawing on extensive literature, categorize the risk of transitioning from a brown to a green economy as a systematic risk factor along with established risk factors like value or size. We propose a framework that identifies three main sources of risk: regulatory, reputational, and technology-based risk, which collectively contribute to carbon-transition risk.

In order to quantify this systematic risk, we introduce four distinct dimensions of constructed factors: the Environmental Pillar Score, Environmental Pillar Momentum Score, Brown-Minus-Green (BMG), and Carbon Futures Dependency Score factor. Each factor is unique in its underlying data, construction, and theoretical rationale, yet all aim to differentiate between green and brown stock portfolios to ultimately establish factor portfolios.

Although the literature has some preference for using various dimensions of ESG scores from different rating agencies (*Friede et al., 2015),* there is a legitimate concern regarding the validity and consistency of such ratings (*Berg et al., 2021*). To account for this, we construct in addition to the Environmental Pillar Score and the Environmental Pillar Momentum Score which utilize such ratings the BMG and Carbon Futures Dependency Score. These latter scores avoid potential pitfalls by relying on market-based variables that use more detailed data. By using multiple factors utilizing various variables and construction methods we are confident to comprehensively capture the various channels through which transition risk may manifest.

To justify transition risk as a conventional risk factor it is essential to demonstrate that risk-takers are compensated with a risk premium. We propose two primary mechanisms through which this risk translates into a risk premium. First, investors may require a premium to offset potential shocks such as regulatory changes like the implementation of a carbon tax. Secondly, as investors increasingly exclude stocks of carbon-intensive companies from their portfolios due to shifting preferences, the pool of investors willing to share this risk narrows. This limited risk-sharing prompts remaining investors to demand higher returns for holding such stocks. This neither exclusive nor complete framework represents our structured approach to empirically find significant risk premia associated with one of our constructed factors.

Our universe includes the stocks listed in the STOXX 600 index, which represents most of the liquid European stock market, over the period from January 1, 2010, to December 31, 2021. For each company within this universe, we collect a range of environmental data points, including environmental pillar scores compiled from Bloomberg and Refinitiv. After constructing factor portfolios we evaluate each of the transition risk factors by running a factor regression analysis. This analysis utilizes the five-factor model proposed by *Fama and French (2015)*, supplemented by the momentum model introduced by *Jegadeesh and Titman (1993)*, applied to each stock in our selection. Moreover, we categorize the stocks into sector portfolios using the Global Industry Classification Standards (GICS) definitions and run the same factor regressions on sector portfolios. In order to find risk premia, we follow the approach introduced by *Fama and MacBeth (1973)*.

Our findings indicate that exposure to transition risk varies strongly over sectors and over time. This holds for each of the four factors we constructed. Contrary to prior beliefs energy-intensive sectors such as energy, utilities, and industrials are not more exposed than less intensive ones like financials or information technology. In fact, it appears that those energy-intensive sectors are even less exposed than their less-intensive counterparts. This trend may be a distinct characteristic of the European market, as European energy companies typically score higher on environmental pillar scores compared to their global counterparts. Significant risk premia were identified for the Environmental Pillar, the Environmental Pillar Momentum, and the BMG risk factor using two different estimation methods. Moreover, we observed an increasing risk premium across all factors over the study period, with particularly strong coefficients in the latter half. Further analysis using elastic net regressions and a random forest model on the BMG risk factor indicates that variables closely associated with direct emissions play a crucial role in explaining stock returns.

In conclusion, our research strongly suggests that transition risk is indeed being priced into the cross-section of stock returns. This risk should, according to our results, be in close relationship to the current emissions of a company and observable through mechanisms like current ratings or structures such as the BMG risk factor. However, we do not think that transition risk can be characterized as a traditional risk factor along the Fama-French factors but represents an increasingly critical risk source for all companies in our universe.

The structure of the thesis is outlined as follows: Section 2 provides a review of the literature pertinent to our topic. Section 3 discusses the theoretical framework, while Section 4 describes the data used in our analysis. Section 5 presents our findings, and Section 6 offers conclusions drawn from our research.

2. Literature Review

The subsequent chapter provides a comprehensive overview of the existing literature on environmental risk within a risk factor framework initially established by *Sharpe (1964)*. Having gained some momentum over the last two decades the research topic has inspired a variety of methodologies and theoretical advancements. Despite this considerable attention, it remains unresolved whether environmental risk in any of its forms or definitions can be integrated into the well-regarded set of risk factors introduced by *Fama and French (2014),* or *Carhart (1997).* Given that this thesis empirically tests a set of different factors, the following literature review will be divided into subchapters, each covering the academic literature surrounding the development methods of these factors.

The first two subchapters will primarily cover the evolution of risk factors within asset pricing and the integration of sustainability considerations into finance and asset pricing theory. It is important to note that the literature cited here represents only a fraction of the extensive body of work in this field and should therefore be considered a subjective selection from this specialized area of academic research.

2.1 Risk factors in asset pricing

The Capital Asset Pricing Model introduced by *Sharpe (1964)* provides a fundamental framework to systematically analyze the relationship between risk and the expected return of an asset. Sharpe categorized risk into unsystematic, idiosyncratic, and systematic parts, the latter stemming from general market movements. Consequently, the expected return of an asset is linked to its co-movement, termed beta, with the market itself *(Sharpe, 1964)*. This paradigm of systematic risk sources has profoundly influenced both academic research and practical applications. The exploration of factors was initiated by Fama and French with their seminal 1992 paper and its subsequent extension in 2014. These papers challenged the Capital Asset Pricing Model (CAPM) by adding two additional factors to the asset pricing model: size and book-to-market equity, proposing that firms with smaller market capitalizations and lower book-to-market ratios yield higher expected returns *(Fama and French, 1992)*. They later enriched their three-factor model with a profitability and investment factor, creating the now widely adopted five-factor asset pricing model *(Fama and French, 2014)*. Fama and French did not directly connect risk premia to these characteristics but instead linked them through their high covariances to abstract risk factors. This approach was challenged by *Daniel and Titman (1997),* who argued that characteristics such as company size directly influence stock behavior. This sparked further research and practical examinations into various company characteristics to uncover additional factors. Before this, *Jegadeesh and Titman (1993)* challenged another important assumption of capital markets: informational efficiency. By observing that past winners outperform past laggards they added the momentum effect to the Fama and French model *(Jegadeesh and Titman, 1993)*. Officially, this factor was added by *Carhart (2012)* and complements the original three factors by Fama and French to form the Carhart four-factor model. *Cochrane (2011)* contributed to the academic discussion, by emphasizing that risk factors affect asset prices and returns through their impact on discount rates, highlighting the need for further research in this area. Since then, numerous additional factors have been introduced with varying degrees of success. To navigate this factor "zoo" *Giglio, Feng and Xiu (2017)* and *Pukthuanthong, Roll and Subrahmanyam (2018)* developed models and techniques to identify and assess risk factors in asset pricing.

2.2 ESG in finance

If ESG investing is defined as a branch of the investment universe that includes considerations about the value-based impact (often related to the environmental impact of companies) of investment, ESG is not a novel concept. Historically, the inclusion of non-financial metrics has been a best-practice approach among most institutional investors. However, ESG's systematic application to differentiate green assets from brown ones was largely anecdotal before 2008. As a result, much of the relevant literature has emerged post-Great Financial Crisis (*Bennani et al., 2018*). This thesis primarily focuses on transition risk, but due to the vague and imprecise terminology in this field, we will briefly explore the role of ESG as a risk factor in asset pricing.

Bennani et al. (2018), along with a subsequent study by *Drei et al. (2019),* examine ESG investing from 2010 to 2019. While they note the growing acknowledgment of ESG factors in asset pricing, they more importantly identify a transition in ESG investing dynamics. While holding ESG assets initially reduced portfolio returns up to 2013 in both the US and Europe, from 2014 onwards, these assets began making positive contributions. This shift reflects the broader, yet inconclusive, body of research at the time on how ESG factors influence returns. At the same time a growing integration of climate risk consideration into portfolios of institutional investors, as shown by *Krueger et al. (2019)*, was undeniably taking part. Despite investors acknowledging the impact of climate risks on financial (and real) assets, academically it remained quite unclear how to grasp those impacts. *Engle et al. (2019)* made a significant contribution by proposing a method to hedge against climate change risks using publicly traded assets. Additionally, *Pedersen et al. (2019)* introduced an ESG-efficient frontier, identifying portfolios that achieve the highest possible Sharpe ratio for each ESG score. *Pastor et al. (2021)* and *van der Beck (2023)* further indicated that more environmentally friendly assets typically have lower expected returns in equilibrium. However, disturbances such as shocks to the ESG factor and large inflows into ESG funds, which reflect changing investor preferences, can disrupt this equilibrium. This evolving landscape is highlighted by the *GSIA Report (2022)*, which outlines the maturation of the sustainable investment industry, noting that global sustainable investments have reached $30.3 trillion.

2.3 Environmental Pillar Score - a proxy for carbon risk

In practice, carbon risk is managed in portfolios through the use of ESG scores, which are developed and issued by rating agencies. Early meta-analyses, such as the one conducted by *Friede et al. (2015)*, demonstrate a positive correlation between ESG metrics and corporate financial performance. Furthermore, *Lins et al. (2017)* found that during the financial crisis of 2008-2009, companies with high social capital—a component of ESG—tended to see higher stock returns and profitability growth. A result, which is detected similarly by *Garel and Petit-Romec (2021)* during the COVID-19 crisis. These findings appear contradictory to theoretical predictions presented in the previous chapter.

Early papers from *Fabozzi et al. (2008)* and *Hong and Kazperczyk (2009)* investigate the impact of social norms on stock performance. They show that “sin stocks” - companies involved in alcohol, tobacco, and gambling - are generally under-owned due to ethical considerations and have historically outperformed the broader market on a risk-adjusted basis. This would suggest that if social norms do influence stock returns, they should lower the expected returns for green stocks, an outcome supported by *Pastor et al. (2020)*. Such conflicting results are common in studies focused on this investment segment.

However, explanations for these discrepancies exist. Researchers such as *Amel-Zadeh and Serafein (2017)*, *Kotsantonis and Serafein (2019)*, and *Berg et al. (2021)* have all pointed out significant challenges in utilizing ESG data. Unlike their credit score counterparts, ESG scores suffer from a lack of comparability, complexity in measurement, and inconsistencies in reporting. Furthermore, rating agencies display surprisingly large disagreements and are periodically and significantly revised. *Berg et al. (2021)* even argue that scores are unreliable for both investment decision-making and academic research. Despite these issues, the role of rating agencies in centralizing sustainable investment within numerous financial decisions remains substantial.

Nonetheless, research by *Elmalt et al. (2021)* reveals only a weak link between emission reductions among major global emitters and their ESG scores. This aligns with findings from *Bonnefon et al. (2022)*, which indicate that investors predominantly prefer portfolios that align with their values rather than actively seeking impact. Amidst these challenges, there is a continuing shift towards sustainable investing that does not rely solely on ESG scores, as indicated by *Ehlers (2023)*.

2.4 Environmental Momentum - a proxy for carbon risk

Environmental Pillar scores are predominantly retrospective, calculated from historical data points. This backward-looking nature could potentially lead to biased estimates when these scores are used to explain current stock returns. Nevertheless, research by *Melas et al. (2016), Nagy et al. (2016) and Giese et al. (2019)* suggests that portfolios favoring companies with improving environmental scores tend to outperform global benchmarks. Interestingly, *Kaiser (2020)* found that such portfolios often receive low overall sustainability ratings. This implies that changes in Environmental Pillar scores may provide additional insights not captured by the static scores themselves.

A possible explanation for this phenomenon is a market overreaction to new sustainability information, which could create a momentum effect in stocks, as demonstrated by *Chen and Yeng (2020)* in the Taiwanese stock market. This momentum effect, however, may not persist in the long term. In a similar vein, research by *Shanaev and Gimire (2022)* in the US stock market found that a downgrade of ESG leaders typically leads to significant negative returns, while upgrades have only a modest positive impact.

The underlying assumption in most of the literature is that there is a certain sentiment for green assets and changes of this sentiment may result in momentum-like effects. An assumption, which is further strengthened by *Briere and Ramelli (2022)*. They construct a sentiment index by assessing arbitrage activity in sustainable exchange-traded funds (ETFs), a measure, which has additional explanatory power in regressions both on stock returns and corporate decisions.

Additionally, *Berk et al. (2023)* can also detect a short-term momentum effect for the European stock market.

While most of the mentioned papers find at least some evidence for a momentum effect in sustainability scores, *Cauthorn et al. (2023)* challenge those results. Contrary to their peers, who found a positive effect, they are using a robust analysis and do not find a significant positive effect. This suggests that, while there might be some sentiment and stock-market reaction to up- and downgrades, a factor based on such information should be approached with caution.

2.5 “Brown-minus-Green” - a market-based approach

As previously discussed and supported by numerous academic studies, there are significant issues associated with using Environmental Pillar scores for constructing investment factors. This has led to an ongoing academic effort to avoid the usage of such scores altogether and rely on raw environmental data instead. A prominent example of such a model was introduced by *Görgen et al. (2020)* and further examined and developed by *Görgen et al. (2020)*, *Roncalli et al. (2020)* and *Roncalli et al. (2021)*. They outline and refine a capital-market-based approach and construct a “Brown-minus-Green”-Score, which is then used to create a factor. A comprehensive assessment of this "Brown-minus-Green" factor has yielded mixed results regarding its integration into standard risk-factor models. However, there is some evidence to suggest that it contributes to explaining certain aspects of risk exposure. This ongoing research underscores the potential for raw environmental data to provide a more robust foundation for financial analysis, challenging traditional methods that rely heavily on synthesized Environmental Pillar scores.

2.6 Carbon certificates - a market-based approach

Several methodologies utilize carbon market data to assess the carbon risk exposure of companies, primarily leveraging the carbon dioxide price set by the EU Emission Trading Scheme (EU ETS). This system, established by the EU, requires companies to trade carbon allowances to offset their emissions, aiming to internalize the costs of these emissions and guide the EU towards a carbon-neutral economy. The EU influences the price of these allowances by adjusting the supply through its Market Stability Reserves (MSRs), which increases market robustness and improves price credibility (*Schopp et al., 2015*).

Early on, there was some evidence that the allocation of free allowances influences stock prices and creates a carbon premium for such companies (*Oestreich and Tsiakas, 2015*). Similar results were found by *Ravina and Hentati-Kaffel (2020)* and *Mueller et al. (2023*), who employed various techniques and data sets to identify a carbon premium. Their research shows that a factor based on such measures enhances the performance of the traditional Fama and French five-factor model. Others like *Witkowski et al. (2021)* and *Liu et al. (2023)* find varying risk premia over time and suggest that if such a premium exists it is dynamic and varies over industries and market conditions. Furthermore, the relationship between energy and oil prices and the price of carbon allowances remains somewhat ambiguous (*Krokida et al., 2020*). Nonetheless, the establishment of primary and secondary markets for carbon allowances likely provides valuable insights into carbon risk.

It is important to recognize that the methodologies and studies mentioned here represent just a segment of the broader field of asset pricing and environmental risk. While the models discussed play a significant role in this area, there is a wide array of additional models, particularly those that vary in their use of "constructed" data such as environmental pillar scores.

3. Theoretical Framework

This section outlines a theoretical framework to explain the potential emergence of a carbon risk premium during the transition from a high-carbon to a low-carbon economy. Generally, the concept of a transitional carbon risk shall capture the uncertainty concerning all changes that companies will face along the road to carbon neutrality in the next couple of decades. *(Bolton and Kacperczyk, 2022)*

Let us first lay out which potential future changes companies might face or in other words what exactly is meant by the term carbon-transition risk. This discussion proposes two primary channels through which a carbon risk premium might materialize and explores additional factors influencing its magnitude and direction.

3.1 Why are companies subject to carbon-transition risk?

As already mentioned, carbon-transition risk generally refers to all drivers of risk linked to the decarbonization process. We will identify some major sub-categories of risk drivers with respect to the decarbonization process.

First, there is regulation-based risk. This type of risk incorporates all measures enacted by policymakers to curb carbon emissions, ranging from pollution-reducing market-based instruments to outright bans of high-emitting technologies and production processes. Some examples of such measures are the EU Emissions Trading System (EU ETS), which is a cap-and-trade carbon certificate system, a carbon tax where one unit of carbon has a set price, or the phasing out of coal usage. All these measures, if enacted, would induce higher costs for firms that are not able to easily deviate from technology and production processes that have proportionately high carbon intensity. Both already known or already enacted, and unknown future regulatory initiatives carry risk concerning a company's operations through potentially higher future costs and therefore more uncertain and possibly lower expected cash flows. Regulation-based uncertainty has heterogeneous effects on firms in an economy, where uncertainty will be more relevant for carbon-intense firms, in contrast to companies that aim at curbing emissions. Therefore, companies with overall poor carbon sustainability will have higher regulation-based risk. *(Bolton and Kacperczyk, 2022; Ravina and Hentati-Kaffel, 2019)*

Secondly, there is reputational risk. This risk refers to the fact that firms with superior reputations tend to have improved operating sustainability and stability, better resilience of stock prices in times of drawdowns, and generally more favorable stakeholder behavior. These arguments hold for reputation as a whole, but also for environmental reputation. Conversely, firms lagging in carbon sustainability face reputational risks, potentially impacting their risk profiles due to negative public and stakeholder sentiment.*(Liu and Lu, 2021)*

Lastly, technological risk stems from underinvestment in more efficient low-carbon production processes of high-carbon emitting companies. High-emission firms not investing in efficient, low-carbon technologies may face future cost escalations and dependency on fluctuating fossil fuel and commodity prices. The shift towards low-carbon technologies, while reducing future costs, poses a risk to companies not adapting to these advancements. *(Bolton and Kacperczyk, 2021)*

3.2 Two hypotheses on the emergence of a carbon risk premium

Having presented the principal risks inherent in the shift towards a low-carbon economy, it becomes possible to conceptualize carbon-transition risk through two distinct hypotheses, offering explanations for the emergence of a carbon risk premium. The first hypothesis is called the “Carbon Risk Premium Hypothesis”, that investors require a higher return for investing in companies predominantly engaged in high-carbon activities ("brown" companies), reflecting a risk premium for their higher exposure. Conversely, the second hypothesis, the "Divestment Hypothesis" suggests that as investors increasingly divest from high-emission firms in favor of more environmentally sustainable alternatives, the diminished liquidity in "brown" companies could necessitate a liquidity premium due to reduced market participation.

The first hypothesis is tied to the fact that risk-averse investors demand a risk premium for holding assets that are subject to higher systematic risk. In our special case, this would mean that companies that are on the lower end of carbon sustainability measures should be subject to higher systematic carbon risk, and therefore investors should be rewarded for holding such companies. This raises the question of carbon sustainability's role as a systemic risk component, potentially universal in its impact across sectors through mechanisms like a broad-based carbon tax, or more localized, affecting specific industries or regions. For instance, the introduction of a carbon tax within a single country in the Stoxx 600 index could have localized implications for carbon risk exposure.*(Bolton and Kacperczyk, 2021; Bolton and Kacperczyk, 2022)*

The alternative hypothesis, centered on divestment and exclusionary practices based on carbon emissions, highlights the potential for under-diversification in investment portfolios. This divestment and exclusionary screening is especially important for institutional investors when implementing sustainable investment policies. If the avoidance of high carbon emitting companies is pronounced, risk sharing would be limited, and idiosyncratic risk could potentially be priced. An important consideration in this respect is how investors identify the firms to divest from. Should investors' selection process be limited and primarily focused on industry classifications, leading to the exclusion of entire sectors such as energy and utilities, then this hypothesis may only be applicable at the industry level. *(Bolton and Kacperczyk, 2021; Bolton and Kacperczyk, 2022)*

While neither hypothesis is exhaustive or mutually exclusive, they represent significant pathways through which a carbon risk premium might arise. There are other possible explanations for the emergence of a carbon risk premium, but we believe these two are the most prominent ones. In this thesis, we will not try to disentangle which of the two hypotheses is the more prominent driver of carbon risk, but we will merely try to answer the question of whether carbon risk is systematically priced within our chosen investment universe.

3.3 Which factors influence the risk premium

A myriad of factors plays a role in determining the magnitude of the risk premium, among which two stand out due to their profound impact on the carbon risk landscape.

The first factor influencing the carbon risk premium stems from the fact that the climate can be understood as a non-stationary process in response to the accumulation of carbon emissions. The underlying economy can also be seen as a non-stationary process. If the climate itself and the economy are non-stationary processes, that means that the carbon-transitioning risk is also a non-stationary process. Therefore, the carbon risk premium is simply changing over time due to the non-stationarity of the underlying economy and due to the changes in the marginal effect of emissions depending on how pressing the environmental crisis is. This results in an escalating risk profile for corporations as the demand for substantial emission reductions grows, especially as we approach critical environmental thresholds. *(Bolton and Kacperczyk, 2022)*

Secondly, shifts in investor preferences and societal expectations regarding climate change also play a critical role. Generally, investors' attitudes and outlooks concerning climate change are shaped by the socio-economic environment. Suppose a society is particularly concerned with protecting the environment and the climate. In that case, investors will also demand a higher risk premium to hold assets that can be associated with higher emissions. However, this dynamic can also reverse direction. Assume, for example, a period where there is an unanticipated increase in environmental concerns. Then, green firms might outperform brown firms since green firms can be seen as a hedge against climate risk and socio-economic pressure might lead investors to demand greener stocks and customers greener products. Such a scenario seems to be consistent with the course toward greater climate solicitude in recent years, as well as the large increase of assets under management that follow some ESG investment approach. *(Bauer et al., 2022; Bolton and Kacperczyk,2021; Bolton and Kacperczyk, 2022; Pástor et al., 2020)*

3.4 Empirical expectations

Based on the framework outlined, we anticipate that firms with low carbon sustainability will exhibit a positive risk premium in the long run. This suggests that the expected returns of brown companies should surpass those of green companies due to their inherently higher exposure to carbon transition risk.

It's worth noting that this expectation doesn't preclude periods where green firms may outperform brown firms, especially during times of heightened environmental concerns. In such scenarios, an unexpected surge in environmental consciousness could tilt investor preferences towards greener investments, temporarily altering market dynamics.

In the subsequent sections of this thesis, we will empirically investigate these hypotheses to ascertain whether carbon risk is systematically priced in financial markets. Through rigorous analysis and interpretation of empirical evidence, we aim to contribute to a deeper understanding of the complexities surrounding carbon transition risk and its implications for investors and financial markets.

4. Data

Our sample consists of companies, which were listed in the STOXX 600 index as of April 4th 2023. The STOXX 600 index is a widely monitored European equity index that tracks most of the European equity market based on market capitalization. Due to the need for many company-specific data points and license limitations, we are using the index composition from April 4th throughout our testing period spanning from January 1st 2010 to December 31st 2021. We acknowledge that composition has significantly changed over this period; nonetheless, our sample still includes 378 companies at the start of the period. Selecting members from this index mitigates liquidity concerns, as these companies are generally heavily traded. We have gathered stock-specific data ranging from 2000 to 2023 from Thomson Reuters Datastream. Figures 1 and 2 illustrate the average market capitalization of our sample and the average price-to-book ratio.

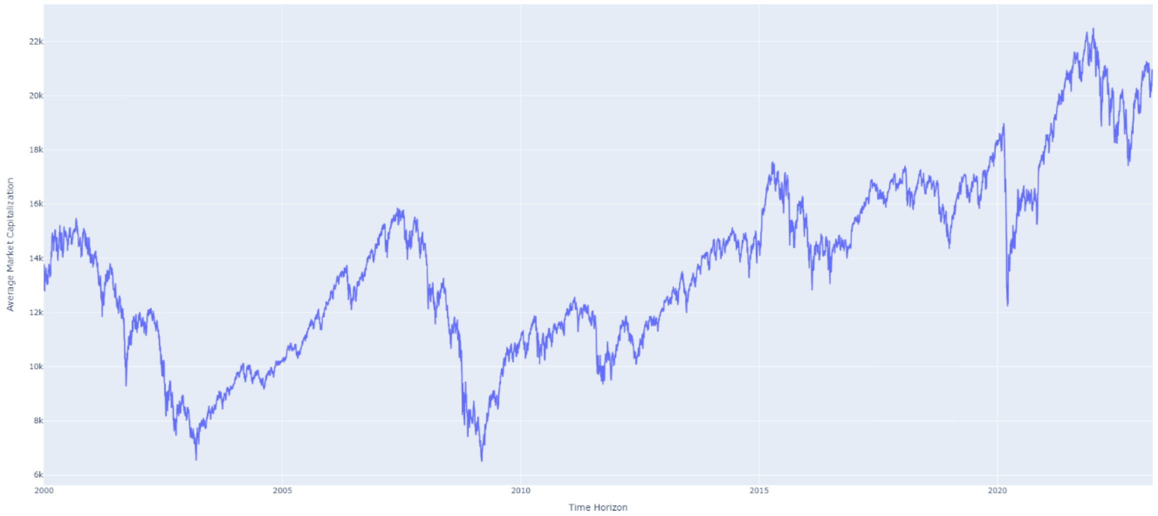

Figure 1: Average Market Capitalization

Figure 2: Average Price-to-Book ratio

This data closely matches the official average market capitalization and price-to-book ratio of the STOXX 600 index. Furthermore, various data points used for the BMG factor were sourced from Bloomberg. A comprehensive table detailing these variables, along with brief descriptions, is available in the appendix.

For the construction of the Environmental Pillar Score factor and the Environmental Pillar Momentum factor, we utilized environmental scores from both LSEG (accessible via Datastream) and Bloomberg. Initially, by integrating two different scoring systems, we aimed to mitigate potential data biases, anticipating that the combined scores would be more robust and less susceptible to methodological changes. However, we quickly revised this approach upon realizing that blending these scores did not yield the expected benefits. Figures 3 and 4 illustrate the average environmental pillar scores for our sample companies from Refinitiv and Bloomberg, respectively.

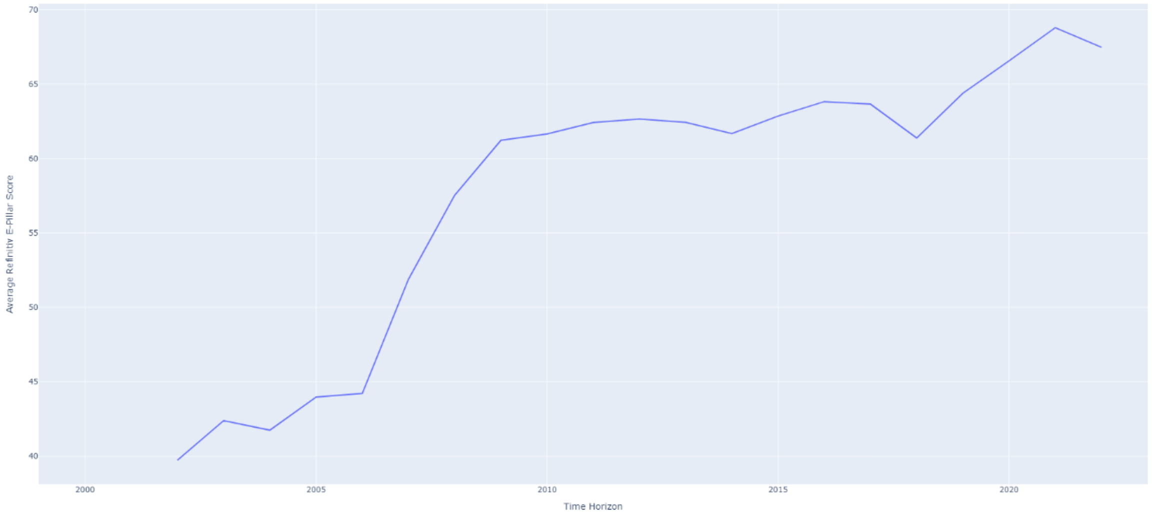

Figure 3: Average Environmental Pillar Score (Refinitiv)

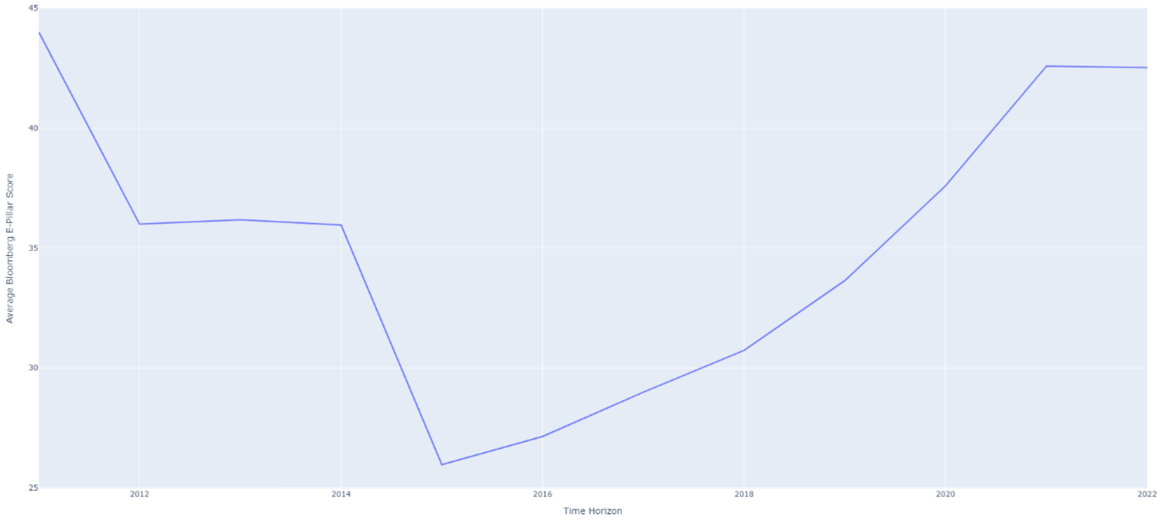

Figure 4: Average Environmental Pillar Score (Bloomberg)

Although Bloomberg only began providing scores in 2011, it is clear that their scores significantly differ from those provided by Refinitiv. Reviewing the period from 2010 onwards, Refinitiv's average scores show only moderate changes and consistently remain above 50, aligning with the generally higher-than-average environmental scores observed in European companies relative to the global average. In stark contrast, Bloomberg's scores exhibit considerable variability and suggest that the average environmental pillar (E-Pillar) score for European companies is below the global average. This finding is particularly unexpected given that both data providers employ similar methodologies for calculating their scores. We added two figures in the Appendix, which offer a visual representation of how Refinitiv and Bloomberg construct their scores, highlighting these discrepancies.

