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# A Reappraisal of Asset Pricing Theory and Finance Practice – the Impacts of Sustainability-Related Market Expectations

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## ARTICLES INCLUDED IN THE DISSERTATION

This dissertation contains the following six research articles. Two of them have already been published and another one is to be revised and resubmitted.

**Article I:**

Jacob, A., 2020. Delayed price adjustment and the estimation of risk – empirical evidence from European stock markets. Working Paper.

**Article II:**

Benz, L., Jacob, A., Paulus, S., Wilkens, M., 2020. Herds on green meadows: the decarbonization of institutional portfolios.
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Revise and resubmit, *Journal of Corporate Finance*.

**Article IV:**

Görgen, M., Jacob, A., Nerlinger, M., 2021. Get Green or Die Trying? Carbon Risk Integration into Portfolio Management.
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**Article V:**

Jacob, A., Nerlinger, M., 2021. Investors' delight? Climate risk in stock valuation during COVID-19 and beyond. Working Paper.

**Article VI:**

Jacob, A., Wilkens, M., 2021. What drives sustainable indices? A framework for analyzing the sustainable index landscape. Working Paper.

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*Note*: References are provided at the end of each chapter. Footnotes, equations, tables, and figures are numbered within each chapter and research paper, respectively.

# 1 INTRODUCTION

The dynamics and determinants of asset prices have long been fascinating for both academics and practitioners. Even after extensive research and practical experience since the advent of financial stock markets hundreds of years ago, they still have not lost their attraction. On the contrary, the interest in the advancement of their theoretical and practical foundation has been growing over time.

This dissertation departs to new frontiers and demonstrates that with progress in time, new aspects need to be incorporated in asset pricing theory and finance practice to effectively account for advancements and changes in societal values and beliefs. More specifically, it scrutinizes underlying model assumptions and captures and analyzes the interconnection between asset pricing theory and an emerging new societal and political mindset arising from sustainability considerations. In addition, it does not stop at theoretical modelling but identifies implications for finance practice. In this manner, the dissertation enhances both the understanding of price formation processes and sustainability in the market and thus enables financial market participants to reallocate capital based on more informed investment decisions.

The remainder of this dissertation is structured as follows: Subchapter 1.1 starts with a description of the traditional conceptual framework of financial economics and asset pricing in particular. Moreover, this subchapter explains the implications for asset pricing caused by sustainability considerations. Subchapter 1.2 presents the aim and objectives of the dissertation on the basis of merging the traditional framework of asset pricing with the impacts of sustainability considerations. It relates all articles part of this dissertation to the components of the framework. Subchapter 1.3 gives a tabulated overview of the articles included and briefly summarizes each of them. The subsequent chapters present all articles in full length. Finally, Chapter 8 provides some concluding remarks and further guidance for future research.

## 1.1 Theoretical background

The beginnings of financial economics date back to the rise of stock trading in Amsterdam in the 1600s. In its early days, trading was limited to the shares of one company – The Dutch East India Company (Vereenigde Oostindische Compagnie, VOC), which was founded for executing long-distance trading expeditions to Asia (Fratianni, 2009). To finance the fitting of the ship voyages, the VOC needed large amounts of funds. These funds were tied up for several years until trading round trips were completed, so that investors faced large liquidity risks. For this reason, shares of the VOC were made transferable in ownership and thus a secondary market in VOC shares emerged to ensure liquidity for shareholders (Gelderblom and Jonker, 2004).

The initial purpose of stock trading was to raise capital for the business needs of the VOC (Ehrenberg, 1896, p. 293). In contrast, investors rather followed their self-interests while participating in the market. By far the liveliest and most prominent description of the scenery of the stock markets in Amsterdam is given by de la Vega (1688). He begins in explaining that stock trading is an "enigmatic business which is at once the fairest and most deceitful in Europe, the noblest and the most infamous in the world, the finest and the most vulgar on earth." (de la Vega, 1688, p. 3). He implies with this statement that participants on the exchange were obsessed with making profit at any price (or loss) leading to speculative behavior.

In essence, the transactions of investors were based on decisions on how to allocate and deploy capital in the stock market. Following their aim of making profits, investors searched for superior information and assessed to what extent new information sets were going to influence stock prices. The first stock traders perceived movements in stock prices as explicable, in that they mirrored three influencing factors: business conditions, political developments, and the opinion on the stock exchange (de la Vega, 1688, p. 9; Ehrenberg, 1892). However, information was costly to obtain and far from being reliable (de la Vega, 1688, p. 9).

In addition, the perception and appraisal of information were highly subjective and different expectations on price movements induced different investment behavior (de la Vega, 1688, p. 15). Overall, decisions on capital allocation were made in an uncertain environment.

This anecdotal evidence illustrates that decisions on the appropriate allocation of capital are highly influenced by time aspects, uncertainty (risk), and information (Merton, 1998). To capture these influencing factors, asset pricing theory has developed as a means to understand how asset prices evolve and thus gives guidance on more profound allocation decisions (Cochrane, 2005, p. xiii).

One of the underlying asset pricing theories states that under ideal conditions, stock prices should provide accurate signals about the true intrinsic value of a stock and therefore enable effective resource allocation. In this sense, stock prices fully reflect all available information on the market, in other words: the market is efficient (Fama, 1970). This theory is known as the Efficient Market Hypothesis (EMH). The first stock traders somehow believed in the existence of an efficient capital market by explaining stock movements via the above mentioned influencing factors. Nevertheless, early traders also believed in their ability to outperform the market – a trait we still observe today for market participants and which is recognized as the overconfidence bias (Daniel et al., 1998). However, according to the EMH, investors cannot generate consistently higher expected returns than the market average given the same information set (Fama, 1970; Malkiel, 2003). This leads to the question who might be mistaken – investors confident in their abilities to consistently gain higher returns or the EMH.

Since the EMH cannot be empirically tested per se, a model for price formation has to be defined to infer whether all available information is actually reflected in prices (Fama, 1970; O'Sullivan, 2018). Fama (1970) explicitly suggests the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) as the underlying return generating process. The CAPM establishes a linear relationship between the expected return of an asset and its systematic risk in market equilibrium. The model is based on the Portfolio Selection Theory (PST) of Markowitz (1952), which explains that portfolio selection should come with maximizing expected return and diversifying risk (maximum expected return and minimum variance). The CAPM assumes that investors act rationally and maximize their utility function based on the PST. In addition, they have homogeneous expectations about risk and return parameters and can borrow or lend funds at the same risk-free interest rate (Sharpe, 1964).

Soon after the introduction of the CAPM, studies revealed misspecifications of the model. For example, Banz (1981) discovers the size effect, the circumstance that smaller stocks have higher risk-adjusted returns not explained by the model. Reinganum (1981) encounters an earnings-to-price ratio anomaly in returns. Rosenberg et al. (1985) find that a book-to-market long-short strategy leads to statistically significant abnormal returns. The implications of such return anomalies, however, are obscured: either a wrong pricing model has been taken as basis or markets do not operate efficiently. This is known as the joint-hypothesis problem (Fama, 1991).

Ross (1976, 1977) introduces an alternative pricing model, the Arbitrage Pricing Theory (APT), which imposes less restrictive assumptions on the model. Ross (1976, 1982) shows that the CAPM does not only hold in an equilibrium condition, but essentially is an arbitrage relation. In addition, the market portfolio does not take on a special role: including multiple factors in the return generating model leads to the same theorems as a single-factor model (Ross, 1976). Even though the APT is based on the assumption of homogeneous expectations, it does not require homogeneous anticipations about the asset pricing model. The model still holds if market participants have the same ex ante expectations about returns and beta coefficients and disagree on the underlying distributions of factors (Ross, 1976; 1977). Crucial to the understanding of the APT is a precise determination of the relevant factor set (Ross, 1977). In recent years, this has given rise to the emergence of a "factor zoo" (Cochrane, 2011). Besides the size and value factors of Fama and French (1993), several other anomalies are captured in additional factors. These include but are not restricted to: momentum (Jegadeesh and Titman, 1993; Carhart, 1997), liquidity (Pástor and Stambaugh, 2003), the low-beta anomaly (Frazzini and Pedersen, 2014), profitability and investment (Fama and French, 2015; Hou et al., 2015), and quality characteristics (Asness et al., 2019).

Currently, studies are concerned with assessing the importance of factors and choosing the most effective return generating model (Cooper et al., 2020; Feng et al., 2020; Fama and French, 2018; Barillas and Shanken, 2017). Agreement on the right factor set seems far from being reachable. The crucial question, however, remains why asset prices move. Cochrane (2011) presents various theories thereof including macroeconomic, behavioral, and finance theories. All of these theories are based on market participants' expectations in one way or another (rational expectations as model assumptions for the macroeconomic and finance theories, and perception of risk for behavioral theories).

The cohesive concept of financial economics and asset pricing theory described so far can be summarized in a conceptual framework (see Figure 1). The final part derives investment strategies and implements tools based on the insights gained from asset pricing theory and models. In this step, decisions on the allocation and deployment of capital are made.

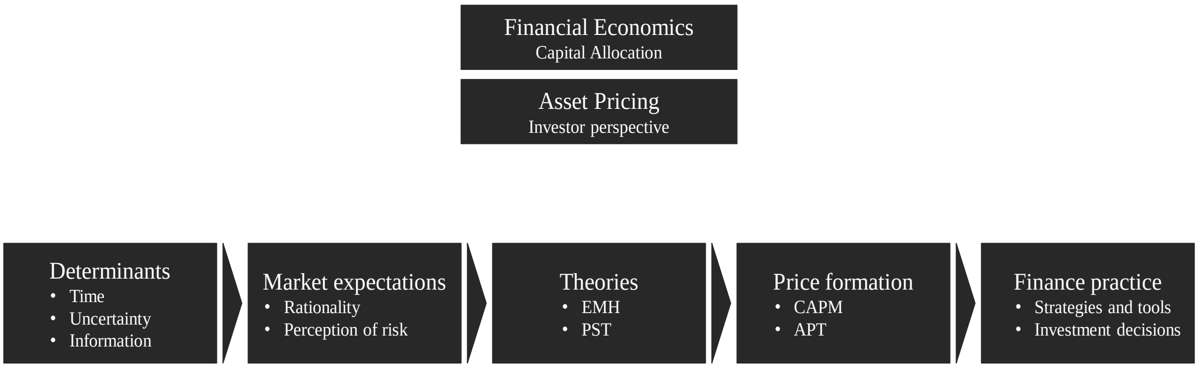


**Figure 1**
**Traditional conceptual framework of financial economics**

In the course of time, human expectations are subject to change when new information arises that is likely to affect future asset performance (Fama, 1995; O'Sullivan, 2018). When investors critically revise their view on how expectations are formed, new foundations for price formation are set requiring a factor model to be adapted to such changing expectations. During the last years, climate change and sustainability have evolved as two of the prevailing topics in society and thus qualify as new influencing factors for the fundamental considerations of investors.

The impacts of global warming are devastating: sea-level rise; changing land and ocean biodiversity and ecosystems including species loss and extinction; climate-related risks to health, livelihoods, food security, and economic growth (IPCC, 2018). The combat against climate change has not only united society but also politics. In 2015, more than 195 nations agreed to limit global warming to well below 2°C above pre-industrial levels (the United Nations Paris Agreement; United Nations, 2015a). The combat of climate change primarily targets the reduction of greenhouse gas emissions, as there is scientific consensus that anthropogenic greenhouse gas emissions are one of the dominant causes for rising temperatures (IPCC, 2014). The transition from a carbon-based to a low-carbon economy gains momentum.

Besides the Paris Agreement, United Nations member states adopted the 2030 Agenda for Sustainable Development in 2015. The Agenda is established based on 17 Sustainable Development Goals (SDGs) to alleviate poverty, protect the planet, and improve living conditions worldwide (United Nations, 2015b). It thus encompasses environmental, social, and economic dimensions of a sustainable development and should serve as a guidance for making decisions in the upcoming years (United Nations, 2015b).

Since climate change mitigation and sustainable development do not come without costs, finance flows should be made consistent with a pathway towards a more sustainable economy (European Commission, 2018; United Nations, 2015a). In Europe, the role of the financial industry is refined in the EU Action Plan on Financing Sustainable Growth that presents measures for aligning finance with the specific needs of the economy for a sustainable development (European Commission, 2018).

Political and financial initiatives targeted at a sustainable development coupled with societal pressure and changing preferences lead to revised market expectations about return and risk exposures of firms and their financial assets. These modified expectations of capital market participants on how sustainability considerations systematically determine the price formation process have to be incorporated in theoretical foundations and existing models to enhance their accuracy (e.g., Pedersen et al., 2020; Pástor et al., 2020). More accurate model foundations and aligned investment strategies and tools lead to more informed investment decisions and eventually to a reallocation of capital based on a more profound understanding of sustainability in the market (see Figure 2).

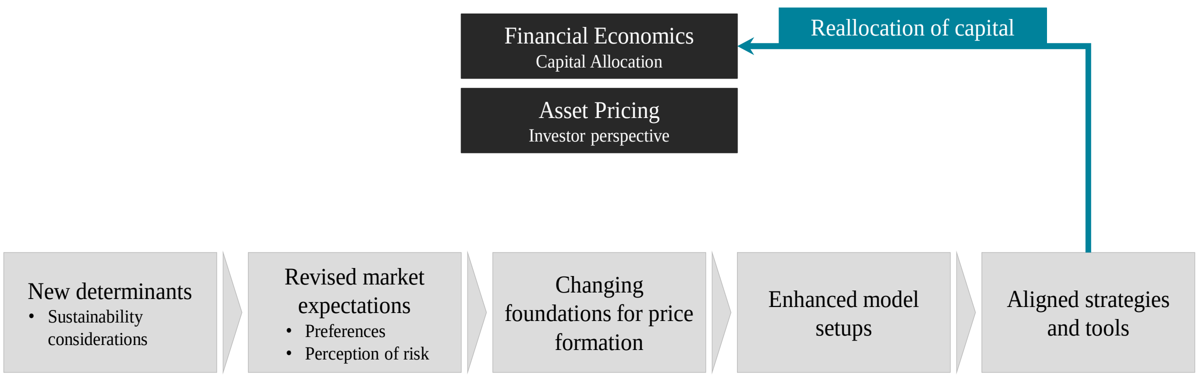


**Figure 2**
**Implications of sustainability considerations**

## 1.2 Aim and objectives

The aim of this dissertation is to effectively capture the impacts of sustainability considerations on asset pricing theory and finance practice. For this purpose, it first scrutinizes underlying model assumptions and derives necessary modifications for traditional models. In a second step, implications for finance practice (i.e., strategies and tools) are assessed. The interconnection between financial economics and sustainability is illustrated in Figure 3 and constitutes the framework of this dissertation.

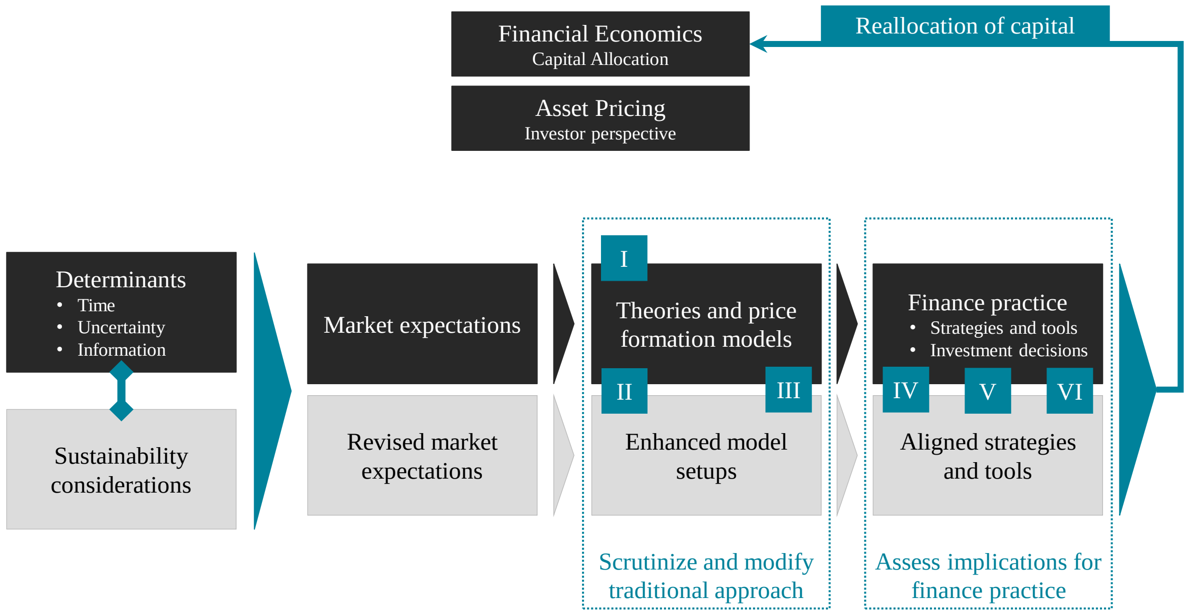


**Figure 3**
**Conceptual framework of dissertation scope and related articles (Roman numerals)**

The dissertation includes six articles that address different components within this framework. Articles I to III scrutinize and modify the traditional approach, while Articles IV to VI assess practical implications. Apart from Article I that is embedded in the traditional context, the remaining articles are based on the implications of revised market expectations resulting from sustainability considerations.

The first two articles reappraise underlying assumptions of traditional price formation models. Article I demonstrates that prices do not necessarily instantaneously adjust to information in the market as suggested by the EMH. This shortcoming has to be taken care of when striving for higher accuracy in the definition of return generating processes. Article II focuses on the assumption of rational investor behavior in return generating models such as the CAPM and APT. Investors do not necessarily act rationally under uncertainty but are confronted with behavioral biases (e.g., Kahneman and Tversky, 1979; De Bondt and Thaler, 1995). One such bias is herding behavior, i.e., investors follow the decisions taken by others regardless of their own information set (Scharfstein and Stein, 1990; Banerjee, 1992). Specifically, the article studies the interconnection between sustainability and herding behavior of investors in light of the emerging decarbonization movement. Article III integrates sustainability considerations into price formation models. It thus accounts for changing market expectations about risk and return determinants and quantifies carbon risk in an asset pricing framework while enhancing the model accuracy. Furthermore, it provides a means for market participants to measure carbon risk exposure without the need for extensive carbon- and transition-related data.

Implications of aligned investment strategies taking account of sustainability-related risks and enhanced models are analyzed for portfolio and risk management (Article IV) and stock analyses (Article V). In the last step, sustainable investment tools are reviewed. Article VI develops a new framework for evaluating one of the top monitoring and benchmarking solutions for integrating sustainability aspects in investment decisions: sustainable market indices. It focuses especially on the measurement and implications of their sustainability-related characteristics and exposures.

In summary, all articles increase the understanding of price formation processes and resulting investment practices. By capturing the impacts of sustainability considerations throughout the framework of asset pricing, this dissertation is at the forefront of defining a holistic concept for sustainability integration in asset pricing theory and finance practice. Eventually, it contributes to more informed decision-making processes and thus drives a more profound reallocation of capital flows.

## 1.3 Overview and summaries of articles included

**Table 1**
**Overview of articles included in the dissertation**

| | Title of article | Co-authors | Publication status | Date |
|---|---|---|---|---|
| I | Delayed price adjustment and the estimation of risk – empirical evidence from European stock markets | | Working Paper,<br>University of Augsburg | 2020 |
| II | Herds on green meadows: the decarbonization of institutional portfolios | Lukas Benz<br>Stefan Paulus<br>Marco Wilkens | Published<br>*Journal of Asset Management*, 21 (1), 13-31[1] | 2020 |
| III | Carbon Risk | Maximilian Görgen<br>Martin Nerlinger<br>Ryan Riordan<br>Martin Rohleder<br>Marco Wilkens | Revise and resubmit<br>*Journal of Corporate Finance*[2] | 2020 |
| IV | Get Green or Die Trying? Carbon Risk Integration into Portfolio Management | Maximilian Görgen<br>Martin Nerlinger | Published<br>*Journal of Portfolio Management*, 47 (3), 77-93[3] | 2021 |
| V | Investors' delight? Climate risk in stock valuation during COVID-19 and beyond | Martin Nerlinger | Working Paper,<br>University of Augsburg and University of St. Gallen | 2021 |
| VI | What drives sustainable indices? A framework for analyzing the sustainable index landscape | Marco Wilkens | Working Paper,<br>University of Augsburg | 2021 |

### 1.3.1 Article I: Delayed price adjustment and the estimation of systematic risk – empirical evidence from European stock markets

Asset prices might not instantaneously adjust to information in the market as theories for price formation suggest. So-called price adjustment delays influence the statistical properties of daily returns and impair the accuracy of return generating models. Using a daily European stock sample, the article first analyzes in how far returns are affected by delayed price adjustments. For this purpose, stocks are sorted into portfolios based on characteristics that mirror the sensitivity towards price adjustment delays. Portfolios which are more sensitive towards price adjustment delays display significantly higher cross-correlations with the lagged market return

[1] VHB-JOURQUAL3: B; DOI: 10.1057/s41260-019-00147-z.
[2] VHB-JOURQUAL3: B.
[3] VHB-JOURQUAL3: B; DOI: 10.3905/jpm.2020.1.200.

than portfolios less affected by delayed information integration into prices. Due to the biased covariance structures, the CAPM delivers biased estimations of systematic risk.

These estimation biases can be overcome by implementing beta adjustment techniques for nonsynchronous trading following Scholes and Williams (1977) and Dimson (1979). The results are robust when controlling for the estimation error following Vasicek (1973) and further factors known to influence variation in returns in the form of a multifactor model. Overall, the article shows how to effectively account for biases caused by price adjustment delays and thus increases the accuracy of price formation models and in turn systematic risk estimates in portfolio and risk management.

### 1.3.2 Article II: Herds on green meadows: the decarbonization of institutional portfolios

The second article focuses on the interconnection between sustainability and rational investor behavior and therefore addresses another assumption of traditional return generating models. Using the Refinitiv ownership database and environmental firm ratings, the article analyzes the decarbonization trend in institutional portfolio management. The article finds that investors engage in herding behavior. More specifically, they are inclined to follow their own previous trades (self-herding) or those of other investors (following-herding) in consecutive quarters. Herding measurement takes place analogous to the methodologies of Sias (2004) and Popescu and Xu (2018). The herding measure as correlation between trades in a security this quarter and trades in the security last quarter additionally is split into decarbonization and carbonization herding. For decarbonization herding, the triggering trades are the purchase of green and the sale of brown stocks and vice versa for carbonization herding.

The empirical results show that investors tend to follow their own trades and those of other investors in the sense of decarbonization. The major part of this herding behavior is driven by following-herding rather than self-herding. By aggregating these results on investor type level, investment advisors and hedge funds turn out to be the major drivers of decarbonization herding in the financial market. This is in line with the expectation that sophisticated investor groups are considered as well-informed, inducing other investors to follow their lead (Eichengreen et al., 1998). In addition, these investor types often act on behalf of reputational concerns (Scharfstein and Stein, 1990; Dasgupta et al., 2011) or are bound by social norms (Hong and Kacperczyk, 2009; Bolton and Kacperczyk, 2020).

### 1.3.3 Article III: Carbon risk

Revised market expectations based on sustainability-related considerations entail changing foundations for price formation processes, which have to be mirrored in adjusted asset pricing models. The article addresses carbon risk that arises from the uncertainty about the pace and direction of the transition process towards a low-carbon economy. It first analyzes the interconnection between a stock's fundamental carbon risk exposure and expected returns to verify reassessments in price formation processes. By making use of four industry-standard databases for capturing carbon- and transition-related information on stock level, a scoring approach determines a stock's fundamental brownness or greenness by calculating the Brown-Green-Score (BGS). Panel regressions show that brown stocks earn higher expected returns, whereas stocks becoming unexpectedly browner are penalized with lower returns. Hence, even though brown stocks earn higher expected returns, green stocks are able to outperform them when becoming unexpectedly greener. Since both expected and unexpected components are of comparable magnitudes, the market has not yet arrived in developing clear-cut propositions on the influence of a stock's fundamental carbon risk exposure on returns.

The second part of the article focuses on enhancing asset pricing models following Fama and French (1993) and builds a factor mimicking portfolio for carbon risk, the Brown-Minus-Green (BMG) factor. Classical and modern asset pricing tests following Gibbons et al. (1989), Hou et al. (2015), Fama and French (2016), and Barillas and Shanken (2017) confirm the validity of BMG in explaining systematic variation in stock returns. Additionally, the estimation of the BMG beta provides a means to calculate the carbon risk exposure of any asset without the knowledge of carbon- and transition-related information.

Cross-sectional tests in the fashion of Fama and MacBeth (1973) lead to the conclusion that the BMG factor is not priced, i.e., it does not command a risk premium in the financial market. A risk decomposition approach following Campbell (1991) and Campbell and Vuolteenaho (2004) shows that stocks with high absolute BMG betas are more exposed to fundamental re-evaluations of firm values than to discount-rate changes. However, in the sample period, investors demanded a premium for the latter. This serves as explanation for the missing carbon risk premium for cash-flow driven absolute high BMG beta stocks.

This article and its underlying concept have received remarkable attention in the academic and practitioner world. The article was presented at high-ranked international academic conferences and workshops with influential institutions such as the European Commission and the Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin). Furthermore, it received two research prizes. Detailed information can be found in Chapter 4. Due to the practical relevance, a manual for practitioners with an accompanying Excel tool and an article in the Occasional Papers series of the Network of Central Banks and Supervisors for Greening the Financial System (NGFS) were published (Wilkens et al., 2019; Görgen et al., 2020a). In addition, an article about carbon risks in asset management appeared in a practitioner journal (Wilkens and Jacob, 2020).

### 1.3.4 Article IV: Get green or die trying? Carbon risk integration into portfolio management

This article studies the implications of aligning investment strategies with carbon risk considerations using a global stock sample. Each stock's carbon risk exposure, the carbon beta, is determined by the factor-based methodology following Görgen et al. (2020b). Quintile portfolios are formed based on a stock's carbon beta and rebalanced quarterly.

Even though mean returns increase for higher carbon beta portfolios, risk-adjusted performance measures are lower for the margin portfolios (i.e., high absolute carbon beta portfolios). By construction, these extreme portfolios have higher risk measures. However, investors are not compensated for their higher risk exposure. In addition, the carbon beta portfolios display differences in common factor exposures, which influence their return patterns. For comparative purposes, the analysis proceeds with constructing a different set of portfolios based on a more fundamental measure of carbon risk – the MSCI carbon emissions score. A comparison of carbon beta exposures reveals that the fundamental score is not able to distinguish green stocks as distinctly as the carbon beta measure.

As part of the empirical analysis, common sustainable investment strategies are implemented. Both extreme positive (brown) and negative (green) screening techniques based on carbon betas lead to lower risk-adjusted performance than the neutral benchmark case. Best-in-class portfolios on sector level focus on integrating a certain carbon risk exposure without excluding carbon-intensive sectors such as Energy and Materials. European best-in-country portfolios turn out to be on average greener than North American portfolios. For Europe, both green and brown portfolios display a low risk-adjusted performance, whereas for North America, the greenest portfolio seems to be remunerated for its higher risk exposure.

### 1.3.5 Article V: Investors' delight? Climate risk in stock valuation during COVID-19 and beyond

This article takes on the analysts' perspective on sustainability integration and analyzes to which extent carbon intensity as a measure for climate risk exposure has entered and established itself in the valuation process of global stocks. Investors drastically change their stock valuation processes in unprecedented and extreme situations. In this way, the beginning of the COVID-19 period in early 2020 constitutes an exogenous shock event to assess investors' preferences towards carbon-related characteristics while holding carbon intensity levels unaffected of firm-specific changes. Moreover, the subsequent recovery period allows an analysis of the impact of carbon intensity in more stable times.

Cross-sectional regressions with cumulative daily returns and abnormal returns as dependent variables reveal that during the COVID-19 period in early 2020, carbon intensity had a significantly negative impact on returns. The higher the carbon intensity level the higher this negative effect materialized. Furthermore, a difference-in-differences setup based on daily returns and abnormal returns confirms that this effect was unique to the crisis period compared to the pre-crisis period. During the following post-crisis period, however, carbon-intensive stocks could recoup some of their additional incurred losses relative to the pre-crisis period.

Risk measures, in contrast, were not significantly driven by carbon intensity in the COVID-19 period. Nevertheless, high-emitting stocks displayed significantly higher risk relative to low-emitting stocks. In the post-COVID-19 period, carbon intensity ultimately influenced stock risk significantly positively. This is in line with expectations on higher risk exposures of carbon-intensive stocks towards stranded assets and climate policy uncertainty.

### 1.3.6 Article VI: What drives sustainable indices? A framework for analyzing the sustainable index landscape

The last article approaches the integration of sustainability in investment tools, namely sustainable market indices. The lack of harmonization in methodologies and the missing transparency on the pursued objectives of sustainable indices impede their effective adoption (EU Technical Expert Group, 2019). This article increases the understanding on the composition and strategy of sustainable indices by developing a customizable framework for their evaluation. It especially emphasizes the measurement and impact of their sustainability-related characteristics and exposures to account for their predefined scope. By incorporating sustainability-related aspects into traditional methods and models, the framework can be easily integrated into existing investment processes.

Four Environmental, Social, and Governance (ESG) and four carbon indices of MSCI serve as a representative test environment of the sustainable index landscape to exemplify the approach. These indices all rely on the MSCI World Index as parent index but differ in their methodology and thematic focus for integrating sustainability aspects. The first step of the framework compares traditional return and risk indicators among the sustainable indices and with their parent index. In the second step, the ESG performance and carbon exposure are measured while addressing the challenge of ESG rating disagreement discussed in literature (e.g., Dimson et al., 2020; Berg et al., 2020; Gibson et al., 2020). Even though divergence in ESG ratings persists on index level, inferences drawn based on the ESG profile remain consistent regardless of the underlying ESG definition. In addition, carbon indices show remarkable reductions in their carbon exposure compared to the conventional parent index. The third step investigates the return and risk drivers based on a return generating model that integrates sustainability-related factors. Index-specific returns and risk of sustainable indices are predominantly driven by their designated thematic focus. In the last step, a performance attribution analysis dissects the different index construction methodologies. Stock selection criteria turn out to be more important for ESG indices, whereas systematic re-weighting of carbon classes is more dominant for carbon indices.

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# 2 ARTICLE I: DELAYED PRICE ADJUSTMENT AND THE ESTIMATION OF SYSTEMATIC RISK – EMPIRICAL EVIDENCE FROM EUROPEAN STOCK MARKETS

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**Abstract.** Even though technological advancement and global interconnected markets lead to persistent information flows and higher trading activity, price adjustment delays still arise as frictions in the financial market. This paper demonstrates that price adjustment delays influence the statistical properties of European daily stock returns. Cross-correlations in returns lead to biased estimation of systematic risk, i.e., the market beta. Traditional adjustment techniques for nonsynchronous trading effects take account of this shortcoming and effectively improve beta estimation. Especially portfolios sorted on stock characteristics known to be sensitive towards price adjustment delays profit from a more defined beta estimation technique. This study demonstrates how to derive an accurate estimation of systematic risk and thus enables more informed decision making in risk and portfolio management.

*JEL classification*: G11, G12, G14

*Keywords*: Price adjustment delays, nonsynchronous trading, systematic risk, beta adjustments

## 2.1 Introduction

The velocity on financial markets and of information flows has steadily increased in recent years. Reasons for this development are growing interrelations due to globalization, market participation, and technological advancement. Chordia et al. (2011) find in their study that share turnover has risen dramatically predominantly driven by institutional trades. Further, they assume that decreasing trading costs fueled trading volume. As a main finding, they show that higher trading activity has been a main driver of market efficiency during the last years. Additionally, Chordia et al. (2008) prove that liquidity enhances market efficiency. Overall, this leads to the conclusion that we face more efficient market structures, thus mitigating microstructure noise. However, some phenomena impeding the rise of efficient markets cannot be eliminated by higher frequency in trades or more efficient technological structures. This paper demonstrates that frictions in the market still lead to inefficiencies inhibiting accurate return modelling. In specific, the analyses give evidence on the presence of price adjustment delays in modern stock markets. More importantly, these delays lead to wrong assumptions about price determination and thus bias the estimation of systematic risk in a return generating model. I provide a means to overcome biases in the estimation of systematic risk by applying seemingly old-fashioned yet timeliness and effective adjustment techniques.

Price adjustment delays describe the circumstance that information is not reflected immediately in stock prices, so that the latter mirror outdated information. Cohen et al. (1980) as well as Kadlec and Patterson (1999) list the following causes for price adjustment delays. First, official closing prices at the end of a trading day are not necessarily obtained by a transaction occurring at the exact closing time of a stock exchange. Transactions rather occur at a random point in time, thus not guaranteeing that prices are recorded in synchronous intervals and all available information on the market is reflected in the determined closing price (Campbell et al., 1997). Second, individual traders might assess information on a noncontinuous basis due to transaction costs. As a result, limit orders might turn stale since they are not updated and hence, prices contain outdated information as well. Third, the intervention of specialists, i.e., market makers, often impedes adjustment of prices, as they take measures to maintain continuity and liquidity on stock exchanges. Another reason for price adjustment delays is straightforward: the non-synchronicity of trading times across exchanges allows some prices to adjust faster to upcoming information while others cannot adjust immediately due to closed trading venues (Eun and Shim, 1989).

All these causes arise as frictions in the market process and thus have influence on stock prices and their underlying properties. More specifically, price adjustment delays lead to positive autocorrelation in equal-weighted portfolios or market returns, respectively, as well as significant positive cross-correlations between portfolio returns and the market return (Lo and MacKinlay, 1990). In addition, such effects of price adjustment delays diminish when the differencing interval of returns is lengthened, as information has more time to be evaluated and recognized (Lo and MacKinlay, 1990; Dimson, 1979). These effects should be especially taken note of when estimating systematic risk exposures. Cross-correlations between returns and the market factor lead to wrong assumptions about covariances and thus biased beta estimations (Scholes and Williams, 1977; Dimson, 1979). Misestimating systematic risk can lead to far-reaching consequences in risk and portfolio management, thus emphasizing the need to account for price adjustment delays in empirical analyses.

I find that all of the aforementioned effects of price adjustment delays are present in daily returns for European stock markets. Consequently, traditional estimation of systematic risk turns out to be biased. Hence, I apply the traditional adjustment techniques of Scholes and Williams (1977) and Dimson (1979). I show that adjustments are important for portfolios with characteristics known to be prone to price adjustment delays.

Several papers study the sources for autocorrelations in (portfolio) returns. Atchinson et al. (1987) and Lo and MacKinlay (1990) conclude that nonsynchronous trading accounts for part of the autocorrelation structure but cannot be the only source for it. Both papers assume other frictional sources responsible for the unexplained positive autocorrelation structure in returns. A more recent study of Kadlec and Patterson (1999) gives more importance to the influence of nonsynchronous trading on autocorrelation but also recognizes the importance of other influencing factors. In this vein, Anderson et al. (2013) find that partial price adjustment is an important source of autocorrelation when eliminating the nonsynchronous trading effect.

The following studies determine stock characteristics that can approximate for the sensitivity towards price adjustment delays. Cohen et al. (1980) derive the size of a stock or portfolio as one determinant of autocorrelation. Since larger stocks are covered by more analysts and information may run more fluently, their prices adjust faster to incoming information than for smaller stocks. Campbell et al. (1993) find that daily return autocorrelation is inversely related to trading volume of stocks or indices. In addition, Chordia and Swaminathan (2000) show that low volume portfolios respond more slowly to information in market returns, so that trading volume constitutes a significant determinant of lead-lag cross-autocorrelations in stock returns.

Nonsynchronous trading is also considered when determining price and volatility spillover effects for exchanges in different time zones or with differing trading hours. Martens and Poon (2001) find that nonsynchronous data has substantial impact on correlation estimates. Schotman and Zalewska (2006) conclude that time mismatch influences estimations on market integration.

Due to the importance of estimating systematic risk, i.e., the market beta, various studies have emerged that focus on differences in beta estimation techniques. Hollstein and Prokopczuk (2016) provide a comprehensive comparison of different beta estimation techniques including historical models, time-series-models, and option-implied techniques. Cohen et al. (1983a) derive a consistent estimate of beta since frictions in the trading process lead to biases in beta estimation. Hollstein et al. (2019) describe differences in beta estimation due to varying sampling frequencies, estimation windows, forecast adjustments, and forecast combinations. The authors state that nonsynchronous adjustment techniques yield high prediction errors compared to a historical estimate. Sercu et al. (2008) analyze different adjustment techniques and conclude that less bias in beta estimations comes with higher standard error, i.e., prediction error. Further studies explicitly investigate the so-called intervalling effect in beta estimation, i.e., that beta estimations vary across return frequencies (Hawawini, 1983; Gilbert et al., 2014). Hawawini (1983) explains the shifts in beta estimation with nonsynchronous trading effects. Cohen et al. (1983b) and Fung et al. (1985) show that lower return frequencies decrease biases in beta estimations that arise due to price adjustment delays. Gilbert et al. (2014) provide evidence on how the ability of stocks to respond to systematic news influences shifts in beta estimations across varying return frequencies.

Since studies predominantly focus on daily returns or higher frequency returns, the traditional adjustments of Scholes and Williams (1977) and Dimson (1979) remain in use for the major part of research. Some prominent examples of their application in literature are: Fama and French (1992), Chordia et al. (2001), Amihud (2002), Bollerslev and Zhang (2003), and Liu et al. (2018). Often, their usage is not justified, so that the intention of their use and relevance remain hidden or unnoticed.

In this paper, I consciously turn the spotlight on price adjustment delays, their effects and consequences, and present the easy-to-use adjustment methods mentioned above to overcome any obstacles. Daily returns of European stocks obviously suffer from positive cross-correlations and hence, biased estimations for systematic risk. I point to the need of adjusting beta estimations for portfolios that are especially prone to price adjustment delays based on certain stock characteristics. The results remain robust when controlling for estimation error and other common risk factors in a multifactor model. This study improves the basis for decision making in risk and portfolio management, i.e., the accurate determination of systematic risk.

The remainder of the paper is structured as follows. The next section describes the consequences of price adjustment delays for returns data and explains the methodology of the adjustment techniques to overcome the consequences of these effects. Section 2.3 presents the European stock sample and highlights on why closing prices on modern stock exchanges are prone to delays in price adjustment. The proof of the existence of price adjustment delay effects is set out in Section 2.4. Section 2.5 summarizes OLS and adjusted estimates for systematic risk and derives important insights on their influence. Their robustness is checked in the following section, whereas the final section concludes.

## 2.2 Theoretical background and methodology

### 2.2.1 Effects of price adjustment delays

Prices reflecting out-of-date information on financial markets still arise even though technological trading systems and interrelated global structures enhance the speed of information delivery. Different trading times and behavior of both institutional and individual market participants lead to frictions in the trading process and thus price adjustment delays. Such frictions do not come without consequences for the return properties of stocks and portfolios since their returns are based on prices affected by these frictions. This circumstance leads to problems in statistical models with the assumption that returns are set simultaneously, whereas, in fact, true returns are set on a nonsynchronous basis and are thus not observable. To be more specific, stocks that delay to price in information compared to a market portfolio, for example, display serial autocorrelations and their covariances with the market portfolio are underestimated. In specific, their true return interval overlaps with the market's lagged return interval leading to positive cross-correlations (Lo and MacKinlay, 1990; Scholes and Williams, 1977). Portfolios of stocks experiencing price adjustment delays will exhibit positive autocorrelations as stocks within that portfolio demonstrate high cross-correlations. This implies that an equal-weighted portfolio has higher positive autocorrelation than a value-weighted portfolio, which gives higher weight on assumingly more synchronous stocks (Cohen et al., 1980). Cross-correlations and underestimated covariance structures between stocks and market returns imply that models of a return generating process such as the CAPM deliver biased estimates (Scholes and Williams, 1977; Dimson, 1979). All of these effects are mitigated when the frequency of return measurement is decreased and thus, information has more time to be included in the price determination process (Cohen et al., 1980).

Overall, if these empirical phenomena of nonsynchronous price adjustment appear in returns data, estimations for systematic risk following a statistical return generating process, such as the CAPM, have to be treated with caution – or nonsynchronous trading effects have to be taken into account in a reasonable way.

### 2.2.2 Adjustment techniques of nonsynchronous trading effects

I apply two common techniques for adjusting for nonsynchronous trading effects: the Scholes and Williams (1977) and the Dimson (1979) model. Both models have gained reasonable attention and still find use in empirical analyses, thus demonstrating their timeliness character. As underlying assumption, returns are generated by a linear relationship to market returns following the CAPM of Sharpe (1964), Lintner (1965), and Mossin (1966):

$$er_{i,t} = \alpha_{i,t} + \beta_{i,t}^{mkt} er_{M,t} + \varepsilon_{i,t} \,, \tag{1}$$

where $er_{i,t}$ is the excess return of asset $i$ at time $t$, $er_{M,t}$ the excess market return at time $t$, $\alpha_{i,t}$ and $\beta_{i,t}^{mkt}$ the parameters of the regression model, and $\varepsilon_{i,t}$ the asset-specific error term with zero mean.

Scholes and Williams (1977) obtain a consistent estimator for systematic risk by running additional two independent regressions:

$$er_{i,t} = \alpha_{i,t} + \beta_{i,t}^{mkt,-1} er_{M,t-1} + \varepsilon_{i,t}\,, \tag{2}$$

$$er_{i,t} = \alpha_{i,t} + \beta_{i,t}^{mkt,+1} er_{M,t+1} + \varepsilon_{i,t}\,, \tag{3}$$

where $er_{M,t-1}$ ($er_{M,t+1}$) is the lagged (lead) excess market return.

The authors explain that stocks trading less frequently than the market (more prone to price adjustment delays) display higher cross-correlations towards the lagged market return and thus have a higher $\beta_{i,t}^{mkt,-1}$ than more frequently traded stocks. Stocks trading more frequently than the market in turn display higher $\beta_{i,t}^{mkt,+1}$ values. In both cases, the usual OLS beta estimation obtained by Equation (1) is biased downward. For determining the adjusted systematic risk estimator, Scholes and Williams (1977) derive Equation (4):

$$\beta_{i,t}^{SW} = \left(\beta_{i,t}^{mkt,-1} + \beta_{i,t}^{mkt} + \beta_{i,t}^{mkt,+1}\right) / \left(1 + 2\rho_M\right), \tag{4}$$

where $\rho_M$ corresponds to the autocorrelation of the market factor.

Dimson (1979) establishes the aggregated coefficients method with Equation (5):

$$er_{i,t} = \alpha_{i,t} + \sum_{k=-n}^{n} \beta_{i,t}^{mkt,k} er_{M,t+k} + \varepsilon_{i,t}\,, \tag{5}$$

where $er_{M,t+k}$ stands for the excess market return at time $t+k$.

The author derives that a return's covariance with the contemporaneous market return is positively related to trading frequency. Hence, stocks experiencing higher price adjustment delays than the market have an OLS beta estimate biased downwards and more frequently traded stocks an OLS beta estimate biased upwards. The relation between trading frequency and lagged and lead beta values follow the same direction as proposed by Scholes and Williams (1977). The true systematic risk according to Dimson (1979) is obtained by summing all estimated beta coefficients:

$$\beta_{i,t}^{Dim\ n} = \sum_{k=-n}^{n} \beta_{i,t}^{mkt,k} \,. \tag{6}$$

The number of leads and lags ($n$) included in the Dimson (1979) model is not specified. This means the researcher can decide on the timely structure of the applied model. I implement both a one and five lead-and-lag structure for the empirical analyses since these cases are often found in literature. In addition, Equation (5) can be augmented by further factors influencing the return generating process. This property will be exploited in one of the robustness tests summarized in Section 2.6.

## 2.3 Data and price structure

The focus of this study is on European stocks primarily traded on exchanges within the euro zone. I extract all stocks fulfilling this criterion from the MSCI All Country Europe All Cap Index. All selected stocks must have available data for return, market capitalization, and trading volume. Financial data is obtained from Refinitiv Datastream and noted in EUR. I focus on daily data since this frequency is primarily used in financial economics. The time period covered goes from December 2007 to October 2019. For the regressions, I calculate the market factor as value-weighted average of all stocks in the sample.[1]

Returns are based on official closing prices assuming that dividends are re-invested. Price determination on the stock exchanges in this sample follows the market model of continuous trading with auctions. The official closing price is determined at the closing auction at the end of the trading day. The system sets the price for which the highest volume is going to be

[1] In this way, it is easier to evaluate biased estimation results since on average, a beta of 1.0 should be obtained when regressing stocks on their value-weighted average.

executed while ensuring the lowest surplus for demand or offerings, respectively. Prices either follow limit orders or are set in accordance with the reference price, i.e., the last official trading price of a stock within the continuous trading phase. In each of the possible cases for price determination, we find either the influence of the last trading price (which might occur nonsynchronously and contain out-of-date information) or the influence of market participants' rationale (specialist interventions or stale orders, for example).[2] This circumstance illustrates the appearance of price adjustment delays even in modern interconnected times.

The impact of nonsynchronous price adjustments is most evident in portfolio returns (Lo and MacKinlay, 1990; Campbell et al., 1997). For this reason, I construct portfolios based on variables approximating for the sensitivity towards price adjustment delays. The first portfolio group is based on turnover ratio, approximating for a stock's trading frequency. The higher its turnover ratio, the less prone to price adjustment delays a stock is said to be (Chordia and Swaminathan, 2000; Scholes and Williams, 1977). Each month, I sort stocks into quintiles based on their turnover ratio of the preceding month and compute a quintile's return as value-weighted average of the returns of the underlying stocks. I repeat this procedure with a stock's size as sorting criterion. Larger stocks face higher analyst coverage and fluent information flows, so that they are less exposed to delays in price adjustments (Cohen et al., 1980; Dimson, 1979). Further, I sort stocks into quintiles based on the relative bid-ask spread of the previous month. The bid-ask spread is a measure for transaction costs and thus liquidity (Amihud and Mendelson, 1986). Stocks with a high bid-ask spread are less liquid or face higher transaction costs. Hence, investors assess relevant information for these stocks less continuously and might restrain orders due to high transaction costs, which leads to higher price adjustment delays (Cohen et al., 1980). Last, stocks are assigned to the exchanges on which they are mostly traded

[2] For a more detailed description of price determination on stock exchanges, see, e.g., https://www.xetra.com/xetra-en/trading/trading-models.

on in terms of number of shares traded. Thus, I can address differences in trading hours more effectively. In the results section, only exchanges with a sufficient number of underlying stocks are displayed.[3] It is notable that trading hours on European stock exchanges do not differ by a large extent. In a separate analyses focusing on synchronized stock exchanges, I still find effects of delayed price adjustments in the data, so I conclude that nonsynchronous opening hours of trading venues are not a prevailing issue in Europe.

Table 1 displays summary statistics for the whole sample.[4] Daily returns are on average close to zero and zero at the median. The market value reveals that the sample covers the full range of size categories from EUR 500,000 to a maximum of EUR 198.79 billion. On average, the sample covers around 253 stocks per day.

[Insert Table 1 here.]

### 2.4 Effects of price adjustment delays on European stock returns

In this chapter, I analyze the three aforementioned effects of price adjustment delays for the European stock sample: autocorrelation structure of portfolio returns, cross-correlations between portfolio and market returns, and the intervalling effect in beta estimations.

#### 2.4.1 Autocorrelation structure in the market portfolio

Following Cohen et al. (1980) and Dimson (1979), I find that the market factor constructed as simple average from all available stocks in the sample displays a significant positive autocorrelation for its first lag of 0.1669 (see Table 2). When stocks are weighted by their market capitalization, the first order autocorrelation becomes smaller and loses significance. In line with literature, this pattern accounts for the fact that value-weighted portfolios overweigh large stocks, i.e., stocks that are less prone to price adjustment delays. Thus, cross-correlations

[3] Abbreviations of exchange codes and their trading opening hours can be found in Appendix A.
[4] Summary statistics on portfolio level are displayed in Appendix B.

among the stocks in the portfolio and in turn the first order autocorrelation are lower. Autocorrelations of higher orders lack significance for both equal- and value-weighted market portfolios. The pattern observed in Table 2 points to the existence of nonsynchronous price adjustments in the returns of the European stock sample.

[Insert Table 2 here.]

### 2.4.2 Cross-correlations of portfolio returns and market returns

Scholes and Williams (1977) as well as Dimson (1979) assert that stocks with higher probability of delayed price adjustment show higher correlations with the lagged market factor and lower correlations with the lead market factor compared to stocks with lower probability of price adjustment delays. These hypotheses are analyzed in Table 3 for the four portfolio groups in the sample. To test whether correlations between the extreme portfolios (portfolio 1 and 5) are significantly different from each other, I use the test of correlated correlations following Meng et al. (1992). The test statistic is displayed in the last column. Since portfolio returns are obtained as value-weighted average of the underlying stocks' return, I use the value-weighted market factor.

[Insert Table 3 here.]

Panel A displays the results for the turnover quintile portfolios. Frequently traded stocks (portfolio 5) have significantly lower correlations with the lagged market return than less frequently traded stocks (portfolio 1). Cross-correlations are monotonically decreasing with increasing trading frequency. In addition, I also find a significant positive difference at the 10% significance level for the lead market return as literature suggests. For the size portfolios, the same pattern emerges (Panel B). In Panel C, stocks exposed to high illiquidity and transaction costs (portfolio 5) have a higher correlation towards the lagged market return than the more liquid portfolio (portfolio 1). For the lead market factor, I do not find significant differences.

When considering stocks on exchange level, I note that cross-correlations are independent of trading times. For example, even though the Frankfurt Stock Exchange has the longest trading hours, it displays the largest correlation towards the lagged market return of 0.2118. I find that stocks assigned to the Frankfurt venue are less traded in terms of their turnover ratio compared to stocks at the remaining exchanges (see Table B.1 in Appendix B). Thus, patterns for exchange portfolios are rather driven by stock characteristics than by nonsynchronous trading times.

Overall, the cross-correlation patterns suggest that all portfolios are prone to nonsynchronous price adjustments. In specific, the underlying proxy variables capture the effects of price adjustment delays in the direction forecasted by the stated hypotheses in literature.

### 2.4.3 Intervalling effect in beta estimations

The intervalling effect states that biases in beta estimation diminish when the return measurement interval increases (Cohen et al., 1980; Perron et al., 2013). To prove this hypothesis, I estimate constant betas over the sample period following Equation (1) with varying return frequencies. Since I use the same sample of stocks and weighting for constructing the market factor, the OLS betas must average 1.0 cross-sectionally absent any beta biases (McInish and Wood, 1986).

As assumed by Dimson (1979), betas for less frequently traded stocks are biased downward (0.7940) and for more frequently traded stocks biased upward (1.1233) using daily returns (see Panel A of Table 4). I also note that the goodness-of-fit increases for more frequently traded stocks as measured by the adjusted $R^2$ and root-mean-square error (RMSE) of the regression. These patterns are valid for all return frequencies, i.e., daily, weekly, and monthly returns. However, the spread between portfolio 5 and 1 diminishes with diminishing data frequency (from 0.3294 for daily returns to 0.1420 for monthly returns). A closer look at the portfolios reveals that especially the low turnover portfolio betas are adjusted upwards with increasing return intervals. This hints at the assumption that especially the low turnover portfolios are prone to price adjustment delays and need respective adjustment techniques to overcome the estimation bias.

[Insert Table 4 here.]

The intervalling effect for size portfolios seems to be even more pronounced (Panel B). The beta spread between large and small portfolios decreases from 0.5525 for daily returns to -0.0635 for monthly returns. Again, especially OLS beta estimates for small portfolios differ across frequencies. For example, the beta estimate for portfolio 1 increases from 0.4675 (daily return frequency) to 0.6323 (1.0566) for the weekly (monthly) interval length. In Panel C, I find the same patterns for the bid-ask spread quintiles. Portfolio 5, i.e., the illiquid portfolio, shows the largest deltas between return frequencies. In addition, the difference in the goodness-of-fit measures almost disappears with an increasing return measurement interval. Panel D illustrates that exchanges with less frequently traded stocks such as Frankfurt (FRA) and Athens (ATH) face higher deltas in beta estimations across frequencies than exchanges with more frequently traded stocks such as Milan (MIL) and Xetra (XET).

The occurrence of the intervalling effect in these portfolios, especially the diminishing spread between the extreme portfolios, is a sign that some of the variation in betas is due to price adjustment delays (Dimson, 1979).

Overall, this section gives evidence on the existence of delayed price adjustment in European stock returns. As a result, their thus induced properties lead to biases in the beta estimation using the CAPM, which has to be taken into account.

## 2.5 Empirical regression analyses and beta adjustments

In this section, I review estimations of systematic risk based on OLS and the adjustment techniques of Scholes and Williams (1977) and Dimson (1979), respectively. Table 5 summarizes all results for each portfolio group. Regressions are run on daily returns for each year.[5] The displayed results are the time-series averages of all regressions in the sample period.

[Insert Table 5 here.]

First, the results for the whole sample are shown for comparative purposes. Due to construction, the OLS CAPM estimate is 1.0 and all the lead and lag coefficients are not statistically different from zero. In Panel A, portfolio 1 with less frequently traded stocks has an underestimated beta in the OLS case, whereas the beta increases monotonically across the frequency portfolios. Portfolio 5 seems to be overestimated with a beta value of 1.1429. The Scholes and Williams models with the lead and lagged market returns display the expected pattern: less frequently traded stocks have a significantly higher $\beta_i^{mkt,-1}$ in the amount of 0.0639 than more frequently traded stocks. The pattern in $\beta_i^{mkt,+1}$ shows the right direction but is not statistically significant. The results are confirmed when using the Dimson model of Equation (5) both for a one and five lead-and-lag structure. Besides, the calculated adjusted beta values for Scholes and Williams ($\beta_i^{SW}$) and Dimson ($\beta_i^{Dim1}$ and $\beta_i^{Dim5}$, respectively) correct the OLS estimates in the predicted direction: for portfolio 1, the OLS estimate of 0.7579 is corrected upwards to 0.8287 for the Scholes and Williams (1977) method, to 0.8280 for the Dimson (1979) one lead-and-lag adjustment, and to 0.8835 for the five lead-and-lag model. Hence, the estimation in systematic risk improves in that the beta is tilted towards 1.0.[6] For the most frequently traded stocks, the

[5] Hollstein et al. (2019) derive that a historical estimator based on daily data over a 12-month horizon yields the most accurate predictions. Hence, we focus on yearly estimations based on daily return data.

[6] I do not expect all single portfolio betas to equal 1.0 since other effects besides price adjustment delays might drive their systematic risk. However, adjustment techniques can alleviate potential biases. For the inclusion of other determinants of systematic risk, see Section 2.6.

beta is adjusted downwards, from an OLS estimate of 1.1429 to 1.1140 for the Dimson five lead-and-lag model.

In effect, I can decide between three adjusted beta values – $\beta_i^{SW}$, $\beta_i^{Dim1}$, and $\beta_i^{Dim5}$ – for each portfolio. How should one recognize the "right" value? Calculating the value-weighted mean of a beta value across all portfolios should lead to a value of 1.0 in the best case absent any beta biases (McInish and Wood, 1986). In the last row of Panel A, a comparison of the value-weighted means shows that the Dimson five lead-and-lag model has a value closest to 1.0. However, I also find that all values are close to each other. When having a closer look at the differences between OLS estimates and adjusted values, it is notable that especially the portfolios most prone to price adjustment delays, i.e., lower quintile portfolios, show significant and relevant delta values. Thus, adjustments are especially worthwhile for portfolios most sensitive towards delayed price adjustments. However, the value-weighted mean underweights these portfolios, so that their remarkable deltas carry less weight than the negligible deltas of higher portfolio groups.

For the size portfolios, I derive basically the same results (see Panel B of Table 5). Adjustments are high for small portfolios and rather low for large portfolios. For the Dimson five lead-and-lag model, I obtain an ideal value-weighted mean of 1.0. For this method, the beta for the small portfolio is adjusted upwards by 0.3014 and for the large portfolio downwards by –0.0132. Even though the value-weighted mean is close to 1.0 in all cases, the results show how important adjustments are for small stocks: instead of predicting their systematic risk to 0.4442 by using OLS estimation, the adjusted systematic risk is instead estimated at 0.7456. One can imagine that this change in risk estimation has far-reaching consequences in portfolio and risk management.

For the relative bid-ask spread portfolios, the Scholes and Williams (1977) model turns out best (see Panel C). Again, deltas are higher for stocks more sensitive towards price adjustment delays, i.e., the higher bid-ask-spread portfolios. For the Scholes and Williams case, portfolio 5 exhibits a significant delta value of 0.0749, whereas portfolio 1 has a lower adjusted beta estimate of 0.0140 compared to the OLS beta.

Exchange portfolios (Panel D) improve their value-weighted mean in beta estimation from 0.8700 to 0.9684. The highest delta for this combination can be found for the Frankfurt Stock Exchange (FRA), where the OLS beta of 0.5146 is adjusted to 0.8246. As already mentioned above, stocks assigned to the Frankfurt Stock Exchange in this sample are low-frequently traded stocks, thus emphasizing their need for a beta adjustment technique. Stocks of the Madrid exchange (MAD), on the contrary, do not display any significant differences between OLS and adjusted beta estimates.

## 2.6 Robustness tests

### 2.6.1 Intervalling effect for adjusted beta values

The intervalling effect should be less pronounced in adjusted beta estimations since it is the aim of the adjustment techniques to alleviate price adjustment delays present in higher frequency data. Table 6 presents the beta calculations across all estimation techniques for different return frequencies. More specifically, I report the values for the difference portfolio 5-1 of each quintile-sorting characteristic. For the daily and weekly frequency, adjustment techniques deliver a more appropriate beta estimation result in the sense of lower beta spreads between portfolio 5 and 1. This points to the ability of the Scholes and Williams (1977) and the Dimson (1979) techniques to account for price adjustment delays in an efficient way as stated in the main analysis of this paper. With monthly returns, adjustment techniques are necessary to a lesser extent. For the size spread portfolio, the CAPM turns out to be more effective than the adjustment models. Thus, for this portfolio, prices adjust more accurately during the course of one month rendering beta adjustments for delayed information integration redundant. For turnover and bid-ask spread portfolios, a one lead-and-lag structure is more efficient than including five leads and lags when using monthly return data. Overall, a monthly return frequency requires less leads and lags than daily or weekly return intervals. This confirms the validity of beta adjustment techniques.

[Insert Table 6 here.]

### 2.6.2 Model-specific robustness tests

As mentioned in literature, both adjustment procedures are prone to estimation error. For this reason, I control for the estimation error by applying the Vasicek (1973) adjustment to the estimated beta values. As prior information, I assume beta to be adjusted towards 1.0 and 0, respectively, for the lead and lagged beta coefficients as proposed by Dimson (1979). In untabulated results, I find the same implications as without controlling for the estimation error. The Scholes and Williams (1977) adjusted beta is more prone to changes due to the Vasicek (1973) adjustment, but still close to the Dimson (1979) estimate.

In a second robustness test, I control for further characteristics known to influence the return generating process of stocks and portfolios. I implement the Fama and French (1993) model and thus control for the size and value effect. As suggested by Sercu et al. (2008), the market, *SMB*, and *HML* factors are all adjusted for nonsynchronous price adjustment since all common risk factors face the same delays in information integration. I make use of the European versions of *SMB* and *HML* provided by AQR Capital Management. Basically, the patterns in the beta estimations remain stable.[7] Thus, even controlling for further factors that

[7] Results for the Fama and French (1993) model can be found in Appendix C.

systematically determine variation in returns does not alter the influence of price adjustment delays and the functioning of traditional adjustment techniques.

### 2.6.3 Further robustness tests

I conduct further tests based on little changes in the analysis. First, I use USD returns and financial data instead of EUR data. Second, for the Fama and French (1993) model, I redo the Fama and French (1993) analyses with the European factors provided by Kenneth R. French in his data library. Last, I construct equal-weighted portfolios instead of value-weighted portfolios. For this case, I use the equal-weighted market factor in the regression analyses. For all modifications, the results remain basically unchanged.[8] The patterns prove to be more pronounced for the equal-weighted setup. Since in literature and practice value-weighted portfolios are of higher relevance, I chose to report this case.

## 2.7 Conclusion

This paper reveals that price adjustment delays are an important influencing factor for daily stock returns on European stock exchanges. When estimating systematic risk based on daily returns, the effects of delayed price adjustment have to be kept in mind as they cause biased beta estimations. This study shows that traditional beta adjustment techniques controlling for nonsynchronous price adjustments can alleviate beta biases effectively. In detail, especially portfolios based on characteristics known to be sensitive towards price adjustment delays can profit from better risk estimation using adjustment techniques. These findings are robust even when additionally adjusting for estimation error in beta following Vasicek (1973) or implementing a multifactor model and thus controlling for common risk factors known to influence variation in returns.

[8] Results are available upon request.

This paper and its analyses are predominantly relevant for portfolio and risk management. One of the most common risk measures in portfolio management is the market beta. Thus, investors and portfolio managers base their investment decisions and strategic orientation on it. If beta suffers from biases, decisions are made on a wrong basis, which might lead to unknown increased risk taking. As shown in this study, especially portfolios tilted towards certain stock characteristics, such as small market capitalization, exhibit biases in beta estimation. Since portfolios specialized on certain characteristics face an upward trend in demand, this finding is of relevance for both portfolio managers and investors. This study provides an easy implementable way of considering biases caused by price adjustment delays and thus enables better and more informed decision making in investing.

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## Tables and Figures

**Table 1**
**Descriptive statistics of the whole sample**

| | mean | std. deviation | min | median | max |
|---|---|---|---|---|---|
| return | 0.0003 | 0.0263 | -0.6000 | 0.0000 | 1.1981 |
| market value | 3,775.66 | 11,452.85 | 0.50 | 334.36 | 198,786.70 |
| no. of shares traded | 1,358.97 | 11,672.41 | 0.00 | 52.76 | 4,153,198.08 |
| no. of shares outstanding | 355,228.69 | 1,740,944.48 | 38.00 | 49,626.51 | 84,974,542.85 |
| value of trades | 10,941.85 | 72,089.58 | 0.00 | 282.67 | 18,366,610.00 |
| daily turnover ratio | 0.0022 | 0.0160 | 0.0000 | 0.0006 | 15.1804 |
| relative bid-ask spread | 0.0112 | 0.0223 | -1.9981 | 0.0051 | 1.9999 |
| daily no. of stocks | 252.71 | 24.93 | 52.00 | 254.00 | 308.00 |

This table presents descriptive statistics of all variables used in the analyses for the sample period from December 2007 to October 2019. Market value is given in EUR million, number of shares traded and number of shares outstanding in thousands, and the value of trades in EUR thousand. Turnover is computed as the number of shares traded divided by shares outstanding. Relative bid-ask spread is calculated as the ratio of the bid-ask spread and the mid-point of bid and ask prices.

**Table 2**
**Autocorrelations of market portfolios**

| | lag 1 | lag 2 | lag 3 | lag 4 | lag 5 |
|---|---|---|---|---|---|
| market equal-weighted | 0.1669 | 0.0655 | 0.0191 | 0.0093 | -0.0315 |
| | (5.15) | (1.64) | (0.65) | (0.31) | (-0.90) |
| market value-weighted | 0.0215 | -0.0401 | -0.0413 | 0.0097 | -0.0709 |
| | (0.87) | (-1.16) | (-1.58) | (0.31) | (-2.15) |

The nth-order autocorrelation is obtained as the slope in the following regression: $r_{M,t+n}=\alpha+\beta_n r_{M,t}$ (Campbell et al., 1993). The market portfolio is the equal-weighted (value-weighted) mean of all stocks in the sample. T-statistics are shown in parentheses and based on Newey-West standard errors.

**Table 3**
**Cross-correlations of portfolio returns with the market portfolio**

| | 1 | 2 | 3 | 4 | 5 | z-score (5-1) |
|---|---|---|---|---|---|---|
| **Panel A. Turnover** | | | | | | |
| corr($r_t$,$r_{M,t-1}$) | 0.0859$^{***}$ | 0.0922$^{***}$ | 0.0521$^{***}$ | 0.0044 | 0.0151 | -6.31$^{***}$ |
| corr($r_t$,$r_{M,t+1}$) | 0.0045 | -0.0102 | 0.0217 | 0.0236 | 0.0241 | 1.75$^{*}$ |
| **Panel B. Size** | | | | | | |
| corr($r_t$,$r_{M,t-1}$) | 0.2298$^{***}$ | 0.2139$^{***}$ | 0.1813$^{***}$ | 0.1225$^{***}$ | 0.0107 | -16.22$^{***}$ |
| corr($r_t$,$r_{M,t+1}$) | -0.0107 | 0.0045 | 0.0166 | 0.0223 | 0.0216 | 2.37$^{**}$ |
| **Panel C. Relative bid-ask spread** | | | | | | |
| corr($r_t$,$r_{M,t-1}$) | 0.0073 | 0.0786$^{***}$ | 0.1105$^{***}$ | 0.1275$^{***}$ | 0.1302$^{***}$ | 8.46$^{***}$ |
| corr($r_t$,$r_{M,t+1}$) | 0.0203 | 0.0290 | 0.0260 | -0.0109 | 0.0007 | -1.35 |

**Panel D. Exchanges**

| | AMS | ATH | BRU | DUB | FRA | HEL | LIS | MAD | MIL | PAR | WBO | XET |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| corr($r_t$,$r_{M,t-1}$) | 0.0277 | 0.1113$^{***}$ | 0.0494$^{***}$ | 0.0586$^{***}$ | 0.2118$^{***}$ | 0.0408$^{**}$ | 0.0651$^{***}$ | 0.0128 | 0.0082 | 0.0101 | 0.1316$^{***}$ | 0.0074 |
| corr($r_t$,$r_{M,t+1}$) | -0.0001 | 0.0392$^{**}$ | 0.0107 | 0.0213 | 0.0160 | 0.0131 | 0.0060 | 0.0196 | 0.0081 | 0.0079 | 0.0053 | 0.0584$^{***}$ |

This table displays cross-correlations between the respective portfolio return and the lagged market portfolio return, corr($r_t$,$r_{M,t-1}$), and the lead market portfolio return, corr($r_t$,$r_{M,t+1}$), respectively. The last column displays the z-score for testing the difference between the correlated correlations of portfolios 5 and 1 on significance following Meng et al. (1992). $^{*}$,$^{**}$, and $^{***}$ denote statistical significance at the 10%, 5%, and 1% level, respectively.

**Table 4**
**Intervalling effect in beta estimations**

| | daily | | | weekly | | | monthly | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE |
| **Panel A. Turnover** | | | | | | | | | |
| 1 | 0.7940 | 0.7206 | 0.0063 | 0.8582 | 0.7898 | 0.0123 | 0.9819 | 0.7962 | 0.0238 |
| | (51.54) | | | (35.86) | | | (16.53) | | |
| 2 | 0.8870 | 0.8226 | 0.0052 | 0.9596 | 0.8479 | 0.0113 | 1.1030 | 0.8549 | 0.0217 |
| | (68.41) | | | (37.10) | | | (15.78) | | |
| 3 | 0.8594 | 0.8916 | 0.0038 | 0.8877 | 0.8732 | 0.0094 | 0.9360 | 0.8550 | 0.0184 |
| | (88.09) | | | (31.48) | | | (18.56) | | |
| 4 | 0.9356 | 0.9646 | 0.0023 | 0.9249 | 0.9656 | 0.0048 | 0.8743 | 0.9539 | 0.0092 |
| | (159.39) | | | (64.09) | | | (31.09) | | |
| 5 | 1.1233 | 0.9699 | 0.0025 | 1.1262 | 0.9640 | 0.0060 | 1.1239 | 0.9570 | 0.0114 |
| | (182.50) | | | (82.23) | | | (55.97) | | |
| 5-1 | 0.3294 | 0.2435 | 0.0073 | 0.2680 | 0.1951 | 0.0151 | 0.1420 | 0.0456 | 0.0290 |
| | (18.28) | | | (8.57) | | | (2.04) | | |

*(to be continued)*

**Table 4 continued**

| | daily | | | weekly | | | monthly | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE |
| **Panel B. Size** | | | | | | | | | |
| 1 | 0.4675 | 0.5436 | 0.0054 | 0.6323 | 0.6016 | 0.0143 | 1.0566 | 0.6944 | 0.0335 |
| | (31.03) | | | (21.86) | | | (11.28) | | |
| 2 | 0.4933 | 0.6510 | 0.0046 | 0.6485 | 0.6921 | 0.0120 | 0.9519 | 0.7514 | 0.0262 |
| | (39.48) | | | (26.79) | | | (16.88) | | |
| 3 | 0.6789 | 0.7334 | 0.0052 | 0.8404 | 0.7737 | 0.0126 | 1.0727 | 0.7856 | 0.0268 |
| | (51.22) | | | (40.50) | | | (15.70) | | |
| 4 | 0.8764 | 0.8780 | 0.0041 | 0.9936 | 0.9034 | 0.0090 | 1.0847 | 0.8971 | 0.0176 |
| | (78.24) | | | (61.78) | | | (23.47) | | |
| 5 | 1.0198 | 0.9988 | 0.0004 | 1.0067 | 0.9987 | 0.0010 | 0.9931 | 0.9982 | 0.0020 |
| | (970.19) | | | (582.62) | | | (203.28) | | |
| 5-1 | 0.5525 | 0.6010 | 0.0057 | 0.3744 | 0.3259 | 0.0149 | -0.0635 | 0.0004 | 0.0350 |
| | (35.17) | | | (12.50) | | | (-0.65) | | |

*(to be continued)*

**Table 4 continued**

| | daily | | | weekly | | | monthly | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE |
| **Panel C. Relative bid-ask spread** | | | | | | | | | |
| 1 | 1.0216 | 0.9957 | 0.0009 | 1.0044 | 0.9955 | 0.0019 | 0.9905 | 0.9937 | 0.0038 |
| | (481.24) | | | (333.22) | | | (112.96) | | |
| 2 | 0.9420 | 0.9153 | 0.0036 | 1.0211 | 0.9355 | 0.0075 | 1.0328 | 0.9149 | 0.0152 |
| | (85.34) | | | (77.44) | | | (30.96) | | |
| 3 | 0.8269 | 0.7670 | 0.0058 | 0.9460 | 0.8176 | 0.0125 | 1.1076 | 0.8390 | 0.0234 |
| | (51.32) | | | (40.34) | | | (19.23) | | |
| 4 | 0.6910 | 0.6366 | 0.0066 | 0.7734 | 0.7148 | 0.0136 | 0.9095 | 0.7534 | 0.0251 |
| | (48.01) | | | (27.79) | | | (15.41) | | |
| 5 | 0.6036 | 0.4959 | 0.0077 | 0.6827 | 0.5256 | 0.0181 | 0.9037 | 0.6282 | 0.0334 |
| | (34.79) | | | (21.47) | | | (14.81) | | |
| 5-1 | -0.4178 | 0.2987 | 0.0081 | -0.3216 | 0.1802 | 0.0191 | -0.0868 | 0.0067 | 0.0356 |
| | (-22.28) | | | (-9.64) | | | (-1.31) | | |

*(to be continued)*

**Table 4 continued**

| | daily | | | weekly | | | monthly | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE | $\beta_i^{mkt}$ | adj. $R^2$ | RMSE |
| **Panel D. Exchanges** | | | | | | | | | |
| AMS | 0.9655 | 0.8964 | 0.0042 | 0.9568 | 0.9022 | 0.0087 | 0.9281 | 0.8585 | 0.0180 |
| | (83.89) | | | (54.07) | | | (24.16) | | |
| ATH | 0.8960 | 0.2227 | 0.0212 | 1.0985 | 0.2983 | 0.0464 | 1.4216 | 0.4375 | 0.0769 |
| | (21.85) | | | (15.81) | | | (10.81) | | |
| BRU | 0.8328 | 0.7130 | 0.0067 | 0.8481 | 0.6894 | 0.0158 | 0.8143 | 0.6149 | 0.0308 |
| | (50.01) | | | (25.29) | | | (14.01) | | |
| DUB | 0.8369 | 0.4609 | 0.0115 | 0.9443 | 0.5046 | 0.0260 | 0.9230 | 0.4749 | 0.0463 |
| | (24.72) | | | (16.13) | | | (10.51) | | |
| FRA | 0.6603 | 0.1633 | 0.0190 | 0.9974 | 0.2932 | 0.0429 | 1.3169 | 0.3734 | 0.0812 |
| | (15.71) | | | (7.80) | | | (8.06) | | |
| HEL | 1.0297 | 0.7993 | 0.0065 | 1.0241 | 0.8044 | 0.0140 | 1.0788 | 0.7870 | 0.0268 |
| | (56.03) | | | (32.83) | | | (11.48) | | |
| LIS | 0.8043 | 0.6480 | 0.0075 | 0.8567 | 0.6530 | 0.0173 | 0.8331 | 0.6373 | 0.0300 |
| | (45.61) | | | (30.51) | | | (13.19) | | |
| MAD | 1.0477 | 0.8379 | 0.0058 | 1.0423 | 0.8346 | 0.0129 | 1.0096 | 0.7479 | 0.0280 |
| | (70.81) | | | (48.22) | | | (19.79) | | |
| MIL | 1.0921 | 0.8666 | 0.0054 | 1.0779 | 0.8682 | 0.0117 | 1.1210 | 0.8589 | 0.0217 |
| | (92.27) | | | (47.21) | | | (28.40) | | |
| PAR | 1.0299 | 0.9690 | 0.0023 | 0.9882 | 0.9683 | 0.0050 | 0.9683 | 0.9609 | 0.0094 |
| | (211.32) | | | (83.45) | | | (48.30) | | |
| WBO | 1.0110 | 0.7063 | 0.0083 | 1.0741 | 0.7577 | 0.0169 | 1.1359 | 0.7155 | 0.0342 |
| | (53.96) | | | (31.26) | | | (14.37) | | |
| XET | 0.9731 | 0.8850 | 0.0045 | 1.0158 | 0.9190 | 0.0084 | 1.0441 | 0.8824 | 0.0182 |
| | (68.92) | | | (48.46) | | | (25.61) | | |

In each panel for each portfolio, the CAPM model of Equation (1) is estimated to obtain a constant beta estimate for the whole sample period. T-statistics are shown in parentheses and are based on Newey-West standard errors. Furthermore, for each regression, the adjusted $R^2$ and root-mean-square error (RMSE) are reported.

**Table 5**
**Summary of regression results and beta adjustments**

| | OLS | Scholes/Williams | | | | Dimson (1) | | | | Dimson (5) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{SW}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim1}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim5}$ | Δ to OLS |
| whole sample | 1.0 | 0.0244 | 0.0241 | 1.0006 | | 0.0000 | 0.0000 | 1.0000 | | 0.0000 | 0.0000 | 1.0000 | |
| | | (1.95) | (1.87) | | | (1.45) | (1.89) | | | (-1.40) | (-0.56) | | |
| **Panel A. Turnover** | | | | | | | | | | | | | |
| 1 | 0.7579 | 0.0887 | 0.0156 | 0.8287 | 0.0707 | 0.0711 | 0.0008 | 0.8280 | 0.0700 | 0.0706 | 0.0014 | 0.8835 | 0.1256 |
| | (19.81) | (7.72) | (1.47) | (21.26) | (4.11) | (5.73) | (0.11) | (21.31) | (3.93) | (4.44) | (0.15) | (21.48) | (3.01) |
| 2 | 0.8501 | 0.0859 | 0.0020 | 0.8958 | 0.0457 | 0.0643 | -0.0175 | 0.8965 | 0.0464 | 0.0672 | -0.0152 | 0.9722 | 0.1222 |
| | (41.89) | (8.44) | (0.12) | (35.68) | (3.51) | (6.92) | (-2.05) | (37.31) | (3.85) | (7.40) | (-1.86) | (27.85) | (4.54) |
| 3 | 0.8575 | 0.0352 | 0.0201 | 0.8728 | 0.0153 | 0.0149 | 0.0005 | 0.8725 | 0.0150 | 0.0135 | 0.0037 | 0.8783 | 0.0207 |
| | (49.66) | (3.01) | (1.64) | (46.56) | (1.62) | (1.87) | (0.09) | (45.47) | (1.41) | (1.74) | (0.58) | (24.06) | (0.68) |
| 4 | 0.9580 | 0.0047 | 0.0214 | 0.9408 | -0.0171 | -0.0176 | -0.0012 | 0.9391 | -0.0189 | -0.0186 | -0.0009 | 0.9429 | -0.0151 |
| | (55.32) | (0.33) | (2.05) | (53.76) | (-3.79) | (-3.38) | (-0.39) | (52.94) | (-3.80) | (-3.40) | (-0.25) | (53.08) | (-1.93) |
| 5 | 1.1429 | 0.0247 | 0.0295 | 1.1399 | -0.0029 | -0.0040 | 0.0013 | 1.1405 | -0.0024 | -0.0036 | -0.0014 | 1.1140 | -0.0289 |
| | (72.96) | (1.44) | (1.82) | (59.32) | (-0.41) | (-0.55) | (0.38) | (58.84) | (-0.32) | (-0.47) | (-0.37) | (29.72) | (-0.92) |
| 5-1 | 0.3850 | -0.0639 | 0.0139 | 0.3113 | -0.0737 | -0.0751 | 0.0005 | 0.3125 | -0.0724 | -0.0743 | -0.0029 | 0.2308 | -0.1542 |
| | (7.43) | (-4.06) | (1.26) | (5.86) | (-4.20) | (-6.02) | (0.06) | (5.88) | (-4.01) | (-4.96) | (-0.29) | (3.48) | (-2.85) |
| vw mean | 0.9929 | | | 0.9942 | | | | 0.9935 | | | | **0.9945** | |

*(to be continued)*

**Table 5 continued**

**Panel B. Size**

| | OLS | Scholes/Williams | | | | Dimson (1) | | | | Dimson (5) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{SW}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim1}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim5}$ | Δ to OLS |
| 1 | 0.4442 | 0.1455 | -0.0109 | 0.5548 | 0.1107 | 0.1358 | -0.0164 | 0.5583 | 0.1141 | 0.1374 | -0.0173 | 0.7456 | 0.3014 |
| | (17.94) | (10.97) | (-1.33) | (15.19) | (6.24) | (9.85) | (-2.47) | (15.72) | (6.37) | (9.50) | (-3.01) | (15.05) | (7.52) |
| 2 | 0.4952 | 0.1361 | -0.0038 | 0.6008 | 0.1057 | 0.1245 | -0.0119 | 0.6044 | 0.1093 | 0.1241 | -0.0141 | 0.7396 | 0.2444 |
| | (21.83) | (11.91) | (-0.42) | (18.53) | (6.99) | (10.92) | (-1.94) | (19.63) | (7.15) | (10.74) | (-1.94) | (17.44) | (8.52) |
| 3 | 0.6954 | 0.1527 | 0.0035 | 0.8135 | 0.1180 | 0.1347 | -0.0094 | 0.8177 | 0.1222 | 0.1365 | -0.0106 | 0.8812 | 0.1857 |
| | (26.56) | (9.05) | (0.43) | (24.40) | (6.85) | (9.41) | (-1.25) | (25.38) | (7.35) | (9.22) | (-1.01) | (15.89) | (4.35) |
| 4 | 0.8999 | 0.1135 | 0.0168 | 0.9826 | 0.0827 | 0.0907 | -0.0027 | 0.9861 | 0.0862 | 0.0901 | -0.0049 | 0.9884 | 0.0884 |
| | (48.25) | (6.77) | (1.88) | (50.76) | (6.29) | (7.53) | (-0.46) | (50.52) | (6.33) | (8.02) | (-0.65) | (29.27) | (3.25) |
| 5 | 1.0186 | 0.0133 | 0.0253 | 1.0090 | -0.0096 | -0.0115 | 0.0005 | 1.0078 | -0.0108 | -0.0116 | 0.0007 | 1.0054 | -0.0132 |
| | (520.46) | (1.05) | (1.87) | (420.88) | (-6.77) | (-8.82) | (0.84) | (419.57) | (-7.41) | (-8.90) | (0.82) | (238.10) | (-4.20) |
| 5-1 | 0.5744 | -0.1321 | 0.0360 | 0.4541 | -0.1203 | -0.1473 | 0.0169 | 0.4495 | -0.1249 | -0.1489 | 0.0179 | 0.2599 | -0.3145 |
| | (22.18) | (-7.96) | (3.46) | (11.81) | (-6.53) | (-10.37) | (2.49) | (12.09) | (-6.69) | (-9.97) | (2.98) | (4.86) | (-7.33) |
| vw mean | 0.9991 | | | 1.0001 | | | | 0.9994 | | | | **1.0000** | |

*(to be continued)*

**Table 5 continued**

**Panel C. Relative bid-ask spread**

| | OLS | Scholes/Williams | | | | Dimson (1) | | | | Dimson (5) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{SW}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim1}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim5}$ | Δ to OLS |
| 1 | 1.0207 | 0.0100 | 0.0237 | 1.0067 | -0.0140 | -0.0145 | -0.0007 | 1.0057 | -0.0149 | -0.0147 | -0.0006 | 1.0038 | -0.0169 |
| | (242.21) | (0.74) | (1.66) | (199.55) | (-4.60) | (-6.28) | (-0.55) | (198.08) | (-4.96) | (-6.03) | (-0.36) | (164.11) | (-3.55) |
| 2 | 0.9419 | 0.0796 | 0.0272 | 1.0013 | 0.0595 | 0.0561 | 0.0053 | 1.0034 | 0.0616 | 0.0577 | 0.0062 | 1.0040 | 0.0621 |
| | (46.62) | (5.34) | (3.12) | (63.94) | (4.26) | (5.49) | (0.77) | (65.76) | (4.53) | (5.45) | (0.73) | (34.04) | (2.58) |
| 3 | 0.8708 | 0.1166 | 0.0245 | 0.9683 | 0.0975 | 0.0949 | 0.0084 | 0.9696 | 0.0988 | 0.1006 | 0.0026 | 0.9968 | 0.1260 |
| | (19.14) | (5.76) | (2.23) | (20.24) | (5.49) | (5.31) | (0.94) | (21.45) | (5.42) | (5.94) | (0.23) | (18.10) | (4.03) |
| 4 | 0.7045 | 0.1124 | 0.0000 | 0.7837 | 0.0792 | 0.0957 | -0.0128 | 0.7850 | 0.0805 | 0.0926 | -0.0176 | 0.7963 | 0.0918 |
| | (14.77) | (5.34) | (-0.00) | (19.22) | (3.48) | (4.73) | (-1.45) | (20.29) | (3.48) | (4.39) | (-1.55) | (17.44) | (1.57) |
| 5 | 0.6219 | 0.1046 | -0.0002 | 0.6967 | 0.0749 | 0.0890 | -0.0146 | 0.6957 | 0.0739 | 0.0848 | -0.0163 | 0.7084 | 0.0865 |
| | (11.84) | (6.46) | (-0.03) | (10.57) | (2.89) | (4.34) | (-1.58) | (10.45) | (2.70) | (4.28) | (-1.59) | (12.78) | (1.80) |
| 5-1 | -0.3988 | 0.0946 | -0.0240 | -0.3099 | 0.0888 | 0.1035 | -0.0139 | -0.3100 | 0.0887 | 0.0995 | -0.0158 | -0.2951 | 0.1037 |
| | (-7.33) | (3.77) | (-2.13) | (-4.47) | (3.13) | (4.70) | (-1.43) | (-4.42) | (2.99) | (4.70) | (-1.49) | (-4.94) | (2.03) |
| vw mean | 0.9975 | | | **0.9996** | | | | 0.9990 | | | | 0.9986 | |

*(to be continued)*

**Table 5 continued**

**Panel D. Exchanges**

| | OLS | Scholes/Williams | | | | Dimson (1) | | | | Dimson (5) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{SW}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim1}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim5}$ | Δ to OLS |
| AMS | 0.9166 | 0.0447 | 0.0053 | 0.9239 | 0.0073 | 0.0238 | -0.0172 | 0.9220 | 0.0054 | 0.0199 | -0.0023 | 0.9510 | 0.0344 |
| | (30.06) | (3.14) | (0.38) | (33.76) | (0.72) | (2.93) | (-2.83) | (33.70) | (0.53) | (2.34) | (-0.32) | (37.82) | (1.61) |
| ATH | 0.9049 | 0.2374 | 0.1155 | 1.2099 | 0.3050 | 0.2173 | 0.1104 | 1.2278 | 0.3229 | 0.2086 | -0.0952 | 1.1417 | 0.2368 |
| | (12.91) | (6.80) | (2.91) | (12.10) | (4.91) | (6.91) | (2.86) | (11.79) | (5.70) | (4.51) | (-1.77) | (5.53) | (1.09) |
| BRU | 0.8464 | 0.0233 | 0.0061 | 0.8398 | -0.0067 | 0.0056 | -0.0154 | 0.8390 | -0.0074 | 0.0084 | 0.0073 | 0.8136 | -0.0328 |
| | (32.60) | (1.41) | (0.45) | (25.44) | (-0.29) | (0.33) | (-1.64) | (24.79) | (-0.31) | (0.52) | (0.68) | (13.03) | (-0.60) |
| DUB | 0.8028 | 0.0629 | 0.0215 | 0.8488 | 0.0459 | 0.0465 | 0.0084 | 0.8553 | 0.0525 | 0.0367 | -0.0184 | 0.7977 | -0.0052 |
| | (19.28) | (2.78) | (1.17) | (16.01) | (2.18) | (2.24) | (0.66) | (16.25) | (2.53) | (1.67) | (-0.89) | (7.44) | (-0.06) |
| FRA | 0.5146 | 0.2846 | 0.0371 | 0.8107 | 0.2961 | 0.2731 | 0.0409 | 0.8094 | 0.2948 | 0.2514 | 0.0074 | 0.8246 | 0.3099 |
| | (5.55) | (7.28) | (1.36) | (6.67) | (5.84) | (6.57) | (1.38) | (6.66) | (5.55) | (5.34) | (0.24) | (4.46) | (2.46) |
| HEL | 0.9930 | 0.0343 | 0.0049 | 0.9959 | 0.0030 | 0.0109 | -0.0091 | 0.9884 | -0.0046 | 0.0188 | -0.0004 | 0.9435 | -0.0495 |
| | (34.21) | (2.41) | (0.26) | (30.12) | (0.27) | (0.83) | (-0.71) | (31.27) | (-0.38) | (1.33) | (-0.03) | (21.18) | (-1.72) |
| LIS | 0.8142 | 0.0780 | 0.0192 | 0.8725 | 0.0584 | 0.0590 | 0.0021 | 0.8770 | 0.0629 | 0.0526 | -0.0091 | 0.8431 | 0.0290 |
| | (20.11) | (4.47) | (1.28) | (17.23) | (3.11) | (3.28) | (0.20) | (16.84) | (3.22) | (2.83) | (-0.54) | (13.12) | (0.47) |
| MAD | 1.0580 | 0.0178 | 0.0322 | 1.0583 | 0.0002 | -0.0060 | 0.0067 | 1.0593 | 0.0013 | -0.0038 | -0.0046 | 1.0375 | -0.0206 |
| | (26.21) | (0.94) | (1.61) | (26.09) | (0.02) | (-0.43) | (0.67) | (26.26) | (0.12) | (-0.26) | (-0.64) | (18.29) | (-0.59) |
| MIL | 1.1254 | -0.0140 | 0.0100 | 1.0696 | -0.0557 | -0.0423 | -0.0175 | 1.0688 | -0.0566 | -0.0360 | -0.0097 | 1.0875 | -0.0379 |
| | (34.48) | (-0.73) | (0.49) | (36.02) | (-3.32) | (-2.78) | (-1.73) | (37.31) | (-3.50) | (-2.08) | (-0.84) | (28.83) | (-1.34) |
| PAR | 1.0311 | 0.0141 | 0.0170 | 1.0133 | -0.0178 | -0.0114 | -0.0092 | 1.0114 | -0.0197 | -0.0129 | 0.0031 | 0.9994 | -0.0317 |
| | (104.08) | (0.84) | (1.10) | (78.64) | (-1.67) | (-1.35) | (-1.81) | (83.06) | (-1.97) | (-1.46) | (0.93) | (76.88) | (-2.14) |
| WBO | 0.9525 | 0.1151 | 0.0015 | 1.0272 | 0.0748 | 0.0955 | -0.0105 | 1.0345 | 0.0820 | 0.0976 | -0.0132 | 0.9090 | -0.0434 |
| | (30.92) | (8.57) | (0.09) | (24.63) | (3.07) | (5.39) | (-0.86) | (25.06) | (3.33) | (4.86) | (-0.88) | (8.75) | (-0.46) |
| XET | 0.9804 | 0.0205 | 0.0474 | 1.0016 | 0.0212 | -0.0035 | 0.0267 | 1.0039 | 0.0235 | -0.0043 | 0.0068 | 1.0227 | 0.0424 |
| | (42.36) | (1.03) | (4.55) | (62.56) | (1.91) | (-0.25) | (3.27) | (57.91) | (1.93) | (-0.31) | (0.71) | (32.99) | (2.37) |
| vw mean | 0.8700 | | | 0.9125 | | | | 0.9013 | | | | **0.9684** | |

This table summarizes the regression results for OLS CAPM estimations, Scholes and Williams (1977) regressions, and the Dimson (1979) model. All regressions are conducted on a yearly basis based on daily return data. $\beta_i^{SW}$, $\beta_i^{Dim1}$, $\beta_i^{Dim5}$ are the adjusted beta coefficients following Equation (4) and (5). The table displays time-series averages and t-statistics in parentheses are based on Newey-West standard errors. The last row in each panel gives the value-weighted mean of the beta values across portfolios. The column "Δ to OLS" shows the difference between the respective adjusted beta and the OLS estimation. Here, t-statistics are based on two-sided significance tests.

**Table 6**
**Intervalling effect for adjusted beta values**

| | daily | | | | weekly | | | | monthly | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta_{5\text{-}1}^{mkt}$ | $\beta_{5\text{-}1}^{SW}$ | $\beta_{5\text{-}1}^{Dim1}$ | $\beta_{5\text{-}1}^{Dim5}$ | $\beta_{5\text{-}1}^{mkt}$ | $\beta_{5\text{-}1}^{SW}$ | $\beta_{5\text{-}1}^{Dim1}$ | $\beta_{5\text{-}1}^{Dim5}$ | $\beta_{5\text{-}1}^{mkt}$ | $\beta_{5\text{-}1}^{SW}$ | $\beta_{5\text{-}1}^{Dim1}$ | $\beta_{5\text{-}1}^{Dim5}$ |
| turnover | 0.3294 | 0.2782 | 0.2764 | **0.1680** | 0.2680 | 0.1308 | 0.1477 | **0.0083** | 0.1420 | **-0.0116** | -0.0417 | -0.2402 |
| size | 0.5525 | 0.4297 | 0.4226 | **0.2045** | 0.3744 | **0.0475** | 0.0910 | -0.2324 | **-0.0635** | -0.2868 | -0.3386 | -0.4856 |
| rel. bid-ask spread | -0.4178 | -0.3211 | -0.3182 | **-0.2266** | -0.3216 | -0.0626 | -0.0950 | **0.0024** | -0.0868 | **0.0385** | 0.0623 | 0.1202 |

This table reports the beta estimations of the difference portfolios for varying return frequencies for the OLS CAPM, the Scholes and Williams (1977), and the Dimson (1979) model both for one and five lead-and-lag structures. The underlying coefficients are estimated using data of the whole sample period. The most efficient value within each portfolio group and frequency is printed in bold.

## Appendix A

**Table A.1**
**Abbreviation of exchange codes**

| | |
|---|---|
| AMS | Euronext Amsterdam |
| ATH | Athens Stock Exchange |
| BRU | Euronext Brussels |
| DUB | Euronext Dublin |
| FRA | Frankfurt Stock Exchange |
| HEL | Nasdaq Helsinki |
| LIS | Euronext Lisbon |
| MAD | Madrid Stock Exchange |
| MIL | Borsa Italiana Milan |
| PAR | Euronext Paris |
| WBO | Vienna Stock Exchange |
| XET | Deutsche Börse Xetra |

This table displays the abbreviation codes for the stock exchanges referred to in this paper.

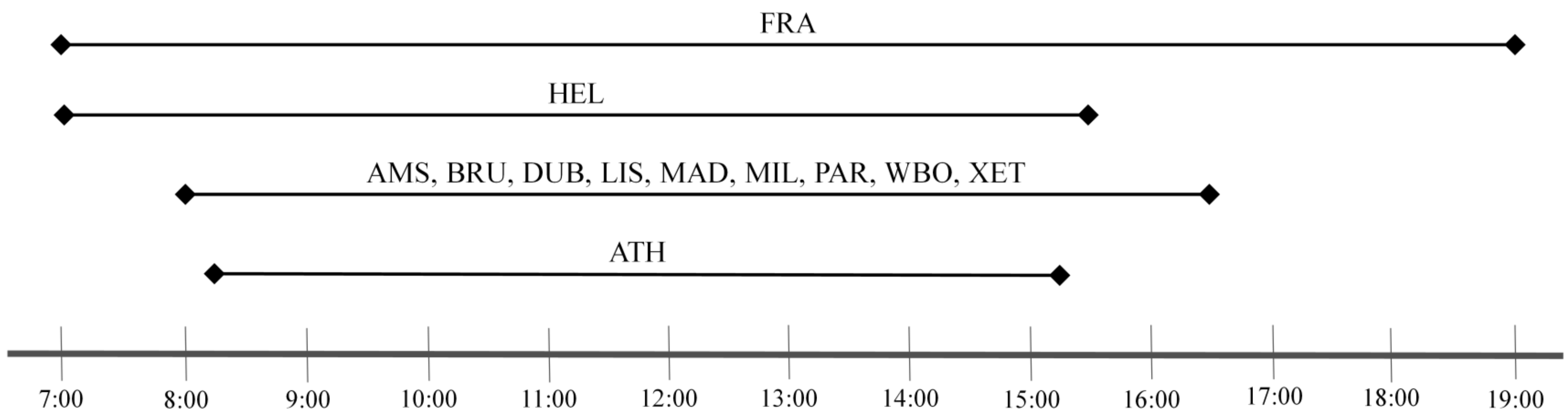


**Figure A.1**
**Trading times on European stock exchanges**

This figure summarizes the opening trading hours of all exchanges referred to in this study.

# Appendix B

**Table B.1**
**Descriptive statistics (mean values) on portfolio level**

| portfolio | return | market value | monthly no. of shares traded | no. of shares outstanding | monthly value of trades | monthly turnover ratio | rel. bid-ask spread |
|---|---|---|---|---|---|---|---|
| **Panel A. Turnover** | | | | | | | |
| 1 | 0.0004 | 913.77 | 5,814.72 | 326,841.89 | 363,491.84 | 0.40 | 0.0213 |
| 2 | 0.0003 | 1,269.97 | 22,055.77 | 181,447.42 | 966,031.94 | 1.46 | 0.0146 |
| 3 | 0.0003 | 3,019.77 | 30,522.67 | 212,661.78 | 1,455,857.07 | 2.96 | 0.0104 |
| 4 | 0.0003 | 6,749.98 | 89,528.53 | 405,261.95 | 2,179,803.38 | 5.97 | 0.0066 |
| 5 | 0.0002 | 6,314.55 | 296,620.32 | 634,113.90 | 2,417,800.12 | 13.80 | 0.0051 |
| **Panel B. Size** | | | | | | | |
| 1 | 0.0002 | 39.83 | 4,795.79 | 68,671.97 | 2,035.05 | 3.71 | 0.0251 |
| 2 | 0.0003 | 113.51 | 8,947.48 | 97,459.43 | 6,309.78 | 3.85 | 0.0164 |
| 3 | 0.0003 | 346.51 | 10,350.21 | 155,643.30 | 25,362.64 | 4.88 | 0.0103 |
| 4 | 0.0003 | 1,444.05 | 21,246.90 | 276,460.18 | 185,340.25 | 7.44 | 0.0045 |
| 5 | 0.0003 | 16,010.53 | 168,037.51 | 1,112,299.38 | 2,260,661.28 | 8.24 | 0.0019 |
| **Panel C. Relative bid-ask spread** | | | | | | | |
| 1 | 0.0003 | 14,526.44 | 151,154.75 | 826,961.67 | 2,227,030.28 | 8.50 | 0.0006 |
| 2 | 0.0003 | 2,360.35 | 109,428.74 | 333,325.57 | 835,687.08 | 6.92 | 0.0036 |
| 3 | 0.0002 | 692.01 | 174,318.42 | 184,529.87 | 1,025,608.24 | 5.71 | 0.0083 |
| 4 | 0.0003 | 434.06 | 42,799.74 | 139,234.82 | 298,130.13 | 3.66 | 0.0149 |
| 5 | 0.0004 | 243.16 | 16,373.43 | 178,330.78 | 73,876.62 | 2.59 | 0.0320 |

*(to be continued)*

**Table B.1 continued**

| portfolio | return | market value | monthly no. of shares traded | no. of shares outstanding | monthly value of trades | monthly turnover ratio | rel. bid-ask spread |
|---|---|---|---|---|---|---|---|
| **Panel D. Exchanges** | | | | | | | |
| AMS | 0.0002 | 6,619.35 | 105,838.78 | 340,281.27 | 1,998,423.52 | 7.38 | 0.0077 |
| ATH | -0.0006 | 729.89 | 18,204.26 | 306,315.90 | 169,081.38 | 3.03 | 0.0135 |
| BRU | 0.0003 | 3,216.08 | 23,477.52 | 89,660.82 | 1,442,164.73 | 4.08 | 0.0104 |
| DUB | 0.0002 | 2,440.57 | 24,591.81 | 1,320,161.85 | 253,475.44 | 3.66 | 0.0000 |
| FRA | 0.0018 | 170.31 | 50.38 | 26,524.14 | 79.02 | 0.28 | 0.0350 |
| HEL | 0.0003 | 2,214.98 | 99,281.41 | 223,738.60 | 1,102,265.98 | 7.63 | 0.0098 |
| LIS | -0.0001 | 1,825.34 | 90,232.82 | 1,609,697.59 | 281,719.64 | 4.06 | 0.0125 |
| MAD | -0.0002 | 5,419.20 | 457,339.51 | 806,698.00 | 2,875,626.54 | 11.74 | 0.0119 |
| MIL | 0.0000 | 2,230.06 | 492,737.75 | 705,896.61 | 2,470,469.63 | 11.72 | 0.0153 |
| PAR | 0.0001 | 4,447.25 | 59,131.62 | 148,829.36 | 2,127,704.35 | 6.46 | 0.0100 |
| WBO | 0.0002 | 2,018.31 | 8,474.04 | 119,714.83 | 209,344.22 | 3.68 | 0.0053 |
| XET | 0.0011 | 4,880.10 | 70,753.67 | 145,793.95 | 16,661.30 | 9.20 | 0.0093 |

This table displays mean values of the respective variables for each portfolio for the sample period from December 2007 to October 2019. Market value is given in EUR million, number of shares traded and number of shares outstanding in thousands, and the value of trades in EUR thousand. Turnover is computed as the number of shares traded divided by shares outstanding and given in percentage. Relative bid-ask spread is calculated as the ratio of the bid-ask spread and the mid-point of bid and ask prices.

# Appendix C

**Table C.1**
**Summary of regression results and beta adjustments for the Fama and French (1993) model**

| | OLS | Dimson (1) | | | | Dimson (5) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim1}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim5}$ | Δ to OLS |
| whole sample | 1.0000 | 0.0000 | 0.0000 | 1.0000 | | 0.0000 | 0.0000 | 1.0000 | |
| | | (1.56) | (0.70) | | | (-0.52) | (-0.12) | | |
| **Panel A. Turnover** | | | | | | | | | |
| 1 | 0.8701 | 0.0516 | 0.0099 | 0.9082 | 0.0381 | 0.0658 | 0.0139 | 0.9076 | 0.0375 |
| | (15.47) | (1.61) | (0.66) | (17.41) | (1.34) | (1.71) | (0.74) | (15.88) | (0.88) |
| 2 | 0.9986 | 0.0372 | -0.0035 | 1.0236 | 0.0249 | 0.0358 | -0.0121 | 1.0950 | 0.0964 |
| | (20.24) | (2.01) | (-0.22) | (20.57) | (1.83) | (1.59) | (-0.62) | (21.46) | (2.62) |
| 3 | 0.8444 | 0.0475 | 0.0042 | 0.8787 | 0.0343 | 0.0433 | 0.0021 | 0.9246 | 0.0802 |
| | (40.23) | (5.58) | (0.35) | (39.36) | (2.15) | (3.82) | (0.18) | (20.23) | (1.90) |
| 4 | 0.9228 | 0.0043 | -0.0105 | 0.9168 | -0.0060 | -0.0013 | -0.0110 | 0.9395 | 0.0167 |
| | (40.72) | (0.41) | (-2.10) | (42.11) | (-0.78) | (-0.10) | (-1.91) | (42.19) | (1.43) |
| 5 | 1.1720 | -0.0387 | 0.0099 | 1.1537 | -0.0184 | -0.0351 | 0.0118 | 1.1015 | -0.0705 |
| | (45.48) | (-4.61) | (1.74) | (50.36) | (-2.12) | (-3.68) | (2.10) | (31.53) | (-3.10) |
| 5-1 | 0.3020 | -0.0904 | 0.0002 | 0.2455 | -0.0565 | -0.1010 | -0.0020 | 0.1944 | -0.1076 |
| | (3.76) | (-2.43) | (0.01) | (3.53) | (-1.65) | (-2.35) | (-0.11) | (2.25) | (-1.83) |
| vw mean | 0.9984 | | | 0.9995 | | | | **1.0001** | |

*(to be continued)*

**Table C.1 continued**

**Panel B. Size**

| | OLS | Dimson (1) | | | | Dimson (5) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim1}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim5}$ | Δ to OLS |
| 1 | 0.7407 | 0.1167 | 0.0100 | 0.8222 | 0.0816 | 0.0952 | 0.0028 | 0.9511 | 0.2105 |
| | (19.14) | (5.38) | (0.91) | (26.31) | (3.72) | (4.80) | (0.18) | (25.57) | (5.24) |
| 2 | 0.7819 | 0.0997 | -0.0004 | 0.8461 | 0.0642 | 0.0816 | -0.0087 | 0.9411 | 0.1592 |
| | (28.62) | (6.16) | (-0.04) | (29.83) | (4.14) | (5.53) | (-0.77) | (26.35) | (5.46) |
| 3 | 1.0259 | 0.0494 | 0.0217 | 1.0636 | 0.0377 | 0.0485 | 0.0167 | 1.0883 | 0.0624 |
| | (52.66) | (3.43) | (2.26) | (43.00) | (4.01) | (3.24) | (1.48) | (32.62) | (1.98) |
| 4 | 1.1218 | -0.0030 | 0.0358 | 1.1359 | 0.0141 | 0.0025 | 0.0291 | 1.0962 | -0.0256 |
| | (55.44) | (-0.28) | (4.30) | (52.71) | (1.46) | (0.21) | (3.42) | (51.53) | (-1.07) |
| 5 | 0.9906 | -0.0015 | -0.0032 | 0.9885 | -0.0022 | -0.0019 | -0.0025 | 0.9905 | -0.0001 |
| | (475.37) | (-1.51) | (-3.95) | (462.15) | (-2.97) | (-1.76) | (-2.83) | (417.66) | (-0.04) |
| 5-1 | 0.2500 | -0.1184 | -0.0131 | 0.1659 | -0.0840 | -0.0974 | -0.0052 | 0.0398 | -0.2102 |
| | (6.45) | (-5.38) | (-1.17) | (5.26) | (-3.76) | (-4.77) | (-0.33) | (1.03) | (-5.24) |
| vw mean | **1.0001** | | | | 1.0004 | | | | 1.0005 |

*(to be continued)*

**Table C.1 continued**

**Panel C. Relative bid-ask spread**

| | OLS | Dimson (1) | | | | Dimson (5) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim1}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim5}$ | Δ to OLS |
| 1 | 0.9853 | -0.0037 | -0.0052 | 0.9792 | -0.0060 | -0.0076 | -0.0059 | 0.9821 | -0.0032 |
| | (171.25) | (-1.11) | (-1.98) | (132.24) | (-1.75) | (-1.90) | (-1.76) | (129.79) | (-0.57) |
| 2 | 1.0970 | -0.0037 | 0.0288 | 1.1143 | 0.0173 | 0.0077 | 0.0241 | 1.0991 | 0.0021 |
| | (74.42) | (-0.37) | (2.26) | (47.19) | (1.32) | (0.60) | (1.96) | (33.56) | (0.08) |
| 3 | 1.0847 | 0.0403 | 0.0274 | 1.1270 | 0.0423 | 0.0581 | 0.0326 | 1.0884 | 0.0036 |
| | (30.18) | (1.83) | (1.86) | (27.31) | (2.14) | (2.32) | (2.01) | (32.48) | (0.10) |
| 4 | 0.8705 | 0.0784 | -0.0181 | 0.8985 | 0.0280 | 0.0804 | -0.0126 | 0.8923 | 0.0218 |
| | (18.64) | (2.23) | (-1.16) | (17.88) | (0.76) | (2.26) | (-0.54) | (15.37) | (0.32) |
| 5 | 0.7939 | 0.1005 | 0.0113 | 0.8815 | 0.0876 | 0.1026 | -0.0028 | 0.8405 | 0.0466 |
| | (10.65) | (3.90) | (0.46) | (9.13) | (2.40) | (3.29) | (-0.14) | (8.58) | (0.77) |
| 5-1 | -0.1913 | 0.1041 | 0.0167 | -0.0977 | 0.0936 | 0.1100 | 0.0033 | -0.1412 | 0.0502 |
| | (-2.43) | (3.92) | (0.64) | (-0.96) | (2.50) | (3.35) | (0.15) | (-1.35) | (0.78) |
| vw mean | 1.0013 | | | 1.0022 | | | | **1.0005** | |

*(to be continued)*

**Table C.1 continued**

**Panel D. Exchanges**

| | OLS | Dimson (1) | | | | Dimson (5) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i^{mkt}$ | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim1}$ | Δ to OLS | $\beta_i^{mkt,-1}$ | $\beta_i^{mkt,+1}$ | $\beta_i^{Dim5}$ | Δ to OLS |
| AMS | 0.8467 | 0.0601 | -0.0234 | 0.8582 | 0.0115 | 0.0497 | -0.0206 | 0.9012 | 0.0545 |
| | (26.29) | (5.24) | (-2.00) | (23.03) | (0.58) | (5.74) | (-1.64) | (24.88) | (2.57) |
| ATH | 1.3978 | 0.0271 | 0.1461 | 1.5568 | 0.1590 | 0.0153 | 0.1230 | 1.3638 | -0.0340 |
| | (8.21) | (0.49) | (1.67) | (8.89) | (2.57) | (0.15) | (1.11) | (6.39) | (-0.13) |
| BRU | 0.8663 | 0.0050 | -0.0055 | 0.8633 | -0.0030 | 0.0033 | -0.0032 | 0.9302 | 0.0639 |
| | (23.49) | (0.34) | (-0.24) | (24.09) | (-0.12) | (0.27) | (-0.14) | (9.00) | (0.62) |
| DUB | 1.0028 | 0.0000 | 0.0435 | 1.0309 | 0.0281 | 0.0242 | 0.0394 | 0.9274 | -0.0754 |
| | (15.37) | (-0.00) | (2.10) | (13.91) | (0.85) | (0.56) | (1.44) | (7.15) | (-0.71) |
| FRA | 0.7294 | 0.1868 | -0.0532 | 0.8108 | 0.0814 | 0.1700 | -0.0576 | 0.8008 | 0.0713 |
| | (6.70) | (4.30) | (-0.85) | (9.89) | (1.19) | (2.99) | (-0.96) | (3.95) | (0.45) |
| HEL | 1.0344 | -0.0324 | 0.0147 | 0.9889 | -0.0455 | 0.0112 | -0.0043 | 0.9734 | -0.0610 |
| | (35.04) | (-1.94) | (1.29) | (28.67) | (-2.83) | (0.50) | (-0.24) | (18.01) | (-1.57) |
| LIS | 0.8962 | 0.0204 | 0.0180 | 0.9198 | 0.0235 | 0.0263 | 0.0102 | 0.8433 | -0.0529 |
| | (16.39) | (1.09) | (0.78) | (15.30) | (1.19) | (1.15) | (0.42) | (7.98) | (-0.61) |
| MAD | 1.0891 | -0.0209 | 0.0081 | 1.0851 | -0.0041 | 0.0012 | 0.0181 | 1.0197 | -0.0695 |
| | (23.52) | (-0.83) | (0.35) | (19.36) | (-0.15) | (0.04) | (0.75) | (15.36) | (-1.63) |
| MIL | 1.1725 | -0.0464 | 0.0098 | 1.1515 | -0.0210 | -0.0353 | 0.0172 | 1.0869 | -0.0856 |
| | (31.96) | (-1.55) | (0.67) | (28.28) | (-0.75) | (-0.96) | (0.97) | (18.41) | (-1.93) |
| PAR | 0.9831 | 0.0170 | -0.0210 | 0.9791 | -0.0039 | 0.0165 | -0.0236 | 0.9805 | -0.0026 |
| | (65.57) | (2.08) | (-2.68) | (64.41) | (-0.36) | (1.77) | (-2.74) | (47.16) | (-0.12) |
| WBO | 1.1181 | 0.0210 | 0.0330 | 1.1447 | 0.0266 | 0.0280 | 0.0298 | 0.9971 | -0.1210 |
| | (30.61) | (0.76) | (1.29) | (26.48) | (0.99) | (0.85) | (0.74) | (12.35) | (-1.71) |
| XET | 0.9899 | -0.0328 | 0.0247 | 0.9901 | 0.0002 | -0.0444 | 0.0243 | 1.0276 | 0.0376 |
| | (27.24) | (-1.45) | (2.26) | (30.77) | (0.01) | (-1.72) | (1.42) | (28.12) | (1.90) |
| vw mean | 0.9263 | | | 0.9595 | | | | **0.9814** | |

This table summarizes the regression results for OLS estimations of the Fama/French (1993) model and the Dimson (1979) model. All regressions are conducted on a yearly basis based on daily return data. $\beta_i^{Dim1}$ and $\beta_i^{Dim5}$ are the adjusted beta coefficients following Equation (5) based on the Fama/French model. The table displays time-series averages and t-statistics in parentheses are based on Newey-West standard errors. The last row in each panel gives the value-weighted mean of the beta values across portfolios. The value closest to 1.0 is printed in bold. The column "Δ to OLS" shows the difference between the respective adjusted beta and the OLS estimation. Here, t-statistics are based on two-sided significance tests.