The scoring processes employed by both data providers are somewhat similar, as they utilize "topics" as proxies for specific environmental risks. Each topic is composed of data points either disclosed by the company or estimated through industry models developed by the data providers themselves. The scores are constructed by comparing each company's performance to industry averages. These topics are then weighted by industry-specific factors intended to reflect the significance of the particular risks faced by each industry. Bloomberg, for example, emphasizes transition risks and greenhouse gas emissions as the most significant for the oil and gas industry, which is consistent with the sector's challenges in moving towards a greener economy.

However, this method of scoring illustrates inherent issues within such models. The selection of proxy variables or data points, the handling of non-disclosure, and the assignment of weights are all areas prone to variability, resulting in scores that can significantly differ from one another. Consequently, these environmental scores should not be interpreted with the same level of confidence as credit scores.

To visually demonstrate the discrepancies and lack of correlation between the scoring methodologies of the two providers, we have presented the scores side-by-side in Figure 5. This comparison clearly highlights the challenges of using these environmental scores interchangeably.

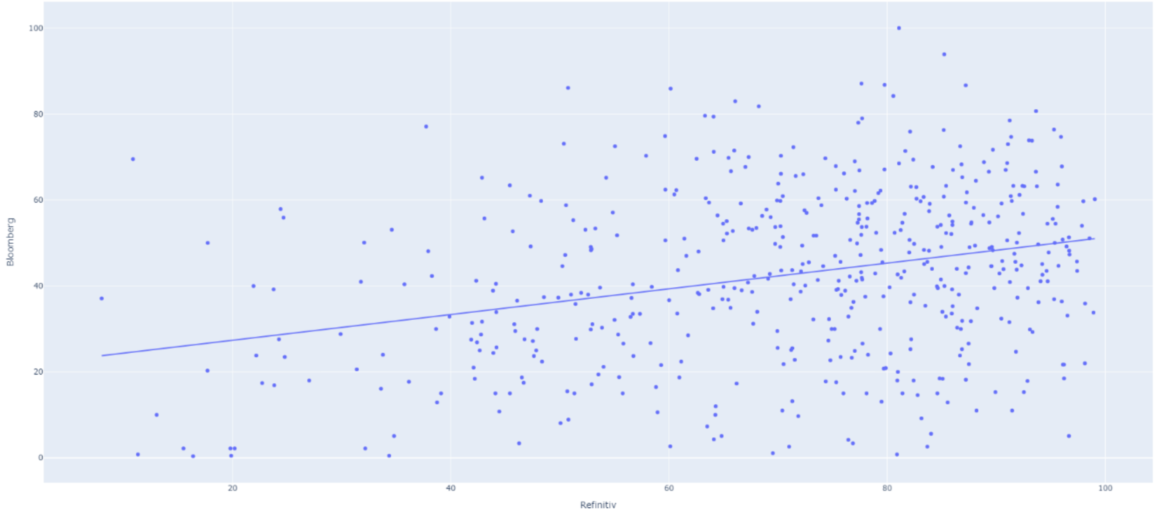

Figure 5: Scatterplot showing the discrepancy between Data providers

The regression line, while showing a positive trend, deviates significantly from the ideal 45-degree angle, and the data points are widely dispersed from this line. This substantial lack of correlation leads us to conclude that relying on a single data provider—Refinitiv in our case—

due to its longer data history and alignment with academic findings, will offer greater accuracy and robustness than a combination of both sources.

Furthermore, we have downloaded daily data for the price of the generic first carbon future from Bloomberg. This data series is a synthetic price index, which is constructed by simulating the rolling of the first nearby futures contract on EU emission allowances. Holding a futures contract on EU emission allowances gives the owner the right to emit 1,000 tons of CO_2eq (carbon dioxide equivalent) under the EU Emission Trading System (*ICE, 2024 and European Commission, 2024*). The EU Emission Trading System works on the “cap and trade” principle and involves most manufacturing and aviation companies in the EU (*European Commission, 2024*). These companies are required to acquire emission rights from a regulated market, where the European Commission controls (and incrementally decreases) the number of available allowances. These allowances can be acquired directly through European Commission auctions or traded on the secondary market—the source of our referenced data. The price of these allowances is intended to reflect the actual market price for carbon, serving as a foundational metric for a market-based assessment of the carbon risk premium. Figure 6 illustrates the price trajectory of the generic first carbon future, providing a visual understanding of its market dynamics.

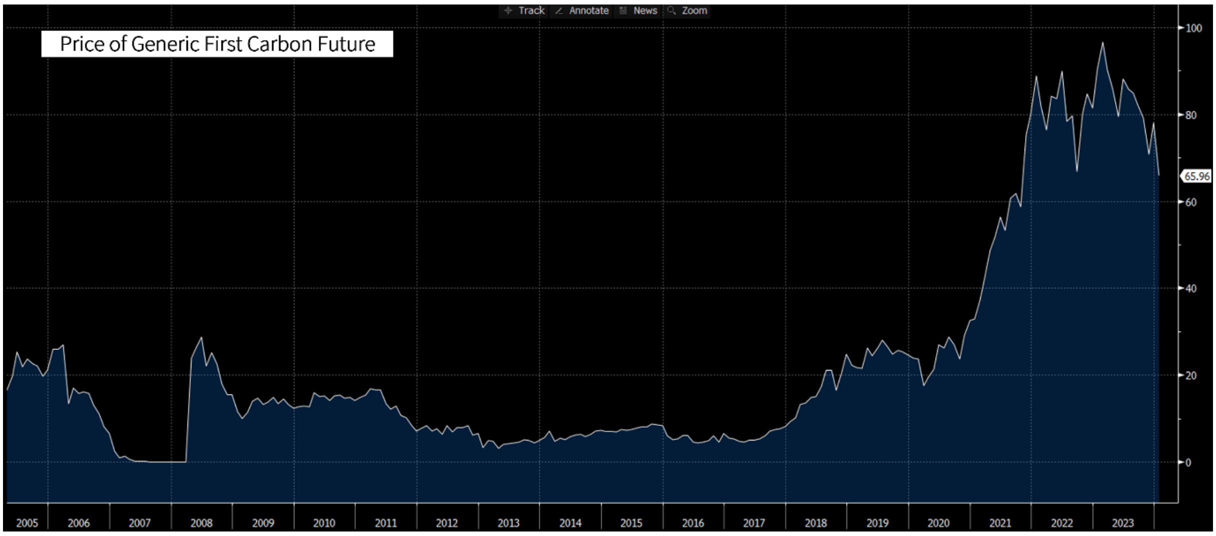

Figure 6: Price of Generic First Carbon Future (Bloomberg, 2024)

5. Methodology

In this chapter, we are going to introduce the underlying methodology of our empirical part. We will first of all give a short overview of traditionally used factors, namely the given factors from the Fama and French Five-Factor framework and the momentum factor. Afterward, we will present the carbon risk proxy variables that we will use. We will give a short reasoning for the choice of these variables and why they act as carbon risk proxies. At last, we will introduce the regression framework that we will implement. We want to quickly present the different regression specifications that we will use to estimate the effect of carbon sustainability on asset prices.

5.1 Traditionally used systemic risk factors

For our factor regression approach, we will use self-constructed systematic risk factors based on specific criteria from our investment universe, the Stoxx 600 index. Therefore, our approach encompasses the Five Factor model proposed by *Fama and French (2015)* and additionally will also incorporate the momentum factor.

The Five Factor model, being an extension of the standard CAPM, consists of the market and four additional risk factors.

The first addition is the SMB factor ("Small-minus-Big), simply called the size factor. This factor measures the historical excess return of small-cap over long-cap stocks, reflecting the size effect documented in empirical studies. Trivially, we use the market capitalization of firms to construct our portfolios.

Secondly, there is the HML factor ("High-minus-Low), also called the value factor. The value factor is based on the principle that value stocks tend to outperform growth stocks, or in other words, stocks that have a low valuation outperform stocks with a high valuation over time. We use the forward price-to-earnings ratio as our portfolio construction criterion.

Then there is the RMW factor (Robust-minus-Weak), also known as the profitability factor. This factor captures the historical tendency of high-profitability stocks to outperform low-profitability stocks. Our selection variable is operating profitability[1].

Lastly, the CMA factor (Conservative-minus-Aggressive), or investment factor is added. Generally, firms with low investments tend to outperform firms with high investments and this is what this factor aims to capture. We will look at growth in total assets to form our portfolios. *(Fama and French, 1993; Fama and French, 2015)*

These four factors plus the market factor constitute the Five Factor model. We will also add the momentum factor, which has been shown to increase model accuracy and has been persistent

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[1] We define operating profitability as: OP = (revenue – costs of goods sold - selling) / total asssets

over time. This factor captures the tendency of stock winners to keep winning and losers to keep losing. We will construct the momentum factor on the performance of a stock over the last 12 months starting from t-1, to adjust for short-term reversal. *(Jegadeesh and Titmann, 1993)*

We will form our traditional factor portfolios as follows. We will use the top and bottom 15% for the size and the momentum factor. All the other portfolios will have a top and bottom 30% split based on the selection criteria mentioned above. These cut-off points are generally in line with what is frequently used in the asset pricing literature

To summarize, our methodology for factor construction in traditional finance models involves the formation of self-built factor portfolios based on specific criteria, we aim to provide a comprehensive analysis of the drivers of asset returns within our investment universe.

We will try to show whether including factors mimicking carbon risk can enhance model accuracy and help us better explain expected stock returns. Subsequently, in the next section, we will propose some carbon risk proxy variables that we will use and show how we construct factor portfolios on these variables.

5.2 Carbon risk proxy variables

For robustness, we will propose 4 different selection mechanisms for our carbon risk portfolios Researchers have used a variety of carbon risk proxy variables to mimic firm-specific carbon risk. Some of those variables include absolute carbon emissions, carbon intensity, and aggregated self-built or data-provider-built scores. Our focus will be on the following four carbon proxies. Namely the Environmental Pillar score from the ESG framework, which will be called the E-Pillar score. Secondly, there is the Environmental Pillar Momentum Score, which is analogous to the traditional Momentum score but with respect to changes in the Environmental Pillar Score. Thirdly, we will build our own carbon risk proxy metric with a forward-looking element, the BGS (Brown-Green-Score). Lastly, we will try to come up with a market-based approach. We will try to use the generic first carbon futures price from the ETS trading scheme implemented by the EU in 2005 and its relationship with respect to stock prices to come up with a ranking of which stocks are most vulnerable to changes in the price of carbon.

We now want to present our four proxy variables, their rationale as well as the corresponding portfolio construction in the following to give a better picture of why we chose to use these variables to get carbon risk proxy portfolios.

5.2.1 Environmental Pillar Score

We want to start with the Environmental Pillar score because it is first of all the most easily available carbon proxy risk metric and secondly, we will use it as sort of a baseline estimate to compare our other carbon risk metrics.

Obviously, the E-Pillar score also incorporates other environmental risk dimensions other than the carbon risk dimension. Generally, across data providers, there are normally dimensions for Natural Capital which include metrics for water and land use, raw material sourcing, pollution and waste, and environmental opportunities. Therefore, the E-Pillar score is probably better suited for mimicking overall environmental risk. *Giese et al. (2021)* showed that the carbon risk dimension of the E-Pillar score is by far the most important and also long-lasting driver of financial performance. Therefore, we feel confident in using it as a carbon risk proxy as a baseline estimate, as the carbon risk captured by the E-Pillar score seems to be the most important driver of overall environmental risk. *(Giese et al., 2021)*

We will adopt an analogous methodology to our traditional factor construction. Therefore, we will sort the stocks with respect to the E-Pillar score and go long the 30% of companies with the lowest E-Pillar score, and short the companies with the highest 30%.

5.2.2 Environmental Pillar Momentum Score

Instead of focusing on levels of carbon risk metrics, we can also use changes in these metrics as a proxy for changes in carbon risk. So, instead of looking at the highest and lowest-rated companies for some metrics, we will now take a look at the "winners" and "losers" concerning the E-Pillar score. This strategy is more short-term in nature and is based on the assumption that future stock returns are linked to changes in the E-Pillar score. An improvement in the E-Pillar score might signal that a company is better equipped to tackle the transition from a brown to a green economy. Because this can be seen as a reduction of potential future liabilities, investors should quickly discount, and this change should be reflected in the stock price of the respective company. This argument applies to E-Pillar "losers" in the same way. Therefore, we would expect "winners" to decrease their respective carbon risk especially, relative to "losers". *(Nagy et al., 2016)*

The implementation of this strategy in our thesis will give a broader and more robust picture of the question of whether carbon risk is systematically priced in the market.

We will, accordingly, look at the 15% of firms that had the biggest increase in the E-Pillar score, and at the 15% of firms that had the biggest drawdown or if there are insufficient firms with decreases, also at the firms that had the lowest increases. Analogous to the traditional momentum strategy, we will build a portfolio where we go long the “winners” and short the “losers”.

5.2.3 BGS and BMG (Brown-minus-Green) portfolio construction

At the heart of our analysis will be a self-built forward-looking proxy score for carbon risk which was originally proposed by *Görgen et al. (2020)* and extended by *Roncalli et al. (2020).* The goal of this proposed new score is to resemble better the opportunities and risks associated with the transition process using a set of objective measures. With this new score, we can then identify whether a firm is green or brown, and we will construct mimicking factor portfolios for carbon risk, where we will have a long exposure to brown firms and a short exposure to green firms.

This methodology presents several key benefits over utilizing scores directly obtained from data providers. One primary advantage is the mitigation of biases inherent to individual data providers, as the BGS incorporates data from multiple sources. This comprehensive approach ensures a broader and more unbiased perspective. *Görgen et al. (2020)* have substantiated the absence of significant country-specific or sector-specific biases within this framework. However, despite these strengths, the BGS methodology is not without its limitations, particularly concerning the transformation of variables. Converting continuous variables into binary (dummy) variables addresses issues associated with extreme values but concurrently removes the ability to distinguish between data points based on their deviation from the median value. Additionally, a notable concern with the BGS approach is the potential overrepresentation of small-cap stocks within the "brown" segment of the portfolios, a subject that warrants further examination in subsequent chapters. *(Roncalli et al., 2020)*

5.2.3.1 BGS (Brown-minus-Green score) categories

In the construction of the BGS (Brown-Green-Score), we will use granular environmental variables from Bloomberg and Refinitiv over the period from 2010 to 2022. After excluding variables with too low response rates by firms, we retain 65 granular variables, which we already mentioned in the chapter on data. We then classify these metrics into three different categories as proposed by *Görgen et al. (2020),* namely Value Chain, Public Perception and Adaptability:

Value chain

We will start with the most important category, the value chain category, which includes metrics of current emissions and current production technologies. Some examples of variables that go in this category are carbon emissions (Scope 1,2,3), renewable energy use, emission reduction, and whether a sustainable supply chain is implemented. This category, therefore, gives us a current picture of the carbon sustainability of a firm. Current carbon sustainability should be one of the main drivers of priced carbon risk, therefore expected cashflows of firms that are seen as brown concerning value chain dimension should be discounted accordingly, due to higher potential future costs.

Public perception

Secondly, the BGS incorporates a public perception category. This category includes for example different kinds of constructed scores, metrics for disclosure of environmental sustainability, and fine amounts that had to be paid by firms due to environmental malpractice. So, this category represents the view of a firm that the public has concerning carbon emissions. We come up with two explanations for why public perception affects firm values. The first is due to the fact that if public perception is particularly bad investors might not want to hold such assets, or as in the case of institutional investors might not even be allowed to do so. If divestment due to public perception is pronounced, there might be a link between our public perception variables and firm value. The second explanation for why this category might affect firm value is that products produced by firms with bad public perception might be shunned away from, and good public perception is used as a signal for product quality, as shown by *Bardos et al. (2020)*. A good perceived product quality or more generally brand perception is associated with decreased levels of cashflow volatility and improved credit ratings. Consequently, we expect that our public perception variables affect a company’s stock price. *(Bardos et al., 2020; Larkin, 2013)*

Adaptability

Lastly, there is a category for firm adaptability concerning the transition process from a brown to a green economy. The variables included in this category are for example whether firms have certain emission targets in place, whether firms have teams that are responsible for implementing environmental plans, or whether there are policies regarding divestment of fossil fuel use. This dimension should capture how adaptable a firm is if the transitioning process picks up pace, so this is in some form the forward-looking part of the BGS that reflects future potential carbon emissions. So, in the long run, more adaptable firms should have more stable and less risky expected cash flows.

5.2.3.2 Construction of the BGS and the BMG portfolio

To construct the BGS score, we first have to build the subscores of the three categories proposed above. We will first transform all 65 variables into dummies, indicating below or above median values. So a firm that for example has higher (lower) Scope 1 emissions than the median of firms will get a value of 0 (1) in the Scope 1 emission variable. Now that we have converted all variables to dummies, we group them into their respective categories and take the average of all variables within one category. We will then have a subscore ranging between 0 and 1 for each category, on which we will apply the following formula to calculate the BGS:

$$BGS_i(t) = \big(0.7 \cdot VC(t) + 0.3 \cdot PP(t)\big) - \frac{1 - A(t)}{3}\big(0.7 \cdot VC(t) + 0.3 \cdot PP(t)\big)$$

The equation comprises two components: an additive and a penalizing term. The additive portion incorporates the value chain subscore, assigned a 70% weight, and the public perception subscore, which carries a 30% weight. The penalizing segment then adjusts the cumulative score based on the firm's adaptability score. Firms demonstrating high adaptability in the transition process will receive a higher adaptability score, which in turn reduces the penalizing factor, ultimately enhancing the overall BGS.

Given the centrality of production, processes, and supply chain management to a firm's operations, *Görgen et al. (2020)* assume the value chain category to be the most important indicator, therefore it is given more weight than the public perception subscore. The adaptability dimension influences BGS differently. In fact, it moderates the positive or negative impacts of the other two dimensions.

As our theoretical framework leads us to the conclusion that brown firms should carry a positive risk premium, therefore having higher expected returns, we again will go long the 30% of firms with the lowest overall BGS and short 30% of the firms with the highest BGS. So again, tailored to our methodological framework, we construct a zero-cost carbon risk-mimicking portfolio that we will use to test whether carbon risk is priced in the European stock market.

5.2.4 Carbon futures dependency score

At last, we will construct a self-built metric, which is solely dependent on market information. As already discussed in the data section above, there are significant revisions for ESG data points from data providers like Bloomberg and Refinitiv. To avoid an inherent bias in our data we only will use market prices, which are not subject of revisions. Our variable of choice is the price of futures contracts on carbon prices since carbon emissions should be one of the major drivers of transition risk.

The price of the first generic futures contract, obtained from Bloomberg, is a synthetic price series, which is constructed by always "rolling-over" the first nearby futures contract on an EU emission allowance traded on the Intercontinental Exchange in Atlanta, USA. We are using "just" the nearby contract since it is by far the most liquid one. The section on data covers the general structure of the EU Emission Trading System more in depth, but it is designed so that companies have to cover there emissions by holding emission allowances, which can be traded on a secondary market. Assuming that affected companies observe their current emissions and extrapolate their future emissions, companies should use futures contracts throughout the year to meet their regulatory requirements at the end of the fiscal year. A liquid enough futures market should, therefore, price the marginal costs of emitting an additional ton of CO_2 emissions *(Krokida et al., 2020)*. While, in theory, such assumptions are not necessarily quite restricting, it is not clear to what extent companies observe their current and future emissions. Moreover, we do not know the composition of market participants in this market. It could be major companies within the Emission Trading System, but also speculators like CTAs, portfolio managers, or hedge funds. One indication of some hedging activity within the market is the futures curve itself, which is, most of the time, in contango. This means that hedging of future emissions is costly and liquidity provision is rewarded under the assumption that we can analyze the futures contract similarly to other commodities (*Borak et al., 2006*). We will leave the in-depth analysis of the emission allowance futures market to future research. For the remaining part of the thesis, we will assume, that companies are involved in the futures market and that the market structure is efficient enough to convey information about demand and supply of the mentioned emission allowances.

As for the construction of our score, we will run rolling window regressions, in which we regress daily stock returns on the Fama-French five factors, our momentum factor, and the daily return of the first generic futures time series. We will use a window size of three years and run these daily regressions from 2010 until the end of our data set including all of our 600 companies. In order to construct a robust score taking into account the sign, size, and significance of the regression coefficient of the futures time series, we divide the coefficient by its standard error. Accounting for auto-correlation in the time-series regression we are using HAC standard errors. A high positive score indicates that the return of a company is increasing if the price of carbon is increasing and a low negative score indicates a lower return if carbon prices increase. Following the factor construction process mentioned above we short the 30% of companies with the lowest score and go long the 30% of companies with the highest score.

Therefore, our self-built score links a rising price of carbon to an increase in the transition risk premium, which is channeled via the secondary market of emission allowance trading within the EU Emission Trading System.

5.3 Factor model setup

In this subchapter, we present the regression methodology used in the empirical part of our thesis. We will first lay out the traditional factor regression model and then present different approaches that we use to test whether carbon risk is priced while pointing out its strengths and weaknesses.

In this analysis, the most cumbersome model is designed to explain the excess return of an asset as a function of the market´s excess return and six well-established factor portfolio returns, along with an additional factor for carbon risk (E-Pillar, E-Pillar Momentum, BMG, Carbon Futures). This is the traditionally used setup to explain an asset's excess return with some priced risk factors. We introduce the most extensive model with all factors here, but we will also use more restricted models like the Fama-French 3 Factor model in our analysis to be able to robustly infer whether carbon risk is priced.

Specifically, the extensive model is specified as follows:

$$
\begin{aligned}
R_{i,t} - r_{F,t} = \alpha + \; & \beta_1 \left(R_{M,t} - r_{F,t} \right) + \; \beta_2 SMB_t + \beta_3 HML_t + \; \beta_4 CMA_t + \beta_5 RMW_t \\
& + \beta_6 MOM_t + \beta_7 Carbon_t + \epsilon_t
\end{aligned}
$$

where the term on the left-hand side represents the excess return of an asset *i* at time *t*.

The term α represents the model's intercept, indicative of the average excess return of an asset that cannot be explained by its market and factor exposure. This unaccounted-for return, often referred to as the asset´s alpha, emphasizes the portion of returns not attributable to known risk factors. If the model is correctly specified, meaning that all factors that influence an asset´s excess return are specified in the model, α is expected to be zero.

The variables in use include the conventional factors previously discussed in an earlier chapter, alongside a novel factor pertaining to carbon risk proposed by us. The coefficients β_1 to β_7 measure the sensitivity of an asset´s excess return to these various factors. The error term, denoted as ϵ, captures any excess return on the asset that remains unexplained by the model.

This specification aims to robustly capture the multifaceted influences on an asset's returns, incorporating both traditional financial factors and the increasingly relevant aspect of carbon risk, reflecting the asset's exposure to environmental concerns.

Now that we laid out the general factor model, we want to continue with the empirical methodology that we used to test the relationship of the model established above. As mentioned above, we will not only restrict our analysis to the extensive model, but we will use different model specifications moving forward.

5.4 Regression methodology

In this section, we will outline the methodology of our empirical analysis, focusing on the regression model's structure. Initially, we will describe the one-step methods employed to examine industry dynamics through the lens of our carbon proxy variables. Subsequently, we will shift our focus to the two-step methods, to evaluate model accuracy and carbon risk premia dynamics in the European stock market.

5.4.1 One-step regression approach

The empirical portion begins with beta estimation within an industry classification framework. Our initial method involves conducting a standard time-series regression for each stock within the Stoxx 600 index. This process will yield beta estimates for all listed stocks, which will subsequently be categorized according to industry. This classification allows us to analyze beta distributions across different sectors. The objective is to gain a comprehensive overview of beta distributions within the Stoxx 600 and identify industries most susceptible to carbon risk, based on their covariance with our carbon risk proxy portfolios.

Furthermore, we will calculate time-varying betas for our industry portfolios. To achieve this, we will first categorize stocks by industry to compute returns for each industry portfolio on a market-cap weighted basis. A rolling-window time series regression will then be applied to assess the variation in dependencies throughout our study period. This analysis aims to identify structural shifts in carbon betas over time, enabling us to segment specific time frames for detailed risk premia examination.

5.4.2 Standard two-step regression approach

To derive risk premia associated with carbon risk, we will employ a two-tiered regression methodology. This process typically unfolds in two stages, beginning with individual stock time-series regressions to compute beta values for each stock. These betas then serve as independent variables in the subsequent cross-sectional regression, which aims at calculating risk premia.

This method would yield unbiased estimates, assuming the premia remain constant over time. However, the reality of financial markets is that risk premia are subject to fluctuation due to economic shifts, changes in investor sentiment, and evolving regulatory landscapes, rendering them inherently unstable. Moreover, we stated above that we believe carbon risk premia to change due to the fact that the climate itself is a non-stationary process that is subject to constant changes. Therefore, we cannot expect that standard errors can be estimated without a bias due to autocorrelation of standard errors over time and statistical inference becomes infeasible.

To accommodate for these variations, we will first of all use HAC standard errors that adjust for autocorrelation and heteroscedasticity of the errors in the standard Two-Step approach. Secondly, we will incorporate a slight modification to the conventional two-step technique, adopting the approach developed by *Fama and MacBeth (1973),* which is specifically designed to address the dynamic nature of risk premia. This approach also has the advantage that we will be able to investigate how risk premia change over time, as we will get estimates of risk-premia on a daily basis. *(Fama and MacBeth, 1973)*

We apply both methods because one key assumption of the two approaches is constant betas over time, which we cannot confirm for our dataset. We will elaborate on this result later in the empirical part of our chapter. It is clear to us though that the exact calculation of risk premia is somewhat unfeasible, but we believe by using both estimation techniques, we will be able to at least show whether a risk premium exists and in what range it may lay.

5.4.3 Fama-MacBeth regression approach

We will now present the approach developed by *Fama and MacBeth (1973)* in their seminal paper which aims to overcome the drawbacks of traditional two-step methods. Again, this approach aims at assessing the relationship between expected returns and various risk factors, by combining time-series and cross-sectional analyses in a new way.

The Fama-MacBeth approach, like the traditional two-step regression approach commences with a time series regression step. We will first estimate betas for each stock over the whole period.

So, the first stage time-series regression looks like this for each stock:

$$R_{i,t} - r_{F,t} = \alpha + \boldsymbol{\beta f_t} + \epsilon_t$$

where $\mathbf{f_t}$ represents the vector of returns of our factor portfolios and $\boldsymbol{\beta}$ the vector of coefficients.

Now, for each stock, we have an estimate of the sensitivity to each of our factors.

The second step in the Fama-MacBeth method now takes these betas for each stock and regresses them on the excess return of the security in question on a monthly basis. So, the difference to the normal two-step approach is that we do not regress our betas on the entire time frame, but we will split our stock return data on a daily basis and do a regression for each day.

The second step therefore looks like this for each trading day t:

$$\bar{z}_{i,t} = \lambda_0 + \widetilde{\boldsymbol{\beta}}_i \boldsymbol{\lambda}_{\boldsymbol{f},\boldsymbol{t}} + a_{i,t}$$

Where $\bar{z}_{i,t}$ represents the average excess return in one period and $\widetilde{\boldsymbol{\beta}_{\iota}}$ the estimated betas from the first stage regression. $\lambda_{f,t}$ are the daily estimated risk premia for the respective stock.

This step therefore ensures that the dynamics of risk premia are captured over time rather than being assumed constant.

Following the daily regressions, the next step involves the aggregation of these daily estimated risk premia. Therefore, we will calculate the average of all daily risk premia estimations to provide a risk premium estimate for the entire time frame.

One of the key advantages of this approach over the traditional two-step methods lies in its ability to capture the temporal variation of risk premia, whereas two-step approaches rely on the static assumptions of time-invariant risk premia. This advantage is particularly important in financial markets, where risk premia can fluctuate significantly due to changes in economic conditions, investor sentiment, and regulatory environments. Mind that all these time-variant influences also apply perfectly to the carbon risk framework. Moreover, this approach mitigates the impact of serial correlation, also addressing potential errors and biases stemming from intertemporal return dependencies. *(Fama and MacBeth, 1973)*

5.4.4 Machine learning approach for variable importance

Lastly, we also want to briefly present the Machine Learning approach that we implement as a robustness check for the BMG construction. We will do a very short and simple analysis of the importance of our granular environmental variables using two machine learning algorithms. We will employ a Random Forest and an Elastic Net regression to determine the significance of environmental variables in explaining the 1-year return across our investment universe. The use of Random Forest allows us to understand the contribution of each environmental variable to the predictive accuracy of the model, while Elastic Net helps to pinpoint the most critical variables by applying regularization techniques that discount the less relevant factors. We will use this short and not extensive analysis to sort of double-check the construction and weighting of the BGS, which approach we directly applied from *Görgen et al. (2020)*. We will not use this analysis to estimate regression coefficients but will merely rank the environmental variables with respect to their predictive power regarding stock returns.

6. Empirical Part

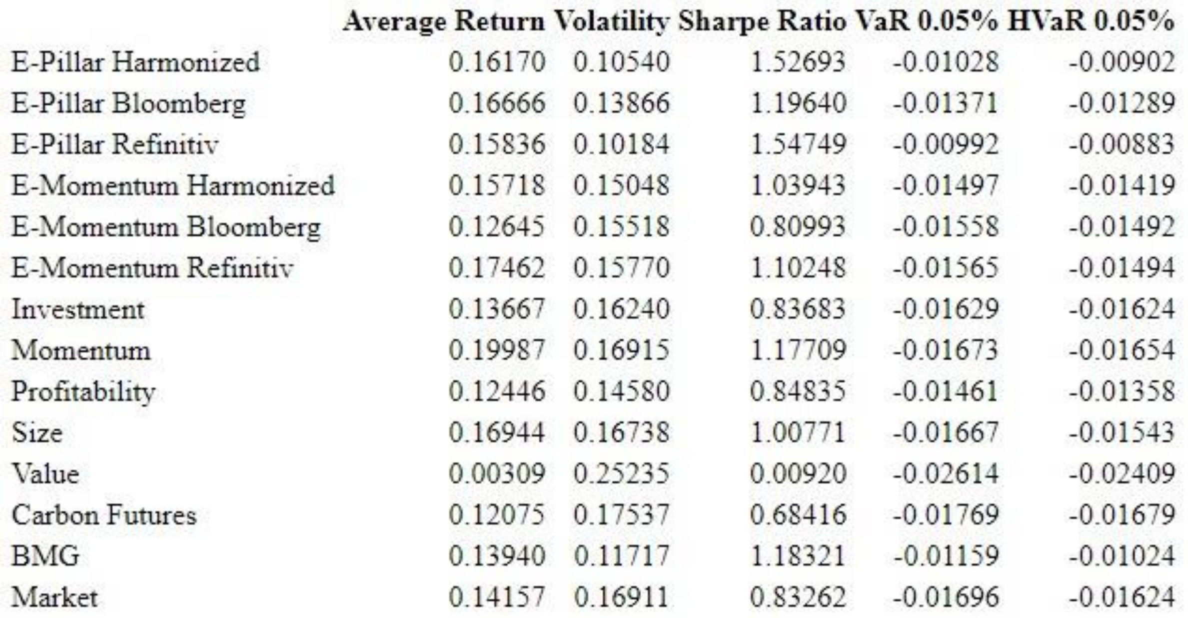
Diving into the empirical analysis, we start by exploring crucial statistics of our constructed carbon-mimicking portfolios. Then, we will shift the focus to the regression analysis starting with the one-step approach on the industry level. Afterward, the results of the standard two-step approach and the Fama-MacBeth approach will be presented. We will also do a brief investigation on the time-varying nature of risk premia. Lastly, we will include a short chapter on robustness.