# 3 ARTICLE II: HERDS ON GREEN MEADOWS – THE DECARBONIZATION OF INSTITUTIONAL PORTFOLIOS

Lukas Benz, Andrea Jacob, Stefan Paulus, Marco Wilkens

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(VHB-JOURQUAL3: B)

**Abstract.** We analyze an emerging sustainable trend in asset management: the decarbonization of institutional portfolios. By using broad institutional ownership data we show that investors exhibit herding behavior in the sense of decarbonization. They are inclined to follow their own or other investors' buys in green stocks and sales in brown stocks over adjacent quarters. Beyond that, we find that Hedge Funds as well as Investment Advisors lead the herd by executing trades in the sense of decarbonization. This is in line with expectations that sophisticated investors, who integrate environmental aspects into their investment decision process, are able to attract imitators. For the aspired achievement of market-wide decarbonization, investors leading the herd should be encouraged to further decarbonize their portfolios in order to trigger follow-up trades.

*JEL Classification*: G11, G15, G23, M14

*Keywords*: Decarbonization, institutional investors, herding

# 4 ARTICLE III: CARBON RISK

Maximilian Görgen, Andrea Jacob, Martin Nerlinger, Ryan Riordan, Martin Rohleder, Marco Wilkens

Working Paper (2020), University of Augsburg

Revise and resubmit: *Journal of Corporate Finance* (VHB-JOURQUAL3: B)

**Abstract.** We investigate carbon risk in global equity prices. We develop a measure of carbon risk using industry standard databases and study return differences between brown and green firms. We observe two opposing effects: brown firms are associated with higher average returns, while decreases in the greenness of firms are associated with lower announcement returns. We construct a carbon risk factor mimicking portfolio to understand carbon risk through the lens of a factor-based asset pricing model. While carbon risk explains systematic return variation well, we do not find evidence of a carbon risk premium. We show that this may be the case because of: (1) the opposing price movements of brown firms and firms becoming greener, and (2) that carbon risk is associated with unpriced cash-flow changes rather than priced discount-rate changes. Investors, regulators, and firms can use our results to better understand the role carbon risk plays in asset pricing.

*JEL classification*: G12, G15, Q51, Q54

*Keywords*: Carbon risk, climate finance, climate change, economic transition, asset pricing

*Conferences*: FRBSF Conference on "The Economics of Climate Change" in San Francisco, 31st NFA Annual Conference 2019 in Vancouver, 2019 FMA European Conference in Glasgow, AEA Annual Meeting 2019 in Atlanta, 45th EFA Annual Meeting 2018 in Warsaw, 2018 EFA Annual Meeting in Philadelphia, 2018 SWFA Annual Meeting in Albuquerque, 2018 MFA Annual meeting in San Antonio, 24th Annual Meeting of the German Finance Association (DGF) in Ulm, CEP-DNB Workshop 2017 in Amsterdam, 2017 GOR AG FIFI Workshop in Magdeburg, and 2017 Green Summit in Vaduz.

*Seminars*: UTS Research Seminar 2019, The Sydney University Research Seminar 2019, Macquarie University Research Seminar 2019 in Sydney, the seminar with the EU Commission DG FISMA, German Bundesbank workshop.

*Prizes*: Best Paper Award at the 2018 SWFA Annual Meeting in Albuquerque and the Highest Impact Award at the 2017 Green Summit in Vaduz.

## 4.1 Introduction

The scientific consensus (NASA, 2019 and IPCC, 2014) points towards a clear relationship between human activities and a warming planet. Firms contribute to global warming by emitting greenhouse gases (GHG) that increase global temperatures and temperature variability, when producing and delivering goods and services for consumption. To try to reduce GHG emissions and avoid the risks associated with a warming planet, numerous jurisdictions have introduced carbon pricing and many more are expected to introduce carbon pricing in the future.[1] Simultaneously, the EU is developing a taxonomy for sustainable climate change mitigation activities and also climate benchmarks to provide investors with better information on the carbon footprint of their investments. As a result of this entire process, institutional investors have committed to divesting \$11 trillion USD in assets of fossil fuel firms.[2] A price to emit carbon, with expectations of future increases coupled with institutional divestment, should lead to lower equity prices and higher expected returns for carbon-intensive firms to compensate for their additional risk: carbon risk. Generally, this new kind of risk includes all positive and negative impacts on firm values that arise from uncertainty in the transition process from a brown to a green economy. Measuring carbon risk is thus not limited to measuring carbon emissions and so-called "stranded assets" (Carbon Tracker Initiative, 2011; Mercure et al., 2018), but a firm's overall strategic and operational exposure to unexpected changes in the transition process towards a green economy. Despite the aforementioned facts, few studies have found a relationship between firms' returns and carbon risk.

In this paper, we study the relationship between carbon risk and equity prices. In the first part of the paper, we determine the greenness or brownness of a firm – the Brown-Green-Score (*BGS*) – as a fundamental measure for carbon risk. In the second part, we study carbon risk in

[1] World Bank Group (2020) - https://carbonpricingdashboard.worldbank.org.
[2] https://350.org/11-trillion-divested/.

equity prices through the lens of a factor-based asset pricing model by constructing the Brown-Minus-Green (*BMG*) portfolio. In the last part, we conduct a formalized test for a priced carbon risk premium.

We start by computing individual carbon emissions-related measures using four comprehensive ESG databases from 2010 to 2017 to determine the greenness or brownness of a firm. We compile three subscores: (1) value chain, (2) public perception, and (3) adaptability of firms with respect to carbon and transition-related issues. The subscores capture different aspects of carbon risk. The value chain captures current emissions related to the production of goods and services. Public perception represents how the public views a firm with respect to carbon emissions. Adaptability is related to the ability of firms to transition from a brown to a green economy. We combine these three subscores into a Brown-Green-Score (*BGS*) for each of the 1,657 firms in our final sample.

We show that the *BGS* has been falling over time suggesting that firms are becoming greener. We regress returns onto a decomposition of the *BGS* into a level and a difference component and variables known to explain returns in the cross-section. The *BGS* level is associated with positive returns, meaning that on average brown firms, as identified using the *BGS*, outperform green firms. In a subsequent paper, Bolton and Kacperczyk (2020) document a similar relationship. In contrast, the change in *BGS* from one year to the next is associated with a negative return. This suggests that firms perform worse if they surprise markets by becoming browner compared to the previous year.

A recent theoretical paper (Pástor et al., 2020) models the environmental, social, and governance (ESG) preferences of investors and their impact on asset prices in equilibrium. Investors vary in their ESG preference and invest in a long short ESG portfolio according to their preferences. In their model, the greener the asset the lower the expected returns. Ex-ante and ex-post asset prices are impacted via unexpected changes in ESG concerns through an investor and a customer channel. The authors introduce the concept of an ESG factor, which is driven by both channels, and show that positive realizations increase green-asset returns even though brown assets earn higher expected returns. In turn, the ESG factor lowers expected returns for brown assets. Overall, ESG risk exposure might be a reason why green assets outperform brown ones.

Our return-related results are consistent with the model of ESG factor risk and asset prices with this theoretical model. The expected *BGS* should be positively associated with returns. The unexpected component of *BGS* should be negatively associated with returns as they increase when firms perform unexpectedly well by emitting less carbon or by publicly announcing carbon abatement plans. Over time as the markets develop a better understanding of carbon risk and the unexpected component falls relative to the expected component, we should expect a positive relationship between returns and carbon risk. If the unexpected component remains consistently large over some period of time, the positive expected return component for the high *BGS* may be masked by the negative return component related to unexpected changes. We find that in our sample period, these two components are similarly large in terms of their contribution to returns, suggesting an ambiguous relationship between carbon risk and returns.

To better understand whether or not differences between brown and green firms can help to explain the carbon risk and return relationship, we calculate differences in all the variables we used to construct the *BGS*, the subscores, and *BGS* over our sample period. We find that overall, firms are becoming greener and that this is mostly driven by green firms becoming significantly greener than brown firms. For instance, green firms reduce their average carbon intensity by roughly 16% annually versus roughly 2% annually for brown firms. The increased reduction for green firms holds for the *BGS* score, all of the *BGS* subscore components, and all but one (environmental innovation) of the individual variables. In our data, green firms becoming significantly greener is associated with a larger increase in their respective stock return than for brown firms, consistent with the theoretical model.

We continue studying the role of carbon risk in equity prices using classical and recent asset pricing tests. Asset pricing models generally have two components (Fama and French, 1993). The first component includes the formation of a portfolio that successfully describes systematic variation in returns. These factor mimicking portfolios can be formed for any firm characteristic. For instance, the book-to-market ratio, firm size, firm liquidity, or profitability have all been used as potential factors that describe systematic variation in returns. For factor mimicking portfolios, that only represent the trading related component of an economic risk, to be valid they should be correlated with the underlying economic risk (Daniel and Titman, 1997; Pukthuanthong et al., 2019). The second component of asset pricing models implies that the factor explains differences in returns across assets. The difference in returns is generally referred to as the risk premium associated with a factor and represents the additional compensation expected by investors for bearing risk associated with the factor.

For analyzing the carbon risk exposure of stocks, we use the *BGS* to place firms into terciles. The highest *BGS* tercile represents "brown" firms and the lowest *BGS* tercile represents "green" firms. We form a zero-cost portfolio that is long brown stocks and short green stocks (*BMG*). The *BMG* portfolio thus mimics a factor related to carbon risk. The factor should be correlated with the risk associated with current, future, and perceived carbon emissions and asset pricing tests should provide evidence on whether or not carbon is a source of systematic variation in returns and whether or not investors require a risk premium for bearing this risk. We find insignificant, but negative realized returns for the *BMG* portfolio, inconsistent with the expectation that brown firms will outperform green firms. However, the results are consistent with the previous results that show a positive return association for the level of *BGS* and a negative association for unexpected changes in *BGS*. While the prices of both brown and green firms have appreciated from 2010 to 2017, the prices of green firms have appreciated faster. The cumulative difference between brown and green firms is roughly 14%. These two opposing effects generate an insignificant relationship between carbon risk and returns in asset pricing tests during our sample period.

An important contribution of our paper is related to data. Comprehensive firm level data is available for roughly 1,600 firms since 2010. Asset-pricing exercises depend on long time-series and a broad cross-section of test assets. Using the *BMG* factor, we can expand the set of test assets via simple returns regressions. We regress the returns for 25,000 firms on the *BMG* factor and other factors known to be correlated with returns, and generate a *BMG* beta for each. The *BMG* beta analysis extends our insight into countries for which no carbon risk data is available. The insight depends on the ability of market participants to impound information on carbon risk into prices not immediately obvious to the econometrician.

We show that the *BMG* factor describes variation in global stock returns of more than 25,000 firms. In general, the *BMG* factor is minimally correlated with other common risk factors pointing to the fact that it possesses unique return-influencing characteristics. In line with expectations, the *BMG* factor enhances the explanatory power of common factor models in *BGS* sorted quintile portfolios. Moreover, the *BMG* factor is of similar (or even greater) magnitude and adds explanatory power when compared to other known sources of variations in single stock returns. For instance, the explanatory power of common asset pricing models increases when adding the *BMG* factor. Finally, the *BMG* factor passes latest asset pricing tests when applied to common test assets, such as the 25 size and value sorted portfolios. Overall, our results indicate that the *BMG* factor is of relevance for asset pricing models and thus able to support market participants in their assessment of carbon risk in equity prices.

In a formalized test for a priced risk premium (Fama and MacBeth, 1973; Pukthuanthong et al., 2019), we show that the *BMG* factor is associated with a statistically insignificantly monthly negative risk premium of –0.097%. This suggests that investors may not require compensation for bearing carbon risk, perhaps because they are able to hedge this risk through non-traded assets. This may also be the case because investors are not fully aware of the financial risks associated with carbon or that the available data and corresponding forecasting models are not sufficiently well-developed to accurately explain and predict carbon risk. This final explanation is consistent with our findings on *BGS* levels and changes and with differences in green and brown firms.

To understand the missing carbon risk premium the Campbell variance decomposition (Campbell, 1991) is used in a further test. By breaking down the variance of the *BMG* factor into a cash-flow news and a discount-rate news component, we show that its variance is primarily dominated by the former. The *BMG* factor price is more sensitive to changes in technologies (investments) and customer preferences for goods and services (revenues) than to changes in the discount rate that investors apply to these cash flows. In a next step, we decompose the market betas of *BMG* beta sorted portfolios as in Campbell and Vuolteenaho (2004). We find that the cash-flow beta is higher than the discount-rate beta for all of the *BMG* beta sorted portfolios. This confirms that during our sample period, returns are rather driven by fundamental re-evaluations of investor expectations about cash-flow news than by discount-rate changes. Following the theory of Pástor et al. (2020), green stocks show a high market beta that is affected by carbon risk through the customer channel (cash-flow news). We argue further that we do not only observe "green shocks" but also unexpected changes towards a brown economy, which raise the market beta of brown stocks. As it turns out, brown stocks are prone to the same risk driver as green stocks, i.e., cash-flow news. In our sample period, there exists a premium for discount-rate news, i.e., especially brown and green firms are not remunerated for their cash-flow risk driver, leading to an insignificant risk premium for the *BMG* beta.

To deepen the results, we conduct additional robustness checks. We provide evidence on the regional distribution of brown and green firms. Since the beta of the *BMG* factor can be estimated for any listed stock regardless of the availability of carbon and transition-related information, we use a global sample to distinguish between brown and green firms. This also allows us to test for carbon risk premia in different regions. Our results for the United States, Europe, and Asia reinforce our hypothesis that there is currently no carbon risk premium.

Our paper is related to nascent but growing literature on the relationship between climate change and asset prices. Physical climate risks impact asset prices, are costly to hedge, and systematic (Engle et al., 2020; Lanfear et al., 2019) making understanding them central to the pricing of assets. Hong et al. (2019) demonstrate that food firms exposed to physical risks underperform in the long-run, whereas Huynh et al. (2020) show that droughts increase the cost of equity capital. Barnett et al. (2020) demonstrate theoretically how climate uncertainty, including physical risks, can be priced in a dynamic stochastic equilibrium model. Bolton and Kacperczyk (2020) provide insights if and how investors do care about carbon risk measured by different carbon emission intensity scopes. Choi et al. (2020) show that high-carbon firms underperform low-carbon firms during extreme heat events. Oestreich and Tsiakas (2015) construct European country-specific “dirty-minus-clean” portfolios based on the number of free emission allowances during the first two phases of the EU Emissions Trading Scheme (ETS) which display positive returns during those time periods. From a bank’s perspective, Delis et al. (2020) show that banks price climate policy risks in their charged loan rates and they have started to develop broader policies on the financing of brown businesses (e.g., Rainforest Action Network et al., 2019). In bond markets, Baker et al. (2018) analyze the pricing and ownership of U.S. Green Bonds and Tang and Zhang (2020) document a positive response of stock prices on the announcement of green bond issuances. Several papers report a link between climate change and property values, e.g., Bakkensen and Barrage (2018), Baldauf et al. (2020), Bernstein et al. (2019), Giglio et al. (2018), Ortega and Taspinar (2018), and Rehse et al. (2019). From an investor's perspective, Krueger et al. (2020) and Nofsinger et al. (2019) suggest that environmental concerns are important factors in the investment decisions of institutional investors, while Monasterolo and De Angelis (2020) explore investors' demand for a risk premium for carbon-intensive assets and Alok et al. (2020) examine the misestimation of climatic disaster risk of fund managers. Other related studies show the influence of carbon emissions on downside risk in options (Ilhan et al., 2021), firm-value effects of carbon disclosure (Matsumura et al., 2014) or corporate environmental performance (De Haan et al., 2012), and the impact of carbon emissions on a firm's cost of capital or capital structure (Nguyen and Phan, 2020; Chava, 2014; Humphrey et al., 2012; El Ghoul et al., 2011).

The remainder of this paper is structured as follows. Section 4.2 presents the data sources. Section 4.3 contains our methodology for carbon risk measurement and panel regressions to infer the relationship between carbon risk and equity prices. Section 4.4 contains tests to determine the relevance of the carbon risk factor in an asset pricing context. Section 4.5 analyzes the missing carbon risk premium followed by some robustness tests in Section 4.6. Section 4.7 concludes.

## 4.2 Data

Following the sample construction of other papers such as Hou et al. (2011), Ince and Porter (2006), and Schmidt et al. (2019), we compile global stock data from Thomson Reuters Datastream. We apply common screening techniques introduced in Ince and Porter (2006) and exclude all firms that are not identified as equity or which are not primary listed. We delete all observations of zero returns at the end of a stock's time series. Moreover, we include only stocks that account for approximately 99.5% of a country's market capitalization to reduce liquidity biases. This leaves us a global stock data sample of 26,664 unique stocks for our sample period from January 2010 to December 2017. For this sample, we obtain financial data from the Worldscope database and Datastream. We apply further data screens for monthly returns following Ince and Porter (2006) and Schmidt et al. (2019).

Measuring carbon risk in the financial market requires the knowledge of fundamental carbon and transition-related information. For this reason, we merge this information from four major ESG databases to our global stock data: (i) the Carbon Disclosure Project (CDP) Climate Change questionnaire dataset, (ii) the MSCI ESG Stats and the IVA ratings, (iii) the Sustainalytics ESG Ratings data and carbon emissions datasets, and (iv) the Thomson Reuters ESG dataset. The use of ESG data does not come without shortcomings. ESG scores are often based on self-reported data, even though data providers claim to conduct profound analyses on the ESG profiles of firms. Furthermore, recent studies conclude that ESG ratings from different data providers disagree (Dimson et al., 2020; Berg et al., 2020; Gibson et al., 2020; Christensen et al., 2019; Kotsantonis and Serafeim, 2019). Sources for disagreement are based on differences in scopes, measurements, and weights of categories (Berg et al., 2020). Since for our analyses, the overall market perception of ESG performance is decisive, we aggregate the scores of different data providers (as also suggested by Berg et al., 2020). With this approach, we simultaneously minimize a potential self-reporting bias by using four ESG databases with different approaches in collecting data including estimations by analysts. To further enhance the measurement of carbon risk, we choose variables explicitly targeting our scope.

We select variables from a total of 785 ESG variables to measure carbon risk in stocks. Leaving out social and governance aspects, 363 variables thereof are potentially useful for describing environmental issues. 131 of the broader environmental variables are directly related to carbon and climate transition issues as opposed to, e.g., waste or water pollution. Thereof, we select ten variables that potentially have the most impact on the financial market via return adjustments and explain the triad of value chain, public perception, and adaptability in our concept (see Section 4.3.1). For example, we take into account carbon emissions since they are the main target of policy measures to mitigate climate change. They are therefore one of the key measures for a firm's brownness. Second, we focus on environmental pillar scores of each of the four databases, as they are most prominent in public and thus can function as readily available decision criteria for investors. Third, we use scores that mirror the environmental friendliness of internal firm processes and therefore future profitability when taking climate change into account. Choosing ten distinct variables does not only eliminate empirically redundant data points, but also ensures to create a straightforward and easily traceable concept for measuring the impact of climate change on the financial market.

For the construction of the *BMG* factor, we exclude all firms with no carbon and transition-related information. To be more precise, we only include a firm if it is available in at least three of the four ESG databases. Thus, we try to take account of potential biases and smooth the effect of ESG rating disagreement across different data providers. Furthermore, we do not take into account firms operating in the financial sector. In the transition process, these firms behave quite differently compared to firms in other industries. For example, the current practice of assigning carbon emissions does not apply to equity financing or lending, which makes financial institutions appear to be less prone to carbon risk. This leaves us with a total of 1,657 stocks. The reduction in sample size from 26,664 global stocks to 1,657 stocks is due to a rather restricted availability for carbon and transition-related data, especially when relying on different databases contemporaneously to account for rater-specific biases. However, the reduced sample size is not of concern in our asset pricing based setup.

Our sample spans the period from January 2010 to December 2017. Classical asset pricing studies focus on a larger time horizon to draw inferences. In our case, there are several reasons to stick to a shorter time frame. First of all, data availability is scarce for larger time horizons. When going back in time, data coverage decreases drastically. Furthermore, most of the ESG databases have started to collect encompassing firm data only in recent years. Besides, the awareness for climate change related topics has steadily increased since the 2000s (Engle et al., 2020). Recent developments further suggest that carbon risk became relevant for financial markets only in the last couple of years. Even though there were remarkable events in previous times such as the establishment of the Kyoto Protocol in 1996, the Energy Policy Act in 2005, the publication of the Stern Review in 2006, and the 3rd IPCC assessment report in 2007, policy actions and societal awareness have not raised great interest. Summary statistics for our data sample are shown in Table 1.

[Insert Table 1 here.]

To avoid penalizing large firms concerning absolute carbon emissions, we standardize emissions by a firm's net sales. The database specific scores are ranging within a predefined bandwidth.

To the best of our knowledge, this unique dataset with the incorporation of four major ESG databases contains the most comprehensive carbon and transition-related information in the climate finance research area.

### 4.3 Carbon risk in equity prices

In this section, we present our methodology to calculate the "Brown-Green-Score" (*BGS*) and investigate the relationship between the *BGS* and equity prices. First, we describe how to identify green and brown firms using the *BGS* via three indicators: value chain, public perception, and adaptability. Second, we conduct panel regressions based on the *BGS* to analyze if carbon risk has a positive or negative effect on returns. Since both the expected and unexpected component of the *BGS* have counteracting effects on returns, we observe an insignificant relationship between carbon risk and return.

### 4.3.1 Carbon risk measurement methodology

We determine the fundamental characteristic of brown or green firms by calculating the *BGS* for each individual firm. The *BGS* is based on three main indicators: value chain, public perception, and adaptability, capturing the impact of the climate transition process on a firm. Value chain accounts for the current emissions of a firm within its production, processes, and supply chain. Public perception covers how carbon emissions and a firm's carbon policy are perceived by its stakeholders (e.g., customers, investors, creditors, and suppliers) expressed by respective ratings. Adaptability captures strategies and policies that prepare a firm for changes with respect to the price of carbon, new technologies, regulation, and future emissions reduction and mitigation strategies.

Carbon emissions related to production processes as well as applied technologies cannot be transformed instantly and without costs (İşlegen and Reichelstein, 2011; Lyubich et al., 2018) and thus might become stranded (Mercure et al., 2018). However, regulatory interventions may provide support for required technological changes (Acemoglu et al., 2012) and prevent carbon leakage (Martin et al., 2014). Worldwide supply chains and their environmental impact are difficult to analyze, highly interrelated, and therefore extraordinarily vulnerable to climate-related risk sources (Faruk et al., 2001; Xu et al., 2017). Therefore, a firm's value is highly affected by the level and the changes of its carbon emissions within its value chain.

Furthermore, the firm's public perception with regard to the transition process can affect its valuation. For instance, value can be created by establishing a comprehensive reporting system (Krueger, 2015). Value of firms with low social capital or trust can be destroyed during a crisis or during negative events in the form of reputational risks (Lins et al., 2017). Environmental strengths increase product market perception and thus firm value (Bardos et al., 2020). In addition, firms may be valued higher if they can demonstrate that their activities support climate change mitigation and are thus able to make use of positive media coverage (Cahan et al., 2015; Byun and Oh, 2018). Even the impact of carbon emissions on stock returns may depend on people's different beliefs about climate change, e.g., when experiencing abnormal temperatures (Choi et al., 2020). In general, ratings are in the focus of most firms' stakeholders (e.g., Liang and Renneboog, 2017; Hartzmark and Sussman, 2019) and provide an external assessment about a firm's transition process related performance. Thus, public perception of a firm's support of the transition process evaluated by ratings may impact its respective value.

Finally, a firm's ability to adapt quickly to changes in the transition process may prevent underperformance due to risks in its own value chain or public perception (Lins et al., 2017). Investors already value environmental corporate policies as a necessary risk prevention measure (Fernando et al., 2017). Nevertheless, stock markets seem to underreact to firms' climate sensitivity (Kumar et al., 2019) creating uncertainty. A firm's adaptability is therefore an additional indicator whether and to what extent it is affected by unexpected changes in the transition process (Deng et al., 2013; Fatemi et al., 2015). Taking all of these theories into account, *BGS* approximates for carbon risk.

To compute the *BGS* we use ten variables containing firm specific information related to one of the three broader indicators described above.[3] For each variable, we assign zero to firms below the median in a given year and one to firms above the median. In the next step, we average the ten values assigned to a firm in a given year separately within the three indicators which results in subscores for value chain, public perception, and adaptablity. Finally, we calculate the *BGS* for each firm $i$ in each year $t$ by combining the subscores using Equation (1).

$$BGS_{i,t} = 0.70\ Value\ Chain_{i,t} + 0.15\ Public\ Perception_{i,t} + 0.15\ Adaptability_{i,t}\ . \qquad (1)$$

[3] For a full list of variables and their mapping to the risk indicators see Internet Appendix Table A.2.

The value chain subscore has a weight of 70% in the *BGS* to reflect its relative importance.[4] The public perception and adaptability subscore carries each 15% weight in the *BGS*.[5] As a result, the *BGS* ranges between zero and one, where zero denotes a green and one denotes a brown firm.

The final selection of variables, the mapping of the proxy variables to the risk indicators, and the aggregation of the subscores are the result of two workshops hosted for this purpose with acknowledged sustainability and finance experts from international institutions, consultancies, universities, asset managers, and NGOs. The variable selection was also subject to data availability and statistical analyses. The weighting scheme has been tested for robustness and our results remain economically similar.

### 4.3.2 Panel regressions

We regress global stock returns onto a decomposition of the *BGS* into a level and a difference component and further variables known to explain returns in the cross-section. Since *BGS* is based on yearly data, we conduct yearly panel regressions following Equation (2):

$$r_{i,t} = \alpha_i + \beta_{i.1}\, BGS_t + \beta_{i,2}\, (BGS_t - BGS_{t\text{-}1}) + \boldsymbol{\delta}_i\, \boldsymbol{controls}_t\,, \tag{2}$$

with $r_{i,t}$ being the yearly return, $BGS_t$ and $(BGS_t - BGS_{t\text{-}1})$ the level and difference component of *BGS*, respectively, and $\boldsymbol{controls}_t$ a vector of common control variables.[6] We also include different types of fixed effects (country, industry, time, and firm).[7]

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[4] We assume value chain to be the most important indicator since production, processes, and supply chain management constitute the core of a firm. Moreover, governmental climate change related regulations are focused predominantly on current emissions. The existence of numerous studies dealing only with carbon emissions confirms the importance of the value chain subscore.

[5] Our results remain robust to changes in predefined weights. In addition, we conducted a more systematic approach in deriving the *BGS* by principal components analysis (PCA). The results remain basically the same.

[6] Basically, $BGS_t$ contains firm information of $t-1$ since ESG ratings are made public with a lag of around 6 months.

[7] In untabulated results, we also cluster standard errors on country, industry, firm, and time level. Even though t-statistics become smaller, the direction of the results remains stable.

Table 2 displays the results. Both the *BGS* level and difference component have a significant effect on stock returns for (almost) all combinations of fixed effects. In general, the level component is a proxy for the expected carbon risk of a firm, whereas the difference component represents unexpected effects. The expected *BGS* shows a positive association with stock returns with a coefficient of, e.g., 0.068 (last model specification) indicating that brown firms have higher returns. On the contrary, becoming greener is rewarded with higher returns as suggested by the negative coefficient of the *BGS* difference component (–0.065).

These results are consistent with the theoretical model of sustainable investing introduced by Pástor et al. (2020). Brown stocks show higher expected returns, whereas unexpected changes towards a green economy are favorable for returns of green stocks. If firms surprise with positive realizations of the *BGS* (lower *BGS*) by, e.g., emitting less carbon or publicly announcing carbon abatement plans, they still can outperform brown stocks. Both the expected and unexpected component show similar effects in magnitude measured by their estimated coefficient, thus confounding clear-cut effects on stock returns. However, the observed level is by nature higher than the observed unexpected (difference) component, so that the positive level effect rather outweighs the negative effect of the unexpected component. Over time as the unexpected component falls or becomes smaller in magnitude relative to the expected effects, we should observe a significant positive relationship. This equilibrium, however, can be achieved solely when markets develop a better understanding of carbon risk, which is not yet the case.

[Insert Table 2 here.]

To better understand differences in brown and green firms, we calculate average annual changes in all variables used to construct the *BGS*, the respective subscores, and the *BGS* itself. Table 3 demonstrates that both brown and green firms have become greener over our sample period from 2010 to 2017. However, green firms have become significantly greener than brown firms.

For instance, green firms reduced their carbon intensity on average by 15.95%, whereas brown firms reduced their carbon intensity by solely 1.90% per year. This remarkable difference is mirrored in the value chain subscore with a difference of 14.06% between the changes of brown and green firms. All variables except the Environmental Innovation Score show the same pattern. Overall, green firms have reduced their *BGS* by 4.00% more than brown firms.

For our sample period, this means that green firms becoming greener is associated with a larger increase in their respective stock return than for brown firms. In other words, the unexpected component of *BGS* dominates the expected level component. However, the expected and unexpected component confound their respective single effect on stock returns due to their opposing relationship with returns.

[Insert Table 3 here.]

### 4.4 Relevance of the carbon risk factor *BMG*

To strengthen the understanding of the relationship between equity prices and carbon risk, we make use of asset pricing theory. Many factor and factor mimicking portfolio papers in the asset pricing literature are seen critically regarding their future impact and relevance. Even though we propose a new factor, we do not want to end up being perceived as another animal of the factor zoo (Cochrane, 2011).[8] Our aim is to develop a framework for measuring and understanding carbon risk in equity prices. Thus, we show the construction and relevance of the *BMG* factor by following common composition methods and latest asset pricing tests. Importantly, this capital-market based approach allows measuring carbon risk exposure for any asset without the need for carbon and transition-related data.

[8] For a comprehensive overview of the discussion about past factors, we suggest reading Harvey and Liu (2020) and Feng et al. (2020).

### 4.4.1 The *BMG* factor – A mimicking factor portfolio for carbon risk

The *BMG* portfolio is constructed to mimic a factor related to carbon risk similar in intuition to the Fama and French (1993) size and book-to-market factors. For the construction of the *BMG* portfolio, we determine the annual *BGS* for each firm. Subsequently, each year we unconditionally allocate all firms into six portfolios based on their market equity (size) and the *BGS* using the median and terciles as breakpoints, respectively. We use the value-weighted average monthly returns of the four portfolios "small/high *BGS*" (*SH*), "big/high *BGS*" (*BH*), "small/low *BGS*" (*SL*), and "big/low *BGS*" (*BL*) to calculate the *BMG* factor following Equation (3). Thus, $BMG_t$ is the return in month $t$ of a zero-cost portfolio that is long in brown firms and short in green firms:

$$BMG_t = 0.5\ (SH_t + BH_t) - 0.5\ (SL_t + BL_t)\ . \tag{3}$$

Figure 1 plots cumulative returns of the *BMG* factor and the corresponding long and short portfolios for the sample period from January 2010 to December 2017. The figure shows a contrast in the performance of the brown and the green portfolio over time. While the cumulative return of the *BMG* factor is slightly positive in the period from 2010 to the end of 2012, the effect reverses in the period from 2013 to the end of 2015, in which the cumulative return of the *BMG* factor drops from around +3% to around −23%, followed by an increase to around −11% in 2017. Hence, brown firms performed on average worse than green firms did during our sample period.

Following the reasoning of Pástor et al. (2020), this development might point to the fact that especially since 2013, we experienced a strengthening in unexpected changes towards a green economy which induced green stocks to outperform brown stocks. In other words, the unexpected favorable development of framework conditions for green stocks is able to overcome the expected negative return effect.

[Insert Figure 1 here.]

Table 4 reports summary statistics and correlations with the global factors of a Carhart (1997) four-factor model in Panel A and the global factors of the Fama and French (2015) five-factor model in Panel B during our sample period. The average monthly return of the *BMG* factor is negative at −0.11%; the standard deviation is 1.70%. The correlations between the *BMG* factor and the factors of the Carhart model market, size, value, and momentum are relatively low. The same applies to the factors of the Fama and French 5F model.[9] This suggests that the *BMG* factor possesses unique return-influencing characteristics that are able to enhance the explanatory power of common factor models.[10]

[Insert Table 4 here.]

### 4.4.2 *BGS* quintile portfolio analysis

We construct *BGS* sorted portfolios to test if the *BMG* factor is able to enhance the explanatory power of common factor models. We sort firms according to their *BGS* into annually rebalanced quintiles such that quintile 1 contains the firms with the lowest *BGS*, i.e., the greenest firms, and quintile 5 contains the firms with the highest *BGS*, i.e., the brownest firms. We then run time-series regressions of the quintiles' equal-weighted monthly excess returns on the global Carhart model and on the Carhart + *BMG* model (see Equation 4).[11]

$$er_{i,t} = \alpha_i + \beta_i^{mkt}\, er_{M,t} + \beta_i^{smb}\, SMB_t + \beta_i^{hml}\, HML_t + \beta_i^{wml}\, WML_t + \beta_i^{BMG}\, BMG_t + \varepsilon_{i,t}\,. \qquad (4)$$

The results of the global *BGS* quintile analysis are shown in Table 5. The market betas are significant and close to one for all quintiles. To test whether the *BMG* factor is able to significantly increase the explanation of the variation in excess stock returns we apply an F-test on nested models (Kutner et al., 2005). For additional details on the *BGS* quintiles, all

[9] We also conducted correlation and regression analyses on potentially related influencing factors including the oil price (oil spot and futures prices) as well as oil industry equity and commodity indices and carbon price (carbon certificates and respective derivatives). There are no remarkable results affecting our factor.
[10] Nevertheless, to completely exclude a potential influence of other risk factors, we conduct an analysis with democratically orthogonalized factors in Internet Appendix C.
[11] Value-weighted quintile portfolios show the same patterns, therefore our results remain robust.

differences in the coefficients compared to the Carhart model are reported on the right-hand side of the table.

[Insert Table 5 here.]

A comparison of the adjusted $R^2$ and the results of the F-test confirm that the *BMG* factor significantly enhances the explanatory power of the Carhart model, especially for the high *BGS* portfolios. In the case of *BGS* quintile 5, the adjusted $R^2$ increases by more than 12 percentage points. The table reports *BMG* beta loadings that increase strictly monotonically from the low *BGS* quintile, which displays a significantly negative loading of −0.30, to the high *BGS* quintile with a significantly positive loading of 0.98. Quintiles 2 and 3 show *BMG* betas close to zero. Tendentially, firms with high *BGS* show the anticipated high carbon risk exposure and vice versa. Overall, the *BMG* factor delivers the expected results and significantly enhances the explanatory power of common factor models in *BGS* sorted quintile portfolios.

### 4.4.3 Comparison of common factor models

To reinforce the results of the previous section on a larger basis, we compare the results of global common factor models with and without the *BMG* factor. Panel A of Table 6 shows the results of more than 25,000 single stock regressions. The first two models compare how (1) *SMB* and *HML* versus (2) *BMG* change the explanatory power of the CAPM. The average increase of model (1) in the adj. $R^2$ is 1.32 percentage points. This increase is significant for 15.00% of the firms in the sample. In comparison, the *BMG* factor alone increases the adj. $R^2$ by 0.86 percentage points and significantly for 13.54% of the regressions. The following two models contrast how (3) *WML* vs. (4) *BMG* changes the explanatory power of the Fama and French model. This comparison shows a more than three times higher increase in the adj. $R^2$ for the *BMG* factor than for *WML*. Finally, the models (5) and (6) provide further evidence that the *BMG* factor increases the explanatory power of common factor models, for example the Carhart model and the Fama and French 5F model. Overall, the inclusion of the *BMG* factor decreases the average RMSE.

[Insert Table 6 here.]

For a more detailed assessment of the impact of the *BMG* factor on the stock returns of single firms, Panel B of Table 6 reports the number of significant factor betas from the Carhart + *BMG* model. Based on two-sided t-tests, 3,708 firms (14.67%) show a significant *BMG* beta on a 5% significance level. This is comparable to the number of significant *SMB* betas (3,756) and higher than the number of significant *HML* (2,174) and *WML* betas (1,893). The average *BMG* beta is positive at 0.173. Overall, compared to common factors, the *BMG* factor performs well highlighting its relative importance for explaining variation in global stock returns.[12]

### 4.4.4 Asset pricing tests

One of the most common asset pricing tests is the GRS test by Gibbons et al. (1989). It tests whether the intercepts are indistinguishable from zero in the time-series regression for a set of test assets' excess returns on the model's factor returns ($H_0$: $\alpha_i = 0 \ \forall \ i$). It is furthermore a test that shows if a linear combination of the factor portfolios is on the minimum variance boundary or if each factor portfolio is the multifactor minimum variance in an S state variable world.

We also provide new insights into alpha by combining the *BMG* factor with various common asset pricing and test asset portfolios by applying latest asset pricing tests following Hou et al. (2015), Fama and French (2016), and Barillas and Shanken (2017). To evaluate alpha, we calculate the average absolute regression intercept for each test asset portfolio. Furthermore, the average adjusted coefficient of determination provides information about the validity of a model in general.

[12] To demonstrate that *BMG* is a relevant factor, we also implement the methodology of Pukthuanthong et al. (2019). Results can be found in Internet Appendix B (Tables B.2 and B.3).

Another approach by Barillas and Shanken (2017) and Fama and French (2018) promises a ranking of models that can be achieved by analyzing the Sharpe ratio rather than $\alpha$. This assumption is based on previous research by Gibbons et al. (1989). They were the first expressing the difference between two maximum squared Sharpe ratios, the one with the combination of $\Pi$ (excess returns of all assets) and $f$ (all factors of a model) and the one with only the latter, as the following Equation (5) displays:

$$\alpha'\Sigma^{-1}\alpha = Sh^2(\Pi) - Sh^2(f)\,. \tag{5}$$

They show that differences in the vector of intercepts ($\alpha$) from the regression of $\Pi$ on $f$ and the residual covariance matrix ($\Sigma^{-1}$) for different models are only driven by $Sh^2(f)$. Therefore, we can find the best fitting model by the largest maximum squared Sharpe ratio of the model's factors. We choose different common models, e.g., the CAPM, the Fama and French model, the Carhart model, and the Fama and French 5F model as well as the latter one including *WML*, and calculate the described measures with and without the *BMG* factor. We repeat this process for two main global test asset portfolios, the 25 size and value sorted portfolios and the 25 size and momentum portfolios from French.[13] In Table 7, we show the best value according to the respective test statistic in bold.

[Insert Table 7 here.]

Starting with the evaluation of the best model of 25 size and value portfolios, we obtain promising results. The Fama and French 6F + *BMG* model has overall the lowest GRS test statistic, the highest adjusted $R^2$ and the lowest average absolute alpha. Furthermore, any previous pairwise model comparison prefers the model with the *BMG* factor. Considering the Sharpe ratio approach, we can determine the Fama and French model as the best fitting model,

[13] We thank Kenneth French for providing test asset portfolios in such an extensive diversity. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. In addition to the reported results, we also use industry portfolios as test assets. Results are available upon request.

followed by the Fama and French model with the *BMG* factor. These findings indicate that the *BMG* factor is able to explain the returns of these test asset portfolios. We obtain even better results with the 25 portfolios constructed on size and momentum. Any model with the *BMG* factor has a lower GRS test statistic than a respective model without the *BMG* factor and it produces a higher adjusted $R^2$, a lower average absolute alpha, and a lower Sharpe ratio. This leads to assume that the *BMG* factor can explain these assets better than common models.[14]

## 4.5 The missing carbon risk premium

For a factor to command a risk premium, it should explain differences in cross-sectional stock returns. We perform cross-sectional regressions following the Fama and MacBeth (1973) methodology as well as a modification introduced by Pukthuanthong et al. (2019). In these analyses, we find that there is no significant carbon risk premium. We show that brown and green portfolios are rather driven by cash-flow news than discount-rate news. Since there is a risk premium for the latter in our sample period, both types of portfolios do not receive a risk premium for their dominant risk driver, leading to an insignificant risk premium of the *BMG* factor.

### 4.5.1 Cross-sectional regressions

This section tests whether the *BMG* factor is a priced risk factor. We run a cross-sectional regression using the methodology of Fama and MacBeth (1973) on single stock level. For this purpose, we estimate 36-month-rolling-window coefficients in the first step, and then regress individual stock returns on the estimated coefficient values. Since the Fama and MacBeth (1973) procedure is prone to the errors-in-variables (EIV) problem, we follow the EIV correction of Pukthuanthong et al. (2019). We thus use the returns of double-sorted portfolios

[14] We also conducted further asset pricing tests like, e.g., excluded factor regressions in Internet Appendix B (Table B.1).

as dependent variable.[15] First, each year in June, we sort all stocks based on their market capitalization into deciles. Second, within each size decile, we sort the respective stocks further into deciles based on their estimated OLS beta of each factor resulting in 100 size/beta portfolios for each factor. Then, for example, the average market beta of each size/beta portfolio is assigned to all stocks in the respective portfolio. This procedure is repeated for all of the other factor betas. Cross-sectional regressions are run with individual stock returns on the left hand side and the assigned beta values on the right hand side.

We re-run both regression models with industry fixed effects. Results of the cross-sectional regressions can be found in Table 8. All factors lack significant risk premia, except for *SMB* in the non-EIV-corrected models. The *BMG* factor is slightly negative, but far from being statistically significant. These results are inconsistent with expectations that brown firms command a positive risk premium. The carbon risk premium amounts to –0.097% in the standard Fama and MacBeth (1973) regression. Correcting for the EIV problem, we obtain a risk premium estimate of –0.218, but still statistically insignificant. This suggests that investors are not fully aware of the financial risks associated with carbon emissions. In the next analyses, we provide more intuition and a new framework for understanding these risks better.

[Insert Table 8 here.]

#### 4.5.2 A risk decomposition of the *BMG* factor and beta portfolios

To further evaluate the non-existence of a risk premium, we analyze the economic mechanisms driving the *BMG* factor and the market beta of *BMG* beta sorted portfolios. We follow the decomposition approaches of Campbell (1991) and Campbell and Vuolteenaho (2004).[16] The

[15] There is a lively debate in literature on which left-hand-side assets to use in cross-sectional regressions (see, e.g., Lo and MacKinlay, 1990; Daniel and Titman, 2012; Harvey and Liu, 2020; Jegadeesh et al., 2019). To account for both sides, we conducted our analyses on individual stock level as well as various characteristic-sorted portfolios. Our results remain unchanged.

[16] Technical details can be found in Internet Appendix D.

analysis is geared towards understanding whether changes in expectations about firm cash flows or changes in discount rates are driving the *BMG* factor and *BMG* beta sorted portfolios.

The methodology is based on a simple discounted cash flow model, where changes of firm values result from changing expectations regarding cash flows and discount rates. Cash-flow changes have permanent wealth effects and may therefore be interpreted as fundamental re-evaluations towards a new equilibrium. In contrast, discount-rate changes have temporary wealth effects on the aggregate stock market driven by investor sentiment.

We use the VAR methodology introduced by Campbell (1991) to decompose the *BMG* factor and assume that the data are generated by a first-order vector autoregression (VAR) model. For the variance decomposition, we modify Campbell's (1991) approach using the *BMG* factor time series as the first state variable. We use global versions of the Shiller PE-ratio, the term spread, and the small stock value spread as additional state variables as in Campbell and Vuolteenaho (2004). In Table 9, we report the absolute and normalized results of the variance decomposition of the *BMG* factor as well as correlations between the components. 14.04% of the total *BMG* factor variance can be attributed to discount-rate news whereas the remaining 85.96% are driven by cash-flow news. This suggests that the *BMG* factor is mainly determined by expectations about future cash flows and not about changes in the discount rate that investors apply to these cash flows. This is consistent with the transition process of the economy that is highly sensitive to changes in technologies (investments) and customers' preferences for goods and services (revenues).

[Insert Table 9 here.]

In a second test, we follow Campbell and Vuolteenaho (2004) more closely and decompose market betas of *BMG* beta sorted portfolios into a cash-flow and a discount-rate beta. In their original paper, the authors apply this approach to Fama and French's 25 size/book-to-market sorted portfolios to explain the value anomaly in stock returns. To adopt their methodology, we construct 40 *BMG* beta and size sorted test asset portfolios by sorting all stocks into 20 5%-quantiles based on their individual *BMG* beta and splitting each portfolio by the stocks' median market capitalization.

[Insert Figure 2 here.]

As shown in Figure 2, the cash-flow beta is higher than the discount-rate beta for all portfolios. This confirms that, during our sample period, returns are driven by fundamental re-evaluations of investor expectations about cash-flow news rather than about discount rates. Furthermore, the discount-rate beta is virtually the same for all 40 portfolios, whereas the cash-flow beta shows a more pronounced U-shaped pattern. This suggests that extreme portfolios, i.e., high absolute *BMG* beta firms, have higher cash-flow betas and are thus more exposed to fundamental re-evaluations of firm values than to discount-rate changes.

According to the theoretical model of Pástor et al. (2020) green stocks should display a higher market beta due to their ESG factor risk exposure. We argue that ESG risk – or carbon risk in our case – works in both directions, i.e., there exist unexpected changes towards a green economy favoring green stocks and unexpected changes towards a brown economy favoring brown stocks. As a result, both brown and green stocks have a high carbon risk exposure and a high market beta. Our analysis confirms this hypothesis. In addition, those high market betas of both kinds of stocks are driven by the customer channel (cash-flow news) and not the investor channel (discount-rate news).

We evaluate the prices of cash-flow and discount-rate beta risk following Campbell and Vuolteenaho (2004). Rational investors should demand higher compensation for fundamental and therefore permanent cash-flow shocks ("bad beta") than for transitory discount-rate shocks ("good beta"). In Table 10, we apply the asset pricing models described in Campbell and

Vuolteenaho (2004) to our 40 *BMG* beta/size sorted test asset portfolios to analyze this hypothesis. We show results of an unrestricted factor model and a two-factor ICAPM that restricts the price of the discount-rate beta to the variance of the market return. Like Campbell and Vuolteenaho (2004), we estimate both models with and without a constant to account for different assumptions about the risk-free rate. For our sample period, the price for cash-flow beta risk amounts to –26.61% per year for the unrestricted factor model. The price for discount-rate beta risk is 76.53% per year. Hence, for our sample period, the "good beta" demands a risk premium compared to the "bad beta".[17] This result remains stable for the restricted factor model and the unrestricted two-beta ICAPM. The restricted two-beta ICAPM shows a bad fit for our sample period ($R^2$ of –0.694) and thus should not be given great importance.

[Insert Table 10 here.]

As seen in Figure 2, especially green and brown portfolios are predominantly prone to cash-flow news. Since the cash-flow risk is not remunerated in the market for this time period, both brown and green firms do not receive a remarkable premium for their risk driver. In turn, this might explain the missing carbon risk premium for *BMG* beta, as both factor legs are driven towards the same risk driver, i.e., cash-flow induced risks.

As the market moves towards an equilibrium state concerning the transition to a green economy, the effect on the market betas of green and brown stocks should diverge clearly resulting in a distinct difference between them.

[17] Due to the sample period, our results are contrary to Campbell and Vuolteenaho (2004) and more recent studies are hard to find. However, Maio (2013) shows that cash-flow price of risk has a long-term and a time-varying component. The latter is negatively correlated with business cycle. Since our time period starts in the recovery phase, we hypothesize that consistent with Maio (2013), the time-varying component has a negative effect on the price for cash-flow risk which outweighs the positive long-term component, so that discount-rate risk displays a higher price. In addition, Campbell et al. (2013) show that after the financial crisis in 2008, there were much stronger good cash-flow news observable, which might point to the fact that investors did not require a premium for cash-flow risk in our period.