6.1 Descriptive statistics of portfolios

We will start our empirical part with some key insights into our constructed factor portfolios, with a special focus on the 4 carbon-mimicking portfolios. Our primary aim is to dissect the intrinsic characteristics of these respective portfolios. We will try to investigate endowed biases towards other influential factors, for example, if some carbon proxy portfolio has a large tilt towards small-cap firms. We will therefore look at average market capitalization and price-to-book values for our portfolios. We will propose a short analysis of the overlap of companies in some of our portfolios to get a better sense of which firms get classified in which portfolios. Afterward, we will present five underlying key return metrics of our portfolios, namely annualized average return, annualized standard deviation, annualized Sharpe ratio, the daily 5% Value-at-Risk (VaR) calculated with the parametric approach (normal distribution of returns), and the daily 5% Historical Value-at-Risk (HVaR), to offer a comprehensive picture of the risk-return profiles of our portfolios.

6.1.1 Risk-return relationship of factor portfolios

In the following, we will provide two tables for the risk-return indicators, for both the long and the short side of our factor portfolios on a daily basis. In Table 1 we present the risk-return metrics for the long side of our portfolios, and in Table 2 the short side. We need to mention here that the table with the returns of the short portfolios are not actually short-sold returns, but long returns of the short side from the factor portfolio construction. So, for example, the return of the “Size” portfolio in Table 2 can be understood as the long return of the firms that are in the highest 15% of firms with respect to market capitalization. For the BMG in Table 2, it is the long return of the 30% of the greenest firms concerning the BGS. We also present the equal-weighted market return in both tables. We will also provide a cumulative performance plot for the long-side environmental factor portfolios.



	Average Return	Volatility	Sharpe Ratio	VaR 0.05%	HVaR 0.05%
E-Pillar Harmonized	0.16170	0.10540	1.52693	-0.01028	-0.00902
E-Pillar Bloomberg	0.16666	0.13866	1.19640	-0.01371	-0.01289
E-Pillar Refinitiv	0.15836	0.10184	1.54749	-0.00992	-0.00883
E-Momentum Harmonized	0.15718	0.15048	1.03943	-0.01497	-0.01419
E-Momentum Bloomberg	0.12645	0.15518	0.80993	-0.01558	-0.01492
E-Momentum Refinitiv	0.17462	0.15770	1.10248	-0.01565	-0.01494
Investment	0.13667	0.16240	0.83683	-0.01629	-0.01624
Momentum	0.19987	0.16915	1.17709	-0.01673	-0.01654
Profitability	0.12446	0.14580	0.84835	-0.01461	-0.01358
Size	0.16944	0.16738	1.00771	-0.01667	-0.01543
Value	0.00309	0.25235	0.00920	-0.02614	-0.02409
Carbon Futures	0.12075	0.17537	0.68416	-0.01769	-0.01679
BMG	0.13940	0.11717	1.18321	-0.01159	-0.01024
Market	0.14157	0.16911	0.83262	-0.01696	-0.01624

Table 1: Risk-Return Characteristics of Long-Side

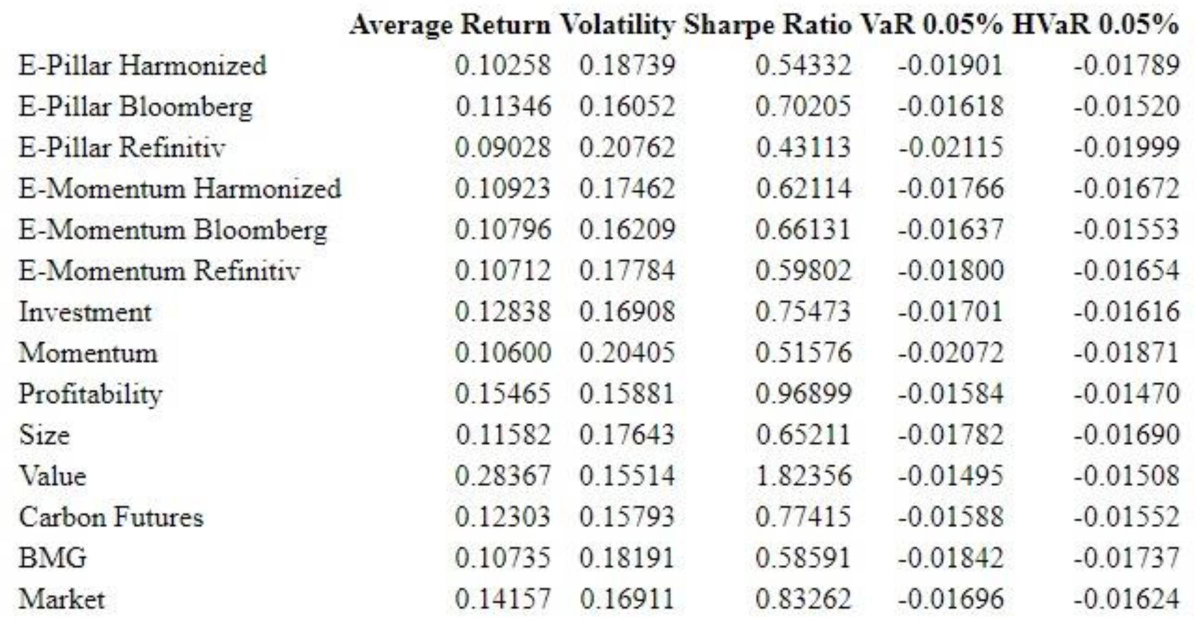
In Table 1 we see that two of our constructed carbon-mimicking portfolios generate an excess return over the market, namely the E-Pillar, where we present estimates for three configurations. We present here portfolio builds on both scores from Refinitiv and Bloomberg, and the average of both (Harmonized). We also observe excess return over the market of the E-Pillar Momentum score. Again, here we present returns of portfolios built on the same three scores as indicated above for the E-Pillar score. The BMG, so the 30% of the brownest firms with respect to the BGS were almost on par with the market, making around 2% less average return on a yearly basis over our period in contrast to the E-Pillar portfolios. Our fourth carbon mimicking portfolio, the Carbon Futures Dependency factor could not generate an excess return, we will elaborate on that a little bit later in this chapter when we present our regression results. Obviously, the total average return is only one side of the picture, therefore we want to also point out that the BMG portfolio and the E-Pillar portfolios also have a smaller annualized volatility, with 11.72% for the BMG portfolio and 10.18% for the E-Pillar portfolio built on Refinitiv`s metrics respectively. This is also reflected in the Sharpe ratio of our portfolios, where we observe again that the BMG and the E-Pillar portfolios have the best risk-return relationship with respect to that metric. Lastly, we look at the two Value at Risk metrics that we calculated that are used to estimate potential downside risk. We can again state that the E-Pillar and the BMG portfolios have considerably less down-side risk than the whole market. So overall, this leads us to the conclusion that "brown" firms do not only generate an excess return over the market but are also subject to the least overall risk as well as down-side risk.

The E-Momentum portfolio return has to be seen a little bit differently, because here we do not look at "brown" companies, but actually at companies that had the highest increase in their E-Pillar score, so according to our logic presented in a chapter above, companies that could reduce their carbon risk the most relative to all other firms. This momentum-like analogy seems to have worked pretty well over our time period, as this portfolio was able to return around 3% in excess over the market on a yearly basis and moreover has lower volatility, therefore also a better Sharpe and less pronounced down-side risk according to the VaR metrics.

Figure 7: Cumulative Returns of Long-Side

We will now take a look at the cumulative performance plots of the environmental long factor portfolios, to get a better understanding of which strategies worked best at which times. The cumulative performance plot reinforces the results obtained from the risk-return metrics presented above. We again observe a stark outperformance of the E-Pillar and the E-Momentum portfolios. The BMG portfolio up until the Covid crisis in 2020 slightly underperformed the market portfolio on a cumulative basis. In the period after 2020, it was able to generate considerable excess return over the market. The E-Pillar portfolio was also outperformed by the market up until around 2016. Afterward, it also generated quiet large excess returns over the market. The E-Momentum portfolio seems to have performed quite well over the whole time period, although with visibly and beforehand confirmed through the risk-return metrics, higher volatility than both the E-Pillar and BMG portfolio.

We will now take a look at the metrics from the short side of our factor portfolio construction. As mentioned above these are still long returns. The calculated metrics are mostly in line with what we expected due to the theoretical framework that we established above.



	Average Return	Volatility	Sharpe Ratio	VaR 0.05%	HVaR 0.05%
E-Pillar Harmonized	0.10258	0.18739	0.54332	-0.01901	-0.01789
E-Pillar Bloomberg	0.11346	0.16052	0.70205	-0.01618	-0.01520
E-Pillar Refinitiv	0.09028	0.20762	0.43113	-0.02115	-0.01999
E-Momentum Harmonized	0.10923	0.17462	0.62114	-0.01766	-0.01672
E-Momentum Bloomberg	0.10796	0.16209	0.66131	-0.01637	-0.01553
E-Momentum Refinitiv	0.10712	0.17784	0.59802	-0.01800	-0.01654
Investment	0.12838	0.16908	0.75473	-0.01701	-0.01616
Momentum	0.10600	0.20405	0.51576	-0.02072	-0.01871
Profitability	0.15465	0.15881	0.96899	-0.01584	-0.01470
Size	0.11582	0.17643	0.65211	-0.01782	-0.01690
Value	0.28367	0.15514	1.82356	-0.01495	-0.01508
Carbon Futures	0.12303	0.15793	0.77415	-0.01588	-0.01552
BMG	0.10735	0.18191	0.58591	-0.01842	-0.01737
Market	0.14157	0.16911	0.83262	-0.01696	-0.01624

Table 2: Risk-Return Characteristics of Short-Side

The short side of both the BMG and the E-Pillar portfolio generated considerably less return over our time period hinting at the existence of a risk-premia for "brown" companies. We also observe that the short side of the E-Momentum portfolio, which includes the companies that had the worst development with respect to their E-Pillar score, also generated significantly less returns than the respective long side, which is also something that was expected.

Something that was kind of surprising to us was that the "greener" companies when looking at the E-Pillar and BGS scores, were subject to substantially larger volatility and downside risk. We would have expected that the stocks of these companies would be more stable over time than their "brown" counterparts since carbon risk should be lower for "green" companies.

In this chapter, we established that in our investment universe and over our time sample, "brown" companies were able to significantly outperform "green" companies when looking at the BMG and the E-Pillar portfolios. Moreover, both "brown" portfolios were also subject to less risk compared to their "green" counterparts. We also presented results that historically winners were able to generate higher returns while being subject to lower volatility than the losers with respect to the E-Pillar score. In the next subchapter, we want to present some other key insights of our factor portfolios, like market capitalization and valuations.

6.1.2 Other key insights of factor portfolios

We want to now look into some other key characteristics of our factor portfolios to investigate potential biases towards other financial risk factors. Therefore, in this sub-chapter, we will first take a look at the average market capitalization of our carbon factor portfolios over time, to see whether we selected portfolios with a clear tilt towards the small-cap or the large-cap side. We will then also look at book-to-market values over time for our portfolios to inspect whether we selected growth or value stocks. This analysis helps us better understand whether the outperformance of our environmental long portfolios might be explained by already known and proven risk factors. Afterward, we will also briefly present some sector composition statistics regarding the environmental factor portfolios that we built. In this section, we will merely analyze the long side of our portfolios.

We will start by investigating the average market capitalization (million EUR) of each of our environmental factor long portfolios, which is shown in Figure 8. We observe quite big differences in average market capitalization across our portfolios. The portfolio with by far the biggest market capitalization is the E-Pillar portfolio, with an average of 33461 million euros over the whole timeframe. In stark contrast, the BMG portfolio is clearly tilted towards small-cap stocks, being the portfolio with the smallest average market capitalization, averaging only

Figure 8: Average Market Capitalization of Portfolios

3922 million euros over the whole timeframe. We want to address here that the BMG portfolio is also the portfolio with the highest growth rate in average market cap, which is due to bad data availability in the first 5 years of our period and our penalizing setup for the construction of the BGS. Due to the fact that we heavily overweight small-cap stocks in the BMG, we will do a short analysis of the overlap of the BMG portfolio with the small-cap portfolio that we constructed to rule out a too-pronounced short bias. We also observe here that the E-Momentum portfolio composition seems to change by far the most every year, indicated by the large jumps in average market capitalization. The average market capitalization of this portfolio over the whole time period is 9041 million euros. The Carbon Futures portfolio is most of the time in line with the market´s average market capitalization, with an average of 15968 million euros in contrast to the market`s average of 14834 million euros.

Overall, we do not believe that our portfolios are too heavily tilted towards small or large-cap factors, but we will take a closer look at the percentage of overlapping companies for the BMG long and small-cap portfolios, as well as for the E-Pillar long and large-cap portfolios. In the Appendix, we provide the two plots where the percentage of companies that are in both the BMG long portfolio and the small-cap portfolio, the E-Pillar long and large-cap respectively, over our time period are presented0. The overlapping percentage ranges from 6% to 12% over the ten years for the BMG. We found that with the construction of the BGS, we always get some of the smallest firms in the index due to them having the worst response rate when it comes to environmental variables. Due to the penalizing nature of non-responses in the BGS, we will select some of the smallest companies in the index, but we believe that the overlap is not pronounced enough that we pick up too much small-cap risk-return relationship with the BMG portfolio. This is also further supported by the correlation between the two portfolio`s returns, which is 0.945. This is in line with the correlation of the BMG with other risk factors. We provide the correlation matrix table in the Appendix. Still, we have to keep the slight overweight of small-cap stocks in our BMG portfolio in mind when analyzing betas and risk premia. Secondly, the E-Pillar long portfolio, so the “brown” portfolio seems to have a tilt toward large-cap stocks. In the Table that you find in the Appendix, we observe significantly high overlap percentages, especially in the period from 2010 until 2014, where we range around 70%. In 2014 we observed a large drop in overlap percentages to values around 52.5%, where it stays for the remainder of our timeframe. Even though the overlap percentage of the E-Pillar long portfolio with the Large-Cap portfolio is quite high and we cannot rule out that this would generally also tilt our results regarding the E-Pillar risk premium analysis towards large-cap premia, we will take the tilts of both the BMG and the E-Pillar portfolio as a further robustness check. On the one hand, we select “brown” companies with a slight tilt toward small-cap stocks, on the other hand, we also select “brown” companies with a clear tilt towards large-cap stocks. This stark contrast in the selection of companies with bad carbon sustainability with respect to the two scores will further strengthen the results, as we are able to select companies with a quite large range in market capitalizations.

Secondly, we also want to investigate whether our environmental portfolios have some clear tilt towards value or growth stocks. Therefore, in Figure 9 we provide the average price-to-book ratio (P/B) of our portfolios. Over the whole time period, we do not see a clear tilt towards either growth or value stocks, as price-to-books ratios generally move very similarly with the market`s P/B ratio. The one thing that stands out for us is that the BMG portfolio which in the first 5 years could be regarded as having a slight tilt towards value stocks, actually transforms into a portfolio that is more tilted towards growth in the following five years relative to the market. Still, with an average P/E of 2.64 in contrast to the market`s 3.1 over the whole time period, we would say that the BMG portfolio is generally well diversified with respect to the value factor. Overall, we do not think that the small tilts with respect to P/E ratios, will trigger any problems in the analysis that follows.

Figure 9: Average Price-to-Book ratio of Portfolios

We decided to not provide the graphs of the market capitalization and P/E ratio for the short side of the carbon risk portfolios. The interested reader can find the graphs in the appendix. The results are in line with what we expected after analyzing the long portfolios. The BMG short side is tilted towards large-cap stocks. This is for the same reason that the BMG long side is tilted toward small-cap stocks.

Analogous, the E-Pillar short portfolio is tilted toward small-cap stocks. For the P/E ratio, we again do not find any portfolios to point out as they are mostly moving in line with the market´s price-to-book ratio.

6.1.3 Sector composition of portfolios

In this subchapter, we will present some data statistics on the sector composition of the environmental portfolios, to dissect whether some sectors are generally selected more frequently as “brown” and to also rule out that estimated carbon risk premia might be driven by certain sectors due to less diversification. In Table 3, we present the sector composition percentages.

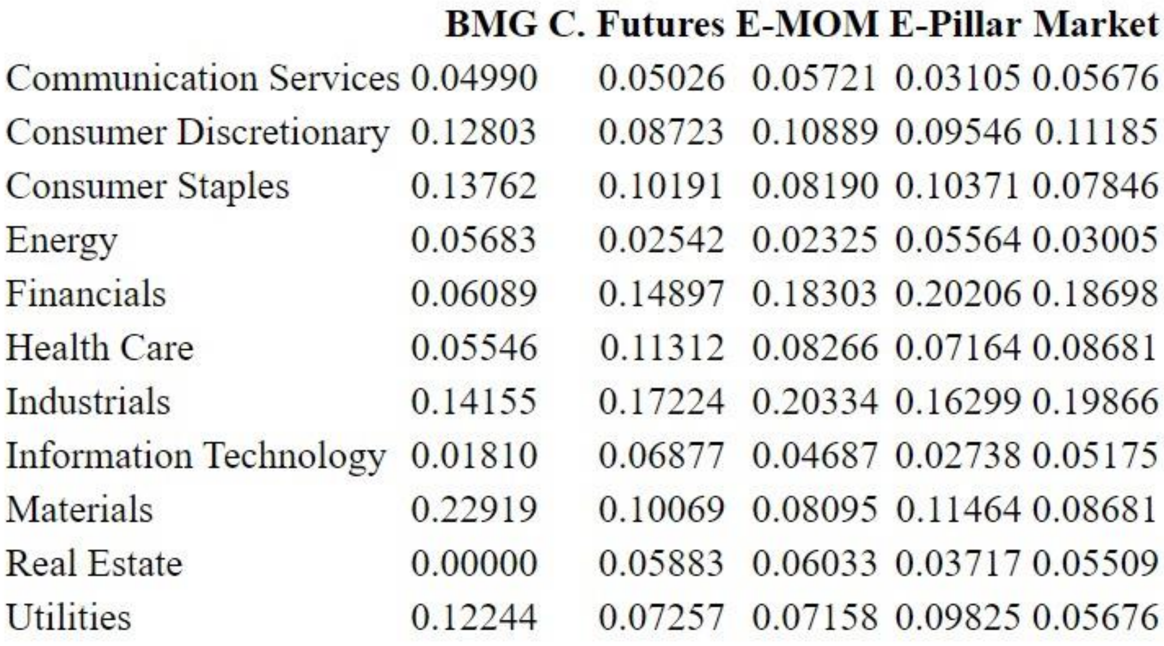
We want to first take a look at the BMG long factor composition, So the portfolio of “brown” firms with respect to the BGS. We observe that through this selection setup, we generally overweight sectors relative to the market that are known to have a higher energy intensity. The industries we overweight are materials, utilities, consumer discretionary, consumer staples, and energy. Analogous, we underweight sectors that are known to be less carbon-intensive. The underweight sectors comprise the healthcare sector, information technology, communication services, and financials. We want to mention two sectors separately here because these two percentages were somewhat surprising to us. First, there is the real estate sector which constitutes around 5.5% of the market portfolio but was never selected in the BMG portfolio. Although we believed that real estate would definitely be a sector that would be underweight relative to the market, we did not expect it to not get picked at all in the BMG long portfolio. Secondly, the industrials sector, which we believed beforehand would be a more than average carbon emitting and generally energy-intense sector is actually underweight in the BMG portfolio.

Secondly, we will take a look at the sector composition of the E-Pillar portfolio. Generally, over most sectors, we see very similar tendencies with the BMG portfolio, although the overweighting and underweighting seem to be less pronounced. Two industries stand out though. First, the financials sector constitutes the biggest share of firms in the E-Pillar portfolio, which`s share (around 20.2%) is even more pronounced than in the overall market (around 18.7%). Secondly, in contrast to the BMG portfolio, the consumer discretionary sector is slightly underweighted in the E-Pillar portfolio.

Next, we will look at the E-Momentum portfolio, that constitutes the winners with respect to the E-Pillar score. Here we only observe very minimal deviations from the market portfolio.

One sector that stands out relative to the others is the utility sector, which gets overweight by about 1.5 percentage points relative to the market. All the other sectors either get overweight or underweight within a range of 0.8 percentage points. This leaves us with the conclusion that winners with respect to the E-Pillar score are generally quite well distributed over all sectors, with the only outstanding sector being the utility sector which seems to have a bigger share of winners relative to the other industries.

Lastly, we present the sector composition for the Carbon Futures portfolio, where we go long the firms that have the highest positive relationship to the generic first carbon certificate futures price. In the carbon futures portfolio, the consumer staples, health care, information technology, materials, real estate, and the utilities sector generally get overweighted. The communication services, consumer discretionary, energy, financials, and industrials sectors get slightly underweighted relative to the market. In this portfolio, we cannot reason that there is a tendency to select low carbon-intense sectors in the portfolio. Again, we will come back to this in the regression analysis on why we believe the selection did not work as we intended.



	BMG	C. Futures	E-MOM	E-Pillar	Market
Communication Services	0.04990	0.05026	0.05721	0.03105	0.05676
Consumer Discretionary	0.12803	0.08723	0.10889	0.09546	0.11185
Consumer Staples	0.13762	0.10191	0.08190	0.10371	0.07846
Energy	0.05683	0.02542	0.02325	0.05564	0.03005
Financials	0.06089	0.14897	0.18303	0.20206	0.18698
Health Care	0.05546	0.11312	0.08266	0.07164	0.08681
Industrials	0.14155	0.17224	0.20334	0.16299	0.19866
Information Technology	0.01810	0.06877	0.04687	0.02738	0.05175
Materials	0.22919	0.10069	0.08095	0.11464	0.08681
Real Estate	0.00000	0.05883	0.06033	0.03717	0.05509
Utilities	0.12244	0.07257	0.07158	0.09825	0.05676

Table 3: Industry Composition in %

Overall, these results leave us with the conclusion that generally our selection process worked well. It seems that companies in high carbon intensity sectors were typically more inclined to get selected in both the E-Pillar and the BMG portfolio. Moreover, we observe that winners with respect to the E-Pillar score were well diversified across all sectors.

We decided that we will not present the sector composition of the short side of our portfolios here. We have investigated the composition and it is almost perfectly mirrored relative to the long-side portfolios, with some minor exceptions. What we mean by that for example, is that the sectors that are overweight in the BMG long portfolio are almost always underweight in the BMG short portfolio and vice versa. This applies to all four carbon proxy portfolios. Therefore, we believe it would not add any value for us to make a dedicated paragraph on this. If you want to take a look at it, you can find the sector composition table of the short-side portfolios in the Appendix.

Now that we have presented the general metrics of our carbon risk portfolios, and have delved into the sector composition of them, we will present the first part of our regression analysis, where we will elaborate on the results of our one-step time series regression setup. In this analysis, we will first of all look at dependencies over time regarding sector portfolios and will also look at the distribution of betas across our sectors.

6.2 One-step regression approach

In this section, we will discuss the results from the one-step regression approach. Initially, we will examine the time-varying betas calculated for industry portfolios and explore some of their implications. Subsequently, we will delve into the distribution of company betas within our industry classification to better understand the factor loadings on our carbon risk-mimicking portfolios.

6.2.1 Sector analysis

The primary objective of this thesis is to examine various factor portfolios to determine whether there is a discernible, priced transitional risk premium. However, it is evident from our data that different sectors exhibit varying degrees of exposure to this type of risk. To evaluate how our factor portfolios differ and to investigate potential time-varying exposures, we will conduct an analysis of their sector exposure. This involves assessing the betas derived from time-series regressions across different times and companies within our dataset.

For our analysis, we have chosen to use the Global Industry Classification Standard (GICS) Sectors as our industry classification system. Below, Table 4 presents the sector code, sector name, and the number of companies from our dataset that fall within each sector. Due to data inconsistencies, one company was excluded from our analysis, which accounts for the total count of companies being 599 instead of 600. This sector-based analysis will provide deeper insights into the varying impacts of transitional risk across different industries.

Sector Code	Sector Name	Number of Companies
10	Energy	18
15	Materials	52
20	Industrials	119
25	Consumer Discretionary	67
30	Consumer Staples	47
35	Health Care	52
40	Financials	112
45	Information Technology	31
50	Communication Services	34
55	Utilities	34
60	Real Estate	33

Table 4: Sector Code Classification

Since we are using the STOXX 600 Price Index, we cover, almost the entire European stock universe based on market capitalization. Specifically, the majority of the companies are clustered within the industrials and financials sectors, with a notably smaller presence in the energy sector. It is important for the reader to approach the forthcoming results with caution, particularly for sectors like energy, information technology, communication services, real estate, and utilities. The underrepresentation or overrepresentation of these sectors may skew perceptions of sector-specific risk and should be taken into account when interpreting the findings.

6.2.2 Dependencies over time

In this section, we will explore how the sector-aggregated betas associated with our carbon risk factors have changed over time. To accomplish this, we have conducted rolling-window regressions on our sector portfolios, which are structured according to the previously mentioned classification system. These portfolios are weighted by market capitalization, which helps prevent a bias towards smaller-cap companies within our analysis.

We run the regression specification, proposed in the section about methodology, using the Fama-French five factors, the momentum factor along with each of our carbon risk factors. To balance the need for capturing the time-dependent nature of the regression coefficients against the risk of excessive variability from too short a window, we have chosen two look-back periods of 300 and 600 trading days. These periods approximately correspond to five quarters and one and a half years, respectively. We run these two specifications on a daily basis throughout our entire sample period from 2010 to 2022. The subsequent content of this chapter is split into four subchapters. Each begins with graphs illustrating the results for each specification and concludes with a discussion of what these results imply.

6.2.2.1 E-Pillar

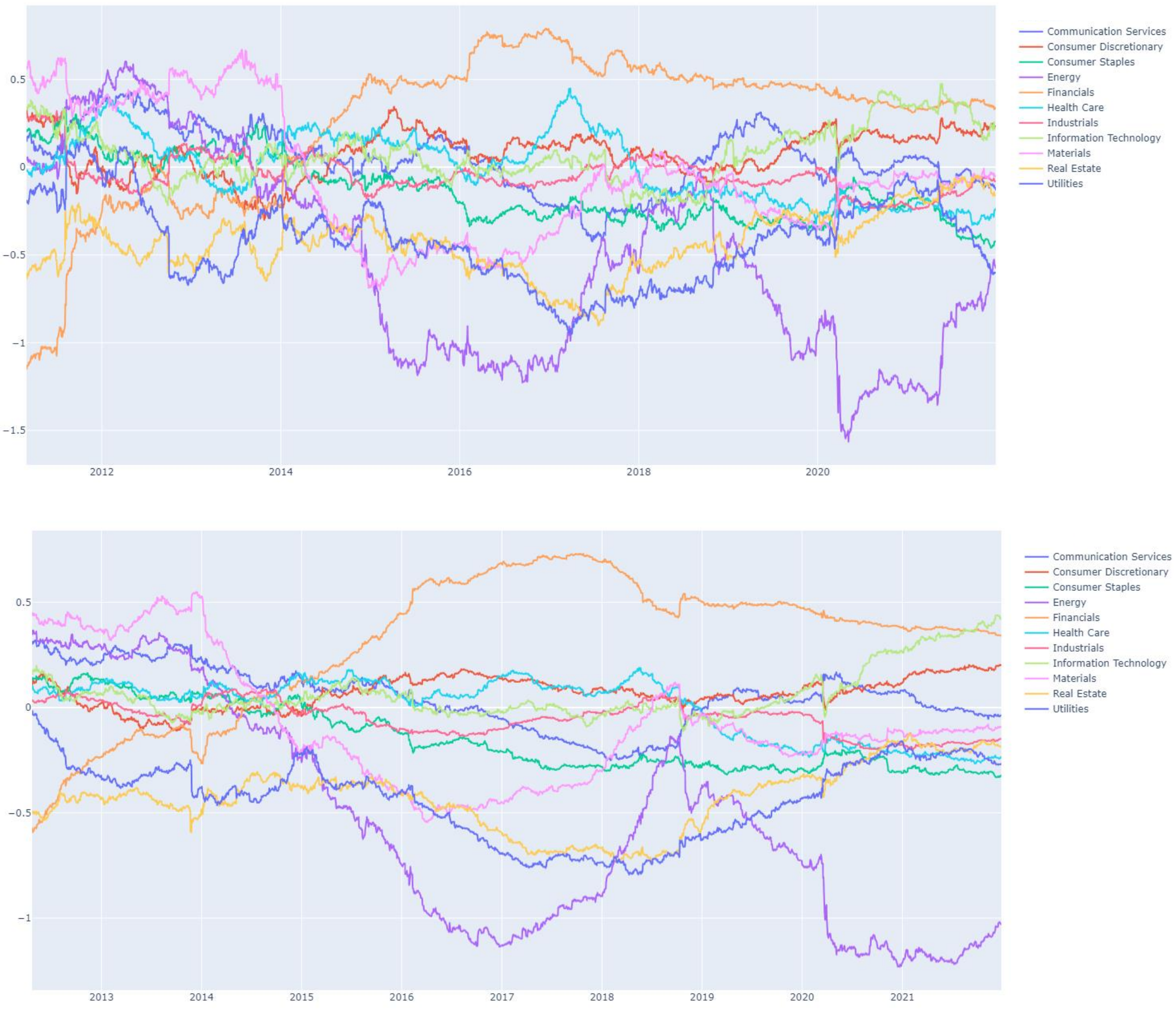


Figure 10: E-Pillar Rolling Regression Results on sector portfolios (300 and 600 day window)

Both charts show sector betas ranging from -1.5 to 0.8 with many sectors exhibiting highly time-dependent estimates. While time-varying betas are not inherently surprising, the extent of variability within individual sectors was unexpected. Many sectors show positive betas for the E-Pillar factor at some point in time, only to reverse course and be negatively impacted by the risk factor at others. For instance, financials, the second largest group in our dataset, initially show the lowest (negative) exposure to the risk factor but later exhibit the highest (positive) exposure for most of the period. Conversely, companies in the energy sector start with positive exposure and transition to a significantly negative beta.