## 4.6 Robustness tests

To demonstrate the validity of our results, we conduct further robustness checks. The advantage of our factor-based model is that a stock's exposure to carbon risk can be measured via the estimation of the *BMG* beta. This means that no carbon and transition-related information on the stock or its *BGS*, respectively, has to be available to judge its carbon risk exposure. In turn, we can evaluate the global risk based on a wide cross-section of stocks.

[Insert Table 11 here.]

Table 11 provides a *BMG* beta landscape and descriptive statistics of the *BMG* beta distribution globally. First, we calculate the average *BMG* beta for each country with at least 30 firms within our sample. Second, we assign all countries according to their *BMG* beta into terciles (brown, neutral, and green) to create the figure in Panel A. Brown countries are mainly fossil and resource dominated economies like, e.g., Canada, Brazil, South Africa, Russia, Australia, or China. In contrast, European countries are mainly green having on average low *BMG* betas, whereas the United States, Poland, Turkey, or Argentina are neutral countries with *BMG* betas around zero. Panel B provides further information on the average *BMG* beta for major countries. It is particularly interesting that all countries have green and brown firms according to the *BMG* beta, the distribution differs, however. This leads to the question whether we can find a carbon risk premium in different regions.

Therefore, we examine the existence of the carbon risk premium for three regions, i.e., the USA, Europe, and Asia. Table 12 contains the results for cross-sectional EIV-corrected regressions for the different regions. All regions show premium estimates on the *BMG* beta of similar magnitude (–0.211, –0.246, and –0.181% for USA, Europe, and Asia, respectively). These estimates are comparable to the global sample (–0.192). Regardless of the region, the carbon risk premium remains statistically insignificant.[18] Hence, our results point to the fact that carbon risk is relevant for explaining variation in returns, but is not priced in our sample period.

[Insert Table 12 here.]

In an additional test, we back-cast carbon and transition-related information to 2002 to test our results for a longer time horizon. We show that the *BMG* factor remains a relevant factor for the larger time period, however, we still do not find a significant carbon risk premium.[19]

## 4.7 Conclusion

The scientific consensus is clear on the link between greenhouse gas emissions and climate change. Investors, firms, regulators, and the general public have been slow to recognize the financial risks associated with climate change despite the seemingly obvious relationship between human activities and a warming planet. Our paper takes a step towards quantifying carbon risk for a broad cross-section of firms across the globe and time.

Our *BMG* factor explains systematic variation in returns as well as other common risk factors. Surprisingly, we find no evidence of a risk premium associated with carbon risk. This is the case for a number of reasons. First, carbon risk may not be priced because investors are unable to adequately predict or quantify carbon risk. We show that brown firms are associated with higher returns and that when firms become relatively browner their returns are lower. Second, we show that green firms are becoming greener faster that brown firms, leading green firms to outperform brown firms. We also show that green and brown firm carbon risk is better explained by unpriced fundamental re-evaluations of firm cash flows than by priced discount-

[18] When considering non-EIV-corrected cross-sectional regressions, the carbon risk premium remains unverified.
[19] We provide results upon request.

rate changes. These results are in line with the theoretical model of Pástor et al. (2020) and adds to the understanding of the functioning of carbon risk.

Our results and methodology can be used to expand the set of test assets and our understanding of carbon risk, absent carbon and transition-related data. We extend our results to firms without carbon-related data. We show that our factor continues to explain systematic return variation well and that carbon risk does not appear to be priced in the broader cross-section.

The results and methodology herein can be used by investors, regulators, and data providers to better understand the role carbon risk and climate change play in a global asset pricing context. As one might expect, a carbon risk premium requires firms, investor expectations, data, and models to be in an equilibrium where most market participants understand and agree on the source and the quantification of the risk. As jurisdictions contemplate and introduce carbon pricing, the public mobilizes behind climate action, and institutional investors divest from carbon-intensive industries, the markets may quickly develop a common understanding of carbon risk. This paper will serve as a guide in understanding future developments in sustainable and climate finance.

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## Tables and Figures

**Table 1**
**Descriptive statistics of variables**

| Variable | N | Mean | SD | Median |
|---|---|---|---|---|
| **Panel A. Raw *BGS* Data** | | | | |
| *Value Chain* | | | | |
| Emissions Intensity (CDP) | 5,462 | 328.15 | 770.83 | 58.46 |
| Emissions Intensity (Thomson Reuters) | 6,195 | 369.69 | 907.67 | 56.58 |
| Emissions Intensity (Sustainalytics) | 6,189 | 341.53 | 745.69 | 59.86 |
| Emissions Intensity (Combined) | 6,968 | 368.88 | 883.01 | 58.31 |
| *Public Perception* | | | | |
| Environmental Score | 7,130 | 16.78 | 20.54 | 7.47 |
| Environmental Pillar Score | 7,170 | 4.34 | 1.98 | 4.40 |
| Performance Band | 5,681 | 4.28 | 2.02 | 4.17 |
| Environmental Score | 6,875 | 36.32 | 12.10 | 36.00 |
| *Adaptability* | | | | |
| Environmental Innovation Score | 7,141 | 38.66 | 25.84 | 35.29 |
| Carbon Emissions Score | 6,385 | 2.77 | 2.36 | 2.50 |
| Preparedness | 6,875 | 4.55 | 0.57 | 4.67 |
| **Panel B. Scored *BGS* Data** | | | | |
| Value Chain Score | 7,195 | 0.50 | 0.50 | 0.50 |
| Public Perception Score | 7,195 | 0.56 | 0.28 | 0.54 |
| Adaptability Scores | 7,195 | 0.51 | 0.34 | 0.50 |
| Brown-Green-Score *BGS* | 7,195 | 0.51 | 0.37 | 0.54 |
| **Panel C. Financial Data** | | | | |
| Returns | 7,171 | 0.12 | 0.35 | 0.10 |
| Market Capitalization | 7,195 | 19,771.43 | 38,513.42 | 7,862.32 |
| Net Sales | 7,195 | 17,228.58 | 32,721.70 | 7,084.00 |
| Total Assets | 7,195 | 24,369.15 | 46,441.11 | 9,248.30 |
| Book-to-Market Ratio | 7,195 | 5.59 | 4.46 | 4.64 |
| Leverage Ratio | 7,194 | 25.88 | 16.06 | 24.46 |
| Invest/Total Assets Ratio | 7,189 | 0.15 | 0.73 | 0.10 |
| Property, Plant, and Equipment | 7,194 | 8,288.05 | 18,910.92 | 2,383.65 |
| Market Beta | 7,165 | 0.98 | 0.50 | 0.95 |
| Idiosyncratic Volatility | 7,167 | 1.71 | 0.72 | 1.57 |

This table reports the descriptive statistics for all financial, carbon and transition-related variables in the data sample grouped in categories (Panels A–C) for the period from January 2010 to December 2017. All scored variables are scaled in such a way that higher values denote browner firms. All accounting variables are denoted in million USD. A country and sector breakdown can be found in Internet Appendix Table A.1 and a short description of each raw *BGS* variable can be found in Table A.2.

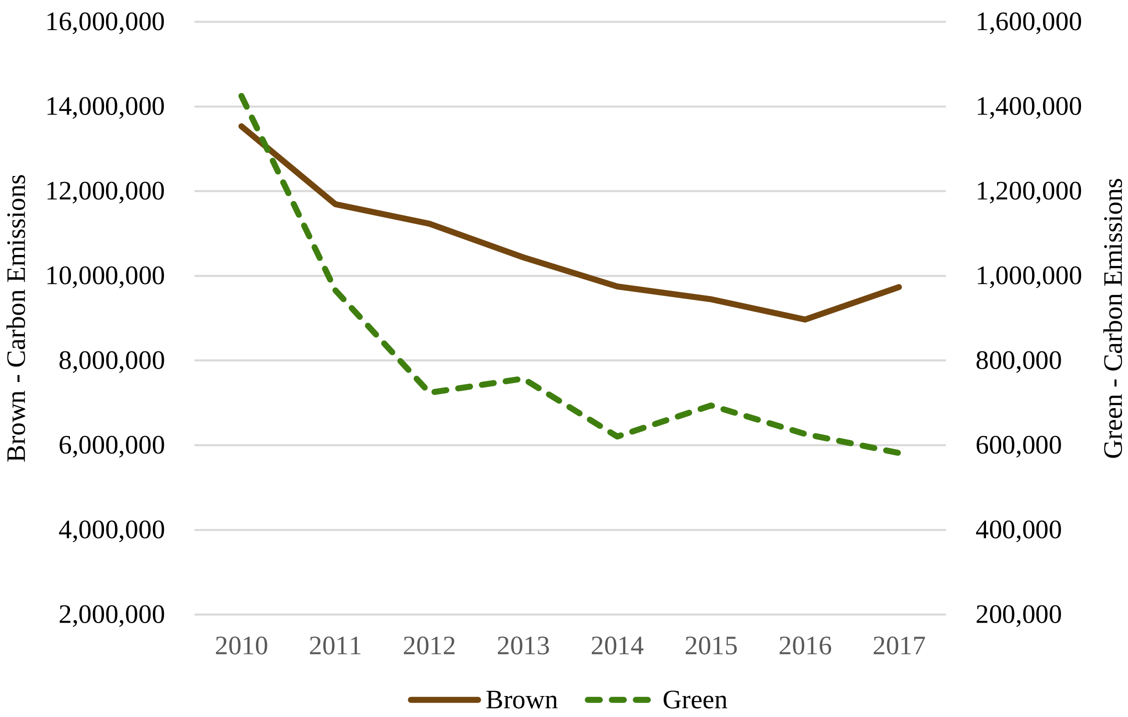
**Table 2**
**Panel regressions**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *BGS* | 0.044*** | 0.062*** | 0.054*** | 0.068* |
| | (3.18) | (4.55) | (3.69) | (1.67) |
| *BGS* Difference | -0.040 | -0.070*** | -0.064*** | -0.065** |
| | (-1.55) | (-2.90) | (-2.63) | (-2.05) |
| Log Total Assets | 0.063*** | 0.059*** | 0.065*** | 0.36*** |
| | (10.83) | (10.50) | (11.26) | (21.56) |
| Book-to-Market Ratio | 0.341*** | 0.047 | 0.105 | 1.795*** |
| | (2.76) | (0.38) | (0.89) | (7.79) |
| Leverage Ratio | 0.000 | 0.000 | 0.000 | 0.001 |
| | (0.32) | (0.79) | (0.03) | (1.35) |
| Invest/Total Assets Ratio | 0.022 | 0.32 | 0.28 | 0.023 |
| | (0.04) | (0.61) | (0.54) | (0.04) |
| Log PPE | -0.040*** | -0.040*** | -0.036*** | -0.25*** |
| | (-9.28) | (-9.60) | (-8.28) | (-13.57) |
| Beta | 0.044*** | 0.062*** | 0.037*** | 0.036** |
| | (4.86) | (5.65) | (4.16) | (2.16) |
| Idiosyncratic Volatility | -2.91*** | -0.73 | -0.17 | 11.1*** |
| | (-3.77) | (-0.90) | (-0.23) | (7.80) |
| Constant | -0.34*** | | | |
| | (-4.75) | | | |
| Country fixed effects | no | yes | no | no |
| Industry fixed effects | no | no | yes | no |
| Firm fixed effects | no | no | no | yes |
| Time fixed effects | no | yes | yes | yes |
| $R^2$ | 0.040 | 0.17 | 0.17 | 0.35 |
| Within $R^2$ | | 0.031 | 0.035 | 0.10 |
| N | 6,055 | 6,053 | 6,055 | 5,871 |

This table shows panel regressions of yearly returns as the dependent variable on the *BGS*, fundamentals, and country, industry, time, and firm fixed effects for the period from January 2010 to December 2017. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively. Significance tests are based on two-sided t-tests.

**Table 3**
**Development of brown and green firms**

**Panel A. Development of carbon emissions of brown and green firms**




**Panel B. Development of carbon and transition-related variables of brown and green firms**

| Variable | Mean | | | Mean ann. change in % | | |
|---|---|---|---|---|---|---|
| | Brown | Green | Difference | Brown | Green | Difference |
| *BGS* | | | | -1.54 | -5.54 | 4.00 |
| Value Chain | | | | -1.90 | -15.95 | 14.06 |
| Public Perception | | | | -1.88 | -2.66 | 0.78 |
| Adaptability | | | | -2.33 | -8.01 | 5.68 |
| Carbon Intensity | 805.05 | 42.14 | 762.91 | -1.90 | -15.95 | 14.06 |
| Environmental Score | 22.27 | 8.66 | 13.61 | -5.47 | -5.82 | 0.35 |
| Environmental Pillar Score | 5.32 | 3.45 | 1.87 | 1.01 | -0.46 | 1.47 |
| Performance Band | 4.52 | 4.09 | 0.42 | 0.21 | -0.05 | 0.26 |
| Environmental Score | 41.79 | 30.27 | 11.52 | -3.28 | -4.33 | 1.06 |
| Environ. Innovation Score | 47.77 | 29.55 | 18.22 | -1.52 | 0.00 | -1.52 |
| Carbon Emissions Score | 4.21 | 1.58 | 2.63 | -4.20 | -22.73 | 18.53 |
| Preparedness | 4.71 | 4.36 | 0.35 | -1.27 | -1.29 | 0.03 |

This table shows in Panel A the development of carbon emissions of brown and green firms. Panel B provides an overview of the development of carbon and transition-related variables of brown and green firms.

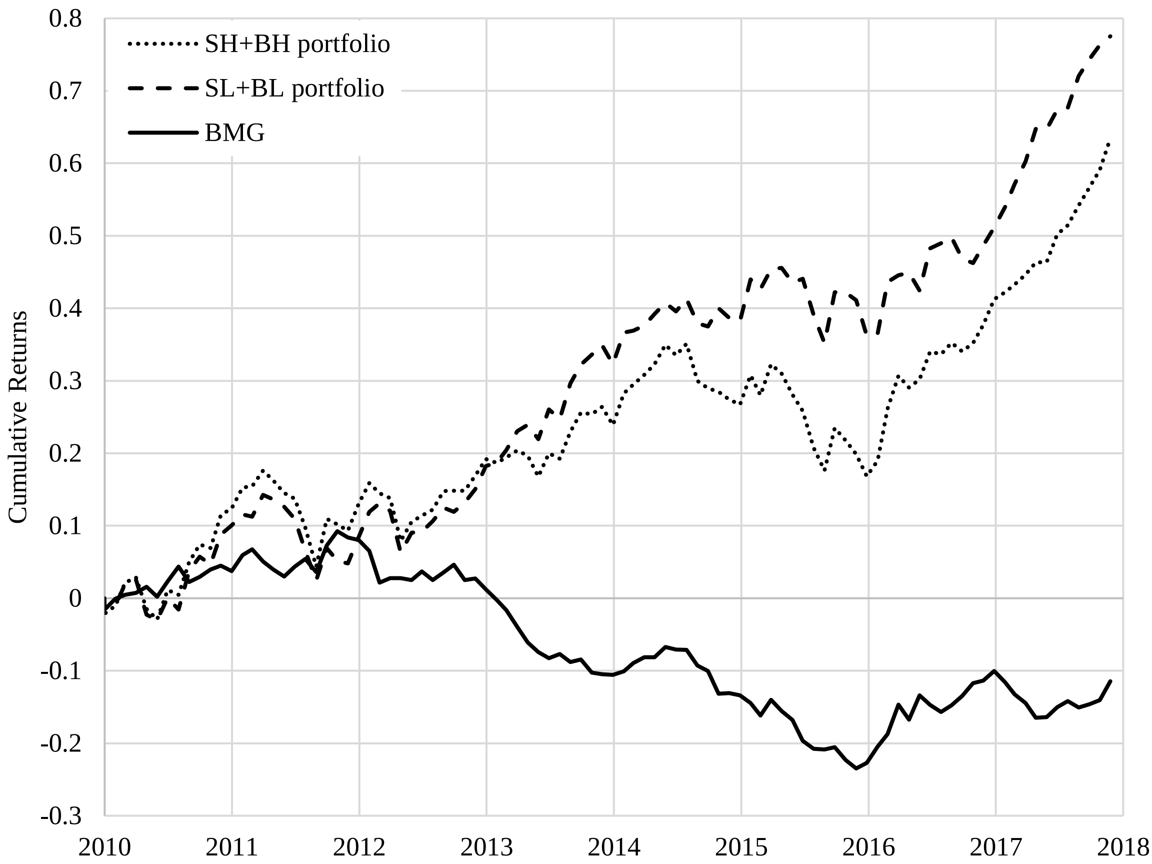



**Figure 1**
**Cumulative returns of the *BMG* factor and the long and short portfolios**

This figure shows cumulative returns of the *BMG* factor and the weighted underlying long "small/high *BGS*" (*SH*) and "big/high *BGS*" (*BH*), and short portfolios "small/low *BGS*" (*SL*) and "big/low *BGS*" (*BL*) for the sample period from January 2010 to December 2017.

**Table 4**
**Factor descriptive statistics and correlations**

**Panel A. Carhart and *BMG***

| Factor | Mean Return (%) | SD (%) | t-stat. | Correlations | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | *BMG* | $er_M$ | *SMB* | *HML* | *WML* |
| *BMG* | -0.11 | 1.70 | -0.65 | 1.00 | | | | |
| $er_M$ | 0.89 | 3.78 | 2.30 | 0.05 | 1.00 | | | |
| *SMB* | 0.07 | 1.33 | 0.55 | 0.06 | -0.02 | 1.00 | | |
| *HML* | -0.07 | 1.65 | -0.41 | 0.29 | 0.17 | -0.02 | 1.00 | |
| *WML* | 0.51 | 2.37 | 2.09 | -0.17 | -0.20 | 0.00 | -0.38 | 1.00 |

**Panel B. Fama/French 5F and *BMG***

| Factor | Mean Return (%) | SD (%) | t-stat. | Correlations | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | *BMG* | $er_M$ | *SMB* | *HML* | *RMW* | *CMA* |
| *BMG* | -0.11 | 1.70 | -0.65 | 1.00 | | | | | |
| $er_M$ | 0.89 | 3.78 | 2.30 | 0.05 | 1.00 | | | | |
| *SMB* | 0.09 | 1.32 | 0.66 | 0.10 | -0.03 | 1.00 | | | |
| *HML* | -0.06 | 1.64 | -0.34 | 0.29 | 0.17 | 0.09 | 1.00 | | |
| *RMW* | 0.27 | 1.17 | 2.21 | -0.11 | -0.44 | -0.37 | -0.54 | 1.00 | |
| *CMA* | 0.08 | 0.99 | 0.81 | 0.16 | -0.08 | 0.00 | 0.55 | -0.15 | 1.00 |

This table displays descriptive statistics and correlations of the monthly global market ($er_M$), size (*SMB*), value (*HML*), momentum (*WML*), profitability (*RMW*), and investment (*CMA*) factors as well as the *BMG* factor for the sample period from January 2010 to December 2017. The global factors $er_M$, *SMB*, *HML*, *WML*, *RMW*, *CMA*, and the risk-free rate are provided by Kenneth French.

**Table 5**
***BGS* quintile portfolio performance**

| Quintile | Median *BGS* | Coefficient Alpha | $er_M$ | *SMB* | *HML* | *WML* | *BMG* | Adj. $R^2$ (%) | Δ Coefficient Δ Alpha | Δ $er_M$ | Δ *SMB* | Δ *HML* | Δ *WML* | Δ Adj. $R^2$ (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Low | 0.07 | 0.00 | $1.04^{***}$ | $0.18^{**}$ | 0.00 | $-0.14^{***}$ | $-0.30^{***}$ | 94.74% | $0.000^{a}$ | $0.000^{a***}$ | $0.030^{a*}$ | $0.090^{a}$ | $-0.020^{a**}$ | $1.42^{***}$ |
| | | (-0.36) | (39.50) | (2.46) | (-0.04) | (-3.14) | (-5.06) | | | | | | | |
| 2 | 0.18 | 0.00 | $0.99^{***}$ | $0.27^{***}$ | -0.09 | -0.06 | -0.10 | 92.88% | $0.000^{a}$ | $0.000^{a***}$ | $0.010^{a***}$ | $0.030^{a}$ | $0.000^{a}$ | 0.12 |
| | | (1.50) | (34.20) | (3.40) | (-1.21) | (-1.29) | (-1.58) | | | | | | | |
| 3 | 0.57 | 0.00 | $1.09^{***}$ | $0.20^{**}$ | 0.02 | $-0.08^{*}$ | 0.00 | 94.41% | $0.000^{a}$ | $0.000^{a***}$ | $0.000^{a**}$ | $0.000^{a}$ | $0.000^{a*}$ | -0.06 |
| | | (-0.60) | (38.56) | (2.55) | (0.31) | (-1.69) | (-0.06) | | | | | | | |
| 4 | 0.87 | 0.00 | $1.05^{***}$ | $0.21^{**}$ | 0.03 | $-0.18^{***}$ | $0.47^{***}$ | 92.80% | $0.000^{a}$ | $0.010^{a***}$ | $-0.040^{a**}$ | $-0.130^{a}$ | $0.020^{a***}$ | $3.03^{***}$ |
| | | (-1.39) | (32.15) | (2.29) | (0.34) | (-3.16) | (6.27) | | | | | | | |
| High | 0.96 | 0.00 | $1.06^{***}$ | $0.34^{***}$ | $-0.19^{**}$ | $-0.14^{**}$ | $0.98^{***}$ | 93.34% | $0.000^{a}$ | $0.010^{a***}$ | $-0.09^{a***}$ | $-0.260^{a}$ | $0.050^{a**}$ | $12.36^{***}$ |
| | | (-0.52) | (32.04) | (3.77) | (-2.35) | (-2.52) | (13.03) | | | | | | | |
| High-Low | 0.89 | 0.00 | 0.02 | $0.17^{**}$ | $-0.19^{***}$ | 0.00 | $1.28^{***}$ | 84.94% | | | | | | |
| | | (-0.32) | (0.69) | (2.39) | (-3.06) | (-0.02) | (22.56) | | | | | | | |

This table shows monthly median Brown-Green-Scores (*BGS*), alpha, and beta coefficients of the Carhart + *BMG* model for annually rebalanced, equal-weighted quintile portfolios based on the *BGS* of the stocks in the data sample for the period from January 2010 to December 2017. On the right panel, the table displays Δ alphas and coefficients between the Carhart + *BMG* model and the Carhart model. $^{*}$, $^{**}$, $^{***}$ denote significance on the 10%, 5%, and 1% level, respectively. For alphas and beta coefficients, significance statistics are based on two-sided t-tests. $^{c}$, $^{b}$, and $^{a}$ denote significance on the 10%, 5%, and 1% level, respectively, for Δ values. Tests on the differences of coefficients are based on two-sided t-tests of bootstrapped Δ values. Significance symbols in the last column are based on the one-sided F-test for nested models ($H_0$: $\beta_i^{BMG} = 0$).

**Table 6**
**Comparison of common factor models**

**Panel A. Significance tests for explanatory power of various models**

| | Avg. Δ adj. $R^2$ (%) | Significant at 5% F-test (%) | Avg. Δ RMSE (%) |
|---|---|---|---|
| (1) CAPM – Fama/French | 1.32 | 15.00 | -0.09 |
| (2) CAPM – CAPM + *BMG* | 0.86 | 13.54 | -0.06 |
| (3) Fama/French – Carhart | 0.29 | 7.20 | -0.03 |
| (4) Fama/French – Fama/French + *BMG* | 0.90 | 14.43 | -0.06 |
| (5) Carhart – Carhart + *BMG* | 0.90 | 14.34 | -0.06 |
| (6) Fama/French 5F – Fama/French 5F + *BMG* | 0.87 | 14.15 | -0.06 |

**Panel B. Significance tests for factor betas for the Carhart + *BMG* model**

| | | T-test of significance of coefficients | | | | | |
|---|---|---|---|---|---|---|---|
| | Avg. coefficient | 10% level | | 5% level | | 1% level | |
| | | # | % | # | % | # | % |
| *BMG* | 0.173 | 5,386 | 21.30 | 3,708 | 14.67 | 1,726 | 6.83 |
| $er_M$ | 0.946 | 19,284 | 76.27 | 17,478 | 69.13 | 13,788 | 54.53 |
| *SMB* | 0.784 | 5,854 | 23.15 | 3,756 | 14.86 | 1,436 | 5.68 |
| *HML* | 0.044 | 3,740 | 14.79 | 2,174 | 8.60 | 699 | 2.76 |
| *WML* | -0.181 | 3,309 | 13.09 | 1,893 | 7.49 | 508 | 2.01 |

This table provides comparisons of global common factor models including and excluding the *BMG* factor. Panel A reports the average Δ adj. $R^2$ and Δ RMSE between different factor models run on single stocks in the sample period from January 2010 to December 2017. Significance statistics are based on one-sided F-tests for nested models ($H_0$: $\beta_i^{BMG} = 0$). Panel B shows average beta coefficients as well as the absolute (#) and relative (%) number of statistically significant beta coefficients from Carhart + *BMG* model regressions run on single stocks. Statistical significance is based on two-sided t-tests.

**Table 7**
**Asset pricing tests**

| Factor model | GRS | p-value | Mean \|Alpha\| | Mean adj. $R^2$ | $SR^2$ |
|---|---|---|---|---|---|
| **Panel A. 5x5 Size/Value Portfolios** | | | | | |
| CAPM | 4.454 | 0.000 | 0.001 | 0.859 | 1.678 |
| **CAPM + *BMG*** | 4.351 | 0.000 | 0.001 | 0.862 | 1.673 |
| Fama/French | 4.399 | 0.000 | 0.001 | 0.928 | **1.723** |
| **Fama/French + *BMG*** | 4.314 | 0.000 | 0.001 | 0.929 | 1.721 |
| Carhart | 4.055 | 0.000 | 0.001 | 0.931 | 1.710 |
| **Carhart + *BMG*** | 3.985 | 0.000 | 0.001 | 0.932 | 1.708 |
| Fama/French 5F | 3.295 | 0.000 | 0.001 | 0.928 | 1.629 |
| **Fama/French 5F + *BMG*** | 3.186 | 0.000 | 0.001 | 0.929 | 1.616 |
| Fama/French 6F | 3.238 | 0.000 | 0.001 | 0.931 | 1.644 |
| **Fama/French 6F + *BMG*** | **3.142** | 0.000 | **0.001** | **0.932** | 1.633 |
| **Panel B. 5x5 Size/Momentum Portfolios** | | | | | |
| CAPM | 4.452 | 0.000 | 0.003 | 0.842 | 1.678 |
| **CAPM + *BMG*** | 4.410 | 0.000 | 0.003 | 0.844 | 1.696 |
| Fama/French | 4.327 | 0.000 | 0.003 | 0.900 | 1.695 |
| **Fama/French + *BMG*** | 4.285 | 0.000 | 0.003 | 0.901 | **1.710** |
| Carhart | 3.883 | 0.000 | 0.002 | 0.933 | 1.637 |
| **Carhart + *BMG*** | 3.854 | 0.000 | 0.002 | 0.934 | 1.652 |
| Fama/French 5F | 3.057 | 0.000 | 0.002 | 0.905 | 1.511 |
| **Fama/French 5F + *BMG*** | 2.965 | 0.000 | 0.002 | 0.906 | 1.504 |
| Fama/French 6F | 2.969 | 0.000 | 0.002 | 0.934 | 1.508 |
| **Fama/French 6F + *BMG*** | **2.889** | 0.000 | **0.002** | **0.935** | 1.502 |

This table shows the results of various asset pricing tests on global test assets. We include 25 global portfolios formed on Size/Value and Size/Momentum from the Kenneth French Data Library. Comparing various models with and without the *BMG* factor, better fitted models according to the GRS test are printed in bold. The best value according to each statistic for each test asset is also printed in bold. The sample period ranges from January 2010 to December 2017. The global factors $er_M$, *SMB*, *HML*, *WML*, *RMW*, *CMA*, and the risk-free rate are provided by Kenneth French.

**Table 8**
**Cross-sectional regressions**

| | No EIV correction | | EIV correction | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *BMG* | -0.097 | -0. 062 | -0. 218 | -0. 192 |
| | (-1.42) | (-0.96) | (-1.18) | (-1.07) |
| $er_M$ | -0. 240 | -0. 232 | -0. 015 | -0. 008 |
| | (-1.09) | (-1.08) | (-0.04) | (-0.02) |
| *SMB* | -0. 115** | -0. 115** | 0. 002 | -0. 003 |
| | (-2.17) | (-2.28) | (0.01) | (-0.02) |
| *HML* | 0. 085 | 0. 094 | -0. 199 | -0. 178 |
| | (1.20) | (1.51) | (-1.12) | (-1.01) |
| *WML* | -0. 062 | -0. 076 | 0. 398 | 0. 388 |
| | (-0.48) | (-0.66) | (1.59) | (1.56) |
| Log Total Assets | -0. 038 | -0. 068 | -0. 039 | -0. 044 |
| | (-0.59) | (-1.16) | (-0.82) | (-0.96) |
| Book-to-Market Ratio | -317.77*** | -307.93*** | -301.05*** | -299.40*** |
| | (-6.69) | (-6.76) | (-8.18) | (-7.99) |
| Leverage Ratio | -0. 623* | -0. 502 | -0. 520* | -0. 447* |
| | (-1.85) | (-1.53) | (-1.95) | (-1.71) |
| Invest/Total Assets Ratio | -0. 014 | -0. 014 | -0.000 | -0.000 |
| | (-1.15) | (-1.15) | (-0.03) | (-0.04) |
| Log PPE | -0. 042 | 0. 011 | -0. 017 | -0. 004 |
| | (-0.80) | (0.24) | (-0.54) | (-0.14) |
| Constant | 2.713*** | 2.204*** | 2.133*** | 1.868*** |
| | (3.70) | (2.98) | (4.50) | (3.65) |
| Industry fixed effects | no | yes | no | yes |
| $R^2$ (in %) | 3.57 | 4.58 | 10.29 | 10.93 |
| N | 792,352 | 792,352 | 1,393,848 | 1,393,848 |

This table shows results of cross-sectional Fama and MacBeth (1973) regressions. We follow the implementation of Pukthuanthong et al. (2019) and use two different methodologies. First, we simply conduct single-stock cross-sectional regressions (no EIV correction). Second, we us double sorted portfolios as test assets. In the first step, we run OLS regressions to estimate betas for the Carhart + *BMG* model. In the second step, all stocks are sorted into size deciles in June each year. Within each size decile, stocks are further sorted into deciles based on their estimated market beta resulting in 100 size/market beta groups. Then, the average market beta of each group is assigned to each stock within that group. This procedure is repeated for all the other estimated betas. Afterwards, cross-sectional regressions of monthly individual stock returns are run on the assigned beta values. The time-series averages over all months with the respective t-values are reported in the table (EIV correction). Models (2) and (4) include industry fixed effects. All coefficients are reported in percent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

**Table 9**
**Variance decomposition**

| | Variance components | | | |
|---|---|---|---|---|
| | Var($N_{CF}$) | Var($N_{DR}$) | –2 Cov($N_{CF}$, $N_{DR}$) | Corr($N_{CF}$, $N_{DR}$) |
| Absolute (%) | 0.0428 | 0.0040 | -0.0183 | 70.05 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Normalized (%) | 150.32 | 14.04 | -64.36 | |
| | (0.21) | (0.02) | (0.06) | |

This table shows the results of the variance decomposition of the *BMG* factor for the sample period from January 2010 to December 2017 following the methodology of Campbell (1991). We report both the absolute and normalized values of variances and covariance of the cash-flow news and discount-rate news for the *BMG* factor. The standard errors in parentheses are calculated using a jackknife method.

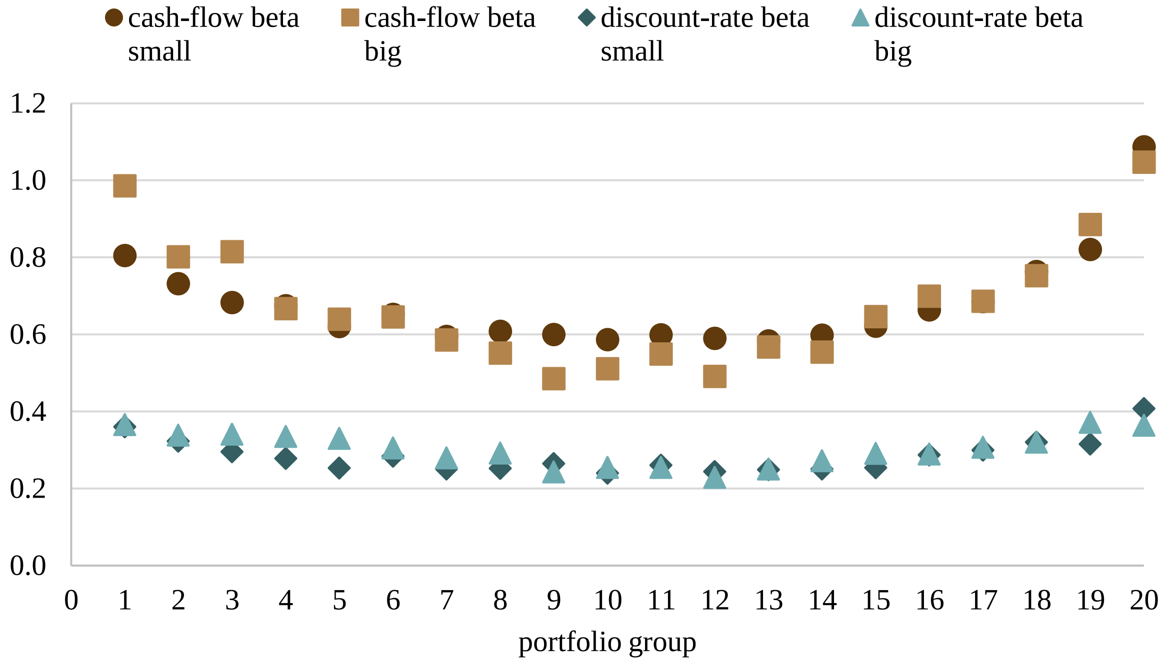



**Figure 2**
**Beta decomposition of 40 *BMG* beta sorted portfolios**

This figure shows the beta decomposition of 40 test assets built in the period from January 2010 to December 2017 following the methodology of Campbell and Vuolteenaho (2004). The 40 test assets are constructed by sorting all stocks into 20 5%-quantiles based on their *BMG* beta (portfolio group) and splitting each portfolio by the stocks' median market capitalization.

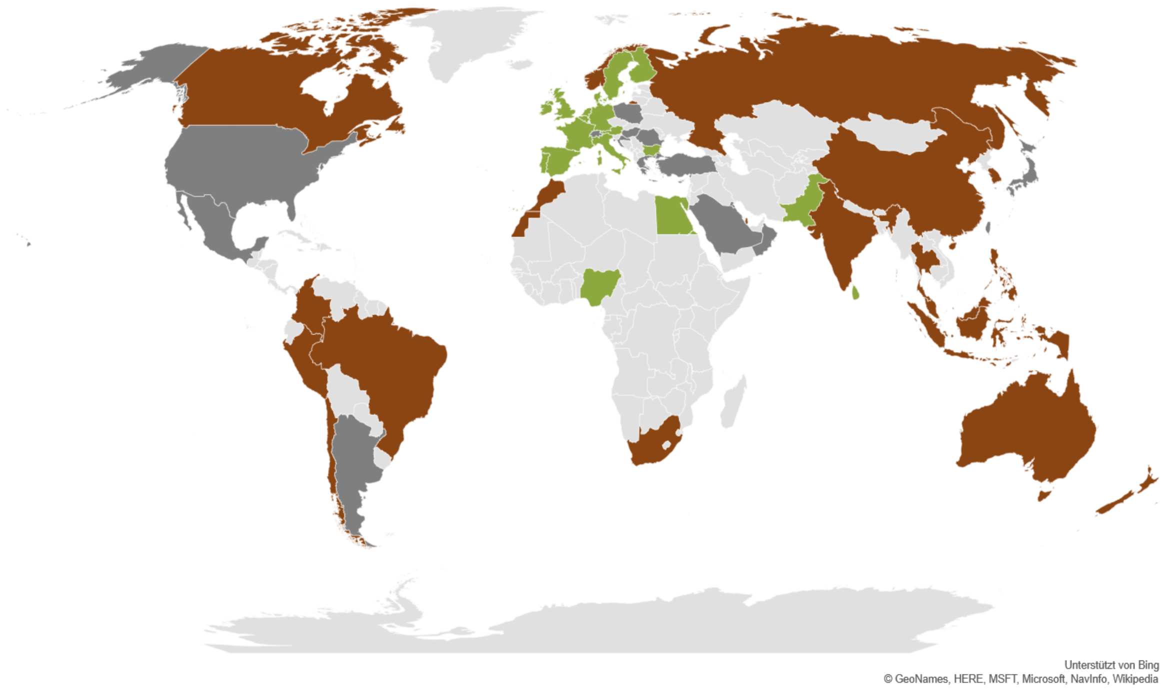
**Table 10**
**Pricing cash-flow and discount-rate betas**

| | Factor model | | Two-beta ICAPM | |
|---|---|---|---|---|
| | Unrestricted | $\alpha = 0$ | Unrestricted | $\alpha = 0$ |
| $R_{zb}$ less $R_{rf}$ ($g_0$) | 0.007 | 0 | 0.014 | 0 |
| % pa | 8.978 | 0 | 16.751 | 0 |
| Std. error | (0.004) | | (0.002) | |
| $\hat{\beta}_{CF}$ premium ($g_1$) | -0.022 | -0.028 | -0.005 | 0.014 |
| % pa | -26.609 | -33.913 | -6.339 | 17.203 |
| Std. error | (0.008) | (0.007) | (0.004) | (0.001) |
| $\hat{\beta}_{DR}$ premium ($g_2$) | 0.064 | 0.104 | 0.001 | 0.001 |
| % pa | 76.533 | 124.322 | 1.704 | 1.704 |
| Std. error | (0.025) | (0.018) | (0.000) | (0.000) |
| $R^2$ | 0.188 | 0.090 | 0.053 | -0.694 |

This table shows premia estimated in the sample period from January 2010 to December 2017 following the methodology of Campbell and Vuolteenaho (2004). The asset pricing models are an unrestricted two-beta model and a two-beta ICAPM with the discount-rate beta price constrained to equal the market variance. The second column per model shows a model with the zero-beta rate equal to the risk-free rate ($\alpha = 0$). Estimates are from a cross-sectional regression using value-weighted portfolio returns of 40 test assets conditionally sorted on *BMG* beta and size. Standard errors are from the respective cross-sectional regression.

**Table 11**
**Global breakdown of *BMG* beta**

**Panel A. *BMG* beta landscape**




**Panel B. *BMG* beta in major countries**

| Country | N | Mean | SD | Min | P25 | Median | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| France | 428 | -0.51 | 0.74 | -3.29 | -0.94 | -0.48 | -0.09 | 2.46 |
| United Kingdom | 1,178 | -0.32 | 1.14 | -3.21 | -0.94 | -0.38 | 0.15 | 4.20 |
| Germany | 507 | -0.19 | 0.98 | -3.29 | -0.71 | -0.24 | 0.22 | 4.07 |
| Japan | 2,586 | -0.11 | 0.84 | -2.95 | -0.61 | -0.13 | 0.34 | 4.07 |
| United States | 5,215 | -0.03 | 1.12 | -3.29 | -0.63 | -0.06 | 0.51 | 4.19 |
| Taiwan | 993 | 0.01 | 0.77 | -2.91 | -0.40 | 0.04 | 0.45 | 4.15 |
| India | 1,045 | 0.23 | 0.91 | -3.25 | -0.28 | 0.20 | 0.77 | 4.01 |
| China | 3,177 | 0.32 | 0.88 | -3.25 | -0.16 | 0.38 | 0.87 | 3.88 |
| Hong Kong | 1,217 | 0.39 | 1.00 | -3.18 | -0.17 | 0.35 | 0.97 | 4.06 |
| Singapore | 403 | 0.43 | 0.93 | -3.22 | 0.00 | 0.47 | 0.88 | 3.79 |
| South Korea | 1,057 | 0.55 | 0.92 | -3.25 | 0.04 | 0.51 | 1.05 | 4.20 |
| Australia | 747 | 0.91 | 1.18 | -2.99 | 0.26 | 0.75 | 1.51 | 4.21 |
| Canada | 1,112 | 1.17 | 1.42 | -3.29 | 0.23 | 0.98 | 2.15 | 4.22 |

This table shows in Panel A the *BMG* beta across the world. We include all countries with at least 30 firms to correct for outliers. A green color indicates a low average *BMG* beta of the country, whereas a brown color states that, on average, the country's firms have high *BMG* betas. A grey color denotes that a country is neutral by having an average *BMG* beta near zero. Panel B provides detailed descriptive statistics about the *BMG* beta in major countries sorted in ascending order by their mean *BMG* beta.

**Table 12**
**Regional cross-sectional regressions**

| | USA | Europe | Asia | Global |
|---|---|---|---|---|
| *BMG* | -0.211 | -0.246 | -0.181 | -0. 192 |
| | (-1.14) | (-1.28) | (-1.04) | (-1.07) |
| $er_M$ | -0.057 | 0.043 | 0.028 | -0. 008 |
| | (-0.16) | (0.11) | (0.07) | (-0.02) |
| *SMB* | -0.018 | 0.004 | 0. 029 | -0. 003 |
| | (-0.14) | (0.02) | (0.19) | (-0.02) |
| *HML* | -0.136 | -0.270 | -0.165 | -0. 178 |
| | (-0.78) | (-1.49) | (-0.92) | (-1.01) |
| *WML* | 0.216 | 0.350 | 0.402 | 0. 388 |
| | (0.90) | (1.42) | (1.58) | (1.56) |
| Log Total Assets | 0.138*** | -0.040 | -0.085 | -0. 044 |
| | (2.90) | (-1.04) | (-1.31) | (-0.96) |
| Book-to-Market Ratio | -315.87*** | -98.46*** | -660.85*** | -299.40*** |
| | (-7.19) | (-6.28) | (-4.57) | (-7.99) |
| Leverage Ratio | -0.420** | -1.340*** | -0.735* | -0. 447* |
| | (-2.18) | (-7.15) | (-1.79) | (-1.71) |
| Invest/Total Assets Ratio | -0.005 | 0.016 | 0.003 | -0.000 |
| | (-0.29) | (0.35) | (0.05) | (-0.04) |
| Log PPE | -0.071** | 0.006 | 0.042 | -0. 004 |
| | (-2.21) | (0.22) | (1.06) | (-0.14) |
| Constant | 0.482 | 1.429** | 2.190*** | 1.868*** |
| | (0.86) | (2.61) | (3.49) | (3.65) |
| Industry fixed effects | yes | yes | yes | yes |
| $R^2$ (in %) | 13.75 | 12.52 | 11.24 | 10.93 |
| N | 240,604 | 232,134 | 769,224 | 1,393,848 |

This table shows results of cross-sectional Fama and MacBeth (1973) regressions for different regions. The last column reports the results for the global sample already shown in Table 8 for comparative purposes. For each of the regions, we sort stocks into double sorted portfolios as in Pukthuanthong et al. (2019). In the first step, we run OLS regressions to estimate betas for the Carhart + *BMG* model. In the second step, all stocks are sorted into size deciles in June each year. Within each size decile, stocks are further sorted into deciles based on their estimated market beta resulting in 100 size/market beta groups. Then, the average market beta of each group is assigned to each stock within that group. This procedure is repeated for all the other estimated factor betas. Afterwards, cross-sectional regressions are run of monthly individual stock returns on the assigned beta values. The time-series averages over all months with the respective t-values are reported in the table. All coefficients are reported in percent. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

# Internet Appendix A

## Further descriptive statistics

**Table A.1**
**Geographic and sectoral breakdown of data sample**

| **Panel A. Geographic** | | | **Panel B. Sectoral** | | | |
|---|---|---|---|---|---|---|
| Country | # | % | Sector | TRBC | # | % |
| United States | 419 | 25.29 | Industrials | 52 | 374 | 22.57 |
| Japan | 231 | 13.94 | Cyclical Consumer Goods & Services | 53 | 281 | 16.96 |
| United Kingdom | 192 | 11.59 | Basic Materials | 51 | 242 | 14.60 |
| Canada | 98 | 5.91 | Technology | 57 | 193 | 11.65 |
| Australia | 74 | 4.47 | Non-Cyclical Cons. Goods & Services | 54 | 169 | 10.20 |
| France | 70 | 4.22 | Energy | 50 | 122 | 7.36 |
| South Africa | 59 | 3.56 | Healthcare | 56 | 108 | 6.52 |
| Germany | 54 | 3.26 | Utilities | 59 | 105 | 6.34 |
| Taiwan | 47 | 2.84 | Telecommunications Services | 58 | 63 | 3.80 |
| South Korea | 35 | 2.11 | | | | |
| Other Europe | 249 | 15.03 | | | | |
| Other Asia | 80 | 4.83 | | | | |
| Other Americas | 37 | 2.23 | | | | |
| Other Australasia | 12 | 0.72 | | | | |
| Total | 1,657 | 100 | Total | | 1,657 | 100 |

This table shows the geographic (Panel A) and sectoral breakdown (Panel B) in absolute numbers and percentages for the data sample for the period from January 2010 to December 2017. The sectoral breakdown is based on the Thomson Reuters Business Classification (TRBC).

Table A.1 reports geographical (Panel A) and sectoral (Panel B) breakdowns for the data sample. The sectoral breakdown is based on the Thomson Reuters Business Classification (TRBC). The numbers show that our sample can be regarded as a representative global sample. The country with the highest number of firms is the United States with 419. The second largest region is Europe with UK, France, and Germany in the top 10. Importantly, the sector breakdown shows that the data sample has a sound mixture of sectors and not a specific focus, e.g., on carbon-intensive or carbon-efficient industries.

**Table A.2**
**Descriptions of environmental variables of the four ESG databases**

| Variable | Description |
|---|---|
| *Value Chain* | |
| Emission Intensity (CDP) | Gross global Scope 1 & 2 emissions figures in metric tonnes $CO_2e$ divided by net sales. |
| Emission Intensity (Thomson Reuters) | Total $CO_2$ and $CO_2$ equivalents emissions in metric tonnes $CO_2e$ divided by net sales. |
| Emission Intensity (Sustainalytics) | Absolute Scope 1 & 2 GHG emissions (reported or otherwise estimated) in metric tonnes $CO_2e$ divided by net sales. |
| Emission Intensity (Combined) | By taking the different data quality and estimation methods within each emissions database into account, we combine the three emission intensity measures using the following preference order: CDP > Thomson Reuters > Sustainalytics. |
| *Public Perception* | |
| Environmental Score (Thomson Reuters) | The environmental score consists of three subscores: Resource Use Score, Emissions Score, and Innovation Score. The Resource Use Score reflects a company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management. The Emission Reduction Score measures a company's commitment and effectiveness towards reducing environmental emission in the production and operational processes. The Innovation Score reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes or eco-designed products. |
| Environmental Pillar Score (MSCI) | The Environmental Pillar Score represents the weighted average of all Key Issues that fall under the Environment Pillar. Among others, it contains the following key issues: carbon emissions, product carbon footprint, financing environmental impact, climate change vulnerability, opportunities in clean tech, green building, and renewable energy. |
| Performance Band (CDP) | The performance band represents a score which assesses progress towards environmental stewardship as reported by a company's CDP response. The score assesses the level of detail and comprehensiveness of the content, as well as the company's awareness of climate change issues, management methods, and progress towards action taken on climate change as reported in the response. |
| Environmental Score (Sustainalytics) | The research framework broadly addresses three themes: Environmental, Social, and Governance. Within these themes, the focus is placed on a set of key ESG issues that vary by industry. The key ESG issues are the most material areas of exposure and, therefore, define key management areas for the company. The key ESG issues were identified based on an analysis of the peer group and its broader value chain, a review of companies' business models, the identification of key activities associated with environmental and/or social impacts, and an analysis of the business impacts that may result from inadequate management of these factors. |
| *Adaptability* | |
| Environmental Innovation Score (Thomson Reuters) | The Environmental Innovation Score reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes or eco-designed products |

*(to be continued)*

**Table A.2 continued**

| | |
|---|---|
| Carbon Emissions Score (MSCI) | This key issue is relevant to those companies with significant carbon footprints. Companies that proactively invest in low-carbon technologies and increase the carbon efficiency of their facilities score higher on this key issue. Companies that allow legal compliance to determine product strategy, focus exclusively on activities to influence policy setting, or rely heavily on exploiting differences in regulatory frameworks score lower. |
| Preparedness (Sustainalytics) | Preparedness measures an issuer's level of commitment to manage environmental risks. It is assessed by analyzing the quality of an issuer's policies, programmes, and systems to manage environmental issues effectively. |

This table provides short variable descriptions of the carbon and transition-related variables from the Thomson Reuters ESG, Carbon Disclosure Project (CDP), MSCI ESG, and Sustainalytics ESG datasets used to construct the firm-specific Brown-Green-Score (*BGS*).

Table A.2 presents all variables used to construct the *BGS*. A short description is compiled from various methodology sheets of each data provider.

**Table A.3**
**Transition probabilities of firms**

**Panel A. from year *t* − 1 to year *t***

| Portfolio | $SL_t$ | $SN_t$ | $SH_t$ | $BL_t$ | $BN_t$ | $BH_t$ |
|---|---|---|---|---|---|---|
| $SL_{t\text{-}1}$ | 94.30% | 1.93% | 0.19% | 3.44% | 0.11% | 0.02% |
| $SN_{t\text{-}1}$ | 1.96% | 92.67% | 1.91% | 0.12% | 3.13% | 0.20% |
| $SH_{t\text{-}1}$ | 0.16% | 1.70% | 95.05% | 0.01% | 0.10% | 2.98% |
| $BL_{t\text{-}1}$ | 1.64% | 0.05% | 0.01% | 96.82% | 1.31% | 0.18% |
| $BN_{t\text{-}1}$ | 0.07% | 1.98% | 0.08% | 1.93% | 93.63% | 2.31% |
| $BH_{t\text{-}1}$ | 0.01% | 0.05% | 2.02% | 0.18% | 2.29% | 95.46% |

**Panel B. from year *t* − 5 to year *t***

| Portfolio | $SL_t$ | $SN_t$ | $SH_t$ | $BL_t$ | $BN_t$ | $BH_t$ |
|---|---|---|---|---|---|---|
| $SL_{t\text{-}5}$ | 81.93% | 7.08% | 0.98% | 9.03% | 0.88% | 0.10% |
| $SN_{t\text{-}5}$ | 7.42% | 73.84% | 7.96% | 1.00% | 8.48% | 1.29% |
| $SH_{t\text{-}5}$ | 0.70% | 6.89% | 82.51% | 0.07% | 0.88% | 8.95% |
| $BL_{t\text{-}5}$ | 3.33% | 0.24% | 0.04% | 90.07% | 5.52% | 0.81% |
| $BN_{t\text{-}5}$ | 0.35% | 3.97% | 0.46% | 8.61% | 77.48% | 9.13% |
| $BH_{t\text{-}5}$ | 0.07% | 0.41% | 4.33% | 0.89% | 9.20% | 85.10% |

This table provides the transition probabilites of firms between the six size/*BGS* sorted portfolios: “small/high *BGS*” (*SH*), “big/high *BGS*” (*BH*), “small/low *BGS*” (*SL*), “big/low *BGS*” (*BL*), “small/neutral *BGS*” (*SN*), and “big/neutral *BGS*” (*BH*).

Table A.3 provides the transition probabilities of firms between the six size/*BGS* sorted portfolios. If a firm is placed within, e.g., the *SL* portfolio, it will be assigned to the same portfolio next year with a probability of 94.30% and five years later with a probability of 81.93%.

## Internet Appendix B

### Further asset pricing tests

We conduct excluded factor regression coefficient estimates for several common factor models (Barillas and Shanken, 2017). Then, we measure the mean absolute alpha for each factor in four different factor models. Technically, we explain in a first step each factor by a respective reference model and determine its alpha. In a second step, we calculate the mean average alpha considering the whole reference model under the condition that the alphas for the factors already included in each model are zero. The mean average alpha functions as decision criteria which factor to include in common factor models.

[Insert Table B.1 here.]

Over the period from January 2010 to December 2017, the mean absolute alpha is determined for each factor within each panel. The results in Panel A of Table B.1 suggest that we should first include the factor with the lowest mean absolute alpha of 0.0403, *SMB*, into the CAPM. As a second factor the *BMG* factor should be included next into the reference model with a value of 0.065. Over all other panels, this analysis clearly favors including the *BMG* factor into common factor models.