Adjusting the window size for the rolling regressions does not alter the direction or magnitude of the exposures, serving as a robustness check for the E-Pillar risk factor. Therefore, the charts consistently demonstrate similar results for time-varying betas across different window sizes.

At this point, it might be important to clarify for the reader, that a positive regression coefficient indicates a sector's positive exposure to the E-Pillar risk factor. This means that if "brown" companies (those less environmentally friendly) outperform "green" companies (those more environmentally friendly), it would, to some extent, positively influence the performance of that specific sector.

Interestingly, the charts counterintuitively show that sectors traditionally associated with high environmental impact, such as energy, utilities, and real estate, have highly negative risk exposures to the E-Pillar factor. On the other hand, sectors like financials and information technology display positive exposure. This unexpected outcome will be further explored and explained towards the end of the chapter. Besides the directional signs of the coefficients, the results underscore the extensive variation in risk exposure across different sectors and over time.

6.2.2.2 E-Pillar Momentum

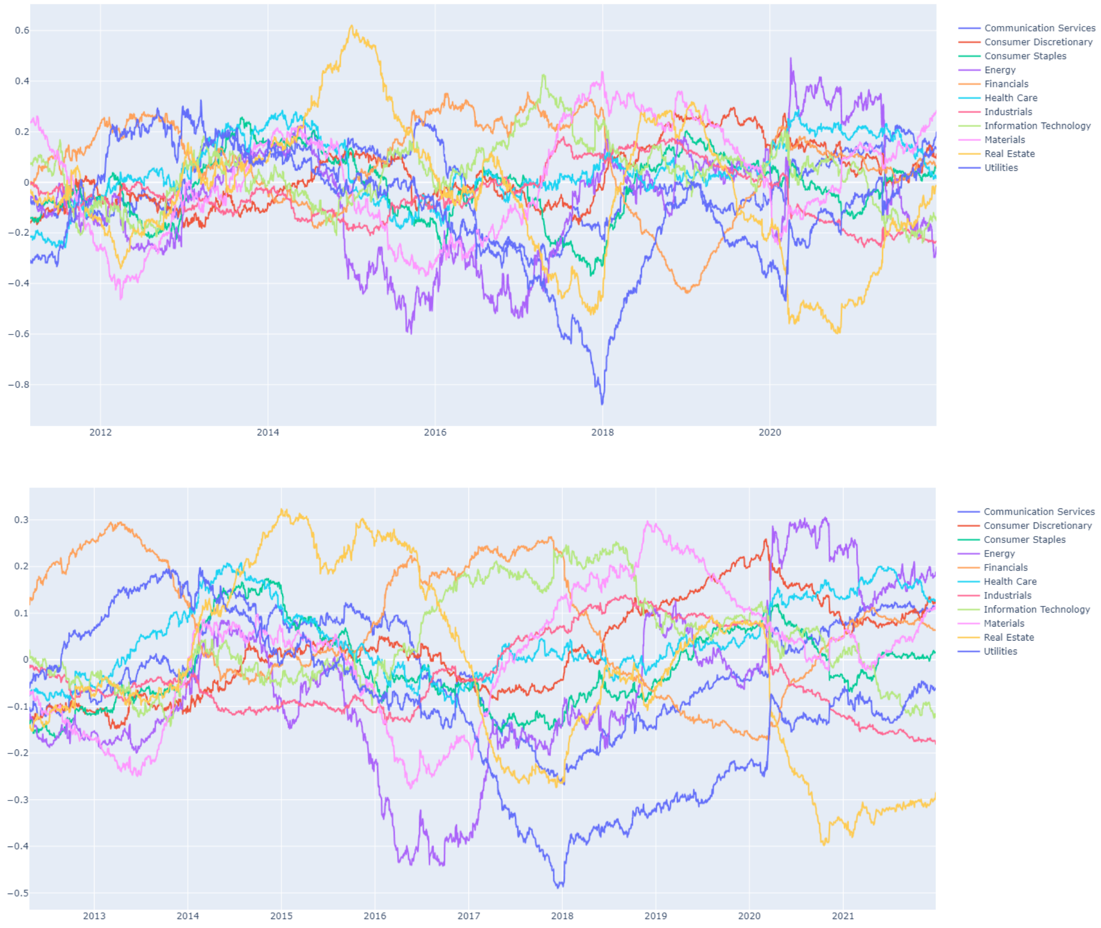


Figure 11: E-Pillar Momentum Rolling Regression Results on sector portfolios (300 and 600 day window)

Similar to the findings for the E-Pillar risk factor, the regression coefficients for the E-Pillar Momentum factor also exhibit high variability over time and across different sectors. However, these coefficients are notably smaller in magnitude compared to those of the E-Pillar risk factor. This reduced magnitude could suggest that the coefficients are generally less significant, or it may indicate a lower level of sector-specific exposure. The question of statistical significance and the quantification of risk premia associated with these coefficients will be addressed in the forthcoming chapter.

Additionally, it is observed that many sectors experience periods of both positive and negative exposure to the E-Pillar Momentum factor over time. The variation in exposure is considerable, yet the direction changes observed in the E-Pillar Momentum factor are not entirely independent of those seen in the E-Pillar factor. Notably, there are similar temporal points across some sectors where exposure either begins to accelerate or decelerate.

Sectors such as utilities, energy, and real estate have shown significant negative exposure at certain times. Conversely, sectors like financials, information technology, materials, and notably real estate again, have displayed high positive exposure to the E-Pillar Momentum risk factor throughout the study period.

6.2.2.3 Carbon Futures

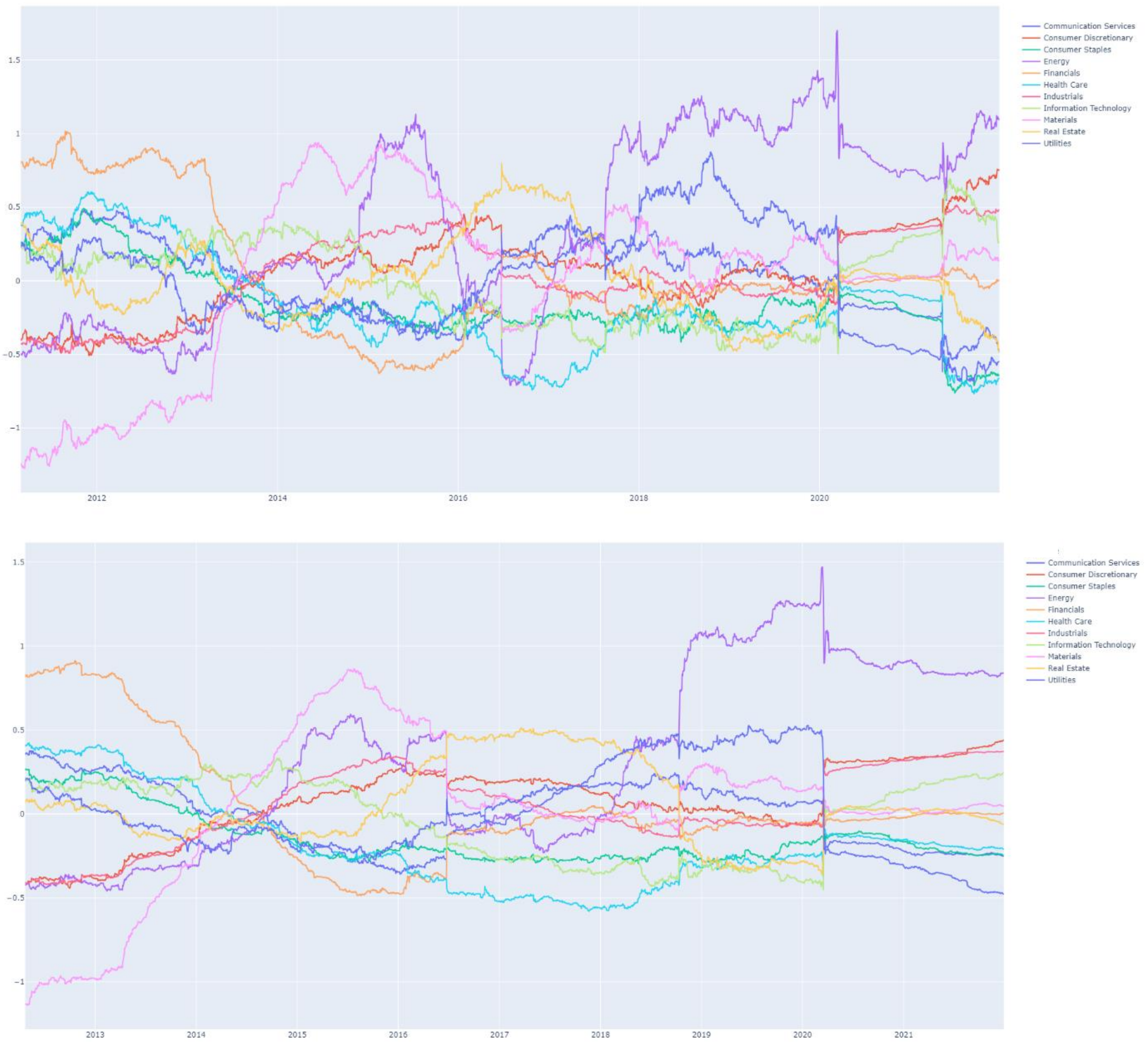


Figure 12: Carbon Futures Rolling Regression Results on sector portfolios (300 and 600-day window)

Risk-factor regressions including the carbon futures factor show comparable results to those obtained from the E-Pillar regressions in terms of both coefficient magnitude and variation of coefficients. These coefficients range from approximately -1 to nearly +1.5. While the variation is quite pronounced, similar to the E-Pillar coefficients, there is some path dependency observed, with inflection points at which directional changes occur for many sectors.

It is important to note that the interpretation of the Carbon Futures beta differs from that of the E-Pillar and BMG factors. The Carbon Futures factor is long companies, which have a high calculated score and show a positive relationship to changes in the price of carbon. Such companies are typically considered "green" because their discounted future earnings are expected to increase due to their minimal need to purchase additional emission allowances or even their potential to sell excess allowances at higher prices.

A positive coefficient for energy companies can be interpreted similarly to a negative coefficient in the E-Pillar regressions. Sectors showing very high exposure to the Carbon Futures risk factor include energy, materials, real estate, and financials (though only at the beginning of the sample period). In contrast, the sectors with the lowest negative exposure are health care, utilities, and information technology.

6.2.2.4 BMG

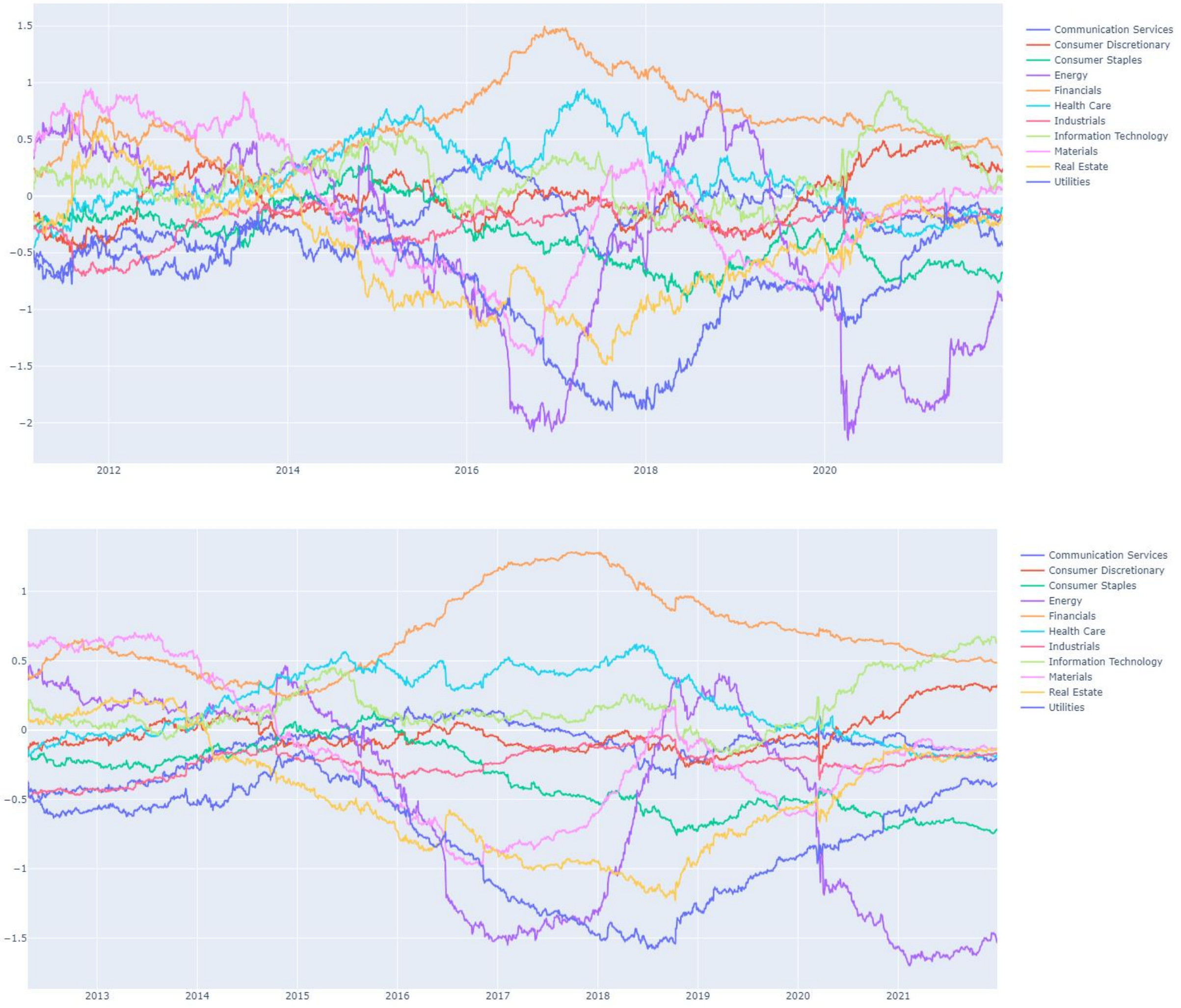


Figure 13: BMG Rolling Regression Results on sector portfolios (300 and 600 day window)

To wrap up our analysis of the time-varying exposure of the sector portfolios to our risk factors, we examine the betas associated with the Brown-Minus-Green (BMG) factor. The magnitude of the sector betas, both positive and negative, is the most pronounced when compared to all other factors, which could suggest a high level of significance. Despite this, for both window sizes, the BMG factor displays the least variation in comparison to the other factors, yet most sectors still experience both negative and positive exposures at different times. Notably, the energy sector exhibits the greatest variation and the most substantial negative exposure across all four factors. Other sectors with notable negative exposure include utilities, consumer staples, and real estate. Conversely, our findings indicate positive exposure for sectors such as financials, information technology, and health care.

Although the risk factors differ significantly in their construction methods, they demonstrate a remarkable similarity in identifying sectors with high betas in either direction. Sectors like energy, real estate, and often utilities consistently show negative exposure to transition risk, whereas financials, information technology, and health care exhibit positive exposure. This outcome is counterintuitive and diverges from our initial expectations.

At the end of this chapter, we will offer a potential explanation for these unexpected findings. Another consistent theme across the results for the risk factors is the high variability of exposure over time for almost all sectors, indicating episodes of both positive and negative exposures. This pattern strongly suggests that transition risk exposure is not static but varies over time.

6.2.3 Distribution of betas within sectors

After analyzing the time-dependent exposure of sector portfolios to our four distinct carbon risk factors, we will next explore the distribution of betas within each sector. This examination will allow us to assess the homogeneity within the sectors and validate the robustness of our preliminary findings. For this analysis, we will use data spanning the entire sample period and apply similar regression methodologies as previously utilized, incorporating the Fama-French five factors, momentum, and one of our carbon risk factors for each regression run.

Once the regressions are complete, we will categorize the companies by sector and compile the carbon risk coefficients for each. Following the methodology outlined by Roncalli et al. (2020), we will then visualize the results for all sectors using a single boxplot chart for each risk factor. This visual representation will help highlight the median, quartiles, and potential outliers within the distribution of beta coefficients across sectors.

Each subchapter, dedicated to one of the risk factors, will begin with the presentation of the boxplot chart. This will be followed by a concise summary of the findings. To ensure clarity and focus in the charts, extreme outliers will be excluded from the visualizations.

6.2.3.1 E-Pillar

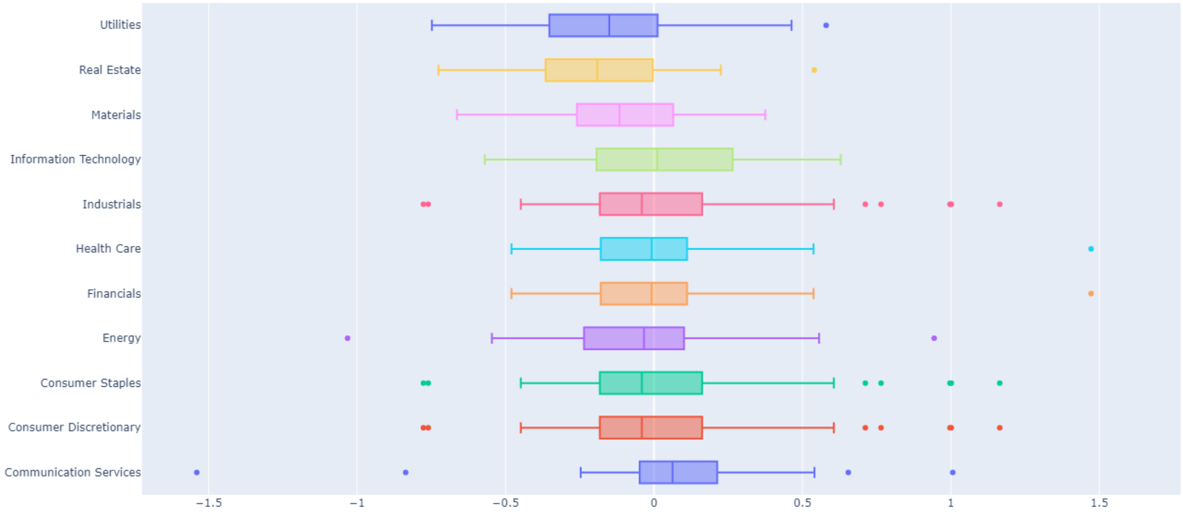


Figure 14: Boxplot Sector Distribution (E-Pillar)

The graph displays a boxplot for each of the eleven sectors, delineating the lower whisker at Q1 minus 1.5 times the interquartile range (IQR), the first quartile (Q1), the median, the third quartile (Q3), and the upper whisker at Q3 plus 1.5 times the IQR. Similar to the observations from the time-dependent analysis, there is notable variability within each sector. No sector exclusively shows negative or positive values; however, sectors such as utilities, real estate, and materials predominantly exhibit values in the negative range.

One possible explanation for the high variability observed could be the small number of companies in some sectors, as highlighted at the beginning of this chapter. Despite using data encompassing the entire sample period, sectors that consistently showed negative coefficients in earlier analyses predominantly exhibit negative coefficients again in this boxplot analysis. The only sector with a positive median value is communication services.

Given that the Environmental Pillar Score is calculated using sector-specific data to ensure comparability across sectors, it inherently measures a company's performance relative to its peers within the same sector. Therefore, it is expected that companies within any given sector will display both positive and negative risk exposures. Nevertheless, because our analysis exclusively involves European companies and the Environmental Pillar Scores are based on global sector benchmarks, it is plausible for an entire sector to exhibit a collective tilt towards either positive or negative exposure.

6.2.3.2 E-Pillar Momentum

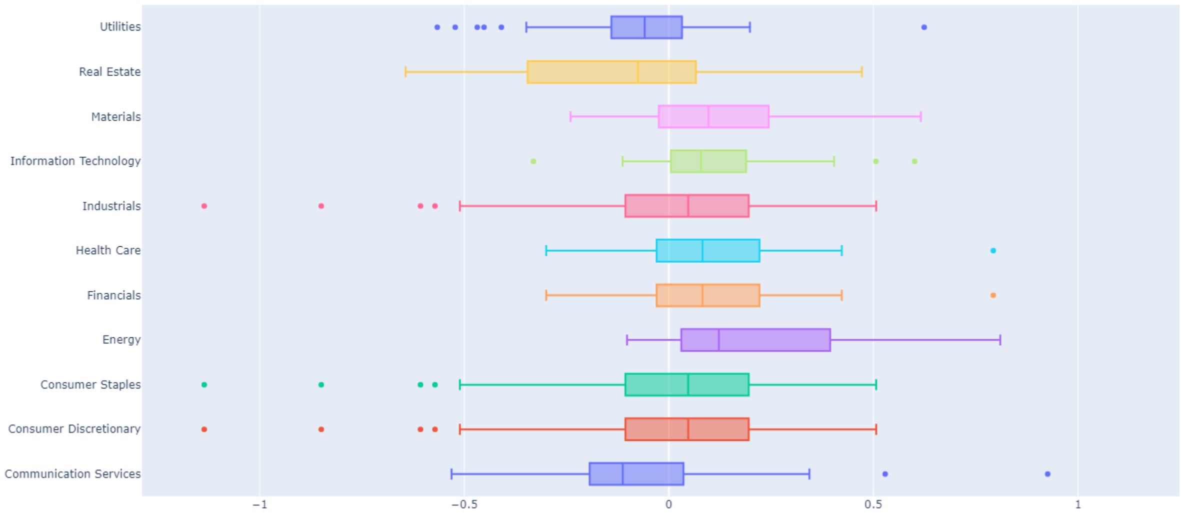


Figure 15: Boxplot Sector Distribution (E-Pillar Momentum)

In contrast to the previous analysis using the E-Pillar boxplot, the E-Pillar Momentum chart reveals that the majority of sectors display positive median values, indicating a generally favorable response to environmental momentum. Moreover, the variation in these values is even greater than that observed with the initial E-Pillar factor. This suggests a more dynamic response to changes in environmental performance scores across different industries.

Sectors such as energy, materials, and financials exhibit the highest positive median values. This indicates that companies within these sectors are particularly sensitive to momentum-like effects driven by changes in environmental pillar scores. These sectors seem to react strongly to improvements in their environmental credentials, which could reflect their higher engagement with sustainability issues or more volatile environmental performance.

Conversely, sectors like utilities, real estate, and communication services show the most negative median values, implying a significant negative exposure to the E-Pillar Momentum factor.

6.2.3.3 Carbon Futures

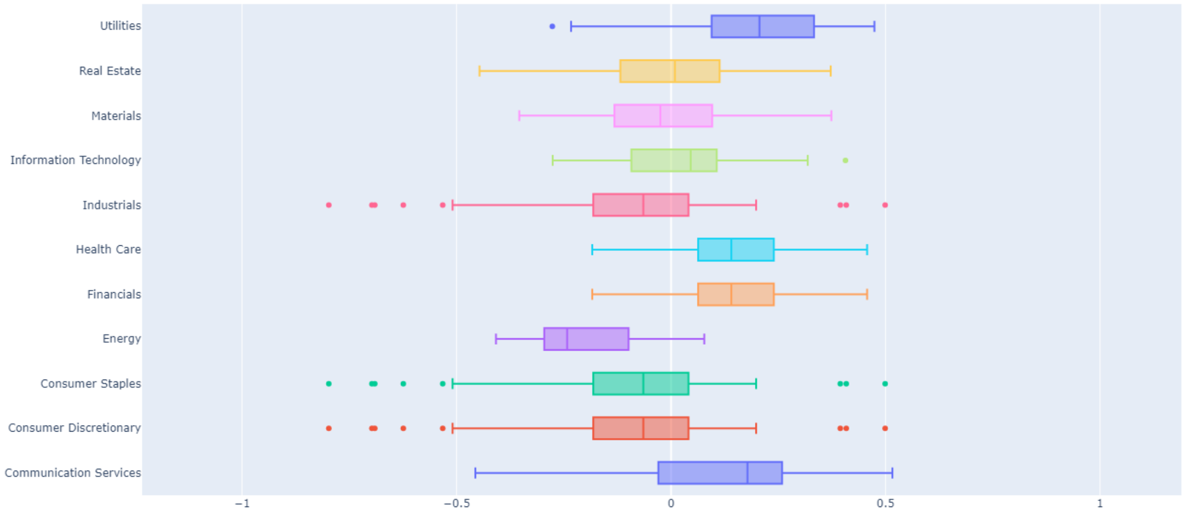


Figure 16: Boxplot Sector Distribution (Carbon Futures)

The analysis of the Carbon Futures risk factor presents a notably different picture from the time-dependent assessments previously discussed. Interestingly, while the energy sector generally showed a positive exposure in the time-dependent case, a more granular examination of individual company coefficients aggregated into this sector's boxplot reveals a negative exposure. This discrepancy can be particularly challenging to interpret, especially considering the small number of energy companies (only 18) in our sample. Additionally, the market capitalization within this sector is highly skewed, with major disparities between very large companies like Shell, Eni, or BP and much smaller entities. This significant variance underscores the complexity of comparing time-dependent analyses with aggregated approaches.

Furthermore, the boxplot data indicates positive exposure for sectors such as financials, utilities, and health care. In contrast, sectors like energy, consumer staples, and consumer discretionary are shown to have negative exposure. This variation suggests that while some sectors are benefiting from or are well-aligned with trends in carbon pricing, others, particularly those traditionally seen as high carbon emitters or less engaged in sustainability efforts, face negative impacts.

6.2.3.4 BMG

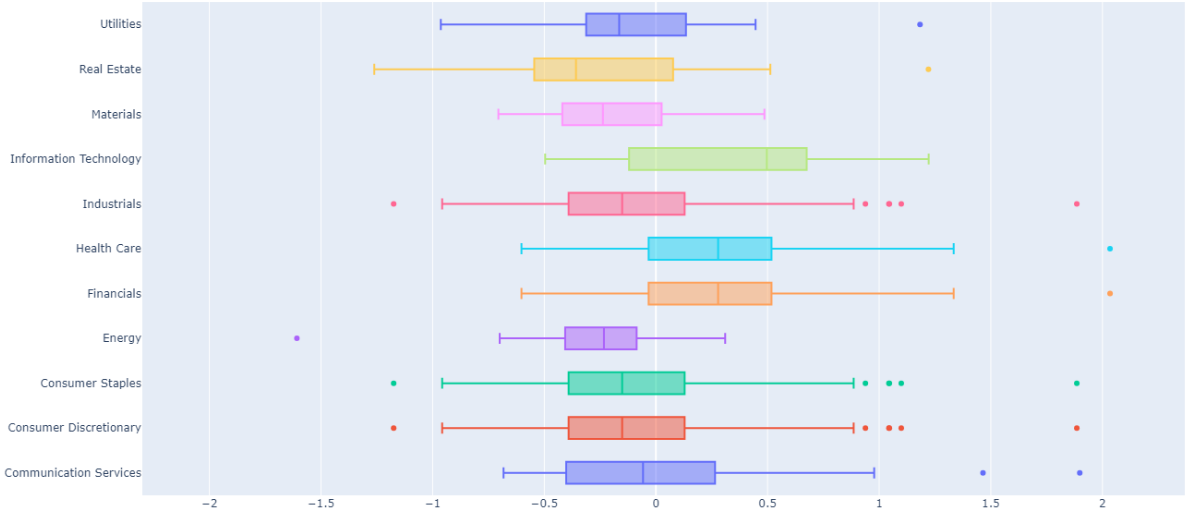


Figure 17: Boxplot Sector Distribution (BMG)

The final graph, illustrating the distribution of regression coefficients for our Brown-Minus-Green (BMG) factor, shows considerable variation within sectors, much like the previous graphs. This variability is logical as companies within the same sector can differ significantly in their specific carbon risk exposure based on their unique risk profiles. However, it is also clear that entire sectors can be more or less vulnerable to carbon risk.

In the case of the BMG risk factor, sectors like real estate, materials, and energy are systematically less exposed to risk, indicating a potentially lower impact of transition risks on these sectors. Conversely, sectors such as information technology, health care, and financials appear to have systematically higher risk exposure.

This consistent observation across our four risk factors—that there is significant variation both over time and within as well as across sectors—highlights the complex nature of transition risk. Additionally, it is evident that certain sectors are systematically more exposed to positive or negative impacts from transition risk. Specifically, financials, health care, and information technology tend to show positive exposure, whereas energy, utilities, and real estate typically exhibit negative exposure.

These findings are counterintuitive, particularly given traditional expectations about which sectors are most at risk from environmental transitions. The next subchapter will explore this anomaly in more detail, using a brief case study to present a theory that explains why these surprising results might be happening.

6.2.4 Case study: European energy companies

Energy companies, often seen at the forefront of the shift from a traditional "brown" economy to a "green" one, generally don't have a reputation as the main drivers of this transition. This perception largely stems from their core business activities—exploring, refining, and marketing oil and gas. Consequently, there's a public notion that these companies are especially vulnerable to risks from the transition process and are not truly "green." While such views may partly reflect personal beliefs, the reality is somewhat different.

Certainly, energy companies are inherently exposed to carbon risk, as their main products are carbon-based. However, they can mitigate this risk by adopting measures such as committing to reduce emissions through improved production standards or by shifting to renewable energy sources. To ensure these commitments are not seen as mere "greenwashing," they can be verified and monitored by public or scientific institutions.