**Table B.1**
**Excluded factor regression coefficient estimates for different models**

**Panel A. Excluded-factor regressions for the CAPM model: {*Mktrf*}**

| LHS | Alpha | $er_M$ | Mean \|Alpha\| | Adj. $R^2$ |
|---|---|---|---|---|
| *SMB* | 0.0806 | -0.00678 | 0.0403 | -0.010 |
| | (0.57) | (-0.19) | | |
| *HML* | -0.136 | 0.0750* | 0.068 | 0.019 |
| | (-0.80) | (1.69) | | |
| *BMG* | -0.13 | 0.0203 | 0.065 | -0.009 |
| | (-0.73) | (0.44) | | |

**Panel B. Excluded-factor regressions for the Fama/French model: {*Mktrf SMB HML*}**

| LHS | Alpha | $er_M$ | *SMB* | *HML* | Mean \|Alpha\| | Adj. $R^2$ |
|---|---|---|---|---|---|---|
| *WML* | 0.55 | -0.0880 | -0.0190 | -0.516*** | 0.1375 | 0.139 |
| | (2.37) | (-1.45) | (-0.11) | (-3.71) | | |
| *BMG* | -0.00097 | -0.00160 | 0.0898 | 0.300*** | 0.0002418 | 0.059 |
| | (-0.56) | (-0.04) | (0.71) | (2.89) | | |

**Panel C. Excluded-factor regressions for the Fama/French 5F model: {*Mktrf SMB HML*}**

| LHS | Alpha | $er_M$ | *SMB* | *HML* | Mean \|Alpha\| | Adj. $R^2$ |
|---|---|---|---|---|---|---|
| *RMW* | 0.377 | -0.116*** | -0.305*** | -0.316*** | 0.1885 | 0.514 |
| | (4.37) | (-5.16) | (-4.77) | (-6.08) | | |
| *CMA* | 0.148 | -0.0477** | -0.0458 | 0.352*** | 0.074 | 0.514 |
| | (1.71) | (-2.10) | (-0.71) | (6.72) | | |
| *BMG* | -0.104 | 0.00005 | 0.0903 | 0.293*** | 0.052 | 0.060 |
| | (-0.60) | (0.00) | (0.70) | (2.80) | | |

**Panel D. Excluded-factor regressions for the Fama/French 6F model: {*Mktrf SMB HML RMW CMA*}**

| LHS | Alpha | $er_M$ | *SMB* | *HML* | *RMW* | *CMA* | Mean \|Alpha\| | Adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|
| *WML* | 0.246 | 0.00808 | 0.221 | -0.639*** | 0.509* | 0.762*** | 0.0615 | 0.239 |
| | (1.02) | (0.12) | (1.22) | (-3.44) | (1.92) | (2.89) | | |
| *BMG* | -0.186 | 0.0254 | 0.157 | 0.366** | 0.221 | -0.00681 | 0.0465 | 0.050 |
| | (-0.96) | (0.49) | (1.09) | (2.46) | (1.04) | (-0.03) | | |

This table provides excluded factor regression coefficient estimates for common factor models in the sample period from January 2010 to December 2017. The global factors $er_M$, *SMB*, *HML*, *WML*, *RMW*, *CMA*, and the risk-free rate are provided by Kenneth French.

In this section, we stick to the “Protocol for Factor Identification” of Pukthuanthong et al. (2019) and follow their two-step procedure. For the first stage, we show that the *BMG* factor moves asset prices systematically, i.e., that it is related to the covariance matrix of returns – a necessary condition for a factor to be relevant. We deal with the second stage in section 4.5.1.

We extract principal components (PCs) from the returns of our global stock dataset using the asymptotic principal components approach of Connor and Korajczyk (1988). The extracted PCs should have an eigenvalue greater than one.[20] For our global dataset, we obtain thirteen PCs that fulfill this requirement.

Next, we compute canonical correlations between the PCs and factors from the Carhart (1997) model and the *BMG* factor. In total, we have $K = 5$ factors. Thus, we have two sets for calculating canonical correlations. Let $u_K$ be the canonical scores out of the set of factors and $v_L$ the canonical scores out of the set of PCs (with $L = 13$). The procedure now allows to determine weights for the linear combinations of the factors and PCs, respectively, which maximize the correlation between both sets. Thus, a canonical variate that maximizes the correlation using the weights can be constructed. One then repeats this procedure to obtain another canonical variate that is orthogonal to the previous one. In total, there are $\min(K, L)$ canonical variates, i.e., in our case five pairs of $u_K$ and $v_L$. The canonical correlations are displayed in Panel A of Table B.2 sorted from the highest to the lowest correlation. We also test the canonical correlations for significance according to Wilks’ lambda. F-statistics for each canonical correlation are displayed in the third column of Panel A. The first canonical correlation is large and close to one with a value of 0.924. Only the fifth correlation falls below 0.5 and is not significantly different from zero at the 5% level with an F-statistic of 0.951.

[20] One could choose also other threshold values, e.g., the cumulative variance explained by the PCs. In our analysis, the extracted PCs explain approximately 60% of global return variances. If we choose a cutoff value of 90% of explained variance, we need more PCs, however, the results remain economically the same.

As Pukthuanthong et al. (2019), we test the significance of each factor using the following procedure. We use the weights for the PCs of each of the canonical pairs to construct the weighted average PC, i.e., the canonical variate that produces the respective canonical correlation. For each of these canonical variates, we run a regression with the variate as dependent variable and the actual factor values as independent variables. Panel B of Table B.2 reports the average absolute t-statistic for each factor resulting from the five regressions. We also report the mean absolute t-statistic when taking only the significant canonical correlations into account. When the canonical correlation is statistically indistinguishable from zero, the factors are irrelevant and using them would be overfitting. Thus, we exclude insignificant canonical correlations in the second row of Panel B.

[Insert Table B.2 here.]

As expected, the market factor $er_M$ displays the highest mean absolute t-statistic. The *BMG* factor follows with a t-statistic of 4.13 and 5.03, respectively. A factor is deemed as relevant if the t-statistic exceeds the one-tailed 2.5% cutoff (1.96). According to this cutoff value, the *BMG* factor is highly significant, but also *SMB*, *HML*, and *WML* show significance. From this analysis, we conclude that the *BMG* factor is related to the covariance matrix of returns and thus passes the necessary condition for being a relevant factor.

**Table B.2**
**Canonical correlations with asymptotic PCs and significance levels of factors**

**Panel A. Canonical correlations**

| Canonical variate | Canonical correlation | F-stat |
|---|---|---|
| 1 | 0.924 | 7.902 |
| 2 | 0.865 | 4.826 |
| 3 | 0.560 | 2.193 |
| 4 | 0.517 | 1.847 |
| 5 | 0.307 | 0.951 |

**Panel B. Significance levels for factors**

| | Factors | | | | |
|---|---|---|---|---|---|
| | $er_M$ | *SMB* | *HML* | *WML* | *BMG* |
| Mean absolute t-stat | 5.44 | 2.93 | 3.03 | 2.20 | 4.13 |
| Mean absolute t-stat of significant canonical correlation | 6.69 | 3.54 | 3.33 | 2.05 | 5.03 |

This table shows canonical correlations between the Principal Components (PCs) and the global market factor, *SMB*, *HML*, *WML*, and the *BMG* factor. We follow the methodology described in Pukthuanthong et al. (2019) to derive the results of this table. Panel A reports five canonical correlations and their respective F-statistics obtained from Wilks' lambda test. Panel B reports the significance level for the respective factor. In order to obtain the t-statistic, each PC canonical variate is regressed on all of the factors for the whole sample period. Since there are five pairs of canonical variates, there are five regressions in total. Panel B reports the average absolute t-statistic for each factor over the five regressions in the first row. The second row reports the mean absolute t-statistic when the canonical correlation itself is statistically significant at the 5% level.

As a further robustness test, we show that the *BMG* factor is a relevant factor and is related to the covariance matrix of returns for the back-casted sample period from January 2002 to December 2017.

[Insert Table B.3 here.]

The results remain basically unchanged. The *BMG* factor shows a mean absolute t-statistic of 5.62 and thus ranks second after the market factor (see Table B.3). When taking into consideration only significant canonical correlations, the *BMG* factor improves and displays a mean absolute t-statistic of 6.95. These results confirm that the *BMG* factor is relevant in the explanation of the covariance structure of returns even for a longer time horizon.

**Table B.3**
**Canonical correlations with asymptotic PCs and significance levels of factors for the long time period**

**Panel A. Canonical correlations**

| Canonical variate | Canonical correlation | F-stat |
|---|---|---|
| 1 | 0.881 | 11.481 |
| 2 | 0.856 | 8.243 |
| 3 | 0.679 | 4.278 |
| 4 | 0.486 | 2.215 |
| 5 | 0.241 | 0.829 |

**Panel B. Significance levels for factors**

| | Factors | | | | |
|---|---|---|---|---|---|
| | $er_M$ | *SMB* | *HML* | *WML* | *BMG* |
| Mean absolute t-stat | 5.84 | 5.28 | 3.15 | 1.80 | 5.62 |
| Mean absolute t-stat of significant canonical correlation | 6.84 | 6.56 | 3.78 | 1.47 | 6.95 |

This table shows canonical correlations between the Principal Components (PCs) and the global market factor, *SMB*, *HML*, *WML*, and the *BMG* factor for the time period from January 2002 to December 2017. We follow the methodology described in Pukthuanthong et al. (2019) to derive the results of this table. Panel A reports five canonical correlations and their respective F-statistics obtained from Wilks' lambda test. Panel B reports the significance level for the respective factor. In order to obtain the t-statistic, each PC canonical variate is regressed on all of the factors for the whole sample period. Since there are five pairs of canonical variates, there are five regressions in total. Panel B reports the average absolute t-statistic for each factor over the five regressions in the first row. The second row reports the mean absolute t-statistic when the canonical correlation itself is statistically significant at the 5% level.

## Internet Appendix C

### Orthogonalization

We are aware of the fact that the *BMG* factor might include effects from other risk factors. Therefore, we perform several analyses based on a democratic orthogonalization introduced by Klein and Chow (2013), so that our factor is perfectly uncorrelated to the other risk factors of the Carhart (1997) model. They emphasize that an asset’s volatility does not only depend on the sensitivities towards the risk factors, the betas, but also by the variances and covariances of them. A simultaneous orthogonalization of all risk factors allows disentangling the uncorrelated component from the correlated components by eliminating the covariance between factors while maintaining the variance structure and the coefficient of determination. Thereby, we isolate the effect the *BMG* factor explains excluding the effects other risk factors already capture.

Table C.1 displays the descriptive statistics of the orthogonalized factors. As desired, the standard deviation of the respective orthogonalized factor does not change compared to its original counterpart. Also, the correlation between the factors is set to 0. The mean excess return decreases in absolute values to −0.09. Nevertheless, the correlations between the non-orthogonalized factor and the respective orthogonalized factor are still high and suggest a high resemblance. In fact, the correlations are 0.986, 0.996, 0.999, 0.959, and 0.979 for the *BMG* factor, $er_M$, *SMB*, *HML*, and *WML*, respectively.

[Insert Table C.1 here.]

Applying the orthogonalized factors to our previous analyses leads to the following conclusions. For the *BGS* quintile portfolio performance, there are basically no changes in our reasoning (Table C.2). Note that although the newly estimated beta coefficients for the orthogonalized factors may change in magnitude and direction, the alpha and the adjusted $R^2$

values remain the same by construction. However, most values are very similar. In addition, the *BMG* factor continues to be highly significant for the extreme portfolios and increases monotonically from the lowest to the highest quintile.

[Insert Table C.2 here.]

Democratic orthogonalization also allows determining the specific contribution of each factor to the variation in the dependent variable via a decomposition of a regression's $R^2$ (see also Klein and Chow, 2013). It thus provides a tool for identifying useless factors in the explanation of excess returns. Table C.3 shows that in the highest *BGS* quintile, the orthogonalized *BMG* factor explains 13.31% of variation in stock returns, whereas *SMB*, for example, only captures 1.15%. In general, the *BMG* factor is especially important for the extreme quintiles, whereas it barely adds to the explanatory power in the middle quintiles 2 and 3. Overall, these results of the $R^2$-decomposition show once more that the *BMG* factor captures exactly what it is supposed to – it explains a significant part of the systematic risk of firms overly sensitive to the transition process of the economy towards a green economy.

[Insert Table C.3 here.]

Additionally, Table C.4 shows the average decomposed-$R^2$ values of the orthogonalized factors on single stock level. Single stock regressions are run with the orthogonalized factors of the Carhart + *BMG* model. The average systematic $R^2$ sums up to 21.14% and the average idiosyncratic variance obtained from the systematic variance is 78.86%. As expected, the market factor $er_M$ explains the most variation in excess returns with an average decomposed-$R^2$ of 12.89%, while $BMG^{\perp}$ is, with an average contribution of 2.28%, approximately on the same level as $SMB^{\perp}$ with 2.38%, and well above the level of $HML^{\perp}$ with 1.68% and $WML^{\perp}$ with 1.90%. Therefore, the orthogonalized *BMG* factor can explain a relevant amount of variance in stock returns.

[Insert Table C.4 here.]

Next, we again assess the importance of our factor related to the significance of its coefficient in single stock regressions. Table C.5 displays the amount of significant coefficients based on the 10%, 5%, and 1% significance level, respectively. The results are very similar to the results without orthogonalized factors. The average coefficient of the orthogonalized *BMG* factor slightly increases to 0.251. To sum up, we notice once again that our orthogonalized *BMG* factor does not stand behind the other factors.

[Insert Table C.5 here.]

**Table C.1**
**Descriptive statistics - orthogonalized factors**

| Factor | Mean excess return (%) | SD (%) | t-stat. | Correlations | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | *BMG* | $er_M$ | *SMB* | *HML* | *WML* |
| $BMG^{\perp}$ | -0.09 | 1.70 | -0.50 | 0.986 | | | | |
| $er_M^{\perp}$ | 0.97 | 3.78 | 2.50 | | 0.996 | | | |
| $SMB^{\perp}$ | 0.08 | 1.33 | 0.60 | | | 0.999 | | |
| $HML^{\perp}$ | -0.01 | 1.65 | -0.09 | | | | 0.959 | |
| $WML^{\perp}$ | 0.58 | 2.37 | 2.40 | | | | | 0.979 |

This table displays descriptive statistics of the monthly democratically orthogonalized factors of the global Carhart model and the *BMG* factor for the sample period from January 2010 to December 2017. Correlations are reported between the orthogonalized factors and the original factors. The original global factors $er_M$, *SMB*, *HML*, and *WML* are provided by Kenneth French.

**Table C.2**
**Quintiles with orthogonalized factors**

| Quintile | Coefficient | | | | | | Adj. $R^2$ (%) | Δ Coefficent | | | | | Δ Adj. $R^2$ (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Alpha | $er_M^{\perp}$ | $SMB^{\perp}$ | $HML^{\perp}$ | $WML^{\perp}$ | $BMG^{\perp}$ | | Δ Alpha | Δ $er_M^{\perp}$ | Δ $SMB^{\perp}$ | Δ $HML^{\perp}$ | Δ $WML^{\perp}$ | |
| Low | 0.00 | 1.04*** | 0.15** | 0.10 | -0.24*** | -0.26*** | 94.74% | 0.000a | 0.000a*** | 0.000a* | 0.190a | -0.120a** | 1.42*** |
| | (-0.36) | (40.66) | (2.11) | (1.65) | (-5.95) | (-4.53) | | | | | | | |
| 2 | 0.00 | 0.98*** | 0.26*** | 0.02 | -0.16*** | -0.08 | 92.88% | 0.000a | -0.010a*** | 0.000a*** | 0.140a | -0.100a | 0.12 |
| | (1.50) | (34.91) | (3.20) | (0.31) | (-3.60) | (-1.25) | | | | | | | |
| 3 | 0.00 | 1.09*** | 0.18** | 0.15** | -0.21*** | 0.04 | 94.41% | 0.000a | 0.000a*** | -0.020a** | 0.130a | -0.130a* | -0.06 |
| | (-0.60) | (39.66) | (2.35) | (2.45) | (-4.88) | (0.60) | | | | | | | |
| 4 | 0.00 | 1.06*** | 0.21** | 0.24*** | -0.33*** | 0.51*** | 92.80% | 0.000a | 0.020a*** | -0.040a** | 0.080a | -0.130a*** | 3.03*** |
| | (-1.39) | (33.45) | (2.33) | (3.32) | (-6.56) | (7.18) | | | | | | | |
| High | 0.00 | 1.06*** | 0.37*** | 0.09 | -0.30*** | 0.98*** | 93.34% | 0.000a | 0.010a*** | -0.060a*** | 0.020a | -0.110a** | 12.36*** |
| | (-0.52) | (33.07) | (4.06) | (1.25) | (-5.84) | (13.78) | | | | | | | |
| High-Low | 0.00 | 0.02 | 0.22*** | -0.01 | -0.06 | 1.24*** | 84.94% | | | | | | |
| | (-0.32) | (0.83) | (3.14) | (-0.08) | (-1.44) | (22.98) | | | | | | | |

This table shows the alpha performance and beta coefficients for orthogonalized factors of the Carhart + $BMG^{\perp}$ model for annually rebalanced, equal-weighted quintile portfolios based on the *BGS* of the stocks for the period from January 2010 to December 2017. On the right panel, the table displays Δ alphas and coefficients between the Carhart + $BMG^{\perp}$ model and the Carhart model. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively. For alphas and beta coefficients, significance statistics are based on two-sided t-tests. [c], [b], and [a] denote significance on the 10%, 5%, and 1% level, respectively, for Δ values. Tests on the differences of coefficients are based on two-sided t-tests of bootstrapped Δ values. Significance symbols in the last column are based on the one-sided F-test for nested models ($H_0$: $\beta_i^{BMG^{\perp}} = 0$).

**Table C.3**
**Decomposition of $R^2$**

| Quintile | Decomposed-$R^2$ $er_M^{\perp}$ | $SMB^{\perp}$ | $HML^{\perp}$ | $WML^{\perp}$ | $BMG^{\perp}$ | Systematic $R^2$ (%) | Idiosyncratic Variance $(1-R^2)$ (%) |
|---|---|---|---|---|---|---|---|
| Low | 91.52 | 0.25 | 0.15 | 1.96 | 1.14 | 95.02 | 4.98 |
| 2 | 91.39 | 0.77 | 0.01 | 0.97 | 0.12 | 93.25 | 6.75 |
| 3 | 92.60 | 0.33 | 0.35 | 1.40 | 0.02 | 94.70 | 5.30 |
| 4 | 84.77 | 0.41 | 0.84 | 3.26 | 3.91 | 93.18 | 6.82 |
| High | 76.71 | 1.15 | 0.11 | 2.39 | 13.31 | 93.69 | 6.31 |

This table shows the decomposed-$R^2$ of each democratically orthogonalized factor for the global *BGS* quintiles. The systematic variance is the sum of all decomposed-$R^2$, whereas the idiosyncratic variance equals $1-R^2$. The original global factors $er_M$, *SMB*, *HML*, and *WML* are provided by Kenneth French.

**Table C.4**
**Decomposition of $R^2$ with orthogonalized factors on single stock level**

| Avg. decomposed-$R^2$ (%) | | | | | Avg. Systematic $R^2$ (%) | Avg. Idiosyncratic Variance ($1-R^2$) (%) |
|---|---|---|---|---|---|---|
| $er_M^{\perp}$ | $SMB^{\perp}$ | $HML^{\perp}$ | $WML^{\perp}$ | $BMG^{\perp}$ | | |
| 12.89 | 2.38 | 1.68 | 1.90 | 2.28 | 21.14 | 78.86 |

This table shows the average decomposed-$R^2$ values of orthogonalized factors. The systematic risk is decomposed following the methodology of Klein and Chow (2013). Regressions are run based on the Carhart + *BMG* model with single stocks. The overall average systematic $R^2$ and the average idiosyncratic variance obtained from the systematic variance on single stock level are displayed.

**Table C.5**
**Significance tests for factor betas for the Carhart + *BMG* model**

| | Avg. coefficient | T-test of significance of coefficients: 10% level # | 10% level % | 5% level # | 5% level % | 1% level # | 1% level % |
|---|---|---|---|---|---|---|---|
| $BMG^{\perp}$ | 0.251 | 4,245 | 20.97 | 2,930 | 14.47 | 1,374 | 6.79 |
| $er_M^{\perp}$ | 0.958 | 15,672 | 77.41 | 14,295 | 70.61 | 11,167 | 55.16 |
| $SMB^{\perp}$ | 0.846 | 4,864 | 24.02 | 3,151 | 15.56 | 1,189 | 5.87 |
| $HML^{\perp}$ | 0.121 | 2,880 | 14.23 | 1,696 | 8.38 | 529 | 2.61 |
| $WML^{\perp}$ | -0.306 | 3,406 | 16.82 | 2,041 | 10.08 | 691 | 3.41 |

This table provides a summary of significance tests of beta coefficients with orthogonalized risk factors. Regressions are run based on the Carhart + $BMG^{\perp}$ model on single stock level. The average coefficients as well as the absolute (#) and relative (%) numbers of statistically significant beta coefficients from the democratically orthogonalized Carhart + $BMG^{\perp}$ model regressions run on single stocks in the sample period from January 2010 to December 2017 are displayed. Statistical significance is based on two-sided t-tests.

## Internet Appendix D

### Further risk decomposition

For the risk decomposition, we use the VAR methodology of Campbell (1991) and assume that the data are generated by this first-order VAR model:

$$\boldsymbol{z}_{t+1} = \boldsymbol{a} + \boldsymbol{\Gamma}\, \boldsymbol{z}_t + \boldsymbol{u}_{t+1}\ , \tag{D.1}$$

where $\boldsymbol{z}_{t+1}$ is an m-by-1 state vector with $BMG_{t+1}$ as its first element, $\boldsymbol{a}$ and $\boldsymbol{\Gamma}$ are an m-by-1 vector and m-by-m matrix of constant parameters, and $\boldsymbol{u}_{t+1}$ is an i.i.d. m-by-1 vector of shocks. Provided that the process in Equation (D.1) generates the data, $t$+1 cash-flow and discount-rate news are linear functions of the $t$+1 shock vector:

$$N_{DR,t+1} = \boldsymbol{e1}'\boldsymbol{\lambda}\, \boldsymbol{u}_{t+1}\ , \tag{D.2}$$

$$N_{CF,t+1} = (\boldsymbol{e1}' + \boldsymbol{e1}'\boldsymbol{\lambda})\, \boldsymbol{u}_{t+1}\ , \tag{D.3}$$

where $\boldsymbol{e1}$ is a vector with the first element equal to one and the others equal to zero and $\lambda = \rho\, \boldsymbol{\Gamma}\, (\boldsymbol{I} - \rho\, \boldsymbol{\Gamma})^{-1}$.[21]

In specifying the aggregate VAR, we follow Campbell and Vuolteenaho (2004) by choosing global proxies for the four state variables. First, we use the log return on *BMG*. Second, we add the term yield spread (TY) as a weighted average of country specific interest rates by Thomson Reuters Datastream.[22] TY is computed as the yield difference between the ten-year and the two-year treasury constant-maturity rate and denoted in percentage points. We construct our third variable, the price-earnings ratio (PE), as the log of the price of the Thomson Reuters Equity Global Index divided by the aggregate earnings of all firms in the index. Fourth, the small-stock value spread (VS) is the difference between the log book-to-market value of the

[21] We set $\rho$ close to one as defined in Campbell and Vuolteenaho (2004).
[22] We use the weighting scheme of the MSCI World index as of the end of our sample period.

small high-book-to-market portfolio and the log book-to-market value of the small low-book-to-market portfolio.[23]

The unexpected return variance is decomposed into three components following Campbell (1991):

$$\mathrm{Var}(BMG_t - E_{t\text{-}1}BMG_t) = \mathrm{Var}(N_{CF}) + \mathrm{Var}(N_{DR}) - 2\,\mathrm{Cov}(N_{CF}, N_{DR}), \tag{D.4}$$

$$1 = \frac{\mathrm{Var}(N_{CF})}{\mathrm{Var}(BMG_t - E_{t\text{-}1}BMG_t)} + \frac{\mathrm{Var}(N_{DR})}{\mathrm{Var}(BMG_t - E_{t\text{-}1}BMG_t)} - 2\,\frac{\mathrm{Cov}(N_{CF}, N_{DR})}{\mathrm{Var}(BMG_t - E_{t\text{-}1}BMG_t)}\,. \tag{D.5}$$

For the beta decomposition, we use the same approach, however, the first state variable equals the excess market return ($r_M$).

For the decomposition of the market beta into a cash-flow and a discount-rate beta we use the computation method of Campbell and Vuolteenaho (2004):

$$\beta_{i,CF} = \frac{\mathrm{Cov}\left(r_{i,t}, N_{CF}\right)}{\mathrm{Var}(r_{M,t} - E_{t\text{-}1}r_{M,t})}, \tag{D.6}$$

$$\beta_{i,DR} = \frac{\mathrm{Cov}\left(r_{i,t}, -N_{DR}\right)}{\mathrm{Var}(r_{M,t} - E_{t\text{-}1}r_{M,t})}, \tag{D.7}$$

where $r_{i,t}$ is the return of a specific test asset.

In addition, Figure D.1 uses the methodology described above to decompose the *BMG* beta into a cash-flow and discount-rate news component. As expected, for both brown and green extreme portfolios, the *BMG* beta is mainly determined by the cash-flow beta component – solely with an opposite sign, i.e., negatively for green and positively for brown portfolios, respectively.

[23] The portfolios are constructed using all firms in the Thomson Reuters Equity Global Index following the approach of Fama and French (1993). As suggested in Chen and Zhao (2009), we used several state variable sets to determine the news components. Our results remain stable.

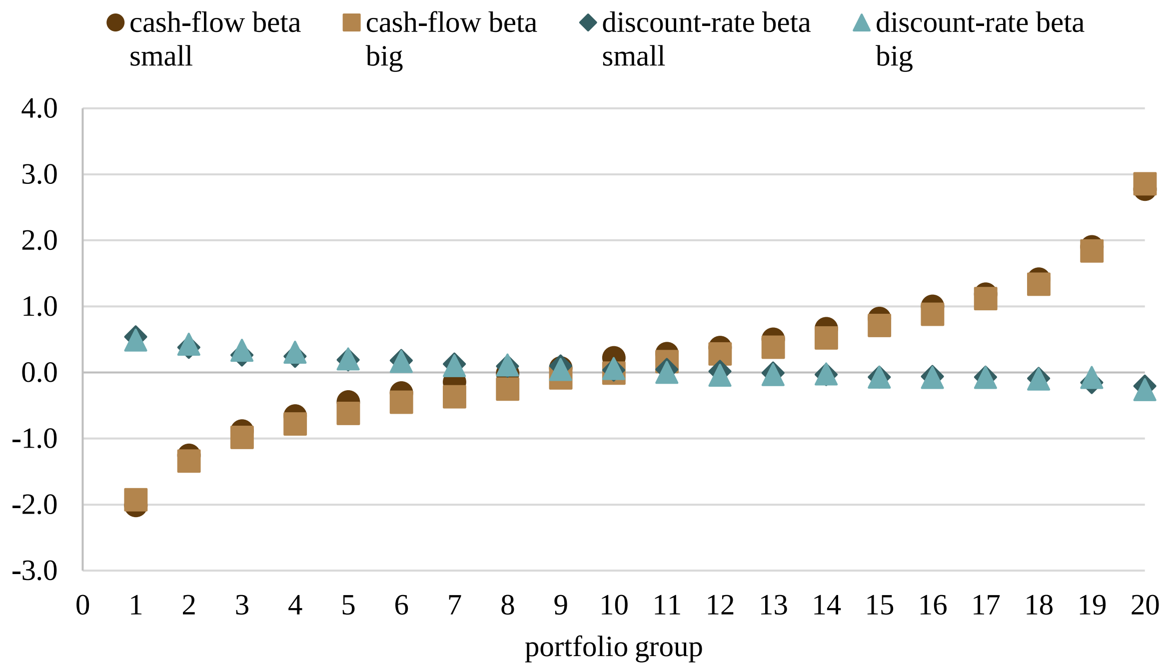



**Figure D.1**
***BMG* Beta decomposition of 40 *BMG* beta sorted portfolios**

This figure shows the *BMG* beta decomposition of the 40 test assets built out of the global sample. The 40 test assets are constructed by sorting all stocks into 20 5%-quantiles based on their *BMG* beta (portfolio group) and splitting each portfolio by the stocks' median market capitalization. The cash-flow and discount-rate betas are obtained by following the methodology of Campbell and Vuolteenaho (2004) with the *BMG* factor as the first state variable.

# 5 ARTICLE IV: GET GREEN OR DIE TRYING? CARBON RISK INTEGRATION INTO PORTFOLIO MANAGEMENT

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(VHB-JOURQUAL3: B)

**Abstract.** Portfolio management is confronted with climate change – stronger and more rapidly than expected. Risks arising from the transition process from a brown, carbon-based to a green, low-carbon economy need to be integrated into portfolio and risk management. We show how to quantify these carbon risks by using a capital markets-based approach. Our measure of carbon risk, the carbon beta, can serve as an integral part to portfolio management practices in a more comprehensive way than fundamental carbon risk measures. Apart from other studies, we demonstrate that both green and brown stocks are risky per se, but there is no adequate remuneration in the financial market. In addition, carbon risk exposure is correlated with exposures towards other common risk factors. This requires due diligence when integrating carbon risk in investment practices. By implementing carbon risk screening and best-in-class approaches, we find that investors can gain a desired level of carbon risk exposure, but this does not come without well-hidden costs.

*JEL Classification*: G11, Q54

*Keywords*: ESG investing, portfolio construction, equity portfolio management, carbon risk, climate change

# 6 ARTICLE V: INVESTORS' DELIGHT? CLIMATE RISK IN STOCK VALUATION DURING COVID-19 AND BEYOND

Andrea Jacob, Martin Nerlinger

Working Paper (2021), University of Augsburg and University of St. Gallen

**Abstract.** We use the COVID-19 pandemic period in 2020 as an exogenous shock event to assess in how far climate risks measured by carbon exposure have entered and established themselves in the valuation of global stocks. We find that carbon intensity affected returns significantly negatively during a time of high uncertainty. However, carbon-intensive stocks could make up for their additional losses in the recovery period. In line with their high risk exposure towards stranded assets and climate policy uncertainty, carbon-intensive stocks face higher risk levels in more stable economic times thus justifying a carbon premium.

*JEL Classification*: G01, G11, G12, Q54

*Keywords*: Climate risk, COVID-19, investment decisions, equity returns

## 6.1 Introduction

Making decisions under uncertainty is one of the indispensable tasks of financial market participants. Dealing with uncertainty involves the proper management of risk. In recent times, investors have had to learn how to cope with a new impending risk source: climate change. Environmental-related risks such as extreme weather events, climate action failure, and human-made environmental damage rank among the top risks by likelihood and impact in the World Economic Forum's Global Risks Report 2021. Apart from physical risks, technological innovations and climate policy measures targeted towards reaching a low-carbon economy may result in stranded assets (Mercure et al., 2018). Governments worldwide are committed towards combatting climate change by reducing carbon emissions (see, e.g., the Paris Agreement of 2015) and clients increasingly demand sustainable investments (Amel-Zadeh and Serafeim, 2018). Hence, climate risks have evolved as real investment risks for financial assets with an expected reallocation of capital towards sustainable investments (Fink, 2021; Krueger et al., 2020).

Even though investors recognize that climate risks have financial impacts on their portfolios, the financial industry still has to elaborate on how to incorporate these risks in their investment practices (Krueger et al., 2020). When one trusts in the reliability of the financial market, asset prices should mirror all available information (Fama, 1970). Therefore, a re-evaluation of assets is essential for managing climate risks. Based on a fundamental stock analysis, the value of carbon-intensive stocks should be impacted by their high exposure towards stranded assets, technological changes, and potential carbon emission mitigation plans such as carbon pricing or carbon taxes (Bolton and Kacperczyk, 2020; Andersson et al., 2016; de Jong and Nguyen, 2016; Litterman, 2011).

Financial market participants drastically revise their expectations on how to evaluate assets when extreme situations occur. Such re-evaluations eventually become apparent in a consequential fall or rise in asset prices. The economic downturn at the beginning of the COVID-19 pandemic in early 2020 constitutes such an extreme tail-risk event that has induced investors to a re-evaluation of their holdings leading to a dramatic drop in stock market values worldwide (e.g., Zhang et al., 2020; Shehzad et al., 2020; Lyócsa et al, 2020; Ashraf, 2021). We use this exogenous shock to assess in how far carbon emissions have entered the valuation process of equity prices. Such an exogenous shock that has arisen unexpectedly allows us to analyze investors' preferences towards carbon-related characteristics while holding carbon intensity levels constant. Since the awareness for climate risk has intensified in recent years, we are now at a point in time with sufficient and adequate data to test implications for stock analyses. The recent pandemic thus provides a first opportunity to derive implications of the integration of climate-related aspects on the stock valuation process. In this way, we gain deeper insights into how carbon intensity establishes itself as a fundamental characteristic in stock analysis during and after a period of heightened uncertainty and fear.

In literature, the role of carbon emissions in stock valuation is studied in different setups. Matsumura et al. (2014) find a negative relation between carbon emissions and firm value and an additional penalty for non-disclosure of emissions. Chava (2014) finds that firms with climate change concerns have to bear higher cost of equity capital and debt capital. In contrast, Delmas et al. (2015) and Busch et al. (2020) both come to the conclusion that higher carbon emissions increase at least short-term performance while disagreeing on their impact on long-term performance. Recent studies focus on a risk premium for holding emissions-intensive stocks. Hsu et al. (2020) attribute the existence of a pollution premium to environmental policy uncertainty. Bolton and Kacperczyk (2020) find a carbon premium that is related to the level of and to changes in carbon emissions. The existence of a carbon premium is consistent with the notion that carbon-intensive stocks face higher tail risks associated with climate policy uncertainty (Ilhan et al., 2021).

Studies on the relationship between stock characteristics, returns, and resilience during crisis periods constitute another relevant strand of literature for our study. For example, Duchin et al. (2010) find that low cash reserves and high net short-term debt led to a greater decline of corporate investment during the Global Financial Crisis (GFC). For the COVID-19 period, markets valued firms lower that were more exposed to international trades, higher corporate debt, and lower cash holdings (Ramelli and Wagner, 2020). In addition, socially responsible and sustainable funds measured by Environmental, Social, and Governance criteria (ESG) have turned out to provide more resilience during the GFC (Lins et al., 2017) and the COVID-19 shock (Albuquerque et al., 2020).

The reasons on why markets and investors impose higher valuations on more sustainable stocks during crisis periods are manifold. Investors have higher trust in sustainable firms (Lins et al., 2017), are more patient, i.e., more loyal (Broadstock et al., 2021; Albuquerque et al., 2020), meanwhile perceive sustainability as a necessity rather than a luxury good (Pástor and Vorsatz, 2020), and have higher preferences for sustainable funds (Hartzmark and Sussman, 2019; Riedl and Smeets, 2017). Additionally, studies prove the risk mitigation potential of sustainable stock traits (e.g., Bouslah et al., 2018; Nofsinger and Varma, 2014).

This study analyzes how climate risk enters the re-evaluation considerations of investors in times of high uncertainty and beyond. Climate risk exposure is best approximated by carbon emissions since they constitute the target measure of climate policies and political agreements. Following the recommendation guidelines of the Task Force on Climate-Related Financial Disclosures (TCFD, 2017) and thus the industry standard in disclosing carbon information for investors, we use carbon intensity as our measure of interest. Our study is most closely related to Wan et al. (2021) and Mukanjari and Sterner (2020). The former compare Chinese fossil fuel and clean energy firms during the COVID-19 period, whereas the latter assess European stock performance during the crisis period based on carbon intensities. Instead of constraining our study to a certain region, we employ a global stock sample. Moreover, to the best of our knowledge, we are the first to address post-crisis implications, i.e., we investigate how investors incorporate carbon characteristics in their valuations in more stable times following the COVID-19 initial shock period.

A first descriptive analysis demonstrates that high-emitting stocks had significantly lower returns and higher traditional risk measures than low-emitting stocks during the COVID-19 period. In cross-sectional regressions, we find that carbon intensity indeed influenced cumulative returns and abnormal returns negatively during the crisis period. This impact strengthens the higher a stock's carbon intensity level. To infer whether the effect is unique to the crisis period and not common to the previous, rather calm economic time, we conduct difference-in-differences regressions on daily return measures. We confirm that high emitters experienced a significantly lower financial performance during the COVID-19 period compared to the pre-crisis period. Hence, investors rather shunned these stocks in times of high economic uncertainty and drove returns of carbon-intensive stocks down. In the post-COVID-19 period, however, high emitters achieved a significantly higher performance than in the pre-crisis period, thus allowing them to make up for some of their additional losses incurred during the crisis period compared to low emitters.

Cross-sectional regressions with volatility and idiosyncratic volatility as dependent variables show that carbon intensity had no significant impact on risk during the crisis period. The major drivers of risk in this period were other firm characteristics such as debt, profitability, and historical volatility. However, high emitters turned out to be significantly riskier relative to low emitters. Eventually, for the post-COVID-19 period, the effect of carbon intensity on volatility turned significantly positive. Increasing risk for carbon-intensive stocks is in line with their higher risk exposure towards stranded assets and climate policy regulation targeted at reducing carbon emissions. Moreover, discussions on combining monetary economic stimulus packages with climate change targets might have magnified risk exposures for carbon-based assets. Apart from that, our results in the post-crisis period, i.e., higher risk exposure and higher returns for carbon-intensive stocks, are in line with discussions about the existence of a carbon premium in the financial market (Bolton and Kacperczyk, 2020).

In summary, carbon-intensive stocks had to suffer from lower returns during the unexpected COVID-19 period and displayed higher risk exposures afterwards. Our results emphasize the importance of fully incorporating climate risks in stock valuation practices. Climate risks constitute an unavoidable risk source and thus have to be part of sound risk management strategies. Our analyses point to the fact that market participants have already shunned carbon-intensive stocks during the COVID-19 shock period driving their returns downward. In addition, increased societal and political interest in a green economic development – exemplified by green recovery packages – imposes an ever higher risk burden on carbon-based stocks. Overall, this study supports financial market participants in deriving more profound forecasts and stock recommendations, constructing more resilient portfolios, and eventually avoiding excessive risk-taking due to an unidentified risk source.

## 6.2 Data description

For our empirical analyses, we use a global stock sample based on stocks of the MSCI All Countries World Investable Market Index (ACWI IMI). We obtain scope 1 and scope 2 carbon emissions data from three sources: CDP, Refinitiv, and Sustainalytics. Since reporting of carbon emission levels is not mandatory yet, we have to face limited data availability. To overcome this shortcoming, we enlarge our data sample by combining the aformentioned databases. If no CDP emissions are available for a stock, the data point is filled by Refinitiv and eventually Sustainalytics. Emissions data refer to 2019 yearly values. In our analyses, we use carbon intensity defined as the sum of scope 1 and 2 emissions divided by a firm's net sales. This is a standard approach for measuring carbon intensity in research (Bolton and Kacperczyk, 2020) and finance practice (TCFD, 2017). To distinguish between high and low carbon-intensive stocks more rigidly, we label all stocks with a carbon intensity higher than the 75th percentile as "high emitters" and the remaining stocks as "low emitters".

We obtain daily return data from Refinitiv Datastream for the years 2019 and 2020. Furthermore, we extract December 2019 accounting data known to influence returns, i.e., size measured by the logarithm of market capitalization, total debt over total assets, cash holdings over total assets, the leverage ratio, return on equity as profitability measure, expenses for selling, general and administrative functions (SGAE), the dividends ratio, and the book value of equity for calculating the book-to-market ratio. We additionally define historical volatility as a stock's daily return volatility during the year 2019. Our key variables are defined as follows. Apart from daily raw excess returns, we calculate abnormal daily returns as the difference between raw excess returns and CAPM-adjusted excess returns. Both for the COVID-19 and post-COVID-19 periods, we compute cumulative returns and cumulative abnormal returns. In addition, return volatility and idiosyncratic volatility (defined as abnormal return volatility) during each period serve as risk measures. Overall, with these definitions, we follow prior studies such as Ramelli and Wagner (2020), Albuquerque et al. (2020), and Lins et al. (2017).

Descriptive statistics of all variables used in this article are summarized in Table 1. In total, we obtain carbon intensity data for 3,247 stocks. At the intersection of all relevant data points for our baseline analyses, we are left with 2,589 global stocks.

[Insert Table 1 here.]

In order to obtain clear-cut results for the impact of the COVID-19 pandemic, we define a more intensive crisis period for COVID-19 from February, 24th until March, 31st in line with previous papers (start of the "fever period" in Ramelli and Wagner (2020) and the "COVID-19 event date" in Albuquerque et al. (2020)). The subsequent period from April, 1st until the end of the year 2020 is defined as the post-COVID-19 or post-crisis period. Even though the COVID-19 pandemic still defines our daily lives one year after the global outbreak, stock markets recovered fairly well from April 2020 on. We explain this circumstance by the fact that the first outbreak and the following lockdowns in February 2020 have been surprising and until then unique in nature. Hence, they constituted an unforeseen shock event. After that, further waves and consequential lockdowns have been expected and propagated by health experts and economists. Stock analysts thus had the possibility to take potential impacts on financial assets into account in their valuation processes. In fact, we did not observe another severe market downturn following March 2020.

As a first motivation for our study, we have a look at the stock market performance and the performance of the high-emitter (brown) and low-emitter (green) portfolio during 2020 in Figure 1. For the stock market, we take the MSCI ACWI IMI as a basis and report both equal- and value-weighted brown and green portfolios.

In line with the overall market, the decline in the portfolio performance was limited to the COVID-19 period from February, 24th to March, 31st. After that, both portfolios recovered from this shock. Moreover, the high emitters (brown portfolio) declined more in the crisis period, but were able to recover their additionally incurred loss in the course of the year compared to the green portfolio. The aim of this study is to elaborate on this observation and find proof that market participants incorporate carbon intensity in their valuation processes of assets.

[Insert Figure 1 here.]

### 6.3 Key characteristics of high versus low emitters

We start with a simple comparison of key performance and risk indicators during the COVID-19 and post-COVID-19 period for high and low emitters. By construction, average carbon intensity levels are far higher for high emitters than low emitters (see Table 2). During the crisis period, mean and median daily returns were significantly lower for high emitters, whereas all volatility measures point to a higher riskiness of carbon-intensive stocks. For example, the maximum drawdown amounted to 40.68% for high emitters in contrast to 37.36% for low emitters. The Value at Risk (VaR) at a 95% confidence level was 1.86% significantly lower (i.e., riskier) for carbon-intensive stocks. With 99% confidence, investors had to face an additional worst daily loss of 2.85% for high emitters.

In line with expectations, during the post-COVID-19 period, daily returns turned positive and risk measures were only a fraction of those during the crisis period. For example, the maximum drawdown values reduced to a tenth of those during the COVID-19 period. This underlines the severity of the stock market crash during February and March 2020. Levels of daily returns were comparable among the two groups, whereas risk measures were higher for carbon-intensive stocks taking account of their higher climate risk exposure. Solely the maximum drawdown displayed no significant differences.

[Insert Table 2 here.]

In summary, we find significant differences in key return and risk indicators of high versus low emitters. In the following, we analyze in how far these differences arise due to carbon intensity having entered the valuation process of market participants.

## 6.4 Methodological framework

In a first step, we determine the influence of carbon intensity on daily stock returns during the COVID-19 and post-COVID-19 period. For this purpose, we use cross-sectional regressions following Equation (1).

$$\begin{aligned} r_i = \beta_0 + \beta_1\, carbon\_int_i + \boldsymbol{\beta_k}\, \boldsymbol{controls}_i + \\ \boldsymbol{\delta}\, \boldsymbol{ind\_fixed\_effects}_i + \boldsymbol{\gamma}\, \boldsymbol{country\_fixed\_effects}_i + \varepsilon_i\,, \end{aligned} \tag{1}$$

where $r_i$ is the performance measure of stock *i* in the respective period, $carbon\_int_i$ its carbon intensity, and $\boldsymbol{controls}_i$ a vector of firm characteristics at their 2019 values including size, debt, profitability, cash intensity, SGAE intensity, historical volatility, dividends, and the book-to-market ratio. By including these firm-specific characteristics, we ensure that the return-influencing effect we attribute to carbon intensity is not driven by other factors correlated with carbon intensity.

As performance measures, we use both the cumulative daily excess return and the cumulative abnormal return over the respective period. We also include industry and country fixed effects. In this way, we take into account that industries and countries were impacted differently by the COVID-19 shock (Mazur et al., 2021; Ashraf, 2021). In addition, climate policies targeted at the reduction of carbon emissions vary greatly among countries and have different impacts on industries. For example, while the European Union takes over a leadership role in the area of climate action, the USA relaxed environmental regulations under the Trump administration rendering their climate action critically insufficient.[1] The inclusion of fixed effects thus avoids that the coefficient of carbon intensity, $\beta_1$, captures mere industry and country effects.

Equation (1) serves as our baseline model. In subsequent analyses, we divide stocks into carbon intensity quartiles and replace $carbon\_int_i$ with dummies for the quartiles two to four. The lowest quartile thus constitutes the reference group. This altered model allows us to dissect the effects of carbon intensity in a more detailed way dependent on the level of carbon intensity.

In a second step, we estimate the effect of carbon intensity on both the total and idiosyncratic volatility of stocks in the crisis and post-crisis period. For this purpose, we use a

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[1] Climate Action Tracker provides a comprehensive overview and analysis of climate action by country and sector: https://climateactiontracker.org/.

stock's excess return volatility and its abnormal return volatility (as idiosyncratic volatility) in the respective time period as dependent variables in Equation (1).

For the validity of our study, it is important that the influence of carbon intensity significantly changed during the crisis or post-crisis period compared to the pre-crisis period. Under this circumstance, we can conclude that investors incorporate carbon intensity as a fundamental characteristic in their asset re-evaluations during shock periods and beyond and attribute value-influencing traits to carbon emissions.

To infer whether investors evaluate carbon intensity significantly differently during extreme shock periods and pre- and post-shock times, we make use of a difference-in-differences model following Lins et al. (2017), Bouslah et al. (2018), and Albuquerque et al. (2020):

$$\begin{gathered} r_{i,t} = \beta_1\, treated_i \times COVID_t + \beta_2\, treated_i \times Post\text{-}COVID_t + \\ \beta_3\, treated_i + \beta_4\, COVID_t + \beta_5\, Post\text{-}COVID_t + \boldsymbol{\beta_k}\, \boldsymbol{controls_i} + \\ \boldsymbol{\delta}\, \boldsymbol{ind\_fixed\_effects_i} + \boldsymbol{\gamma}\, \boldsymbol{country\_\, fixed\_effects_i} + \varepsilon_i\,, \end{gathered} \tag{2}$$

where $r_{i,t}$ is the daily excess return or abnormal return of stock $i$ at time $t$, $treated_i$ is a dummy variable equal to one for stocks in the highest quartile measured by carbon intensity, $COVID_t$ a dummy variable equal to one for all days between February, 24th and March, 31st, and $Post\text{-}COVID_t$ a dummy that identifies days between April 2020 and December 2020. The regression is run based on observations from January 2020 to December 2020. Therefore, we also capture a pre-crisis period with this setup. Furthermore, we include the same control variables as in Equation (1) and industry and country fixed effects. Hence, our results are not distorted by firm-specific, industry, or country effects. Standard errors are clustered at the firm level.

Our main measures of interest are the coefficients of the interaction terms. The coefficient $\beta_1$ ($\beta_2$) describes the additional return effect high emitters had to face explicitly during the COVID-19 (post-COVID-19) period. If $\beta_1$ ($\beta_2$) is significantly different from zero, we observe a significant difference between the pre-crisis and the COVID-19 period (post-crisis period) for high emitters. $\beta_3$ captures the return effect for high emitters compared to low emitters in the pre-crisis period. $\beta_4$ and $\beta_5$ mirror performance impacts of the crisis and post-crisis period, respectively. The total return effect for high emitters in the crisis period amounts to $\beta_1 + \beta_3 + \beta_4$, and for the post-crisis period to $\beta_2 + \beta_3 + \beta_5$.

### 6.5 The interconnection between carbon intensity and performance

Table 3 summarizes the results of our baseline model. During the COVID-19 period, carbon intensity had a significant negative effect on both raw and abnormal cumulative returns. To be more specific, an increase of one standard deviation in carbon intensity (1.3581) decreased cumulative daily (abnormal) returns by 0.3667% (1.3581×0.0027) and 0.4482%, respectively. Hence, carbon intensity had a higher impact on stock-specific abnormal returns compared to cumulative returns. Even though the return impacts appear small in nature, we have to bear in mind that this effect realizes for only 27 trading days (the COVID-19 period). The annual return loss would amount to around 3.40% and 4.15% for a one-standard deviation increase in carbon intensity, which emphasizes its economic significance.[2]

Besides that, we can confirm results of previous studies that lower debt and higher cash had a significant positive influence on returns during the pandemic period (Ramelli and Wagner, 2020; Albuquerque et al., 2020). In addition, larger and more profitable firms achieved significantly higher performance during COVID-19 (in line with Ramelli and Wagner, 2020;

[2] As an approximation, we break down the effect during the COVID-19 period on one day and subsequently scale it to 250 trading days.

Albuquerque et al., 2020). High historical volatility impacted cumulative returns negatively, but had a reverse effect on abnormal returns. This shows a stock's high dependence on systematic risk exposures.

[Insert Table 3 here.]

After the exogenous shock, the significant impact of carbon intensity vanishes (columns (3) and (4)). Our results point to the fact that investors facing a period of high uncertainty are more aware of long-term risks and increase their stakes in potentially safe haven stocks. The COVID-19 pandemic has proven that a highly improbable risk can suddenly materialize. Climate risks, in contrast, are far from being improbable to occur – they will materialize either in form of physical impacts or policy regulations. Thus, investors might have drawn the conclusion to withdraw their funds from riskier and potential stranded assets driving the performance of such assets downwards. In the recovery period, however, there was no reversal or multiplier effect of carbon intensity on returns because investors had already revised their stock valuations during the crisis period.

In our second analysis for the relationship between carbon intensity and financial performance, we dissect this effect further. We re-run our baseline model and replace the carbon intensity measure with dummy variables indicating the quartile group of stocks based on their carbon intensity. We exclude the dummy variable for quartile one, so that all effects are estimated relative to our lowest emitting group.

High emitters achieved a 2.8% lower cumulative return in the COVID-19 period compared to low emitters (Table 4, column (1)). The return difference to low emitters decreases the more similar stocks become with regard to their carbon intensity measure. Medium emitters have a 1.9% lower return than low emitters, whereas there are no significant differences between the two lowest emitting quartiles. We find an even more pronounced pattern for abnormal cumulative returns (column (2)). High emitters lost a significant 3.6% in abnormal returns compared to low-emitting stocks. This return difference diminishes to 1.9% for lower emitting stocks.

In the post-COVID-19 period, the effect reverses but is not statistically significant anymore. Hence, during the calmer post-COVID-19 period, there was no significant difference between the carbon groups. In other words, during the recovery phase, the level of carbon intensity did not drive return patterns. This result reinforces our conclusions drawn from Table 3. Overall, this analysis emphasizes that the higher the carbon intensity of stocks, the higher their performance loss during the shock period.

[Insert Table 4 here.]

Following Lins et al. (2017) and Albuquerque et al. (2020), we conduct a difference-in-differences regression to investigate whether our return effect is uniquely found for the COVID-19 period or common to most periods. Table 5 contains the results both for daily excess and abnormal returns. The treated variable equals 1 for high emitters, i.e., stocks with a carbon intensity in the highest quartile.

[Insert Table 5 here.]

Compared to the pre-COVID-19 period, stocks lost 0.96% in performance during COVID-19. In contrast, returns in the post-COVID-19 period were higher by 0.31%. This mirrors the fast recovery of the overall stock market during the course of the year 2020. High emitters lost an additional 0.099% in return compared to low emitters in the pre-crisis period. More importantly, high emitters had to forgo an additional 0.17% in performance compared to low emitters in the COVID-19 period. This effect is statistically significant, so that we conclude that high emitters had to suffer significantly more during the shock period compared to the more stable pre-crisis period. In the post-COVID-19 period, in contrast, high emitters gained an additional significant

0.15% compared to the pre-crisis period. Hence, even the post-crisis period differed significantly from the pre-crisis period in that carbon-intensive stocks recovered faster. In summary, the total return effect for high emitters in the COVID-19 (post COVID-19) period amounted to –1.229% (0.361%), which is significantly different to the pre-crisis period.

This reinforces our previous results that investors modified their valuations of carbon-intensive stocks and valued them lower in times of high uncertainty. In the post-COVID-19 time, however, carbon-intensive stocks could recover more than low emitters. Higher returns also speak for the fact that investors might demand a premium for holding carbon-risky stocks as suggested by Bolton and Kacperczyk (2020), for example.

In order to assess in how far the relevance of carbon intensity for returns changed over time, we plot the evolution of the coefficient of carbon intensity obtained in a recursive window regression with daily excess returns as dependent variable and the control variables of Equation (1) as further independent variables (similar to Ramelli and Wagner, 2020). For the first estimation at the beginning of the year 2020, we use data for all trading days during 2019 and for each further day, we add the additional day to our estimation window.

We note that the coefficient remains negative throughout the year (see Figure 2). However, sensitivities towards carbon intensity are especially pronounced in the COVID-19 period. The relevance of carbon intensity thus intensified during the uncertain crisis period confirming our previous results. In the post-COVID-19 period, the coefficient is absolutely lower and less volatile but keeps its negative influence on returns.

[Insert Figure 2 here.]

### 6.6 The impact of carbon intensity on risk

In the previous section, we found that investors re-evaluated especially carbon-intensive stocks during the market downturn. Now, we focus on their risk profile during and after the pandemic period. Table 6 repeats the cross-sectional regressions of Table 3 with volatility and idiosyncratic volatility as dependent variables. In columns (1) and (2), we find that carbon intensity had no significant impact on stock risk during the crisis period. Risk was rather driven by other fundamentals such as debt, profitability, SGAE intensity, historical volatility, and dividends. The pattern changes in the post-COVID-19 period (columns (3) and (4)). Carbon intensity influenced stock volatility and idiosyncratic volatility significantly positive. In more stable times, carbon intensity drives stock risk. This is in line with the argumentation that carbon-intensive stocks face higher long-term risks. Furthermore, in the aftermath of the first lockdown, discussions heightened on whether to use economic stimulus packages to drive the long-term transition towards a low-carbon economy (Andrijevic et al., 2020; Mukanjari and Sterner, 2020). Shan et al. (2021) state that fiscal stimulus plans can either be a threat to global climate change mitigation or a jumpstart to achieve emission targets. For example, as of March 2021, the Energy Policy Tracker estimates that around 36% of monetary commitments for the energy sector in G20 countries are targeted towards the production and consumption of fossil fuels (Energy Policy Tracker, 2021). Investing in carbon-intensive assets increases the risk of incurring more stranded assets in the future (Andrijevic et al., 2020). In either case – support for carbon-intensive assets or green stimulus packages – carbon-intensive stocks have to face higher climate risk exposures.

[Insert Table 6 here.]

For our last analysis, we repeat the regressions of Table 4 with risk measures as dependent variables. When focusing on emitter groups, we find important differences between high and low emitters (see Table 7). Returns of high emitters are significantly more volatile than low emitters irrespective of the time period in question. For example, high emitters faced a 0.24% higher idiosyncratic volatility than low emitters during the COVID-19 period (column (2)). In the post-COVID-19 period, this effect decreased to 0.18% but remained significant. These results emphasize that extremely carbon-intensive stocks have to suffer from higher risk exposures than low-carbon stocks. Even during the crisis period, high emitters prove to be relatively riskier than their cleaner counterparts. This is in line with our argumentation that high emitters face high climate risks due to stranded assets and climate policy uncertainty.

[Insert Table 7 here.]

## 6.7 Robustness tests

To ensure the validity of our results, we conducted several robustness test.[3] First, we enlarged the COVID-19 period and focused on the first quarter of 2020 as a crisis period. Thus, we take into consideration that the COVID-19 pandemic has already started to spread as early as January 2020. In fact, the World Health Organization was first informed of cases of pneumonia of unknown cause in China on 31 December 2019 (World Health Organization, 2020). From this date on, events accelerated justifying the definition of a larger crisis period. The results for the first quarter 2020 are comparable to our more focused COVID-19 period.

Second, we conducted the cross-sectional regressions of Equation (1) without fixed effects. For the difference-in-differences specification, we replaced the control variables for firm characteristics with firm fixed effects. All results remained stable.

Last, instead of relying on carbon intensity, we conducted all analyses based on absolute carbon emissions. Bolton and Kacperczyk (2020) discover that the carbon premium is related to absolute emissions levels but not to carbon intensity. They justify their finding with the explanation that climate regulations target activities with high emissions levels. Taking absolute carbon emissions levels as our variable of interest does not alter our findings.

[3] All results are available upon request from the authors.

## 6.8 Conclusion

In recent years, climate risks have materialized as investment risks for financial assets (Fink, 2021). Financial market participants are thus expected to incorporate this impending risk source in their stock valuation processes. We use the downturn of the stock market during the COVID-19 period in early 2020 as an exogenous shock to assess in how far market participants incorporated carbon intensity (as measure for climate risk exposure) in their re-evaluation considerations of stocks during and after the crisis period. The COVID-19 period constituted a time of heightened uncertainty and fear leading investors to re-evaluate their assets and preferences. It thus provides an opportunity to measure the impact of carbon intensity on stock returns and risk while holding carbon intensity levels constant. Furthermore, we analyze the subsequent recovery period to infer to what extent carbon intensity has established itself as a fundamental stock characteristic in stock analysis.

In a first descriptive analysis, high emitting stocks had lower returns and higher risk measures during the COVID-19 period. In cross-sectional regressions, we find that carbon intensity had a significantly negative impact on returns and abnormal returns during the crisis period. This effect was more pronounced the higher the carbon intensity level was. Furthermore, carbon-intensive stocks gained significantly more in the post-COVID-19 recovery period compared to the pre-crisis period. Hence, they could make up for their additional losses incurred during the crisis period compared to low-emitting stocks.

Focusing on the risk perspective, carbon intensity did not have a significant effect in the COVID-19 period. Risk was rather driven by other firm characteristics such as debt and profitability. However, high emitters were still significantly riskier than low emitters. For the post-crisis period, the relationship between carbon intensity and risk turned significantly positive. Discussions on green economic stimulus packages and long-term risk exposures to stranded assets might have reinforced the riskiness of carbon-based assets. Higher risk and higher returns in the recovery period are also in line with the discussion on the existence of a carbon premium in stock markets (Bolton and Kacperczyk, 2020).

Our results clearly show that market participants incorporate carbon intensity in their stock valuation considerations. More importantly, our results point to the assumption that high emitters are perceived as riskier and thus are more prone to being shunned by investors especially during times of high economic and societal uncertainty. With our study, we reinforce the need to account for climate risks in investment decisions. Their integral assessment allows more profound risk management strategies, more accurate stock analyses with more precise forecasts and stock recommendations, and thus might impede huge losses in unforeseen crisis periods. With the COVID-19 pandemic, we had to learn that improbable risks can materialize quickly and have huge impacts on our portfolios. Hedging highly probable climate risks thus can turn out as a winning strategy in the future avoiding a rude awakening.

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## Tables and Figures

**Table 1**
**Descriptive statistics**

| Variable | N | Mean | SD | P25 | Median | P75 |
|---|---|---|---|---|---|---|
| Carbon Intensity | 3,247 | 0.3374 | 1.3581 | 0.0088 | 0.0371 | 0.2025 |
| Cum. Ret. COVID-19 | 3,234 | -0.2789 | 0.1536 | -0.3830 | -0.2697 | -0.1678 |
| Cum. Ret. post-COVID-19 | 3,230 | 0.6401 | 0.5086 | 0.2554 | 0.5291 | 0.8811 |
| Cum. AR COVID-19 | 3,245 | -0.1127 | 0.1859 | -0.2393 | -0.1114 | 0.0207 |
| Cum. AR post-COVID-19 | 3,230 | 0.1626 | 0.4123 | -0.1292 | 0.0653 | 0.3615 |
| Volatility COVID-19 | 3,245 | 0.0584 | 0.0208 | 0.0424 | 0.0549 | 0.0703 |
| Volatility post-COVID-19 | 3,245 | 0.0493 | 0.0178 | 0.0361 | 0.0453 | 0.0587 |
| Idio. Volatility COVID-19 | 3,230 | 0.0276 | 0.0093 | 0.0206 | 0.0258 | 0.0326 |
| Idio. Volatility post-COVID-19 | 3,230 | 0.0255 | 0.0089 | 0.0188 | 0.0238 | 0.0300 |
| Size | 2,977 | 15.5062 | 1.3882 | 14.4591 | 15.4784 | 16.5134 |
| Debt | 2,916 | 0.2837 | 0.1656 | 0.1506 | 0.2783 | 0.4046 |
| Profitability | 2,862 | 0.1093 | 0.1105 | 0.0473 | 0.1005 | 0.1625 |
| Cash Intensity | 2,724 | 0.0860 | 0.0729 | 0.0283 | 0.0653 | 0.1238 |
| SGAE Intensity | 3,247 | 0.0921 | 0.1077 | 0.0000 | 0.0487 | 0.1492 |
| Historical Volatility | 3,247 | 0.0184 | 0.0059 | 0.0137 | 0.0175 | 0.0222 |
| Dividends | 3,247 | 0.7989 | 1.3879 | 0.0193 | 0.0653 | 0.8850 |
| BTM | 3,180 | 0.6905 | 0.4949 | 0.3003 | 0.5780 | 0.9524 |
| Daily Return | 826,568 | 0.0538 | 3.2432 | -1.3899 | 0.0118 | 1.4601 |
| Daily Abnormal Return | 826,568 | -0.0030 | 2.8618 | -1.3690 | -0.0678 | 1.2658 |

This table provides descriptive statistics of all variables used in this study. The (abnormal) cumulative return and (idiosyncratic) volatility are given for each respective period. Carbon intensity is defined as the sum of scope 1 and 2 emissions over net sales. Control variables are defined as follows: size is measured as the natural logarithm of the market capitalization. Debt represents total debt over total assets. Profitability is measured by the return on equity calculated as net income less preferred dividend requirements over the average of last year's and current year's common equity. Cash intensity represents cash holdings over total assets. SGAE intensity represents the expenses for selling, general, and administrative functions over total assets. The historical volatility is the daily return volatility of a firm during 2019. Dividends are measured as a ratio to the stock price. The book-to-market ratio (BTM) is calculated as a firm's book value over its market value. Daily (abnormal) return is given in percent.

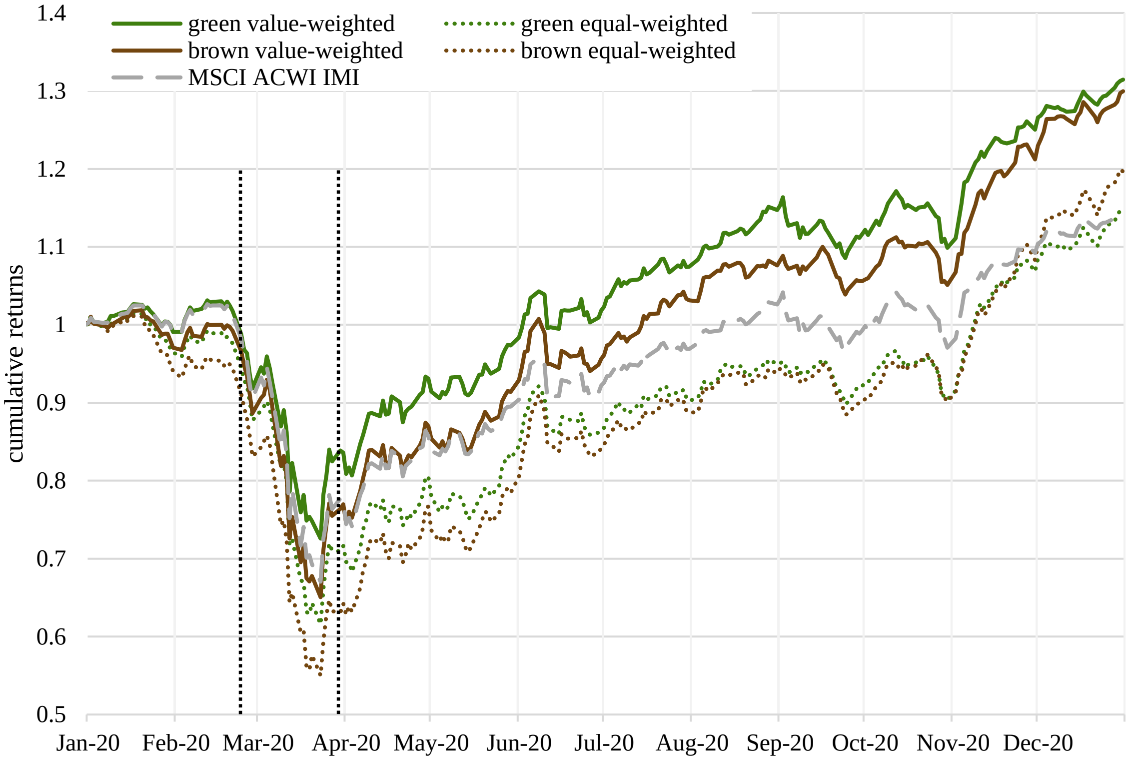


**Figure 1**
**Stock performance during the year 2020**

This figure plots the development of the MSCI ACWI IMI and four stock portfolios from 01/01/2020 to 12/31/2020. The brownish (greenish) color indicates portfolios consisting of high (low) emitting firms. The vertical lines enclose the COVID-19 period as defined in the text.

**Table 2**
**Comparison of key characteristics between high and low carbon emitters during and after the COVID-19 period**

| | COVID-19 | | Post-COVID-19 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | High Emitters | Low Emitters | High Emitters | Low Emitters |
| Carbon Intensity | 0.7306 | 0.0369 | 0.7333 | 0.0371 |
| | | (0.6937***) | | (0.6961***) |
| Mean Daily Return | -0.0132 | -0.0107 | 0.0033 | 0.0025 |
| | | (-0.0025***) | | (0.0008***) |
| Median Daily Return | -0.0146 | -0.0128 | 0.0013 | 0.0012 |
| | | (-0.0018***) | | (0.0001) |
| Volatility | 0.0684 | 0.0571 | 0.0321 | 0.027 |
| | | (0.0113***) | | (0.0051***) |
| VaR 25% | -0.0509 | -0.0426 | -0.0147 | -0.0128 |
| | | (-0.0082***) | | (-0.0020***) |
| VaR 10% | -0.0968 | -0.0818 | -0.0311 | -0.0271 |
| | | (-0.0150***) | | (-0.0039***) |
| VaR 5% | -0.1188 | -0.1001 | -0.043 | -0.0376 |
| | | (-0.0186***) | | (-0.0054***) |
| VaR 1% | -0.1619 | -0.1334 | -0.0769 | -0.0662 |
| | | (-0.0285***) | | (-0.0106***) |
| Maximum Drawdown | 0.4068 | 0.3736 | 0.0428 | 0.0441 |
| | | (0.0332***) | | (-0.0014) |
| Observations | 811 | 2,433 | 807 | 2,423 |

This table provides a comparison of different key characteristics for high and low carbon emitters in the COVID-19 period (02/24/2020 to 03/31/2020) and the post-COVID-19 period (04/01/2020 to 12/31/2020). High Emitters represent high carbon intensity firms in the last carbon intensity quartile, and Low Emitters represent low carbon intensity firms in the first to third carbon intensity quartiles. Return, volatility, VaR, and maximum drawdown measures are given in absolute values. Differences (high emitters – low emitters) and their significance levels are displayed in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 3**
**Influence of carbon intensity on financial performance during and after the COVID-19 period**

| | COVID-19 | | Post-COVID-19 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Return | Abnormal Return | Return | Abnormal Return |
| Carbon Intensity | -0.0027*** | -0.0033** | -0.0039 | -0.0032 |
| | (-2.85) | (-2.51) | (-0.81) | (-0.67) |
| Size | 0.0074*** | 0.030*** | 0.012 | -0.043*** |
| | (3.57) | (10.57) | (1.53) | (-6.30) |
| Debt | -0.068*** | -0.063*** | 0.071 | 0.063 |
| | (-4.76) | (-3.09) | (1.21) | (1.26) |
| Profitability | 0.15*** | 0.19*** | -0.17 | -0.40*** |
| | (5.99) | (5.29) | (-1.64) | (-4.72) |
| Cash Intensity | 0.15*** | 0.29*** | 0.057 | -0.088 |
| | (4.53) | (6.08) | (0.41) | (-0.74) |
| SGAE Intensity | -0.0031 | 0.062 | 0.11 | 0.15* |
| | (-0.12) | (1.64) | (1.00) | (1.73) |
| Historical Volatility | -5.80*** | 1.52** | 34.6*** | 7.57*** |
| | (-10.83) | (2.01) | (15.57) | (4.07) |
| Dividends | -0.0054* | -0.0020 | -0.015 | -0.0083 |
| | (-1.76) | (-0.48) | (-1.33) | (-0.83) |
| BTM | -0.0090 | 0.049*** | -0.0055 | 0.070*** |
| | (-1.46) | (5.52) | (-0.20) | (2.95) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Observations | 2,589 | 2,589 | 2,587 | 2,587 |
| Adjusted $R^2$ | 0.4937 | 0.3329 | 0.3544 | 0.2689 |

This table provides the results of cross-sectional regressions for the COVID-19 period (02/24/2020 to 03/31/2020) and the post-COVID-19 period (04/01/2020 to 12/31/2020). The dependent variable is defined as the (abnormal) cumulative return during the respective period. All variables are as defined in Table 1. Industry and country fixed effects are included in all specifications and heteroscedasticity-robust standard errors are estimated. T-statistics are provided in parentheses. $^{*}$, $^{**}$, and $^{***}$ indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 4**
**Influence of carbon intensity quartiles on financial performance during and after the COVID-19 period**

| | COVID-19 | | Post-COVID-19 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Return | Abnormal Return | Return | Abnormal Return |
| High Emitter | -0.028*** | -0.036*** | 0.045 | 0.045 |
| | (-3.18) | (-2.84) | (1.27) | (1.48) |
| Medium Emitter | -0.019*** | -0.022** | 0.011 | 0.013 |
| | (-2.68) | (-2.24) | (0.40) | (0.54) |
| Lower Emitter | -0.0090 | -0.019** | -0.0055 | 0.015 |
| | (-1.29) | (-2.01) | (-0.21) | (0.67) |
| Size | 0.0080*** | 0.031*** | 0.011 | -0.044*** |
| | (3.87) | (10.89) | (1.46) | (-6.39) |
| Debt | -0.063*** | -0.056*** | 0.065 | 0.058 |
| | (-4.37) | (-2.77) | (1.12) | (1.16) |
| Profitability | 0.15*** | 0.18*** | -0.16 | -0.39*** |
| | (5.91) | (5.26) | (-1.57) | (-4.68) |
| Cash Intensity | 0.14*** | 0.27*** | 0.074 | -0.073 |
| | (4.21) | (5.86) | (0.53) | (-0.61) |
| SGAE Intensity | -0.013 | 0.052 | 0.12 | 0.17* |
| | (-0.50) | (1.34) | (1.17) | (1.86) |
| Historical Volatility | -5.75*** | 1.59** | 34.6*** | 7.54*** |
| | (-10.77) | (2.12) | (15.56) | (4.05) |
| Dividends | -0.0052* | -0.0017 | -0.015 | -0.0089 |
| | (-1.70) | (-0.40) | (-1.35) | (-0.89) |
| BTM | -0.0068 | 0.052*** | -0.0097 | 0.066*** |
| | (-1.10) | (5.79) | (-0.35) | (2.79) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Observations | 2,589 | 2,589 | 2,587 | 2,587 |
| Adjusted $R^2$ | 0.4951 | 0.3342 | 0.3546 | 0.2690 |

This table provides the results of cross-sectional regressions for the COVID-19 period (02/24/2020 to 03/31/2020) and the post-COVID-19 period (04/01/2020 to 12/31/2020). The dependent variable is defined as the (abnormal) cumulative return during the respective period. We use dummy variables for carbon intensity quartiles such that High Emitter takes the value of one if the firm is in the last carbon intensity quartile and zero otherwise, Medium Emitter takes the value of one if the firm is in the third carbon intensity quartile and zero otherwise, and Lower Emitter takes the value of one if the firm is in the second carbon intensity quartile and zero otherwise. Control variables are as defined in Table 1. Industry and country fixed effects are included in all specifications and heteroscedasticity-robust standard errors are estimated. T-statistics are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 5**
**Difference-in-differences model results**

| | (1)<br>Return | (2)<br>Abnormal Return |
|---|---|---|
| High Emitter × COVID | -0.0017*** | -0.0013*** |
| | (-4.46) | (-3.03) |
| High Emitter × Post-COVID | 0.0015*** | 0.0015*** |
| | (8.30) | (8.50) |
| High Emitter | -0.00099*** | -0.00098*** |
| | (-6.27) | (-5.88) |
| COVID-19 | -0.0096*** | -0.0023*** |
| | (-51.19) | (-12.39) |
| Post-COVID-19 | 0.0031*** | 0.0015*** |
| | (40.46) | (19.72) |
| Controls | Yes | Yes |
| Industry fixed effects | Yes | Yes |
| Country fixed effects | Yes | Yes |
| Observations | 644,255 | 644,255 |
| Adjusted $R^2$ | 0.01789 | 0.003481 |

This table presents results of difference-in-differences regressions for daily excess and abnormal returns. High Emitter equals one for high carbon intensity firms in the last carbon intensity quartile and zero otherwise. COVID-19 equals one from 02/24/2020 to 03/31/2020, and Post-COVID-19 equals one from 04/01/2020 to 12/31/2020. Control variables, industry, and country fixed effects are included in all specifications. Standard errors are clustered at the firm level. T-statistics are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

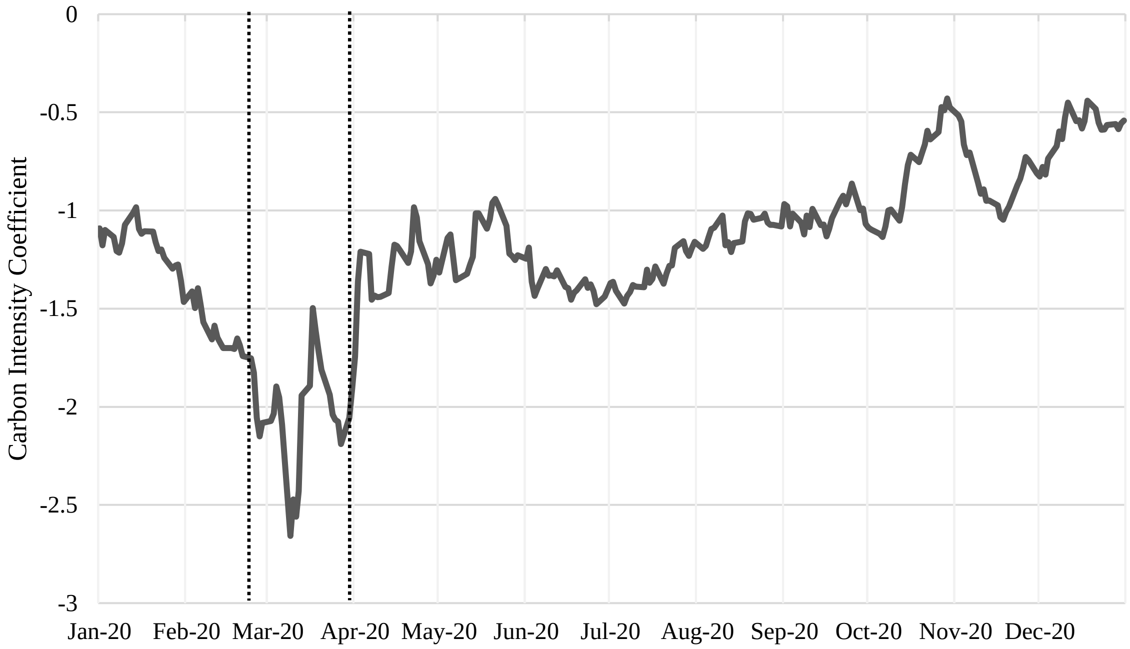


**Figure 2**
**Evolution of the carbon intensity coefficient in the year 2020**

This figure plots the daily carbon intensity coefficients (in percent) from panel regressions from 01/01/2020 to 12/31/2020. The panel regressions include all control variables from Table 3 and are estimated in a recursive window starting with all trading days of 2019 for the first estimation. The vertical lines enclose the COVID-19 period.

**Table 6**
**Influence of carbon intensity on risk during and after the COVID-19 period**

| | COVID-19 | | Post-COVID-19 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Volatility | Idio. Volatility | Volatility | Idio. Volatility |
| Carbon Intensity | 0.000089 | 0.000062 | 0.00018*** | 0.00013** |
| | (0.70) | (0.48) | (2.74) | (2.03) |
| Size | 0.00014 | -0.00076*** | -0.00068*** | -0.00092*** |
| | (0.56) | (-3.11) | (-5.90) | (-8.36) |
| Debt | 0.0077*** | 0.0089*** | 0.0032*** | 0.0033*** |
| | (4.41) | (5.24) | (4.03) | (4.16) |
| Profitability | -0.013*** | -0.011*** | -0.011*** | -0.0094*** |
| | (-4.31) | (-3.72) | (-7.64) | (-7.10) |
| Cash Intensity | -0.0081** | -0.0055 | -0.0020 | -0.0014 |
| | (-2.06) | (-1.45) | (-1.07) | (-0.75) |
| SGAE Intensity | -0.0077** | -0.0076** | 0.0013 | 0.00090 |
| | (-2.35) | (-2.40) | (0.86) | (0.62) |
| Historical Volatility | 1.07*** | 1.25*** | 0.77*** | 0.77*** |
| | (17.72) | (19.51) | (25.81) | (26.78) |
| Dividends | -0.00079** | -0.00058* | 0.000070 | 0.000023 |
| | (-2.26) | (-1.68) | (0.45) | (0.15) |
| BTM | -0.00080 | -0.00087 | 0.00059* | 0.00035 |
| | (-1.13) | (-1.22) | (1.74) | (1.09) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Observations | 2,589 | 2,589 | 2,587 | 2,587 |
| Adjusted $R^2$ | 0.6401 | 0.4917 | 0.5837 | 0.5704 |

This table provides the results of cross-sectional regressions for the COVID-19 period (02/24/2020 to 03/31/2020) and the post-COVID-19 period (04/01/2020 to 12/31/2020). The dependent variable is defined as the volatility of the (abnormal) returns during the respective period. All variables are as defined in Table 1. Industry and country fixed effects are included in all specifications and heteroscedasticity-robust standard errors are estimated. T-statistics are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

**Table 7**
**Influence of carbon intensity quartiles on risk during and after the COVID-19 period**

| | COVID-19 | | Post-COVID-19 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Volatility | Idio. Volatility | Volatility | Idio. Volatility |
| High Emitter | 0.0017* | 0.0024** | 0.0018*** | 0.0018*** |
| | (1.69) | (2.27) | (3.50) | (3.80) |
| Medium Emitter | -0.00013 | 0.00056 | 0.00075* | 0.00077** |
| | (-0.15) | (0.66) | (1.91) | (2.05) |
| Lower Emitter | -0.00092 | -0.00044 | 0.00032 | 0.00050 |
| | (-1.14) | (-0.55) | (0.86) | (1.41) |
| Size | 0.000089 | -0.00081*** | -0.00073*** | -0.00096*** |
| | (0.37) | (-3.33) | (-6.31) | (-8.80) |
| Debt | 0.0075*** | 0.0085*** | 0.0029*** | 0.0030*** |
| | (4.26) | (5.02) | (3.65) | (3.79) |
| Profitability | -0.013*** | -0.011*** | -0.011*** | -0.0094*** |
| | (-4.25) | (-3.63) | (-7.57) | (-7.03) |
| Cash Intensity | -0.0076* | -0.0047 | -0.0015 | -0.00079 |
| | (-1.92) | (-1.23) | (-0.78) | (-0.44) |
| SGAE Intensity | -0.0071** | -0.0067** | 0.0019 | 0.0015 |
| | (-2.15) | (-2.11) | (1.23) | (1.00) |
| Historical Volatility | 1.07*** | 1.24*** | 0.76*** | 0.77*** |
| | (17.66) | (19.43) | (25.73) | (26.72) |
| Dividends | -0.00079** | -0.00059* | 0.000061 | 0.0000093 |
| | (-2.26) | (-1.69) | (0.39) | (0.06) |
| BTM | -0.00100 | -0.0011 | 0.00044 | 0.00020 |
| | (-1.39) | (-1.53) | (1.29) | (0.60) |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Observations | 2,589 | 2,589 | 2,587 | 2,587 |
| Adjusted $R^2$ | 0.6411 | 0.4934 | 0.5852 | 0.5725 |

This table provides the results of cross-sectional regressions for the COVID-19 period (02/24/2020 to 03/31/2020) and the post-COVID-19 period (04/01/2020 to 12/31/2020). The dependent variable is defined as the volatility of the (abnormal) returns during the respective period. We use dummy variables for carbon intensity quartiles such that High Emitter takes the value of one if the firm is in the last carbon intensity quartile and zero otherwise, Medium Emitter takes the value of one if the firm is in the third carbon intensity quartile and zero otherwise, and Lower Emitter takes the value of one if the firm is in the second carbon intensity quartile and zero otherwise. Control variables are as defined in Table 1. Industry and country fixed effects are included in all specifications and heteroscedasticity-robust standard errors are estimated. T-statistics are provided in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

# 7 ARTICLE VI: WHAT DRIVES SUSTAINABLE INDICES? A FRAMEWORK FOR ANALYZING THE SUSTAINABLE INDEX LANDSCAPE

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**Abstract.** This article presents an encompassing four-step customizable framework for analyzing the heterogeneous sustainable index landscape. Compared to previous studies, we present means and methods to move the measurement and impact of sustainability performance in the center of attention and thus emphasize the often neglected aim of sustainable indices: incorporating sustainability into investment tools. Besides traditional comparisons of return and risk indicators (step one), we analyze the sustainability profile of sustainable indices while actively managing the presence of ESG rating disagreement (step two). For the determination of index-specific return and risk sources, we integrate sustainability factors in common factor analyses and risk decomposition approaches (step three). A performance attribution analysis based on sustainability classes increases the transparency on the composition strategies of sustainable indices (step four). Our framework supports investors in understanding sustainable indices and thus drives more informed decision making with respect to sustainability integration.

*JEL Classification*: G11, M14, Q56

*Keywords*: Market indices, sustainable investing, investment decisions, equity portfolio management

## 7.1 Introduction

Sustainability is on the rise. At least since 2015 with the adoption of the UN 2030 Agenda for Sustainable Development and the Paris Agreement, the world is committed to follow a more sustainable path towards the future. However, the achievement of set targets and milestones does not come without costs. According to estimates, we face a yearly investment gap of USD 2.4 trillion worldwide (Schmidt-Traub, 2015). Put differently, sustainable targets yield investment needs of 2.5% of average world GDP annually. To raise these horrendous funds, the financial system is required to take over a key role in promoting a greener and more sustainable economy (European Commission, 2018; Ahlström and Monciardini, 2021).

Not only BlackRock in its letter to CEOs recognizes that “we are on the edge of a fundamental reshaping of finance” (Fink, 2020). We want to consume sustainably, demand firms to act sustainably, and require investors to invest sustainably. Hence, portfolio managers increasingly integrate these investment beliefs and values in their portfolio management strategies.

This article turns the spotlight on one of the top monitoring and benchmarking solutions for financial market participants ready to integrate sustainability into their investment process: market indices. Indices are not only used as benchmarks for all types of financial products, but also as basis to create and rebalance new and existing products. In recent times, we have observed the launch of various sustainable indices of the largest and most important index providers such as MSCI, S&P Dow Jones, FTSE Russell, and STOXX. When deciding on which index might be the most suitable for mirroring sustainability aspects, even the most sophisticated investors are possibly left clueless. A myriad of different construction methodologies and investment focuses for measuring sustainability leaves them rather puzzled than providing real insights.

In its Action Plan on Financing Sustainable Growth, the European Commission actively has addressed this issue and set up a Technical Expert Group (TEG) to elaborate standards for the construction of low-carbon benchmarks and to enhance Environmental, Social, and Governance (ESG) disclosure requirements for investment indices to reduce greenwashing (EU TEG, 2019). In its final report, the EU TEG asserts that the lack of harmonization of the construction methodologies and the lack of transparency on the pursued objectives impede comparability, reliability, and adoption of sustainable benchmarks. As a result, a significant outreach for overall portfolio allocation remains limited (EU TEG, 2019). In general, Hamilos and Ribando (2016) emphasize the importance of a right understanding of the index construction methodology for correct evaluations and proper capital allocation decisions. Ghayur et al. (2018) reinforce that transparency in structure and design is essential for asset owners. Transparency thereby implies that the sources of risk and return are well recognized and understood.

With this article, we aim at creating a deeper understanding on the composition and strategy of sustainable indices and supporting their users in their decision-making processes to drive sustainable economic growth. Hence, we remove one of the barriers impeding their adoption in finance practice as stated by the EU TEG (2019). For this purpose, we develop an easy-to-implement and customizable approach for analyzing construction strategies and the sources of risk and return of sustainable indices.

In literature, there are several studies concerned with the comparison of conventional and sustainable indices majorly based on risk and return indicators (Sauer, 1997; Statman, 2006; Schröder, 2007; Fowler and Hope, 2007; Consolandi et al., 2009; Wan-Ni, 2012; Cunha and Samanez, 2013). Their results point to the assumption that sustainable and conventional indices perform at least equal. Belghitar et al. (2014) show that risk-averse investors can improve their expected utility when investing in conventional holdings and reducing socially responsible holdings. More recent studies such as Cunha et al. (2019) and Giese et al. (2019) conclude that sustainable indices have higher risk-adjusted performance than their conventional counterparts. Bianchi and Drew (2012) compare different sustainable indices, whereas Lesser et al. (2014) compare green and SRI indices. Kollias and Papadamou (2016) examine how climatic events such as storms, droughts, and floods impact the risk and return profiles of a sustainable index. Monasterolo and De Angelis (2020) analyze how the financial market's perception on carbon-intensive and low-carbon indices has changed after the Paris Agreement announcement. Furthermore, several event studies analyze the effects of being included in or excluded of a sustainable index (Consolandi et al., 2009; Robinson et al., 2011; Cheung, 2011; Oberndorfer et al., 2013; Kappou and Oikonomou, 2016; Hawn et al., 2018; Durand et al., 2018).

With this article, we expand the scope of previous research. In essence, our aim is to provide a customizable framework for investors on how to approach the analysis of sustainable indices in an encompassing way. We present four steps that move the measurement and impact of sustainability performance in the center of attention. This emphasis corresponds to the main objective of sustainable indices – capturing sustainability in the capital market – and thus distinguishes our article from previous studies. By incorporating sustainability-related aspects into traditional methods and approaches, we assure that our framework can be easily implemented into existing investment processes and at the same time, we clearly augment the insights obtained on sustainable indices from previous studies.

We exemplify our approach and possible interpretations of results by choosing eight different sustainable MSCI indices that are representative of the overall index landscape in the financial market. Our framework consists of four fundamental steps to make sustainable indices transparent.

In the first step, we stick to traditional return and risk indicators to compare sustainable indices among each other and with their parent index, the MSCI World Index. As expected for passive benchmarks, there are no remarkable differences between the sustainable indices and the conventional index.

In the second step, we analyze one of the prevailing characteristics of sustainable indices – their ESG performance and carbon exposure. Instead of focusing on one definition of ESG, we apply three different data providers (MSCI ESG, Refinitiv ESG, and Sustainalytics) and actively address the challenge of ESG rating disagreement widely discussed in literature (e.g., Dimson et al., 2020; Berg et al., 2020; Gibson et al., 2020; Christensen et al., 2019). We find that divergence in ESG ratings persists on index level. However, implications drawn based on ESG scores and a "market consensus ESG performance" remain stable across data providers. This step demonstrates investors how to use and interpret ratings and carbon exposure even when relying on different data providers.

In the third step, we investigate the return and risk drivers of sustainable indices using factor analysis and risk decomposition approaches. Compared to traditional model setups, we reinforce the need to account for systematic influences attributed to sustainability. By integrating sustainability factors, we determine to which degree index-specific components are characterized by their designated sustainable thematic focus. These analyses support portfolio managers in drawing right inferences about return and risk implications for their portfolio strategy when integrating sustainability.

In the last step, we dissect the different index construction strategies by implementing a performance attribution model based on sustainability classes. This analysis increases the understanding of the composition and strategies underlying sustainable indices. In turn, it allows investors to draw more profound conclusions for their own portfolio strategies or compare an index composition strategy to an individually chosen sustainability definition.

These steps provide an in-depth analysis of sustainable indices and can be customized towards individual preferences such as the preferred definition of ESG performance. They provide an encompassing view on key return and risk indicators, the sustainable profile, sources of risk and return, and the strategy drivers of sustainable indices. By applying all steps, financial market participants gain a deeper understanding of sustainable indices and thus can steer their portfolio decisions more in line with their sustainability targets without facing the risk of greenwashing.

The remainder of this paper is structured as follows. The next section presents the index and sustainability data sets. Section 7.3 starts with traditional descriptive analyses on index level and the investigation of the ESG and carbon profile (steps one and two). The following section describes the methodologies used for the analysis of the return and risk drivers (step three), and index strategies (step four). Sections 7.5 to 7.7 contain the empirical results of the test environment and Section 7.8 summarizes further robustness tests. The last section concludes.

## 7.2 Data description and preparation

This study requires different types of data sets. First, we review the sustainable index landscape and systematically categorize sustainable indices. Next, we employ different data providers for ESG ratings to address the divergence in ESG ratings. Lastly, we compose a carbon data set for measuring carbon exposure.

### 7.2.1 Sustainable index landscape

Investors can find numerous sustainable indices provided by different corporations. Hamilos and Ribando (2016) emphasize that understanding a benchmark’s design is crucial for its proper use. Therefore, in this section, we examine the construction strategies and characteristics of sustainable indices.

The largest and most important index providers such as MSCI, S&P Dow Jones, FTSE Russell, and STOXX offer a wide range of thematic sustainable indices covering a reasonable period and varying regions. All index providers basically divide sustainable indices in two categories: ESG and carbon indices. ESG indices focus on the integration of environmental, social, and corporate governance aspects, whereas carbon indices intend to reduce carbon exposure. ESG indices thus concentrate on a broader set of themes, carbon indices, in contrast, emphasize the more fundamental climate aspect. In essence, there are three index construction methodologies (selection, re-weighting, and hybrid approaches) to implement the designated thematic focus originating from an eligible universe of stocks.

Testing our framework with all available indices from all providers would result in a complex and possibly unclear representation without being of real help for financial market participants.[1] Thus, we focus our analysis on MSCI indices as a “test environment” and illustrate how to analyze sustainable indices in a suitable and customizable way.

For comparability, we choose to restrict our analyses to developed markets with the MSCI World Index as parent index, which is also considered as one of the most important global equity indices in the financial market. This ensures that all sustainable indices have a common basis and differ only in their integrated sustainability focus. We select the following MSCI ESG indices: World ESG Leaders, World SRI, World ESG Universal, and World ESG Focus. As carbon indices, we choose World ex Coal, World ex Fossil Fuels, World Low Carbon Target, and World Low Carbon Leaders. The eligible universe of stocks for each sustainable index is comprised of the constituents of the MSCI World Index. The World ESG Leaders and World SRI Indices single out their constituents based on certain selection criteria. The World ex Coal and World ex Fossil Fuel Indices focus on excluding certain business activities (sector

[1] At this time, S&P Dow Jones offers 17 diverse sustainable indices, MSCI and FTSE Russell each 18, and STOXX 9 different thematic construction focuses. All of these indices are usually available for different regions, thus multiplying the number of available sustainable indices in the market.

exclusion). The World ESG Universal and World Low Carbon Target Indices re-weight the constituents of the parent index to attain an improved sustainable exposure. The World ESG Focus and World Low Carbon Leaders Indices make use of both selection criteria and re-weighting combined in an optimization approach. A more detailed view on the designated index objectives and construction criteria is provided in Table 1.

[Insert Table 1 here.]

With these eight indices, we cover all prevalent construction and thematic methodologies and therefore have a convenient test environment for a deeper analysis of sustainable indices at our disposal.

### 7.2.2 Sustainability data and ESG rating disagreement

In recent years, various corporations developed own methodologies for assessing a firm's ESG performance. As a result, there does not exist any consistent standard ESG evaluation framework and ESG ratings diverge significantly based on rater-specific biases and disagreements about the scope, measurement, and weighting of underlying data points (Berg, et al., 2020; Dimson et al., 2020; Gibson et al., 2020; Christensen et al., 2019; Kotsantonis and Serafeim, 2019). As a consequence, a firm's ESG performance can be evaluated differently dependent on the chosen rating provider (Dimson et al., 2020; Li and Polychronopoulos, 2020). For investors, this implies that a deep understanding of the underlying ESG methodologies is necessary to choose an adequate benchmark in line with their investment preferences. However, a crucial component of sustainable benchmarks is the improvement in the ESG performance compared to the parent index. We demonstrate how to compare different ESG ratings on index level and derive implications thereof for their legitimacy as being labelled as sustainable.

For ESG data, we make use of three different data providers: MSCI ESG, Refinitiv ESG[2], and Sustainalytics. Each provider covers a different set of global stocks for which relevant data is available and assesses a firm's sustainability performance according to its own defined methodology. In order to make ESG ratings comparable across all providers, we adjust ESG scores for their individual distributions as in Gibson et al. (2020). At each point in time for each score and data provider, we calculate the adjusted score as percentile rank of the respective firm according to the respective rating normalized to a range between 0 and 1. Hence, the adjusted scores depend on their ranking within the whole sample for which the data provider has assessed ESG ratings. Additionally, we calculate the overall adjusted score as average over all adjusted scores of the three data providers to derive a "consensus ESG performance" as pointed out by Berg et al. (2020) and also implemented by Christensen et al. (2020). This approach requires that a firm is part of each of the three ESG data providers. This leaves us with four different ESG samples – the original data samples of MSCI ESG, Refinitiv ESG, and Sustainalytics, and our own ESG sample as intersection between these three data providers and comprising overall adjusted scores.

The measurement of carbon exposure is more fundamental in nature and thus less prone to divergent calculation methodologies. Carbon performance is usually measured as carbon intensity. We calculate yearly carbon intensity as the sum of scope 1 and 2 emissions reported to CDP. If no CDP emissions are available for a stock, we fill data by Refinitiv and Sustainalytics reported emissions.[3] Emissions are subsequently normalized by enterprise

[2] Formerly known as Thomson Reuters ESG.
[3] Reliable data on scope 3 emissions is rather scarce. Therefore, we focus on scope 1 and 2 only as also suggested by the Task Force on Climate-related Financial Disclosures (TCFD) recommendations for calculating carbon footprinting and exposure metrics (TCFD, 2017).

value.[4] This financial metric allows cross-sectoral comparisons and thus qualifies as suitable denominator for carbon intensity (EU TEG, 2019).

The ESG and carbon data sets are matched to the index constituents, so that we can judge the ESG performance and carbon exposure of each index. An overview of all data sets and the number of available and matched stocks, respectively, can be found in Figure 1.

[Insert Figure 1 here.]

We aggregate the carbon and ESG performance measures on index level by value-weighting the constituents' data at each point in time. Following the construction methodologies of MSCI and Morningstar, we re-scale weights and calculate index-level measures only over those stocks with the respective available carbon or ESG measures. In addition, we exclude all points in time for which less than 40 percent of carbon or ESG data is available on constituents level. Besides the overall ESG score, we also report the single pillar (environmental, social, and governance) scores. In addition, we calculate the reduction in carbon intensity from the parent index for each year.

## 7.3 Descriptive analyses

### 7.3.1 Index factsheets

We start with simple descriptive statistics usually found in index factsheets. This first step constitutes the standard procedure for evaluating index characteristics and thus has to be part of a profound index analysis. Table 2 summarizes key indicators of all indices in our test environment. Monthly data runs from April 2011 to December 2019. The most restrictive index is the MSCI World SRI Index with an average number of included stocks of 407 compared to an average of 1,633 for its parent index. This leads to a low market capitalization coverage of

[4] Enterprise value is defined as the sum of the market capitalization of common and preferred stocks, the book value of total debt and minority interest, minus cash (Worldscope item 18100).

24.56%. In contrast, the World ex Coal Index excludes the least stocks and displays a market capitalization coverage of 99.57%. This pattern is mirrored in the tracking error. Overall, the tracking error ranged from a low of 0.07% for the ex Coal Index to a high of 0.44% for the SRI Index. Among the lowest tracking errors are the indices which incorporate tracking error targets into their construction methodologies, such as the World ESG Focus, World Low Carbon Target, and World Low Carbon Leaders Indices.

Monthly return and risk levels only varied slightly across indices. The Sharpe Ratio lied between 0.22 and 0.24, thus not permitting to seek out a high performer. Active return was slightly positive albeit low in our sample period. In line with literature (Giese et al., 2019; Lesser et al., 2014), the price-to-book ratio and return on equity (ROE) were on average slightly higher for ESG indices compared to the conventional index, i.e., ESG indices are more valuable. Liquidity measured by the annualized traded value ratio (ATVR) turned out to be high for all indices, even for the most restrictive index, the World SRI Index, with 94.79% on average.

[Insert Table 2 here.]

### 7.3.2 ESG and carbon profiles

In the second step of our approach for index evaluation, we assess the core of sustainable indices: their sustainability performance measured by ESG ratings and carbon exposure. More importantly, we demonstrate how to manage different ESG definitions and the resulting ESG rating disagreement. For the evaluation of the sustainability performance, we first compare the distributions of the sustainability measures for each index. Distributions for the ESG scores and carbon intensities are displayed in Figure 2.[5] For each sustainability measure (ESG scores, carbon intensity), we use the matched samples of the respective ESG data provider or carbon data set with the constituents of the respective index.

[5] Distributions of pillar scores can be found in Figure A.1 of the Internet Appendix.

[Insert Figure 2 here.]

Distributions follow the same pattern regardless of the underlying data provider (Panel A). The conventional MSCI World Index has most constituents in the middle class measured by the ESG score. The distribution for each data provider moves more to the right for ESG indices. For example, three quarters of the constituents of the MSCI SRI Index display an MSCI ESG score of 61 and higher. For the MSCI Index, only a third of all constituents are found in these classes. When measuring scores with Refinitiv ESG (Sustainalytics), percentages in the upper classes move from 32.37% (39.90%) for the MSCI World Index to 58.48% (65.59%) for the MSCI SRI Index. Hence, irrespective of the data provider, we draw similar inferences for ESG indices: regardless of their underlying ESG definition, they contain proportionally more stocks with higher average ESG ratings.

In a next step, we focus on our constructed adjusted scores to compare the different indices. In Panel A of Figure 2, we find that our overall adjusted ESG score unequivocally allocates a higher percentage of ESG index constituents in the upper ESG classes compared to their parent index.

In Panel B, we draw similar conclusions for carbon indices. Carbon indices effectively allocate towards stocks within lower carbon intensity classes than the MSCI World Index. Only 6.63% of the constituents of the World Low Carbon Target Index are to be found in the highest carbon intensity quintile, whereas 15.77% of the stocks in the MSCI World Index are members of the same quintile class.

For a more detailed view on the ESG and carbon profile, Table 3 illustrates the average adjusted scores and carbon intensity reductions for each index over the sample period. To increase comparability of the data providers, we only include the scores of those constituents which are available in all three ESG data sets. Therefore, we also show how to assess ESG rating disagreement on index level.

[Insert Table 3 here.]

When adjusting the scores of each data provider for their different distributions, we find that in general, MSCI assigns lower scores than Sustainalytics and Refinitiv (Panel A). This is in line with the findings of Christensen et al. (2019). The high dispersion implies low correlations across data providers. In accordance with Gibson et al. (2020) and Berg et al. (2020), rank correlations are somewhat higher for the ESG score than for the single pillar ratings (see Table A.1 in the Internet Appendix). The average correlations between providers are 55.12% for the ESG score, 45.38% for the environmental pillar, 33.64% for the social pillar, and 23.46% for the governance pillar. Hence, data providers do not converge in assigning ranks to firms in our sample. However, what's more important for investors, the implications drawn remain basically unchanged across data providers. Focusing on the ESG score, there are no significant deviations for carbon indices from the parent index, the MSCI World Index. For ESG indices, we find slightly differing results across data providers. For MSCI and Sustainalytics ratings, all ESG indices improve their ESG profile, whereas the World ESG Universal Index performed marginally worse than the MSCI World Index when measured by the Refinitiv ESG score. However, for this index, even the MSCI and Sustainalytics ESG ratings only measure a marginal improvement compared to the parent index. For the environmental scores, we find that carbon indices do not display a superior ESG profile indicating that they are not optimized towards the environmental pillar of the data providers. The World SRI performs best across all pillar scores for the MSCI and Sustainalytics ratings, pointing to the fact that it actively excludes firms with a negative social and environmental impact. For Refinitiv scores, the World ESG Focus Index performs best even though it is closely followed by the World SRI Index.

When we measure the ESG profile by our consensus ESG measure, the overall adjusted scores, we see that scores turn out similar to the Sustainalytics ratings. Based on the figures in Panel A, we think that the overall adjusted scores are a good approximation for ESG ratings as they alleviate both the low scores of MSCI and the high scores of Refinitiv while taking all possible definitions of sustainability aspects into account.

With regard to carbon exposure, we expect carbon indices to display higher carbon intensity reductions since this constitutes the aim of their thematic focus. The World Low Carbon Target Index in fact achieved the highest reduction with 64.18% compared to the parent index, closely followed by the World Low Carbon Leaders Index with 43.06% (see Table 3, Panel B). One might have assumed that the World Low Carbon Leaders Index is more successful in reducing carbon exposure when considering its construction framework (Table 1). However, in this analysis, we focus on carbon intensity only (following EU TEG, 2019), whereas the World Low Carbon Leaders Index additionally captures potential carbon emissions sources, i.e., fossil fuel reserves. Once again, this emphasizes the need to fully understand the underlying construction criteria when analyzing indices. Mere sector exclusion indices such as the World ex Coal and World ex Fossil Fuels Indices provide some degree of carbon intensity reductions (4.61% and 21.86%), but demonstrate that construction methodologies based on selection and re-weighting of constituents are more effective. Thus, excluding sectors is not as efficient as selecting stocks based on their carbon exposure (in line with Andersson et al., 2016 as well as Mercereau et al., 2020). These indices are even outpaced by the World SRI and the World ESG Focus Indices.

## 7.4 Methodology

In the following analyses, we derive a deeper understanding on the sources of return and risk specific to sustainable indices and thus increase transparency on performance attribution (Ghayur et al., 2018). Specifically, we determine whether sustainable indices are driven by their pursued objectives, so that investors can better manage their return and risk exposure while integrating sustainability aspects. In addition, we investigate the drivers of the index strategies by a performance attribution model following Brinson and Fachler (1985).

### 7.4.1 Reference models for regression analyses

First, we incorporate sustainability factors into common asset pricing models as a means to capture the impacts of sustainability integration on return and risk profiles.[6] We estimate factor exposures using the common Carhart (1997) model as baseline case. Besides the common risk factors *market*, *smb*, *hml*, and *wml*, we estimate models by including different global sustainability factors. For this purpose, we build zero-cost investment portfolios that mirror sustainability aspects. For the factor construction, we consider all global stocks part of the ESG data sets irrespective of their membership in the MSCI World Index. For example, in June of each year, we sort all stocks with available ESG data into quintile portfolios based on their ESG score. Stocks retain their quintile membership throughout the following twelve months. The monthly ESG factor return time-series is then obtained by subtracting the value-weighted portfolio return of the stocks in the lowest quintile from the value-weighted portfolio return of the stocks in the highest quintile. The ESG factor is thus invested long in high ESG performers and short in low ESG rated stocks.

We apply this procedure to different sustainability ratings introduced before, i.e., the overall adjusted ESG, environmental, social, and governance scores. In this way, we focus on the consensus ESG performance on the market and analyze return and risk drivers not solely based on one ESG definition. For example, sustainability factors based on MSCI ESG ratings are assumed to efficiently capture specific return and risk drivers of the sustainable MSCI indices since the construction of these indices relies on these scores. Demonstrating that return

[6] The idea of including sustainability factors into common factor models is widely used in literature. See, e.g., Görgen et al. (2020), Hübel and Scholz (2020), Gregory et al. (2020), Maiti (2020), and Xiao et al. (2013).

and risk drivers using consensus rating factors remain similar to MSCI factors increases the reliability and credibility of sustainable indices.