These strategies underpin the environmental pillar scores assigned by rating agencies like Bloomberg and Refinitiv, as discussed earlier. Furthermore, these ratings are often normalized within sectors and should be seen as "Best-In-Class" metrics rather than absolute measures. This approach to assessing risk exposure differs fundamentally from the "sin-stock" strategy, which outright excludes such companies from investment consideration.

This methodology is incorporated into every risk factor we construct, affecting the environmental pillar scores in the E-Pillar and E-Pillar Momentum factors, as well as the inclusion of dummy variables about future strategies and current emissions handling in the BMG factor, and the size and sign of the beta estimates in the carbon futures factor. These calculations are made using data from the global investment universe, not just European companies.

In light of this, it is possible for energy companies to exhibit a negative exposure to transition risk, contrary to typical expectations. To support this assertion, we have compiled the current (2024) environmental pillar scores for all 18 companies in our sector in the table below.

Name of Company	Refinitiv Environmental Pillar Score (2024)
Aker BP ASA	62.87
BP PLC	87.17
Energean PLC	69.34
Eni SPA	87.57
Equinor ASA	76.37
Frontline PLC	38.37
Galp Energia SGPS SA	70.87
Gaztransport et Technigaz SA	48.49
Harbour Energy PLC	82.54
Neste Oyj	78.54
OMV AG	84.0
Polski Koncern Naftowy Orlen SA	61.64
Repsol SA	85.34
Shell PLC	93.5
Subsea 7 SA	75.15
Technip Energies NV	70.33
Tenaris SA	66.73
Totalenergies SE	82.65

Table 5: Environmental Pillar Score of Energy Companies

At this juncture, it's important for the reader to recall that the scores are normalized on a scale from 0 to 100. Thus, any score above 50 indicates performance that is above average. Within our sample, only 2 out of the 18 energy companies have a score below 50, with an overall average score of 73.15. This suggests that our sample is less exposed to transition risk compared to the average global company in this sector, at least according to Refinitiv's metrics.

This relative lack of exposure may explain why we observe a negative exposure in most of our risk factors. Additionally, it is crucial to note that our risk factors are specifically tailored to European companies and successfully capture this distinct behavior, which bolsters our confidence in the robustness of their construction methods.

6.3 Two-step regression approaches

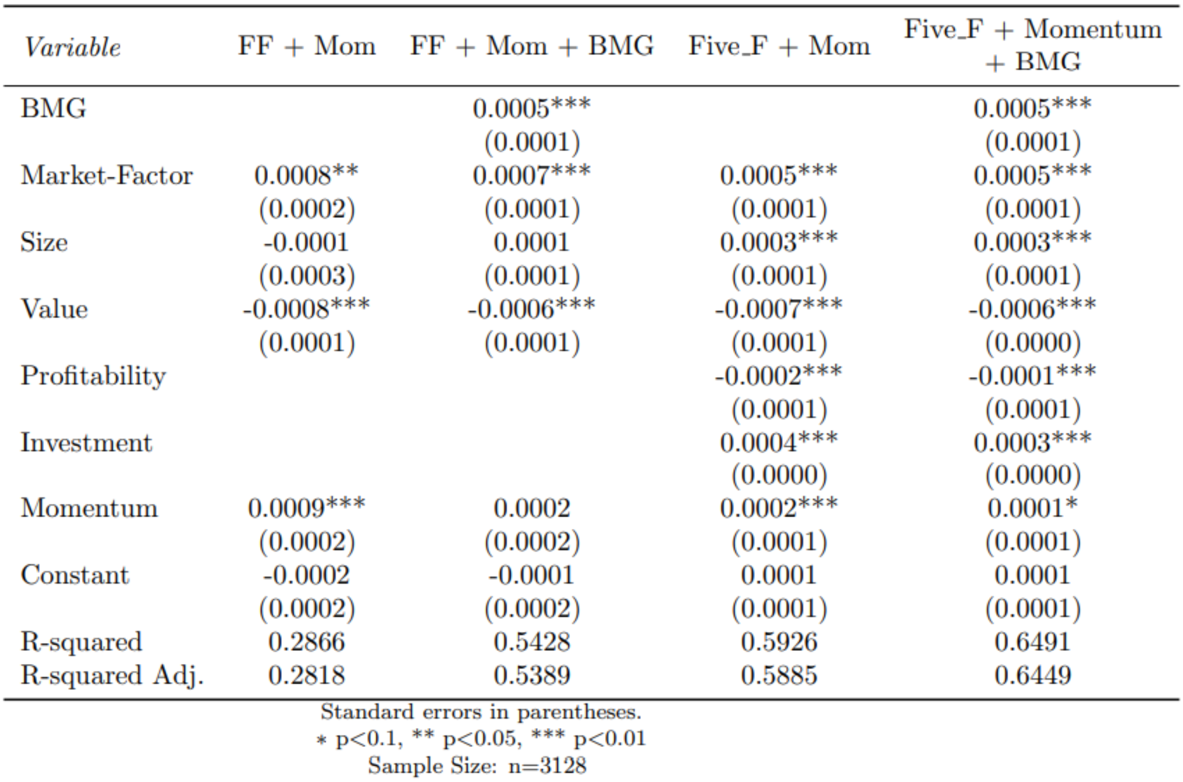
In this next chapter, we will present the results of our two-step regression approaches. This analytical approach encompasses both the conventional two-step regression analysis and a nuanced modification tailored to address the dynamic nature of risk premia, through the application of the Fama-MacBeth regression technique.

6.3.1 Standard two-step approach

Our initial focus lies on dissecting the results of the standard two-step approach. We aim to evaluate various model accuracy indicators, including R^2, adjusted R^2, AIC, and BIC. This analysis seeks to answer the question of whether the integration of specifically designed carbon-mimicking portfolios into well-established factor regression model frameworks can enhance model accuracy with respect to the metrics mentioned above. Rather than extensively examining every model specification, our intention here is to spotlight the most relevant results derived from our analysis.

In the following tables, we present the regression results of the model specifications with the addition of one of our carbon risk proxy portfolios. In each table, you can find four model specifications. The Fama-French + Momentum and the Five Factor + Momentum, once without our newly added carbon risk portfolio, and once with the addition of it, to see whether model accuracy improves. Moreover, we also include tables for each carbon risk proxy regarding the AIC and BIC criteria of the respective portfolio.

6.3.1.1 BMG

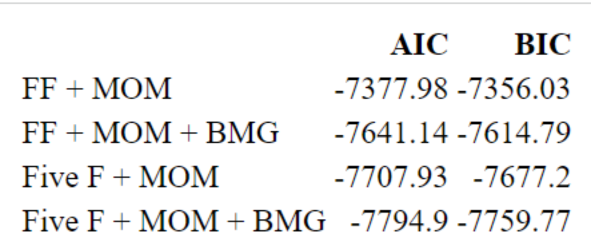


Variable	FF + Mom	FF + Mom + BMG	Five_F + Mom	Five_F + Momentum + BMG
BMG		0.0005***		0.0005***
		(0.0001)		(0.0001)
Market-Factor	0.0008**	0.0007***	0.0005***	0.0005***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Size	-0.0001	0.0001	0.0003***	0.0003***
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Value	-0.0008***	-0.0006***	-0.0007***	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Profitability			-0.0002***	-0.0001***
			(0.0001)	(0.0001)
Investment			0.0004***	0.0003***
			(0.0000)	(0.0000)
Momentum	0.0009***	0.0002	0.0002***	0.0001*
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Constant	-0.0002	-0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
R-squared	0.2866	0.5428	0.5926	0.6491
R-squared Adj.	0.2818	0.5389	0.5885	0.6449

Standard errors in parentheses.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$
Sample Size: n=3128

Table 6: Two-step regression results with various model specifications including one carbon risk proxy (BMG). The coefficients represent daily risk premia with their respective standard errors in the parentheses below.

In Table 6, we observe that generally the R^2 and the adjusted R^2 increase significantly if we add the BMG factor portfolio to the traditional factor frameworks. The BMG portfolio is associated with a risk premium that is not only positive but also exhibits a high degree of statistical significance at the 1% level across both model variations.



	AIC	BIC
FF + MOM	-7377.98	-7356.03
FF + MOM + BMG	-7641.14	-7614.79
Five F + MOM	-7707.93	-7677.2
Five F + MOM + BMG	-7794.9	-7759.77

Table 7: AIC and BIC for regressions in table 6 (BMG)

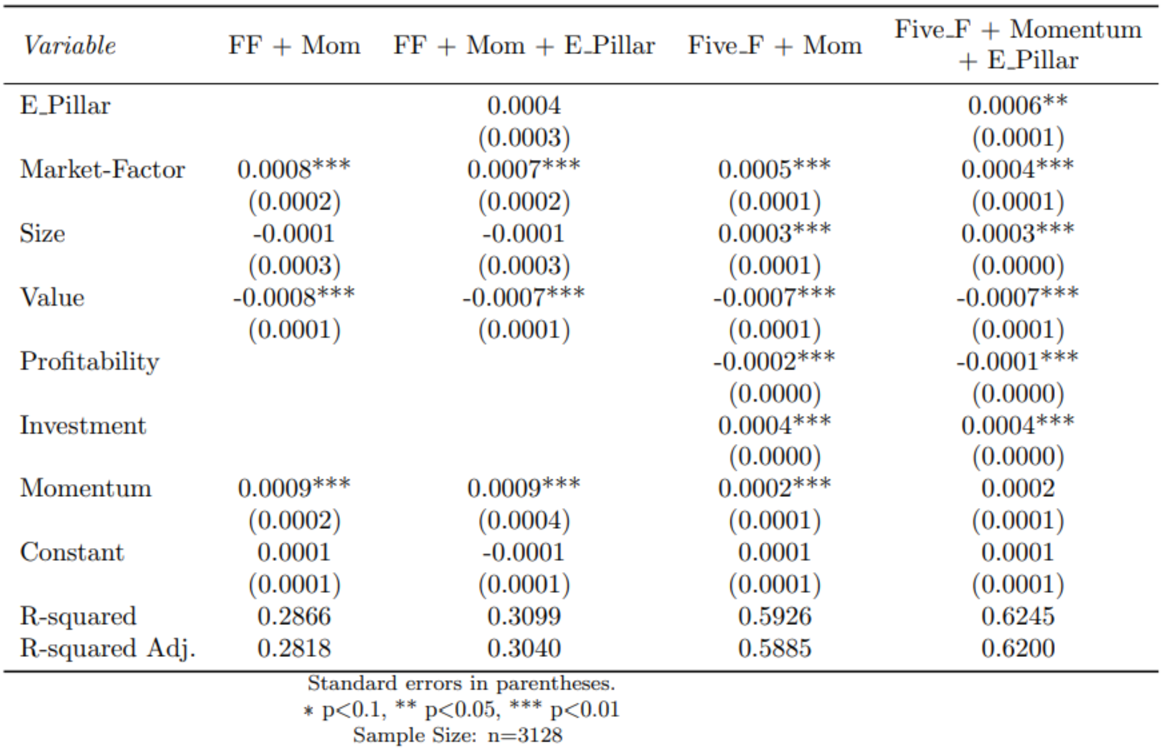
In Table 7 we present the AIC and BIC criteria for the BMG factor regression. These metrics corroborate our initial findings, affirming that the inclusion of the BMG portfolio within traditional factor model regressions notably enhances model accuracy.

6.3.1.2 Environmental Pillar

The examination of the regression results associated with the E-Pillar portfolio, as shown in Table 8, suggests a similar relationship. The inclusion of the E-Pillar portfolio yields improvements in both the R^2 and the adjusted R^2 metrics, albeit to a slightly lesser magnitude compared to the BMG case. It is of particular interest to note that the risk premium attributed to the E-Pillar portfolio, while insignificant in the Fama-French + Momentum + E-Pillar model configuration, becomes positive and highly significant at the 1% level within the Five-Factor + Momentum + E-Pillar model setup.

Subsequently, in Table 9, we revisit the AIC and BIC metrics across the model specifications concerning the E-Pillar portfolio. These two metrics further underscore the model accuracy enhancements achieved through the inclusion of the E-Pillar portfolio, though the magnitude of improvement is less pronounced in comparison to the BMG portfolio.

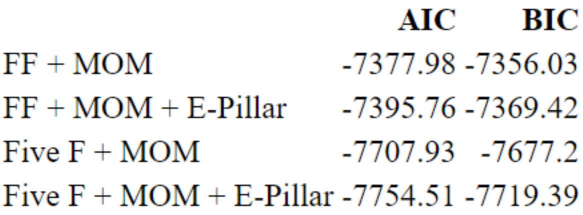
The results of these two carbon risk proxy portfolios are very much in line with what we expected to find from the theoretical framework that we introduced earlier. Our findings here strongly hint towards the existence of a risk premium for “brown” companies.



Variable	FF + Mom	FF + Mom + E_Pillar	Five_F + Mom	Five_F + Momentum + E_Pillar
E_Pillar		0.0004		0.0006**
		(0.0003)		(0.0001)
Market-Factor	0.0008***	0.0007***	0.0005***	0.0004***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Size	-0.0001	-0.0001	0.0003***	0.0003***
	(0.0003)	(0.0003)	(0.0001)	(0.0000)
Value	-0.0008***	-0.0007***	-0.0007***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Profitability			-0.0002***	-0.0001***
			(0.0000)	(0.0000)
Investment			0.0004***	0.0004***
			(0.0000)	(0.0000)
Momentum	0.0009***	0.0009***	0.0002***	0.0002
	(0.0002)	(0.0004)	(0.0001)	(0.0001)
Constant	0.0001	-0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R-squared	0.2866	0.3099	0.5926	0.6245
R-squared Adj.	0.2818	0.3040	0.5885	0.6200

Standard errors in parentheses.
∗ p<0.1, ** p<0.05, *** p<0.01
Sample Size: n=3128

Table 8: Two-step regression results with various model specifications including one carbon risk proxy (E-Pillar). The coefficients represent daily risk premia with their respective standard errors in the parentheses below.

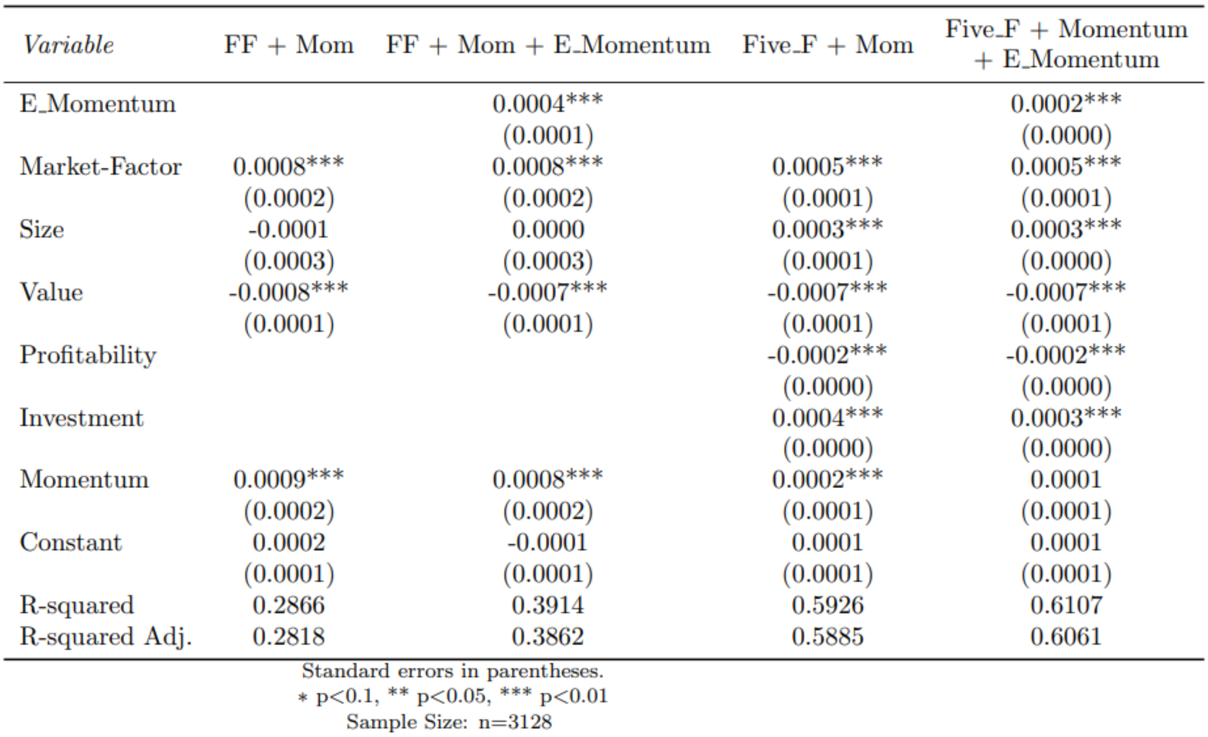


	AIC	**BIC**
FF + MOM	-7377.98	-7356.03
FF + MOM + E-Pillar	-7395.76	-7369.42
Five F + MOM	-7707.93	-7677.2
Five F + MOM + E-Pillar	-7754.51	-7719.39

Table 9: AIC and BIC for regressions in table 8 (E-Pillar)

6.3.1.3 Environmental Pillar Momentum

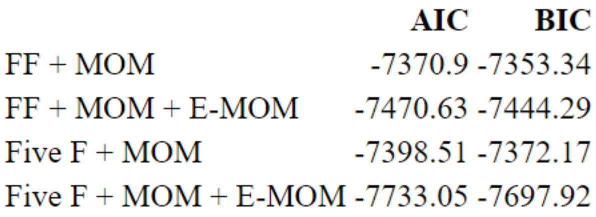
We will now elaborate on the regression results of the model specifications with the addition of the E-Momentum portfolio, which we present in Table 10. R^2 and adjusted R^2 improve significantly when we include the E-Momentum factor portfolio in our regression setup. The risk premium associated with the E-Momentum portfolio, characterized by its positivity and statistical significance at the 1% level across both model configurations, suggests that companies exhibiting superior increases on the E-Pillar score indeed command a positive risk premium. These findings are further strengthened by the clear improvement of the AIC and BIC criteria.



Variable	FF + Mom	FF + Mom + E_Momentum	Five_F + Mom	Five_F + Momentum + E_Momentum
E_Momentum		0.0004***		0.0002***
		(0.0001)		(0.0000)
Market-Factor	0.0008***	0.0008***	0.0005***	0.0005***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Size	-0.0001	0.0000	0.0003***	0.0003***
	(0.0003)	(0.0003)	(0.0001)	(0.0000)
Value	-0.0008***	-0.0007***	-0.0007***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Profitability			-0.0002***	-0.0002***
			(0.0000)	(0.0000)
Investment			0.0004***	0.0003***
			(0.0000)	(0.0000)
Momentum	0.0009***	0.0008***	0.0002***	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Constant	0.0002	-0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R-squared	0.2866	0.3914	0.5926	0.6107
R-squared Adj.	0.2818	0.3862	0.5885	0.6061

Standard errors in parentheses.
∗ $p<0.1$, ** $p<0.05$, *** $p<0.01$
Sample Size: n=3128

Table 10: Two-step regression results with various model specifications including one carbon risk proxy (E-Pillar Momentum). The coefficients represent daily risk premia with their respective standard errors in the parentheses below.



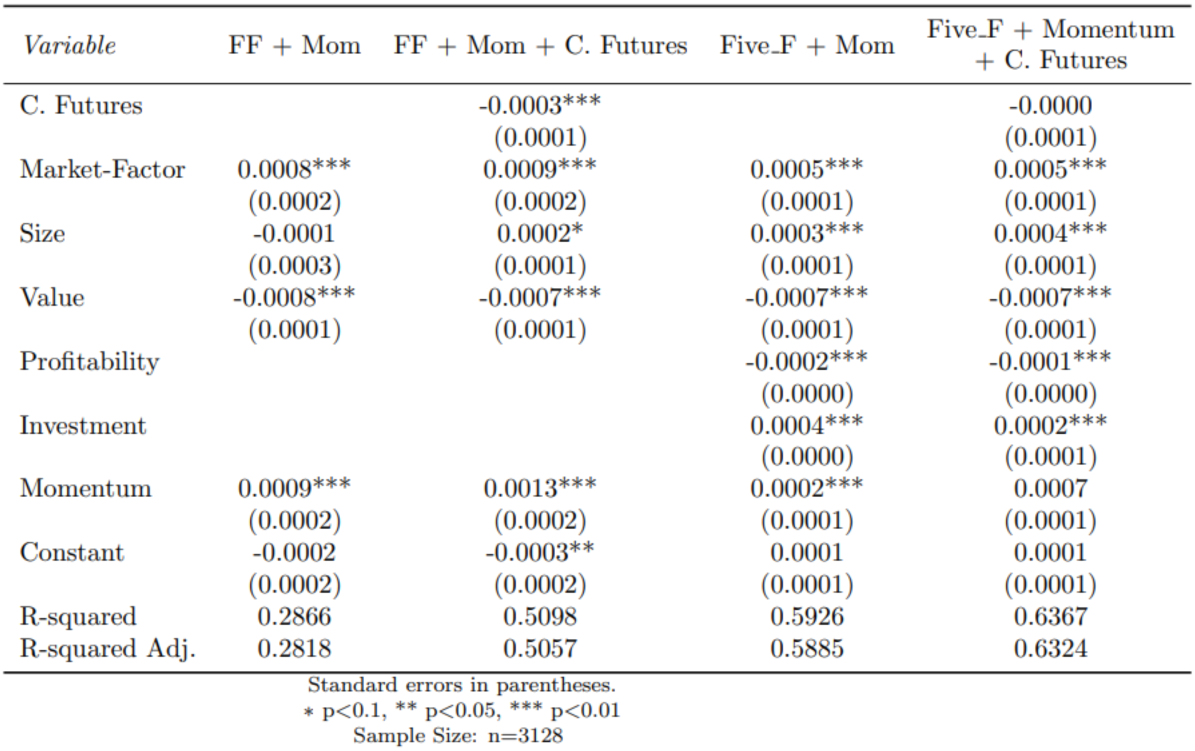
	AIC	**BIC**
FF + MOM	-7370.9	-7353.34
FF + MOM + E-MOM	-7470.63	-7444.29
Five F + MOM	-7398.51	-7372.17
Five F + MOM + E-MOM	-7733.05	-7697.92

Table 11: AIC and BIC for regressions in table 8 (E-Momentum)

6.3.1.4 Carbon Futures Dependency

Subsequently, our analysis shifts towards the market-based carbon futures factor, with its regression outcomes presented in Table 12. As with the other carbon risk proxies that we introduced to the traditionally used factor models, we again observe an improvement in R^2 and adjusted R^2 It is pertinent to highlight that the risk premium associated with this factor, while negative, registers statistical significance in at least one of the model specifications. We want to add here though that we believe that this significance might be attributable to the exclusion of the investment and profitability factor in this specification with the Carbon Futures factor potentially capturing some aspects of covariance with these excluded factors.

We also want to remind the reader here that the negative risk premium in this case would not contradict our theoretical framework, as the construction of the carbon futures factor portfolio is different from the E-Pillar and BMG portfolios. For the carbon futures portfolio, we go long the firms that improve their market value if the future price of carbon rises, so we go long the "green" companies, in contrast to the other two portfolios, where we go long "brown" companies.

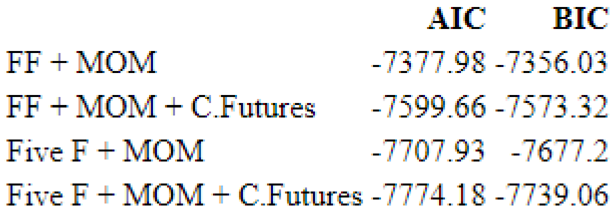


Variable	FF + Mom	FF + Mom + C. Futures	Five_F + Mom	Five_F + Momentum + C. Futures
C. Futures		-0.0003***		-0.0000
		(0.0001)		(0.0001)
Market-Factor	0.0008***	0.0009***	0.0005***	0.0005***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Size	-0.0001	0.0002*	0.0003***	0.0004***
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Value	-0.0008***	-0.0007***	-0.0007***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Profitability			-0.0002***	-0.0001***
			(0.0000)	(0.0000)
Investment			0.0004***	0.0002***
			(0.0000)	(0.0001)
Momentum	0.0009***	0.0013***	0.0002***	0.0007
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Constant	-0.0002	-0.0003**	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
R-squared	0.2866	0.5098	0.5926	0.6367
R-squared Adj.	0.2818	0.5057	0.5885	0.6324

Standard errors in parentheses.
∗ p<0.1, ** p<0.05, *** p<0.01
Sample Size: n=3128

Table 12: Two-step regression results with various model specifications including one carbon risk proxy (Carbon Futures). The coefficients represent daily risk premia with their respective standard errors in the parentheses below.

In Table 13, we present the AIC and BIC criteria for the model specifications with the inclusion of the Carbon Futures factor. These metrics reaffirm the notion that the inclusion of this carbon-mimicking portfolio contributes to an enhancement in model accuracy.

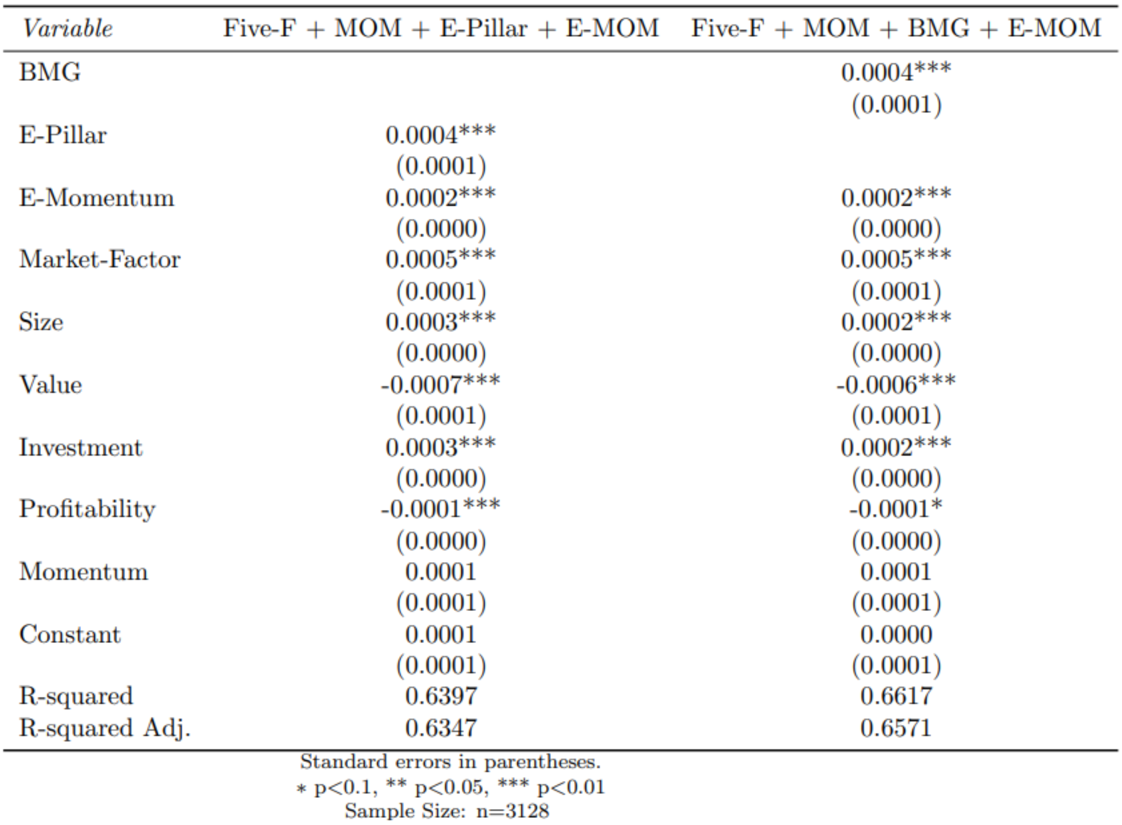


	AIC	BIC
FF + MOM	-7377.98	-7356.03
FF + MOM + C.Futures	-7599.66	-7573.32
Five F + MOM	-7707.93	-7677.2
Five F + MOM + C.Futures	-7774.18	-7739.06

Table 13: AIC and BIC for regressions in table 12 (Carbon Futures)

6.3.1.5 Level and momentum specification

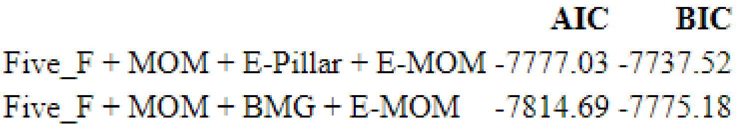
Given the positive and statistically significant risk premiums identified for portfolios capturing both level effects and momentum-like behaviors, our investigation extends to a model specification that integrates both the E-Momentum portfolio and one of the level portfolios, either the E-Pillar or the BMG. This exploration is motivated by the hypothesis that these combined portfolios may pick up distinct facets of carbon risk premia, potentially leading to further enhancements in model accuracy. The results of this regression setup can be found in Table 14. In the specification with the addition of the BMG and the E-Momentum score, we do get the highest adjusted R^2 out of all the specifications that we tested. Moreover, this setup also exhibits the most favorable model fit concerning the AIC and BIC criteria. The specification with the E-Pillar and the E-Momentum portfolios also improves model accuracy by a lot. This specification also improves accuracy relative to the specifications that do not include both level and momentum carbon risk portfolios. This result strengthens our belief that the two-level and the momentum portfolios pick up different tendencies of carbon risk. The fact that we can show significant carbon risk premia for two inherently different selection mechanisms corroborates the existence of a premium for holding companies with bad carbon sustainability.



Variable	Five-F + MOM + E-Pillar + E-MOM	Five-F + MOM + BMG + E-MOM
BMG		0.0004***
		(0.0001)
E-Pillar	0.0004***	
	(0.0001)	
E-Momentum	0.0002***	0.0002***
	(0.0000)	(0.0000)
Market-Factor	0.0005***	0.0005***
	(0.0001)	(0.0001)
Size	0.0003***	0.0002***
	(0.0000)	(0.0000)
Value	-0.0007***	-0.0006***
	(0.0001)	(0.0001)
Investment	0.0003***	0.0002***
	(0.0000)	(0.0000)
Profitability	-0.0001***	-0.0001*
	(0.0000)	(0.0000)
Momentum	0.0001	0.0001
	(0.0001)	(0.0001)
Constant	0.0001	0.0000
	(0.0001)	(0.0001)
R-squared	0.6397	0.6617
R-squared Adj.	0.6347	0.6571

Standard errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01
Sample Size: n=3128

Table 14: Two-step regression results with two model specifications including the five factor model, a "level" carbon risk proxy (E-Pillar or BMG) and the "momentum" carbon risk proxy "E-Pillar Momentum". The coefficients represent daily risk premia with their respective standard errors in the parentheses below.