In addition, we form an emissions factor that invests in stocks with the 20 percent highest carbon intensities of the carbon data set and is short in those with the 20 percent lowest intensity measures (i.e., a dirty minus clean investment portfolio). Overall, all sustainability factors are constructed in such a way that they resemble the other common risk factors in their methodological scope following Fama and French (1993) and Carhart (1997).[7]

In total, we apply four different global models: (1) the Carhart (1997) model, (2) the ESG model, (3) the pillar factors model, and (4) the emissions factor model as shown by the respective equation below.

$$r_{i,t} = \alpha_i + \beta_i^{mkt}\, mktrf_t + \beta_i^{smb}\, smb_t + \beta_i^{hml}\, hml_t + \beta_i^{wml}\, wml_t + \varepsilon_{i,t}\,, \tag{1}$$

$$r_{i,t} = \alpha_i + \beta_i^{mkt}\, mktrf_t + \beta_i^{smb}\, smb_t + \beta_i^{hml}\, hml_t + \beta_i^{wml}\, wml_t + \beta_i^{esg}\, esg_t + \varepsilon_{i,t}\,, \tag{2}$$

$$r_{i,t} = \alpha_i + \beta_i^{mkt}\, mktrf_t + \beta_i^{smb}\, smb_t + \beta_i^{hml}\, hml_t + \beta_i^{wml}\, wml_t + \beta_i^{env}\, env_t + \beta_i^{soc}\, soc_t + \beta_i^{gov}\, gov_t + \varepsilon_{i,t}\,, \tag{3}$$

$$r_{i,t} = \alpha_i + \beta_i^{mkt}\, mktrf_t + \beta_i^{smb}\, smb_t + \beta_i^{hml}\, hml_t + \beta_i^{wml}\, wml_t + \beta_i^{emi}\, emi_t + \varepsilon_{i,t}\,. \tag{4}$$

with $r_{i,t}$ being the return measure of index $i$ at time $t$, $mktrf_t$, $smb_t$, $hml_t$, and $wml_t$ the common global risk factors from Kenneth French's data library, $esg_t$, $env_t$, $soc_t$, $gov_t$, and $emi_t$ being the global zero-cost portfolios constructed based on overall adjusted ESG ratings and carbon intensity, respectively. For the dependent variable, we focus on the index-specific return drivers and use active returns, i.e., the difference between the return of an index and its benchmark return, the MSCI World Index return. In general, the construction of sustainability factors and the setup of the regression model can be customized to the preferences of each individual investor.

[7] Descriptive statistics of all factors can be found in Table A.2 in the Internet Appendix.

### 7.4.2 Risk decomposition approach

The determination of risk drivers is based on the decomposition framework of Klein and Chow (2013). The authors develop a methodology to democratically orthogonalize factors. In turn, this allows calculating the contribution of each risk factor to the variation in the dependent variable, in our case the return measure. The construction of sustainability factors that mimic sustainability aspects enables us to allocate risk to the different sustainable thematic focuses and thus, we can assess more transparently what drives sustainable indices. Klein and Chow (2013) derive the following equations, which we use for our risk decomposition approach.

$$DR_{i,k}^2 = \left(\beta_{k_i}^{\perp} \frac{\hat{\sigma}_{f_k}}{\hat{\sigma}_i}\right)^2, \tag{5}$$

$$R_i^2 = \sum_{k=1}^{K} DR_{i,k}^2 , \tag{6}$$

$$IR_i = 1 - R_i^2 . \tag{7}$$

Equation (5) describes the risk contribution $DR_{i,k}^2$ of factor $k$ to index $i$ with $\beta_{k_i}^{\perp}$ being the beta exposure of index $i$ towards the democratically orthogonalized factor $k$ in the respective factor model, $\hat{\sigma}_{f_k}$ the standard deviation of factor $k$, and $\hat{\sigma}_i$ the standard deviation of the return measure of index $i$. The contributions of all factors in the factor model sum up to the coefficient of determination $R_i^2$ (Equation (6)). Finally, the idiosyncratic risk can be calculated as shown in Equation (7).

### 7.4.3 Performance attribution analysis

The last analysis focuses on traditional performance attribution models following Brinson and Fachler (1985). Even though performance attribution applies to the evaluation of active investment strategies, it serves as a tool for strategy evaluation for passive investment products such as indices (see, e.g., Andersson et al., 2016 and Giese et al., 2019). It relates active return to allocation and stock selection effects as well as to interaction effects of both. Allocation measures the effect of over- or underweighting performance classes compared to the benchmark case (Equation (8)). The selection effect measures in how far stock selection influences returns within one class and turns out differently compared to the benchmark portfolio (Equation (9)). The interaction effect takes both effects, i.e., weighting and selection, into account (Equation (10)). The sum of allocation, selection, and interaction over all classes equals the active return of the index.

$$allocation_x = \left(w_{x,i} - w_{x,b}\right)\left(r_{x,b} - r_b\right), \tag{8}$$

$$selection_x = \left(r_{x,i} - r_{x,b}\right) w_{x,b}, \tag{9}$$

$$interaction_x = \left(w_{x,i} - w_{x,b}\right)\left(r_{x,i} - r_{x,b}\right), \tag{10}$$

with $w_{x,i}$ ($w_{x,b}$) being the weight of class $x$ in index $i$ (benchmark index $b$), $r_{x,i}$ ($r_{x,b}$) the return of class $x$ in index $i$ (benchmark index $b$), and $r_b$ the return of the benchmark index $b$.

In order to relate the sustainable investment focus to active returns, we consider the attribution model for sustainability classes. For this purpose, we divide the stock universe of the matched sample of the ESG data sets into five ESG classes based on the overall adjusted ESG score at each point in time. The first class contains all low ESG stocks and the fifth class the highest ESG performing stocks. We follow the same procedure with carbon intensities for emissions classes using the carbon data set. The lowest class contains the low carbon intensity stocks and the highest class the high carbon intensity stocks. Again, the definition of classes can be defined according to individual preferences.

The class membership can then be matched to the constituents of the indices to calculate all attribution effects compared to the benchmark (parent) index.

### 7.5 Index-specific return drivers

Madhavan et al. (2018) point out that factor analysis for market indices has gained importance in recent years. Thus, for the third step of our framework, we start with the evaluation of active return drivers based on factor sensitivities. Since passive investment strategies are majorly driven by their overall market exposure, we extract the index-specific component, i.e., active returns. In this way, we focus on the index component that is specific to the respective sustainable index, i.e., the part that investors additionally gain to the benchmark case. This part should mirror the designated objective of the index.[8]

Table 4 illustrates regression results for active returns. Panel A contains the results for the ESG model.[9] The exposure towards the ESG factor is significantly different from zero at the five percent level for most ESG indices. In specific, the index-specific return of ESG indices is positively sensitive towards it. The highest sensitivity towards ESG aspects is achieved by the World SRI Index with a beta value of 0.0768 closely followed by the World ESG Universal Index (0.0751). In contrast, the ESG factor lacks significance for explaining active returns of carbon indices. This indicates that ESG and carbon indices differ in their sensitivity towards ESG stocks.

Panel B delivers a more detailed view by breaking up the ESG factor in its three pillar factors. When comparing the exposures of the three pillar factors, the index-specific return fraction of the World ESG Leaders Index is most sensitive towards governance aspects. The World ESG Universal and ESG Focus Indices are more exposed to the social factor. This shift in focus might be attributable to the re-weighting approach used by these two indices. In addition, it is noteworthy that the World SRI Index does not display any significant exposure towards the pillar factors. In fact, the goodness-of-fit for the pillar factors model decreases for the World SRI index compared to the ESG model (4.46% compared to 7.12% in adjusted $R^2$). For all other indices, the pillar factors model delivers a higher fit.[10] Hence, the active return of

[8] An analysis of factor exposures based on the total return of an index can be found in Internet Appendix B.
[9] Results for the Carhart model can be found in Table A.3 in the Internet Appendix.
[10] Overall, goodness-of-fit measures seem relatively low. However, we explain index-specific returns. They are expected to be driven by rather idiosyncratic exposures (see Section 7.6 and Internet Appendix B).

the World SRI Index might be more suitably explained by the overall ESG model. The sector exclusion carbon indices show their highest sensitivities towards the environmental pillar factor. The World Low Carbon Target and Low Carbon Leaders Indices lack significant positive exposures to the pillar factors. For carbon indices, this is to be expected since they are not specifically optimized towards a specific ESG pillar.

In Panel C for the emissions factor model, the carbon indices follow their designated target: they show highly significant exposures towards the emissions factor. As expected, they are negatively exposed, i.e., more sensitive to the short leg of the emissions factor (low carbon intensity stocks). In comparison, ESG indices are not significantly exposed towards the emissions factor.

[Insert Table 4 here.]

This analysis illustrates that sustainability factors capture systematic variation in active returns of sustainable indices. A re-weighting of constituents based on their ESG performance such as implemented for the World ESG Universal or World ESG Focus Index can shift the active return driver from governance to social aspects. More importantly, factor exposures are in line with the respective thematic focus of the index. The beta sensitivities towards sustainable factors are among the highest across all factors pointing to their importance in determining index-specific components. Hence, investors are advised to include factors capturing sustainability aspects when evaluating the sources of return for sustainable indices.

### 7.6 Risk drivers

It is often claimed that sustainability integration comes with additional risk since investors have to forgo stocks of the whole investment universe that do not comply with sustainability criteria. We investigate this issue further by analyzing risk exposures in more detail. In Table 2, total risk (as measured by standard deviation) and systematic risk (measured by the historical market beta) were similar for the MSCI World Index and its sustainable counterparts. Hence, portfolio managers do not have to fear a significant change in conventional risk measures when relying on sustainable indices.

To get a more detailed view, we analyze the drivers of systematic risk sources. We decompose the systematic risk into factor contributions as outlined in section 7.4.2. In untabulated results, we find that most of the systematic risk is driven by systematic market exposures, i.e., by the market factor. For passive benchmarks, this result is to be expected. Thus, we focus our risk analysis on the index-specific component similar to the analysis of the return drivers. In this way, we explicitly take account of the risk components specific to each sustainable index. To derive risk sources, we apply the methodology of Klein and Chow (2013) to regression models with active returns as dependent variable.

Table 5 reports the results for the individual factors' risk contributions. In Panel A, we find that the pillar factors drive a major part of systematic risk in active returns. For example, 13.57% of the systematic variation in active returns of the MSCI World ESG Universal Index are attributable to the social pillar factor, whereas the proportions of risk contributed systematically by the market factor are only 1.25%. However, for the World SRI and World ESG Focus Indices, expectations are not met. Their active risk is rather driven by conventional factors, even though the governance (social) pillar factor constitutes the second (third) highest risk contribution for the World SRI (World ESG Focus) Index.[11] The highest risk contribution is achieved by the governance factor for the World Low Carbon Leaders Index. As seen in Table 4, active returns of this index are negatively sensitive towards governance aspects, thus explaining its high risk exposure towards this factor.

[11] When repeating the analyses with factors constructed based on MSCI ESG scores, results are more in line with expectation. The systematic risk of active returns of the World SRI (World ESG Focus) Index is then predominantly driven by the governance (social) pillar factor. See also the robustness tests in Section 7.8.

For comparison, we also report the idiosyncratic risk proportions for the ESG and Carhart model. We notice that both the ESG and the pillar factors model decrease idiosyncratic risk compared to the Carhart model, pointing to the fact that the sustainable factors capture systematic variation of active returns, which is attributed to idiosyncratic risk when the factors are not included.

In Panel B, we implement the same methodology for the emissions factor model. Variation of active returns in all carbon indices is majorly caused by the emissions factor. Since the emissions model does not capture ESG effects per se, all ESG indices are more prone to other common risk sources. In comparison to Panel A, the part of systematic risk explained is lower and idiosyncratic risk sources in turn higher for ESG indices and vice versa for carbon indices. This implies that the pillar factors model (emissions factor model) is better suited for ESG indices (carbon indices) to capture and explain systematic risk sources.

[Insert Table 5 here.]

Summing up, the index-specific risk of sustainable indices is significantly driven by sustainable aspects. Investors thus cannot only diminish idiosyncratic risk exposure by hedging systematic sustainable risk sources, but also steer portfolio risk more appropriately. Our results imply that investors can easily gain risk exposure for a desired sustainability focus or even hedge ESG and carbon risk while optimizing both sustainability aspects.

## 7.7 Evaluation of index strategies

In our last step, we turn to a traditional performance attribution analysis using the Brinson and Fachler (1985) model, which has become an industry standard in this field. By investigating attribution effects for ESG and emissions classes, we increase the understanding on how and which classes contribute most to the different index strategies.

### 7.7.1 Aggregated attribution effects

The attribution effects for both performance class categories are shown in Table 6.[12] The strategies of all sustainable indices are predominantly driven by selection effects for ESG classes (Panel A). For example, the negative active return of the World ESG Leaders Index of –0.0302% consists of 0.0393% attributable to allocation, –0.1033% to selection, and the remaining component to interaction. This means that picking stocks within ESG classes is a more prominent strategy driver than systematically allocating weights to certain ESG classes. For the re-weighting index strategy of the World ESG Universal Index, this result is surprising. Stock selection basically only plays a minor role in the construction framework of the index; however, single firm exclusions based on the criteria specified in Table 1, the re-weighting of constituents, and the class return impact following the re-weighting are more pronounced than systematic changes in class weights compared to the parent index. Overall, for ESG indices, the eligibility criteria for index construction drive the respective strategies. As expected, the carbon indices are majorly driven by stock selection within ESG classes, i.e., picking low carbon stocks within ESG classes is more important than ESG exposure.

Panel B reports the results for emissions classes. All carbon index strategies follow allocation effects. This means they are triggered by their strategy in allocating different weights towards emissions classes compared to their parent index, the MSCI World Index. In addition, both the World ESG Universal and the World ESG Focus index systematically assign different weights to emissions classes than the MSCI World Index. This might be connected to their re-weighting strategy of constituents. For the World ESG Leaders and SRI Index, stock selection within emissions classes is more dominant than allocation.

[Insert Table 6 here.]

[12] The active return of an index turns out slightly differently across performance class categories since ESG and emissions data are not available for every constituent at each point in time.

### 7.7.2 Attribution effects on class level

To dissect attribution effects further, we analyze the single performance classes in more detail. For each class, we determine its active return and attribution effects. In this way, we get a deeper understanding which strategies and decisions drive the investment focus of sustainable indices.

Figure 3 graphically depicts performance attribution effects for each class.[13] In Panel A, we see the dominance of the selection and interaction effects for the ESG indices when attributing their performance to ESG classes. The margin ESG classes, i.e., low and high ESG classes, majorly determine the performance of ESG indices. For example, the World SRI Index heavily overweighed the high ESG class during our sample period on average by 26.68% compared to the MSCI World Index and underweighted the low ESG class by 4.99%. For the low ESG classes, however, selection and interaction effects within these classes dominated. The lowest ESG class achieved an average return of –2.11%, whereas the benchmark class performed better with a return of -0.0039%. Hence, this led to a large negative stock selection effect for this class. Since this class underperformed the benchmark index and the index simultaneously underweighted this class, the interaction effect turns out positive.

Panel B of Figure 3 displays attribution effects for emissions classes. For carbon indices, the high carbon class was by far the dominant performance driver. The pattern is most distinct for the World ex Fossil Fuels Index. We find that this index underweighted the high emissions class by 5.75% on average during the sample period compared to its parent index. The class performed better for the World ex Fossil Fuels Index by 0.22% compared to the same class of the MSCI World Index. Even though this does not seem much, the combination of both underweighting and outperforming the benchmark's emissions class has driven active returns substantially.

[13] A more granular view with weights and returns of the respective classes within each index is provided in Table A.3 in the Internet Appendix.

[Insert Figure 3 here.]

In summary, we find that the index strategies are majorly influenced by their stock selection when focusing on ESG classes and by allocation effects when taking emissions classes as a basis. In general, this step is important in dissecting and understanding the construction strategy of an index. As an extension, it is possible to analyze an index with regard to individualized sustainable class categories. The respective attribution effects then reveal how the index behaves towards the chosen classes.

## 7.8 Robustness tests

To prove the robustness of our results, we perform several further tests.[14] For the regression models, we apply different sets of sustainable factors. We construct factors based on the MSCI ESG ratings instead of the overall adjusted scores. In addition, we slightly change the calculation of carbon intensity and use net sales as denominator – a definition which is widely used in research and finance practice (e.g., Bolton and Kacperczyk, 2020; TCFD, 2017). For both new factor sets, the results for the return and risk drivers basically remain unchanged. We notice, however, that the decomposition of risk drivers based on MSCI ESG factors is even more tilted towards the thematic focus of ESG indices.

For the calculation of the “market consensus ESG performance” we additionally apply another approach by simply standardizing scores of each data provider instead of relying on the percentile ranks (as in Berg et al., 2020). Using the overall adjusted scores based on standardized ratings leads to comparable results.

[14] Results of all robustness specifications are available upon request.

To account for multicollinearity between factors, we also repeat the return analyses with democratically orthogonalized factors following the methodology of Klein and Chow (2013). All results remain stable.

For the performance attribution model, we adjust the definition of ESG classes and build them based on the MSCI ESG score. Again, the selection effect outweighs the allocation effect for all sustainable indices. For emissions classes, we analogously rely on carbon intensity measured by net sales. Except for the World ex Fossil Fuels Index, the results are unchanged. The active return of the World ex Fossil Fuels Index displays a slightly higher selection than allocation effect. The distinction between these two effects has not been very pronounced with the original definition of carbon intensity neither, so that the new results are in line with previous findings.

Instead of focusing on sustainability classes, we also perform a more traditional form of performance attribution based on sector, size, and book-to-market classes (see, e.g., Hsu et al., 2010). Sector allocation is especially pronounced for carbon indices. For size classes, we find that all sustainable indices do not systematically allocate towards them. For book-to-market classes, the World ESG Universal, World ESG Focus, and World Low Carbon Target Indices systematically overweigh growth stocks.

## 7.9 Conclusion

A myriad of different sustainability indices of various index providers in connection with different ESG ratings makes it difficult for investors to orientate themselves. In turn, this lack of transparency impedes effective capital allocation towards a sustainable economic development necessary to combat climate change (European Commission, 2018). Even though there are many studies analyzing sustainable indices and their conventional counterparts, there are no insights on the measurement and impact of their sustainability performance. We provide a customizable approach based on conventional methods to analyze the strategies as well as sources of risk and return of sustainable indices. We test our framework with a MSCI index sample representative for the whole sustainable index landscape.

In the first step, we summarize traditional and thus necessary return and risk indicators of market indices. In the second step, we focus on the ESG and carbon profile. Even though ESG rating disagreement is also present at index level, we demonstrate how to handle different ESG definitions. Thus, we find that inferences drawn on the ESG profile remain unchanged regardless of the underlying ESG definition. This allows investors to apply their own ESG rating definition. In the third step, index-specific return and risk drivers are determined to demonstrate the importance of sustainability-related influences. Our analyses emphasize the need to include sustainability aspects in factor analysis when evaluating the sources of risk and return. With this step, investors can focus on specific exposures towards self-defined sustainability issues and bundle as well as hedge various sustainability themes more effectively. In the fourth and last step, we dissect index strategies into their attribution effects. Performance attribution analyses with sustainability classes provide investors with a means to dissect index strategies and draw conclusions for their own portfolio management towards sustainability integration.

With this study, we increase the transparency on the design, composition, and driving forces of sustainable indices and thus, actively address the European Commission's criticism on the lack of transparency in the construction and scope of sustainable indices (EU TEG, 2019). Investors can use our approach and tailor it towards their individual preferences and needs. In this way, they can infer more informed decisions on capital allocation while taking their own sustainability-related preferences into account.

In the upcoming years, the development of sustainability initiatives and regulations might influence the sustainable index landscape to a large extent. Index providers have already started to provide provisional indices aligned with the proposals of the EU TEG report. A comparison between benchmarks aligned with the standards proposed by the EU TEG and existing sustainable indices with regard to their composition as well as sources of risk and return presents an interesting area for future research. At this point in time, however, the financial market still is targeted towards already existing indices, which also serve as underlyings of, e.g., exchange traded funds. This study supports all financial market participants in their decision-making process for effective sustainable capital allocation.

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## Tables and Figures

**Table 1**
**Overview of construction frameworks of sustainable indices**

| | Objective | Exclusion of business activities | Exclusion based on controversies | Selection/re-weighting based on ESG measures | Optimization approach* |
|---|---|---|---|---|---|
| **World ESG Leaders** (Best-in-class) | Exposure to highest ESG rated stocks in each sector of the parent index | Alcohol, gambling, tobacco, nuclear power, conventional and nuclear weapons | MSCI ESG Controversies Score < 3 | MSCI ESG Rating ≥ ‘BB’ (2.9)<br>Ranking based on: ESG rating, ESG trend, index membership, industry adjusted ESG scores, market capitalization | -- |
| **World SRI** (Best-in-class) | Exposure to companies with outstanding ESG scores while excluding companies whose products have negative social or environmental impacts | Controversial weapons, civilian firearms, conventional and nuclear weapons, tobacco, alcohol, adult entertainment, gambling, genetically modified organisms, nuclear power, thermal coal | MSCI ESG Controversies Score < 4 | MSCI ESG Rating ≥ ‘A’ (5.7)<br>Ranking based on: ESG rating, ESG trend, index membership, industry adjusted ESG scores, market capitalization | -- |
| **World ESG Universal** (Re-weighting approach) | Exposure to companies with both a robust ESG profile as well as a positive ESG trend | Controversial weapons | MSCI ESG Controversies Score = 0 | Re-weighting based on combined ESG score consisting of ESG rating and ESG trend score | -- |
| **World ESG Focus** (Optimization approach for both selection and re-weighting) | Exposure to companies with positive ESG characteristics while maintaining risk and return profile of the parent index | Tobacco, controversial weapons | MSCI ESG Controversies Score = 0 | -- | Maximize ESG score |

*(to be continued)*

**Table 1 continued**

| | | | | | |
|---|---|---|---|---|---|
| **World ex Coal** (Sector exclusion) | Exposure to companies of the parent index while excluding those that own coal reserves | Companies with proved and probable coal reserves used for energy purposes | -- | -- | -- |
| **World ex Fossil Fuels** (Sector exclusion) | Exposure to companies of the parent index while excluding those that own oil, gas, and coal reserves | Companies with proved and probable coal reserves and/or oil and natural gas reserves used for energy purposes | -- | -- | -- |
| **World Low Carbon Target** (Optimization approach for re-weighting) | Lower carbon exposure compared to parent index while maintaining low tracking error | -- | -- | -- | Minimize carbon exposure |
| **World Low Carbon Leaders** (Both selection and optimization approach for re-weighting) | Limit exposure to carbon emissions and fossil fuel reserves while achieving at least 50% reduction in carbon footprint and minimizing tracking error | -- | -- | Exclusion of the top 20% of companies based on carbon emission intensity Exclusion of companies until the cumulative potential carbon emission of the excluded securities reaches 50% of the sum of the potential carbon emission of the parent index | Reduction in carbon intensity and potential emissions at least 50% relative to parent index |

This table summarizes the designated objectives and main construction criteria of all MSCI indices part of this study. For more details on the construction methodologies, see https://www.msci.com/esg-indexes.
[*] The optimization approach underlies constraints in the following categories: tracking error, constituent weights, sector weights, country weights, and turnover.

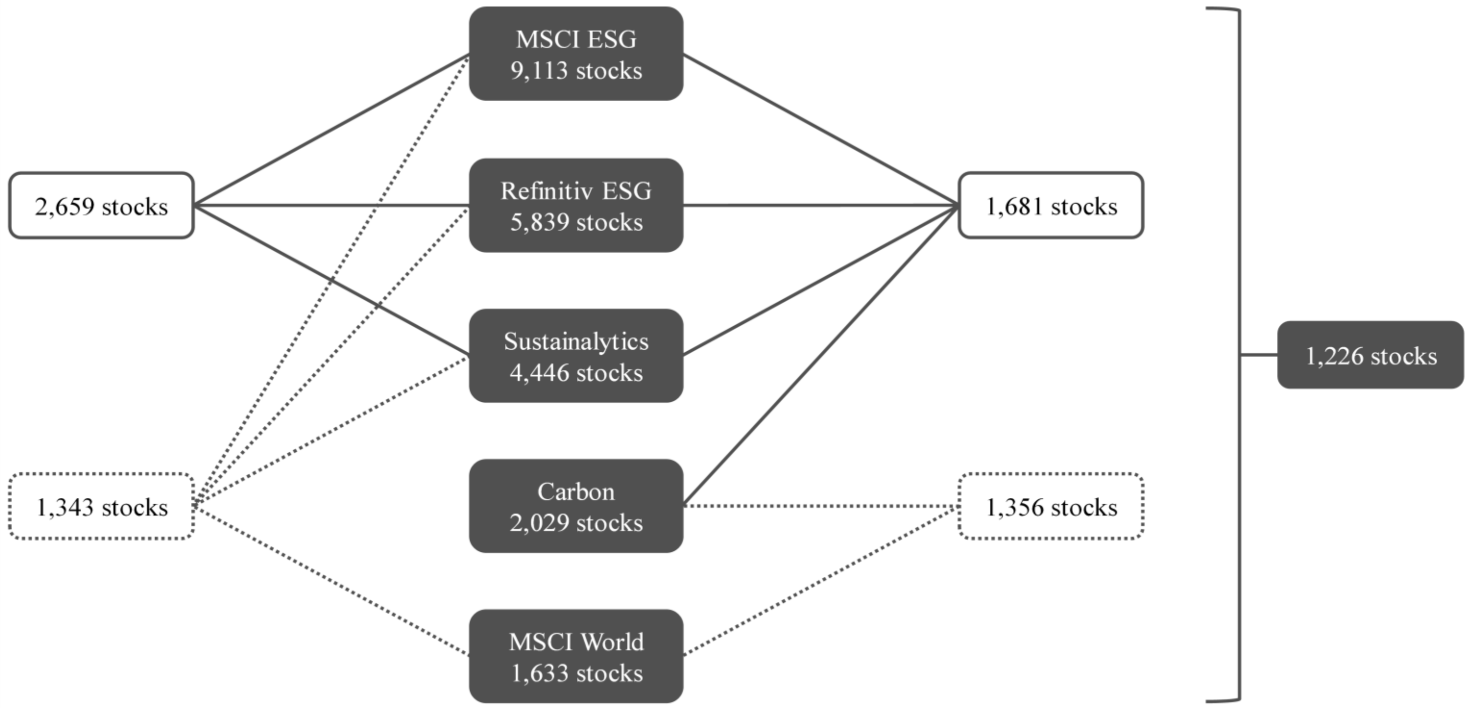



**Figure 1**
**Overview of data sets and matched samples**

This figure summarizes all data samples used in this study. The numbers refer to the average number of available stocks for each month in the sample period from April 2011 to December 2019. The lines connect different data samples and the attached box refers to the number of matched stocks. The box to the right refers to the total number of stocks which are available in all five data sets.

**Table 2**
**Index factsheets**

| | World | World ESG Leaders | World SRI | World ESG Universal | World ESG Focus | World ex Coal | World ex Fossil Fuels | World Low Carbon Target | World Low Carbon Leaders |
|---|---|---|---|---|---|---|---|---|---|
| Avg. number of stocks | 1,633 | 807 | 407 | 1,501 | 486 | 1,620 | 1,553 | 1,268 | 1,287 |
| Market cap coverage (%) | | 49.26 | 24.56 | 92.27 | 61.37 | 99.57 | 96.83 | 88.59 | 82.71 |
| Monthly return (%) | 0.82 | 0.82 | 0.85 | 0.82 | 0.83 | 0.84 | 0.89 | 0.84 | 0.84 |
| Volatility (%) | 3.50 | 3.43 | 3.42 | 3.49 | 3.57 | 3.48 | 3.45 | 3.51 | 3.53 |
| Sharpe Ratio | 0.22 | 0.22 | 0.23 | 0.22 | 0.22 | 0.22 | 0.24 | 0.22 | 0.22 |
| Active Return (%) | | 0.00 | 0.02 | 0.00 | 0.01 | 0.01 | 0.07 | 0.02 | 0.02 |
| Tracking Error (%) | | 0.31 | 0.44 | 0.19 | 0.21 | 0.07 | 0.26 | 0.11 | 0.15 |
| Historical market beta | 1.00 | 0.97 | 0.97 | 0.99 | 1.02 | 0.99 | 0.98 | 1.00 | 1.01 |
| VaR 95% | 0.07 | 0.06 | 0.06 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 |
| Max Drawdown (%) | 19.43 | 18.51 | 17.74 | 19.31 | 19.73 | 19.11 | 18.47 | 19.17 | 19.58 |
| Price-to-book ratio | 2.13 | 2.33 | 2.36 | 2.19 | 2.16 | 2.13 | 2.19 | 2.16 | 2.12 |
| ROE (%) | 11.86 | 12.68 | 12.62 | 12.22 | 12.21 | 11.85 | 12.10 | 12.15 | 12.01 |
| Weighted avg. ATVR (%) | 97.99 | 96.76 | 94.79 | 95.44 | 97.66 | 98.03 | 99.15 | 98.29 | 99.01 |

This table displays descriptive statistics for the analyzed indices from April 2011 to December 2019. All values shown are calculated on index level using monthly data except for the annualized traded value ratio (ATVR), which is based on constituents data. The historical market beta is estimated by a CAPM model with the MSCI World Index as benchmark portfolio.

**Panel A. ESG scores**

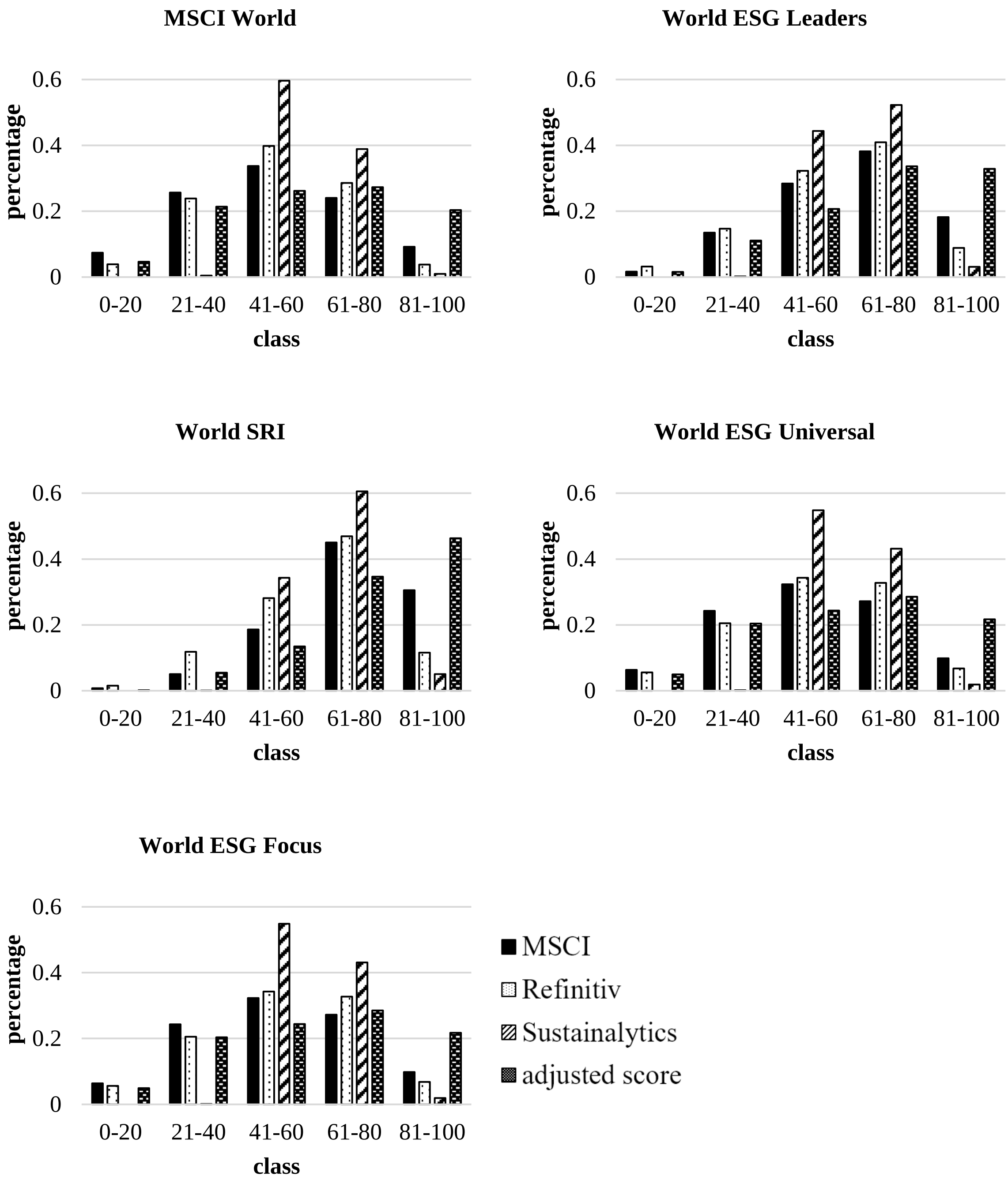



**Figure 2**
**Distribution of scores**

*(to be continued)*

**Panel B. Carbon intensity**

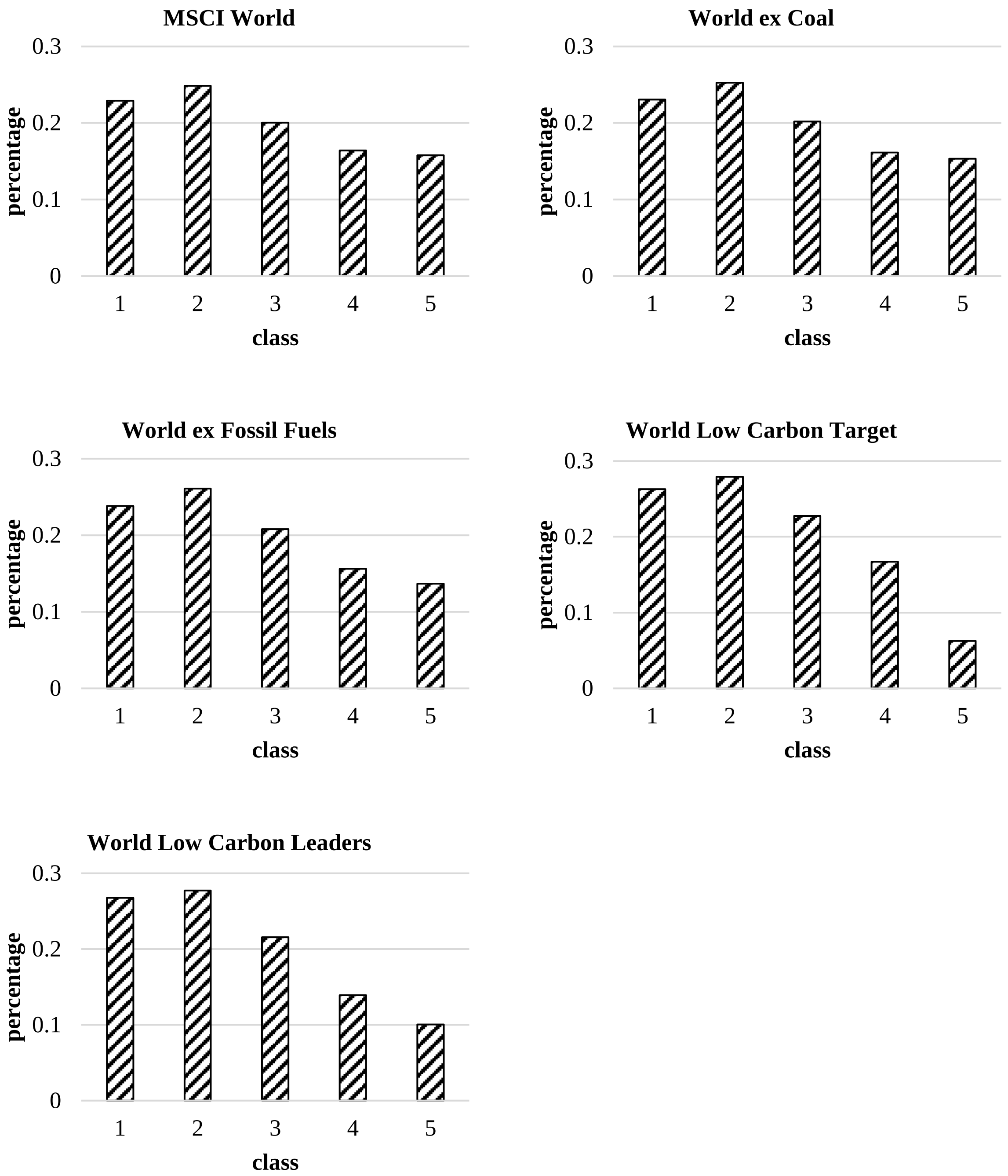
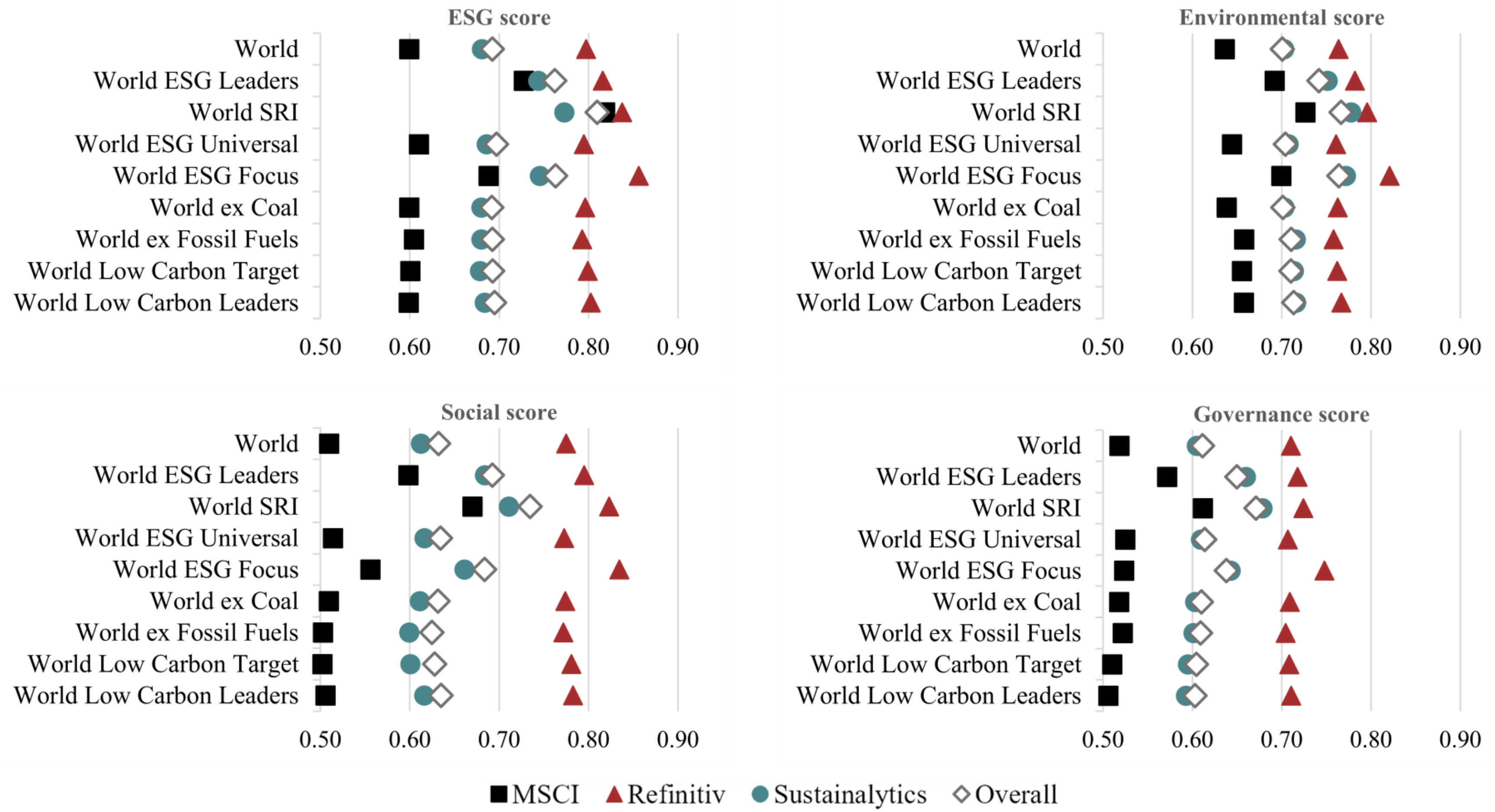



**Figure 2 continued**

This figure shows the average distribution of ESG scores (Panel A) and carbon intensities (Panel B) of select indices over the sample period. ESG scores are based on scores provided by MSCI ESG, Refinitiv ESG, and Sustainalytics. The adjusted score is calculated as described in the data section. MSCI ESG scores are multiplied by 10 to put them on the same scale as Refinitiv ESG and Sustainalytics data (following Christensen et al., 2019). Carbon intensity is measured as scope 1 and 2 emissions divided by enterprise value. Carbon intensities are divided into quintile classes with class 1 containing stocks with the lowest carbon intensities and class 5 comprising stocks with the highest carbon intensities.

**Table 3**
**ESG profile of indices**

**Panel A. Adjusted ESG scores**




*(to be continued)*

**Table 3 continued**

**Panel B. Carbon intensity measures**

| | World ESG Leaders | World SRI | World ESG Universal | World ESG Focus | World ex Coal | World ex Fossil Fuels | World Low Carbon Target | World Low Carbon Leaders |
|---|---|---|---|---|---|---|---|---|
| Carbon intensity reduction (%) | 14.01 | 29.40 | 2.28 | 35.72 | 4.61 | 21.86 | 64.18 | 43.06 |

This table shows average adjusted ESG measures of different data providers on index level for the sample period in Panel A. Each month, ESG data for the constituents of an index are aggregated on a value-weighted basis. If less than 40 percent of constituents' ESG data are available for an index, the respective month is excluded. ESG scores for constituents are only included if they are reported by all three ESG data providers. Panel B reports the average carbon intensity reduction compared to the MSCI World Index. Carbon intensity is measured as tonnes of $CO_2e$ divided by enterprise value. Emissions data are taken from CDP, Refinitiv, and Sustainalytics (in this preference order).

**Table 4**
**Regression results for active returns**

**Panel A. ESG model**

| | alpha | $\beta_{mkt}$ | $\beta_{smb}$ | $\beta_{hml}$ | $\beta_{wml}$ | $\beta_{esg}$ | $R^2$ | adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|
| World ESG Leaders | 0.0003 | -0.0232 | 0.0180 | -0.0071 | 0.0009 | 0.0379 | 0.1021 | 0.0568 |
| | (0.89) | (-2.63) | (0.70) | (-0.34) | (0.06) | (1.55) | | |
| World SRI | 0.0007 | -0.0269 | 0.0742 | -0.0359 | -0.0022 | 0.0768 | 0.1158 | 0.0712 |
| | (1.55) | (-2.16) | (2.05) | (-1.22) | (-0.11) | (2.21) | | |
| World ESG Universal | 0.0002 | -0.0035 | 0.0105 | -0.0325 | -0.0031 | 0.0751 | 0.2638 | 0.2266 |
| | (1.17) | (-0.71) | (0.72) | (-2.76) | (-0.39) | (5.38) | | |
| World ESG Focus | 0.0002 | 0.0131 | 0.0108 | -0.0233 | -0.0219 | 0.0350 | 0.1716 | 0.1298 |
| | (0.86) | (2.31) | (0.66) | (-1.75) | (-2.40) | (2.21) | | |
| World ex Coal | 0.0001 | -0.0052 | -0.0061 | -0.0080 | 0.0037 | 0.0098 | 0.2247 | 0.1855 |
| | (2.24) | (-2.79) | (-1.13) | (-1.83) | (1.23) | (1.90) | | |
| World ex Fossil Fuels | 0.0007 | -0.0152 | -0.0132 | -0.0549 | 0.0105 | 0.0149 | 0.2347 | 0.1961 |
| | (2.73) | (-2.19) | (-0.66) | (-3.37) | (0.94) | (0.77) | | |
| World Low Carbon Target | 0.0001 | 0.0006 | -0.0105 | -0.0193 | -0.0060 | -0.0061 | 0.0904 | 0.0445 |
| | (1.14) | (0.18) | (-1.12) | (-2.56) | (-1.16) | (-0.68) | | |
| World Low Carbon Leaders | 0.0002 | 0.0081 | 0.0150 | 0.0185 | 0.0013 | -0.0009 | 0.0986 | 0.0531 |
| | (1.47) | (1.94) | (1.24) | (1.89) | (0.19) | (-0.07) | | |

*(to be continued)*

**Table 4 continued**

**Panel B. Pillar factors model**

| | alpha | $\beta_{mkt}$ | $\beta_{smb}$ | $\beta_{hml}$ | $\beta_{wml}$ | $\beta_{env}$ | $\beta_{soc}$ | $\beta_{gov}$ | $R^2$ | adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| World ESG Leaders | 0.0002 | -0.0091 | 0.0274 | 0.0044 | -0.0035 | 0.0284 | -0.0389 | **0.0587** | 0.1623 | 0.1018 |
| | (0.52) | (-0.88) | (1.08) | (0.20) | (-0.26) | (1.21) | (-1.33) | (2.70) | | |
| World SRI | 0.0006 | -0.0233 | 0.0718 | -0.0317 | -0.0049 | 0.0097 | 0.0193 | **0.0466** | 0.1089 | 0.0446 |
| | (1.29) | (-1.53) | (1.92) | (-0.98) | (-0.24) | (0.28) | (0.45) | (1.46) | | |
| World ESG Universal | 0.0002 | -0.0126 | 0.0027 | -0.0441 | -0.0023 | 0.0096 | **0.0683** | -0.0015 | 0.2401 | 0.1853 |
| | (1.20) | (-2.04) | (0.18) | (-3.37) | (-0.28) | (0.69) | (3.91) | (-0.12) | | |
| World ESG Focus | 0.0002 | 0.0055 | 0.0013 | -0.0286 | -0.0207 | -0.0105 | **0.0439** | -0.0080 | 0.1749 | 0.1153 |
| | (0.89) | (0.80) | (0.08) | (-1.96) | (-2.24) | (-0.68) | (2.25) | (-0.55) | | |
| World ex Coal | 0.0001 | -0.0019 | -0.0047 | -0.0057 | 0.0028 | **0.0151** | -0.0126 | 0.0076 | 0.2950 | 0.2442 |
| | (1.85) | (-0.91) | (-0.89) | (-1.25) | (0.97) | (3.10) | (-2.07) | (1.69) | | |
| World ex Fossil Fuels | 0.0007 | -0.0143 | -0.0205 | -0.0579 | 0.0118 | **0.0906** | -0.0388 | -0.0559 | 0.4746 | 0.4367 |
| | (3.13) | (-2.06) | (-1.20) | (-3.91) | (1.26) | (5.73) | (-1.97) | (-3.81) | | |
| World Low Carbon Target | 0.0001 | 0.0017 | -0.0121 | -0.0178 | -0.0058 | 0.0143 | **-0.0159** | -0.0109 | 0.1444 | 0.0827 |
| | (1.06) | (0.44) | (-1.30) | (-2.21) | (-1.14) | (1.66) | (-1.49) | (-1.37) | | |
| World Low Carbon Leaders | 0.0003 | 0.0011 | 0.0119 | 0.0080 | 0.0036 | 0.0189 | 0.0203 | **-0.0395** | 0.2486 | 0.1944 |
| | (2.08) | (0.23) | (1.04) | (0.81) | (0.57) | (1.80) | (1.55) | (-4.05) | | |

*(to be continued)*

**Table 4 continued**

**Panel C. Emissions factor model**

| | alpha | $\beta_{mkt}$ | $\beta_{smb}$ | $\beta_{hml}$ | $\beta_{wml}$ | $\beta_{emi}$ | $R^2$ | adj. $R^2$ |
|---|---|---|---|---|---|---|---|---|
| World ESG Leaders | 0.0003 | -0.0227 | -0.0004 | -0.0052 | 0.0009 | 0.0166 | 0.0933 | 0.0476 |
| | (0.84) | (-2.54) | (-0.02) | (-0.25) | (0.06) | (1.19) | | |
| World SRI | 0.0005 | -0.0286 | 0.0385 | -0.0207 | -0.0020 | 0.0068 | 0.0733 | 0.0265 |
| | (1.14) | (-2.22) | (1.16) | (-0.69) | (-0.10) | (0.34) | | |
| World ESG Universal | 0.0000 | -0.0060 | -0.0240 | -0.0142 | -0.0028 | -0.0012 | 0.0484 | 0.0004 |
| | (0.02) | (-1.05) | (-1.62) | (-1.06) | (-0.31) | (-0.14) | | |
| World ESG Focus | 0.0000 | 0.0111 | -0.0048 | -0.0112 | -0.0217 | -0.0091 | 0.1393 | 0.0958 |
| | (0.17) | (1.91) | (-0.32) | (-0.82) | (-2.34) | (-0.99) | | |
| World ex Coal | 0.0001 | -0.0067 | -0.0100 | -0.0005 | 0.0038 | -0.0120 | 0.3277 | 0.2938 |
| | (0.97) | (-3.84) | (-2.21) | (-0.12) | (1.35) | (-4.40) | | |
| World ex Fossil Fuels | 0.0002 | -0.0243 | -0.0156 | -0.0141 | 0.0111 | -0.0870 | 0.7144 | 0.7000 |
| | (1.22) | (-5.69) | (-1.41) | (-1.41) | (1.62) | (-12.96) | | |
| World Low Carbon Target | 0.0000 | -0.0019 | -0.0063 | -0.0092 | -0.0059 | -0.0269 | 0.3427 | 0.3095 |
| | (0.07) | (-0.69) | (-0.89) | (-1.43) | (-1.34) | (-6.21) | | |
| World Low Carbon Leaders | 0.0001 | 0.0049 | 0.0171 | 0.0326 | 0.0015 | -0.0332 | 0.3267 | 0.2927 |
| | (0.39) | (1.33) | (1.82) | (3.82) | (0.26) | (-5.79) | | |

This table shows the results for regressions with the active return of the respective index as dependent variable. In Panel A, we display all estimated coefficients in the sample period for the ESG model (equation (2)). The last two columns display $R^2$ and adjusted $R^2$ values. Panel B displays results for the ESG pillar factors model (equation (3)) and Panel C for the emissions factor model (equation (4)). T-statistics are reported in parentheses. In Panel B, the highest absolute beta estimate across all three pillar factors is printed in bold.

**Table 5**
**Risk decomposition of active index returns**

**Panel A. Pillar factors model**

| | Decomposed $R^2$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | *mkt* | *smb* | *hml* | *wml* | *env* | *soc* | *gov* | Syst. risk | Idiosyncr. risk | Idiosyncr. risk ESG | Idiosyncr. risk Carhart |
| World ESG Leaders | 5.59 | 0.39 | 0.00 | 0.09 | 1.58 | 0.86 | **7.71** | 16.23 | 83.77 | 89.79 | 91.95 |
| World SRI | **4.60** | 2.56 | 0.71 | 0.15 | 0.12 | 0.06 | 2.68 | 10.89 | 89.11 | 88.42 | 92.77 |
| World ESG Universal | 1.25 | 0.31 | 4.73 | 0.09 | 2.70 | **13.57** | 1.36 | 24.01 | 75.99 | 73.62 | 95.17 |
| World ESG Focus | 5.43 | 0.01 | 1.06 | **5.62** | 0.12 | 5.05 | 0.19 | 17.49 | 82.51 | 82.84 | 86.93 |
| World ex Coal | 6.50 | 1.63 | 2.82 | 3.91 | **7.65** | 2.43 | 4.56 | 29.50 | 70.50 | 77.53 | 80.37 |
| World ex Fossil Fuels | 4.93 | 0.96 | 12.54 | 5.58 | **13.58** | 4.39 | 5.48 | 47.46 | 52.54 | 76.53 | 76.99 |
| World Low Carbon Target | 0.30 | 1.34 | **6.35** | 0.13 | 0.95 | 3.29 | 2.09 | 14.44 | 85.56 | 90.96 | 91.38 |
| World Low Carbon Leaders | 2.16 | 1.28 | 2.32 | 0.27 | 2.61 | 2.48 | **13.74** | 24.86 | 75.14 | 90.14 | 90.14 |

**Panel B. Emissions factor model**

| | Decomposed $R^2$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | *mkt* | *smb* | *hml* | *wml* | *emi* | Syst. risk | Idiosyncr. risk |
| World ESG Leaders | **7.42** | 0.00 | 0.01 | 0.20 | 1.70 | 9.33 | 90.67 |
| World SRI | **5.24** | 1.27 | 0.50 | 0.20 | 0.13 | 7.33 | 92.67 |
| World ESG Universal | 1.05 | **2.48** | 1.20 | 0.03 | 0.09 | 4.84 | 95.16 |
| World ESG Focus | **6.18** | 0.09 | 0.19 | 6.18 | 1.29 | 13.93 | 86.07 |
| World ex Coal | 10.64 | 3.45 | 0.81 | 3.99 | **13.88** | 32.77 | 67.23 |
| World ex Fossil Fuels | 7.47 | 0.65 | 4.42 | 4.65 | **54.25** | 71.44 | 28.56 |
| World Low Carbon Target | 0.03 | 0.56 | 3.16 | 0.22 | **30.29** | 34.27 | 65.73 |
| World Low Carbon Leaders | 2.64 | 1.98 | 7.92 | 0.66 | **19.47** | 32.67 | 67.33 |

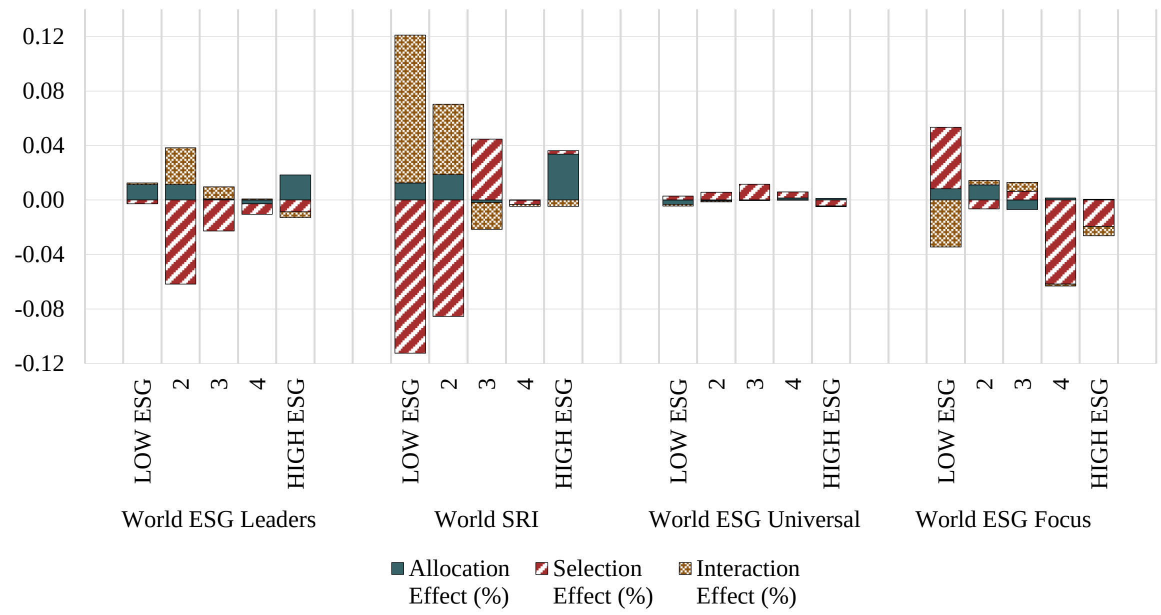
This table displays the risk decomposition of active returns based on the methodology of Klein and Chow (2013). The systematic risk contribution of each of the factors in the model is calculated as shown in equation (5). The sum of the risk contributions (systematic risk) equals the coefficient of determination of the respective regression ($R^2$). The idiosyncratic risk is obtained as $1–R^2$. Panel A reports the results for the pillar factors model (equation (3)) and Panel B for the emissions factor model (equation (4)). For comparative purposes, we display the idiosyncratic risk of the ESG and Carhart model in the last two columns in Panel A. All numbers are reported in percent. The highest factor risk contribution per index is printed in bold.

**Table 6**
**Performance attribution effects**

| | Active Return | Allocation Effect | Selection Effect | Interaction Effect |
|---|---|---|---|---|
| **Panel A. ESG classes** | | | | |
| World ESG Leaders | -0.0302 | 0.0393 | **-0.1033** | 0.0338 |
| World SRI | 0.0437 | 0.0632 | **-0.1536** | 0.1341 |
| World ESG Universal | 0.0164 | -0.0012 | **0.0205** | -0.0029 |
| World ESG Focus | -0.0544 | 0.0145 | **-0.0360** | -0.0328 |
| World ex Coal | -0.0144 | -0.0014 | **-0.0131** | 0.0001 |
| World ex Fossil Fuels | 0.0116 | -0.0030 | **0.0139** | 0.0007 |
| World Low Carbon Target | -0.0510 | -0.0085 | **-0.0425** | 0.0001 |
| World Low Carbon Leaders | 0.0395 | -0.0089 | **0.0529** | -0.0045 |
| **Panel B. Emissions classes** | | | | |
| World ESG Leaders | -0.0319 | 0.0055 | **-0.0389** | 0.0015 |
| World SRI | -0.0030 | 0.0224 | **-0.0428** | 0.0174 |
| World ESG Universal | 0.0101 | **0.0117** | -0.0008 | -0.0008 |
| World ESG Focus | 0.0338 | **0.0384** | -0.0082 | 0.0037 |
| World ex Coal | 0.0086 | **0.0052** | 0.0036 | -0.0002 |
| World ex Fossil Fuels | 0.0673 | **0.0416** | 0.0387 | -0.0130 |
| World Low Carbon Target | 0.0441 | **0.0514** | -0.0167 | 0.0093 |
| World Low Carbon Leaders | 0.0293 | **0.0548** | -0.0326 | 0.0071 |

This table displays attribution effects of active index returns of the indices following the methodology of Brinson and Fachler (1985) and calculated following equations (8) to (10). All numbers are given in percent. The effect with the highest absolute contribution for each index is printed in bold.

**Panel A. ESG classes**




**Panel B. Emissions classes**

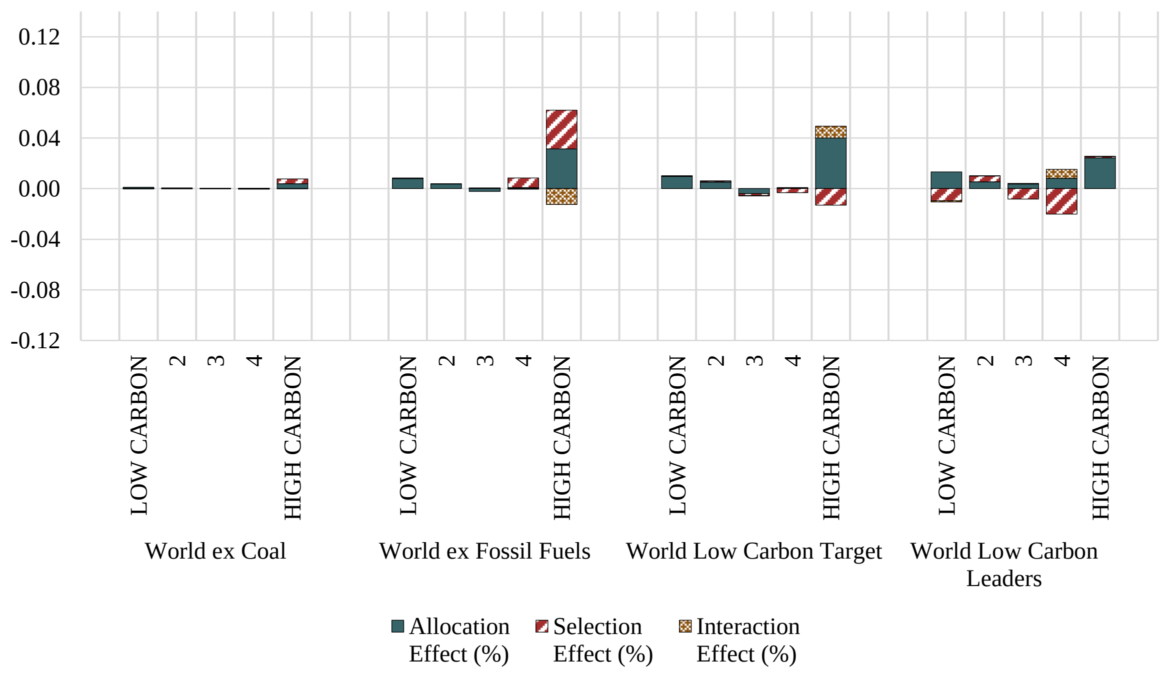



**Figure 3**
**Performance attribution of classes**

This figure graphically depicts performance attribution effects for each performance class within one index following the model of Brinson and Fachler (1985).

## Internet Appendix A

**Panel A. Environmental pillar scores**

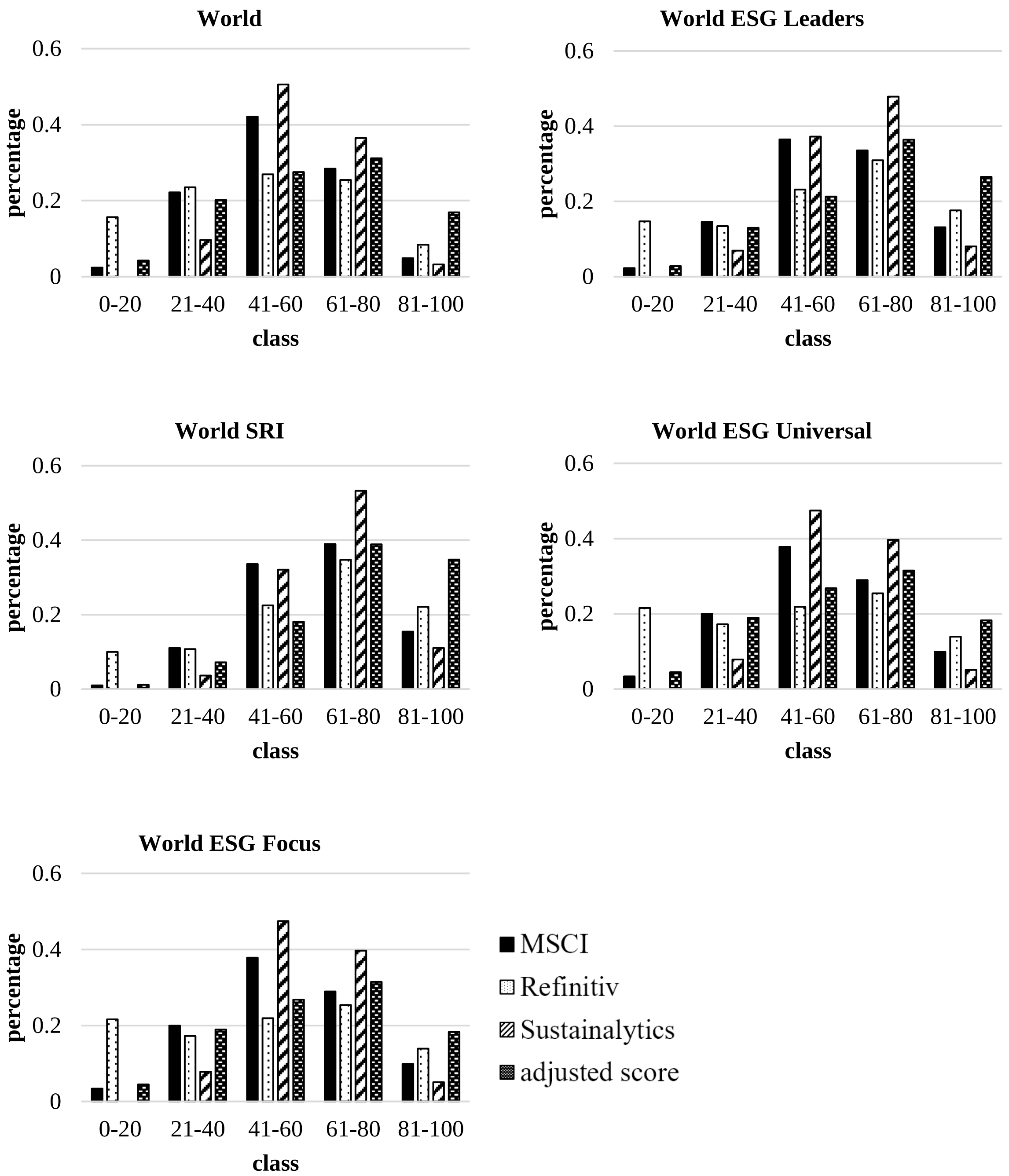



**Figure A.1**
**Distribution of scores**

*(to be continued)*

**Panel B. Social pillar scores**

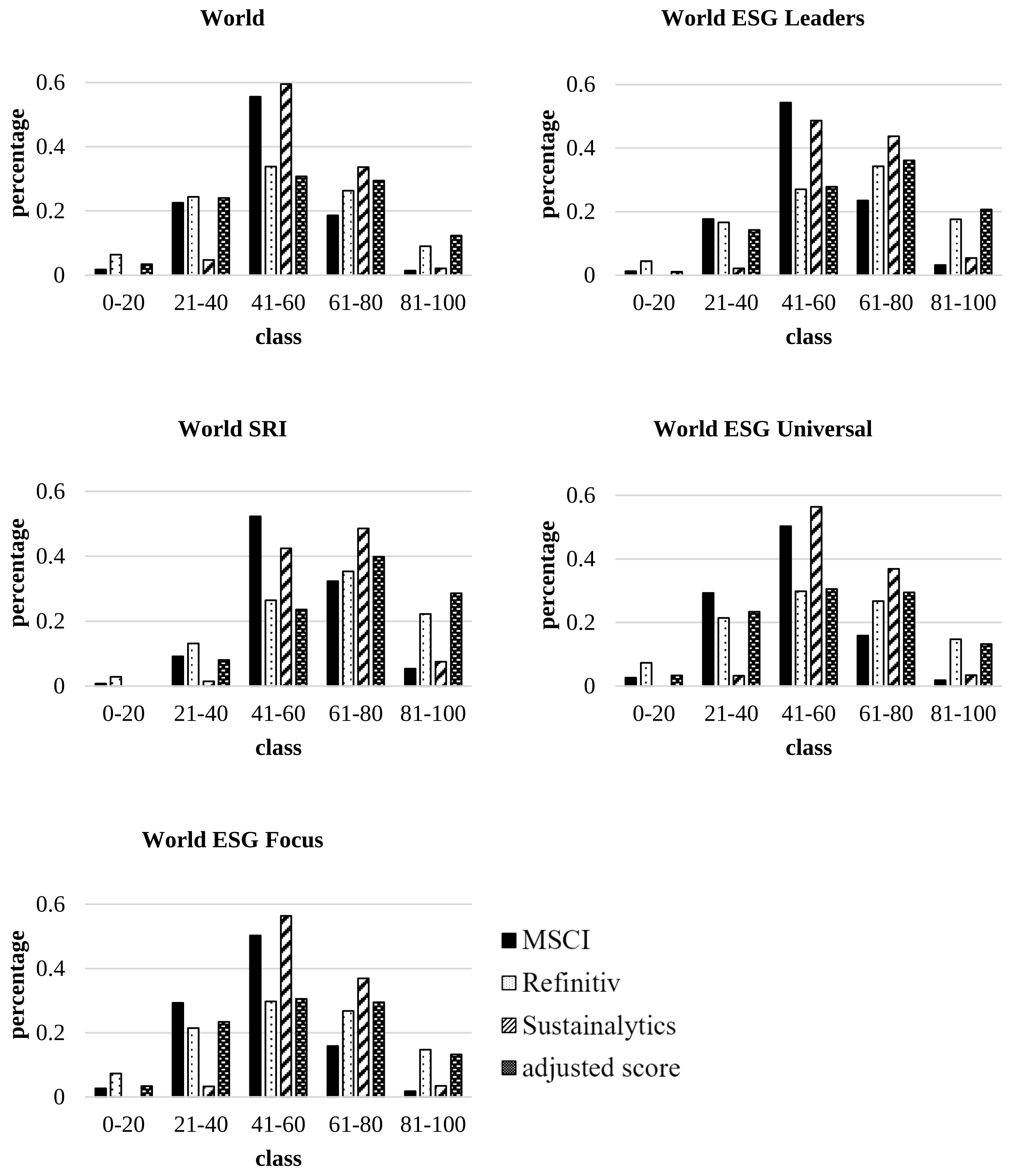



**Figure A.1 continued**

*(to be continued)*

**Panel C. Governance pillar scores**

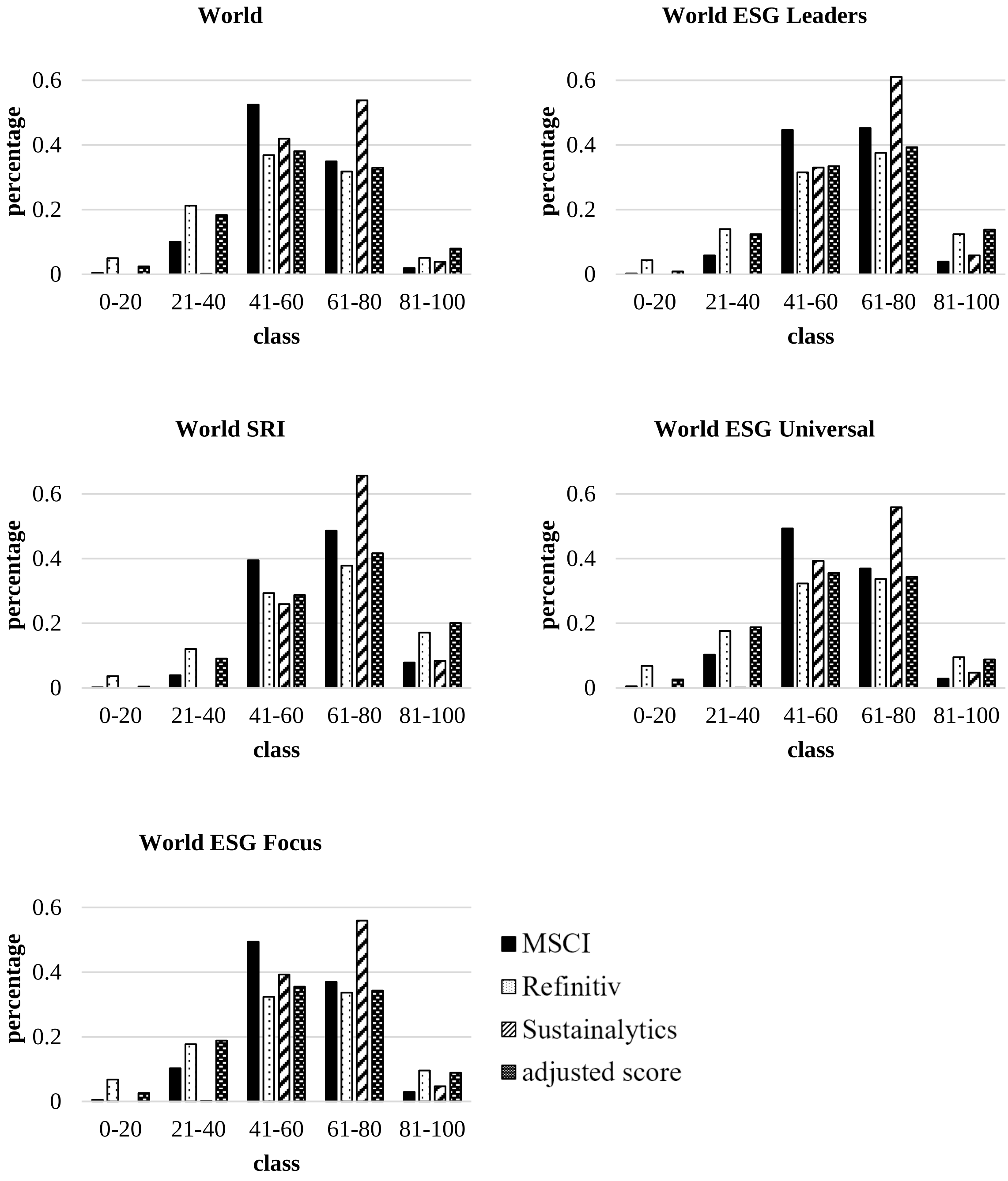



**Figure A.1 continued**

This figure shows the average distribution of the environmental (Panel A), social (Panel B), and governance (Panel C) pillar scores of ESG indices over the sample period. The pillar scores are based on scores provided by MSCI ESG, Refinitiv ESG, and Sustainalytics. The adjusted score is calculated as described in the data section. MSCI ESG scores are multiplied by 10 to put them on the same scale as Refinitiv ESG and Sustainalytics data (following Christensen et al., 2019).

**Table A.1**
**Spearman correlations of ESG scores**

| | ESG MSCI | ESG Refinitiv | ESG Sust | env MSCI | env Refinitiv | env Sust | soc MSCI | soc Refinitiv | soc Sust | gov MSCI | gov Refinitiv | gov Sust |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ESG MSCI | 1 | | | | | | | | | | | |
| ESG Refinitiv | 0.4272 | 1 | | | | | | | | | | |
| ESG Sust | 0.5256 | 0.7009 | 1 | | | | | | | | | |
| env MSCI | 0.4365 | 0.3091 | 0.3232 | 1 | | | | | | | | |
| env Refinitiv | 0.4096 | 0.8382 | 0.6818 | 0.2952 | 1 | | | | | | | |
| env Sust | 0.4873 | 0.6310 | 0.8664 | 0.3924 | 0.6738 | 1 | | | | | | |
| soc MSCI | 0.5835 | 0.1876 | 0.2973 | 0.1077 | 0.2196 | 0.2620 | 1 | | | | | |
| soc Refinitiv | 0.4060 | 0.8913 | 0.6689 | 0.3029 | 0.7020 | 0.5856 | 0.1776 | 1 | | | | |
| soc Sust | 0.4217 | 0.5843 | 0.8608 | 0.1941 | 0.5367 | 0.5850 | 0.2601 | 0.5714 | 1 | | | |
| gov MSCI | 0.3182 | 0.1168 | 0.1933 | 0.0025 | 0.0409 | 0.0755 | 0.0569 | 0.1043 | 0.2078 | 1 | | |
| gov Refinitiv | 0.2113 | 0.6647 | 0.3448 | 0.1211 | 0.3580 | 0.2727 | 0.0691 | 0.3915 | 0.2904 | 0.1433 | 1 | |
| gov Sust | 0.3714 | 0.5022 | 0.7064 | 0.1869 | 0.4145 | 0.4445 | 0.1923 | 0.4964 | 0.5204 | 0.2405 | 0.3199 | 1 |

This table displays pairwise Spearman correlations between the ESG (ESG), environmental (env), social (soc), and governance (gov) pillar scores of the data providers MSCI ESG, Refinitiv ESG, and Sustainalytics (Sust) for all stocks of the MSCI World Index for the period from April 2011 to December 2019.

**Table A.2**
**Summary statistics of factors**

**Panel A. Descriptive statistics**

| | mean | sd | t-stat |
|---|---|---|---|
| *mktrf* | 0.0073 | 0.0355 | 2.11 |
| *smb* | -0.0015 | 0.0128 | -1.22 |
| *hml* | -0.0021 | 0.0173 | -1.25 |
| *wml* | 0.0048 | 0.0255 | 1.93 |
| *esg* | -0.0027 | 0.0140 | -1.95 |
| *env* | -0.0022 | 0.0157 | -1.40 |
| *soc* | -0.0024 | 0.0147 | -1.70 |
| *gov* | -0.0009 | 0.0168 | -0.57 |
| *emi* | -0.0069 | 0.0225 | -3.15 |

**Panel B. Correlations between factors**

| | *mktrf* | *smb* | *hml* | *wml* | *esg* | *env* | *soc* | *gov* | *emi* |
|---|---|---|---|---|---|---|---|---|---|
| *mktrf* | 1 | | | | | | | | |
| *smb* | 0.0122 | 1 | | | | | | | |
| *hml* | 0.0266 | -0.0371 | 1 | | | | | | |
| *wml* | -0.3066 | 0.0197 | -0.5053 | 1 | | | | | |
| *esg* | -0.0780 | -0.4309 | 0.3025 | -0.1257 | 1 | | | | |
| *env* | -0.1580 | -0.3650 | 0.3083 | -0.0875 | 0.7193 | 1 | | | |
| *soc* | 0.2643 | -0.3097 | 0.4853 | -0.3310 | 0.7657 | 0.5106 | 1 | | |
| *gov* | -0.3641 | -0.3647 | 0.0369 | 0.1484 | 0.6121 | 0.3842 | 0.2966 | 1 | |
| *emi* | -0.1500 | 0.0152 | 0.3217 | -0.1113 | 0.2078 | -0.0512 | 0.1524 | 0.3952 | 1 |

This table reports descriptive statistics of all factors used in this study for the sample period from April 2011 to December 2019. The market factor (*mktrf*), *smb*, *hml*, and *wml* are the global factors from Kenneth R. French's data library. The factors *esg*, *env*, *soc*, *gov*, and *emi* are constructed as long-short portfolios based on the overall adjusted ESG, environmental pillar, social pillar, governance pillar scores, and carbon intensity, respectively. T-statistics are based on two-sided t-tests.

**Table A.3**
**Regression results for active returns – Carhart model**

| | alpha | $\beta_{mkt}$ | $\beta_{smb}$ | $\beta_{hml}$ | $\beta_{wml}$ | $R^2$ | adj. $R^2$ |
|---|---|---|---|---|---|---|---|
| World ESG Leaders | 0.0002 | -0.0244 | 0.0005 | 0.0019 | 0.0010 | 0.0805 | 0.0437 |
| | (0.59) | (-2.76) | (0.02) | (0.10) | (0.07) | | |
| World SRI | 0.0005 | -0.0293 | 0.0389 | -0.0178 | -0.0020 | 0.0723 | 0.0352 |
| | (1.10) | (-2.31) | (1.17) | (-0.62) | (-0.10) | | |
| World ESG Universal | 0.0000 | -0.0059 | -0.0241 | -0.0148 | -0.0029 | 0.0483 | 0.0102 |
| | (0.06) | (-1.04) | (-1.63) | (-1.16) | (-0.31) | | |
| World ESG Focus | 0.0001 | 0.0120 | -0.0053 | -0.0151 | -0.0218 | 0.1307 | 0.0959 |
| | (0.41) | (2.09) | (-0.35) | (-1.16) | (-2.34) | | |
| World ex Coal | 0.0001 | -0.0055 | -0.0106 | -0.0057 | 0.0037 | 0.1963 | 0.1641 |
| | (1.86) | (-2.93) | (-2.16) | (-1.34) | (1.22) | | |
| World ex Fossil Fuels | 0.0006 | -0.0156 | -0.0201 | -0.0514 | 0.0105 | 0.2301 | 0.1994 |
| | (2.63) | (-2.27) | (-1.11) | (-3.30) | (0.95) | | |
| World Low Carbon Target | 0.0001 | 0.0008 | -0.0077 | -0.0207 | -0.0060 | 0.0862 | 0.0497 |
| | (1.31) | (0.24) | (-0.92) | (-2.87) | (-1.17) | | |
| World Low Carbon Leaders | 0.0002 | 0.0082 | 0.0154 | 0.0183 | 0.0013 | 0.0986 | 0.0625 |
| | (1.53) | (1.97) | (1.42) | (1.95) | (0.19) | | |

This table shows the results for regressions of the global Carhart (1997) model with the active return of the respective index as dependent variable. We display all estimated coefficients in the sample period for the Carhart model (equation (1)). The last two columns display $R^2$ and adjusted $R^2$ values. T-statistics are reported in parentheses.

**Table A.4**
**Performance attribution on class level**

**Panel A. ESG classes**

| | portfolio weight | bm weight | portfolio return | bm return | bm index return | Allocation Effect | Selection Effect | Interaction Effect | Total |
|---|---|---|---|---|---|---|---|---|---|
| **World ESG Leaders** | | | | | **0.2622** | **0.0393** | **-0.1033** | **0.0338** | **-0.0302** |
| LOW ESG | 2.2176 | 5.5901 | -0.0322 | -0.0039 | | 0.0113 | -0.0026 | 0.0013 | 0.0100 |
| 2 | 6.2161 | 10.4342 | -0.3232 | 0.0671 | | 0.0114 | -0.0617 | 0.0270 | -0.0234 |
| 3 | 11.5628 | 16.7620 | 0.2130 | 0.3365 | | 0.0008 | -0.0227 | 0.0089 | -0.0129 |
| 4 | 25.5958 | 28.5239 | 0.2665 | 0.2960 | | -0.0026 | -0.0077 | 0.0008 | -0.0095 |
| HIGH ESG | 54.4077 | 38.6898 | 0.2927 | 0.3192 | | 0.0185 | -0.0085 | -0.0043 | 0.0057 |
| **World SRI** | | | | | **0.2622** | **0.0632** | **-0.1536** | **0.1341** | **0.0437** |
| LOW ESG | 0.6049 | 5.5901 | -2.1122 | -0.0039 | | 0.0126 | -0.1124 | 0.1084 | 0.0086 |
| 2 | 3.8510 | 10.4342 | -0.4962 | 0.0671 | | 0.0187 | -0.0854 | 0.0516 | -0.0151 |
| 3 | 8.2287 | 16.7620 | 0.5936 | 0.3365 | | -0.0017 | 0.0448 | -0.0198 | 0.0233 |
| 4 | 21.9473 | 28.5239 | 0.2862 | 0.2960 | | -0.0002 | -0.0031 | -0.0014 | -0.0047 |
| HIGH ESG | 65.3681 | 38.6898 | 0.3079 | 0.3192 | | 0.0337 | 0.0025 | -0.0046 | 0.0316 |
| **World ESG Universal** | | | | | **0.2622** | **-0.0012** | **0.0205** | **-0.0029** | **0.0164** |
| LOW ESG | 5.5432 | 5.5901 | 0.0648 | -0.0039 | | -0.0033 | 0.0030 | -0.0011 | -0.0013 |
| 2 | 10.0182 | 10.4342 | 0.1291 | 0.0671 | | -0.0006 | 0.0056 | -0.0008 | 0.0043 |
| 3 | 16.2076 | 16.7620 | 0.3927 | 0.3365 | | 0.0000 | 0.0115 | -0.0005 | 0.0111 |
| 4 | 28.3606 | 28.5239 | 0.3142 | 0.2960 | | 0.0014 | 0.0046 | -0.0001 | 0.0059 |
| HIGH ESG | 39.8703 | 38.6898 | 0.3084 | 0.3192 | | 0.0012 | -0.0043 | -0.0005 | -0.0035 |
| **World ESG Focus** | | | | | **0.2622** | **0.0145** | **-0.0360** | **-0.0328** | **-0.0544** |
| LOW ESG | 1.7079 | 5.5901 | 1.0957 | -0.0039 | | 0.0083 | 0.0452 | -0.0343 | 0.0192 |
| 2 | 4.3678 | 10.4342 | 0.0412 | 0.0671 | | 0.0111 | -0.0066 | 0.0033 | 0.0079 |
| 3 | 12.2693 | 16.7620 | 0.3436 | 0.3365 | | -0.0070 | 0.0065 | 0.0064 | 0.0059 |
| 4 | 30.1461 | 28.5239 | 0.0766 | 0.2960 | | 0.0016 | -0.0617 | -0.0014 | -0.0615 |
| HIGH ESG | 51.5089 | 38.6898 | 0.2714 | 0.3192 | | 0.0005 | -0.0194 | -0.0068 | -0.0258 |

*(to be continued)*

**Table A.4 continued**

**Panel B. Emissions classes**

| | portfolio weight | bm weight | portfolio return | bm return | bm index return | Allocation Effect | Selection Effect | Interaction Effect | Total |
|---|---|---|---|---|---|---|---|---|---|
| **World ex Coal** | | | | | **1.1407** | **0.0052** | **0.0036** | **-0.0002** | **0.0086** |
| LOW CARBON | 31.0504 | 30.7407 | 1.4149 | 1.4150 | | 0.0010 | 0.0000 | 0.0000 | 0.0010 |
| 2 | 26.2157 | 25.9669 | 1.3053 | 1.3054 | | 0.0004 | 0.0000 | 0.0000 | 0.0004 |
| 3 | 19.3836 | 19.1963 | 0.9619 | 0.9618 | | -0.0003 | 0.0000 | 0.0000 | -0.0003 |
| 4 | 10.7382 | 10.8553 | 0.9111 | 0.9135 | | 0.0002 | -0.0001 | 0.0000 | 0.0001 |
| HIGH CARBON | 12.6121 | 13.2408 | 0.6377 | 0.6194 | | 0.0038 | 0.0037 | -0.0001 | 0.0074 |
| **World ex Fossil Fuels** | | | | | **1.1407** | **0.0416** | **0.0387** | **-0.0130** | **0.0673** |
| LOW CARBON | 33.3662 | 30.7407 | 1.4161 | 1.4150 | | 0.0078 | 0.0003 | 0.0000 | 0.0082 |
| 2 | 28.0959 | 25.9669 | 1.3055 | 1.3054 | | 0.0035 | 0.0000 | 0.0000 | 0.0035 |
| 3 | 20.7050 | 19.1963 | 0.9645 | 0.9618 | | -0.0021 | 0.0004 | 0.0001 | -0.0016 |
| 4 | 10.3416 | 10.8553 | 0.9818 | 0.9135 | | 0.0009 | 0.0074 | -0.0005 | 0.0079 |
| HIGH CARBON | 7.4913 | 13.2408 | 0.8426 | 0.6194 | | 0.0315 | 0.0305 | -0.0127 | 0.0493 |
| **World Low Carbon Target** | | | | | **1.1407** | **0.0514** | **-0.0167** | **0.0093** | **0.0441** |
| LOW CARBON | 34.3158 | 30.7407 | 1.4159 | 1.4150 | | 0.0097 | 0.0003 | 0.0000 | 0.0101 |
| 2 | 28.9161 | 25.9669 | 1.3084 | 1.3054 | | 0.0051 | 0.0007 | 0.0001 | 0.0060 |
| 3 | 21.2194 | 19.1963 | 0.9535 | 0.9618 | | -0.0039 | -0.0016 | -0.0002 | -0.0057 |
| 4 | 10.4091 | 10.8553 | 0.8853 | 0.9135 | | 0.0005 | -0.0032 | 0.0001 | -0.0026 |
| HIGH CARBON | 5.1397 | 13.2408 | 0.5017 | 0.6194 | | 0.0400 | -0.0130 | 0.0093 | 0.0363 |
| **World Low Carbon Leaders** | | | | | **1.1407** | **0.0548** | **-0.0326** | **0.0071** | **0.0293** |
| LOW CARBON | 35.5725 | 30.7407 | 1.3823 | 1.4150 | | 0.0132 | -0.0094 | -0.0010 | 0.0027 |
| 2 | 29.0374 | 25.9669 | 1.3240 | 1.3054 | | 0.0055 | 0.0044 | 0.0004 | 0.0103 |
| 3 | 19.5094 | 19.1963 | 0.9229 | 0.9618 | | 0.0036 | -0.0083 | 0.0005 | -0.0042 |
| 4 | 7.0743 | 10.8553 | 0.7245 | 0.9135 | | 0.0082 | -0.0201 | 0.0072 | -0.0048 |
| HIGH CARBON | 8.8065 | 13.2408 | 0.6160 | 0.6194 | | 0.0244 | 0.0008 | 0.0000 | 0.0253 |

This table reports the portfolio and benchmark (bm) weights and returns of the respective classes for each index. The column “bm index return” is the average index return of the MSCI World Index during the sample period. In addition, the attribution effects per class are presented. All figures printed in bold are on index level. All numbers are given in percent.

**Internet Appendix B**

This appendix includes analyses based on the total excess return of indices. In comparison to the main analyses, this implies that return and risk impacts common to both the conventional parent index and the sustainable index are taken into consideration besides the index-specific part. In the following, we present both active return exposures and systematic risk tilts.

**Active Exposures**

We estimate factor exposures using our four factor models as described in Equations (1) to (4) of the main analysis. As dependent variable, we employ the excess return over the risk-free rate for each index. Subsequently, we subtract the respective beta exposure of the MSCI World Index from the estimated exposure of each sustainable index to attain the active beta exposure (see Figure B.1).

In line with literature, we barely find any differences for common risk factors (Wan-Ni, 2012). The World SRI Index displays the highest size tilt with a 0.0389 higher *SMB* beta than the MSCI World Index. Even though the World ex Fossil Fuels Index has shown high similarities with the MSCI World Index before, it has a 0.0514 lower *HML* beta than its parent index. All ESG indices display positive active exposures towards the ESG factor (Panel A). We find the highest ESG tilt for the World SRI Index closely followed by the World ESG Universal Index. When splitting the ESG factor in its thematic components, the high active exposure towards ESG of the World SRI Index (World ESG Universal Index) is mainly caused by a tilt towards governance (social) issues. Additionally, the pillar factors model demonstrates that ESG indices can also display lower exposures towards sustainability issues than their parent index. For example, the World ESG Leaders Index has a 0.0389 lower beta exposure towards the social pillar factor than the MSCI World Index. However, it is more sensitive towards the governance pillar factor by 0.0587. Active exposures towards the emissions factor are comparatively small.

[Insert Figure B.1 here.]

Carbon indices are significantly less exposed towards the emissions factor than their parent index (Panel B). This is in line with expectations as it implies that carbon indices are tilted towards the short leg of the emissions factor, i.e., low-carbon stocks. In addition, we find positive tilts for the environmental pillar factor in line with the thematic environmental focus of carbon indices. The World ex Fossil Fuels Index thereby has the largest active exposure of 0.0870.

Overall, sustainable indices do not show systematically high deviations from their parent index for common risk factor exposures. Since we analyze passive investment strategies, small differences are to be expected. More importantly, indices with an ESG focus are more sensitive towards a systematic ESG factor and pillar factors, respectively. Additionally, carbon indices display absolute high active exposures towards an emissions factor and the environmental pillar factor. Hence, sustainable indices conform to their investment focus and are more exposed to their respective thematic emphasis.

**Systematic risk tilts**

We estimate the systematic risk exposure of an index explained by all factors in the underlying factor model as coefficient of determination of the assumed factor model ($R^2$). To be more specific, we estimate models (1) to (4) with the excess return of the index as dependent variable. In the next step, we subtract the risk exposure of the parent index, the MSCI World Index, from the systematic risk exposure of the respective sustainable index to obtain risk tilts.

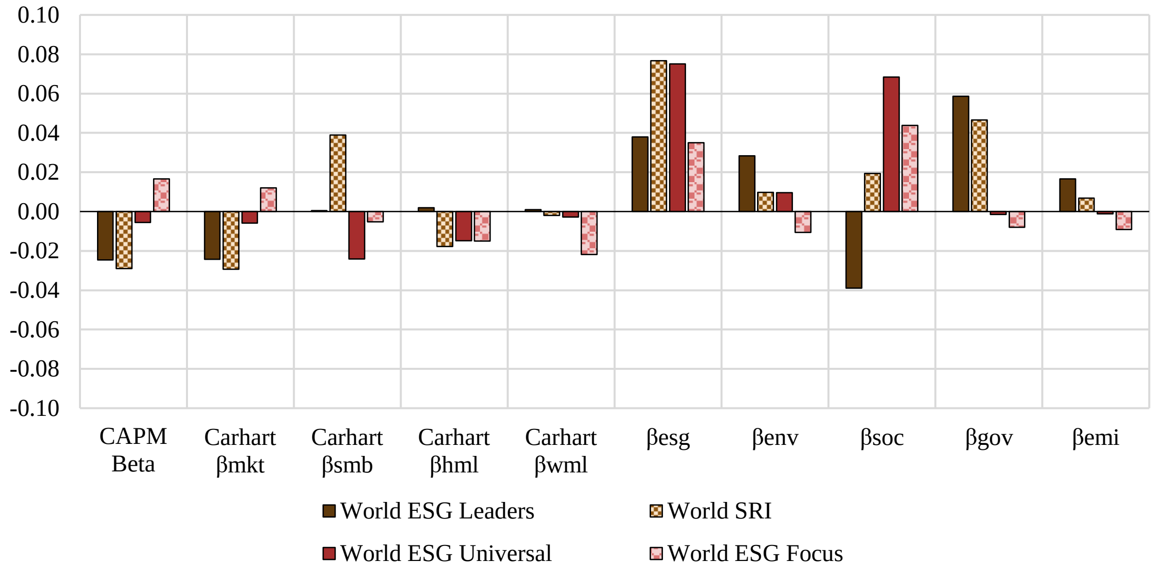
In Table B.1, we report the tilts for all of the models in equations (1) to (4). All indices show negative deviations from their parent index, i.e., they have lower systematic risk.

However, this implies that they contain higher idiosyncratic risk following equation (7). This is in line with the hypothesis that sustainability is part of stock-specific characteristics (see, e.g., Nagy et al., 2016).

[Insert Table B.1 here.]

The World SRI Index achieves the highest absolute systematic risk tilt with the Carhart model of –1.3683%. The tilt remains the highest even when accounting for the ESG factor, the three pillar factors, or the emissions factor. The lowest risk deviations are found for the World Low Carbon Leaders Index with a small tilt of, e.g., 0.0158% for the emissions factor model. We notice that the systematic risk tilt is diminished when applying the ESG, pillar factors, or emissions factor model in most of the cases. When including additional relevant factors, systematic risk rises by definition. In our case, systematic risk increases more for sustainable indices than for the parent index (i.e., the difference between the two decreases) confirming that sustainable indices are more exposed to systematic sustainable risk sources.

**Panel A. ESG indices**




**Panel B. Carbon indices**

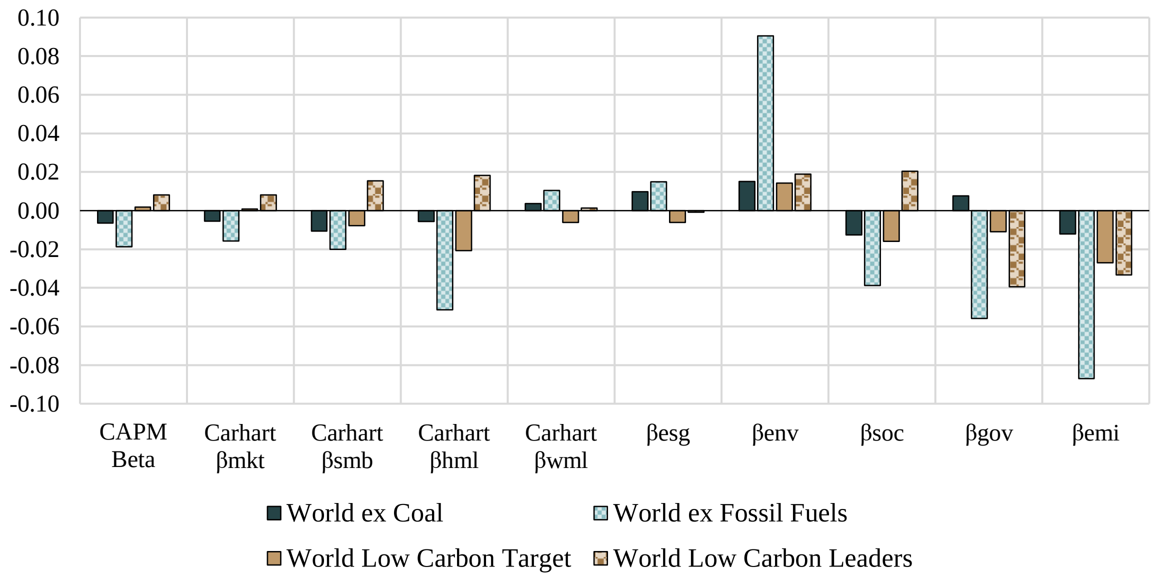



**Figure B.1**
**Index active exposures**

This figure displays active exposures of the indices compared to the MSCI World Index (the difference between the beta exposures of the index and the MSCI World Index). The Carhart βmkt, Carhart βsmb, Carhart βhml, and Carhart βwml values are estimated by a global Carhart (1997) model (equation (1)). The βesg value is the result of a Carhart model including a global ESG zero-cost portfolio (equation (2)). The environmental, social, and governance exposures (βenv, βsoc, βgov) are estimated by a Carhart model including the three ESG pillar factors (equation (3)). As a last model, we implement a Carhart model plus an emissions zero-cost portfolio to obtain βemi (equation (4)).

**Table B.1**
**Systematic risk tilts**

| | Carhart model | ESG model | Pillar factors model | Emissions model |
|---|---|---|---|---|
| World ESG Leaders | -0.6996 | -0.6885 | -0.5326 | -0.6858 |
| World SRI | -1.3683 | -1.3095 | -1.2521 | -1.3651 |
| World ESG Universal | -0.1347 | -0.0807 | -0.1067 | -0.1349 |
| World ESG Focus | -0.2370 | -0.2287 | -0.2537 | -0.2359 |
| World ex Coal | -0.0737 | -0.0741 | -0.0518 | -0.0709 |
| World ex Fossil Fuels | -0.4338 | -0.4336 | -0.3334 | -0.1721 |
| World Low Carbon Target | -0.0682 | -0.0669 | -0.0673 | -0.0477 |
| World Low Carbon Leaders | -0.0482 | -0.0481 | -0.0786 | -0.0158 |

This table reports systematic risk tilts as the difference between the systematic risk exposure of sustainable indices and the MSCI World Index. The systematic risk exposure for each index is obtained as the coefficient of determination ($R^2$) of the regression models in equations (1) to (4) with the index excess return as dependent variable. All numbers are shown in percent.

# 8 CONCLUDING REMARKS

This dissertation effectively captures the impacts of changing market expectations on asset pricing theory and finance practice. It scrutinizes underlying model assumptions and modifies traditional model setups to account for sustainability considerations. Moreover, it assesses the implications for finance practice, i.e., investment strategies and tools.

The framework of this dissertation starts with a review of the underlying assumptions of asset pricing models. Article I addresses market efficiency in the traditional context. It shows that delayed price adjustments limit market efficiency and influence the statistical properties of daily returns. In turn, the CAPM relying on a right price formation process delivers biased estimates of systematic risk. These biases can be overcome by applying techniques that correct nonsynchronous information integration into prices. Overall, the article demonstrates how to mitigate shortcomings in model assumptions to derive at better risk estimates in the investment decision process. The adjustment techniques are especially effective for portfolios formed on stock characteristics known to be sensitive towards price adjustment delays. The rising demand for style portfolios, such as small cap investing, increases the need to adopt these techniques. Analyses on how common portfolio strategies change when taking delayed price adjustment into account are to be conducted in future work. The existence of market frictions in the sense of price adjustment delays in other stock markets not part of this study and spillover effects between markets constitute other interesting fields for future research.

Article II examines the assumption of rational investor behavior. Investors do not act rationally but exhibit biases in their decision making under uncertainty (see, e.g., Kahneman and Tversky, 1979; De Bondt and Thaler, 1995). Article II provides evidence on herding behavior of institutional investors. This behavior occurs in light of the decarbonization movement, i.e., investors follow buy trades of green stocks and sell trades of brown stocks.

Sophisticated investor groups lead the herd, which is in line with expectations that others follow sophisticated investors since they expect them to have superior information and skills (Eichengreen et al., 1998). In addition, reputational concerns and the tie to social norms might be responsible for following the decarbonization movement. Overall, this article provides a description of investor behavior in a sustainability-related context and points out potential motives for it. Therefore, the article contributes to a better understanding of sustainable investment decisions in the financial market. More profound analyses on why this investor behavior occurs and its impacts on prices have to be carried out in future studies. Additionally, these behavioral patterns of investors might be useful to lead the financial market towards more sustainable actions by directing respective measures at the leaders of the herd. The impacts of such potential measures, however, still have to be determined.

Political movements, societal preferences, and a changing perception of risk sources with regard to sustainability considerations lead to reassessed foundations for price formation processes. Article III demonstrates that asset pricing models need to be adjusted to integrate these revised expectations as they influence asset prices. The carbon risk factor Brown-Minus-Green (BMG) accomplishes this aim and mirrors carbon risks while significantly determining variation in returns. Since the market is not in an equilibrium state yet, the factor does not demand a premium. The methodology developed in this paper adds to the understanding of carbon risk and provides a way of measuring carbon risk exposure of financial assets without the need for carbon- and transition-related data. Moreover, the measurement approach can be adjusted to fit individual needs. All market participants can thus derive their individual carbon risk exposure to better understand the role of carbon risk in their strategies. At the same time, new insights on sustainability ratings and larger data time series can be used to calibrate the approach further. For example, the scoring approach for determining a firm’s brownness or greenness can be refined by taking ratings disagreement into consideration (Dimson et al., 2020;

Berg et al., 2020; Gibson et al., 2020). For a more timely assessment of sustainability risks, a daily model setup is feasible. To increase the model's accuracy in this case, the impact of delayed price adjustments has to be taken into account. This case is left for future work. Moreover, as soon as expectations of market participants derive at a consensus and an equilibrium state emerges, carbon risk might demand a risk premium. This hypothesis is to be tested in future research.

Integrating sustainability in investment practices requires a deeper analysis of practical strategies and their implications. Article IV focuses on portfolio strategies and shows that both brown and green stocks are exposed to high risk but differ in their return patterns. These patterns are driven by differing factor exposures. When implementing screening strategies to reach a certain threshold value of carbon risk exposure, investors are confronted with lower risk-adjusted performance. Best-in-class approaches on sector level demonstrate that investors do not have to forgo investments in certain sectors to integrate carbon risk. Last, best-in-class strategies on country level reveal that a European stock portfolio is greener than an American portfolio. This article about carbon risk integration on portfolio level emphasizes the interrelation between a stock's greenness or brownness with other risk and return characteristics. Furthermore, the construction methodology of the carbon risk measurement tool influences the nature of this interrelation. Hence, portfolio managers need to apply due diligence when integrating carbon risk into their investment strategies. For future research, a comparison of different carbon risk measurement tools and their impacts on portfolio management strategies can contribute to a more effective alignment of capital flows and investment objectives.

Article V moves towards the analysts' perspective and investigates the impact of carbon intensity on stock valuation processes by focusing on the COVID-19 crisis and post-crisis period in 2020. Carbon-intensive stocks had to face lower returns during the intense COVID-19 period in early 2020. However, in the following recovery period, they could achieve higher performance relative to the pre-crisis period allowing them to recoup their additional incurred losses in the crisis period. From a risk perspective, carbon intensity impacted stock risk positively in the recovery period. The discussions about green economic stimulus packages coupled with an increased exposure towards stranded assets and climate policy uncertainty might have increased the risk of carbon-intensive assets. This circumstance also justifies the occurrence of higher returns for carbon-intensive stocks, i.e., a carbon premium. The article emphasizes the importance to take climate risk into account for sound risk management strategies. Furthermore, these results enable better risk assessments for financial analysts and thus more profound forecasts and recommendations. Stimulus packages targeted at promoting more sustainable business models could lead to a strengthening influence of carbon intensity on stock analyses. This has to be tested in future work. Back-testing the results to periods when climate risk has not been as present in the markets yet and comparisons to other crisis periods, such as the financial crisis in 2008, might reinforce the assumption that carbon intensity has recently established itself as a fundamental influencing factor in stock valuation processes.

The last article covers sustainable market tools that should guide successful capital allocation towards sustainable activities. Article VI provides a customizable step-by-step framework for analyzing the sustainable index landscape. Besides traditional return and risk indicators, the approach assesses the ESG profile of indices taking different ESG definitions into account. Furthermore, index-specific return and risk drivers are identified via a regression framework with sustainability factors. Last, the index strategy is evaluated by a performance attribution analysis based on sustainability-related stock classes. Overall, the analyses provide customizable guidelines for market participants on how to assess the efficacy of sustainable indices concerning sustainability aspects. In specific, they support investors in their decision-making process for sustainability integration and thus allow a more informed and effective resource allocation in line with an individually desired level of sustainability exposure. In the future, a reshaping of the sustainable index landscape is to be expected as soon as index providers start in complying with the standards introduced by the European Commission (EU Technical Expert Group, 2019). An empirical comparison between existing indices and provisional benchmarks aligned with these standards can improve the transparency of the sustainable index landscape further.

In its entirety, this dissertation increases the understanding of price formation processes and defines a holistic concept for capturing the interconnection between sustainability considerations, asset pricing theory, and finance practice. In this way, financial market participants gain deeper knowledge of sustainability-related influences and make more informed investment decisions.

In summary, sustainability considerations should no longer be perceived as isolated and subordinate decision-making parameters but as indispensable determinants of investment processes. In practice, however, they are not yet a standard integral component of financial decision making. Among investors, data issues remain a key barrier to an adequate integration of sustainability in investment practices: poor quality or availability together with a lack of standardized reporting of sustainability metrics impede an efficient use (see, e.g., BlackRock, 2020; Amel-Zadeh and Serafeim, 2018). Furthermore, the real impacts of sustainable investing on the environment and society often remain uncertain (Kölbel et al., 2020; Wilkens and Klein, 2021). Studies on how and to which degree investments achieve sustainable targets could drive more purposeful investment decisions. In short, more transparency on sustainable data and impacts of sustainable investing is needed.

Access to consistent, high-quality, and encompassing information about sustainability and its implications will increase market efficiency and thus support a more profound reallocation of capital with regard to sustainability-related influencing factors. The framework and insights from this dissertation are at the forefront of filling this gap and pave the way for further necessary research. At present, financial market participants are not doomed to inaction. The accelerating shift towards sustainable investing opens up new opportunities for each financial market participant – from the ordinary private investor to large financial institutions – to reshape their investment approach in an effective and forward-thinking way.

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