	AIC	**BIC**
Five_F + MOM + E-Pillar + E-MOM	-7777.03	-7737.52
Five_F + MOM + BMG + E-MOM	-7814.69	-7775.18

Table 15: AIC and BIC for regressions in table 14

In conclusion, from the standard two-step approach, we can state that adding some carbon risk proxy portfolio can greatly enhance model accuracy. We showed this with four different portfolio selection mechanisms, which further enhanced the robustness of our findings. The BMG portfolio, which is specifically constructed to pick up the most relevant dimensions of carbon risk improved model accuracy the most for all metrics that we presented. Additionally, we observed that the inclusion of both a level portfolio and a momentum portfolio for carbon risk could enhance model accuracy even more, with the best specification being the Five Factor + Momentum + BMG + E-Momentum portfolio. Our results are in line with other factor regression setups (e.g. CAPM) that we tested but decided not to present here due to redundancy.

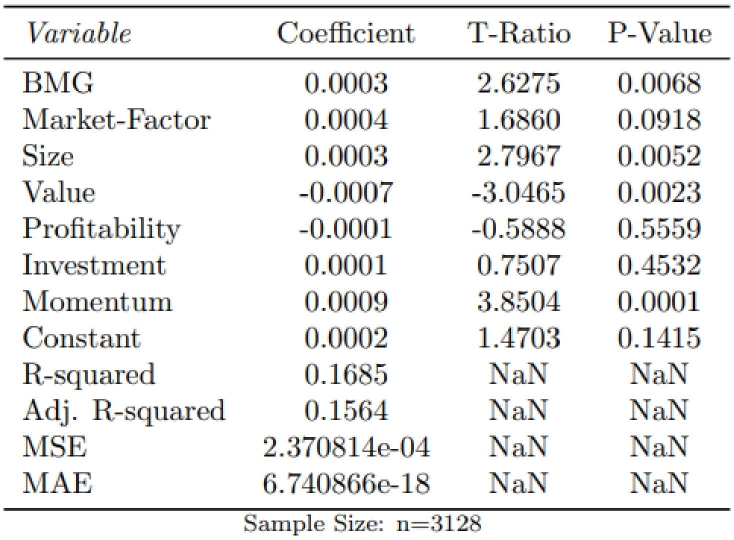
We want to now present the results of our Fama-MacBeth regression setup, to once again confirm the findings above and to also take a closer look at the time-dependent variation in risk premia.

6.3.2 Fama-MacBeth approach

In this section we will present the findings derived from a nuanced adaptation of the conventional two-step approach, employing the Fama-MacBeth methodology. As we have already explained in an earlier chapter, this technique distinguishes itself by conducting cross-sectional regressions on a daily basis, rather than aggregating data over longer periods. By averaging these daily risk premium estimates, we acquire a comprehensive risk premium estimate for the entire study period. The Fama-MacBeth method is advantageous because it allows for the estimation of standard errors without bias, facilitating reliable statistical inference. Although we are adjusting for autocorrelation and heteroscedasticity in our error term in the standard two-step approach, we still believe that the Fama-MacBeth method can potentially further confirm our results obtained before. Moreover, this method offers not only a singular risk premium estimate over the entire timeframe but also daily estimates, enabling an analysis of the dynamic nature of risk premiums. This section will be structured similarly to the subchapter before. We will again provide regression tables for different model specifications, including different carbon proxies. Additionally, we will explore the fluctuating nature of risk premiums through graphical representations.

6.3.2.1 BMG

We will again start with the results obtained for the BMG factor portfolio. As in the standard two-step approach, we again find a statistically significant and positive risk premium for the BMG portfolio over the entire time frame. We estimate a slightly lower risk premium with this method compared to the standard approach. We believe that this is due to the different setup of the two methods combined with the fact that the assumption of constant betas over time is not fulfilled. Still, applying both methods leaves us confident in the overall existence of a positive risk premium for the BMG portfolio. The estimates of the other traditionally used risk factors are also more or less in line with the results from the standard approach, which corroborates the findings for the BMG portfolio.



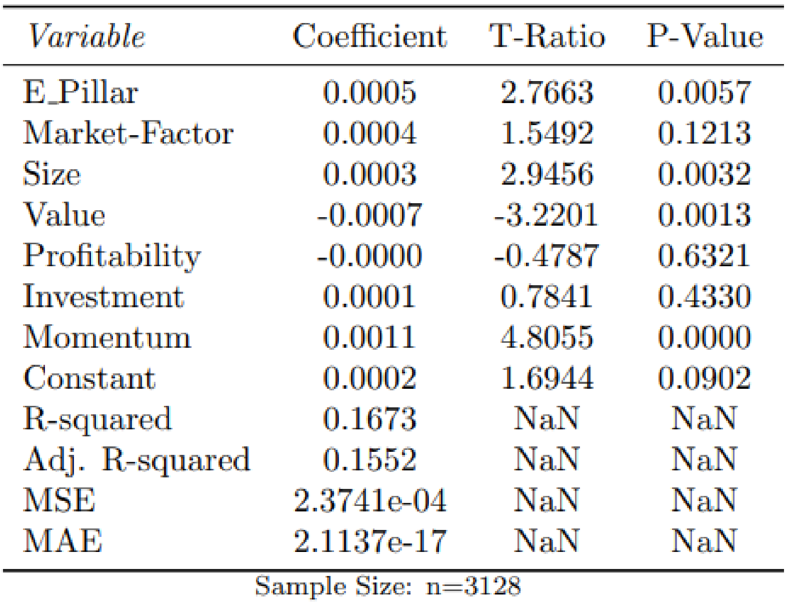
Variable	Coefficient	T-Ratio	P-Value
BMG	0.0003	2.6275	0.0068
Market-Factor	0.0004	1.6860	0.0918
Size	0.0003	2.7967	0.0052
Value	-0.0007	-3.0465	0.0023
Profitability	-0.0001	-0.5888	0.5559
Investment	0.0001	0.7507	0.4532
Momentum	0.0009	3.8504	0.0001
Constant	0.0002	1.4703	0.1415
R-squared	0.1685	NaN	NaN
Adj. R-squared	0.1564	NaN	NaN
MSE	2.370814e-04	NaN	NaN
MAE	6.740866e-18	NaN	NaN

Sample Size: n=3128

Table 16: Fama-MacBeth regression results with our standard model specifications including one carbon risk proxy (BMG). The coefficients represent average daily risk premia.

6.3.2.2 Environmental Pillar

Secondly, we present the results for the portfolio formed on the E-Pillar score. The E-Pillar portfolio analysis reveals a significant positive risk premium, similar to the BMG portfolio, with traditionally used risk factors aligning with previous findings. Something somewhat unexpected is that the risk premium obtained for the E-Pillar portfolio is higher than for the BMG portfolio with the Fama-MacBeth approach, which contrasts the results obtained from the standard two-step approach. We want to mention again that the estimate of risk premia is most likely biased in both approaches. We believe that this is the reason why we might get slightly different results for both estimation techniques. Nevertheless, both estimation methods were able to generate similar results. Therefore, we can state with reasonably high confidence that there is in fact a positive risk premium for “brown” firms in the European Stoxx 600 in our time period.



Variable	Coefficient	T-Ratio	P-Value
E_Pillar	0.0005	2.7663	0.0057
Market-Factor	0.0004	1.5492	0.1213
Size	0.0003	2.9456	0.0032
Value	-0.0007	-3.2201	0.0013
Profitability	-0.0000	-0.4787	0.6321
Investment	0.0001	0.7841	0.4330
Momentum	0.0011	4.8055	0.0000
Constant	0.0002	1.6944	0.0902
R-squared	0.1673	NaN	NaN
Adj. R-squared	0.1552	NaN	NaN
MSE	2.3741e-04	NaN	NaN
MAE	2.1137e-17	NaN	NaN

Sample Size: n=3128

Table 17: Fama-MacBeth regression results with our standard model specifications including one carbon risk proxy (E-Pillar). The coefficients represent average daily risk premia.

6.3.2.3 Environmental Pillar Momentum

We will now shift our focus to our momentum-based carbon risk proxy, the E-Momentum portfolio. Once more we observe risk premia in line with the other model specifications with respect to the traditionally used risk factors. The risk premium estimate for the E-Momentum portfolio falls short of significance though. Although insignificant, the magnitude of the risk premium estimate again is in line with the results captured by the standard approach. Overall, there seems to be some premium driving the returns of the respective E-Momentum portfolio, although we cannot confirm this indefinitely at this moment. We will leave a definitive conclusion out for now and will come back later to this when we analyze risk premia for two separate timeframes which we believe have quite different dependencies concerning transitional risk.

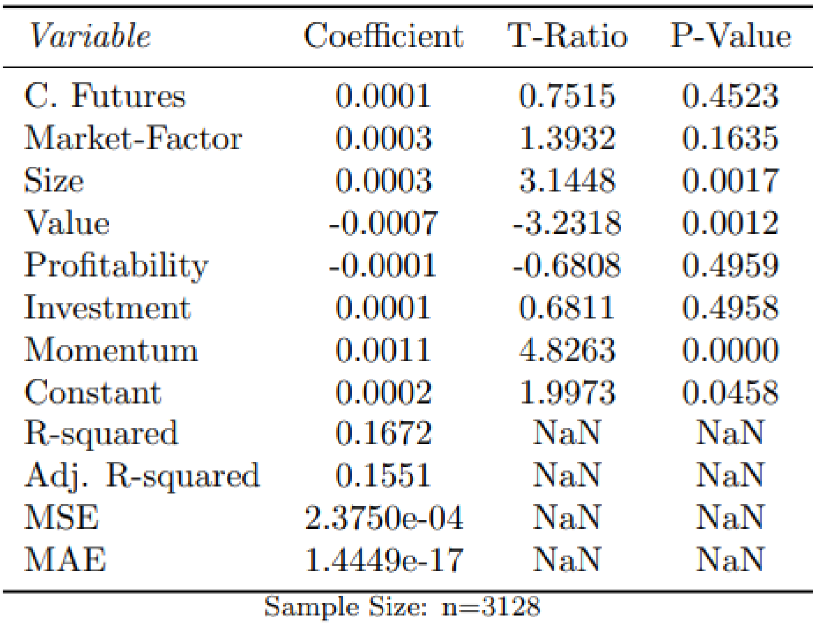
Variable	Coefficient	T-Ratio	P-Value
E_Momentum	0.0002	1.3872	0.1654
Market-Factor	0.0004	1.4892	0.1364
Size	0.0003	3.4617	0.0005
Value	-0.0007	-3.0937	0.0020
Momentum	-0.0001	-0.6185	0.5362
Profitability	0.0000	0.4118	0.6805
Investment	0.0010	4.4514	0.0000
Constant	0.0002	1.8553	0.0636
R-squared	0.1725	NaN	NaN
Adj. R-squared	0.1604	NaN	NaN
MSE	2.3593e-04	NaN	NaN
MAE	1.4862e-17	NaN	NaN

Sample Size: n=3128

Table 18: Fama-MacBeth regression results with our standard model specifications including one carbon risk proxy (E-Pillar Momentum). The coefficients represent average daily risk premia.

6.3.2.4 Carbon Futures Dependency

A brief examination of the carbon futures portfolio, similar to the standard approach, fails to identify a significant risk premium. The other traditionally used factors are again in line with other model specifications that we did before. The lack of significant findings suggests our market-based approach may not adequately capture carbon risk as anticipated. A more detailed discussion on this topic will be addressed in the forthcoming chapter on robustness, which will include a time-split analysis.



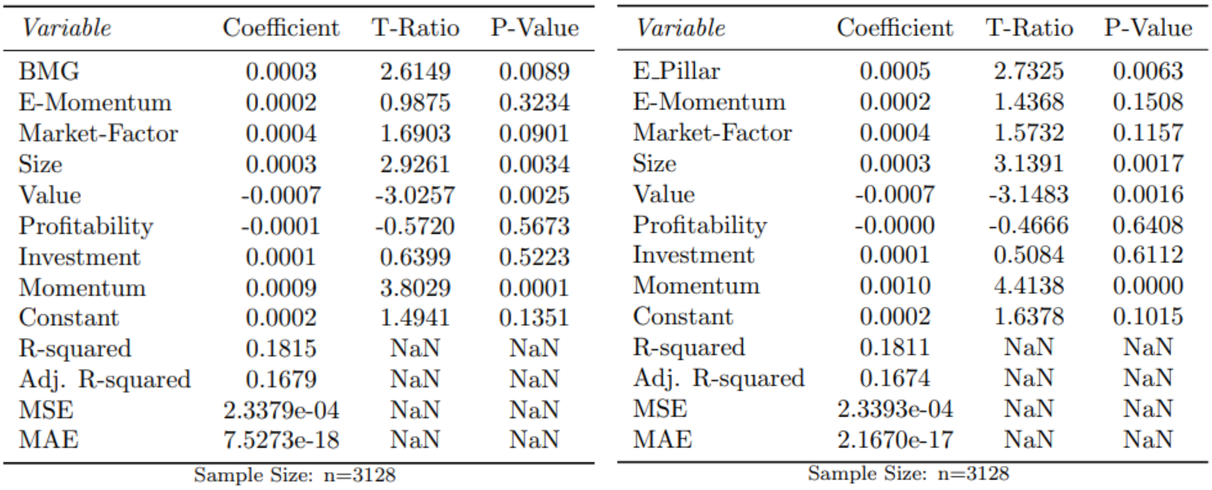
Variable	Coefficient	T-Ratio	P-Value
C. Futures	0.0001	0.7515	0.4523
Market-Factor	0.0003	1.3932	0.1635
Size	0.0003	3.1448	0.0017
Value	-0.0007	-3.2318	0.0012
Profitability	-0.0001	-0.6808	0.4959
Investment	0.0001	0.6811	0.4958
Momentum	0.0011	4.8263	0.0000
Constant	0.0002	1.9973	0.0458
R-squared	0.1672	NaN	NaN
Adj. R-squared	0.1551	NaN	NaN
MSE	2.3750e-04	NaN	NaN
MAE	1.4449e-17	NaN	NaN

Sample Size: n=3128

Table 19: Fama-MacBeth regression results with our standard model specifications including one carbon risk proxy (E-Pillar Momentum). The coefficients represent average daily risk premia.

6.3.2.5 Level and momentum specification

Analogous to the standard two-step approach we will again analyze two model specifications where we implement both a level and the momentum carbon portfolios. These carbon risk portfolios will again be tested in the Five Factor + Momentum framework.



Variable	Coefficient	T-Ratio	P-Value
BMG	0.0003	2.6149	0.0089
E-Momentum	0.0002	0.9875	0.3234
Market-Factor	0.0004	1.6903	0.0901
Size	0.0003	2.9261	0.0034
Value	-0.0007	-3.0257	0.0025
Profitability	-0.0001	-0.5720	0.5673
Investment	0.0001	0.6399	0.5223
Momentum	0.0009	3.8029	0.0001
Constant	0.0002	1.4941	0.1351
R-squared	0.1815	NaN	NaN
Adj. R-squared	0.1679	NaN	NaN
MSE	2.3379e-04	NaN	NaN
MAE	7.5273e-18	NaN	NaN

Sample Size: n=3128

Variable	Coefficient	T-Ratio	P-Value
E_Pillar	0.0005	2.7325	0.0063
E-Momentum	0.0002	1.4368	0.1508
Market-Factor	0.0004	1.5732	0.1157
Size	0.0003	3.1391	0.0017
Value	-0.0007	-3.1483	0.0016
Profitability	-0.0000	-0.4666	0.6408
Investment	0.0001	0.5084	0.6112
Momentum	0.0010	4.4138	0.0000
Constant	0.0002	1.6378	0.1015
R-squared	0.1811	NaN	NaN
Adj. R-squared	0.1674	NaN	NaN
MSE	2.3393e-04	NaN	NaN
MAE	2.1670e-17	NaN	NaN

Sample Size: n=3128

Table 20: Fama-MacBeth regression results with two model specifications including the five factor model, a "level" carbon risk proxy (E-Pillar or BMG) and the "momentum" carbon risk proxy "E-Pillar Momentum". The coefficients represent average daily risk premia.

Using the Fama-McBeth approach here gives us significant and positive risk premia for the two level portfolios in the two specifications. The E-Momentum portfolio falls short of statistical significance again, as in the case where we only included the E-Momentum portfolio without the two level portfolios. This is again in contrast to the results obtained from the standard approach, where we found a positive and significant risk premium for both level and momentum portfolios regarding carbon risk in both specifications. As in the case above, we believe this is due to non-constant betas over time and the different setups of the two regression methodologies.

As already mentioned above, we will now finish our main regression analysis chapter with a short subchapter on the time-varying nature of our carbon risk premia estimates.

6.3.3 Time-varying risk premia analysis

This section concludes the main regression analysis by examining the temporal dynamics of risk premia across various carbon risk proxy portfolios. Using the Fama-MacBeth method risk premia were calculated on a daily basis. Here we will then present the 300-day moving average plots of these daily risk premia. While other moving average windows were considered, the 300-day window was chosen for its efficacy in mitigating the inherent volatility of daily estimated risk premia, thus providing a clearer view of the underlying trends. The discussion will focus on the risk premia of the BMG, E-Pillar, and E-Momentum portfolios, excluding the carbon futures portfolio due to its negligible risk premium over the observed period.

In Figure 18 below, we present the moving average graph for the BMG risk premium. As illustrated in the moving average plot for the BMG risk premium, the period from 2010 to 2015 is characterized by fluctuations around zero, indicating no significant yearly risk premium. However, from 2015 onwards, a consistent positive risk premium is observed, peaking in late 2020. The fundamental change starting in 2015 was also reflected in an analysis done earlier on the betas over time. There we also observed some fundamental change in factor loading on the BMG portfolio starting somewhere around 2015. We believe that this might also be the reason for the continuously positive risk premium for the BMG portfolio in that time frame.

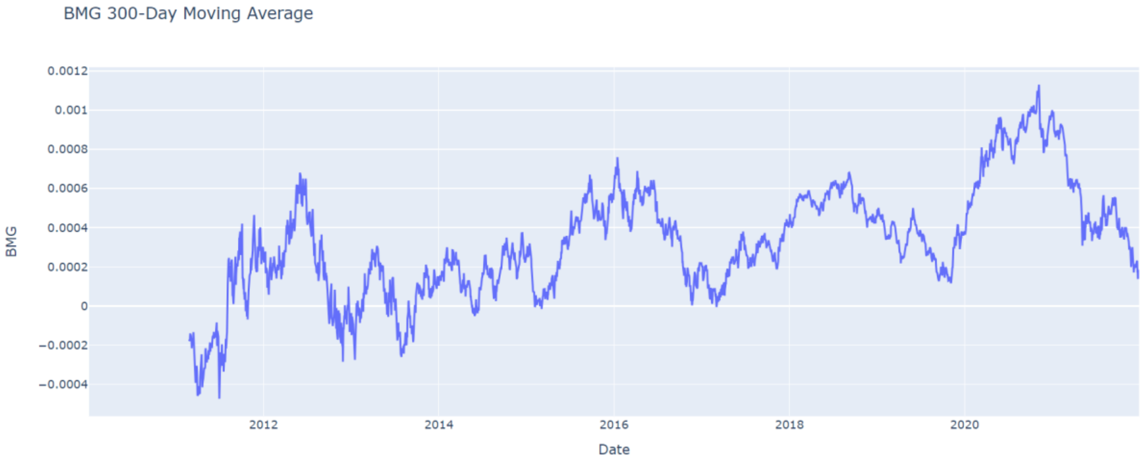


Figure 18: Risk Premium Moving Average (BMG)

The risk premium for the E-Pillar portfolio, presented in Figure 19, generally seems to be highly correlated with the risk premium for the BMG portfolio. Something that stands out though, is that the E-Pillar risk premium had its highest value in 2012, with generally quite high variance up until 2015. Post-2015, similar to the BMG portfolio, the E-Pillar risk premium consistently remained positive up until the end of our sample period. Notably, the only significant downturn was observed from 2013 to 2015, contrasting with the otherwise predominantly positive risk premium.

Figure 19: Risk Premium Moving Average (E-Pillar)

In Figure 20, the risk premia plot for the E-Momentum portfolio is displayed. The E-Momentum portfolio's risk premium trend also highlights a pivotal change around 2015. Before that point in time, the risk premium is negative for most of the time, with the lowest level being around the start of 2012. After 2015, the E-Momentum risk premium is again positive over the remainder of our time period, with maximum values in 2020.

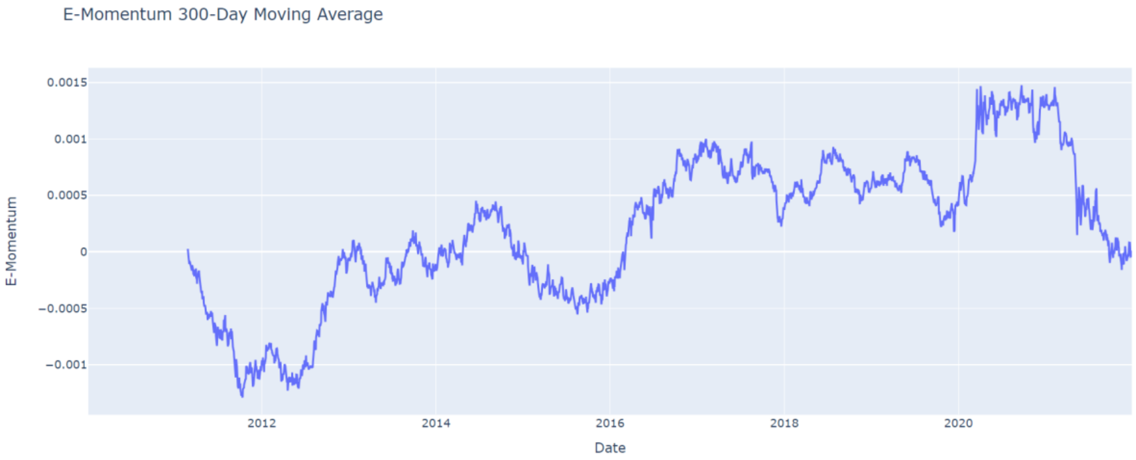


Figure 20: Risk Premium Moving Average (E-Momentum)

This short analysis on the time-varying nature of risk premia, showed that there seems to be some change in underlying fundamentals around 2015. We already expected this when we analyzed the factor loadings of our sector portfolios on the respective carbon risk proxy portfolios over time. There we also observed largely different dependencies after 2015 in contrast to the period before. Due to this observed change in fundamentals in both factor loadings as well as risk premia for these three carbon risk portfolios, we will also briefly analyze risk premia with a time series split in the next chapter on robustness. Moreover, as already mentioned, we will also present a small Machine Learning analysis on the importance of the granular environmental variables that we used to construct the BGS score, to check for the empirical validity of the weights used in the construction formula.

6.4 Robustness

To wrap up the empirical section, we will present the outcomes of two robustness checks for our risk premia calculations. First, akin to the rolling window estimates for the sector betas, we will divide our sample into two distinct subsets and compute the risk premia using the Fama-MacBeth method described in the previous chapter.

The second robustness check focuses solely on the Brown-Minus-Green (BMG) risk factor. A potential concern with this factor's construction is the seemingly arbitrary weighting of its three components. We aim to validate the substantial weight assigned to the VC variable by employing two different machine learning algorithms—elastic net and random forest. These algorithms will analyze the original set of 66 input variables to identify those that most significantly explain sectoral and cross-sectional returns. The results are expected to confirm that only a select few variables, predominantly from the VC category, hold substantial explanatory power. These findings will provide empirical support for the weighting choices made in constructing the BMG risk factor.

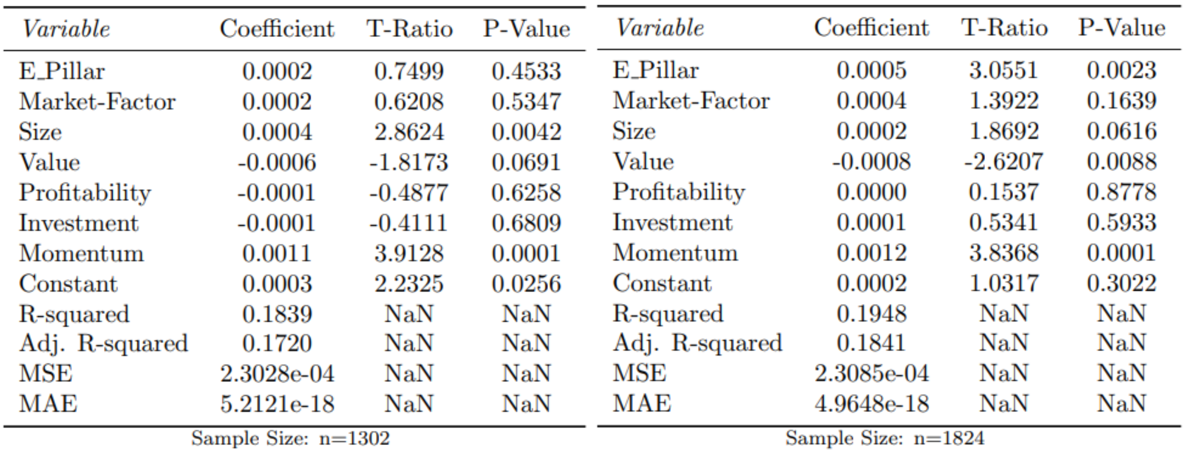
6.4.1 Time period split

Throughout this thesis, we aim to demonstrate that transition risk differs fundamentally from traditional risk factors. This distinction does not imply that assets are not exposed to transition risk or that a risk premium cannot be calculated. Rather, it suggests that such a risk factor does not manifest consistently over time. This variability largely stems from the relatively recent widespread recognition of concepts like "sin" stocks or sustainability, which have only become well-known in recent years. We will explore this issue more thoroughly in the conclusion, but this understanding prompts us to question whether the risk premium calculated in the previous chapter might be biased. Specifically, if the risk premium has been increasing over the period of our study, we may have underestimated the size and significance of one or more of our risk factors.

To investigate this hypothesis, we will divide our sample into two distinct periods. The first spans from 2010 to December 31st, 2014, and the second from 2015 to the end of our sample on December 31st, 2021. This segmentation is not arbitrary; it is based on observations from our data showing that estimated betas tend to exhibit higher variation and greater absolute values after 2014. For both periods, we will conduct the Fama-MacBeth regression using the same specification that includes the Fama-French five factors and the momentum factor, as detailed in the previous chapter.

Each period's analysis will be presented in a dedicated subchapter, featuring two tables—one for each sample period—to illustrate the findings and enable a clear comparison.

6.4.1.1 Environmental Pillar



Period 1

Variable	Coefficient	T-Ratio	P-Value
E_Pillar	0.0002	0.7499	0.4533
Market-Factor	0.0002	0.6208	0.5347
Size	0.0004	2.8624	0.0042
Value	-0.0006	-1.8173	0.0691
Profitability	-0.0001	-0.4877	0.6258
Investment	-0.0001	-0.4111	0.6809
Momentum	0.0011	3.9128	0.0001
Constant	0.0003	2.2325	0.0256
R-squared	0.1839	NaN	NaN
Adj. R-squared	0.1720	NaN	NaN
MSE	2.3028e-04	NaN	NaN
MAE	5.2121e-18	NaN	NaN

Sample Size: n=1302

Period 2

Variable	Coefficient	T-Ratio	P-Value
E_Pillar	0.0005	3.0551	0.0023
Market-Factor	0.0004	1.3922	0.1639
Size	0.0002	1.8692	0.0616
Value	-0.0008	-2.6207	0.0088
Profitability	0.0000	0.1537	0.8778
Investment	0.0001	0.5341	0.5933
Momentum	0.0012	3.8368	0.0001
Constant	0.0002	1.0317	0.3022
R-squared	0.1948	NaN	NaN
Adj. R-squared	0.1841	NaN	NaN
MSE	2.3085e-04	NaN	NaN
MAE	4.9648e-18	NaN	NaN

Sample Size: n=1824

Table 21:Fama MacBeth regression results using the Fama and French model and one carbon risk proxy (E-Pillar).
Period 1 ranges from January 1st 2010 to December 31st 2014
Period 2 ranges from January 1st 2015 to December 31st 2021

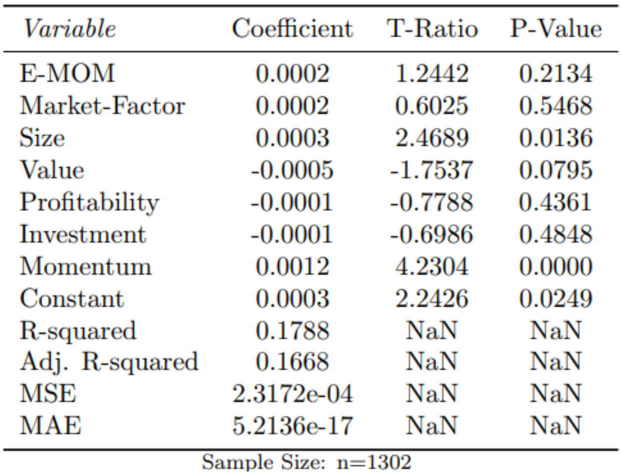
The table above presents the results from the Fama-MacBeth regressions, with the regression coefficients displayed in the first columns followed by the t-ratios and p-values. For "traditional" factors such as momentum, size, or value, there are no substantial differences in either the coefficients or their statistical significance across the two periods. Notably, the profitability and investment factors show high insignificance in both periods. Interestingly, the market factor, despite having one of the highest coefficients in both periods, is not statistically significant in either period. This is particularly puzzling given that in almost all our other analyses using the entire sample period, the market factor consistently yielded significant results.

However, our primary focus in these regressions is on the E-Pillar estimates. It is important to recall that the E-Pillar coefficient was significant when using the entire sample. This significance is not observed in period 1, where the factor is far from significant. In contrast, during period 2, the coefficient not only increases substantially in size but also becomes highly significant. Moreover, this coefficient in period 2 is larger than when the entire period is considered. Additionally, both the R-squared and the adjusted R-squared are higher in period 2, indicating a better fit of the model.

These findings strongly suggest that the E-Pillar risk factor is only significant in the later period, reinforcing the idea that the risk premium associated with this factor has grown over time. This also hints at improvements in the construction of these scores over time, enhancing their ability to efficiently capture the relevant risk premium.

6.4.1.2 Environmental Pillar Momentum

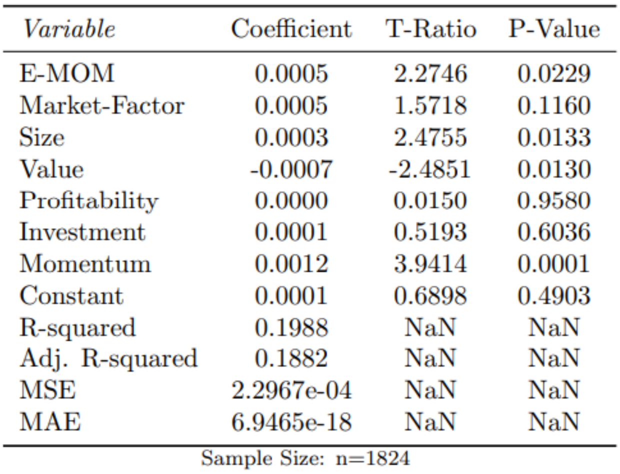
Period 1



Variable	Coefficient	T-Ratio	P-Value
E-MOM	0.0002	1.2442	0.2134
Market-Factor	0.0002	0.6025	0.5468
Size	0.0003	2.4689	0.0136
Value	-0.0005	-1.7537	0.0795
Profitability	-0.0001	-0.7788	0.4361
Investment	-0.0001	-0.6986	0.4848
Momentum	0.0012	4.2304	0.0000
Constant	0.0003	2.2426	0.0249
R-squared	0.1788	NaN	NaN
Adj. R-squared	0.1668	NaN	NaN
MSE	2.3172e-04	NaN	NaN
MAE	5.2136e-17	NaN	NaN

Sample Size: n=1302

Period 2



Variable	Coefficient	T-Ratio	P-Value
E-MOM	0.0005	2.2746	0.0229
Market-Factor	0.0005	1.5718	0.1160
Size	0.0003	2.4755	0.0133
Value	-0.0007	-2.4851	0.0130
Profitability	0.0000	0.0150	0.9580
Investment	0.0001	0.5193	0.6036
Momentum	0.0012	3.9414	0.0001
Constant	0.0001	0.6898	0.4903
R-squared	0.1988	NaN	NaN
Adj. R-squared	0.1882	NaN	NaN
MSE	2.2967e-04	NaN	NaN
MAE	6.9465e-18	NaN	NaN

Sample Size: n=1824

Table 22:Fama MacBeth regression results using the Fama and French model and one carbon risk proxy (E-Pillar Momentum). Period 1 ranges from January 1st 2010 to December 31st 2014
Period 2 ranges from January 1st 2015 to December 31st 2021

The pair of tables above presents the regression results using the E-Pillar Momentum risk factor as a proxy for transition risk. The findings for the size and value factors show similar trends to those observed with the E-Pillar results, displaying significance, while the profitability and investment factors remain markedly insignificant in both time periods. Consistent with the previous analysis, the momentum factor is highly significant and offers the highest risk premium in both samples.

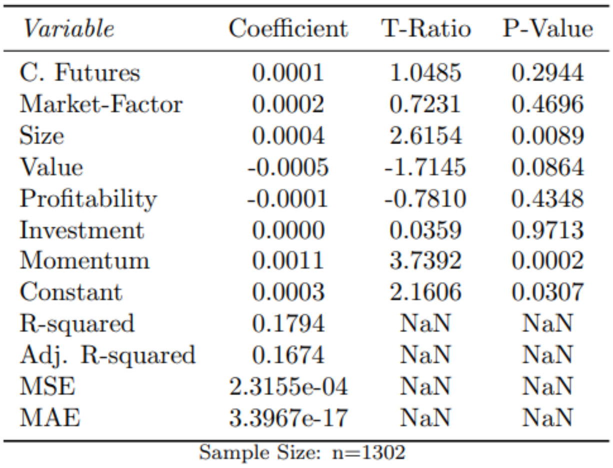
The market factor again exhibits higher significance in the second period compared to the first, which aligns with the observed trends for other factors. The E-Pillar Momentum risk factor, however, does not show significance in the first period but displays very high significance in the second period. This pattern reinforces our hypothesis that the risk premium associated with this factor has improved over time. Notably, when considering the entire sample period, this factor does not achieve significance, suggesting that its impact is more pronounced in more recent periods.

Additionally, both the R-squared and the adjusted R-squared are higher in the second period than in the first, indicating a better model fit. This improvement in model performance in the later period further supports the notion that the ability of the E-Pillar Momentum factor to capture transition risk has strengthened over time.

6.4.1.3 Carbon Futures

Our analysis of the third risk factor, the carbon futures factor, reveals that it does not capture a significant risk premium in either time period examined. The behavior of the other factors remains consistent with the patterns observed in the previous regression specifications. Given these outcomes, we are increasingly confident that the construction of the carbon futures factor does not effectively capture transition risk. This ineffectiveness could be attributed to several potential issues: the stock market may not efficiently transmit this type of risk through the carbon futures market, the carbon allowance market itself may be inefficient, or disturbances within the market for allowances might have obscured the signal we intended to capture. In the conclusion of this thesis, we will delve more deeply into these potential reasons, exploring why the carbon futures factor fails to reflect transition risk adequately and discussing possible improvements or alternative approaches that could enhance the robustness and relevance of this risk factor in future research.

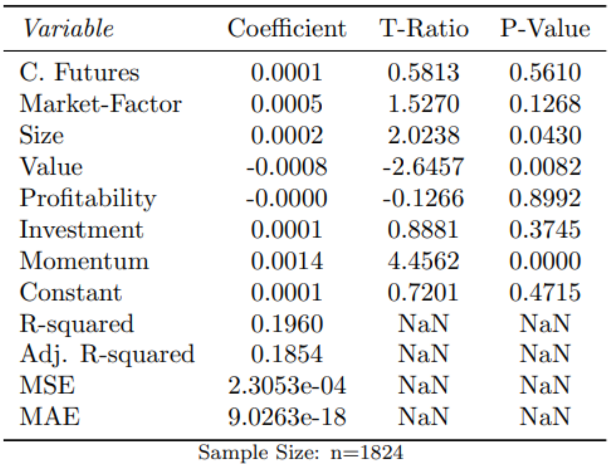
Period 1



Variable	Coefficient	T-Ratio	P-Value
C. Futures	0.0001	1.0485	0.2944
Market-Factor	0.0002	0.7231	0.4696
Size	0.0004	2.6154	0.0089
Value	-0.0005	-1.7145	0.0864
Profitability	-0.0001	-0.7810	0.4348
Investment	0.0000	0.0359	0.9713
Momentum	0.0011	3.7392	0.0002
Constant	0.0003	2.1606	0.0307
R-squared	0.1794	NaN	NaN
Adj. R-squared	0.1674	NaN	NaN
MSE	2.3155e-04	NaN	NaN
MAE	3.3967e-17	NaN	NaN

Sample Size: n=1302

Period 2



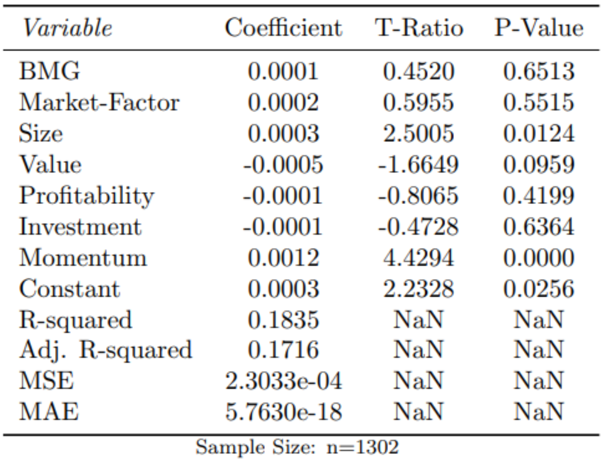
Variable	Coefficient	T-Ratio	P-Value
C. Futures	0.0001	0.5813	0.5610
Market-Factor	0.0005	1.5270	0.1268
Size	0.0002	2.0238	0.0430
Value	-0.0008	-2.6457	0.0082
Profitability	-0.0000	-0.1266	0.8992
Investment	0.0001	0.8881	0.3745
Momentum	0.0014	4.4562	0.0000
Constant	0.0001	0.7201	0.4715
R-squared	0.1960	NaN	NaN
Adj. R-squared	0.1854	NaN	NaN
MSE	2.3053e-04	NaN	NaN
MAE	9.0263e-18	NaN	NaN

Sample Size: n=1824

Table 23:Fama MacBeth regression results using the Fama and French model and one carbon risk proxy (Carbon Futures). Period 1 ranges from January 1st 2010 to December 31st 2014
Period 2 ranges from January 1st 2015 to December 31st 2021

6.4.1.4 BMG

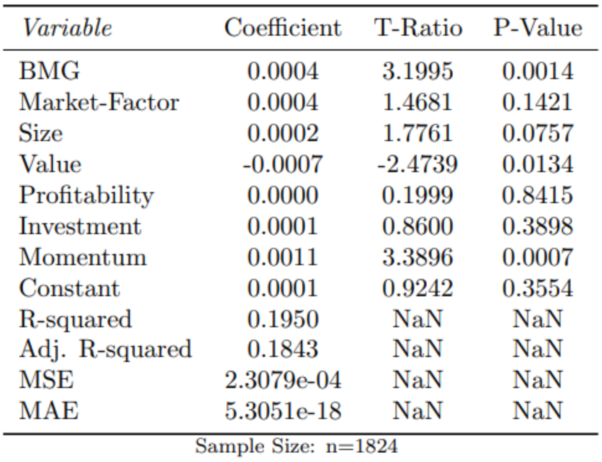
Period 1



Variable	Coefficient	T-Ratio	P-Value
BMG	0.0001	0.4520	0.6513
Market-Factor	0.0002	0.5955	0.5515
Size	0.0003	2.5005	0.0124
Value	-0.0005	-1.6649	0.0959
Profitability	-0.0001	-0.8065	0.4199
Investment	-0.0001	-0.4728	0.6364
Momentum	0.0012	4.4294	0.0000
Constant	0.0003	2.2328	0.0256
R-squared	0.1835	NaN	NaN
Adj. R-squared	0.1716	NaN	NaN
MSE	2.3033e-04	NaN	NaN
MAE	5.7630e-18	NaN	NaN

Sample Size: n=1302

Period 2



Variable	Coefficient	T-Ratio	P-Value
BMG	0.0004	3.1995	0.0014
Market-Factor	0.0004	1.4681	0.1421
Size	0.0002	1.7761	0.0757
Value	-0.0007	-2.4739	0.0134
Profitability	0.0000	0.1999	0.8415
Investment	0.0001	0.8600	0.3898
Momentum	0.0011	3.3896	0.0007
Constant	0.0001	0.9242	0.3554
R-squared	0.1950	NaN	NaN
Adj. R-squared	0.1843	NaN	NaN
MSE	2.3079e-04	NaN	NaN
MAE	5.3051e-18	NaN	NaN

Sample Size: n=1824

Table 24:Fama MacBeth regression results using the Fama and French model and one carbon risk proxy (Carbon Futures). Period 1 ranges from January 1st 2010 to December 31st 2014
Period 2 ranges from January 1st 2015 to December 31st 2021

In our final analysis, we conducted a Fama-MacBeth regression including our preferred measure for transitional risk, the Brown-Minus-Green (BMG) risk factor. Previous chapters indicated that when considering the entire sample period, the BMG risk factor effectively captures the risk premium. However, a split-sample analysis reveals a pattern similar to that observed with the E-Pillar and E-Pillar Momentum risk factors. Specifically, the BMG factor's estimate is insignificant in the first period (2010-2014), but it increases significantly in both size and significance during the second period (2015-2021). The behavior of other risk factors remains consistent with previous findings, and both the adjusted and non-adjusted R-squared values increase over time.

By estimating risk premia for our proposed transition risk factors across two different periods, we have demonstrated that the risk premium is substantial and significant, but only for the later sample covering 2015 to 2021. The earlier period from 2010 to 2015 does not yield a significant transition risk premium. This discrepancy leads us to conclude that transition risk is not uniformly estimable across all time periods but has become more pronounced over the past decade. This recent period coincides with growing societal and business focus on sustainability and carbon reduction initiatives.

Our findings also show that the E-Pillar and BMG risk factors are capable of efficiently capturing this emerging premium. While the E-Pillar Momentum factor captures it to some extent, the carbon futures risk factor fails to effectively transport the risk premium. In the upcoming sections, we will explore the environmental variables included in the BMG factor and demonstrate that its construction is not as arbitrary as it might initially appear.

6.4.1.5 Level and momentum specification

Period 1

Variable	Coefficient	T-Ratio	P-Value
BMG	0.0001	0.3655	0.7142
E-MOM	0.0002	1.1936	0.2326
Market-Factor	0.0002	0.6051	0.5451
Size	0.0003	2.4517	0.0142
Value	-0.0006	-1.7666	0.0773
Profitability	-0.0001	-0.8519	0.3943
Investment	-0.0001	-0.6982	0.4851
Momentum	0.0013	4.4972	0.0000
Constant	0.0004	2.3835	0.0172
R-squared	0.1902	NaN	NaN
Adj. R-squared	0.1768	NaN	NaN
MSE	2.2894e-04	NaN	NaN
MAE	5.8901e-18	NaN	NaN

Sample Size: n=1302

Period 2

Variable	Coefficient	T-Ratio	P-Value
BMG	0.0004	3.1646	0.0016
E-MOM	0.0004	1.8519	0.0640
Market-Factor	0.0004	1.5083	0.1315
Size	0.0002	2.1477	0.0317
Value	-0.0007	-2.3771	0.0174
Profitability	0.0000	0.2828	0.7773
Investment	0.0001	0.5511	0.5815
Momentum	0.0010	3.2397	0.0012
Constant	0.0001	0.7393	0.4597
R-squared	0.2097	NaN	NaN
Adj. R-squared	0.1977	NaN	NaN
MSE	2.2695e-04	NaN	NaN
MAE	6.5492e-18	NaN	NaN

Sample Size: n=1824

Table 25: Fama-MacBeth regression results with two model specifications including the five factor model, a "level" carbon risk proxy (BMG) and the "momentum" carbon risk proxy "E-Pillar Momentum". The coefficients represent average daily risk premia. Period 1 ranges from January 1st 2010 to December 31st 2014
Period 2 ranges from January 1st 2015 to December 31st 2021

Period 1

Variable	Coefficient	T-Ratio	P-Value
E-Pillar	0.0002	0.6987	0.4846
E-MOM	0.0002	1.5137	0.1309
Market-Factor	0.0002	0.6349	0.5255
Size	0.0004	2.7584	0.0058
Value	-0.0006	-1.9807	0.0476
Profitability	-0.0001	-0.5995	0.5488
Investment	-0.0001	-0.6806	0.4961
Momentum	0.0012	4.1094	0.0000
Constant	0.0004	2.3743	0.0176
R-squared	0.1914	NaN	NaN
Adj. R-squared	0.1780	NaN	NaN
MSE	2.2862e-04	NaN	NaN
MAE	8.8053e-18	NaN	NaN

Sample Size: n=1302

Period 2

Variable	Coefficient	T-Ratio	P-Value
E-Pillar	0.0005	2.7991	0.0051
E-MOM	0.0004	1.8830	0.0597
Market-Factor	0.0004	1.4401	0.1498
Size	0.0003	2.2567	0.0240
Value	-0.0007	-2.4941	0.0126
Profitability	0.0000	0.2581	0.7963
Investment	0.0000	0.2548	0.7987
Momentum	0.0011	3.5395	0.0004
Constant	0.0001	0.8327	0.4050
R-squared	0.2092	NaN	NaN
Adj. R-squared	0.1970	NaN	NaN
MSE	2.2718e-04	NaN	NaN
MAE	7.2585e-18	NaN	NaN

Sample Size: n=1824

Table 26: Fama-MacBeth regression results with two model specifications including the five factor model, a "level" carbon risk proxy (E-Pillar) and the "momentum" carbon risk proxy "E-Pillar Momentum". The coefficients represent average daily risk premia. Period 1 ranges from January 1st 2010 to December 31st 2014
Period 2 ranges from January 1st 2015 to December 31st 2021

In our final analysis, we incorporated the BMG and E-Pillar factors into the E-Pillar Momentum factor model in two separate regressions, keeping all other variables constant. This was done to determine whether adding these factors improves our model fit or if they capture the same risk premium. Consistent with our previous findings, significant results were only observed in the second sample period. Interestingly, in both model setups, both risk factors produced significant results, indicating that the level and momentum measures capture distinct risk premia. We will explore the implications of these findings and provide a comprehensive summary in the conclusion of our thesis.

6.4.2 Examining the BMG risk factor

The framework developed by *Görgen et al. (2020)*, which includes the creation of the BGS score and the subsequent development of the BMG factor, has performed surprisingly well within our risk factor and risk premium analysis. The element of "surprise" in its success arises from the somewhat subjective nature of the BGS score's construction, which involves the categorization of variables and the application of specific weights along with a penalizing term. These components, though well-rationalized, ultimately reflect chosen preferences rather than intrinsic properties.

In the formula, a significant weight (0.7) is allocated to the "value chain" category, while "public perception" and "adaptability" are assigned relatively lower weights. Görgen and colleagues argue that variables within the "value chain" category—such as scope 1 emissions, emission intensity, and environmental supply management—are more crucial for assessing a company's risk exposure compared to variables like disclosure scores or air pollution reduction policies. This perspective is reasonable, considering that current emissions directly influence transition risk more than potential future emissions, which might be captured under "adaptability".

However, the precise origins of these weight choices are not entirely clear. It's conceivable that transition risk could also be significantly driven by a firm's ability to adapt and public perceptions of its environmental efforts. To further validate the robustness of the BMG factor, we will employ machine learning algorithms to identify which variables most significantly impact company returns. The chosen methods are elastic net regressions and random forest analysis. Both approaches will utilize annual stock returns as the dependent variable to explain current performance, using data from the same year to avoid predictive biases.

This chapter will briefly introduce the concepts behind these two algorithms and will present a summary of our findings, shedding light on the most impactful variables and thereby assessing the validity of the weightings used in the BMG factor's construction.

6.4.2.1 Elastic Net regression

To identify the subset of our 65 variables that significantly explain the BMG factor, we are implementing two strategic approaches. Firstly, we have created a panel dataset by incorporating an additional variable, “Company ID.” This addition enables us to stack the time series data of each company, thus addressing the challenge of having too many independent variables relative to our sample size. Although this high dimensionality is not inherently problematic for the algorithms we are using, this approach allows for a unified analysis of all companies, rather than evaluating each firm individually.

Secondly, we have organized panel datasets for each sector, continuing the systematic sector analysis established earlier. This sector-specific approach helps maintain the structural integrity of our analysis and allows for nuanced insights specific to each industry.

Given that some of our variables are highly correlated, our objective includes not just analysis but also variable selection. To achieve this, we utilize the elastic net algorithm proposed by *Zou and Hastie (2005)*. Elastic net is ideal for our needs because it combines the best aspects of both ridge and LASSO regressions. This combination helps reduce problems caused by related variables (multicollinearity) and simplifies the model by selecting only the most important variables.

Ridge regression introduces a penalty term that shrinks all coefficients towards zero but does not set any to zero; this regularization helps manage multicollinearity without eliminating any variables entirely. LASSO regression, on the other hand, can set some coefficients to zero, thus effectively selecting a more manageable subset of variables for the model.

Elastic net merges these techniques by using a penalty that is a combination of both Ridge and LASSO’s penalties. This hybrid approach not only helps in dealing with multicollinearity (like ridge) but also aids in variable selection (like LASSO), making it highly effective for our dataset with numerous correlated predictors:

$$L(\lambda_1, \lambda_2, \beta) = |y - X\beta|^2 + \lambda_2|\beta|^2 + \lambda_1|\beta|_1,$$

where

$$|\beta|^2 = \sum_{j=1}^{P} \beta_j^2,$$

$$|\beta|_1 = \sum_{j=1}^{P} |\beta_j|.$$

The estimator can obtained by minimizing the following optimization problem:

$$\hat{\beta} = \arg\min_{\beta}\{ L(\lambda_1, \lambda_2, \beta)\}.$$

The first additive term in the formula applies the penalty from LASSO regression, and the second term applies the penalty from ridge regression. The parameters lambda 1 and lambda 2 are used to adjust the strength of each penalty (*Zou and Hastie, 2005*).

6.4.2.2 Random Forest

A significant limitation of elastic net regressions is that they assume a linear relationship between independent and dependent variables. This assumption may not hold, especially for non-normally distributed variables, which are common in the BMG factor dataset, potentially leading to non-linear relationships. To address this issue, we employ a machine learning approach that does not require linearity, specifically using a random forest algorithm. The concept of the random forest was proposed by *Ho (1995)*, who described it as a "Random Decision Forest." This method involves the use of multiple decision trees to improve classification accuracy. Each tree in the forest uses the full set of training data but only a random subset of the features, helping to diversify the learning process and reduce the risk of overfitting that single decision trees often face. This diversification also helps mitigate the accuracy problems that occur when trees become overly complex *Ho (1995)*.

The diagram below illustrates a simplified version of a random forest. Each of the three nodes at the top represents the start of a decision tree. The lighter paths leading down from these nodes show the routes taken to classify a new data point. Ultimately, a voting mechanism determines the final classification outcome. This voting can be done by averaging the results, a majority vote among the trees, or other methods, thus combining the strengths of various trees to achieve more reliable predictions.

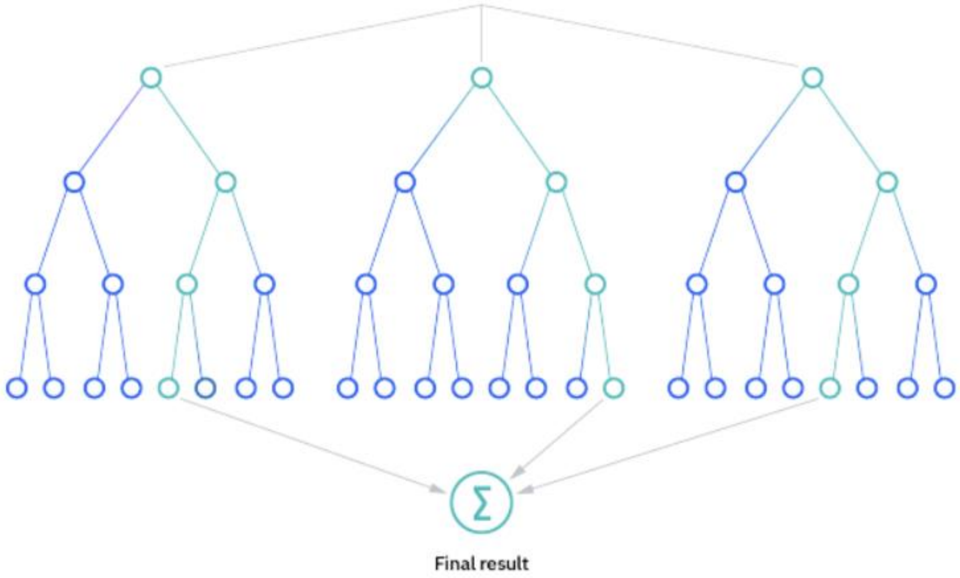


Figure 21: Random Forest Structure

6.4.2.3 Machine learning results

As mentioned at the beginning of this chapter, we use annual company returns since all our variables are reported annually. While this is standard practice, it inherently limits our expectations for model accuracy. To assess the accuracy of our models, we are using the simple R-squared (R2) metric. Given that a company's annual return is influenced by numerous factors beyond just exposure to transition risk, we are not expecting very high R2 values. To account for this, we are employing two distinct models which, ideally, should indicate the same key variables.

To further ensure accuracy and avoid potential misconfigurations within the algorithms, we are conducting a grid search. This method involves systematically exploring a range of reasonable parameter choices, rather than selecting them arbitrarily and evaluating their impact on R2. This approach allows us to adjust parameters across different model specifications. After calculating our coefficients, we ranked them by their absolute size to facilitate comparison between the two models. We applied this methodology uniformly across each sector and over the entire sample.

A table in the appendix displays the variable rankings from both the elastic net and random forest approaches. Notably, three of the top five variables identified by the elastic net are directly related to CO2 emissions. These include Scope 2 and Scope 1 emission scores from CDP and Bloomberg, alongside Bloomberg's total greenhouse gas emissions variable. This suggests that our models effectively capture emissions from the entire production process, including manufacturing and energy use. The other two top variables are comprehensive environmental scores from Refinitiv and CDP, which incorporate several other reported variables.

Interestingly, the random forest model selected very similar variables, with a tendency to prefer aggregated scores. The top three positions are occupied by the ESG disclosure score from CDP and the emissions and environmental pillar scores from Refinitiv. The next two highest-ranked variables are directly tied to CO2 emissions: Scope 2 emissions and greenhouse gas emission intensity per sale. Like the elastic net, subsequent variables predominantly relate to company emissions.

We are only presenting the aggregated data rankings here, as displaying tables for each sector would be redundant; most sectors show very similar results to the overall sample. In nearly every sector with sufficient data, both models converge on similar conclusions: absolute emissions, relative emissions, and aggregated scores from rating agencies are the most influential on annual returns. This finding is somewhat unexpected given that such scores are often criticized in the academic literature for being flawed. However, our results indicate that transition risk premiums are significantly dependent on current emissions, empirically supporting the substantial weighting given to these factors in the BMG formula.

7 Conclusion

In this research, we explored how asset prices are affected by the transition risk associated with carbon. Through a comprehensive analysis that included the construction of various carbon risk proxy portfolios, representing somewhat different degrees of carbon risk, and several empirical methodologies, we aimed to comprehensively resolve the relationship between carbon risk and asset prices in the European equity market.

In our analysis, we constructed portfolios based on four distinct carbon risk metrics, namely the Environmental Pillar Score, the Environmental Pillar Momentum, the BGS, and the market-based carbon futures dependency score. Apart from the Environmental Pillar Momentum portfolios, the other three aim to select “brown” and “green” companies based on a level metric for carbon risk. The E-Momentum portfolio on the other hand distinguishes between losers and winners with respect to the E-Pillar score, therefore showing whether a reduction in carbon risk proxied by the E-Pillar score, is increasing firm value. Through the application of both static and dynamic selection criteria, our approach permits a more nuanced dissection of the carbon risk premium.

With this empirical methodology, we found that carbon risk was significantly priced in the European Stoxx 600 Index in the period from 2010 until 2020, using different proxy portfolios for carbon risk. Additionally, incorporating certain carbon risk portfolios into established factor model frameworks markedly improved model precision. The period split that we employed showed that the significant and positive risk premium over the entire timeframe can be largely attributed to the post-2015 period, where we found risk premia to be highly significant and positive in contrast to the period up until 2015. This result is also reflected in the sector betas which after 2015 exhibited larger absolute values. Our analysis of the time-varying nature of carbon risk premia further corroborates this tendency.

The Machine Learning approach on granular environmental variable importance with respect to yearly stock returns that we employed showed that variables directly related to carbon emissions and aggregated scores have the highest predictive power out of the 66 variables that we tested. This finding underscores the potential relevance of specific environmental metrics in assessing carbon risk. However, to determine definitively which variables are most effective and efficient for carbon risk measurement, a more comprehensive and detailed analysis is required, to refine the understanding of how environmental variables correlate with financial performance, offering a clearer roadmap for investors and policymakers in integrating environmental considerations into risk assessment models.

However, our attempts to deploy a market-based carbon futures dependency model yielded no statistically significant outcomes. This suggests that the linkage between carbon futures prices and stock returns may not robustly delineate "brown" from "green" stocks. Theoretical considerations posit that higher carbon prices should favor "green" over "brown" firms, yet this hypothesis necessitates further research for definitive conclusions.

Another result that we want to mention here again is that factor loadings of the sector portfolios on our carbon risk proxy portfolios were generally negative for most sectors, unexpectedly also for sectors like Energy and Utilities. We believe that this is due to the distribution of Environmental Scores in our investment universe together with the general methodology of “Best-in-Class” score construction. Our reasoning for this is that in the European Stoxx 600, there are typically more companies regarded as “green” than “brown” due to the global normalization of scores. These results are also in line with the results obtained by *Roncalli et al. (2020).*

Despite demonstrating that incorporating carbon risk proxies can significantly refine traditional factor models and display a positive risk premium for "brown" companies, we argue against treating carbon risk as a traditional risk factor. This stance is twofold: firstly, the relevance of a carbon risk factor may be transient, pertinent only during the transition to a "green" economy—a shift that, once fully realized, could render transitional climate risks obsolete. Secondly, from a financial industry viewpoint, leveraging a carbon factor for portfolio diversification does not align with our perspective, as carbon risk pertains more to risk management. This fact is further corroborated by ethical considerations by investors not wanting to invest in “brown” companies.

Nonetheless, the presence of carbon risk in the European stock market underscores its significance for investors, emphasizing the imperative of its measurement and management.

Figure citation

Figure 7: Bloomberg, Bloomberg Terminal, 12.05.2023

Figure 22: IBM, https://www.ibm.com/topics/random-forest, 01.04.2024

Appendix, Figure I: “Environmental, Social and Governance Scores from LSEG” December 2023. https://www.lseg.com/content/dam/data-analytics/en_us/documents/methodology/lseg-esg-scores-methodology.pdf.

Appendix, Figure II: “BESG <GO> Overview of Bloomberg ESG” December 2023. Bloomberg Terminal.

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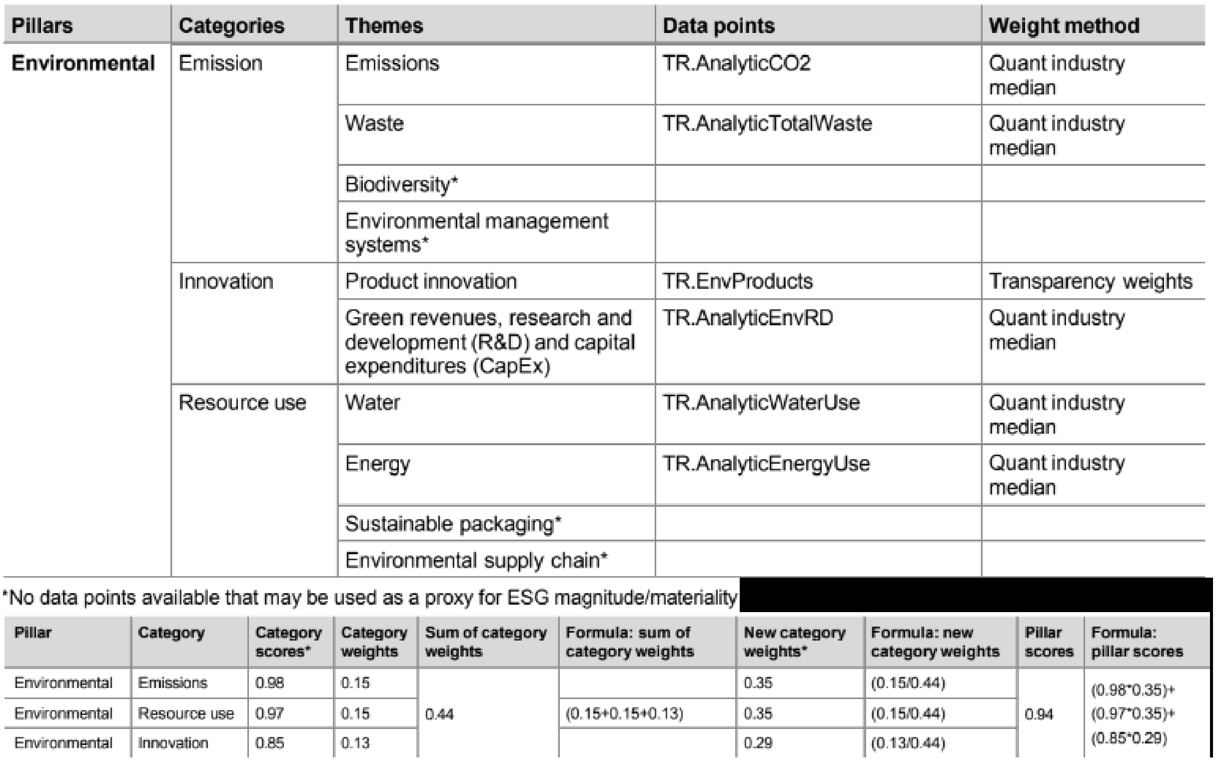
Appendix

Fields (Bloomberg and Refinitiv)	Name
RENEW_ENERGY_USE	Renewable Energy Use
SA_ESG_RISK_SCR	ESG Risk Score
SCOPE_OF_DISCLOSURE	Scope of Disclosure
GHG_EMISSIONS_REDUCTION_POLICY	Greenhousegas Emission Reduction Policy
ENVIRON_SUPPLY_MGT	Environmental Supply Management
ENVIRON_QUAL_MGT	Environmental Quality Management
CDP_INCENT_IND_MGT_OF_CLIMATE_C	Incentives for Individual Management of Climate Change
EMISSION_REDUCTION	Emission Reduction
CARBON_PER_UNIT_OF_PROD	Carbon per Unit of Production
GHG_EMISS_INTENS_REDUCT_TGT	Greenhousegas Emission Intensity Reduction Target
SUSTAINABLE_PRODUT_ISSUE_SCORE	Sustainable Production Issue Score
CLIMATE_CHG_POLICY	Climate Change Policy
ENV_SPPLY_CHAIN_MGMT_ISSUE_SCR	Environmental Supply Chain Management Issue Score
RENEWABLE_ELECTRICITY_TARGET_PL	Renewable Electricity Target Policy
AIR_POLLUTION_REDUCTION_POL	Air Pollution Reduction Policy
CDP_CLMT_REL_OPP_SUBSTANTIVE_IMP	Climate Related Opportunity Substantive Impact
GRI_COMPLIANCE	GRI Compliance
CDP_CLMT_REL_RSK_SUBSTAN_IMP	Climate Related Risk Substantive Impact
ENVIRONMENTAL_SCORE	Environmental Pillar Score
CDP_SCOPE_1_EMISSIONS_GLOBALLY	Scope 1 Emissions Globally
CDP_SCORE_2_EMISSIONS_GLOBALLY	Scope 2 Emissions Globally
CDP_REPORTED_CO2	Reported CO2
CDP_EMISSIONS_REDUCT_ABS_TARGET	Emission Reduction Absolute Target
CDP_EMISSION_REDUCT_ACT_PLAN_IP	Emission Reduction Action Plan in place
CDP_EMISS_RED_TGT_REACHED_OR_CP	Emission Reduction Target reached or caped
ESG_DISCLOSURE_SCORE	ESG Disclosure Score
CDP_INTEGRATED_PERFORMANCE_SCR	Integrated Performance Score
SCOPE_1_GHG_CO2_EMISSIONS	Scope 1 Greenhousegas CO2 Emissions
SCOPE_2_GHG_CO2_EMISSIONS	Scope 2 Greenhousegas CO2 Emissions
TOTAL_GHG_CO2_EMISSIONS	Total Greenhousegas CO2 Emissions
RISKS_CLMT_CHNG_DISCSSD_FLD_SCR	Climate Change Risks Discussed Field Score
TOT_GHG_CO2_EM_INTENS_PER_SALES	Total Greenhousegas CO2 Emission Intensity per Sale
GHG_EMISSION_TARGETS_SUB_IS_SCR	Greenhousegas Emission Targets Score
ENVIRON_FINES_AMT	Environmental Fines Amount
CLIMATE_CHG_OPPORTUNITIES	Climate Change Opportunities
CLIMATE_RISKS	Climate Risks
ENVIRONMENTAL_PILLAR_DISCLOSURE	Environmental Pillar Disclosure Score
CLIMATE_EXPOS_ISSUE_SCORE	Climate Exposure Issue Score
PHYSICAL_RISK_IDENTIFIED	Physical Risk identified
ENRRDP033	Energy Use Total
ENERDP023	CO2 Equivalents Emission Total
ENPIDP066	Clean Technology
ENRRDP058	Sustainable Supply Chain
ENRRDP046	Renewable Energy Use
ENERDP089	Climate Change Risks/Opportunities
ENRRDP0122	Energy Efficiency Policy
ENERDP0161	Emission Reduction Target/Objective
ENRRDP0192	Energy Efficiency Target/Objective
ENERDP095	Environmental Investments Initiatives
ENERO24V	Environmental Expenditures Investment
ENERDP091	Environmental Expenditures
ENERDP070	Environmental Parnterships
ENERDP092	Environmental Provisions
ENERDP0051	Policy Emissions
EPIDP023	Environmental R&D Expenditures
TRESGENRRS	Resource Use Score
ENSCORE	Environmental Score
TRESGENPIS	Environmental Innovation Score
TRESGENERS	Emissions Score
ENRRD01V	Value - Resource Reduction/Policy
ENRRO06V	Value - Resource Reduction/Renewable Energy Use
ENRRDP004	Environment Management Team
ENRRO04V	Value - Resource Reduction/Energy Use
ENPIDP015	Fossil Fuel Divestment Policy
CGVSDP041	ESG Reporting Scope

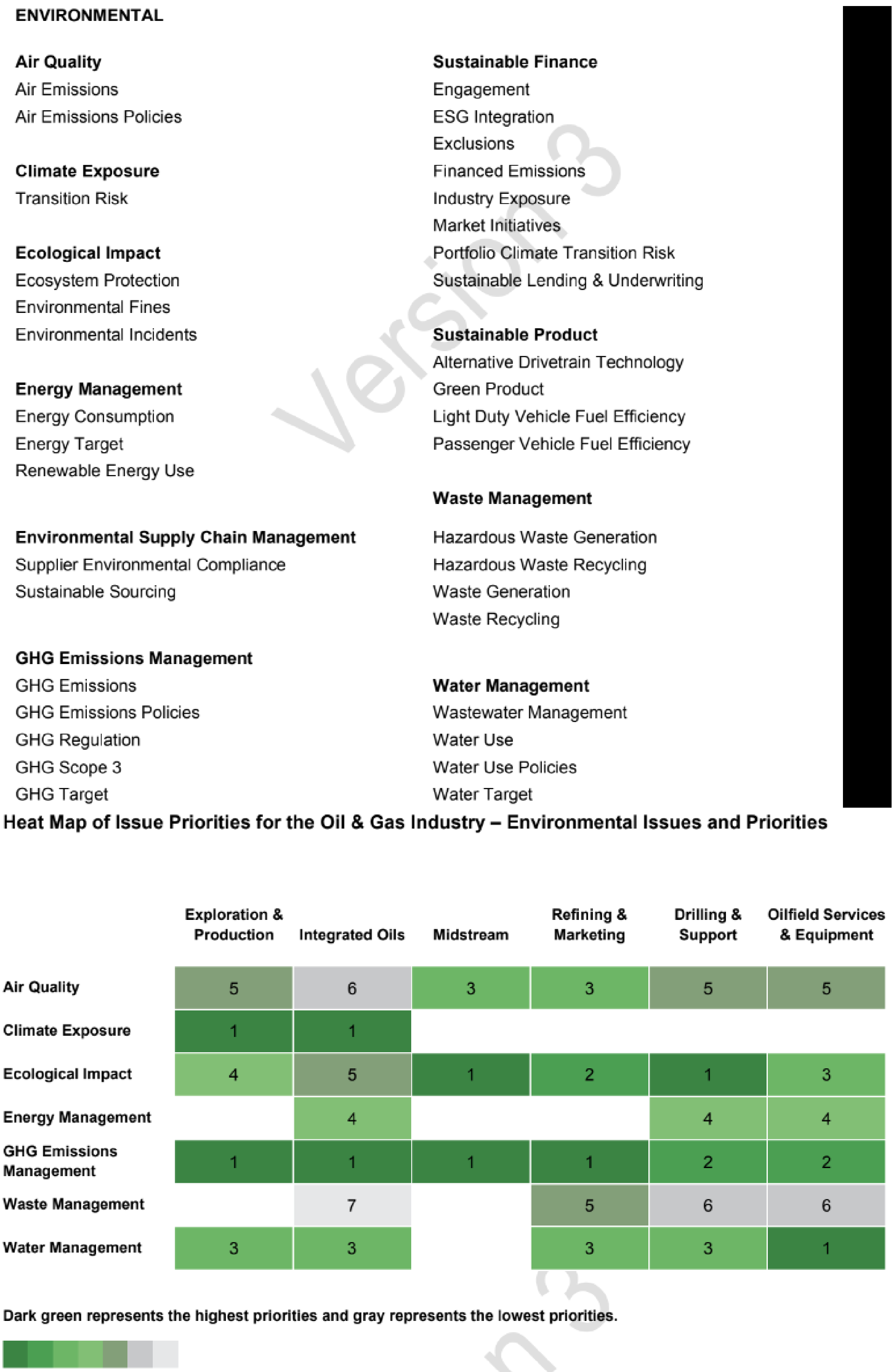


Pillars	Categories	Themes	Data points	Weight method
Environmental	Emission	Emissions	TR.AnalyticCO2	Quant industry median
		Waste	TR.AnalyticTotalWaste	Quant industry median
		Biodiversity*		
		Environmental management systems*		
	Innovation	Product innovation	TR.EnvProducts	Transparency weights
		Green revenues, research and development (R&D) and capital expenditures (CapEx)	TR.AnalyticEnvRD	Quant industry median
	Resource use	Water	TR.AnalyticWaterUse	Quant industry median
		Energy	TR.AnalyticEnergyUse	Quant industry median
		Sustainable packaging*		
		Environmental supply chain*		

*No data points available that may be used as a proxy for ESG magnitude/materiality [redacted]

Pillar	Category	Category scores*	Category weights	Sum of category weights	Formula: sum of category weights	New category weights*	Formula: new category weights	Pillar scores	Formula: pillar scores
Environmental	Emissions	0.98	0.15	0.44	(0.15+0.15+0.13)	0.35	(0.15/0.44)	0.94	(0.98*0.35)+ (0.97*0.35)+ (0.85*0.29)
Environmental	Resource use	0.97	0.15			0.35	(0.15/0.44)		
Environmental	Innovation	0.85	0.13			0.29	(0.13/0.44)		

Figure I: Methodology of Environmental Pillar Score construction by Refinitiv



ENVIRONMENTAL

Air Quality
Air Emissions
Air Emissions Policies

Climate Exposure
Transition Risk

Ecological Impact
Ecosystem Protection
Environmental Fines
Environmental Incidents

Energy Management
Energy Consumption
Energy Target
Renewable Energy Use

Environmental Supply Chain Management
Supplier Environmental Compliance
Sustainable Sourcing

GHG Emissions Management
GHG Emissions
GHG Emissions Policies
GHG Regulation
GHG Scope 3
GHG Target

Sustainable Finance
Engagement
ESG Integration
Exclusions
Financed Emissions
Industry Exposure
Market Initiatives
Portfolio Climate Transition Risk
Sustainable Lending & Underwriting

Sustainable Product
Alternative Drivetrain Technology
Green Product
Light Duty Vehicle Fuel Efficiency
Passenger Vehicle Fuel Efficiency

Waste Management
Hazardous Waste Generation
Hazardous Waste Recycling
Waste Generation
Waste Recycling

Water Management
Wastewater Management
Water Use
Water Use Policies
Water Target

Heat Map of Issue Priorities for the Oil & Gas Industry – Environmental Issues and Priorities

	Exploration & Production	Integrated Oils	Midstream	Refining & Marketing	Drilling & Support	Oilfield Services & Equipment
Air Quality	5	6	3	3	5	5
Climate Exposure	1	1				
Ecological Impact	4	5	1	2	1	3
Energy Management		4			4	4
GHG Emissions Management	1	1	1	1	2	2
Waste Management		7		5	6	6
Water Management	3	3		3	3	1

Dark green represents the highest priorities and gray represents the lowest priorities.

Figure II: Environmental pillar weights for Oil & Gas Industry by Bloomberg

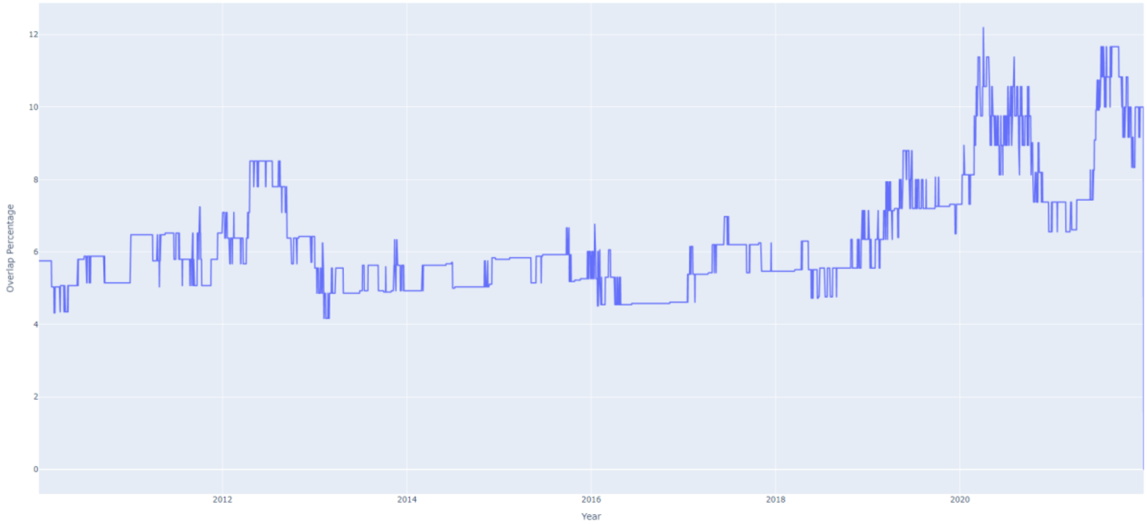


Figure III: Small-Cap and Green (BMG) Overlap Percentage

Figure IV:Large-Cap and Brown (BMG) Overlap Percentage

	E-Pillar	E-Momentum	Investment	Momentum	Profitability	Size	Value	C. Futures	BMG	Market
E-Pillar	1.00000	0.86350	0.85159	0.83505	0.89109	0.91025	0.72493	0.79223	0.96171	0.87121
E-Momentum	0.86350	1.00000	0.95695	0.92506	0.93827	0.94783	0.84935	0.90070	0.90448	0.97066
Investment	0.85159	0.95695	1.00000	0.91559	0.93234	0.94407	0.89174	0.89896	0.90332	0.98071
Momentum	0.83505	0.92506	0.91559	1.00000	0.89275	0.90153	0.76634	0.86429	0.88650	0.92913
Profitability	0.89109	0.93827	0.93234	0.89275	1.00000	0.95053	0.84315	0.86841	0.92822	0.95507
Size	0.91025	0.94783	0.94407	0.90153	0.95053	1.00000	0.88152	0.85192	0.94456	0.97494
Value	0.72493	0.84935	0.89174	0.76634	0.84315	0.88152	1.00000	0.74187	0.78834	0.91167
C. Futures	0.79223	0.90070	0.89896	0.86429	0.86841	0.85192	0.74187	1.00000	0.82141	0.89715
BMG	0.96171	0.90448	0.90332	0.88650	0.92822	0.94456	0.78834	0.82141	1.00000	0.92355
Market	0.87121	0.97066	0.98071	0.92913	0.95507	0.97494	0.91167	0.89715	0.92355	1.00000

Figure V: Portfolio Return Correlation Matrix

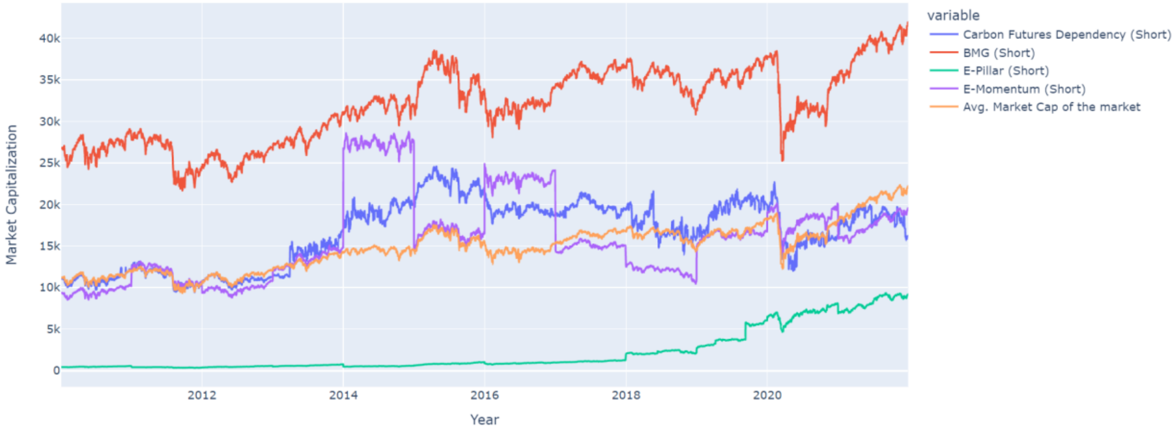
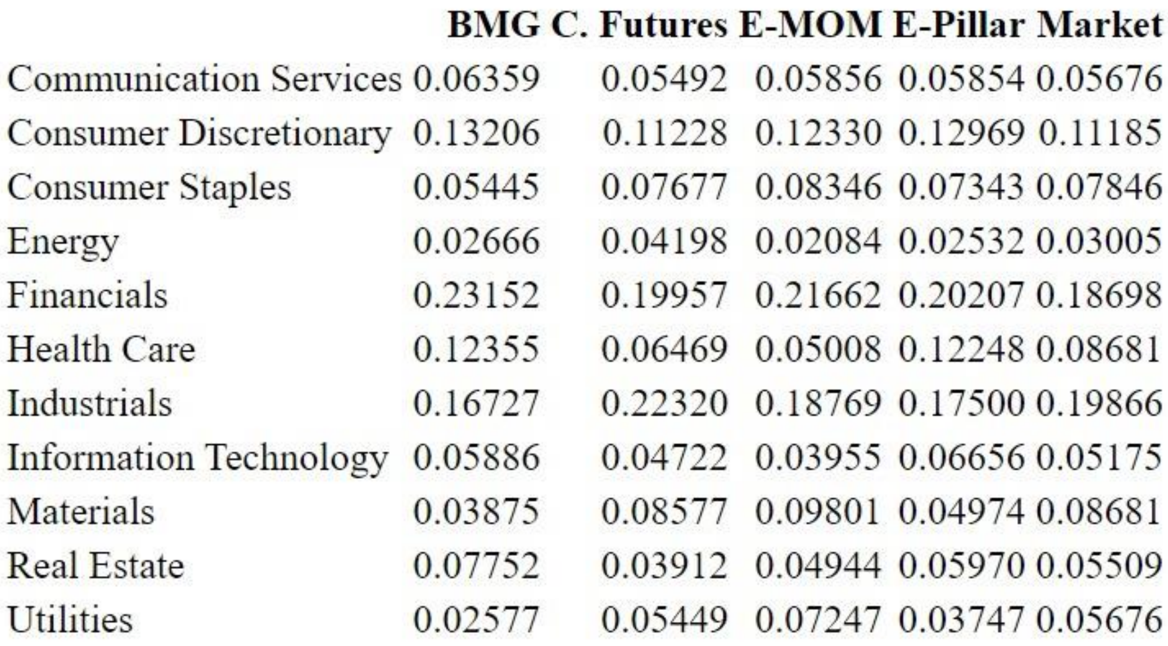


Figure VI: Market Capitalization of Short-Side Portfolios

Figure VII: Price-to-Book ratio of Short-Side Portfolios



	BMG	C. Futures	E-MOM	E-Pillar	Market
Communication Services	0.06359	0.05492	0.05856	0.05854	0.05676
Consumer Discretionary	0.13206	0.11228	0.12330	0.12969	0.11185
Consumer Staples	0.05445	0.07677	0.08346	0.07343	0.07846
Energy	0.02666	0.04198	0.02084	0.02532	0.03005
Financials	0.23152	0.19957	0.21662	0.20207	0.18698
Health Care	0.12355	0.06469	0.05008	0.12248	0.08681
Industrials	0.16727	0.22320	0.18769	0.17500	0.19866
Information Technology	0.05886	0.04722	0.03955	0.06656	0.05175
Materials	0.03875	0.08577	0.09801	0.04974	0.08681
Real Estate	0.07752	0.03912	0.04944	0.05970	0.05509
Utilities	0.02577	0.05449	0.07247	0.03747	0.05676

Figure VIII: Sector Composition of Short-Side Portfolios

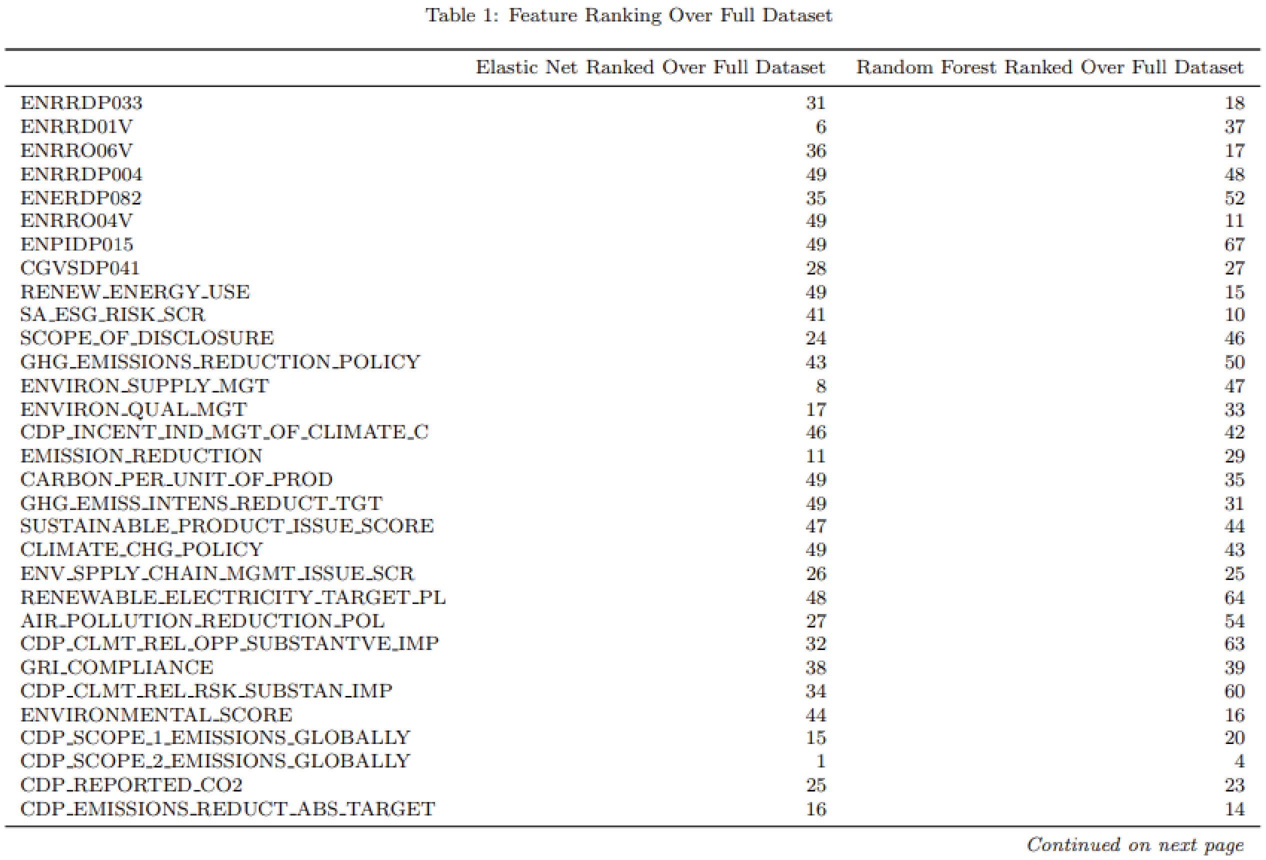


Table 1: Feature Ranking Over Full Dataset

	Elastic Net Ranked Over Full Dataset	Random Forest Ranked Over Full Dataset
ENRRDP033	31	18
ENRRD01V	6	37
ENRRO06V	36	17
ENRRDP004	49	48
ENERDP082	35	52
ENRRO04V	49	11
ENPIDP015	49	67
CGVSDP041	28	27
RENEW_ENERGY_USE	49	15
SA_ESG_RISK_SCR	41	10
SCOPE_OF_DISCLOSURE	24	46
GHG_EMISSIONS_REDUCTION_POLICY	43	50
ENVIRON_SUPPLY_MGT	8	47
ENVIRON_QUAL_MGT	17	33
CDP_INCENT_IND_MGT_OF_CLIMATE_C	46	42
EMISSION_REDUCTION	11	29
CARBON_PER_UNIT_OF_PROD	49	35
GHG_EMISS_INTENS_REDUCT_TGT	49	31
SUSTAINABLE_PRODUCT_ISSUE_SCORE	47	44
CLIMATE_CHG_POLICY	49	43
ENV_SPPLY_CHAIN_MGMT_ISSUE_SCR	26	25
RENEWABLE_ELECTRICITY_TARGET_PL	48	64
AIR_POLLUTION_REDUCTION_POL	27	54
CDP_CLMT_REL_OPP_SUBSTANTVE_IMP	32	63
GRI_COMPLIANCE	38	39
CDP_CLMT_REL_RSK_SUBSTAN_IMP	34	60
ENVIRONMENTAL_SCORE	44	16
CDP_SCOPE_1_EMISSIONS_GLOBALLY	15	20
CDP_SCOPE_2_EMISSIONS_GLOBALLY	1	4
CDP_REPORTED_CO2	25	23
CDP_EMISSIONS_REDUCT_ABS_TARGET	16	14

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Figure IX: Feature Ranking of Elastic Net and Random Forest Algorithms (Part 1)

Table 1 – *Continued from previous page*

	Elastic Net Ranked Over Full Dataset	Random Forest Ranked Over Full Dataset
CDP_EMISSION_REDUCT_ACT_PLAN_IP	18	62
ESG_DISCLOSURE_SCORE	40	1
CDP_INTEGRATED_PERFORMACE_SCR	2	22
SCOPE_1_GHG_CO2_EMISSIONS	3	7
SCOPE_2_GHG_CO2_EMISSIONS	49	9
TOTAL_GHG_CO2_EMISSIONS	4	8
RISKS_CLMT_CHNG_DISCSSD_FLD_SCR	12	66
TOT_GHG_CO2_EM_INTENS_PER_SALES	29	5
GHG_EMISSION_TARGETS_SUB_IS_SCR	10	40
ENVIRON_FINES_AMT	21	28
CLIMATE_CHG_OPPORTUNITIES	9	58
CLIMATE_RISKS	49	59
ENVIRONMENTAL_PILLAR_DISCLOSURE	49	21
CLIMATE_EXPOS_ISSUE_SCORE	49	34
PHYSICAL_RISK_IDENTIFIED	23	65
ENERDP023	30	19
ENPIDP066	19	57
ENRRDP058	42	36
ENRRDP046	13	49
ENERDP089	33	55
ENRRDP0122	7	45
ENERDP0161	49	51
ENRRDP0192	20	41
ENERDP095	49	53
ENERO24V	39	56
ENERDP091	22	24
ENERDP070	37	32
ENERDP092	14	30
ENERDP0051	49	38
ENPIDP023	45	26
TRESGENRRS	49	6
ENSCORE	5	3

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Figure X: Feature Ranking of Elastic Net and Random Forest Algorithms (Part 2)

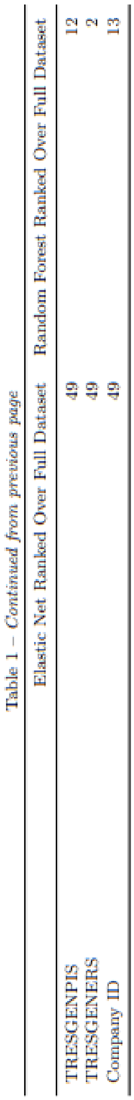

Table 1 – *Continued from previous page*

	Elastic Net Ranked Over Full Dataset	Random Forest Ranked Over Full Dataset
TRESGENPIS	49	12
TRESGENERS	49	2
Company ID	49	13

Figure XI: Feature Ranking of Elastic Net and Random Forest Algorithms (Part 3)

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Chat GPT in order to improve readability and language. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.